LONDON'S GLOBAL UNIVERSITY

Doctoral Thesis

Through a Model, Darkly: An Investigation of Modellers' Conceptualisation of Uncertainty in Climate and Energy Systems Modelling and an Application to Epidemiology

Luke David Bevan

Department of Science, Technology, Engineering and Public Policy
Faculty of Engineering Sciences

and

UCL Energy Institute
Faculty of the Built Environment

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy at University College London, UK.

This thesis consists of 99,889 words, excluding front matter, appendices.

This version of the thesis is formatted to be printed on double-sided A4 paper.

Declaration of Authorship

I, Luke David Bevan, confirm that the work presented in this Doctoral Thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in this thesis.

The following work of the author is partially integrated into this thesis and was undertaken throughout the time that the author was registered at UCL working towards the completion of this thesis.

- Bevan, L.D. 2022. "The ambiguities of uncertainty: A review of uncertainty frameworks relevant to the assessment of environmental change." Futures, 137, https://doi.org/10.1016/j.futures.2022.102919
- Bevan, L., Milne, G., 2021. Towards an Uncertainty Taxonomy for Epidemiological Models. [Working Paper] https://doi.org/10.13140/RG.2.2.26804.78722

Luke D. Bevan

London, 1st July 2022

Abstract

Policy responses to climate change require the use of complex computer models to understand the physical dynamics driving change, to evaluate its impacts and to evaluate the efficacy and costs of different mitigation and adaptation options. These models are often complex and built by large teams of dedicated researchers. All modelling requires assumptions, approximations and analytic conveniences to be employed. No model is without uncertainty.

Authors have attempted to understand these uncertainties over the years and have developed detailed typologies to deal with them. However, it remains unknown how modellers themselves conceptualise the uncertainty inherent in their work.

The core of this thesis involves the interviews of 38 modellers from climate science, energy systems modelling and integrated assessment to understand how they conceptualise the uncertainty in their work. This study finds that there is diversity in how uncertainty is understood and that various concepts from the literature are selectively employed to organise uncertainties.

Uncertainty analysis is conceived as consisting of different phases in the model development process. The interplay between the complexity of the model and the capacities of modellers to manipulate these models shapes the ways in which uncertainty can be conceptualised. How we can attempt to wrangle with uncertainty in the present is determined by the path-dependent decisions made in the past; decisions that are influenced by a variety of factors within the context of the model's creation.

Furthermore, this thesis examines the application of these concepts to another field, epidemiology, to examine their generalisability in other contexts.

This thesis concludes that in a situation such as climate change, where the nature of the problem changes in a dynamic way, emphasis should be placed on reducing the grip of these path dependencies and the resource costs of adapting models to face new challenges and answer new policy questions.

Impact Statement

The benefits to the research base that this confers are, I hope, manifold. As an interdisciplinary piece of work, it speaks to several bodies of literature, but is best categorised as part of the loosely-defined field of 'uncertainty studies'. It is hoped that it is of use to philosophers of science, energy systems modellers, climate scientists and integrated assessment modellers.

The literature review conducted as part of this thesis that examines the different frameworks for uncertainty available in the literature is by far the most extensive and complete of its kind. As such, I hope that it provides a useful starting point for others entering this field and allows some sort of consolidation in the practice of creating uncertainty frameworks.

This review has been used to frame discussions around uncertainty by colleagues working with Westminster City Council, the Department of Business, Energy and Industrial Strategy (BEIS) and the Department for Levelling Up, Housing and Communities (DLUHC). Additionally, I have presented the findings of the paper to a workshop on modelling for Net Zero attended by civil servants from BEIS, the Defence Science Technologies Laboratory (DSTL) and the Climate Change Committee (CCC).

Methodologically I have taken a novel approach to interviewing in which mental models methods have been adapted to explore philosophical concepts as used in practice. Such an approach could have value to other researchers exploring the operationalisation of other concepts in research practice.

The evidence base produced is intended to begin more evidence-based discussions on how uncertainty is conceived of. The recommendations of this thesis may help researchers and funders of research better organise modelling efforts to explore particular kinds of uncertainty. I further intend to increase this academic impact by deriving additional scholarly articles from the contents of this thesis.

Outside of academia, I would argue, the ideas in this thesis have already achieved impact. Many of the ideas herein I operationalised whilst seconded to the Joint Biosecurity Centre (now UKHSA) whilst working on modelling issues directly analogous to the ones my participants are working on. I instituted several systems for model documentation informed by my research practice that have persisted within government and are used to understand and categorise the latest classes of pandemic models used by the UK Government. Further to this, my understanding of the practice of uncertainty exploration in Multi-Model Ensemble building has informed the communication of model results.

Acknowledgements

When one sets out to do a PhD they generally hope to expand the frontier of knowledge. In many ways, doing a PhD on uncertainty I hope that I have extended the frontier of our knowledge about knowing we don't know.

There are numerous people to thank without whom this thesis would not have been possible or indeed enjoyable to write. I would like to thank some of them below, though there are numerous more who I may omit. I am most grateful for all.

Firstly, I must thank my supervisors Prof Arthur Petersen and Dr Will McDowall for their patience and sage support over the years. Arthur is inspiring in his fearlessness at striding across multiple disciplines and being at ease on most any topic area. Conversations with Will have unfailingly illuminated perspectives I had not considered and have been crucial in helping me organise the maelstrom of uncertainty issues. They formed a truly complimentary supervision team, which I know how very lucky I am to have had to support me.

I would not have departed on this PhD adventure were it not for the encouragement and support of the people I worked with whilst at Imperial College: Dr Mark Workman, Dr Thomas Colley well as those that the Grantham Institute and Centre for Climate Finance and Investment (CCFI), including Prof Charlie Donovan.

STEaPP is a truly unique department and being around so many interesting people motivated about topics that truly matter has been a balm to my anxieties about disciplinary homelessness. The department has undergone many changes since I joined and there are many STEaPPle I need to thank (has no one used that awful pun before?). I thank all the academic staff with whom I have had stimulating conversations over the years: Prof Jo Chataway, Dr Chris Tyler, Dr Adam Cooper, Prof Rear Admiral Neil Morisetti, Dr Leonie Tanzcer, Dr Irina Brass, Dr JC Mauduit, Dr Jenny McArthur, Dr Julius Mugwagwa, Prof Sir Geoff Mulgan, Prof Yacob Mulugetta, Dr Lucas Somavilla, Dr Carla-Leanne Washbourne. STEaPP has been a tremendously supportive environment and unique in the kinds of opportunities it presents. Special thanks to Dr Ine Steenmans for all the advice, support and opportunities that she has sent my way over the years.

The department is very lucky to have great professional service staff who have been endlessly helpful over the years. My particular thanks go to Robert Ebsworth (you'll be glad not to receive any more emails about my fees admin!), Ayden Wilson, Alan Seatwo, Laura Pullen, Siobhan Pippa, Jasmina Cubra and Joe Fitzsimmons.

The milieu at STEaPP is nought without all the fantastic Doctoral Candidates, past and present. I thank Dr Jeremy Webb for the advice and being a great companion at Cop23. I thank Dr Andy Kopp for the wisdom and for always being a fountain of practical knowledge. Others who have shown the way before include (Doctors) Emilia Smeds, Michael Veale, Zoe Henderson, Enora Robin. I thank Joanna Sawkins for being a great colleague at the beginning of the PhD.

There are great present students who no doubt will ace their PhDs. I thank George Salter for the mental and physical workouts, I hope you can find a decent conversationalist to replace me at my desk. I thank Anina Henggeler for her help navigating the world of the JBC. Laurent Liote has always been a conscientious friend. I thank Wafa Elahi for all the joyous conversation, and Yasmina El Amine for encouraging me to express gratitude. I also thank Mai Idris, Chloe Colomer, Basil Mahfouz, Stefan Wolf Stärtzel, Jamie Tooth and Remy Twirngiyimana.

The atmosphere in the department is also made all the better by sharing space with the department of Security and Crime Science (SCS). I thank the STEaPP/SCS "Piglets" for all the camaraderie. It would be good to see some academic collaborations emerge in time! Hopefully, our reading retreat to Snowdonia is the first of many such adventures.

Without data, a thesis is little more than conceptualisation and lit review. My humble thanks to all my unnamed participants who gave up their time to have strange conversations about models and uncertainty! Their passion for their work was always inspiring. Throughout my conversations, I was left with a strong impression of the conscientiousness of their efforts and the importance of their work.

I would like to thank my former colleagues at JBC/ UKHSA for sharing a strange and vital part of all our lives: these include Josie Park, Jasmina Panovska Griffiths, James Hetherington, the rest of the Ensemble Modelling team. I thank other colleagues, Jobie Budd, Isabel Bennett, Balint Stewart, Andrew Engeli, Tim Chadborn and Astrid Bessler. Special thanks to Greg Milne for helping me with a working paper that became chapter 7. My thanks to Jonathan Lewis for obtaining approval for material included in chapter 8.

I thank the UBEL DTP programme and the Economic and Social Research Council (ESRC) for their generous support with my studentship and fees (grant number 1923238).

Outside of academia, I have many people to thank. My friends: I hope you can read this and find out what Bevan was up to all along. Thanks to my flatmates past and present Apoorva Joshi, Kelly Brotherhood, Reiss Wood, Henry Edwards, Julia Ollila, Kaley Pak and Alex Bish. Other friends are too numerous to mention; but I hope you will recognise yourself and know your support does not go unnoticed.

The love and support of my partner, Flora Charbonnier, has been a constant throughout my studies. Academically; I can only hope that her immense discipline and conscientiousness have rubbed off on me. Personally; she has always there to pick me up when I was down and to carry me when I could not walk. I would also like to thank Flora's family for the kindness and love they always show me.

My family are my bedrock. I thank my parents David and Annette, whose love and belief in me is always a vaccination against any imposter syndrome. The dedication and perseverance of my brother, Christian, is always an inspiration to me. I thank you for your support.

These past years have not been without tragedy. The devastating loss of Robert Frome in 2019, taken from us in a mountaineering accident, brought me low. Without the love of all those mentioned above the grief would have been too great. To those that were there for me then, I thank you.

London, July 2022

In memory of Robert Frome

A great friend who taught me not to fear the unknown.

Through a Model, Darkly

An Investigation of Modellers' Conceptualisation of Uncertainty in Climate and Energy Systems Modelling and an Application to Epidemiology

Luke David Bevan

Table of Contents

Detailed Table of Contents

List of Figures

List of Tables

List of Boxes

List of Acronyms and Initialisms

ABM	Agent Based Model
AC	Air Conditioning
AFOLU	Agriculture, Forestry and Other Land Use
AMOC	Atlantic Meridional Overturning Circulation
ANT	Actor Network Theory
AOGCM	Atmosphere-Ocean General Circulation Model
BECCS	Bioenergy Carbon Capture and Storage
BEIS	Business Energy and Industrial Strategy (UK Government Department)
BME	Bayesian Model Averaging (method for model result combination)
CanESM	Canadian Earth System Model
CCAM	Conformal Cubic Atmospheric Model (at CSRIO)
CCS	Carbon Capture and Storage
CCSM	Community Climate System Model
CDR	Carbon Dioxide Removal
CESM	Community Earth System Model
CGE	Computable Generalisable Equilibrium
CI	Confidence Interval
COP	Conference Of Parties
CSIRO	Commonwealth Scientific and Industrial Research Organisation (Australia)
DECK	Diagnostics, Evaluation and Characterisation of Kilma
DMDU	Decision-Making under Deep Uncertainty
ECMWF	European Medium-Range Weather Forecasts
ECR	Early-Career Researcher
ECS	Equilibrium Climate Sensitivity
EMF	Energy Modelling Forum
EPA	Environmental Protection Agency (United States)
ESM	Earth System Model
ESOM	Energy System Optimisation Model
GAMS	General Algebraic Modeling System
GCM	General Circulation Model
GCAM	Global Change Analysis Model (PNNL's IAM)
GDP	Gross Domestic Product

GHG	Greenhouse Gas
GLS	Generalised Least Squares
HIPPO	Highest Paid Person's Opinion
HPC	High-performance Computing
IA	Integrated Assessment
IAM	Integrated Assessment Model
ICE	Initial Condition Ensemble
ICLE	Initial Condition Large Ensemble
ICU	Initial Condition Uncertainty
iESM	Integrated Earth System Model
IIASA	International Institute of Applied Systems Analysis
IMAGE	Integrated Model to Assess the Global Environment (PBL's Integrated Assessment Model)
IMC	Inter-Model Comparison
IPCC	Intergovernmental Panel on Climate Change
JBC	Joint Biosecurity Centre (now part of UKHSA)
LCA	Life Cycle Assessment
LE	Large Ensemble
LHS	Latin Hypercube Sampling
MAGICC	Model for the Assessment of Greenhouse Gas Induced Climate Change
MARKAL	Market Allocation (An Energy System Optimisation Model)
MCMC	Markov Chain Monte Carlo
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact (IIASA's IAM)
MIP	Model Intercomparison Project
MGA	Modelling to Generate Alternatives
MLE	Maximum Likelihood Estimation (method for fitting linear models)
MMC	Multi-Model Comparison
MME	Multi-Model Ensemble
MNP	Mileu- en Natuurplanbureau (Netherlands Environmental Assessment Agency, from 2002–2008)
MOOC	Massive Online Open Course
NEIS	National Institute for Environmental Studies (Japan)

NOAA	National Oceanic and Atmospheric Administration (United States)
NPI	Non-pharmaceutical Intervention
NRC	National Resource Council
NSF	National Science Foundation (United States)
NUSAP	Numerator, Unit, Spread, Assessment, Pedigree
OAT	One-At-a-Time (Sensitivity Analysis)
OLS	Ordinary Least Squares
OMOV	One Model One Vote (approach to model weighting in an ensemble)
PBL	Planbureau voor de Leefomgeving (Netherlands Environmental Assessment Agency, from 2008)
PDF	Probability Density Function
PIK	Potsdam-Institut für Klimafolgenforschung (Potsdam Institute for Climate Impact Research)
PNNL	Pacific Northwest National Laboratory (United States)
PNS	Post-Normal Science
PPE	Perturbed Physics/Parameter Ensemble
RCP	Representative Concentration Pathway
RDM	Robust Decision-Making
REML	Restricted Maximum Likelihood (method for fitting linear models)
REMIND	Regionalized Model of Investments and Technological Development (PIK's IAM)
RIVM	Rijksinstituut voor Volksgezondheid en Milieu (Netherlands National Institute for Public Health and the Environment)
SCC	Social Cost of Carbon
SMILE	Single-Model Initial Conditions Large Ensemble
SPI-M	Scientific Pandemic Influenza Group on Modelling
SRES	Special Report of Emissions Scenarios
SSP	Shared Socioeconomic Pathway
SST	Sea-Surface Temperature
TIMES	The Integrated MARKAL-EFOM System (An Energy System Optimisation Model)
TQF	Total Quality Framework
UA	Uncertainty Analysis
UKHSA	United Kingdom Health Security Agency

UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
UQ	Uncertainty Quantification
WAIFW	Who Acquires Infection from Whom
WCRP	World Climate Research Programme

"For now we see through a glass, darkly;

but then face to face:

now I know in part;

but then shall I know even as also I am known."

1 Corinthians 13:12

1 Introduction: The Many Faces of Uncertainty

1.1 Chapter Summary

The planning of mitigation and adaptation approaches to anthropogenic climate change requires the modelling of global climate and energy systems. All modelling necessitates assumptions to be made so that target systems may be conveniently represented; however, when modelling of coupled natural-social systems, systemic uncertainties abound and decision risks associated with climate change are extremely high. Consequently, uncertainties must be handled with rigour.

Uncertainty itself is a multifaceted topic that is subject to many conceptualisations. This thesis examines the conceptualisations of climate modellers, energy systems modellers and integrated assessment modellers using an interview study. It examines the key types of uncertainty identified by these participants and how they distinguish between different aspects of uncertainty. It also examines contextual factors from the participants' practices and how these shape the handling of different kinds of uncertainty, and it builds a picture of how these uncertainty handling practices can be better understood in the context of model development.

This first chapter, the introduction, lays out the agenda for the thesis. It begins by describing the problem context and the role that evidence from modelling climate and energy systems has come to play in policy. It describes the selection of acute issues arising from the various uncertainties at play and the possibilities of multiple interpretations of these uncertainties. It then argues for an approach that studies the conceptualisations of these uncertainties through engaging with modelling practitioners themselves. Finally, it gives an overview of the forthcoming chapters of the thesis.

1.2 Problem Context

This section gives an overview of the context of climate-related modelling, the thematic focus of this thesis. It begins by outlining how a set of complex modelling tools have emerged to model the climate and the impacts of climate change and to assess the viability and desirability of different mitigation strategies. These tools necessarily try to explore possible futures to inform action in the present. As with all modelling tools, these models are imperfect and rely on uncertain assumptions and limited data. These uncertainty issues are made even more important considering the complexity and the cost of the actions that are required to mitigate anthropogenic climate change, on the one hand, and to adapt to climate change (depending on, among other factors, the extent of mitigation), on the other hand.

The uncertainty problem is made even more challenging as different disciplines must come together to synthesise their findings, both in assessments, in government advice and indeed in models themselves. The nature of uncertainty in different areas of study is, of course, very different and hence different kinds of knowledge may be challenging to synthesise.

In the first two subsections (§1.2.1 & §1.2.2) I give a very brief account of climate modelling and energy modelling and the role that they play in informing critical policy decisions. I then describe the important role that these play in informing policymaking at different levels of government and the associated issues with the uncertainty that have been identified by authors at the boundaries between disciplines (§1.2.3).

1.2.1 Climate Modeling

Climate modelling has advanced from simple origins to include many complex computer models that simulate not only the evolution of the atmosphere, but other elements of the earth system coupled to the atmosphere such as the oceans, land, and ice sheets. These massive computer models require years, nay decades, of development by dedicated specialist teams collaborating with researchers across the world.

Climate models fulfil a variety of functions in knowledge production. Perhaps most prominently they predict the response of the climate system to anthropogenically forced changes due to the emission of greenhouse gases (GHGs). This is a persistent high-level goal of the models, but they also provide granular regional information regarding changing weather and climate patterns such as wind fields, humidity, precipitation, and temperature. All these predictions are necessarily conditional on the model and its inputs, and the true trajectory of future anthropogenic GHG emissions cannot be known.

In this section, I briefly give an overview of these models, the context of their emergence, the current state of the world's climate models and the unique challenges they face in assessing uncertainty when providing policy-relevant information.

1.2.1.1 An Extremely Short History of Climate Modelling

Climate modelling can be argued to have ancient roots. Edwards (2011) traces the most primitive climate models to early conceptual models of the atmosphere espoused by Greek philosophers such as Eratosthenes and Ptolemy[1]. The earliest forms of conceptual climate models that took into account the chemical composition of the atmosphere were from the 19th century, with models such as John Tyndall's informed by his experiments on the heat radiative properties of gasses (Edwards, 2011; Tyndall, 1861).

> *"Now if, as the above experiments indicate, the chief influence be exercise by the aqueous vapour, every variation of this constituent must produce a change of climate. Similar remarks would apply to the carbonic acid[2] diffused through the air; while an almost inappreciable admixture of any of the hydrocarbon vapours would produce great effects on the terrestrial rays and produce corresponding changes of climate." - Tyndall (1861, p. 28)*

Further development occurred with physical analogue models. In the late 1800s, energy balance models emerged that described mathematically the relationship between outgoing and incoming radiation and how this drives climatic conditions (Edwards, 2011, p. 129). A notable example of early energy-balance climatology involved Swedish scientist Svante Arrhenius's 1896 calculation that a doubling of atmospheric carbon dioxide levels would increase global temperature by 5-6˚C. His findings suggested that as CO_2 concentrations increase geometrically, the temperature would increase arithmetically (Crawford, 1997).

Energy balance models in the early 20th century developed to include physical factors such as albedo. The spatial dimensionality of these models also increased with the advent of radiative–convective models which considered energy flows between layers in the atmosphere (and sometimes energy transfers in longitudinal directions). With increasingly detailed spatial

---

[1] Who deduced that the earth was round and that the inclination of the sun in different climatic zones affected climate (Edwards, 2011).

[2] Carbon dioxide.

descriptions of the atmosphere, equations were developed to describe the hydrodynamic and kinetic states of interacting parcels of the atmosphere by Vilhelm Bjerknes (Edwards, 2011, pp. 129–130). However, these equations did not have exact solutions and manual methods of calculation were prohibitively laborious. With the birth of the computer after the Second World War, computational methods initially developed for weather modelling were extended to long time scales, and the first General Circulation Models[3] (GCMs) were born, the first being at Norman Phillip's Princeton Laboratory in 1955.

The basis of GCMs involves the partition of the atmosphere into three dimensional parcels, most commonly rectangular in latitude-longitude and with varying number of height layers, and the simulation of chemical, fluid and thermodynamic interactions of these parcels. Of particular importance are advances in the study of radiative transfer through layers of the atmosphere[4]. Some models since then have rejected the description of the spherical surface in grid form in favour of representing spatial patterns in terms of the phase space of interacting harmonic waves of atmospheric motion (Edwards, 2011).

The further development of these GCMs has expanded their representation of elements of the physical earth system in sub-grid scale 'parameterisations'[5], such as atmosphere–ocean interaction, cloud microphysics and atmospheric chemical interactions. These parameterisations may be extensive and are highly consequential for the ways in which different climate models produce different results. Of particular importance are cloud parameterisations due to the role of clouds in moving mass around the atmosphere, producing precipitation, reflecting radiation and a host of other mechanisms (IPCC, 2007).

---

[3] These may also be referred to by some as "Global Climate Models", though the acronym remains the same.

[4] The study of radiative transfer through atmospheric layers constitutes a major separate field of research. Models, sub-models and/or codes that simulate radiative transfer are both produced in a standalone fashion and incorporated into large climate models. These models may calculate the absorption and emission of one spectral line (a short spectral interval) and integrate the results across the spectrum. Such modelling projects are also subject to intercomparisons such as in the Intercomparison of Radiation Codes in Climate Modelling (IRCCM, now historic) (Ellingson and Fouquart, 1991), the Continual Intercomparison of Radiation Codes (CIRC) (Oreopoulos et al., 2012) or the Radiation Transfer Model Intercomparison (RAMI, for radiation near the terrestrial surface) (Joint Research Council, 2019).

[5] As the grid sizes of climate models are finite, several important processes that have characteristics over finer scales must be parameterised. Examples of these include cloud physics and atmosphere–surface interactions (IPCC, 2007).

1.2.1.2 The Current State of GCM Modelling

The most important recent development in climate modelling has been the coupling of GCMs to other modelled elements of the planetary system, as in the case of Atmosphere–Ocean Coupled[6] General Circulation Models (AOGCMs). Nowadays, many highly computationally complex models are available and compared with each other in efforts such as the Coupled Model Intercomparison Project (CMIP), currently in its sixth iteration alongside the Intergovernmental Panel on Climate Change's (IPCC) sixth assessment report, with the contribution from WGI released in 2021 (Eyring et al., 2018; IPCC, 2021). CMIP6 consists of 100 distinct climate model realisations developed and run by 49 different modelling groups around the world (Hausfather, 2019).

Aside from the large GCMs, various more specialised climate models exist, such as Regional Climate Models (RCMs) and Earth System Models of Intermediate Complexity (EMICs). RCMs provide more detailed descriptions of the atmosphere of limited areas of the earth's surface. They can provide more granular descriptions of climatic patterns over detailed topographic features and richer information regarding variables such as near-surface wind speed (Feser et al., 2011). EMICs allow the future of the climate system to be explored with a reduced computational cost, albeit with lower spatio-temporal resolutions. This can enable longer-term forecasts or greater numbers of model runs for different scenarios (Claussen et al., 2002).

1.2.1.3 Uncertainty and Climate Models

GCMs are incredibly complicated technological artefacts. No individual modeller could possibly understand the entirety of the workings of a GCM and as such they are epistemically opaque. Given the complexity of these objects and the importance of their results to our understanding of the earth's climate system it is necessary to consider how uncertainty analysis can be performed and how one can conceptualise the uncertainties inherent in the process of model building.

Over recent decades climate modellers have wrestled with uncertainty, considering how to quantify, analyse and communicate the uncertainty of their results to a variety of audiences, lay and specialist. However, the march of technological complexity continues apace with recent

[6] The coupling of oceans is of great importance due to, for instance, its function as a massive store of heat energy.

calls to increase the detail of climate models using exascale computing (Paulsen, 2020). Given the complicated and diffuse distribution of epistemic agency, it is still an open question how one can best conceptualise uncertainty in a climate model.

1.2.2 Energy Modelling and Integrated Assessment

Energy models are a vital instrument for policy and decision-makers. The fates of climate modelling and energy modelling have collided, to a degree, in integrated assessment modelling.

In this subsection, I briefly chart the history of energy modelling and the current state of energy and integrated assessment modelling. I then consider the importance of understanding uncertainty in these models in order that policymakers may be better informed as to the information that they provide. Both modelling areas overlap significantly in their modelling of emissions pathways and their consequences. The personnel involved in these two modelling areas also overlap significantly.

1.2.2.1 A Very Short Overview of Energy Systems Modelling

Energy models are very structurally diverse technological objects adapted to many problem contexts. This thesis is concerned with those energy models that take a systemic perspective on the energy system either nationally or internationally. For brevity, henceforth, when referring to energy models, this thesis means specifically these whole energy systems models.

Perhaps the most significant classification that can be made between different energy systems models is that of fundamental approach, namely those which are *bottom-up* and those which are *top-down*.

The development of top-down or macroeconomic models was initially motivated to allow energy companies and governments to respond to rapidly rising energy demands in the 1950s (Herbst et al., 2012). This is somewhat of a simplification for many models, but a typical top-down model may begin with macroeconomic considerations (such as Computable General Equilibrium[7] models (CGE)). Such models may represent the economy in broad sectorally

[7] CGE models do produce some optimising behaviour as they may optimise with changing elasticities (parameters determining some behavioural response). However, they are conventionally separated from optimisation models due to their different model structure with a focus on inter-sectoral interactions.

aggregated terms and consider monetary flows, energy demand and supply dynamics with implications for macroeconomic outcomes such as trade and growth. These, however, may struggle to simulate the dynamics of specific energy technologies and the effects of detailed policies at sectoral levels (Helgesen, 2013; Herbst et al., 2012).

Bottom-up or process-oriented energy models were first developed in the wake of the 1973 oil crisis to examine the potential of different energy sources and technologies to provide energy security under volatile hydrocarbon prices (Herbst et al., 2012). They often describe detailed techno-economic processes and can simulate the detailed effects of the introduction and prices of new technologies and the engineering performance of these technologies. This can then be used to evaluate the cost implications of possible policy options. They suffer from several shortcomings such as an inability to simulate structural impacts to economies such as employment (Helgesen, 2013; Herbst et al., 2012).

Within these two broad categories of models there are sub-types that can be adapted to various purposes and that assume different ontologies. Table 1-1 presents a typology of energy systems models adapted from Helgesen (2013), among others.

Table 1-1: Typology of prevalent Energy Systems Models. Sources: Helgesen (2013) Figure 1 and pages 8,9; (Herbst et al., 2012) (Meadows et al., 1972), (Guevara and Domingos, 2017), (Bhattacharyya and Timilsina, 2010)

Architecture	**Model Type**	**Description**	**Examples**
Bottom-Up (Process-based)	Optimisation	These evaluate different combinations of technology options and optimise for outcomes such as price. These models typically require data or estimates of energy technology costs to perform the optimisation. Resulting optimisations may not account for market imperfections.	TIMES/MARKAL, MESSAGE, PRIMES
	Simulation	This covers a very heterogenous class of models that generally attempt to replicate the relationships between system elements such as energy demand and energy technologies. This class can also include some game-theoretic models.	ENPEP, POLES, REEPS, MURE
	Accounting	These model technological development by making several exogenous assumptions. Some consider these models to be a sub-set of simulation models.	MAED, MED-PRO, BUENAS, LEAP, NIA
	Multi-agent	A broad class of models involving the simulation of agent behaviour which thus can simulate market imperfections. These are more popular in electricity planning and have seen limited application to whole models of final energy use.	LIBEMOD, PowerACE
	Partial Equilibrium	These are like CGE models (see below), but in this case only one sector or subsets of sectors. These may include aspects of other	WEM, PRIMES

		model ontologies such as agent-based objective functions.	
Top-Down (Macroeconomic)	Input-output	These follow monetary and product flows through different economic sectors. Ideally suited to the short-term evaluation of policies as they describe current economy using historical data.	MF-EIO
	Econometric	Based on time-series analysis tracking correlations between various economic variables. These have a strong reliance on data.	UK Department of Trade and Industry Energy Model, E3ME
	Computable General Equilibrium	Based on microeconomic theory and calculation of prices and activities in different sectors to reach economy-wide equilibrium. Often used for long term simulations. These do not include aspects such as detailed technology descriptions and market failures.	WorldScan, GEM-E3 CGE
	System Dynamic	These describe complex behaviour between elements in a system including stocks and flows. These can often be used experimentally and by interdisciplinary teams.	Limits to Growth (Club of Rome), ASTRA, TIMER (IMAGE)

The two types of models are also generally developed by different types of people: process-oriented techno-economic models are most generally employed by those with a STEM background, whereas top-down models are favoured by economists and political scientists (Herbst et al., 2012).

There is long-standing controversy as to the extent to which the two approaches, broadly characterised, are compatible and can or should be integrated (Jacobsen, 1998). There are different means of integrating models from *soft linking*, where the transfer of information is mediated by the user, to *hard linking*, where the transfer of information between models is automated with some programme, to *integration*, where the models are not run separately and continuously share information.

Energy models have been used in many ways to inform key policy decisions. A review by Hall & Buckley (2016) into the current state of energy systems modelling in the UK, both in the available academic literature and their prevalence in a set of UK Government Policy Papers, found that the MARKAL[8] family of models were the most prevalent in both sources. The MARKAL model was born in the 1970s as part of a reaction to the oil price instability of the period (Taylor et al., 2014). Typically, it optimises an energy generation technology mix for a least-cost configuration, given various constraints, such as carbon emissions.

[8] Stands for MARket and ALlocation.

The MARKAL family of models have been used as mainstream tools of policy advice in the UK since 2000, coinciding with a shift in policy concern from oil import dependency to reducing Greenhouse Gas (GHG) emissions (Taylor et al., 2014, sec. 4). MARKAL is described as having several distinct advantages as a policy advice tool over other models (Chiodi et al., 2015, sec. 2.4):

- The model is untethered to historical relationships, which allows for exploring very different forms of future energy systems.
- The technological representation is detailed, which allows a broad range of technical mitigations options to be examined.
- MARKAL optimises for cost, which fits in well with dominant cost–benefit analysis (CBA) forms of decision-making.

Modelling from the MARKAL family has played a role in the 2008 Climate Change Assessment, the Low Carbon transition plan in 2009 and the 2011 Carbon plan (Chiodi et al., 2015).

Energy systems models also play a role in other policy analysis domains outside of pure energy source cost optimisation under climate mitigation constraints. For example, Technology Innovation Needs Assessments (TINAs) have been a significant exercise in determining which Low Carbon Technologies merit funding prioritisation from the UK government (Davis et al., 2013).

1.2.2.2 A Concise Overview of Integrated Assessment Modelling

Integrated assessment modelling emerged from energy-economic modelling in the 70s, with an early policy application supporting acid rain negotiations in the 1970s. In the late 1980s, the practice was explicitly established to consider the changing climate with models such as IMAGE developed at the Netherlands National Institute for Public Health and the Environment (RIVM) (van Beek et al., 2020)[9].

Integrated Assessment (IA) and Integrated Assessment Modelling (IAM) seeks to recognise the cross-disciplinary nature of complex problems, such as climate change, by integrating the results of different disciplines (Parson and Fisher-Vanden, 1995, sec. 1). Though IA is a broad

[9] In 2006, the IMAGE team moved out of the RIVM, as part of the MNP Netherlands Environmental Assessment Agency (named PBL Netherlands Environmental Assessment Agency since a merger in 2008).

set of activities, the two fundamental tenets of IA are seen to be firstly that it uses an inter- or multi-disciplinary approach, and secondly that it must have relevance to some real-world decision-making (such as policy) (Salter et al., 2010, pp. 697–698). IA has been applied to some non-climate environmental problems, but this thesis is concerned with climate IAMs that typically link energy production, the atmosphere, and climate-change impacts.

In Integrated Assessment Modelling, models are integrated so that the outputs of one model (or 'disciplinary module' (Tol and Vellinga, 2008, p. 184)) may form the inputs of others; an illustrative example of this is Figure 1-1 which shows the model structure for an entirely fictitious IAM. Such a systemic approach provides a holistic and valuable *ex-ante*[10] approach to policy analysis (van Ittersum and Sterk, 2014, p. 102). In climate change this involves a broad category of research approaches, but typical of the genre is the simultaneous modelling of emissions, costs and impacts so that different responses to the climate problem can be evaluated (Parson and Fisher-Vanden, 1995, sec. 1). These models may represent aspects of the world as structurally diverse as the causes of GHG emissions, policy effects, the carbon cycle and the dynamics of the atmosphere[11] (Beck and Krueger, 2016, p. 268). IA approaches have been integrated into the work of the IPCC from a relatively early stage, notably in the SRES and TAR and continuing to an increasing extent in the AR4, AR5, and AR6[12].

Earth System Models (ESMs) are another class of coupled models that couple climate models with models of biogeochemical processes such as the carbon cycle or human emissions (Flato, 2011). ESMs and IAMs may themselves be coupled, as in the case of the integrated Earth System Model (iESM) (Collins et al., 2015); a matryoshka doll of models. Modelling is by no means the only method by which IA can be conducted; for example, some engage in IA through participatory methods[13] (Tol and Vellinga, 2008).

---

[10] Meaning 'before the event'. *Ex-ante* policy analysis seeks to evaluate policy options with reference to some intended future outcomes.

[11] Though these climate dynamics may be much simplified versions of the climate models discussed earlier (Beck and Krueger, 2016, p. 268). These simplified models may take as their inputs the results of much more complicated climate models.

[12] Special Report on Emissions Scenarios (2000), Third Assessment Report (2001), Fourth Assessment Report (2007), Fifth Assessment Report (2013–14), and Sixth Assessment Report (2021–22).

[13] Participatory Integrated Assessment (PIA) is a field that emerged in the latter part of the 90s. It recognises several limitations of IAM: IAM has difficulties including intentional, normative, qualitative or political aspects

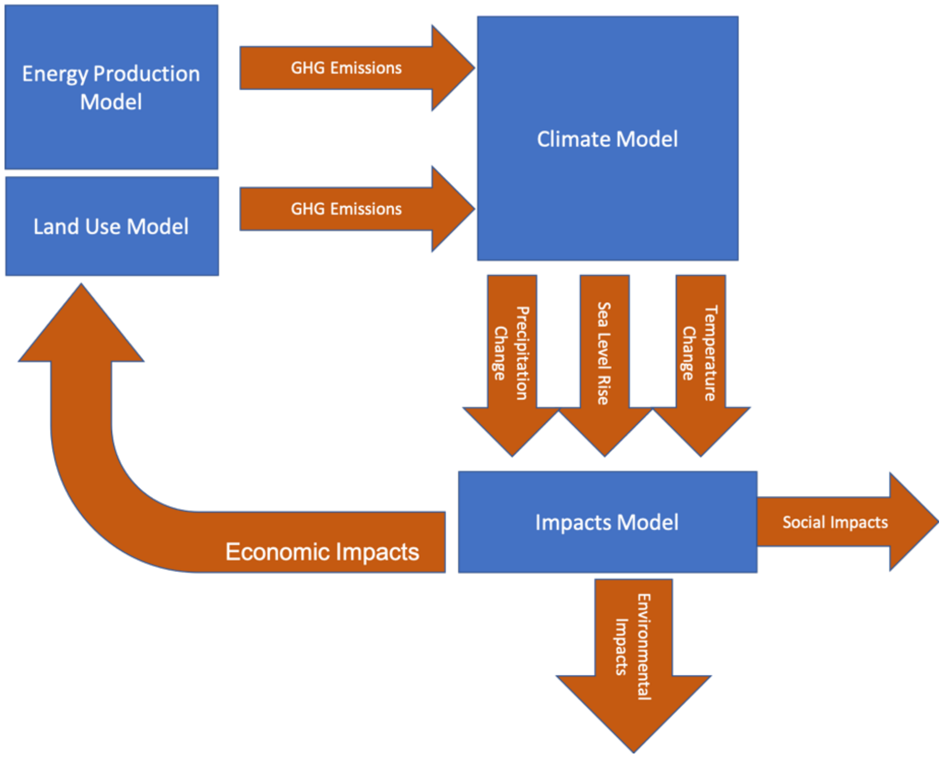

Figure 1-1: Example Integrated Assessment Model structure for purely fictitious Integrated Assessment Exercise. Blue boxes represent disciplinary modules, and orange arrows represent information flows between the disciplinary modules.

IAMs see important use as tools for policy advice on both national and international stages. Weyant (2014) describes two key uses of IAMs in policy advice: firstly, the use of IAMs in informing which emissions trajectories maximise global welfare and, secondly, their use in the calculation of the Social Cost of Carbon[14] (SCC).

of complex problems. PIA may involve different techniques, such as scenario planning and stakeholder workshops. See, for example, a review by Salter et al. (2010).

[14] The social cost of carbon is a measure of the size of the externality (the social cost (damages in this case) not included in the private price of a good) of emitting a given amount of carbon into the atmosphere i.e., a SCC of $X per tonne implies that there is a damage of $X for each tonne of carbon emitted.

A calculation of the social cost of carbon is policy relevant as advocates for a 'carbon price' may argue for it to be set at the SCC to create a Pigouvian tax (a tax that corrects undesirable market outcomes by being set to the size of the externality). Calculations of global SCC is complicated by the fact that impacts that contribute to the SCC are not homogenously distributed geographically and socially (Ricke et al., 2018). SCC analysis may also inform cost–benefit analyses of various policy options related to carbon abatement (Beck and Krueger, 2016, p. 628).

However, arguments have raged over the value of integrated assessment to policymaking and indeed what integrated assessment should fundamentally involve – policy simulation, policy optimisation (Rotmans and van Asselt, 2006)? For example, Pindyck argues both that Integrated Assessment models have "crucial flaws that make them close to useless as tools for policy analysis" (Pindyck, 2013, p. 860) and that there are fundamental issues with the ways uncertainties are handled; for instance that probability distributions are improperly applied to parameters that modellers know little about (Pindyck, 2017, p. 104). Pindyck is not alone in his criticisms of the practice, and uncertainty plays a problematic role politically and epistemically in IAM (Beck and Krueger, 2016).

1.2.3 The Problems of Uncertainty

1.2.3.1 The Centrality of Uncertainty in Modelling

The centrality of uncertainty to the scientific process has been argued widely (see for example Kirkup and Frenkel, 2006). Authors such as Nowotny (2016a) argue that uncertainty is ascendent in many of the most pressing research fields of the day. The importance of the communication of uncertainty is also critical to policy advice, with some authors claiming differential understanding of *what uncertainty is* being a particularly acute issue (Budescu et al., 2014; Shackley and Wynne, 1996; Walker et al., 2003, p. 5).

Broadly speaking, it is recognised that "every empirical claim is uncertain" (Blau, 2011, p. 360), however not all research activities are empirical. Some branches of science and academia involve extensive modelling using a variety of assumed relationships between modelled elements of natural or social systems as core research activities. In addition to the unavoidable difficulties in empirical research, we must contend with the host of uncertainties brought to the table by the process of modelling itself. These uncertainties have genesis in places such as auxiliary assumptions, idealisations, approximations, and computational limits. We must be able to understand how those constructing the models understand how models are imbued with uncertainty as they are being created, evaluated, and amended.

Uncertainty is notable in climate modelling for several reasons:

- The models are inherently complex, with nonlinear equations and high dimensionality, and are computationally laborious (Curry and Webster, 2011, pp. 1668–1669)

- The expected lifetime that a model will be used for is shorter than its lead time (the length of time until a forecasted date from when it is made) (Smith, 2002)
- A variety of physical processes that one may wish to model, such as ice-sheet dynamics, are relatively unknown (Curry and Webster, 2011, p. 1671)

Similarly, the value of IAMs is contested due to the uncertainties involved. IAMs have the additional issue of including what Beck & Krueger (2016) describe as *ethical*[15] *uncertainties*, in which a diversity of worldviews requires decisions as to what one values in an analysis. Such an example of an ethical uncertainty is temporal discounting[16] considering ideas about intergenerational justice[17].

1.2.3.2 Interdisciplinary Collaboration

The uncertainty problem is further compounded in climate-related research due to the coupled nature of the problems and the resulting need for different research disciplines to collaborate. It is not only that this knowledge is produced by different fields of study, but this knowledge must be in some way synthesised and integrated so that coherent decisions with a broad-based rationale can be made by decision-makers and policymakers.

One of the key places for knowledge synthesis is the IPCC, where assessment reports and special reports review the findings of different disciplines and intend to present the findings in a policy-relevant manner.

The IPCC has evolved the uncertainty communication within its reports over the years and now uses a system with two dimensions of uncertainty and calibrated probabilistic language. Despite this, there is some periodic handwringing about the correct way of handling uncertainty and the uncertainty guidance documents that are produced will not be suitable for all disciplines. Indeed, the kinds of uncertainty that are inherent to the knowledge of different

---

[15] As will be discussed in Chapter 2 this also has some similarities with 'value-ladenness' as used by van der Sluijs et al. (2003), Petersen (2006), and others.

[16] A measure of how much future costs should be discounted relative to the present day. This is typically measured by a 'discount rate' *r* which reduces the value of costs in year n+1 to year n by a factor of (1/(1+r)).

[17] This concerns the way in which resources and damages are apportioned across generations, including generations not yet alive who have no say over current decision making. See for example Page (1999).

disciplines may be unsuitable for combination. The admixtures of uncertainties that occur in these forums of interdisciplinarity may be conceptually confusing to understand. Hence, understanding how scientists themselves think about these uncertainties may be useful.

1.2.3.3 The Secular Growth of Uncertainty

On the broader backdrop of the issue of the conceptualisation of uncertainty is the awareness that uncertainties in many walks of life are on the rise. Over the past 20 years, several authors have discussed different kinds of radically uncertain problems in which values are at stake – variously termed 'unstructured problems' (Hisschemöller and Hoppe, 1995; Hoppe, 2018), 'divergent problems' (Schumacher, 1977), 'wicked problems' (Rittel and Webber, 1973) or 'super wicked problems' (Levin et al., 2012).

In response to these significant societally complex problems, academics have reconsidered the role of science in society. Intellectual normative movements have sprung up, such as 'mode-2 knowledge production' (Gibbons et al., 1994; Nowotny et al., 2001), 'Post-Normal Science' (Ravetz, 1999; Ravetz and Funtowicz, 1993) and 'the New American University' (Crow and Dabars, 2018). These differ substantially in their focus and recommendations, but there is a loose isomorphism in their following three phases of argument:

1. Traditional modes of knowledge production associated with the conventional scientific enterprise are insufficient to cope with the high-uncertainty linked problems we increasingly face today and the demands for creating public value that society places on science.
2. There are on-going trends in knowledge production where centralised, hierarchical systems are moving towards more decentralised forms of knowledge production with an extended franchise on who is allowed to interact with the knowledge production process. This secondary mode is associated with the democratisation of science: cross-, multi-, inter- and trans-disciplinarity.
3. This trend should be facilitated by opening academia further, creating new institutional structures, and embracing some uncertainties. There should be a teleological shift in our knowledge production enterprises from the objectivity of knowledge to forms of knowledge that are "socially robust" or have "high integrity". This may involve the inclusion of non-scientists into the knowledge production process or the review of knowledge.

1.2.3.4 Summary

Uncertainty is a highly complex topic and a feature of modern decision-making that is arguably on the rise. The complex modelling in climate and energy systems means that understanding all the uncertainties in an investigation is highly difficult. Nonetheless, different kinds of evidence must be brought together for decisions to be made. This presents a conceptual challenge for how these combined uncertainties can be communicated and summarised.

Therefore, what is needed is research into how uncertainty is conceptualised within these research communities.

In my literature review, chapter 2, I shall also further argue that attempts to organise the various types of uncertainty have become unwieldy with a vast swathe of overlapping and often incompatible concepts used. I review 156 different frameworks that organise uncertainty. None of these has universal applicability. Instead, what is needed is an approach that engages with how practitioners truly organise uncertainty in their minds and their practice.

In the next section, I shall lay out my problem statement and define the research questions that guide this thesis. The Problem, Purpose and Research Questions.

1.2.4 Problem Statement

The problem that I am seeking to address is the conceptual haze around the idea of uncertainty.I aim to build an account of how uncertainty is conceptualised by modellers in climate modelling, energy modelling and integrated assessment modelling. Furthermore, I aim to examine the factors that influence the ways in which they conceive of the uncertainties in their models and subsequently how they handle these uncertainties with uncertainty analyses.

1.2.5 Research Questions

This thesis argues that a deep understanding of interdisciplinary collaboration and communication on uncertain issues must begin with a description of how uncertainty exists both within and at the boundaries of those communities. To begin to answer this, one must first ask the empirical question:

RQ1: How do different modelling communities understand uncertainty in climate and energy systems modelling?

Once this descriptive question has been answered one can begin to build an account for how this understanding is consequential and how the issues this creates can be resolved. Implicit in this research question are several sub-questions:

RQ1a: What kinds of uncertainty do these research communities frequently use to describe their work?

RQ1b: What conceptual distinctions do they employ to separate different kinds of uncertainty?

RQ1c: What normative views do they hold on the ways these kinds of uncertainty should be handled?

Naturally, as these disciplines are modelling ontologically very different systems, we should expect a divergence in the inventory of concepts used to manage uncertainties. However, collaboration and synthesis between these two bodies of work must occur for effective decision support. To better understand how collaboration can occur I also ask the comparative question:

RQ2: In what ways do the understandings substantially differ between the two groups, and how may this be consequential?

Finally, I seek to begin to explain the reasons for these differences and to understand the institutional configurations that lead to ways of understanding uncertainty. I hence ask:

RQ3a: What factors contribute to the handling of uncertainty in a modelling process?

RQ3b: How can we conceptualise the process of uncertainty management in the contexts in which it occurs?

Given these research questions, I now briefly outline several studies that have considered similar questions or used similar methods to that employed in this thesis. This exploration will help to refine the research gap and explain what makes this research distinct from that which has gone before.

1.3 Approach and Assumptions

1.3.1 Previous Research in this area

Several other authors have approached either a similar or related research question or have employed similar methods to my own. I now briefly review these to better describe the research gap that I address, including research that studies:

- the uncertainty conceptualisations of scientists and researchers themselves (§1.3.1.1)
- the sociology of uncertainty in scientific research and boundary work that negotiates uncertainty (§1.3.1.2)
- the uncertainty understandings of other audiences such as policymakers and lay audiences (§1.3.1.3)
- the possible conceptualisations of uncertainty in order to improve communication of scientific results (§1.3.1.4)

I then refine the gap in the literature that my work addresses based on this.

1.3.1.1 Investigating Scientists' Conceptualisations

There are several pieces of work that have considered aspects of the ways that modellers conceptualise or define uncertainty.

Barrieu; Dialogues around Models and Uncertainty

A very relevant piece of work is that of Barrieu (2020), who in a recent book "*Dialogues around Models and Uncertainty*" interviews a variety of researchers from different modelling fields such as Mathematics, Immunology, Philosophy of Science, Energy Engineering and Molecular biology. The book presents these interviews, edited in collaboration with their participants, simply as transcripts and does not conduct comparison, synthesis or analysis. The author describes themselves as a 'facilitator' or as a 'transmitter' of the thoughts of these researchers.

Most of the interviews focus on the modellers' views on the role of modelling and the relationship between models and target systems. The interview strategy is that of a semi-structured interview with deviations from a relatively strict protocol, and the book states that the modellers were asked to respond in a way that would be accessible to a broad audience.

Though this book is thematically similar to what I am proposing here, there are some important differences in approach and limitations of the work. As the book presents the edited transcripts from participants and as participants were asked to respond to questions in an inaccessible way it is difficult to glean the extent to which the discussions are truly representative of the daily practices of the modellers. Further, my work intends to perform a more focused comparison between two research areas. The heterogeneity of the book in terms of participants yields interesting reading but renders comparative analysis difficult. And finally, my approach intends to focus more narrowly on uncertainty itself and not on wider issues around the conceptualisation of modelling.

Lahsen; Seductive Simulations?

Relevant to my latter research questions, Lahsen (2005) documents ethnographic fieldwork carried out with climate scientists seeking to understand the social dynamics underpinning disputes about climate science results. The paper identifies four factors that contribute to the perceived uncertainty in model results in climate modelling:

1) Models are produced at different sites.
2) Model developers play different roles, such as being users.
3) Modellers are not aware of empirical issues.
4) Difficulties in maintaining a critical distance from modelling work.

This paper deals more with the perception and negotiation of uncertainty in model results and not explicitly how uncertainty can be conceptualised.

Skeels et al.; Revealing Uncertainty for Information Visualisation

A paper by Skeels et al. (2010) produces a classification of uncertainty for the purpose of aiding information visualisation with five types of uncertainty comprising of approximation, prediction, disagreements, completeness and credibility. They then subject this classification to some empirical evaluation in interviews with people from different domains to better refine it.

The interviews with knowledge workers revealed that many struggled to provide ready definitions of uncertainty. The authors did not analyse but used the results of the interviews to sort their uncertainty types into three levels, with some kinds of uncertainty spanning multiple levels.

Though this approach does pay some attention to the types of uncertainty identified by participants it is unsuitable for my project. The paper is thematically unfocused, meaning that the sample of participants cannot be easily compared with one another. Furthermore, the approach, which begins with a framework and then attempts to amend it, leads to a weak examination of the different concepts available.

Guillaume et al.; Towards Best Practice Framing of Uncertainty in Scientific Publications

Guillaume et al. (2017) examined the ways in which uncertainty conclusions are framed in the abstracts of water quality research. They propose a typology of uncertain claims that relate to:

- Maturity and utility (the usability of the conclusion)
- The scope of the claim (limits to its applicability)
- The level of belief of the author
- The depth of analysis (the thoroughness of the investigation)
- Relatability (where claims are related to prior knowledge and one's expectations)

Each of these aspects is subdivided into a scale of claims. For example, the 'level of belief' can express a conclusion as a fact at one end of certainty. On the other end, authors may make statements about the insufficiency of evidence to draw conclusions.

They then test the relative prevalence of these different frames by manually coding a corpus of abstracts. They find that most abstracts express some conclusion as a fact, and the most frequent claims about uncertainty indicate incremental progress in a research area. Often authors attempt to manage uncertainty by limiting the scope of their claims or indicating that evidence is insufficient.

This work is an interesting examination of the communication of uncertainty within the scientific research communities themselves. I am seeking more to examine the way that researchers themselves understand uncertainty within an investigation and not merely the presentation of the results of that work. The result of scientific research may embody some aspects of uncertainty, but they may only be the most visible uncertainties. A fuller gamut of uncertainties is only accessible to those directly involved in the knowledge production process, so my work must engage with them directly.

Silvast et al.; What Do Energy Modellers Know?

A paper by Silvast et al. (2020) details an ethnography with energy modellers. They use concepts from both anthropology and the philosophy of science to examine the conceptual issues around modelling experienced by modellers. They examined the epistemic values guiding model choice and construction and found that decisions had to be made as to which epistemic values the models would attempt to uphold. They found that modellers were critical of the limitations of their models and relied on a variety of different critiques.

1.3.1.2 The Sociology of Uncertainty and Ignorance

A variety of scholars have turned their attention to the social dynamics that create the state of uncertainty and ignorance. These studies tend to focus either on the processes that drive decision-making in uncertain environments or the strategic use of different kinds of knowledge. The social science literature that understands risk is more developed than that of uncertainty (Mehta et al., 1999).

Heymann et al. (2017a) suggest calling particular scientific cultures concerned with the production of knowledge about the future 'cultures of prediction'. They outline five characteristics of these cultures:

1) The social role of prediction
2) The character and significance of computational practices
3) The domestication of uncertainty
4) The degree of institutionalisation and professionalisation of predictive expertise
5) The cultural impact of predictive practices

Of the third aspect, they describe how this is not simply the formulation of practices to produce knowledge, but "a matter of conflict, negotiation and boundary work" (Heymann et al., 2017b, p. 27).

Daipha (2012) reviews how expert decision-makers manage high-uncertainty situations in weather forecasting and concludes that interdisciplinary research is needed that examines the interrelationship between expertise and uncertainty.

Boundary Work

In an influential paper, Shackley & Wynne (1996) argue that climate scientists conduct boundary work in their communication of uncertain results to policymakers. As uncertainty can be perceived as an issue that threatens the authority of science, they use several boundary ordering devices to allow scientific authority to be managed and upheld. The paper identifies empirically several such devices existing in the discourse of advisory scientists:

- *The clarification and management of uncertainty* through auditing knowledge claims so that various kinds of consensus around uncertainties can be communicated.
- *The reduction of uncertainty* through claims or promises that research will reduce uncertainty and hence that policy is led by advances in science.
- *The transformation of uncertainty*, when different types of uncertainty are recast as others. For example, ignorance could be recast as risk. This can minimise the perceived threat to the ability of science to produce robust predictions. This is similar to what Stirling (2008a) calls the closing down of uncertainty.
- *The condensation of uncertainty*, where multiple kinds of uncertainty are combined into one category. This allows multiple interpretations of the uncertainty by scientists and policymakers and facilitates cooperation.
- *Scheduling into the future*, when problematic aspects of uncertainty are described as being manageable at a future date.
- *The displacement of uncertainty*, when the responsibility for investigating some uncertainty is said to be that of some other discipline, thus deflecting criticism.

Despite the apparent lack of adherence to specific epistemic values that may be obvious from these devices, Shackley and Wynne (1996) describe these as necessary for the cooperation and collaboration between scientists and policymakers.

Comparing Conceptualisations by Experts and Non-Experts

I now briefly describe two papers that have gone some way to explore how uncertainty is conceptualised by experts and non-experts, both of which I believe provide valuable contributions to the literature. But they ultimately fail to give a deep account of the conceptual issues at play in assessing and managing uncertainty.

Landström et al. (2015) interviewed several climate scientists to gauge their perceptions of uncertainty and how policymakers, publics and the media engaged with it. The beginning of their interview protocol engaged with how the scientists conceptualised uncertainty. They find that there was consensus amongst their participants that uncertainty is an inevitable aspect of research. However, they find some divergence in how scientists conceptualised uncertainty, with those with a natural science background more likely to describe uncertainty as quantifiable. These natural scientists were accustomed to using *practice languages*[18] amongst their peers.

Whereas the natural scientists they interviewed had a relatively consistent set of ways of talking about uncertainty, the social scientists they interviewed did not, and they did not profess to talking regularly about uncertainty amongst their peer group.

This study begins to consider what aspects of the disciplinary background may affect uncertainty but the discussion of the conceptualisation of uncertainty in the groups under study is superficial. The grouping of experts into 'natural science' and 'social science' is also rudimentary. As some sociologists of science recognise, the relevant social unit for disaggregating scientific practices can be the sub-discipline. Furthermore, the focus of the study is very much on the vocabulary of those interviewed and does not consider any of the plethora of concepts that are important for understanding the different kinds of uncertainty.

Höllermann and Evers (2017) describe a study in which they conducted semi-structured expert interviews and questionnaires with both scientists and practitioners in order to compare their perspectives on uncertainty management. The analysis of results focussed on several aspects such as the perception of uncertainty, the types of uncertainty they dealt with and how those uncertainties were handled.

---

[18] See Collins (2011) who discusses the relationship between the language used by domain specialists and their practices.

Amongst the experts that they interviewed, they found that the majority make distinctions between *uncertainty* and *risk*. The latter they conceptualised in different ways, relating it to things such as the probability of occurrence or damage, for example. They also found that practitioners were more sensitive to 'process uncertainties', the uncertainties inherent to planning and decision-making processes. Whereas experts focussed more on 'fundamental' or scientific uncertainties. Whilst this is a useful insight into the interplays between experts and practitioners, the description of the deep uncertainties that are involved in complex and technical-scientific work lacks descriptive depth. This shallowness is likely due to the breadth of the kinds of participants interviewed.

1.3.1.3 The Interpretation of Uncertain Information by Audiences

The Interpretation of Probabilistic Information

Several authors have studied the interpretation of uncertain information, such as probabilistic language, by different audiences.

Wallsten et al. (1986) consider the meanings of various probability terminology such as "doubtful" and "likely" by measuring the maximum and minimum probability values that a selection of participants found appropriate. Some terms such as "possible" were found to be very inconsistently evaluated.

Other studies have considered what factors influence someone to interpret a probability in a particular way. For example, Flugstad & Windschtil (2003) examined the effect of negative and positive valence information on the assessments of likelihoods of adverse events, using a medical scenario.

The Public Understanding of Uncertainty

Related to the communication of uncertainty, there are several studies in which researchers study how non-specialist audiences understand uncertainty concepts. Often, uncertainty is defined in such studies as a general perception of uncertainty in science.

Visschers (2018) conducted an extensive survey that examined participants' understandings of different kinds of uncertainty about climate change and identified three types of uncertainty from factor analysis of the responses: *future uncertainty*, *measurement uncertainty* and *ambiguity* (unclear evidence or incomplete knowledge).

Zehr (2000) examined global warming in the US popular press between 1986 and 1995. The paper finds that uncertainty was a salient theme in the coverage. It argues that uncertainty plays a role in constructing the boundary between publics and researchers through the implied requirement for future scientific research to address the problem. This effect goes alongside the perceived reduction in scientific prestige that uncertainty is usually assumed to create. The paper also identified three ways in which uncertainty was constructed in the press: through the emphasis on scientific controversy, the introduction of new research areas that answer uncertain questions, and the expansion of the problem domain of climate change to introduce more areas of uncertainty.

Wardekker et al. (2008) also examined views on uncertainty at the science–policy interface. Using computer-assisted workshops and surveys, the researchers studied, amongst other things, the types of uncertainty that were of interest to policy advisors. They also surveyed participants as to their interpretation of various probability terminology. They found that although some improvements had been made over the previous terminology used, the probability terminology of the IPCC was still ambiguous.

Gustafson and Rice (2019) examine the effect of different uncertainty frames on the beliefs, credibility perceptions and behavioural intentions using a psychological survey methodology.

1.3.1.4 The Communication of Uncertainty

Whilst examining the conceptual implications of how uncertainty is communicated lies well outside of the scope of this thesis, it is informative to consider works that assume some ontology for uncertainty for communication to different audiences as these may imply psychological models for mental conceptualisations of mental uncertainty.

'Uncertainty' has ambiguous colloquial meanings recognising this, Stirling (2008b) resorts to using the French *incertitude* instead and unpacks the term with a levels-related framework. Furthermore the language that we use to describe our interactions with uncertainty, such as *to control, manage* or *cope with*, can also be ambiguous (Roe, 2020).

Van der Bles et al. (2019) base their uncertainty communication approach around Lasswell's (1971) model of communication, which asks "Who – says what – in which channel – to whom

– to what effect?". As part of their examination of *what* is communicated, they describe the object that uncertainty refers to either be facts, numbers, or hypotheses. They also propose various sources of uncertainty and levels of uncertainty (see discussion in the chapter 2). However, it does not appear that this typology has a grounding in either the psychological literature or empirics and is more a continuation of the long literature on uncertainty typologies.

There are significantly divergent normative opinions in the literature as to the extent to which uncertainty can at all be communicated from scientists to the public. One position claims that uncertainty should be communicated in nuanced and albeit complex ways to different audiences so that they may come to know the true nature of the scientific debate (Scoones and Stirling, 2020; Stirling, 2010).

Another position is more pessimistic and believes that scientific uncertainty is ultimately too complicated to communicate to lay audiences. Instead, some authors suggest that uncertainties be reframed as risks, as this has more salience with the public and decision-makers (Corner, 2015; Corner et al., 2015; Weaver et al., 2017). Stirling (2008a) calls this process of transmuting uncertainties into risks 'closing down'.

1.3.2 My Approach

Thematically, my approach is focussed on two research communities: climate modellers and energy system modellers (including IAM). I am confining my study to within the scientific communities that model climate change and energy systems.

The sense in which I am exploring uncertainty is that I am engaging with the concept itself as subject to social negotiation and with how people understand it existing as a property of models and their results. I am looking to explore how uncertainty can have multiple meanings beyond the credence that one places in a result or the spread around an estimate.

Broadly speaking, to examine the conceptualisations of participants, I must include some version of an idealist ontology. Furthermore, as I am interested in how these ideas manifest at a community level and the factors influencing them, my epistemology must have a constructivist component. The assumptions employed in this thesis will be further examined in the methodology chapter.

1.4 Rationale and Significance

Climate change is the most prominent of a growing class of 'wicked problems' that require new interdisciplinary approaches to problem-solving and collaboration on exercises such as integrated assessment modelling. These interdisciplinary approaches and large modelling projects require cross-disciplinary communication, description, and management of uncertainty. It has been established that inter-group communication of uncertainty may be problematic for several reasons, such as its variable interpretation and political significance. Research thus far has mainly focused on the experiential or epistemic dimensions of uncertainty. I consider uncertainty a socially constructed aspect of scientific practice, estranged from its epistemic or epistemological roots yet made practical as a part of scientists' quotidian modelling practice. Several philosophers of science point to how disciplinary training and borrowed conceptual models are used to understand new scientific situations. There is also a literature base that looks at the understanding scientific concepts through the lens of mental models.

With a more profound account of how scientists *understand* uncertainty, the routes and vehicles of interdisciplinary uncertainty communication can be strengthened and made more sympathetic to how uncertainty really exists. It is anticipated that this will help clarify issues around uncertainty for policy advice.

The extensive literature review in this thesis is intended to help the field of 'uncertainty studies' consolidate somewhat as no such extensive reviews exist to date. It is hoped that the clarity this provides will help avoid future conceptual conclusions. The principal study will hopefully give an empirical basis for future work that seeks to make claims about how people conceptualise uncertainty.

It is hoped that the research may have some impact beyond academia's confines, and I would argue it already has. As a result of the COVID-19 pandemic, I was seconded to the UK Government to work on several pressing issues in the technical response. I made a conscious effort to use my experience and the ideas developed in this thesis throughout. As a result, I managed to institutionalise practices around documenting models' limitations and the uncertainty communication in key government documents.

As a researcher, I am ideally suited to carry out this work. I have an interdisciplinary background that permits me a technical understanding of the issues that will be discussed by modellers. I have a Physics undergraduate degree, which is helpful when engaging with participants from the physical sciences who work on climate science. Furthermore, I hold a master's degree in Sustainable Energy, which involved studying the techno-economic of energy technologies and markets. In addition to this academic background, I have undertaken additional useful modules at UCL such as "Energy, Technology and Innovation", "Energy People and Behaviour", "Knowledge and Governance", "Public Administration" and "Evidence for Decision-making".

1.5 Thesis Outline

Chapter 2 presents an extensive literature review of typologies and frameworks that authors have used to understand uncertainty over the years. It reviews the key concepts that are used to differentiate different kinds of uncertainty in fields relevant to the assessment of environmental change. This builds a solid conceptual foundation to examine and compare how practitioners themselves actually conceptualise uncertainty. It questions the routes forward for uncertainty frameworks and argues that many of the ideas used to organise uncertainty have conceptual inconsistencies.

This literature review provides an instrument for the rest of the thesis to examine concepts as they emerge in the empirical work.

Chapter 3 presents the methodology used in this thesis. The methodology's core is a set of semi-structured interviews with different groups of modellers in climate, energy and integrated assessment. The method considered borrows some techniques from mental models interviews to elicit conceptualisations from modellers in a thorough and naturalistic manner.

Chapter 4 then presents the results of the interviews with energy systems and Integrated Assessment modellers. It describes the principal concepts they used to organise uncertainties and their beliefs about the compatibility of different concepts such as probabilities and scenarios.

Chapter 5 then presents the results from the interviews with climate modellers. Here it conducts much of the same analysis as in the previous chapter and begins to flesh out some of the differences between the energy modellers. It focuses on the important role variability plays in climate modelling and how different participants conceptualise it. It also examines the contextual factors that appear to have a bearing on how uncertainty is conceptualised and handled.

Chapter 6 then compares the two sets of results and discusses the findings in the light of the broader literature. It argues that the interactions between modellers, models, and their communities can be understood by considering them to be actants in a network. It then considers how modellers and models continuously reconstitute each other in an ongoing process of re-realisation. This explains how some uncertainty analyses become prevalent and possible within a community. From this chapter, three key themes are distilled that relate to the conceptualisation of uncertainty, the differences between groups of modellers and finally, a description of the ways that models interact with their local socio-technical environment that shapes uncertainty analysis procedures.

In the following two chapters I use my experience in another domain, epidemiology, to reflect and build upon these three key emergent themes. By exporting ideas from climate and energy into a new domain, I can better appreciate what makes the ideas distinctive in the contexts in which they emerge. Furthermore, the application to another field helps identify the extent to which my findings may be generalisable outside of climate and energy modelling.

Chapter 7 begins this foray into epidemiology. Over the course of my studies, the Coronavirus pandemic hit. As a result, I was approached to assist in the UK Government's effort to combat the virus. I was seconded for nine months to a scientific unit inside the Joint Biosecurity Centre (JBC, subsequently the UK Health Security Agency, UKHSA). The team I worked with and my role involved ensuring various kinds of evidence quality were met. Hence the thematic area was directly analogous to the issues I am exploring in climate science. As epidemiology is a field without a strong uncertainty assessment culture, I attempted to import some climate and integrated assessment modelling ideas into the field. This chapter explores the kinds of uncertainties inherent in epidemiological models and how epidemiologists handle uncertainty. I attempt to establish a working uncertainty framework for assessing these models that draws upon concepts from the literature review in chapter 2 and reflect on the generalisability of these concepts.

Chapter 8 then continues this diversion into epidemiology and more explicitly links the practices I was involved in to the literature on climate change modelling and uncertainty. It details the creation of a Multi-Model Ensemble for the UK government's estimates of the status of the epidemic. It conducts a brief review of some of the live issues in the philosophy of Multi-model Ensembles, and using the case study of the UKHSA MME, it reflects on the justifications used for producing such ensembles and how best practices for evidence quality can be assured. This provides an opportunity to reflect on the third theme that emerged from the empirical work about importance of understanding the relationship between models and the socio-technical infrastructure required to run them.

Chapter 9 concludes the thesis, lays out the overall findings from the study's different aspects, and draws upon the three themes. Drawing upon this understanding, I make recommendations primarily aimed at modellers and those administrating modelling work. Furthermore, I consider areas for future research in light of the study limitations and reflect on my experience completing this research.

1.6 Summary

This chapter has introduced this doctoral thesis. It has described the problem context in which increasingly complex computer models are used to inform critical policy decisions. These models are complex and involve the collaboration of different researchers and disciplines; hence understanding the uncertainty inherent in them is critical.

Uncertainty can be conceptualised in different ways, and these conceptualisations are consequential: for the way that uncertainty is assessed, and for the practices of model development and communication. Much work has gone into producing typologies of uncertainty; however, as of yet, there is little detailed work that considers how modellers themselves conceptualise uncertainties in their work. This thesis aims to address this gap.

It is anticipated that a fuller description of how uncertainty is conceptualised may be impactful in several ways. Firstly, for the literature base, a detailed account of the conceptualisation of uncertainty and the underlying reasons would allow those planning modelling efforts to go beyond their own opinion when designing uncertainty management practices.

2 The Ambiguities of Uncertainty

A Review of Uncertainty Frameworks Relevant to the Assessment of Environmental Change

2.1 Abstract

As awareness of deep uncertainties in many disciplines has grown over the last half-century, researchers have developed many frameworks, typologies, and taxonomies to understand, analyse, and communicate them. Uncertainty analysis is critically important in fields of study that deal with large, complex, societally-coupled problems, such as those dealing with environmental change. However, as of yet, no wide-ranging review exists that systematically compares the features of these frameworks.

This chapter surveys a huge number of uncertainty frameworks (N=156) relevant to the assessment of environmental change, identifying their key features and highlighting the conceptual foundations of these frameworks. It shows that although many authors have employed very similar methods of classification, significant ambiguities may exist because of overlapping concepts or polysemous terminology. Further to this, philosophical inconsistencies are pervasive in the frameworks. This chapter argues that the synthesis of these frameworks into one with general applicability is likely unachievable, and given the ambiguity of the meaning of much of the uncertainty lexicon, a more fruitful approach would be to start by examining the conceptual understandings of practitioners themselves.

This chapter provides a conceptual basis for the examination of modellers' conceptualisations that will be explored later in the thesis. I will use the understanding developed here as a tool to compare concepts used by participants to the literature base.

2.2 Introduction

2.2.1 The Use of Uncertainty Frameworks

Uncertainty undergirds many aspects of public life, often referred to in media as some amorphous evil, an anathema to business and a frequent subject of discourse during turbulent political times. Perceptions of uncertainty have been exploited by opponents of environmental policy to bring the edifice of science into disrepute and stymie political action on environmental issues such as climate change, acid rain and ozone depletion (Björnberg et al., 2017; Lewandowsky et al., 2015; Oreskes and Conway, 2012).

To analyse uncertainty in their research, many authors writing in both theoretical and applied literature over the years have turned to the production of frameworks, typologies, categorisations and taxonomies. For example, in environmental modelling, frameworks may help identify opportunities for model development. However, many uncertainty typologies only have relevance in narrow fields; *there is no one uncertainty framework to rule them all.*

2.2.2 Aims

There is a very substantial corpus of literature containing uncertainty frameworks; this literature is not homogeneous and aspects of uncertainty are conceptualised differently. This chapter aims to take an overarching view on what these frameworks are and how they employ different concepts. The following questions, therefore, guide our review:

- How are uncertainty frameworks typically structured?
- What are the most important conceptual features of uncertainty frameworks in literature, and what distinctions are typically made between different kinds of uncertainty?
- How do these conceptual distinctions relate to one another?

Frigg et al. (2015) describe the field of uncertainty typologies as *pre-paradigmatic*. Whilst I agree that the landscape of this literature is fractured and riven with confusion, I do not believe that a paradigm in uncertainty classification is achievable; it is hoped instead that the reader will be provided with a clearer map of some of the more prominent features of this terrain and will be better able to navigate the conceptual rifts that run through it.

2.2.3 The Importance of Understanding Uncertainty Frameworks

Uncertainty frameworks are particularly important in fields lying at the nexus of multiple disciplines and addressing significant societal problems, such as the climate change-related studies that are the subject of this thesis. Through the alignment of terminology, they standardise the communication of uncertainty, which is important for decision-making (Morgan and Henrion, 1990). Thus *uncertainty guidances* are used by organisations such as the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2005a; Mastrandrea et al., 2010; Moss and Schneider, 2000), the Netherlands Environmental Assessment Agency (PBL) (Petersen et al., 2013; van der Sluijs et al., 2003), the World Meteorological Organization (WMO) (Gill et al., 2008) and the US Environmental Protection Agency (EPA) (Krupnick et al., 2006). Given the prominence of these uncertainty frameworks and their role in communicating scientific findings to both decision-makers and lay audiences, it is important that they are well understood.

Uncertainty frameworks have various important purposes in different research contexts. Inventories of uncertainties have been used variously for:

- Identifying opportunities for improvement of the work through further research (e.g. Walker et al., 2003)
- Providing a basis for decision-making on complex issues (e.g. Morgan and Henrion, 1990; Walker et al., 2003),
- Identifying risks (e.g. NRC, 1994)
- Aligning work with ethical values such as transparency (e.g. Hamel and Bryant, 2017)
- Identifying appropriate tools and techniques for uncertainty analysis (e.g. Dreier and Howells, 2019; van der Sluijs et al., 2003; Ricci et al., 2003; Stirling, 1998)

Uncertainty frameworks also play a role in standardising the treatments of uncertainty in a particular research area, creating semantic alignment to ensure similar issues receive consistent treatment (Moss and Schneider, 2000). Furthermore, they may provide the first step in guiding appropriate communication of findings among scientists, policy analysts, decision-makers, lay audiences and other end-users (Fischhoff and Davis, 2014; IPCC, 2005b; Petersen et al., 2013; van der Sluijs et al., 2003; Walker et al., 2003)

2.2.4 Previous Research

Several previous papers have conducted literature reviews in this area, focussing on the conceptualisations of uncertainty. These are summarised in Table 2-1, below.

Table 2-1: Summary of previous reviews of uncertainty conceptualisations, the number of frameworks reviewed and their approaches.

Reference	N	Thematic Focus	Approach
Walker et al. (2003)	13	Model-based decision support/ Integrated Assessment	The authors present a highly influential framework for uncertainty that brings together several concepts. This has been variously described in literature as a review. They identify 13 papers from literature but do not explicitly identify divergences; instead, "*the aim of this paper is to highlight the agreements*".
Krupnick et al. (2006)	18	Environmental Protection, Regulation	As part of this report for the US EPA they review several uncertainty typologies that have influenced discussions of uncertainty in EPA documents. This is then used to build their own typology. It is unclear how sources were selected.
Kwakkel et al. (2010)	12	Model-based Policy analysis	The authors specifically review uncertainty frameworks influenced by Walker et al. (2003). They reviewed citations of the original paper and selected those relevant for analysis.
Skinner et al. (2014)	30	Environmental Risk Assessments (ERAs)	The methodology for selection of uncertainty typologies is unclear. However, they later conduct a separate review of how ERAs use uncertainty using a novel systematic technique.
Baustert et al. (2018)	14	Ecosystems Services, Integrated Environmental Models (IEMs)	They review several frameworks relevant to IEMs. They acknowledge their review is partial and the original corpus is unclear; but select frameworks that have at least a classification and recommendations for uncertainty handling.
Doyle et al. (2019)	35	Disaster Risk Management	A broader systematic review of papers on the topic of *communicating model uncertainty*. They identify the categorisation of uncertainty as one of the themes within this corpus and review some frameworks. They identify styles of classifications, including those specifically for spatial uncertainties and matrix-type

			typologies. Their thematic focus is *disaster risk management* but include literature from a broad array of disciplines such as health and visualisation.
Kirchner et al. (2021)	16	Integrated Modelling	They review several uncertainty conceptualisations relevant to Integrated Assessment Modelling. The authors conducted initial searches using several key terms. Following the identification of key articles, they then employed a snowball method to gather more relevant publications.

Six of the seven previous reviews identified have subsequently developed their own synthesis framework or improvements on an original framework. Most arrive at dimensions frameworks such as that of Walker et al. (2003). The reviews identified utilise either opaque literature selection methodologies (Baustert et al., 2018; Krupnick et al., 2006; Skinner et al., 2014; Walker et al., 2003), search for citations of one existing framework (Kwakkel et al., 2010) or employ a limited snowball approach (Kirchner et al., 2021). Doyle et al. (2019), as part of a broader review on the communication of model uncertainty in disaster risk planning, identify a number of frameworks containing categorisations but do not analyse the concepts used in these frameworks.

2.2.5 Review Approach

This chapter's core is a review of literature spanning multiple disciplines relevant to environmental change modelling. This locus of study therefore encompasses both key subject areas of study of this thesis.

The literature base's fragmentary nature and the inconsistency of terminology renders highly systematic keyword searches ineffective and vulnerable to significant omissions. Instead, an extensive snowball approach was employed: literature was initially found through searches of *Scopus* and the *Web of Science*, manually sorted to include frameworks relevant to environmental change-related studies. From this initial sample, other papers containing frameworks referenced were found and recursively analysed in turn in a branching manner until leads were exhausted. Such systematic snowball approaches are commonly employed when terminology is not consistently used across sources (Lecy and Beatty, 2012) and can yield larger corpora than keyword searches alone (Wohlin, 2014). This technique has been used to a much more limited extent in this subject area by Kirchner et al. (2021).

Appendix A gives a detailed account of the review process and an overview of the literature reviewed. Appendix B contains summaries of the uncertainty frameworks in each of the sources reviewed.

Limited unintentional omissions are unavoidable given the thematic and structural diversity of sources that could be included in such a review. However, manually exhausting all leads from an initial corpus produces a very extensive corpus, and conceptual exhaustion was noted. Resultingly, this review incorporates a far greater body of literature (N=156) than previous reviews and is far more extensive in its analysis.

2.2.6 Structure

The literature review is presented in two phases. *Section 2.3* considers *what these frameworks classify* and *how they are generally structured* to clarify exactly *what are* the conceptual frameworks reviewed. *Section 2.4* analyses the content of these frameworks through identification of key conceptual features and offers an emerging account of the considerable number of epistemic issues described in these frameworks. *Section 2.5* discusses these issues and presents challenges to consider for those using, developing or selecting from frameworks. *Section 2.6* then concludes this review.

2.3 The *Structure* of Uncertainty Frameworks

2.3.1 How Is Uncertainty Defined?

Uncertainty is one of the more capricious terms in the modern scientific lexicon and is defined variously by different authors for different purposes. Its polysemous nature has been recognised by a number of authors (Dequech, 2011; Kwakkel et al., 2010; Milliken, 1987). Table 2-2 gives some of the definitions on offer in the literature reviewed.

Table 2-2: A selection of definitions of uncertainty available in the literature reviewed

Reference	Definition of ***Uncertainty***
Walker et al. (2003)	"…any departure from the unachievable ideal of complete determinism."
Brown (2004)	"…our inability to resolve a unique, causal, world, either in principle or in practice…"
Brouwer and De Blois (2008)	"… limited (incomplete or imperfect) knowledge and information about current or future environmental, social, economic, technological, political and institutional conditions, states and outcomes and the implications or consequences of these current or future conditions, states and outcomes"
Brugnach et al. (2008)	"we consider uncertainty impinging on a decision situation has no meaning in itself, but acquires meaning through the relationships established between the decision maker and the socio-technical environmental system. […] Uncertainty then becomes a property of how an individual in a social context relates to a system through certain practices and activities […] involving knowledge of different types."
Sigel et al. (2010)	"A person is uncertain if he/she lacks confidence about his/her knowledge relating to a concrete question"

Most generally, uncertainty definitions vary in three ways. *Firstly,* uncertainty is conceptualised as existing in different sites: either as something truly existing in nature, as a property of one's mental state (*psychological)* (e.g. Sigel et al. (2010)), or as an object of social construction (*sociological)* (e.g. Brugnach et al., 2008; Wynne, 1992).

Secondly, the idealised yet unachieved epistemic state to which the uncertainty is constructed in reference varies. This may be a state of complete understanding (Brugnach et al., 2008), knowledge of some particular outcome, determinism (Petr et al., 2019; Walker et al., 2003; Warmink et al., 2010), knowledge sufficient for a particular purpose (Sigel et al., 2010) or confidence in one's knowledge (Kirchner et al., 2021).

Thirdly, uncertainty may be in reference to different possible knowable things: past, present and future states of systems (Brouwer and De Blois, 2008); future trends and events (Kutiel, 2019); the outputs of models (Kann and Weyant, 2000); answers to concrete questions (Sigel et al., 2010); the relationships laws or mechanisms that drive the behaviour of systems (Bergman et al., 2010); the consequences of actions both in terms of material outcomes and human subjective evaluation of these outcomes (Brouwer and De Blois, 2008). In the context of futures studies, one may differentiate types of claims by whether they are truth claims about future system states or explanations of mechanisms driving system behaviour (Bergman et al., 2010).

Furthermore, when used as a noun, 'uncertainties' may refer to facts or propositions about a situation that lead to a position of uncertainty.

2.3.2 The Ontology of Frameworks

The frameworks examined in this review take various forms. The earliest are simple definitions that clarify key concepts such as risk, probability, uncertainty, ignorance and ambiguity (e.g. Ellsberg, 1961; Keynes, 1921; Knight, 1921). The complex relationship between these has seen an exchange of ideas over the last century, with conceptual boundaries frequently renegotiated and ideas exchanged between disciplines.

The next level of framework complexity involves listing sorts of uncertainty that one may face. These categories of uncertainty may be distinct (e.g. Funtowicz and Ravetz, 1990) or non-exclusive (a single uncertainty can be given multiple labels) (e.g. Smith and Stern, 2011; Wynne, 1992). Increasing in complexity are 'taxonomies' which organise uncertainties in hierarchical categories, frequently represented by dendrograms (e.g. Ascough II et al., 2008; Faber et al., 1992; Suter et al., 1987).

The most complex class of frameworks conceptualise uncertainties as having orthogonal traits, different *dimensions* defining scales or categorisations (Bradley and Drechsler, 2014; Davies et al., 2014; Ekström et al., 2013; Faucheux and Froger, 1995; van der Sluijs, 1997; Walker et al., 2003). Many of these are influenced by Walker et al.'s (2003) highly prominent paper. Dimensions may be exclusive (e.g. Warmink et al., 2010) or allow overlaps, with individual uncertainties inhabiting multiple points in the space constructed by these dimensions, in which case the categories may be best described as *traits* (e.g. Petersen, [2006] 2012). These systems are also frequently represented by *uncertainty matrices*. Norton et al. (2006) point out that matrices with a small number of classes along each dimension (such as that of Walker et al., 2003) can be better described as taxonomies.

2.4 The *Content* of Uncertainty Frameworks

I now consider the most prominent categorisations of uncertainty within these frameworks and how distinctions are made. The features of uncertainty frameworks identified in this section include:

1. *The aleatoric/epistemic divide:* two fundamental species of uncertainty are often described, yet in different ways.
2. *Levels of uncertainty* that generally range from complete indeterminacy to determinacy.
3. *The division of uncertainty by one's cognisance* (or lack thereof) of the uncertainties and their causes (varieties of ignorance and its border).
4. *The location (or source)* of an uncertainty within a knowledge production or decision-making process.
5. Uncertainties due to difficulties in communication or forming consensus within social groups; and
6. The incorporation into frameworks of *human values, subjectivity and normativity*: ethical, moral, epistemic and political.

2.4.1 The Aleatoric/Epistemic Divide

Perhaps the most common and abiding feature of uncertainty discussions is a separation between two different fundamental species of uncertainties, in contemporary literature most generally labelled *aleatoric* and *epistemic* uncertainty. There is a loose correspondence between these fundamental types in the literature, though their divide is inconsistently described. We identify four means by which these two types of uncertainty are generally distinguished from one another:

- *Measurability* (measurable versus non-measurable)
- Meta-uncertainty (described uncertainty versus uncertainty about that uncertainty)
- *Nature* (due to variability in a system versus due to a lack of knowledge)
- *Reducibility* (non-reducible versus reducible)

Measurability

The most famous early elucidation of this divide came from Frank Knight (1921) in his book *Risk, Uncertainty and Profit*: *Risk* is measurable, while *True Uncertainty* defies attempts to measure it. Either an uncertainty is known *a priori*[19] (like a dice roll), or we cannot know the probabilities of outcomes (Sakai, 2016, p. 15). This distinction is often called 'Knightian Risk or Uncertainty'.

Keynes[20] made a similar distinction between *probability* and *uncertainty* (Carvalho, 1988) in his *Treatise on Probability* (Keynes, 1921). *Probability* for Keynes also includes probability intervals (e.g. 10–20% chance), likelihood ordering (e.g. p(a)>p(b)>p(c)) and non-orderable likelihood judgements (e.g. subjective statements) (Sakai, 2016). Probability links a set of premises one holds to possible conclusions: "As our knowledge or our hypothesis changes, our conclusions have new probabilities, not in themselves, but relatively to these new premises" (Keynes, 1921, p. 7). This interpretation of probability has been subject to contestation, famously by Ramsey (2016 [1931]), who criticised these probability relations as not existing in reality (Runde, 1994).

Uncertainty, on the other hand for Keynes, has its generation in the capriciousness of human behaviour (so-called *animal spirits*), with an unknowable or unimaginable range of outcomes (Sakai, 2016). Keynes also is known for the concept of the *weight of evidence* in which one apportions more importance to premises containing more relevant evidence. Keynes relates this to the "degree of completeness of information" (Runde, 1990), which some subsequent authors have related to a degree of certainty (Runde, 1990 after Lawson, 1985).

The ideas of Ellsberg dovetail, to an extent, with those of Keynes and Knight. *Ellsberg's paradox* observes that individuals prefer gambles with known probabilities over *ambiguity*[21] in which probabilities are unknown, despite equal expected utility (Ellsberg, 1961, p. 656). Within Ellsberg's ambiguity, subjects are able to make judgements on the strength of information affecting their beliefs (Ellsberg, 1961, pp. 657–8). Thus, *uncertainty* and *ambiguity* are separated

[19] This could apply to situations where probability distributions may be stable over some relevant temporal or spatial period.

[20] The interpretation of Keynes' ideas about uncertainty are subject to some forthright contestation (e.g., Brady, 2014); it is described here in a broad sense in order to convey the difference with Knight.

[21] An example of *ambiguity* is the outcome of a bet on the colour of a ball drawn at random from an urn: in the first situation an urn contains 50 red and 50 black balls; in the second situation the number of black and red balls is unknown. This latter situation Ellsberg describes as '*ambiguity*' as the probability distribution is unknown. People are said to prefer the former situation to the latter, even though the expected utility may be equal.

by their *measurability,* and *ambiguity* describes a sort of *meta-uncertainty* (uncertainty about uncertainty).

Meta-Uncertainty

If we can produce a measurement or estimate of uncertainty, may we be confident in it? Funtowicz & Ravetz (1990, p. 22) define uncertainties as having three sorts: *inexactness*, a measure of the spread of some data; *unreliability,* a measure of confidence in a quantitative statement; and *border with ignorance* in which fundamental ignorance is unavoidable. The difference between inexactness and unreliability is therefore a kind of *meta-uncertainty*, i.e. the confidence one has about some uncertainty that is described. Similarly, Suter et al. (1987) separate using *meta-uncertainty* with *defined uncertainty* about a fact and *undefined uncertainty* about one's level of ignorance. Van der Blés et al. (2019) separate uncertainty directly expressed about a fact and that about one's level of ignorance (see also Gaudard and Romerio, 2020). A form of meta-uncertainty may be the difference between *error* (the actual difference between an estimate and a value) and *uncertainty* (the estimate of the error) (Henrion and Fischhoff, 2014).

Nature

In recent literature, uncertainty is often described as being *aleatoric*[22]*/ontic*[23] *or systematic/epistemic* (Kwakkel et al., 2010; Petersen, 2006; Rotmans and van Asselt, 2001; Spiegelhalter and Riesch, 2011, p. 4731; van Asselt et al., 2001, pp. 17–19; van Asselt and Rotmans, 2002a, pp. 78–80; Walker et al., 2003). This divide is labelled as '*nature*': there is an incommensurable difference between uncertainty due to the fundamental nature of a system and its variability or indeterminacy, and uncertainty due to a limited knowledge state. Authors are often in disagreement as to whether ontic uncertainty includes uncertainty due to social structuring within the system or whether this nature of the system is simply physical variability (Knol et al., 2009). This terminology originated in Hacking's (1975) distinction between *aleatory and epistemic probabilities* and is particularly prevalent in frameworks influenced by Walker et al. (2003).

[22] The connotation of 'aleatoric' – which refers to the Latin *alea*: 'bone' or 'dice' – is uncertainty that is statistical or stochastic in nature.

[23] The connotation of 'ontic' – which refers to the Greek *on*: 'being' – is uncertainty that is related to the way of being of the system, in particular being intrinsically indeterminate or variable.

Reducibility

The final distinction is *reducibility*: whether uncertainties are reducible through acquiring more knowledge (See for example Ascough II et al., 2008; Kelly and Campbell, 2000). This perhaps provides a simpler method of distinguishing between two types; however, the acquisition of more knowledge may increase uncertainty.

A loose yet highly imperfect coherence can be seen between these four mechanisms; many measurable uncertainties are also characterised as aleatoric, non-reducible and measurable, and vice versa. Table 2-3 summarises a number of these two-type uncertainty separations, the nomenclature used and the mechanism that separates them.

Table 2-3: Selected fundamental divisions of uncertainty into type-1 and type-2.

Author(s)	'Aleatory' Label	'Epistemic' Label	Mechanism of Separation
Knight (1921) Luce & Raiffa (1957)	Risk	Uncertainty	*Measurability*: Risk is measurable, uncertainty is not
Keynes (1921)	Probability	Uncertainty	*Measurability* (Broadly): Probabilistic (in a very broad sense) information is organisable (either numerically, ordinally or some kind of non-numerical degree of belief may be affixed). Uncertainty has origin in capriciousness of human behaviour.
Shackle (1955)	[Unnamed]	True Uncertainty	*Measurability*: Probabilities (frequency ratios) of outcomes cannot be known *a priori* or through repeated trials
Ellsberg (1961)	Uncertainty/Risk	Ambiguity	*Measurability (and Meta-*Uncertainty): In former, probabilities are known. In ambiguity probabilities are not known and is a "quality depending on the amount, type, reliability and 'unanimity' of information, giving rise to one's degree of 'confidence' in an estimate of relative likelihoods"
Einhorn & Hogarth (1986)	Uncertainty	Ambiguity	*Meta-Uncertainty and Measurability:* Ambiguity is "uncertainty about uncertainty" and is associated with families of possible probability distributions.
Suter et al. (1987)	Defined Uncertainty	Undefined Uncertainty	*Meta-Uncertainty:* "Defined uncertainty is uncertainty about a state of the world; undefined uncertainty is uncertainty concerning one's actual level of ignorance."
Funtowicz & Ravetz (1990)	Inexactness	Unreliability	*Meta-Uncertainty:* Unreliability gives an assessment of confidence of a given spread in results.
Helton (1994)	Stochastic Uncertainty	Subjective Uncertainty	*Nature:* Subjective Uncertainty a property of the analyst
Hoffman & Hammonds (1994)	Type B Uncertainty	Type A Uncertainty	*Nature and Measurability :* "when the assessment end point is a fixed quantity, distributions of values obtained from repeated observations represent uncertainty of Type B". Type A is associated with knowledge state and B is associated with variability.
Ferson & Ginzburg (1996)	Variability	Ignorance	*Nature and Reducibility"* Variability (due to stochasticity in underlying system) and Ignorance (due to underlying knowledge state); also Ignorance is described as reducible.
Paté-Cornell (1996)	Aleatory Uncertainty	Epistemic Uncertainty	*Nature:* Aleatory represents randomness, Epistemic is due to lack of knowledge
Kelly & Kolstad (1999) Kann & Weyant (2000) Peterson (2006)	Stochastic Uncertainty	Parametric Uncertainty	*Nature:* "Parametric uncertainty, which arises due to imperfect knowledge, and stochasticity, which is due to natural variability in certain processes." Kelly & Kolstad (1999)
Van der Sluijs et al. (2003) Meijer et al. (2005)	Variability-Related Uncertainty	Knowledge-Related Uncertainty	*Nature:* Knowledge related being that which is a property of the decision-maker.
Hayes et al. (2007)	Variability	Incertitude	*Nature and Reducibility:* Incertitude is due to lack of knowledge and is reducible

Refsgaard et al. (2007)	Stochastic Uncertainty	Epistemic Uncertainty	*Nature:* due to imperfect knowledge versus due to inherent variability
Van der Keur et al. (2008)	Ontological Uncertainty	Epistemic Uncertainty	*Nature:* due to imperfect knowledge versus due to inherent variability
Ascough et al. (2008)	Variability Uncertainty	Knowledge Uncertainty	*Reducibility* and *nature:* Knowledge uncertainty may be reduced with additional research
Warmink et al. (2010)	Natural Variability	Epistemic Uncertainty	*Nature:* "…natural variability as random system behaviour that cannot be adequately explained great the available resources."
Petersen ([2006] 2012), Knol et al. (2009)	Ontic Uncertainty	Epistemic Uncertainty	*Nature*: Ontic is indeterminacy or variability associated with inherent nature of the system, epistemic is due to knowledge state
Smith & Stern (2011)	Imprecision	Ambiguity	*Measurability and Meta-uncertainty (also Nature) :* Imprecision is statistical and where PDFs can be provided. Ambiguity is where PDFs cannot be given and also is related to uncertainty about a PDF. They also liken ambiguity to 'un-nature' and the inadequacies of knowledge.
Dequech (2011)	Weak Uncertainty	Strong Uncertainty	*Measurability:* Weak uncertainty has complete and reliable probability distribution, strong does not
Beven (2016)	Aleatory Uncertainty	Epistemic Uncertainty	*Measurability*: Aleatory uncertainty has stationary statistical characteristics
Van der Bles et al. (2019)	Aleatory Uncertainty	Epistemic Uncertainty	*Nature:* Epistemic uncertainty as product of knowledge state. Aleatoric due to variability
	Direct Uncertainty	Indirect Uncertainty	*Meta-uncertainty:* Direct relates to a particular fact, Indirect relates to underlying knowledge base

2.4.2 Scales of Uncertainty

Often some of the particularly intractable epistemic uncertainties of the above two-type systems are described as 'strong' (Dequech, 2011), 'radical' (Kay and King, 2020), 'severe' (Ben-Haim, 2019, 2006) or 'deep' (Marchau et al., 2019; Walker et al., 2013). This adjectivisation implies some dimension along which some uncertainties are more challenging or problematic than others. *Scales of uncertainty* may be used to characterise the depth of uncertainty by defining the specificity with which the possible states of a system and their probability distributions may be described (Risbey et al., 2002 call this *predictive capability*). Several uncertainty frameworks thus conceptualise uncertainties falling between extremes of indeterminacy and determinacy, with intermediate states falling between them (Rotmans and van Asselt, 2001; van Asselt and Rotmans, 2002b). This classification has significant overlap with *measurability* described previously and has been identified by some authors as descendant from Knight's original risk-uncertainty distinction (Enserink et al., 2013).

Walker et al. (2003) describe levels of knowledge ranging from *deterministic knowledge* (unachievable) to *indeterminacy/total ignorance.* They define four levels along this spectrum of *statistical uncertainty* (uncertainties can be described in statistical terms), *scenario uncertainty* (possible outcomes and mechanisms for arriving at those outcomes are not well defined), *recognised ignorance* (fundamental relationships unknown) and *total ignorance* (we do not know what we do not know).

Warmink et al. (2010, p. 1521) and Refsgaard et al. (2007) add a level to the Walker et al. (2003) scale, including *qualitative uncertainty*: non-quantifiable statements can be made, expressing expert opinion, linguistic probabilities and ambiguities between people. They also omit total ignorance as what is not known cannot be known. Harremoës (2003) uses the Walker et al. system but describes two reasons for indeterminacy: practical (too many functional relationships) and theoretical (relationships inherently undefinable) indeterminacy. Kwakkel et al. (2007) attempt to reduce confusion in the original Walker et al. (2003) and other subsequent frameworks by clarifying the mathematical structures behind the levels described.

Bradley & Drechsler (2014) include 'magnitude of uncertainty' as one of their three fundamental dimensions of uncertainty. They differentiate their levels by one's ability to make a judgement: *ignorance* (no judgement possible), *severe uncertainty* (partial judgement possible), *mild uncertainty* (judgement possible) and *certainty* (outcome of judgement known).

Another framework that does not include probability as a discriminator between different levels of uncertainty is that of Courtney et al. (1997), with levels based on what can be known about outcomes*: a single outcome can be known*, *a discrete set of outcomes known*, or a *range of outcomes known* or *true ambiguity* (no way to forecast the future).

Table 2-4 presents a list of levels systems approximately aligned along 'increments' on these scales, though equivalences are imperfect, as discussed in *section 2.5.2*

Table 2-4: An eclectic selection of author's labels for 'levels' of uncertainty and how they may be seen to line up against one another. This is an imperfect comparison and as will be discussed in Section 2.5, these levels are not directly commensurable.

Knight 1921	Keynes 1921	Courtney et al. 1997	Walker et al. 2003	Kandlikar et al. (2005)	IPCC (2005a)	Kwakkel et al. 2010	Warmink et al. 2010, Refsgaard et al. 2007, Brown 2004, Van Der Keur et al. (2008)	Van der Bles et al. 2019
		Single Clear Future	(Determinism)					
Risk	Probability (numerical)		Statistical Uncertainty	PDF Given	PDFs given	Shallow Uncertainty	Statistical Uncertainty	Full PDF Defined
					Indicative probabilities given			A summary of a distribution
	Probability (Comparable)					Medium Uncertainty		A Rounded number, range
								A predefined categorisation of uncertainty
Uncertainty	Probability (non comparable)	Alternate futures	Scenario Uncertainty	Bounds given	Range given	Deep Uncertainty	Scenario Uncertainty	A list of possibilities or scenarios
		Range of futures		Order of Magnitude	Order of magnitude estimate			
				Expected Trend identified	Expected trend identified		Qualitative Uncertainty	A qualifying verbal statement
	Uncertainty		Recognised Ignorance	Ambiguous trend	Ambiguous relationships	Recognised Ignorance	Recognised Ignorance	Informally mentioning the existence of uncertainty
		True Ambiguity	Total Ignorance	Effective Ignorance				No mention of uncertainty
								Denial that uncertainty exists

In addition to describing the predictive legitimacy of a situation, levels may be used as a diagnostic tool used to select appropriate analytical techniques for a given situation (see the matrix of Stirling, 1998). They may also help classify how uncertainties are described (legitimately or not) in practice (see for example Paté-Cornell, 1996; Tennøy et al., 2006). Levels may also mix modalities of what *can* be stated and what *is* stated in practice (Enserink et al., 2013).

In essence, most of these scales categorise ways of enumerating or describing possible states of a system and making statements relating to their likelihood, probabilistic or otherwise. A list of these is given in Table 2-5.

Table 2-5: Several ways in which state spaces and probability statements are typically expressed in different uncertainty frameworks that utilise level concepts. Original analysis based on literature reviewed.

Ways of Describing the State/Possibility Space	**Ways of attaching likelihood estimations to states**
Exhaustive yet limited set of possible states described	Full probability density function
Range of states given	Ordinal ranking of states in terms of probability
Some (but not all) possible states given	Interval Probabilities given
Some states excluded	Central estimate with spread given
Order-of-magnitudes estimated	Fuzzy categories described (likely, unlikely, possible etc.)
Direction of a trend given	Qualitative description of the likelihood of those states

2.4.3 Known-unknowns: Meta-knowledge, Cognisance and Ignorance

On the border of some of the level systems described above are many varieties of *ignorance*. These scales of uncertainty have described what is and can be known about states and probabilities, but several frameworks go further and taxonomise the boundary with what is *not known*.

> *"… there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns – the ones we don't know we don't know. And if one looks throughout the history of our country and other free countries, it is the latter category that tend to be the difficult ones."*
>
> *- Donald Rumsfeld, February 2002.*

One who knows and knows that he knows…
His horse of wisdom will reach the skies.
One who knows, but doesn't know that he knows…

He is fast asleep, so you should wake him up!
One who doesn't know, but knows that he doesn't know…

His limping mule will eventually get him home.
One who doesn't know and doesn't know that he doesn't know…

He will be eternally lost in his hopeless oblivion!

-14th Century Persian Poet Ibn Yamin. Translation by Niayesh Afshordi (2016)

The above quote from Donald Rumsfeld is ubiquitous in lay discussions of uncertainty, though said to be a paraphrasing of 14th-century Iranian poet Ibn Yamin. Frameworks like this *Rumsfeld-Yamin system* organise uncertainties by one's awareness of them or one's ability to gain an awareness of them. Of particular interest are ideas about ignorance and the limits of knowledge, both from the point of view of an individual and that of an epistemic community (see e.g. Knorr-Cetina, 1999). Of particular importance is the idea of cognisance: do you know what you do not know?

A prominent early classification in this style is that of Faber et al. (1992), who present an extensive dendrogram that separates *ignorance* from *uncertainty and risk*. Ignorance is further subdivided into *open* (recognised) and *closed* (unrecognised) ignorance, and the latter is then classified as reducible (may be lessened) and irreducible. Figure 2-1 lays out their framework as an illustration.

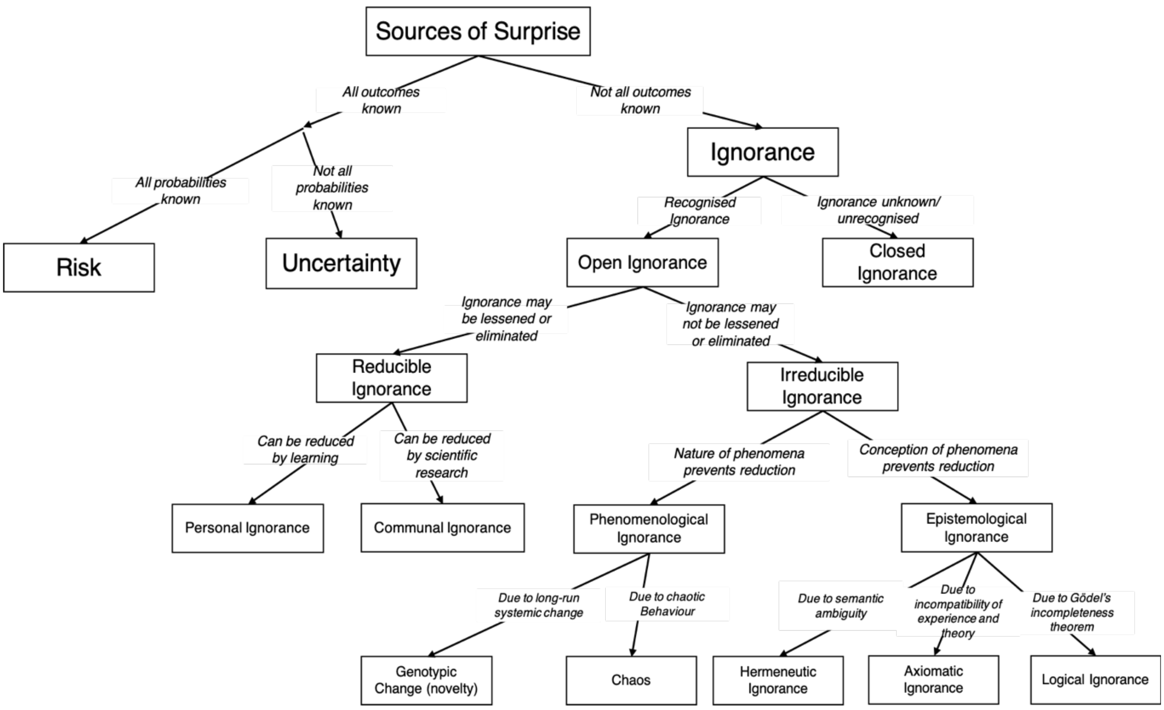

Figure 2-1: Compiled framework for ignorance adapted from diagrams in Faber et al. (1996) with distinctions added

The relationship between *ignorance* and *uncertainty* is contentious. Funtowicz & Ravetz (1990) describe the *border with ignorance* as including the gaps in one's knowledge that cannot be characterised statistically or through confidence statements, i.e. probing the edge of what is knowable. Wynne (1992) builds upon their work and limits *ignorance* to not knowing what one doesn't know. Petersen's framework ([2006] 2012) classes *recognised ignorance* as acknowledgeable and does not include unrecognised ignorance. Chow & Sarin (2002) define *known, unknown* and *unknowable uncertainty* by one's ability to know probabilities of outcomes. In other cases, variously: the term *ignorance* is used for *epistemic uncertainty* (Ferson and Ginzburg, 1996), *uncertainty* is considered a subcategory of *ignorance* (Dovers et al., 1996), ignorance is considered a subset of uncertainty (Smithson (1989)), ignorance is considered something that can be acknowledged (Faber et al., 1992) or something that is inherently unacknowledgeable (Brown, 2004).

Some typologies of uncertainty that interrogate ideas around ignorance have seen intellectual exchange with typologies of *surprise*. Perhaps, *surprise* could be considered the fruit that uncertainty bears. Typologies that study of the phenomenology of surprise answer questions such as 'how does the surprise appear to occur?' (Brooks, 1986), 'what caused it?' (Schneider et al., 1998) and 'was it anticipatable?' (Toth, 2009).

2.4.4 Source and Location of Uncertainty

The concepts of *source* and *location* of uncertainty are frequently used in uncertainty frameworks: how we conceptualise where uncertainties reside, originate from, or enter an analysis.

The *source of the uncertainty* either refers to the ultimate generator of the state of uncertainty itself (and hence trivially synonymous with 'an uncertainty'), or to a set of generalised causes of uncertainty. The latter conceptualisation will often involve listing some common causes of uncertainty in the given setting of the analysis, be it resolution errors, measurement instability, alignment errors, and the instability of human behaviour. For example, Manning & Petit (2004) describe five fundamental origins of uncertainty: incomplete observations, incomplete conceptual models, inaccurate understandings of processes, chaos and lack of predictability.

Location – sometimes also confusingly called *source* – has two general interpretations:

- In an analysis involving decomposable or interacting target systems, the aspect of a system regarded as uncertain (e.g. economic uncertainty in a coupled economic-biosphere model). Van der Keur et al. (2008) call this *context*.
- The point in the process of the knowledge production, model process or assessment process where uncertainty enters, is identified or is experienced (e.g. during model parameterisation or collection of data) (Zumwald et al., 2020)

These two conceptions of location may also end up blending in some typologies where different stages of the assessment process correspond to different interacting target subsystems, each receiving its own technical treatment (e.g. Beven et al., 2014).

Location as Sub-System

The former conceptualisation may be particularly intuitive in environmental assessment, which involves the cascade of knowledge and concepts across the boundaries of different systems. Meijer et al. (2006) (after Milliken. 1987) define the *source* as the "domain of the organisational environment which the decision-maker is uncertain about". In futures studies dealing with socio-technical change and scenarios, the use of interacting subsystems of analysis is common; for example, Hughes et al. (2013) present a model of interacting systems of actor dynamics and technical systems dynamics and separate those uncertainties that lie outside of actor's control and those which are uncertain due to actors not having yet made strategic decisions.

Examples of uncertainty locations in studies from climate economics may be: emissions scenarios, climate response, climate impacts and optimal policy responses (Gjerde et al., 1999; Peterson, 2006). This echoes the format of climate assessments such as IPCC assessment reports and their three-working-group structure. Wilby & Dessai (2010) describe a cascade of uncertainties in the assessment of climate adaptation options that broaden the *envelope of uncertainty* as one moves between these stages of an assessment. Such cascading conceptualisations of uncertainty are prominent in work describing coupled models or multi-stage assessments (Refsgaard et al., 2016).

These sub-systems can also be conceptualised as having broad thematic categories (e.g. Wätzold, 2000). This approach is common in environmental economics. Examples include Heal and Kriström (2002), who define *scientific, impact* and *policy uncertainty* (see also Heal & Millner, 2017, and Brouwer & De Blois, 2008, who separate uncertainties into *environmental, economic* and *political.*

Typologies may be adapted to the particular modelling problem of specific disciplines; in population ecology some typologies thus consider *phenotypic, demographic, environmental* and *spatial* uncertainty sources (Burgman et al., 1993; Shaffer, 1987).

Uncertainties may also be categorised as endogenous or exogenous to the system one is modelling, organisational theorists have organised uncertainties in this way concerning the organisation under study (Dreier and Howells, 2019; Duncan, 1972).

Location as a Point in the Knowledge Production Process

Many frameworks describe *location* as the point at which uncertainty is experienced in a knowledge production process. Some view *location* as a part of a linear process of knowledge creation, while others may consider knowledge creation as part of a flow between different elements of a system (e.g. (Ekström et al., 2013; Link et al., 2012; Peterman, 2004; Zumwald et al., 2020)).

The uncertainty in climate models is organised by Hawkins & Sutton (2009) as due to the internal variability (of the climate system), model uncertainty (different responses of models) and scenario uncertainty (different emissions forcing scenarios). Similar formulations listing selections of scenario, climate response, model structure, parameterisation and initial condition uncertainties are common in the climate-related modelling literature (Cheung et al., 2016; Knutti et al., 2008; Kutiel, 2019; Linkov and Burmistrov, 2003; Monier et al., 2015; Stainforth et al., 2007).

Examples of locations of uncertainty within a model, or 'model uncertainties', are described in Table 2-6. Sources are inconsistent about relevant locations, but most commonly, *model structural uncertainty, parametric uncertainty, scenario uncertainty* and *model implementation uncertainty* are described.

Table 2-6: Table detailing common locations of modelling uncertainty in the literature with some general definitions. General Location has been introduced by this review as an approximate organising concept.

General Location	Model-related Uncertainty	General Description	Cox & Bavbutt (1981)	Vesely & Rasmuson (1984)	Hall (1985)	Alcamo & Bartnicki (1987)	Suter et al. (1987)	Beck (1987)	Finkel (1990)	NRC (1994)	Ferson & Ginzburg (1996)	Cardwell & Ellis (1996)	Van der Sluijs (1997)	Huijbregts (1998)	Kann and Weyant (2000)	Rotmans & van Asselt	Huijbregts et al. (2001)	Linkov & Burmistrov (2003)	Walker et al. (2003)	Petersen (2006)	Pappenberger et al. (2006)	Hawkins & Sutton (2009)	Parker (2010a)	Mirakyan & De Guio (2015)	Refsgaard et al. (2016)
Conceptual Model	Model Choice	The effect of choices made by modellers												√											
	Modell***er*** Uncertainty	Difference in interpretation of the model problem																√						√	
Conceptual/ mathematical Model	Structural Uncertainty (conceptual)	Uncertainty in the correct relations between variables or mathematical forms. Sometimes this is just called *model uncertainty*	√	√	√	√	√	√		√	√	√			√	√		√	√	√	√	√	√	√	√
	Model Completeness	Are all relevant variables included?	√	√	√				√					√		√									
Mathematical Model	Model Boundaries	Uncertainty due to selection of boundary conditions					√														√		√		
	Parametric Uncertainty	Uncertainty in setting/ calibrating of parameters.	√		√	√	√		√	√	√	√		√	√	√		√	√	√	√		√	√	√
	Model Aggregation	Errors due to the aggregation of model elements					√																		√
Technical Implementation	Data Uncertainty	Uncertainty in the data used in model construction, calibration and tuning, including descriptions of terrain etc	√	√	√												√		√	√	√				√
	Model Implementation	Uncertainty introduced due to the computational implementation of a model, including numerical approximations		√		√							√		√	√			√	√	√			√	√
Model Driving	Initial Conditions	The effect of varying initial conditions in model settings				√		√															√		
	Model Forcing/ Scenario Uncertainty	Assumptions about conditions exogenous to the model system that drive behaviour.			√	√												√	√	√		√		√	√
Interpretation of model as a whole	Internal Variability (of model)	Spontaneous fluctuations in the model condition due to complexity of relationships			√																				
	Internal Variability (of system)	Spontaneous fluctuations in the system under study due to natural stochasticity					√															√			√
	Model Output Interpretation	Difference in interpretation of processed model outputs																	√	√				√	
	Inter-model Uncertainty	Difficulty in interpretation of result of alternative models										√													

2.4.5 Ambiguity, Quality, Dis-consensus and Linguistic Uncertainty

Uncertainties may arise due to difficulty communicating ideas or reaching consensus in epistemic communities. *Ambiguity* is most often used to refer to these kinds of uncertainty. However, the term is used inconsistently and not all authors agree it should be included in uncertainty frameworks (Bedford and Cooke, 2001).

Linguistic Uncertainty

Linguistic uncertainties originate in the non-specificity of language or the lack of reliable conceptual representation in communication (Ascough II et al., 2008). Regan et al. (2002) define five kinds: *vagueness* (borderline cases in scientific vocabulary), *context dependence*, *under specificity* (unwanted generality), *ambiguity* (multiple meanings) and *indeterminacy of theoretical terms* (see also Elith et al., 2002; Hayes et al., 2007*)*. *Linguistic uncertainty* may also be known as *semantic uncertainty* (Lane and Maxfield, 2005) or *translational uncertainty* (Rowe, 1994). In some cases it is identified as a form of epistemic uncertainty (e.g. Kirchner et al., 2021).

Multiple Knowledge Frames

Ambiguity may also refer to conflicting evidence, knowledge frames or epistemic values (Brugnach et al., 2008; Ekström et al., 2013; Enserink et al., 2013; Warmink et al., 2010). This could form a sort of meta-epistemic uncertainty or could be identified with epistemic uncertainty itself. Alternatively, ambiguity may be conceptualised as a third 'nature' of uncertainty (Brugnach et al., 2008; Petr et al., 2019).

Social Reliability and Pedigree

The NUSAP system is a notation system for the communication of quantitative and qualitative uncertainty, intended for science for policy (Funtowicz and Ravetz, 1990), which has been adopted by various authors (Fischhoff and Davis, 2014; Pye et al., 2018). The final letter of the acronym denotes *pedigree* – a description of the quality of the underlying science behind a statement. 'Indirect uncertainty' in van der Bles et al.'s (2019) uncertainty communication system is directly analogous. *Pedigree* may be somewhat ambiguously defined, and a description of the pedigree of knowledge may be a matter of expert assessment. The IPCC has produced a succession of frameworks for uncertainty communication, with statements assessed along two qualitative dimensions: *amount of evidence* and *level of agreement* (Mastrandrea et al., 2010; Moss and Schneider, 2000).

Smith & Petersen (2014) (also Petersen, 2006 [2012]) describe how the reliability of a piece of evidence can be referred to in three ways: its statistical reliability (*$reliability_1$*), its methodological reliability (*$reliability_2$*) and its social reliability (*$reliability_3$*).

There is some difficulty in extricating these forms of social uncertainty from one another. Uncertainties at the group level manifest themselves at the individual level and vice versa. Dovers et al. (1996) offer a partial solution by making the scale of the social unit at which the uncertainty manifests a dimension of uncertainty.

2.4.6 Values-related Uncertainties

In his famous "Beauty Contest Example", Keynes (1936, chap. 12) described a contest in which a panel of judges compete to choose the most popular face amongst the panel itself, rather than their personal preference. Thus, the judges must attempt to anticipate the subjective preferences of the other judges. Authors have long noted how the variety of human evaluations is an aspect of uncertainty. Human values are an important part of our social reality and come into play in various ways in scientific investigations, modelling and decision-making processes. Different people hold different values about various topics such as epistemology, politics and ethics. Conflicting values create uncertainties even within the minds of individuals, as reflected in some uncertainty frameworks. We identify four ways in which values-related uncertainties are incorporated into uncertainty frameworks (cf. Figure 2-2):

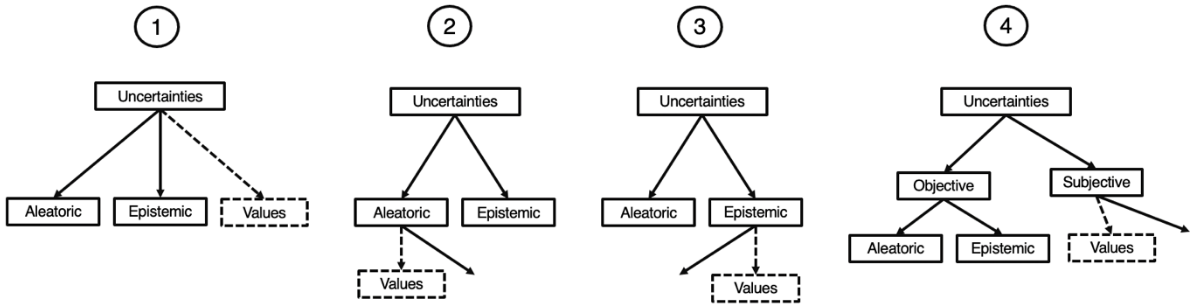

Figure 2-2: Summary of different methods of incorporating value-based uncertainties into frameworks

1) As an additional fundamental nature of uncertainty, Beven (2016) describes 'ontological' uncertainty[24] (associated with different belief systems) as separate from epistemic and aleatoric uncertainty. Bradley & Drechsler (2014) defines 'normative uncertainty' as a fundamental nature of uncertainty.

2) As just another aspect of the natural variability of the world. Knol et al. (2009) thus includes, 'normative uncertainty' as a sub-category of ontic (aleatoric) uncertainty which results from "a multitude of 'socio-ethical-normative' considerations within a society". Other classifications call this 'value diversity' (Rowe, 1994) and Smith & Stern (2011) describe a difference in values contributing to the indeterminacy of some variables.

[24] Not to be confused with the *ontic* uncertainty of other classifications. Here this means differences in belief systems (one's ontological beliefs) rather than due to the ontology of a system.

3) As relevant assumptions that affect knowledge production to be identified and frankly acknowledged in the process of an assessment. In this way there is implicit normativity in epistemic frameworks used by people. Values are integrated into our way of knowing and are an integral aspect of epistemology. For example, Petersen (2006 [2012]) includes uncertainties that are due to *value-laden assumptions* in an uncertainty matrix. This is congruent with ideas from Post Normal Science (PNS) which advocates a frank inventory of values and assumptions in science.

4) As belonging to a separate class of uncertainty entirely, along with other subjective uncertainties. Tannert et al. (2007, p. 894) thus propose a taxonomy in which *epistemic* and *aleatoric* are separate from *subjective uncertainty*[25], which includes as a sub-class of *moral uncertainty*. Sigel et al. (2010) divide uncertainty into factual and normative uncertainty, though the latter is mostly concerned with regulation and legality. Other authors, perhaps following trends in policy sciences, may describe issues of factual uncertainty separate from 'normative dissent' (Grin et al., 2004). *Subjective* uncertainties may include other uncertainties experienced by decision-makers or more broadly, 'human-dimension' uncertainties (Baecher and Christian, 2020; Moser, 2005, 1997).

One may further ask what *kind* of values are being incorporated: epistemic values (what is valued as knowledge), ethical/moral values, political values, aesthetic values? The interaction of different values with knowledge production is rarely considered in these frameworks.

2.5 Discussion: Challenges in Uncertainty Studies

Having reviewed the most important categorisations of uncertainty in the literature, this section presents several challenges to the current state of affairs in uncertainty studies. It considers whether conceptual synthesis between frameworks is achievable and suggests routes forwards to more productive uncertainty dialogues.

[25] Tannert et al. (2007) link this to Durkheim's idea of *anomie:* a state in which societal values become clouded and ambiguous.

2.5.1 The Fundamental Nature of Uncertainty and Its Inconsistencies

Frameworks for uncertainty analysis and the definitions they employ should be philosophically robust to have applicability across different domains, even within environmental assessment.

This chapter has reviewed many systems that posit the two fundamental types of aleatoric and epistemic uncertainty and identified four ways to distinguish them: *measurability, meta-ness, reducibility* and *nature*. Despite these ways of separating being often inconsistent, this conflation exists commonly in the literature.

This chapter suggests that this confounding of different ways of separating uncertainties may be due to the experience of different kinds of prediction tasks, such as weather- and climate-like tasks. Weather forecasting is a paradigmatic repeatable task in which system dynamics are well understood and can generally produce reliable probability distributions of future weather states in the short term. Yet the chaotic nature of the system prevents exact foreknowledge of the weather state and uncertainty is practically irreducible. In non-repeatable tasks like climate-like forecasting, the system drivers (such as anthropogenic emissions) cannot be known, and feedback processes (such as due to aerosols) are not well-defined (see also Smith, 2002). Thus, these situations abound with epistemic-type uncertainties.

More specifically, the use of *nature* itself, though predominant in recent literature, is imperfect for several reasons. Triaging a given uncertainty between epistemic and aleatoric uncertainties is indeed often difficult practically; expert opinion and analytical convenience may determine the classification used (Baecher and Christian, 2020; Beven et al., 2015; Hora, 1996; Walker et al., 2003). Moreover, conceptually, the idea of a fundamental separation between mind/epistemology and system/ontology implies a specific view of metaphysics.

Oftentimes the variability in a system is not easily attributed to some true system variability or to some hitherto unknown process. Skinner et al. (2014) therefore define an intermediate category to overcome this difficulty in judgement. Others may describe individual sources of uncertainty as having both epistemic and aleatoric components (Beven et al., 2015).

This uncertainty triage is particularly fraught when considering the unreliability of human behaviour and social systems. Individuals may disagree about the extent to which regularities of human behaviour could be eventually knowable. If these uncertainties are reducable, these behaviours may yield epistemic uncertainty; otherwise, the human-system yields aleatoric uncertainty. In essence, this depends on one's view on the nature of human or social behaviour.

Chaotic systems seem a paradigmatic case of the effect of aleatoric uncertainties. However, in situations where an effect is due to some hidden emergent phenomena, we may not be able to recognise it as such. The epistemic/aleatoric divide is thus influenced by one's attitude towards different possible positions regarding determinism. If one views nature as purely deterministic with all outcomes inevitable given the antecedent nature of the world (what Gigerenzer et al., 1989 call *metaphysical* or *epistemic determinism*), then all uncertainty is ultimately epistemic (Riesch, 2012). For researchers with a more Bayesian strand of thinking, the divide is ultimately false and purely useful for instrumental purposes (Bedford and Cooke, 2001; Winkler, 1996). More subtle versions of determinism, such as the *effective determinism* (Gigerenzer et al., 1989a), may see determinism coexisting with indeterminism as the two can apply at different levels of analysis. Thus, the level of aggregation and the domain of a study or model can allow the two natures of uncertainty to coexist pragmatically without making strong claims about the ultimate nature of a system.

Many issues described here have their origin in the difficulty of partitioning epistemology and system ontology. This divide ignores that knowledge creation occurs, in part, through a dialectic between epistemology and a system; the way one intervenes, measures and conceptualises a system is based on epistemic assumptions. Perhaps a more useful approach considers the epistemic capacities available in a situation: would improving data, conceptual, intellectual and computational resources improve understanding?

2.5.2 The Value of Scales of Uncertainty

Organising uncertainty into levels is an attractive idea. In situations where the likelihood of different outcomes are difficult to estimate, it allows for a representation of knowledge and indicates appropriate analytical tools (e.g. scenario analysis in situations of *deep uncertainty*). However, this idea of uncertainties being rank-orderable should be understood as a helpful metaphor only, as underlying it are profound inconsistencies.

'Level-systems' do not imply that some uncertainties are 'larger' in some abstract sense, but they do encode information about the state space of possibilities and their probability. While it seems intuitively legitimate to have two poles of knowledge states, full determinism and complete indeterminacy, we cannot draw a straight line between them with stops along the way. Even individual level frameworks are inconsistent as to what is tracked in transition between uncertainty levels (Kwakkel et al., 2010; Norton et al., 2006). What these do in fact track one's ability to enumerate and describe possible states of a system and make statements relating to their likelihood, probabilistic or otherwise, as shown in Table 2-5.

Several other inconsistencies compromise the robustness of level-based organisations of uncertainty. *Firstly*, we may be able to only partially define both state spaces and probability distributions: we can give probabilities to some outcomes but not others. For example, in 'Black Swan' situations the likelihood and nature of day-to-day occurrences is well known, but unexpected events with unknowable probabilities have large impacts (Taleb, 2007).

Secondly, one must caution against the propensity to transform deep uncertainties into something more tractable such as probabilities (Derbyshire, 2017a; Shackley and Wynne, 1996). According to Van der Bles et al. (2019), the deepest uncertainty level is an explicit denial of the existence of uncertainty – this seems circular as it may be impossible to distinguish a denial of uncertainty and a legitimate claim that significant uncertainties do not exist.

The conceptualisation of how our knowledge of state/possibility spaces may be constrained is a powerful organisational principle, but more textured descriptions of our knowledge states are possible. As acknowledged since the time of Keynes, we may also make less formal probability judgements, such as ordinal probabilities, interval probabilities, fuzzy sets, or qualitative judgements. Scenarios themselves can fulfil predictive, explorative and normative purposes (Börjeson et al., 2006). It is common to make value-based judgements over scenario sets in the form of worst- and best-case scenarios.

2.5.3 The Ambiguity Created by Multitudinous Frameworks

This review has explored how concepts such as *nature, level* and *ignorance* intersect with one another. This may create confusion for those uninitiated in the esoteric teachings of uncertainty studies.

The profusion of uncertainty lexicography also creates a form of linguistic ambiguity – similar to the linguistic uncertainty described in section 3.5. The terms *ambiguity* and *uncertainty* themselves are ambiguous and uncertain (Milliken, 1987), and analysts may struggle to remember all terminology (Casman et al., 1999). While the ambiguous meaning of probability terminology has been well examined (e.g. Morgan and Henrion, 1990), that of uncertainty terminology more broadly has been less so.

If linguistic ambiguities already exist, framework constructors should reflect whether applying such labels to the uncertainties they identify is productive. It may be best to use terminology with the smallest risk of creating confusion.

2.5.4 The Relevant Boundary for Inclusion of Uncertainties within a Framework

A huge number of issues have found their home in uncertainty frameworks. As quotidian difficulties in research practice have been framed as *uncertainty*, the term has perhaps become inflated. In attempting to be as comprehensive as possible, uncertainty frameworks may be insufficiently clear as to the range of analytical activities to which they have relevance.

Firstly, including concepts such as *risk, ambiguity* and *ignorance* within the boundary of uncertainty is contentious in the literature. Why particular concepts to include in uncertainty frameworks is a matter of analyst choice. If one is designing a framework to describe all hindrances to achieving a desired knowledge state, then exhaustiveness is desirable. But at this point, the term 'uncertainty' seems too petty for the summary of knowledge and potential defects thereof that is being produced. Perhaps some other more all-encompassing term is required.

Secondly, uncertainty frameworks may be insufficiently clear as to what parts of the system of knowledge production are within the bounds of analysis. For example, a typology for summarising uncertainties associated with an environmental model may limit its scope to uncertainties endogenous to the model and in the mind of the individual modeller. But the model is not immune to uncertainties within the epistemic community that its creator inhabits. Modelling involves the appropriation of elements from a wide variety of domains (Boumans, 1999), and drawing a boundary around the model process may be conceptually challenging.

2.5.5 The Challenge of Meaningfully Incorporating Values

Many frameworks do not account for how different values, epistemic, moral, ethical, political and otherwise, contribute to uncertainty. Others attempt to include values somehow, though very few delve deeply into these mechanisms rather than treating values as an afterthought.

The inconsistency in the treatment of values may be, partly, due to philosophical divergence over what roles values and normativity have in informing scientific and decision-making processes. Many philosophers of science argue that values are inextricable from scientific assessments and modelling processes in their methodological design and interpretation, while positivists wish to imagine a firebreak between human subjectivity and science.

Normative uncertainties are frequently brought up in commentary of the difficulties of Integrated Assessment (e.g. Giampietro et al., 2006). Disagreements over the selection of important variables such as *pure rate of time preference* and the *marginal utility of consumption* have origins in fundamental differences over moral values (Davidson, 2015). Heal & Millner (2017) call for some process of preference aggregation to move past an impasse over "primitive ethical questions". However, ethical preferences involve complexly interacting disagreements over how the world is and how it should be. Values are inherently unamenable to aggregation, else politics and collective decision-making would be no more than an optimisation exercise.

The theory and practice of Post Normal Science (PNS) advocates a form of strong candour about one's values and assumptions (Giampietro et al., 2006; Kønig et al., 2017). Perhaps frameworks should consider better what role values play and form appropriate accommodations, rather than considering them tokenistic additions.

2.5.6 Productive Routes Forward

A changing environment impacts many coupled environmental, human, technological and economic systems and requires studies that lie at their nexus. Addressing uncertainties found in the spaces between disciplines requires the collaboration and communication of individuals from different epistemic communities.

This chapter has examined how frameworks are espoused in the theoretical sections of literature, but not necessarily how these frameworks are operationalised in the resulting literature which uses these concepts. The existence of uncertainty concepts in the literature does not necessarily mean that researchers in general conceptualise uncertainties in these ways.

Skinner et al. (2014) note that the development of frameworks for uncertainty analysis is often a crystallisation of the opinion of an individual researcher. If we wish interdisciplinary researchers to be able to communicate effectively with each other, we should start by examining empirically how researchers themselves relate to uncertainty in their work and understand it conceptually. From this firmer ground of understanding, bridges can then be built to aid interdisciplinary collaboration on complex issues.

This review has demonstrated that underlying epistemic values and philosophical commitments have a role to play in the development of frameworks. There are several well-known theoretical disagreements on topics such a probability, caricatured in some quarters as a tribal argument between Frequentists and Bayesians. Comprehensive genealogies exist for *probability* as a concept (e.g. Hacking, 1975), but scant research traces the conceptual roots of uncertainty concepts prominent in contemporary discourse. Tracing the heritage of these ideas could help account for the epistemic values and contingency of ideas underlying the uncertainty analysis frameworks reviewed in this chapter.

We should understand frameworks for uncertainty analysis as collections of conceptual tools that allow us to examine, identify and communicate uncertainties in imperfect yet improved ways. Our ability to understand uncertainties in a system will be as imperfect as our knowledge of that system itself. We should recognise the possibility for different aims of uncertainty handling: are we trying to reduce perceived uncertainty, make our predictions more reliable, make our decisions more robust or justify predetermined positions? If our aim is to improve interdisciplinary collaboration, perhaps we should begin with engaging with uncertainty as *it is understood,* rather than *how we think it should be understood.*

2.6 Conclusion

This review has examined a large corpus of frameworks for the analysis of uncertainty of relevance to environmental change studies from disciplines including environmental economics, ecology, climate science, environmental assessment, integrated assessment, energy studies, risk theory and decision-making theory. This corpus is highly heterogeneous with different forms, aims and intended applicability, yet is recognisable as a body. Common features have been analysed and organised, such as the use of levels and scales to describe uncertain situations, the different meanings of *ambiguity* and the divide between *epistemic* and *aleatoric uncertainty*.

Presenting a series of challenges to the broader status of the literature, this chapter has then suggested a route forward: engaging with uncertainty more empirically to investigate meanings and conceptual models employed by practitioners in their daily work and lives. Using this empirical basis, uncertainty handling can be described in a way more sympathetic to the real needs of researchers. The collection of concepts identified in this chapter provides a basis for this empirical work, which is conducted throughout later chapters in this thesis.

This review has conveyed the sheer inconsistency of treatments of uncertainty. While this inconsistency may hamper communications efforts with peers, policymakers and other stakeholders, this is hardly surprising given the range of epistemic issues represented under the banner of uncertainty.

Uncertainty frameworks deal with the forms knowledge can take and the conditions for drawing inferences from that knowledge to the past, present or future states of systems. *Uncertainty analysis* can seem almost too parochial a term for the act of accounting and describing one's knowledge state while accounting for the values inherent in decision-making. *Un*-certainty seems to imply that certainty is to be expected; in studies of the changing environment, uncertainty is inescapable. Perhaps a defunct term such as *gnosiology* could be resurrected to refer to the practical process of accounting for and describing one's knowledge state when assessing complicated systems.

Do not mistake the map for the terrain: the uncertainties described in uncertainty frameworks are not complete descriptions of all the ways in which we may be surprised. Let us recognise frameworks for uncertainty analysis for what they often are: imperfect but useful conceptual tools.

3 Methodology

3.1 Introduction

In this chapter, I present the methodology employed in this thesis. The principal methodology was a set of in-depth semi-structured (guided) interviews that used techniques derived from mental models interviews to elicit conceptualisations of uncertainty from participants. The interview also included a section in which the context of a participant's modelling work was examined in greater detail.

As discussed in the previous chapter, this thesis aims to explore the understanding of uncertainty of modellers working in climate modelling and energy systems modelling. I therefore consider what methods are suitable for examining these understandings.

The chapter is in three parts. Section 3.2 considers the theoretical and philosophical underpinnings of the general approach, detailing the necessary ontological and epistemological assumptions and the explication of the interview-based research. It argues for the relevance of interview methods to the research question.

Section 3.3 then looks more specifically at the methodological literature concerned with the design of interview studies. It considers the literature on mental models interviews and their potential utility for this study in which conceptual representations are elicited from participants.

Section 3.4 then gives a detailed account of the research methodology employed, the construction of the sample, the approach to data analysis and synthesis, how the interviews were conducted, ethical considerations, reflexive considerations, and limitations of the study.

Finally, I conclude the chapter (§3.5) and reflect on the implications of the overall methodology employed.

3.2 Theoretical Underpinnings

I now outline some of the theoretical underpinnings of the interview methodology that has been employed by this thesis, considering some of the necessary ontological and epistemological assumptions. I start by restating the project's research aims and examining the kind of information I seek to acquire (§3.2.1).

Reflecting briefly on some of the literature on the history of the conceptualisation of uncertainty (§3.2.2), I argue that to understand these ideas' transmission and reinterpretation, I must make some limited idealist ontological assumptions (§3.2.3). Furthermore, to pay attention to the role of interpretation in creating multiple possible meanings of these concepts I must appreciate the relevance of certain forms of social constructionism in my epistemology.

I then argue that as I am dealing with researchers' understandings and meanings, I must necessarily adopt the broadly termed 'qualitative paradigm' (§3.2.4). Therefore, interview-based methods for exploring this knowledge with participants are relevant to my study (§3.2.5) – a set of methods I shall examine in more detail in Section 3.3.

3.2.1 Aim of the Methodology

The methodology aims to explore the conceptualisations of modellers around the various uncertainty concepts that appear in the literature. I wish to explore what concepts are used; how different types of uncertainty are separated from each other in the minds of modellers. Therefore, it is worth reflecting on the types of information I wish to acquire (Bloomberg and Volpe, 2008). Knowledge about conceptualisations of participants is to a large extent based on my perception and the account of how participants think about uncertainty that I am trying to build is at first a descriptive account.

However, I also hope to go deeper and explore with participants the factors that influence their conceptualisations of uncertainty. Thus, this extends the descriptive account to the social environment in which they work and begins to consider causality.

The kinds of knowledge I am interested in exploring with participants is idiographic in that it relates to the utilisation of different concepts within a very particular context. I do not expect that all my findings will necessarily be generalisable to other fields. In fact, it is the expectation of a lack of generalisability that motivates the comparative aspect of the thesis between the two fields of climate modelling and energy/IAM modelling. This expectation is informed by the various sources in the introduction that have decried the difficulties in communication between different epistemic communities collaborating in climate-related studies. I shall return to questions of generalisability towards the end of this thesis where I consider uncertainty concepts from climate and energy transposed into the context of epidemiology and use this to revaluate my findings.

3.2.2 Aside on the Historical Evolution of Uncertainty Concepts

As I turn towards issues of the history of uncertainty conceptualisations, the history and philosophy of science show that *uncertainty-concepts*[26] have emerged in surprising contingent ways from their social and intellectual contexts. It shows that there was often little inevitability about their emergence. I briefly delve into this literature to illustrate the nature of the knowledge I am interested in and what informs my ontological and epistemic assumptions.

In *The Emergence of Probability*, Hacking (1975) demonstrates how *probability* emerged only after the mid 17th century despite the concept's utility and potential profitability in finance and gambling. *Probability* would eventually schism into competing concepts once the incompatibility of subjective and objective (epistemic and aleatoric) interpretations could no longer be ignored.

Bernstein's (1996) *Against the Gods*, a history of the concept of *Risk,* track elements of the same story as Hacking's, with a financial focus, through the ideas of eminent thinkers such as Poincaré and members of the Bernoulli family, concentrating on the implications for risk management. The book shows how the emergence of these concepts made possible different financial markets such as insurance.

Enberg-Pedersen's (2015) *The Empire of Chance* recounts the epistemic turbulence following the Napoleonic wars. He considers a variety of military and literary sources in the post-Napoleonic age and argues that the chaos of the conflict inspired a crisis in the understanding of uncertainty and contingency; in the words of Enberg-Pedersen, "Epistemology suffered a

[26] I use this term here just as a grouping for all the groups of concepts that are commonly associated with uncertainty such as variability, probability, and scenarios.

concussion at Austerlitz”. The result of the wars was a shift away from rationally ordered ways of thinking about military planning, as exemplified by the neat, symmetrical geometric fortifications of the Marquis de Vauban, towards more empirically grounded ways of thinking about strategy. This rethinking of the nature of contingency by thinkers such as Carl von Clausewitz drew on advances in philosophy and mathematics, such as probability theory. Furthermore, these ways of understanding uncertainty and contingency were reified into new technologies such as tabletop war-games.

Hacking’s (1990) *The Taming of Chance* also explores this collapse in deterministic thinking during the 1800s. He explores how technologies of statistics, including the printing of numbers, lead to epistemic upheavals. The technologies made possible the contingency of human actions to be understood as statistical regularities. This resulted in conceptualisation of statistical regularities as explanatory laws in themselves, and thus chance was tamed.

Gigerenzer et al.’s (1989b) book, amusingly also named *The Empire of Chance,* tracks the emergence of statistics and significance testing. They show how concepts around probability and statistical inference, as they exist in many fields today, are the results of an inconsistent fusion of ideas from two schools of thought: the Fisher and Neyman-Pearson schools. These ideas about statistics appear to those that learn them as inevitable, neutral and universal ideas. However, in fact, this synthesis occurred only as the result of the adoption of different ideas by textbooks. Their book shows how the uncertainty routines of modern science have become unmoored from their conceptual basis and are then institutionalised through a variety of actors. Gigerenzer et al. (1989b) also show how ideas about probability have moved between fields of study, such as physics and biology, and in each case have been recontextualised and reinterpreted.

In each of these histories, we can see that the emergence of uncertainty concepts is not inevitable, but is informed by the material, social and intellectual contexts in which researchers work. Uncertainty concepts are contingent in that they could exist and be used by researchers in other ways. These concepts move between fields of human learning, both academic and non-academic, and are reinterpreted and recontextualised wherever they are found. In other terms, they are the subject of social construction. These conceptualisations are also reified in technological artefacts, such as games and models, and pedagogical artefacts such as textbooks.

3.2.3 Ontology and Epistemology

I am interested in the conceptualisation of uncertainty in the minds of modellers; somewhat unavoidably an element of idealist ontology must run through my methodology. An idealist ontology centres on thought and the interpretation of events as the principal objects of study (Given, 2008). My participants are interviewed as individuals, and as such, I am looking to understand their personal constructions. Still, I acknowledge that these representations are shared among people and dependent on their context. Therefore, this is best characterised as 'collective idealism' (Ritchie et al., 2003).

Furthermore, the aside above shows the contingency of meta-scientific concepts around uncertainty. It is not that the contingency of the concepts I am interested in means that they could exist in *any way*, but it shows that the concepts as they exist in scientific intellectual life could exist in *other ways*.

My research strategy must be sensitive to this social construction. However, there are multiple senses in which one can understand a thing to be subject to social construction (Hacking, 2000). When I discuss how the conceptualisations of uncertainty that participants have as being the subject of social construction, this is not the social construction of knowledge necessarily, but the social construction of higher-order ideas about the process of research and about knowledge itself. So, I must tread a careful line, incorporating aspects of the philosophy of science to understand better the potential referents that participants could be discussing and to understand their conceptualisations themselves.

There are multiple senses in which one could describe uncertainty as the subject of social construction. The first is that the concepts associated with uncertainty themselves are derivative of a process of social negotiation. This is undeniable as with all concepts created through human interactions.

The second is that the uncertainty that is 'produced' through social construction is the result of being engaged with a model or an assessment process. To create an estimate of uncertainty in science is, in a way, to produce a form or order from disorder.

My focus on mental constructions of uncertainty is compatible with the form of constructivism I use. As Giere (1988, p. 15) notes, "The mere existence of evolved cognitive capacities does not determine the uses to which they are put. That depends on many things, including, of course, the social context. This, although one may need to invoke social factors to explain why scientists use their cognitive capacities in some ways rather than others, one must still appeal to their cognitive abilities to understand what they are doing when they employ those abilities in the specified ways."

Though I acknowledge the role of social construction, and my epistemological assumptions can be broadly described as constructivist, I do not take the approach popular in some textbooks of assigning an overall philosophical paradigm primacy over all elements of the methodological selection (see discussion in Matta, 2021). This is because there is a strong philosophical component to my work, and I require some flexibility in the way that I can perform conceptual analysis.

3.2.4 The Qualitative Paradigm

3.2.4.1 The Relevance of the Qualitative Paradigm

Given the ontologically idealist and epistemologically constructivist angle that my methodological grounding takes, adopting the qualitative paradigm is necessitated. My primary research question concerns the way that scientists understand concepts. Meaning is specific to individuals and concerns the relationships between what people say and what they intend to say (Dilley, 2004). When people understand concepts, I aim to understand these in terms that I might not naturally understand; hence, I must be prepared to conduct some form of interpretation.

The investigation of meaning is problematic to engage with outside of a qualitative approach. Some naïve methods may be possible to look quantitatively at applying the raw concepts through some frequency-based analysis of an appropriately chosen corpus of scientists' discourse, but deeper analysis would not be possible.

Furthermore, my conceptual literature review in chapter 2 has qualitatively analysed the key uncertainty concepts that are present in the literature that gives typologies of uncertainty.

3.2.4.2 Aside on Abandoned Methodological Ideas

At an early stage of my doctoral research, I briefly tried to consider how some of the toolkits used by the emerging field of *experimental philosophy* could be used to understand how researchers related to various kinds of uncertainty. Experimental philosophers use a variety of empirical methods to examine the philosophical intuitions of participants, often relying on providing participants with vignettes of situations and using quantitative questionnaire-based methods to assess their assessment of it (Alexander, 2012).

I contemplated, for example, whether researchers could be provided with vignettes describing some uncertain situations, and their understandings of these situations could be gauged with a questionnaire. However, I judged that this family of approaches would ultimately not suit my research project for several reasons.

- The questionnaire design would be problematic as designing a flexible questionnaire that looked to assess respondents' responses to uncertain situations may be overly reliant on my understanding of these uncertainty concepts.
- The very object I am most interested in exploring is the flexibility in the interpretation of these concepts and a questionnaire would be too rigid a format to elicit participant responses.

I recount this to underscore the importance of the qualitative paradigm and the infeasibility of other approaches.

I also considered pursuing a more ethnographic method, such as participant observation, in which I might embed myself with a group of modellers for some time and observe how issues around uncertainty were managed. This might have given the benefit of providing very rich data about how social dynamics inform uncertainty treatments. However, I decided that the gains would be limited because of the potential low density of interactions that I might be able to observe on the thematic topic of interest. Furthermore, this would potentially only have given me access to the conceptual understandings of a very limited pool of participants and the issues of access might have precluded comparative work between different disciplines.

3.2.5 Basis of the Interview Study

I employ an interview method to interrogate the understanding of uncertainty by modelling researchers. The benefit of an interview method is that it can allow detailed theoretical discussion and, therefore, useful and dense data for analysis. I would also be able to flexibly interrogate the understandings by a broad sample of participants from the target groups that I am interested in.

In the following section, I review some of the literature on interview methods to identify considerations that must be heeded in interview design. I consider a set of specialist interview methods called mental model interviews and appraise their usefulness in assessing the conceptual understandings of participants.

3.3 Approaches to Interview Methodologies

I now consider recommendations from methodological literature on planning, organising and performing interview studies. Firstly, I look at some of the interviewing methods literature and recommendations for interview design (§3.3.1). I then consider several techniques from mental models interviews that may be efficacious for my method in eliciting conceptualisations from participants (§3.3.2).

3.3.1 Designing Interviews

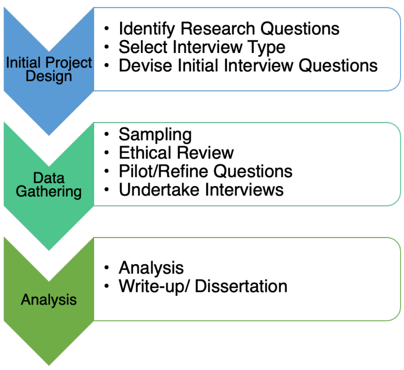

Figure 3-1: The structure of a typical interview study according to Young et al. (2018) (adapted from figure 1)

Several considerations informed the interview design:

- How to explore conceptualisations with participants
- The structure of questioning and type of interview (unstructured, structured, semi-structured, guided)

- Considerations of the role of the interviewer in the study
- Reflexivity
- The design and structure of the interview protocol

I examine each of these in turn.

3.3.1.1 Exploring Concepts in Interviews

Interviewing is an interactive method in which a conversation occurs with "a structure and purpose determined by one party" (Kvale, 2007) and learning can occur through the interaction of participant and interviewer (Young et al., 2018). Interviews are an extremely flexible method of data acquisition, and as such, the kinds of information gleaned from an interview can include opinions (e.g. Keeley and Matsumoto, 2018), attitudes (e.g. Bercht, 2021), narratives (e.g. Jovchelovitch and Bauer, 2000), experiences (e.g. de Vet, 2013), framings (e.g. Robbins, 2020) and conceptualisations of ideas (e.g. Lewis and Linn, 1994).

Interviews can be used to explore the meanings of concepts to participants. One area where this purpose of interviewing is prevalent is in education research. Understanding students' understandings is informative for the development of pedagogical techniques (see for examples Lewis and Linn, 1994; Tasquier et al., 2016).

Brinkman (2007) claims that qualitative research communities often overlook methodological innovations that originate in psychology. Brinkman (2007) described the concept of *epistemic interviews*, which are about developing knowledge, rather than *doxastic interviews* which merely convey experience or opinions. Indeed, some influential guides to interviewing, such as Kvale (1994), argue that researchers should avoid eliciting abstract reflection and instead ask questions about actual experiences. The epistemic interviews described by Brinkman are relevant to this thesis as I am attempting to elicit more than mere reactions from participants and to attempt to engage with conceptual models of uncertainty that may be implicit.

3.3.1.2 Interview Style

Interviews can be categorised by the extent to which the conduct of the interview is either predetermined or flexible. There are several terminological differences between different kinds of interview technique.

In ***structured interviews***, the interviewer presents each participant with the same set of questions in the same sequence. The advantage of this interview style is that it is relatively simple to implement and not cognitively taxing for the interviewer, and allows easy and direct comparison for participants' responses to different research questions. Such a method is used by Barrieu (2020), discussed in §1.3.1.1, to examine the understandings of modelling and uncertainty of researchers in different fields. However, the rigidity of this approach does not allow exploration and the potential for heterogeneous interpretations of conceptual questions from participants can lead to incomparability. As I cannot be sure that participants will provide the responses I require on my first asking, I cannot rely on a structured interview methodology.

Semi-structured interviews follow an interview protocol with a set of questions but allow interviewers to improvise follow-up questions that adapt to participants' responses (Kallio et al., 2016). The advantages of this are many-fold, but commonly authors emphasise the ease of implementation and the flexibility of the method for pursuing topics that the interviewer is interested in exploring.

Unstructured interviews may involve no preparation of questions in advance, and the interviewer may explore questions and topics in a free-flowing way (McGrath et al., 2019). No interview can be completely unstructured in the truest sense (DiCicco-Bloom and Crabtree, 2006). These interviews can lead to difficult issues of comparability between participants but have various advantages such as the comfort of participants and resulting natural dialogue.

McIntosh & Morse (2015) distinguish between semi-structured interviews and ***guided interviews***. Semi-structured interviews consist of interviews guided by a set of predetermined questions which may permit some additional elaboration. On the other hand guided interviews may be more exploratory, beginning with broad questions and then following very loosely organised set of questions (McIntosh and Morse, 2015). As the conceptual models of participants are individualistic, a 'one-size-fits-all' approach to the interview questionnaire would not have been appropriate.

There is a tension between the ability to organically explore a subject and the desire for replicability and comparability between transcripts. Therefore, my methodology may be best described a *guided interview*, in the terminology of McIntosh & Morse (2015), in that has an overall set of questions but allows the interviewer to divergently explore concepts with the participant wherever that may take them. I require this flexibility as participants' responses to conceptual questions will not be standardised. For convenience, however, I shall refer it as semi-structured as this term is more widely used by other literature.

3.3.1.3 The Role of the Interviewer

Research interviews can require much of the researcher conducting them, both in terms of skills that they embody, the knowledge they have and how they create participation in the interview.

Skills

In interview studies, the role of the interviewer is crucial both in terms of the role they play during the interview and studying transcripts. Semi-structured interviews necessarily involve a certain amount researcher skill such as the ability to engage in 'active listening' (Fujii, 2018, chap. 1). In order to conduct effective interviews, the interviewer must also attempt to create rapport with the interviewee (Fujii, 2018, chap. 2). However, the possibility of creating rapport may be limited by the time allotted to the interview (DiCicco-Bloom and Crabtree, 2006).

Knowledge

Interviews on complex subjects require that the interviewer have a requisite conceptual, theoretical and thematic knowledge to effectively engage with the participant (Kvale, 2007, chap. 4). One can acquire familiarity with these topics in a variety of ways, but it was anticipated that my own academic background in undergraduate Physics and Masters in Energy Studies would allow a requisite understanding of issues around modelling to engage effectively with participants.

Participation

Interviewers must also consider *how* they intervene in interviews beyond the styles of questions they ask. They can consider the extent to which they encourage participants to co-create knowledge in the dialogue.

Phenomenological interviewing often requires minimal interventions from interviewers to allow the stories of participants to flow in a natural way. More Socratic modes of interviewing allow presenting more probing and challenging questions to participants to test the robustness of ideas (Brinkmann, 2007; Kvale, 2006; Shanahan, 1987).

It is also essential to pay attention to the power dynamics that may be at play in an interview. Power dynamics can have ethical implications and affect the quality of the interview. For example, power dynamics that erode the possibility of trust can lead to difficulties in accessing the interview subjects' true opinions (Kvale, 2006).

Berner-Rodoreda et al. (2018) build on Brinkmann's (2007) concept of the difference between epistemic and doxastic interviews and propose a typology that also considers the additional dimension of the *role of the interviewee*. This can range from the interviewee playing the role of 'respondent' merely responding to the interviewers' questions, to being an 'equal partner' where the interviewee can question or even challenge the interviewer.

3.3.1.4 Reflexivity

Reflexivity involves the "critical ongoing examination of the way that the researcher engages with others" and the "consideration of how issues of positionality – such as the researcher's personal characteristics or theoretical vantage points – shape the research process" (Fujii, 2018). To exercise this reflexivity, I must consider how my role as a researcher talking about the topic of uncertainty may have an indirect influence on participants. I must also consider how my own theorisation and conceptualisations of uncertainty can shape the research process and inadvertently guide interviews.

3.3.1.5 Designing Interview Protocols

Semi-structured interviews can be prepared with a variety of materials. Most commonly, a set of questions can be prepared accompanied by prompts, sub-questions or probes (McIntosh and Morse, 2015).

Question sets can be prepared in a logical structure and may typically consist of 5-15 questions, depending on the intended length of the interview. It is sometimes recommended that the interview commence with 'easier' questions to allow the interviewee to acclimatise. When preparing interview questions, researchers should avoid the use of esoteric jargon, which may confuse participants (McGrath et al., 2019).

The additional questions asked by an interviewer in a semi-structured interview can include 'prompts', 'follow-ups' and 'probes' (Kallio et al., 2016). These can be improvised by the interviewer or, in some cases where clarifications can be expected, can be partly prepared in advance.

The following section considers the design of interviews in terms of protocols and procedures from the perspective of mental models interviews.

3.3.2 Mental Models Interview Approaches

As I am attempting to access the participants' conceptualisations, I pay attention to what can be learned in terms of interview design and performance from the technique of mental models interviewing. Uncertainty conceptualisations I elicit will be individual and researchers have developed techniques for eliciting the different mental models of participants.

3.3.2.1 Background on Mental Models Approaches

In essence, the *mental models hypothesis* is the assertion that individuals use mental models to understand the world. Such a view can be argued to have a Kantian or Neo-Kantian heritage, where people may argue that people cannot gain access to *things-in-themselves* (*Dinge an sich*). Instead, people are said to use concepts to mediate between the world and themselves. Mental models are "personal internal representations of external reality that people use to interact with the world around them" (Jones et al., 2011).

The mental-models paradigm found in psychology originates from authors such as Phillip Johnson-Laird, Ruth Byrne, Dedre Gentner and Albert Stephens, writing in the early 1980s[27] (Greca and Moreira, 2000, p. 2). Gentner & Stevens (1983) are notable for their early application of mental models to ideas about science, with an assumption that mental models of mechanistic systems must be 'computationally simulable' (Greca and Moreira, 2000). Johnson-Laird's (1983) theory differs subtly from Gentner & Stephens's (1983) in that it assumes that people are confronted with a situation and then select models that will provide a substitutive internal model to understand the situation. Most mental models theorists agree that these mental constructs are imperfect, parsimonious representations of things in the real

[27] Though the idea can be most originally traced back to the work of Scottish Psychologist Kenneth Craik who suggested that the mind anticipates event through the construction of small-scale models (Johnson-Laird et al., 1998)

world. They disagree to the extent that mental models are simulable or manipulatable in the subjects' minds.

Mental models approaches have been adapted for many context-specific purposes in the social sciences as valuable tools to understand how human cognition affects social preferences, people's behaviours, actions and beliefs. They have proven fruitful in a diverse range of studies such as those on science education, risk communication, human–computer interaction, cultural anthropology and equipment operation (Morgan, 2017, p. 395). Particular attention to mental models has been paid in the field of cultural anthropology in which the techniques have been used to study how cultural information informs people's understandings of topics (Jones et al., 2011).

Philosophers and sociologists of science have examined the ways in which mental models are reflective of the social context in which they may emerge. Knorr-Cetina (1999) argues that some mental models of different groups of scientists may predominate due to the action of power and resources. Latour & Woolgar (1979) have shown how as part of the process of the construction of scientific facts, a variation in conceptual understandings of scientists can be productive.

This approach of eliciting mental models is consistent with the ontological and epistemic approach I have previously outlined and the idea that conceptual elements are transferred in science from one domain into another and reinterpreted on arrival.

3.3.2.2 Eliciting Mental models

There are two primary methods of eliciting mental models: direct and indirect (Jones et al., 2011). Direct methods involve asking participants to represent their understanding of some system either verbally, diagrammatically or using some pre-provided materials. Various distinct methods exist that vary the tasks required of participants. Indirect methods may involve inferring the models implicit in documents or interview transcripts[28]. Similar methods exist for both directly and indirectly eliciting the cultural models[29] such as participatory modelling

[28] From interviews that do not involve direct elicitation.

[29] Shared conceptual models within a culture

techniques such as the 'Actors, Resources, Dynamics and Interaction' (ARDI) method (Jones et al., 2011).

Indirect methods include *consensus analysis* which finds overlaps in shared understanding between a group of individuals. The first stage involves setting a group of individuals an open-ended task, such as an open-ended interview. Selected content derived from this first stage is then presented to a secondary group of individuals in which they are asked to sort, rank or otherwise apply criteria to statements to determine the similarity of responses. Statistical analysis, such as factor analysis, may be applied to measure the degree of consensus between individuals (Jones et al., 2011).

Some authors have elicited the mental models used by different actors in to ameliorate communication issues. For example, Abel et al. (1998) use mental models to understand how a range of actors conceive of landscape processes in a region of rural Australia.

3.3.2.3 Examples of Relevant Mental Models Approaches

Morgan et al.'s Models of Risk

A prominent mental models approach was taken in risk communication, which began with an effort led by Granger Morgan, Baruch Fischoff, Lester Lave, Ann Bostrom and Cynthia Atman in the late 80s (Morgan, 2017, p. 390). It began with recognising that "there is no such thing as an expert who can tell you the best content or format for a risk communication message." Morgan argues that before we can develop an appropriate risk communication, we must know about their mental model of risk[30] (Morgan, 2017, p. 395).

Morgan et al. examined mental models of risks using an interview and questionnaire approach. Expert risk models were formulated and conceived as webs of relations between concepts relevant to the given risk. These expert models were then used as guides for semi-structured interviews to explore how participants themselves related the given concepts to each other. This approach was used to create risk-related communications (Morgan et al., 2002b). For example, the process of forming conceptual graphs[31] can be used to discretise the elements in

[30] I make a similar claim for uncertainty. Too little attention has been paid to the way people properly understand uncertainty and are likely to contextualise any new information about uncertainty.

[31] Maps of concepts and their relationships

a mental model and to produce a meta mental model (Plantinga, 1987, p. 188). Morgan's process for creating risk communications can be summarised very briefly (Morgan, 2017, p. 394):

1) "Create an expert model" that describes the nature and magnitude of the risk
2) "Conduct mental model interviews" that elicit people's belief about the causes and consequences of the hazard
3) "Conduct a closed-form survey" that attempts to confirm the findings of stage 3, using beliefs captured in the mental model interviews
4) "Prepare a draft communication"
5) "Evaluate communication"

The open-ended approach of the interviews is important to ensure that any information provided to the recipient is not likely to colour their response (Morgan, 2017, p. 395). During this interview, it is recommended that the interviewer bring up no new concepts of their own, and simply skilfully elaborate on concepts generated by the interviewee. Morgan (2017, pp. 396–397) provides examples of this technique in which an interviewer simply asks for more information on a topic (in this case climate change) or repeats a concept already brought up by the interviewee with a phrase such as "you said… tell me more about that". The interview protocol described has several basic prompts such as "*anything else?*" and questions that aim to elicit responses without giving any leading information.

Morgan describes how mental model interviews tend to reach an "asymptotic limit" after around 15-20 interviews, at which new mental models of the phenomenon become rarefied (Morgan, 2017, pp. 396–398). The number of concepts found in studies described by Morgan after 20 to 30 interviews ranges from around 80 to 150.

Mental Models of Higher-Order Concepts

The concepts examined by Morgan et al. (2002b) were very topical in that they were amenable to the description in terms of lots of different parts. I am examining philosophical ideas and concepts around uncertainty which are higher-order concepts. One may ask, what relevance do mental model interviews have for this thesis? These methods and similar ones have been used for such concepts in the past. For example, a paper by Tasquier et al. (2016) describes a study in which the understanding of high-school students of the concept of *modelling* itself. Testing student's knowledge of models after an educational intervention, through phenomenological analysis they identified categories of answers relating to 'what a model is' and 'what a model is for' as well as the relationships between models, experiments and reality (Tasquier et al., 2016, pp. 547–548). Other students were found to offer an answer which was 'prudent', emphasising the complex relationship between the three and purportedly showing epistemological maturity.

Mayer et al. (2017) employed a variant of a mental models approach to examine how 11 scientists make decisions when developing models for climate risk management. They employed a 'Values-informed Mental Models' approach, originally developed by Bessette et al. (2017).

Thus, mental models approaches using an open semi-structured interview format can elicit the conceptual models of a variety of different kinds of concepts. The most instructive aspect of this methodology for my interviews is the elicitation procedure described by Morgan et al. (2002b) in which a wealth of concepts are explored without new concepts necessarily being brought into the conversation by the interviewer. This is achieved through systematic and skilful interviewing.

3.4 Research Design

3.4.1 Overall Study Design

The heart of the interview study consisted of semi-structured interviews that incorporated techniques from mental models interview methods. The interview protocol was divided into three parts:

- A conceptual exploration of various uncertainty concepts and types of uncertainty
- Contextual exploration of why uncertainty is handled in particular ways and the methods used to investigate it
- A reflexive wrap-up section where the participant is asked to reflect on the interview

Thirty-eight participants were recruited and interviewed from the climate modelling and the energy/IAM community. Table 3-1 gives a summary of the steps taken in this methodology.

Table 3-1: Timeline summary of the key events and processes in the study

Stage	Task	Dates
Ethics	Initial Ethics Approval Sought and Obtained	09/2018- 13/12/2018
	Ethics Extension due to secondment granted	04/01/2021
Pilot Study	Participants Recruited for Pilot Study	13/12/2018 - 01/02/2019
	Interviews for Pilot Study Conducted	13/12/2018 - 01/02/2019
	Interviews for Pilot Transcribed	01/2018 - 03/2019
	Analysis of Pilot Interviews	02/2018 - 05/2019
	Submission of Pilot report and Upgrade Seminar	06/05/2019- 06/06/2019
Preparation	Revision of Interview Protocol with Feedback	06/2019 - 08/2019
	Widening of literature review to gather concepts	06/2019 - 08/2019
Data Collection	Recruitment of Participants in Person	08/12/2020 - 12/12/2019
	Interviews (in Person)	09/12/2020- 12/12/2019
	Implementation of lockdown restrictions	03/2020 -
	Recruitment of Participants Virtually	18/03/2020 - 08/2020
	Interviews (Online)	01/05/2020 - 03/09/2020
Interruption of studies	Due to government COVID Secondment and injury/concussion/ surgery	09/2020 - 06/2021
Analysis	Transcription of interviews in NVivo	06/2021 - 09/2021
	Note making with key themes	06/2021 - 12/2021
	Coding of Interviews in NVivo	08/2021 - 11/2021
	Production of one page summaries	08/2021 - 11/2021
	Synthesis Analysis	11/2021 - 01/2022

The following subsections dive deeper into the different aspects of the study design, the sample and the pragmatic considerations that were considered in the conduct of the interview study. I first outline the ethical considerations that went into preparing the study and how these were addressed (§3.4.2). I then outline the construction of the interview protocol (§3.4.3) and how my experience of the pilot study for this thesis caused me to revise elements of the protocol (§3.4.4). I give an overview of how and why the groups of participants were recruited for the study (§3.4.5), and how the interviews were conducted (§3.4.6) and analysed (§3.4.8). I finally reflect on the limitations of this research design and the challenges for reliability (§3.4.9).

3.4.2 Ethical Considerations

Prior to implementing the interviews, I sought ethical approval through UCL's Ethics approval procedures. The decision was made to pseudonymise all participants and store interviews securely on a password-protected hard drive.

As part of the ethics review process, I identified several potential ethical issues that could be faced during the research and planned accordingly to mitigate these. The table below summarises these issues and outlines the approach taken to mitigate them.

Table 3-2: Summary of key ethical issues that I identified in the UCL ethics review process and the steps taken to mitigate them.

Issue	Participants may be worried that their professional status within their immediate research group could be compromised by an unwillingness to engage with issues of uncertainty. If the snowball sampling technique leads to a recommendation of a potential participant they may feel as if they are obliged to participate due to the status of the one who suggested them.
Approach	I stressed that participation is entirely optional and not a reflection on the researcher. Other participants were not informed of the participation or otherwise nonparticipation of researchers, including those who were recommenders/gatekeepers.
Issue	There is a long history of narratives around uncertainty in climate-related research being misused by bad-faith actors. Some participants may be anxious to discuss the topic for this reason.
Approach	It was made clear to participants that the aim of this research is not to criticise or audit the practices of modellers and that any publications emanating from this research would emphasise this.
Issue	Many research groups are quite close-knit, and researchers may be anxious about professional dynamics of talking about uncertainty.
Approach	Discretion has been used to ensure that nothing potentially embarrassing has been included in quotes from transcripts. Participants were pseudonymised and contextual information that could be reasonably used to identify either the researcher or the research institution was not presented in analysis. It was also made clear to participants that colleagues would not be informed of participation in the research.

Furthermore, participants were provided with an information sheet that explained the purpose of the research, how data would be handled and what to do should they wish to withdraw themselves from the study. All participants signed a consent form.

Ethics approval was obtained without complications. A time extension of the ethics approval was sought and obtained due to the delay in the research because of my secondment to the UK government during the COVID-19 pandemic.

3.4.3 Interview Protocol Design

To address the central research questions, the initial interview protocol was split into several subsections. The first section of the interview concerned the conceptualisation of uncertainty and used a version of Morgan et al.'s (2002b) process of conceptual call-backs. The questions were very open-ended, and participants were briefed at the beginning of the interview that the opening section might seem a little bit odd at first.

The interview then followed an exploration of the factors that might influence an uncertainty analysis or motivate the exploration of particular uncertainties.

The interview was constructed to balance tension in the study design between the need to allow participants to freely explore the aspects of uncertainty that were salient to them in their everyday research practice and the need to have comparable results that addressed the key questions of this thesis.

Following the completion of initial interviews, the interview protocol was refined. This is detailed in the following subsection. The final interview protocol is available in Appendix E of this thesis. Figure 3-2 gives an overview of the interview procedure developed for this thesis.

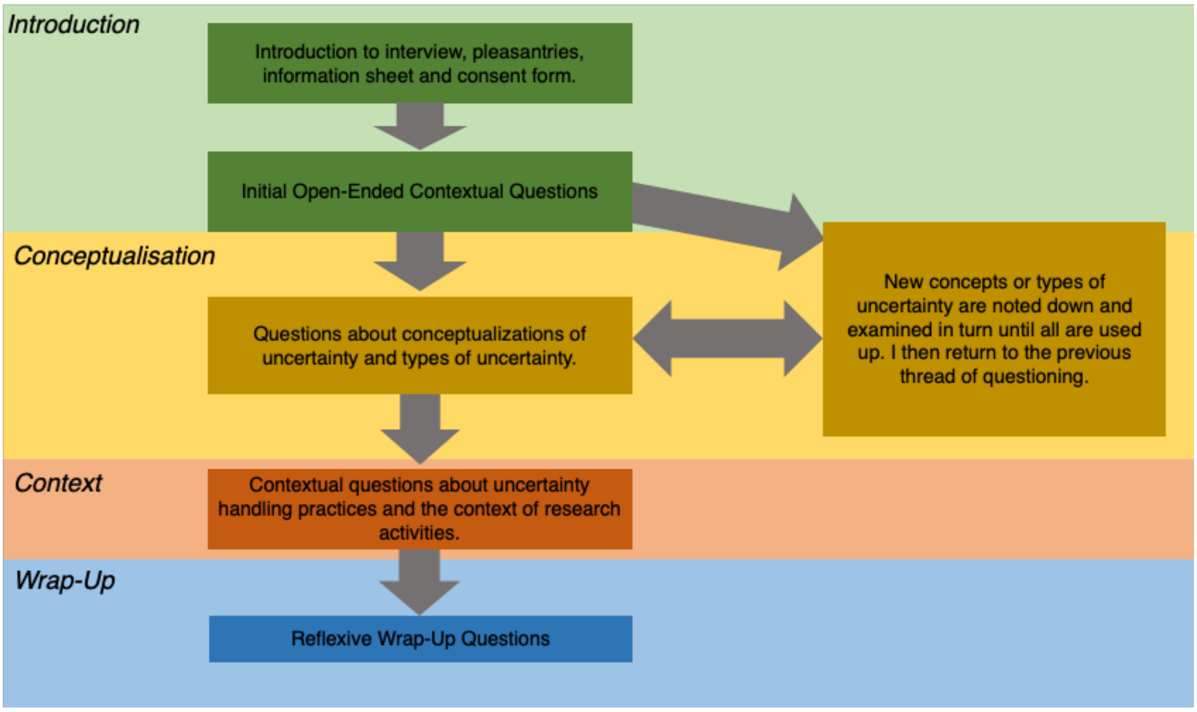

Figure 3-2: Overview of the structure and process of the interview, showing how new concepts or ideas that emerged were systematically returned to during the conceptualisation phase.

3.4.4 Pilot Study

The first five participants were interviewed as part of the pilot study. From these interviews and the upgrade seminar process, several issues with the interview protocol were identified and subsequently addressed.

Firstly, as part of an effort to understand participants' understanding of various uncertainty concepts such as *variability* and the role values play in uncertainty analysis, I had initially begun my interviews by asking a variety of questions directly eliciting responses to these concepts from the participants.

However, I identified a potential trade-off between ensuring that interviews consistently covered similar subjects and ensuring that those subjects and concepts covered were indeed an integral part of the participant's normal research practices. If a particular concept was not well known to them or doesn't play a significant role in their mental model of uncertainty, their response may be uncertain or involve on-the-spot speculation.

I decided to amend the interview protocol slightly in response to this issue. Instead of beginning with many very abstract questions, I began with a more open-ended question to allow participants to start talking about uncertainty on their own terms. I began with some more contextual questions, asking them about their modelling work, what kinds of models they used and what kinds of uncertainty analysis they had conducted in the past. Then when they naturally began to invoke various uncertainty concepts I focussed on these and went through the conceptual exploration process, first noting down the concepts they had mentioned on my iPad and then systematically returning to previously mentioned concepts until no more emerged.

Secondly, the interview was previously very clearly demarcated into a conceptual section and a contextual section. The interview was often a little disjointed in the middle with a rapid shift in cadence. Moreover, the separation of the discussion of contextual issues from the conceptual discussion meant that it was more challenging to identify the relationship between concepts and the modelling practices of participants.

Instead, the two sections were better blended with the interview initiated with some contextual questions. Furthermore, during the more contextual discussion towards the latter half of the interview, I continued the conceptual call-back technique when new concepts were brought up.

3.4.5 Participants

3.4.5.1 Participant Sample

My sampling method is purposive as I needed to rely on my own judgement to form a suitable array of participants (Palinkas et al., 2015). The criteria for inclusion in the study were twofold:

- *Thematic relevance*: is this person a researcher active in the fields in which I am interested in studying? I describe this in more detail below for each epistemic community.
- *Activity Relevance*: is this person engaged in model development or the running of models? If they are not frequently running models, are they involved in the post-processing of model results and would they be generally considered by their peers to be a member of their community?

When approaching potential participants, I also aimed to capture a range of seniorities and roles within the community.

3.4.5.2 Energy and Integrated Assessment Modellers

The community of participants from the energy/IAM community are twin. Firstly, those who develop or operate whole-energy system models. Those who develop models of limited aspects of the energy system, such as local grid modelling, were not considered for this study as I am interested in exploring uncertainty with those whose work is most immediately relevant to national-scale and international-scale mitigation efforts.

The second group of intended participants are those who develop or operate Integrated Assessment models of the climate-economic kind. There is a very porous border between these two groups and hence I have treated them as one community. Most IAMs have an energy model component and many energy models are extended into IAMs by adding impacts models of various kinds.

3.4.5.3 Climate Modellers

The community of participants from the climate modelling world are those involved with the development, running and analysis of GCMs and coupled GCMs. This includes those who operate the models as a whole and those who develop aspects of the models. All participants were involved, in some way, with models that eventually would be included in the ensemble produced for CMIP6.

Participants were recruited for both groups from both academic institutions and research labs that produced academic publications.

3.4.5.4 Participant Recruitment

Participants were recruited by various means: though professional networks, contacts out of the blue, and snowballing the sample through the recommendations of other participants.

I have a more developed professional network in the energy/IAM space because of having studied and worked in it for some time. So, I initially recruited these participants through my professional network. The sample then snowballed from these participants, particularly within a few research institutes. Senior individuals served as gatekeepers for two of these institutions, allowing me access and recommending colleagues to approach. When I noted that conceptual exhaustion was being reached, in that new concepts were not regularly being discussed, I ceased conducting these interviews.

Climate modellers were less well known to me so I also leveraged other means of collecting the sample. Firstly, I attended the 2019 Fall Meeting of the American Geophysical Union in San Francisco. There I was able to meet and talk with many climate scientists, both at presentations and at poster sessions. The poster sessions were particularly beneficial as a pedagogical opportunity as I was able to first understand the research before asking potential participants if they would be interested in being interviewed. In this way, I interviewed 6 participants who then recommended more potential participants to continue the snowball.

In general, potential climate participants were less responsive to email requests. This could have been due to any number of reasons, including the perceived discomfort of discussing an idea of uncertainty or different practices in time scheduling.

3.4.5.5 Overview of Participants

Table 3-3, below, gives an overview of the participants recruited for this study and how they were interviewed. Participants have been pseudonymised using the names of mountains within the Lake District National Park in Cumbria in England. The pseudonyms were randomly assigned and have no further meaning.

In total 38 participants were recruited. Various sources recommend different sample sizes of participants. Kvale (2007, chap. 4) claims a typical number of interviews is 15 ± 10 interviews. Often interview guides recommend continuing until some kind of saturation is reached (Townsend, 2013). The number recruited from both communities is sufficient on its own for the study.

Table 3-3: Overview of participants recruited for the study. I categorise the seniority of participants in three ways: if they run a group or have multiple researchers working for them I categorise them as 'senior', if they are an ECR I categorise them as such, otherwise they default to 'researcher'. To preserve pseudonymity, I have not included detailed biographic information of specialisms.

Pseudonym	Models	Thematic Specialisms	Seniority	Interview Mode	Date Interviewed
Gable	Energy Systems	Climate Economics	Researcher	In Person	13/12/2018
Skiddaw	Energy	Energy Technology Cost Specialist	ECR	In Person	16/12/2018
Scafell	IAM	Climate Economics and Agriculture	Senior	In Person	13/01/2019
Helvellyn	Energy Systems	Interdisciplinary	Researcher	In Person	15/01/2019
Bowfell	Climate/ Weather	Climate and Weather	Senior	In Person	01/02/2019
Coniston	Climate	Climate and Aerosols	Researcher	In Person	09/12/2019
Lingmell	IAM/ Impacts/ Simplified Climate Models	Interdisciplinary, sea levels	Researcher	In Person	10/12/2019
Swirl	Climate	Land-air interactions	Researcher	In Person	11/12/2019
Pillar	Climate	Climate Generalist	Senior	In Person	12/12/2019
Scoat	Energy	Energy Systems	Researcher	In Person	12/12/2019
Nethermost	Climate	Oceans in GCMs	Researcher	In Person	12/12/2019
Branstree	Energy	Energy Systems	Researcher	Video Call	09/01/2020
Loughrigg	Energy	Energy Systems	Researcher	Video Call	04/05/2020
Whitston	Energy	Bioenergy, Energy, IAMs	Researcher	Video Call	06/05/2020
Yewbarrow	Energy	Interdisciplinary	Senior	Video Call	07/05/2020
Blencathra	Energy	Interdisciplinary	Senior	Video Call	11/05/2020
Catbells	Energy	Energy Systems	Researcher	Video Call	18/05/2020
Fairfield	Energy	Energy Systems	Researcher	Video Call	29/05/2020
Rannerdale	Energy	Energy/ IAMs	Researcher	Video Call	08/06/2020
Lattrigg	Energy	Energy/ Electricity	Researcher	Video Call	12/06/2020
Brisco	Energy	Energy Systems	Researcher	Video Call	15/06/2020
Weatherlam	Energy	Energy Systems	Researcher	Video Call	01/07/2020
Greatend	IAM	IAMs	Researcher	Video Call	03/07/2020
Esk	IAM	IAMs	Senior	Video Call	05/07/2020
Crinkle	IAM	IAMs	Senior	Video Call	08/07/2020
Catstye	Climate	Climate Models	Senior	Video Call	14/07/2020
Grasmoor	IAM	IAMs	Researcher	Video Call	16/07/2020
Brandreath	IAM	IAMs	Senior	Video Call	17/07/2020
Grisedale	Climate	Climate	Senior	Video Call	20/07/2020
Glaramara	Climate	Climate	Researcher	Video Call	04/08/2020
Bleaberry	IAM	IAMs	ECR	Video Call	18/08/2020
Dolywaggon	Climate	Climate	Senior	Video Call	04/09/2020
Harterfell	Energy	Energy Systems	Senior	Video Call	20/08/2020
Pavey	Climate	Climate	Senior	Video Call	20/08/2020
Causey	Climate	Climate	Researcher	Video Call	21/08/2020
Carrock	IAM	Interdisciplinary	Senior	Video Call	27/08/2020
Hartcrag	IAM	IAMs	Researcher	Video Call	03/09/2020
Redscrees	Energy	Interdisciplinary	Senior	Video Call	20/08/2020

3.4.6 Conducting the Interviews

Interviews were conducted both in-person and online. When the COVID-19 pandemic emerged I was in the midst of interviews and hence had to try and reorganise many of them. Most of these were conducted online.

Demographic and contextual information about the participants was gathered from the interview transcripts (participants were asked about their experiences with models as an opening question) and through reviewing the participants' publications, LinkedIn profiles and online staff profiles.

Participants were given all the time they needed to read the information sheet if they had not already, and I invited them to ask any questions they might have. All participants filled in a consent form, either a physical copy or an electronic version.

If the interviews were conducted online, the audio was recorded using a recording app on my laptop and then transferred to the storage, in compliance with the ethics approval. If interviews were conducted in person, the audio was recorded on my phone and then transferred to the storage.

During the interviews, I kept a copy of the interview protocol on an iPad and was able to cross off questions once they were addressed and I kept a note on the protocol of concepts that had emerged that needed to be called back to.

Interviews were scheduled with participants for an hour as a pragmatic balance between getting adequate time with the participant to explore all the concepts that warranted exploring and a block of time that could be easily scheduled in their diaries.

3.4.7 Reflexivity

I was aware of the possibility that my own conceptual models for uncertainty could inadvertently guide the interview project and meditated on this issue after the pilot study interviews. This, in part, motivated the move to a more flexible interview protocol.

To practice my interviewing technique, several colleagues kindly agreed to allow me to practice non-recorded interviews about their own conceptualisations of uncertainty before I began my initial interviews. I found that the quality of the interviews improved when I connected the most abstract questions to what they had previously said. Otherwise, very open-ended questions could seem difficult to approach.

I also conducted a self-interview before the pilot study to try and understand my own conceptualisation of uncertainty. I sat in a room and made notes about how I imagined organising kinds of uncertainty. I found this challenging as my thinking has been influenced by my own interest in the subject and literature I had read. I also noticed that over the course of the interviews my thinking about uncertainty progressed because of my reading and interactions with participants.

Other aspects of reflexivity can involve understanding and respecting the local norms of participants (Fujii, 2018, chap. 2). However, this was not problematic for me as most of my participants are drawn from academic institutions in developed western economies and I am very familiar with the practices of the world they inhabit. Nonetheless, I was sensitive to the idea that there may be uncomfortable questions about local institutional cultures to which I am not privy.

3.4.8 Analysis and Processing of Data

The analysis of the data here is *thematic* rather than *discourse* (see Bloomberg and Volpe, 2008) as the data are not naturally occurring as it has been created as a result of a productive event between myself and my participants.

3.4.8.1 Transcription of Data

I transcribed the interviews by hand in the programme NVivo. Transcription was performed verbatim as this captured some of the uncertainty with which participants discussed concepts. Some non-verbal cues were also captured, such as 'umms' and extended silences. Therefore, it was possible to discern from the transcribed text when participants seemed to be speaking about things they were more familiar with. Naturally, transcription is still an interpretive activity, and so there can be no one truly verbatim transcript of a given interview (Poland, 1995). However, the *NVivo* software allows the transcriptions to be examined and replayed alongside the original audio to ensure fidelity when reinterpretation of the transcribed text is challenging.

Manual transcription, as opposed to contracting out the transcription, was laborious but was beneficial as it gave an immersive opportunity to understand the data. This was also compliant with the ethics approval. I interrupted my studies after the interviews were conducted due to being seconded to the UK Government to work on COVID science and policy. The transcription allowed a deep refamiliarisation of the content of the interviews.

After transcription, the transcripts were analysed in two ways, through coding and through drafted summaries of interviews. A notebook with rough notes about themes was also maintained.

3.4.8.2 Transcript Coding

The codes for were organised in several ways to structure the analysis around the research questions of this thesis. My aims with the coding were to help draw out commonalities between the participants in terms of their conceptualisations of different kinds of uncertainty, to group alternative conceptualisations of similar concepts for comparison, and to explore the relationships between various factors and the conceptualisation and handling of uncertainty.

The nodes were clustered in NVivo into four groups. The first three codes were *a priori* codes developed before I began the coding process (albeit which received some modification from my empirical observations) and the final was empirical (Gibson and Brown, 2009).

- The first group of codes were intended to help identify different conceptualisations of uncertainty. These concepts were structured primarily from the concepts identified in the literature review. Under this cluster, I also included several other concepts that were used to describe uncertainty.

- Secondly, I noted when participants discussed the methods they used so that I could link together conceptualisations and practice.

- Thirdly, I noted the various influences that appeared to shape how people performed uncertainty analysis. These nodes were organised into sub-clusters according to the general types of influence I could identify. I started with general influences such as the research group they occupied and the models themselves and gradually disaggregated them.

- The final group of codes was not planned before the coding began but emerged in response to my experience coding the initial set of interviews. I realised it was important to record and understand the normative views of participants regarding various issues that seemed contentious. For example, their beliefs about the proper relationship between scenarios and probabilities.

3.4.8.3 Interview Summaries

I summarised each interview in one page for the salient aspects of them to the research questions. This was to capture aspects of the interviews that I deemed noteworthy that did not fit into the coding scheme described above and to foster contemplation on the themes of the research. These pseudonymised summaries are available in *Appendix B*.

3.4.8.4 Note-making and Synthesis

Further to this, I kept a notebook where I made handwritten notes about themes that I identified throughout the interview analysis. In this way, I could capture detailed thoughts and relevant aspects of the data at different levels of abstraction: the individual quotes, the summaries of interviews and the overarching themes.

When drafting my write-up of the analysis, I was aided by excel spreadsheets that I created to help further synthesise various aspects of the analysis. For example, I noted the frequency of the employment of various concepts and methods.

3.4.8.5 Revisiting My Data

Having written up my analysis chapters I later revisited my data by listening to a selection of interviews and reviewing the interview summaries. This was to ensure that the written analysis aligned well with the content of the interviews.

3.4.9 Limitations of Design

In terms of limitations of the design, the first issue is that drawing links between conceptualisations and practices will be difficult as in an interview the whole of the research process will not be visible to me. Situated research, say an ethnography at an institute, may be able to create a deep description of the link between concepts and practices, but this type of method is impractical for reasons described earlier.

Ensuring comparability of the data is a challenge for several reasons. Firstly, I anticipate variation in my participants' conceptualisation of uncertainty and thus I cannot overly standardise the interview protocol. The length of an interview is also pragmatically limited, and the range of possible concepts that can be discussed is therefore restrained.

I must also be aware of the limitations of the analysis in terms of reliability. As the concepts discussed are complex and require expert analysis, it is difficult to attempt anything such as interrater reliability. Therefore, I have endeavoured to analyse my interviews with several complementary approaches, such as coding and summarising, described above.

I shall return to the wider issues identified throughout the study later in this thesis, where I will apply the Total Quality Framework to an analysis of the study's strengths and weaknesses (§6.6).

3.5 Chapter Conclusion

This chapter has presented the methodology employed for the interview study, alongside the conceptual and theoretical groundings for it. It has presented a semi-structured interview method that incorporates aspects of mental models interview techniques to elicit a detailed conceptualisation from participants without relying on an a-priori model to guide questioning.

The following chapter 4 presents the results of the energy/IAM group of participants. Chapter 5 presents the result of the interviews with climate modellers. Chapter 6 will compare and analyse the two groups of participants and propose an overarching understanding of the relationships between models, uncertainty concepts and modellers.

4 Analysis of Energy/IAM Interviews

4.1 Chapter Overview

This chapter presents the results and analysis of the interviews conducted with modellers in the energy and Integrated Assessment community.

It begins by analysing how participants most commonly conceptualise uncertainty and the practice of conducting different forms of uncertainty analysis (§4.3). The interview data shows that energy and IAM modellers have complex understandings of uncertainty in the context of their work. Several frames were identified within the interviews, including the conceptualisation of uncertainty exploration and analysis as essentially synonymous with the process of model development and as a sub-practice separate from normal development activities.

The way modellers distinguished conceptually between different types of uncertainty is also analysed (§4.3.2). This thesis finds that the use of *location* to distinguish between different types of uncertainty was the most prevalent, and in particular a simple distinction between *parametric* and *structural* uncertainty.

I then focus on the role of *scenarios* – a fundamental concept for understanding these modellers' conceptualisations of uncertainty. Finally, section 4.3 concludes examining the types of uncertainty analysis methods participants discussed and their relationship to different kinds of uncertainty.

This chapter then examines the reasons espoused by modellers for how they treat uncertainty in the way they do (§4.4). It details the factors specific to their profile (e.g. disciplinary training) the models they use, the research group that they inhabit (local context), the influences of the wider epistemic community which they inhabit (wider context) and the demands of stakeholders outside of their discipline.

After reflecting on the relationship between these factors and the conceptualisations espoused (§4.5.1) it identifies a number of limitations of the study pertaining to this particular set of interviewees (§4.5.5).

4.2 Introduction

This introduction gives a high-level overview of the interviews, including how they were distributed amongst disciplines, how interviews were conducted, how they were analysed and a summary table of their of information gleaned from the interviews pertaining to the research questions.

4.2.1 Overview of Participants

The participants for this aspect of the study exist within the Energy-IAM nexus. They all develop, operate, and analyse the results of a set of socio-technical-economic models that examine the potential futures of systems of energy production and the associated costs of this, both direct (through the production of energy and other goods) and indirect (through externalities and damage related to the climatic response to these anthropogenic emissions). A convenient heuristic for understanding the background of these participants is that they would be most at home participating in the work of the IPCC's WGIII on the mitigation of climate change.

Many energy modellers engage with Integrated Assessment Models and vice-versa. Also within this sample were a set of people who had a certain level of specialism in the 'Impacts' community, though all of these were involved in some way of producing impacts submodules that went into integrated assessment. Figure 4-1 gives a breakdown of the different disciplinary roles of participants.

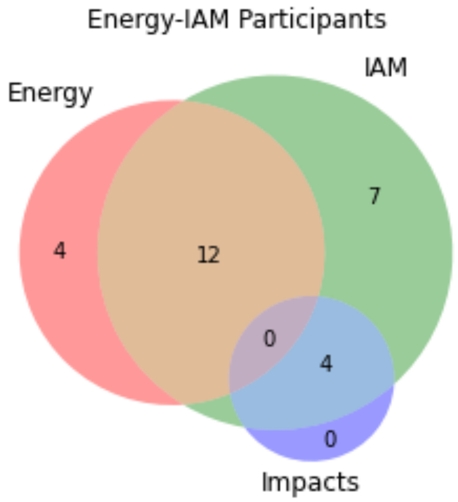

Figure 4-1: Categorisation of participants who fall into the Energy-IA nexus. Note that classification has been performed based on participants self-identification and from publishing record.

Participants had a variety of seniorities and academic backgrounds. The largest contingent were engineers who then transitioned into energy modelling. They also had a range of roles within their modelling groups. Most participants were actively engaged with model development, though often more senior researchers were not involved in this and instead either ran existing models, analysed results from model runs others had performed or administrated modelling exercises.

4.2.2 How Interviews Were Conducted

Participants were recruited through a snowball method and through professional networks. In a limited number of cases, direct requests for participation were emailed to the participants. Transcripts were manually transcribed by the researcher and coded using the software NVivo. In addition to this, one-page summaries for each interview were produced by the researcher and, as analysis proceeded, extensive hand-written memos were diarised. A high-level summary of each of the interviews and some of the salient themes that emerged is available in Table 4-1, below. A fuller description of this process has been detailed in chapter 3.

4.2.3 High-Level Overview of Results

Table 4-1, over the pages that follow, gives a high-level summary of many of the most important features of each interview.

Table 4-1: Summary of 'WGIII'-style participants including general information about disciplinary background, relationship to the modelling process and some key conceptualisations gleaned from each of the interviews. 'Category' = The high-level groups into which the participant can be sorted; 'Modeller status' = the relationship the modeller has to the model development process; 'Types of Uncertainty'= types of uncertainty that the modeller mentioned in the interview; 'Type of Distinction'= The conceptual mechanism by which these types of uncertainty are differentiated from each other

	Pseudonym	Category	Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
1	Gable	Energy, IAMs	Developer, User	Academic Researcher	Economics	Energy Economics	{Variability, Parameter uncertainty, Data Uncertainty} {Known-unknowns, Unknown Unknowns}*	Location Rumsfeld-Yamin System	A way of harmonising assumptions by packaging them together.	Scenario Analysis, (Simple) Sensitivity Analysis	Disciplines, Modeller predispositions
2	Skiddaw	Energy	User, Developer (Basic Models)	ECR	Engineering	Energy Technologies	{Statistical Uncertainty, Decision Uncertainty}, {Variability, Estimate of Variability}?	Endogenous/ Exogenous, Meta-Uncertainty	Scenarios are related somehow to hypotheses	Statistical regression analysis, Scenario development	Modeller Skills
3	Scafell	Impacts, IAMs	User	Veteran Academic Economist	Economics, Maths, Finance	Climate Impacts, Food Production	{Variability/ Statistical Uncertainty vs Uncertainty}	Knightian	What-if exercises with conceivable and likely futures	Scenario Analysis	Modeller Skills
10	Scoat	Energy	Developer	Academic Researcher	Physics, Energy	Renewables Variability	Data Errors, Statistical Uncertainty, Variability (with different temporal levels)	Location (approx.)	Related scenarios to parameter space exploration	Parameter space exploration, MMEs*, Algorithmic data evaluation, IMCs*	Disciplinary Background, Credibility seeking
12	Branstree	Energy, IAMs	Developer, User	Academic Researcher	Engineering	UA Methods	Technology uncertainty, discount rates, climate sensitivity, {black swans, black elephants}, Unknown-unknowns Structural uncertainty	Topical Uncertainty menagerie, Rumsfeld-Yamin, Location (P-S)	Internally consistent sets of assumptions that may or may not be realistic, attached to a plausible narrative.	Monte Carlo, LHS sampling, Simple scenarios/sensitivity, Scenario Analysis	Disciplinary background, Existing Models, Data availability, IPCC requirements, type of model group
13	Loughrigg	Energy, IAMs	Former Developer, Former user, Analyst	Academic Researcher	Engineering and Economics	UA Methods	Parametric uncertainty, structural uncertainty	Location (P-S)	Likened scenarios to narratives	Monte Carlo, MGA, Scenario Analysis	Disciplinary culture, Research aims

	Pseudonym	Category	Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
14	Whitston	Energy, IAMs	Developer, User	Academic Researcher	Chemical Engineering	CCS, Bioenergy	Supply Vs Demand Uncertainty	Topical	Differences between parameterisations	Scenario Analysis, Workshops, Sensitivity analysis*	Technical feasibility, literature base, policy preferences
15	Yewbarrow	Energy, IAMs	Former Developer, Model User, Analyst	Senior Modeller	Physics, Policy Studies	Generalist	Aleatory Uncertainty, Epistemic Uncertainty, Structural Uncertainty, Socio-political uncertainty Deep Uncertainty	Nature Location (para-structure) Domain Deepness	Coherent and understandable sets of assumptions	Scenario Analysis, OOAT Sensitivity Analysis	Policy interactions, prior beliefs, data availability, institutional cultures
16	Blencathra	Energy, IAMs	Former developer, user, analyst, administrator of programme	Academic Researcher	Engineering, Policy Studies	UA methods	Parametric uncertainty, Structural Uncertainty	Location (P-S)	Things exogenous to the model that one changes	Scenario Analysis, Method of Morris, Monte Carlo, RDM, Stochastic Optimisation, MGA, Sensitivity Analysis	Effort Required, Availability of ECRs
17	Catbells	Energy, IAMs	Developer, User	Academic Researcher	Technology Policy	UA Methods	Levels of Uncertainty, Dynamic Uncertainty, Unknown-Unknowns	Levels Temporality Rumsfeld-Yamin	A plausible representation of the future, normally without probabilistic representation.	Open sourcing, Monte Carlo, Stochastic Programming, Adaptive Pathways, Global Sensitivity Analysis, Real Options Analysis	Uncertainty conceptualisation, open Sourcing, Disciplinary background, training
18	Fairfield	Energy	Developer	Academic Researcher	Maths, Engineering	Transport, Technology	Different sub systems, Scenario uncertainties	Sub-system ?Location	What-if exercises about assumptions	Scenario Analysis, Monte Carlo*, Robustness Analysis	Local institutional culture, Funder (academic vs consultancy), Individual interest

	Pseudonym	Category	Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
19	Rannerdale	Energy, IAMs	User	Academic Researcher	Chemical Engineering, Economics	Generalist	Some thematic areas	Topical	Elements of narratives to input into models. Pathways are outputs from scenarios in models.	Scenario Analysis, Monte Carlo, Scenario discovery*	HPC capacity, familiarity with UA techniques, Cognitive availability of themes, Funder relationships,
20	Lattrigg	Energy	Developer, User, Analyst	Academic Researcher	Maths	Energy Systems Risk	Statistical Uncertainty, Imprecisely defined quantities/ Ambiguity; Qualitative Uncertainties Knightian Uncertainty vs risk	Statistical Quant/ qual Knightian	A possible realisation of the future. Stressed no other implication than that.	Regret Analysis, Scenario Analysis, Bayesian Methods	Policy question don't convert to RQs, hidden assumptions, models mapped to decision questions, requirement of publishing, skills of analysts, interpretation of model frameworks
21	Brisco	Energy, IAMs	User, Analyst	Academic Researcher	Engineering, Policy Studies	Long term projections	Parametric vs Structural, Unknown Unknowns	Locations (P-S) Rumsfeld-Yamin	What-if exercises.	Scenario Analysis, MGA, Scenario Discovery, Expert Elicitation*, Robust Decision-making	Effort required, Personal interest, Funding, Model technical factors, Policy interest, Interpretation of results
22	Weatherlam	Energy, IAMs	User, Analyst	Academic Researcher	Technology, Environment	Fossil fuels, decision-making	Structural uncertainty, Scenario Uncertainty Value ladenness	Location Values	A future of an energy system, plausible or not.	NUSAP, Scenario Analysis	Availability of ECRs, Political leanings, policy demands, personalities in groups, funders, disciplinary training, value ladenness, path dependency from previous work

	Pseudonym	Category	Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
23	Greatend	IAMs	Developer	Academic Researcher	Engineering	Bioenergy	Parametric uncertainty, Scenario uncertainty, Implementation uncertainty	Location	A consistent storyline about how key parameters will develop.	Simple sensitivity analysis, Scenario Analysis, Global sensitivity analysis, Model Intercomparison	Availability of ECRs, Literature feedback, Funding, MIPs, Technical requirements
24	Esk	IAMs	Former Developer, Administrator of Programme	Programme manager	Engineering	Generalist	{Objective vs Subjective Uncertainty}, {Methodological uncertainties vs real uncertainties}	Nature Meta- Uncertainty?	Manifestations of the way the future could play out	Monte Carlo, RDM, MMEs, Expert Elicitation	Modeller myopia, Disciplinary training
25	Crinkle	IAMs	Former Developer, Administrator of Programme	Programme manager	Natural Sciences, Environmental Sciences	Generalist	Topical uncertainties Parametric Uncertainty, others unclear due to audio fault. {Uncertainty vs sensitivity}	Topical Location (P-S) Nature (?)	Unclear due to audio fault. But appears consistent with storylines that are exogenous to model.	IMC, Scenario Analysis, Monte Carlo Analysis, Sensitivity Analysis	Researcher Inspiration, Target system nature, Funding, Model Style, Disciplinary Backgrounds
27	Grasmoor	IAMs, Impacts	Model Developer, User	Academic Researcher	Economics	Impacts	Socioeconomic uncertainty, technology uncertainty, climate uncertainty	Domain/ Sub-system	Scenarios are detailed and include impacts, whereas pathways are not	MMC, Scenario Analysis	Policymakers understanding, Research questions, Technical issues
28	Brandreath	IAM	Administrator of Programme, Former Developer	Senior Researcher	Energy Economics	Technologies	Exogenous demand uncertainty, Technology Uncertainty, Representational Uncertainty	Exo-endo Sub-system (?)	An exploration of the future inside a possible space of solutions.	Scenario Analysis, Literature Review, Expert elicitation	Coding languages, Data availability, Funding, Existing literature
31	Bleaberry	IAM, Impacts	Model Developer	ECR	Engineering, Economics	Distributional Impacts	{Risk Vs Uncertainty} Normative framework choice	Knightian Values	A form of model output	Prime Analysis, Monte Carlo, Sensitivity Analysis	Skills, Supervisors influence, Maturing of the discipline
33	Harterfell	Energy	Former Developer, Model User, Analyst	Programme manager	Engineering	Generalist	Scenario Uncertainty/ Data Uncertainty, Model uncertainty, Unknowns (micro, institutional, macro)	Exo, Endo, Ignorance	Conceived as these uncertainties as levels. Complicated distinction	Scenario analysis, MMC*, Model soft-linking, Sensitivity Analysis	Disciplinary arrogance, interdisciplinarity, Stakeholder demands, institutional culture

	Pseudonym	Category	Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
37	Hartcrag	IAMs, Energy	Developer	Academic Researcher	Policy, Energy	Emissions	Structural Uncertainty, Calibration Uncertainty, Parameter sensitivity, {socioeconomic vs physical}	Location Domain	A kind of projection and a thinking tool	Monte Carlo, Sensitivity Analysis	IPCC Requirements, Disciplinary experience, prevalence of scenario thinking, definitional ambiguities
38	Redscrees	Energy	Former Developer, Model User, Analyst	Senior Academic	Physics, Engineering and Policy	Policy	Parametric uncertainty, Structural Uncertainty	Locations (P-S)	A view of how the world may be in the future	Monte Carlo, Scenario Analysis, Stochastic programming, MGA, Open sourcing, Limited foresight	Technical factors, Policymaker understanding, Simplicity of optimisation frameworks
4	Helvellyn	Climate, IAMs	User	Prominent IPCC Scientist	Climate Science, Engineering	Interdisciplinary	Intractability, Imprecision, Ambiguity, Scenario Uncertainty, Meta-Uncertainty	Generalised causes, Meta	What-if exercises. Not ranges of outcomes but paths to outcomes.	Scenario Analysis, (Simple) Sensitivity Analysis	Working group conceptualisation, Limited expertise of individuals, Desire for the illusion of certainty, Disciplinary Training
7	Lingmell	Impacts, IAMs, Climate	User	Academic Researcher	Maths, Philosophy, Engineering	Sea level rise, Coastal Risk	{Geophysical Uncertainty vs Socioeconomic Uncertainty} , {Shallow Vs Deep Uncertainty}, {Ambiguity vs Uncertainty}, {Parametric Uncertainty, Scenario Uncertainty}	Domain Deepness Ellsbergian (?) Location	Specific realisation about how an uncertain factor might resolve. Especially useful for deep uncertainty	Scenario Analysis, Data Assimilation	Availability of Data Assimilation Frameworks, Data Availability, Sophistication of different kinds of stakeholders, Availability of HP and Emulators

36	Carrock	Climate, IAMs, Impacts	Analyst	Senior Academic	Engineering, Physics	Long term projections	Emissions uncertainty, Forcing uncertainty, Deep uncertainty	Location/Sub-System Deepness	Scenarios as a tool for deep uncertainty	PPEs, Sensitivity Analysis, Scenario Analysis	IAMs involve more expert judgement, Interactions between model groups and funders, technical factors to do with models

4.3 Conceptualisation of Uncertainty

4.3.1 The conceptualisation of uncertainty itself

From the analysis of the interviews, I observed several different ways of conceptualising uncertainty as a whole and uncertainty analysis. These were not mutually exclusive, and participants could be observed using multiple frames. I now examine each of these conceptualisations in turn and consider their implications for the practice of energy and Integrated Assessment modelling. Further to this, I consider what I term the 'loci of uncertainty' – where participants conceptualised uncertainty as residing within a knowledge production process.

4.3.1.1 General Frames for Uncertainty

Uncertainty as the Frontier of Model Development

The first major frame identified is the conflation of the entire model development process with that of uncertainty analysis – essentially that by modifying a model and including more system elements or to represent more things, uncertainty has been explored. This could be noticed when participants talked about uncertainty synonymously with aspects of the target systems that they were interested in that were not represented in the model. For example, if I asked a participant about what uncertainty analysis techniques they employ and they instead began talking about model elements they wished to incorporate in future model development. In this way, all model elements that could be improved in terms of their representation of reality can be upgraded in time. The model is slowly nudged to a state in which it more faithfully represents a target system. This way of presenting uncertainty has a correspondence with the *scheduling into the future* identified by Shackley & Wynne (1996).

Uncertainty as a Sub-practice

The second framing of uncertainty analysis is that it constitutes a niche sub-practice within the discipline that is different from the quotidian tasks of model development and operation. This may be an activity that only certain people are interested in or have the time to do, or it may serve as an addendum to everyday modelling practices.

It was also possible for people to view the methods that were used for exploring uncertainty interchangeably with the types of uncertainty themselves. For example, *Greatend* frequently referred to uncertainty analysis methods when speaking of types of uncertainty and then secondarily related these with types of uncertainty that one might encounter.

Uncertainty as Epistemology

In most cases, participants did not have a purely quantitative understanding of uncertainty and instead understood uncertainty to have epistemic aspects, even if they did not use the terminology themselves.

It is possible to naturally conceive of uncertainty as some real property of reality that one wishes to estimate properly. This is coherent with the 'meta-uncertainty' concept identified in the literature review (§2.4.1) and is perhaps intuitively understandable as practitioners know that they may be mistaken in their attempts to estimate a quantity such as uncertainty. This conceptualisation may lend itself more to situations where uncertainty is numerically estimated as it is perhaps more difficult to conceive of situations where one can imagine a truly-existing non-numerical form of uncertainty in reality.

4.3.1.2 The Locus of Uncertainty

Throughout interviews, participants often referred to uncertainty as being a property of different situations. For convenience, I refer to this as the *locus of uncertainty*[32]. Participants identified uncertainty existing in the different loci, which I examine in turn.

A Property of Reality

Some participants seemed to understand the real world, both social and natural systems having some inherent uncertain properties. This inherent uncertainty was often contrasted against some other uncertainty, such as that which is a property of a model. *Crinkle* articulated their awareness of the this, they distinguished between sensitivity as a property of the model and uncertainty as a property of the real world.

[32] A term that has also been used in some medical literature (Han et al., 2011)

Crinkle: *So for me the difference between the word 'sensitivity' and 'uncertainty' should be a little bit [like] the difference between: are you interested in the model or are you interested in the real world? And so since sensitivity is clearly about the model, and it is simply looking at how the model responds to different [things]. Uncertainties, in principle, you're trying to define already.*

A Property of Models

Modellers talked casually about uncertainty being 'in' their models. This may reflect a genuine understanding of where uncertainty manifests itself, or alternatively, this could just be a linguistic convention.

Redscrees: *Well, I mean, I'm not sure there are uncertainties in the model – they are there are techniques for trying to gauge uncertainty. Yeah, I suppose like that type of uncertainty whether or not, you know, day to day stuff, we know that everything is... we have lots of parameters in the model that we know are uncertain. Monte Carlo is a method of trying to understand the impact of that.*

The idea of uncertainty existing in a model is also compatible that one may reify an epistemic state in a model structure. Hence, the model structure is representative of epistemic uncertainty.

As a Kind of Consensus

Several participants understood uncertainty to have an inter-subjective nature, either in the difficulty of communication between different people or as a lack of consensus amongst a group of people. *Gable*, quoted below, described how they conceived of difficulty in communicating understanding led to a lack of consensus.

Gable: *You know, one example of uncertainty would be, I guess, people talking across purposes a lot. There is uncertainty simply around what one person is talking about compared to the other. Both of those people will be certain about what they are talking about. The uncertainty exists in a sort of world by itself, where you might be a third party witnessing the fact that these two people are completely at odds but they don't seem to realise that there is not a consensus on what it is that they are even discussing. That would be a very simple example of where uncertainty exists and how [inaudible] and consensus, where people do agree, can begin to reduce uncertainty.*

I guess you are then trying to do that not just for what the meaning of a word it but for what a certain approach or a certain number should be. That's it at its most general form. You are trying to reduce uncertainty among people as well […]. A person can be uncertain about a thing. Two people can be certain about a thing but are certain in completely different ways and therefore uncertainty exists around those two people.

As a Personal Epistemic State

This conceptualisation is probably the most compatible with uncertainty as discussed in the philosophical literature. This was most evident when modellers talked about their confidence in their results. However, this was less common than other loci of uncertainty within the sample of modellers interviewed. This is somewhat surprising, and I consider how the way I ask questions could have contributed to this result as part of my consideration of study limitations (§6.6).

These different conceptualisations of the loci of uncertainty have some resonance with the classic philosophical puzzle of the division between ontology and epistemology. Though it raises an interesting question of how one should consider the uncertainty 'in' models and if it is meaningful to locate uncertainty there. Models have uses as epistemic tools for agents to attempt to understand things about the world they inhabit, or as Cartwright (2009) says models can reveal capacities through the isolation of factors. They certainly manifest some epistemic uncertainties – as modellers develop models, some of their personal uncertainties may become reified in the computer code of the model.

4.3.2 The Types of Uncertainty Identified

Table 4-1, above, summarises several different types of uncertainty identified by participants and the ways in which these types are conceptually differentiated from one another. This analysis draws upon the literature review in chapter 2. When participants list kinds of uncertainty, they may be doing so without an appreciation for the underlying concepts that organise the typologies. Here I note the types of uncertainty and, as far as possible, identify these with the concepts in literature.

4.3.2.1 Location

Location is most generally defined in literature as the aspect of the model development and execution process in which uncertainty manifests. The location of uncertainty was the most frequently used way of separating different kinds of uncertainty by participants in this study. The popularity of types of uncertainty that correspond to different aspects of the modelling process is perhaps unsurprising given the grounding of the concept of *location* in the experience of modellers.

Of notable popularity was the simplest form of this distinction between parametric and structural uncertainty. This is perhaps born of a simplistic conceptualisation of models as being assemblages of model structures, held together with parameterisations. Six of the participants invoked this distinction.

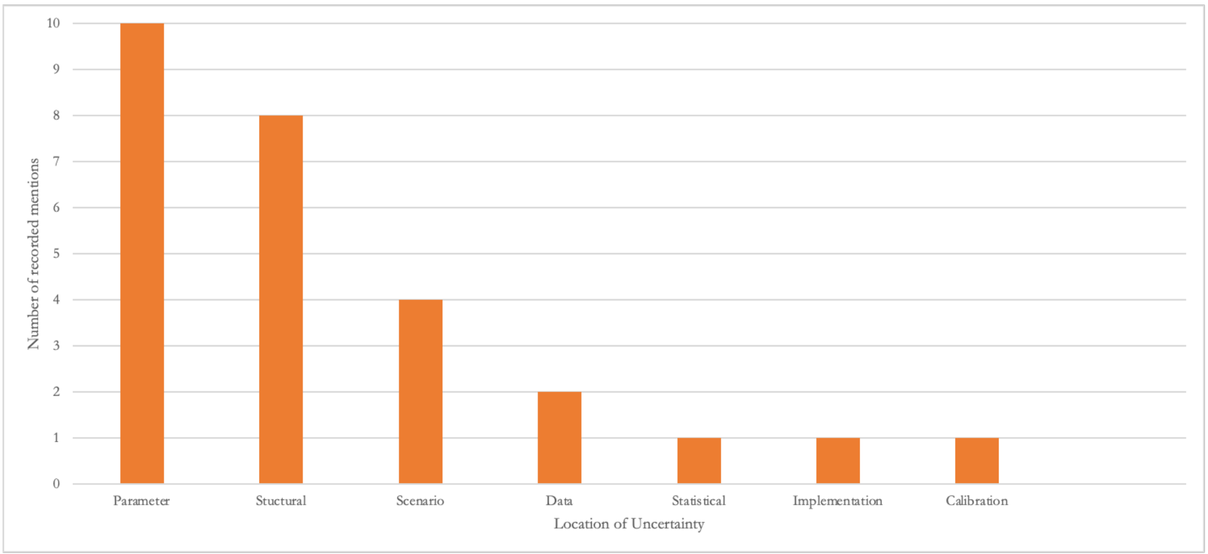

Figure 4-2: Frequency of locations of uncertainty mentioned by participants. Note that this is a non-systematic comparison. However, the prevalence of Parametric, Structural and Scenario uncertainty indicates the popularity of these concepts within the discipline.

One participant distinguished between scenario analysis and parametric analysis by the number of varied parameters in such an analysis. The conceptual porosity between scenarios and parameters will be revisited later in Section 4.3.3. These categories are not mutually exclusive. For example, a modeller could consider parametric uncertainty to be due to data uncertainty. However, I have used the terminology to group these employed by the participants.

4.3.2.2 Nature-like Distinctions

Several different conceptualisations were noted that corresponded to the various 'two-type' distinctions identified through the literature review[33]. The nature/two-types of uncertainty was evoked in different ways. Meta-uncertainty, the distinction between an estimate of uncertainty and one's confidence in that estimate (uncertainty-about-uncertainty) was made by three participants.

[33] Examples of these in the literature review included epistemic/aleatoric, uncertainty/risk, uncertainty/ambiguity, subjective/objective and knowledge-related/variability-related uncertainties. See section 2.4.1.

> ***Helvellyn:*** *There is an uncertainty that is even at a meta-level, the fact that somehow we can be sure that there are things we don't know. There is the uncertainty that we don't know about, which is actually one of the hardest to take into account when you are assessing the confidence in any results or projections.*

This is perhaps somewhat of an inevitable way of conceptualising uncertainty as one makes an uncertainty estimate and then expresses doubt in it. It also implicitly acknowledges that an estimate of uncertainty itself may not be doxastic.

Skiddaw, a junior researcher specialising in modelling energy technologies, similarly distinguished between variability and uncertainty.

> ***Skiddaw:*** *Variability....? My First intention would be that's the same. Variability I am thinking about weather variability. Oh wait, I know it's not the same. I think... Wait, first I said they are the same, now I am about to say that they have nothing to do with each other. Variability is a physical phenomena. I am thinking about wind-powered generation or solar generation which varies over time. And uncertainty is associated with trying to predict the patterns of variability.*

Esk, a senior researcher, also used a 'meta-ness' distinction to separate their idea of *methodological* uncertainties and *real* uncertainties. These were identified with subjective and objective uncertainties. However, they admitted their confusion on the topic and noted the trouble of demarcating between these two kinds of uncertainty at the highest level. It appeared as if the question of these two types of uncertainty were too philosophical to have much practical utility for them.

> ***Esk:*** *I'm actually quite interested in the confluence of all of those [uncertainties], and how do you think about when you're actually trying to convey this to someone outside of these purely methodological issues which are not a full representation of uncertainty, they are methodologies. How do you actually then convey real uncertainty?*
>
> *... and what does real uncertainty even mean in that case? Because again at some point, this difference between... I'm sure you're way more on top of it.*
>
> *So my own way of thinking about it, this difference between, at the highest level, objective and subjective uncertainty becomes very problematic. The idea is that there really is objective uncertainty in a meaningful way, about things that are so complex that are not repeatable. I mean, it gets into all sorts of philosophy about it. But just from a practical perspective, you know, we're not doing repetitions. So that sort of paradigm doesn't work real well and a lot of it's just subjective. It's really subjective, and how do you integrate models with that subjectivity?*

Thus, the two kinds of uncertainties were separated by the *repeatability* of measurements of the target system in order to obtain distributions of outcomes.

The classic Knightian distinction was made by several participants, though notably, all three of these participants (*Bleaberry, Lattrigg* and *Scafell*) had a background that included some substantial training in economics. As part of a larger point about the importance of treating uncertainty frameworks non-prescriptively, *Latrigg* criticised the understanding of others of Knightian uncertainty as a binary between situations where probabilities can be used and those where they cannot.

> ***Latrigg:*** *I am quite unusual among people that talk about Knightian uncertainty in that I have read Knight's book. People end up saying that if you can't estimate from data then you are in Knightian uncertainty and "thou shalt not use probabilities!" Whereas this is very far from what Knight said. And in any case, we have the last century of developments of understanding of representations of uncertainty. But it's often presented as if there is a binary flip from a thing in which you can very confidently use probabilities to where you can never.*

Lingmell, a highly interdisciplinary researcher, also invoked the idea of uncertainty and ambiguity – directly along the lines of Ellberg's (1961) distinction.

Although participants made these distinctions, none dwelled deeply on the implications of these fundamental natures of uncertainty for their work. Perhaps these kinds of uncertainty are too abstracted to have practical relevance in the everyday practice of scientific research, and the boundaries between the two kinds can be too problematic for reliable use of the concepts.

4.3.2.3 Domains, Sub-Systems and Topics

In the literature review (§2.4.4), I noted that several typologies for uncertainty conceptualised the location of uncertainty by the system within which uncertainty resides. Such a conceptualisation has been identified among the participants, with four levels of aggregation of these sub-systems in the way that people organise uncertainty: the *topical separation* of uncertainty, the *sub-system* of uncertainty, the *domains* of uncertainty and *exo/endogeneity*.

Four of the participants made the lowest level form of this distinction. This *topical separation* of uncertainties merely noted the theme of the uncertainty within the model or the general issues that are surrounded by the uncertainty. The clearest example of this is when participants would talk about issues such as 'technology uncertainties' or 'discount rate uncertainties'. These can, of course, be disaggregated further into other kinds of uncertainty. For example, technology uncertainties could be decomposed into technology cost uncertainties, technology learning uncertainties and technology performance uncertainties. This is perhaps an intuitive and naïve way of classification as one talks about the particular thing that may be uncertain.

A more aggregated approach to discussing uncertainties in the model is to group them by the target *sub-system* that one is interested in. The modular nature of Integrated Assessment, where different modules explicitly correspond to different coupled interacting target systems, lends itself well to such a characterisation. Examples of this include 'bioenergy uncertainties' and 'land-use' uncertainties.

The most aggregated way of distinguishing uncertainties in this theme is where participants drew very broad distinctions between different thematic *domains* which may be uncertain. These domains are commonly prefixed 'socio', 'economic', 'technical', 'natural', 'physical' and 'politico'; or perturbations and combinations thereof. Perhaps one can understand these domains to refer to the ontologically distinct aspects of the world within which consistent types of knowledge apply and interactions are of a similar kind. For example, *Hartcrag* divides up their uncertainties into those that are physical and those that are socio-economic:

> ***Hartcrag:*** *I mean, I always try to categorise uncertainty in socio-economic, and in physical things. So, climate models, for example, that's kind of a physical-based model. So, based on physics, and that has certain uncertainties, okay. But then you have the other big category which are the socio-economics and that includes a population, GDP, that we just talked about, but also had price developments, trade, geopolitics. And normally, this category is the elephant in the room even though the physical uncertainties are also really large.*

Finally, participants may have referred to uncertainties by their *endogeneity or exogeneity* to the systems that they were modelling. Uncertainties that are represented in the model system are endogenous. Making the distinction between endogenous and exogenous uncertainty is an intuitive way of organising uncertainties as one also considers those elements of the target system *not* represented in the model. These may be conceptualised as scenario uncertainties or data uncertainties related to the factors responsible for the evolution of a scenario that provides an external forcing to the model are outside of their domain of the model.

This exogeneity of uncertainties can, of course, be conceptualised as another location. For example, *Greatend* identified 'implementation uncertainty' as the uncertainty associated with the social feasibility of their results.

> ***Greatend:*** *It's the implementation uncertainty of our scenarios. Because the IAMs, as I said, we're mostly engineers, maybe economists, we come up with these nice abstract models and we project the future. And then we have people on the social sciencey side, telling us, "you know, what the hell are you talking about. This is this stuff is insane!" Or they're saying "you're not going far enough!" I don't know. So how uncertain are our results from a social perspective? Now, I don't have any solid research questions there or a research program. So I don't know how to define it.*

In the case of *Harterfell*, as part of their broader description of the uncertainties they encounter in their energy modelling work, they described scenario uncertainties as associated with data inputs and the response of the models to these scenarios as another uncertainty associated with epistemic uncertainty. Scenarios can play a role in representing uncertainties far from the context of a particular research exercise.

4.3.2.4 Ignorance and the Rumsfeld-Yamin System

Harterfell went further and described a third kind of uncertainty beyond scenario uncertainty and model uncertainty. They described the "things left out" of the model system, primarily aspects of society. They categorised these aspects to which their model was ignorant about to the social scale at which they were relevant: the political, institutional, and micro level.

> ***Harterfell:*** *The third one is trickier. And we haven't got there yet. And it's something I grapple with a lot currently, in terms of thinking. Is that none of these models, whatever way we look at them capture what's happening in society. And so I don't mean, in that just individual purchasing patterns, I mean what's happening in politics. Like Trump, compared to Obama that is having a significant impact on the evolution of the energy system in the States. And we don't have a good way of capturing that. So politics, or that macro level sort of changes.*
>
> *Another one that's interesting is looking at a layer below that macro-layer would be an institutional level. So one example there is that we had a number of years ago, the head of [our transmission system operator] was wary about the growth of wind energy. So they established effectively a moratorium on new wind energy connections, until certain information could be teased out, understood, and to help with planning. So a very cautious approach and coming from the perspective that, the grid is ours, so you know, any messing with it, you know, we need to take cautiously. That person then retired, and a new person came in to run the grid company, with a very different perspective. They looked at what the government objective is, and then said, "Okay, well, we need to change how the grid operates to meet that objective." So that had a very strong impact on the reality of the energy system evolution. So that institutional change, or personnel change within an institution.*
>
> *And then you've got changes at the micro level, we've a very interesting project [in] an isolated rural area. And we've started to experiment with the transition. So we've got a multi-partner project, a big investment of resources […] And what we're starting to see then is some of the people who get engaged in this and kind of agree to persuade their friends, neighbours so that individual behavioural change piece was one of the starting points. But then we see that they've*

> *some of them have gathered together, collectively and developing "Okay, well, we need let's do a feasibility [on an energy technology]. Let's look at what all the farms [in the area] can do." So that initial focus on technology diffusion transmorphing into a kind of diffusion of sustainability. Again, it's something that is very important in terms of how the energy system changes, and yes, our models don't capture it at all.*

This participant showed how different forms of recognised ignorance can still be organised according to some criteria. Not all participants who invoked ideas about ignorance went to such lengths to describe how their thinking was structured, and these could be classified. Several participants referred to the concept of 'known-unknowns and 'unknown-unknowns', familiar to us from the literature review, labelled by this thesis as the Rumsfeld-Yamin system of knowledge classification. None of these references to the concept of known-unknowns went significantly beyond an invocation of the concept.

Other concepts from popular nonfiction literature were briefly mentioned, such as 'Black-Swans' (Taleb, 2007) and another related concept in the uncertainty/risk menagerie of the 'Gray Rhinos' (Wucker, 2016). However, it was not clear from interviews to what extent, if any, these concepts may be operationalised in research practices. Not using this explicit terminology, *Skiddaw* was unsure if these kinds of catastrophes were statistical uncertainty.

4.3.2.5 Levels and Deep Uncertainty

Despite its prevalence in literature, the concept of *levels of uncertainty* was only mentioned by one participant, who did not elaborate on its significance to their research. The concept most related to levels of uncertainty that some participants used was that of *deep uncertainty*.

Yewbarrow understood this situation of deep uncertainty to be stemming from several aspects of the nature of the target system they were attempting to model such as system complexity, long timescales used and social agents' presence in the target system.

> ***Interviewer:*** *On your first comment there, what in your mind distinguishes a situation of deep uncertainty from... you mentioned, like a modelling discipline might look at a physical system, like pollutants in a river? What distinguishes that situation of "deep uncertainty" from other situations?*
>
> ***Yewbarrow:*** *I would think three things. I would say, the sheer complexity of the system you're looking at, if you're trying to look at an energy system for a whole country, that's different than just looking at the water flow in a river, in terms of the number of parameters you need.*
>
> *The second thing is the timescales we look at. I mean, you're looking out over years and decades. So that's clearly challenging to deal with in uncertainty.*

> *And thirdly, the role of people in societies, right. So we're not just modelling physical systems, we're modelling this thing that doesn't have natural laws. You know, people in society will do things that you don't expect.*

Others understood that this idea of deep uncertainty distinguished a realm of the appropriateness of methods. In particular situations where scenarios methods become most relevant and probabilities for outcomes cannot or should not be provided.

> ***Carrock:*** *I think of scenarios as a tool just like a model. And it's a tool for understanding the future [inaudible] possible future states of the world. And it's particularly useful in these cases where we have very deep uncertainty, that we have uncertainty in the physical mechanisms, so we can't do traditional error propagation and uncertainty analysis.*

Deep uncertainty is a concept with some cachet in the community. However, in these interviews, it was primarily used to add emphasis to the epistemic challenges presented in projecting the evolution of coupled, complex socio-technical systems. Some participants addressed the methods that could be employed to investigate deep uncertainty, including discussing the fruitful exchanges that are happening with the Decision-making Under Deep Uncertainty (DMDU) community. How the relationship between these kinds of uncertainty and methods was conceptualised will be discussed in Section 4.3.4.

4.3.2.6 Qualitative Uncertainties and Values

One can argue that normativity is represented in the fundamental makeup of many ESOM and IAMs. These models often optimise policy or energy mixes for a given objective function, such as cost and are subject to various constraints, such as emissions, environmental impacts or limits to feasible technology deployment rates. Alternatively, they may simulate system developments given a normative decision-making rule. As such, the relationship of normativity to knowledge in this field is important. Despite this, participants did not frequently discuss the relationship to values of their work, or alternatively just understood the normative assumptions at the heart of optimisation as a form of model uncertainty.

The most common way in which participants discussed values was in the context of the stylised assumptions in an optimisation model of a 'benevolent dictatorial optimiser'. *Bleaberry,* for example*,* understood the choice of normative framework as something that was uncertain but not an *uncertainty*.

Other value-laden assumptions were not consistently discussed, though *Weatherlam* was familiar with the concept and explained how value-ladenness encroached into modelling exercises both through the emphasis that one places on a given topical area of the model and through the framing of the research one is conducting.

> ***Weatherlam:*** *I think [value-ladenness] can intrude in modelling in a number of different ways. I think in terms of the disciplinary bias that one might have. I know I have colleagues who have a very strong interest, for example, in hydrogen. They might have come from an engineering background, and have been working in industry, I can think of a couple of individuals in that space who, I don't know if it's unconscious bias or what, but maybe have a stronger interest in those sorts of technologies, those sorts of solutions. And somehow maybe they spend additional time in terms of specifying that part of the model in terms of thinking about those different assumptions and the different options around, say, the hydrogen economy. And in that way, you quite often see hydrogen-based solutions.*
>
> *[…]*
>
> *You know, you see you see scenarios that may be a little bit more skewed in that direction. So it's those sorts of aspects, I think, that has come about from having a key interest in an area or having a sort of disciplinary background that maybe pushes people in a certain direction or makes them think about framing their analysis in a certain way. So of course, it's not just about the assumption space, but it's about how you run the model, how you think about the analytical framing of the research that you're doing.*

One concept that clearly involved the presence of values was the idea of 'decision uncertainty' – an external uncertainty that comes post-analysis and is the property of a decision-maker.

4.3.2.7 Other Types of Uncertainty Mentioned

Several other distinctions were made by some participants that warrant some examination.

An interesting distinction was that made by *Catbells* who considered how one's actions affect one's ability to know about uncertainty – a kind of reflexivity that they labelled *dynamic uncertainty*. Some other participants briefly referred to other aspects of temporality and its interaction with epistemology, but none comfortably used ideas about time in their arguments.

Participants also made several two-type distinctions using ideas of *Nature, Meta-Uncertainty, Knightian Uncertainty* and *Ellsbergian Ambiguity*. However, it was notable from the discussion that these concepts were not used instrumentally by the participants either to explain their work or to explain the relationship of methods to types of uncertainty.

Other ideas about ignorance were frequently invoked, including the Rumsfeld-Yamin distinction of Known-Unknowns and Unknown-Unknowns. Though, again, these were infrequently used to discuss actual research practice.

In summary, the most available way in which energy and Integrated Assessment participants discussed uncertainty was by discussing different *locations* within the process of model development. The most common of these were structural, parametric and scenario uncertainties. This is perhaps unsurprising as this classification is grounded in the experience of model production.

The following sub-section considers the role of scenarios: how they were conceptualised and how participants understood their appropriate usage, and situations in which it was considered appropriate to use probabilities in uncertainty-analysis exercises.

4.3.3 Scenarios, Uncertainty and Probability

Scenarios were the most consistently discussed feature of uncertainty analysis with participants from the energy and IAM community. As such, they warrant examination and consideration of their conceptualisation and their relationship to uncertainty. This sub-section considers firstly how participants defined and conceptualised scenarios. I then discuss how participants often shared opinions and normative views about the appropriate use of scenarios, particularly their relationship to probabilities.

Of course, the word 'scenario' is polysemic. Participants did discuss scenarios in the context of "types of uncertainty", with *scenario uncertainty* being related to both *location* (as a stage of the modelling process) and *deep uncertainty* (as an appropriate way of conceptualising deep uncertainties). However, here this examination considers the role of scenarios as intangible objects used in the practice of energy and IA research.

4.3.3.1 The Conceptualisation of Scenarios

I identify scenario conceptualised by participants in different ways, the most prominent being:

- As **narratives** or their representations/simplifications
- As **thinking tools** to reveal the consequences of assumptions
- As **samplings** of uncertain possibility spaces or of parameter spaces
- As data or **inputs** that are exogenous to the model or its target system
- As **outputs** or projections

Table 4-2, below, summarises the presence of these conceptualisations for the different participants in this group of the study.

	Participant	Gable	Skiddaw	Scafell	Scoat	Branstree	Loughrigg	Whiston	Yewbarrow	Blencathra	Catbells	Fairfield	Rannerdale	Latrigg	Brisco	Weatherlam	Greatend	Esk	Crinkle	Grasmoor	Brandreth	Bleaberry	Harterfell	Hartcrag	Redscrees	Helvellyn	Lingmell	Carrock	Total
Conceptualisations	Narratives					√	√				√		√	√		√	√	√	√	√	√				√		√		13
	Assumptions/Tools	√	√	√	≈	√	√		√			√			√									√		√	√	√	11
	Samples/ Perturbations				≈			√									√				√				√		√		5
	Exogenous									√									√										2
	Projections/ Outputs																					√		√					2
Qualities	Internal Consistency/ Coherence	√				√			√		√	√					√												6
	Possiblity		≈				√				≈			√							√								3+
	Concievability/ Understandability			√					√																				2
	Plausibility	X					√				√					X												√	2–2
	Probability/ Likelihood			√							X				√													X	2–2
	Realism					X																							-1
	Usefulness																				√								1

Table 4-2: Summary of major conceptualisations of scenarios elicited from participants. Note that not all categories are exclusive. '√' Indicates that participant endorsed conceptualisation, '≈' indicates an implied endorsement of this conceptualisation and 'X' indicates that the participant said this condition was not required for a scenario. Note that although many participants discussed the relationship between probabilities and scenarios, their views on the appropriateness of probabilities statements elude easy classification.

Further to this, I identify several inconsistencies at play in the conceptualisation of scenarios:

- Different participants required that scenarios be imbued with different properties such as internal consistency, plausibility, consensus, and probability.
- As inputs to models or as outputs of models. Scenarios may be either.
- Scenarios as a parameter setting vs. groups of parameter settings.
- Temporal and non-temporal scenarios (e.g., assumptions for an interval of change into the future vs. assumptions pertaining to a snapshot in time).

Each of these is not necessarily mutually exclusive, and the difference between the high-level conceptualisations such as narrative and assumptions may be the emphasis that one places on the different meanings of scenarios. I now examine each of these conceptualisations in turn.

Scenarios as Narratives

Some participants stressed the relationship between scenarios and narratives. They either did this by identifying scenarios as narratives, or by describing scenarios as representations of those narratives in terms of data inputs or parameter settings of models.

> **Loughrigg:** *Well, to me, scenarios are essentially they're especially in the context of decade-long time horizons, they're essentially narratives, stories, more or less, that describe how specific events might unfold. Then models might be used to basically add some richness to the story. They're still part of the story as opposed to something else.*

Alternatively, scenarios might be conceptualised as numerical representations that are either derivative of these stories or consistent with them. In this way, one may consider scenarios as numerical data or model settings evolving over time that are descriptions of a higher-level qualitative storyline. This conceptualisation can be argued to be consistent with the approach of the Shared Socioeconomic Pathways (SSPs), in which high-level narratives produced through an expert consultation practice were turned into numerical input for models. These were then used to produce model results that described the pathways suitable for the inputting into other models. See Box 4-1 for a short account of the SSP creation process.

For convenience, I have grouped participants who described scenarios as *futures* here. The noun 'future' is often synonymous with 'scenario' in literature.

Box 4-1: A short summary of the development of the Shared Socioeconomic Pathways (SSPs)

The SSP framework emerged after the creation of the RCPs (van Vuuren et al., 2011). After the long establishment of frameworks for understanding emissions trajectories, some argued for establishing a framework to better look at other socio-economic aspects of climate change (van Vuuren and Carter, 2014). There was then the establishment of a conceptual framework to produce a set of socio-economic scenarios that accompanies the RCPs (O'Neill et al., 2014) to better study aspects of mitigation, impacts and adaptation.

The narratives for the SSPs were first developed through aggregating narrative elements and categories of variables deemed important from expert discussion and elicitation exercises (O'Neill et al., 2017; Schweizer and O'Neill, 2014; Wilbanks and Ebi, 2014). After discussion among the team of researchers creating the narratives, it was decided to focus on two 'axes' of challenges: *challenges to adaptation and mitigation* and *challenges to governance*. This resulted in a set of five narratives: four that described different combinations of low and high challenges to adaptation and mitigation and one central pathway in which all challenges were moderate (O'Neill et al., 2017).

These narratives were then extended into model input tables (Kc and Lutz, 2017; O'Neill et al., 2017). Different teams then fed input assumptions about technological progress, human capital, physical capital and other drivers into different economic models to produce projections of key variables such as GDP (Crespo Cuaresma, 2017; Dellink et al., 2017;

Leimbach et al., 2017). The resulting GDP projections from Dellink et al. (2017) then formed the basis of further development of the scenarios.

Five model teams then produced quantitative outputs for each of the SSPs, with each team producing one SSP (Riahi et al., 2017):

Table 4-3: SSPs and the models used to produce their marker versions. Adapted from Riahi et al. (2017 Table 2)

SSP	Model	Institution	Reference
1 "Sustainability"	IMAGE	PBL	(van Vuuren et al., 2017)
2 "Middle of the Road"	MESSAGE-GLOBIOM	IIASA	(Fricko et al., 2017)
3 "Regional Rivalry"	AIM/GCE	NIES	(Fujimori et al., 2017)
4 "Inequality"	GCAM	PNNL	(Calvin et al., 2017)
5 "Fossil-Fuelled Development"	REMIND-MAgPIE	PIK	(Kriegler et al., 2017)

Finally, the GHG and Aerosol outputs of these marker scenarios were then fed into the MAGICC-6 simplified climate model (Riahi et al., 2017), an emulator of AOGCMs and Carbon Cycle models tuned to, among others, the CMIP3 AOGCM results (Meinshausen et al., 2011).

The resulting five scenarios are provided to the community as a resource and contain projections of. They are accessible through an online database hosted by IIASA (IIASA, 2018).

Scenarios as Tools

Many participants described scenarios as 'what-if' exercises or epistemic tools that allowed one to discover useful information about a situation and interrogate assumptions. *Helvellyn* provided a clear explanation that cohered with this view and described how many scenarios are dependent on human choices:

> ***Helvellyn:*** *Yeah so scenarios are what-if exercises. They are not predictions, they are projections of our current set of assumptions into the future. And these can be varied. And the point is that while at this point we don't know how they will precisely evolve into the future. Some of these and some scenarios might be more likely than others. Many of those depend on choices that we make. And these choices are the driving force in where we end up. That's not something that is unfathomable, or that we can't influence.*

Alternatively, scenarios may be imagined as tools to harmonise assumptions so that the future that they describe is not highly inconsistent.

Scoat, a researcher who transitioned to energy modelling from natural sciences, understood them to be specific negative events that one should plan for. This is like a what-if exercise as the scenario is a contingency planning tool. This is perhaps close to a lay conceptualisation of scenarios, reflecting the recency of the participant's induction into the world of energy modelling.

Scenarios as Samples

Scoat further described the scenario analysis they were doing as something like the exploration of parameter or possibility space.

> ***Interviewer:*** *You mentioned that you used scenarios on your poster [at the conference]. In what sense were you using scenarios?*
>
> ***Scoat:*** *I was talking about just exploring different configurations of renewable energy policies. So I was exploring one scenario, which was essentially like the cost optimal solution to our model would be where we let our model solve for wind, solar, installed nuclear and storage capacity. I let all of those parameters float around.*
>
> *And there was another scenario where I was looking at if we have lots of wind, but no solar, or lots of solar and no wind to see how the behaviour of the system differs in its reliability and predictability characteristics. Yeah, so I think that's helpful. I think it's nice to be able to explore a lot of parameter space as well.[…] I've just been saying, "What if installed solar is x? What if it's 2x 3x or 4x?" And marching along to larger values and doing the same with the other [energy sources]. Just trying to use similar ways to begin to see patterns at large scales that you wouldn't be able to see if you just did cost optimisation and you had your single answer and went off with that and published it.*

Some participants described scenarios as samples of possiblity spaces or as possible futures. *Whiston* , fits this description, understanding a scenario as varying parameters in a model to reflect policy options.

Scenarios as Exogenous

Some participants related scenarios to things that were exogenous to their model, and in particular input data. Input data in an ESOM or IAM can take different forms, such as parametric settings, descriptions of systems states and policy representations.

> ***Blencathra:*** *So the way that I would define a scenario is: I have my model, and I have an input data set. And when I formulate a scenario, I'm going to change one or more exogenous assumption that then affects the input data.*
>
> *Just to give an example, I might want to run a scenario with lower solar photovoltaic costs. So that's an exogenous assumption. And then I'm going to bring that into the model by changing, you know, the cost trajectory for that solar PV, and then rerunning the scenario with low solar costs, and then seeing how it changes the results. So the vast majority of the work that I see is along those lines, there's some assumption about the way things might unfold in the real world. And then that then boils down to changing an exogenous assumption within the model that's related to data and then rerunning the model to see what the results are. So high demand, low demand, you know, high fuel prices, low fuel prices, things like that.*

This conceptualisation is consistent with the idea that scenario analysis is a location in a model and is a kind of analysis that comes after model development and calibration.

4.3.3.2 Qualities of Scenarios Plausibility, Consistency, Consensus and Probability

Participants noted different qualifying properties that a conceptual object required to qualify as a scenario. The properties can be imagined as imposed on top of the ontological conditions such 'being a narrative', 'being a tool' or 'being external inputs'. As shown in Table 4-2, participants most commonly said that scenarios required internal consistency between the assumptions they embody. They also variously required that they be plausible, possible or in some cases more *probable* than other potential outcomes.

Van der Helm (2006) approaches the issue of these qualifiers in a conceptual paper in futures studies, dissecting the difference between the terms *probable, possible* and *plausible.* They define *probability* as indicating some scenarios that are more likely than others. *Possibility* relates to a binary classification over whether an outcome can or cannot be. Whereas *plausibility* is a more complex construct that evaluates the argument behind an assertion; whether it has internal consistency, convincingness and credibility. In these interviews, the latter two qualifiers were not always possible to distinguish, with participants discussing aspects such as internal consistency.

Only two participants mentioned that scenarios needed to in some way be probable. Conversely, participants did not explicitly say that probabilities could *never* be given to scenarios, but that "[scenarios] normally have no kind of probabilistic interpretation" (*Catbells).* The views about the relationships between scenarios and probabilities of participants were not that probabilities played a qualifying/disqualifying role something to be considered a scenario, but rather they held nuanced beliefs about the appropriateness of linking probabilities to scenarios (I discuss this below).

4.3.3.3 Other Conceptual Issues

I now detail some additional conceptual distinctions between different kinds of scenarios identified in interviews.

Inputs and Outputs

Some participants distinguished between the scenarios that are the inputs or outputs of models. They used different terminology to describe the two, differentiating between *scenarios* and *pathways*. This reflects the status of major scenario sets in Integrated Assessment in which the detailed quantitative elements of scenarios are derivative of modelling assumptions derived from qualitative narratives (see Box 4-1). Therefore, the SSPs are both derivative of models and provide harmonised sets of input metrics describing a set of consensually agreed relevant future socioeconomic scenarios.

Minimal and Maximal Scenarios

Participants differed as to whether they considered simple selections of parameters or turning module elements on/off sufficient to constitute a scenario. To some participants the practice of conducting a 'simple sensitivity analysis' was synonymous with a kind of limited scenario analysis. *Gable* expressed their conceptualisation that scenarios are about packaging multiple assumptions together, the value being that many low-level assumptions can be identified with a broader theme in system trajectories.

> ***Gable:*** *... well it's not actually to do with plausible futures. A scenario is a creation of a modeller or individual that you think would play out in the future. So it's a way of harmonising your assumptions.*
>
> *So if you make several assumptions that you think are maybe quite strong assumptions and if you package them together and say "this is what the world is going to be". And often people try to make them fairly consistent. I guess you could have a very inconsistent scenario but I guess it's a way of sort of merging the very bottom-up small scale assumptions that you are*

making in the model. And marking that with what people consider to be a version of the world or reality.

Some participants seem to require that scenarios can be very simple assumptions that one tries to represent in their model through switching on/off model elements. In contrast, other participants see scenarios as more elaborate constructions where multiple assumptions may have been harmonised.

Temporality in Scenarios

An implication of the different conceptualisations of the word *scenario* is that some representations do not necessarily explicitly require time to be represented. Scenarios could therefore alternatively describe single snapshots of an outcome (in past, present or future), a change at a particular moment in time (a diachronic representation) or some relevant variable over different temporal intervals (typically into the future).

The Appropriate Use of Scenarios

There were interviews with differing claims about the proper role of scenarios and their appropriate relationship to kinds of probabilistic information and methodologies.

The clearest divide in opinions regarding the proper use of scenarios was over how probabilistic statements could be attached to them. *Crinkle* said these opposing views were characterised by arguments in a series of papers during the creation of the SRES, a process in which they were involved. On the one hand, the "Nakicenovic position" which says that scenarios cannot be given probabilities and the "Schneider position" that without probabilities, non-expert users would come to incorrect conclusions regarding the likelihood of results.

> ***Interviewer:*** *There's another science fiction book I've got quite a lot of quotes for my thesis – do you know Dune? [Participant: Yeah] Because Frank Herbert [author of Dune] was an ecological consultant. And he talks about uncertainty quite frequently. In Dune, there's a phrase "On Arrakis, one does not talk of probabilities, one talks only of possibilities." So that's quite good. So it's about ecological management.*
>
> ***Crinkle:*** *The [quote]on the possibilities versus probabilities – that was a big fight, of course, during SRES. Nobody saw that at the time, but there is this almost very comparable quote from Steve Schneider, responding on SRES saying "it's a little useless to say that there's a meteorite going hit the Earth, unless you specify that the chances are less than one in 10 million."*
>
> *And so it's in response to Nakicenovic who published SRES and said, "Okay, we have these storylines, it could be a B1 world, it could be an A1 world. And please notice this because as*

> *a policymaker you have to be aware of this uncertainty. And as a scientist, I can never indicate the probability of any of these scenarios, because it's..."*
>
> *And then Steve Schneider comes back and says, "yes, thank you very much. How am I supposed to work with this? And you can tell me that there is a chance at the asteroid hitting the Earth, but I need to have some clue about the probability!"*

Crinkle also described the Nakicenovic position as being dominant among modellers currently, though the argument is not yet settled. This argument can be seen in literature from the time. The "Nakicenovic position" is perhaps summarised well in conclusion to the SRES report itself:

> *"Any scenario has subjective elements and is open to various interpretations. While the writing team as a whole has no preference for any of the scenarios, and has no judgment as to the probability or desirability of different scenarios, the open process and initial reactions to draft versions of this report show that individuals and interest groups do have such judgments." (Nakićenović et al., 2000, p. 46)*

Schneider laid out his position in a *Nature* Commentary (2001). He argues that without some subjective probabilities to indicate the likelihood of the different scenarios, non-expert users would default to making an incorrect assumption of equiprobability over the scenario set. This is problematic as policymakers may make decisions based on incorrect probabilities for events such as breaking certain warming thresholds.

Responding to this commentary, again in *Nature*, Grübler & Nakicenovic (2001) argue that probabilities are inappropriate for social sciences as they come from natural sciences in which frequentist interpretations can be maintained through the repetition of experiments. Furthermore, they believed that providing probabilities would minimise uncertainties and give undue deference to experts' opinions.

The view of *Lingmell* was perhaps intermediate to those described above. They believed that probabilities could not be assigned to certain deeply uncertain factors, but that wherever possible probabilities should be provided conditional on those factors.

> ***Lingmell:*** *That's tricky, because those are conditional, right? Those are very dependent on other underlying assumptions you make. Your assessment of the likelihood of RCP 2.6 is going to be deeply tied to your prior belief about how quickly we can develop and deploy negative emissions technologies. Your belief about the possibility of RCP 8.5 is going to be based on how much we think that really high emitting sources of energy will come back into vogue. So there are a couple papers on "is there enough coal in the world?" for the assumptions that are made in RCP 8.5.*

> *I don't think they should be given a likelihood. But I think it's important to understand how sensitive their likelihoods are to those types of underlying uncertainties. We can say something about how likely RCP 8.5 is given how quickly we think we're going to decarbonise, how do we think negative emissions are possible? What is the fossil fuel resource base that is still out there? What do we think the world's governments are going to be? There's a lot of those, a lot of things that are intractable. But we can kind of think about under different scenarios, how do those play out, to show how likely RCP 8.5 or how likely RCP 2.6 is? That I think helps give a little more nuance to this idea of, "what are the outcomes associated with those different scenarios?" So instead of just being "well, under 2.6 you get this, under 8.5 you get this". And what does that really mean? Then you can kind of say, "Well, almost in any case, here RCP 8.5, may not be likely, you know, hypothetically." Then that means that maybe we should think about RCP 8.5 as a tail risk scenario, which is out there. But it's not like the scenario that we give tons of weight to as far as what are the expected outcomes?*

Branstree described how the different conceptualisations of scenarios as probabilistic and non-probabilistic operated within the Integrated Assessment community, with some researchers using expert elicitation to produce ranges for uncertain parameters and others producing very large sets of scenarios without probabilities attached. At the fulcrum of this issue is the disagreement over the power of expert elicitation as an appropriate method of circumventing the indeterminacy of complex social systems. They also said that looking for other qualities such as robustness in scenario studies may be more practical and useful for policy-informing work.

> ***Branstree:*** *…And then through clustering of all those expert elicitation studies, if they calibrate their whole model using the expert elicitation studies, they can say that their model might have a certain probabilistic outcome.*
>
> *The flip side of that is that most people would say expert elicitation studies, while there may be a theoretical basis to say that those are probabilistic, a lot of people would say that they are absolute rubbish and there's no basis to say that those are probably correct or probably incorrect. They are just expert elicitation studies. So [there is] an assumption that experts know what they are talking about and that their best guesses on what parameters of a model might be are assumed to be a reasonable representation of the probabilistic distribution of those parameters. They might not be.*
>
> *So what other people are doing is saying "look, we know the range, we know what a maximum value and a minimum value might be, and let's just explore within that maximum range, let's not assign a probability to it, but let's try to find robust scenarios within that solution space". So like robustness or resilience is maybe more important than probabilistic scenarios. So reverse engineering: finding where you want to go and finding what are the resilient or the common choices that keep coming up again and again and again to enable you to get to that point. That's maybe more valuable than 'what is the most probable outcome from a set of scenarios'.*

Lattrigg provided an interesting perspective on this issue. They identified the objection to probabilistic scenarios as due to a fear of undue subjectivity. However, they noted that defining a non-probabilistic set of scenarios over an interval also involved subjective assessments. This is because modellers must choose what they think are appropriate limits for the scenario sets.

Perhaps in recent literature, the most contentious arguments have moved from the question of the appropriateness of probabilities over scenario sets to the nature and necessity of plausibility conditions attached to scenario sets. An example of this is an essay by Pielke Jr & Ritchie (2021) which decries the prevalence of RCP8.5 (or SSP5/RCP8.5) in climate-related studies, as well as Pielke Jr's (2020, 2019a, 2019b, 2019c, 2019d, 2019e, 2019f, 2019g) extensive polemical writing on this topic for a lay audience. Responses to this have disagreed with Pielke Jr & Ritchie's (2021) methodological approach and characterisation of the use of scenarios in climate-related studies (Marvel, 2021; Schmidt and Jacobs, 2021). The debate is contested to the point that an online dashboard has been set up to aggregate the most salient points in the debate in the academic literature, general-audience literature and social media (Monticone, 2020).

Crinkle also discussed this issue, noting that RCP8.5 has become less probable over time as countries have implemented mitigation policy.

> ***Crinkle:*** *RCP 8.5, that whole discussion, I don't know if you saw [a paper] in* Nature *from Zeke Hausfather[34]? For me, he is more or less right. So RCP 8.5, the chance of getting us getting there has become smaller over time. So there is a point where it's become so unlikely that you don't want to use it anymore. But even before that, already from [its inception] it's an unlikely scenario. So you can't use the baseline to scare everybody saying this is what's going to happen with climate change. And so apparently probability plays a role, even if the RCP 8.5 can happen. At some point. You can't present this as the most certain outcome.*
>
> *Here in [my country], I'm advising [a government scientific department] for new scenarios. They are saying we want to have the range, so they still are again choosing RCP 8.5 and RCP 2.6 because we have the full range. Fine. But at the same time, you are also confusing people because all the people [involved in some climate adaptation projects] will build against RCP 8.5 because that's the only information you give them. And so it matters that maybe the chance of RCP 8.5 coming through is only 2% or something like that.*

This issue of the plausibility of pessimistic scenarios was also discussed by *Brandreath*, another senior Integrated Assessment modeller. They discussed an exchange of emails they had with another academic who had been involved in previous IPCC-related scenario creation exercises.

[34] See (Hausfather and Peters, 2020). The authors argue in a Nature comment piece that the use of RCP8.5 is misleading, especially when comparing different outcomes between scenarios, as it is extreme and unlikely.

> ***Brandreath:*** *So, this is a discussion we have now in the IPCC. For example, in AR5 there was this what we call "the spaghetti curves" where you see thousands of scenarios with RCPs from 2.6 Watts per square meter up to 8.5. It's a huge spread. We are discussing these into the IPCC now. Whether or not it is useful to explore the RCP8.5 if you already believe that this is not reasonable. We say "OK lets [?eventualise] now that the top line should be RCP 6.0 and not 8.5 anymore". Why? Because you want to explore a future that is still possible and not a future that it seems to be out of our radar.*

Participants also identified other potential problems associated with certain scenario analyses. These included:

- *Blencathra* noted that limited scenario sets provide an anchor around which people assume the scenario sets completely describe future probabilities and this issue was identified by a paper from Morgan & Keith (2008). A similar argument can be seen in Hulme (2011) who argues that reductions of descriptions of the future to narrow descriptions of climatic causes alone is reductive.
- *Catbells* believed that good and useful scenarios were those that showed most strongly the signal of systemic drivers when fed into a model.

Table 4-4 summarises other issues in scenario analysis identified by participants and how they are alleged to cause problems

Table 4-4: Summary of other issues identified by participants in the handling of scenarios. The 'pathology' refers to the practice identified by the participant as problematic, the 'mechanism' refers to the way in which the pathology creates an issue.

Issue	Mechanism	Assumed Problem	Participant(s)
Defining scenario sets as ranges without probabilities	There is a subjective choice of maximum and minimum scenarios and no information is given about the values in between the two	Policymakers are not informed about likely outcomes in the middle of scenario distributions	Latrigg
		Policymakers may be overly drawn to certain kinds of decision analysis such as least-regret.	Latrigg
Using limited scenario sets in policy analysis	Small sets provide an anchor around which decision-makers base thinking. Possibly availability heuristic is an issue.	Policymakers assume that the limited scenario sets are more likely	Blencathra
A large proliferation of scenarios from different teams all producing their own scenario sets	Scenario space is over explored.	Difficult to determine which scenarios are more likely	Brisco
	Large scenario sets encourage people to start treating them in a pseudo-statistical manner	"Nonsense" work is generated from incorrect assumption	Grisedale
Modellers doing Simple Sensitivity Analysis using SSP parameters	Work is incorrectly labelled as scenario analysis	Miscommunication	Greatend
Standard scenario sets are not ambitious enough	Scenarios are shown to be wrong. Scenarios may not explore low-probability possibilities.	Potential for surprise	Greatend, Hartcrag
Pessimistic scenarios (e.g. RCP8.5) are not presented as very unlikely, or simply presented alongside others	People assume scenario is plausible or probable	Maladaptation and overbuilding for most pessimistic scenarios	Crinkle, Brandreath
Scenarios do not contain discontinuities	The world has non-linear behaviours not represented by scenarios	Lack of preparation for eventualities	Brandreath

In summary, the view that scenarios should not be assigned probabilities either quantitative, ordinal, or qualitative, seems prevailing within the community. The core of the arguments revolved around the appropriate role of subjectivity in assessments: should expert opinion be legitimately used?

Within some domains of energy modelling, frequentist interpretations of probabilities of scenarios are perhaps much more defensible as one may model the occurrence of foreseeable and repeated adverse events such as power supply failures of adverse weather conditions. In IA, however, one is often modelling changes with structural consequences for the target system. So given a consensus around the inability to interpret probabilities on scenarios in such a case there is disagreement over whether expert opinions are meaningful. Furthermore, there are a range of anxieties about how policymakers may misinterpret sets of scenarios. I shall return to the role this 'scarecrow policymaker' in the minds of modellers Section 4.4.1.

4.3.4 The Relationship Between Methods and Uncertainty

Finally, in this subsection, I detail how participants viewed their methods as interacting with uncertainty. Participants discussed various methods in both their work and other's and related these kinds of uncertainty analysis to different kinds of uncertainty. I have adopted a convention of referring to all analysis methods intended to probe an aspect of uncertainty as 'Uncertainty Analysis'; others may use a narrower definition of this terminology as the activity of producing distributions or uncertainty bounds on model outputs (Saltelli and Annoni, 2010).

Literature broadly recognises that the processes used to handle uncertainties reflect conceptualisation in some way (e.g. Scoones and Stirling, 2020, p. 5). Table 4-5 below summarises the methods discussed by participants. Unsurprisingly, the most frequently discussed method was scenario analysis. Many participants also discussed sensitivity analysis and other methods of exploring parameter space.

Table 4-5: Summary of the frequency of mentions of different uncertainty analysis methods by participants. Note that many of these overlaps and some methods were only fleetingly mentioned. Thus frequency does not give an indication of outright importance. The column of "related uncertainties" indicates which kinds of uncertainty this method was associated with by participants. The methods are clustered for convenience.

Technique	Mentions	Types of Uncertainty Related by Participants
Scenario Methods (All)	25	
Scenario Analysis	20	Scenario, Parametric
Simple Scenarios	2	
Scenario Discovery	2	
Scenario Development	1	Decision
Sensitivity methods (All)	16	
Sensitivity Analysis	7	
Simple Sensitivity Analysis	3	
One-at-a-time (OAT) Sensitivity Analysis	1	Parametric
Morris Method Sensitivity Analysis	1	
Global Sensitivity Analysis	3	
Perturbed Parameter/Physics Ensembles (PPEs)	1	
Monte Carlo (All)	12	
Monte Carlo	10	Parametric, Filling Solution Space (Tails)
Parameter Space Exploration	1	
Latin Hypercube Sampling	1	
External (All)	6	

Open Sourcing Code	2	Structural, Code Bugs
Workshops	1	Filling Solution Space (Tail)
Expert Elicitation	3	
Literature Review	2	Parametric
Model Comparisons (All)	8	
Multi-Model Ensembles (MMEs)	2	
Inter-Model Comparisons (IMCs)	6	
Others		
Stochastic Programming	2	
Bayesian Methods	1	
Robustness Analysis	2	
Real Options Analysis	1	Dynamic
Adaptive Pathways	1	
Modelling to Generate Alternatives (MGA)	3	Dynamical
NUSAP	1	

Scenario Methods

Most participants discussed scenario analysis. Though I have already discussed the conceptualisation of scenarios at length, it is worthwhile to note the conceptual muddling of simple scenario and simple sensitivity analysis. *Yewbarrow* noted that these uncertainty analyses fell on a spectrum and that one cannot easily demarcate between sensitivity analysis and scenario analysis; as the number of variables that are changed at once increases, a sensitivity analysis becomes a scenario analysis.

> ***Yewbarrow:*** *I think there is a spectrum of uncertainty analysis from scenario-driven to simple sensitivity analysis, if you're talking about capturing parameter uncertainty, that way. I think both are heavily weighed heavily influenced by the model stakeholder and user, but they're both also influenced by this iterative feedback loop between the modelling community and the model users.*
>
> ***Interviewer:*** *Without sounding too psychoanalytical, why do you describe that as a spectrum? What's the difference there between a scenario and the sensitivity analysis in terms of the quality of the uncertainty analysis?*
>
> ***Yewbarrow:*** *The sensitivity analysis is often one-at-a-time. So let's have oil prices low and see what difference that makes? Or let's have a set of eight sensitivity runs, right? So there's high oil price plus good technology learning, versus low oil price and poor technology learning; And then the other possibilities on that spectrum.*
>
> *Whereas at some point that does blend into scenario analysis, right? Because you, you start thinking about, "well, in our high oil price world would you expect, you know, more development of technology learning of new technologies?" For example, would that be a reasonable thing? But there is a spectrum because there are other scenarios that have many many things in them, and they just bundled up and they're often given names, right? So you hear different groups call things... what does the Energy Systems Catapult use... patchwork and clockwork? What does Shell use: mountains and oceans and sky? So these are things with lots of different things in them. IPCC has the same, you know, all the different IPCC scenarios*

> *and that's a whole bunch of things about how many people live here how green we are, what policy ambition is there as well as technology learning oil prices and all the rest?*

This ambiguity between the two methods may be acute when scenarios provide the parameters for some uncertain processes, rather than input data or other exogenous assumptions to the model. Different participants understood scenario analysis to involve the varying of parameters, input data and switching on/off different model components (thereby capturing something like structural uncertainty). A mixed conceptualisations can be seen in the interview with *Whiston*.

> **Whiston:** *So it was running the model many many times to try to get an idea of how important bioenergy is within the model because bioenergy is just one little bit of the big model on the side of other many other thing. So what I did was pretty much scenario analysis, clicking on and off features of the models to the model to see how do they affect energy uptake.*

Sensitivity Methods

Participants described various versions of sensitivity analysis. The simplest kind, the varying of a limited set of parameters, was generally viewed as perfunctory. Computationally, this may also be one of the technically simplest forms of uncertainty analysis and only requires a handful of model runs to achieve results. However, some authors caution against one-at-a-time (OAT) sensitivity analysis due to its inadequacy in high-dimensionality systems (Saltelli and Annoni, 2010).

Some participants discussed more extensive and advanced sensitivity analysis methods such as Global Sensitivity analysis[35] and Morris Method[36].

Some participants discussed Monte-Carlo analysis. It was occasionally viewed by some as a sort of ideal end goal in terms of comprehensiveness. However, this method is technologically challenging as it requires repeated dense sampling of the possibility space with large numbers of computationally expensive model runs, limited by the availability of High-Performance Computing (HPC). The feasibility of Monte-Carlo analyses is also limited by the ability to assign input distributions of variables.

---

[35] For an overview on Global Sensitivity Analysis see Saltelli et al. (2008)

[36] For the original article on Morris Method see Morris (1991)

External Methods

There are several ways in which participants described analyses conducted externally to a model that shine a light on the uncertainty in a model or its results.

Three participants discussed expert elicitation (*Brisco, Esk, Brandreath*). I have already covered the disagreements over the role that expert judgement can play in assessing the probability of different scenarios. Expert elicitation can also be used in model construction for estimating unknown parameter values. *Brandreath* described some issues that they had acquiring reliable estimates for technology costs and hence expert elicitation was a way out of this conundrum.

Two participants (*Catbells and Redscrees)* discussed how Open Sourcing code could help to eliminate data errors and have others examine the structural assumptions of models. The open sourcing of code may also assist in model intercomparison as models can be easily downloaded, installed and run against one another.

Model Comparisons

Participants discussed various practices for comparing the results of different models.

There is a difference between Multi-model comparisons (MMCs) and MMEs. I adopt the following convention in this thesis: MMCs are the broader class of activities where the features, structures and results of models are formally or semi-formally compared to one another; MMEs are activities in which models are given highly standardised inputs, parameterisations and scenarios and run to produce directly comparable output. MMEs are used to either assess the relationship between model structure and outputs or to attempt to better characterise the uncertainty in an estimated value when compared the single model investigations. I discuss the philosophical issues associated with uncertainties and MMEs in chapter 8.

The practice of model comparison is more mature in Integrated Assessment than in energy. There have been several structured efforts at model comparison in the Integrated Assessment and in the energy space, both under the auspices of the IPCC (as in the MIPs) and outside of the IPCC (as in the case of the Energy Modelling Forum (EMF). *Greatend* discussed the role these intercomparisons play:

> ***Greatend:*** *(Participant lists and describes several of the major modelling groups and their styles of models)*
>
> *So each of these models, they all, let's say, run the SSP2 scenario. Same input data when it comes to population and GDP. But yet they produce a range of results – what the hell's going on? So this shows you methodological uncertainty. So model inter-comparisons are extremely important.*
>
> *And this is another place where the whole SSP process have been very helpful, because on the 1.5 [degrees] database[37], you've got all of these models and you can filter the results across models. And for somebody who's like really geeky and really technical, probably gets paid to do it, and [who] takes too much time [doing it], [that person] can sit and try to assess how different models and their representation of complex systems leads to biases. So you come up with a so-called model inter-comparison project, the MIPs. Where lots of teams come together, they run harmonised scenarios and they see how the results differ.*
>
> *A particularly famous MIP is the EMF Energy Modelling Forum, which is hosted by Stanford University. But it's kind of a pro-bono thing, which people do because the science is cool, but there's no money there.*

Model comparisons face some inherent difficulties with energy models and IAMs as often results are incomparable (e.g., different metrics are used and results are only produced for certain geographies) or the implementation of scenarios is different (e.g., policies are represented in models in inconsistent ways). Some recent efforts have been made towards reducing these issues to produce MMEs (Giarola et al., 2021).

Other Methods

Several participants espoused the utility that Modelling to Generate Alternatives (MGA) has found, especially in energy modelling. MGA is a technique first pioneered in the 1980s in which maximally-different solutions to an optimisation problem are sought (Brill et al., 1982) and has found utility in energy studies (DeCarolis, 2011; DeCarolis et al., 2016; Pedersen et al., 2021; Price and Keppo, 2017). One method for achieving this involves finding an optimal solution with a model solver and taking this value, with some additional tolerance, as a constraint to the optimisation rather than an objective function. The optimisation is then run again with an objective function that seeks to maximise the distance in solution space from the original optimal solution. This process can then be performed again with this second solution to find yet more different solutions. This kind of analysis was conceptualised as useful for exploring the structural uncertainty associated with the use of optimisation frameworks.

[37] A database of mitigation pathways to reach 1.5 degrees target that contributed towards the IPCC' 1.5˚C Special Report. Hosted online by IIASA (2019).

Other methods discussed by participants include real options analysis and stochastic programming that can assess the dynamical uncertainty inherent in decision-making by capturing the path dependency of choices (*Catbells)*.

Summary of Methods Discussed

Whilst some participants used methods themselves to describe different kinds of uncertainty, it was most common for participants to identify methods with different *locations*. This should perhaps be expected given that uncertainty analysis methods can only be applied to different aspects of the model. Perhaps more striking is the very limited discussion of methods of external validation of uncertain elements of models. Few participants discussed aspects such as workshopping, literature review, calibration and expert elicitation to explore uncertainty through reference to some external body of work.

The broadest range of uncertainty methods had been discussed by energy modellers rather than Integrated Assessment Modellers. Perhaps this reflects the relative simplicity of (often uncoupled) energy models compared to the coupled models of IAMs.

4.4 Influences on Uncertainty Handling

I now turn my attention to the influences on the practices surrounding uncertainty analysis and uncertainty handling, considering the role of the context in which the work occurs. As I coded the transcripts, I noted the various factors that appeared to influence the way that uncertainty was treated. These factors originated from the local context of the work of the modellers, the practices of their research communities and the various stakeholders.

Structuring this Analysis Using Actants

In the structuring of this examination, I have conceptualised each of the factors within my consideration as *actants*. I did not initially anticipate doing so, but it became clear through my coding of the transcripts that this may be a productive approach to organising the factors that I had identified. I therefore now explain how I have chosen to draw upon Actor-Network Theory (ANT) selectively and instrumentally as a set of tools for this analysis, using the *actant* concepts and several other ideas originating in ANT. However, I stop well short of employing ANT as an overall ontological framework to guide analysis, for reasons I shall explain.

ANT is a disparate group of tools and ideas for use in social theory, employed differently by different people (Law, 2008). There are many versions of ANT, but here I only sketch the most canonical (Michael, 2017, chap. 3). The figure most associated with the emergence of ANT is Bruno Latour. A key text in its development was *Laboratory Life*, which documented Latour's ethnography of the Salk laboratory in the 1970s, showing how practices and interactions within the laboratory between humans and technological objects resulted in the production of knowledge (Latour and Woolgar, 1979).

The term 'ANT' emerged in 1982 after its use by Michael Callon (Law, 2008, sec. 2). Much of the early classical work is influenced by the works of the semiotician Algirdas Greimas (e.g. 1983) and the philosopher of science Michael Serres (e.g. 1974).

In ANT, the most important unit of analysis is the 'actant'. It does not see the world in the way that some sociologies do as composed of human actors and social structures, but rather as composed of human and non-human actants that may be arranged in networks (Michael, 2017, chap. 2). The "social" is not a force unto itself, but rather is emergent from the heterogeneous interactions within these networks. These actor networks emerge as an actor connects other elements to enact its will (Michael, 2017, chap. 3).

A central idea is that non-human objects, like technical objects, can have a form of limited agency. This notion of agency is hotly debated in the literature – do actants have the capacity to intervene according to their will in social processes? To what extent to which non-human objects can be considered to possess agency (Michael, 2017, chap. 4)? For my purposes I merely assume that the actants I am considering have restricted agency – they cannot pursue strategic goals, but there is a sense in which they may consistently influence the other actants to interact with them. I must also outline several other concepts that I borrow from ANT for this analysis: *translation* and *inscription*.

Translation is a metaphor that originates with Serres (1974) and was used in a seminal chapter by Callon (1986). It is a process by which the web of relationships is made and remade in the actor-network. The concept of translation implies a sense of betrayal (*trahison*) of the original meaning of a thing (Law, 2008, sec. 2). Thus, when translating something in an actor-network, one must necessarily betray the original meaning of the thing in some way.

Inscription is a process in which some aspects of social practices and performances can be embedded in actants in the actor-network. For example, in producing some technology, like an automatic door-closer, the practice of closing a door is inscribed into the technology (Johnson, 1988)[38]. The relative immutability of technological and physical objects can help these practices endure.

An unfettered adoption of ANT also requires several other assumptions which are incompatible with the wider approach I have taken. Methodologically, ANT generally requires that one takes participants at their word: when they describe what is happening, that is what is literally happening. For my purposes, where I must re-interpret technical discussions involving modelling and compare between participants, this is unfeasible and unhelpful.

Furthermore, ANT is agnostic to a priori distinctions between the technical and social (Michael, 2017, chap. 3). I do employ these distinctions in the categorisations of my actants, though I acknowledge how these distinctions can become mixed up and partially fungible[39].

The Ontology of the Actants

Conceiving the factors affecting uncertainty handling as actants, I have therefore organised these in two ways.

The first considers the factor's proximity to the modelling process: does the influence come from within the modelling group, the wider disciplinary community, from other institutions within the scientific enterprise or from outside of science (such as the demands of policymakers)? These various boundaries have an epistemic significance; as the actants become more estranged from the modelling process, the actants within that sphere will be less epistemically familiar with the practices of the modeller and the functions of the model.

This concept of proximity in this schema is inspired by Mackenzie's (1990) *certainty trough*. This is the observation that those in knowledge production processes tend to have less confidence in knowledge than those less proximate and committed to the technological paradigm. Those alienated from the knowledge-producing institutions are said to have the least confidence in

---

[38] An alias for Bruno Latour

[39] See my later discussion about the socio-technical infrastructure required for the running of models.

the knowledge. Lahsen (2005) criticises Mackenzie's (1990) certainty trough as not capturing all the dynamics at play as models may be produced at different sites. Nonetheless, I employ the idea is an approximate sense.

The second way I have organised the factors is by the kinds of actants involved in the interaction. The most apparent actants are actors – people involved in modelling or in interacting with the modelling process. During the interviews, a variety of cultural and formal institutions were mentioned that played an important role in shaping how uncertainty is handled. Also, the role of the technologies of modelling turned out to be essential to understand, as models themselves exert a strong influence on those that use them. Furthermore, models rely on an infrastructure of technical objects, such as the availability of High-Performance Computing, to fulfil their functions.

Figure 4-3 below gives a schematic of this classification of actants. Those less proximate to the model building process moving outwards in a radial direction and the categories of actants change in the angular direction.

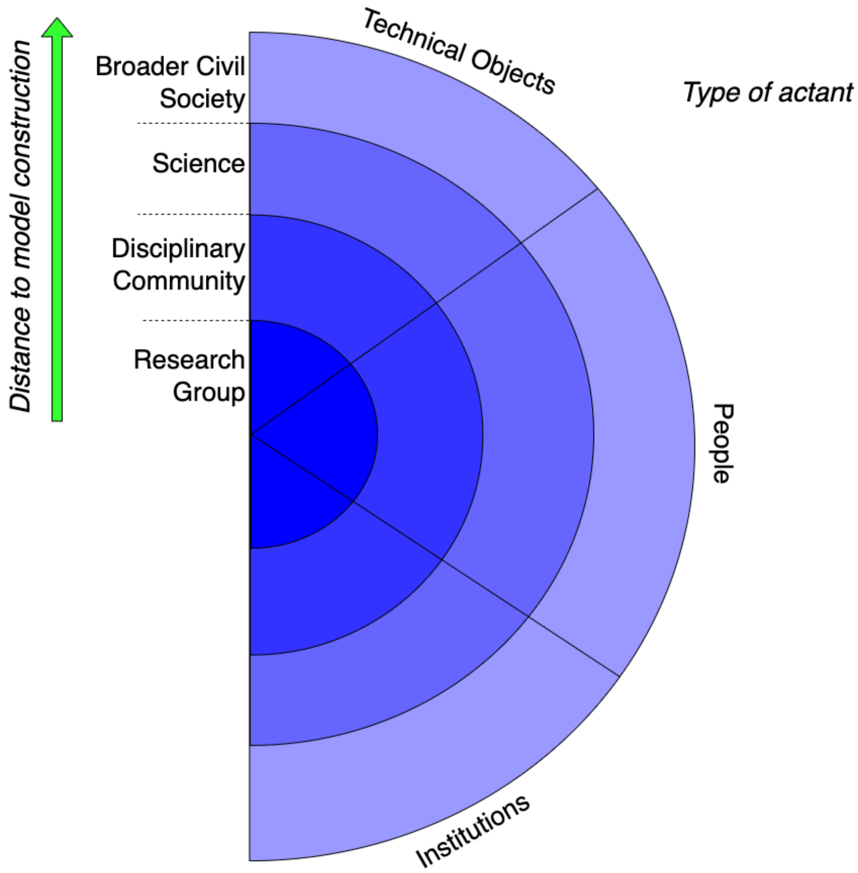

Figure 4-3: Scheme of factors/actants that I have used to structure the discussion of influences on uncertainty handling

This analysis proceeds by examining each of these kinds of actants and the type of effect that they have on the handling of uncertainty. With each category of actant, I move in my analysis from the proximate to the remote.

Section 4.4.1 deals with the role of human actants and considers their motivations and capacities as epistemic agents. Section 4.4.2 deals with the various institutions shaping uncertainty analysis and considers how actors interact with them. Section 4.4.3 then considers the role of technical objects in shaping the way that actors deal with them and the effects that this may have on uncertainty analysis.

One crucial influence is missing from this schema – the role of the target systems themselves. Fundamentally, these modellers are modelling very different types of systems, and thus we would expect them to call on different analytical repertoires. Often the actual target systems that researchers may hope to represent are remote from them both in a spatio-temporal sense and because they interact with them only through layered intermediary actants. This will be discussed in greater detail in chapter 6, where I compare the different influences on uncertainty handling between the climate science and energy/IA communities.

4.4.1 People

The Agency of Researchers Themselves

The personal interests and motivations of researchers themselves may have a bearing on the types of uncertainty that they are predisposed to investigate. Several researchers discussed how their motivations informed their choice of uncertainty analysis. These motivations generally push them in a thematic direction, rather than modelling uncertainty in a particular way. Several participants noted that the personality of a researcher would affect the extent to which they were willing to explore uncertainty.

The Training and Skills of Participants

The disciplinary background of a modeller affects the handling of uncertainty in several different ways. The three primary ways in which this appears to bring a bearing on uncertainty handling were:

- The kinds of uncertainty analysis techniques one is familiar with and the skills available to apply them.
- The selection of conceptual resources and models that one has available to them because of their training.
- The culture of the discipline and the epistemic and aesthetic values it holds dear.

Some participants with a background in engineering confessed that uncertainty analysis had not been a major part of their training and that the handling of uncertainty was something that they had only started doing as they progressed through academia and began working on large models. *Helvellyn* described how in Engineering, uncertainty analysis was often limited to imprecision and intractability and is dealt with using safety margins in designs. They described how contact with real-world problems enlightened them to the importance of uncertainty analysis:

> ***Helvellyn:*** *[In engineering, uncertainty] is never really discussed conceptually. It just kind-of … you do the brainstorm, and you look at all the options and you choose one and you go. […] I worked as an engineer [on projects in a developing nation setting]. And then you already get into the uncertainty in what the hydroelectric regime is and what water will be available for this kind of thing. And then you have to project this into the future.*
>
> *When I started my PhD...then we need this diversity in the different types of uncertainty – this became more and more conceptually clearer. And I think that there is still quite a bit that [inaudible] involved in the future*

Scafell, an economist by training, said that "at grad school now, still the degree of uncertainty was limited as I wasn't doing a lot of modelling in grad school." However, this understanding changed then they started working for a major intergovernmental organisation "and started seeing *oh yeah there are a lot of unknowns here.* I was working on deforestation on my first 7 or so years…my ability to predict where is going to be deforested was somewhat limited.".

The key skill sets required for many technical uncertainty analysis methods are primarily mathematical, computational and statistical.

The difference between disciplines could also be noticed in how modellers talked about uncertainty. In terms of uncertainty types, the only participants to discuss *Knightian Uncertainty* were those with some formal training in economics. This is perhaps somewhat surprising as the literature review in chapter 2 has shown that the concept of Knightian uncertainty has permeated many fields of study since its conception in the 1920s (Knight, 1921).

Scoat noted issues with how data providers inadequately represented uncertainty. This participant has recently transferred into energy modelling after working in natural sciences. They described how previously they had been used to rigorous statistical quantification of uncertainties on pieces of technical apparatus and how the nature of quantum mechanical interactions meant that probability distributions could be assigned to different outcomes. In their new role working on energy systems, they found the data provision from utility operators, which did not attach error bars to outcomes, concerning.

> ***Scoat:*** *I'm now concerned with things like the hourly electricity demand on the electric grid and the values at noon. The values of 1pm are going to rely heavily on what the values are at noon. If it's a hot day, we're gonna have some kind of continuity in these time series. And I feel like we just often just rely on utilities provide us this information. And there is no reporting uncertainty on what the uncertainty is in their equipment or anything like that. So, we just kind of have a value, we say, "it looks like the demand was 100 gigawatts right now". That just is the value. Yeah, no error bars on it or anything.*

Scoat was one of a limited number of participants who discussed the idea of 'State Spaces' that their models could occupy. This concept exists in many disciplines but can be traced back to the concept creation of *phase space* by the physicists Boltzmann, Poincaré and Gibbs at the end of the 19th Century. The concept of *state spaces* is a newer entrant to engineering and economics and was first popularised in the engineering of dynamical systems in papers by Kalman (1960; Kalman and Bertram, 1959a, 1959b). It is a powerful conceptual resource for the practice of uncertainty analysis, as if one imagines that uncertainties have some multidimensional space, one can describe this uncertainty in roughly spatial or geometrical terms: the corners of state spaces, bounding state spaces etc. Indeed, some participants did discuss the need to find corner solutions to their optimisation problems in this way. I shall return to the issues of state spaces and the influence of the ideas of Lorenz when examining the conceptualisation of uncertainty by climate scientists (§5.4.1).

The influence of training was not limited to that received at undergraduate level. Several participants discussed how the doctoral studies programmes they had undertaken had prepared them well to deal with uncertainty and how these programmes, in part, were the result of the influence of some researchers (*Yewbarrow, Blencathra).*

Conceptual Resources

Greatend discussed how the use of a niche programming language meant that certain changes to their model were very difficult to perform due to a lack of trained computer scientists.

> ***Greatend:*** *So the software constraint is just really technical, that our language doesn't support this without massive investment in probably needing third party programmers to do it for us. Because keep in mind, we're not programmers, most of us we're just former engineers, or former economists. In some cases, not even that. So sure, we can sit and write some equations. But you know, we're not programmers, we can't really go on to a higher level of computer language in order to do some really advanced stuff. We'd have to hire people specifically for that. And you know, that kind of money simply doesn't exist, unless it's part of a project.*

An emphasis on parametric uncertainty, or an equivalation of this with the totality of the uncertainty in the model, is compatible with a state-space conceptualisation of uncertainties. In this way, the kinds of uncertainty analysis that one can perform are in dialogue with how one conceptualises uncertainty. Different uncertainty analysis techniques assume different ontologies of the uncertain knowledge that one is exploring.

For example, one interpretation of the process of expert elicitation requires that researchers assume that the subjective belief of experts are legitimate estimates of real-world uncertainties. This may imply certain understandings about the epistemic access that experts can have to the world's true nature.

Division of Labour

Accounting for uncertainty and analysing uncertainties embodied in a model takes time that could be allocated to other research, teaching, administrative activities, or anything else for that matter that consumes the day of a modeller. Having funding available for an activity allows a modeller to justify allotting a more significant amount of their work time to a particular activity. With funding, a modeller can devote resources to the deep development time required to either investigate new uncertainties not yet included in the model or to re-wire the model structure to allow different kinds of uncertainty analysis (e.g., Monte-Carlo analysis).

I have previously discussed how the particular skills of a researcher may limit or open up the kinds of uncertainty analysis that they can engage with. These skills are acquired through formal academic training or 'on-the-job' training.

However, understanding the division of labour within a modelling group is crucial for understanding this model development work. Senior researchers who allot more time to oversight tasks do not perform much of the deep and monotonous work on code development. Several participants talked about the importance of a ready supply of ECRs and funding to support them. ECRs do not face many of the responsibilities that other researchers do. For example, they may not face the burden of teaching commitments that senior researchers do, and their PhD funding may not require a steady stream of journal publications. Hence ECRs and PhD are ideally placed to engage in long, laborious model development and overhaul tasks that are not feasible for other researchers.

> ***Greatend:*** *Interns that do a decent job and show promise, they offer them a job, usually through some sort of project. So you know, there's [funding available], they need somebody, and they just fish some intern. And that's exactly what happened with me. When I finished my master's degree, [an academic] got some money to look into [a topic] using an integrated assessment model. […] And that's what works for most people, we get interns, and then if we see promise in them, and there is money, we immediately take them. I've actually hired two people like that through that method.*

Leaders in Research Groups

Aside from the influence that senior researchers have within their research group, they can also influence the broader research community through the material they produce and through the institutions of the disciplines such as editorial roles. Several participants in this study were senior in their respective fields. Participants such as *Brandreath* narrativised historical model development, with themselves as protagonists.

Reputation amongst Peers in Field

Some participants discussed a dynamic by which uncertainty in a result can be seen to validate or invalidate it. In the former situation, uncertainty can be used strategically, either consciously or not, to dial one's results so that the uncertainty interval that one has overlaps with the generally accepted figure of others in the field.

> ***Skiddaw:*** *To be honest to say that I think we rarely talk about uncertainty. The few occasions I do remember is people complaining about how others don't correctly quantify uncertainty. […]*
>
> ***Interviewer:*** *Why do you think people might rarely talk about uncertainty?*
>
> ***Skiddaw:*** *I think because maybe people feel uncertainty maybe invalidates your results. I personally also feel that. I would actually sometimes think, you know, if I correctly quantified the uncertainty, the ranges of my result would span the whole result space and I could therefore not make a specific statement. I think that is a reason why some people are happy to neglect certain sources of uncertainty or spend not so much time quantifying uncertainty. Because they would like to see a specific concrete outcome of their research.*

Blencathra also discussed how this was both a conscious and unconscious process.

> ***Blencathra:*** *And so these are all things that modellers do consciously and subconsciously, I think, to adjust the numbers. Nobody really wants to be a major outlier, right? So in this world where we're all simply running a half dozen scenarios, you don't want any of those scenarios to look too crazy, right? Because then people are going to question your judgement.*
>
> *But the way that I've tried to inoculate myself from that sort of criticism is to do ... again, if you do really rigorous sensitivity and uncertainty analysis, you will capture those outliers, but you get a range, right? So you're not focused too much on any particular single scenario.*
>
> *[…]*

> *I don't think people walk around, constantly thinking that in themselves like, "well, I can't do that because, you know, I'll get laughed at when I go to this conference." But it's just, it's kind of subconscious, right? Like you want the results to kind of conform to your mental model of the way things work. And in part of that mental model is knowing what other people are, are projecting.*

Yewbarrow also told the story of how one researcher opted out of a model comparison exercise because their results were incompatible with the results of others in the process.

> ***Yewbarrow:*** *There are two processes at work. One is there is this fear of being different, and that these other teams, maybe they're bigger teams, better funded than you, and they are quite convincing in their arguments, and you actually say "So but that's a good point. And I didn't have to have that data in my model, or I didn't have that feedback." So there is this element of convergence.*
>
> *The other element is that the people who really don't converge, drop out of the model comparison projects. So [a researcher] used to be the only one who said, "Look, if you decarbonise the economy, the economy will be larger." We can have a system that is, you know, that is better than what we have. And everyone else says "no, the economy … a bit smaller". Because and after a while, [they] just got fed up going to those meetings, because people just told him he was wrong all the time. So he just stopped going. And so there is a selection bias going on here.*

Thus, we can observe two dynamics at play in the effect of embarrassment and reputation on the presentation of uncertainties: the dialling of results or uncertainty ranges and the non-inclusion of non-conforming results.

Model development may also occur in reaction to legitimate critiques. But model development can only occur within the bounds of what is possible given the state of the existing model, the funding available and the skills that researchers have. *Greatend* discussed several such critiques and how they were able to react to them, given the models that they had available.

> ***Greatend:*** *Obviously the critique drives us. But it also has to do with how advanced our models are. Because to be able to do something like this, you have to have a model that can represent it. So for instance, the lifestyle scenario that I mentioned, that benefited from the residential energy model that I had made. Previously, as I told you before I started, there was a smaller GDP, residential energy use and a regression. There, you don't know how much the shift of the line based on improved behaviour. But once we had a model that was more detailed, that different energy functions, different income groups and things like that, you could immediately come up with a better estimation for how much behavioural change affects people choices.*

Policymakers

Outside of the immediate epistemic communities of researchers, policymakers are often the most important stakeholders to energy systems and IAM modellers.

When questioned about the role that other stakeholders, such as policymakers, play in shaping uncertainty analysis, many participants invoked what I label the "*scarecrow policymaker*". They described policymakers as giving different preferences for types of uncertain information to be provided to them. They would often say alternatively that policymakers demand probabilistic information, that policymakers demand single estimates, or that policymakers demand simple sets of scenarios. Alternatively, that they would claim that policymakers do not understand some particularly complicated mathematical concepts and that large simplifications need to be made. In this discussion of policymaker's purported competencies and interests, this is the closest that participants truly came to thinking about the *levels* of uncertainty and the representation of uncertainty that the levels entail.

Some of the more policy-experienced participants understood the difference between different kinds of policymakers. For instance, they may have understood policymakers as policy analysts, model users, or ministers who have little time for complicated information. The more proximate a participant appeared to be to the policymaking process, the more nuanced their understanding of the texture of competencies and demands of different actors within the policy-making community.

4.4.2 Institutions

Research Group Cultures and Practices

Many participants cited the cultures of research groups as the determinant of the kinds of uncertainty practices that they undertake. This may manifest in several different ways, such as the preference for uncertainty analysis techniques, the willingness of modellers to engage in uncertainty analysis in the first place, and the styles of research questions preferred by the modellers.

There are several different research institutions maintaining different cultures. For example, one participant noted that the major Integrated Assessment research groups in Europe had historically different hiring practices in terms of the disciplines that they hired from: PBL in the Netherlands generally recruits natural scientists, PIK in Germany generally recruits economists and IIASA in Austria primarily recruits systems engineers. This disciplinary training is apparently evident in the approaches that they take; although there has been a convergence of approaches in recent years due to the proliferation of collaborative exercises funded by EU projects.

Within research groups and institutions, the influence of senior individuals was also highly noted as influencing approaches to uncertainty as the senior individuals perform direction setting exercises and determine research priorities within groups. They are often also responsible for recruitment decisions, and through mentorship can mould modellers in their image.

It was not only senior individuals that influenced uncertainty cultures within research groups. Some participants discussed the role of ECRs in introducing new techniques to institutions. Several participants involved in one energy modelling institution described how a set of PhD candidates that had studied with them had managed to introduce and prove the utility of some new uncertainty analysis techniques. Early career researchers may be able to perform higher-risk research with a lesser chance of sure reward, when compared to more senior researchers who have demands of publishing weighing upon them.

Disciplinary Cultures

The different understandings of uncertainty between disciplines were legible in how different researchers discussed the uncertainty analysis of other disciplines. For example, the handling (or lack thereof) of uncertainty in the field of Life Cycle Analysis (LCA) drew the ire of several modellers (e.g., *Skiddaw)* who viewed the lack of uncertainty ranges in the characteristic outputs of the field as problematic.

Several participants discussed the increasing influence of outside communities especially interested in uncertainty – the futures community and the Decision-making Under Deep Uncertainty community (DMDU). *Branstree* said several individuals act as go-betweens between the energy/IAM community and this DMDU community.

The Requirements of Publishing and Journals

Various disciplinary practices may be enforced by the institutions of those disciplines, such as journals, conferences, and disciplinary bodies. Considering first the role of journals, the types of uncertainty analysis acceptable to journals may be standardised, e.g., journals may recognise certain kinds of sensitivity analysis is necessary or valid. Indeed, some kinds of uncertainty analysis may be required by journals to qualify a paper for inclusion. Journals may also require a level of research novelty in a paper. As such, this will preclude exercises that simply perform meta-modelling exercises from publication. Given the incentive for researchers to publish, this may provide a damper on meta-modelling exercises.

The state of the literature within a discipline's favoured journals may help set priorities for model development and identify key research questions for the discipline. These research questions could be conceptualised as uncertainties that exist on a scale of a research community.

Funding Organisations

Certain kinds of uncertainty analysis, such as the engagement in MIPs, may be constrained by a lack of funding available for these analyses. Many MIPs are unfunded, and scientists engage with them as the result of personal interest.

Energy systems modelling and integrated assessment modelling receive funding from different sources. The kind of institution one works at changes the characteristic nature of the funding. Broadly speaking, modelling exercises are funded through government and research-council grants, philanthropy or consultancy work for either private sector or public clients.

Research councils may set thematic directions. These directions may be influenced by previously successful research in a given polity or even issues within the zeitgeist. Several participants discussed this nature of switching research direction rapidly to pursue topics that were in vogue at a given time – a practice one participant called "chasing the ball" (*Rannerdale*). As a topic becomes popular, different research groups race to try and colonise the space.

An example of this "chasing the ball" is that of low demand scenarios. At some point, low demand scenarios have been created by several different modelling groups in an attempt to assess how major international climate targets such as 1.5 and 2 degrees could be accomplished without the use of technology such as carbon dioxide removal (CDR). Naturally, this aspect of the zeitgeist was related to the COVID-19 pandemic. During the initial phases of the pandemic, energy demand fell precipitously due to reductions in industrial activity, working from home orders and other non-pharmaceutical interventions.

Some participants also discussed how a dialogue occurs between modellers[40] and funders through both formal (e.g., workshops) and informal channels to decide research priorities. Model teams have a vested interest in ensuring calls for proposals are aligned with their models' capabilities. Modellers may therefore attempt to influence calls funding proposals strategically to align with the strengths of their models.

In energy modelling funding also comes from consultancy work either on behalf of private organisations or for policy advice. Participants who engaged in this consultancy work noted that the types of uncertainty analysis demanded by consultancy work might only involve some simple scenario analysis or sensitivity analysis. Furthermore, this analysis was geared less towards meta-modelling/model introspection and more towards decision-making uncertainties.

There is an incompatibility between the nature of research questions as they appear to research funders, consultants and policymakers, and the ways of engaging in uncertainty analysis which explore locations in the model development process.

Interdisciplinary Collaboration

Gable noted that even within institutions with different models, interdisciplinary individuals have to play a mediation role.

> ***Gable:*** *In my PhD I did some more CGE and economics, and when I moved here I did Integrated Assessment and now I do both. It is interesting talking here, even within a group or an institute where we have both of those groups. Even then, it's really hard to talk to one group about the other model. And these are people that are highly competent modellers. But just trying to explain how one differs to another, because everyone has their own lens with how they see it, which is how ever their experience is. Trying to explain the concepts and assumptions behind one model to another group. I feel like I spend a lot of time as this sort of facilitator, saying "we made this in this model with those kinds of assumptions, which means it's not like…"*

[40] And in particular senior modellers.

How these deeply interdisciplinary individuals emerge is a separate issue, but looking at the professional experience of several people within the energy and integrated assessment space, such interdisciplinarity is relatively common. Undergraduate programmes that teach engineering and coupled modelling do not exist; naturally, people must study this at a graduate and doctoral level. Furthermore, as climate-related studies involve issues of global importance, it is conceivable that many researchers arrive in this space due to personal concern with the issues at hand and may transfer from different disciplines.

This interdisciplinary collaboration forced some researchers to note the incommensurability of the concepts they use in their daily research with other fields. For instance, *Harterfell* noted that they had presented their energy modelling work to a group of researchers from the *Transitions* community. They thought that people in that transition community viewed a relatively standard presentation giving an overview of their modelling framework as beyond the pale due to the stylised assumptions made in the economic modelling.

> ***Harterfell:*** *So the first response I got to giving, what I would consider, a normal energy systems modelling presentation was "Well, this is madness!" That narrow linear approach of GDP leading to a certain energy service demand, and then we meet that – there's so many factors and uncertainties. And so uncertainty does come into those discussions. But it's even more fundamental than a discussion on uncertainty. It's a discussion on the approach being daft.*
>
> *[…]*
>
> *I gave a simple, not simplified [presentation], but I pitched it to a more general audience what I was presenting. But the fundamental approach that I was using that would be typical in the energy systems modelling or the integrated assessment modelling community was kind of seen as a crazy starting point. So in terms of communication, even the terms like socio-technical, techno-economic, and what they mean, they were kind of also..... And, of course, some of the language or some of the terminology in sociology and these disciplines it is new to me as an energy systems modeller. That's where you get the communication challenge.*

In summary, interdisciplinary collaboration brings with it both profound challenges and opportunities from an uncertainty assessment standpoint. The presence of interdisciplinary researchers can reveal unrealised uncertainties in research but performing the boundary work between disciplines can be challenging.

The IPCC

The IPCC is a site of interdisciplinary collaboration where productive conversations that reveal blind spots and uncertainties can occur (*Greatend).* Within the IPCC process some interdisciplinary individuals can communicate across working groups. *Helvellyn* expressed the importance of these researchers for eliciting uncertainties from researchers in other areas.

> ***Helvellyn:*** *I mean in the IPCC you want to have experts about each area, or experts covering every required area. So not everybody thinks equally sophisticatedly about uncertainty. And maybe not everybody needs to.*
>
> *What is important is that there are some people involved that can cut across different working groups that can cut across different chapters. Because often you can elicit uncertainty by asking the right questions. Even if someone has just very specific domain knowledge and is not aware of the larger uncertainties. But by asking that person the right questions you can still elicit what the impact would be of that uncertainty.*

Several participants discussed the influence of the IPCC's process requirements on the way that they present their results. However, as will be discussed in the following chapter, the IPCC is not the only customer for these modellers' results.

4.4.3 Technical Objects

The Models Themselves

Perhaps the most frequently discussed aspect of research that participants reported to affect the kinds of uncertainty analysis that one can perform is the technical nature of the model.

The most cited issue, and perhaps the most immediately intuitive, is the computational complexity of the model and its relationship to the availability of high-performance computing (HPC) capacity. Many uncertainty analysis methods investigate the effect of varying some elements of the model system (e.g., parameters, input data, model structure) by running the model repeatedly whilst varying only that thing. Therefore, *ceteris paribus*, the variation in results observed can be wholly or partially attributed to the changes one affected in the model. As such, multiple model runs are required, and if output distributions are warranted, the model may be run many times. Naturally, running the model many times may require a great deal of computational capacity and more complex models or more cumbersome models may prove difficult in this regard.

It is not only the complexity of models that hinders the ability to perform multiple model runs but other more subtle aspects, such as how the code is structured and how that code can be executed. Some participants gave the example of a model written in a legacy programming language that did not permit Monte Carlo formulations. This meant that performing multiple model runs was practically impossible even if high-performance computing capacity was available. The participants discussed the ambition to reformulate the model in a more contemporary language such as Python or Julia, but the task seemed to be particularly arduous. Aspects of the model such as the programming language used, the documentation available to non-developers of the model, and other aspects such as shell scripts may therefore become important technically.

Modellers may have to prioritise what kind of uncertainty analysis they perform given a set of technical constraints. There may be trade-offs between the number of parameters explored and the sampling density of that parameter space. One participant talked about how the pressure to incorporate novel elements into a model drove high model complexities, which hindered uncertainty analysis.

> ***Blencathra:*** *"Okay, here's the outcome of my model – look, I can better predict what the future is going to be. And therefore, this version of the model is better than the one that I had previously." Okay, fine then that's unnecessary complexity. […]*
>
> *I feel like in some cases, it's almost like signalling. It's like, "look what I've done". But we don't really know whether that additional work is making the model better. And the reason why I care about that is because if you make the models bigger and more complicated, it makes it harder to do all that uncertainty analysis that I talked about.*
>
> ***Interviewer:*** *So you said you said that there was maybe a pressure... You said, people want to say "Oh, look, what I've done"…*
>
> ***Blencathra**:* *[Laughs] Yeah, I mean, I'm guilty of it as well... I think to some degree, we all do this, right? Like, you go to see your same cohort. And you're presenting at the same conference year after year, and even got to show that, you know, you've done something new and cool, right? Otherwise, how do you get the paper abstracts accepted? And, again, it's a very grey area. It's not like I think all this sort of work that I've seen is worthless; there's a lot of really good stuff that's being done. But I just observe this trend in increasing complexity, and I'm not sure that it's received the level of scrutiny that it should, you know, is it? How much better are we really making the models? Is it giving us insight that we didn't have before? I think in some cases Yes, in some cases No.*

Finally, the fundamental nature of different types of modelling both limits the kinds of uncertainty analysis that can be performed and the interpretations of that uncertainty analysis that can be sustained. Within energy and Integrated Assessment, many of these models are optimisation models which is fundamentally different to simulation. As such any distributions of outputs cannot be interpreted easily as probability distributions that some event may occur.

Model Transfer

A sort of lock-in can occur when one is trained to operate or develop a model. When models are transferred from one context to another researchers require training on them and are inducted into their methods.

> ***Catbells:*** *Yes, so we work now with a number of development organisations… And then we work directly with government partners in in the countries. So, in particular African countries we might run a capacity building workshop, training government stakeholders, or civil servants. Essentially training academics on how to use the modelling tools that we've developed, we might co-create some scenarios together. And then implement those in the modelling framework and create a model of the of the particular country situation.*

Model transfer also occurs between modelling groups in energy systems and the integrated assessment. In the interview with *Brandreath*, the head of a national integrated assessment modelling group described this model transfer process in detail. They had in the past imported a model from another group before adapting it and transforming it to suit their own context.

> ***Brandreath:*** *Basically we were trained here [our country], myself and a colleague at the time, to develop a [this] model for [our country] and by doing that we really started our work with IAMs. Then from that original version, which was energy only, we greatly improved that model.*

The model had changed to the extent that it could no longer be described as the previous model. However, the fundamental architecture still reflects the decisions made at the beginning of model construction. This determines the kinds of uncertainty that the model was particularly suited to explore. The model had been pushed in the development direction of exploring different technology uncertainties as this was particularly useful for their national context.

In this example, it was also interesting that model development and uncertainty analysis was seemingly influenced by the modellers' conception of uncertainty analysis as a process of incorporating and better-representing system elements within the model, rather than as a decision support exercise or meta-modelling exercise. The modeller was not particularly interested in building a high-level characterisation of the aspects of the model that might be most uncertain or the consequences of that uncertainty.

4.5 Discussion

4.5.1 Some Themes

From some of the interviews, the role that uncertainty analysis practices play in the overall knowledge production process was ambiguous. It is possible to conceive of the exploration of uncertainty as driving the process of model development, as uncertain aspects of the target system are incorporated into a model. Alternatively, one could see uncertainty analysis as purely an aspect of evaluating a model after its construction. Given the multitude of ways uncertainty can be related to the general practices of modelling, it is unsurprising that the most prevalent way of organising uncertainties was by their location within a model-complex.

4.5.2 Model Introspection

Model introspection is the process of examining the model one has at hand to characterise its uncertain behaviour and assumptions. Complex models obscure the uncertainties within them. Individual model elements become more difficult to examine as they are assembled within larger interconnected model structures. *Greatend* gives the example of MIP which simply found more uncertainties within the models than intended.

> ***Greatend:*** *What the [MIP] process revealed... […] but also another paper by [another academic] where [they] looked at why different models projected different futures for the electricity sector. What we show is the actually techno-economic parameters, costs and efficiencies, aren't that important. It's actually more complicated like that. Model structure is way more important.*
>
> *And there's lots of critical areas. So, this uncertainty – we didn't clarify the uncertainty, we just kind of put it into boxes. And which is a bit annoying, because one of the purposes of these experiments was to kind of open the black box of the model, because we get a lot of criticism that IAMs are black boxes – a valid criticism. So, part of these MIPs is to open the black box, like, "Okay, this is how the model works. This is what drives the results." But in the process of looking into these details, we're like, "oh, okay, in the big black box, there's lots of brown boxes." So that has to be looked into first.*

4.5.3 The Incongruity of Uncertainty Analysis

There is a central incongruity in the practice of uncertainty analysis for models. Modellers may wish to characterise the uncertainty associated with the structure of their models and the choices they have made in constructing those models. However, the model may be in a formation that does not permit uncertainty analysis due to intractability or the lack of representation of certain key system elements within the model. Thus, a modeller must transform the model to be able to perform such tasks. However, in transforming the model, the modeller then has a new conceptual object, and the characterisation of that object will be different. Therefore, there are models for which it is impossible to perform meta-modelling exercises.

Like a building with no windows, some models are constructed without the means for introspection. Best practice when building complicated computer models is for modellers to build the capacity for easy introspection from the ground up. This may be a structure that allows the easy variation of parameters, clearly documented open-sourced code or by maximising algorithmic efficiency to allow it to be run multiple times at a low computational cost.

4.5.4 Path Dependency and Model Histories

The story emerging is one of multiple interacting path-dependencies. Modellers go through their careers accumulating and forgetting skills, techniques, conceptual models, and values. Within the context and incentive structures in which they are embedded they may seek to investigate uncertainties in particular ways. But they are limited by the resources they have available to them in terms of funding, time, motivation and HPC availability.

At a given time, a model can address a number of questions that may be posed, and the exploration of uncertainty is one such way in which a question can be posed. To give a concrete example: a user may wish to understand the relationship between some technology cost and a systemic outcome such as carbon mitigation. Thus, they may frame this work as an uncertainty exploration of technology costs. This could be achieved with a given model in any number of ways, such as creating scenarios or changing parametric settings.

4.5.5 Limitations of These Interviews

There are several limitations immediately obvious from this group of interviews. The field of energy systems modelling, and Integrated Assessment Modelling is in some respects relatively close-knit. One participant estimated to me that the entire world community of IAM modellers was around 200–300 people. Therefore, I have taken great care that participants cannot be identified through contextual description of their work. Furthermore, in accordance with my ethics application I did not discuss the participants' views within the same research groups with each other. However, this has limited some of the analysis that I can perform as I could not discuss all the interpersonal relationships in detail.

In designing the interview protocol, I have attempted to balance various competing aims of the methodology: for example, the consistency of subjects covered vs. freedom to explore subjects most relevant to participants. However, during the interviews, I also noticed trade-offs between exploring areas thematically related to different research questions. For example, more time spent dwelling on the various conceptualisations of uncertainty yielded less time to explore aspects that influence uncertainty handling.

I shall systematically explore the limitations of the study in greater detail in chapter 6.

4.6 Chapter Summary

This chapter has presented the results and analysis of the sets of interviews conducted for this thesis with energy and Integrated Assessment modellers. These two communities are deeply enmeshed, and academics frequently work between the two.

This chapter has presented a dense description of the results of interviews with energy systems modellers and integrated assessment modellers. It began by dissecting the concepts and ideas these modellers invoke to describe the uncertainties inherent in the practices of their research, using the wealth of concepts identified through the extensive literature review (§2). It found that although many concepts are mentioned, the most prevailing organising principle for describing different kinds of uncertainty is that of *location* – the point during the modelling process in which uncertainty is experienced.

Several other concepts were used; however, many of them were only discussed in a tokenistic way and did not appear to structure significantly the understanding or practices of these modellers.

The role of scenarios in this community is of central importance, and scenarios provide an organisational principle around which work centres. Scenarios were described in several ways: as narrative or representations of narratives, as tools for evaluating assumptions and as objects externals. The different conceptualisations of scenarios reveal a great deal of ambiguity in the relationships between scenarios and sensitivity analysis. Participants held different beliefs about the appropriateness of probabilistic statements made over these scenario sets.

The factors influencing uncertainty analysis were then examined and broken down by types of actants involved. The role of path dependencies in model development is crucial and I began to prize apart the different interactions that create this path dependency.

In the following chapter, the same analysis is presented for the participants in the study who were purely climate modellers. Then, in chapter 6, the disciplines are compared and analysed.

5 Analysis of Interviews with Climate Modellers

5.1 Chapter Overview

This chapter summarises and analyses the results of the interviews conducted with researchers from the climate modelling community. I also begin to reflect on the differences in the conceptualisations of uncertainty between the first group of participants analysed, the energy and IAM modellers, and the climate participants.

The analysis presented here follows much of the same structure as the previous chapter. Section 5.2 provides overviews of the participants, analysis methods and the interview results in tabular form. Section 5.3 then analyses the overall conceptualisations of uncertainty by considering frames for uncertainty as a whole (§5.3.1), and the types of uncertainty identified in the interviews (§5.3.2). Next, it departs from the analysis conducted in the previous chapter. It looks at the interesting role of the conceptualisation of variability (§5.3.3), followed by examining views regarding the relationship between scenarios and probabilities (§5.3.4). I also detail the conceptualisations of different methods for probing uncertainty that were discussed by participants (§5.3.5).

I then review the factors that influenced uncertainty practices (§5.4), considering the models used and modelling context.

Subsequently, I reflect on some of the critical themes of the chapter (§5.5) and the limitations specific to this set of interviews (§5.5.1); and, finally, I conclude the chapter (§5.6).

5.2 Introduction

5.2.1 Overview of Participants

The participants were drawn from different areas of climate modelling, all linked to the development of GCMs. Figure 5-1 shows the roles of these modellers and the number of interdisciplinary researchers also involved in impacts or IAM research. In common, they all had experience developing, running, or analysing the results of AOGCM modelling experiments. Most of these participants had a physical science background and progressed through climate science or atmospheric physics doctoral studies.

The analysis here mirrors to a large degree that of the previous chapter, but I begin with reflection on the salient differences between the two communities. I examine both the overall conceptualisation of uncertainty by participants and how they distinguished between different kinds of uncertainty.

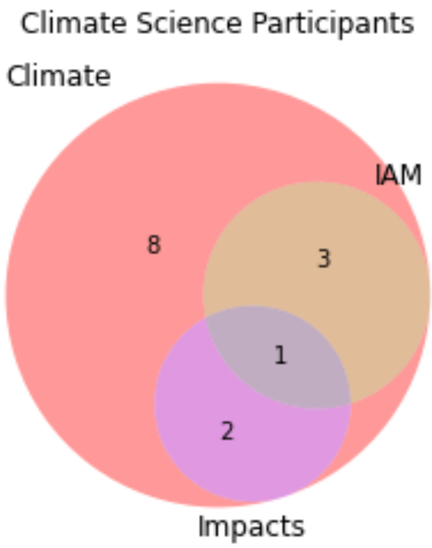

Figure 5-1: Summary of climate science participants. Note that the categorisation was based on participant self-identification and though review of published materials.

5.2.2 Interviews

I recruited participants using a snowball method and through professional networks. As my professional network does not extend as deeply into the climate modelling community, compared to energy systems, I also recruited several participants via personal conversations at conferences, such as at the American Geophysical Union (AGU). As with the other cohort, transcripts were manually transcribed and coded using the software NVivo. Additionally, I produced one-page summaries for each interview and diarised hand-written memos. A high-level summary of each of the interviews and some of the themes that emerged is available in Table 5-1, below.

Table 5-1: Summary of climate modelling participants including general information about disciplinary background, relationship to the modelling process and some key conceptualisations gleaned from each of the interviews. 'Category' = the high-level groups into which the participant can be sorted; 'Modeller Status' = the relationship the modeller has to the model development process; 'Types of Uncertainty'= types of uncertainty that the modeller mentioned in the interview; 'Type of Distinction'= The conceptual mechanism by which these types of uncertainty are differentiated from each other

	Pseudonym	Category		Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
5	Bowfell	Climate	C	Analyst, Developer, Programme Manager	Senior former climate programme lead	Climate Science, Meteorology, Physics	Generalist	Measurement Uncertainty, Model discretisation, Physical feedbacks/ processes, Emission Scenarios	Location/ Sub-system	Possible futures. When in models they are partial descriptions of those futures.	Emissions Scenario Analysis	Personalities of Modellers, Policy stakeholders understanding, Balance between effort and accuracy, Influence of Lorenz, 'worse-then better' in development
6	Coniston	Climate	C	Developer	Academic Researcher	Statistics, Climate Science	Clouds, Aerosols	Parametric Uncertainty, Data Uncertainty, Sensitivity (Emulator) Internal Variability	Location Variability confusion	Only mention was briefly in context of emissions scenarios, which they weren't involved with.	PPEs	HPC Availability, Path dependency in model development, 'worse-then better' in development, Decision-maker demands, Subjective choices of modellers
8	Swirl	Climate	C	Developer	Model Developer	Climate Science	Air-sea-land interactions	Chaoticity, Boundary Condition sensitivity, {Signal Vs Noise}	Location/ Exo-endo	Not a user of scenarios but understood these as just forcing scenarios. Also mentioned	ICEs, Monte Carlo, MMEs*	Modeller myopia, seniority of modeller, Data availability, Influence of Lorenz in physics, Nature of target system
9	Pillar	Climate	C	Model Developer, User	Senior Modeller	Physics, meteorology, climate science	Convection	Observational uncertainty, coupling uncertainty, Internal Variability {model response uncertainty vs scenario uncertainty},	Location/ Sub-system Forcing + Response	Unsure about scenario definition- stressed they were not involved. However, saw this as a different level of uncertainty to model uncertainty.	PPEs, MMEs, Scenario Analysis*	Intricacy of model development, Character driven influences, model group philosophy, Embarrassment at weird results, "Worse-then-better" cycle,

	Pseudonym	Category		Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
11	Nethermost	Climate	C	Developer	ECR	Oceanography	Sea level rise	{Single Vs Inter-model uncertainty}, {Parameter uncertainty, Initial conditions, System representation uncertainty}	Methodological Location	Scenarios are information from other disciplines	MMEs, ICEs*, PPEs*	HPC capacity, Ease of scenario implementation, Consolidation of literature base, Ease of error conceptualisation
26	Catstye	Climate	C	Former Developer, Model User, Analyst	Senior Researcher	Engineering	Generalist	Anthropogenic forcing, Variability in climate system, Model responses	Location (H&S2009)	Forcings or things external to the model system	Scenario Analysis, ICEs, MMEs	Technical trade-offs: spatial resolution, temporal interval, number of experiments, Disciplines, IPCC conventions
29	Grisedale	Climate	C	Former model developer	Senior Academic	Climate Science	Generalist	{Aleatoric vs Epistemic uncertainties}, Definitional Ambiguities	Nature Ambiguity	Scenarios are possible outcomes, trajectories are scenarios with probabilities	Bayesian Methods, Scenario Analysis, ICEs, PPEs	Trends for epistemic uncertainties, Arguments about Bayesians, arguments about scenarios
30	Glaramara	Climate	C	Model User, Analyst	Academic Researcher	Climate Science, Physics	Clouds	{Single model vs Multi-model uncertainty}, Chaotic Uncertainty/ Internal variability, Structural Uncertainty, Observational Uncertainty, Bugs in code	Methodological Location	Scenario were specifically about those used by CMIP	PPEs, ICEs, MMEs, MIPs	Observational uncertainty from other disciplines, MIPs and their protocols, Different roles of different modellers
32	Dolywaggon	Climate, IAMs	C	Former Developer, Former model User, Analyst	Senior Academic	Physics, Climate Science	Generalist	{Initial conditions, parametric, structural}, Unknown- Unknowns, Deep Uncertainty	Location Rumsfeld-Yamin Deepness	Acknowledged multiple meanings	Bayesian Methods, MCMC, ICEs, MMEs, MIPs	Disciplines with characteristic backgrounds, Model complexity, requirements of decision-making, HPC availability, Prevalence of scenario-thinking

	Pseudonym	Category		Modeller Status	Role	Training/ Background	Thematic Specialism	Types of Uncertainty	Type of distinction	Scenario Conceptualisation	Uncertainty Analysis Methods Discussed	Some Influences on Uncertainty Handling
34	Pavey	Climate	C	Former Developer, Analyst	Senior Academic	Physics, Climate Science	Generalist with UA interest	{Forcing Uncertainty, Model Uncertainty, Internal Variability}, {Forcing and response}, {Model uncertainty (inc. structural), Parametric}, Unknown-Unknowns	Location Forcing + Response Location (P+S) Rumsfeld-Yamin	Plausible and internally consistent assumptions about what could happen.	Scenario Analysis, MMEs*	National differences in scenario approaches, Climate science is out-growth of meteorology, Training in methods
35	Causey	Climate	C	Developer	Academic Researcher	Physics, Climate Science	Tuning, Atmosphere	Internal Variability, Observational Uncertainty, Model uncertainty (inc parametric uncertainty)	Location	Unfamiliar with scenarios	ICEs	Model development priorities, personalities in modelling groups, tuning methods, Imaginary policymaker
4	Helvellyn	Climate, IAMs	B	User	Multidisciplinary IPCC-associated Scientist	Climate Science, Engineering	Interdisciplinary	Intractability, Imprecision, Ambiguity, Scenario Uncertainty, Meta-Uncertainty	Generalised causes, Meta	What-if exercises. Not ranges of outcomes but paths to outcomes.	Scenario Analysis, (Simple) Sensitivity Analysis	Working group conceptualisation, Limited expertise of individuals, Desire for the illusion of certainty, Disciplinary Training
7	Lingmell	Impacts, IAMs, Climate	B	User	Academic Researcher	Maths, Philosophy, Engineering	Sea level rise, Coastal Risk	{Geophysical Uncertainty vs Socioeconomic Uncertainty}, {Shallow Vs Deep Uncertainty}, {Ambiguity vs Uncertainty}, {Parametric Uncertainty, Scenario Uncertainty}	Domain Deepness Ellsbergian (?) Location	Specific realisation about how an uncertain factor might resolve. Especially useful for deep uncertainty	Scenario Analysis, Data Assimilation	Availability of Data Assimilation Frameworks, Data Availability, Sophistication of different kinds of stakeholders, Availability of HPC and Emulators

36	Carrock	Climate, IAMs, Impacts	B	Analyst	Senior Academic	Engineering, Physics	Long term projections	Emissions uncertainty, Forcing uncertainty, Deep uncertainty	Location/Sub-System Deepness	Scenarios as a tool for deep uncertainty	PPEs, Sensitivity Analysis, Scenario Analysis	IAMs involve more expert judgement, Interactions between model groups and funders, technical factors to do with models

5.3 Conceptualisation of Uncertainty

As with the energy participants, analysis was performed using a multi-pronged approach, detailed in section 3.4.8. Firstly, the audio recordings of transcripts were manually transcribed and coded using the programme NVivo. A page-long summary of each of the interviews was produced detailing aspects of the interviews salient to the research questions of this thesis. Alongside this, extensive memos of handwritten notes were made to identify themes within this analysis.

5.3.1 The Conceptualisation of Uncertainty Itself

5.3.1.1 General Frames for Uncertainty

I identify several general frames for uncertainty from the discussions:

- Uncertainty as essentially synonymous with the inaccuracy of an estimate.
- Related to this, uncertainty as a quality of a prediction.

Uncertainty for many of these participants was heavily associated with the practice of prediction. This is understandable given the early history of climate science as an offshoot of meteorology.

> ***Bowfell***: *It means not knowing what the future holds, not knowing what the present is. And in a professional context, I suppose it relates both to measurement and to prediction. So even though you might have a measurement of the temperature, there is an uncertainty attached to that because you don't know... the instrument might have inaccuracy. You might not have enough measurements around the world to get a complete picture of what is happening.*

As Bowfell's quote above shows, uncertainty can also be related to instrumental accuracy. This may also relate to other areas of the natural sciences where ideas about uncertainty are often associated with measurement precision and experimental results. *Nethermost*, an AOGCM modeller described the conceptual challenge in distinguishing uncertainty as it exists in climate modelling from that in more conventional scientific experiments.

> ***Nethermost:*** *I guess in your conventional sort of science experiment, you try to measure something and then you might compare your measurements against some sort of calibration or known truth. And you try to get a handle on your ability to detect things like the threshold to detection or reproducibility. And all of these things have a kind of well-defined quantifiable*

properties in the observation world. Because if you're trying to measure some real-world property, it's possible through the use of standards and things to try and determine things like measurement accuracy and measurement precision.

And these kinds of quantities are useful and very important when talking about observations. But [they] have no real parallel in the modelling world because your precision doesn't result from you missing the bull's eye with your simulations, because they're kind of there is no bull's eye. And you can create a spread of model results, but not in a way that corresponds to instrumental precision, for example. And you can try to compare some model property absolutely against some known value. And you can get some handle on like model accuracy in that regard.

But, again, it's kind of difficult to try to think about, "this sensor system, has this measurement accuracy and sensor system has that measurement accuracy". They're quite different sorts of concepts. I think it's kind of a mistake to try and deal with modelled uncertainty in that same sort of way. And I know that that sometimes frustrates observational scientists when they begin to look at models because they say, "Well, you know, where are the error bars? And how do they kind of creep in?" The assignment of percentage uncertainties and this sort of thing that has to be done in a kind of a very much a case-by-case basis, depending on exactly what science you're running. And what kind of scientific questions that you're asking? There's not so much of a consensus as to how to handle uncertainty in models generally. Because the models, I think, are just inherently more flexible tools that work in different ways. So, there's no one way to handle these things.

The language of 'experiments' pervades climate modelling – individual model runs are often called experiments. The aptness of the analogy of model-experiments to real-world-experiments is somewhat controversial in the philosophy of science. Both involve manipulation of a system, but model-experiments involve manipulating assumptions (which may be embedded in data, for example) and real-world-experiments involve manipulating material objects (Mäki, 2005).

Glaramara, too, showed how this basis in principles from experimental/observational science was a guiding force in their conceptualisation of uncertainty.

Glaramara: … there's just many different ways to think about it. And you have to think about all of it. And so, the most fundamental question is: you have a picture in front of you, some graph or plot or map, and you have to ask yourself, "Number 1: What is this telling me? Do I believe it or not? But what would I learn from this? And then number 2, do I have a reason to believe it or think it's accurate?"

And probably the most basic way of assessing uncertainty with a model is asking yourself, "Does it match with observations of what I'll call the observable world?" So that's a question that we would love to be able to answer. That's one of the hardest things to show [for many] different reasons. But we don't have as many observations as we'd like. We have a lot of observations especially compared to the past, but it's hard. And a lot of times, you find that you just get bogged down in the details.

5.3.1.2 The Locus of Uncertainty

Most participants did not give explicit definitions of uncertainty. Instead, it was apparent that some understood the locus of uncertainty differently: as a relational property between models and reality (*Glaramara*), as a property of the model system (*Consition*, *Nethermost*, *Swirl*), as something that exists in reality that can be captured in some way (*Swirl),* as more focussed around particular results (*Catstye*, *Grisedale*, *Pavey*), or as a general acknowledgement that uncertainty has different meanings (*Dollywaggon*, *Causey*). Although these participants were diverse in how they conceptualised the locus of uncertainty, they more prevalently discussed their target system, when compared with energy participants.

Consistent with some of the energy and IAM modellers, there was a conceptualisation of uncertainty and discussion of uncertainty synonymous with the model development process (*Pillar*). This way of talking about uncertainty seemed more common among those deeply involved in model development and the development of submodules. Discussing the day-to-day practice of exploring uncertainties, *Pillar* discussed the "devil in the detail" of model development and how the minor and intricately woven issues in model development have significant impacts on uncertainty.

The role of prediction in the climate science community is markedly different from that in the energy systems community, as one often compares a climate model directly to observations. The predictions a climate model makes are contingent on human actions and emissions trajectories; however, the vestigial influence of weather prediction is still visible. In climate modelling, the possibility of comparing systems is much more significant, and understandably that will structure the understanding of uncertainty. This is not to say that IAMs and energy systems models do not have some aspects of the models that are directly comparable to their climate systems. IAMs do contain simplified climate models. Rather, in an ESOM/IAM one can rarely look at the model behaviour as a gestalt and compare it to measured system behaviour (DeCarolis et al., 2012).

5.3.2 The Types of Uncertainty Identified

Participants regularly invoked several different 'types' of uncertainty throughout the interviews. In this subsection, I outline the most prevalent conceptions identified and consider the conceptual basis of these types of uncertainty.

5.3.2.1 Location

Location was the most consistently described kind of uncertainty concept in the interviews. Participants consistently described different locations within the model but often in different ways. In total, 11 participants mentioned at least one kind of location of uncertainty.

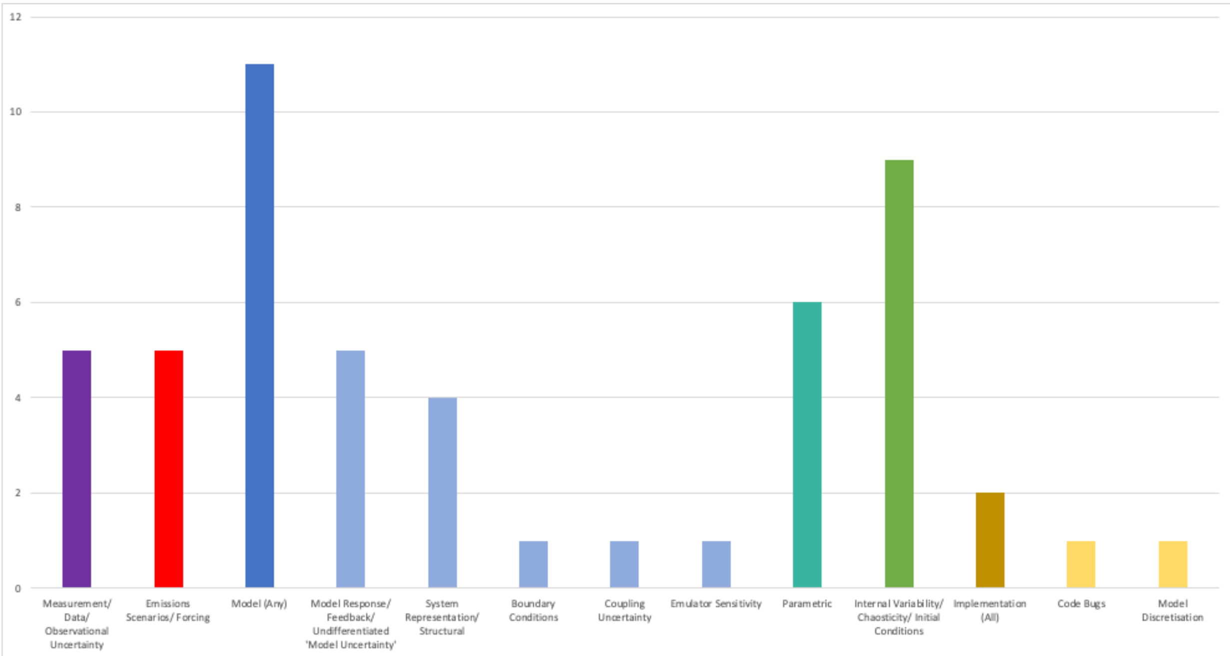

Figure 5-2: Summary of locations of uncertainty mentioned by participants. Note the bold blue bar for all kinds of model uncertainty counts the participants that mentioned any kind of model or model response uncertainty

All participants who mentioned more than one location of uncertainty described at least one kind of model uncertainty, either undifferentiated (i.e., just *model response*) or some sub-locations (such as *structure* and *parametric* uncertainty).

The location of *initial conditions uncertainty* was exclusively mentioned together with *internal variability/chaoticity* (hence they have been grouped on the bar chart). Although the internal variability of the model system can be conceptualised as a property of the model, and therefore a model uncertainty, most participants tended to view this separately to model response uncertainty – this perhaps reflects a traditional signal/noise distinction.

In cases where participants mentioned parametric uncertainty, it was almost always (5/6 cases) accompanied by either structural uncertainty or response uncertainty, reflecting the conceptualisation of "models = structure + parameters".

Variability can also be conceptualised as the stationary statistical characteristics of the unforced system – or the Lorenz attractor of that climate system without it being driven from its original condition.

The most common grouping of locations mentioned was the triad of *Forcing–Model–Variability*. This separation is ubiquitous in the literature such as the influential paper by Hawkins & Sutton (2009). This paper was mentioned explicitly by *Catstye,* who explained how it had synthesised several concepts that were in the intellectual milieu into one framework.

> **Catstye:** *The Hawkins and Sutton [2009] paper was very influential in [the conceptual synthesis]. I think people had understood [the concepts] in the past and had been analysing both observations and models in that way. I think that that paper was useful from the point of view that it very clearly codified it and laid out a nomenclature that everyone could then use. I think, probably prior to that, the nomenclature was a bit uneven. People referred to certain things using different words, which is never good for communication. So, I think from that perspective, it helped.*
>
> *I don't think it was like that paper introduced a bunch of concepts that no one had ever heard of at the time. I mean, it was just kind of people went, "Okay. Yeah, that's a nice way of illustrating things [and a] nice way of talking about it." But I think it was influential from the point of view of just kind of organising the way that people thought about it and work on the way people communicate about it. But I'm not aware of any sort of alternative kind of typologies or anything that you could use. Again, that may just be ignorance on my part.*

The simplest version of locations of uncertainty was evident in two interviews (*Pillar*, *Pavey*): description of uncertainty as either being in *forcing* or *response*. This demarcates uncertainty as either being within the model or within the realm of the human actions, assuming one considers forcing the bundled aggregate of anthropogenic GHG and aerosol emissions.

Some participants identified types of uncertainty with *the method used to explore those uncertainties*. As will be discussed in Section 5.3.5, the field is dominated by ensemble-based analyses of three kinds each associated with a different kind of uncertainty: ICEs, PPEs and MMEs. Some participants talked interchangeably about both the method used to investigate that uncertainty and the uncertainty *location*. Two participants also described uncertainty as either being 'single model' or 'multi-model' at a more aggregate level (*Nethermost*, *Glaramara*).

5.3.2.2 Deep Uncertainty and Levels

Several participants invoked ideas of deep uncertainty or known-unknowns/unknown-unknowns (the Rumsfeld-Yamin distinction). Along with the concept of *Deep* Uncertainty, and similarly to the ESOM/IAM participants, this was not then more deeply explored further than in a rhetorical manner to emphasise the profundity of the situation and the challenge of the task of handling uncertainty.

5.3.2.3 Natures of Uncertainty

A limited number of participants described ideas to do with the nature of uncertainty (*Grisedsdale*) – however, in this case, epistemic uncertainty was related to *locations* and 'varying parameters and models'.

In summary, among the participants interviewed, the most common way of demarcating different uncertainties was among different locations of uncertainty, and particularly model uncertainties, parametric uncertainties, internal variability and forcing uncertainties. Participants rarely discussed other kinds of uncertainty in detail. They in fact discussed several locations of uncertainty within the model itself, particularly differentiating different types of model uncertainty such as coupling uncertainty and boundary conditions.

Absent from their discussion was the allocation of uncertainty into topics, sub-modules and domains that we saw in the ESOM/IAM sample. Perhaps this has something to do with the siloing of climate modellers into areas of model development. Very few climate modellers have an overview of the whole system they are modelling and so will not apportion uncertainties to the different sub-modules.

5.3.3 Variability in Systems and Models

The role of variability in climate modelling is interesting as is both a source of uncertainty in model results and an important aspect of systemic behaviour to recreate. The variability of model results is routinely subjected to different forms of analysis, such as spectral and spatial decompositions and other statistical analyses (Frankignoul, 1995a, 1995b).

There was some evident ambiguity present in participants' discourse about where the internal variability they were discussing resided; whether internal variability is a property that belongs to the model or whether it belongs to the climate system. It exists in both. But participants could be observed casually slipping between the two ways of speaking about internal variability, implying that the variability in a model system was uncomplicatedly identifiable with that in a target system. This warrants some additional consideration.

Internal variability plays an important role in climate modelling providing justification and validity to models. A comparison between observed variability and that simulated by a climate model can be performed statistically. It can also be done qualitatively by observing if the climate system produces the same qualitative feature by inspection.

Different participants discussed how the *variability* or *noise* inside a climate model manifests itself spatially and temporally at different scales. For example, *Pillar* described that despite model runs closely tracking each other at the macro level, there was a large deviation from expected results at the small scale and for different variables such as precipitation.

> ***Pillar:*** *Regionally as well, [there are] signal-to-noise [ratio] problems. For example, […] large ensembles […] we plan to do that with our current version. We did that with the CMIP5 version of the model. The argument essentially is the global surface temperature. We are pretty certain about what it will be if a scenario happens. We are as certain as we can be about the response. If you ran one version of the model and then ran 40 versions of the model, like the weather forecast people do, they will track each other pretty damn close. So, the signal-to-noise [ratio] is pretty high, so you have only some uncertainty about that. But if you look at precipitation over Western Europe from individual members, you get very different answers. If you look 50 years in time individually at these ensemble members – even though the surface temperatures are pretty similar, precipitation is a killer.*

This internal variability inside a climate model may recreate the observational record variability patterns quantitatively (e.g., different measures of goodness of fit) and qualitatively (e.g., an aesthetic judgement about the agreement of lines on a graph). However, this may be getting the correct answer for the wrong reasons if the model does not have a good representation of the target system. *Glaramara* identified this issue and noted the difficulty they had in determining which model system variabilities could be identified with real-world variability.

> ***Glaramara:*** *And so, any kind of variability that you see in the model, I think we have to be careful not to just immediately attribute that to reality. But a lot of effort goes into determining what types of variability in the model are, what we'd say 'real' and what types are 'not real'. And so sometimes, for a very technical reason, you can get fluctuations happening in the model that are just based on what size your grid boxes are in the model, for example. And*

> *so that type of thing, when the size of your grid box influences your results, you know, it's a somewhat artificial result.*

Initial conditions uncertainty has a slightly complex relationship to *internal variability*. The internal variability of a single model realisation can be understood through the range of states that the model passes through as it evolves in time steps. The model's variability and chaoticity during this evolution is the result of the structure of the model. Another way of exploring this tendency of the model to display variable behaviour is by initialising the model with subtly different initial conditions so that the behaviours diverge. The set of model realisations will then evolve through states differently, and this set of evolutions can be treated as a sample for the state at a given time.

Werndl (2019) describes *initial conditions dependence* as the dependence of final results on initial conditions; and *initial conditions uncertainty* (henceforth ICU) as the uncertainty in final results because initial conditions are not precisely known, or calculations cannot be performed using precise values of initial conditions. The author identifies *internal variability* with the first kind of ICU, that of the spread of results that result from an ensemble of perturbed initial conditions simulations. They note that often climate scientists imagine that climate projections are relative to the set of initial conditions. However, a perfect ensemble is impossible to create in practice as a limited set of initial conditions must be used. Hence this is the ICU of the second kind that Werndl (2019) identifies[41].

Imagine a system in which the response function to initial conditions was purely linear – small changes in the initial conditions could result in uncertainty in the final outputs of that model. It would be incorrect to describe that model as meaningfully having any internal variability. Now imagine a model whose behaviour can be described by some chaotic attractor. Different simulations beginning with perturbed initial conditions would result in very different final states in such a situation. However, on a long enough timescale, the distribution of states observed from an ensemble of only slightly perturbed initial conditions would be practically indistinguishable from that that was more starkly perturbed – hence initial conditions

[41] Another third kind of ICU the Werndl (2019) identifies is specifically related to projections that initialise in 1850. Models are often calibrated to the present day and then run with decreasing forcing until values approximate those in 1850. However, there is uncertainty about the best way to perform this.

dependence is lost. Therefore, the contribution to initial conditions uncertainty from the size of initial perturbation will fall away as the chaoticity of the system increases.

Stainforth et al. (2007) describe two distinct kinds of Initial Conditions Uncertainty (ICU) that correspond to these two extreme versions of systems. *Macroscopic initial conditions uncertainty* occurs in systems that mix slowly such that the distribution of the prediction depends on the imprecision of our knowledge of the initial conditions. *Microscopic initial conditions uncertainty* instead occurs in systems with rapid mixing, and the distribution of inputs will not significantly affect the distribution of outputs.

Internal variability is also conceptualised as 'climate noise' in the literature (Deser et al., 2012). One can conceive the probability density function of the attractor as constituting this *noise* and the evolution of the attractor – as a result of the climate system being 'forced' by greenhouse gases and other factors – as constituting the *signal*.

In summary, we have multiple causes of uncertainty that are explored in tandem by the varying initial conditions settings – the imprecise knowledge of initial conditions and the chaotic nature of the system. Throughout the interviews, participants used the terms 'initial conditions' and 'internal variability' interchangeably. Perhaps there is not a requirement to distinguish between these two in any meaningful way in practice.

It is ambiguous whether different kinds of variability can be considered locations of uncertainty. According to the different senses of location I have discovered one would get different answers. Certainly, model internal variability is *experienced* by modellers at a late stage of modelling where models are run, or repeatedly run for ensemble results. Some differences in internal variability between model runs in an ensemble are attributable to model structure and parameterisations (Deser et al., 2014). However, whether these variable results are a part of the model complex seems a more difficult question. Undoubtedly, participants equated variability with other kinds of uncertainty that are normally classed as locations.

5.3.4 Probabilities, Normative Values and Scenarios

5.3.4.1 The Conceptualisation of Scenarios

When analysing the transcripts of interviews with the energy systems and IAM modellers, the importance of scenarios to their epistemic enterprise was clear. This was not the case with the climate modelling participants. Rarely did participants organically begin conceptualising in terms of scenarios. Most generally, scenarios were discussed only after prompts from the interviewer or after the participants mentioned scenario sets like the SRES or RCPs. Scenarios play only a minor role in the thinking of the climate modellers interviewed for this study. Nonetheless, several conceptualisations were identified which were consistent with those in the previous chapter, although the emphasis was different.

Other participants merely mentioned that scenario analysis was an activity that they were not involved in (*Causey*, *Consiton*) or did not conceptualise scenarios beyond the standardised scenario sets that exist (*Glaramara*). *Pillar* was unfamiliar with scenarios but opined that they might be an uncertainty different to model uncertainty. Excepting *Glaramara*, these participants could be classed more as model developers rather than model users or analysts. This focus on development rather than running the model in different configurations and forecasting may explain some of the unfamiliarity with scenarios here.

Swirl was familiar with the RCP framework and considered the 1% CO_2/year increase control run a scenario, despite no other scenarios compared to it. Many developers are not involved in running the RCPs; however, they are responsible for characterising overall model performance. *Pillar* discussed these sensitivity experiments in the context of scenarios, though they said that these were not properly to be considered scenarios. The interview, conducted at an academic conference, moved onto the topic of the poster session:

> ***Pillar:*** *I think you were at some of the same posters that I was at [at the conference]. I mean, more sensitivity experiments based on the expectation of a very warm climate, for example, four-times-CO_2. These kinds of impulses: four-times-CO_2... Boom! In an instant!*
>
> *So that's not a scenario, but it's a mechanism for understanding. [...] [An academic's] paper, he has a nice poster on the ECS [equilibrium climate sensitivity]. And basically, you're not only looking for time sensitivities. We're looking for non-linearities. Things in the current climate, even though you can observe these linear changes like it was warming, and then the clouds respond – do we really know that when you [have strong warming], the clouds might respond in a very different way? And it's these types of experiments that give us a sense that maybe our feedback [will be a certain amount] in the next 30 years. [They show that suddenly*

> *non-linearities might emerge] for worse or for better. So, we're looking for these kinds of transitions.*

Thus, this idea of using varied assumptions as a tool or "mechanism for understanding" did arise, albeit not labelled as a *scenario*.

Another related conceptualisation was that scenarios represent some aspect of the world exogenous to the model system. This conceptualisation sees the forcing scenarios as either some external object from a different discipline (*Nethermost*) or something external to the model itself (*Catstye*).

Some participants understood scenarios to be possible futures or partial representations thereof (*Bowfell, Grisedale, Pavey*). One participant clearly distinguished between *scenarios* and *trajectories*, the latter being scenarios with probabilities attached. *Dolywaggon* and *Bowfell* acknowledged that there are multiple meanings of scenarios.

Absent from the conceptualisations of any of the climate modellers (excluding the interdisciplinary researchers who fell into both camps) was the idea of scenarios being a 'tool' for revealing something about the model systems, assumptions, or the target system.

5.3.4.2 The Meanings of Probability Density Functions

A probability density function is an important object in climate science. When one has a collection of model results one may wish to interpret these statistically. Whether such an interpretation is justified varies from case to case.

There is disagreement in literature about what objects that have the mathematical properties of PDFs can legitimately relate to the concept of 'probability'. A distribution may have the properties that we ascribe to a PDF: some well-defined state space over which a density function is defined or approximated, and the integral of that density function taken over the domain of that space to equal unity. But it may not have the relational property, as understood by Keynes of being a probability that a proposition may be true or that an event may occur. I now briefly examine how participants understood the role of probability functions.

One participant seemed unsure whether PDFs could be considered a property of nature. They described how those senior to them at their institution seemed to treat real-world values as if they could be PDFs.

> **Swirl:** *But nature- isn't it supposed to be a PDF instead of one single truth [value]? And now scientists tend to believe that at any location, any time for any variable, some value doesn't need to be one single truth. It should be a PDF. But that's a funny way to interpret it. I still don't get it. But that's what my boss says- they're all they were all talking about in the team. And sometimes I follow, sometimes I don't. But nature is supposed to have a PDF. So many possible 'alternative facts'!*

A common way to produce a PDF of climate model simulations is using initial conditions ensembles. Since the work of the father of modern meteorology, Lorenz, meteorologists have captured the uncertainty associated with the chaotic systems they study through running perturbations of initial conditions. Lorenz's ideas have had a lasting impact in atmospheric sciences (McWilliams, 2019).

There was less conflict over the general appropriateness of assigning probabilities to various outputs than with the of ESOM/IAM modellers. Instead, there seemed to be a consensus on the value and relevance of probabilistic statements. As PDFs are valued items, researchers are willing to put resources into producing them.

5.3.4.3 The Relationship Between Probabilities and Scenarios

In *Grisedale*'s interview, a veteran climate scientist, we discussed the role of scenarios and probabilities in the community. They understood how with the large numbers of scenarios available it was inevitable that some would begin to treat these as a sample

> **Grisedale**: *Unfortunately, although everybody says this is true. And everybody sort of says, "Oh, yes, no, no, we never regard scenarios as probabilistic". Because we now have so many scenarios, I mean, in AR5, there were basically four scenarios that everyone focused on. But now, there are dozens and dozens of scenarios. And it's very difficult to deal with that many without starting to treat them as a sample. And so, an awful lot of nonsense is getting generated at the moment based on misinterpreting the available scenarios as some kind of probabilistic representation of possible futures.*

They wanted there to be many fewer scenarios that the climate science community deals with: "*I think even four was probably too many, most people focused on the two extreme ones, a sort of high scenario and a low scenario. And, we probably only need three scenarios: a sort of Paris extension scenario, a 2-degree* *scenario and a 1.5-degree scenario.*" They were also of the opinion that probabilities should not be attached to scenarios.

There was some limited discussion of the relevance of Bayesian ideas for conceptualising uncertainty and deciding the role of probabilities. *Grisedale* described the different 'tribes' of Bayesians: objective, subjective, formal subjective and pragmatic. They described modellers varying in their adherence to the dogma of these tribes.

Dollywaggon suggested that being a Bayesian was incompatible with their academic self-identity as a climate scientist: "*I'm not that Bayesian at all. I would say, I'm more of a climate scientist, a modeller, a physicist, more than a statistician.*"

In summary, it appeared as if there was a general consensus about the utility of the production of probabilistic estimates from ensemble experiments. However, I was not able to produce a deep account of how the nuanced interpretations of probabilities (e.g., different versions of Bayesianism) affected views on the appropriateness of interpreting different kinds of ensemble results. I shall return to the issue of ensemble interpretation in chapter 8.

5.3.5 Uncertainty Analysis Methods

Within climate science, ensemble[42] methods for characterising uncertainties in projections reign supreme. Participants discussed three primary groups of methods, Initial Conditions Ensembles, Perturbed Parameter Ensembles and Multi-model Ensembles. *Glaramara* described this triad of methods as unavoidable: "*I would say all three of those ways are things that modelling people really can't avoid.*" Table 5-2, summarises the methods that were discussed by participants, which I now examine.

[42] Also called 'sampling methods' in some literature

Table 5-2: Table summarising the frequency of mentions of different kinds of uncertainty by climate participants. Note that frequency is just indicative and does not measure the importance which participants ascribe to methods.

Technique	Mentions
Scenario Analysis/ Forcing Ensembles	5
ICEs	7
PPEs	5
MMEs	6
Bayesian Methods	2
Monte Carlo	3

Initial Conditions Ensembles (ICEs)

As I have already discussed, the ensemble most frequently discussed by participants were Initial Conditions Ensembles, used to explore the variability in the model and display the model chaoticity. *Catstye* described this process as involving different 'realisations' of the same model.

> ***Catstye:*** *We try to break these kinds of uncertainty up and look at them separately and quantify them separately. The second kind of uncertainty [that we look at] is, of course, variability in the climate system at different timescales. And trying to understand and communicate to users the difference between the single realisation that will occur versus the large ensemble of possible realisations that are all statistically equivalent. But for which each simulation will provide a different realisation. And we have to be able to communicate that. So that typically involves running large ensembles of simulations where you can run the same forcing over and over again, both for the historical period and the future, and quantify that natural variability, that internal variability that is part of uncertainty going forward?*

Perturbed Parameter/Physics Ensembles (PPEs)

Several participants discussed how they could explore parametric uncertainty within either a model or a module using PPEs. *Coniston* was a specialist in some aspects of running PPEs.

> ***Coniston:*** *So, I do perturbed parameter ensemble work, which means that we perturb around 20 to 50 parameters within a single simulation. Therefore, we'd have to have an ensemble of those, which is around 200 to 250 simulations. You don't want to have noise on those simulations. We need a clear, clean output on those. So, when we remove the coupling and suppress the atmospheric variability, we get a nice clear signal from each of the individual ensemble members.*

They described how they had developed novel techniques to reduce the parametric uncertainty. They hoped that other groups would follow suit and they could eventually form large multi-model ensembles of different models running combined PPE-ICE experiments.

Parametric uncertainty can also be explored with stochastic parameterisation schemes in which parameters take different values in time and space. Furthermore, multiparametersiations have been pioneered by the Canadian Meteorological Centre (Arnold, 2013, p. 9).

Multi-Model Ensembles (MMEs)

In this thesis, I distinguish between MMCs (Multi-Model Comparisons, the general practice of comparing models and their outputs), MMEs (the combination of the model outputs run under similar conditions) and MIPs (the institutional setups that allow the practices of MME building and MMCs).

Swirl discussed the famous IPCC spaghetti plots as an incarnation of the uncertainty in a prediction and gives an indication of the 'whole uncertainty'.

> ***Swirl:*** *But this spaghetti [plot] shows you how uncertain the climate prediction is. So, it could be this low or that high. So why is that? It's just because the models are all different. The conditions are different. And the way they run it – it could be in the physics, it could be in the dynamics, it could be simply the conditions, the response, the chemistry – many things. So that's uncertainty. So, they actually give us a clue of how uncertain we are about our future. And we better catch the whole picture, not just one single run, that will tell you what it's like for Miami tomorrow, for example.*

There is a sizable literature that has emerged over the last decade about the interpretation of MMEs. In this philosophical literature, there is a consensus that the range of an MME does not give the full uncertainty associated with the prediction of a value. The key to this is that these are 'ensembles of opportunity'[43] – ensembles that are not purposively sampled from a set of all possible models for the system, but a set of models that have come about by happenstance. The challenge of maintaining the justification for MMEs is explored in chapter 8, where I examine whether the justifications used in climate science can be applied to other case studies.

Scenario Analysis or Forcing Ensembles

Several participants mentioned scenario analysis (*Bowfell*, *Pillar*, *Catstye*, *Grisedale*, *Pavey*, *Helvellyn*, *Lingmell*, *Carrock)*. However, except for the interdisciplinary climate scientists, none mentioned scenario analysis as part of their everyday research. Scenario analysis is perhaps the very final thing climate models may be used for after being subjected to other forms of characterisation. Scenario analysis is particularly far from the day-to-day experience of a model developer.

Summary of Methods

The relationship of methods to types of uncertainty appeared to be relatively straightforward in the minds of climate modellers. MMEs explore structural uncertainty, PPEs explore parametric uncertainty, ICEs explore initial conditions uncertainty and forcing ensembles explore scenario uncertainty.

5.4 Influences on Uncertainty Handling

I now turn my attention to the factors and influences identified in the interviews that lie behind the handling of uncertainty. Here as in the previous chapter, I have organised the factors using the ontology of actants developed in the previous chapter (see Figure 4-3).

I examine how different factors come to bear on the shaping and conceptualisation of uncertainty analysis. Naturally, the demarcation of factors here is imperfect as the shaping often occurs in the interaction of factors. However, for convenience, these have been clustered in the same way as for the ESOM/IAM participants.

5.4.1 People

Training

The career paths of the climate scientists studied were generally uncomplicated in their progression from physical sciences into atmospheric or climate modelling. Therefore, it is unsurprising that they used a wide range of technical terminology to describe how they interacted with uncertainty.

When confronted with deeply uncertain situations, several scientists professed that they attempted to overcome their state of confusion by using ‘physically-based reasoning’. This appeared to constitute a combination of an understanding of fundamental physics and various types of intuition.

Peer Group Perceptions

One of the mechanisms by which the norms and expectation of a discipline seem to exert a push on climate modellers is in the way that modellers maintain esteem and seek to avoid various forms of embarrassment. The importance of reputation, esteem and prestige to researchers has been long attested in various literatures such as administrative science (e.g., Shepherd and Brown, 1956) and sociology of science (e.g., Merton, 1968). Therefore, it should be unsurprising that some participants discussed the need to avoid embarrassment in their model results.

A senior modeller in a large AOGCM modelling group discussed how theirs and other groups all came across a persistent issue in the sea-ice module of their model. At some point in their simulation, an area of ocean was persistently frozen, even in the summer months. This phenomenon was clearly not seen in nature and was therefore problematic. They were unsure as to what aspect of the model was causing this error. Subsequently, all the different sub-groups responsible for different model components attempted to work out what was causing the freezing in the model. However, the complexity and the opacity of the model rendered an easy answer impossible, and accommodations had to be made amongst the modellers.

Reputational concern was also reported to exist at the level of the research community. One participant talked about how their subfield had failed to seriously reduce their estimates of the range of forcing from aerosols.

> **Consiton:** *Reducing uncertainty in this field of aerosol–cloud interactions does need to be the central focus. And it is becoming that, because people feel moderately embarrassed about the fact that we've not been able to reduce it for the last 20 years. So, there is a shift in the paradigm – people are starting to think about it in more of a structured way, thinking "what sorts of targeted experiments can we make that actually genuinely address this uncertainty as the main problem?" Rather than just the end result of some analysis that we've done that says, "Oh, yes, here's a PDF."*

I then pushed the participant on this sense of embarrassment that the field might have. The audience that they seemed to consider important were decision-makers.

> ***Consition:*** *I get a sense that there's some embarrassment that we can't just make near-term projections with very small uncertainty bars on them. This historic forcing uncertainty translates directly into uncertainty in future projections. So even if we're looking 10–15 years down the line, there's this big, 5–6 year gap in terms of when we might pass 1.5 degrees in a single model because of parametric uncertainty.*
>
> *And it doesn't make sense for there to be that much uncertainty remaining. We should be able to just tell the decision makers, "this is the likely trajectory that we're on because of the choices that have been made here." And they should therefore be able to [? scale] with much more confidence than they currently can because our climate models still have these inherent uncertainties. If we'd had managed to reduce them, like 15–20 years ago (obviously the models weren't developed enough to that point for aerosol–cloud interactions but if we could have done that then), the projections from that time through to now would have been much more reliable. You'd have removed that uncertainty from the conversation.*

Disciplinary Cultures

The climate science field is undoubtedly larger in terms of numbers of researchers than that of ESOM/IAM modelling. There are many more sub-disciplines in climate modelling than there are in Integrated assessment, reflecting the size of the field.

> ***Nethermost:*** *I suppose I'm most familiar with people working on these sorts of things similar to me. So, I know that, at least back in [my home country], where I do most of my research, there are handfuls of other researchers in a couple of other institutes that are interested in this sort of thing. I guess for other things, it's difficult to say. So other sources of uncertainty like initial condition uncertainty and parameter uncertainty – those sorts of things... Yeah, I suppose I don't really have a feel for the relative sizes of those different fields.*

Some model developers seemed to have relatively little contact with other developers outside of their institute. They professed uncertainty about how different modelling efforts were organised.

> ***Pavey****: I think there's two things driving [a tendency to use probabilities in climate science]. One is a certain sort of customer demand. So, you know if I say, "well, this can happen in the future", it is natural to say, "well, how likely is that, versus how likely is this?"*
>
> *But the other the other thing that's driving it, which I wrote about partly in paper I referred to, I do just think comes from the history of climate science: the fact that climate science evolved out of meteorology, where people were familiar with thinking about numerical weather prediction, and so forth. I think it is a big part of the reason. So, the kind of assumptions that go around numerical weather prediction have been applied to climate prediction without enough scrutiny.*

Policymakers and Other Stakeholders

Existing research has demonstrated how climate scientists anticipate the reception of information by policymakers by how they represent uncertainty (Shackley and Wynne, 1996) and general results such as climate sensitivity (van der Sluijs et al., 2016).

The role of policymakers in climate scientists' minds was noticeably less significant than for the ESOM/IAM participants. When climate scientists talked about policymakers, they did so in a less concrete way and had a vaguer understanding of what their needs may be in terms of information provision.

The most senior climate scientists, who had overseen institutes and therefore had some exposure to the policymaking process, perceived a range of sophistication of policy consumers. For example, *Bowfell* understood policy analysts were used to dealing with quantitative information and were not "*Joe Bloggs off the street.*"

Catstye, a senior researcher at a national government lab, understood the policy requirements of their situation intimately as they were providing information to national and regional governments and understood how different stakeholder groups were engaged through intermediaries in regional government. They explicitly used the language of 'boundary organisations' to refer to these kinds of intermediaries, reflecting cognisance of ideas from science policy studies.

> ***Catstye:*** *For the most part, as a government lab, our primary client is the [national government] …*
>
> *We tend to rely more on intermediaries to deal with users in different sectors. And that kind of happens in a number of ways. There are these other [regional government organisations concerned with impacts that are] collections of people who have some expertise in climate science but are more working with individual users or collections of users. For example… industry-related groups. The farming agriculture industry has a number of groups that work on behalf of farmers to look at, you know, crops and soil and water and all those kinds of issues related to climate change in agriculture. And so, these intermediary groups tend to work directly with them. So, we generally work with these kinds of boundary organisations, and then they work with users directly. We do produce some reports and things that are aimed more at the general public and general users. But we don't have a big kind of outreach machinery of ourselves. So, it is a little bit indirect the way that we link up.*

Some thought the IPCC reports and the Summaries for Policymakers (SPMs) were the avenue by which their work was most proximate to the policy process. *Consiton* was representative of this.

> ***Consition:*** *My research doesn't have a direct impact on those decision-makers. It goes through IPCC and it goes through different meetings where these things are written up into much more formal recommendations for policymakers. But the IPCC does a great job in their summary for policymakers. That just includes the diversity across models. The IPCC report coming out now [1.5°C report], I think, will include some recommendations based on single*

> *model uncertainty as well. It's a step in the right direction. But they're not in a position where they're going to be able to say, "these are the choices that you definitely have to make to limit warming to 1.5 degrees."*

However, the relevant pool of users was described by *Pavey* to be expanding as of late as the business and financial sectors become consumers of climate model information. This has particularly been happening in the wake of the Taskforce on Climate-related Financial Disclosures (TCFD), an industry-led group from the Financial Security Board (FSB), that released a 2017 report recommending organisations exposed to climate-related risks should perform scenario analysis, of which modelling may be a part (TCFD, 2017, sec. D).

5.4.2 Institutions

Institutional Cultures in Research Groups

Different institutions have their own approaches to the handling of uncertainty. Parker (2010a) notes the difference in emphasis on uncertainty analysis techniques at the ECMWF, MSC and NCEP. For example, the Hadley Centre in the UK is known for running PPEs.

Participants noted this strong difference in institutional culture between groups with different institutions either taking bottom-up or top-down approaches to model development management. In a top-down setting, priorities are determined by senior management and requirements then trickle down through the organisation. In a bottom-up setting, modellers pursue their own priorities and decisions are made at a more disaggregated level. They also noted the specialisms in some institutions.

Using a case study of the UK Met Office, Martin-Nielsen (2017) demonstrates that the history of UK climatology has seen profound arguments about epistemic standards. Moreover, these standards have been shaped by institutions, which themselves in turn have been influenced by individuals. The inability to form a deep description of these institutional cultures is perhaps a shortcoming of my methodology.

The IPCC

The IPCC seemed to affect how uncertainty was dealt with in several ways, both in the actions of the institution and in the way in which it required uncertainty-based information to be provided. The IPCC has changed how it characterises and assesses uncertainty in the underlying literature base over the iterations of its report cycles. The individual chapters within

IPCC assessments may also take different approaches to conceptualising probability and uncertainty. This was identified as an inconsistency by some participants.

> ***Grisedale:*** *I think IPCC has definitely played a role in the formal treatment of uncertainty in our field because one of the questions we get asked every few years is, "what's the confidence level you can assign to this outcome?" I think it is a problem that IPCC has never properly formalised its treatment of uncertainty. I think there was an opportunity when they introduced the formal uncertainty language to make clear whether it referred to Bayesian probability or likelihood, or what [else]? Because it's a consensus-based process, they couldn't really get consensus on what they were getting consensus on. So, as a result, within IPCC reports these likely ranges are a complete mishmash of traditional frequentist confidence intervals in the observational chapters, through to full Bayesian posterior probabilities in some of the forecast chapters – and everything in between. So, you know, it is what it is.*

Box 5-1: A short overview of the role of Model Intercomparison Projects (MIPs)

Model Intercomparison Projects (MIPs) are an academic exercise of growing importance. The essence of a MIP is to use similar driving (exogenous) assumptions and scenarios for models with different structures to create an ensemble of outcomes for direct comparison. These processes allow scrutiny of models and the creation of benchmark calculations (Randall et al., 2007).

The most prominent is the Coupled Model Intercomparison Project (CMIP), which the World Climate Research Programme (WCRP) convenes. The first incarnation of CMIP began in 1995 with CMIP1, whose chief aim was to collect present-day control runs and involved 25 models. CMIP2 expanded the scope to include model runs that simulated 1%/year increases of atmospheric CO_2 (Meehl et al., 2005). CMIP3 functioned in support of Working Group 1 (WGI) in IPCC AR4 (PCMDI, 2019). CMIP5's[43] results were integrated in the IPCC's AR5. Since its proposal in 2014 (Eyring and Meehl, 2016), CMIP6 has supported AR6 (Eyring et al., 2016), whose findings from Working Group 1 were published in August 2021 (IPCC, 2021).

As part of CMIP6 many other MIPs have received endorsement from the WCRP with a standardised procedure by which MIPs are proposed and approved. Amongst the criteria for inclusion are that they must answer the three central CMIP6 themes (Eyring and Meehl, 2016):

[43] Confusingly the successor to CMIP3

- How Earth Systems will respond to radiative forcing
- Assessment of the origins and results of model biases
- Future climatic change given scenario uncertainties

Among the 23 MIPs endorsed by CMIP6 are MIPs that focus on a particular aspect of the world system, such as the ISMIP6 (Ice Sheet MIP for CMIP6), MIPs that focus on coupled systems such as C^4MIP (Coupled Climate Carbon Cycle MIP) and MIPs that focus on particular model structures such as HighResMIP (High-Resolution MIP) and the simulation of mitigation interventions such as GeoMIP (Geoengineering MIP) or CDRMIP (Carbon Dioxide Removal MIP) (WCRP, 2021).

A key aspect of many MIPs the use of the DECK (Diagnostic Evaluation and Characterisation of Klima) a set of core simple experiments that all models must perform and that will be used in future phases of CMIP to ensure continuity (Eyring et al., 2016). The DECK consists of four key experiments:

- A simulation of historical climate
- A control simulation of pre-industrial climate
- A simulation with 1% increase in CO_2 per year
- A simulation in which atmospheric concentrations of CO_2 abruptly increase by a factor of 4

Model Intercomparison Projects

For most modellers who are not themselves IPCC authors, MIPs are one way their work ends up influencing IPCC assessments. The requirements of MIPs, therefore, focus the activities they perform to make the models suitable to run standard experiments such as the DECK (see Box 5-1) and the timeframes within which their modelling work proceeds so that model releases can coincide with the IPCC/MIP cycle.

Funders

The funding for climate modelling is generally perennial. Climate modellers do not generally rely on rapid grant cycles to sustain model development in the way that some energy/IA modellers may have to. Some climate scientists even seemed a slightly taken aback that the interviewer may wish to discuss funding sources.

> ***Interviewer:*** *Are there any influences in how funding is organised that might affect particular uncertainties that people will explore?*
>
> ***Grisedale:*** *No, not particularly, I don't think. I've never seen that. I mean, I guess the fact that people want their papers cited in IPCC means there's a sort of incentive for people to actually think about uncertainty in some form. Yeah. Which is helpful.*

One participant discussed how the National Science Foundation (NSF) funding in the United States changed with topical priorities.

> ***Causey****: This is also another good question because at some point, there will be funding more available for one topic. And then the proposal that will get funded would be the proposal that is going to study this topic, and then you will have progress done into this field because it's where you have some funding and the time.*
>
> *For example, I know that one of the priorities of NSF right now is the new Arctic. The fact that the Arctic is changing a lot. They consider 10 priorities, and I cannot truly give you the list, but it's one of them. And then I'm sure they're going to fund more proposals on this because it's one of the priorities right now. And then you will have more research done in this area. Then there will be some research, some priority that will be driven by the fact that there would be funding available for that topic.*
>
> *But then if you have nobody care, for example, about let's say deep convection, it's so true but, then you will get no funding when you write a proposal about this, and then it will not get funded. And then you will advance the research on the topic. Yeah, then it can be a driven priority. It's not the only priority; it would be the priority of the funding agency.*

It was not possible to discern from these interviews the extent to which funding arrangements may encourage or discourage specific approaches to uncertainty in more subtle ways, such as the prioritisation of specific methods or how uncertain information is presented.

5.4.3 Technical Objects

The Models Themselves

The most important factor limiting an uncertainty analysis was the technical limitations of the models. Climate models are immensely complicated technical objects and interacting with them requires high degrees of technical skill. The specifics of how they are constructed control how modellers can investigate their properties.

The most significant limitation is simply the computational expense of running ensembles many times despite the often vast amount of supercomputing capacity available for running these models. The primary uncertainty analysis methods for whole-model uncertainty involve ensembles, and there has been coevolution with the growth of computational capacity in the direction of more intensive ensemble runs.

Ensemble Methods Trade-offs

As computational capacity is a limited resource, it must be apportioned appropriately according to the research priorities of the modellers. One participant described a trilemma trade-off between the spatial resolution of a model, the temporal interval (both total interval and time steps) and the number of model experiments run.

Development Strategy

An interesting example of the interplay between development requirements and uncertainty analysis is provided by the well-known example of the UK Met Office's Hadley Centre. The Met Office requires that the same dynamical core is at the heart of all their models and, where possible, the same parameterisations are used across their suite of models (Met Office, 2021). This approach of setting the high-level specification of a model was described as 'top-down' by one participant.

Again, the path dependence of model development is important. Not only the path dependence in the model itself but in the community superstructure that makes decisions about how the models are to be run. The choice of standardised experiments in the DECK, for example, provides basic experiments for which the models must perform adequately.

Simulacra in Models

Climate models also produce simulations of events on a lifelike earth, complete with maps and arresting visual images. The ease with which modellers can identify the results of a climate model with the target system they are attempting to simulate may cause them to conflate the model system and the target system.

> ***Carrock**: I think there are people in both communities that have very similar ideas [about] uncertainty. But I think it is easy when dealing with a climate model to sort of slip into mistaking the model for reality. And because you have a model that looks a lot like reality, right, it has the same numbers, you can draw maps, you can show how the maps are similar to reality. And you'll even see language in papers "well, our model has shown this." Well, you've shown it in that model. But the caveat is that's only in that model.*

This conflation has also been described in ethnographic research of climate modellers by Lahsen (2005) who notes that model results may be visually indistinguishable from observational data. They describe simulations as 'seductive' giving modellers a 'god's eye view'. Such an effect is said to cause modellers to underestimate the uncertainties in simulations.

5.5 Discussion

Examining the relationships between different factors and how uncertainty is explored, the nature of the model and how it got to be that way was of crucial significance.

In the previous chapter, we discussed how in ESOM and IAM studies, research questions about the real world underwent a process of translation into the model's grammar to attempt to answer questions that the researcher may be interested in. In climate science, the relationship with the research question is markedly different. Here the sets of outputs of interest are well established and agreed on by the climate science community and its sub-communities.

Here too, one must interact with a model in the way that the model determines. In the case of climate science, the principal set of tools for interacting and performing model introspection are various ensemble techniques.

Considering Equilibrium Climate Sensitivity (ECS) as an example, the dynamic where one must translate questions into the language of the model is clear. The motivating research question behind ECS is wanting to know the rate at which the atmosphere is likely to warm in response to increases in CO_2. However, the derivation of this relationship from model results is not altogether straightforward. In addition to trying to determine the *transient* climate sensitivity to realistic possible evolutions of CO_2, the *equilibrium* climate sensitivity is determined, primarily by running unrealistic instantaneous doubling of CO_2 experiments, a relatively unproblematic simulation to achieve in many models. Thus, the original sense of the question must in a small way be betrayed to become answerable by the model.

Thus, we can see here that if we are to understand how uncertain a model's results may be, the model must be constructed with the in-built capability for introspection. The most obvious way in which models occlude examination is complexity, but other aspects of model development, such as the model's modularity, also plays a role.

Considering all the evidence from the study, I shall explore these dynamics further in the following discussion chapter.

5.5.1 Chapter Limitations

The number of participants involved in this part of the study was smaller than that of the IAM/energy community, for several reasons. Firstly, my professional networks are very much centred around energy and Integrated Assessment and hence access to these participants was easier. Secondly, there was perhaps more a caution noted amongst the climate modellers about engaging in a study thematically engaging with uncertainty. I approached several participants in person at conferences, which meant that I could give a fuller overview of the topic of study. Climate scientists approached through email were less likely to respond or to be able to find the time to participate.

In the analysis, I have noted several instances where themes have emerged, but I have insufficient data to explore their dynamics more closely. This reflects both the limited sample size and the need to remain focussed during interviews to avoid long side-tracks that lead far away from the principal object of study, namely, the varieties of uncertainty experienced by modellers.

I shall explore the limitations of the whole study in greater detail in section 6.6.

5.6 Chapter Conclusion

This chapter has examined the conceptualisations of uncertainty by climate scientists.

Climate scientists most used concepts that can be broadly classified as *locations* of uncertainty. The locations most frequently discussed were those of initial conditions uncertainty/internal variability. The kinds of uncertainty they discussed generally had uncomplicated relationships to the family of ensemble methods used to explore them.

Climate scientists face an interesting conceptual challenge of portioning the uncertainty they experience in their work from the target system they are studying – this challenge is evident in how uncertainties such as internal variability can be attributed to either the model or the actual target climate system. Despite this, they sit far from the system, hidden behind a veil of observational and model uncertainties and without access to the systems-in-themselves.

The division of labour in the field is important for understanding how different kinds of modellers may experience uncertainty in very different ways. The stratification of epistemic labour occurs in many dimensions: modellers vary in seniority, in proximity to model development and thematically within different silos.

The following chapter will compare between the conceptualisation identified in energy and that in climate. It will then consider the nature of these conceptualisations given several frameworks, before considering routes forward for future research and limitations in the methodological design.

6 Discussion and Comparative Analysis

6.1 Chapter Summary

In this chapter, I synthesise findings from the previous two chapters relevant to the research questions posed by this thesis. I compare the two groups of participants in the interview study and consider my findings under several lenses.

This chapter begins (§6.2) summarising the previous two chapters, outlining the key differences between the sample groups in terms of their conceptualisations of uncertainty and the dynamics at play in their environments that influence their choices about uncertainty handling.

In Section 6.3 I then look in more depth at some of the concepts discussed in the interviews and examine these each in turn: location (§6.3.2), scenarios (§6.3.3), and variability (§6.3.4). I consider the different roles these concepts play in each discipline and how they interact with the modelling context.

In Section 6.4 I consider the most prominent influences on uncertainty handling identified in the interviews and compare their presence in both groups of participants. I first consider the relationships that modellers can have to their target systems (§6.4.1). I next then consider the nature of the model system and the negotiation of model boundaries in the process of model development (§6.4.2), before examining the different factors from both the local (§6.4.3) and wider contexts (§6.4.4) of model development.

I then consider my findings and distil the themes that have emerged thus far in the thesis. I develop an argument that traces the control modellers and models have over one another to understand the role that uncertainty analysis can play in the context of model development. I then expand this understanding, drawing on biological metaphors to explain the way that models alter their immediate socio-technical environment to suit their operation. This socio-technical infrastructure that surrounds model experiments is a vital and under-appreciated aspect of uncertainty practices.

I consider the limitations of the interview study from a number of perspectives, drawing upon the Total Quality Framework to assess the reliability of my method and potential limits to my findings (§6.6). Finally, I summarise the chapter (§6.7).

6.2 Summary of Findings

This chapter now draws together all the analyses from the previous two chapters and discusses the implications of the findings for the state of research. It begins by examining the role of the most prominent conceptualisations of types of uncertainty for the practices of the two disciplines. It then further surveys these conceptualisations and begins to deconstruct the reasons for their prominence.

Figure 6-1, below, gives an overview of categorisations the researchers who participated in this study fell into.

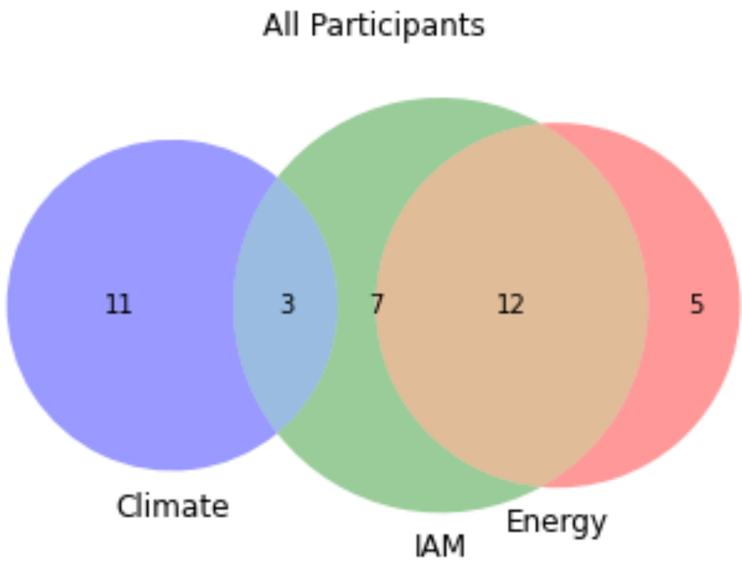

Figure 6-1: Venn diagram summarising the domains of all participants in the study. The classification was performed through participants' self-identification and examination of published materials.

An overall summary of the findings of the interview study is displayed in Table 6-1 detailing the general differences between the groups of participants.

Table 6-1: Summary of differences between energy/IAM and climate participants in the study, examining their different conceptualisations of uncertainty, the espoused relationship between uncertainty analysis methods and types of uncertainty and the various factors identified that have a bearing on uncertainty analysis.

<table>
<tr><th>Category</th><th colspan="2">Energy/IAM</th><th colspan="2">Climate</th></tr>
<tr><td colspan="5">General Profile of Participants</td></tr>
<tr><td>Number</td><td>24</td><td colspan="2">3</td><td>11</td></tr>
<tr><td>Disciplinary Background</td><td colspan="2">The majority have an engineering background. Many with economics training or postgraduate experience with some aspect of techno-economics.

Some pure economists or economists who have specialised in aspects of environmental economics.

Some reformed natural scientists.</td><td colspan="2">Dominated by physical sciences. A typical career path either begins in physics or atmospheric physics and then moves to a PhD in atmospheric science.

Some mathematicians and engineers who have moved laterally.</td></tr>
<tr><td>Division of Modelling Labour</td><td colspan="2">Most involved in model development, running and analysis. Some limited cases of pure model developers in larger IAM groups.

More senior participants tended to no longer be involved in model development.</td><td colspan="2">Can be broadly categorised into three types of modellers.
• Developers are involved in the detailed work of model development but will seldom run the model.
• Operators will run the AOGCMs under different experimental designs and process the outputs.
• Analysts will take the results of AOGCM experiments and examine these in detail.</td></tr>
<tr><td>Models Worked With</td><td colspan="2">Energy systems optimisation models, Integrated assessment models of various stripes: mainly process-based IAMs. Some simplified economic models and CGE models.</td><td colspan="2">AOGCMs and the various submodules of which they are comprised: land–ocean–atmosphere interactions, clouds, ocean components, air chemistry.</td></tr>
<tr><td colspan="5">Conceptualisations of Uncertainty Concepts</td></tr>
<tr><td>General Conceptualisation of Uncertainty</td><td colspan="2">Generally multifaceted. Participants leaned towards an epistemic interpretation.

Some discussed uncertainty as synonymous with opportunities for model development.</td><td colspan="2">Participants thought most about variability, but most generally conceived of uncertainty in mathematical terms.</td></tr>
<tr><td>Ways of Classifying Uncertainty</td><td colspan="2">Locations of uncertainty are the most used. Key locations of parametric and structural uncertainty.

Deep uncertainty used to emphasise certain situations.

Knightian distinction (economic participants).</td><td colspan="2">The types of uncertainty discussed were nearly exclusively locations of uncertainty. The distinctions most commonly compatible with H&S 2009 typology.</td></tr>
</table>

Most Important Types of Uncertainty	Scenario uncertainties. Parametric uncertainties. Structural uncertainty.	Internal variability (of either model or target system). Model uncertainties (of various kinds including structural and parametric). Forcing uncertainty.
Role of Scenarios	Scenarios are a central concept in the organisation of the field. Conceptualised as: • Narratives • Tools • Exogenous inputs Different qualities applied to scenario sets such as internal consistency and plausibility.	Scenarios are not generally of great interest. Often conceptualised as inputs generated externally to either the model or the research community.
Role of Variability	Not considered in detail apart from in discussions of how to statistically characterise some quantities.	Separating signal from noise is important. Likewise, the role of internal variability. Analysis of characteristics of variability is key for model validation.
Normative Views on Probabilities and Scenarios	"Oil and Water" or "Naki" position of scenarios and probabilities is dominant. Though some dissenters argue that scenarios need probabilities to be useful to decisionmakers. Controversy over the use of low-probability/ worst case scenarios.	Discussion over the role of probabilities is influenced by attitudes towards forms of Bayesianism. Distributional outputs viewed as a desirable goal.
Uncertainty Analysis Methods		
Methods Discussed	Scenario analysis and sensitivity analysis are dominant in the minds of modellers. Other methods specific to optimisation models.	Key methods discussed were: • Initial Conditions Ensembles • Perturbed Parameter Ensembles • Multi-Model Ensembles • (To a lesser extent) Forcing Ensembles
Relationship to Types of Uncertainty	Generally identified with different locations in the model process. But the identification is as inconsistent as the locations identified.	The triad of MMEs, PPEs and ICEs were related respectively to Initial Conditions, Parametric and structural uncertainty.
Influences on Uncertainty Conceptualisation and Handling		
Resources Funding	Funding is either academic or for consultancy. Much academic funding is project-based and in consortia: • Convergence in methods between groups who collaborate	Funding is usually perennial for climate modelling groups. Especially those connected to meteorological offices and/or government departments.

		• Thematic funding incentivised researchers to pursue voguish topics Large model groups advocate for their models for funding.	
	Human	Supply of PhD candidates/ECRs important for aspects of model development. Heterogeneity of skills due to diversity in academic background broadens range of UA methods used. Most modellers are not computer scientists.	Similarity of training in physical and atmospheric sciences. Technical specialisations differ in model groups.
	Effort	Limited development time available to effect fundamental changes in the model.	Many MMEs/MIPs are voluntary. Limited time for engagement. Satisficing on model quality.
Local Institutions	Division of Labour	Based mainly on seniority. Modellers develop less as they become more senior.	Seniority and role within modelling are two dimensions.
	Seniority	More experienced modellers tend to have a greater understanding of uncertainty. Junior modellers tend to be focussed on development.	More experienced modellers tend to have a greater understanding of uncertainty. Junior modellers tend to be focussed on development.
	Culture	Different model groups may place an emphasis on themes of uncertainty. Different groups have different disciplinary hiring practices.	Different model groups have different development philosophies and protocols.
Disciplines	Training	Familiarity with mathematical techniques allows participants to perform certain kinds of uncertainty analysis. Economists may understand uncertainties differently to engineers.	Participants are primarily from the physical sciences so make use of physics concepts in understanding uncertainties.
	Culture	Minimal uncertainty analyses are required by the community. General confusion of the meanings of multiple optimisation runs.	PDFs are valued by the community due to their flexibility of use in other areas.
	Literature Base	Requirement to 'chase after' popular topics. Requirement for novelty rather than meta-modelling.	Less influence on climate modellers.
	Publishing	Need for novelty.	No Clear influences.

Technical	Model Specialisation	Models may specialise in representation of some aspect of socio-technical system.	Models generally geared towards same purpose.
	Style of Model	Large difference between optimisation, simulation, and temporal iterative optimisation hybrid models. leads to difficulties in uncertainty interpretation.	Most models can be interpreted in similar 3 ways. Differences in parametric uncertainty schemes the most significant for difference in interpretation of parametric uncertainty.
	Complexity and HPC Capacity	Limited HPC Capacity for model runs. Difficulty in interpreting Optimisation model run results. IAM modellers may not always have their own dedicated HPC capacity.	Limited HPC capacity. Trade-offs between temporal interval, model runs and spatial resolution.

6.3 Conceptualisation of Uncertainty

6.3.1 The Overall Conceptualisation of Uncertainty

Conspicuously absent was a doxastic interpretation of uncertainty: uncertainty as the degree of belief. In all cases, discussion of uncertainty was disembodied from the minds and credences of researchers. The locus of uncertainty was most frequently described as being a property of the model, its results, or the target system. This lack of doxastic understanding is perhaps understandable given that the training that one receives in uncertainty methods will naturally estrange the concepts from an epistemic interpretation. However, I must also consider how this may be an artefact of the questioning style, where we discussed uncertainties in general, rather than uncertainty about specific results. Had the interview protocol presented researchers with specific results and findings and asked them to discuss uncertainty, they may have made statements relating more specifically to their own confidence in those results.

The idea of the locus of uncertainty has also been deployed in a healthcare setting (Han et al., 2011). The relational nature of uncertainty in such a context is understandably important in an environment where the relationship between healthcare professionals and patients is key and the epistemic state of both is created in their interaction.

Although there was heterogeneity amongst the study groups, the conceptualisations of uncertainty for the energy/IAM participants were more characteristic of uncertainty being some disembodied social concept. For the climate participants, the conceptualisation reflected that typically found in the natural sciences of the spread around a result. This incongruency is perhaps the largest opportunity for miscommunication between the two groups.

This discussion contemplates three concepts that differentiate the two groups of participants and examines them in turn: *location*, *variability*, and *scenarios*. Firstly, I turn my attention to *location* the most prominent concept used to differentiate different types of uncertainty.

6.3.2 Understanding the Role of Location

6.3.2.1 The Prominence of Location in Interviews and in Literature

Amongst all participants, the most popular concept that differentiated the uncertainties they discussed was *location*. Most commonly, participants named *model uncertainty* with subsets consisting of *parametric* and *structural* uncertainty.

The use of location to organise uncertainties is intuitive as modellers can apportion their work into various tasks that contribute to the development, maintenance, and running of their models. However, how these locations can be reliably differentiated is unexplored in the technical and philosophical literature.

When modellers attribute an uncertainty to some aspect of the model or modelling process, they are constructing that uncertainty within the model. This construction of uncertainty into model locations can occur in a bottom-up fashion, during model construction, or in a top-down manner where the uncertainties in model results are decomposed into different elements. These *analytic* and *synthetic* constructions of uncertainty occur in both fields, with synthetic constructions being more prominently associated with climate modelling.

6.3.2.2 Locations in ESOM/IAMs

Walker et al. (2003), perhaps the most prominent uncertainty typology, define the location of uncertainty as "an identification of where uncertainty manifests itself within the whole model complex". The locations discussed in the literature include those involved with the model (e.g., structural and parametric), exogenous assumptions (e.g., data, scenarios), the frame (the overall bounds of the target systems that one aims to model) and the context of the modelling practice (see for example Baustert et al., 2018).

When discussing models, participants focussed mainly on model uncertainties, parametric uncertainties, and scenario uncertainties. The conceptualisation of models as the marriage of a model structure with a parametric set is prominent in various literature (see for example Whyte, 2021). Still, this conceptually convenient formulation may mask obscure or omit important aspects of the models as they are realised in computer code.

Other aspects of model structure, such as the temporal and spatial structure, affect results and parameterisations. Some issues may arise in implementing the conceptual model, such as model bugs that can be hidden but cause the implementation of model structure to depart from the modeller's intended structure.

Within the broader context of the model-complex, there are additional ways in which uncertainty can manifest, such as the normative choices made in optimisation models. Participants frequently discussed model structure when discussing the overall paradigm (i.e., linear optimisation) used in an IAM or ESOM. The choice of paradigm can be identified as an aspect of the framing of the entire exercise or a choice in the model structure. It is perhaps the most fundamental choice that modellers must make, though various forms of optimisation models are the most prevalent. The model paradigm choice is intimately tied to the implicit normativity in the model. One participant used the metaphor of the model being some 'benevolent omniscient dictator', and another considered these optimisation models to represent 'liberal authoritarian socialism'. Real-life decision-makers do not have perfect foresight, apply rational expectations, or are necessarily benevolent. Instead, Beckert (2016) centres on 'fictional expectations', assumed narratives about the future, as a unit of analysis in understanding economic decision-making.

Furthermore, there can be an ill-defined conceptual boundary between model structure and parameterisations. When parameterisations serve as a dimmer switch to turn off and on different system elements, they contribute to changing model structure. Additionally, where parameterisations are approximations for underlying processes, they serve as an alternative to additional finer-grained model structures.

In summary, the boundaries between distinct locations of uncertainty are open for negotiation as the choice of model structure closely reflects aspects of the framing of the model exercise. Within the definitions of types of location, there are possibilities for ambiguous boundaries (e.g., parameters and structure, structure and model framing, etc.) A focus on a limited set of locations of uncertainty that look only at the mathematical formulation of the model itself will ignore important aspects of uncertainty that manifest both in the knowledge created by the modelling exercise and in the numerical results of simulations.

6.3.2.3 Locations in Climate Models

The literature concerning types of climate model uncertainty does not use the explicit term *location* and prefers to use the term *source* of uncertainty. However, the kinds of uncertainty most prevalent both in the literature and in the interviews are understandable as locations. Most generally, participants mentioned at least one kind of model uncertainty, be that *structural*, *boundary condition*, *parameterisation or coupling* uncertainty. They also discussed internal variability and forcing (scenario) uncertainties. Some participants said that ideas about location in climate science had been used for a long time and the effect of the prominent Hawkins & Sutton (2009) paper was to settle the terminology that had previously been used in other works[44] and within the community as a whole.

In climate science, uncertainty may be apportioned to different locations in different ways. *Firstly*, uncertainties are directly investigated as the results of ensemble experiments (ICEs, PPEs, MMEs) in which the spread of the results is, *ceteris paribus*, attributable to the aspect of the model system that has been varied between model runs. The affinity of these methods with their respective types of uncertainty was clear from the interviews.

Secondly, several methods are used to apportion uncertainty retrospectively from sets of model results; the method for apportioning uncertainties may change how we conceptualise these locations. Consider firstly a simplistic approach, which may involve estimating the mean contribution from external (anthropogenic) forcing over many initial conditions model runs, then subtracting this from each model run to estimate the contribution of uncertainty from the internal variability (Deser et al., 2014). An alternative approach is described by Hawkins & Sutton (2009 Appendix A) in which internal variability was defined as the residual of a fourth-order ordinary least-squares polynomial fit of the set of CMIP3 multi-model runs for the years 1950–099.

[44] See for example Cox & Stephenson (2007), with the uncertainty types of Internal Variability, Emissions Scenario Uncertainty and Process/Parameter Uncertainty.

Thus, different modellers experience different locations of uncertainty, dependent on their role within the modelling process. Model developers working on some aspect of the model, say a convection scheme, may be able to explore the elements of the model that uncertainty manifests in by direct manipulation. For example, through the running of the model component under a variety of model configurations. Whereas modellers with a more tertiary view of the model process, such as *operators* and *analysts*, may apportion uncertainty to location post-hoc after running the model experiments.

As with the disciplines of IAMs/ESOMs, the different locations of uncertainty may be inextricable from one another in climate modelling. As Deser et al. (2014) note, some of the apparent internal variability in an ensemble of model runs may be attributable to differences in the model structure or parameters. In addition, different model structures and parameters do affect internal variability.

The location of parametric uncertainty has a different role in climate modelling as it does in energy and IAM modelling. Parameterisations have additional meaning in climate science as the aggregate representations of small-scale processes and thus can form an alternative to more detailed model structure. They can be assigned in several ways, either through estimates using data, model fitting or stochastic schemes.

Parametric uncertainty in climate models has an additional function as it mediates between different kinds of uncertainty in model tuning. Models can be tuned by altering the parameterisation schemes to best recreate past climate data (Hourdin et al., 2017). The resulting parameterisation is then a mediation or accommodation between the data that represents the target system and the chosen model structure. I shall return to the role of the target system and the model system in Sections 6.4.1 and 6.4.2.

6.3.2.4 Locations Inside and Outside the Computer Model

Most *locations* discussed by participants were manifested inside the model as aspects of model structure or parameterisations. However, the modelling process involves more than simply the mathematical formulation of models and we cannot ignore the technical implementation of these models in a computational environment.

Structural and *parametric uncertainty* may be convenient to designate, and the conditions sets used to initialise models can be easily described. There are many aspects of the model creation and execution process that bear on results that are less visible to outside observers. Many small decisions about the modelling infrastructure never make it into the materials that are the outputs of modelling work, such as scientific publications. The interview data shows that the infrastructure that allows the model process to be carried out is consequential to both the decisions made in developing models and ultimate results obtained.

Uncertainties that emerge in the context of modelling, such as the framing of research questions, may percolate into the model itself and manifest in some way in the equations and code of the model. For this reason, one could argue that as uncertainties from the problem context make it into the model, we need only centre our analysis of the model's uncertainties on the various aspects of the formal model (structure, parameters, scenarios, etc.). I argue that it is not sufficient only to consider the formal aspects of the model in our uncertainty accounting as we cannot be sure that the uncertainties from the modelling context do indeed end up translated into model structure.

6.3.2.5 Location is an Underexplored Concept

To summarise, *location* is a pervasive yet under-problematised concept in the study of uncertainty in modelling. The central idea is that there are categorically different tasks and processes in the knowledge creation process that scientists engage with, and that uncertainty manifests itself at each stage. By identifying how uncertainty manifests itself in different stages of the research process, scientists can formulate plans to mitigate or better characterise this uncertainty.

However, the locations of uncertainty that one experiences depend on the fundamental set-up of the model-complex. The locations of uncertainty interact with one another in complex ways, and the apportioning of uncertainty to different locations may be performed as a matter of convenience. This is seen in climate modelling, where uncertainty is commonly partitioned between model uncertainty, internal variability, and scenario uncertainty according to the availability of methods available to perform this.

Location can have multiple meanings and can be identified with the activities that one engages in when modelling, objects within the model-complex and even be identified with different aspects of the target system. There is very approximate fungibility between these ideas as demonstrated in Table 6-2, though they are not directly equivalent. How modellers will think about the location of their uncertainty will depend on the context in which they are working. Future research could delve deeper into the relationship between *location* as the set of generalised labels for modelling activities and the reification of the model in code or outputted results.

Table 6-2: Demonstration of the very loose fungibility between different versions of location. Author's analysis of interviews and literature.

Typical Location Labels	**Model Activities**	**Model Objects**	**Example aspects of Target systems**
Data Uncertainties	Observing Systems, Formatting Data, Data Cleaning	Input data files	Initial state of target system
Structural Uncertainties	Documenting mathematical forms, Coding Equations	Computer code, documents	Interactions between systems, Fundamental Physics
Parametric Uncertainty	Parametric Fitting, Literature review	Parameter sets	Subscale Processes
Scenario Uncertainties	Running model with input scenarios	Scenario sets and libraries	Emissions

6.3.3 The Space of Scenario Spaces

6.3.3.1 The Importance of Scenarios

Scenarios see routine employment in energy systems and Integrated Assessment Models and are important as an organising principle for research communities. The scenarios used by climate scientists are more limited, and they often only enter an analysis at the very final stages of the climate modelling cycle. Scenarios are not routinely produced within climate science itself. Hence it is unsurprising that climate modellers are less familiar with them. Nonetheless, the results of climate models run under various scenarios are of critical policy importance and thus it behoves us to consider how climate scientists understand them.

6.3.3.2 The Different Ways of Conceptualising the Structure of a Scenario

Overall, scenarios were conceptualised in different ways as narratives, tools and exogenous data inputs. The former two of these three are more common in the Integrated Assessment interviews and the latter is more common with climate scientists (or no conceptualisation at all).

From the range of ways one can imagine scenario sets, I identify three ways in which their form differs from one another. Firstly, scenarios can be understood to vary in the level of *narritivisation* that they include. Some scenarios can simply be numerical descriptions of assumptions, whereas others can consist of highly embellished stories[45].

Secondly, scenarios may vary in the number of variables that changes between scenarios. Some participants understood simple changes in single variables as a form of scenario analysis. Scenarios can constitute data inputs to a model and changes in parametric settings. So, the border with sensitivity analysis is the space of scenario analyses where one changes small parametric settings that have some other interpretable meaning relevant to the research question you are trying to answer. On the other hand, some believed that scenarios involved the simultaneous variations of larger collections of unknown parametric settings harmonised with one another to produce a consistent thematic change in the model. For example, the SSPs consist of many variables that vary in a consistent way with one another both from a narratological perspective and in line with the best available scientific knowledge.

Thirdly, the required representation of temporality may differ. Simple low-temporality scenarios may involve single snapshots of an outcome (in past, present or future) or a change at a particular moment in time (a diachronic representation). More detailed representations may include relevant variable(s) over different temporal intervals (typically into the future, over days, years or decades).

Figure 6-2 gives a sketch of the space of possible versions of a 'scenario' in terms of these three distinctions.

[45] For an extreme example of an embellished narrative scenario see the UK-SSPs, where the five SSPs have been contextualised for a UK context (Pedde et al., 2021). The artistic embellishment of these scenarios provoked some media backlash against them.

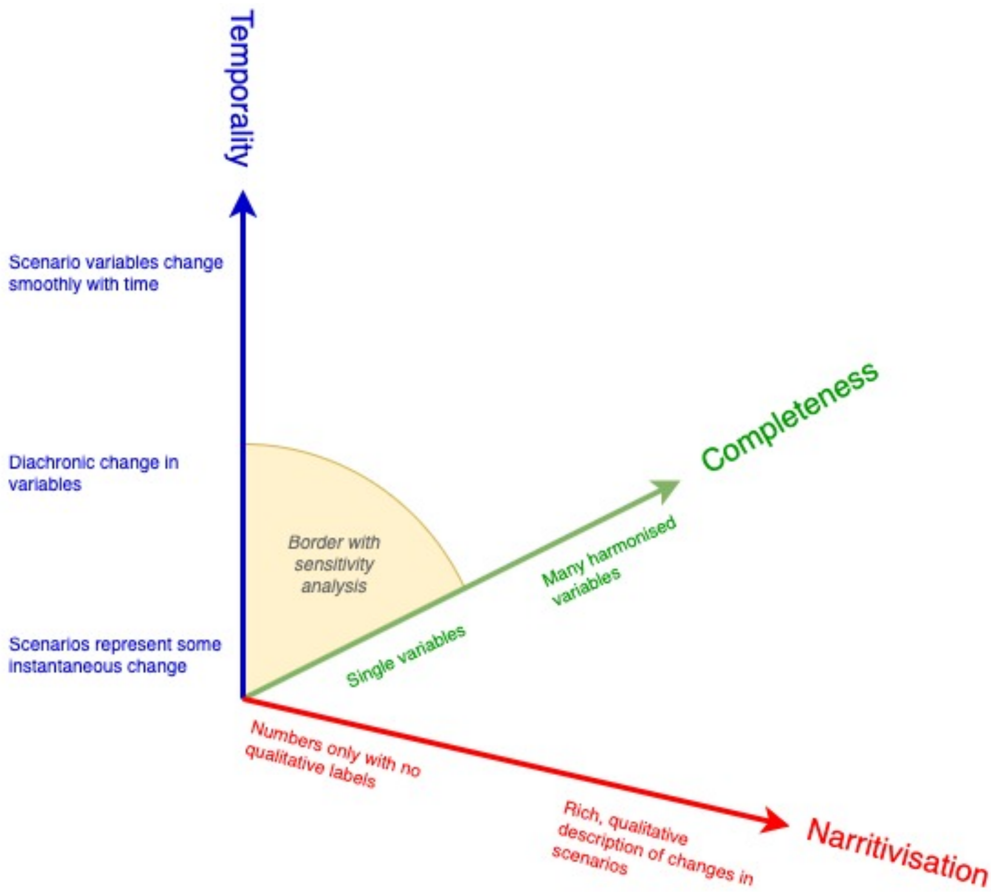

Figure 6-2: The space of different conceptual objects identified as scenarios. Author's own analysis of interviews.

One can use this schema to attempt to plot different scenario sets and understand the evolution of the major scenario sets employed in international and national climate assessments. For example, the SSPs contain a much larger degree of narritivisation than other prominent scenario sets, and recent efforts to downscale the SSPs, such as the UK-SSPs project (Pedde et al., 2021), move the scenarios further in both the completeness and narritivisation directions.

6.3.3.3 The Qualities of Scenario Sets

Further to these structural differences between different scenario exercises, participants expressed different views about what types of confidence statements should be made over scenario spaces. The most common requirement is that the changes that each variable undergoes within a scenario should be conceptually consistent with our knowledge. Others required that scenarios be plausible or possible. Plausibility and possibility are generally considered to constitute different concepts[46], though in the context of the interviews, the terms were essentially synonymous.

Internal consistency was generally considered to be an important property of scenarios. This criterion can mean different things. For example, it could mean that the relationship between variables in a scenario has been assessed by the research community using the most advanced tools at their disposal. This is the case with the SSPs, where scenarios are generated, in part, through a suite of different models judged adequate for the purpose. There are also various techniques available to ensure the consistency of scenario elements at different scales (see for example Schweizer and Kurniawan, 2016). Internal consistency could also mean that in the subjective judgement of the modeller, how different elements vary is perceived to have verisimilitude.

Several participants wanted scenarios to be *useful*. How usefulness is defined depends on the epistemic strategy of the scenario analysis. Participants talk about scenarios as being 'useful' in the sense that the differences between scenarios are informative about some underlying dynamics that may be at play in the target system, or that a particular scenario can reveal something novel in and of itself. One can imagine how the property of *usefulness* in some scenario analysis situations may compete with *plausibility*; some participants discussed using low plausibility or far-fetched scenarios to explore the mechanisms at work in their models or to consider particular low-carbon futures that may.

6.3.3.4 The Understanding of Whole Sets of Scenarios

Aside from conceptualising scenarios, there is also a difference in how whole sets of scenarios can be conceived. As discussed in section 4.3.3, participants had several views about the potential dangers to the policy process of presenting scenario sets in different ways. For example, a participant worried that a scenario set presented as a range could be interpreted as spanning the entire possibility space.

[46] Van der Helm (2006) claims that possibility is that a scenario simply has some non-zero probability of occurring; whereas plausibility is subjective

I contend that there are essentially two issues at work here:

i. The relationship that scenarios have to a well-defined space of things can vary. Scenarios can be conceptualised as spanning a space of some variables where the span of the scenarios gives the range of plausible or possible outputs. Alternatively, they can be understood or treated as samples over the outcome space.

ii. There may be disagreement on whether scenarios are sufficient for exploring the model or target system dynamics one is interested in. A potential future of a system may be represented by some system of variables that evolve in time, but this collection of variables may not accurately represent the real changes in this system as other more salient variables may be missing. Therefore, there is an issue with the representativeness of a scenario for a potential future, and the range of variables for a scenario may be incorrectly assumed to be all that requires consideration.

6.3.3.5 The Expansiveness of Scenario Concepts

In ESOM/IAM, the meaning of the term *scenario* is expansive both in interviews and in literature. Everything from large communally agreed sets of assumptions over large variable sets accompanied by narrativisations of those projected changes to individual model runs with tweaked parametric settings are understood to be *scenarios*. This conceptual ambiguity is also present in the way that methods are conceptualised; simple sensitivity analyses also occasionally conceptualised as a kind of scenario analysis. *Greatend* gave an example of this ambiguity, describing how limited aspects of the SSPs can be taken and implemented in models in a simplified form and labelled as ‘scenario analysis’.

This ambiguity may have consequences for communicating scenario results between modellers and other audiences such as policymakers and the public. Furthermore, it is conceivable that the ambiguous terminology may cloud the epistemic strategy of the scenario analysis. The epistemic strategy of scenario analysis has received much attention in futures studies and technological forecasting (e.g. Aligica, 2005), but has received less attention in other literatures.

Scenarios have a more restricted conceptualisation in climate modelling, with participants most generally conceptualising them as an exogenous input. This is except for the occasional characterisation of certain model experiments such as “2xCO_2” or “4xCO_2” used as benchmarks to compare climate models and make estimates of key quantities such as ECS.

The lack of clear communication of issue (ii) identified above means that sometimes the RCPs can be understood to span the range of plausible futures.

Terminology and Scenarios

There are, however, some ways in which these different kinds of scenarios are differentiated in the literature. *Pathways* are differentiated from scenarios in that scenarios are considered the whole future and the *pathway* represents an aspect of the system in that future. The term *pathway* is intended to emphasise the importance of both the systemic outcome and the trajectory taken to reach it (Moss et al., 2010).

The amount of narrativisation in a scenario can distinguish between qualitative scenarios, quantitative scenarios and indeed hybrid scenarios[47]. The IPCC's 1.5-degree report also made use of 'illustrative model pathways', selected from a larger range of pathways to demonstrate how potential mitigation approaches vary in fundamental ways (IPCC, 2018). A variety of terminology from the scenarios literature can be used to discuss various scenario-like objects. However, participants infrequently made clear distinctions between these.

Reconsidering the Epistemic Strategies Present in Scenario Exercises

Let us consider the role of scenarios in the light of Cartwright's concept of models being nomological machines that can isolate capacities. A scenario may describe the unfolding of several different factors $F = \{F_1, \dots, F_n\}$. By manipulating these factors and keeping all else equal within the model we are attempting to understand the capacity of this set of factors to produce a particular result R. In this understanding, the interpretation of the scenario analysis as isolating capacities or revealing possibilities is unproblematic to comprehend.

In optimisation modelling, this relationship is more difficult to maintain. The way the model links results, factors and capacities is different. Perhaps we are doing the reverse – we are taking an extreme result and trying to find which arrangement of factors may have the capacity to produce it.

[47] In an ethnography of Energy Modellers, Silvast et al. (2020) mention their participants discussed 'hybrid scenarios'.

In a scenario analysis, we have some uncertain factor or a set of factors is uncertain because history has not unfolded yet or we are yet to make some decision. When different models use the same set of scenarios, they seek to represent those scenarios consistently within their respective models, with similar sets of lawlike premises. The range of different results from these different scenario analyses gives an indication of different capacities that that set of factors may have.

However, these factors are not the same in different nomological machines, and the way they are represented depends on the nature of the set of lawlike conditions. Optimisation models may, for example, subject their optimisations to constraints that are normatively determined.

In summary, scenario analyses differ in their epistemic strategy, depending on the kind of model used. Firstly, the mechanism by which the relationship between outcomes and the factors that have the capacity to create those outcomes differs between simulation and optimisation modelling. Furthermore, these factors can be represented in terms of different kinds of nomological relations like physical laws, empirically derived relationships and normative rules. Therefore, causality may have multiple possible interpretations in different types of models. It is simplistic to describe scenario exercises as simply 'what-if exercises'. They contain a diversity of possible epistemic strategies that reveal different kinds of knowledge about the world.

The Embedding of Scenarios

As scenarios are developed, models will evolve to be able to run them and will be tailored for the sets of inputs that the scenarios provide. There is a co-dependency between models and the scenarios.

Given that scenarios neither necessarily span the space of plausible outcomes within the outcome spaces that they describe (impossible to achieve in high dimensionality scenario spaces) and that these outcome spaces may not adequately represent the desired factors of system evolution that we are concerned about, it may be desirable to see a range of scenarios employed that take heterodox approaches. There is a danger that the co-dependence of model and scenarios may close off exploration of important futures.

To create scenarios with the high level of detail and internal consistency of something like the SSPs requires the coordinated effort of many actors. The production of the SSPs required the collaboration of many modelling groups and using a suite of smaller models such as economic models to ensure plausibility and consistency with the best estimates of the research community at the time. So the technical complexity and the requirement for internal consistency precludes the use of 'wildcard' scenarios.

Given that we know that scenarios will turn out to be wrong, what role is there for more unconventional scenarios, and how can the research community facilitate their use? This will be a suggested topic for future research outlined in section 9.4.

6.3.4 The Nature of Target Systems and Variability

I have discussed at several points throughout the analysis how the nature of the target systems of the different disciplines plays a role in determining the appropriate analytical tools to try and comprehend the uncertainties in the models that seek to represent them. This is entirely what we would expect.

The target systems for the two groups of disciplines are fundamentally different from one another (see for illustration Table 6-3), correspondingly the way that models are assembled. The most important difference between these systems is the role of reflexivity and agency. In human systems, decision makers both respond dynamically to developments (agency) and respond in anticipation of the predictions made about hat system (reflexivity). The latter is impossible to model and hence the modelling frameworks used will inevitably have to accommodate exogenous assumptions about how decisions are made. Most commonly, these take the form of scenarios.

However, it is too simplistic to end the story of the relationship between the modellers and their target systems there. Modellers do not have perfect epistemic access to their target systems to determine the correct analytic repertoires to use. They enter modelling exercises with a range of prior beliefs and receive information about their systems through intermediaries such as observations.

Table 6-3: Stylised examples of differences in the target and model systems between two areas of study

	Energy/IAM	**Climate**
Model Styles	Simulation, optimisation, exploratory	Simulation
Rule-like Elements	Economic rules, normative preferences, physical laws	Physical-law based
Reflexivity	System contains decision-making agents performing reflexive behaviour	Non-reflexive
Observability of Target System	Data generated through economic statistics	A variety of direct and remote sensing methods

Variability or aleatory uncertainty pervades and enters many aspects of real and model systems. It is an instructive exercise to examine the role of variability in modelling to explore this relationship between modellers and their target systems. How variability was conceptualised by modellers appears to have something to do with the relationship between their models and their target systems. I shall first outline broadly how the two different groups conceived of variability and then explain how this relates to the different roles validation plays in the two areas of study.

6.3.4.1 Variability in Climate

Variability plays an important role in the field of climate modelling and is iconic as one of the uncertainty wedges familiar to readers of IPCC reports. Climate models are not just assessed for how well they recreate things like previous temperature trends but whether they create a reliable simulacrum of the phenomena observed in the real system. Some of these phenomena can be just described simply as 'variability'. For example, ENSO is the dominant mode in climate variability and models must recreate this; there are multiple measures that can be used to determine how well it has been simulated (Guilyardi et al., 2012; Lu et al., 2018).

6.3.4.2 Variability in Energy Systems and IAMs

Amongst energy systems modellers, participants discussed how variability entered their work through a variety of different statistical uncertainties. There was also a firm notion that the real unfolding of events was unknowable due to the variable nature of systems that contained within them some amount of human decision-making.

The variability of natural systems plays an indirect role in Integrated Assessment and will feature in energy models occasionally through things like the variability of the supply of renewable energies in models that contain some representation of electricity despatch. Some typologies of uncertainty, especially for Integrated Assessment, are vague about where it is that variability enters the system.

6.3.4.3 Where Variability Comes From in an Analysis

Aleatoric uncertainty that is due to the nature of a system can come from many different systems. The variability of a target system can be described through the collection and analysis of data. Aleatoric uncertainty can also emerge from the internal variability of a model system itself. This can come from both the relationships between variables and the chaoticity of those relationships in aggregate. There can also be unwanted sources of variability within model systems such as that caused by aliasing[48]. Equating the variability observed in a target system with that in a model system is not always straightforward and may require some justification.

Different sources of variability also arise in the interaction among the intermediary systems that sit between the model system and the target system. For example, many kinds of measurement uncertainty manifest as variability, since the nature of the system that records measurements means that measurements are distributed around some value. Another example is variability emergent from certain parametric fitting methodologies.

Data can rarely be inputted into a model directly from observations. Various processes often occur to make a dataset compatible with the structure of the model, such as data cleaning, structuring, transformation and validation. In the interactions between these systems, variability is created.

6.3.4.4 Variability in System Structures

Models that deal with socio-technical change also deal with another kind of variability that results from the restructuring of systems, what Derbyshire (2017b) terms *ontological uncertainty*.

[48] The appearance of new frequencies in a signal due to a low sampling rate of a variable.

Some phenomena can fundamentally shift whole systems so that previous assumptions are no longer functional. It is legitimate to take different positions about such uncertainty. On the one hand, we could categorise these *ontological* uncertainties as *epistemic* as it could be our ignorance of underlying dynamics that cause us to be uncertain. On the other hand, if it is because a system contains social agents that it restructures itself – the ontology of the system is what creates the variation and hence the uncertainty is *aleatoric.*

An example of this, relevant to forecasting the evolution of energy systems, is the possibility of surprise from emergent technologies. The emergence of novel technology can fundamentally restructure a target system. Defence theorists call this phenomenon where a technology rapidly emerges into our considerations that causes a re-evaluation of previous approaches 'technological surprise' (Handel, 1987).

6.3.4.5 The Relationship of Energy and IAMs to Target Systems

Not all disciplines seek to simulate their target systems. This is another reason why we cannot say that the use of different analytic repertoires is just the result of studying different target systems.

Optimisation models, like those used in Integrated Assessment and energy systems modelling, do not necessarily attempt to recreate system behaviour. As such, they cannot be directly validated against past or present data. This is due to the known incompatibility of the law-like relationships that govern the system evolution and the model evolution. The decision rules that guide policymakers are complex and opaque and not amenable to any kind of easy representation in a model system. The decision rules that govern model systems are normative law-like rules that a real decisionmaker could, in principle, attempt to follow. And thus, they could have the capacity to create similar effects in the target systems.

In simulation models, the normative rules that drive systems behaviour may be the same as for optimisation as the same kinds of decision variables around carbon abatement are present. These decision rules are not claiming to represent the real mechanisms that drive system behaviour. Model validation cannot occur for these models with reference to the real-world system. Validation may occur through an analytic process in that the different aspects of the model system are independently judged to be credible and sufficient for the given task.

Trutnevyte (2016) presents a novel idea to investigate the relationship between real world decision-making and optimisation rules. The approach tries to resolve a tension in the bottom-up modelling community between caused by the inability of optimisation models to provide scenarios that realistically portray possible future energy systems developments, which will not be cost-optimal. The approach aims to provide ex-post evidence of the realism of cost optimisation by comparing the real historical evolution of the UK energy sector from 1990–2014. The paper finds that the actual evolution of the system differs from the ex-post modelled cost optimisation with perfect foresight. In essence, such an approach seeks to mediate between normative rules that could govern policy choices and the empirical effect of the interaction between decision-makers and target system responses.

Given the practical and conceptual difficulties of comparing energy systems optimisation models to reality, there are many approaches not to model *validation* but to *evaluation*. Schwanitz (2013) review the reasons that complicate model evaluation for IAMs, such as the openness of the target systems, ambiguity over the appropriate levels of spatial and temporal aggregation and a lack of knowledge about the fundamental relationships that govern future system behaviour. They outline several approaches to model evaluation that are sensitive to the model's intended purpose and consider both the structure and behaviour of the model. They propose an evaluation framework that evaluates separately the conceptual model used, the model code, the model structure, and the model behaviour.

However, different energy models and IAMs are comparable to various degrees. Some models produce aggregate economic outputs and some produce 'physical' outputs. The actual system itself does not determine what the relevant outputs to compare with one another in model evaluation are and the selection of outputs will depend on contextual values. DeCarolis et al. (2012) note that many of the assumptions inherent in Energy–Economy Optimisation (EEO) models are not visible to those outside the modelling process[49] and, at the time the paper was authored, model runs were difficult to replicate for most models they reviewed. In response to this issue, they propose several measures to increase the repeatability of model runs.

[49] I shall return to this issue of the non-replicability of model runs for reasons unknown to modellers or outsiders to the modelling practice in chapter 8, where I problematise this issue as 'model dark matter'.

In sum, the fundamental nature of IAMs and energy systems models in terms of both the nomological relations with which they are constructed and their relationship to their target systems prevents model validation. However, various approaches for model evaluation exist, though the comparability of models to each other and to target systems is limited by the replicability of model runs.

Variability manifests in different aspects of the model, target, observational and other systems. It also emerges in the interactions between these systems. Different kinds of variability have very different effects and should not be confused with one another. The aleatoric uncertainty in a model system is not the same as that in the target system, and the way we interact with it is fundamentally different. Model variability lies within our locus of control, and, in principle, we can comprehend the mechanisms that produce it. The collision of causes that creates variability in the real world is beyond mortal human comprehension, especially when dealing with socio-technical systems.

We can only comprehend aleatoric uncertainty by interacting with systems. When we interact with systems, we do so using our prior assumptions about the nature of that system, and hence we are open to misinterpreting the meaning of the variability we observe. As Scoones & Stirling (2020) argue, uncertainty is relational between knowledge and epistemic agents; it is impossible to divorce subjectivity from uncertain knowledge. We cannot know fully systems-in-themselves, and thus all aleatoric uncertainty is tinged with epistemic uncertainty.

6.4 Influences on Uncertainty Handling

I now examine several themes related to the influences on uncertainty handling in greater detail. The factors that influence uncertainty are organised here in their relation to the modelling process. Firstly, I consider the fundamental nature of the target system and the ability of modellers to observe and epistemically access its dynamics, and then I discuss the role of the model. Next, I examine the role of the immediate context of the modellers: their modelling groups. Finally, I consider the greater context of the modelling work: the research community and funding organisations. In the two previous chapters, I detailed the analysis working through types of actants; here I move in the other dimension described in the actant taxonomy in Figure 4-3, moving away from the modelling process.

The previous section has considered several concepts and the contextual influences on their utilisation and deployment. This section now looks from the other side on the structural factors in the disciplines being studied. With these two halves, it is hoped that a joined-up account of uncertainty practices can be established that runs through from conceptualisations to practices.

6.4.1 Target System

6.4.1.1 Nature of the Target System

As I have detailed in the previous section, the fundamental natures of different target systems require different types of rules (nomology) within models. In practice, models will consist of different assemblages of rules such as physical laws, approximations, statistical techniques, rules-of-thumb and stylised facts. Different types of nomology lend themselves to uncertainty analysis differently due to their differing epistemic status. The confidence statements we can make about the action of physical laws are different from those we can make about, say, a stylised fact.

There are many forms of model appraisal and evaluation that can be justified in different contexts. For example, statistical validation of model outputs is not possible in certain situations, such as when models are intended to produce forecasts. Also, when model results from different models are incomparable to either other model results or target system data; alternative analytic methods of model evaluation are possible where individual model components are inspected.

In summary, the nature of the target system constrains the types of uncertainty analysis and model quality assurance activities that can be performed. Thus, the interpretations of uncertainty that can be maintained for different models attempting to describe different target systems are constrained.

6.4.1.2 Relationship to Target System

I have already argued it is simplistic to say that it is only the nature of the target system that determines the suitable analytic framework to employ to analyse uncertainty. The web of relations and interactions between modellers and target systems is also important to consider.

Different modellers obtain data about their target systems in different ways and through mediators.

Data availability depends on many things such as the cost of measurement equipment (e.g., autonomous sensors, weather stations), the presence of technology capable of conducting measurement (e.g., remote sensing technologies), data ownership (e.g., technology cost data) and the value that one places in measurement. Human factors that affect data availability were present in the interviews, such as *Brandreath*'s description of how a technology manufacturing association were unwilling to share technology costs because of commercial sensitivities.

Modellers may not understand the breadth of data uncertainties as they are downstream of the data production process. An example of this from the climate participants was their unfamiliarity with the work of the observational community. In the IAM community, some participants expressed concerns with the presentation of data by the LCA community; such data often plays a crucial role in IAMs for the characterisation of technologies.

In climate science, models rely on observational data for credibility and quality assessments (Guillemot, 2010). Edwards (1999) has examined the relationship between climate models and observational data that are both integrated and relied on for validation by climate models. His research finds that there is an ambiguous boundary between the two. The use of the term 'validation' is not preferred by all modellers. They may prefer 'evaluation' (Guillemot, 2010). A notable article by Oreskes et al. (1994) argued that climate models could not be rigorously validated and ignited great debate on this topic. Climate modellers spend much of their time studying simulations and not necessarily observational data directly. Some researchers have observed tensions between observationalists and modellers (Lahsen, 2005). Modellers are estranged form direct contact with the variability in the systems they study.

In summary, the relationship that modellers have to data relating to their target system is more complex than a simple availability or unavailability. The division of labour both within and between research communities has a bearing on availability. Modellers may be unaware of uncertainties incarnate in the data they use due to the distribution of epistemic responsibility for the quality of that data lies outside of their community.

6.4.2 Model Systems

6.4.2.1 Model Boundaries and Model Development

I identified a frame that conflates uncertainty analysis with the expansion of the boundary of the model system to include more uncertain aspects of the target system. Modellers must attempt to partition some aspect of the target/world system that they would like to represent. The delineation of model boundaries is continually renegotiated with changing research priorities. These research priorities are determined by their research communities and models must evolve to have relevance to a shifting variety of research questions.

The shifting of a model boundary to respond to the requirement of novelty was discussed by several participants. There is a tension between the demand for novelty and knowledge consolidation. We can also imagine the bounds of the model system being redrawn as complex system components are being replaced with emulators for computational efficiency.

Unlike ESOM/IAMs, climate models may evolve more slowly in their fundamental structures. The class of complex climate models currently used has a long heritage and has been run in similar modes for a significant time period. Producing a certain kind of uncertainty analysis with a model is not the kind of work that would be detailed in a short paper – it requires the coordination of multiple modellers and the purposive movement of a whole research group.

As the boundaries of a model are renegotiated, uncertainties shift their location within the model complex. For example, the incorporation of new uncertainties that may have either been ignored or dealt with through scenario analysis into some aspect of model parameterisation or structure. Henceforth I will call this process of conceptually bounding the domain of the model and demarcating aspects of target systems outside the bounds of the *model enclosure*.

6.4.2.2 Model Complexity and Technical Constraints

This process of expanding the conceptual bounds of the model in terms of system elements, spatio-temporal sampling density and extent increases model complexity. In both domains, models include an increasing number of coupled subsystems and more fine-grained representations of processes internal to their respective subsystems. This increased complication makes models harder to understand due to epistemically opacity (Beisbart, 2021).

Modellers must make trade-offs between competing demands of model representation, as well as balance the overall complexity of the model to the requirement that it be simple enough to be flexibly used for different purposes. Model complexity limits the possibility of using different uncertainty analysis methods, such as various ensemble-based methods, and increases epistemic uncertainty due to the difficulty of comprehending the dynamics of the model system.

Various ways of reducing this epistemic opacity are available, such as the open sourcing of code (see for example the OSeMOSYS model (Gardumi et al., 2018; Howells et al., 2011; Niet et al., 2021)), thorough model documentation (see for example the documentation of IMAGE (PBL, 2021)). Though even in the cases in which code can be made available, the provision of said code is not sufficient to ensure it can be used by others because of the systems requirements of models, the coding languages used and the complexity of implementation.

6.4.2.3 Aesthetic Simulacra

An interesting way a model influences a modeller to consider uncertainty in different ways is the production of aesthetic simulacra of real systems. Here I am talking primarily about maps in climate science that represent results. People are used to comprehending the world cartographically. If the model produces similar results, it may encourage an identification of the model system with the target system, as observed by Lahsen (2005). It has been established elsewhere that the presentational aesthetics of uncertain information will affect the perceived uncertainty associated with it (Theocharis et al., 2019). Energy systems models do not typically produce results that are so visually identifiable with a target system and this issue did not emerge in their set of interviews. Perhaps future research could consider the necessary conditions for model-system confounding to occur.

6.4.3 Local Context

6.4.3.1 The Cultures and Priorities of Research Groups

Different research groups may have distinctive philosophies toward the process of model development and uncertainty analysis. In the interview data, several aspects of these practices were identified, including:

- Hiring practices that control the disciplinary makeup of research groups.
- The decision-making process by which model development priorities were chosen (e.g., top-down and bottom-up).
- Characteristic uncertainty analysis techniques with which modelling groups attain expertise.

This culture may be influenced by different factors such as the preferences of senior individuals and the institutional arrangements of that modelling groups. For example, those attached to governments may have requirements to produce policy-relevant information, so they may tailor their outputs to be comprehensible by policy audiences.

6.4.3.2 Authority, Seniority, Epistemic Labour

The dynamics of epistemic responsibility within a group may influence how individuals conceptualise uncertainty. Due to a division of epistemic labour, modellers vary in their familiarity with different aspects of the model and the attendant uncertainties (Lahsen, 2005).

A division of labour within research groups is required, individual researchers cannot operate and analyse the results of complex models. I have previously characterised some of these roles as *developers, operators and analysts*. But this is still only approximate as seniority also determines one's involvement in certain modelling tasks. More senior individuals will likely be less involved in the nitty-gritty of model development but will have a larger agency over the direction of model development. Developers may be more prone to conceiving uncertainty narrowly in the part of the model they are most concerned with and not the total uncertainty of the model.

Junior researchers, doctoral and some Master's-level students, are also in a unique position regarding the level of agency that they have over the activities that they pursue. They are not necessarily pressured by the requirement to publish journal articles, free from some project funding requirements and free to explore curiosity-driven limes of enquiry.

On the other hand, doctoral researchers were viewed by some participants as a resource for model development as they could be dispatched on longer and more arduous pieces of work over the course of several years without other requirements usually placed on academics such as regular publications or teaching commitments.

The role that one plays within a modelling team affects how one interacts with a model and the kinds of uncertainty with which one is likely to be concerned. The social infrastructure that supports model development is adapted to the requirements of the model. The division of epistemic responsibilities within an institute includes identifying and managing different aspects of uncertainty.

6.4.3.3 Epistemic Agency

Epistemic agency is distributed throughout the network of individuals and models that compose a modelling community. It is structured differently in different research communities through the sharing of models and the capability of researchers to make fundamental decisions about model building. Here I describe a few dynamics by which this distribution of epistemic agency bears on the meaning of uncertainty.

In climate science, models share a wide variety of features. There is a lot of heritability in the design of climate models that can be described both qualitatively and quantitatively (Knutti et al., 2013). Epistemic agency is very diffuse amongst the community of individuals responsible for model production.

The distribution of epistemic agency in the energy and IAM community is quite different. Although some models, such as the TIMES/MARKAL framework or the MAGICC climate model emulator, are shared amongst groups, models tend to be bespoke.

Due to the broad diffusion of epistemic agency, epistemic uncertainty in climate science can have no meaningful interpretation at an individual level. It can only be a consensus property as there are too many participants in the process. It is perhaps unproblematic to state that energy and Integrated assessment modellers have greater ownership of their modelling results.

6.4.3.4 The Role of Values

Most evidently, different epistemic values played a role in deciding what kinds of uncertainty analysis to perform. We have also seen that there are trade-offs in modelling between different kinds of epistemic values when designing an uncertainty analysis. Do we wish to better explore the parameter space, or do we characterise the model structural uncertainty? Do we value comprehensiveness in our characterisation of one model realisation or do we value the ability to span a lot of things? Limited computational resources force modellers into trade-offs in uncertainty analyses between different aims of an uncertainty analysis. They must answer questions like which parameters they find the most important and which kinds of uncertainty are the most epistemically valuable to explore?

The philosophy of science literature features some debate over the extent to which non-epistemic values influence the decisions of modellers and the extent to which value-laden choices are manifested in model results. The past decade has seen a variety of papers in which a number of philosophers of science discussed the extent to which values are involved in climate simulation (e.g. Morrison, 2014; Parker, 2014; Winsberg, 2012).

Rarely did participants explicitly discuss the role of values in their work. This is perhaps a limitation of the methodology and there may be alternative methods that could more explicitly explore values with participants. Despite this, the role of normativity was clear. With the energy/IA participants the most common ways in which values ended up being discussed were in the following two contexts:

- The optimisation models include within them an explicit representation of some normative goal. This is incarnated either in the objective function which one aims to minimise or maximise. Furthermore, in the constraints of an optimisation one may set a number of acceptable limits, such as other forms of pollution or socio-economic impacts of policies.
- Normativity was understood to be something involved in decisions but not necessarily something to do with uncertainty in a scientific analysis.

Both are correct in terms of how they describe the role of normativity in modelling. However, this is not the whole story, as there are several different ways in which human values can find themselves represented in a model or in a scientific investigation. Table 6-4, below, details several mechanisms identified in the literature by which value-laden assumptions enter climate models.

Table 6-4: A collection of some of the ways in which authors describe value-laden assumptions manifesting in the processes around uncertainty quantification and analysis in climate modelling.

Location	**Value-ladenness**	**Reference**
Research Question	The influence of, for example, funding organisations is strong when deciding upon research questions or directions for model development	(Pulkkinen et al., 2022)
Model Verification	Representations of models can be considered adequate for cost–benefits purposes	(Morrison, 2014)
Model Tuning/ Validation	Graphical methods to compare model results require subjective choices of the adequacy of fit. This subjectivity may include value-ladenness	(Morrison, 2014)
Model tuning/ Validation/ Parameterisation	Some uncertainties (e.g., experimental uncertainties) are considered free parameters in model fitting. This may represent the particular interest of the modeller.	(Morrison, 2014)
Interpretation of Results	The interpretation of the meaning of results	(Pulkkinen et al., 2022)
Model Structure	Structural Choices in models reflect modellers perceptions of issues around inductive risk	(Winsberg, 2012)
Overall Process	Models are developed over time to be optimised for particular kinds of task that are valued by the research community. E.g., recreation of past temperature trends.	(Winsberg, 2012)

Participants understood many of their decisions regarding what kind of modelling agenda to pursue to be related to personal interests and non-epistemic values, though were not explicit about the mechanisms by which normativity enters a model.

Investigating how non-epistemic or contextual values permeated the model process is challenging as the role of subjective judgements is ubiquitous. However, as Morrison (2014) argues, we should not assume that contextual values have played a role just because a subjective judgement has been made. Other pragmatic considerations require subjective judgements, such as the availability of methods, or chance considerations, such as the modeller's familiarity with a technique, may play a role and were evident in interviews.

6.4.4 The Wider Context

6.4.4.1 Disciplinary Training

The conceptual toolbox that modellers have will affect their conceptualisation of uncertainty. For example, the prevalence of ideas about state/phase spaces in some disciplines may provide a flexible set of concepts that can be used to think about all kinds of uncertain information. The differences between participants with economics, engineering and natural science backgrounds could be distinguished. However, it was not possible from these interviews to delve much deeper than this into the effect of specific fields.

6.4.4.2 The Research Community

The wider research community and the set of institutions (e.g., the literature base, journals, conferences, consortia) of which it is composed may change the uncertainty analyses incentivised or disincentivised. This will have a role in deciding priorities for model development.

6.4.4.3 Funders

Funders have more of a role in deciding thematic priorities for model development and less in determining the kinds of uncertainty that one engages in. Nonetheless, there is an indirect influence as funding can come with stipulations for how closely researchers much adhere to research plans; often uncertainty analysis requires a certain amount of exploratory modelling work to be conducted which cannot be easily built into funding proposals.

The funding for climate modelling is more perennial than energy and IA modelling. This reflects the longer cycle time of model development that lines up with the approximately 6-year period of the IPCC process.

Recently, a significant amount of funding in the IAM space has been available through the EU's Horizon-2020 programme. A stipulation of this funding has often been the creation of large consortia of model groups[50]. Some participants claimed that the close interaction of these model groups was creating a convergence in methods and approaches.

[50] See for example: NAVIGATE (EIEE, 2019), PARIS REINFORCE (2021), ECEMF (2022), MEDEAS (2022)

6.4.4.4 Policymakers and Other Stakeholders

Participants did discuss the kinds of information demands that policymakers had. However, it seems that the needs of policy audiences did not so much alter the approaches to uncertainty used within a modelling process, but instead altered uncertainty communication. For example, whether probabilistic statements should be attached to uncertain outcomes.

Different participants varied in their understandings of the technical sophistication of policymakers. However, the most prevalent way they were invoked is in the form of the *scarecrow policymaker*, a crudely characterised version of what a policymaker wants.

6.5 Understanding Models in Their Contexts

This chapter and the previous two chapters of this thesis have described how in the disciplines of energy/IA modelling and of climate modelling, the factors that influence how uncertainty is handled are not necessarily purely epistemic. They include factors from within the local context in which modelling is performed and from without the modelling communities. For example, the availability of modeller labour time may constrain the amount of effort that can be expended getting an uncertainty analysis technique to work.

Having described this general issue, I now wish to consolidate this understanding in such a way as to allow me to make recommendations.

Here I deploy several ideas from Actor-Network Theory. I do so more in an instrumental fashion, using ANT as a tool rather than as an ontology, as with other researchers such as Cordella & Shaikh (2006).

6.5.1 The Key Interaction: Modeller and Model

When considering how uncertainty is investigated in a model, the interaction of immediate importance in the interviews is that between the modeller and their models. The most obvious way of conceiving of this interaction is of the modeller manipulating their model. However, the models themselves influence the modellers.

Firstly, due to path-dependent decisions made over a model's lifetime, models are only easily manipulable in specific ways. For example, a model may have been built to accept certain scenario inputs in a particular file format. It may also be easy to change the parametric settings of a model using a configuration file. Some models may even permit stochastic parametric inputs. This inscription of uncertainty practices into the model structure stabilises these practices.

The models discipline the modellers into handling their uncertainty in a particular way. Imagine, say, a modeller believes that an unknown parametric quantity lies within some range. To explore the effect of this uncertainty on the model the modeller requires some way of inputting this range into the model, which may be achievable by running the model multiple times with parametric settings chosen within the range.

Uncertain questions that a modeller may have must be translated in some way so to be represented in the language of the model. In this process of translation, some essence of the original meaning may be lost, as the question as represented in the grammar of the model may not perfectly represent the question as formulated in the mind of the modeller. Law (2008) notes that in actor-network theory, the idea of *translation* implies a sense of betrayal (*trahaison*) of the original communication.

Often the uncertain outcomes and options we wish to assess may have a qualitative nature. To be communicable through the model they must be shepherded into quantitative scenario descriptions of these questions.

Models also influence modellers in deeper ways. To interact with a model, many of my participants underwent specialist training and to acquire the kinds of tacit knowledge necessary to deal with its quirks and idiosyncrasies.

6.5.2 Models Interact with Their Contexts

Complex computer models shape their contexts in the actor-networks they live in interesting ways.

To run and remain up to date, they require maintenance from specialists, trained on using the models. Divisions of labour around the management of the models arise to most efficiently manage the production and analysis of model results.

Models also require specialised technical infrastructure. This is particularly true as models become more complex and require access to HPC facilities (Maslin and Austin, 2012; Osprey, 2021). Repeatedly in interviews, this availability of computing resources was a key constraint on model expansion.

Those invested in the success of the models will also seek out additional resources such as HPC capacity and the funds for it. They may strategically represent the capabilities of the models to funders and decision-makers. Models have an influence; as teams become invested in the success of their models, they advocate for their continued operation to funding organisations. There is a rhetorical burden to show how the models are relevant to and suitable for addressing uncertainties and policy-relevant questions.

Although I did not directly observe this strategic representation of models, I identified how senior members of their teams would advocate for the utility of their models in funding rounds and to policymakers. This effect has been described in the past by authors looking at the science–policy interface (Lahsen, 2005; Shackley and Wynne, 1996, 1995)

All this shows that as models develop, the actor-network that supports their continued operation increases in density. These complex computer models become embedded in their context.

6.5.3 Thinking Biologically

It is perhaps not too farfetched to think biologically about the nature of the models studied here. A crude understanding of models can see them eating data and excreting results, but the analogy with the functions of life goes deeper.

Winsberg (2003) argues that Hacking, Cartwright, Giere, Morrison and Morgan have shown that models function semi-autonomously from theory. Winsberg goes further and claims that models have ‘a life of their own’. The techniques, practices and assumptions that go into producing simulation models are credentialed by tradition. They are ‘self-vindicating’ as their success over time adds to the weight of their credibility.

Models play roles within the wider research communities. Climate models are all unique, though they all share commonalities in terms of the kinds of experiments they run and the ultimate results that researchers are interested in obtaining. The shared epistemic standards to which they are all held is mutually reinforcing – almost symbiotic.

Energy models and IAMs are more specialised for particular purposes when compared with climate models. The results they produce are often incomparable and the purposes for which they are developed are non-standardised. Thus, they can specialise in niches.

These specialised roles and the deepening of the socio-technical infrastructure around the models is analogous to the concept of 'niche construction'. In biology, the concept of 'niche construction' is where an organism alters its environment to support itself and produce a niche that is mutually beneficial for it and other organisms (Laland et al., 2016). This occurs as models live symbiotically with their environment, building research infrastructures around themselves that permit their continual reformation and operation.

6.5.4 Implications of Uncertainty Analysis

Understanding that models shape the context for their own justification is useful as we know that there may be a misalignment between the uncertainties that appear most salient in models and those most salient to real-world decision making. McDowall et al. (2014) note the prevalence of certain parametric uncertainties in UK Energy modelling studies, despite a lack of clarity as to whether results are necessarily particularly sensitive to these parameters and not others. To explore difficult and broad research questions, we must think about how we can ensure that models are not unassailable within the research communities that we construct.

This problem involves limiting the path dependencies and limiting the core complexity of the models that we use so that they can be readily adapted to a range of purposes.

Uncertainty exists due to the interaction of epistemic agents and their environments and models. Paying attention to the constrained nature of these interactions shows us how uncertainty analyses can be improved and made more comprehensive.

6.6 Limitations of the Study

I now examine limitations of this study in two ways. Firstly, I use a heuristic called the *Total Quality Framework* to guide my discussion of the benefits and disbenefits of the method and analysis techniques employed. Using this framework, I consider the limitations of my answers to each of the research questions posed by the thesis. The hope is by purposely adopting the multiple perspectives, I can create a holistic image of the value of this study and its limits.

The total quality framework in a system is composed of four interlocking components (credibility, analysability, transparency and usefulness) intended to help one assess the quality of qualitative research (Roller and Lavrakas, 2015). *Credibility* assesses how complete and accurate the data collected is. *Analysability* considers the quality of the analysis conducted and the interpretations thereof. I examine each of these in turn. *Transparency* assesses how rich the descriptions of the analysis are and the extent to which readers can determine applicability for themselves. *Usefulness* cuts across the other and relates to the value of the outcomes. I shall address each of these in turn, and I focus on the study's utility for answering my research questions.

6.6.1 Credibility

6.6.1.1 Sample

The sample size that I achieved was sufficient to ensure that conceptual exhaustion was experienced by the end of the interviews. However, there are multiple ways in which the structure of the sample could have been otherwise. The most obvious shortcoming of the sample is the asymmetry in the number of participants between those in energy/IA and climate. This is partially explicable by my personal professional networks being more deeply rooted in energy and integrated assessment. Furthermore, additional sampling in the climate space was not pursued due to the relative agreement in conceptualisations observed amongst these participants.

During the interviews, it became apparent how the different roles of participants were salient in understanding their relationship to uncertainty analyses. For example, those working at the coalface of model development may be only concerned with the uncertainty in some small aspect of a model. It was also noted that senior researchers tended to have a broader understanding of uncertainty concepts than more junior researchers. The sample did include a good diversity between these different categories with a range of seniorities and roles interviewed.

6.6.1.2 Data Gathering

I have noted in this chapter the relative paucity of discussions about the uncertainty that related explicitly to participants' confidence in their specific results[51]. This could be related to aspects of the interview protocol and that I asked generally about uncertainty and not specifically about individual things that a researcher may be uncertain about. This may limit my ability to discern the relationship between types of uncertainty and confidence in results. For example, do different kinds of uncertainty cause researchers real discomfort with their results?

Suppose my intention had been to probe the relationship between researchers' beliefs and their propensity to use different kinds of uncertainty statements. In that case, I could have employed a research design that involved working with researchers to interrogate specific results. Perhaps I could have brought some of their research outputs to the interview to explore specific uncertainties. However, I purposely did not wish to talk about individual outputs as such an approach could have been interpreted as critical and I was cautious not to elicit defensive responses.

6.6.2 Analysability

6.6.2.1 Processing

Transcription was conducted manually by the interviewer for several reasons. Firstly, I transcribed most of the interviews after returning from secondment to the UK government. This was an invaluable opportunity to re-immerse myself in the data. Secondly, much of the discussion was technical, and it was anticipated alternatives to manual transcription by the researcher would not capture this complexity. Finally, I wished to transcribe the interviews in such a way as to capture some of the vocal cues that indicated uncertainty. In this way, I could be more sensitive when a participant was not confidently expressing existing opinions.

The transcripts were densely coded using the scheme described in the methodology. Coding the transcripts for individual concepts was powerful, and the tools in NVivo were useful for

---

[51] A doxastic interpretation of uncertainty.

comparing transcripts. However, coding the qualitative relationships between concepts was more difficult to achieve. I believe this shortcoming is at least partially mitigated using other analysis tools, such as the one-page summaries of each of the interviews (see Appendix F) and the journaling of themes.

6.6.2.2 Verification

Verification was performed to a certain degree using multiple analysis methods of coding, summarisation, and journaling. Other forms of verification, such as using multiple researchers were deemed unsuitable as the analysis of the concepts used by participants is inherently interpretative. Thus, I was the only researcher to conduct the analysis for consistency.

6.6.3 Transparency

To provide you, the reader, with the most transparent account of the interviews that preserves the pseudonymity of the participants I have provided the interview summarises in Appendix F. I have also made use of extensive quotes from the interviews. I hope that the two chapters preceding this one, alongside the methodology, have given a thick description of the method and analysis that would be repeatable for other researchers interested in exploring this topic area.

6.6.4 Usefulness

The first set of research questions concerns the conceptualisation of uncertainty and what concepts are used to structure participants' understandings of uncertainty. In this aspect of the study, the literature review proved an essential toolkit in identifying the differences between uncertainty conceptualisations of participants.

Uncertainty is a wide-ranging topic; it was impractical to include within the interview every possible related concept. To gain access to participants, some cap on the time of the interview needed to be established. Typically, this was around an hour. Thus, there are natural omissions of fruitful areas of discussion from different interviews.

Part of my argument throughout this thesis is that *uncertainty* has become in some ways nebulous. Uncertainty is concerned with all manner of epistemic issues. However, discussions about these issues are flattened if they are merely labelled as *uncertainty* and do not receive individual treatments. Discussions of uncertainty in the context of modelling have become unproductive due to a lack of clarity about the precise epistemic and methodological issues involved, and a lack of reflection on how people experience uncertainty and the tools they use to understand it. Thus, the topics discussed in this thesis are adjacent to many other issues in modelling. There are perturbations to the methodology employed here that could either explore the conceptualisation of uncertainty in different ways or explore related concepts, such as scenarios. Therefore, there is a quandary when attempting to cut such a Gordian knot of what plane to slice through.

Amongst the concepts that emerged in the interviews that could have been explored in greater detail but lay beyond the scope of the study were: model verification, sensitivity, consensus and probability.

The later interview questions concerned the factors that influence uncertainty conceptualisation and practices. Here the methodology has revealed several dynamics at play. Though undoubtedly there are more relationships linking conceptualisations of uncertainty and practices. To understand these dynamics, we must appreciate the contingent history of the co-development of uncertainty handling practices and conceptualisations, the recounting of which is beyond the scope of this thesis. However, as part of the literature review, some of the tantalising threads of this story can be seen to emerge.

Frequently during the interviews, participants invoked ideas about how policymakers understood forms of uncertain information provision. For example, some believed that policymakers were best served with the provision of probabilistic information over scenario sets. Whilst some participants did have personal experience, many were not proximate to the policymaking process. Thus, the policymaker was little more than a stylised character in their imagination.

Examining the science–policy interface was outside of the scope of this study. However, research could delve deeper into this characterisation of policymakers in the minds of scientists and understand the range of opinions about who policymakers are and what their demands are. There could even be an opportunity for a comparative piece that compares scientists' beliefs about the needs of policymakers with the actual needs as they are presented.

6.6.5 Summary

In summary, the most salient limitations of this study exist due to the need to find compromises to several methodological tensions:

- Exploring a wide of range of concepts vs. constructing a deep understanding of the key concepts employed to explore uncertainty. This tension is created by the practical need to keep interviews at a reasonable length.
- Encouraging participants to discuss uncertainty concepts on their own terms vs. ensuring that similar concepts are discussed in interviews. This creates a challenge for analysis.

In each of these tensions, I have endeavoured to navigate an appropriate course to answer the research questions that I have defined in this thesis. Deviations from this line show the opportunity for extensions to this study or other lines of inquiry. I shall discuss recommendations for future research further in the concluding chapter of this thesis.

6.7 Chapter Summary

This chapter began by documenting the similarities and differences between the conceptualisations of uncertainty found in the interviews with climate and energy/integrated assessment modellers.

Throughout this chapter, three key themes have emerged.

The first concerns the uncertainty concepts used by modellers. The literature contains a plethora of ways of understanding uncertainty and classifying it. Despite this diversity, the most prevalent way of discussing uncertainty was by its *location*. Other concepts were used, such as *deep uncertainty*, but not always in ways consistent with the literature. It is also notable that participants did not talk about uncertainty in multi-dimensional ways, preferring to discuss one aspect of uncertainty at a time.

The second theme identifies the structural differences in the disciplines that create the differences in handling uncertainty. The most obvious and primary difference between the disciplines is that the fundamental nature of the systems that they study is very different. One system is a natural system governed by physical laws and the other involves coupled socio-technical systems, including reflexivity. Naturally, there will be different analytic repertoires as a result. However, beyond this, there are other structural factors that are not only purely epistemic but determine the shape of uncertainty analyses.

The final theme is the story of actants and path dependencies. Models influence the way that researchers interact with them, and they reform the environment around them to serve their needs. To understand what it means for a model to be uncertain we must pay attention to this socio-technical context. Uncertainty in a model is relative to some purpose and the purpose of the model may be ambiguous due to the need to justify its existence. Therefore, the understanding of uncertainty in a complex computer model has an inescapably rhetorical aspect.

In the next chapter, I examine these themes in a different topical domain – epidemiology. In two brief chapters, I examine the state of uncertainty conceptualisation in epidemiology and use this as a lens to reconsider these key themes of my findings. This will furthermore allow me to consider the generalisability of these findings to other study areas involving complex computer models.

7 Towards an Uncertainty Taxonomy for Epidemiological Models

For a period during the COVID-19 pandemic, I was seconded to the UK Government's Joint Biosecurity Centre (JBC, now part of UK Health Security Agency – UKHSA). During this time, I was involved in a number of issues involving epidemiological modelling. Partially as the result of coincidence, and partly by design, I came to work on issues very similar to those I had been grappling with in my doctoral studies: issues of model uncertainty and evidence quality.

Reflecting on these ideas from climate and the epidemiological environment I was working in, I subsequently wrote these two chapters concerning the conceptual and philosophical issues involved in epidemiological modelling.

I include these chapters here in the thesis for three important reasons.

Firstly, these chapters provide an opportunity to reflect on and strengthen the three key themes that have emerged through this thesis. They provide additional insights that helps consolidate the ideas and understand better the role that uncertainty thinking has played around the problem of climate change. I clarify below on what aspects each of these chapters shines a light.

The second reason is that the production of these chapters has aided my thinking. After I returned from my secondment to finalise the transcription and analysis of my interview data, the additional experience I had gained proved very useful in empathising with the experiences of the modellers I had interviewed. Consequently, I consider it important to recognise the value that thinking through these issues has had.

The third reason is that the interrogation of these findings in a different disciplinary context allows me to contemplate how generalisable uncertainty concepts may be and if the dynamics that I have identified as part of my third theme are present in other areas.

This first of two chapters considers the role of uncertainty in epidemiology. I review how uncertainty seeps into epidemiological models and the ways that uncertainty has been conceptualised in the epidemiological literature. I find that, in fact, epidemiology does not have a deep resource of ideas about uncertainty to draw upon in the way that climate and energy modelling do.

This chapter was written, in part, in collaboration with Greg Milne, an epidemiologist. Greg was chiefly responsible for drafting the original versions of what became 7.3.1 and 7.3.2, which describe the ways uncertainty can manifest into an epidemiological model. Greg also assisted in general editing of earlier drafts of the working paper that eventually transformed into this chapter. This contribution is stated *in Appendix G: Declaration Forms*.

I then consider how concepts from Integrated Assessment and environmental modelling could be adapted to create a dimensional framework tailored to epidemiology. This shows me that these concepts that emerged in IAM are highly adaptable to different contexts. However, ideas such as these are not already diffused into epidemiology. This may be the result of the history of the discipline.

The following chapter 8 concerns a case study of the creation of a Multi-Model Ensemble that I was involved in. It examines the philosophy of science literature that concerns MMEs and finds that it is very focussed on climate ensembles. I examine the case study of the MME in the light of this literature. In accordance with the third theme identified in this thesis, the socio-technical infrastructure into which the model is embedded is important to understand. I expand on this understanding and problematise the nature of this infrastructure.

Both chapters demonstrate the transferability of ideas developed in a climate and energy context to other fields. This underscores just how much fundamental thinking has taken place in climate and energy about uncertainty and the limits of our knowledge. Each chapter builds a richer understanding of the three emergent themes from the interview study and allows me to consider what aspects of my findings have some generalisability to academic computer modelling exercises. At the end of chapter 8, I return to considering the lessons of these chapters and how it improves the knowledge synthesis thus far.

7.1 Abstract

Since the advent of the SARS-CoV-2 (COVID-19) pandemic, epidemiological modellers have provided critically important policy advice to governments and decision-makers. Epidemiological models have come to be used for epidemic tracking more intensively than ever before with, urgent and emergent developments incorporated and with constant re-training of models on the latest data. Such work is, unavoidably and naturally, beset with uncertainty.

This chapter argues that the practice of uncertainty taxonomisation in policy-relevant epidemiology is pre-paradigmatic, without a settled conceptualisation of different kinds of uncertainty or a stable nomenclature. This chapter considers and adapts ideas from studies relevant to environmental change, that were reviewed in chapter 2 of this thesis, to examine the extent to which these ideas are transferrable between disciplines. It then reflects on best practices for model-based policy advice within this context and suggests routes forwards for robust model-based decision support.

7.2 Introduction: Assessing Model Quality for Policy-making

Understanding complex natural phenomena, such as spatially and temporally dynamic patterns of infection transmission, is a problem which lends itself to the use of mathematical and statistical models. Models can provide a useful framework to simplify these relatively complex natural systems into their constituent parts, allowing questions to be asked about the relative influence of different systemic aspects on key outcomes. In communicable epidemiological systems, these outcomes might include cases, fatalities and hospitalisations resulting from a particular infectious disease. In this respect, models are invaluable for estimating outcomes in the near- and short-term (often termed *nowcasting*) or in the medium- to long-term (forecasting), particularly in times of public health crisis.

Inherent to the development and implementation of epidemiological models are assumptions that attempt to distil a conceptual understanding of a coupled biological-social system into a mathematical and/or statistical formulation. Therefore, it is imperative to understand how the interplay of these two themes affects the quality of model inference and associated uncertainties. Ultimately, a robust understanding of how well the mathematical and technical formulation of a given model maps to the underpinning conceptual basis may have significant downstream effects on how conclusions are framed when providing policy advice. This, in turn, has profound practical implications for decisions made about the implementation of public health policies.

Since the emergence and spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in late 2019, models have played a pivotal role in numerous wide-ranging public health policy decisions and infection control strategies across the globe, including social distancing, quarantining, regional and local stay-at-home orders, and travel restrictions (see for example McBryde et al., 2020; UK Government, 2020). Therefore, it is of considerable importance to consider the process of model quality assurance which can ensure robustness of inferences and of associated uncertainties. By appropriately considering these various uncertainties during model development and analysis, researchers and policy-makers can be more aware of the potential caveats of methodological choices and, in turn, reflect this in public health policy decisions.

7.2.1 The Importance of Evidence Quality and Uncertainty Analysis

Decision-making theorists have long argued that decision-makers unaware of critical uncertainties are likely to make sub-optimal decisions (Morgan and Henrion, 1990). Transparent acknowledgements of uncertainty may also aid in avoiding certain pathologies of the science-policy interface. For example, in the communication between science advisors and policymakers, there may be a propensity to downplay uncertainties or transmute them into more manageable forms like ‘risk’ (Shackley and Wynne, 1996).

Following Christley et al. (2013) and Wynne (1992), I do not claim that there is any really existing and knowable uncertainty in the real world, or at least if there was, that information would be unlikely to be accessible to us. Consistent with the analysis of this thesis, I note that one can conceptualise uncertainty as existing in many loci: as subjectively assessed qualities of our models, as psychological states and as the result of social construction.

As discussed in chapter 2, many fields that deal with high consequence decision-making about interventions in complex coupled systems have produced uncertainty frameworks. These have been used variously to provide grounding for decision-making (Morgan and Henrion, 1990; Walker et al., 2003), to identify the appropriate methodologies for uncertainty analysis and quantification (Ricci et al., 2003; Stirling, 1998), to align work with normative values like transparency (Hamel and Bryant, 2017b), to identify routes for improvement of models through further research and development, to ensure the semantic consistency of key terminology and to aid communication from scientists to decision-makers and lay audiences (Fischhoff and Davis, 2014; Petersen et al., 2013; van der Bles et al., 2019).

Given the volume of work that has gone into considering uncertainty in fields dealing with environmental change, to what extent do these have applicability in other fields working on natural-social systems? There may be significant utility in drawing concepts from these fields. Despite the urgency with modelling may be conducted, epidemiological modellers benefit from characterising the uncertainty present in their work in multifaceted ways. This is particularly true when modelling informs policy-making on highly consequential issues, such as pandemic mitigation.

7.2.2 Structure

Section 7.3 explores the uncertainties inherent in epidemiological modelling. The analysis here acknowledges how the term 'model' may reference multiple conceptual objects. I consider in turn uncertainties associated with the different 'layers' by which one can imagine a given model consisting: a conceptual model, a mathematical formulation and a technical implementation of the model. Uncertainty manifests in the modelling process in different ways and these uncertainties may have complex interactions.

Section 7.4 then examines the status of uncertainty handling for epidemiological modelling by examining the uncertainty quantification (UQ), uncertainty analysis (UA) and uncertainty taxonomisation/categorisation techniques most employed. It argues that, although various UQ and UA techniques are ubiquitous, they lack a synthesis into commonly accepted conceptual frameworks that might allow researchers to better account for the full spectrum of different kinds of uncertainties present when producing model results intended to inform policy-making. Unlike fields dealing with environmental change, the challenge for synthesis is not the profusion of different conceptual frameworks, but the dearth of thinking abstractedly about these issues.

Section 7.5 then draws on ideas from climate-related studies, suggesting a framework for taxonomising uncertainties in epidemiological models for policy advice. This framework considers different *dimensions of uncertainty* and includes an uncertainty matrix for mapping them. Such an approach gained popularity in environmental sciences after Walker et al. (2003) and has seen a fruitful development by many authors working in fields relating to decision-making and environmental change subsequently (Knol et al., 2009; Kwakkel et al., 2010; Petersen, 2006; van der Sluijs et al., 2005). As I explain each dimension, I reflect on the limits of the applicability of the concepts outside of the context of their initial use.

In Section 7.6 discusses the implications of a fulsome accounting of uncertainty in epidemiological modellin. It considers what this relocation of concepts that have thewir origin in fields concerned iwht environmental change tells us about those concepts.

7.3 Uncertainties in Different Model 'Layers'

This section examines some of the ways uncertainty may manifest in epidemiological modelling. When defining a model to represent a natural system, one can loosely describe a model being manifested in different forms: *conceptual* (an abstracted view of a complex reality), *mathematical* (a mathematical description of a conceptual model) and *technical* (the implementation of the model in computer code) (see for more detailed discussion Petersen (2006) §2) presenting the uncertainties as distinct layers that cascade into one another in this way is a simplification. Indeed, the philosophy of science literature contains many nuanced distinctions around how models can be understood ontologically, their purpose, and the relationship between models, data and theory (Frigg and Hartmann, 2020). Nonetheless, I present these 'layers' in a way that a modeller may intuitively understand them, and therefore, be of greater utility.

7.3.1 Conceptual Model

The conceptual model is concerned with how well the defined model represents the current conceptual understanding of the system. I outline two examples of how uncertainties are manifest in the conceptual models in the conceptualisation of group-specific effects.

Age often features in the conceptual models of many pathogens. For example, for a simple compartmental model of disease transmission (where individuals are grouped according to their infection status), one could ask whether the model adequately represents the effect of an individual's age on both the likelihood of infection and the severity of disease. For models of pathogens with highly age-specific effects, such as SARS-CoV-2 (O'Driscoll et al., 2021), not accounting for the influence of age on the model's outcomes would represent a flaw in the conceptual model with potentially dramatic consequences on the conclusions drawn. Regional effects are another policy-relevant factor to consider, especially when trying to inform how public health interventions should be most efficiently distributed across a given country (Della Rossa et al., 2020; Scala et al., 2020) or internationally (Ruktanonchai et al., 2020).

This shows that an inadequate representation of the conceptual model or the particularities of assumptions made can have a marked influence on the quality of evidence derived from epidemiological models and policy decisions. Often a decision must be made as to the relative importance of these various group-specific effects to make the conceptual model's implementation computationally tractable (see Section 7.3.3). For example, age effects might be traded off against the inclusion of regional effects in a model, or vice versa, depending on the prioritised policy or research questions. Therefore, the choice of conceptual framing will introduce uncertainty that propagates through the mathematical and technical models (see section 7.5.2).

7.3.2 Mathematical Model

A mathematical model is the mathematical realisation of a conceptual model and provides an opportunity for understanding through the formal manipulation and variation of model elements. However, the mathematical representation may require additional assumptions to render a conceptual understanding in equation form.

Consider the example for age in a simple 'SIR' model. Suppose age is a crucial aspect of the rate of infection of a given pathogen, as well as the rate of recovery, then the model should reflect this. To give a simple example, for a given population, undergoing an outbreak of a directly-transmitted pathogen, comprised of susceptible individuals, S, infected (infectious) individuals, I, and recovered (immune) individuals, R, with force of infection, λ, and rate of recovery, γ, one can define the rate of change in each of the sub-population compartments as

$$\frac{dS}{dt} = \mu_B + \delta R - \lambda SI - \mu_S S \quad (1)$$

$$\frac{dI}{dt} = \lambda SI - \gamma I - \mu_I I \quad (2)$$

$$\frac{dR}{dt} = \gamma I - \delta R - \mu_R R \qquad (3)$$

where μ_B represents the birth rate, μ_S, μ_I and μ_R the mortality rates for susceptible, infected, and recovered individuals, respectively, and δ defines the rate of waning of protective immunity (where $1/\delta$ = the duration of immunity). In this basic SIR model, some simplifying assumptions have been made that may not be in keeping with the conceptual model of a given pathogen. For instance, we know that many infectious diseases exhibit age-specific infection patterns, but this simple model does not account for these effects. Also, in its current formulation, this model presumes equal probability of death across all age groups. This conceptual information could be included by modelling different functional forms of λ_a over age and by using demographic data to infer age-specific patterns of mortality.

Thus, uncertainty is inherent in this formulation, and when defining such a model it is of paramount importance to consider whether the mathematics is in keeping with the conceptual understanding of the target system.

7.3.3 Technical Model

The technical model is concerned with the programmatic implementation of a given mathematical or statistical model in computer code. In moving from a mathematical to a technical model, several additional simplifying assumptions often must be made to distil relatively complex natural phenomena into a technical formulation and allow for computational tractability. If chosen wisely, simplifying assumptions allow for the core dynamics of the system to be captured. On the other hand, omitting simplifying assumptions can lead to over-fitting, making conclusions ungeneralisable to the wider context. This issue could have significant downstream consequences for models that are often re-purposed to answer questions in rapidly evolving contexts. Ultimately, a balance must be struck between computational tractability, generalisability, and capturing the inherent complexity of the system (Korsbo and Jönsson, 2020).

In writing code, errors may be introduced. These can be reduced by adopting best practices and thorough systematic code reviews. Different programming languages themselves may be amenable to achieving particular simulation tasks. For example, the STAN computer language has seen widespread epidemiological use due to its ability to conveniently handle Bayesian models and Markov-Chain Monte-Carlo (MCMC) processes (Chatzilena et al., 2019).

The discretisation of mathematical equations both temporally and spatially may introduce uncertainties as the continuous nature of reality is transformed into something computationally implementable. These errors may be reduced or transformed by using smaller spatio-temporal intervals, however, this may run up against the limits of computational power and the practicalities of model run-time. Some of these problems may be overcome using high-performance computer facilities (HPCs) and cloud-based computing servers.

As was clear from the interviews with climate and energy/IA modellers, detailed in chapters 4 and 5, the possibility of employing certain uncertainty quantification (UQ) and analysis (UA) techniques can also be limited by issues of computational practicalities. Many of the techniques employed in epidemiology have analogues in energy and climate studies and therefore encounter similar issues. Models with long run-times, such as agent-based models (ABMs), may not be amenable to fitting procedures involving exploration of all corners of their parameter space, as performed in Monte-Carlo analysis. Computational techniques may be introduced to reduce computationally onerous random sampling from joint probability distributions to instead use near-random sampling techniques such as Latin Hypercube sampling (LHS) (Blower and Dowlatabadi, 1994; Seaholm et al., 1988). Alternatively, computationally burdensome sub-modules may be replaced with emulators (Andrianakis et al., 2015). Thus, the assumptions made as part of the conceptual model determine that model's mathematical and technical expressions, therefore determining the range of techniques applicable for the analysis of the uncertainties associated with model estimates.

7.4 Uncertainty Handling in Epidemiology

The rapid timelines of model-based epidemiological research during a pandemic unavoidably constrain the comprehensiveness of analyses of model-based uncertainty. Governments worldwide have made use of epidemiological models and ensembles of models assembled in short order and in new fashions (see for example Dean et al., 2020; Ray et al., 2020). Nonetheless, several different uncertainty analysis techniques are routinely employed in both the pre-pandemic and within-pandemic literature. I argue that conceptual consensus over *the types of uncertainty* encountered is currently weak despite a diversity of techniques employed. I briefly overview the uncertainty handling` in epidemiology in three parts: uncertainty quantification, uncertainty analysis techniques and uncertainty conceptualisations.

7.4.1 Uncertainty Quantification

Various techniques for parameter estimation and UQ are well established in the epidemiological literature, with the techniques chosen depending on the type of model employed, such as compartmental models or ABMs (Capaldi et al., 2012). Parameter estimation is important when modelling emergent infections as not all decision-relevant parameters can be directly measured or otherwise calculated accurately or precisely. Instead, models must be fitted to data such as incidence rates, prevalence and mortality rates (Capaldi et al., 2012; Lloyd, 2009). Hence UQ can give estimates of the uncertainty associated with this parametric fitting process and can be subsequently used to characterise uncertainty associated with further estimates derived from running the fitted models in a forecasting mode. The range or distribution of a parameter setting resulting from this uncertainty quantification may vary depending on the technique employed. For example, fitting a model using a Bayesian technique like MCMC involves sampling other parameters in a model over their pre-specified ranges ('priors') while iteratively fitting the desired parameter within the model. Hence the resulting 'posterior' distribution represents some of the uncertainty due to the prior existing uncertainty in the parameters fit.

Other techniques for simpler model fitting and UQ exist such as Ordinary Least Squares (OLS) or Generalised Least Squares (GLS) and then quantification around this fitting can be performed with other statistical techniques (Capaldi et al., 2012). Various Bayesian and non-Bayesian methods (e.g., maximum likelihood) are also regularly used (Hazelbag et al., 2020; Taghizadeh et al., 2020) (see also discussion in §8.4)

The numerical range associated with parametric fitting does not necessarily represent the totality of the parametric uncertainty in the system. Other uncertainties may escape the UQ process. For example, *parametric identifiability* issues (Capaldi et al., 2012; Cobelli and DiStefano, 1980) occur when multiple parametric sets are observationally equivalent. This may be a problem in situations where there is a high-dimensionality to the parametric sets being chosen. This can be examined through techniques known as *identifiability analysis* (Cobelli and DiStefano, 1980).

7.4.2 Other Uncertainty Analysis Techniques

Not all uncertainties are amenable to quantification. Some other techniques are used to otherwise interrogate the characteristics of a model or to describe uncertainty, examples of which are detailed here.

Scenario Analysis, the topic of much discussion in energy/IA studies, is also employed in epidemiology. It has been employed in both contingency planning (Chowell and Castillo-Chavez, 2003; van Genugten et al., 2003), and during epidemics to consider the range of futures stemming from policy actions (Barbarossa et al., 2015). Scenario analysis has been prominently used during the COVID-19 pandemic, as models have been used to evaluate different mitigation strategies (McBryde et al., 2020; Pinto Neto et al., 2021; Reiner et al., 2021).

Sensitivity Analysis can allow modellers to understand how to apportion the uncertainty in a model output to different aspects of the model (Saltelli, 2002). Sensitivity analyses vary in the sophistication of their methods and the variety of assumptions that need to be made (Ding and VanderWeele, 2016), and, as I identified in chapter 6, some sensitivity analyses can border on scenario analysis. More sophisticated analyses leverage various statistical techniques to explore the effect of changing parametric settings by sampling in structured ways from plausible ranges of parametric settings. For situations of high parameter space dimensionality, various dimension-adaptive techniques exist (Edeling et al., 2021).

In some situations, a model may be coded such that it may be possible to explore the effects of perturbations of model structure on outputs; thus, sensitivity analysis can be extended to model structure. For example, Lloyd (2009) explores the characteristics of different possible SEIR models by varying the numbers of compartments for *Exposed* and *Infected* individuals. However, the nature of programming will naturally prohibit many models from varying structure so conveniently, and hard-coded changes may be necessary. The difficulties in conceiving the systematic variation in model structure will be discussed in the following chapter.

Multi-Model ensembles (MMEs) allow the exploration of the effects of different possible model structures on outcomes (den Boon et al., 2019). Most simply, they draw together the results of simulations with different models and compare the results. The conceptualisation of MMEs and their employment in different contexts is the subject of the case study in chapter 8. MMEs have been constructed to model and monitor the COVID-19 pandemic (Panovska-Griffiths et al., Forthcoming; Shea et al., 2020), as well as infections as varied as HIV (Eaton et al., 2014), Influenza viruses (Reich et al., 2019) and Ebola virus (Chowell et al., 2020; Roosa et al., 2020; Viboud et al., 2018).

7.4.3 The Conceptualisation of Uncertainty

Each of the techniques outlined above explores the uncertainty inherent in the modelling process in different ways. As different techniques examine different kinds of uncertainty, it is important to acknowledge how uncertainty is conceptualised. In any given modelling exercise for policy support, a wide variety of uncertainties may be present, and these may be taxonomised in different ways. Table 7-1 gives examples of the types of uncertainty described by several different authors in the epidemiological modelling literature.

Table 7-1 Some examples of uncertainty distinctions made in epidemiological modelling literature.

Reference	Types of Uncertainty	Note
Edeling et al. (2021)	Parametric Uncertainty, Model Structure uncertainty, Scenario Uncertainty	The authors, citing non-epidemiological literature, describe this tripartite description as common.
D'Agostino McGowan et al. (2021)	Data Uncertainty, Stochastic Uncertainty and Structural Uncertainty	The authors describe data uncertainty being in model parameters and due to sampling from distributions or incomplete observations; Stochastic uncertainty arises from Monte-Carlo inference or from stochastic processes in disease transmission; Structural Uncertainty is associated by the authors with model choice
Chowell (2017)	Uncertainty in parameter estimates	The author describes parametric uncertainty as having two sources: (i) noise in the data (ii) underlying assumptions in the model. I note that other literature might typically consider model structure uncertainty separately to parametric uncertainties
Gilbert et al. (2014)	Parametric Uncertainty and Uncertainty in Model specification	The paper focuses primarily on parametric uncertainty. As part of their discussion, they describe how uncertainty in the model specification would be expected to further increase the uncertainty of model predictions.

Foss et al. (2009)	Inherent or Natural Uncertainty, Structural Uncertainty, Parametric Uncertainty	The authors describe this as coming from the broader medical or bio-science literature, and not from epidemiology specifically
Lloyd (2009)	Parameter-based uncertainty and Model-based uncertainty	The chapter primarily discusses methods of exploring parametric uncertainty but acknowledges the importance of model-based uncertainty.
Coelho et al. (2008)	Parametric uncertainty from multiple sources	The authors describe parametric uncertainty stemming from both issues of measurement (lack of data, measurement error, sample variability) and from the intrinsic variability of parameters (as inadequate representations of underlying stochastic processes)

Most prominently, the epidemiological literature focuses on *parametric* uncertainties that have their source in data uncertainties (D'Agostino McGowan et al., 2021). The term *uncertainty* may be erroneously used to reference quantified parametric uncertainties specifically. Other forms of uncertainty may be variously conceptualised as *structural* uncertainty or *model* uncertainty. Occasionally, *scenario uncertainty* may be conceptualised as another form of uncertainty. These characterisations are inconsistent in the literature and explicit taxonomies of model-related uncertainties are not commonly given. This perhaps reflects a lack of consensus over the conceptualisation of uncertainty. I have previously noted a lack of consensus in climate and energy/IA, with a crowded space of concepts all vying for attention. In the case of epidemiology, there are not such a plethora of ideas about uncertainty in use.

For modelling tasks that intend to inform and support policy-making, a broader palette of uncertainties is salient beyond the *parametric/structural/scenario* distinction. For example, modelling may respond to a particular policy question; the variable possible interpretations and framings of the policy question by a modeller may significantly alter model outputs.

As demonstrated in Section 7.3, uncertainties exist within modelling for different reasons and are manifest in different stages of the modelling process. Only showing quantifiable uncertainties will likely produce over-confident assessments as other uncertainties remain hidden and important information relevant to decisions may be omitted. Others have noted the importance of exploring not only parametric forms of uncertainty and have also made explicit links to practices of other fields such as climate modelling. Edeling (2021) emphasises the importance of communicating these different kinds of uncertainty to policymakers. The following section draws on practices from climate, energy/IA and other fields dealing with environmental change to consider some of the ways in which uncertainty can be classified and if these ideas have wider applicability

In summary, epidemiologists employ various uncertainty analysis techniques that explore several aspects of uncertainty. However, overarching conceptual frameworks to categorise uncertainties are not currently a routine feature of epidemiological practice. The literature base is far less extensive than in

7.5 A Framework for Uncertainty in Epidemiological Models

Having surveyed some of the various ways uncertainties can manifest in epidemiological models, and how uncertainty is commonly investigated and characterised, I undertake an exercise to taxonomise uncertainties. Over the past decades, several fields that deal with high-stakes modelling of coupled systems for decision-making, such as climate change mitigation and adaptation, have created extensive taxonomies for assessing uncertainties. The extensive review of these typologies detailed in chapter 2 finds that although many concepts have been deployed, recent thinking has settled around understanding uncertainties along key *dimensions*.

I now consider how these ideas can be adapted into a new context and propose a similar framework for use in epidemiological modelling. Such a style of framework can ultimately be traced back to the approach of Walker et al. (2003) and has been variously adapted and altered by many authors (Knol et al., 2009; Kwakkel et al., 2010; Meijer et al., 2006; Petersen, 2006; Refsgaard et al., 2007; van der Keur et al., 2008; Warmink et al., 2010). The different dimensions of uncertainties assessed by the framework are discussed in turn.

7.5.1 Nature

The Nature of uncertainty is perhaps the most abiding distinction that is made in the literature. Terms such as 'Knightian risk', 'variability', 'aleatoric uncertainty', 'ontic uncertainty' and 'stochastic uncertainty' have been distinguished from 'Knightian uncertainty', 'knowledge uncertainty', 'epistemic uncertainty', and 'ambiguity' (e.g. Einhorn and Hogarth, 1986; Ferson and Ginzburg, 1996; Paté-Cornell, 1996; Petersen, 2006; Suter et al., 1987; Warmink et al., 2010). The literature I reviewed concerned with environmental change distinguishes between these species of uncertainty in four ways, summarised in Table 7-2.

Table 7-2: Different ways of describing two fundamental kinds of uncertainty from review in chapter 2.

	Epistemic Uncertainty	**Aleatoric Uncertainty**
1. Nature	Property of a knowledge state	Property of a system
2. Measurability	Immeasurable	Measurable and/or amenable to statistical characterisation
3. Reducibility	Reducible (through the acquisition of more information)	Irreducible
4. 'Meta-ness'	Uncertainty about uncertainty	Uncertainty directly expressed about a numerical value or fact

Chapter 2 explored the difficulty in triaging boundary cases between these two fundamental natures of uncertainty and the fact that these four mechanisms are not entirely consistent. However, for this framework, I draw the distinction to allow analysts to consider important aspects of the situation they face such as whether there are good prospects for reducing the uncertainty of an underlying situation and as a conceptual aide to promote reflection on the relationship between the model and target system.

To give an example from the COVID-19 pandemic to demonstrate the utility in considering aleatoric and epistemic uncertainties. As the pandemic emerged, the situation was dominated by epistemic uncertainties. A scientific community, not already in possession of purpose-built models, often turned to re-awakening dormant models intended for pandemic influenza (Simpson et al., 2020). In this instance, modelling took place in a high analogical mode and only loose inferences about the target epidemiological system were appropriate. However, as more information emerged, models became purpose-built and tuned to enormous quantities of high-quality observational data. That allowed routinised modelling tasks, such as the now-casts of reproduction number, R_t, to be carried out and these are subject to some significant aleatoric uncertainties. However, this aleatoric-dominated regime is never certain to last; as novel SARS-CoV-2 variants emerged throughout the pandemic, such as the B.1.1.7 "Alpha". strain originating in the UK, the B.1.351 "Beta" (501Y.V2) variant from South Africa or the

B.1.617.2 "Delta" variant from India, the relatively stable aleatoric-dominated regimes repeatedly collapsed during strain replacements.

Thus, it is useful to consider this two-type distinction to provoke reflection on our relationship to knowledge, but as in other fields, triaging between these two types can be challenging.

7.5.2 Location

The location of uncertainty refers to *the point in the modelling process in which uncertainty can be said to be manifest* (Walker et al., 2003). By examining these locations in turn, an uncertainty assessment can inventory many possible uncertainties. Many of these locations can be identified with the three model layers discussed earlier (conceptual, mathematical and technical), however, some of them can transcend these boundaries.

The modelling process, especially a model intended for decision support, is not limited to interaction with the model itself, but additional uncertainties can be identified both within the context of the modelling exercise and in the interpretation of model results. For example, a modelling exercise may attempt to find the stringency of interventions needed to achieve the aim of 'adequate viral suppression'. However, such an ambiguously defined aim could have various interpretations and be difficult to formulate into a well-structured research question. Different modellers may reasonably approach this question in quite different ways. Thus, due to polysemous, ill-defined or fuzzy concepts, linguistic uncertainty may influence the context of the modelling exercise (for a discussion of linguistic uncertainty see Ascough II et al. (2008)).

Within the conceptual model, there is considerable scope for modellers to choose which modelling paradigm they wish to adhere to, such as compartmental models (e.g., SEIR models), agent-based models (ABMs) or network models. Furthermore, assumptions may be formulated about the qualitative mechanisms of phenomena and the relationships between system elements.

The mathematical formulation may attempt to represent the conceptual formulation of the model faithfully. However, one is frequently uncertain of the functional relationship between key inputs, variables, and outputs. Furthermore, several processes require parameterisation, such as the rate coefficients in an SEIR model as discussed earlier. As discussed in Section

7.4.1, the parameterisations may be arrived at in several ways such as model fitting, measurement, estimation, and guesswork.

Uncertainty may manifest in the technical implementation of models as mathematics is turned into computer code. Any number of issues may arise here. Network models that represent the epidemiological state of entire nations will necessarily be complex and may require specialised computational facilities to allow their running.

Models will frequently output results that have a measure of uncertainty, such as the results of multiple input scenarios or probability distributions obtained through Monte-Carlo simulations. However, the interpretation of these model results is also an opportunity for uncertainty to manifest itself with variable interpretations of what the model results show. There may be issues around the appropriateness of making real-world inferences on based on model results (for a discussion, see Thompson & Smith (2019)). The interpretation of model results may be particularly important when the modelling occurs proximate to policymakers who are unlikely to have received formal training in computational epidemiology.

Table 7-3 gives a non-exhaustive overview of some of these *locations of uncertainty* within the model production process for epidemiology.

Table 7-3: Description of various model locations relevant to the context of policy-focused epidemiological models

General Location	Location	Description
Context	Research Question	Different possible interpretations of the model problem
Conceptual Model	Expert Judgement	Uncertainty due to choices made by modellers. E.g., selection of model paradigm to use
	Completeness	Are all consequential variables and phenomena represented in the model?
	Scenario Uncertainties	Assumptions about conditions exogenous to model system
Mathematical Model	Structure	Uncertainty about the correct relationships between variables and mathematical forms
	Parameterisation	Uncertainties due to parameter settings
Technical Model	Data Uncertainty	Uncertainties in data used to run model
	Scenario Implementation	Are driving scenarios faithfully represented by model formulation?

	Initial Conditions	Uncertainties in the initial state of the system
	Aggregation	Uncertainties introduced in model assembly and down-scaling to make it computationally tractable
	Software Implementation	Uncertainties due to software e.g., bugs
Results	Output Uncertainties	Uncertainties as represented in the model outputs (e.g., error bars)
	Interpretation	Uncertainties due to variable possible interpretations of model results

Location, is a concept with transferability to different domains. However, individual locations may be subject to ambiguous interpretation in different contexts. To give the example of *parametric uncertainty*, the uncertainty is about the fact that parameters cannot be known exactly. However, in different modelling contexts, parameters are arrived at in different ways and are associated with different kinds of activities. In climate science parameters may be measured or arrived at through model tuning, in energy systems modelling parameters like technology costs may form model inputs, and in epidemiology, parameters may be the result of model fitting. Indeed, in this later case, parameters end up being a sort of output, especially with they represent key epidemiological variables such as reproduction number, *R*.

7.5.3 Representation

Numerous authors have attempted to define different *levels or scales of uncertainty* that range from a state of complete ignorance to a state of fully deterministic knowledge (e.g. Courtney et al., 1997; IPCC, 2005; Kandlikar et al., 2005; Kwakkel et al., 2010; van der Bles et al., 2019; van der Keur et al., 2008; Walker et al., 2003). They define numerous states such as knowing a discrete set of possible outcomes, knowing a range, or having a probability density function. However, as argued in section 2.5.2, this is a flawed metaphor as between these levels there are not consistent changes, beyond something loosely analogous to informational entropy. Due to the conceptual shortcomings of the *scales or levels metaphor* I instead define the *representation* of uncertainty to be how uncertainty can be represented by mathematical objects such as ordered sets, fuzzy sets, scenario sets and probability distributions over state spaces. This is the conjunction of the description of a state-space and confidence statements make over that state-space; hence how the uncertain information may be *represented*.

By assessing how uncertainty may be represented mathematically, analysts can consider the legitimacy of statistical assumptions more deeply. Such an assessment can also be used to inform the choice of uncertainty analysis technique (Stirling, 1998). Of particular interest here is the separation between situations in which probability distributions can be defined and those where they cannot. Common terminology describes situations or uncertainties for which only partial or full sets of states can be given as *scenario uncertainties*. In epidemiological modelling, scenario uncertainties may be both exogenous to the model-system (as in system drivers such as public health interventions) or endogenous to the model system where reliable estimates of key parameterisations, such as vaccine transmission-blocking efficacy, cannot be provided.

Table 7-4: Different ways in which uncertainty can be represented by describing possible system states and confidence statements

Ways of describing state spaces	**Ways of making confidence statements**
Exhaustive Set of all possible states	Full probability Density Function
Range of possible states given	Interval Probabilities Given
Partial set of possible states given	Ordinal Ranking In terms of Likelihood
Some states excluded	Central Estimate with Spread
Order of Magnitude given	Fuzzy Categories
Direction of trend given	Qualitative Likelihood statements

It is difficult to assess the extent to which this concept may be transferrable when operationalised in epidemiology, or what changes it might undergo in such a context.

7.5.4 Recognised Ignorance

In situations where no judgements are possible, yet one is aware of the uncertainty, one faces a situation of *Recognised Ignorance* (Petersen, 2006). Scientists routinely encounter situations where they cannot confidently judge how some phenomena or factor should be represented. The literature on uncertainty has seen a fruitful overlap with *ignorance* over the years (see for examples Faber et al., 1992; Funtowicz and Ravetz, 1990; Smithson, 1989; Wynne, 1992). However, other forms of ignorance are of little utility for uncertainty accounting as by their very definition they are inaccessible, though that is not to say one should not strive to roll back ignorance's frontier.

7.5.5 Pedigree

Pedigree is a qualitative assessment of the quality of evidence, rigour, methodological reliability and peer group support for a particular assumption or assertion through an account of the production of that information (Funtowicz and Ravetz, 1990; Petersen, 2006; van der Sluijs et al., 2005). For example, one may be able to arrive at a well-defined probability density function, but only through an unreliable method. Similarly, parameterisations may be arrived at by variously methodologically questionable processes, such as estimation and guesswork. However, even guesswork can be made more rigorous through the correct and considered use of expert elicitation procedures (Morgan, 2014).

In emerging infectious diseases, traditional systems of ensuring scientific quality may be rendered moot. For example, traditional peer review processes may take several months to review findings. As a result, a proliferation of working papers (as seen during the COVID-19 pandemic (Vlasschaert et al., 2020)) may create significant ambiguity around the consensus opinion of important findings. Hence, modellers may wish to seek alternative methods to display and assess the pedigree of their work, such as the open sourcing of code.

Pedigree is as applicable in the epidemiological context as it is in the climate/energy/IA context. However, these different communities will hold different epistemic values dear and hence one can expect that methods of assessing pedigree in one domain will not be readily applicable in others. Different epistemic cultures will hold information to different evidentiary standards.

7.5.6 Value-ladenness

Value-laden assumptions are prevalent in many fields and may manifest themselves in models in several ways (Kloprogge et al., 2011; Petersen, 2006). Reasonable people may disagree on any number of values and how they are incorporated into a model: epistemic, normative, political and ethical. It is of particular importance in fields that deal with high-stakes decision-making that researchers are cognisant of the inevitable influence of values in their work. Consequently, this uncertainty framework recommends that researchers consider the potential role of human values in forming uncertainty and uncertainties.

Modelling tasks often have political or ethical values built into them implicitly. For example, an epidemic model may select from possible output variables of consequence, such as excess mortality or hospitalisations, whilst ignoring other possible deleterious outcomes such as long-term consequences of non-fatal infections amongst the general population. Thus, a value judgement, however legitimate it may be, has been made.

Epistemic values may surround the whole model production process. For example, the high valuation of predictive modes of modelling may lead to sub-optimal results through the orientation of efforts towards aspects of the problem that lend themselves well to prediction (for example if large numbers of scenario uncertainties are present). Authors such as Lempert (2019) advocate for the paradigm of Robust Decision Making (RDM) which refocuses modelling efforts away from prediction to explore the range of possible futures and consequences that a decision may entail.

Value-ladenness is challenging in its transferability between disciplines for multiple reasons. Firstly, the activities associated with different modelling exercises provide different opportunities for values to enter a process. Secondly, the nature of the values prevalent will be different for different epistemic cultures.

7.5.7 Uncertainty Matrix

To operationalise this framework, I present an uncertainty matrix. This is a tool that can be used to examine and map individual uncertainty uncertainties in the context of epidemiological modelling. This is included in Table 7-5. Analysts can use this matrix to systematically organise different uncertainties and to make a frank account of areas for model improvement.

Table 7-5: The Uncertainty matrix for analysis of uncertainties in epidemiological models

Location		**Nature**		**Representation**		**Recognised Ignorance**	**Pedigree**	**Value-Ladenness**
		Aleatoric (Variability Related)	**Epistemic** (Knowledge-related)	**State Space** (e.g. Unknown, Partially Defined, Full)	**Probability Statements** (e.g. Problematic, PDF available, Partial)		(Methodological and Social Reliability)	(Epistemic, Ethical, Political, Normative. Also Value diversity)
Context	Research Question							
Conceptual Model	Expert Judgement							
	Completeness							
	Scenario Uncertainties							
Mathematical Model	Structure							
	Parameterisation							
Technical Model	Data Uncertainty							
	Scenario Implementation							
	Initial Conditions							
	Aggregation							
	Software Implementation							
Results	Output Uncertainty							
	Interpretation							

7.6 Discussion

Epidemiological modelling uses different techniques for exploring different aspects of uncertainty inherent in modelling. However, at present, epidemiology does not make routine use of conceptual frameworks to organise the different types of uncertainty encountered. The attempt at conceptual transferral described in this chapter also has implications for how the concepts can be understood in their original context.

7.6.1 Implications for Epidemiology

I contend that the conceptualisation of uncertainty in epidemiology is pre-paradigmatic. Epidemiologists may be acutely aware of the deep uncertainties involved in the knowledge production process, especially after a period in which modellers were called upon to produce outputs of a consequence and frequency that few scientists will have ever experienced in peacetime. However, I believe that improvements can be made to the evidence and policy-advice process through a more systematic handling of uncertainty

Firstly, uncertainty communication may be ameliorated as a fuller account of uncertainties is available, and scientists become cognisant of those most salient to a decision. To further assist in this endeavour, there exist frameworks and techniques for uncertainty communication to policy such as Funtowicz & Ravetz's (1990) NUSAP initialism (Number, Unit Spread, Assessment, Pedigree). Other scholars in recent years have incorporated findings from psychology in developing uncertainty communications frameworks (van der Bles et al., 2019). Epidemiologists can deploy professional uncertainty communication techniques to inform policy and lay audiences.

Secondly, appropriate uncertainty analysis and/or uncertainty quantification techniques can be more easily selected. Different kinds of uncertainty are amenable to different forms of analysis. The *nature* of uncertainty may, in part, determine the extent to which they uncertainty can be reduced. Aleatory Uncertainties may be amenable to quantification and statistical analysis, whereas epistemic uncertainties may not always be possible to capture in formalised ways.

Uncertainties in different *locations* of the model production process require different types of analysis. There are many well documented methods of exploring parametric uncertainty through techniques such as Monte-Carlo analysis or sensitivity analysis. Uncertainty in model structure is often explored through inter-model comparison. Efforts such as Model Inter-comparison Projects (MIPs) have been used extensively in the climate science community to map and understand the structural differences between climate models. This structural uncertainty can also be investigated using Multi-Model Ensembles (MMEs), which will be explored further in the following chapter.

Finally, an appreciation of a more comprehensive range of uncertainties can improve the knowledge production process. Modelling does not occur in a vacuum; there is a wider social and political context around it. When models exist to inform impactful decisions, it is incumbent on those involved in the knowledge production process to consider the fallibility of their knowledge and seek to remedy the situation where possible, and where it is not, to admit the shortcomings of their work. Epistemic humility allows researchers to self-correct in short order and more easily identify opportunities to improve their models.

7.6.2 Implications for Climate/Energy/IA

More importantly, I must consider what my attempted transferral of these concepts means for their native context of studies dealing with environmental change.

I observe that concepts like *location* have general applicability in different contexts, but the sub-concepts like the individual locations themselves (e.g., parameters, inputs etc.) may be experienced in very different ways due to the different kinds of modelling exercises engaged in by different fields and the natures of the models.

Different values are characteristic of different epistemic cultures and research communities. These too have a bearing on how aspects of uncertainty such as *pedigree* and *value-ladeness* may be characterised in different contexts.

Other aspects of uncertainty, such as *representation*, it is difficult to estimate *a priori* what reconceptualisation they may experience when imported into new contexts.

7.7 Conclusion

This chapter has examined the state of play in uncertainty assessment for epidemiological model-based decision support. Such a topic was shown to be of vital importance by the COVID-19 pandemic. It is argued that although a wide variety of uncertainty analysis techniques are commonly employed in epidemiological modelling, there is currently a lack of consensus on how these uncertainties can be conceptualised and categorised. This state of affairs stands in contrast to that in energy/IA and climate

This chapter has examined some of the uncertainties present within epidemiological models, in the context of their creation and in their interpretation for the answering of policy questions. Adapting ideas found in other disciplines concerned with highly uncertain coupled socio-technical systems, I have proposed a framework for uncertainty analysis that examines uncertainties along several dimensions. It is not hoped that this framework has universal and immutable applicability to all situations mathematical epidemiologists may find themselves in; rather, I wish this to be a nucleation site for a fulsome discussion of uncertainties that are inherent in epidemiological models and in the process of their creation and use.

8 The Conceptualisation and Interpretation of Multi-Model Ensembles

A Case Study from the United Kingdom Health Security Agency

8.1 Abstract and Context

The use of Multi-Model Ensembles (MMEs) has risen in prominence in several fields in recent years. Their use and conceptualisation have been the subject of significant philosophical study, with work considering their relationship to structural uncertainty. However, the practices have spilt over into other disciplines and this has been less studied. This chapter considers a case study from epidemiology as an opportunity to meditate on aspects of MMEs salient to climate science. In this case study, I explore how one needs to pay attention to the socio-technical infrastructure that surrounds an MME.

During the COVID-19 pandemic, MMEs have been employed for epidemic tracking in several countries, with models being repeatedly trained on the latest data to estimate policy-relevant epidemic variables such as the Effective Reproduction number, R_t. This chapter documents several conceptual challenges faced by a team working in the UK Government's Health Security Agency (UKHSA) to construct one such epidemiological ensemble. I detail the philosophical quandaries I noted in ensemble compilation, model weighting, uncertainty quantification, consensus forming and in summarising outputs for other stakeholders.

In this chapter, I provide my personal perspective on the philosophical issues that were engaged with by the team and reflect on establishing a best practice for MME construction and management. I argue that an approach that emphasises increased accuracy of outcomes from an ensemble is problematic. Different stakeholders may pursue different goals within such a project and possess different conceptual understandings of the ensemble process. Instead, focusing on consensus epistemic values such as transparency can ensure different types of evidence quality.

This chapter gives another perspective on the third theme of this thesis: the nature of models and the socio-technical infrastructure required to support their operation. I show how this infrastructure has additional relevance for uncertainty handling as it can hamper standardisation between different model implementations in ensemble experiments. I problematise this *location* of uncertainty as *model dark matter*. This refocuses attention on the general importance I have previously

8.2 Introduction: MMEs and Epidemic Tracking

8.2.1 Multi-model Ensembles

Disciplines that model of complex systems often find themselves in the situation of model selection ambiguity, in which, for a given modelling task it is unclear which of many models that may be available is the most suitable. Alternatively, in the situation of underdetermination, multiple models may predominate in different standards of scientific success, and hence no model dominates (Betz, 2009). The last 15 years has seen the rise of the practice of multi-model ensemble (MME) building to manage these structural uncertainties. MMEs allow scientists to explore structural uncertainties in models through standardising initial conditions, parameterisations and scenarios used between models, so that the variation between model outputs is primarily attributable to the structural differences between the models. The spread of ensemble predictions represents some of the epistemic uncertainty associated with model structure, within the constraints of computational possibilities (Parker, 2013).

MMEs vary in their structure and complexity significantly. The essential motivation for ensemble modelling is that using a single model run with a single set of inputs is often overly approximate for a given task; a model of a complex or complicated system can only approximately represent the total dynamics that determine the system behaviour and outcomes. The use of multiple models, or multiple realisations of a single model allows some uncertainty associated with the choice of model elements and structure to be explored. The combination of multiple model results is often analogised to the familiar *wisdom of crowds* phenomenon, where some aspects of the error of estimations are reduced when combined with other guesses (Baker and Ellison, 2008; Stumpf, 2020).

A simple form of MME, which I term a *Multi-Model Comparison* (*MMC*), may simply draw together the estimates of several models and perform some systematic comparison. For this thesis, I refer to MMCs as exercises that draw together model results. In contrast, MMEs constitute exercises where efforts towards the standardisation of inputs and configurations have been made.

MMEs may also draw together the results of model experiments in probability distributions, and the results of model runs using various scenario sets. The process of the aggregation of results for consensus predictions (I henceforth term *model combination*) may be more or less sophisticated with different model weightings employed and using different algorithmic methods such as mixed-effects models, the linear or logarithmic summation of mass functions (Clemen and Winkler, 1999) and Bayesian model averaging (Clemen and Winkler, 1999; Duan et al., 2007).

Model Ensembles first developed in weather forecasting after the discovery by Lorenz (1965, 1963) of the high sensitivity of model outputs to small perturbations in initial conditions in complex models (Parker, 2013). For decades, ensembles of weather models have been run under different initial conditions to produce output probability distributions. MMEs differ from other model ensembles in that they include model realisations with differences in model structure. They have seen relatively widespread use in a number of fields such as weather forecasting (Krishnamurti et al., 1999), agriculture, public health, hydrology (Georgakakos et al., 2004), flood losses (Figueiredo et al., 2018), traffic management (Li et al., 2014) cancer prediction (Xiao et al., 2018) and climate science (Eyring and Meehl, 2016; Taylor et al., 2012).

Presently, MMEs are heavily associated with the Model Intercomparison Projects (MIPs) used in climate science (see Box 5-1). MIPs involve large exercises comprising standardised experiments, historical simulations, standardised outputs and dissemination of results. The Coupled Model Inter-comparison Project (CMIP) under the auspices of the World Climate Research Programme (WCRP) is currently in its sixth phase (CMIP6)(Eyring et al., 2016). Within CMIP6 there are now many MIPs that cover different aspects of climate science, such as the Carbon Cycle (Jones et al., 2016) and paleoclimate modelling (Kageyama et al., 2018).

In the climate literature, both perturbed physics ensembles (ensembles of single models run under different parametric assumptions sampled from within credible ranges) and multi-model ensembles are commonplace (Collins et al., 2011). In this chapter, I shall only consider the latter. In a limited number of studies, initial condition uncertainty is also considered (Parker, 2013). Table 8-1 summarises several different styles of model ensembles and examples of their application.

Table 8-1: Summary of several styles of model ensemble and examples of their applications in the literature. Note that these categorisations of model ensembles are somewhat fuzzy.

Terminology	**Structure**	**Examples of Applications**
Multi-Model Comparisons (MMCs)	Multiple models are systematically compared in some way in order to provide different lines of evidence in some field	Epidemiology (den Boon et al., 2019; Hollingsworth and Medley, 2017), Landscape Ecology (Iverson et al., 2017)
Multi-Model Ensembles (MMEs)	Structurally different models used to predict the same outcomes. The range of outcomes can be used to explore *structural or model uncertainty*	Traffic Management (Li et al., 2014), Space Weather (Schunk et al., 2014)
Single Model Ensemble (SME), Perturbed Physics Ensemble (PPE)	Structure and driving scenarios held constant, model is driven under different parametric assumptions to explore *parametric uncertainty*.	Regional climate modelling (Bellprat et al., 2012)
Initial Conditions Ensembles (ICE)	Structure and parameterisation held constant in order to explore effect of *initial condition uncertainty*, multiple model runs with different initial conditions.	Weather forecasting (Leutbecher and Palmer, 2008)
Initial Condition Large Ensembles (LE) / Single Model Initial Conditions Large Ensembles (SMILE)	Particularly large ICEs using large initial conditions sets. This may be used to produce probabilistic forecasts.	Earth System Modelling (Deser et al., 2020)
Model Inter comparison Projects (MIPs)	Large structured inter-comparison exercises of multiple models with standardised model experiments.	Climate models (Eyring et al., 2016), Carbon cycle modelling (Jones et al., 2016), Paleoclimate modelling (Kageyama et al., 2018)
Superensemble Fore-casts	A forecast used by combining a set of different models, adjusted for various biases with time-varying weights	Weather and Seasonal Climate (Krishnamurti et al., 2016, 1999)
Grand Ensembles	Ensembles of ensembles that explore multiple kinds of uncertainty	Climate Modelling (Maher et al., 2019)

8.2.2 The Philosophy of MMEs

Philosophers of science have paid increasing attention to model ensembles in recent years (Betz, 2009; Dethier, 2022; Jebeile and Crucifix, 2021, 2020; Katzav et al., 2012; Lenhard and Winsberg, 2010; Schmidt and Sherwood, 2015), and most prominently in the work of Parker (2018, 2013, 2011, 2010a, 2010b, 2009, 2006). They have examined different aspects of ensemble formation, such as the conceptualisation of model ensembles, the justification of practices, the role of expert judgements (Jebeile and Crucifix, 2020), the significance of robust results (Parker, 2011), the suitability of 'ensembles of opportunity' (Knutti et al., 2010; Tebaldi and Knutti, 2007) and the appropriateness of probabilistic or statistical treatments of ensemble results (Dethier, 2022; Parker, 2010b). I now briefly survey a number of these themes relevant to the subsequent discussion.

8.2.2.1 The Motivation for MMEs

Ensemble modelling generally receives three primary justifications in the philosophical literature. *Firstly*, that the compilation of model results reduces much of the error from individual models (Tebaldi and Knutti, 2007). This has been criticised as the errors inherent in different models are rarely independent and therefore only cancel to a limited extent (Katzav et al., 2012; Odenbaugh and Alexandrova, 2011). Such a justification is analogous to the 'wisdom of crowds' phenomenon.

The second predominant motivation is that producing an ensemble of models captures a wider range of uncertainty, as the differences between models also include a variety of assumptions. However, as noted by Parker (2011), the agreement of models does not necessarily indicate robustness as models may share uncertain assumptions. Indeed, a frequent criticism of MMEs is that the ensembles produced constitute 'ensembles of opportunity' (Jebeile and Crucifix, 2020; Knutti et al., 2010; Tebaldi and Knutti, 2007). I discuss this further in section 8.3.1.

The third justification, closely related to the second, is that different types of uncertainty can be isolated by comparing different models (Jebeile and Crucifix, 2020). I consider this as different from the second motivation as the isolation of the effects of uncertainties does not necessarily attempt to capture all kinds of uncertainty and represent the totality of the limitations of an epistemic state. Such an approach can be seen to different ends in Table 8-1; PPEs can explore the sensitivity of results to different parameterisations; ICEs explore initial conditions uncertainty and MMEs can explore different kinds of structural uncertainty. However, as I will discuss, the variation of individual model elements within structurally different models is complex as the same model structural element may create very different results when included in different models (Lenhard and Winsberg, 2010).

8.2.2.2 The Conceptualisation of MMEs

There are a range of prominent interpretations of MMEs in both philosophical and practitioner literature.

Firstly, competing conceptualisations determine how one should understand the numerical combination of model results. Parker (2018) describes the 'truth plus error' framework as the assumption that model results are drawn randomly from a set of possible models centred on some true value (Tebaldi et al., 2005). A competing 'statistically indistinguishable' framework imagines that model results are drawn alongside the truth from some distribution. I contemplate these issues in section 8.5.

How one conceptualises the entire process of MME construction may depend on how one understands the role of the models involved (Jebeile and Crucifix, 2020). On the one hand, the motivation for MMEs for exploring model structural uncertainty may carry with it an understanding of models as ensembles of modules, structures and parameterisations that can be swapped out interchangeably. The latter interpretation focuses on the socio-epistemic role that models play; conceptualising them as crystallisations of expert judgements. Jebeile & Crucifix (2020) argue that both interpretations are useful in that they highlight different kinds of issues involved in MMEs.

8.2.2.3 Issues in MMEs

Parker (2018) identifies several open questions important to the philosophy of MMEs in climate science:

- "How can ensemble studies be designed so that they probe uncertainty in desired ways?"
- "How significant are robust results?"
- "...to what extent do non-epistemic values influence ensemble results?"

In this chapter, I pay particular attention the former and the latter of these questions in the context of epidemiology. To date, the majority of philosophical attention regarding MMEs has been applied in climate science. More parochially, philosophers of science have mainly examined the use of ensembles of General Circulation Models (GCMs). Recognising that MMEs increasingly find deployment to a wide variety of problem contexts with vital policy importance, I will consider the use of MMEs in epidemiology and reflect on some of the philosophical implications that emerge in their application to this context that may apply back to climate science.

8.2.3 MMEs and Epidemiology

MMEs have found utility in both communicable and non-communicable disease epidemiology. Aside from recent MMEs constructed to model and monitor the current COVID-19 pandemic (Panovska-Griffiths et al., Forthcoming; Shea et al., 2020), MMEs have been used to model infections as varied as HIV (Eaton et al., 2014), Influenza viruses (Reich et al., 2019) and Ebola virus (Chowell et al., 2020; Roosa et al., 2020; Viboud et al., 2018).

The use of MMEs and MMCs in infectious disease epidemiology has proliferated in the last decade (den Boon et al., 2019; Drolet et al., 2018) and the practice is "increasingly regarded as standard" (Hollingsworth and Medley, 2017). In order to provide guidance in this emerging space, and responding to a commission from the World Health Organisation's (WHO) Vaccines-related Implementation Research Advisory Committee (IVIR-AC), den Boon et al. (2019) produced a set of principles and guidelines. They make several recommendations such as the formation of clearly defined policy questions, transparency in model selection criteria and the accompaniment of the MMC with uncertainty analysis techniques such as scenario analysis and sensitivity analysis.

Though the distinction between MMCs and MMEs in epidemiology is blurred somewhat, the former terminology is generally preferred in the epidemiology literature. In this chapter, I use the term 'MME' and focus primarily on those exercises in which multiple model experiments are performed using the sets of models with some input standardisation.

The use of MMEs in pandemic epidemiology is distinctive in several ways, when compared to other academic disciplines using MMEs. *Firstly*, the characteristic timescales over which ensembles are employed are typically very short; the UK government receives weekly pandemic estimates using the SPI-M and UKHSA model ensembles (UKHSA, 2021a). In long-timescale MME processes, such as MIPs, model comparison experiments may be planned over the course of months, if not years.

Secondly, ensemble modelling of pandemics runs in several different modalities. The first and most prominent is nowcasting, where models are fitted to data-streams to estimate key parameters and therefore calculate quantities such as the *effective reproduction number*, R_t. Using these parameterisations, the models may then be used to make short term forecasts of policy-relevant decision variables, such as hospitalisations and hospital bed occupancy. The ensembles may also be used to model different medium- and long-term scenarios that correspond to potential policy options or uncertainties the future behaviour of the epidemic (such as the emergence of new variants).

8.2.4 The JBC/UKHSA MME

Throughout the COVID-19 pandemic, the Scientific Advisory Group on Emergencies (SAGE) has provided the UK government with regular estimates of epidemiological metrics, provided to it by the Scientific Pandemic Influenza group on Modelling (SPI-M). The group is comprised of academic epidemiological modellers from UK institutions who run a variety of models. As part of their routine operations these models have been fit to various data streams to produce nowcasted estimates of key policy-relevant quantities such as effective reproduction number (R_t), growth rate (I), incidence, prevalence, and doubling time.

Since November 2020, as part of an ongoing plan to relieve unnecessary burden from these academics, a team within the Joint Biosecurity centre (JBC), and subsequently in its successor within the UK Health Security Agency (UKHSA, 2021b), has worked to build a Multi-model Ensemble to carry out the routine task of production of epidemic estimates (henceforth I shall use UKHSA to refer to both JBC and UKHSA). Efforts have been ongoing to install the various models used by SPI-M on UKHSA computer systems and to establish a process by which a consensus between the various model outputs can be formed. The process developed by UKHSA has been primarily modelled on that of SPI-M.

The UKHSA ensemble contains a variety of models primarily acquired from SPI-M academic partners and other academic partners (see for a technical overview of the ensemble characteristics (Panovska-Griffiths et al., Forthcoming)). As of June 2021, the time of writing, the ensemble contained 13 distinct models, that can be broadly categorised into three classes: *data-driven models*, *compartmental models* and *agent-based models*. Figure 8-1 summarises the models used in the UKHSA ensemble. Whilst all SPI-M models are represented within the ensemble, as of JUNE 2021, not all models were run entirely by UKHSA itself.

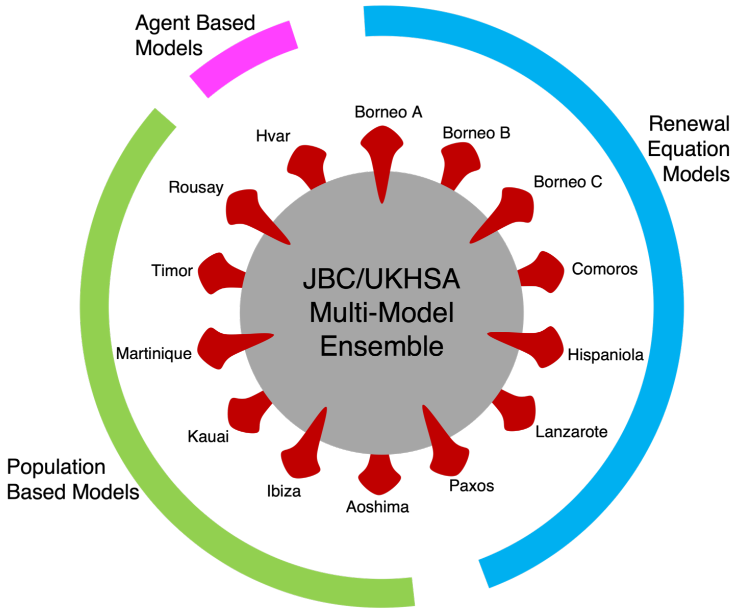

Figure 8-1: An overview of the models employed in the model ensemble. Individual models have been given code-names of different islands to ensure a stable nomenclature.

The process discussed within this chapter is accurate to June 2021, however, model development, ensemble development and pandemic science are dynamically evolving processes. Thus, the description given will not constitute a precise contemporaneous account. This chapter does not give a full technical account of the ensemble methodology, as this is capably documented elsewhere (Bowman et al., 2020; Maishman et al., 2021; UKHSA, 2021c).

8.2.5 Structure

This chapter describes the efforts of the UKHSA MME team, a multi-disciplinary scientific team comprised of epidemiologists, data scientists, computer programmers and other academics, to ensure rigour in the analytic process and reflects upon the epistemic and philosophical challenges diagnosed in the implementation of the UKHSA MME. Figure 8-2 below summarises the primary phases of the ensemble's formation and the sections of this chapter that consider them.

Section 8.3 details the issues identified associated with ensemble membership on several levels. *Firstly*, the nature of the *ensemble of opportunity* formed by the available selection of SPI-M models and other models from academic partners. *Secondly*, it describes the issue of determining the selection of models to include in consensus estimates on a given week. The decision to include/exclude a given model may consider a variety of factors such as beliefs about reliability and attempts to maintain consistency across weekly estimates. *Thirdly*, it describes the rejection of models due to various factors and the challenges this creates for consistency.

Section 8.4 discusses the challenges and choices involved in model combination. Firstly, it examines the choices possible in selecting model weighting schemes and the reasoning implicit in different choices. It then details the trade-offs between different possible combination techniques, both qualitatively driven and algorithmic.

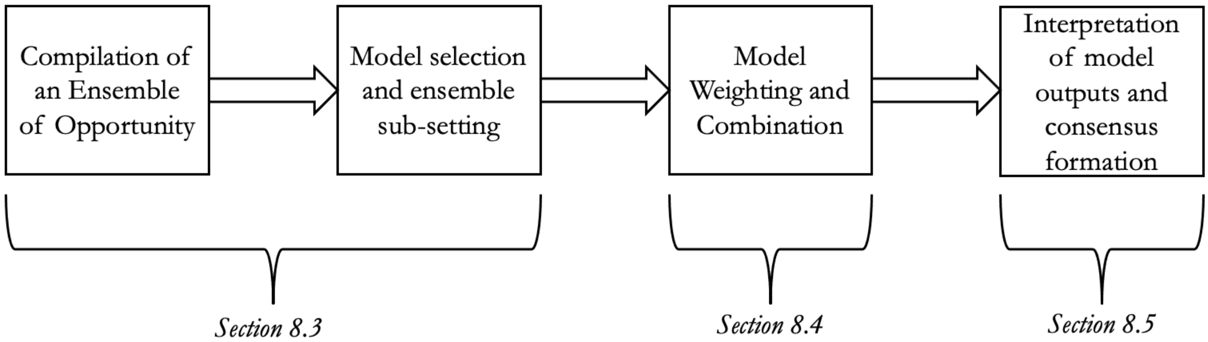

Figure 8-2: Overview of the key processes involved in the JBC/UKHSA MME formation and interpretation in and their presence in this chapter

Section 8.5 examines the challenge of MMEs interpretation. It considers how, given an understanding of the process of MME compilation, the ensemble can be more reliably understood. This is particularly important when results will be communicated to other epistemic communities.

Section 8.6 discusses the unique issues identified here and argues that in such a large exercise, different actors will naturally possess different conceptual understanding of the process, teleologies of multi-model ensembles and epistemic values. Therefore, a consensus philosophical interpretation of the process is problematic and the choices which go into MME process design will be reflective of these differing viewpoints. Instead, the toolkit of social epistemology is best suited for understanding multi-model ensembles.

8.3 MME Assembly and Membership

8.3.1 Ensembles of Opportunity

For any given MME, the set of models available for selection is heavily contingent on what models are available for inclusion, both in the literature and as ready-written computer software. Ensembles may depend on the willingness of modelling groups to add their models into the mix (Tebaldi and Knutti, 2007), or the requirements of expediency. Thus, when speaking of multi model ensembles it may be appropriate to refer to them as '*ensembles of opportunity*'. In this sense, models are rarely purposely developed to sample the space of possible models or give a high diversity of model structures. Historically, in climate science, MMEs and MIPs emerged opportunistically out recognising and capitalising on the range of available models (Jebeile and Crucifix, 2020).

On the 'modular interpretation' sketched out by Jebeile & Crucifix (2020) and outlined in section 8.2.2.2, one can imagine model sampling from a space of possible model structures. Therefore, the individual model estimates can be imagined to be randomly distributed around some true value. This interpretation is problematic for several reasons:

1. It is difficult to conceptualise how model structure can be thought of to constitute a space, and how that space could be randomly sampled over. PPEs may be better to conceptually imagine than MMEs as the parameter space over which they sample is easily understood as a space of numerical values (Jebeile and Crucifix, 2020; Parker, 2010b).
2. In practice, many models share significant structural similarities and model building is rarely purely independent.
    - Models may share a common lineage from older models. This is common in areas such as climate science where extensive genealogies of model structures have been produced (Knutti et al., 2013; Masson and Knutti, 2011).
    - Some individual modules may have elements in common. In the case of epidemiology, this could include, contact matrices.
    - Models share common structural elements from the available literature.
    - Models typically share assumptions.

Jebeile & Crucifix (2020) note that the implicitly disparaging label *ensemble of opportunity* leaves a kernel of optimism that other more systematic ensembles are possible. They argue that three desirable properties in an ensemble are *systematicity, comprehensiveness* and *model independence*. The former two properties are compromised because the idiosyncratic interests of modellers influence development and construction. Therefore, the selection of models available will not systematically and comprehensively sample from a space of possible models. The criterion of model independence is undermined by the shared design features of models, the sharing of assumptions and the genealogical relatedness of different pieces of model code.

The inconceivability of what an adequate model space might constitute is widely identified as an issue. Facing this, Parker (2010b) reframes the conceptual task as selecting between a selection of possibly *adequate* model structures, rather than *perfect* model structures. Thus, using background knowledge, scientists can then specify a set of structures to investigate that will be informative about some structural uncertainty. However, Parker (2010b, p. 991) notes that how this set of structures can then be systematically sampled is unclear.

In the absence of the possibility of a sampling methodology for model space, some MME projects instead assign minimal criteria required for model inclusion to ensure quality, functionality and compatibility. Two common ways to examine the suitability of a model for inclusion in an ensemble are by examining the model's *skill* and *independence* (Solazzo and Galmarini, 2014).

Consistent with Parker's (2010b) suggested approach, in the following subsection I attempt a description of the model space informed by background knowledge by defining the broad *paradigms* from which models emerge and the options for model structuring within these paradigms.

8.3.2 The UKHSA Epidemiological Ensemble

8.3.2.1 Ensemble Membership and Model Types

The UKHSA MME was composed of an array of academic models, primarily acquired through partnerships with SPI-M modellers. Other non-SPI-M models were also included within the ensemble brought in through other academic partnerships. Three seconded academics within the JBC were also model developers of three Non-SPI-M models (*Hvar*, *Comoros* and *Ibiza*). Models were not also uniformly available as the team worked to run different models and gradually incorporated more models. The available models broadly consisted of three fundamental types, which I label *paradigms*: renewal-equation based models, compartmental models and agent-based models.

Renewal-equation based models (REMs) have the *renewal equation* at their core, which describes the number of infectives at a given time determined according to the time integral of remaining susceptibles with some time-varying infectivity function and some other force of infection. Such a model has both deterministic and stochastic formulations, and the literature on such models is longstanding (Gielen, 2000; Kendall, 1956; Kermack et al., 1927; Metz, 1978).

$$S'(t) = s(t)\left[\int_0^t S'(t-\tau)g(\tau)d\tau - f(t)\right] \quad (1)$$

$$i'(t) = \int_0^t I'(t-\tau)g(\tau)d\tau + f(t) \quad (2)$$

Equations (1) and (2) give an example of the renewal equation where $S(t)$ is the remaining population of susceptibles at time t, $I(t)$ is the number of infectives, $g(\tau)$ is the infectivity function with τ being the age of infection and $f(t)$ is a secondary infectivity function representing an external force of infection (Gielen, 2000; Kermack et al., 1927). Within the UKHSA MME, *Borneo-type models, Comoros, Hispaniola, Lanzarote* and *Paxos* are REMs.

Compartmental models (CMs) are perhaps the most conceptually intuitive form of epidemic model. In a compartmental model, the population is segmented according to its epidemiological status; in an 'SIR' model these compartments are S susceptible, I Infectious and R recovered. The allocation between these epidemiological bins then changes in each time interval according to some system of ordinary differential equations; eqs. (3) to (5) give a simple example of an SIR model:

$$\frac{dS}{dt} = \mu_B + \delta R - \lambda SI - \mu_s S \quad (3)$$

$$\frac{dI}{dt} = \lambda SI - \gamma I - \mu_I I \quad (4)$$

$$\frac{dR}{dt} = \gamma I - \delta R - \mu_R R \quad (5)$$

where λ is the force of infection, γ is the rate of recovery, μ_B represents the birth rate, μ_S, μ_I and μ_R are the mortality rates for susceptible, infected and recovered individuals, and δ is the rate of waning of protective immunity.

CMs can contain additional compartments to represent different epidemiological states such as exposed E, hospitalised H, carriers C, semi-susceptible M, vaccinated V and dead D (Dashtbali and Mirzaie, 2021). These epidemiological compartments may be subdivided into so that, for example, there may be multiple stages in a course of infection $I, \ldots, I_n$. Additionally, they may be structured according to demographics so that, for example, each of the epidemic states has several sub-compartments that represent different age categories. The force of infection λ in such a case can be replaced by an age-specific force of infection, λ_j calculated from a *contact matrix* that represents the frequency of contact between individuals form different age compartments. Within the UKHSA MME, *Aoshima, Ibiza, Kauai, Martinique, Timor* and *Rousay* are CMs.

Agent-based Models (ABMs) are often the most computationally complex class of epidemic models as they simulate a population of individual agents, each with their own epidemiological state that may change according to some stochastic process influenced by interactions with other agents. The models are typically composed of three aspects: a synthetic population, a social contact network and a disease model (Eubank et al., 2004; Venkatramanan et al., 2018). The flexibility of these models comes from how different social structures and populations can be simulated with differing disease functions. Synthetic populations can be described using data from censuses and information about workplace and school structures, and social contact networks can be simulated from real-world data, such as social contact surveys. Within the UKHSA MME, *Hvar* and *Santorini* are ABMs.

Different model paradigms typically have different strengths. Simple compartmental models have utility in early-stage emerging infections due to their simple structure and short build- and run-times. ABMs may be favoured in situations where detailed descriptions of the behaviour of a synthetic population are needed (Venkatramanan et al., 2018). Other modelling paradigms are also possible, such as purely data-driven or machine learning approaches for epidemic calculation which have seen some popularity in recent times (see for examples Akhtar et al., 2019; Cook et al., 2011; Siriyasatien et al., 2016). Though to estimate quantities such as R_t, these may have limited utility as they do not directly describe some underlying epidemic state, but rather forecast outcomes.

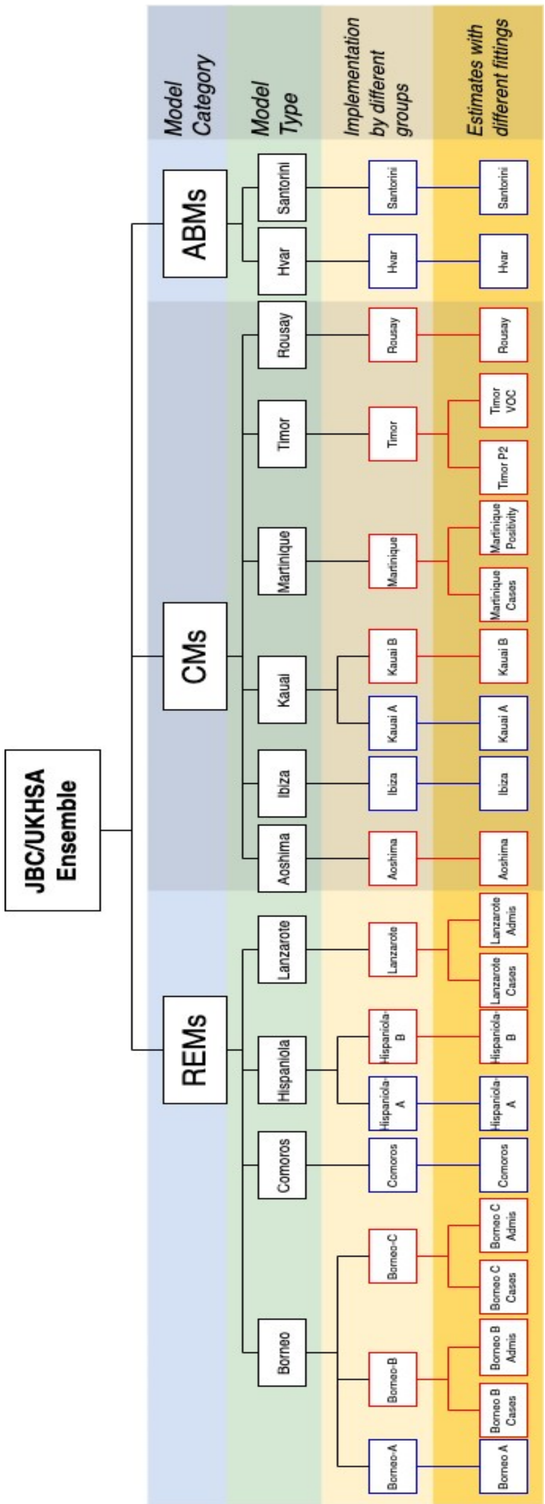

Figure 8-3: Overview of the categories, types, implementations and fittings of models within the MME. Note that blue outlined boxes indicate model versions implemented by the UKHSA MME team and red indicates models run by external stakeholders.

8.3.2.2 The Space of Epidemiological Model Structure

These three paradigms do not describe the entire space of possible models; they represent three ontological approaches to describing the entire epidemiological state of a system: as continuous totals (REMs), as discrete bins (CMs) or as individuals with states attached (ABMs). Within each of these paradigms, there are many other elements that can be reasonably varied, such as the mechanism of infection, the choice of age structuring, the representation of geographical units and how different variants within a system are represented, to name but a trifling few.

Even if one accepts that 'representatively sampling the space of possible models' is both conceptually problematic and impossible to achieve in practice, one could instead demand that models are not highly similar upon expert inspection. The original SPI-M ensemble, which the UKHSA ensemble is intended to supersede, does not contain any ABMs. I will further address the issue of accounting for similarity in section 8.4.2.

Perhaps the most significant difference between models is the choice of data stream to calibrate the model. As the models are being run in now-casting mode their free parameters are fitted to different data streams (such as cases, deaths, hospitalisations etc.). The choice of data stream is a significant source of variation between the model runs. However, the choice of data stream for parametric calibration is not typically considered an aspect of formal model structure as defined by the set of functional relationships between model elements.

As part of the ensemble, three models are of a *Borneo-type*, but implemented and run by different researchers at different institutions. The three models did indeed show significant differences. The *Borneo type* models are also distantly genealogically related to the *Hispaniola-type* models. Though the *Hispaniola* models raise an ontological question about to what the term 'model' in this context refers. The *Hispaniola* framework mostly consists of a particular fitting methodology. So, the term 'model' of this ensemble may refer to either the mathematical formulation, the software package or the fitting approach.

The JBC MME represents an ensemble of opportunity, as all ensembles do, though one constructed with some very significant diversity in model structures that can be expected to explore at least some of the epistemic uncertainty associated with the suitability of different model structures for epidemic tracking. The availability of suitable models across paradigms is variable, perhaps reflecting preferences of the literature and the requirements of model development in a short time horizon. For example, the preponderance of REMs and CMs may reflect their less onerous model development time requirements before a 'minimum viable product' model is available and operational.

8.3.2.3 The Challenge of Implementation and Learning

Model on-boarding was identified to be both a technical and pedagogical challenge with various kinds of knowledge needed to run the models, both *episteme* (know-what) and *techne* (know-how). Not all available models had a uniform availability of code, working papers and published literature. Individual model leads were assigned to each of the models for on-boarding. To manage institutional knowledge of the idiosyncrasies of each of the models, internal documentation was set up to record both theoretical and technical learning.

Technical learning also has an informal component, where modellers became accustomed and aware of the typical behaviour of different models during calibration and the nature of the changing results between weeks. This *techne* knowledge was vital for identifying when there may be issues causing model errors that were not immediately obvious from model outputs.

Within an MME, the description of a model purely in terms of its mathematical structure is reductive. As used in MMEs, models consist of the nexus of conceptual formulations, mathematical formulations, technical formulations in computer code, calibration methods, their hardware and software dependencies, the *techne* required to implement them and the myriad choices made in implementation. This techno-social superstructure is necessary for the model to perform its role as mediator between data and theory and for the routinised production of model results.

8.3.3 Sub-Ensembles and Model Transience

8.3.3.1 Sub-Ensembles

Aside from the process of overall ensemble membership, the UKHSA also faced the need to produce sub-ensembles. Not all models were constructed to produce estimates of all desired quantities for all geographies (e.g., home nations of the United Kingdom and English Regions) and all epidemic indicators (R, growth rate, incidence etc.). Typically, this may be dealt with in a longer time-horizon MME process through standardisation and non-admittance of non-conforming models. This meant that inevitably, for any given estimate a different subset or sub-ensemble of models was available. Different subsets of models may be available for the following reasons:

- Models are designed to now-cast some quantities and geographies and not others
- Models are routinely brought offline for development and maintenance
- Models may encounter bugs, errors or structural issues which warrant their exclusion

8.3.3.2 Selective Exclusion of Models

Models encounter transient issues during their usage. There may also be several issues with the various data-streams used, as is natural with low latency epidemiological data collected over a large geographical area. Therefore, it may be necessary to exclude a model result on a given week as the team believes that there may be a significant model error. This model error may reduce the reliability statistically, methodologically or socially of the ensemble results (Smith and Petersen, 2014).

How exactly to decide to exclude a model on a given occasion is a more complex matter. The development of *techne* and tacit knowledge of the modeller is crucial in this regard. However, this a hunch that something is wrong must be translated into some sufficient reasons so that others can understand why a model might warrant exclusion. The results on a given week may show inconsistent behaviour, such as wide or highly skewed confidence intervals, or very high or low central estimates, when compared to other ensemble members or their past behaviour. To consistently produce a traceable account of the ensemble behaviour, a set of criteria was produced that, if met, would lead to a model's exclusion on a given week. These criteria were then applied each week and the reasons for exclusion were recorded.

8.3.3.3 The Reliability-Consistency Trade-off

Rejecting models that one believes to be in error may increase some aspects of the ensemble reliability. It does, on the other hand, produce a series of inconsistencies that render the various results of the ensemble more difficult to compare with one another:

- Inconsistency is introduced between different types of epidemic estimates if some models do not produce. This may produce divergence between indicators such as R and r when not all models produce both. Theoretically speaking, one should expect these to be highly correlated throughout an epidemic. Without correlation, the state space of the epidemic may be inconsistently described.

- Geographic inconsistency is introduced when different regions are estimated with different sub-ensembles. Moreover, larger regions may have estimates (such as England) that are inconsistent with their constituent smaller regions due to models being preferentially designed to produce estimates at a national level.
- Estimates may not be comparable over time due to the different sub-ensembles used over time. Furthermore, the gradual changes in model structure of individual models through updates may make long-term comparisons unreliable. The latter issue is particularly relevant in situations where an ensemble is used to monitor the effect of interventions over time. There is therefore significant inferential risk when using high-frequency ensembles of models, such as ours.

8.4 Model Combination and Weighting

Within an ensemble, perhaps the action that gives meaning to the process is the combination of multiple model outputs into a single estimate. This may combine multiple point estimates from different models into a single estimate, with or without an uncertainty range. Alternatively, it may combine multiple distributions into a single distribution. In this section I consider two aspects of the methodological choices that need to be made when combining models: i) the algorithm used to combine the estimates and ii) the weighting schemes used in these algorithms. I examine these in turn.

8.4.1 Methods for Model Combination

The literature contains a wide variety of techniques used to combine model estimates. The simplest of these is often called *model averaging*, in which a simple mean or median of model results are taken of model point estimates. A step more complex than this may be a weighted mean of model results (see section 8.4.2).

The process of model combination becomes more complex when combining ranges or distributions. Increasingly, MMEs do not just provide ranges, but also central estimates and probabilistic ranges of uncertainty (Parker, 2013). Depending on the problem context, it may be desirable to include some aspect of both the inter-model variability in the final combination and the variability in the outputs of each of the models so that the final combination represents multiple kinds of uncertainty or variability.

A simple weighted linear combination of model PDFs resulting PDF of all models is given by:

$$p(y) = \sum_{i=1}^{n} \theta_i p(y|M_i) \qquad (6)$$

where $p(y|M_k)$ is the forecast pdf based on model M_k and the set of model weights $\{\Theta = \theta_1, \ldots, \theta_n\} :$ $\theta_i \in [0,1]$I= 1,...,n with $\sum_k \theta_k = 1$.

Alternative approaches may be taken to estimate central estimates and intervals around these estimates for computational simplicity. Several methods developed for meta-analyses are also applicable to combining model estimates in which model estimates are modelled in different ways to relate to some true underlying distribution. The use of fixed effects models for model combination may assume that all models are estimating the same underlying value (Riley et al., 2011). Therefore, differences between model results are analogous to sampling from a distribution of observations. The use of *random-effects models*, on the other hand, may assume that model estimates vary across studies due to real differences in underlying differences in the quantity estimated, as well as some sampling variability. Hence the model estimate is modelled as such (Maishman et al., 2021):

$$\hat{\theta} = \theta_i + \epsilon_i \qquad (7)$$

$$\theta_i \sim (\theta, \tau^2) \qquad (8)$$

where $\hat{\theta}$ is the combined estimate, θ_i is an individual model estimate. Thus, when fitted, the combined estimate has a variance composed of two components: between model and in-model variance. This model can be fitted using various techniques, many of which assume the random variables are normally distributed, such as Maximum Likelihood Estimation (MLE) and Restricted Maximum Likelihood (REML) techniques.

In some cases, multiple combination methodologies such as random, fixed and mixed-effects models can be used and then compared, thus revealing the sensitivity of ensemble outputs to the choice of combination technique itself. The reasons for the discrepancies between the model combinations may be informative (Poole and Greenland, 1999).

8.4.2 Model Weighting

8.4.2.1 Metrical Weighting

The practice of equally weighting models is known as *model democracy* or *one model one vote* (OMOV) (Knutti et al., 2017, 2010; Parker, 2018). There are various arguments that, at least from an instrumental standpoint, that model democracy is often the most effective way of producing robust estimates. The use of OMOV assumes that models are sufficiently independent, equally plausible descriptions of the underlying system, distributed around some reality and that the range of projections properly represents our uncertainty (Knutti et al., 2017). In the case of the UKHSA ensemble, 'model democracy' is problematic for many reasons, most prominently the fact that models are known to be highly non-unique with inter-relatedness through shared code, assumptions and fitting algorithms, as documented in section 8.3.2.1. Further to this, the ensemble contains different realisations of the same models run multiple times, fitted to different data streams. Therefore, model democracy would overweight particular model structures significantly. Figure 8-3 shows some of the inter-relatedness between model types.

The relative simplicity of OMOV provides an additional benefit: knowing that the models all contribute equally means that analysts can more easily understand the model combination in terms of its constituents. This confers a sort of legibility on the model combination to multiple stakeholders and may help to ensure transparency.

Bayesian Model Averaging (BMA) is a popular technique similar to linear model averaging. The weights of individual models in the combination are determined by the posterior model probability (PMP). This can be interpreted as the likelihood of a model prediction being correct given available observational data, and given an initial prior distribution over the available models (Duan et al., 2007; Hinne et al., 2020). The individual weights for a model M_i and given training data y^T are given by (Raftery et al., 2005):

$$\theta_i = p(M_i|y^T) \qquad (9)$$

Other model weighting schemes may use measures of skill and independence to weight models. *Skill* can measure how well a model performs when recreating a data set or training data. It can be measured through different metrics such as Root-Mean Sure Error (RMSE) (Sanderson et al., 2017). Skill is not an intrinsic property of a model, but simply a measure of how well it recreates a change and how well suited it may be for a particular purpose (Parker, 2009). BMA, therefore, represents a method of purely weighting based on skill. Skill is only relative to a particular purpose. To assume skill is transferable between estimates may court a difficult inference that a model skilful in one domain may be skilful in another.

Skill metrics do not account for model similarities – adding multiple copies of the same model will change the result (Sanderson et al., 2017). Models can be selectively excluded from ensembles when they are insufficiently independent. For example, Sanderson et al. (2017) present a methodology that iteratively takes each model result in an ensemble to be the 'truth' and measures the similarity of other models to that model. The model pair is excluded where the similarity between a model and the 'truth model' is greater than the best performing model in the ensemble against reality (some observations).

Models can also be weighted purely in terms of their independence. Sanderson et al. (2015) describe one such independence measure in their 'representative democracy'. In such a method the distances between models' outcomes are obtained through principal component analysis (PCA) of model results, and an effective model repetition can be calculated. Weights are then set as the inverse of effective model repetition number.

Some interesting model weighting methods attempt to minimise error against some data by allowing model weights to be negative. The model weight then has no direct interpretation in terms of a belief that a model is true. Hence the authors transform the model outputs themselves to create metamodels (Abramowitz and Bishop, 2015). These transformed model results are then problematic to interpret as they are not the results of model experiments that are consistent with any understanding of reality (Sanderson et al., 2017).

8.4.2.2 Categorical Weighting

Estimates of model skill cannot be easily used in the pandemic-epidemiology context for several reasons. Primarily, the epidemiological variables of most significant policy interest are latent. So models cannot be assessed against real-world data for skill and their sufficiency for estimating variables such as R_t. If the ensemble is being used to estimate multiple important epidemic variables at once, the selection of a particular metric may be a matter of choice over which is the most important to accurately predict. Moreover, models and the system they describe are changing on a timescale so short that any estimates of performance and skill may have a fleeting validity.

Perhaps proxies for model skill could be used in which some non-latent variables are used to estimate model skill, such as case data. However, this may bias the weighting towards models which select data-streams that co-vary with the selected skill data-stream. There is also limited availability of out-of-sample data to test the performance of the models. Instead, we considered variations of model democracy that could be implemented, given what is known *a priori* about the models and their structure. Equally weighting all estimates could be misleading for several reasons:

- Multiple models are closely interrelated and share common features
- The same models are run by different groups
- Some modelling groups produce multiple estimates using the same model, fitting the model to different data streams.

Thus, the ensemble team considered equally weighting each categorical class of models (CMs, REMs and ABMs), within each of these classes equally weighting the unique model types, within these model types equally weighting their implementations by different model groups and within each of these implementations, equally weighting each of their fittings to different data streams. I term this weighting scheme '*model corporatism*'. However, this involves an element of discretion and choice: other known aspects of the model-systems may reduce the independence of model outputs and one could equally decide that the lower-level properties, such as data stream calibrated to, are more important to weight equally. The choice of data stream calibrated to, for example, may mean that some models are less independent. In fact, the within model-type similarity of outputs may well be smaller than the within data-type similarity.

However, a OMOV weighting system was employed to ensure the credibility of results and continuity between the SPI-M and UKHSA processes.

8.4.3 The CrystalCast Combination

A mathematical process was established, modelled on the SPI-M process, to combine model results and produce consensus estimates. Model combination was performed using the *CrystalCast* software package, which provides a variety of facilities for results management. The process by which this software package combines estimates is capably detailed elsewhere (Bowman et al., 2020; Maishman et al., 2021) so, I only provide a very simple summary here.

The package combined models by fitting a normal distribution to a random-effects model. Equal weights for each of the model fitting were used, which necessarily over-weighted some model structures. Other weighting schemes, such as the categorical 'model corporatism' weighting described earlier, were experimented with. The fitting of the model to the combined results was then performed with either a Restricted Maximum Likelihood (MEL) or a Hartung-Knapp-Sidik-Jankman (HKSJ) method. Consensus results were outputted in the form of the 5th and 95th percentiles of the resulting distribution.

8.5 Consensus Formation and Ensemble Interpretation

This section discusses the aspects of the process after the combination has been performed- how the consensus estimate was agreed upon, interpreted, and communicated.

8.5.1 Consensus Formation

To produce an official government statistic, it was necessary to establish a process by which the model results and model combination result could be condensed into a single range of communication to policymakers and to the public. This process is documented on the UKHSA (2021c) website.

In early trial runs of the ensemble, the model combination estimate was not used, and it was decided to opt for an explicitly social-epistemic process, by which model outputs were reviewed in concert and a consensus opinion was negotiated as to what range of values was considered to be non-discountable. In general, this range was at least inclusive of all the central estimates of the models that the analysts deemed to be credible on a given week.

However, later a numerical approach relying on the model combination algorithm described above would be employed. This ensures that a traceable account could be easily constructed from the model outputs to the resulting consensus. It also ensured week-on-week consistency of methodology that was not vulnerable to the subjective judgments of participants. In this way the process also more closely resembled the SPI-M process that preceded it, therefore ensuring social acceptance of the ensemble results and continuity of practices during the transition between the two epidemic monitoring regimes.

8.5.2 Ensemble Conceptualisation and Interpretation

Having produced this ensemble range, it is then necessary to reflect on what this is and what kinds of confidence statements can be attached to it. I therefore now consider how this ensemble can be conceptualised and therefore interpreted.

I argue that both overarching conceptualisations of ensembles discussed earlier, 'ensembles and compilations' and 'ensembles as elicitation' face a number of challenges in the context of the case study we present here.

In the case of the 'ensembles as compilations' interpretation, the model structures available for epidemiological modelling do not comprise an exhaustive set of all possible model structures. It is also clear, given the significant constraints on the academic community in terms of computational resources, development time and pre-existing software, the model structure space that can be circumscribed is sampled inconsistently and non-systematically.

Aside from the problematic interpretation of sampling model structure space, other uncertain aspects of the modelling process are challenging to standardise. To take the example of training data: models that train to the same data stream, such as case rates or hospitalisations, may not be able to fit to the same temporal interval in the data-stream due to the peculiarities of the fitting methodologies employed. Multi-model ensembles often do not account for structural uncertainties in systematic ways (Parker, 2013, p. 218).

Perhaps the 'ensembles as elicitation' interpretation is more appropriate and may be an avenue to rescue the interpretation of model outputs as probabilistic.

Let us consider Parker's (2010b) requirements for results presented as PDFs to be considered appropriate of *ownership*, *justification* and *robustness*. *Ownership* requires that scientists are willing to claim the distributions as their own. As is common in quotidian scientists' discourse, it is common for scientists to express hedging statements about results or distance themselves from model outputs that appear qualitatively erroneous. Scientists may also feel comfortable about the individual judgements that go into model construction and development but feel unease with model results. Conversely, scientists may describe the limitations of their models in many aspects yet express the belief that the model is an adequate description of the target system when taken as a gestalt.

I raise two further problems for the ownership criterion: firstly, that it is reductive to consider models to be distillations of modeller's judgments. Models contain more elements than simply modellers beliefs about the world. As Boumans (1999) argues, that in order for models to achieve adequacy for various tasks they may also contain items such as stylised facts, policy views or metaphors. Relatedly, once models are assembled, they achieve a kind of autonomy from their theoretical or experimental contexts (Morrison, 1999). It is difficult to say that a relationship of ownership between modeller and model can be maintained once removed from the context of their creation.

Justification requires that scientists can produce reasonable justifications for their PDFs. Parker also argues that scientists should bring all their available evidence and background knowledge to bear on this issue.

Robustness requires that the results are not subject to contentious assumptions, and secondly that the model results are not expected to change a great deal in the short term (Parker, 2010b). Both requirements are not met in the case of rapid pandemic epidemiology. The former as the models used contain many idiosyncratic assumptions (such as about the effect of contact networks or the effects of contacts in educational settings). The latter as the target system evolves at such a rapid pace that no model result can be expected to have validity outside a small time window.

So given, as I have argued, that probabilistic interpretations are inappropriate for model ensembles such in this case study, what interpretation can be defensible? A more cautious approach that allows something like a probabilistic interpretation is to treat ensemble results as 'estimates of probability' (Parker, 2013, p. 216).

Another alternative interpretation of the range of outcomes from an MME is that of a 'non-discountable envelope'. For this to be true, each model must necessarily be considered plausibly adequate for the modelling task (Parker, 2013, p. 216). Thus, the range given by, [sa]y, the 1st to 99th percentiles can be treated as a minimal estimate of uncertainty, acknowledging that other sources of uncertainty are not accounted for in this range. In practice, this lattermost approach was taken, with the ensemble output ranges communicated and rounded outwards to the next 1 decimal place to reflect that the ranges given were likely to be underestimates of uncertainty. For example, an outputted interval of [1.12,1.52] would map to [1.1,1.6]. The resulting interval value embodies a greater portion of the epistemic uncertainty associated with estimating epidemic metrics and has a greater utility to decision-makers than a selection of un-combined outputs alone.

8.6 Discussion

I now reflect on several philosophical themes that have arisen. I first consider how our understanding of the practicalities of producing a model ensemble impacts on the available interpretations of model ensembles. I suggest two analogies for aspects of model ensembles, *model dark matter* and *model bureaucracy* intended to draw attention to the unseen aspects of model implementation, development, combination, and administration.

8.6.1 The Unique Challenge Pandemic Ensemble Modelling

The challenge of estimating key, policy-relevant epidemiological variables *in media res* of a global pandemic is not for the faint of heart. The academic community in the United Kingdom has responded to the needs of policy with an unprecedented volume of research, much of it relying on complex epidemiological models to make estimates of current and future epidemic states as well the evaluation of policy options through scenario analysis.

Though the construction of model ensembles is a well-established practice in many fields, seldom has the practice been applied to such a time-sensitive, impactful, and fevered setting as a pandemic. Consequently, the practice as it has been realised in this case study is idiosyncratic in several ways. Amongst the peculiarities I have detailed is the key policy-relevant variables of interest being unobservable, the rapid adaption of generic epidemic models to a particular disease and the rapidly evolving disease parameters with new variants becoming prevalent.

8.6.2 Model Dark Matter: The Unseen Infrastructure of Ensembles

Within ensemble construction, as within model construction, there are many small and large decisions that are made. To name but a few: decisions need be made about how models qualify for the ensemble, the formats of standardised input files, which data sources to use for training models, how to initialise the models, the algorithm used for model combination, the weightings used for model combination, how outputs are presented (as ranges, point estimates, PDFs etc) and how these are communicated. There are also more subtle and unseen decisions made during quotidian model development and running such as the small adjustments to correct the outputs of 'misbehaving' modules or the random seeds chosen for stochastic processes. Many of these individual decisions are visible to outside observers of such a process, inscribed in the publications and communications associated with the ensemble. However, many remain too small, inconvenient, or apparently insignificant to document. Besides, an entire account of every micro-decision made would be interminable.

Further to the plethora of small decisions that are manifest, I have documented in this case study that running model ensembles requires a large amount of infrastructure: epistemic, social and technical. For example, the technical computational constraints experienced by different modelling groups will alter how models are run, which may influence results.

The models are more than just their mathematical formulations and the software they are run on- in fact, what even *is* model structure may be ontologically ambiguous. A mathematical compartmental model of an epidemic could be equally realised in the form of a water-bucket analogue system and the form of a computer model. The required investment and practicality of the two may, of course, differ.

One common aim of ensemble modelling is to isolate and probe the uncertainty associated with some aspects of model development. By varying that aspect across model runs, *ceteris paribus*, the variation in outputs will be wholly or for the most part attributable to that varied aspect. MMEs are often intended to probe aspects of structural uncertainty- that is uncertainty associated with what an adequate or ideal model structure may be for the given task.

The context of the modelling practice and ensemble creation seeps into the model results and the consensus estimates of an ensemble. However, in the published literature, this is seldom demonstrated. Given the condition of *ceteris paribus* between model realisations may be very difficult to maintain. It is foreseeable that given identical literature and software different model practitioners may arrive at different results.

Much of this socio-technical infrastructure surrounding the model process is hidden from view; like a massive unseen body altering the movement of celestial bodies in incomprehensible ways. I therefore term this unseen socio-technical infrastructure the 'model dark matter'.

8.6.3 Conceptualisation, Values and Ensemble Telos

I have argued that both standard conceptual interpretations of multi-model ensembles identified by Jebeile and Crucifix (2020) are difficult to maintain in the case study described here. The former interpretation, 'ensembles as compilations', is problematic for the reasons ably documented elsewhere by other authors. Further to this, I draw attention to all the hidden decisions and infrastructure surrounding these processes; the great range of aspects in an ensemble process that may be varied, intentionally or not, makes attribution of inter-model differences challenging.

The second interpretation has at its core the analogy between expert elicitation and model building. I have argued that this analogy is inappropriate as to describe models as mere aggregations of modeller judgements is reductive. Furthermore, modellers vary in their faith in the results of their models.

So, what kind of interpretation is possible here? I start by considering some observations.

Different stakeholders involved in the modelling process may have very different views about how the process should proceed, the value of the ensemble and the ideal form of results. These views may indeed be linked with how they conceptualise an ensemble. Values around systematicity and exploration of uncertainty dovetail very well with the 'models as compilations' interpretation. Likewise, values around pluralism gel well with the 'models as elicitation' interpretation. The difference in possible epistemic values of different stakeholders may mean that they seek different ends in the project or *teloi*.

I observe, however, that an aspect of the value of model ensembles to epistemic communities is not necessarily the epistemic value of exploring uncertainty but rather the manufacture of consensus and the soothing of incompatible results. Disciplinary communities may, at one time or another, be required to produce consensus understandings of their systems of study that are relevant to decision-makers. In situation such as these, the epistemic authority of the discipline may be called into question if some reasonable level of consensus cannot be achieved. Thus, model ensembles provide a way to arrive at a result that can be broadly accepted by all.

8.6.4 Model Bureaucracy

I introduce an alternative conceptualisation of model ensembles, which provides a new analytic lens to understand their practices and how knowledge is managed within them. I liken the processes within a model ensemble to that of a *bureaucracy*; a set of formal procedures and (complex) rules results in the production of model results for use in governance and decision-making. These *model bureaucracies* share many features and accoutrements that one may associate with traditional bureaucracies: fixed official duties, formal hierarchies, standardised forms, opacity of practices, disinterested administrators and qualifications for entry into processes (such as standardised model experiments).

This conceptualisation of MMEs as 'model bureaucracies' is far from a criticism. It recognises the importance that ensemble processes can have in creating epistemic authority. It is also an analytic framing that can be used to further interrogate their practices by drawing attention to the procedures and processes that govern MMEs.

8.6.5 Shining a Light on Model Dark Matter

Using this framing of *model bureaucracies* one can then consider how to make better MMEs. I argue that, like traditional bureaucracies, model bureaucracies are improved through increased transparency. By assigning the guiding value of transparency, other stakeholders can have oversight on the process. This also allows limitations to be much better understood and a better comprehension of the idiosyncrasies of an MME. The opaquer a model process, the more massive the aforementioned 'model dark matter' may become.

The rationale for exploring model structural uncertainty with an MME (or any other aspect of uncertainty within an ensemble for that matter) is that by standardising the specification of all other model elements, the effect of changing model structure can be isolated and understood. In such a case by better standardising model specifications, the effect of different model structures is better isolated. This can be done in many ways, such as standardising configuration files that control model parameterisation.

However, as evidence of the pandemic shows, ensemble modelling does not always proceed in such an orderly manner with long lead times between model experiments. There are situations of crisis science where long and negotiated design of MME experiments is not possible. In such situations there will be inevitable inconsistencies between model runs that go beyond the differences in formal model structure. This *dark model matter* is, at least in part, an inevitable part of the complex and chaotic process of model development, calibration, implementation and running. Some aspect of the variation between models will be due to this dark model matter. The strategy here is to then think of the ways in which a light can be shone on these variations. Even if the effect of the dark model matter cannot be quantified, it can at least be analysed by expert analysts.

Throughout the UKHSA MME, efforts have been taken at multiple levels to ensure oversight from relevant stakeholders and visibility of the process to a wide audience: from the oversight of the model creation by SPIM, the weekly EMRG expert meetings, to academic publications detailing the technicalities of the ensemble to the clear explanations published on the internet for the public.

No MME process can ever be perfect, but with good oversight and transparency they can be improved and allow all stakeholders to understand the interplay of different epistemic values and to explore the limitations of their knowledge.

8.7 Conclusion

This chapter has used a case study from pandemic crisis-science of the compilation of an MME for COVID-19 epidemic tracking by the UK Government's Joint Biosecurity centre, and subsequently by the UK Health Security Agency. I have examined several contemporary issues in the study and design of multi-model ensembles that has a broad relevance to the issues already emergent in this thesis. This has provided an opportunity to consider issues around the third theme discussed in chapter 6 about how models are surrounded by important socio-technical infrastructure.

The ensemble described is intended for the prediction of epidemic indicators in the COVID-19 pandemic. It constitutes an *ensemble of opportunity*, albeit one with significant diversity in model approaches and model structures.

I showed how in the creation of sub-ensembles for the forecasting of different metrics at different geographies, there are several trade-offs between different values. For example, different forms of reliability may be traded off against consistency in approach as different models may require exclusion from the ensemble at different times.

Several choices need be made when deciding on the methods by which model results are technically processed and combined algorithmically. Different weighting schemes represent different assumptions about what the model results represent conceptually, and the level of epistemic trust placed in them.

I have shown that in the case study presented, the conceptualisation of model ensembles as either samplings of the model structure space or as the compilation of researchers' opinions are not appropriate.

Modellers may have very different understandings and beliefs about what their estimates represent. It is also entirely possible for a modeller to compose a model by making a series of decisions that in isolation they believe are defensible, but not agree with the results as credible. The process of model harmonisation also presents an issue for the model results-as-beliefs interpretations as the process of harmonisation replaces some aspects of the model (such as parameterisations) with those most favoured by the wider community, not those of the creators and maintainers of the model itself.

Overall, ensemble interpretation is further complicated by the different potential for different participants to hold different epistemic values and teloi around the whole process. Different stakeholders and actors within a model ensemble process may have different conceptual understandings of the purpose of model ensembles, the uncertainties probed by model ensembles, the nature of models and what constitutes different model elements. I have suggested, perhaps provocatively, that some aspects of a probabilistic interpretation can be recovered if one imagines the models themselves as having some sort of belief, that is, that the models have a restricted form of agency.

This chapter has furthered my examination of how the compilation of small decisions, both in the implementation of the models and ensemble may significantly affect results. This *dark model matter* is difficult to harmonise across model runs, and it is therefore difficult to be confident that the between-model variability (and variability of variance for that matter) is attributable primarily to the aspects of model structure that one intends to explore.

It has also introduced another analytical lens to understand the socio-epistemic process of model ensemble constructions and maintenance: that of *model bureaucracy*. This draws attention to the formalisation of procedures surrounding a model ensemble and underscores the importance of governance in the ensemble process.

This lens furthers the understanding of the third theme emergent from the discussion chapter (§6) as we see how the socio-technical infrastructure that springs up around models is key to their justification. The emergence of this socio-technical infrastructure is far more rapid than the principal areas of study in this thesis. Nonetheless, many of the dynamics are the same. Ensembles such as these are crucial for boundary work as they can produce consensus amongst an epistemic community.

Both the difficulty in interpretation and the struggles of consistency demand of those designing MMEs to place emphasis on transparency and auditability of the process. Such that different actors can evaluate the usefulness of the knowledge produced by the process against their own purposes. In this way, transparency and value pluralism can go hand in hand.

This chapter has lent credence to the generalisability of my findings that one needs to pay attention to the socio-technical infrastructure that surrounds modelling exercises. In complex computer modelling, much of the justification for the work occurs in therein. Furthermore, underneath uncertainty analyses can lie very different epistemic aims that may not always be explicit.

9 Conclusion

Not known, because not looked for
But heard, half-heard, in the stillness
Between two waves of the sea.

- T.S. Eliot, *Little Gidding*

9.1 Introduction

I now return to the questions which began my journey. This chapter concludes the thesis, reflecting on the three key themes that have emerged over the preceding chapters.

I begin the conclusion on reflecting on these themes and what they mean for the research questions that I posed in the introduction (§9.2).

I then make a range of recommendations for the climate and energy/IA research communities studied, for modelling communities more generally and for policymakers using model-based information (§9.3).

I subsequently consider the previously identified limitations and the opportunities that these suggest for future research avenues (§9.4).

Finally, I reflect on the nature of the research, considering my role as a researcher and reflecting on the process of writing this thesis (§9.5).

9.2 Three Key Themes

Over the course of this thesis, findings have emerged that cluster into three key themes. The first theme concerns how concepts from the literature are employed (or indeed not employed) by modellers. The second theme understands that the main disciplinary areas of study (climate and energy/IA modelling, respectively) have differences in how they handle and conceptualise uncertainty due to their very different target systems and other non-epistemic factors. The third theme delves deeper into the complex web of relationships between actants within the modelling complex to understand what uncertainty analysis involves. The way these themes have emerged thus far over the course of the thesis is show in Figure 9-1, below. I now examine these in turn.

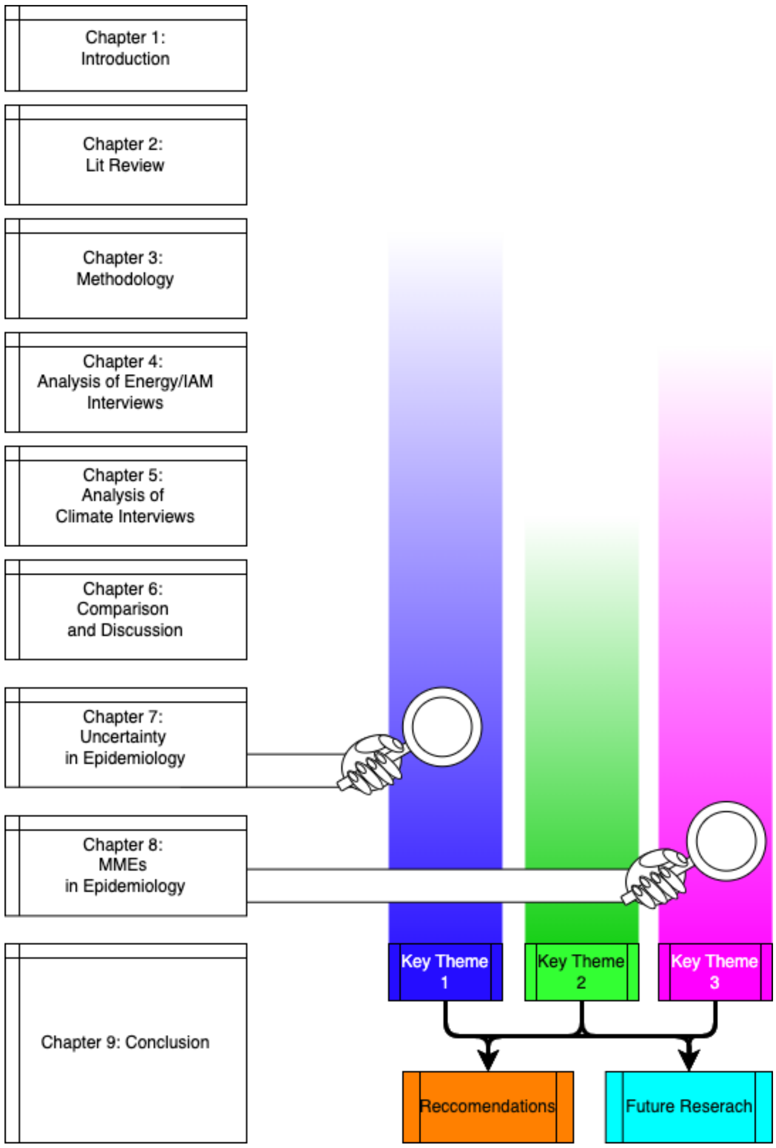

Figure 9-1: Diagram showing how the key themes have emerged over the course of the thesis thus far. The first theme emerges most strongly over the analysis chapters and is re-examined in the context of chapter 7. Chapter 2 emerges from the comparison in chapter 6, using the analysis from chapters 4 and 5. The final theme grows throughout the analyses and the conceptualisation of the socio-technical infrastructure of modelling is re-examined in chapter 8.

9.2.1 Theme 1: The Uncertainty Concepts

Chapter 2 explored in detail how different kinds of uncertainty are conceptualised in the literature relevant to the assessment of environmental change. Though controversies remain, recent literature around integrated assessment has focussed on producing uncertainty frameworks that organise uncertainties around various dimensions. I concluded that given the range of issues and limitations of modelling practices that have found themselves framed as types of uncertainty, a totalising and overarching uncertainty framework is neither possible nor desirable. Uncertainty is too monstrous an issue to allow neat organisation as a variety of epistemic issues have fallen under the umbrella of uncertainty. Instead of producing more frameworks, I suggested that one should begin with a stocktake of how uncertainty is understood and conceptualised by modelling practitioners.

Armed with this in-depth literature review as a toolbox, I examined how different communities use these concepts to discuss the uncertainties in their work through interviewing a broad swathe of climate modellers, energy modellers and integrated assessment modellers.

The different groups of researchers that I have studied understand uncertainty in different ways. This is to be expected given the different kinds of problems and practices that exists within these research areas. I have also discovered significant heterogeneity within the two groups regarding how uncertainty is understood and conceptualised.

Common to both groups, I found that the concept most often deployed to partition uncertainties, either explicitly or not, was *location*. This finding seems intuitive once stated, as locations of uncertainty are perhaps those most clearly rooted in the practice of modelling. Modellers deal with uncertainty according to the associated activities in their research practices and aspect of the model they are concerned about. Thus, the location of uncertainty in modelling practice corresponds to the elements of a model complex.

However, as I noted in my literature review, location can have several interpretations. It can correspond to the actual types of activities engaged with and choices made when constructing a model. Alternatively, one can think of locations in a model independent of the activities, such as the parameter sets, input data and model structure. Indeed, some location systems of uncertainty consider the choices that modellers make as a separate location within the model complex itself (e.g. Huijbregts, 1998; Mirakyan and De Guio, 2015).

Participants also used other concepts, but in inconsistent ways. For example, the idea of 'deep uncertainty' usually belongs to typologies that manage uncertainty by diagnosing different uncertainty *levels*. However, amongst the participants it was normally used to emphasise the intractability of certain sets of problems. Other levels were not invoked.

Despite the enormous preponderance of uncertainty typologies in the literature, these can be seen to have only a limited influence on the conceptualisations of modellers themselves. Notably, uncertainty was rarely described multi-dimensionally, which has recently been one of the prevalent trends in the uncertainty literature. Generally, researchers described uncertainty using one concept at a time; or else they grouped the changing traits that uncertainty had together, e.g., by characterising uncertainties associated with social systems as being both deep and epistemic.

This rich wealth of ideas about uncertainty has developed over the preceding decades. The influence of this literature has indeed been felt across many policy-relevant areas such as the guidance that determines how IPCC reports are communicated.

To understand the influence this kind of intellectual groundwork has on the field, I reflected on this finding through some recent work I performed in epidemiology, whilst seconded to the UK government where I worked on assessing uncertainty and model quality for an ensemble of epidemiological models.

In chapter 7, I examined the role that uncertainty and uncertainty typologies play in communicable epidemiology. I found no equivalent deep literature that specialised in organising the types of uncertainty encountered in epidemiological modelling. I then contemplated how a dimensional framework of the Walker et al. (2003) lineage, might be adapted to the space.

Epidemiological modelling has previously focussed on the various uncertainties around parametric fitting. It is only recently that the field has developed intense contact with the kinds of decision-making contexts because of the COVID-19 pandemic. The challenge in epidemiology is that the system is both natural and reflexive and the most popular classes of models do not contain representations of social agents responding to shifting environments. The issues around epidemiological modelling came under intense political contestation in the media.

This underscores that the epistemic infrastructure and norms around modelling in climate and energy are relatively mature. It is encouraging that there is a ready language to describe the diverse epistemic issues one encounters. A considerable amount of epistemic labour has gone into building up these ideas. The fruits can be seen in the gradual incorporation into things like IPCC communications guidance and government advice. The question then becomes one of how these ideas can be best put into practice and awareness of these concepts can be inculcated amongst the research community given that there may be a limited capacity for highly complex combinations of uncertainty concepts to be used in combination with one another due to the natural need for parsimony and clarity.

This comes back to my conclusion from the literature review. A huge number of issues can be framed as aspects of 'uncertainty'. A broad class of epistemic issues affect the suitability of information for informing various conclusions and decision-making. Uncertainty remains too parochial a term. It also implies that knowledge short of certainty is imperfect. We need some way of talking about these issues that acknowledges the possibility of different epistemic goals and values in modelling and assessment processes.

9.2.2 Theme 2: The Structural Differences in the Subject Areas

Differences between the two fields in how uncertainty is conceptualised, and analytic repertoires are inevitable, given the differences in the target systems they study. Put simply: one system has human agents making decisions in it.

Energy systems modelling and IAM are disciplines inherently interested in evaluating the future. The difficulty in evaluating futures in a social system is that reflexivity prevents anticipation of the dynamics that drive system evolution. Actors do not know what world they and others will create (Beckert and Bronk, 2018a). Therefore, it is inevitable that assumptions about the development of deeply uncertain factors are used. These assumptions are often packaged as scenarios.

Scenarios provide a flexible concept that structures much of the work done in this space. They are the bread and butter of energy systems and integrated assessment modellers. I have shown the activity of scenario analysis to be conceptualised in different ways. For some, a scenario analysis has a very parsimonious definition and is simply the systematic variation of some assumptions to determine the effect on outcomes. As such, this shares a conceptual boundary with the practice of sensitivity analysis. For other energy participants, scenario analyses are more baroque conceptual constructions involving harmonising a variety of assumptions. These scenarios are detailed descriptions, enriched with qualitative narrative elements that are the products of consensus processes and modelling.

There are also various normative ideas about how scenarios should be used. There are disagreements over the relationship that scenario assumptions can have to probabilities, both formal and informal. At the root of these disagreements are not conceptual disagreements necessarily about what scenarios are but rather more pragmatic considerations, such as beliefs about what kinds of information are best provided to decisionmakers and what they will do with that information once they get it. However, from the interview data it was not entirely possible to discern how these normative disputes manifested themselves in the modeller's everyday practices.

In climate modelling, scenarios are of less significance to the daily practices of modellers. They are often understood as exogenous to both models and modelling practices – the artefacts of other disciplines that are incorporated into models.

The concept of *variability* was revealing in the analysis of interviews with climate modellers, albeit it did not have the corresponding significance of *scenarios*. As climate models are concerned with forecasting and recreating previous system behaviour, variability has multiple roles for climate modellers both as a source of uncertainty in their results, but also as a necessary phenomenon to recreate for model evaluation and validation. The discussion of variability with climate modellers betrayed several the difficulties that modellers can have in separating their model system from their target system.

Moving beyond these factors related to the fundamental natures of the systems and aims of the sciences, I uncovered a variety of non-epistemic factors that affected how people handled uncertainty.

The relationship between methods and types of uncertainty is generally uncomplicated in climate science. Ensemble methods such as MMEs, PPEs, ICEs, ICLEs all correspond to a type of uncertainty. The diversity of fundamental model structures in energy systems and integrated assessment means that standardised interpretations of model experiments are more challenging.

Non-epistemic considerations strongly influence which uncertainties a modeller may be most keen to explore. The topical priorities of funders inform what sorts of projects can be funded with grant money. Participants described that in energy/IA modelling, there was frequently a dynamic where different groups 'chased the ball' of the most recent issues in the zeitgeist. The cycle-time of model development in climate is longer than that of energy, though there are nonetheless themes that emerge in popularity.

9.2.3 Theme 3: Dynamics in the Model-Complex

The final theme that has emerged throughout this thesis is an understanding of the local context of the model and the interactions between modellers and their models. This is the theme that I believe may have the most generalisability to other academic contexts where complex computer models are the focus of research efforts.

The first important dynamic is between the modeller and the model. When a modeller wishes to examine some uncertain issue using a model or to explore the uncertainties embedded within a model, they must interact with or manipulate the model in some way. The models themselves control this as they only permit certain kinds of interactions. For example, a model may only allow scenario inputs in a particular file format. A model may be so complex that running it many times to produce an ensemble of results is not practicable given available HPC capacity.

Thus, models have a disciplining effect on those who interact with them and constrain the ways that uncertainty can be explored. The structure of a model is the result of its development history – the accrual of a myriad of decisions made over years of work by a variety of individuals. These decisions may involve all sorts of non-epistemic considerations such as convenience.

The second dynamic considers how the models shape and are shaped by their contexts over the longer term. I have already said how the models influence their operators, but another way they change their operators is by the training necessary to use them in the first place. Having invested oneself in the work of a model, those associated with it will advocate for its utility in addressing further uncertainties to stakeholders outside of the immediate modelling context.

As a model beds itself in, a socio-technical infrastructure emerges around it to support its operations and development. This process of integration and altering the local environment is analogous to the idea of 'niche construction' in ecology where an organism modifies its and other organisms' environments.

It is this myriad of small decisions and elements around the model-complex that can influence the results of the model. In chapter 8 I showed how this finding is also visible in the context of epidemiological modelling. I problematised the socio-technical infrastructure that has an ambiguous effect on model outputs as 'model dark matter'. Many of the small decisions that go into running a model are undocumented and invisible to outsiders of the modelling process. Thus, they constitute an under-appreciated location of uncertainty.

Further to this, I explored how the different aims and understandings of an MME process can cause inconsistencies within the ensemble. I suggested that these ensemble processes are better characterised as 'model bureaucracies'. Collaborative uncertainty analysis exercises fulfil the function of formalising a process for consensus creation.

This understanding of the difficulties of assessing uncertainty when different actors pursue different epistemic strategies underscores the point that emerged from the literature review: there is no absolute uncertainty and uncertainty can only be understood relative to the task at hand.

9.2.4 Summary of Key Themes

Models are created to achieve a variety of epistemic goals. The diversity of these goals means that often claims that models have some total uncertainties are nonsensical. When dealing with topics relevant to decision-making we must consider the sufficiency of knowledge our purposes.

I have shown that there is an inextricable connection between the conceptualisation of uncertainty and the methods used to handle it. The relation goes both ways: modellers may prefer certain techniques for managing uncertainty due to their prior beliefs about the nature of those uncertainties. Similarly, specific uncertainty analysis techniques imply a legitimate structure of knowledge.

Nearing et al. (2016) argue that any proper understanding of uncertainty must ultimately rest on a well-defined philosophy of science. However, as Beven (2002) describes, scientists do not normally possess neat philosophies. The concepts used by practicing scientists may imply aspects of a legitimate structure of knowledge, but philosophies of science in practice are not programmes to which one can easily declare a formal allegiance. Models embody multiple forms of knowledge and rules (Boumans, 1999), which may originate from practices with different epistemologies. When dealing with epistemic hodgepodges like modellers and models, it is unreasonable to request absolute philosophical clarity.

The ability to perform a formal uncertainty analysis is dependent on the present configuration and status of a model. This state of a model is dependent on the path dependent decisions made by a community of modellers. The desire to alter a model is conditioned by the environment of the modelling practice, such as the funding organisations' priorities. The possibility of achieving the development is mediated by the resource available to an organisation: the human capital, the time, and the money available.

The understanding I have built of the myriad unseen decisions that affect the outcomes of modelling work is very consistent with a recent paper by Melsen (2022), detailing an interview study with 14 hydrological modellers. The study involved examining the practices of hydrological modellers and distilled their motivations for different modelling decisions. Melsen (2022) argues that "model results are time and place dependent and therefore each modelling study can only tell a little part of the story." They find that most decisions made by modellers related not to epistemic concerns but circumstantial issues, such as the experience of colleagues, time resources or data availability.

Indeed, the attention paid by Melsen (2022) to non-epistemic decisions of consequence is congruent with my second theme, albeit in a different topical area. They too argue that to understand the full uncertainty associated with a model, one must account for the context in which the modelling occurs. To achieve this, they advocate transparency and value diversity within model groups.

Other work has paid attention to the choice-making processes of modellers (Beck and Krueger, 2016; Krueger et al., 2012; Mayer et al., 2017). Mayer et al. (2017) find that modellers hold a large variety of values and preferences that affect the decisions they make when modelling. Furthermore, Krueger et al. (2012) detail the opinions of experts that can enter a modelling process in many locations of the modelling process. Whilst my findings are broadly compatible with these approaches, I do not narrowly focus on the agency that the modellers have and the factors that may impinge on it.

My argument is not just that models are socially constructed, as has been argued for decades (e.g., Pinch and Bijker, 1984). My emphasis is that models *also* construct their environments around them. The most important conclusion regarding the nature of uncertainty analysis in modelling is the dialogic relationship between a modeller as an epistemic agent and a model as an epistemic artefact.

Models alter the epistemic state of those who interact with them and have durable impacts on those who use them. This was most tangible in my interviews at their beginning when I asked participants about how they arrived at the work they currently participate in. Models require modellers to retrain themselves and force particular representations of the world on the minds of modellers. Often models or model frameworks themselves may outlive the active lifespan of the researchers that made them. They are durable participants in the research process.

I conclude that uncertainty as a term, especially in communicating to lay audiences, papers over the vast diversity of epistemic uses that it can represent. Uncertainty *is the default condition* of all knowledge and as such, we should find ways of portraying uncertainty not as an unwelcome appendage of our work, but as the motivation that pushes us to better our past efforts.

Different researchers require different epistemic standards from their knowledge and hold different epistemic values dear. We need to think of ways of communicating this to diverse audiences.

9.3 Recommendations

Based on the understanding that I have built throughout this thesis, I now advance several suggestions for modellers, funders of modelling work and policymakers. Some of these suggestions are speculative and are intended as starting points for contemplation.

Through the interviews, I found a wealth of ideas used to structure how we find ourselves uncertain when we undertake modelling of natural and social systems. The way that modellers discussed uncertainty did correspond to these concepts, whether they were aware that they were using them or not. However, not all the concepts, such as *pedigree* and *ignorance*, were regularly employed. **(R1) The distance between the sizable corpus of ideas and their use amongst modelling professionals implies a role for training**, either by making such training readily available to the community through building resources like MOOCs or through the institutions that modellers work in. Conducting deep literature reviews is not always a practical way of consistently educating modellers and so resources about epistemic issues in various modelling disciplines could be created, such as wikis.

However, as I have found, modellers did not seem to regularly employ multiple uncertainty concepts at the same time. This suggest that there may be a limited return from simply trying to teach scientists about uncertainty. Perhaps we need to think about the issue in two ways.

Firstly, when we teach scientists about uncertainty, our end goal may be to instil certain kinds of epistemic virtue in the scientist, such as rigour, epistemic humility, and openness to pluralism. This is perhaps evident in the direction that uncertainty frameworks have moved in recent years, expanding the dimensions of uncertainty to include pedigree (indicating rigour), value-ladenness (indicating openness) and recognised ignorance (indicating humility).

Secondly, we may wish to think structurally about how to encourage these virtues and values. Uncertainty analyses often appear as an ex-post exercise to digest and communicate research. How can uncertainty practices be built into the products that research produces? Alas, I do not have ready answers to this, but I believe it warrants contemplation.

It is also important to consider what the value of these frameworks is. Aside from the formal functions outlined in section 2.2.1, they play an informal role in provoking and promoting introspection and contemplation about the limitations of results. **(R2) In the future, researchers could consider how these frameworks could be turned into lightweight heuristics to sense-check various aspects of model quality**.

I have explored how non-epistemic factors such as the availability of human resources constrain the abilities of modellers to perform uncertainty analysis exercises. Pursuing new and vital research questions is always important. However, those administrating modelling work should consider the optimal allocation of resources between exploring new avenues of research and knowledge consolidation, uncertainty analysis being a part of this. **(R3) Funders can consider how to incentivise the unglamorous work of long-term model building, through the deployment of long-term funding.**

(R4) Find novel accounting methods for the 'model dark matter' and aspects of the modelling practice that are not normally visible to non-participants in model construction. I have explored how much of the modelling process involves complex interactions between modellers and the socio-technical infrastructure surrounding the model. The nature of this infrastructure has a strong effect on the ultimate results of modelling work. However, it is often invisible to outsiders. To shine a light on these consequential aspects of modelling, novel ways of documenting the model process, which are not overly onerous on modellers, could be developed. Such as automatic archiving of failed model runs and disclosure of the division of labour within a model team in publications.

The complexity of models is a key constraint to understanding their very worth. Finding ways of making this complexity manageable so that we can understand the value of the models that we use to inform policy is important. We should recognise that to easily examine models and perform model introspection, the functionality to do so must be in-built during development.

If models are prohibitively complex, models may be implemented using code or packages unfamiliar to users, explanations of decisions made in model construction may not be available and epistemic agency for model construction is distributed amongst a wide group of stakeholders. Many of these issues can be ameliorated with greater accessibility of model code.

Several authors have described this complex model lock-in. Shackley et al. (1998) writing in climate science and Tol (2006) in Integrated Assessment argue that respectively that complex GCMs and IAMs are dominant in their communities. Tol (2006) suggests this incumbency is maintained through funding, risk-aversion and a lack of incentives to promote interdisciplinarity. Shackley et al. (1998) ascribe the dominance of GCMs due to their utility in producing regional climate projections and a set of mutually reinforcing dynamics with other communities such as policy and impacts researchers. Stirling (2010) also describes this lock-in where sub-optimal models and analyses become established and perceived as valuable to policymakers and likens this to technology lock-ins (e.g., the Qwerty keyboard).

The path dependencies of model development favour creeping complexity. Overcoming these path dependencies means making models simpler and more flexible to answer a wider variety of research questions. **(R4) Funders should promote simple modelling frameworks focussing on adaptability and transparency.** With flexible and lighter-weight models, other epistemic values can be incorporated into evidence for decision-making, such as robustness.

Overconfident reliance on technical sets of tools that try to manage areas of high uncertainty leads to what Jasanoff (2003) calls 'technologies of hubris'. Instead, she argues that policymakers should be afforded with 'technologies of humility' to allow the humble exploration of uncertainties. These technologies of humility can be complementary to their hubristic counterparts and can consist of institutionalised ways of thinking.

Mehta et al. (2019) use the term 'uncertainty from above' for the process of dealing with uncertainty from the view of the policymaker using technocratic forms of expert knowledge. In contrast, 'uncertainty from below' is that experienced by local actors and is derivative of experience. 'Uncertainty from the middle' can attempt to mediate between these levels and broker translations. Mehta and Srivastava (2020) recommend stakeholder dialogues as opportunities to break down disciplinary siloes and power structures.

How to institutionalise 'uncertainty from below' and 'technologies of hubris' is an important area of study, outside of the scope of this thesis. Nonetheless, it is interesting to consider how some aspects of the sociotechnical infrastructure of modelling that I have described can interact with more democratic forms of knowledge production.

9.4 Avenues for Future Research

Using my exploration of the limitations of the main empirical study (§6.6), and subsequent discussion, I identify avenues for future research in this space along the following themes:

- Scope for expansion of the main study described here
- Investigation of other concepts
- Related areas of study
- Other important things

9.4.1 Expanding the Study

This study has looked at the conceptualisations of uncertainty in two areas that are key to planning global responses to mitigate climate change. These areas can be categorised with the shorthand of being relevant to WGI and WGIII of the IPCC. Another important community, which could be included in a comparative work like this, are those modellers who deal primarily with climate impacts, or in other words, WGII modellers. They model both physical and social systems, often taking outputs from climate models, and their work informs Integrated Assessment.

Alternatively, the method developed here could be deployed outside of the boundary of science to build on the literature that examines lay and policymaker understanding of scientific concepts. Such work would have direct relevance to the design of scientific communications.

9.4.2 Other Concepts

The methodology could also be deployed to examine the conceptualisation of other ideas in science. The study has dealt with a wide variety of concepts related to uncertainty, each of which could be pursued in this way.

At several points I have noted the trade-off inherent in the methodology of exploring the broad gamut of uncertainty concepts, versus exploring related ideas in depth. A future study could look much more narrowly at one of these related concepts like consensus or rigour.

I have also noted in my limitations that this study has identified various non-epistemic value at play in deciding what kinds of uncertainty analysis to pursue, but it has not been able to systematically compare the different values identified. An approach that accommodates mental models methodologies, but also is more sensitive to values could be taken, such as that of Mayer et al. (2017) who employ a 'Values-informed Mental Models' approach.

9.4.3 Related Areas of Study

This thesis has studied and compared two communities in partial isolation[52]. Future research could seek out and study sites where competing conceptualisations of uncertainty come into contact and are negotiated.

I have begun to examine the intellectual heritage of some of these ideas. Historical work could consider the genealogy of recent uncertainty concepts in greater detail, as has been performed for statistical and probabilistic ideas.

A factor on the treatment of uncertainty is the disciplinary background of modelling participants, the conceptual resources that have available to them and the training that they have received. Future research could consider examining the key texts used for training modellers and examine their implications philosophically. As such, this would be similar to the approach of Giere (1988).

A theme touched on, but not deeply explored through the interview data, is how uncertainty provides both a threat to and support for the perceived credibility of a piece of research. The strategic use of uncertainty goes beyond the boundary work described by Shackley & Wynne (1996), but there is scope for additional research that considers the strategic use of uncertainty within the boundaries of science. In what ways is uncertainty instrumentalised by researchers?

9.4.4 Other Ideas

Temporality

In all research that seeks to explore possible futures of systems, temporality is an important aspect. However, how the nature of temporality interacts with different kinds of knowledge states and uncertainties is under-researched. For example, some epistemic uncertainties are said to be reducible and there is a general expectation that they will be reduced over time.

[52] Some participants belonged to both communities.

Furthermore, the lifetimes and cycle-lives of models compared to the systems they describe are important for understanding how they can form decision-making.

Future research should consider how we can locate uncertainties temporally: whether uncertainties can be expected to be reduced in time, whether the aspects of the world that are uncertain are transient, and the dynamics of how learning occurs.

Scenario Strategies

This thesis has demonstrated that there are a diversity of ways of conceiving what a scenario or scenario analysis exercise is or ought to be. Scenario analyses can embody different epistemic strategies such as providing a basis for the comparison of studies or the discovery of unexpected possible outcomes.

Beckert and Bronk (2018a) argue that models can embody a form of storytelling. But embedded assumptions in models hide normativity in the story and this can help entrench certain forms of power. The imaginaries dominant in a society are consequential and the subject of political contestation (Jasanoff and Kim, 2009).

Future research could consider the interaction between the normative dimensions of the imaginaries that scenarios embody and their implicit epistemic strategies.

9.5 Researcher Reflection

The process of completing a doctorate at STEaPP is relatively long for a UK university. The baseline is intended to be a four-year course of study with taught elements covering a large part of the first year. Additionally, I interrupted my studies for most of a year to assist the UK government in the COVID pandemic response. The process of returning to my thesis after my secondment to the government was interesting as I had forgotten enough of the content of the data, and I had the chance to view it with somewhat fresh eyes. I firmly feel that the overall way I have been able to interpret this data has benefitted from the experiences I had working directly with models and communicating those model results.

Before starting my doctoral research, I received a piece of advice from someone who had completed theirs: “A PhD is also about all the things you do along the way.” This has certainly rung true for me.

My hope is that this thesis reflects my personal search for clarity in this immensely confusing research space. Confusing by its very nature as it deals with the fringes of what we know and what can be known. I hope that it provides a window into how uncertainty is thought about, not just how we think it should be thought about.

"Le doute n'est pas un état bien agréable, mais l'assurance est un état ridicule."

– Voltaire, letter to Frederick William II of Prussia, November 1770

References

Abel, N., Ross, H., Walker, P., 1998. Mental Models in Rangeland Research, Communication and Management. The Rangeland Journal 20, 77–91. https://doi.org/10.1071/RJ9980077

Abramowitz, G., Bishop, C.H., 2015. Climate Model Dependence and the Ensemble Dependence Transformation of CMIP Projections. Journal of Climate 28, 2332–2348. https://doi.org/10.1175/JCLI-D-14-00364.1

Afshordi, N., 2016. He will be eternally lost in his hopeless oblivion! URL https://nafshordi.com/2016/07/

Akhtar, M., Kraemer, M.U.G., Gardner, L.M., 2019. A dynamic neural network model for predicting risk of Zika in real time. BMC Medicine 17, 171. https://doi.org/10.1186/s12916-019-1389-3

Alcamo, J., Bartnicki, J., 1987. A framework for Error Analysis of a Long-Range Transport Model with an emphasis of parameter uncertainty. Atmospheric Environment 21, 1021–1031.

Alexander, J., 2012. Experimental Philosophy: An Introduction. Polity Press, Cambridge, UK.

Aligica, P.D., 2005. Scenarios and the growth of knowledge: Notes on the epistemic element in scenario building. Technological Forecasting and Social Change 72, 815–824. https://doi.org/10.1016/j.techfore.2005.01.001

Andrianakis, I., Vernon, I.R., McCreesh, N., McKinley, T.J., Oakley, J.E., Nsubuga, R.N., Goldstein, M., White, R.G., 2015. Bayesian History Matching of Complex Infectious Disease Models Using Emulation: A Tutorial and a Case Study on HIV in Uganda. PLOS Computational Biology 11, e1003968. https://doi.org/10.1371/journal.pcbi.1003968

Arksey, H., Knight, P., 1999. Interviewing for Social Scientists. SAGE Publications Ltd, London, UK.

Arnold, H.M., 2013. Stochastic Parametrisation and Model Uncertainty. University of Oxfrod.

Ascough II, J.C., Maier, H.R., Ravalico, J.K., Strudley, M.W., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecological Modelling 219, 383–399. https://doi.org/10.1016/j.ecolmodel.2008.07.015

Baecher, G., Christian, J., 2020. Natural variation, limited knowledge, and the nature of uncertainty in risk analysis. Presented at the Risk-Based Decisionmaking in Water Resources IX, Santa Barbara, CA, USA.

Baker, L., Ellison, D., 2008. The wisdom of crowds — ensembles and modules in environmental modelling. Geoderma 147, 1–7. https://doi.org/10.1016/j.geoderma.2008.07.003

Barbarossa, M.V., Dénes, A., Kiss, G., Nakata, Y., Röst, G., Vizi, Z., 2015. Transmission Dynamics and Final Epidemic Size of Ebola Virus Disease Outbreaks with Varying Interventions. PLOS ONE 10, e0131398. https://doi.org/10.1371/journal.pone.0131398

Barrieu, P., 2020. Dialogues Around Models and Uncertainty: An Interdisciplinary Perspective. WORLD SCIENTIFIC (EUROPE). https://doi.org/10.1142/q0230

Baustert, P., Othoniel, B., Rugani, B., Leopold, U., 2018. Uncertainty analysis in integrated environmental models for ecosystem service assessments: Frameworks, challenges and gaps. Ecosystem Services, Demonstrating transparent, feasible, and useful uncertainty assessment in ecosystem services modeling. 33, 110–123. https://doi.org/10.1016/j.ecoser.2018.08.007

Beck, M., Krueger, T., 2016. The epistemic, ethical, and political dimensions of uncertainty in integrated assessment modeling. WIREs Climate Change 7, 627–645.

Beck, M.B., 1987. Water quality modeling: A review of the analysis of uncertainty. Water Resour. Res. 23, 1393–1442. https://doi.org/10.1029/WR023i008p01393

Beckert, J., 2016. Imagined Futures: Fictional Expectations and Capitalist Dynamics. Harvard University Press, Boston, MA, USA.

Beckert, J., Bronk, R., 2018a. An Introduction to Uncertain Futures, in: Beckert, J., Bronk, R. (Eds.), Uncertain Futures: Imaginaries, Narratives and Calculation in the Economy. Oxford University Press, Oxford, UK, pp. 1–38.

Beckert, J., Bronk, R., 2018b. Uncertain Futures: Imaginaries, Narratives and Calculation in the Economy. Oxford University Press, Oxford, UK.

Bedford, T., Cooke, R., 2001. Probabilistic Risk Analysis: Foundations and Methods, 1st ed. Cambridge University Press. https://doi.org/10.1017/CBO9780511813597

Beisbart, C., 2021. Opacity thought through: on the intransparency of computer simulations. Synthese 199, 11643–11666. https://doi.org/10.1007/s11229-021-03305-2

Bellprat, O., Kotlarski, S., Lüthi, D., Schär, C., 2012. Exploring Perturbed Physics Ensembles in a Regional Climate Model. Journal of Climate 25, 4582–4599. https://doi.org/10.1175/JCLI-D-11-00275.1

Ben-Haim, Y., 2019. Info-Gap Decision Theory (IG), in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty: From Theory to Practice. Springer International Publishing, Cham, pp. 93–115. https://doi.org/10.1007/978-3-030-05252-2_5

Ben-Haim, Y., 2006. Info-Gap Decision Theory: Decisions Under Sever Uncertainty, 2nd ed. Academic Press.

Bercht, A.L., 2021. How qualitative approaches matter in climate and ocean change research: Uncovering contradictions about climate concern. Global Environmental Change 70, 102326. https://doi.org/10.1016/j.gloenvcha.2021.102326

Bergman, A., Karlsson, J.C., Axelsson, J., 2010. Truth claims and explanatory claims—An ontological typology of futures studies. Futures, Europe 2030: Territorial Scenarios 42, 857–865. https://doi.org/10.1016/j.futures.2010.02.003

Berner-Rodoreda, A., Bärnighausen, T., Kennedy, C., Brinkmann, S., Sarker, M., Wikler, D., Eyal, N., McMahon, S.A., 2018. From Doxastic to Epistemic: A Typology and Critique of Qualitative Interview Styles. Qualitative Inquiry 26, 291–305. https://doi.org/10.1177/1077800418810724

Bernstein, P.L., 1996. Against the Gods: The Remarkable Story of Risk. Wiley, New York, USA.

Bessette, D.L., Mayer, L.A., Cwik, B., Vezér, M., Keller, K., Lempert, R.J., Tuana, N., 2017. Building a Values-Informed Mental Model for New Orleans Climate Risk Management. Risk Analysis 37, 1993–2004. https://doi.org/10.1111/risa.12743

Betz, G., 2009. Underdetermination, Model-ensembles and Surprises: On the Epistemology of Scenario-analysis in Climatology. J Gen Philos Sci 40, 3–21. https://doi.org/10.1007/s10838-009-9083-3

Beven, K., 2016. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication. Hydrological Sciences Journal 61, 1652–1665. https://doi.org/10.1080/02626667.2015.1031761

Beven, K., Lamb, R., Leedal, D., Hunter, N., 2015. Communicating uncertainty in flood inundation mapping: a case study. International Journal of River Basin Management 13, 285–295. https://doi.org/10.1080/15715124.2014.917318

Beven, K., Leedal, D., McCarthy, S., Lamb, R., Hunter, N., Bates, P., Neal, J., Wicks, J., 2014. Framework for assessing uncertainty in fluvial flood risk mapping. CIRIA, London, UK.

Beven, K.J., 2002. Towards a coherent philosophy for environmental modelling. Proceedings of the Royal Society A Methematical, Physical & Engineering Sciences 458, 2465–2484. https://doi.org/10.1098/rspa.2002.0986

Bhattacharyya, S.C., Timilsina, G.R., 2010. A review of energy system models. International Journal of Energy Sector Management 4.

Björnberg, K.E., Karlsson, M., Gilek, M., Hansson, S.O., 2017. Climate and environmental science denial: A review of the scientific literature published in 1990–2015. Journal of Cleaner Production 167, 229–241. https://doi.org/10.1016/j.jclepro.2017.08.066

Blau, A., 2011. Uncertainty and the History of Ideas. History and Theory 50, 358–372.

Bloomberg, L., Volpe, M., 2012. Completing Your Qualitative Dissertation: A Roadmap from Beginnign to End. SAGE Publications Ltd, Thousand Oaks, CA, US.

Bloomberg, L., Volpe, M., 2008. Presenting Methodology and Research Approach, in: Completing Your Qualitative Dissertation: A Roadmap from Beginning to End. SAGE Publications, Inc., 2455 Teller Road, Thousand Oaks California 91320 United States. https://doi.org/10.4135/9781452226613

Blower, S.M., Dowlatabadi, H., 1994. Sensitivity and Uncertainty Analysis of Complex Models of Disease Transmission: An HIV Model, as an Example. International Statistical Review / Revue Internationale de Statistique 62, 229–243. https://doi.org/10.2307/1403510

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., Finnveden, G., 2006. Scenario types and techniques: Towards a user's guide. Futures 38, 723–739. https://doi.org/10.1016/j.futures.2005.12.002

Boumans, M., 1999. Built-in Justification, in: Morgan, M.S., Morrison, M. (Eds.), Models as Mdiators, Ideas in Context. Cambridge University Press, Cambridge, UK, pp. 66–96.

Bowman, V.E., Silk, D.S., Dalrymple, U., Woods, D.C., 2020. Uncertainty quantification for epidemiological forecasts of COVID-19 through combinations of model predictions. arXiv:2006.10714 [stat].

Bradley, R., Drechsler, M., 2014. Types of Uncertainty. Erkenn 79, 1225–1248. https://doi.org/10.1007/s10670-013-9518-4

Brady, M.E., 2014. Interval Probabilities, and Not Ordinal Probabilities, are the Foundation of J M Keynes's Approach to Probability. SSRN Online.

Brill, E.D., Chang, S.-Y., Hopkins, L.D., 1982. Modeling to Generate Alternatives: The HSJ Approach and an Illustration Using a Problem in Land Use Planning. Management Science 28, 221–235.

Brinkmann, S., 2007. Could Interviews Be Epistemic?: An Alternative to Qualitative Opinion Polling. Qualitative Inquiry 13, 1116–1138. https://doi.org/10.1177/1077800407308222

Brooks, 1986. The Typology of Surprise in Technology, Institutions and Development, in: Clark, W.C., Munn, R.E. (Eds.), Sustainable Development of the Biosphere. Cambridge University Press, Cambridge, UK, pp. 325–350.

Brouwer, R., De Blois, C., 2008. Integrated modelling of risk and uncertainty underlying the cost and effectiveness of water quality measures. Environmental Modelling and Software 23, 922–937.

Brown, J.D., 2004. Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. Trans Inst Br Geog 29, 367–381. https://doi.org/10.1111/j.0020-2754.2004.00342.x

Brugnach, M., Dewulf, A., Pahl-Wostl, C., Taillieu, T., 2008. Toward a Relational Concept of Uncertainty: about Knowing Too Little, Knowing Too Differently, and Accepting Not to Know. Ecology and Society 13. https://doi.org/10.5751/ES-02616-130230

Budescu, D. V, Por, H., Broomell, S.B., Smithson, M., 2014. The interpretation of IPCC probabilistic statements around theworld. Nature Climate Change 4, 508–512. https://doi.org/10.1038/NCLIMATE2194

Burgman, M.A., Ferson, S., Akcakaya, H.R., 1993. A Probabilistic Framework, in: Risk Assessment in Conservation Biology. Chapman & Hall, London, UK.

Callon, M., 1986. Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay, in: Law, J. (Ed.), Power, Action and Belief: A New Sociology of Knowledge? Routledge, London, UK, pp. 196–233.

Calvin, K., Bond-Lamberty, B., Clarke, L., Edmonds, J., Eom, J., Hartin, C., Kim, S., Kyle, P., Link, R., Moss, R., McJeon, H., Patel, P., Smith, S., Waldhoff, S., Wise, M., 2017. The SSP4: A world of deepening inequality. Global Environmental Change 42, 284–296. https://doi.org/10.1016/j.gloenvcha.2016.06.010

Capaldi, A., Behrend, S., Berman, B., Smith, J., Wright, J., Lloyd, A.L., 2012. Parameter estimation and uncertainty quantification for an epidemic model. Math Biosci Eng 9, 553–576. https://doi.org/10.3934/mbe.2012.9.553

Cardwell, H., Ellis, H., 1996. Model uncertainty and model aggregation in environmental management. Applied Mathematical Modelling 20, 121–134. https://doi.org/10.1016/0307-904X(95)00086-Y

Cartwright, N., 2009. If No Capacities Then No Credible Worlds. But Can Models Reveal Capacities? Erkenntnis 70. https://doi.org/10.1007/s10670-008-9136-8

Cartwright, N., 1983. How the Laws of Physics Lie. Oxford University Press, New York, US.

Carvalho, F.J.C.D., 1988. Keynes on Probability, Uncertainty, and Decision Making. Journal of Post Keynesian Economics 11, 66–81.

Casman, E.A., Morgan, M.G., Dowlatabadi, H., 1999. Mixed Levels of Uncertainty in Complex Policy Models. Risk Analysis 19, 33–42. https://doi.org/10.1111/j.1539-6924.1999.tb00384.x

Chatzilena, A., van Leeuwen, E., Ratmann, O., Baguelin, M., Demiris, N., 2019. Contemporary statistical inference for infectious disease models using Stan. Epidemics 29, 100367. https://doi.org/10.1016/j.epidem.2019.100367

Cheung, W.W.L., Frölicher, T.L., Asch, R.G., Jones, M.C., Pinsky, M.L., Reygondeau, G., Rodgers, K.B., Rykaczewski, R.R., Sarmiento, J.L., Stock, C., Watson, J.R., 2016. Building confidence in projections of the responses of living marine resources to climate change. ICES Journal of Marine Science 73, 1283–1296. https://doi.org/10.1093/icesjms/fsv250

Chiodi, A., Taylor, P.G., Seixas, J., Simoes, S., Fortes, P., Gouveia, J.P., Dias, L., O Gallachoir, B., 2015. Energy Policies Influenced by Energy Systems Modelling- Case Studies in UK, Ireland, Prtugal and G8, in: O Gallachoir, B., Toasto, G., Labriet, M., Giannakidis, G. (Eds.), Informing Energy and Climate Policies Using Energy Systems Models: Insights from Scenario Analysis Increasing the Evidence Base. Springer, Switzerland, pp. 15–42.

Chow, C., Sarin, R.K., 2002. Known, Unknown, and Unknowable Uncertainties. Theory and Decision 52, 127–138. https://doi.org/10.1023/A:1015544715608

Chowell, G., 2017. Fitting dynamic models to epidemic outbreaks with quantified uncertainty: A primer for parameter uncertainty, identifiability, and forecasts. Infectious Disease Modelling 2, 379–398. https://doi.org/10.1016/j.idm.2017.08.001

Chowell, G., Castillo-Chavez, C., 2003. 2. Worst-Case Scenarios and Epidemics, in: Banks, H.T., Castillo-Chavez, C. (Eds.), Bioterrorism: Mathematical Modeling Applications in Homeland Security. Society for Industrial and Applied Mathematics, pp. 35–53. https://doi.org/10.1137/1.9780898717518.ch2

Chowell, G., Luo, R., Sun, K., Roosa, K., Tariq, A., Viboud, C., 2020. Real-time forecasting of epidemic trajectories using computational dynamic ensembles. Epidemics 30, 100379. https://doi.org/10.1016/j.epidem.2019.100379

Christley, R.M., Mort, M., Wynne, B., Wastling, J.M., Heathwaite, A.L., Pickup, R., Austin, Z., Latham, S.M., 2013. "Wrong, but Useful": Negotiating Uncertainty in Infectious Disease Modelling. PLOS ONE 8, e76277. https://doi.org/10.1371/journal.pone.0076277

Claussen, M., Mysak, L., Weaver, A., Crucifix, M., Fichefet, T., Loutre, M.-F., Weber, S., Alcamo, J., Alexeev, V., Berger, A., Calov, R., Ganopolski, A., Goosse, H., Lohmann, G., Lunkeit, F., Mokhov, I., Petoukhov, V., Stone, P., Wang, Z., 2002. Earth system models of intermediate complexity: closing the gap in the spectrum of climate system models. Climate Dynamics 18, 579–586. https://doi.org/10.1007/s00382-001-0200-1

Clemen, R.T., Winkler, R.L., 1999. Combining Probability Distributions From Experts in Risk Analysis. Risk Analysis 19, 17.

Cobelli, C., DiStefano, J.J., 1980. Parameter and structural identifiability concepts and ambiguities: a critical review and analysis. American Journal of Physiology-Regulatory, Integrative and Comparative Physiology 239, R7–R24. https://doi.org/10.1152/ajpregu.1980.239.1.R7

Coelho, F.C., Codeço, C.T., Struchiner, C.J., 2008. Complete treatment of uncertainties in a model for dengue R0 estimation. Cadernos de Saúde Pública 24, 853–861. https://doi.org/10.1590/S0102-311X2008000400016

Collins, H., 2011. Language and practice. Soc Stud Sci 41, 271–300. https://doi.org/10.1177/0306312711399665

Collins, M., Booth, B.B.B., Bhaskaran, B., Harris, G.R., Murphy, J.M., Sexton, D.M.H., Webb, M.J., 2011. Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles. Clim Dyn 36, 1737–1766. https://doi.org/10.1007/s00382-010-0808-0

Collins, W.D., Craig, A.P., Truesdale, J.E., Di Vittorio, A.V., Jones, A.D., Bond-Lamberty, B., Calvin, K.V., Edmonds, J.A., Kim, S.H., Thomson, A.M., Patel, P., Zhou, Y., Mao, J., Shi, X., Thornton, P.E., Chini, L.P., Hurtt, G.C., 2015. The integrated Earth system model version 1: formulation and functionality. Geoscientific Model Development 8, 2203–2219. https://doi.org/10.5194/gmd-8-2203-2015

Cook, S., Conrad, C., Fowlkes, A.L., Mohebbi, M.H., 2011. Assessing Google Flu Trends Performance in the United States during the 2009 Influenza Virus A (H1N1) Pandemic. PLOS ONE 6, e23610. https://doi.org/10.1371/journal.pone.0023610

Cordella, A., Shaikh, M., 2006. From Epistemology to Ontology: Challenging the Constructed Truth of ANT. https://doi.org/10.13140/RG.2.1.1546.5367

Corner, A., 2015. How to communicate effectively about climate change uncertainty [WWW Document]. Climate Outreach. URL https://climateoutreach.org/communicating-uncertainty/ (accessed 5.20.22).

Corner, A., Lewandowsky, S., Phillips, M., Roberts, O., 2015. The Uncertainty Handbook: A Practical Guide for Climate Chnage Communicators. University of Bristol, Bristol, UK.

Courtney, H., Kirkland, J., Viguerie, P., 1997. Strategy Under Uncertainty. Harvard Business Review.

Cox, D.C., Baybutt, P., 1981. Methods for Uncertainty Analysis: A Comparative Survey. Risk Analysis 1, 251–258. https://doi.org/10.1111/j.1539-6924.1981.tb01425.x

Cox, P., Stephenson, D., 2007. A Changing Climate for Prediction. Science 317, 207–208. https://doi.org/10.1126/science.1145956

Crawford, E., 1997. Arrhenius' 1896 Model of the Greenhouse Effect in Context. Ambio 26, 6–11.

Crespo Cuaresma, J., 2017. Income projections for climate change research: A framework based on human capital dynamics. Global Environmental Change 42, 226–236. https://doi.org/10.1016/j.gloenvcha.2015.02.012

Crow, M.M., Dabars, W.B., 2018. Designing the New American University. John Hopkins University press, Baltimore, Maryland, USA.

Curry, J.A., Webster, P.J., 2011. Climate Science and the Uncertainty Monster. Bull. Amer. Meteor. Soc. 92, 1667–1682. https://doi.org/10.1175/2011BAMS3139.1

D'Agostino McGowan, L., Grantz, K.H., Murray, E., 2021. Quantifying Uncertainty in Mechanistic Models of Infectious Disease. American Journal of Epidemiology kwab013. https://doi.org/10.1093/aje/kwab013

Daipha, P., 2012. Weathering Risk: Uncertainty, Weather Forecasting, and Expertise. Sociology Compass 6, 15–25. https://doi.org/10.1111/j.1751-9020.2011.00437.x

Dashtbali, M., Mirzaie, M., 2021. A compartmental model that predicts the effect of social distancing and vaccination on controlling COVID-19. Scientific Reports 11, 8191. https://doi.org/10.1038/s41598-021-86873-0

Davidson, M.D., 2015. Climate change and the ethics of discounting. WIREs Climate Change 6, 401–412. https://doi.org/10.1002/wcc.347

Davies, G., Prpich, G., Strachan, N., Pollard, S.J.T., 2014. UKERC Energy Strategy Under Uncertainties: Identifying techniques for managing uncertainty in the energy sector (Working Paper No. UKERC/WP/FG/2014/001). UK Energy Research Centre.

Davis, R., Pandhit, M., Patel, T., Weingard, J., Goldsmith, J., 2013. Public funding for innovation in low carbon technologies in the UK Briefing for the House of Commons Energy and Climate Change Select Committee. London.

de Regt, H.W., 2017. Understanding Scientific Understanding, 1st ed, Oxford Studies in Philosophy of Science. Oxford University Press, Oxford, UK.

de Vet, E., 2013. Exploring weather-related experiences and practices: examining methodological approaches. Area 45, 198–206. https://doi.org/10.1111/area.12019

Dean, N.E., Pastore y Piontti, A., Madewell, Z.J., Cummings, D.A.T., Hitchings, M.D.T., Joshi, K., Kahn, R., Vespignani, A., Halloran, M.E., Longini, I.M., 2020. Ensemble forecast modeling for the design of COVID-19 vaccine efficacy trials. Vaccine 38, 7213–7216. https://doi.org/10.1016/j.vaccine.2020.09.031

DeCarolis, J.F., 2011. Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. Energy Economics 33, 145–152. https://doi.org/10.1016/j.eneco.2010.05.002

DeCarolis, J.F., Babaee, S., Li, B., Kanungo, S., 2016. Modelling to generate alternatives with an energy system optimization model. Environmental Modelling & Software 79, 300–310. https://doi.org/10.1016/j.envsoft.2015.11.019

DeCarolis, J.F., Hunter, K., Sreepathi, S., 2012. The case for repeatable analysis with energy economy optimization models. Energy Economics 34, 1845–1853. https://doi.org/10.1016/j.eneco.2012.07.004

Della Rossa, F., Salzano, D., Di Meglio, A., De Lellis, F., Coraggio, M., Calabrese, C., Guarino, A., Cardona-Rivera, R., De Lellis, P., Liuzza, D., Lo Iudice, F., Russo, G., di Bernardo, M., 2020. A network model of Italy shows that intermittent regional strategies can alleviate the COVID-19 epidemic. Nat Commun 11, 5106. https://doi.org/10.1038/s41467-020-18827-5

Dellink, R., Chateau, J., Lanzi, E., Magné, B., 2017. Long-term economic growth projections in the Shared Socioeconomic Pathways. Global Environmental Change 42, 200–214. https://doi.org/10.1016/j.gloenvcha.2015.06.004

den Boon, S., Jit, M., Brisson, M., Medley, G., Beutels, P., White, R., Flasche, S., Hollingsworth, T.D., Garske, T., Pitzer, V.E., Hoogendoorn, M., Geffen, O., Clark, A., Kim, J., Hutubessy, R., 2019. Guidelines for multi-model comparisons of the impact of infectious disease interventions. BMC Medicine 17, 163. https://doi.org/10.1186/s12916-019-1403-9

Dequech, D., 2011. Uncertainty: A Typology and Refinements of Existing Concepts. Journal of Economic Issues XLV, 621–640. https://doi.org/10.2307/23071564

Derbyshire, J., 2017a. The siren call of probability: Dangers associated with using probability for consideration of the future. Futures 88, 43–54. https://doi.org/10.1016/j.futures.2017.03.011

Derbyshire, J., 2017b. Potential surprise theory as a theoretical foundation for scenario planning. Technological Forecasting and Social Change 124, 77–87. https://doi.org/10.1016/j.techfore.2016.05.008

Deser, C., Knutti, R., Solomon, S., Phillips, A.S., 2012. Communication of the role of natural variability in future North American climate. Nature Clim Change 2, 775–779. https://doi.org/10.1038/nclimate1562

Deser, C., Lehner, F., Rodgers, K.B., Ault, T., Delworth, T.L., DiNezio, P.N., Fiore, A., Frankignoul, C., Fyfe, J.C., Horton, D.E., Kay, J.E., Knutti, R., Lovenduski, N.S., Marotzke, J., McKinnon, K.A., Minobe, S., Randerson, J., Screen, J.A., Simpson, I.R., Ting, M., 2020. Insights from Earth system model initial-condition large ensembles and future prospects. Nature Climate Change 10, 277–286. https://doi.org/10.1038/s41558-020-0731-2

Deser, C., Phillips, A.S., Alexander, M.A., Smoliak, B.V., 2014. Projecting North American Climate over the Next 50 Years: Uncertainty due to Internal Variability. Journal of Climate 27, 2271–2296. https://doi.org/10.1175/JCLI-D-13-00451.1

Dethier, C., 2022. When is an ensemble like a sample? “Model-based” inferences in climate modeling. Synthese 200, 52. https://doi.org/10.1007/s11229-022-03477-5

DiCicco-Bloom, B., Crabtree, B.F., 2006. The qualitative research interview. Medical Education 40, 314–321. https://doi.org/10.1111/j.1365-2929.2006.02418.x

Dilley, P., 2004. Interviews and the Philosophy of Qualitative Research. The Journal of Higher Education 75, 127–132.

Ding, P., VanderWeele, T.J., 2016. Sensitivity Analysis Without Assumptions. Epidemiology 27, 368–377. https://doi.org/10.1097/EDE.0000000000000457

Dovers, S.R., Norton, T.W., Handmer, J.W., 1996. Uncertainty, ecology, sustainability and policy. Biodivers Conserv 5, 1143–1167. https://doi.org/10.1007/BF00051569

Doyle, E.E.H., Johnston, D.M., Smith, R., Paton, D., 2019. Communicating model uncertainty for natural hazards: A qualitative systematic thematic review. International Journal of Disaster Risk Reduction 33, 449–476. https://doi.org/10.1016/j.ijdrr.2018.10.023

Dreier, D., Howells, M., 2019. OSeMOSYS-PuLP: A Stochastic Modeling Framework for Long-Term Energy Systems Modeling. Energies 12, 1382.

Drolet, M., Bénard, É., Jit, M., Hutubessy, R., Brisson, M., 2018. Model Comparisons of the Effectiveness and Cost-Effectiveness of Vaccination: A Systematic Review of the Literature. Value Health 21, 1250–1258. https://doi.org/10.1016/j.jval.2018.03.014

Duan, Q., Ajami, N.K., Gao, X., Sorooshian, S., 2007. Multi-model ensemble hydrologic prediction using Bayesian model averaging. Advances in Water Resources 30, 1371–1386. https://doi.org/10.1016/j.advwatres.2006.11.014

Duncan, R.B., 1972. Characteristics of Organizational Environments and Perceived Environmental Uncertainty. Administrative Science Quarterly 17, 313–327. https://doi.org/10.2307/2392145

Dunleavy, P., 2003. Authoring a PhD: How to plan, draft, write and finish a doctoral thesis or dissertation. Palgrave Macmillan UK, London, UK.

Eaton, J.W., Menzies, N.A., Stover, J., Cambiano, V., Chindelevitch, L., Cori, A., Hontelez, J.A.C., Humair, S., Kerr, C.C., Klein, D.J., Mishra, S., Mitchell, K.M., Nichols, B.E., Vickerman, P., Bakker, R., Bärnighausen, T., Bershteyn, A., Bloom, D.E., Boily, M.-C., Chang, S.T., Cohen, T., Dodd, P.J., Fraser, C., Gopalappa, C., Lundgren, J., Martin, N.K., Mikkelsen, E., Mountain, E., Pham, Q.D., Pickles, M., Phillips, A., Platt, L., Pretorius, C., Prudden, H.J., Salomon, J.A., van de Vijver, D.A.M.C., de Vlas, S.J., Wagner, B.G., White, R.G., Wilson, D.P., Zhang, L., Blandford, J., Meyer-Rath, G., Remme, M., Revill, P., Sangrujee, N., Terris-Prestholt, F., Doherty, M., Shaffer, N., Easterbrook, P.J., Hirnschall, G., Hallett, T.B., 2014. Health benefits, costs, and cost-effectiveness of earlier eligibility for adult antiretroviral therapy and expanded treatment coverage: a combined analysis of 12 mathematical models. The Lancet Global Health 2, e23–e34. https://doi.org/10.1016/S2214-109X(13)70172-4

ECEMF, 2022. Hompage. URL https://www.ecemf.eu/ (accessed 1.28.22).

Eco, U., 2015. How to Write a Thesis. MIT Press, Boston, MA, USA.

Edeling, W., Arabnejad, H., Sinclair, R., Suleimenova, D., Gopalakrishnan, K., Bosak, B., Groen, D., Mahmood, I., Crommelin, D., Coveney, P.V., 2021. The impact of uncertainty on predictions of the CovidSim epidemiological code. Nature Computational Science 1, 128–135. https://doi.org/10.1038/s43588-021-00028-9

Edwards, P.N., 2011. History of climate modeling: History of climate modeling. Wiley Interdisciplinary Reviews: Climate Change 2, 128–139. https://doi.org/10.1002/wcc.95

Edwards, P.N., 1999. Global climate science, uncertainty and politics: Data‐laden models, model‐filtered data. Science as Culture 8, 437–472. https://doi.org/10.1080/09505439909526558

EIEE, 2019. NAVIGATE. EIEE - European Institute on Economics and the Environment. URL https://www.eiee.org/project/navigate-next-generation-of-advanced-integrated-assessment-modelling-to-support-climate-policy-making/ (accessed 1.28.22).

Einhorn, H.J., Hogarth, R.M., 1986. Decision Making Under Ambiguity. The Journal of Business 59, S225–S250.

Ekström, M., Kuruppu, N., Wilby, R.L., Fowler, H.J., Chiew, F.H.S., Dessai, S., Young, W.J., 2013. Examination of climate risk using a modified uncertainty matrix framework—Applications in the water sector. Global Environmental Change 23, 115–129. https://doi.org/10.1016/j.gloenvcha.2012.11.003

Elith, J., Burgman, M.A., Regan, H.M., 2002. Mapping epistemic uncertainties and vague concepts in predictions of species distribution. Ecological Modelling 157, 313–329. https://doi.org/10.1016/S0304-3800(02)00202-8

Ellingson, R.G., Fouquart, Y., 1991. The intercomparison of radiation codes in climate models: An overview. Journal of Geophysical Research: Atmospheres 96, 8925–8927. https://doi.org/10.1029/90JD01618

Ellsberg, D., 1961. Risk, Ambiguity, and the Savage Axioms. The Quarterly Journal of Economics 75, 643–669. https://doi.org/10.2307/1884324

Engberg-Pedersen, A., 2015. The Empire of Chance: The Napoleonic Wars and the Disorder of Things. Harvard University Press, Camridge, USA.

Enserink, B., Kwakkel, J.H., Veenman, S., 2013. Coping with uncertainty in climate policy making: (Mis)understanding scenario studies. Futures 53, 1–12. https://doi.org/10.1016/j.futures.2013.09.006

Eubank, S., Guclu, H., Anil Kumar, V.S., Marathe, M.V., Srinivasan, A., Toroczkai, Z., Wang, N., 2004. Modelling disease outbreaks in realistic urban social networks. Nature 429, 180–184. https://doi.org/10.1038/nature02541

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2018. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization.

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geoscientific Model Development 9, 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Eyring, V., Meehl, G.A., 2016. Brief Overview of CMIP6.

Faber, M., Manstetten, R., Proops, J., 1992. Humankind and the Environment: An Anatomy of Surprise and Ignorance, in: Ecological Economics. Edward Elgar Publishing, Cheltenham, UK, pp. 205–230.

Faucheux, S., Froger, G., 1995. Decision-making under environmental uncertainty. Ecological Economics 15, 29–42. https://doi.org/10.1016/0921-8009(95)00018-5

Ferson, S., Ginzburg, L.R., 1996. Elsevier. Reliability Engineering and System Safety 54, 133–144.

Feser, F., Rockel, B., von Storch, H., Winterfeldt, J., Zahn, M., 2011. Regional Climate Models Add Value to Global Model Data: A Review and Selected Examples. Bulletin of the American Meteorological Society 92, 1181–1192. https://doi.org/10.1175/2011BAMS3061.1

Figueiredo, R., Schröter, K., Weiss-Motz, A., Martina, M.L.V., Kreibich, H., 2018. Multi-model ensembles for assessment of flood losses and associated uncertainty. Natural Hazards and Earth System Sciences 18, 1297–1314. https://doi.org/10.5194/nhess-18-1297-2018

Finkel, A.M., 1990. Confronting Uncertainty in Risk Management: A Guide for Decision Makers. Center for Risk Management, Washington D.C., USA.

Fischhoff, B., Davis, A.L., 2014. Communicating scientific uncertainty. PNAS 111, 13664–13671. https://doi.org/10.1073/pnas.1317504111

Flato, G.M., 2011. Earth system models: an overview: Earth system models. Wiley Interdisciplinary Reviews: Climate Change 2, 783–800. https://doi.org/10.1002/wcc.148

Flugstad, A.R., Windschitl, P.D., 2003. The influence of reasons on interpretations of probability forecasts. Journal of Behavioral Decision Making 16, 107–126. https://doi.org/10.1002/bdm.437

Foss, A.M., Vickerman, P.T., Chalabi, Z., Mayaud, P., Alary, M., Watts, C.H., 2009. Dynamic Modeling of Herpes Simplex Virus Type-2 (HSV-2) Transmission: Issues in Structural Uncertainty 30.

Frankignoul, C., 1995a. Statistical Analysis of GCM Output, in: von Storch, H., Navarra, A. (Eds.), Analysis of Climate Variability: Applications of Statistical Techniques. Springer, Berlin, Heidelberg, pp. 139–158. https://doi.org/10.1007/978-3-662-03167-4_8

Frankignoul, C., 1995b. Climate Spectra and Stochastic Climate Models, in: von Storch, H., Navarra, A. (Eds.), Analysis of Climate Variability: Applications of Statistical Techniques. Springer, Berlin, Heidelberg, pp. 29–51. https://doi.org/10.1007/978-3-662-03167-4_3

Fricko, O., Havlik, P., Rogelj, J., Klimont, Z., Gusti, M., Johnson, N., Kolp, P., Strubegger, M., Valin, H., Amann, M., Ermolieva, T., Forsell, N., Herrero, M., Heyes, C., Kindermann, G., Krey, V., McCollum, D.L., Obersteiner, M., Pachauri, S., Rao, S., Schmid, E., Schoepp, W., Riahi, K., 2017. The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change 42, 251–267. https://doi.org/10.1016/j.gloenvcha.2016.06.004

Frigg, R., Hartmann, S., 2020. Models in Science, in: Zalta, E.N. (Ed.), The Stanford Encyclopedia of Philosophy. Metaphysics Research Lab, Stanford University.

Frigg, R., Thompson, E., Werndl, C., 2015. Philosophy of Climate Science Part II: Modelling Climate Change. Philosophy Compass 10, 965–977. https://doi.org/10.1111/phc3.12297

Fujii, L.A., 2018. Interviewing in Social Science: A Relational Approach. Routledge, New York, NY, USA.

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D.S., Dai, H., Hijioka, Y., Kainuma, M., 2017. SSP3: AIM implementation of Shared Socioeconomic Pathways. Global Environmental Change 42, 268–283. https://doi.org/10.1016/j.gloenvcha.2016.06.009

Funtowicz, S.O., Ravetz, J.R., 1990. Uncertainty and its Management, in: Uncertainty and Quality in Science for Policy. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 17–34.

Gardumi, F., Shivakumar, A., Morrison, R., Taliotis, C., Broad, O., Beltramo, A., Sridharan, V., Howells, M., Hörsch, J., Niet, T., Almulla, Y., Ramos, E., Burandt, T., Balderrama, G.P., Pinto de Moura, G.N., Zepeda, E., Alfstad, T., 2018. From the development of an open-source energy modelling tool to its application and the creation of communities of practice: The example of OSeMOSYS. Energy Strategy Reviews 20, 209–228. https://doi.org/10.1016/j.esr.2018.03.005

Gaudard, L., Romerio, F., 2020. A Conceptual Framework to Classify and Manage Risk, Uncertainty and Ambiguity: An Application to Energy Policy. Energies 13, 1422. https://doi.org/10.3390/en13061422

Gentner, D., Stevens, A.L., 1983. Mental Models. Psychology Press.

Georgakakos, K.P., Seo, D.-J., Gupta, H., Schaake, J., Butts, M.B., 2004. Towards the characterization of streamflow simulation uncertainty through multimodel ensembles. Journal of Hydrology, The Distributed Model Intercomparison Project (DMIP) 298, 222–241. https://doi.org/10.1016/j.jhydrol.2004.03.037

Giampietro, M., Mayumi, K., Munda, G., 2006. Integrated assessment and energy analysis: Quality assurance in multi-criteria analysis of sustainability. Energy, The Second

Biennial International Workshop “Advances in Energy Studies” 31, 59–86. https://doi.org/10.1016/j.energy.2005.03.005

Giarola, S., Mittal, S., Vielle, M., Perdana, S., Campagnolo, L., Delpiazzo, E., Bui, H., Kraavi, A.A., Kolpakov, A., Sognnaes, I., Peters, G., Hawkes, A., Köberle, A.C., Grant, N., Gambhir, A., Nikas, A., Doukas, H., Moreno, J., van de Ven, D.-J., 2021. Challenges in the harmonisation of global integrated assessment models: A comprehensive methodology to reduce model response heterogeneity. Science of The Total Environment 783, 146861. https://doi.org/10.1016/j.scitotenv.2021.146861

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., Trow, M., 1994. The New Production of Knowledge: The Dynamics of Science and Research in Contemporary Societies. Sage Publications.

Gibson, W., Brown, A., 2009. Identifying Themes, Codes and Hypotheses, in: Working with Qualitative Data. SAGE Publications, Ltd, 1 Oliver’s Yard, 55 City Road, London England EC1Y 1SP United Kingdom. https://doi.org/10.4135/9780857029041

Gielen, J., 2000. A stochastic model for epidemics based on the renewal equation. Journal of Biological Systems Vol 8, 2000 (2000) 1 8. https://doi.org/10.1142/S021833900000002X

Giere, R.N., 1988. Explaining Science: A cognitive Approach. Univeristy of Chicago Press, Chicago, Il, USA.

Gigerenzer, G., Swijtink, Z., Porter, T., Daston, L., Beatty, J., Kruger, L., 1989a. The Implicatiosn of Chance, in: The Empire of Chsnce: How Probability Changed Science and Everyday Life, Ideas in Context. Cambridge University Press, Cambridge, UK, pp. 271–292.

Gigerenzer, G., Swijtink, Z., Porter, T., Daston, L., Beatty, J., Kruger, L., 1989b. The Empire of Chance, Ideas in Context. Cambridge University Press, Cambridge, UK.

Gilbert, G.N., Mulkay, M., 1984. Opening Pandora’s Box: A Sociological Analysis of Scietists’ Discourse. Cambridge University Press, Cambridge, UK.

Gilbert, J.A., Meyers, L.A., Galvani, A.P., Townsend, J.P., 2014. Probabilistic uncertainty analysis of epidemiological modeling to guide public health intervention policy. Epidemics 6, 37–45. https://doi.org/10.1016/j.epidem.2013.11.002

Gill, J., Rubiera, J., Martin, C., Cacic, I., Mylne, K., Dehui, C., Jiafeng, G., Xu, T., Yamaguchi, M., Foamouhoue, A., Poolman, E., Guiney, J., 2008. Guidelines on Communicating Forecast Uncertainty (No. 1422). World Meteorological Organisation.

Given, L., 2008. Idealism, in: The SAGE Encyclopedia of Qualitative Research Methods. SAGE Publications, Inc., 2455 Teller Road, Thousand Oaks California 91320 United States. https://doi.org/10.4135/9781412963909.n205

Gjerde, J., Grepperud, S., Kverndokk, S., 1999. Optimal climate policy under the possibility of a catastrophe. Resource and Energy Economics 3–4, 289–317.

Godfrey-Smith, P., 2003. Theory and Reality: An introduction ot the Philosophy of Science. Univeristy of Chicago Press, Chicago and London.

Greca, I.M., Moreira, M.A., 2000. Mental models, conceptual models, and modelling. International Journal of Science Education 22, 1–11. https://doi.org/10.1080/095006900289976

Greimas, A.J., 1983. Structural semantics: An attempt at a method. University of Nebraska Press.

Grin, J., Felix, F.R., Bos, B., Spoelstra, S.F., 2004. Practices for reflexive design: lessons from a Dutch programme on sustainable agriculture. International Journal of Foresight and Innovation Policy 1, 126–149. https://doi.org/10.1504/IJFIP.2004.004618

Grübler, A., Nakicenovic, N., 2001. Identifying dangers in an uncertain climate. Nature 412, 15–15. https://doi.org/10.1038/35083752

Guevara, Z., Domingos, T., 2017. The multi-factor energy input–output model. Energy Economics 61, 261–269. https://doi.org/10.1016/j.eneco.2016.11.020

Guillaume, J.H.A., Helgeson, C., Elsawah, S., Jakeman, A.J., Kummu, M., 2017. Toward best practice framing of uncertainty in scientific publications: A review of Water Resources Research abstracts. Water Resources Research 53, 6744–6762. https://doi.org/10.1002/2017WR020609

Guillemot, H., 2010. Connections between simulations and observation in climate computer modeling. Scientist's practices and "bottom-up epistemology" lessons. Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics, Special Issue: Modelling and Simulation in the Atmospheric and Climate Sciences 41, 242–252. https://doi.org/10.1016/j.shpsb.2010.07.003

Guilyardi, É., Cai, W., Collins, M., Fedorov, A.V., Jin, F.-F., Kumar, A., Sun, D.-Z., Wittenberg, A.T., 2012. New Strategies for Evaluating ENSO Processes in Climate Models. Bulletin of the American Meteorological Society 93, 235–238. https://doi.org/10.1175/BAMS-D-11-00106.1

Gustafson, A., Rice, R.E., 2019. The Effects of Uncertainty Frames in Three Science Communication Topics. Science Communication 41, 679–706. https://doi.org/10.1177/1075547019870811

Hacking, I., 2000. The Social Construction of What? Harvard University Press, Boston, MA, USA.

Hacking, I., 1990. The Taming of Chance, Ideas in Context. Cambridge University Press, Cambridge, UK.

Hacking, I., 1975. The Emergence of Probability: A Philosophical Study of Early Ideas About Probability Induction and Statistical Inference. Cambridge University Press, Cambridge, UK.

Hall, L.M.H., Buckley, A.R., 2016. A review of energy systems models in the UK: Prevalent usage and categorisation. Applied Energy 169, 607–628. https://doi.org/10.1016/j.apenergy.2016.02.044

Hall, M.C.G., 1985. Estimating the Reliability of Climate Model Projections- Steps towards a Solution, in: MacCracken, M.C., Luther, F.M. (Eds.), Projecting the Climate Effects of Increasing Carbon Dioxide. Department of Energy, Washington D.C., USA, pp. 337–364.

Hamel, P., Bryant, B.P., 2017a. Uncertainty assessment in ecosystem services analyses: Seven challenges and practical responses. Ecosystem Services 24, 1–15. https://doi.org/10.1016/j.ecoser.2016.12.008

Hamel, P., Bryant, B.P., 2017b. Uncertainty assessment in ecosystem services analyses: Seven challenges and practical responses. Ecosystem Services 24, 1–15. https://doi.org/10.1016/j.ecoser.2016.12.008

Han, P.K.J., Klein, W.M.P., Arora, N.K., 2011. Varieties of uncertainty in health care: a conceptual taxonomy. Med Decis Making 31, 828–838. https://doi.org/10.1177/0272989X11393976

Handel, M.I., 1987. Technological surprise in war. Intelligence and National Security 2, 1–53. https://doi.org/10.1080/02684528708431875

Harremoës, P., 2003. The Need to Account for Uncertainty in Public Decision Making Related to Technological Change. Integrated Assessment 4, 18–25. https://doi.org/10.1076/iaij.4.1.18.16465

Hausfather, Z., 2019. CMIP6: the next generation of climate models explained [WWW Document]. Carbon Brief. URL https://www.carbonbrief.org/cmip6-the-next-generation-of-climate-models-explained (accessed 3.22.22).

Hausfather, Z., Peters, G.P., 2020. Emissions – the 'business as usual' story is misleading. Nature 577, 618–620. https://doi.org/10.1038/d41586-020-00177-3

Hawkins, E., Sutton, R., 2009. The Potential to Narrow Uncertainty in Regional Climate Predictions. Bull. Amer. Meteor. Soc. 90, 1095–1108. https://doi.org/10.1175/2009BAMS2607.1

Hayes, K.R., Regan, H.M., M A Burgman, 2007. Introduction to the Concepts and Methods of Uncertainty Analysis, in: Kapuscinski, K., Hayes, K.R., Dana, L.G. (Eds.), Environmental Risk Assessment of Genetically Modified Organisms: Vol. 3 Methodologies for Transgenic Fish. CAB International.

Hazelbag, C.M., Dushoff, J., Dominic, E.M., Mthombothi, Z.E., Delva, W., 2020. Calibration of individual-based models to epidemiological data: A systematic review. PLOS Computational Biology 16, e1007893. https://doi.org/10.1371/journal.pcbi.1007893

Heal, G., Kriström, B., 2002. Uncertainty and Climate Change. Environmental and Resource Economics 22, 3–39.

Heal, G., Millner, A., 2017. Uncertainty and Ambiguity in Environmental Economics: Conceptual Issues (No. 314). Centre for Climate Change Economics and Policy.

Helgesen, P.I., 2013. Top-down and Bottom-up: Combining energy system models and macroeconomic general equilibrium models (CenSES working paper No. 1). Project: Regional Effects of Energy Policy (RegPol).

Helton, J.C., 1994. Treatment of Uncertainty in Performance Assessments for Complex Systems. Risk Analysis 14, 483–511. https://doi.org/10.1111/j.1539-6924.1994.tb00266.x

Henrion, M., Fischhoff, B., 2014. Assessing uncertainty in physical constants 9.

Herbst, A., Toro, F., Reitze, F., Jochem, E., 2012. Introduction to Energy Systems Modelling. Swiss Journal of Economics and Statistics 148, 111–135. https://doi.org/10.1007/BF03399363

Heyman, M., Gramelsberger, G., Mahony, M., 2018. Cultures of Prediction in Atmospheric and Climate Science. Earthscan from Routledge, London, England.

Heymann, M., Gramelsberger, G., Mahony, M., 2017a. Introduction, in: Heymann, M., Gramelsberger, G., Mahony, M. (Eds.), Cultures of Prediciton in Atmospheric and

Climate Science, Routledge Environmental Humanities Series. Earthscan from Routledge, Cambridge, UK, pp. 1–17.

Heymann, M., Gramelsberger, G., Mahony, M., 2017b. Charcateristics of Cultures of Preidction, in: Heymann, M., Gramelsberger, G., Mahony, M. (Eds.), Cultures of Prediciton in Atmospheric and Climate Science, Routledge Environmental Humanities Series. Earthscan from Routledge, Cambridge, UK, pp. 18–41.

Hinne, M., Gronau, Q.F., van den Bergh, D., Wagenmakers, E.-J., 2020. A Conceptual Introduction to Bayesian Model Averaging. Advances in Methods and Practices in Psychological Science 3, 200–215. https://doi.org/10.1177/2515245919898657

Hisschemöller, M., Hoppe, R., 1995. Coping with intractable controversies: The case for problem structuring in policy design and analysis. Knowledge and Policy 8, 40–60. https://doi.org/10.1007/BF02832229

Hoffman, F.O., Hammonds, J.S., 1994. Propagation of Uncertainty in Risk Assessments: The Need to Distinguish Between Uncertainty Due to Lack of Knowledge and Uncertainty Due to Variability. Risk Analysis 14, 707–712. https://doi.org/10.1111/j.1539-6924.1994.tb00281.x

Höllermann, B., Evers, M., 2017. Perception and handling of uncertainties in water management—A study of practitioners' and scientists' perspectives on uncertainty in their daily decision-making. Environmental Science & Policy 71, 9–18. https://doi.org/10.1016/j.envsci.2017.02.003

Hollingsworth, T., Medley, G., 2017. Learning from multi-model comparisons: Collaboration leads to insights, but limitations remain. Epidemics 18, 1–3. https://doi.org/10.1016/j.epidem.2017.02.014

Hoppe, R., 2018. Heuristics for practitioners of policy design: Rules-of-thumb for structuring unstructured problems. Public Policy and Administration 33, 384–408. https://doi.org/10.1177/0952076717709338

Hora, S.C., 1996. Aleatory and epistemic uncertainty in probability elicitation with an example from hazardous waste management. Reliability Engineering & System Safety, Treatment of Aleatory and Epistemic Uncertainty 54, 217–223. https://doi.org/10.1016/S0951-8320(96)00077-4

Hourdin, F., Mauritsen, T., Gettelman, A., Golaz, J.-C., Balaji, V., Duan, Q., Folini, D., Ji, D., Klocke, D., Qian, Y., Rauser, F., Rio, C., Tomassini, L., Watanabe, M., Williamson, D., 2017. The Art and Science of Climate Model Tuning. Bulletin of the American Meteorological Society 98, 589–602. https://doi.org/10.1175/BAMS-D-15-00135.1

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M., Roehrl, A., 2011. OSeMOSYS: The Open Source Energy Modeling System: An introduction to its ethos, structure and development. Energy Policy, Sustainability of biofuels 39, 5850–5870. https://doi.org/10.1016/j.enpol.2011.06.033

Hughes, N., Strachan, N., Gross, R., 2013. The structure of uncertainty in future low carbon pathways. Energy Policy, Special Section: Transition Pathways to a Low Carbon Economy 52, 45–54. https://doi.org/10.1016/j.enpol.2012.04.028

Huijbregts, M.A.J., 1998. Application of uncertainty and variability in LCA. Int. J. LCA 3, 273–280. https://doi.org/10.1007/BF02979835

Huijbregts, M.A.J., Norris, G., Bretz, R., Ciroth, A., Maurice, B., von Bahr, B., Weidema, B., de Beaufort, A.S.H., 2001. Framework for modelling data uncertainty in life cycle inventories. Int J LCA 6, 127. https://doi.org/10.1007/BF02978728

Hulme, M., 2011. Reducing the Future to Climate: A Story of Climate Determinism and Reductionism. Osiris 26, 245–266. https://doi.org/10.1086/661274

IIASA, 2019. IAMC 1.5°C Scenario Explorer hosted by IIASA [WWW Document]. Integrated Assesment Modelling Consoritum. URL https://data.ene.iiasa.ac.at/iamc-1.5c-explorer/#/login?redirect=%2Fworkspaces (accessed 1.27.22).

IIASA, 2018. SSP Database (Shared Socioeconomic Pathways) - Version 2.0 [WWW Document]. International Institute for Applied Systems Analysis. URL tntcat.iiasa.ac.at/SspDb (accessed 1.9.22).

IPCC, 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

IPCC, 2018. Summary For Policymakers, in: Masson-Delmotte, V., Zhai, P., Portner, H.-O., Roberts, D.F., Skea, J., Shukla, P.R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R. (Eds.), Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.

IPCC, 2007. 8.2.1.3 Parametrizations - AR4 WGI Chapter 8: Climate Models and their Evaluation, in: Climate Change 2007: Working Group I: The Physical Science Basis. Intergovernmental Panel on Climate Change.

IPCC, 2005a. Guidance Notes for Lead Authors of the IPCC Fourth Assessment Report on Addressing Uncertainties. Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IPCC, 2005b. Guidance Notes for Lead Authors of the IPCC Fourth Assessment Report on Addressing Uncertainties. Intergovernmental Panel on Climate Change, Geneva, Switzerland.

Iverson, L.R., Thompson, F.R., Matthews, S., Peters, M., Prasad, A., Dijak, W.D., Fraser, J., Wang, W.J., Hanberry, B., He, H., Janowiak, M., Butler, P., Brandt, L., Swanston, C., 2017. Multi-model comparison on the effects of climate change on tree species in the eastern U.S.: results from an enhanced niche model and process-based ecosystem and landscape models. Landscape Ecol 32, 1327–1346. https://doi.org/10.1007/s10980-016-0404-8

Jacobsen, H.K., 1998. Integrating the bottom-up and top-down approach to energy–economy modelling: the case of Denmark. Energy Economics 20, 443–461. https://doi.org/10.1016/S0140-9883(98)00002-4

Jasanoff, S., 2003. Technologies of Humility: Citizen Participation in Governing Science. Minerva 41, 223–244. https://doi.org/10.1023/A:1025557512320

Jasanoff, S., Kim, S.-H., 2009. Containing the Atom: Sociotechnical Imaginaries and Nuclear Power in the United States and South Korea. Minerva 47, 119. https://doi.org/10.1007/s11024-009-9124-4

Jebeile, J., Crucifix, M., 2021. Value management and model pluralism in climate science. Studies in History and Philosophy of Science Part A 88, 120–127. https://doi.org/10.1016/j.shpsa.2021.06.004

Jebeile, J., Crucifix, M., 2020. Multi-model ensembles in climate science: Mathematical structures and expert judgements. Studies in History and Philosophy of Science Part A 83, 44–52. https://doi.org/10.1016/j.shpsa.2020.03.001

Johnson, J., 1988. Mixing Humans and Nonhumans Together: The Sociology of a Door-Closer. Social Problems 35, 298–310. https://doi.org/10.2307/800624

Johnson-Laird, P., Girotto, V., Legrenzi, P., 1998. Mental models: a gentle guide for outsiders.

Johnson-Laird, P.N., 1983. Mental models : towards a cognitive science of language, inference, and consciousness. Cambridge, MA: Harvard University Press.

Joint Research Council, 2019. RAMI, RAdiation transfer Model Intercomparison - European Commission [WWW Document]. URL http://rami-benchmark.jrc.ec.europa.eu/HTML/ (accessed 3.26.19).

Jones, C.D., Arora, V., Friedlingstein, P., Bopp, L., Brovkin, V., Dunne, J., Graven, H., Hoffman, F., Ilyina, T., John, J.G., Jung, M., Kawamiya, M., Koven, C., Pongratz, J., Raddatz, T., Randerson, J.T., Zaehle, S., 2016. C4MIP: The Coupled Climate–Carbon Cycle Model Intercomparison Project: experimental protocol for CMIP6. Geoscientific Model Development 9, 2853–2880. https://doi.org/10.5194/gmd-9-2853-2016

Jones, N., Ross, H., Lynam, T., Perez, P., Leitch, A., 2011. Mental Models: An Interdisciplinary Synthesis of Theory and Methods. Ecology and Society 16. https://doi.org/10.5751/ES-03802-160146

Jovchelovitch, S., Bauer, M.W., 2000. Narrative Interviewing, in: Bauer, M.W., Gaskell, G. (Eds.), Qualitative Researching with Text, Image and Sound: A Practicval Handbook. SAGE Publications, Inc., London, UK.

Kageyama, M., Braconnot, P., Harrison, S.P., Haywood, A.M., Jungclaus, J.H., Otto-Bliesner, B.L., Peterschmitt, J.-Y., Abe-Ouchi, A., Albani, S., Bartlein, P.J., Brierley, C., Crucifix, M., Dolan, A., Fernandez-Donado, L., Fischer, H., Hopcroft, P.O., Ivanovic, R.F., Lambert, F., Lunt, D.J., Mahowald, N.M., Peltier, W.R., Phipps, S.J., Roche, D.M., Schmidt, G.A., Tarasov, L., Valdes, P.J., Zhang, Q., Zhou, T., 2018. The PMIP4 contribution to CMIP6 – Part 1: Overview and over-arching analysis plan. Geoscientific Model Development 11, 1033–1057. https://doi.org/10.5194/gmd-11-1033-2018

Kallio, H., Pietilä, A.-M., Johnson, M., Kangasniemi, M., 2016. Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. J Adv Nurs 72, 2954–2965. https://doi.org/10.1111/jan.13031

Kalman, R.E., 1960. A New Approach to Linear Filtering and Prediction Problems. Transactions of the ASME–Journal of Basic Engineering 82, 35–45.

Kalman, R.E., Bertram, J.E., 1959a. General synthesis procedure for computer control of single-loop and multiloop linear systems (an optimal sampling system). Trans. AIEE, Part II: Applicat. Ind. 77, 602–609. https://doi.org/10.1109/TAI.1959.6371508

Kalman, R.E., Bertram, J.E., 1959b. A unified approach to the theory of sampling systems. Journal of the Franklin Institute 267, 405–436. https://doi.org/10.1016/0016-0032(59)90093-6

Kandlikar, M., Risbey, J., Dessai, S., 2005. Representing and communicating deep uncertainty in climate-change assessments. Comptes Rendus Geoscience 337, 443–455. https://doi.org/10.1016/j.crte.2004.10.010

Kann, A., Weyant, J.P., 2000. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. Environmental Modeling and Assessment 5, 29–46.

Katzav, J., Dijkstra, H.A., (Jos) de Laat, A.T.J., 2012. Assessing climate model projections: State of the art and philosophical reflections. Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics 43, 258–276. https://doi.org/10.1016/j.shpsb.2012.07.002

Kay, J., King, M., 2020. Radical Uncertainty: Decision-Making for an Unknowable Future. The Bridge Street Press, London, UK.

Kc, S., Lutz, W., 2017. The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Global Environmental Change 42, 181–192. https://doi.org/10.1016/j.gloenvcha.2014.06.004

Keeley, A.R., Matsumoto, K., 2018. Investors' perspective on determinants of foreign direct investment in wind and solar energy in developing economies – Review and expert opinions. Journal of Cleaner Production 179, 132–142. https://doi.org/10.1016/j.jclepro.2017.12.154

Kelly, D.L., Kolstad, C.D., 1999. Bayesian learning, growth, and pollution. Journal of Economic Dynamics and Control 23, 491–518.

Kelly, E.J., Campbell, K., 2000. Separating Variability and Uncertainty in Environmental Risk Assessment—Making Choices. Human and Ecological Risk Assessment: An International Journal 6, 1–13. https://doi.org/10.1080/10807030091124419

Kendall, D.G., 1956. Deterministic and Stochastic Epidemics in Closed Populations. Proceedings of the Third Berkeley Symposium on Mathematical Statistics and Probability, Volume 4: Contributions to Biology and Problems of Health 149–165.

Kermack, W.O., McKendrick, A.G., Walker, G.T., 1927. A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character 115, 700–721. https://doi.org/10.1098/rspa.1927.0118

Keynes, J.M., 1936. The General Theory of Employment, Interest and Money.

Keynes, J.M., 1921. A Treatise on Probability. MacMillan and CO. Limited, London, UK.

Kirchner, M., Mitter, H., Schneider, U.A., Sommer, M., Falkner, K., Schmid, E., 2021. Uncertainty concepts for integrated modeling - Review and application for identifying uncertainties and uncertainty propagation pathways. Environmental Modelling & Software 135, 104905. https://doi.org/10.1016/j.envsoft.2020.104905

Kirkup, L., Frenkel, R.B., 2006. The importance of uncertainty in science and technology, in: An Introduction to Uncertianty in Measurement Uisng the GUM (Guide to the Expression of Uncertianty in Measurement). Cambridge University Press, pp. 1–10.

Kloprogge, P., van der Sluijs, J.P., Petersen, A.C., 2011. A method for the analysis of assumptions in model-based environmental assessments. Environmental Modelling & Software, Thematic issue on the assessment and evaluation of environmental models and software 26, 289–301. https://doi.org/10.1016/j.envsoft.2009.06.009

Knight, F.H., 1921. Risk, Uncertainty, and Profit. New York, US.

Knol, A.B., Petersen, A.C., van der Sluijs, J.P., Lebret, E., 2009. Dealing with uncertainties in environmental burden of disease assessment. Environ Health 8, 21. https://doi.org/10.1186/1476-069X-8-21

Knorr Cetina, K., 1999. Epistemic Cultures: How the Sciences Make Knowledge. Harvard University Press, Cambridge, MA, USA.

Knutti, R., Abramowitz, G., Colllins, M., Eyring, V., Glecker, P.J., Hewitson, B., Mearns, L., 2010. Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections, in: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Midgley, P.M. (Eds.), Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections. IPCC Working Group I Technical Support Unit, Bern, Switzerland.

Knutti, R., Allen, M.R., Friedlingstein, P., Gregory, J.M., Hegerl, G.C., Meehl, G.A., Meinshausen, M., Murphy, J.M., Plattner, G.-K., Raper, S.C.B., Stocker, T.F., Stott, P.A., Teng, H., Wigley, T.M.L., 2008. A Review of Uncertainties in Global Temperature Projections over the Twenty-First Century. J. Climate 21, 2651–2663. https://doi.org/10.1175/2007JCLI2119.1

Knutti, R., Masson, D., Gettelman, A., 2013. Climate model genealogy: Generation CMIP5 and how we got there. Geophysical Research Letters 40, 1194–1199. https://doi.org/10.1002/grl.50256

Knutti, R., Sedláček, J., Sanderson, B.M., Lorenz, R., Fischer, E.M., Eyring, V., 2017. A climate model projection weighting scheme accounting for performance and interdependence. Geophysical Research Letters 44, 1909–1918. https://doi.org/10.1002/2016GL072012

Kønig, N., Børsen, T., Emmeche, C., 2017. The ethos of post-normal science. Futures, Post-Normal science in practice 91, 12–24. https://doi.org/10.1016/j.futures.2016.12.004

Korsbo, N., Jönsson, H., 2020. It's about time: Analysing simplifying assumptions for modelling multi-step pathways in systems biology. PLOS Computational Biology 16, e1007982. https://doi.org/10.1371/journal.pcbi.1007982

Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B.L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.-P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., Biewald, A., Bonsch, M., Giannousakis, A., Kreidenweis, U., Müller, C., Rolinski, S., Schultes, A., Schwanitz, J., Stevanovic, M., Calvin, K., Emmerling, J., Fujimori, S., Edenhofer, O., 2017. Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change 42, 297–315. https://doi.org/10.1016/j.gloenvcha.2016.05.015

Krishnamurti, T.N., Kishtawal, C.M., LaRow, T.E., Bachiochi, D.R., Zhang, Z., Williford, C.E., Gadgil, S., Surendran, S., 1999. Improved Weather and Seasonal Climate

Forecasts from Multimodel Superensemble. Science 285, 1548–1550. https://doi.org/10.1126/science.285.5433.1548

Krishnamurti, T.N., Kumar, V., Simon, A., Bhardwaj, A., Ghosh, T., Ross, R., 2016. A review of multimodel superensemble forecasting for weather, seasonal climate, and hurricanes. Reviews of Geophysics 54, 336–377. https://doi.org/10.1002/2015RG000513

Krueger, T., Page, T., Hubacek, K., Smith, L., Hiscock, K., 2012. The role of expert opinion in environmental modelling. Environmental Modelling & Software, Thematic issue on Expert Opinion in Environmental Modelling and Management 36, 4–18. https://doi.org/10.1016/j.envsoft.2012.01.011

Krupnick, A., Morgenstern, R., Batz, M., Nelson, P., Burtraw, D., Shih, J.-S., McWilliams, M., 2006. Not a Sure Thing: Making Regulatory Choices under Uncertainty. Resources for the Future.

Kutiel, H., 2019. Climatic Uncertainty in the Mediterranean Basin and Its Possible Relevance to Important Economic Sectors. Atmosphere 10, 10. https://doi.org/10.3390/atmos10010010

Kvale, S., 2007. Doing Interviews. SAGE Publications, Ltd, 1 Oliver's Yard, 55 City Road, London England EC1Y 1SP United Kingdom. https://doi.org/10.4135/9781849208963

Kvale, S., 2006. Dominance Through Interviews and Dialogues. Qualitative Inquiry 12, 480–500. https://doi.org/10.1177/1077800406286235

Kvale, S., 1994. InterViews: An introduction to qualitative research interviewing, InterViews: An introduction to qualitative research interviewing. Sage Publications, Inc, Thousand Oaks, CA, US.

Kwakkel, J.H., Walker, W.E., Marchau, V.A.W.J., 2010. Classifying and communicating uncertainties in model-based policy analysis. IJTPM 10, 299. https://doi.org/10.1504/IJTPM.2010.036918

Lahsen, M., 2005. Seductive Simulations? Uncertainty Distribution Around Climate Models. Soc Stud Sci 35, 895–922. https://doi.org/10.1177/0306312705053049

Lakoff, G., Johnson, M., 1980. Metaphors we Live By. Univeristy of Chicago Press, Chicago and London.

Laland, K., Matthews, B., Feldman, M.W., 2016. An introduction to niche construction theory. Evol Ecol 30, 191–202. https://doi.org/10.1007/s10682-016-9821-z

Landström, C., Hauxwell-Baldwin, R., Lorenzoni, I., Rogers-Hayden, T., 2015. The (Mis)understanding of Scientific Uncertainty? How Experts View Policy-Makers, the Media and Publics. Science as Culture 24, 276–298. https://doi.org/10.1080/09505431.2014.992333

Lane, D.A., Maxfield, R.R., 2005. Ontological uncertainty and innovation. J Evol Econ 15, 3–50. https://doi.org/10.1007/s00191-004-0227-7

Laswell, H.D., 1971. The Structure and Function of Communication in Society, in: Schramm, W., Roberts, D.F. (Eds.), The Process and Effects of Mass Communication. University of Illinois Press, Illinois, USA, pp. 84–99.

Latour, B., 2005. Reassembling the Social. Oxford University Press, Oxford, UK.

Latour, B., Woolgar, S., 1979. Laboratory Life: The Social Construction of Scientific Facts. SAGE Publications, Inc., CA, USA.

Law, J., 2008. Actor-network theory and material semiotics, in: Turner, B.S. (Ed.), . Blackwell, Oxford, pp. 141–158.

Lawson, T., 1985. Uncertainty and Economic Analysis. The Economic Journal 95, 909–927. https://doi.org/10.2307/2233256

Lecy, J.D., Beatty, K.E., 2012. Representative Literature Reviews Using Constrained Snowball Sampling and Citation Network Analysis (SSRN Scholarly Paper No. ID 1992601). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.1992601

Leimbach, M., Kriegler, E., Roming, N., Schwanitz, J., 2017. Future growth patterns of world regions – A GDP scenario approach. Global Environmental Change 42, 215–225. https://doi.org/10.1016/j.gloenvcha.2015.02.005

Lempert, R.J., 2019. Robust Decision Making (RDM), in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty: From Theory to Practice. Springer International Publishing, Cham, pp. 23–51. https://doi.org/10.1007/978-3-030-05252-2_2

Lenhard, J., Winsberg, E., 2010. Holism, entrenchment, and the future of climate model pluralism. Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics, Special Issue: Modelling and Simulation in the Atmospheric and Climate Sciences 41, 253–262. https://doi.org/10.1016/j.shpsb.2010.07.001

Leutbecher, M., Palmer, T.N., 2008. Ensemble forecasting. Journal of Computational Physics, Predicting weather, climate and extreme events 227, 3515–3539. https://doi.org/10.1016/j.jcp.2007.02.014

Levin, K., Cashore, B., Bernstein, S., Auld, G., 2012. Overcoming the tragedy of super wicked problems: constraining our future selves to ameliorate global climate change. Policy Sci 45, 123–152. https://doi.org/10.1007/s11077-012-9151-0

Lewandowsky, S., Oreskes, N., Risbey, J.S., Newell, B.R., Smithson, M., 2015. Seepage: Climate change denial and its effect on the scientific community. Global Environmental Change 33, 1–13. https://doi.org/10.1016/j.gloenvcha.2015.02.013

Lewis, E.L., Linn, M.C., 1994. Heat energy and temperature concepts of adolescents, adults, and experts: Implications for curricular improvements. J. Res. Sci. Teach. 31, 657–677. https://doi.org/10.1002/tea.3660310607

Li, L., Chen, X., Zhang, L., 2014. Multimodel Ensemble for Freeway Traffic State Estimations. IEEE Trans. Intell. Transport. Syst. 15, 1323–1336. https://doi.org/10.1109/TITS.2014.2299542

Link, J.S., Ihde, T.F., Harvey, C.J., Gaichas, S.K., Field, J.C., Brodziak, J.K.T., Townsend, H.M., Peterman, R.M., 2012. Dealing with uncertainty in ecosystem models: The paradox of use for living marine resource management. Progress in Oceanography 102, 102–114. https://doi.org/10.1016/j.pocean.2012.03.008

Linkov, I., Burmistrov, D., 2003. Model Uncertainty and Choices Made by Modelers: Lessons Learned from the International Atomic Energy Agency Model Intercomparisons. Risk analysis : an official publication of the Society for Risk Analysis 23, 1297–308. https://doi.org/10.1111/j.0272-4332.2003.00402.x

Lloyd, A.L., 2009. Sensitivity of Model-Based Epidemiological Parameter Estimation to Model Assumptions, in: Chowell, G., Hyman, J.M., Bettencourt, L.M.A., Castillo-Chavez, C. (Eds.), Mathematical and Statistical Estimation Approaches in Epidemiology. Springer Netherlands, Dordrecht, pp. 123–141. https://doi.org/10.1007/978-90-481-2313-1_6

Lorenz, E.N., 1965. A study of the predictability of a 28-variable atmospheric model. Tellus 17, 321–333. https://doi.org/10.1111/j.2153-3490.1965.tb01424.x

Lorenz, E.N., 1963. Deterministic Nonperiodic Flow. Journal of the Atmospheric Sciences 20, 130–141. https://doi.org/10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2

Lu, Z., Fu, Z., Hua, L., Yuan, N., Chen, L., 2018. Evaluation of ENSO simulations in CMIP5 models: A new perspective based on percolation phase transition in complex networks. Sci Rep 8, 14912. https://doi.org/10.1038/s41598-018-33340-y

Luce, R.D., Raiffa, H., 1957. Games and Decisions. Wiley, New York, US.

MacKenzie, D., 1990. Inventing Accuracy: A Historical Sociology of Nuclear Missile Guidance, Inside Technology. MIT Press, Cambridge, MA, USA.

Maher, N., Milinski, S., Suarez-Gutierrez, L., Botzet, M., Dobrynin, M., Kornblueh, L., Kröger, J., Takano, Y., Ghosh, R., Hedemann, C., Li, C., Li, H., Manzini, E., Notz, D., Putrasahan, D., Boysen, L., Claussen, M., Ilyina, T., Olonscheck, D., Raddatz, T., Stevens, B., Marotzke, J., 2019. The Max Planck Institute Grand Ensemble: Enabling the Exploration of Climate System Variability. Journal of Advances in Modeling Earth Systems 11, 2050–2069. https://doi.org/10.1029/2019MS001639

Maishman, T., Schaap, S., Silk, D.S., Nevitt, S.J., Woods, D.C., Bowman, V.E., 2021. Statistical methods used to combine the effective reproduction number, R(t), and other related measures of COVID-19 in the UK. arXiv:2103.01742 [physics, q-bio, stat].

Mäki, U., 2005. Models are experiments, experiments are models. Journal of Economic Methodology 12, 303–315. https://doi.org/10.1080/13501780500086255

Manning, M.R., Petit, M., 2004. A Concept Paper for the AR4 Cross Cutting Theme: Uncertainties and Risk, IPCC Risk and Uncertainty Workshop. IPCC, Maynooth, Ireland.

Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W., 2019. Introduction, in: Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W. (Eds.), Decision Making under Deep Uncertainty: From Theory to Practice. Springer International Publishing, Cham, pp. 1–20. https://doi.org/10.1007/978-3-030-05252-2_1

Martin-Nielsen, J., 2017. Hubert H. Lamb and boundary work at the UK Meteorlogical Office, in: Heymann, M., Gramelsberger, G., Mahony, M. (Eds.), Cultures of Prediciton in Atmospheric and Climate Science, Routledge Environmental Humanities Series. Earthscan from Routledge, Cambridge, UK, pp. 84–97.

Marvel, K., 2021. Climate Scenarios and Reality. Issues in Science and Technology. URL https://issues.org/climate-scenarios-reality-pielke-jr-ritchie-forum/ (accessed 1.27.22).

Maslin, M., Austin, P., 2012. Climate models at their limit? Nature 486, 183–184. https://doi.org/10.1038/486183a

Masson, D., Knutti, R., 2011. Climate model genealogy: CLIMATE MODEL GENEALOGY. Geophys. Res. Lett. 38, n/a-n/a. https://doi.org/10.1029/2011GL046864

Mastrandrea, M.D., Field, C.B., Stocker, T.F., Edenhofer, O., Ebi, K.L., Frame, D.J., Held, H., Kriegler, E., Mach, K.J., Matschoss, P.R., Plattner, G.-K., Yohe, G.W., Zwiers, F.W., 2010. Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. IPCC, Jasper Ridge, CA, USA.

Matta, C., 2021. Philosophical Paradigms in Qualitative Research Methods Education: What is their Pedagogical Role? Scandinavian Journal of Educational Research 0, 1–14. https://doi.org/10.1080/00313831.2021.1958372

Mayer, L.A., Loa, K., Cwik, B., Tuana, N., Keller, K., Gonnerman, C., Parker, A.M., Lempert, R.J., 2017. Understanding scientists' computational modeling decisions about climate risk management strategies using values-informed mental models. Global Environmental Change 42, 107–116. https://doi.org/10.1016/j.gloenvcha.2016.12.007

McBryde, E.S., Meehan, M.T., Adegboye, O.A., Adekunle, A.I., Caldwell, J.M., Pak, A., Rojas, D.P., Williams, B.M., Trauer, J.M., 2020. Role of modelling in COVID-19 policy development. Paediatric Respiratory Reviews 35, 57–60. https://doi.org/10.1016/j.prrv.2020.06.013

McDowall, W., Trutnyevte, E., Tomei, J., Keppo, I., 2014. Reflecting on Scenarios, UKERC Energy Systems Theme. UKERC, London, England.

McGrath, C., Palmgren, P.J., Liljedahl, M., 2019. Twelve tips for conducting qualitative research interviews. Medical Teacher 41, 1002–1006. https://doi.org/10.1080/0142159X.2018.1497149

McIntosh, M.J., Morse, J.M., 2015. Situating and Constructing Diversity in Semi-Structured Interviews. Global Qualitative Nursing Research 2, 2333393615597674. https://doi.org/10.1177/2333393615597674

McWilliams, J.C., 2019. A Perspective on the Legacy of Edward Lorenz. Earth and Space Science 6, 336–350. https://doi.org/10.1029/2018EA000434

Meadows, D.H., Meadows, D.L., Randers, J., Behrens, W.W. (III), 1972. Limits to Growth. The Club of Rome.

MEDEAS, 2022. Medeas | Modeling the renewable energy transition in europe [WWW Document]. URL https://www.medeas.eu/#project (accessed 1.28.22).

Meehl, G.A., Covey, C., McAvaney, B., Latif, M., Stouffer, R.J., 2005. Meeting Summaries: Overview of the Coupled Model Intercomparison Project. Bulletin of the American Meteorological Society 86, 89–96. https://doi.org/10.1175/BAMS-86-1-89

Mehta, L., Leach, M., Newell, P., Scoones, I., Sivaramakrishnan, K., Way, S.-A., 1999. Exploring understandings of institutions and uncertainty: new directions in natural resource management. Institute of Development Studies.

Mehta, L., Srivastava, S., 2020. Uncertainty in Modelling Climate Change: The possibilities of co-production through knowledge pluralism, in: Scoones, I., Stirling, A. (Eds.), The Politics of Uncertainty: Challenges of Transformation. Earthscan from Routledge, Abingdon, UK.

Mehta, L., Srivastava, S., Adam, H.N., Alankar, Bose, S., Ghosh, U., Kumar, V.V., 2019. Climate change and uncertainty from 'above' and 'below': perspectives from India. Reg Environ Change 19, 1533–1547. https://doi.org/10.1007/s10113-019-01479-7

Meijer, I.S.M., Hekkert, M.P., Faber, J., Smits, R.E.H.M., 2006. Perceived uncertainties regarding socio-technological transformations: towards a framework. International Journal of Foresight and Innovation Policy.

Meinshausen, M., Raper, S.C.B., Wigley, T.M.L., 2011. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. Atmospheric Chemistry and Physics 11, 1417–1456. https://doi.org/10.5194/acp-11-1417-2011

Melsen, L.A., 2022. It Takes a Village to Run a Model—The Social Practices of Hydrological Modeling. Water Resources Research 58, e2021WR030600. https://doi.org/10.1029/2021WR030600

Merton, R.K., 1968. The Matthew Effect in Science. Science 159, 56–63. https://doi.org/10.1126/science.159.3810.56

Met Office, 2021. Unified Model [WWW Document]. Met Office. URL https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/index (accessed 1.14.22).

Metz, J.A.J., 1978. The epidemic in a closed population with all susceptibles equally vulnerable; some results for large susceptible populations and small initial infections. Acta Biotheor 27, 75–123. https://doi.org/10.1007/BF00048405

Michael, M., 2017. Actor-Network Theory: Trials, Trails and Translations. SAGE Publications, Inc., London, England.

Milliken, F.J., 1987. Three Types of Perceived Uncertainty about the Environment: State, Effect, and Response Uncertainty. The Academy of Management Review 12, 133–143. https://doi.org/10.2307/257999

Mirakyan, A., De Guio, R., 2015. Modelling and uncertainties in integrated energy planning. Renewable and Sustainable Energy Reviews 46, 62–69. https://doi.org/10.1016/j.rser.2015.02.028

Monier, E., Gao, X., Scott, J.R., Sokolov, A.P., Schlosser, C.A., 2015. A framework for modeling uncertainty in regional climate change. Climatic Change 131, 51–66. https://doi.org/10.1007/s10584-014-1112-5

Monticone, P., 2020. The RCP8.5 Debate [WWW Document]. ["The RCP8.5 Debate"]. URL https://pitmonticone.github.io/rcp85-debate/ (accessed 1.27.22).

Morgan, M.G., 2017. Risk Communication, in: Theory and Practice in Policy Analysis. Cambridge University Press, Cambridge, UK, pp. 389–409.

Morgan, M.G., 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. PNAS 111, 7176–7184. https://doi.org/10.1073/pnas.1319946111

Morgan, M.G., Fischhoff, B., Bostrom, A., Atman, C., 2002a. Risk Communication: A Mental Models Approach. Cambridge University Press, Cambridge, UK.

Morgan, M.G., Fischhoff, B., Bostrom, A., Atman, C.J., 2002b. Risk Communication, A Mental Models Approach, 1st ed. Cambridge University Press, Cambridge, UK.

Morgan, M.G., Henrion, M., 1990. Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge, UK.

Morgan, M.G., Keith, D.W., 2008. Improving the way we think about projecting future energy use and emissions of carbon dioxide. Climatic Change 90, 189–215. https://doi.org/10.1007/s10584-008-9458-1

Morgan, M.S., Morrison, M., 1999. Models as Mediators; Perspectives on Natural and Social Science, Ideas in Context. Cambridge University Press, Cambridge, UK.

Morris, M.D., 1991. Factorial Sampling Plans for Preliminary Computational Experiments. Technometrics 33, 161–174. https://doi.org/10.2307/1269043

Morrison, M., 2014. Values and Uncertainty in Simulation Models. Erkenn 79, 939–959. https://doi.org/10.1007/s10670-013-9537-1

Morrison, M., 1999. Models as Autonomous Agents, in: Morgan, M.S., Morrison, M. (Eds.), Models as Mediators: Perspectives on Natural and Social Science, Ideas in Context. Cambridge University Press, Cambridge, UK, pp. 38–65.

Moser, S.C., 2005. Impact assessments and policy responses to sea-level rise in three US states: An exploration of human-dimension uncertainties. Global Environmental Change 15, 353–369. https://doi.org/10.1016/j.gloenvcha.2005.08.002

Moser, S.C., 1997. Mapping the territory of uncertainty and ignorance: Broadening current assessment and policy approaches to sea-level rise - ProQuest. Clark University.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756. https://doi.org/10.1038/nature08823

Moss, R.H., Schneider, S.H., 2000. UNCERTAINTIES IN THE IPCC TAR: Recommendations To Lead Authors For More Consistent Assessment and Reporting, in: Guidance Papers on the Cross Cutting Issues of the Third Assessment Report of the IPCC. World Metrological Organisation.

Nakićenović, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grübler, A., Jung, T.Y., Kram, T., La Rovere, E.L., Machaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., 2000. Special report on emissions scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge ; New York.

Nearing, G.S., Tian, Y., Gupta, H.V., Clark, M.P., Harrison, K.W., Weijs, S.V., 2016. A philosophical basis for hydrological uncertainty. Hydrological Sciences Journal 61, 1666–1678. https://doi.org/10.1080/02626667.2016.1183009

Niet, T., Shivakumar, A., Gardumi, F., Usher, W., Williams, E., Howells, M., 2021. Developing a community of practice around an open source energy modelling tool. Energy Strategy Reviews 35, 100650. https://doi.org/10.1016/j.esr.2021.100650

Nordhaus, W.D., 2013. The Climate Casino: Risk, Uncertainty and Economics for a Warming World. Yale University Press, New Haven and London.

Norton, J.P., Brown, J.D., Jaroslav Mysiak, 2006. To what extent, and how, might uncertainty be defined: Comments engendered by... The Integrated Assessment Journal 6, 83–88.

Nowotny, H., 2016a. The Cunning of Uncertainty, 1st ed. Polity Press, Cambridge, UK.

Nowotny, H., 2016b. The Cunning of Uncertainty. Polity Press, Cambridge, UK.

Nowotny, H., Scott, P., Gibbons, M., 2001. Rethinking Science: Mode 2 in a Societal Context. Polity Press.

NRC, 1994. Uncertainty, in: Science and Judgement in Risk Assessment. National Reserach Council, Washington, DC, USA.

Odenbaugh, J., Alexandrova, A., 2011. Buyer beware: robustness analyses in economics and biology. Biol Philos 26, 757–771. https://doi.org/10.1007/s10539-011-9278-y

O'Driscoll, M., Ribeiro Dos Santos, G., Wang, L., Cummings, D.A.T., Azman, A.S., Paireau, J., Fontanet, A., Cauchemez, S., Salje, H., 2021. Age-specific mortality and immunity patterns of SARS-CoV-2. Nature 590, 140–145. https://doi.org/10.1038/s41586-020-2918-0

O'Neill, B.C., Kriegler, E., Ebi, K.L., Kemp-Benedict, E., Riahi, K., Rothman, D.S., van Ruijven, B.J., van Vuuren, D.P., Birkmann, J., Kok, K., Levy, M., Solecki, W., 2017. The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. Global Environmental Change 42, 169–180. https://doi.org/10.1016/j.gloenvcha.2015.01.004

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 122, 387–400. https://doi.org/10.1007/s10584-013-0905-2

Oreopoulos, L., Mlawer, E., Delamere, J., Shippert, T., Cole, J., Fomin, B., Iacono, M., Jin, Z., Li, J., Manners, J., Räisänen, P., Rose, F., Zhang, Y., Wilson, M.J., Rossow, W.B., 2012. The Continual Intercomparison of Radiation Codes: Results from Phase I. Journal of Geophysical Research: Atmospheres 117. https://doi.org/10.1029/2011JD016821

Oreskes, N., Conway, E.M., 2012. Merchants of Doubt. Bloomsbury, London, UK.

Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. Science 263. https://doi.org/10.1126/science.263.5147.641

Osprey, A., 2021. How do we actually run very high resolution climate simulations? [WWW Document]. Weather and Climate @ Reading. URL https://blogs.reading.ac.uk/weather-and-climate-at-reading/2021/how-do-we-actually-run-very-high-resolution-climate-simulations/ (accessed 6.27.22).

Page, E., 1999. Intergenerational Justice and Climate Change. Political Studies 47, 53–66. https://doi.org/10.1111/1467-9248.00187

Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J.P., Duan, N., Hoagwood, K., 2015. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Adm Policy Ment Health 42, 533–544. https://doi.org/10.1007/s10488-013-0528-y

Panovska-Griffiths, J., Park, J., Bevan, L.D., Melas, I., Moore, R.E., Voehringer, H., Slattery, C., Akutekwe, A., Wilby, D., Semashkov, D., Ward, T., Burton, R., Hetherington, J., Forthcoming. Combining reproduction number and gowth rate estimates across an epidemiological Multi-Model Ensemble 1–8.

Pappenberger, F., Harvey, H., Beven, K., Hall, J., Romanowicz, R., Smith, P., 2006. Implementation Plan for Library of Tools for Uncertainty Evaluation (No. UR2). FRMRC, Manchester, UK.

PARIS REINFORCE, 2021. Home | Paris Reinforce [WWW Document]. URL https://paris-reinforce.eu/ (accessed 1.28.22).

Parker, W., 2018. Climate Science, in: Zalta, E.N. (Ed.), The Stanford Encyclopedia of Philosophy. Metaphysics Research Lab, Stanford University.

Parker, W., 2014. Values and uncertainties in climate prediction, revisited. Studies in History and Philosophy of Science Part A 46, 24–30. https://doi.org/10.1016/j.shpsa.2013.11.003

Parker, W.S., 2013. Ensemble modeling, uncertainty and robust predictions. WIREs Climate Change 4, 213–223. https://doi.org/10.1002/wcc.220

Parker, W.S., 2011. When Climate Models Agree: The Significance of Robust Model Predictions. Philosophy of Science 78, 579–600. https://doi.org/10.1086/661566

Parker, W.S., 2010a. Predicting weather and climate: Uncertainty, ensembles and probability. Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics, Special Issue: Modelling and Simulation in the Atmospheric and Climate Sciences 41, 263–272. https://doi.org/10.1016/j.shpsb.2010.07.006

Parker, W.S., 2010b. Whose Probabilities? Predicting Climate Change with Ensembles of Models. Philosophy of Science 77, 985–997. https://doi.org/10.1086/656815

Parker, W.S., 2009. II—Wendy S. Parker: Confirmation and adequacy-for-Purpose in Climate Modelling. Aristotelian Society Supplementary Volume 83, 233–249. https://doi.org/10.1111/j.1467-8349.2009.00180.x

Parker, W.S., 2006. Understanding Pluralism in Climate Modeling. Found Sci 11, 349–368. https://doi.org/10.1007/s10699-005-3196-x

Parson, E.A., Fisher-Vanden, K., 1995. Thematic Guide to Integrated Assessment Modeling. Center for International Earth Science Information Network (CIESIN), Palisades, NY, USA.

Paté-Cornell, M.E., 1996. Uncertainties in Risk Analysis: Six Levels of Treatment. Reliability Engineering and System Safety 54, 95–111.

Paulsen, J., 2020. Attack the Climate Crisis with Exascale Supercomputing. Seagate Blog. URL https://blog.seagate.com/human/attack-the-climate-crisis-with-exascale-supercomputing/ (accessed 3.22.22).

PBL, 2021. Welcome to IMAGE 3.2 Documentation - IMAGE [WWW Document]. PBL Netherlands Environmental Assessment Agency. URL https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.2_Documentation (accessed 1.24.22).

PCMDI, 2019. CMIP3 [WWW Document]. Program for Climate Model Diagnosis & Intercomparison. URL https://pcmdi.llnl.gov/mips/cmip3/ (accessed 4.5.19).

Pedde, S., Harrison, P.A., Holman, I.P., Powney, G.D., Lofts, S., Schmucki, R., Gramberger, M., Bullock, J.M., 2021. Enriching the Shared Socioeconomic Pathways to co-create consistent multi-sector scenarios for the UK. Science of The Total Environment 756, 143172. https://doi.org/10.1016/j.scitotenv.2020.143172

Pedersen, T.T., Victoria, M., Rasmussen, M.G., Andresen, G.B., 2021. Modeling all alternative solutions for highly renewable energy systems. Energy 234, 121294. https://doi.org/10.1016/j.energy.2021.121294

Peterman, R.M., 2004. Possible solutions to some challenges facing fisheries scientists and managers. ICES Journal of Marine Science 61, 1331–1343. https://doi.org/10.1016/j.icesjms.2004.08.017

Petersen, A.C., 2006. Simulating Nature: A Philosophical Study of Computer-Simulation Uncertainties and Their Role in Climate Science and Policy Advice, Second. ed. CRC Press, Boca Raton, FL, US.

Petersen, A.C., Janssen, P., Risbey, J., Ravetz, J.R., Wardekker, J.A., Martinson Hughes, H., 2013. Guidance for uncertainty assessment and communication (Second Edition). Netherlands Environmental Assessment Agency (PBL).

Peterson, S., 2006. Uncertainty and economic analysis of climate change: A survey of approaches and findings. Environ Model Assess 11, 1–17. https://doi.org/10.1007/s10666-005-9014-6

Petr, M., Vacchiano, G., Thom, D., Mairota, P., Kautz, M., Goncalves, L.M.S., Yousefpour, R., Kaloudis, S., Reyer, C.P.O., 2019. Inconsistent recognition of uncertainty in studies of climate change impacts on forests. Environ. Res. Lett. 14, 113003. https://doi.org/10.1088/1748-9326/ab4670

Pielke Jr, R., 2020. How Billionaires Tom Steyer and Michael Bloomberg Corrupted Climate Science [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2020/01/02/how-billionaires-tom-steyer-and-michael-bloomberg-corrupted-climate-science/ (accessed 1.27.22).

Pielke Jr, R., 2019a. It's Time To Get Real About The Extreme Scenario Used To Generate Climate Porn [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/09/26/its-time-to-get-real-about-the-extreme-scenario-used-to-generate-climate-porn/ (accessed 1.27.22).

Pielke Jr, R., 2019b. It's Time To Move Beyond The Toy Models that Guide Climate Policy [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/10/07/its-time-to-move-beyond-the-toy-models-that-guide-climate-policy/ (accessed 1.27.22).

Pielke Jr, R., 2019c. If Climate Scenarios Are Wrong For 2020, Can They Get 2100 Right? [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/10/21/if-climate-scenarios-are-wrong-for-2020-can-they-get-2100-right/ (accessed 1.27.22).

Pielke Jr, R., 2019d. Global Carbon Dioxide Emissions Are On The Brink Of A Long Plateau [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/11/30/global-carbon-dioxide-emissions-are-on-the-brink-of-a-long-plateau/ (accessed 1.27.22).

Pielke Jr, R., 2019e. The Incredible Story Of How Climate Change Became Apocalyptic [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/12/06/the-incredible-story-of-how-climate-change-became-apocalyptic/ (accessed 1.27.22).

Pielke Jr, R., 2019f. In 2020 Climate Science Needs To Hit The Reset Button, Part One [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/12/22/in-2020-climate-science-needs-to-hit-the-reset-button-part-one/ (accessed 1.27.22).

Pielke Jr, R., 2019g. In 2020 Climate Science Needs To Hit The Reset Button, Part Two [WWW Document]. Forbes. URL https://www.forbes.com/sites/rogerpielke/2019/12/23/in-2020-climate-science-needs-to-hit-the-reset-button-part-two/ (accessed 1.27.22).

Pielke Jr, R., Ritchie, J., 2021. How Climate Scenarios Lost Touch With Reality. Issues in Science and Technology. URL https://issues.org/climate-change-scenarios-lost-touch-reality-pielke-ritchie/ (accessed 1.27.22).

Pinch, T.J., Bijker, W.E., 1984. The Social Construction of Facts and Artefacts: Or How the Sociology of Science and the Sociology of Technology Might Benefit Each Other. Social Studies of Science 14, 399–441.

Pindyck, R.S., 2017. The Use and Misuse of Models for Climate Policy. Review of Environmental Economics and Policy 11, 100–114. https://doi.org/10.1093/reep/rew012

Pindyck, R.S., 2013. Climate Change Policy: What Do the Models Tell Us? Journal of Economic Literature 51, 860–872. https://doi.org/10.1257/jel.51.3.860

Pinto Neto, O., Kennedy, D.M., Reis, J.C., Wang, Y., Brizzi, A.C.B., Zambrano, G.J., de Souza, J.M., Pedroso, W., de Mello Pedreiro, R.C., de Matos Brizzi, B., Abinader, E.O., Zângaro, R.A., 2021. Mathematical model of COVID-19 intervention scenarios for São Paulo—Brazil. Nature Communications 12, 418. https://doi.org/10.1038/s41467-020-20687-y

Plantinga, E., 1987. Mental models and metaphor. Proceedings of the 1987 workshop on Theoretical issues in natural language processing - 30, 185. https://doi.org/10.3115/980304.980347

Poland, B.D., 1995. Transcription Quality as an Aspect of Rigor in Qualitative Research. Qualitative Inquiry 1, 290–310. https://doi.org/10.1177/107780049500100302

Poole, C., Greenland, S., 1999. Random-Effects Meta-Analyses Are Not Always Conservative. American Journal of Epidemiology 150, 469–475. https://doi.org/10.1093/oxfordjournals.aje.a010035

Price, J., Keppo, I., 2017. Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models. Applied Energy 195, 356–369. https://doi.org/10.1016/j.apenergy.2017.03.065

Pulkkinen, K., Undorf, S., Bender, F., Wikman-Svahn, P., Doblas-Reyes, F., Flynn, C., Hegerl, G.C., Jönsson, A., Leung, G.-K., Roussos, J., Shepherd, T.G., Thompson, E., 2022. The value of values in climate science. Nat. Clim. Chang. 12, 4–6. https://doi.org/10.1038/s41558-021-01238-9

Raftery, A.E., Gneiting, T., Balabdaoui, F., Polakowski, M., 2005. Using Bayesian Model Averaging to Calibrate Forecast Ensembles. Monthly Weather Review 133, 1155–1174. https://doi.org/10.1175/MWR2906.1

Ramsey, F.P., 2016. Truth and Probability, in: Arló-Costa, H., Hendricks, V.F., van Benthem, J. (Eds.), Readings in Formal Epistemology: Sourcebook, Springer Graduate Texts in Philosophy. Springer International Publishing, Cham, pp. 21–45. https://doi.org/10.1007/978-3-319-20451-2_3

Randall, D.A., Wood, R.A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J., Srinivasan, J., Stouffer, R.J., Sumi, A., Taylor, K.E., AchutaRao, K., Allan, R., Berger, A., Blatter, H., Bonfils, C., Boone, A., Bretherton, C., Broccoli, A., Brovkin, V., Dirmeyer, P., Doutriaux, C., Drange, H., Frei, A., Ganopolski, A., Gent, P., Gleckler, P., Goosse, H., Graham, R., Gregory, J.M., Gudgel, R., Hall, A., Hallegatte, S., Hasumi, H., Henderson-Sellers, A., Hendon, H., Hodges, K., Holland, M., Holtslag, A.A.M., Hunke, E., Huybrechts, P., Ingram, W., Joos, F., Kirtman, B., Klein, S., Koster, R., Kushner, P., Lanzante, J., Latif, M., Pavlova, T., Federationi, R., Petoukhov, V., Phillips, T., Power, S., Rahmstorf, S., Raper, S.C.B., Renssen, H., Rind, D., Roberts, M., Rosati, A., Schär, C., Schmittner, A., Scinocca, J., Seidov, D., Slater, A.G., Slingo, J., Smith, D., Soden, B., Stern, W., Stone, D.A., Sudo, K., Takemura, T., Tselioudis, G., Webb, M., Wild, M., Manzini, E., Matsuno, T., McAvaney, B., 2007. Climate Models and Their Evaluation, in: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, p. 74.

Ravetz, J.R., 1999. What is Post-Normal Science. Futures 7.

Ravetz, J.R., Funtowicz, S.O., 1993. Science for the Post-Normal Age. FUTURES 17.

Ray, E.L., Wattanachit, N., Niemi, J., Kanji, A.H., House, K., Cramer, E.Y., Bracher, J., Zheng, A., Yamana, T.K., Xiong, X., Woody, S., Wang, Y., Wang, L., Walraven, R.L., Tomar, V., Sherratt, K., Sheldon, D., Reiner, R.C., Prakash, B.A., Osthus, D., Li, M.L., Lee, E.C., Koyluoglu, U., Keskinocak, P., Gu, Y., Gu, Q., George, G.E., España, G., Corsetti, S., Chhatwal, J., Cavany, S., Biegel, H., Ben-Nun, M., Walker, J., Slayton, R., Lopez, V., Biggerstaff, M., Johansson, M.A., Reich, N.G., Consortium, on behalf of the C.-19 F.H., 2020. Ensemble Forecasts of Coronavirus Disease 2019 (COVID-19) in the U.S. medRxiv 2020.08.19.20177493. https://doi.org/10.1101/2020.08.19.20177493

Refsgaard, J.C., Sonnenborg, T.O., Butts, M.B., Christensen, J.H., Christensen, S., Drews, M., Jensen, K.H., Jørgensen, F., Jørgensen, L.F., Larsen, M.A.D., Rasmussen, S.H., Seaby, L.P., Seifert, D., Vilhelmsen, T.N., 2016. Climate change impacts on groundwater hydrology – where are the main uncertainties and can they be reduced? Hydrological Sciences Journal 61, 2312–2324. https://doi.org/10.1080/02626667.2015.1131899

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – A framework and guidance. Environmental Modelling & Software 22, 1543–1556. https://doi.org/10.1016/j.envsoft.2007.02.004

Regan, H.M., Colyvan, M., Burgman, M.A., 2002. A TAXONOMY AND TREATMENT OF UNCERTAINTY FOR ECOLOGY AND CONSERVATION BIOLOGY. Ecological Applications 12, 11.

Reich, N.G., McGowan, C.J., Yamana, T.K., Tushar, A., Ray, E.L., Osthus, D., Kandula, S., Brooks, L.C., Crawford-Crudell, W., Gibson, G.C., Moore, E., Silva, R., Biggerstaff, M., Johansson, M.A., Rosenfeld, R., Shaman, J., 2019. Accuracy of real-time multi-model ensemble forecasts for seasonal influenza in the U.S. PLOS Computational Biology 15, e1007486. https://doi.org/10.1371/journal.pcbi.1007486

Reiner, R.C., Barber, R.M., Collins, J.K., Zheng, P., Adolph, C., Albright, J., Antony, C.M., Aravkin, A.Y., Bachmeier, S.D., Bang-Jensen, B., Bannick, M.S., Bloom, S., Carter, A., Castro, E., Causey, K., Chakrabarti, S., Charlson, F.J., Cogen, R.M., Combs, E., Dai, X., Dangel, W.J., Earl, L., Ewald, S.B., Ezalarab, M., Ferrari, A.J., Flaxman, A., Frostad, J.J., Fullman, N., Gakidou, E., Gallagher, J., Glenn, S.D., Goosmann, E.A., He, J., Henry, N.J., Hulland, E.N., Hurst, B., Johanns, C., Kendrick, P.J., Khemani, A., Larson, S.L., Lazzar-Atwood, A., LeGrand, K.E., Lescinsky, H., Lindstrom, A., Linebarger, E., Lozano, R., Ma, R., Månsson, J., Magistro, B., Herrera, A.M.M., Marczak, L.B., Miller-Petrie, M.K., Mokdad, A.H., Morgan, J.D., Naik, P., Odell, C.M., O'Halloran, J.K., Osgood-Zimmerman, A.E., Ostroff, S.M., Pasovic, M., Penberthy, L., Phipps, G., Pigott, D.M., Pollock, I., Ramshaw, R.E., Redford, S.B., Reinke, G., Rolfe, S., Santomauro, D.F., Shackleton, J.R., Shaw, D.H., Sheena, B.S., Sholokhov, A., Sorensen, R.J.D., Sparks, G., Spurlock, E.E., Subart, M.L., Syailendrawati, R., Torre, A.E., Troeger, C.E., Vos, T., Watson, A., Watson, S., Wiens, K.E., Woyczynski, L., Xu, L., Zhang, J., Hay, S.I., Lim, S.S., Murray, C.J.L., IHME COVID-19 Forecasting Team, 2021. Modeling COVID-19 scenarios for the United States. Nature Medicine 27, 94–105. https://doi.org/10.1038/s41591-020-1132-9

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change 42, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Ricci, P.F., Rice, D., Ziagos, J., Cox, L.A., 2003. Precaution, uncertainty and causation in environmental decisions. Environment International 29, 1–19. https://doi.org/10.1016/S0160-4120(02)00191-5

Ricke, K., Drouet, L., Caldeira, K., Tavoni, M., 2018. Country-level social cost of carbon. Nature Climate Change 8, 895. https://doi.org/10.1038/s41558-018-0282-y

Riesch, H., 2012. Levels of Uncertainty, in: Roeser, S., Hillerbrand, R., Sandin, P., Peterson, M. (Eds.), Handbook of Risk Theory: Epistemology, Decision Theory, Ethics, and Social Implications of Risk. Springer Netherlands, Dordrecht, pp. 87–110. https://doi.org/10.1007/978-94-007-1433-5_4

Riley, R.D., Higgins, J.P.T., Deeks, J.J., 2011. Interpretation of random effects meta-analyses. BMJ 342, d549. https://doi.org/10.1136/bmj.d549

Risbey, J.S., Lamb, P.J., Miller, R.L., Morgan, M.C., Roe, G.H., 2002. Exploring the Structure of Regional Climate Scenarios by Combining Synoptic and Dynamic Guidance and GCM Output. JOURNAL OF CLIMATE 15, 15.

Ritchie, J., Lewis, J., Nicholls, C.M., Ormiston, R., 2003. Qualitative research practice: a guide for social science students and researchers. Choice Reviews Online 41, 41-1319-41–1319. https://doi.org/10.5860/CHOICE.41-1319

Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a General Theory of Planning. Policy Sciences 4, 155–169.

Robbins, D., 2020. Climate Change Frame Production: Perspectives from Government Ministers and Senior Media Strategists in Ireland. Environmental Communication 14, 509–521. https://doi.org/10.1080/17524032.2019.1691620

Roe, E., 2020. Control, Manage or Cope? A politics for risks, uncertainties and unknown-unknowns., in: Scoones, I., Stirling, A. (Eds.), The Politics of Uncertainty: Challenges of Transformation. Earthscan from Routledge, Abingdon, UK, pp. 73–84.

Roller, M.R., Lavrakas, P.L., 2015. Applied qualitative research design: A total quality framework approach. Guilford, New York, USA.

Roosa, K., Tariq, A., Yan, P., Hyman, J.M., Chowell, G., 2020. Multi-model forecasts of the ongoing Ebola epidemic in the Democratic Republic of Congo, March–October 2019. Journal of The Royal Society Interface 17, 20200447. https://doi.org/10.1098/rsif.2020.0447

Rotmans, J., van Asselt, M., 2006. Integrated Assessment Modelling, in: Climate Change: An Integrated Perspective. pp. 239–275. https://doi.org/10.1007/0-306-47982-6_7

Rotmans, J., van Asselt, M., 2001. Uncertainty Management in Integrated Assessment Modeling: Towards a Pluralistic Approach. Environmental Monitoring and Assessment 69, 101–130.

Rowe, W.D., 1994. Understanding Uncertainty. Risk Analysis 14, 743–750. https://doi.org/10.1111/j.1539-6924.1994.tb00284.x

Ruktanonchai, N.W., Floyd, J.R., Lai, S., Ruktanonchai, C.W., Sadilek, A., Rente-Lourenco, P., Ben, X., Carioli, A., Gwinn, J., Steele, J.E., Prosper, O., Schneider, A., Oplinger, A., Eastham, P., Tatem, A.J., 2020. Assessing the impact of coordinated COVID-19 exit strategies across Europe. Science 369, 1465–1470. https://doi.org/10.1126/science.abc5096

Runde, J., 1994. Keynes after Ramsey: In defence of a treatise on probability. Studies in History and Philosophy of Science Part A 25, 97–121. https://doi.org/10.1016/0039-3681(94)90022-1

Runde, J., 1990. Keynesian Uncertainty and the Weight of Arguments. Economics and Philosophy 275–292.

Sakai, Y., 2016. J. M. Keynes on probability versus F. H. Knight on uncertainty: reflections on the miracle year of 1921. Evolut Inst Econ Rev 13, 1–21. https://doi.org/10.1007/s40844-016-0039-0

Saltelli, A., 2002. Sensitivity Analysis for Importance Assessment. Risk Analysis 22, 579–590. https://doi.org/10.1111/0272-4332.00040

Saltelli, A., Annoni, P., 2010. How to avoid a perfunctory sensitivity analysis. Environmental Modelling & Software 25, 1508–1517. https://doi.org/10.1016/j.envsoft.2010.04.012

Saltelli, A., Ratto, M., Andres, T., Campognolo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Introduction to Sensitivity Analysis, in: Global Sensitivity Analysis. The PRimer. Wiley, Chichester, West Sussex, UK, pp. 1–52.

Salter, J., Robinson, J., Wiek, A., 2010. Participatory methods of integrated assessment-a review: Participatory methods of integrated assessment. Wiley Interdisciplinary Reviews: Climate Change 1, 697–717. https://doi.org/10.1002/wcc.73

Sanderson, B.M., Knutti, R., Caldwell, P., 2015. A Representative Democracy to Reduce Interdependency in a Multimodel Ensemble. Journal of Climate 28, 5171–5194. https://doi.org/10.1175/JCLI-D-14-00362.1

Sanderson, B.M., Wehner, M., Knutti, R., 2017. Skill and independence weighting for multi-model assessments. Geoscientific Model Development 10, 2379–2395. https://doi.org/10.5194/gmd-10-2379-2017

Scala, A., Flori, A., Spelta, A., Brugnoli, E., Cinelli, M., Quattrociocchi, W., Pammolli, F., 2020. Time, space and social interactions: exit mechanisms for the Covid-19 epidemics. Sci Rep 10, 13764. https://doi.org/10.1038/s41598-020-70631-9

Schmidt, G.A., Jacobs, P.J., 2021. Climate Scenarios and Reality. Issues in Science and Technology. URL https://issues.org/climate-scenarios-reality-pielke-jr-ritchie-forum/ (accessed 1.27.22).

Schmidt, G.A., Sherwood, S., 2015. A practical philosophy of complex climate modelling. Euro Jnl Phil Sci 5, 149–169. https://doi.org/10.1007/s13194-014-0102-9

Schneider, S.H., 2001. What is 'dangerous' climate change? Nature Commentary 411, 3.

Schneider, S.H., Turner, B.L., Garriga, H.M., 1998. Imaginable surprise in global change science. Journal of Risk Research 1, 165–185. https://doi.org/10.1080/136698798377240

Schumacher, E.F., 1977. A Guide for the Perplexed. Jonathan Cape, London, UK.

Schunk, R.W., Scherliess, L., Eccles, V., Gardner, L.C., Sojka, J.J., Zhu, L., Pi, X., Mannucci, A.J., Butala, M., Wilson, B.D., Komjathy, A., Wang, C., Rosen, G., 2014. Multimodel Ensemble Prediction System for Space Weather Applications. Presented at the Proceedings of the 2014 International Technical Meeting of The Institute of Navigation, pp. 725–729.

Schwanitz, V.J., 2013. Evaluating integrated assessment models of global climate change. Environmental Modelling & Software 50, 120–131. https://doi.org/10.1016/j.envsoft.2013.09.005

Schweizer, V.J., Kurniawan, J.H., 2016. Systematically linking qualitative elements of scenarios across levels, scales, and sectors. Environmental Modelling & Software 79, 322–333. https://doi.org/10.1016/j.envsoft.2015.12.014

Schweizer, V.J., O'Neill, B.C., 2014. Systematic construction of global socioeconomic pathways using internally consistent element combinations. Climatic Change 122, 431–445. https://doi.org/10.1007/s10584-013-0908-z

Scoones, I., Stirling, A., 2020. Uncertainty and the Politics of Transformation, in: The Politics of Uncertainty: Challenges of Transformation. Earthscan from Routledge, Abingdon, UK.

Seaholm, S.K., Ackerman, E., Wu, S.C., 1988. Latin hypercube sampling and the sensitivity analysis of a Monte Carlo epidemic model. Int J Biomed Comput 23, 97–112. https://doi.org/10.1016/0020-7101(88)90067-0

Serres, M., 1974. La Traduction. Hermès III. Minuit.

Shackle, G.L.S., 1955. Uncertainty in Economics and Other Reflections. Cambridge University Press, Cambridge, UK.

Shackley, S., Wynne, B., 1996. Representing Uncertainty in Global Climate Change Science and Policy : Boundary-Ordering Devices and Authority. Science, Technology, & Human Values 21, 275–302.

Shackley, S., Wynne, B., 1995. Integrating knowledges for climate change. Global Environmental Change 5, 113–126. https://doi.org/10.1016/0959-3780(95)00017-I

Shackley, S., Young, P., Parkinson, S., Wynne, B., 1998. uncertainty, complexity and concepts of good science in climate change modelling: are GcMs the best tools. Climatic Change 159–205.

Shaffer, M., 1987. Minimum Viable Populations: Coping with Uncertainty, in: Soulé, M.E. (Ed.), Viable Populations for Conservation. Cambridge University Press, Cambridge, UK.

Shanahan, D., 1987. Habits of the heart: Individualism and commitment in American life. The Social Science Journal 24, 229–231. https://doi.org/10.1016/0362-3319(87)90045-0

Shea, K., Borchering, R.K., Probert, W.J.M., Howerton, E., Bogich, T.L., Li, S., Panhuis, W.G. van, Viboud, C., Aguás, R., Belov, A., Bhargava, S.H., Cavany, S., Chang, J.C., Chen, C., Chen, J., Chen, S., Chen, Y., Childs, L.M., Chow, C.C., Crooker, I., Valle, S.Y.D., España, G., Fairchild, G., Gerkin, R.C., Germann, T.C., Gu, Q., Guan, X., Guo, L., Hart, G.R., Hladish, T.J., Hupert, N., Janies, D., Kerr, C.C., Klein, D.J., Klein, E., Lin, G., Manore, C., Meyers, L.A., Mittler, J., Mu, K., Núñez, R.C., Oidtman, R., Pasco, R., Piontti, A.P. y, Paul, R., Pearson, C.A.B., Perdomo, D.R., Perkins, T.A., Pierce, K., Pillai, A.N., Rael, R.C., Rosenfeld, K., Ross, C.W., Spencer, J.A., Stoltzfus, A.B., Toh, K.B., Vattikuti, S., Vespignani, A., Wang, L., White, L., Xu, P., Yang, Y., Yogurtcu, O.N., Zhang, W., Zhao, Y., Zou, D., Ferrari, M., Pannell, D., Tildesley, M., Seifarth, J., Johnson, E., Biggerstaff, M., Johansson, M., Slayton, R.B., Levander, J., Stazer, J., Salerno, J., Runge, M.C., 2020. COVID-19 reopening strategies at the county level in the face of uncertainty: Multiple Models for Outbreak Decision Support. medRxiv 2020.11.03.20225409. https://doi.org/10.1101/2020.11.03.20225409

Shepherd, C., Brown, P., 1956. Status, Prestige, and Esteem in a Research Organization. Administrative Science Quarterly 1, 340–360. https://doi.org/10.2307/2390928

Sigel, K., Klauer, B., Pahl-Wostl, C., 2010. Conceptualising uncertainty in environmental decision-making: The example of the EU Water Framework Directive. Ecological Economics 69, 502–510. https://doi.org/10.1016/j.ecolecon.2009.11.012

Silvast, A., Laes, E., Abram, S., Bombaerts, G., 2020. What do energy modellers know? An ethnography of epistemic values and knowledge models. Energy Research & Social Science 66, 101495. https://doi.org/10.1016/j.erss.2020.101495

Simpson, C.R., Thomas, B.D., Challen, K., Angelis, D.D., Fragaszy, E., Goodacre, S., Hayward, A., Lim, W.S., Rubin, G.J., Semple, M.G., Knight, M., 2020. The UK hibernated pandemic influenza research portfolio: triggered for COVID-19. The Lancet Infectious Diseases 20, 767–769. https://doi.org/10.1016/S1473-3099(20)30398-4

Siriyasatien, P., Phumee, A., Ongruk, P., Jampachaisri, K., Kesorn, K., 2016. Analysis of significant factors for dengue fever incidence prediction. BMC Bioinformatics 17, 166. https://doi.org/10.1186/s12859-016-1034-5

Skeels, M., Lee, B., Smith, G., Robertson, G.G., 2010. Revealing Uncertainty for Information Visualization. Information Visualization 9, 70–81. https://doi.org/10.1057/ivs.2009.1

Skinner, D.J.C., Rocks, S.A., Pollard, S.J.T., Drew, G.H., 2014. Identifying uncertainty in environmental risk assessments: the development of a novel typology and its implications for risk characterisation. Human and Ecological Risk Assessment: An International Journal 20.

Smith, L., 2002. What might we learn from climate forecasts? PNAS 99, 2487–2492.

Smith, L.A., Petersen, A.C., 2014. Variations on Reliability: Connecting Climate Predictions to Climate Policy, in: Boumans, M., Hon, G., Petersen, A.C. (Eds.), Error and Uncertainty in Scientific Practice. Pickering & Chatto, London, England, pp. 137–156.

Smith, L.A., Stern, N., 2011. Uncertainty in science and its role in climate policy. Proc. R. Soc. A 369, 4818–4841. https://doi.org/10.1098/rsta.2011.0149

Smithson, M., 1989. Ignorance and Uncertainty: Emerging Paadigms. Springer, New York, US.

Solazzo, E., Galmarini, S., 2014. Multi-model Ensembles: How Many Models Do We Need?, in: Steyn, D., Mathur, R. (Eds.), Air Pollution Modeling and Its Application XXIII, Springer Proceedings in Complexity. Springer International Publishing, Cham, pp. 505–510. https://doi.org/10.1007/978-3-319-04379-1_83

Spiegelhalter, D.J., Riesch, H., 2011. Don't know, can't know: embracing deeper uncertainties when analysing risks. Philosophical Transactions of the Royal Society 369, 4730–4750. https://doi.org/10.1098/rsta.2011.0163

Stainforth, D. a, Allen, M. r, Tredger, E. r, Smith, L. a, 2007. Confidence, uncertainty and decision-support relevance in climate predictions. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 365, 2145–2161. https://doi.org/10.1098/rsta.2007.2074

Stirling, A., 2010. Keep it complex. Nature 468, 1029–1031. https://doi.org/10.1038/4681029a

Stirling, A., 2008a. "Opening Up" and "Closing Down": Power, Participation, and Pluralism in the Social Appraisal of Technology. Science, Technology, & Human Values 33, 262–294. https://doi.org/10.1177/0162243907311265

Stirling, A., 2008b. Science, precaution, and the politics of technological risk: Converging implications in evolutionary and social scientific perspectives. Annals of the New York Academy of Sciences 1128, 95–110. https://doi.org/10.1196/annals.1399.011

Stirling, A., 1998. Risk at a turning point? Journal of Risk Research 1, 97–109. https://doi.org/10.1080/136698798377204

Stumpf, M.P.H., 2020. Multi-model and network inference based on ensemble estimates: avoiding the madness of crowds. Journal of The Royal Society Interface 17, 20200419. https://doi.org/10.1098/rsif.2020.0419

Suter, G.W., Barnthouse, L.W., O'Neill, R.V., 1987. Treatment of risk in environmental impact assessment. Environmental Management 11, 295–303. https://doi.org/10.1007/BF01867157

Taghizadeh, L., Karimi, A., Heitzinger, C., 2020. Uncertainty quantification in epidemiological models for the COVID-19 pandemic. Computers in Biology and Medicine 125, 104011. https://doi.org/10.1016/j.compbiomed.2020.104011

Taleb, N.N., 2007. The Black Swan: The Impact of the Highly Improbable. Penguin, New York, US.

Tannert, C., Elvers, H.-D., Jandrig, B., 2007. The ethics of uncertainty. In the light of possible dangers, research becomes a moral duty. EMBO Rep 8, 892–896. https://doi.org/10.1038/sj.embor.7401072

Tasquier, G., Levrini, O., Dillon, J., 2016. Exploring students' epistemological knowledge of models and modelling in science: results from a teaching/learning experience on climate change. International Journal of Science Education 38, 539–563. https://doi.org/10.1080/09500693.2016.1148828

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society 93, 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Taylor, P.G., Upham, P., McDowall, W., Christopherson, D., 2014. Energy model, boundary object and societal lens: 35 years of the MARKAL model in the UK. Energy Research & Social Science 4, 32–41. https://doi.org/10.1016/j.erss.2014.08.007

TCFD, 2017. Reccomendations of the Task Force on Climate-related Financial Disclosures. Task Force on Climate-Related Financial Disclosures.

Tebaldi, C., Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Phil. Trans. R. Soc. A. 365, 2053–2075. https://doi.org/10.1098/rsta.2007.2076

Tebaldi, C., Smith, R.L., Nychka, D., Mearns, L.O., 2005. Quantifying Uncertainty in Projections of Regional Climate Change: A Bayesian Approach to the Analysis of Multimodel Ensembles. Journal of Climate 18, 1524–1540. https://doi.org/10.1175/JCLI3363.1

Tennøy, A., Kværner, J., Gjerstad, K.J., 2006. Uncertainty in environmental impact assessment predictions: the need for better communication and more transparency. Impact Assessment and Project Appraisal 24, 45–56.

Theocharis, Z., Smith, L.A., Harvey, N., 2019. The influence of graphical format on judgmental forecasting accuracy: Lines versus points. FUTURES & FORESIGHT SCIENCE 1, e7. https://doi.org/10.1002/ffo2.7

Thompson, E.L., Smith, L., 2019. Escape from model-land. Economics E-Journal Discussion Papers 23.

Tol, R.S.J., 2006. Why Worry About Climate Change? A Research Agenda (SSRN Scholarly Paper No. 945044). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.945044

Tol, R.S.J., Vellinga, P., 2008. The European Forum on Integrated Environmental Assessment. Environmental Modeling and Assessment 3, 181–191.

Toth, F.L., 2009. Dealing with Surprises in Environmental Scenarios, in: Alcamo, J. (Ed.), Environmental Futures: The Practice of Environmental Scenario Analysis, Developments in Integrated Environmental Assessment. Elsevier, pp. 170–191.

Townsend, P.K., 2013. Saturation And Run Off: How Many Interviews Are Required In Qualitative Research? Human Resource Management 17.

Trutnevyte, E., 2016. Does cost optimization approximate the real-world energy transition? Energy 106, 182–193. https://doi.org/10.1016/j.energy.2016.03.038

Tyndall, J., 1861. The Bakerian Lecture: On the Absorption and Radiation of Heat by Gases and Vapours, and on the Physical Connexion of Radiation, Absorption, and Conduction. Philosophical Transactions of the Royal Society of London 15, 1–36.

UK Government, 2020. The Health Protection (Coronavirus, Business Closure) (England) Regulations 2020. Queen's Printer of Acts of Parliament.

UKHSA, 2021a. UK Health Security Agency to take on the modelling of the R value and growth rate [WWW Document]. GOV.UK. URL https://www.gov.uk/government/news/uk-health-security-agency-to-take-on-the-modelling-of-the-r-value-and-growth-rate (accessed 9.8.21).

UKHSA, 2021b. New UK Health Security Agency to lead response to future health threats [WWW Document]. GOV.UK. URL https://www.gov.uk/government/news/new-uk-health-security-agency-to-lead-response-to-future-health-threats (accessed 9.15.21).

UKHSA, 2021c. Reproduction number (R) and growth rate: methodology [WWW Document]. GOV.UK. URL https://www.gov.uk/government/publications/reproduction-number-r-and-growth-rate-methodology (accessed 5.10.22).

van Asselt, M.B.A., Langendonck, R., van Asten, F., van der Giessen, A., Janssen, P., Heuberger, P.S.C., Geuskens, I., 2001. Uncertianty & RIVM's Environmental Outlooks: Documenting a Learning Process. Bilthoven, NL.

van Asselt, M.B.A., Rotmans, J., 2002a. Uncertianty in Integrated Assessment Modelling: From Positivism to Pluralism. Climatic Change 54, 75–105.

van Asselt, M.B.A., Rotmans, J., 2002b. Uncertianty in Integrated Assessment Modelling: From Positivism to Pluralism. Climatic Change 54, 75–105.

van Beek, L., Hajer, M., Pelzer, P., van Vuuren, D., Cassen, C., 2020. Anticipating futures through models: the rise of Integrated Assessment Modelling in the climate science-policy interface since 1970. Global Environmental Change 65, 102191. https://doi.org/10.1016/j.gloenvcha.2020.102191

van der Bles, A.M., van der Linden, S., Freeman, A.L.J., Mitchell, J., Galvao, A.B., Zaval, L., Spiegelhalter, D.J., 2019. Communicating uncertainty about facts, numbers and science. R. Soc. open sci. 6, 181870. https://doi.org/10.1098/rsos.181870

van der Helm, R., 2006. Towards a clarification of probability, possibility and plausibility: how semantics could help futures practice to improve. Foresight 8, 17–27. https://doi.org/10.1108/14636680610668045

van der Keur, P., Henriksen, H.J., Refsgaard, J.C., Brugnach, M., Pahl-Wostl, C., Dewulf, A., Buiteveld, H., 2008. Identification of Major Sources of Uncertainty in Current IWRM Practice. Illustrated for the Rhine Basin. Water Resour Manage 22, 1677–1708. https://doi.org/10.1007/s11269-008-9248-6

van der Sluijs, J.P., 1997. Anchoring amid uncertainty: On the management of uncertainties in risk assessment of anthropogenic climate change (PhD Thesis). University of Utrecht.

van der Sluijs, J.P., Craye, M., Funtowicz, S., Kloprogge, P., Ravetz, J., Risbey, J., 2005. Combining Quantitative and Qualitative Measures of Uncertainty in Model-Based Environmental Assessment: The NUSAP System. Risk Analysis 25, 481–492.

van der Sluijs, J.P., Risbey, J.S., Kloprogge, P., Ravetz, J.R., Funtowicz, S.O., Quintana, S.C., Pereira, A., de Marchi, B., Petersen, A.C., Janssen, P., Hoppe, R., Huijs, S.W.F., 2003. RIVM/MNP Guidance for Uncertainty Assessment and Communication (Guidance Document No. 3), The RIVM/MNP Guidance for Uncertainty Assessment and Communication Series. Copernicus Institute for Sustainable Development and Innovation, Utrecht, Netherlands.

van der Sluijs, J.P., van Eijndhoven, J., Shackley, S., Wynne, B., 2016. Anchoring Devices in Science for Policy: The Case of Consensus around Climate Sensitivity. Social Studies of Science 28.

van Genugten, M.L.L., Heijnen, M.-L.A., Jager, J.C., 2003. Pandemic Influenza and Healthcare Demand in the Netherlands: Scenario Analysis. Emerg Infect Dis 9, 531–538. https://doi.org/10.3201/eid0905.020321

van Ittersum, M., Sterk, B., 2014. Computerized models: tools for assessing the future of complex systems?, in: Jordan, A.J., Turnpenny, J.R. (Eds.), The Tools of Policy Formulation: Actors, Capacities, Venues and Effects, New Horizons in Public Policy. Edward Elgar Publishing, Cheltenham, UK, pp. 100–120.

van Vuuren, D.P., Carter, T.R., 2014. Climate and socio-economic scenarios for climate change research and assessment: reconciling the new with the old. Climatic Change 122, 415–429. https://doi.org/10.1007/s10584-013-0974-2

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., HIbbard, K., Hurrtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The Representative Concentration Pathways: an overview. Climatic Change 109, 5–31.

van Vuuren, D.P., Stehfest, E., Gernaat, D.E.H.J., Doelman, J.C., van den Berg, M., Harmsen, M., de Boer, H.S., Bouwman, L.F., Daioglou, V., Edelenbosch, O.Y., Girod, B., Kram, T., Lassaletta, L., Lucas, P.L., van Meijl, H., Müller, C., van Ruijven, B.J., van der Sluis, S., Tabeau, A., 2017. Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. Global Environmental Change 42, 237–250. https://doi.org/10.1016/j.gloenvcha.2016.05.008

Venkatramanan, S., Lewis, B., Chen, J., Higdon, D., Vullikanti, A., Marathe, M., 2018. Using data-driven agent-based models for forecasting emerging infectious diseases. Epidemics, The RAPIDD Ebola Forecasting Challenge 22, 43–49. https://doi.org/10.1016/j.epidem.2017.02.010

Vesely, W.E., Rasmuson, D.M., 1984. Uncertainties in Nuclear Probabilistic Risk Analyses. Risk Analysis 4, 313–322. https://doi.org/10.1111/j.1539-6924.1984.tb00950.x

Viboud, C., Sun, K., Gaffey, R., Ajelli, M., Fumanelli, L., Merler, S., Zhang, Q., Chowell, G., Simonsen, L., Vespignani, A., 2018. The RAPIDD ebola forecasting challenge: Synthesis and lessons learnt. Epidemics, The RAPIDD Ebola Forecasting Challenge 22, 13–21. https://doi.org/10.1016/j.epidem.2017.08.002

Visschers, V.H.M., 2018. Public Perception of Uncertainties Within Climate Change Science. Risk Anal. 38, 43–55. https://doi.org/10.1111/risa.12818

Vlasschaert, C., Topf, J.M., Hiremath, S., 2020. Proliferation of Papers and Preprints During the Coronavirus Disease 2019 Pandemic: Progress or Problems With Peer Review?

Advances in Chronic Kidney Disease, Kidney Health and COVID-19 27, 418–426. https://doi.org/10.1053/j.ackd.2020.08.003

Von Furstenberg, G., 1990. Acting Under Uncertainty: Multidisciplinary Conceptions. Kluwer Academic Publishers, Norwell, MA, USA.

Walker, W.E., Harremoes, P., Rotmans, J., Sluijs, J.P. van der, Asselt, M.B.A. van, Janssen, P., Krauss, M.P.K. von, 2003. Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. Integrated Assessment 4.

Walker, W.E., Lempert, R.J., Kwakkel, J.H., 2013. Deep Uncertainty, in: Gass, S.I., Fu, M.C. (Eds.), Encyclopedia of Operations Research and Management Science. Springer US, Boston, MA, pp. 395–402. https://doi.org/10.1007/978-1-4419-1153-7_1140

Wallsten, T.S., Budescu, D.V., Rapoport, A., Zwick, R., Forsyth, B., 1986. Measuring the vague meanings of probability terms. Journal of Experimental Psychology: General 115, 348–365. https://doi.org/10.1037/0096-3445.115.4.348

Wardekker, J.A., van der Sluijs, J.P., Janssen, P.H.M., Kloprogge, P., Petersen, A.C., 2008. Uncertainty communication in environmental assessments: views from the Dutch science-policy interface. Environmental Science & Policy 11, 627–641. https://doi.org/10.1016/j.envsci.2008.05.005

Warmink, J.J., Janssen, J.A.E.B., Booij, M.J., Krol, M.S., 2010. Identification and classification of uncertainties in the application of environmental models. Environmental Modelling & Software 25, 1518–1527. https://doi.org/10.1016/j.envsoft.2010.04.011

Wätzold, F., 2000. Efficiency and Applicability of economic concepts dealing with environmental risk and ignorance. Ecological Economics 33, 299–311.

WCRP, 2021. CMIP6-Endorsed MIPs [WWW Document]. World Climate Reserach Programme. URL https://www.wcrp-climate.org/modelling-wgcm-mip-catalogue/modelling-wgcm-cmip6-endorsed-mips (accessed 4.5.19).

Weaver, C.P., Moss, R.H., Ebi, K.L., Gleick, P.H., Stern, P.C., Tebaldi, C., Wilson, R.S., Arvai, J.L., 2017. Reframing climate change assessments around risk: recommendations for the US National Climate Assessment. Environ. Res. Lett. 12, 080201. https://doi.org/10.1088/1748-9326/aa7494

Werndl, C., 2019. Initial-Condition Dependence and Initial-Condition Uncertainty in Climate Science. The British Journal for the Philosophy of Science 70, 953–976. https://doi.org/10.1093/bjps/axy021

Weyant, J., 2014. Integrated assessment of climate change: state of the literature. Journal of Benefit Cost Analysis 5, 377–409.

Whyte, J.M., 2021. Model Structures and Structural Identifiability: What? Why? How?, in: de Gier, J., Praeger, C.E., Tao, T. (Eds.), 2019-20 MATRIX Annals, MATRIX Book Series. Springer International Publishing, Cham, pp. 185–213. https://doi.org/10.1007/978-3-030-62497-2_10

Wilbanks, T.J., Ebi, K.L., 2014. SSPs from an impact and adaptation perspective. Climatic Change 122, 473–479. https://doi.org/10.1007/s10584-013-0903-4

Wilby, R.L., Dessai, S., 2010. Robust adaptation to climate change. Weather 65, 180–185. https://doi.org/10.1002/wea.543

Winkler, R., 1996. Uncertainty in probabilistic Risk Assessment. Reliability Engineering and System Safety 54, 127–132.

Winsberg, E., 2012. Values and Uncertainties in the Predictions of Global Climate Models. Kennedy Institute of Ethics Journal 22, 111–137. https://doi.org/10.1353/ken.2012.0008

Winsberg, E., 2003. Simulated Experiments: Methodology for a Virtual World. Philosophy of Science 70.

Wohlin, C., 2014. Guidelines for snowballing in systematic literature studies and a replication in software engineering, in: Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering, EASE '14. Association for Computing Machinery, New York, NY, USA, pp. 1–10. https://doi.org/10.1145/2601248.2601268

Wucker, M., 2016. The Gray Rhino: How to recognise and act on the obvious dangers we ignore. St Martin's Press, New York, NY, USA.

Wynne, B., 1992. Uncertainty and environmental learning: Reconceiving science and policy in the preventive paradigm. Global Environmental Change 2, 111–127. https://doi.org/10.1016/0959-3780(92)90017-2

Xiao, Y., Wu, J., Lin, Z., Zhao, X., 2018. A deep learning-based multi-model ensemble method for cancer prediction. Comput Methods Programs Biomed 153, 1–9. https://doi.org/10.1016/j.cmpb.2017.09.005

Young, J.C., Rose, D.C., Mumby, H.S., Benitez-Capistros, F., Derrick, C.J., Finch, T., Garcia, C., Home, C., Marwaha, E., Morgans, C., Parkinson, S., Shah, J., Wilson, K.A., Mukherjee, N., 2018. A methodological guide to using and reporting on interviews in conservation science research. Methods in Ecology and Evolution 9, 10–19. https://doi.org/10.1111/2041-210X.12828

Zehr, S.C., 2000. Public representations of scientific uncertainty about global climate change. Public Underst Sci 9, 85–103. https://doi.org/10.1088/0963-6625/9/2/301

Zumwald, M., Knüsel, B., Baumberger, C., Hadorn, G.H., Bresch, D.N., Knutti, R., 2020. Understanding and assessing uncertainty of observational climate datasets for model evaluation using ensembles. WIREs Climate Change n/a, e654. https://doi.org/10.1002/wcc.654

Appendix A: Review Methodology

In this review a systematic backwards snowball approach was used that built on an initial corpus of papers. Pure literature keyword searches were deemed unsuitable for several reasons:

- Only small numbers of uncertainty typologies are gleaned from keyword searches
- Different disciplines and sub-disciplines frequently use inconsistent nomenclature
- Uncertainty frameworks often appear at different levels of prominence within sources: from papers that have uncertainty frameworks as their centrepiece, to papers that utilise an uncertainty framework as part of some larger piece of analysis to literature that only passing proposes uncertainty frameworks without further application
- Some influential uncertainty frameworks do not occur in journal articles, but also books and other literature, such as governmental reports.

Such systematic snowball approaches are commonly employed when terminology is not consistently used accords sources (Lecy and Beatty, 2012). They can also yield larger corpuses than keyword searches alone (Wohlin, 2014). They come with the limitation of being highly laborious due to the inefficiency of manually searching references and articles and requiring literature selection criteria that prevents overgrowth of the corpus examined (Wohlin, 2014). This technique has been used to a much more limited extent in this subject area by Kirchner et al. (2021).

The process utilised was as follows:

1) An initial search of Scopus and Web of science yielded several uncertainty frameworks. Search terms included a thematic indicator such as "climate", "energy", "environment" or "ecosystem" with *terms denoting typologies such as "uncertainty taxonomy"*. This was combined with a small corpus of papers already known to the author.
2) Papers were read and short summaries were produced that described their uncertainty frameworks. These summaries are available in Appendix B. An excel spreadsheet was used to collate these notes and additional columns were created to compare similar aspects of different frameworks (for example if and how the authors distinguished between aleatoric and epistemic uncertainty).
3) Influences from or references to other frameworks were noted down and the sources for these were added to a backlog for potential inclusion in the corpus.
4) These were triaged in turn for uncertainty frameworks relevant to environmental change and analysed in the same way if found to be suitable.
5) This was continued until all leads were exhausted. Conceptual exhaustion, where additional frameworks were not yielding novel concepts, was also achieved.

Error! Reference source not found. explains this recursive snowballing approach.

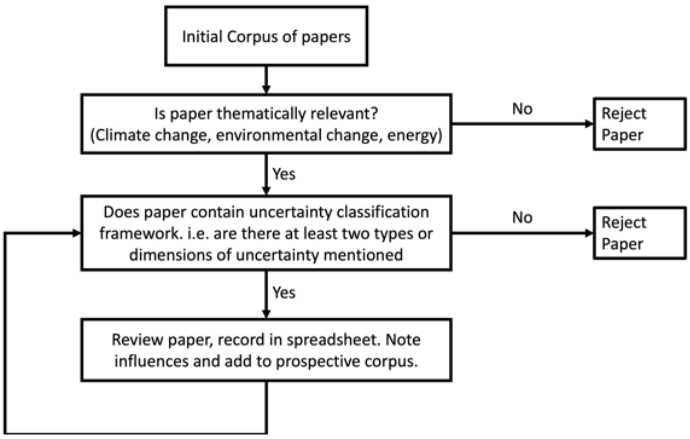

Figure 0-1: Flow chart showing snowball approach for corpus assembly from an initial sample of uncertainty frameworks.

This process resulted in the analysis of 156 distinct sources containing frameworks, primarily in the form of journal articles (115), but also in books or book chapters (21), reports (7), guidance documents (6), doctoral theses (3), working papers (3), a conference proceeding and a magazine article. The distribution of publication dates is shown in Figure 0-2.

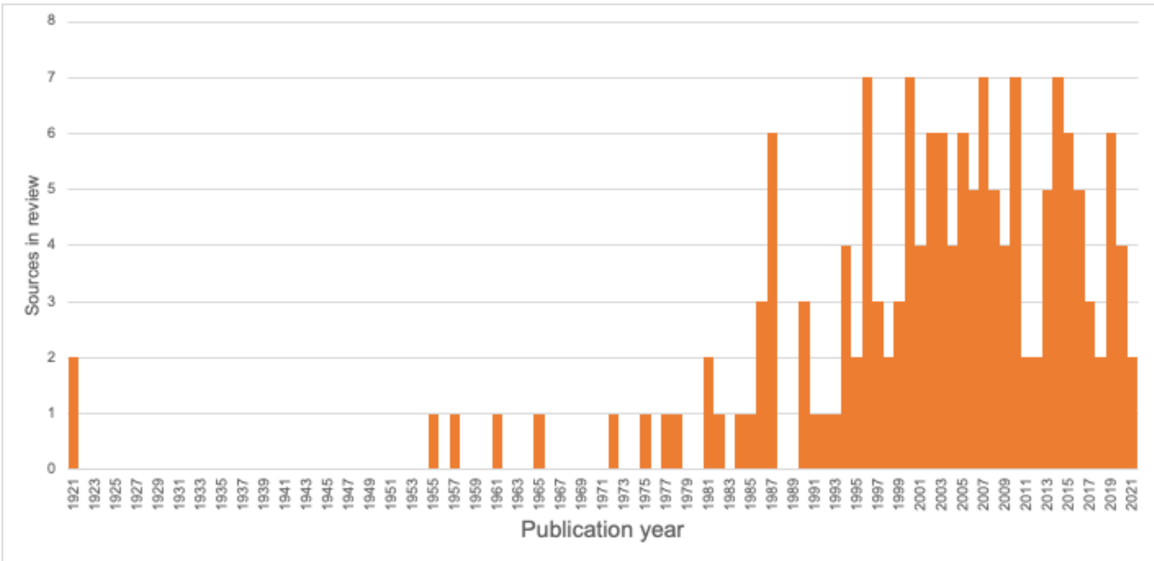

Figure 0-2: Distribution of publication year of literature reviewed in this paper

Appendix B: Summaries of Reviewed Literature

The table below summarises the literature reviewed in this article and some of the distinctive features described therein.

Authors	Year	Source	Type of Framework	Context	Brief Description of Notable Features
Knight	1921	Book	Definition	Economics	A definition of risk (probabilities can be known) and uncertainty (unknown probabilities).
Keynes	1921	Book	Definition	Economics	A fundamental distinction between uncertainty and probability. Probability is disaggregated into i) numerical ii) non-numerical yet comparable and iii) non-comparable
Shackle	1955	Book	Distinction	Economics	A key text in the consideration of uncertainty in economics. The definition of Knight is restated/ refined. Further examination of the nature of experiments and repeatability is explored. Divisible experiments are defined as those whose result is comprised of multiple experiments. *Seriability* exists in situations where experiments can be repeated. This all leads to his concept of 'potential surprise' as key decision-making variable.
Luce & Raiffa	1957	Book	Distinction	Decision Theory	Part of a classic tome on decision theory, based around a utility model of decision making. They distinguish between *risk* (one set of outcomes, probabilities known) and *uncertainty* (known outcomes, unknown probabilities). This is almost identical to Knight's definition. They also describe situations (such as statistical inference) where both risk and uncertainty are present in a mix. They describe utility theory as dealing with decisions under risk and game theory dealing with a mixture of risk and uncertainty as the decisions of others are considered as separate decision-under-risk problems.
Ellsberg	1961	Journal Article	Definition	Decision Theory	A classic article on decision theory that displays an inconsistency (paradox) between people's choices and evaluations subjective expected utility. An ambiguity aversion is identified where subjects prefer gambles where odds can be known, rather than gambles where odds are ambiguous (even if they may be larger).
Emery & Trist	1965	Journal Article	Typology of uncertain environments (for organisation)	Organisational Theory/ Management	A classic article that considers the types and complexity of environments that organisations find themselves in. i) Placid environment: goals unchanging and uncertainties are local and random, ii) strategy is required as imperfect competition exists between actors, iii) 'disturbed-reactive' highly competitive environments, iv) uncertainties arise not only from other actors but from the 'turbulent field' itself
Duncan	1972	Journal Article	Dimensions	Management Studies	A framework for understanding environmental uncertainty (that exogenous to an organisation). Two dimensions of the factors affecting uncertainty in an organisations external environment are: 1) Simple vs Complex- number of components in decision environment to consider 2) static-dynamic- do factors in the decision environment change in time? A third dimension is also given in less detail regarding ability to assign probabilities to outcomes. They also develop a measure of uncertainty that uses all three of these.
Hacking	1975	Book	Conceptual Distinction	History of Science	As part of Hacking's famous history of the concept of probability he defines two senses of probability: aleatory and epistemic probability. This terminology is later picked up and applied in a number of uncertainty classifications.
Rowe	1977	Book	Definition of Risk	Risk Studies	A book examining the concept of societal risk which includes a classic definition of risk as "the functional combination of the probability of occurrence and its value to the risk taker."
Howell & Burnett	1978	Journal Article	Three distinctions for uncertain events for cognitive uncertainty	Psychology, decision-making	A typology of uncertain events for understanding human decision-making under uncertainty. Three distinctions made: 1) is the event frequency related, 2) is the underlying process causing the event stochastic, 3) is the event outside of the control of the observer?
Kaplan & Garrick	1981	Journal Article	An influential anatomy of Risk	Risk Studies	An influential conceptualisation of risk that characterises it as comprising a set of triplets: *scenario* (what can happen), *probability,* and *consequence* (what is the result of what happens).
Cox & Baybutt	1981	Journal Article	Sources of Model uncertainty	Risk Analysis	Towards the beginning of this paper they explain a number of sources of model output uncertainty: *parameters* (may be due to data, expert opinions or "uncertainties about uncertainties", *which sub-model is correct, statistical sampling variability, completeness of the analysis in a model.*
Kahneman & Tversky	1982	Journal Article	Typology	Decision-making, Psychology	A framework that builds on Howell & Burnett (1978). They recognise that uncertainty may be attributed to either the external world (dispositions) or the internal world (ignorance). External judgement of uncertainty may be distributional (relative frequencies may be estimated) or singular (probabilities assessed from propensities of case at hand). Internal uncertainty may be reasoned (deducing answer from other knowledge) or introspective (confidence in answers that seem familiar).
Vesely & Rasmusson	1984	Journal Article	Typology	Nuclear Risk Assessment	Firstly, a distinction between physical variability and knowledge uncertainties are made. Then three kinds of knowledge uncertainties are described: parameter, knowledge, and completeness. Parameter

					uncertainty is described as having a variety of sources. Model uncertainty is described as either due to model comprehensiveness (are all relevant variables included) or characterisation (the relationships between variables in the model. Completeness uncertainty concerns whether all relevant phenomena have been considered.
Hall	1985	Report Section	Types of Uncertainty	Climate Modelling	Description of several sources of uncertainty in climate modelling: process (uncertainties in data), model, statistical (fluctuations in the model or the world)-, forcing. Describes uncertainties to communicate validity of physical assumptions (structural), model completeness, parameterisation. Recognises that there can be both quantitative and qualitative expressions of uncertainty.
Einhorn & Hogarth	1986	Journal Article	Conceptual Distinction	Decision making, Economics	They examine Ellsberg's concept of and attempt to formalise and explain it with a new model of ambiguity. They describe ambiguity as 'uncertainty about uncertainties'. They also associate ambiguity with families of distributions "ambiguity results from the uncertainty associated with specifying which of a set of distributions is appropriate in a given situation".
Henrion & Fischoff	1986	Journal Article	Two conceptual distinctions.	Physics	Overall, the paper is an application of psychological ideas to a new area to show the fallibility of error estimates in physics. Argues that uncertainty is not just probabilistic. Separates *Error* (the actual difference between an estimate and a value) and *Uncertainty* (an estimate of this error). Also discusses random error/uncertainty versus systematic error/uncertainty.
Brooks	1986	Book Section	Typology of Surprise	Policy, Environment	Describes three types of surprises: unexpected discrete events (e.g., reactor meltdown), discontinuities in trends, and the emergence of new information/knowledge.
Shaffer	1987	Book Chapter	Types of uncertainty	Ecology	A list of major types of uncertainty for consideration in conservation biology: *demographic uncertainty* (randomness in the survival of individuals), *environmental uncertainty* (randomness in the environmental setting), *natural catastrophes* and *genetic uncertainty* (random changes in genetic makeup).
Alcamo & Bartnicki	1987	Journal Article	Typology (they call it taxonomy)	Atmospheric Modelling	They present a typology of model uncertainty: *model structure uncertainty*, *parametric uncertainty, forcing functions* (the forcing from time and space dependent functions), *initial state* and *model operation* (due to implementation of model processing). They also distinguish between *diagnostic uncertainty* (model description of past or present conditions) and *prognostic uncertainty* (model use for forecasting). They describe uncertainties as either having diagnostic, prognostic or both components.
Beck	1987	Journal Article	Taxonomy	Water Quality Modelling	Reviews a number of approaches to uncertainty in water quality modelling. Borrows 'taxonomy' of uncertainty terminology from Alcamo & Bertnicki (1987). Examines several kinds of uncertainty and sorts them into those associated with *prior knowledge, identification* and those associated with *prediction*. Prior knowledge uncertainties: aggregation errors, numerical errors, model structure. Identification uncertainties: errors in field data for input, parameter error, state errors, initial state errors. Prediction errors: propagation of uncertainty errors.
Bogen & Spear	1987	Journal Article	Conceptual Distinction	Environmental Health and Risk Analysis	They attempt to design a framework for modelling both uncertainty and variability for Risk Assessments (rather than approaches that rely on tabulations of risks). *Uncertainty* is a lack of knowledge concerning some characteristic. *Variability* in this context is interindividual heterogeneity with respect to some risk. *Risk* is the probability of harm from a particular cause.
Suter et al	1987	Journal Article	Taxonomy	Environmental Impact Assessment	Adapts risk frameworks of Rowe (1977) and Fairley (1975) with a three-level dendrogram of uncertainty. Fundamental distinction is between defined and undefined (a form of meta-uncertainty). Defined uncertainty is then split between being either *identity* (uncertainty over victims of impacts) and *analytical*. Analytical uncertainty is either due to *model error, natural stochasticity or parameter error*. These are then subdivided as well.
Milliken	1987	Journal Article	Typology	Management Studies	Identification of three types of environmental uncertainty relevant to management(uncertainty about environment exterior to an organisation). Argues that previous authors had considered sources, but it will consider types. The types are: 1) *State uncertainty*- the inability to predict how components of environment are changing (authors stress not same as not defining pdf). 2) *Effect uncertainty* - inability to predict how environmental changes affect one's organisation. 3) *Response uncertainty*- uncertainty about what response options one has and effects of response choice (close to decision theorists).
Finkel	1990	Report	Typology	Risk Assessment	A report defining techniques for decision-making under uncertainty. The typology at the highest level gives four principal kinds of uncertainty: parameter uncertainty, modelling uncertainty, decision-rule uncertainty and variability. Parametric uncertainty is due to measurement errors, systematic errors or random errors. Model uncertainty is due to surrogate variables, excluded variables, abnormal conditions or incorrect model form. Decision-rule uncertainty is related to the choice of risk variables, acceptable risks, utility functions, aggregation of individual utility functions and temporal discounting. Variability is described in some way being separate from uncertainty and being some kind of separate dimension of an uncertainty analysis.
Morgan & Henrion	1990	Book	Taxonomy	Policy and Risk Analysis	As part of a book on the topic of policy and risk analysis a typology of uncertainties for policy relevant models is given. At the highest level there are uncertainties in quantities and in model form. Different types of quantities are described (defined constants, decision variables, value parameters, index variables, model domain parameters, state variables, outcome criteria). Empirical quantities are classified by sources of uncertainty: random error/statistical variation, systematic error/subjective judgement, linguistic imprecision, variability, randomness/unpredictability, disagreement and approximations.
Funtowicz & Ravtez	1990	Book	Multiple	Philosophy of Science	This book contains a number of ideas that have had a great deal of influence in this space. First of all, they distinguish between different *sorts* of uncertainty: • *Inexactness*: the spread in a value • *Unreliability*: the confidence given in a quantitative statement • *Border with Ignorance*: gaps in knowledge not encompassed by inexactness or unreliability.

					Their NUSAP acronym is intended for the communication of uncertain information. It is thus: Number (the estimated quantity of a variable), Unit (the unit the number is given in), Spread (a measure of the range of uncertainty around the number given), Assessment (a judgement about the information such as significance level or qualitative judgement), Pedigree (evaluation of the production of the evidence and the intended use of the information) They also define different domains of decision-making: basic science (where systems uncertainties and stakes are low), consultancy (where they are moderate) and post normal science (where they are high).
Dosi & Egidi	1991	Article	Distinction / Matrix	Economics	The principal distinction made is between procedural (lack of capacity to solve problems) and substantive (lack of information about the environment one is in) uncertainty. Substantive uncertainty is subdivided into weak substantive uncertainty (probabilities known and analogous to risk and strong substantive (analogous to Knightian uncertainty).
Wynne	1992	Article	Typology	Environment	In this article Wynne reworks the ideas of Funtowicz & Ravtez to reject the implicit scale. Says that four categories of uncertainty are risk (odds known), uncertainty (odds unknown), ignorance (unknown unknowns), indeterminacy (causal chains or networks open).
Burgman et al	1993	Book Section	Typology	Ecology	A typology of uncertainties in ecology that classifies by the specific source: *phenotypic* (variation between individuals in population), *demographic* (variation of average chances of survivorship), *environmental* (changes in environment through time) and *spatial* (variation between patches of habitat).
Helton	1994	Journal Article	Distinction	Risk Assessment	A distinction between *stochastic* and *subjective uncertainty*. Also, adaptation of a risk framework to use for probabilistic risk assessment uncertainties.
Rowe	1994	Journal Article	Dimensions	Risk Assessment	Distinguishes four classes or dimensions of uncertainty: *temporality* (uncertainty in past, present or future states), *structural* (uncertainty due to the complexity of the system), *metrical* (uncertainty in measurement) and *translational* (uncertainty in explaining uncertain results). Variability is described as contributing to all four classes. Various factors contributing to all of these classes are given.
Hoffman & Hammonds	1994	Journal Article	Conceptual Distinction	Risk Assessment	A conceptual distinction between *Type A and Type B* uncertainty is included in this paper. Type A uncertainty is immeasurable and associated with a lack of knowledge (and is captured in this paper by the choice of statistical distribution). Type B uncertainty is measurable, associated with variability and fixed the midpoint and tails of a distribution.
NRC	1994	Book	Typology	Risk Assessment	This book section reviews a number of approached to uncertainty management and the EPA's previous approach to uncertainty. It recommends a typology of uncertainties into *parameter* and *model* uncertainties. It also notes other typologies such as that of *bias* (result of study design), *randomness* (due to sample size) and variability (what risk assessors' study).
Faucheaux & Froger	1995	Journal Article	Dimensions	Ecological Economics	Following the Knightian distinction they define a scale from *Ignorance, Strong uncertainty, Weak Uncertainty and Certainty*. These are displayed on the diagonal on a map of two dimensions of uncertainty: probability (imprecise to well defined) and reliability (low to maximum). This typology is also stated in Froger & Zyla 1995.
Myers	1995	Journal Article	Conceptual Distinction (two kinds of surprise)	Environment	A distinction between two kinds of surprise: discontinuities (sudden changes in the natures of a system) and synergisms (interacting factors lead to unexpected effects).
Hora	1996	Journal Article	Conceptual Distinction	Safety Engineering/ Risk Analysis	The paper uses example of permeability of geologic formation to discuss the separation between aleatory and epistemic uncertainty in risk analysis. The paper argues that sharp distinctions between the two do not normally exist. They argue that the classification between the two is somewhat determined by the purpose of the study and expert opinion.
Cardwell & Ellis	1996	Journal Article	Conceptual Distinction	Environmental Management	In this paper examining aggregation (multiple models) issues in water quality modelling. Defines Type-I Uncertainty as due to the simplifications necessary to form a mathematical model of a physical system. Type-II uncertainty is parameter value uncertainty.
Paté-Cornell	1996	Journal Article	Conceptual distinction+ List of 6 type of Risk Analysis	Safety Engineering/ Risk Analysis	Makes a distinction between epistemic and aleatory uncertainties. Then defines six levels of analysing uncertainty in risk analysis: 0. recognition of a hazard, 1. defining a worst-case scenario, 2. defining a plausibly worst-case scenario, 3. a central estimate of outcome, 4. provision of a probability density function, 5. families of PDFs
Winkler	1996	Journal Article	Distinctions (4)	Risk Assessment	The paper argues against the broad use of types of uncertainty, insisting that at root there are only two things: uncertainty and probability. It does however provide a number of distinctions that can be used to organise uncertainty: 1) uncertainty about observables vs about un-observables; 2) the separation between parametric uncertainty and model uncertainty; 3) different forms of information; 4) apparently/practically reducible vs irreducible uncertainties
Ferson & Ginzburg	1996	Journal Article	Matrix (2D)	Safety Engineering/ Risk Analysis	Makes distinction between *Variability* (due to underlying system) and *Ignorance* (due to underlying knowledge state); also, Ignorance is described as reducible. Presents these in a table/matrix with two kinds of model uncertainty: *parameters* and *model formulation*.
Faber et al	1996	Book	Taxonomy	Ecological Economics	In this book on uncertainty analysis, they classify sources of surprise in an extensive dendrogram. At the highest tier separating risk + uncertainty from ignorance by ability to know all outcomes. • Ignorance is then split into open (knowable) and closed (unaware) ignorance. • Open ignorance is split into reducible and irreducible. These are then further subdivided by the causes of the reducibility (personal or communal ignorance) or lack thereof (phenomenological or epistemological). • These categories are subdivided further

Dovers et al	1996	Article	Taxonomy/ Dimensions	Biodiversity and Conservation	Following Smithson (1989) describe uncertainty as a subset of ignorance. They then define three particular kinds of ignorance: apparently reducible, apparently irreducible and self-generated (inadequate information management). They define some dimensions of ignorance as gradients: certainty-complete ignorance, individual-societal etc. A number of sources of ignorance are given.
Moser	1997	PhD Thesis	Loci of human-dimension uncertainties	Environmental Assessment	Reviews a number of previous taxonomies of uncertainty. Identifies that human-dimension uncertainties are often neglected and gives a number of 'loci' of human dimension uncertainties: epistemology, perception & human cognition; problem definition; science and analysis; decision-stakes & decision-making; policy goals, policy-making & strategy; management & implementation; human behaviour, actions & choices; values, preferences & goals; communication; emerging societal futures.
Courtney et al	1997	Magazine Article	Typology (Levels)	Business Strategy/ decision-making	An influential Harvard Business Review article in which four levels of uncertainty are described: a single outcome can be known, a discrete set of outcomes known, or a range of outcomes known or true ambiguity (in which there is no way to forecast the future).
van der Sluijs	1997	PhD Thesis	Matrix (2 dimensions)	Integrated Assessment Modelling	In chapter 6 of his PhD thesis, he reviews a number of typologies of Uncertainty. He develops a framework which crosses Funtowicz & Ravtez's three sorts of uncertainty (inexactness, unreliability, ignorance) with Versely & Ramusson's types of modelling uncertainty (conceptual model structure, technical model structure, model completeness). This creates a 2D matrix of uncertainty types. Later in the thesis chapter (6.7) also describes a methodology for incorporating quality estimates in modelling).
Schneider et al	1998	Journal Article	Taxonomy of Surprise	Environmental Change	A paper that reviews a number of different typologies of uncertainty and surprise in. They develop a variant of the Faber et al. 1992 typology that organises by the sources of expectations and considers impediments to preventing surprise. At the highest level, risk (probabilities known) & uncertainty are separated from imaginable surprise by whether all outcomes are known. Imaginable surprise is separated into those due to an unwillingness to change expectations and those where people are open to changing expectations. These open expectations are subdivided into those that are easy to enlarge (due to a lack of learning or research) and those that are harder (epistemological or phenomenological impediments).
Stirling	1998	Journal Article	Matrix	Risk Assessment	A typology that separates Risk, Uncertainty, Ambiguity and Ignorance along two dimensions: knowledge about outcomes (fuzzy outcomes, known outcomes) and knowledge about probabilities (no basis for probabilities, firm basis for probabilities).
Huijbregts	1998	Journal Article	Taxonomy	Life-Cycle Assessment	A list of types of uncertainty relevant for Life-cycle assessment. A fundamental distinction between uncertainty and variability is made at the highest level though the difference is not explicit. Uncertainty is *parameter uncertainty, model uncertainty* or *choice uncertainty*. Variability is *spatial, temporal* or *between source and object* (in accounting for loadings in a life cycle analysis).
Gjerde et al	1999	Journal Article	Three uncertain areas.	Integrated Assessment	The paper details the use of an Integrated Assessment Model to model the possibility of catastrophic events is detailed. Describes three primary uncertainty aspects from an economist's point of view being GHG emissions, effectiveness of policies and damage from global warming. Catastrophes are a subset of damage uncertainties.
Kelly & Kolstad	1999	Journal Article	Typology	Integrated Assessment	The article focusses on reducing uncertainty through learning for policy and IAMs. Makes distinction between two main kinds of uncertainty being *stochastic* (due to variability) and *parametric* (reducible). They describe a third aspect of uncertainty being *learning*- which is associated with agents making imperfect decisions and adapting over time.
Casman et al	1999	Journal Article	Some conceptual distinctions	Integrated Assessment	Paper that considers the temporal domains of validity for different model complexities. They describe the epistemic/aleatoric divide as often. They mainly separate uncertainties into parametric uncertainties and model uncertainties. Model uncertainties can be assessed with variations in model structure. Different domains of model validity are defined: detailed model is relevant; order of magnitude mode is relevant; bounding analysis is relevant; total ignorance.
Baecher & Christian	2000	Conference Proceedings	Taxonomy	Risk Analysis in Water Resources	In this Conference paper they mainly consider the nature of the aleatoric epistemic divide. They also present a taxonomy with three major kinds of uncertainty each with sub-categories: • *Natural Variability* (Temporal, Spatial) • *Knowledge Uncertainty* (Model, Parameters) • *Decision Model Uncertainty* (Objectives, Values, Time Preferences)
Arentsen et al	2000	Journal Article	Distinction	Environmental Policy, Decision-making	They highlight two kinds of uncertainty in particular (seemingly taking some influence from Hempel): Uncertainty in Problem Definition and Uncertainty of Policy Response. They also introduce the idea of some normative confusion.
Streets & Glantz	2000	Journal Article	Reviews several Taxonomies of Surprise	Environmental Policy, Climate Change	As part of this paper, they review a number of taxonomies of surprise. Makes distinctions between closed (where someone is willing to admit there are unknown outcomes) and open ignorance (where someone is not willing to admit there are unknown outcomes)
Kann & Weyant	2000	Journal Article	Typology	Energy Systems Modelling	In this paper the authors describe a number of approaches to uncertainty analysis of large energy models. They sort uncertainty into two broad categories: stochastic and parametric uncertainty. They discuss additional categories of uncertainty values uncertainties (such as differences over discount rate) and model structure uncertainty. Model structure uncertainty is also described as relating to the choices that modellers make. They also describe probabilities as being the ideal outcome of a probability assessment.
Kelly & Campbell	2000	Journal Article	Distinction	Ecological Risk Assessments	In this article they emphasise the importance of distinguishing between uncertainty and variability. Variability is defined as the true spread of a variable, whereas uncertainty is the approximation of this true spread. They describe variability as irreducible. They also relate variability to the situation of having good quality data and uncertainty to bad.
Moss & Schneider	2000	Uncertainty Guidance	Dimensions	IPCC, Uncertainty Communication	Guidance document prepared for the Third Assessment report of the IPCC (TAR). Gives calibrated language for expressing confidence terms by probability. Recommends also qualitatively describing uncertainty along

					two axes: level of agreement and amount of evidence. This creates a 2 x 2 matrix.
Wätzold	2000	Journal Article	Dimensions (3 Criteria)	Environmental Economics, Risk Assessment	Gives three criteria with which to assess a given environmental uncertainty. 1) Behaviour (of emission in the environment): accumulation, diffusion in time and space, synergistic damage etc. 2) Extent of Knowledge: Risk or ignorance. 3) Number of actors involved (number of polluters)
Rotmans & van Asselt	2001	Journal Article	Typology + Scale	Integrated Assessment	Restatement and development of framework in van Asselt's (2000) PhD Thesis and combination of ideas from Funtowicz & Ravetz (1990) about epistemic, methodological and technical uncertainties. At a first level they distinguish between uncertainty due to variability and due to lack of knowledge. They then present three kinds of uncertainty that are practically faced: • *epistemological* (does model correspond to real world), • *methodological* (a lack of knowledge over appropriate analytical tools) • *technical* (due to quality and appropriateness of data). These types are then attached diagrammatically to a scale of uncertainties: • *Inexactness* • *Lack of Observations* • *Practically Immeasurable* • *Conflicting evidence* • *Ignorance* • *Indeterminacy* Particular issues in modelling are also diagnosed and related diagrammatically (such as model structure, model validity, parameter uncertainties etc.)
Bedford & Cooke	2001	Book Section	Types	Probabilistic Risk Assessment	5(6) sorts described: Epistemic, Aleatory, Parameter (uncertainty in the true parameter of the model), Model, Volitional (will an individual do what they have agreed to do), Ambiguity (considered not really a form of uncertainty)
Van Asselt et al	2001	Report		Environmental Assessment	In this report they distinguish at the highest level of aggregation between: • *Variability* having sources in the inherent randomness of nature, value diversity, human behaviour, socio-cultural dynamics and technological surprises • *Limited knowledge* is described as having a partial source in variability and existing on a continuum from inexactness, lack of observations, immeasurability, conflicting evidence, reducible ignorance indeterminacy to irreducible ignorance.
Huijbregts et al	2001	Journal Article	Taxonomy of Data Uncertainties	Life Cycle Analysis	Different data uncertainties present in Life cycle analyses. At the highest level this is due to *inaccuracy* or a *lack of specific data*. Lack of data may be due to *data gaps* or *unrepresentative data*.
Heal & Kristrom	2002	Journal Article	Types	IPCC, Economics	Discussion of economic uncertainties after the Third Assessment Report. It re-evaluates the five categories from TAR from economic perspective into: 'scientific', 'impacts' and 'policy'. Also includes brief mention of meta- uncertainties.
Risbey et al	2002	Journal Article	Levels	Climate Science	A set of scenarios for regional climate are developed in this paper. In order to describe the level of knowledge about the relationships between dynamical processes, five uncertainty levels are developed: • *Quantitative Estimate*: sign and magnitude of change can be given • *Definitive sign*: can give direction of the sign • *Ambiguous sign*: plausible arguments for sign going either way • *Speculative sign*: can give arguments for sign in one direction, but cannot rule out the other or provide arguments • *Ignorance*: cannot give arguments for either direction
Regan et al	2002	Article	Taxonomy	Ecology and Conservation Biology	Uncertainty is split into epistemic and linguistic uncertainty. Epistemic in this case also includes inherent randomness. • Epistemic (measurement error, systematic error, natural variation, inherent randomness, model uncertainty, subjective judgement) • Linguistic Uncertainty (vagueness (borderline cases in natural language). context dependence, ambiguity (polysemy of words), under specificity (unwanted generality), indeterminacy of theoretical terms)
Elith et al	2002	Journal Article	Taxonomy	Ecological modelling	This paper adapts and uses the typology from Regan et al. 2002. They remove the categories of 'inherent randomness' and 'context dependence'. Each type of uncertainty is discussed in turn. The authors also discuss the compounding of uncertainty and discuss the appropriateness of confidence intervals for characterising certain epistemic uncertainties.
Chow & Sarin	2002	Article	Three Types	Psychology Decision Theory	For this psychological study they define three kinds of uncertainty: • Known uncertainty = probabilities known, • Unknown uncertainty= probabilities unknown, • unknowable uncertainty = probabilities unknown to everyone and unknowable
van Asselt & Rotmans	2002	Journal Article	Various schema	Integrated Assessment	A restatement and elaboration on the Rotmans & van Asselt 2001 typology. Additional content includes a more elaborated list of sources of variability: • Inherent randomness of nature • Value diversity • Human behaviour • Social, economic and cultural dynamics • Technological Surprises
Walker et al.	2003	Article	Matrix/Dimensions	Model based science advice	In this highly influential paper, the authors introduce a dimensions framework and matrix for understanding uncertainty in model-based decision support. Dimensions given are: • *Location*- where the uncertainty manifest in the process of modelling • *Level*- on a spectrum between deterministic knowledge and total ignorance

					• *Nature*- due to variability or imperfection of knowledge
van der Sluijs et al.	2003	Guidance Document	Matrix/ Dimensions	Environmental Assessment	This is the first detailed guidance for uncertainty assessment/communication for the Netherlands environmental assessment agency (PBL). It adapts the Walker et al. (2003) framework, adding two extra dimensions (or columns in the matrix: • *Qualification of knowledge base:* weak, fair or strong • *Value-ladenness of choices*: small, medium or large
Harremoës	2003	Journal Article	Levels of uncertainty	Integrated Assessment	Restates and explains the level dimensions of Walker et al. (2003). The levels given are: • *determinism* (an unachievable ideal), • *statistical uncertainty* (outcomes and statistics known), • *scenario uncertainty* (range of outcomes but no statistics), • *recognised ignorance* (where we know we do not know the functional relationships), • *indeterminacy* (we do not know that we do not know some functional relationship) to absolute ignorance. Indeterminacy can either be *practical* (due to large number of parameters) or *theoretical* (knowledge impossible due to chaotic nature of system).
Ricci et al	2003	Journal Article	Levels	Environmental Decision-making	As part of this article examining different decision making frameworks, they present levels of variability/ uncertainty and relate these to levels of representation of causal relationships: • Probabilities > Model Uncertainties • Probability distributions > Bayes Factors • Probability Bounds > Entropy of Information • Interval Analysis > Partial Ignorance • Other.. > Complete Ignorance
Harwood & Stokes	2003	Journal Article	Typology	Ecology	They identify four sources of epistemic uncertainty in ecological management: • *process stochasticity* (variability), • *observation error*, • *model error* (incomplete or misleading representation of system dynamics) • *implementation error* (the failure to implement a policy).
Linkov & Burmistrov	2003	Journal Article	Typology	Model based science advice	They present four kinds of uncertainty. Three are common to other frameworks: parameter uncertainty, model uncertainty and scenario uncertainty. In addition, they include modeller uncertainty which is due to uncertainty in the interpretation of a problem by the modeller.
Peterman	2004	Journal Article	Typology	Fisheries modelling/management	A number of types of uncertainty in fisheries management: *Natural Variability, Observation error, Communication difficulties, Unclear management objectives, Implementation error*. Also, sources are described in a network diagram
Brown	2004	Journal Article	Taxonomy	Physical Geography	A framework taxonomy that distinguishes uncertainty (an expression of confidence in knowledge) from ignorance. Uncertainty can either be bounded (outcome space known) or unbounded (outcomes unknown). Bounded uncertainty can be divided by whether one known some, none or all probabilities of outcomes. Unbounded uncertainty is divided by whether no outcomes are known, some are known or whether some probabilities and outcomes are known.
Manning & Petit	2004	Working Paper	Types	Climate Science Assessment	As part of a consideration of the IPCC's handling of uncertainty ahead of AR4. The paper distinguishes between five key origins of component of uncertainty: 1. Incomplete or imperfect observations (this is a joint property of the system under study and our ability to measure it) 2. Incomplete conceptual frameworks (not all relevant processes included) 3. Inaccurate prescriptions of known processes (e.g., poor models or parameterisations) 4. Chaos (uncertainty is a property of the system being studied) 5. Lack of predictability (e.g., social systems)
Grin et al	2004	Journal Article	Conceptual Distinction	Foresight and Innovation	A fleeting conceptual distinction between informational uncertainty and normative dissent.
Brown et al	2005	Journal Article	Model of Locations of Uncertainty	Environmental Change	The authors present a conceptual model for where uncertainties can manifest in a data recording. They define three aspects to assessing uncertainties: • The empirical quality of data: magnitude of uncertainty and empirical quality • Sources of uncertainty: in the methods and concepts used • The fitness the data has for its application • The 'goodness of the uncertainty model. Furthermore, they differentiate between different kinds of data and the uncertainty (position and attributes).
Moser	2005	Journal Article	Study where sources and types of human-dimension uncertainty are identified	Coastal Management	Moser Interviews a number of scientists to identify oft-neglected human-dimension uncertainties present in coastal management decision making. Through the interviews, four groups of uncertainties are collated: human factors that determine sea-level rise, human factors that co-determine sea level rise impact assessments, uncertainties in policymaking/management processes, uncertainty in condition for policy change.
IPCC	2005	Guidance Note	A number of features	Climate Science Assessment	This is the guidance note for the IPCC's fourth assessment report (AR4). It contains a number of recommendations for dealing with and communicating uncertainty. They present a simple typology of uncertainty: • Unpredictability (not amenable to prediction) • Structural Uncertainty (inadequate models etc) • Value uncertainty (unknown parametric values etc.)

					Advice about language used to describe probabilities is given. The Moss & Schneider (2000) matrix is re-stated. They also provide different levels of information provision in a hierarchy: A. Direction of change is ambiguous B. An expected trend is identified C. An order of magnitude can be given for the degree of change D. A range can be given for the change E. Likelihoods can be given for representative outcomes F. Probability distributions can be given
Kandlikar et al	2005	Journal Article	Levels of Uncertainty	Climate Science Assessment	They critique uncertainty communication methodologies (such as in IPCC TAR) that attempt to separate likelihood and confidence as likely to create confusion. Instead, they present a set of ways of representing deep uncertainty. They propose a cascade of steps for determining the way in which uncertainty can be described. This creates a hierarchy of treatments of uncertainty: 1. *Full PDF* (Q: is it reasonable to apply a full probability distribution) 2. *Bounds* (Q: is it reasonable to specify bounds for the outcome) 3. *First-order estimates* 4. *Expected sign or trend* 5. *Ambiguous sign or trend* 6. *Effective Ignorance*
Lane & Maxfield	2005	Journal Article	Typology	Innovation Economics	They identify three sorts of uncertainty: truth uncertainty (uncertainty in the truth of a proposition), semantic uncertainty (actors uncertainty related to the meaning of statements) and ontological uncertainty (uncertainty related to actors' assumptions about the ontology of a system)
Meijer et al	2006	Journal Article	Dimensions	Foresight and Innovation	They organise uncertainties in socio-technical transformation by: • *Source*: technology, resources, supplier, consumers, politics • *Level*: low to high
Pappenberger et al	2006	Report	Typology	Hydrology, Flooding	In this report on flood risk, the authors distinguish five primary sources of uncertainty: • Model structure (choice of simplification of reality) • Numerical approximations • Definition of flow domain considered (specification of geometry of terrain etc) • Boundary conditions • Parameter choices
Peterson	2006	Journal Article	Typology	Economics and Environmental Assessment	A review paper that brings together a couple of conceptualisations of uncertainty. Makes a distinction between *parametric* (knowledge related, also includes functional forms in models) and *stochastic* (variability related) uncertainties. Then describes ways in which uncertainties can be organised by their position in the cascading climate problem: uncertainty in emissions path, uncertainty in climate response, uncertainty about impacts and uncertainty about optimal policies.
Tennøy et al	2006	Journal Article	Sources and Levels of treatment	Environmental Impact Assessment	They describe four explanatory factors for uncertainty, based on de Jongh (1988): *change in project, model error, data errors* and *bias*. They describe four levels for the treatment of uncertainty: • 0- no description of uncertainty; • X- uncertainty is suggested but not explicitly named; • XX- uncertainty indicated or estimate but not explained; • XXX- uncertainty is explained to some degree
Krupnick et al	2006	Report	Taxonomy	Resource management	Types of uncertainty are: • Variability (dispersion of values around a central tendency) • Parameter uncertainty (described as a subset of epistemic uncertainty) {measurement errors, unpredictability, conflicting data, extrapolation errors …} • Model uncertainty (subset of epistemic) {structural choices, simplification, incompleteness, choice of pdfs, correlations, system resolutions}; • Decision uncertainty (uncertainties that affect risk managers about valuing social objectives) {choice of risk measure, choice of discount rate, decisions about risk tolerance, utility functions, distributional considerations}
Petersen	2006 [2012]	Book	Matrix	Modelling in Climate Science and Policy advice	Adapts the Walker et al. 2003 framework in a number of ways: • Splits off recognised ignorance from Walker et al's 'levels'. Levels are re-labelled as 'range'. • Adds two additional dimensions of 'methodological unreliability' (relevant to theoretical basis, empirical basis, other simulations and peer consensus) and 'value diversity' (epistemic, discipline bound, socio-political and practical). Also relates his framework to that of Funtowicz & Ravetz: e.g., identifies his 'location' dimension with their 'source'.
Stainforth et al	2007	Journal Article	Taxonomy of Sources	Climate modelling, decision-making	The authors describe a number of sources of uncertainty: • *Forcing uncertainty* • *Initial condition uncertainty* (ICU). Subdivided into microscopic ICU (small rapid mixing scales) and macroscopic ICU (slow large mixing scales) • *Model Imperfections*. The two types of this are (i) *model inadequacy* (shortcomings of models due to non-representativeness of model structure to target system) and (ii) *model uncertainty* in parameterisations which can be quantified with ensemble experiments.
Patt	2007	Journal Article	Distinction	Environmental Change, IPCC	The paper distinguishes and explores the difference between *modmodel-basedel based and conflict-basedbased uncertainty*. The former relates to uncertainties in modelling in particular. The latter are conflicts due to the different opinions of experts.

Blind & Refsgaard	2007	Journal Article	Some Sources	Water Resources Management	Aside from using Brown et al. (2004)'s framework, they identify and document several sources of uncertainty and issues that arose in a modelling process: • Modeller's understanding of input data • Lack of metadata on observations • Lack of consistent bias handling in data • Poor correction factors that account for unrepresentative samples • Complexity due to links of data streams to society
Pindyck	2007	Working Paper	Some Sources	Environmental Economics	Describes a number of sources of uncertainty relevant for environmental economics: uncertainty in costs, uncertainty in benefits and disagreement over discount rates. Some natures of uncertainties that make the issues worse ae *nonlinear damage functions, irreversibilities* and *long-time horizons*.
Refsgaard et al	2007	Journal Article	Dimensions	Environmental Modelling	Adapts the Walker et al. (2003) framework with influence from Brown (2004). • Relabels Walker et al's variability as stochastic uncertainty • Adds a level of qualitative uncertainty in the Walker et al's levels. Renames levels as type.
Tannert et al	2007	Journal Article	Taxonomy	Science and Society	Presents a dendrogram of uncertainty as 'the igloo of uncertainty' • At highest level knowable probabilities separates ignorance from knowledge. • Ignorance and knowledge are either open or closed. • Open knowledge and ignorance are within the 'field of uncertainty'
Hayes et al	2007	Book Chapter	Taxonomy	Ecological Modelling	They provide a general introduction to a number of uncertainty concepts and treatments. Their taxonomy identifies three primary kinds of uncertainty: • *Linguistic* (due to various ambiguities of language; examples: ambiguity, context dependence, under specificity, vagueness), • *Variability (*fluctuations in a process • *Incertitude* (lack of knowledge; example: model uncertainty and measurement error). This is largely adapted from Regan et al. 2002.
Gill et al	2008	Guidance Document	Sources of Uncertainty	Weather Forecasting	A World Meteorological Organisation guidance document on the communication of uncertainty. Outlines the following sources of uncertainty: • Atmospheric Unpredictability • Data interpretation • Composition of the forecast (uncertainty in linguistic presentation of forecast) • Forecast interpretation
Ascough II et al	2008	Journal Article	Typology	Ecological Modelling/ Decision-making	Three fundamental categories of uncertainty: Knowledge, Variability and Linguistic. Each of these is subdivided and all contribute to decision uncertainty. Decision uncertainty also consists of goals and assessment criteria.
Brugnach et al	2008	Journal Article	Dimensions	Ecology, Natural Resource Management, Water Resource Management	A two-dimensional system: • Three fundamental natures of uncertainty: *Unpredictability, Incomplete Knowledge and Multiple Knowledge Frames*. These natures are described in a relational way • They then separate three different objects of knowledge: natural systems, social systems and technical systems. This is then manifested in a 3x3 grid of types of uncertainties
Brouwer & De Blois	2008	Journal Article	Typology/Taxonomy	Environmental (Water) modelling and decision-making	Two lists of kinds of uncertainty given. Environmental, Economic and Political (subdivided into *goal* uncertainty and *yield* uncertainty). They take Brown's (2004) version of an uncertainty scale of statistical, scenario, qualitative and recognised ignorance.
van der Keur et al	2008	Journal Article	Dimensions of Uncertainty	Water management	They present a typology of uncertainty, adapted from Walker et al. (2003) and Refsagaard et al. (2007). They give four dimensions of uncertainty: • *Nature*: ontological or epistemic • *Type* (this is equivalent to what others call levels): statistical, scenario, qualitative, recognised ignorance, total ignorance • *Source*: data uncertainty, model uncertainty, multiple knowledge frames, boundary conditions • *Context*: natural technical or social
Knutti et al	2008	Journal Article	Contributions to Uncertainty	Climate modelling	In this review of uncertainty in global temperature rejections there is not an explicit framework, but uncertainty is divided up into four contributions: scenario uncertainty, climate feedback, carbon cycle feedback and structural uncertainty. The authors also distinguish between uncertainties that are the result of single methods and those the result of multiple methods.
Brown & Damery	2009	Book Section	Distinction	Environmental Geography	As part of a chapter discussing the differences between the concepts of Uncertainty and Risk, the authors identify a number of psychological, sociological and situational aspects of uncertainty and risk.
Toth	2009	Book Section	Taxonomy of Surprise	Environmental Assessment/ Scenarios	A taxonomy of surprises that summarises some previous literature. Described two dimensions to classify surprises: knowability and whether one expects them. This creates three general types of surprises: anticable, conjecturable, and out of the blue.
Hawkins & Sutton	2009	Journal Article	Typology	Climate Modelling	These kinds of uncertainty are identified: Scenario (associated with emissions scenarios), model (differences in model outcome due to model structure) and internal variability (due to inherent variability of the climate)
Knol et al	2009	Journal Article	Dimensions/ Matrix	Environmental Health	Adapts Petersen (2006) in *location* and to make more useful for specific application. *Normative uncertainties* are included in ontic uncertainty. *Contextual uncertainty* appears included in *location*
Kwakkel et al	2010	Journal Article	Dimensions/ Matrix	Model-based policy support	Reviews a number of uncertainty frameworks that built upon the Walker et al. framework. Based on criticisms of these they attempt a synthesis by: • Refining the *level* dimension to four levels.

					• Adding a fundamental nature of uncertainty of *ambiguity* (different interpretation with different frames and values) • Clarifying different locations of uncertainty in the model process
Mastrandrea et al	2010	Uncertainty Guidance	Guidance Document/ Report	IPCC, Communication	A guidance notes from a workshop in advance of the IPCC's 5th Assessment report. They recommend: • A two-dimensional communication of evidence (low mid high) and agreement (low mid high) • Calibrated likelihood language to refer to specific probability intervals
Parker	2010	Journal Article	Typology	Philosophy of (climate) Science	Details three major kinds of representational uncertainty associated with climate modelling: • *Initial Condition uncertainty* • *Parametric Uncertainty* (uncertainty in parameterising processes) • *Structural Uncertainty* (uncertainty about the form of equations) Choice of boundary conditions are also mentioned as a source of uncertainty.
Spielgelhalter & Reisch	2010	Journal Article	Dimensions	Risk, Modelling	They describe a number of characteristics of uncertainty: • Object of uncertainty- they describe five levels: event, model, parameter, acknowledged and unknown inadequacies • The form of expression of uncertainty (another scale); • the Source of Uncertainty; • the Subject of uncertainty (whose uncertainty is is?); • Affect (feelings associated with uncertainty)
Warmink et al	2010	Journal Article	Dimensions	Environmental Modelling	The Walker et al. (2003) system is refined with a decision tree for each of the dimensions of uncertainty. Additional level of uncertainty is given. Additional nature of uncertainty due to competing evidence.
Sigel et al	2010	Journal Article	Typology	Environmental Decision-making	They describe two types of uncertainty: • Factual (relating to facts) a • Normative uncertainty (relating to legal or regulatory demands). The source of uncertainty is what the uncertainty relates to. Causes of uncertainty are variously given.
Wilby & Desai	2010	Journal Article	A cascade of sources of uncertainty	Climate Adaptation	They frame the uncertainties relevant to adaptation planning as coming from a cascade of uncertainties that create a growing envelope of uncertainty. The cascade described is: future society > GHG emissions > Climate Model > Regional Scenario > Impact Model > Local Impacts > Adaptation Responses
Dequech	2011	Journal Article	Dimensions	Economics	Builds on Dosi & Egidi and Knightian uncertainty. Adds own distinction between ambiguity and fundamental uncertainty. The three distinctions are: • Strong vs weak uncertainty (can pdf be defined); • substantive (due to lack of information) vs procedural (lack of capacity to gain information); • ambiguity (state space known)) vs fundamental (state space unknown)
Smith & Stern	2011	Journal Article	Typology	Climate Policy	They distinguish a number of (not mutually exclusive) types of uncertainty: • *Imprecision* – outcomes where probability can be provided • *Ambiguity* – outcomes may be known, probabilities cannot • *Intractability* – computations cannot be performed due to lack of mathematical or computational capacity • *Indeterminacy* quantities relevant for policy for which no precise value exists. This may occur when there is value diversity of a physical quantity does not really exist.
Riesch	2012	Book Chapter	Levels of Uncertainty	Risk Theory, Decision-making	Asks a number of questions: Why are we uncertain: aleatoric or ontological ; Who is uncertain?; How is uncertainty represented?; They describe three types of uncertainty within the modelling process and two without. They describe 5 non-exclusive levels of uncertainty in some detail. These levels do not describe pdfs, but describe model adequacy.
Link et al	2012	Journal Article	Typology	Ecosystem Models	They define types of ecosystem model uncertainty: • Natural Variability (inconsistency in a state variable); • Observation error (failures of observation); structural complexity (complexity of model due to many parameters etc); • Inadequate communication (difficulty in conveying information between scientists); • Unclear management objectives (vagueness of objectives); • Outcome uncertainty (failure to implement a management plan)
Enserink et al	2013	Journal Article	Dimensions	Futures/ Climate Scenarios	This article discusses how creators and users of scenario studies deal with uncertainty. They present three dimensions of uncertainty, with similarities to the framework by Kwakkel et al. (2010): • *Nature* (Epistemic, Ambiguity, Ontic) • *Level* (Five levels) • *Location* (Where in the model or object under study uncertainty is located)
Hughes et al	2013	Journal Article	N/A	Energy Policy	In this scenarios and futures-focusses paper the authors describe potential conceptualisations for low carbon scenarios and a methodology for constructing them. They describe how the design of scenarios can focus on unknow future elements that are either dependent on the actions of agents or not. The also distinguish between things with are uncertain "*because [they] lie beyond the control of system actors*" and those that are uncertain because "*actors have not yet decided upon their strategies in respect of it*".
Ekström et al	2013	Journal Article	Matrix	Climate Risk and Water	They adapt the Walker et al. (2003) framework for water risk assessments. They include the Warmink et al. (2010) added nature of *ambiguity*, but

					broaden it to include differences in understanding/interpretation. In addition, their matrix involves: • An accounting of the aims of the assessment • The stages of a climate vulnerability assessment form Füssel & Klein (2006)
Petersen et al	2013	Uncertainty Guidance	N/A	Environmental Assessment	The second edition of uncertainty communication guidance for the Netherlands Environmental Assessment Agency (PBL).
Parker	2013	Journal Article	Typology	Climate Science, Philosophy	As part of a review of Ensemble modelling practices defines the following types of climate model uncertainty: • *Scenario Uncertainty*- uncertainty about emissions and forcing • *Response Uncertainty*- the response of the climate system given a forcing, which has both epistemic and ontic components
Fischoff & Davis	2014	Journal Article	Protocol for Uncertainty Elicitation and communicatio n	Climate Science	As part of this paper they describe an expert uncertainty elicitation protocol that is derived partially from the NUSAP system of Funtowicz & Ravetz 1990 (also from the CONSORT criteria for medical trials). The uncertainties to be elicited are: • *variability*, • *internal validity* (of a study in question), • *external validity* (how well can results be extrapolated), • *strength of science* (directness, empirical basis, methodological rigour and validation) and • *credible intervals* (a measure of both the variability in a situation and the strength of the underlying science to give an estimate of an interval).
Bradley & Drechsler	2014	Journal Article	Dimensions	Philosophy	Three dimensions of uncertainty: Nature, Object and Severity. • Nature is split between modal (what could be the case), empirical (what is the case) and normative (what is the case). • The object of uncertainty is either factual (about the world) or counterfactual (the way things could; or would be if they were different). • Severity is a scale of uncertainty.
Lehmann & Rillig	2014	Journal Letter to Editor	Distinction	Climate Change, Ecology	The letter proposes terminology to distinguish between uncertainty (a measure of unexplained variation) and natural variability (explained variation)
Gould et al	2014	Journal Article	Taxonomy	Ecology	Uncertainty is described as having three components: • Natural Variability • Measurement Error • Incomplete Knowledge They also give additional classes of: • Unpredictability of the future • Modelling error They describe a conceptual model that gives different sources (effectively locations) within species distribution models.
Davies et al	2014	Report	Dimensions	Energy Sector Planning	Adaption of the Funtowicz & Ravetz (1990) map of system uncertainties versus decision stakes for use in Energy systems planning. They then include Skinner et al's framework in this adapting the nature, location and level of uncertainty.
Skinner et al	2014	Journal Article	Taxonomy	Environmental Risk Assessment	A novel approach to forming a classification is employed. In which papers utilising uncertainty assessment frameworks in environmental risk assessments were assessed to see what locations of uncertainty were espoused. These locations were then organised into Epistemic, Aleatory and Combined (could be described as both) camps. These sources were then clustered.
Beven et al	2014	Report	Typology	Hydrology, Flood Mapping	In this report the authors provide and extensive framework and implementation guide for analysing uncertainty in fluvial flood risk mapping. They acknowledge a difference between epistemic and aleatoric uncertainties. They define a number of key sources of uncertainty: • Uncertainty in fluvial flood sources (essentially a collection of uncertainties that define the magnitude and nature of the causes of flood events) • Uncertainties in pathways (uncertainties in the way that flood events are modelled) • Uncertainties in receptors (Uncertainties in the vulnerabilities of systems to flood events) • Uncertainty due decisions of implementation (to the way uncertainty analysis is carried out)
Beven et al	2015	Journal Article	Typology	Hydrology, Flood Mapping	The authors describe various *sources* of uncertainty in flood risk mapping. Each of these sources is described as having *aleatory* (due to natural variability and treatable with probabilities) and *epistemic* components. This typology presented in this paper in tabular form is said to be adapted from of that of Beven et al. 2014, though Beven et al. 2014 do not sort epistemic and aleatoric components of uncertainties this way.
Watson et al	2015	Journal Article	Dimensions	Energy Policy	They combine a version of Funtowicz & Ravetz's (1990) two dimensions of uncertain situations from Davies et al. (2014) with the Risk framework of Millar & Lessard (2008). They adapt the risk framework to include *instrumental* (relating to specific energy technologies) and *systemic* (that could have systemic impact). The end result is a framework which organises uncertainties on source (instrumental and systemic) and rates these on two dimensions of complexity and impact.
Grubler et al	2015	Journal Article	Types	Technological Forecasting	In this article the authors define a number of types of uncertainty. • Parametric uncertainties • Functional uncertainties (exact relationship between entities is not known) • Unknown Unknowns They also distinguish between three classes of uncertainty: • Epistemic (uncertainty data and/or models) • Linguistic Uncertainty (vagueness) • Contingency/agency (due to human intentionality)
Monier et al	2015	Journal Article	Typology	Climate Modelling	They describe there being four sources of uncertainty in the context of climate modelling:

					• Emissions projections uncertainty • Response of the climate system to changing GHG and aerosol concentrations • Natural variability • Model structure uncertainty
Mirakyan & De Guio	2015	Journal Article	Typology and levels.	Energy Planning	The define six categories of uncertainty, with five of these appearing to be mutually exclusive: linguistic uncertainty, Knowledge uncertainty, Variability uncertainty), Decision (similar to ambiguity with competing options) Uncertainty, Level of uncertainty and procedural uncertainty. They also define 4 *Levels*: Determinism, Risk, Uncertainty (sub levels: fuzzy probabilities, belief or plausibility function, and possibility membership function), Ignorance
Frig et al	2015	Journal Article	Set of questions	Philosophy of (Climate) Science	A philosophical article that among other things, considers how climate scientists have wrestled with uncertainty. They present a number of difficult questions left unanswered after Knightian the risk/uncertainty distinction: 1. Why are precise probabilities not possible in uncertain situations? Are there unknown unknowns? 2. Can uncertainty be quantified (not necessarily by quantitative measures)? 3. How can uncertainty be communicated to decisionmakers? 4. What is the rational way of making decisions under uncertainty?
Payne et al	2016	Journal Article	Typology	Marine ecosystems modelling	An adaption of Hawkins & Sutton's typology for use in marine ecosystems research. Structural (how model is built up), Initialisation/ Internal Variability (the combination of the variability of the model and complex model feedbacks), Parametric, Scenario
Refsgaard et al	2016	Journal Article	Uncertainty cascade	Hydrology and Climate modelling	The authors describe and conceptualise the uncertainty 'cascade' between different stages of the modelling process. The particular cascade they describe sees uncertainty flow between GHG emission scenarios -> to Climate models -> to Downscaling and bias correction -> to Hydrological models which then results in uncertainties in different relevant outputs. Within each of the model they also describe other sources of uncertainty such as natural variability, process equations, data & parameter values, discretisation numerics.
Cheung et al	2016	Journal Article	Typology	Marine resources, Climate change	The authors adapt Hawkins & Sutton's typology for use in marine ecosystems research. They describe four types: Internal Variability, Structural, Parametric, Scenario. They also make use of some use of the ideas of Link et al. 2012 in their description of parametric uncertainty.
Usher	2016	PhD Thesis	Conceptual Distinction	Energy Systems Modelling	Following other authors, broadly describes there being two relevant sources of uncertainty: parametric and structural uncertainty. Describes the idea of *dynamic uncertainty* which involves the temporal development due to the agency of decisionmakers, learning and the interactions of variables.
Beven	2016	Journal Article	Taxonomy (2 levels)	Hydrological Modelling	4 fundamental types of uncertainty in hydrological modelling: • *Epistemic* is subdivided into three sub-classes (system dynamics, forcing and response data, disinformation) • *Aleatoric-* uncertainty with stationary statistical characteristics • *Semantic/linguistic-* uncertainty over meaning of statements • *Ontological-* differing belief systems
Hamel & Bryant	2017	Journal Article	Matrix	Ecosystems Services	This paper is primarily focussed on practical issues involved in uncertainty analysis in Ecosystems Services Modelling. They adapt the Walker et al. (2003) framework for this use. They adapt the *locations* of the uncertainty to be specific to Ecosystems Services. They include an extra dimension of uncertainty of 'overall importance' to business cases, optimal design or impact estimates.
Schick et al	2017	Journal Article	4 Types	Ecosystem Health and Sustainability	They deploy the 'VUCA' system, an uncertainty accounting tool previously popular in strategy and leadership literature, in an ecology context. The VUCA mnemonic provides for dimensions to assess a strategic situation: • Volatility: the speed of change in the system • Uncertainty within the main drivers of the situation • Complexity: a high number of interlinkages within the system and with other systems • Ambiguity: multiple interpretations of current and future conditions
Heal & Millner	2017	Working Paper	Implicit taxonomy (2 Levels)	Ecological Economics	Uncertainty relevant to environmental economics is at the first level divided between scientific uncertainties and socio-economics (by system domain). Scientific uncertainties are subdivided into internal variability, model uncertainty and emissions uncertainty. Socio-economic uncertainties are divided into model uncertainties (including parameter uncertainties) and disagreements about values.
Baustert et al	2018	Journal Article	Dimensions/ Stages in Uncertainty Assessment	Ecosystems Services, Integrated Environmental Models	The authors review a number of conceptualisations of uncertainty for integrated modelling. They describe a number of dimensions of uncertainty that are identified with stages of an uncertainty analysis. *Location:* Which model element the uncertainty manifests in. This is subdivided into context, frame, variables, structure. *Identification:* How uncertainty is described by a number of dimensions, such as nature (epistemic or ontic) and level (a scale from complete knowledge to blind ignorance). *Characterisation*: How the uncertainty is represented using a mathematical structure *Treatment:* A calculation of the influence of one or more uncertainties *Communication*: Linguistic or visual communication of uncertainty in results
Benjamin & Budescu	2018	Journal Article	Taxonomy	Climate Science Communication	For this study examining participants responses to a number of different kinds of uncertainty, the authors divide uncertainty into *model uncertainty* and *Source uncertainty*. Model uncertainty is either due to structural uncertainty (difference between models) or judgemental uncertainty

					(different initial conditions). Sources of uncertainty are either conflict (difference between precise forecasts) or two identical imprecise forecasts.
Doyle et al	2019	Journal Article	Review	Disaster Risk Reduction	A broader systematic review of papers on the topic of *communicating model uncertainty* relevant to the field of disaster risk management. They identify the categorisation of uncertainty as one of the themes within this corpus and review. They identify styles of classifications, including those specifically for spatial uncertainties and matrix-type typologies. As part of the framing of the review they give sub-categories of model uncertainty of model structure uncertainty (uncertainty in how model describes system), model technical uncertainty (due to choices made in technical implementation), initial condition uncertainty, external driving force uncertainty, forcing data, parameter value uncertainty, scenario uncertainty, data uncertainty, and model outcome uncertainty. They collect together row and column categories from matrix-type classifications (table 15), including level, location, nature, qualification of knowledge base and value-ladenness of choice.
Derbyshire	2019	Journal Article	Distinction	Scenarios, Geography	This paper distinguishes between 'Epistemic' uncertainty and 'Ontological' uncertainty. The former is described as "the known and bounded inaccuracy of our knowledge". Ontological Uncertainty "stems … from the tendency of fundamental changes to disrupt our present knowledge". This uncertainty also includes the changes in attitudes, belief and behaviours of actors in the wake of these developments. The two kinds are described as existing on a continuum, with certain kinds of analysis being particularly problematic in situations characterised by ontological uncertainty.
van der Bles et al	2019	Journal Article	Aspects of uncertainty (essentially dimensions)	Uncertainty communication	They develop a model for communication of uncertainty four relevant aspects of uncertainty to communicate: • *Object* (what is uncertain), • *the Source* (the cause of the uncertainty), • *the level* (direct (about a fact) or indirect uncertainty (about underlying knowledge base)), • *the magnitude of uncertainty*
Marchau et al	2019	Book Section	Levels	Decision-making	They first provide an ontology of a decision support system to use in uncertainty analysis. Then then present 5 levels of uncertainty: • A clear enough future • Alternative futures with probabilities • A few plausible futures • Many plausible futures • Unknown future They relate each of these to appropriate system models.
Dreier & Howells	2019	Journal Article	Dimensions	Energy Modelling	The paper presents a new piece of software for stochastic energy systems modelling. They present two dimensions of uncertainty as a diagnostic tool to aide selection of uncertainty analysis technique. They classify uncertainty analysis techniques as to whether they are endogenous/exogenous to the model system and whether the technique is stochastic/deterministic.
Petr et al	2019	Journal Article	Dimensions	Climate and Forestry	They adapt the framework of Walker et al. (2003), Refsgaard et al. (2007) and Warmink et al. (2010) to define three dimensions of uncertainty: • *Location*: Context & framing, driving forces, system, data, model structure, technical model (model selection, model implementation), parameter uncertainty, model output uncertainty (type of information output, information selection decision) • *Level:* statistical, scenario or recognised ignorance • *Nature*: Epistemic, Stochastic/Aleatory, Ambiguity They then use their framework in a review of the forest science literature to determine how often different locations of uncertainty appear.
Kutiel	2019	Journal Article	Typology	Climate Modelling	The article focusses on temporal uncertainties (changes in time). They give three contributions to uncertainty in climatic variables: natural variability, lack of sufficient data and erroneous scenarios. A taxonomy of temporal uncertainty is presented where it is split into long term trends, inter-annual uncertainty and intra-annual uncertainty.
Pye et al	2020	Journal Article	Matrix	Energy Systems	A paper in which the NUSAP framework is adapted and applied to Energy Systems Modelling. They create a matrix which plots uncertainties in a 2-d space with axes of strength of evidence (pedigree) and spread (influence on outcome).
Gaudad & Romero	2020	Journal Article	Dimensions	Energy Planning	Three dimensions of uncertainty (within a risk context) given: probability (low or high), doubt (confidence in that probability assessment; low or high) and impact (low or high). These are combined into a 16 point 'acuity scale', a term borrowed from medical vocabulary.
Zumwald et al	2020	Journal Article	Sources	Climate Datasets	They describe a framework to understand uncertainties in climate datasets. They describe a number of sources and sub-sources: 1a) How the data is measured 1b) How the data is processed (e.g. the model used to understand the measurement) 2) When and where a measurement is taken and how that relates to the phenomenon of interest e.g. biased samples) 3) The adequacy of the dataset to provide a description of the phenomenon
Kay & King	2020	Book	Various distinctions/ Dimensions	Economics	In this book, aimed at a popular audience, they make the Knightian distinction between 'resolvable' and 'radical' uncertainty. Radical uncertainty has a number of dimensions to it: • Obscurity • Ignorance • Vagueness • Ambiguity • Ill-defined problems

					• A lack of information that in some cases but not all we might hope to rectify at a later date They relate the resolvable/radical difference to aleatoric/epistemic (p23)
Workman et al	2021	Journal Article	Taxonomy	Integrated Assessment	At the highest level they separate those uncertainties that are within the modelling process and those between modelling and policy-making. Each has a number of sub types • Uncertainties in modelling: stochastic, epistemological, ontological (entities not in conceptual models), computational, scope (processes not within scope of model), judgement (expert decisions about parameters or convergence criteria), modelling errors • Uncertainty in policy: Endpoint uncertainties (required endpoint not certain), semantic uncertainties, implicit value judgements, implementation uncertainty, ethical uncertainties
Kirchner et al	2021	Journal Article	Dimensions/ Taxonomy	Integrated Modelling, Global Change	They review a number of uncertainty conceptualisations in the literature. They develop their own uncertainty matrix, based on the original Walker et al. (2003) framework. They describe three dimensions of uncertainty: *Nature*: Epistemic or Stochastic – epistemic is said to be *reducible*. They subdivide these two into different sub categories Epistemic = {unreliability, structural, system understanding, linguistic}; Stochastic= {natural variability, human variability}. *Type*: is described as the way that uncertainty can be expressed. There are four types given: Statistical, Scenario, Qualitative Ignorance *Location*: where uncertainty manifests in the model process or framework. They give four major locations, each subdivided into minor locations: Context (System boundaries, system resolution), Inputs (System Data, System Drivers), Model (Parameter calibration, Structure, Hardware & Software), Outcome (Linkage, Extrapolation, Decision Support).

Appendix C: Consent form Sample

CONSENT FORM FOR PARTICIPANTS IN UNCERTAINTY REPRESENTATION RESEARCH STUDY

Please complete this form after you have read the Information Sheet and/or listened to an explanation about the research.

Title of Study: Investigating Conceptual Representations of Uncertainty in Climate Change and Energy Systems Modelling

Department: UCL Department of Science, Technology, Engineering and Public Policy (STEaPP)

Name and Contact Details of the Researcher:

[redacted]

Name and Contact Details of the Principal Researcher:

[redacted]

Name and Contact Details of the UCL Data Protection Officer:

[redacted]

This study has been approved by the UCL Research Ethics Committee: Project ID number: 14243/001

Thank you for considering taking part in this research. The person organising the research must explain the project to you before you agree to take part. If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time.

I confirm that I understand that by ticking/initialling each box below I am consenting to this element of the study. I understand that it will be assumed that unticked/initialled boxes means that I DO NOT consent to that part of the study. I understand that by not giving consent for any one element that I may be deemed ineligible for the study.

		Tick Box
1.	I confirm that I have read and understood the Information Sheet for the above study. I have had an opportunity to consider the information and what will be expected of me. I have also had the opportunity to ask questions which have been answered to my satisfaction and would like to take part in an individual interview	
2.	I understand that I will be able to withdraw my data up to 4 weeks after the interview	

3.	I consent to participate in the study. I understand that my personal information will be used for the purposes explained to me. I understand that according to data protection legislation, 'public task' will be the lawful basis for processing.	
4.	I understand that all personal information will remain confidential and that all efforts will be made to ensure I cannot be identified. I understand that my data gathered in this study will be stored pseudonymously and securely. It will not be possible to identify me in any publications.	
5.	I understand that my information may be subject to review by responsible individuals from the University for monitoring and audit purposes.	
6.	I understand that my participation is voluntary and that I am free to withdraw at any time without giving a reason. I understand that if I decide to withdraw, any personal data I have provided up to that point will be deleted unless I agree otherwise.	
7.	I understand the potential risks of participating and the support that will be available to me should I become distressed during the course of the research.	
8.	No promise or guarantee of benefits have been made to encourage me to participate.	
9.	I understand that the data will not be made available to any commercial organisations but is solely the responsibility of the researcher(s) undertaking this study.	
10.	I understand that I will not benefit financially from this study or from any possible outcome it may result in in the future.	
11.	I agree that my pseudonymised research data may be used by others for future research. [No one will be able to identify me when this data is shared.]	
12.	I understand that the information I have submitted will be published as a report and I wish to receive a copy of it. **Yes/No**	
13.	I consent to my interview being audio recorded and understand that the recordings will be stored securely, using password-protected software and will be used for research purposes.	
14.	I hereby confirm that I understand the inclusion criteria as detailed in the Information Sheet and explained to me by the researcher.	
15.	I am aware of who I should contact if I wish to lodge a complaint.	
16.	I voluntarily agree to take part in this study.	

If you would like your contact details to be retained so that you can be contacted in the future by UCL researchers who would like to invite you to participate in follow up studies to this project, or in future studies of a similar nature, please tick the appropriate box below.

	Yes, I would be happy to be contacted in this way.	
	No, I would not like to be contacted.	

Name of participant	Date	Signature
Researcher	Date	Signature

Appendix D: Information Sheet Example

<u>Participant Information Sheet For Interview Participants</u>
UCL Research Ethics Committee Approval ID Number: 14243/001

Title of Study:
Investigating Conceptual Representations of Uncertainty in Climate Change and Energy Systems Modelling
Department:
UCL Department of Science, Technology, Engineering and Public Policy (STEaPP)

Name and Contact Details of the Researcher:

[redacted]

Name and Contact Details of the Principal Researcher:

[redacted]

You are being invited to take part in a research project. Before you decide to participate, it is important for you to understand why the research is being done and exactly what participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Thank you for reading this.

1. **What is the project's purpose?**

   This study aims to explore the way that people working in different research communities think about and mentally represent uncertainty. To this end you are being asked to participate in an interview, which is intended to be informal and semi-structured.

   The aim is to paint a picture of the variety of ways in which uncertainty can be described to help facilitate communication between different research communities working on interdisciplinary tasks such as integrated assessment modelling.

   This project is intended to last until mid-2019.

2. **Why have I been chosen?**
   As part of this research we wish to interview people involved in the modelling of energy systems or the climate, research communities that integrate findings from a great number of fields, who is involved in integrated assessment and whose members originate from a diverse number of academic backgrounds (economics, engineering, natural sciences etc). Self-identification as someone who models energy systems or the climate is sufficient for inclusion in this study.

Your input is important as we attempting to build a comprehensive picture of the ways in which people conceptualise uncertainty. There are no "right answers" to any of the questions being asked, we are simply looking to capture a diversity of thought.

3. **Do I have to take part?**
It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and you will be asked to sign a consent form. You can withdraw at any time without giving a reason. If you decide to withdraw part way through the study, you will be asked what you would like us to do to the data you have provided up that point.

4. **What is involved in participating in this study?**

The researcher would like to interview you for around 30-60 minutes. The interview will be semi-structured, but is intended to be relaxed and informal. You will not be given guidance on the questions in advance.

The initial phase of questions may seem a little abstract, but you are encouraged to feel free to say whatever comes to mind. The researcher will be more than happy to discuss the reasoning for the abstract/highly conceptual questions later in the interview. Later questions may delve into more concrete specifics and ask you about your experiences in handling uncertainty. You may refuse to answer any questions you wish for whatever reason, but it is not anticipated that any of the questions are likely to be discomforting.

No personal information will be taken apart from your name and professional role. The value to this research is the interview and your professional opinions about the relationship between uncertainty and modelling from the perspective of someone involved in modelling exercises.

Consent will be recorded with a consent form. If you would like to withdraw yourself from the study, please notify the researcher within four weeks of the interview. This time period is intended to give you adequate time to reflect on your participation whilst avoiding excessive disruption of the data analysis.

Furthermore, if you wish, the researcher may ask if you would like to participate in a short follow-up study/ secondary task. This would involve a task that would attempt to validate/test some of the findings from the initial stage of the research. You will be asked to sort a number of printed cards with statements about uncertainty on in a particular way according to your personal preference (a Q-methodology). The way that you have decided to arrange the card will be recorded by the researcher. This task is expected to take around 10 minutes.

5. **Will I be recorded and how will the recorded media be used?**

The researcher will record you using either a dictaphone or an audio recording application. After the interview, the recording will be uploaded to a secure server at UCL and/or an encrypted hard drive then deleted from the recording device. The audio recording of your activities made during this research will be used only for analysis. No other use will be made of them without your written permission, and no one outside the project will be allowed access to the recordings.

If you participate in the follow-up card-sorting task, data will be recorded by the researcher in an Microsoft excel sheet before being similarly uploaded to a secure server at UCL and/or an encrypted hard drive then deleted.

6. What are the possible disadvantages and risks of taking part?

We do not foresee negative repercussions from engaging in this research, however please do get in touch with either the researcher or principal researcher if you have any concerns about the methodology employed- comments are very welcome.

We understand that some may consider *uncertainty* a contentious topic. It is stressed by the researchers that discussions about uncertainty are not intended to be critical of any particular modelling paradigm or practice. We are merely interested in exploring the ways that people think about uncertainty in their day-to-day work and it is hoped that findings will aide modellers to better communicate to other communities, such as policy-makers. Any publications emanating from this work will note this.

7. What are the possible benefits of taking part?

Whilst there are no material benefits for those people participating in the project, it is hoped that this work will help advance cross-disciplinary discussion around issues of uncertainty which could help construct traceable accounts of uncertainty on projects which cross disciplinary boundaries, as well as identify new ways of communicating uncertainty to policy audiences. You may also be interested to understand how your own conceptualisation of uncertainty relates to that of others.

8. What if something goes wrong?

Should you have any concerns or complaints, please refer these to the Principal Researcher, Prof Arthur Petersen (contact details at head of this sheet). However, should you feel your complaint has not been handled to your satisfaction, you can contact the Chair of the UCL Research Ethics Committee – ethics@ucl.ac.uk

9. Will my participation in this project be kept confidential?

All the information that we collect about you during the course of the research will be kept strictly confidential. You will not be able to be identified in any ensuing reports or publications. Participants' individual contributions will be pseudonymised so your name will be replaced in any future publications in the style of "Energy Systems Modeller A" or "Participant B" etc. The key that links your name to your pseudonym will not be shared with anyone. Information that could uniquely identify participants will not be included in any publications. Data will be stored securely on an encrypted hard drive and in a secure server at UCL.

10. Limits to confidentiality

Effort to maintain confidentiality will be taken through secure handling of the data, and the pseudonymised transcripts will be used in publication in such a way as to avoid participants being identifiable. However, research communities may be tight-knit and the pool of participants is limited. In order to maintain confidentiality, colleagues will not be told of your decision to participate or not participate and the interviews of others will not be discussed. If your participation was recommended by a friend or colleague they will not be told of your participation similarly.

Effort will be taken to remove all identifying information from any published transcript sections.

11. What will happen to the results of the research project?

The results of the analysis of interview transcripts may be used to author articles for publication, likely within six months of the interview. The analysis of interview transcripts may also help in the formulation of the secondary card-sorting task. All of this will be presented as part of a PhD thesis.

Should you wish to receive copies of any materials emanating from this project (articles, thesis chapters), these will be emailed to you.

Data collected during the course of the project might be used for additional or subsequent research, though participants will not be identified in future research.

12. Data Protection Privacy Notice

Notice:
The data controller for this project will be University College London (UCL). The UCL Data Protection Office provides oversight of UCL activities involving the processing of personal data, and can be contacted at data-protection@ucl.ac.uk. UCL's Data Protection Officer can also be contacted at data-protection@ucl.ac.uk.

Your personal data will be processed for the purposes outlined in this notice.

The legal basis that would be used to process your *personal data* will be performance of a task in the public interest.

Your personal data will be processed so long as it is required for the research project. If we are able to anonymise or pseudonymise the personal data you provide we will undertake this, and will endeavour to minimise the processing of personal data wherever possible.

If you are concerned about how your personal data is being processed, please contact UCL in the first instance at data-protection@ucl.ac.uk. If you remain unsatisfied, you may wish to contact the Information Commissioner's Office (ICO). Contact details, and details of data subject rights, are available on the ICO website at: https://ico.org.uk/for-organisations/data-protection-reform/overview-of-the-gdpr/individuals-rights/

13. Who is organising and funding the research?
This research is being conducted as part of the PhD studies of Luke D. Bevan. He receives a studentship from the Economic and Social Research Council (ESRC) as part of the UCL, Bloomsbury and East London (UBEL) Doctoral Training Centre.

14. Contact for further information

[redacted]

You will be given a consent form to sign, and should you wish a copy of the consent form to take with you along with this information sheet.

Thank you for reading this information sheet and for considering taking part in this research study.

Appendix E: Interview Protocol

Initial Opening Questions (first 5 minutes)

- What sorts of models are you working with presently/ have you been working with?
- How did you come to working in the space that you have?
- What sorts of uncertainty analyses are you familiar with performing?

Key/Guiding Questions

About conceptualising uncertainty

- What does uncertainty mean to you?
- What types of uncertainty do you encounter?
- What does an uncertainty analysis tell you about your model/ the real world?
- [Not to directly ask] In uncertainty a property of a model, a modeller or the real world?
- [Not to directly ask] What are some conceptual models to understand uncertainty?
- Do other have the same understanding of uncertainty as you?

About influences on uncertainty handling

- What are some of the factors that might determine/influence the way you analyse uncertainty?
    - How do ones assumptions/ choices affect uncertainty?
    - What might prevent one from engaging with uncertainty fully?
    - How does your research group approach uncertainty?
    - Is uncertainty different in different kinds of modelling?
- What sorts of issues in uncertainty communication do they face (especially across disciplinary boundaries)?
- To what extent do you believe uncertainty can be reduced in your modelling?
- Has your handling of uncertainty changed over your career? If so, why?

Example concepts to be sensitive to and to loop back on

Scenarios; Variability; Intractability; Values, Ignorance, Unknown Unknowns, Ambiguity, Probabilities, Assumptions,

Expanding Prompts

- You mentioned _______, what do you mean by/ how do you understand that?
- How is that influenced by ______?
- Tell me more about/ can you unpack ______?
- Do you see that as common opinion among your peers?

Wrapping up questions to ensure thoroughness (10 mins to go)

- We have mentioned a number of types of uncertainty such as …… what other kinds of uncertainty do you encounter in your work?
- What are some of the uncertainties you are most optimistic about ameliorating the handling of? Why?
- What are some of the uncertainties that you are most pessimistic about being able to handle better? Why?

Final questions to end interview (last minute)

- Were any of the questions too hard, or otherwise unpleasant to answer?
- When I approached you to ask if you would be willing to participate in an interview about uncertainty, were there any questions that you expected that I would ask, but that I did not ask?
- Do you have any suggestions of other potential participants?

Appendix F: One-page Summaries of Interviews

Each of these summarise includes notes form some of the salient topics that were raised in each of the interviews.

Participant:	**01- Gable**
Category:	Energy/ IAM
Description	Energy ad Climate Economist working with CGE models and IAMs
Background	Economist
Methods discussed	Scenario analysis, sensitivity analysis
Types	Variability, parameter uncertainty, data uncertainty passingly mentioned; known-unknowns, know-knowns
Conceptualisation as a whole	
Uncertainty for them was mostly related to values of things that they might want to know. They related it to subjects where things have been studied less deeply. The amount of literature in the particular subject area seemed important. *Whereas if you only have a couple of studies, if something is incredibly new and therefore uncertain then those people who have looked at it then their viewpoint or perspective will be weighing more on the types of results that you will get. I think something becomes less uncertain as more people study it, because those sort of 'human' aspects tend to disappear to some extent although maybe it disappears [inaudible] to the extent that an average person would think but then I guess that is all we can really try to achieve.* They understood models to be simpler versions of reality. They understood the data that one puts into the model as reality. Parameters are the link between the inputs and the outputs. They used an extended metaphor to describe uncertainty: *I think uncertainty kind of feels a bit like space in the sense that you look at the things and there are lots of things. You see planets and there are lots of things that you can see, uncertainty kind of feels like the space in between stars and planets. I mean this is.... I've started going down this way so I will finish. It's... You can have an idea of what is there. In some sense you might have an idea of what is there and in another sense you might not. You might be... I don't know. I'm just going to see this through. With planets you are aware that if you, you know, were to take a spaceship and drive or go in that direction, this is what you would hit. The certain things are there, and with the spaces in between there is the potential that it's just a space. It's not known at all, there is nothing there or there is something there, but you don't know what it is.*	
Types of Uncertainty and Distinctions	
The participant did not mention many types of uncertainty though they understood uncertainty to be associated with a number of different things. They understood variability as a property of reality and something that one would wish to capture in a model. Scenarios were conceptualised as packaged groups of assumptions that are coherent. They are also useful for communication ("communicating tool") to non-modellers in qualitative ways. Known unknowns and unknown unknowns were briefly mentioned. They mentioned that the limit of their uncertainty analysis was often just sensitivity analysis. They also conceptualised there being a type of uncertainty associated with the different potential opinions of people.	
Influences on uncertainty handling	
They understood uncertainty to be quite different in different disciplines but not elaborate exactly how. They said that social science models were inherently less certain. Also, there was said to be difference with individuals: *And these are people that are highly competent modellers. But just trying to explain how one differs to another because everyone has their own lens with how they see it, which is however their experience is. Trying to explain the concepts and assumptions behind one model to another group. I feel like I spend a lot of time as this sort of facilitator, saying we made this in this model with those kinds of assumptions means it's not like.*	
Normative views	
Other Notable Themes	

Participant:	**02- Skiddaw**
Category:	Energy
Description	Energy Modeller
Background	A researcher
Methods discussed	Regression analysis/ R-squared, Scenario development
Types	Statistical Uncertainty, decision uncertainty

Conceptualisation as a whole

They related uncertainty to the opposite of confidence i.e., a lack of confidence in something. They said it was related to both a lack of tools and a lack of data.

They said that uncertainty existed within the models. Models were discussed as something with an exploratory function.

Types of Uncertainty and Distinctions

They mentioned that their main use of uncertainty was statistical uncertainty and regression analysis. Later in the interview, this was said to be a result of input parameters and the model being used.

When asked for more kinds of uncertainty they also said there was decision uncertainty- the uncertainty associated with the fact that people may make decisions.

They also talked about black swan-type events, but not in those words: "*I'm thinking about you know sort of catastrophes, like uncertainty on whether there will be a hurricane or something like that. I wonder if that is also statistical uncertainty. I am trying to think about different categories of uncertainty.*"

Scenarios were related to hypotheses.

The participant seemed a bit confused about variability and related uncertainty as an estimate of variability- meta uncertainty. V*ariability I am thinking about weather variability. Oh wait, I know it's not the same. I think... Wait, first I said they are the same, now I am about to say that they have nothing to do with each other. Variability is a physical phenomenon. I am thinking about wind powered generation or solar generation which varies over time. And uncertainty is associated with trying to predict the patterns of variability.*

Influences on uncertainty handling

Like Gable, this participant too talked in hand-wavy terms about physics. And how energy modelling had a difference as it had to deal with decision uncertainty.

Knowledge of statistical skills seemed to be important for this participant as they had said they had improved in this area.

Normative views

Other Notable Themes

They mentioned how they had issues with the data coming from LCA:
Skiddaw: *I to be honest to say that I think we rarely talk about uncertainty. The few occasions I do remember is people complaining about how other don't correctly quantify uncertainty. I am very specifically thinking about Life Cycle Assessment Models where we had a discussion this summer about how most of these don't give uncertainty with their life cycle assessment of a certain product. And that is incredibly important, because again you input parameters are uncertain.*

They also discussed how some were frightened that uncertainty might invalidate results. But also, uncertainty ranges shouldn't be too small. So, you have to meet in the middle. This 'dialling effect' is what has been seen with other participants.

Participant:	**03- Scafell**
Category:	Climate, Impacts
Description	Economist working on issues to do with climate impacts and crops
Background	Economist. Maths undergrad. Worked in major bank.
Methods discussed	
Types	Variability vs Uncertainty. Statistical uncertainty.

Conceptualisation as a whole

They conceptualised uncertainty in a vaguely Knightian way.

They naively believed that the median of several models represented something like the truth.

And because we know under what conditions some of the crop models perform really poorly, the median kind of sorted out the poor aspects of their performance to get something that was probably closer to true. It seemed morally and philosophically better somehow to get rid of that variance and to focus on what truth was.

They then conceded this want the truth, but since they could not achieve a real-world experiment, they settled for something less.

Types of Uncertainty and Distinctions

They started off by distinguishing between variability and uncertainty.
Well so variability- there are many things that change every day. You expect things to vary. You don't expect the same temperature every day, the same amount of precipitation every day, [ummm], so I think about that as normal expected variability. I suppose if you frame it differently you could even call that uncertainty. If you were trying to say: "well what is the weather going to be two weeks from now" you might say "well that's uncertain because it's a variable thing". Well then there is uncertainty as well about the whole climate model. There is a whole uncertainty about how things play out and how [entire?] systems play out. Even if you know the greenhouse gas levels, the uncertainty of how it turns out in terms of the climate itself is unclear.

They said it was difficult to impose a variance structure of assumptions.

They conceptualised scenarios as conceivable, likely future states of the world. Or as policy what-if exercises.

They also mentioned big surprises (Trump e.g.) as a kind of uncertainty but didn't give this a label.

Influences on uncertainty handling

They talked about how they had to present their uncertainty in a way that would be understandable and appealing to policymakers. So, they selected the uncertainties in the climate models (not in the crop models) as that is what they wanted to tell a story about.

They described how they did not show a lot of uncertainties as they did not have the ability to characterise them. *We aren't smart enough even to [inaudible] [laughs]. Well, I'm not smart enough; my colleagues probably are smart enough!*

Normative views

Other Notable Themes

Participant:	**04 Helvellyn**
Category:	Climate + IAMs
Description	Senior interdisciplinary IPCC-associated academic

Conceptualisation as a whole

The participant identified the concept as being polysemous. They try to avoid the use of the term due to this.

They identified and referred to uncertainty as existing in several forms: as a psychological property, they talked about confidence in an intersubjective and relative sense. They also identified uncertainty existing in reality (e.g., quantum mechanics).

Types of Uncertainty and Distinctions

They explicitly identified five kinds of uncertainty and claimed they were influenced by Smith & Stern 2000:

- Intractability: the impossibility of calculating something despite high computing power
- Imprecision: when you can't measure something precisely enough
- Ambiguity and Scenario uncertainty were identified as being related concepts. Scenario uncertainty was also described as being from formal scenario assessments and also from the unseen variety of choice made by different modelling groups. For example, the different definitions of global mean surface air temperature used in the 1.5°C report.
- Uncertainty on a "meta-level" where we are sure about things we don't know

Scenarios were described as 'what-if exercises'. When the participant identified the value of scenario uncertainties as not revealing the range of outcomes but understanding the pathways to outcomes.

The participant also made reference to 'deep uncertainty'- it was related to the limitations and accumulated knowledge that sits outside of a given modelling framework.

Influences on uncertainty handling

They described how different values can constrain the selection of scenarios that one employs. For example, one may not choose to have solar radiation management in a scenario.

They described how scientists from the different working groups have different understandings of uncertainty:

- WGIII were characterised as being very interested in scenario uncertainties. However, how uncertainties around the implementation of policies are captured seemed less clear to them.

  WGIII were described as "not understanding always internal variability"- that even with big computational power we can't always do multi-decadal forecasts.

  WGII were described as wanting simple climate models and not necessarily appreciating the uncertainty in current warming as it prevents their ability to make simple conclusions.

- WGI was described as being all about measurement uncertainty and imprecision. The participant was unsure how the internal variability of the model systems related to this but affirmed that this was more like chaos or intractability.

  WGI was described as not understanding that RCP2.6 is not the only path to two degrees- perhaps that they had a lower dimensionality conception of the scenario space.

People are described as being naturally limited to think about uncertainties in particular ways as not everyone can be an expert on everything.

Some scientists want the illusion of certainty. Low dimensional results are easier to explain. This is an explanation not only to policymakers but to themselves as an audience.

The scenarios and futures community has pushed scenario development and thinking deeply about ranges of outcomes- but there is now inertia there as the community is so large and you have to get them all to agree.

Engineers are taught to think more about imprecision and intractability. Working on real-world engineering problems first awakened them to wider ranges of uncertainty. Then their PhD did so as well.

Normative views

- That scenario uncertainty is generally underexplored
- "Scenario thinking" is important

Other Notable Themes

We had a conversation about how some scientists are able to sit in an interdisciplinary capacity. Scenario development exercises and cross-working group themes were described as good opportunities for this. These very interdisciplinary people are formed through their work on interdisciplinary questions. "Researchers who are interested in the bigger picture not the deep detail".

Participant:	**05 Bowfell**
Category:	Climate
Description	Former senior government metrological/climate modelling programme leader

Conceptualisation as a whole

It means not knowing what the future holds, no knowing what the present is. And in a professional context I suppose it relates both to measurement and to prediction. So even though it you might have a measurement of the temperature, there is an uncertainty attached to that because you don't know... the instrument might have inaccuracy.

Models are conceptualised as a manifestation of ones understanding of the world.

Types of Uncertainty and Distinctions

Identifies uncertainty existing in both the activities of measurement and in prediction.

They distinguish between accuracy and precision in the expected way.

Risk is conceptualised as the consequence of something happening.

Scenarios are conceptualised as possible futures. The scenarios used in climate models are conceptualised as limited as they only contain part of the description of that possible future.

When asked for types of uncertainty the participant mentioned:

- Measurements
- Uncertainty from discretisation of the model- not all details are being represented at every scale
- Emission scenarios
- Uncertainty in physical feedbacks and processes

Uncertainty in parameters is also mentioned and expert elicitation is suggested as something that can deal with this. The participant also described parameterisations as manifestations or replications of more complex underlying processes.

Influences on uncertainty handling

They note that there are different standards to prediction in different fields.

They note that some people consider observational data to be the absolute truth. However, they note that actually, these are often indirect measures, and there is a common misunderstanding as to what an observation constitutes.

Stakeholders were described as not understanding the models' PDF outputs and preferring the 'best' answer that models give you.

The participant described how the personalities of modellers might affect their displayed uncertainty due to the choice they make when parameterising. People may be more cautious or more cavalier.

They described how in model development, a model often gets worse before it gets better and that the benefits of part work at improving accuracy may only come later.

They claimed their personal understanding of uncertainty was primarily statistical as they are "a numerical person".

They described that having had some experience with policy, they understood what was considered useful for decision-making. They talked about trying to find a compromise in the models that they use between accuracy and effort expended.

They stressed the importance and influence of Lorenz's ideas on the field. Also, the training that physics gives with state spaces.

Normative views

- Many scientists do not consider decision-making enough

Other Notable Themes

- Traceability between simplified analogue models and more complex models is needed.

Participant:	**06 Coniston**
Category:	Climate
Description	Climate modeller working on cloud-aerosol interactions

Conceptualisation as a whole

Uncertainty for the participant was mainly conceptualised throughout the interview as a property of models. Their work concerned metamodeling, so this is perhaps unsurprising. When discussing wider uncertainties, they were generally more uncomfortable and seemed unsure about how these could be dealt with.

The participant discussed the idea of certain models being 'plausible'. When pushed on this they described how they ruled models out rather than ruled models in. The choice of metric that you tune the model to seems important and they seemed to conceptualise these metrics and being identifiable with the real world, despite also discussing observational representation issues.

Types of Uncertainty and Distinctions

The participant clearly identified two kinds of uncertainty: variability and parametric uncertainty. Most of their work concerns the latter. Forcing uncertainty was also mentioned later in the interview and was identified with their work on exploring parametric uncertainty.

They mentioned that they had a PhD student working on more policy relevant modelling involving geopolitical uncertainty. However, the participant seemed to suggest this was being managed with a perturbed parameter ensemble. Geopolitical uncertainty around the impending US election was mentioned as a major source of uncertainty.

Data uncertainty was also discussed in the context of representational errors of observations. The participant discussed a new experiment being planned to densely sample a GCM grid box at sea in order to improve the characterisation of SST (Sea Surface Temperature).

Late in the interview they mentioned variability. When questioned about variability they identified this with *internal variability*.

The uncertainty to do with emulators was discussed. The participant conceptualised the uncertainty associated with the emulator more like the sensitivity and spread that the emulator produces, rather than any uncertainty with the fact that you are using an emulator. They needed to pass some test to do with an 'implausibility metric'.

Influences on uncertainty handling

The participant had described how other modellers had not done big sensitivity analyses on their models yet due to the amount of effort it requires. They described an inertia among the scientists they talk to and how the community was changing its practices

"*And it takes a long time before they get used to the idea of treating uncertainty this way. And treating uncertainty reduction as like one of the key goals of science, rather than just leaving it as something which is too hard to deal with. So, I think that is the standard, is it's just too problematic. So, let's leave it be. So, people, 5-10 years ago, people would just take their standard model variant, it was released by the centre, and they perturbed a single thing once to some extreme value and they would look at the comparison between those two, write a paper on it, and have a grand result that says, "here's what this thing does". That's still happens in a lot of cases. But you see a lot less than you did five years ago, I think people moving on*"

Another of other influences on uncertainty handling were found:

- Model run times and the availability of HPC
- The path dependency and priorities in model development. Making structural changes to the standard model variants mean your results become less comparable to others.
- The same issue as with Bowfell described that improving characterisations of processes makes the model worse for a while.
- The desire to do some meta-modelling first about your own model before other activities

The participant described how there was moderate embarrassment that the uncertainty ranges in aerosol-cloud interaction have not reduced significantly in the last 20 years. So, they have been thinking more about targeted experiments. They described how the ideal reduction in uncertainty may be useful for decisionmakers, but that their work had to pass through the IPCC before it reached decisionmakers.

The participant described how in one major modelling group they were working with there were lots of subjective choices that went into their selection of ensemble members to use at the end of the day. This subjectivity was viewed as legitimate because: "*They've done it based on that subjective knowledge base. They've done it subjectively, based on that quite wide knowledge base. That is appropriate because these are the model experts. The people know how their model performs and why works the way it does. So, I think that's reasonable.*"

Normative views

They believed that not enough other modelling teams have put the work in to produce PDFs for their model outputs. He said that many had perturbed physical atmosphere parameters got round to doing that in conjunction with aerosol parameters. He believed that eventually people will want to know how their model performs. With these pdfs available the participant believed then a number of hypotheses could be properly tested about the differences between the models. It seemed that only when you had a pdf can a comparison be properly facilitated. "So *okay, the PDF might have a different shape. It might not be as broad and might be broader in someone else's model. I'd like to see that- I'd like to know. So, what we learned from that scientifically is if we all apply the same constraints, having densely sampled our model uncertainty range, then we're going to get a combined constraint on that role as a forcing. That includes both parameter stuff, and the model structural differences.*"

The view was expressed that uncertainty reduction is one of the key goals of science. The participant also described there being an optimum balance between the availability of HPC capacity and the insights that one can get from observations.

We discussed how some of the work on uncertainty from one generation of models to another was kept on and some wasn't when the frameworks were refreshed. "*And then I go through this postdoc where we're quantifying uncertainty, a new model version, and now we're constraining it, we've got this nice tight constraint. But yet again, the model's moved on, and someone that's informed by our work, and some of it isn't, and you've got all sorts of new processes in there. And so, it's got to be repeated in a new framework, in a larger more ambitious sense. But this is a cyclical approach. So, it's that idea of the relevance of the insights gained by constraining uncertainty into the next generation. Yeah, I find that really interesting.*"
Other Notable Themes
We discussed how they were doing lots of computationally cheap model runs and details of the method they were using to explore the parameter space in the most effective way possible. There was an acknowledgement that their own area of research was quickly becoming less important to the overall climate issue as aerosol concentrations are decreasing.

Participant:	**07- Lingmell**
Category:	Climate Impacts, IAM
Description	A multifaceted scientist with a particular interest in uncertainty. Particular interests in flooding. Model user rather than developer.
Background	Mathematics, Philosophy, PhD on Energy Engineering
Methods discussed	Scenario Analysis, Data assimilation,
Types	Geophysical uncertainty, socioeconomic uncertainty, deep uncertainty vs shallow uncertainty; ambiguity vs uncertainty. Parametric uncertainty mentioned. Scenario uncertainty.

Conceptualisation as a whole

It was difficult to pin down the exact conceptualisation of uncertainty here. However, the participant was very interested and concerned with the different types of information that one could provide, be it probabilities or scenarios. Whilst concerned about deep uncertainty they nonetheless thought that probabilistic information should be provided wherever possible.

Types of Uncertainty and Distinctions

Some of the types of uncertainty discussed were thematic. For example, geophysical uncertainty and socio-economic uncertainty.

Scenarios were conceptualised as "specific realisation of how an uncertain factor might resolve". The participant identified scenario analysis being applicable to situations of deep uncertainty.

Lingmell: *I think those are the main ones. You can broadly think about deep uncertainty versus shallow uncertainty or ambiguity versus uncertainty, knighting uncertainty- whatever your preferred terminology is. As can you provide probability distributions or can you not? Or can you not come up to a consensus about what these probability distributions are? So, there's that level as sort of a more abstract kind of mathematical way of doing it. Then since I work on climate the main two classes of uncertainty are geophysical and socio-economic. So how are we going to continue to emit or what are the vulnerabilities for how we develop and how we make decisions about adaptation. And then what are the actual physical system uncertainties? These of course interact and they interact and there are non-linear interactions between them. But they are the two main categories of uncertainties that combine in the work I am interested in doing.*

They discussed how there was a growing appreciation for deep uncertainty.

Influences on uncertainty handling

The participant talked about the importance of data assimilation frameworks and how the probabilistic framework used to understand these had to be different in different contexts. The selection of data sources was described a bit like an art. This fusion of different types of data in integrated assessment was described as involving expert judgement.

So, for example, if you're thinking about socio economic development, and potential uncertainties future socio-economic development, in a location - let's say if you're assessing what is our future growth and vulnerability to flooding. Then you need to be able to take into account... you might have to use satellite imagery to kind of help calibrate a land use change model for future actual development of housing stock or [? notional] stock. You may need to take into account other population level records and just say, "Well, how does the population change in different census tracts over time?" You may have to use some sort of expert assessment. And so how do you kind of fuse all these things together in a way that respects the uncertainties, so you don't produce overconfident estimates.

We discussed a consultancy project they had done on the topic of coastal flooding. We talked about the different stakeholders that they dealt with and their demands. E.g., a resilience manager or a mayor.

The increasing availability of HPC and emulators was described as opening the number of scenarios that could be examined. Emulators were discussed particularly in the context of the geo-physical work.

Normative views

Very early on in the interview the participant stressed that it was important to give an idea of how likely scenarios are. They said that one needed to have probabilities, conditional on other deeply uncertain factors.

So, I think there are some people who are happy with scenarios, and don't feel the need to quantify things probabilistically. And so, I think that's an ongoing- where they sort of say, you know, "probabilities create a false sense of confidence". There is something true to that, if you say the probability of this is this, that kind of gets reified a little bit. Which is why I think it's important to present, you know... when things are deeply uncertain, it's important to acknowledge that and say, "Here's sort of a range that we can come up with, of different probabilities" You say that, you know, "either the probabilities tend to cluster here, no matter what assumptions" or they're very sensitive to some of these other things.

The participant viewed decision-making as a little incoherent without probabilities.

They also thought that the SSPs were very coarse, and the elements could be disaggregated. *We have the SSPs, but then those are very coarse, you know, just very different visions of how the world might look. But, you know, the probability of any given one of them being right is zero, right? Because they are point representations. And so, there's also the side where you say, "is it enough to actually just do like these SSPs" and see what you get. Or do you actually need to kind of do more exploratory modelling and say, "Well, maybe agriculture follows this SSP. But fossil fuel demand follows this SSP." There's no reason why those have to be linked. intrinsically. And so that also provides a level of uncertainty and what is the prediction for the future in the outcome where now you start to get a little more detail, at least for that IAM of how everything fills in. Rather than just what we get these five-point estimates associated with each of the SSPs.*

Other Notable Themes

They were more pessimistic about dealing with decision-related uncertainties such as future emissions due to their intractability. They were optimistic about new data sources such as mobility and social media data helping us to understand social systems.

Participant:	**08- Swirl**
Category:	Climate
Description	Climate Scientist working on air-land-sea interactions. Model user and developer.
Background	Atmospheric Science undergrad, professional government organisation weather forecasting
Methods discussed	Initial conditions ensembles, (MMEs mentioned), Monte Carlo
Types	Chaocity, Boundary condition sensitivity; signal Vs Noise

Conceptualisation as a whole

Uncertainty was not necessarily entirely numerical for this participant. It is something that can be captured or used rhetorically. The participant discussed different ways of capturing it. Seeming to imply it was something in reality. An example of this was MMEs as well.

I'm not saying that that is 100% right, it's just the best we can do. But the problem is: does that represent the true uncertainty of prediction? So, another way to look at this is if you treat the spaghetti plot as truth, you tend to forget nature already. Nature has its own uncertainty. It doesn't need to be like the model uncertainty. So, because how do I say that- it's so hard to interpret. So, there's only one truth at any location at any time for any variable.

The participant was also unsure if reality really did have a pdf or if there was some kind of ultimate truth that could be found.

Types of Uncertainty and Distinctions

The participant repeatedly discussed the quality of 'chaocity' in systems. *a small initial condition difference I results in very drastic system behaviour sometimes down in the future.*

They also discussed the issues associated with boundary conditions. The two boundaries were surface boundaries and atmosphere top. The latter was less influential.

The participant also discussed signal and noise. This was related to the scales in the model. The quality of the signal and the variability depends on the scales the model works at.

Scenarios were related to both forcing scenarios, but also the result of models. For example, the different outcomes of ENSO.

The participant described three elements of the fundamental dynamics of models which influence predictability: chaoticity (Lorenz), turbulence (nonlinear term effects, energy jumps between scales) and stochasticity (random noise).

Influences on uncertainty handling

They admitted that early on in their career they ignored the uncertainty in their work. This was related to the idea that they were doing more foundational research and working on behalf of another researcher.

He gave a very interesting example of a senior researcher who got very deep into the detail of his model on the mesoscale and missed a lot of the truth.
[The professor that I worked for] is a very famous person in that area. He claimed that when you give the moist soil moisture a different number, for very dry soil and a very wet soil, you can create a huge... with wet soil, you can create a thunderstorm easily. With dry soil, you can't. So, if you compare these two, you will say that moisture itself is very important at least for the mesoscale. Let's say for the great plain of the USA. So that was true. But that's not the whole truth. Because we don't know the soil moisture very much. And we can't pinpoint what part of the great plan is wet or dry.

The most interesting thing we ended up talking about on what you can examine in terms of uncertainty was the discussion of observations, grid box size, data availability and time.

So all these together, I can guarantee you, there's a huge amount of uncertainty in the boundary conditions alone. And you don't even need to go far down to this forecast. To start with this initial condition or uncertainty in the boundary condition, you've already got this noise. If you want to call it a noise. Then you can't expect the forecast will be better. It's just gets worse. Or you can call that uncertainty and live with it. That's another story.

The participant described how you had to satisfice at a certain point about model quality. Otherwise, you would never graduate from grad school.

The participant discussed the influence of Lorenz in the context of whether nature had PDFs. As nature is deterministic but chaotic, the best we can do is use statistics to characterise it.

Normative views

Other Notable Themes

They described sensitivity analysis as a rising trend in their area.

Swirl: *Well, it's already in the wake of the trend. Yeah, I hope so. Yeah, I just don't want to see that anymore. And now people are playing with the parameterisations. And I don't blame them. I'm even part of one of them is just what people are doing now. But there are some fundamental questions about the dynamic system. Let's go back to the Lorentz experiment, there's one tiny difference in the initial condition, you will get a very large difference in the forecast in the future. And that's one big statement. But how do you solve the problem? And I have seen a few posters this morning, they again use the PDF to describe the results. And that's good. You know, I don't quite understand the details. But that's another trend. But I personally want to start another trend- encourage people to go back to the dynamics, chaoticity, stochasticity, turbulence, all that these three should be combined together to quantify the predictability of the model. That's my dream.*

Participant:	**09- Pillar**
Category:	Climate
Description	Senior Climate modeller in a large GCM group. Model developer.
Background	Undergrad physics and metrology PhD on climate models
Methods discussed	Perturbed Physics Ensembles, Scenario Analysis (not used by modeller)
Types	Observational uncertainty, coupling uncertainty; model response + scenario uncertainty

Conceptualisation as a whole

Uncertainty to a certain degree was also associated with opportunities for model development.

The sorts of issues they associated with uncertainty can be seen to a degree in the following section. A lot of it is about the 'devil in the detail' of model development.

Pillar: *The concern and the bottom line is given an increase in CO2 and methane, how will climate change on average. And the statistics of those extreme events... an individual extreme event tomorrow- what is the weather forecast? Whereas how that PDF of extreme events changes on average? And one of the things from the atmospheric side is how atmospheric processes regionally response to changes in surface temperature. And that's where these feedbacks come in. A positive feedback you can imagine is warming of Sea Surface Temperature and the cloud responds by thinning and going away. So, it's positive feedback. Or it could respond by a warmer surface, there is more water in the atmosphere, liquid in the moulds that reflect more- so that's negative feedback.*

Types of Uncertainty and Distinctions

The participant most commonly referred to uncertainties associated with particular elements of the model, such as climate sensitivity, cloud aerosol feedbacks and ocean heat uptake.

They understood PPEs + MMEs as encompassing all the uncertainty.

But in terms of the ensembles ensemble in the future is a scenario ensemble, the SSPs. But it's also a model response. So, if you look at all your models in the future you have two levels of uncertainty: the model with their feedbacks and then the actual scenario themselves. For your best estimate that spans al the uncertainty. So, if you have your 30 models doing your most extreme scenario and you have 30 models doing your least extreme scenario. That's your uncertainty- that's your model and future scenario all in. So that's the way the CMIP models are used.

MME averages were understood to be the signal.

They understood internal variability statistically displayed in a model to be different to that of the real system itself.

They stressed that they were not really involved with scenarios themselves.

Influences on uncertainty handling

We discussed a lot about the culture at their modelling group. Their modelling group was not very hierarchical, and the different sub-elements of the model were prioritised and developed by the different sub-teams (e.g., atmosphere, ocean, land, ice etc.). Then a series of structured meetings would decide on the priorities for model development.

Aside from this devil in the detail stuff they discussed tuning a lot. A requirement is recreating the climate since 1850. The issue of what to do when you put all your best guesses into a model, and it doesn't turn out right. The participant discussed how you exploit uncertainty in order to tune your models.

This tuning issue came up again later in the interview talking about the rocky road they had integrating new data and how the model got worse before it got better.

Yeah, so that was our second painful few months of trying to fix that. You do something and you come back two days later. You follow this path. Come back two days later- "oh that didn't work. Any ideas?" Really a scratching of "what are we doing wrong and what do we need to look at more?" There wasn't a certain kind of "Oh were doing research and toddling along, getting things done." It was pressure! Pressure from people higher up "what are you doing? Why haven't you finished?" Thank God, other modelling groups had not as well because they were having the same problems! I know of four of five models [with] similar problems that when they switched these emissions datasets their cloud feedbacks, that we talked about at the start, these aerosol-cloud feedback were way too strong.

The participant discussed the meetings they had about model development and how this could be 'character driven'. They particularly discussed an issue they had where a region of sea ice kept spontaneously forming. The different sub teams tried to work out what the issue was and came up with competing plausible explanations.

Everyone could make an argument that the sea ice was expanding out for one or two or three combinations of all these things. And so, you sit and have a conversation- no-one really knows the answer. And so you have a conversation about what are we going to do? We do not know why this is happening. So, the question is.... It's not about observational uncertainty. It's a coupling uncertainty which you have to deal with a lot.

This was resolved: ***Pillar:*** *So, in the end it was ... we used something new. You could argue that it was the rivers: the rivers were coming out and putting fresh water right on the top of the ocean and that has the effect of making the ocean very stable and not mixing. You get an ocean very fresh and cold so the ice can form. They went away and figured out that that was not the best way to do it. And so, they just pushed and mixed it further in the vertical and it solved the problem. That did not shut off these ocean circulations and that fixed it.*

We also discussed the father ted whack a mole situation of model development.

Normative views

Other Notable Themes

They were optimistic about new satellite data improving climate models. Especially those that can deal with the clouds in the vertical.

Participant:	**10- Scoat**
Category:	Energy
Description	An Energy systems modeller, recently converted from physics
Background	Physics
Methods discussed	Parameter Space exploration, Multi-model ensembles, Inter-model comparison algorithmic data evaluation
Types	Data Errors, Statistical Uncertainty, Variability
Conceptualisation as a whole	
The participant was clearly in the middle of an intellectual transition between different ways of understanding the world from natural science to energy studies. They talked very comfortably about outcome spaces and parameter spaces.	
Types of Uncertainty and Distinctions	
A number of sources of uncertainty were discussed. However, the participant was generally unfamiliar with different types of uncertainty. We discussed data issues, exploring parameter space and statistical uncertainty. They were vaguely familiar with intermodal comparisons and understood their value to be in understanding the discrepancies between model results. They were unsure if the intermittency of renewable resources and variability was a kind of uncertainty. Their understanding of scenarios was a bit odd, showing that they were new in the space: they understood scenarios as potentially negative events. *Ah OK. Different scenarios. If you think about what negative events could largely impact our ability to either produce energy or what kind of events would lead to really really high electricity demand. So, if you have a grid where there is a huge amount of electric heating, a really really cold event would be one of these scenarios where you want to have a good understanding of how often do we have extreme cold events and how long do they last? And when they happen is it in general pretty cloudy, so we have zero solar and the wind is dead. So those are the kinds of scenarios we are interested in. So long cloudy periods where solar is going to be not producing much. Events where there is not much wind, so still events. And I guess heat events that would drive AC way up and cold events which could drive electric heating way up. Not just understanding them on their own but trying to understand how correlated they are in the extremes, which is something that I really haven't thought about much.* Then later asked why they had explored scenarios on their poster they related this to different policy options. And this was related to explorations of parameter space.	
Influences on uncertainty handling	
They admitted through about being junior to the space. They said their physics training had prepared them to think that there would be one correct model for everything. And the situation they were in now was very different with lots of different competing models. They also described how they were very used to dealing with statistical uncertainties in their physics work. However, in the energy space much of the data they were supplied with (e.g., by utilities) did not come with error at all. They thought that energy systems modellers had not done much to characterising uncertainty. However, they thought that uncertainty analysis imbues the results with credibility.	
Normative views	
Other Notable Themes	
Like some other participants they noted the technology cost issue of much of the costs of technology being trade secrets and unavailable to modellers.	

Participant:	**11- Nethermost**
Category:	Climate
Description	Post doc modeller on the topic of sea-level rise.
Background	Oceanography background
Methods discussed	Multimodel comparison, Initial conditions ensembles (mentioned), parameter ensembles (mentioned)
Types	Single model vs inter-model uncertainty; Parameter uncertainty, initial conditions, system representation

Conceptualisation as a whole

Uncertainty as a property of the models themselves seems to be the best way of describing this.

I guess there wasn't so much of an element of uncertainty in a kind of conventional sense, in the sense that you know exactly what your model did. It's a very well sort of determined system, you've got loads of data describing exactly what your individual simulation did, and how it kind of got to the state that it did. So, in that sense you're not dealing with uncertainty in terms of "how well do I know this quantity?" Because in the model world, you know perfectly. The kind of the uncertainties come into it in a more kind of abstract sense of, "Well, how well does this model represent the system that it's trying to simulate?"

They described how their ultimate aim was understanding this inter-model spread better.

They conceptualised uncertainty being different in models and in observations. In observations there are standardised methods for comparing something to reality. Precision and error and other concepts do not have a parallel I the context of modelling.

Types of Uncertainty and Distinctions

The participant made a big distinction between single-model uncertainty and inter-model uncertainty. The latter was described as not relating particularly to reality but was captured by the inter-model spread of results.

They had presented a post involving some scenarios at the conference. When asked about them, scenarios were narrowly about emissions trajectories.

So, these scenarios they're sort of like a piece of information that comes from a completely different area of expertise, that are a necessary input to feed my models and my research.

Influences on uncertainty handling

Early on in their studies they did not deal with uncertainty that much as they were just dealing with a single well understood model. See quote in top section.

They said that computational cost was a limit on how many scenarios they could explore. They also chose scenarios based on how easy they were to implement- like the 1% rise in CO2 per year scenario. This was also selected to allow them into AOGCMIP.

They said that they weren't modelling some uncertainties such as the methane effect in their models as it was not well understood in the literature. They were aiming at consolidation of one area of the literature base.

They talked about having to choose between different types of uncertainty and 'nail one part of the system down' for the sake of effort. They said that they took it on trust that others had made sensible decisions about ICs and parameter choices.

They said that parametric ensembles were more possible with more computing power. There was progress being made at nailing down what parameters DON'T matter.

They talked about being optimistic about pushing back the frontier of model development and including more uncertain elements such as glacial ice.

Nethermost: *Yeah, because these systems are new, and they're uncertain, and quite how to include them in earth system models is a really big frontier of climate prediction at the moment. They represent a really big part of, for example, sea-level change. Glacial melt is expected to be a larger contributor to sea level change by the end of the century than, for example, thermal expansion is. So, this suggests a really increasing role for spending more time thinking about those models and those systems, how we understand them, and how we incorporate them into climate models. More so than I guess the kind of the conventional, more sort of well understood, historically modelled atmosphere-ocean world. I think I think basically ocean models and atmosphere models, atmospheric physics models, are representing an increasingly small proportion of the total inter-model uncertainty of future predictions of particularly sea level change, but probably other climate relevant properties too.*

They said that some error-bar conceptualisations of model error were suitable in some situations, but not others due to the nature of the target system.

So, I think with models, it really depends exactly on the detail of the question that we're trying to ask. So, let's say you want to forecast temperature at a particular location 10 years from now. You could create an ensemble of forecasts with slightly different initial conditions. And you can run 10s, 100s, 1000s of simulations, and that would give you some sort of spread, some statistically tangible spread of your forecast of temperature at some point in the future. That's a useful way of trying to understand uncertainty that the uncertainty that's kind of inherent in the system, it's kind of trying to understand the chaotic nature of the model, its sensitivity to internal variability. But you can't do that for all sorts of modelling questions, right? Like, you couldn't do that for the sort of research that I do. If you were to run these simulations 100,000 times, how would you get a spread of sea level predictions? Well, on that kind of climate scale you wouldn't get an ensemble that has a sort of a spread in that same sort of way.

Normative views

Other Notable Themes

They talked about how they were confronted with an uncertainty about how different levels of forcing translated into different sea level rises. They said they just relied on the belief that the pattern would remain the same and the findings of others.

Participant:	**12- Branstree**
Category:	Energy, IAM
Description	Energy modeller delving into the world of IAMs
Background	Mechanical Engineering, Energy masters
Methods discussed	Monte Carlo, LHS Sampling, Simple scenarios, Scenario analysis
Types	Technology uncertainty, discount rates, climate sensitivity; black swans, black elephants; Rumsfeld system; structural uncertainty

Conceptualisation as a whole

Broad and a bit difficult to describe. A mature understanding of different types of uncertainty.

Types of Uncertainty and Distinctions

The participant was clearly very interested in uncertainties. They did not immediately talk about different kinds of uncertainty, but they did offer thematic areas where uncertainty is important.

Then when prompted they offered up:
[Laughs] I suppose there are black swans and there are black elephants, or I don't know what Taleb calls them. But Covid! Obviously! You know, the GDP impact of Covid, the kind of massive structural changes that a pandemic can drive that we just never envisaged. We have had two... are they called black elephants?

They understood the underpinning of scenarios to be a consistent set of assumptions that may or may *not realistic but are there to have a coherent and internally consistent set of assumptions that fulfil a narrative that made plausible and logically explore*

Influences on uncertainty handling

The participant was involved in developing a Monte Carlo Framework for IAMs. This uses Latin hypercubes. This gives a probabilistic rather than deterministic output. When asked about the motivation for this study they said that there was a hierarchy of information: single points > ranges. The aim was to fill the solution space. Previously things had been wrong in IPCC, and this keeps you robust against that.

When asked about the biases in parameter choices

They had also done some more basic work with some scenario analysis.

The awareness of the fallibility of parametric assumptions was said to be something like maturing and how much one reads across different literature bases.

You would hope the peer review would correct for some of that, but often times I can see that it doesn't. Certainly, regards Carbon Capture and Storage and how it is modelled. There is very limited technical robustness in how it is modelled. [Say] one group publishes, and then the next model publishes using the same kind of approach, then the next model publishes with the same approach even though the first one was wrong. Not wrong but... but overly simplified. I'm not sure I am answering your question. [….] There is a certain amount of echo chamber that goes on in the literature. I suppose branching out from your own normal literature to answer specific questions in depth, I suppose, is the main way of correcting your own biases. I would think.

They talked about uncertainty due to the overreliance on certain types of models. For example, CGE modellers at the time have become very reliant on their models.

They said that within IAM community only a certain set of people (who they were able to name) were interested in uncertainty. There was said to be a nascent bridge to the DMDU community as well.

When asked why some were dealing with things probabilistically and others weren't it was said to be able to models that people have available to them. *If I were to hazard a guess it's come from down to what people can do with their models, you know is it easy or not to reprogram your model to run thousands of scenarios or not and also the relationships that people have, the literature that people read will encourage them down one avenue or not. Ultimately a lot of the Integrated Assessment community is really small. It's like 200 people. They can't read everything. So, there are six dominant teams and there are maybe another 6 players there or thereabout. There are 12-15 models globally that are doing this so, you know, uncertainty analysis needs to bubble up to the surface to be a priority and then the feasibility of doing it can be kind of a limiting factor which either somebody grabs the bull by the horns and does it or otherwise focusses on something else*

They also gave a nice overview of how these factors related to different models.

Data availability was said to be a limit on how one could go about studying structural uncertainty in models.

They said that the national teams there was often more of a focus on uncertainty. Other groups were said to be a bit limited.
I haven't at the ETSAP meetings I am not sure that I see much, kind of, taking a structured approach to uncertainty. It's like here's 5 scenarios. Take of them what you will. Not really grappling with what are the insights that you are learning from this, and does it help your policymakers or does it muddy the water and give them false sense of accuracy and security in their decision-making process.

Normative views

We discussed the range of opinions regarding scenarios and probabilities. They said that some researchers used expert elicitation and then took this to be probabilistic.

Other Notable Themes

Participant:	**13 Loughrigg**
Category:	Energy, IAMs
Description	Energy Academic with a specialism in the assessment and modelling of uncertainty

Conceptualisation as a whole

They conceptualised modelling as not itself as aiming to describe reality. Uncertainties in their view were not about describing some truly existing thing in reality but are relative to what one is trying to achieve with their modelling. The participant repeatedly stressed that the models could not be identified with the real systems they are describing.

Modelling and scenarios were both likened to narratives, with models providing some tools for thinking through how particular futures might develop. They viewed the model result as suggesting potential dynamics that one can then evaluate to see if they may be relevant to the real world.

Types of Uncertainty and Distinctions

The participant likened scenarios to narratives: "*Well, to me, scenarios are essentially they're especially in the context of decade long time horizons, they're essentially, they're narratives, stories, more or less, that describe how specific events might unfold. Then models might be used to basically add some richness to the story, they're still part of the story as opposed to something else. So, the logic, of course, being that when you're looking at these very very long-time horizons and very very complex systems, the uncertainty space is so huge that what you're essentially then to do is that you tell different stories about how the system might develop; that then are to some extent, internally consistent, and so on, and also have a story about how things get there.*"

The participant mentioned parametric uncertainty and structural uncertainty.

Much of their conceptual understanding was rooted around scenarios. They used scenarios to describe many different methods such as Monte-Carlo.

Influences on uncertainty handling

They described broadly two approaches to uncertainty in a model:

- The isolation of some aspect of the model that one is interested in to find out how consequential it may be for something you care about
- Metamodeling exercises used to better understand the models as tools themselves.

The participant acknowledged that they themselves are no longer doing the model development but was involved in studies and uncertainty analysis.

They described how in the IAM community scenarios were the standard and had been for some time for exploring uncertainty. They described how the community has organised itself around the SSPs, which cannot describe the full range of possible futures. They also said that it was not only the scenarios chosen within a framework but the variables that you choose to vary the scenarios over.

Normative views

The participant expressed their displeasure at the use of some of the more extreme scenarios as they may be less useful. They discussed how there was pressure to attach qualitative probabilities to the scenarios.

"For scenarios as a whole. I wouldn't attach anything that even sounds even like a qualitative probability. I might, at best discuss plausibility like how drastic changes from how things look like now would be required for a specific thing to go somewhere? But again, I would have absolutely no way of estimating the likelihoods."

They viewed scenarios as useful when

Other Notable Themes

Participant:	**14- Whiston**
Category:	Energy, IAM
Description	Energy modeller. CCS into IAMs
Background	Chemical Engineering background
Methods discussed	Scenario Analysis, Workshops, Sensitivity analysis (mentioned)
Types	(Tentative) supply and demand uncertainties

Conceptualisation as a whole

This participant did not comfortably use a lot of uncertainty concepts. Uncertainty was really very thematic for them and seemed to relate to opportunities for model development.

Types of Uncertainty and Distinctions

The participant did not really talk about types of uncertainty. They talked more about uncertain areas or opportunities for model development.

Scenarios were conceptualised as differences between parameterisations. There was also a very limited conceptualisation of what scenario analysis might be: *scenario analysis, clicking on and off features of the models.*

Influences on uncertainty handling

The selection of constraints that one place on a model were described to be dependent on the literature base, the choice of the modeller and the model that one has. For example, overshoot from models was disfavoured in the literature for policy reasons.

The interview repeatedly came back the technical feasibility of running particular scenarios. For example, some are more suited to particular SSPs:
Whiston: *There are some integrated assessment models which are specialising in it. So usually what the integrated assessment models do- one team their model is better set for SSP1 others is for SSP2, others for the other models. And then they do the Intermodel comparison where they look at different pathways. Or they try to model the other SSPs in their own model and see what happens. So, the big integrated assessment modelling teams they do this kind of exercise.*

They mentioned that a thematic focus was driven by funding. In the UK for example, funders were interested in CDR.

They also said trends in this area had changed as now BECCS is not the only CDR in the game.

Normative views

Other Notable Themes

There was a limited conceptualisation of what scenario analysis might be: *scenario analysis, clicking on and off features of the models.*

They were pessimistic about being able to characterise the demand side in EnSMs and IAMs. They were optimistic about technology cost uncertainties due to the growing literature base.

Participant:	**15- Yewbarrow ***
Category:	Energy, IAM
Description	Senior energy Modeller with an interest in Uncertainty and Policy advice. Used lots of different kinds of models.
Background	Physics Undergrad, Science and Technology Policy Grad
Methods discussed	Scenario analysis, OOAT sensitivity analysis
Types	Deep uncertainty, Aleatory uncertainty, Epistemic Uncertainty, Structural Uncertainty

Conceptualisation as a whole

It is a bit difficult to pin down how this participant understood uncertainty. It was clear they understood it to be many different things as they separated uncertainty by system model system sub-element and also aleatoric/epistemic.

Types of Uncertainty and Distinctions

The participant identified energy modelling and IAMs dealing with situations of deep uncertainty. When asked to define what made these situations deeply uncertain, they said it was the system complexity, the long timescales of the models and the fact that they were modelling social systems.

They conceptualised there being a spectrum of sophistication of uncertainty analysis. At some point one-at-a-time sensitivity analysis becomes scenario analysis. They said that scenarios had to be at least partially explainable or understandable.

They mentioned aleatoric uncertainty and then defined it as uncertainty that would not be reduced with more information.

Structural uncertainty was mentioned in a discussion of intermodal comparison.

Influences on uncertainty handling

The participant said that a lot of the big energy models focussed on uncertainties associated with things like technology costs as that is what they are most familiar with, being engineers. The nature of the systems and the lack of observations mean that people sometimes just give one number.

So, because we're dealing with deep uncertainty, that's slightly different than if you're taking measurements of pollutants in a river or you're trying to measure the density of a metal. I mean, any scientist in those fields would never give one number without some measure of uncertainty around it. So, because we're dealing with deep uncertainty, then sometimes we're worse at dealing with uncertainty.

They seemingly endorsed a sort of Boumas-y approach to understanding what modellers do:
Yewbarrow: *So, there are two things. One is, is because modellers are like magpies, right, they take different bits from different people, right? So, we take population estimates, but we don't know anything about demographics. So, it's harder to do uncertainty analysis- you just choose someone else's outputs, you know, the UN's population figures. You might have a high, medium or low, but you don't really challenge that too much. Whereas we know much more about individual technologies, people really do understand how wind turbines work, and what their efficiencies are, and what their costs are. So, they're much more comfortable doing uncertainties.*

They said that the 'client' so to speak affected the theme of the uncertainty analysis in terms of the topic that they may be interested in. For example, nuclear power. They then said this influenced the uncertainty analysis in two ways:

- The tenders for proposals that go out
- Direct or indirect feedback when engaging with the researchers in things like workshops

We discussed how people's prior beliefs might affect their scenario selection. They described how policy priorities can affect this and also big events like climate conference shift the agenda on scenario selection. But the speed at which one can adapt to the changing agenda depends on if they need to build a new model.

Pretty quickly, I mean, if you have to build a new model, that takes a long time, and you probably should scrap models, then you should build new models. But that is not what happens because you've invested so much money in the data and the calibration and the software and the publication. So, you have many models that can be applied very well, or not very well, or not very well at all, but it can be applied to whatever is the topic of the day. So, you see, you've seen lots of integrated assessment models recently trying to run on low demand scenarios. They're not very good at doing that, right. So, they have technologies and economics and climate interactions, but they don't have much about society and individual choice. But they're still trying to run these very low energy demand scenarios, because that's what seems to be the hot topic at the moment.

The participant said that when you start trying to model something that your model is not designed for you end up going for more scenario-based approaches. *Because if you're, if your model doesn't have super detailed workings of population demographics, all you can really do is run, you know, here's population scenario one, population scenario two.* We also discussed how only some smaller models could run probabilistically due to computation constraints.

They said that in the UK there is the most sophisticated selection of model users for energy versus any other area like public health. However, many policymakers do like having hi-mid-lows. *And as you go higher and higher up the policy chain, you have to simplify more and more and more while still convincing them that look, if you wanted there's all this uncertainty analysis waiting for you, but they're not interested. By the time you get right up to it. If you have ever talked to the Secretary of State, when they're really not interested in more than more, let's just think about two or three key scenarios two or three key decision points. And that's all I have time to think about.*

They also talked about the cultures at different national institutes: I *think it's more about the culture of the individual teams. Or their particular training. As a rule of thumb, then the Japanese modellers are more comfortable doing scenario analysis and thinking about, about that process. And the Germans are more comfortable just doing a bog-standard sensitivity analysis in a very structured way. Now, that is a cultural stereotype. But it's also driven quite a lot by who was the main model leader is, who is the leader of the of the lab, how he or she thinks about uncertainty- that feeds into the team quite a lot.*

They also said training at different institutes was a factor.
They described how model intercomparisons were reducing model diversity as people self-selected to avoid embarrassment,

Normative views

Other Notable Themes

They were pessimistic about being able to deal with socio-political uncertainties. They said that more social scientists need to be hired by modelling teams. They actually characterised IAM work as not very interdisciplinary. They later said it was difficult finding social scientists who might want to get involved in the modelling.

Participant:	**16- Blencathra ***
Category:	Energy/ IAM
Description	Energy modeller with an interest in uncertainty and policy
Background	Engineering background with policy masters
Methods discussed	Scenario Analysis, Method of Morris, Monte Carlo, Robust Optimisation, Stochastic Optimisation, Modelling to generate Alternatives, Sensitivity Analysis
Types	Parametric Uncertainty, Structural Uncertainty

Conceptualisation as a whole

There were two (related) contexts in which uncertainty analysis was understood to take place.

- As a form of model introspection
- For decision support

Types of Uncertainty and Distinctions

They divide all uncertainty into either parametric or structural:
So, the one key distinction I would make with regard to uncertainty is the way that I think about it is: you have parametric uncertainty, and then you have structural uncertainty. So, everything I've mentioned so far is you know, parametric uncertainty. And the way that I think of parametric uncertainty, it's uncertainty in the parameters associated with things that I'm modelling. […] And then basically everything else that's an uncertainty, that's exogenous to the model I consider to be a structural uncertainty. And there's tons of those, and we tend for the most part to ignore them. Even though the probably swamp... well, I shouldn't say that. But they're at least as important as the parametric uncertainty. And I think for structural uncertainty, there's a couple things. One is we've applied to a method called "modelling to generate alternatives", where you have you heard of this before, where you modify...

Later in the interview structural uncertainty was related to the fundamental structure of the model. Things such as the assumption of an omniscient social planner. Unk-Unks were described as a subset of structural uncertainty. They were optimistic about improving parametric uncertainty and pessimistic about structural ones. When asked how scenario uncertainty fit into this schema, they said that they didn't know. But then it seemed from their discussion as if this was more of a tool for exploring either, but mostly exogenous uncertainties.

Interesting structural uncertainty was described as exogenous to the model. Perhaps in the sense that parameters represent all the structures that are in the model.

They conceptualised scenarios as those things that are exogenous to the model that one changes. They said that most of the work out there that does scenario analysis is quite limited. The selection of a particular scenario set might actually belay the true underlying uncertainty.

Influences on uncertainty handling

They understood some methods to be involved in what they called 'model introspection'. The other kind of task was described as being related to decision-making or planning. But the two were linked in interesting ways:
A lot of times will actually we've done studies where the introspection actually informs more of the planning and the uncertainty we account for in the planning. We've done work, for example, in South Sudan, where we were trying to look at electricity planning under conflict. And so, the first step was we applied method of Morris to figure out "well, what are the most sensitive parameters in the model?" Oh, an even better example. So, there's that example, there's also one that we did looking at emissions uncertainty in the US. And we did the same thing, we applied method of Morris figured out what are the most sensitive parameters. And then we use that to do a Monte Carlo simulation with just the 10 most sensitive parameters. So, a lot of times the introspection can help you narrow down the uncertainties you need to focus on when you're trying to answer that more specific research question.

We discussed the issue of increasing model complexity (below) and the causes for it. It was their view that this was linked to the need to show that you have done something. Also, novelty is necessary for publishing.

Other factors constraining exploration of uncertainty:

- Availability of grad students
- Effort
- Funding

They said that uncertainty analysis is often related to research questions. Which may come from projects or from policy agendas.
So, in a lot of cases, as an academic, we're kind of coming up with them on our own, we're serving the policy landscape, the academic landscape, and saying, "What are interesting questions that we can that we can answer?" And, of course, those questions are bound by the models that we're using, there's tons of interesting questions where you know, using an energy system model is inappropriate. So, you know, when we're doing the model base work, of course, we steer clear of those.

They understood that energy models could not deal with values-related questions like equity and justice.

Normative views

Other Notable Themes

They said that most of the work out there that does scenario analysis is quite limited. The selection of a particular scenario set might actually belay the true underlying uncertainty. They also talked about how these scenarios act an anchoring heuristic where people then assume that people then just get focussed on that set of possibilities. They described this as one pathology of the peer group. They also lamented slightly the increase in model complexity.

One was what I already mentioned, with the just very limited number of scenarios, like "we're going to look at, you know, global emissions trajectories. And then here are the five that you get!" You know. And then the second is I noticed an increasing creep in model complexity, that isn't necessarily warranted. And I could go on about this forever, and I've written about it. But essentially, the argument boils down to we don't really have a way that we can strongly validate the models. So, in the absence of strong validation criteria, what do people do? They continue to be energy modellers, they continue to do the work, they just make the model more complicated. But we don't know if that increase complexity makes actually makes the model better.

We discussed how values could be approached as a sort of qualitative addendum to scenario analysis. That this could be achieved through discussion. They acknowledged that many energy models were in fact already normative, and this made some interpretation of model outputs difficult.

We also talked about model dialling and how choices of data and so on can help modellers get results into believable ranges.

Participant:	**17- Catbells**
Category:	Energy/ IAM
Description	Energy modeller with a particular interest in uncertainty analysis methods. Model developer but mainly now does model interpretation.
Background	
Methods discussed	Open sourcing, Monte Carlo, Stochastic Programming, Adaptive pathways, Global sensitivity analysis, real options analysis
Types	Andy Stirling's framework, dynamic uncertainty; unknown-unknowns

Conceptualisation as a whole

Scenarios for them: *So, a scenario is a plausible representation of the future, and normally has no kind of probabilistic interpretation. But it needs to be internally consistent in that the assumptions encapsulated within the scenario must make sense together. And it must be plausible, so that future must be possible and must be able to occur.* This plausibility condition may be subjective however in their mind.

Types of Uncertainty and Distinctions

The participant mentioned Andy Stirling's framework in particular when relating methods to types of uncertainty.

They said that scenario analysis does not capture dynamic uncertainty. This was related to things like temporal system change and path dependency. This could be understood with stochastic programming.

They also mentioned Unk unks and related this to the world of the DMDU community.

Influences on uncertainty handling

We talked about how the different uncertainty analysis techniques require a different interpretation of uncertainty. MC can run into issues as it may require the distributions of things that we simply don't know what they are. An interpretation is difficult when you have an optimisation model. In a simulation model this is a bit easier to interpret.

They discussed how they had done some work training academic in the third worked to use their models and make scenarios.

They talked about budget, individual interest and effort being constraints on exploring uncertainty.
Catbells: *I think, probably the key thing to say is that it's often not even thought of [laughs] unless someone has a specific research interest in that, right. Quite often uncertainty is deemed as a sort of second order issue. And that often the most pressing issue, particularly in the domains that our group works in, the key issue is just getting the tools, the basic tools in the hands of the people that need them so they can better plan their energy systems. And the budget constraints and so on of the projects mean that really developing a set of scenarios and running the model a few times is, is kind of all you can do.*

We discussed this more and they said that it wasn't really budget precluding things and that some simple sensitivity analyses were low hanging fruit that are easy to implement.

We discussed how the open-source paradigm was making certain kinds of uncertainty analysis easier as they got over path dependencies:
But with the open-source modelling, if the models are built using open-source software, like Python, or any other type of modelling language, and you can go in and edit the source code, and the data structures are transparent, and so on. Then it just becomes a lot easier to extend and link that to the Energy system models or to other tools. And that's exactly the approach that I'm able to take with some of these open-source tools.

There was an interesting discussion of how the different understandings of policymakers on the nature of uncertainty.

We talked about the different conceptualisations in the disciplines. Engineers were characterised as being used to factors of risk, economists were Knightian, and natural sciences are used to the uncertainty as conceptualised in experimentation.

Normative views

They had a number of views on scenarios:
So, a useful scenario, or useful set of scenarios, are those that actually illustrate how the outputs change in your model as, as the inputs in the scenario change, and represents the changes of the key drivers to the energy system. So, these can be, for example, like technology costs or key resources or demands. In comparison, that an unusual scenario is one in which lots of things changed but there's no difference in the output from the model. That doesn't really provide any type of insight into what's important. That just shows what isn't important. I mean, that may be interesting, but it doesn't make the scenario particularly useful.

They discussed an interesting method that they had where they started with a global sensitivity analysis and then found the most important parameters and then worked back to designing scenarios from this. This is interesting as it is sort of a metamodeling exercise describing an exogenous output.

Other Notable Themes

Pessimistic about Unk Unks. Optimistic about things policy has influence over.

Participant:	**18 Fairfield**
Category:	Energy
Description	Energy modeller who has worked in a number of different teams

Conceptualisation as a whole

There is an extent in this interview to which the idea of exploring uncertainties becomes synonymous with exploring different questions one may have about the energy system. They did not have a particularly numerical conception of uncertainty and seemed to see the activity of exploring uncertainty as separate to normal modelling activities.

All modelling was related to the idea of running 'what-if exercises' but in particular simulation modelling. The participant underscored the importance of the conceptual difference between optimisation modelling and simulation modelling. Simulation modelling was described as the amalgam of all of one's assumptions. Optimisation modelling was described as more normative. They described models as being analogous to toy train systems and only being as good as the level of detail allows.

Types of Uncertainty and Distinctions

The participant did not conceptualise a wide number of different scenarios but focussed on scenario uncertainties. The identified uncertainties associated with different target sub-systems.

Towards the end of the interview the participant mentioned that there were particular kinds of uncertainty like 'epistemic' but confessed to not knowing enough to give a full description of these.

Robustness seemed important for this researcher. They conceptualised robustness as something similar to traditional definitions of rigour, including transparency and openness to scrutiny, understanding the relationship of drivers to outputs, proper version controlling and code management.

Influences on uncertainty handling

The participant had worked at a number of different institutions and noted that there were different influences on uncertainty handling at each one: A major UK research University, an intergovernmental organisation concerned with energy and a national university providing advice to a small country.

At the IGO the participant noted that it had a very particular product that was expected to be produced in a very particular way and the maintenance of its reputation was very important, given the public scrutiny it is under. It was described as very top-down

In their current line of work, they described how their modelling time was split between traditional curiosity-driven research and consultancy work for stakeholders such as the government. The way that these stakeholders understand the role of modelling and uncertainty information was repeatedly described as being very important and the phrase 'mature understanding' came up repeatedly. On one end some stakeholders see the modelling as a predictive crystal ball and on the other they understand the limitations of modelling. The presence of these mature stakeholders was described as being conditioned on a nation's history of consuming energy modelling- for example the UK has used the results of energy models for a long time.

The presence of different kinds of staff was important for the uncertainties explored. At their current group they focus a lot on technology uncertainties as they are engineering. At the previous university they had a much more interdisciplinary team, so they had a broader understanding of uncertainty.

They described the main kind of uncertainty analysis that they do being a sort of ad-hoc scenario analysis as that was demanded by stakeholders. *And honestly the main form of uncertainty analysis that we do, are these just kind of ad hoc scenario variants? So, turning on and off key technologies, I suppose, is the main one. And those are really driven by how our stakeholders would ...what questions they would ask, like "What if this doesn't work? What if that doesn't work?"*

They also described how the presence of individuals with interest in particular areas of uncertainty in a group affected the trajectory of that group. At some institutions it is a central focus and at some it is secondary.

Normative views

Other Notable Themes

They mentioned that many people will not think about uncertainty in their day-to-day work and will just get on with the job of modelling. It seemed that 'doing uncertainty analysis' is considered a research stream in itself rather than the natural and inevitable accompaniment running models.

The participant relayed an anecdote about how some of their model results has been misinterpreted in the national news.

Participant:	**19- Rannerdale**
Category:	Energy, IAM
Description	Energy Modeller Stepping into the world of IAMs. Not a developer but a model user.
Background	Chemical Engineering and Economics
Methods discussed	Scenario analysis, Monte Carlo, Scenario discovery techniques
Types	None apart from thematic areas

Conceptualisation as a whole

They frequently used the concept of 'axes of uncertainty' to discuss the ways in which one could be uncertain.

Rannerdale*: Yes. By that I mean... umm... an axis of uncertainty is a thing that is a particular aspect of the future which is uncertain. The axis describes the range from one extreme of that thing to another, so an example axis of uncertainty is future GDP growth. At one end of the axis is low growth and at the other growth is high growth. Similarly with solar costs at one end of the axis is low costs and the other is high costs... or investibility or cost of capital of renewables, one is high cost of cap, and one is low cost of cap and so on. In this sense I use axis to mean the particular aspect, or the particular input variable that we are looking at.*

Overall, I would say that the understanding of uncertainty of this modeller was very synonymous with opportunities for model development.

Types of Uncertainty and Distinctions

They did not mention any particular types of uncertainty outside of thematic areas.

Scenarios were conceptualised as elements of storylines that codify inputs to EnSMs. Pathways on the other hand are the outputs of models that you get from scenario inputs.

Influences on uncertainty handling

A lot of the beginning of the interview was all about the selection of scenarios. We had discussed how they had gone from running simple sets f scenarios in the past and were moving towards doing Monte Carlo analyses. At the time of the interview, they were still trying to decide which parameters they were going to vary and by how much.

- They were limited in terms of the number of models runs they could do due to HPC capacity
- They said that they would like to be more familiar with scenario discovery through clustering of model results
- They admitted that a lot of the conversations were driven by what seemed cognitively available to them. Like what is big on twitter or in the news. The example of the pandemic was used.
- They said that they had to make pragmatic choices about what to do due to the intractability of dealing with too many uncertainties.

They admitted unfamiliarity with a number of techniques on a number of occasions and this seemed to be a potential limit on the ways they could deal with uncertainty.

We talked about funding and how it shapes uncertainty analysis. They described how grant proposals require quite established processes and methodologies and this was a constraint.

I don't think anyone would fund a grant proposal that said "we will sit in a room and we will look up, not only different uncertainties about the future, but we will look up all the different ways to understand the uncertainties about the future and we will think about how to model those and we can't give you techniques to do that because the project will be about arriving at techniques to do that." In a sense that would be a really great grant proposal and if I felt that the people proposing that had track record and credibility, I would fund it. But that won't get funded because it doesn't have milestones and methodologies and that is actually one of the kinds of fundamental limitations of science in my view, as I have discovered it over the last ten years since I have been a research scientist. It's that writing grant proposals forces us to overly constrain what we will do and how we will do it.

They said UK funders gave modellers more scope, but EU Horizon2020 was quite restrictive. Very few grant proposals explore uncertainty as a primary goal.

We discussed how research groups will strategically present funding requirements to research funders. T*hey come from the big groups like PBL or IIASA or.. whatever. They kind of say "we need urgent discussion on negative emissions technologies as this is really prominent in scenarios or pathways." But then you kind of think "but it's you guys who made it really prominent and you're kind of running round saying the house is on fire, because you have produced all this analysis saying there is a massive role for BECCS or METS [?] or whatever" And so there is quite a lot of grabbing of attention and prestige and money, and it is all part of the same thing, I think.*

They were quite cynical about institutional steers on uncertainty handling and believed it was much of the same 'running after the ball' or following the zeitgeist.

Normative views

Other Notable Themes

Optimistic about technology costs and characterisation. Pessimistic about the fields ability to anticipate large scale systemic changes that will be significant.

Participant:	**20- Latrigg**
Category:	Energy
Description	Mathematical Energy Systems Modeller
Background	Maths
Methods discussed	Least-worst regret analysis
Types	Statistical uncertainty, Imprecisely defined quantities

Conceptualisation as a whole

Uncertainty for this participant was, at first, most associated with statistical uncertainty and numerical values. However, they were keen to stress there were a multitude of ways to interpreting these things. They also described a number of non-mathematical ambiguities.

Types of Uncertainty and Distinctions

Their conceptualisation of scenarios was very minimal: *A Scenario is simply a possible realisation of the future. It doesn't... The word scenario alone doesn't carry any implication other than that. There are various things one can unpack around that and quite often effectively scenario ends up meaning quite different things when it is used in different contexts*

They were clearly familiar with things like Knightian uncertainty and thought this to be too binary a distinction and misapplied in their field. They talked about how uncertainty taxonomies should not be prescriptive but were better off as pragmatic tools.

Influences on uncertainty handling

We started off the conversation by chatting about what was a good uncertainty analysis for decision support. A few things came out:

- Having the right people with the right skills to do the analysis.
- Good communication with policy
- There is a difficulty as modellers cannot make value judgements about what the political trade-offs for courses of action are.

This participant was very interested in risk to energy systems. They understood that many of the vents that they were predicting may be very hard to understand theoretically as they were talking about events that may never occur. They said how this went against the grain f a lot of people's frequentist intuitions. They also talked about how people with different disciplinary trainings of probability thought differently.

They described how all uncertainty assessments necessarily contain an element of expert judgement.

We talked a bit about imprecisely defined quantities and how some people wanted to add numbers to things that were inherently non-numerical. Or they wanted to mix things with fundamentally different meanings (like by giving them monetary value). *You have to be very careful when monetising these because you can end up with a sort of false precision in your calculation or you end up losing sight of fact that what you really have is a multi-objective situation where you have a number of different factors which are not naturally quantifiable on at the same numerical scale. So that is the kind of thing we want to try and make some contribution on through the medium of electricity security of supply and risk analysis, which has the benefit of both being a big deal and it's something where actually the mechanics of doing the calculations are quite simple.*

When we discussed the specification of uncertainty analyses the participant gave the following influences

- People have different agendas
- Policy questions do not always convert into value-neutral outcomes so easily (example of 'what will happen in winter')
- Lots of small assumptions that go into models are hidden from decisionmakers
- Models are mapped onto decision questions
- Publishing incentivised people to keep *banging out papers*. But REF pushes against this tendency.

The participant gave the example of TIMES as a framework that was difficult to interpret due to the perfect foresight optimisation. The difficulty in interpretation is locked in due to all the work that has been put into the tool. *Actually, I became known as something of a TIMES sceptic from the first seminar I attended in early 2007, which was about TIMES: I asked a question "you are doing deterministic runs on different scenarios, that's not how the world works. The difficulty is that a lot of work has gone into these conventional frameworks, which from a decision analysis perspective there are perhaps some problems.*

They felt that linear programmes are popular as they are easy to build, and y*ou just stick them through a commercial solver, and you get results out for quite large problems.*

Normative views

A LOT of the interview covered issues around the use of scenarios probabilities and the appropriateness thereof. Here are some of the points:

- It is not only a debate over whether it is OK to define probabilities- but defining scenarios is also subjective *Of course, that is nonsense because defining a list of scenarios or an interval is subjective in exactly the same way as quantifying probabilistically would be. […] If you are defining effective your interval, which is, even though it is overtly a list of scenarios, implicitly it is an interval that they are defining by the most optimistic and pessimistic scenarios. So, the ends of that interval are a matter for human judgement it has to be done somehow by expert elicitation.*
- Least worst regret analysis is chosen as you only need optimistic and pessimistic scenarios to do it. So, it is convenient.
- If you can cover the uncertain space densely with scenarios, then the choice of scenarios becomes less of a sensitivity.
- Having a small number of scenarios may imply these are the only possible futures. 'Scenario weights' can be given instead of probabilities to avoid this implication
-

Other Notable Themes

Participant:	21 Brisco
Category:	Energy / IAMs
Description	Energy systems researcher working on models and long-term energy projections.

Conceptualisation as a whole

Uncertainty for this participant was quite a broad concept that covered the whole of the modelling process and the academic community.

It was clear that 'doing uncertainty' was conceptualised as a special kind of task outside of that from normal scientific practice and tha1t only certain people were interested in it.

Types of Uncertainty and Distinctions

The participant clearly identified two kinds of uncertainty:

- Parametric uncertainty that includes uncertainty in all the numerical inputs into a model. This included the scenarios that one uses.
- Structural uncertainty that includes everything else in the modelling process: alterations of models, choice of model framework, decisions on behalf of the modeller, influences from research institutes.

Yeah. So, I think for me in that sense it quite broad. Because it's anywhere in between basically model equations or model formula... because input parameters are really a kind of parametric uncertainty, it's really more the numbers that go into the model. But then anything that can... any model modifications are already for me a structural uncertainty. So that's one aspect.

And then later in the conversation when asked to elaborate on types of uncertainty: "*Yeah, I think for me, it's kind of anything that is not 'parametric', I always call it 'structural'. But I think one can expand that, right. Because to some extent, I already mentioned it, sometimes it's just model structure. And in other cases, model framing, what the model is used for who is the modeller. It all eventually still boils down for me to structural uncertainty, although it's much, much broader.*"

They conceptualised scenarios as at a minimum 'what-if' exercise. However, they regarded as there being too large a proliferation of different energy scenarios and that it is better to have scenario sets that are considered 'more likely futures'. At one point a scenario exercise they engaged in was conceptualised as exploring structural uncertainty.

When probed for more types of uncertainty the participant discussed the "unknown-unknowns". But said that in many ways these are a kind of structural uncertainty. Structural uncertainty later on was also conceptualised as being reducible.

Influences on uncertainty handling

The participant described a number of potential influences on uncertainty conceptualisation and handling:

- In their national context the funder will not provide funding for the re-use and adaptation of models as there is a strong focus on novelty. This limits how baroque the models can become and means they focus more on different modelling techniques.
- The effort or time that one has to give to ana analysis
- The interest one has in performing an uncertainty analysis
- The type of institution one is at: more policy-focussed institutions are less interested in 'academic' issue of uncertainty
- One's disposition towards chasing trendy topics versus one's interest in uncertainty
- The effort required to automatise the model that you have to perform an uncertainty analysis (is the model 'big' etc). The size of the models in some fields was said to preclude any uncertainty analysis (e.g., hourly electricity dispatch models)

They also discussed the difficulties that a researcher may have themselves in interpreting their results and that when uncertainties become very large, researchers may no longer know how to interpret their results. This may make them want to limit their uncertainties.

Normative views

Unhappy about the large proliferation of different scenarios from different energy groups and in the grey literature. Thought that this has become too unwieldy.

Other Notable Themes

The participant also described an issue of runaway uncertainty. That when they start properly investigating their uncertainty, the uncertainty will just grow and grow and become somewhat unbounded. Their model result would then have a smaller range of cases in which they are applicable.

The participant talked also how one realised that when your uncertainty is large enough you can get practically any outcome. They wanted to see more research about making models more accurate by closing off the uncertainties that are not relevant to a particular context.

They described how there has been a partial switch to looking more at structural uncertainty with the availability of more computing power.

They said that a challenge was to address is what we do once we have found out that uncertainty is large. This was brought back to the point about increasing accuracy by finding out what is not relevant for an analysis. They seemed to believe that pursuing an understanding of uncertainty is only useful to a point. They suggested that I ask future participants about what uncertainties can be left out of analyses.

Participant:	**22- Weatherlam**
Category:	Energy, IAMs
Description	Energy academic primarily working with ESMs, but also IAMs

Conceptualisation as a whole

This academic discussed uncertainty in a way that was almost synonymous with opportunities for model development.

Types of Uncertainty and Distinctions

They described themselves as mainly exploring the different *assumptions* inputted into the model rather than the *structure* of the model.

When questioned about the structural uncertainties they related this to the basic modelling paradigm that is used (optimisation etc), the detail of the different sectors within the model.

They described scenarios as 'a future of an energy system'. They said that this could be plausible or not and that plausibility is quite subjective and that they should explore both implausible and plausible futures.

Influences on uncertainty handling

They described how the kinds of uncertainties they explore had a path dependency originating from some high-profile research conducted previously by a number of PhD students. They described how this had given their institute a lot of credibility both among the research community and with wider stakeholders due to the media reception of the work.

They described how the apportioning of detail to different sectors in the model was important to the outcomes that you would see.

The participant mentioned that value-ladenness had an influence on the uncertainties that one wanted to explore. When asked to expand on this they described the value-ladenness as disciplinary bias where, for example, engineers may be more interested in exploring solutions to do with technical fixes like hydrogen. They described having used NUSAP to try and understand this bias in analytical framing of research.

These disciplinary biases were described as the amalgam of disciplinary training, previous research experience and previous employment.

The participant also discussed how one's political leaning affected the framing of modelling exercises. "*I don't know if you know the Grubler [at al Nature paper] 2018 paper that looked very strong demand slide actually. [Interviewer: I think I do, yeah] It showed that the global energy system could reduce energy demand by 40% relative to current levels. And that was done using a whole load of kind of strategies. I suppose what I'm trying to say is I'm not sure that the [Centre-right think tank] would come up with that specific analysis because of the kind of interventions they were talking about. Whereas the [Left wing think tank] might. So, I think I think there's a lot in terms of in terms of our sort of political leaning that also influences how we think. More in terms probably the sort of analysis framing piece in particular.*"

They said they had done some modelling work that included some extremely ambitious demand side scenarios with strong restrictions on many activities such as housebuilding. However, they understood that these scenarios could be viewed as less plausible, depending on your political persuasion.

We discussed how the model 'paradigm' restricts and limits the kinds of uncertainty that one can pull from an investigation. The focussing on specific objectives removes 'the messiness of the real world'.

We also discussed

- how the policy environment created a demand for papers on particular themes
- How particular funders championed and pushed particular modelling frameworks over time
- How different funders and stakeholders may be interested in different themes. But not so much about how those stakeholders want those uncertainties presented.
- How the personalities in a group might shape the uncertainties one explores "*I mean if you have Arthur Petersen in your group, you might be more likely to be working on these issues than if you were working with others who hadn't really touched on these kinds of areas before?*"

Although the participant often discussed uncertainty exploration as synonymous with model development, they also discussed how whether or not an uncertainty analysis is built into a grant proposal is based on the interest of the researcher. It's also more about the application of methods known to the researcher, rather than the thematic area.

Normative views

We discussed how they considered it useful to explore potential scenarios that may be considered politically unacceptable or highly improbable and how this might reveal certain things. When asked about how they understood 'unrealistic' they described it as more of a feeling.

Other Notable Themes

We discussed how the normal mode for model collaborations was not necessarily inter-model comparisons for Energy systems modellers, but collaboration with other disciplines, often on a national level towards some aim. They described how this had broadened some of their scenario thinking at their institution.

They conceptualised the socio-political domain as something external to their area of study, despite modelling socio-technical systems. They mentioned that some colleagues were trying to model aspects of political economy and behaviour. They seemed unsure if this was ultimately intractable.

Participant:	23- Greatend
Category:	IAMs
Description	IAM modeller/developer working in a large IAM modelling group, specialising on Bioenergy

Conceptualisation as a whole

They discussed how they believed that uncertainty in the context of Integrated assessment was irreducible, and that scenario analysis was therefore needed.

Often during this interview, the participant discussed methods for exploring uncertainty as synonymous with the *types* of uncertainty themselves.

Types of Uncertainty and Distinctions

When asked for types of uncertainty the participant was more comfortable talking about methods for uncertainty analysis than the types themselves. They were aware that parametric uncertainty is related the model sensitivity analysis. They drew a distinction between this and scenario analysis, which requires varying multiple parameters at the same time.

Parametric uncertainty was described as having the ability to be 'multiple' when different kinds of parametric uncertainty combine. Monte Carlo analysis is the 'cumulative effect of parametric uncertainty'.

The participant also discussed 'implementation uncertainty' as uncertainty about the social feasibility of the solutions that their models find:
"*It's the implementation uncertainty of our scenarios. Because the IAMs, as I said, we're mostly engineers, maybe economists, we come up with these nice abstract models and we project the future. And then we have people on the social sciencey side, telling us, "You know, what the hell are you talking about? This is this stuff is insane." Or they're saying, "you're not going far enough!" I don't know. So how uncertain are our results from a social perspective? Now, I don't have any solid research questions there or a research program. So, I don't know how to define it.*"

Later in the interview the participant also mentioned methodological uncertainty as being explored when the results of different models are compared.

Influences on uncertainty handling

They said that the principal kind of uncertainty analysis they do is simple sensitivity analysis. They distinguished this from scenario analysis by the fact that in a scenario analysis you change lots of parameters at once.

The technical factors at this person's organisation were sever, not only due to the computational complexity of the models that lead to long model run times, but due to the use of a bespoke programming language to code the mode. This had a number of other repercussions such as the fact that it made it impossible for other to audit their code.

They discussed in some detail how they came to work on sets of low demand scenarios. The described how they had been previously criticised for relying too much on CDR in their model. There came to be a race to design a scenario where deep mitigation could take place without the use of BECCS. A number of institutes published on this with different approaches. They described the role of these different scenarios that allows you to look at the commonalities between successful ones and to learn something.

When asked about what was causing this rush to find these new 1.5 scenarios the participant descried a history of critique and reaction to that critique that had driven model development for some time. However, the reaction they could have to these critiques depended on the structure of the model that they already had. "*And this depends... obviously the critique drives us. But it also has to do with how advanced our models are. Because to be able to do something like this, you have to have a model that can represent it. So, for instance, the lifestyle scenario that I mentioned, that benefited from the residential energy model that I had made. Previously, as I told you before I started, there was a smaller GDP, residential energy use and a regression. There, you don't know how much the shift of the line based on improved behaviour. But once we had a model that was more detailed, that different energy functions, different income groups and things like that, you could immediately come up with a better estimation for how much behavioural change affects people choices.*"

Model development was described as requiring both funding and a supply of good interns who could then be hired to work on some aspect of the model.

Policymaking at the moment is pushing for downscaling of model results to more useful scales. Apparently, there is money available to do this kind of research.

MIPs were described as a very useful exercise, but as they are unfunded this throttles the amount they can be engaged with. They talked about how some of their MIP work had piggybacked on other money that was available. Some EU-funded MIPs are more generous.

Normative views

The participant seemed slightly frustrated that MIPs had not managed to fully unpack uncertainties form the black boxes.:

What the [MIP] process revealed... […] but also another paper by [another academic] where [they] looked at why different models projected different futures for the electricity sector. What we show is the actually techno-economic parameters, costs and efficiencies, aren't that important. It's actually more complicated like that. Model structure is way more important. And there's lots of critical areas. So, this uncertainty- we didn't clarify the uncertainty, we just kind of put it into boxes. And which is a bit annoying, because one of the purposes of these experiments was to kind of open the black box of the model, because we get a lot of criticism that IAMs are black boxes- a valid criticism. So, part of these MIPs is to open the black box, like, "Okay, this is how the model works. This is what drives the results." But in the process of looking into these details, we're like, "oh, okay, in the big black box, there's lots of brown boxes." So that has to be looked into first.

These MIPs are also limiting as you have to design a single experiment compatible with all MIPs.

Other Notable Themes

Participant:	**24- Esk**
Category:	IAM
Description	Senior IAM modeller, previously developer, now coordinates the programme
Background	Engineering Undergrad and PhD
Methods discussed	Monte Carlo, Robust decision-making, MMEs, Expert Elicitation
Types	Objective vs Subjective uncertainty; Methodological Uncertainties vs Real Uncertainties

Conceptualisation as a whole

They seemed to understand that uncertainty was a part of everything. But especially it was about decision-making, and they always came back to the research questions that uncertainty was in reference to.

So, I mean, I don't think about uncertainty is its own thing, I only think about uncertainty in the context of answering questions that might be that we care about. So, I'm, that's maybe not super helpful for you. Yeah, so to me, you want it you want to narrow uncertainty around where you care about something. I've never been a big fan of this idea, the [? flam-post] thing. Let's find out the questions that really matter and then let's actually see if we can work on those and not try and do a better job of things that don't matter.

So, I mean, decision-making doesn't actually... Look, you're always in some sense, in sort of an implied way, thinking about uncertainty. Anytime you pick a range on a variable or anything, you are doing that with subjective or potentially more physical science-based reason for that.

Types of Uncertainty and Distinctions

They distinguished between objective and subjective uncertainty. The former was repeatable and the latter not repeatable. They described how integrated assessment is dominated by the latter.

They also conceptualised methodological uncertainty associated with formal procedures with real uncertainty, which is associated with the full information needed to make decisions.

Scenarios were manifestation of the way that the future could play out.

Influences on uncertainty handling

They said their training in engineering was the weakest in terms of the uncertainty that they had to deal with.

They said that in IAMs there were two dominant ways of approaching uncertainty: Monte Carlo and robust decision-making RDM was described as turning the problem around as situating it from the decisionmaker point of view.

They also discussed MMEs which they saw as problematic (and that they themselves were part of the problem).

Whereas this other thing, is just taking outputs. And they're not typically... there's no sort of underlying distributional way in which they were constructed. The problem is just that they're represented in a way where you say 50% of them lie here. And that implies, just even using the word percent in a way implies, that you are representing something that does have some sort of rigorous distributional character- and it just simply doesn't.

The participant believed that modellers could use things other than models to think about uncertainty. *Anyway, so it's across all of those. So, I see the Monte Carlo stuff, I see robust decision making, I see the sort of problematic boxplots that I'm very much partially responsible for or invested in, that convey uncertainty about joint distributions. I see all of that stuff. I don't see a lot honestly, though in my community of making expert assessment of likelihoods based on multiple lines of evidence. Modellers end up using models to do uncertainty.*

They described how different centre have different 'business propositions' that might lead them to deal with uncertainty in particular ways. But ultimately the size of the model that you have has a big effect on things. Some are designing models to be more compact to do more MC type work.

Normative views

They were quite worried about people over representing subjective distributions as objective. This may lead people to plan around this in a bad way. *The worry is just that it's interpreted as 'truth'. And so, then you might not be exploring other possibilities for what might happen, things that might on the tails might be far more important, and you should be planning for that. And that could then apply methodologically, you just spread out the distributions- there all sorts of stuff you could do.*

They felt strongly that models are one input to evidence, but others are possible.

Other Notable Themes

The participant noted as other have the tendency to just do a limited uncertainty analysis of a couple of sensitivities and then you're done.

Optimistic about figuring out economic benefits of mitigation; pessimistic about figuring out economic impacts and costs of mitigation

Participant:	**25- Crinkle**
Category:	
Description	Head of an IAM modelling group
Methods discussed	Inter-model compassion, Scenario Analysis, Monte Carlo Analysis, Sensitivity Analysis
Types	Not clear due to audio fault

Conceptualisation as a whole

A short part of the interview was lost in which the participant discussed types of uncertainty and overall conceptualisation; hence this section is a little sparse.

From what remained it appeared that the participant had quite a board understanding of what uncertainty is, relating it to a number of aspects of the modelling and research process, including qualitative aspects. Perhaps this is more an 'epistemic' understanding of uncertainty. They clearly said that uncertainty was in relation to the real world, but sensitivity was more related to the model.

In the context of their individual model, however, they described a full uncertainty analysis as a full Monte Carlo- so just parametric. uncertainty.

Types of Uncertainty and Distinctions

When asked about kinds of uncertainty, the participant's instinct was to talk about thew particular aspects of the model system that were uncertain (e.g., Bioenergy modules and so on)

There may have been more types mentioned in the interview, but this was lost due to the audio fault.

The participant appeared to be discussing parametric uncertainty and monte Carlo analysis when the audio cut back in. They were also describing how in model comparison studies "*more or less all different aspects of the things that are endogenously created in the model can be dealt with*". On the other hand, they described scenario studies as exploring those things exogenous to the model.

Some parametric uncertainties were described as relating to the real-world uncertainties if they are measured or physically-based. Whereas others

Influences on uncertainty handling

They said that often inspiration caused researchers to explore particular things.

The nature of the target system necessitates certain kinds of uncertainty analysis as in the case of IAMs, one hopes that the target system of energy production will encounter large structural changes.

They also talked a lot about the structure of EU projects such as the Horizon 2020 projects and how the conditions of the funding necessitated collaboration. This was apparently drawing the major institutes together into a community of practice. "*With lots of collaborations between the [different modelling] teams. But it also means that you're ... because actually, most of the agenda, the work that we do is driven by these projects... We would be more creative if this team would... I'm not sure.... There is a downside and a pro-side. I think you can inspire yourself to new ideas, and you can also be somehow much more lead than to groupthink. And there's not somebody that is doing some really outside work.*"

The model style was said to contribute to the way that one can explore uncertainty. And the model style was said to be related to the kinds of approaches that model groups had taken from the beginning. The participant described the different perfectives of three of the largest European modelling groups: PIK come from an economic perspective, IIASA/MESSAGE from and Energy Systems Perspective and PBL from a natural science perspective. The IIASA people were described as having been influenced by their experience with SRES. The respective groups were described as maintaining hiring practices that kept some of this perspective. The people who have the most difficulty dealing with it were said to be CGE modellers who come from a science with aspirations to being very positive.

They described how some previous papers had been very influential for them on how to deal with qualitative aspects of uncertainty and different worldviews. They described the SSPs in some way looking at different values that people hold.

Normative views

Other Notable Themes

The participant described how the fight over the conceptualisation over scenarios in the SRES had played out. They characterised two positions:

- The 'Nakicenovic' position of saying that scenarios and probabilities don't mix
- The "Snyder' position that at some point it becomes absurd to say that scenarios can't have probabilities (as in the case of asteroids). And that probabilistic information was more useful.

They described a tension between the two approaches:
"*At the same time, if you can only run to runs and [you get this argument eventually] high-low or something like that. But then people get confused, because at that point of time that they've done this and we started to put it out, people automatically want to interpret it, this will act in process actions. And so, it either means that you conclude that it's not possible to put a high and a low without creating this interpretation. And that you, therefore, always need to also have the middle one or something like that- I don't know. Or you really have to upgrade your communication and make sure that people know what these scenarios are about, and that they choose the scenario that is best for them for their particular question. But I think there's something to, to win here. And you probably want to involve people that know something about communication and decision theory also in a debate like this.*"

Participant:	**26- Crinkle**
Category:	Climate
Description	Senior IPCC Climate Scientist working with a national bureau
Methods discussed	Scenario Analysis, Variability in
Types	Anthropogenic forcing, Variability in the climate system, Model response

Conceptualisation as a whole

The uncertainty conceptualisations as broadly in line with Hawkins and Sutton 2009. That uncertainty can be partitioned, but ultimately it is about uncertainty in particular results. The participant discussed both model uncertainty and uncertainty about the real world.

They also believed that uncertainty is a sort to of corollary of confidence and that 'confidence language' was more useful than 'uncertainty language'.

Types of Uncertainty and Distinctions

The participant clearly identified the following kinds of uncertainty:

- Anthropogenic forcing, which was explored with scenario analysis
- "Variability in the climate system at different timescales" explored through running large ensembles of the same forcing
- Model responses explored with multi-model ensembles

It was explicit in the interview that this typology related to Hawkins & Sutton 2009. They discussed the importance of communicating these different uncertainties to users.

The participant acknowledged the polysemy of the word 'Scenario'. For them, a scenario is about forcing or things that are external to the model system.

"One of a set of plausible future time series of all of these forcing elements that can be used to drive in an earth system model. And I think plausibility is a kind of important characteristic. So, we typically don't run, you know, wildly hypothetical sort of scenarios. They're typically connected with some underlying storyline that is based on reality or some realistic assumption."

We discussed this variability and the relationship of the model variability to the real-world variability. The participant expressed the view that they were trying to simulate this variability.

And so, the extent to which the statistics of that variability change under a changing climate, that's an important signal or an important outcome that we would like to be able to communicate to people; and often the more extreme they are, the more difficult it is to make quantitative statements. And the more difficult it is to provide robust information, but it's often that's the kind of thing that is much more important in terms of the use of climate model output than simpler things like changing mean, for example.

Influences on uncertainty handling

It was clear that the standard three-part distinction of Hawkins and Sutton 2009 was a strong influence on the conceptualisation of this participant.

So, I think from that perspective it helped. I don't think it wasn't like that paper introduced a bunch of concepts that no one had ever heard of at the time. I mean, it was just kind of people went "Okay. Yeah, that's a nice way of illustrating that are a nice way of talking about it." But I think it was influential from the point of view of just kind of organizing the way that people thought about it and work on the way people communicate about it. But I'm not aware of any sort of alternative kind of typologies or anything that you could use.

The difference between physicists and statisticians was apparent in the discussion of variability and the physicist perhaps striving to understand the mechanisms. Though within the group the approach was said to be relatively homogeneous, perhaps due to the smallish size of the group.

The participant clearly described the technical trade-offs in deciding what uncertainty to explore. The trilemma described consisted of:

- The spatial resolution of the model
- The length of time simulated, including pre-industrial controls
- The number of experiments performed (scenarios, perturbations etc)

They were limited in what they could do as they shared HPC with weather-forecasting people. They described how UK groups had really got into PPEs. We also discussed how data assimilation infrastructure was necessary for doing certain kinds of research tasks.

The gradual increasing coupling of ESMs was a key trend that was affecting uncertainty analysis.

Institutionally their group tries to align themselves with IPCC outputs and language wherever possible.

Normative views

"But I think from a scientific perspective, and this is just sort of my personal thing, I really believe that scientists to have the most credibility should remain as objective and be perceived as objective as possible. And so going down that path of really, not even advocacy, but just sort of ... now I'm losing the English language words here. Just I think just avoiding the perception of being sensationalist or alarmist and just focusing on quantitative facts on scientifically based information. I think that and I don't know whether that really is the case or not. That to me that's what I look for in scientific expertise in general, and what I think is needed in terms of having faith in scientific information."

The participant also believed in the value of demarcating what uncertainty there is control over and which there aren't.

Other Notable Themes

We discussed how their group was increasingly involved in seasonal climate prediction as that is a policy demand that is useful to the national government that they work with. Ditto with regional downscaling this increases the policy salience of their results.

Participant:	**27- Grasmoor (IAM)**
Category:	IAM
Description	IAM modeller in a large IAM team
Background	Environmental economics academic background. Working on climate policy tools in IAMs. Involved in a number of international projects.
Methods discussed	Multi-model comparison, Scenario Analysis
Types	Socio-economic uncertainty, technology uncertainty, climate uncertainty

Conceptualisation as a whole

For this participant, uncertainty analysis seemed synonymous with research questions and opportunities for model development. They always returned to research questions when asked about model suitability for various things.

Types of Uncertainty and Distinctions

We discussed quite a bit about value judgements and how the participant did not see value judgements as an aspect of uncertainty. Though they had difficulty explaining why these two things were distinct and what the consequences of this was.

When asked about types of uncertainty the participant gave the following:

- Social-economic uncertainty
- Technology uncertainty
- Climate system uncertainty. The participant thought that these would be possible to decrease.

For the former two, where behaviour plays a role, the participant thought these were more difficult to manage. They were optimistic about technology uncertainties and pessimistic about socio economic ones.

The participant drew a distinction between scenarios and pathways. The former was described as more detailed and included the impacts of the changing variables. The pathways on the other hand were more like just numerical sequences.

We discussed robustness as a property that comes out of intermodal comparisons. They described less and more formal versions of robustness where people causally saw that results were similar and inferred the results are robust.

Influences on uncertainty handling

The participant imagined that policy stakeholders do not like uncertainty, and if they did, they preferred statistical uncertainty.

Grasmoor: *I think that most of them prefer statistical uncertainty, especially when there are clear results and clear differences. Because the problem with this 'what-if' analysis is that they feel that they still have to make... the problem is shifts, right, instead of when you just have a statistical analysis you can just have results like, and they say "ok given this uncertainty you have a 60% greater chance that A happens" you can go for that. If you have a what-if your problem shifts to a level up. We don't know what the what will be, so you didn't help us! For them, it is sometimes shifting the problem of the underlying costs. So, they would rather have a bit more direct advice.*

The key stakeholders they had were policy. However much of their work was funded through EU grants so they had to do a lot of collaborative work. They said that as so much of their work is project-based, they were not up to date with trends for uncertainty in the literature and instead uncertainty was most closely linked to research questions.

When asked about how the model they worked with affected how they could handle uncertainty they described how the model worked. But they were not so sure about how this affected uncertainty analysis. They then refocussed on the research questions that they were then able to answer.

The language the model was written in came up as a limitation on development.

Normative views

Other Notable Themes

Participant:	**28- Brandreath**
Category:	IAM
Description	Senior IAM modeller in charge of a national IAM group
Methods discussed	Scenario analysis, literature review, expert elicitation
Types	Exogenous demand uncertainty, technology cost/performance uncertainty, representational uncertainty of optimisation models,

Conceptualisation as a whole

Uncertainty exploration for this participant was evidently highly associated with opportunities for model development. Different uncertainties were generally conceptualised as different thematic areas that could be brought within the model. This was therefore quite an externalising view of the uncertainty of the model.

Types of Uncertainty and Distinctions

They admitted to not thinking profoundly on the issue of different types of uncertainty analysis.

They recognised demand as being exogenous to the model. They noted the uncertainty on relying on the forecasts of others and how the aggregate and disaggregated economic performance of different sectors was uncertain.

They described how technology costs were uncertain. This was described as the major uncertainty in "*how to represent those technologies and how those technologies are going to behave into the future in technological terms but also in terms of cost.*"

They talked about the uncertainty that is associated with having a linear least-cost optimisation model. They recognised that real values are not quite like this.

So, I have uncertainty. I say OK, how much is the industrial capacity of Brazil or the world for building new nuclear power plants? What is the willingness of different societies or different social groups to accept these kinds of technologies? Although we have a mathematical model here that is supposed to be neutral, I know for sure that the real solution or a real future is not only based on rational things or on least-cost only but there are other dimensions that we have to try and incorporate into that. There is also this uncertainty on how to represent those kinds of things in a model that only understands numbers.

When asked about scenarios they described them as "*a kind of exploration of the future inside a possible space of solutions. So, for me let's say, a scenario is an exploration into the future of a range of possibilities, but possibilities that are within a certain frame that can provide with useful information.*"

Influences on uncertainty handling

The participant received funding from both their government and EU sources (despite being non-EU).

The language they use for the model is still based on the original model they adapted from the other, larger, group that they got it from.

They discussed their reliance on the existing literature base when discussing technology cost uncertainties. They had to go with whatever s published in the literature at the time they are working.

We talked about how there was an issue with technology costs where the real numbers are subject to industrial secrets. They provided an anecdote about how they had been invited to an Asian country, all expenses paid, to meet with a technology manufacturer's association who tried to persuade them to be more bullish about technology cost reductions in their area. But they ultimately wouldn't provide technology cost data so there was nothing the modeller could do.

This availability of data was even an issue when discussing the model paradigm uncertainty and they had to rely on their own judgement to overcome this.

So OK, the typical number that you find in the literature for the build period of a nuclear power plant is 5 years. In that [? task] we used to say, "OK a nuclear power plant costs $4,000 per KW installed and can be built in 5 years." If you put that information into the model, the model will choose lots of nuclear as 5 years is not that much and $4,000 is not that much. So, what we have been doing is saying "let's look at the real costs of nuclear in Brazil, let's look at the real construction times of nuclear in [our country] ad then we begin to let say 'tropicalise' a little bit our numbers. To try to put things that are not exactly technical but are based on our own experience.

A repeated theme in the way that uncertainty was handled was the engagement with the wider IAM community and in particular 'international European projects.

They described how their personal dietary habits pushed them into exploring particular thematic uncertainties to do with meat consumption.

The availability of fresh PhD students to do model development to push thematic areas was also important.

Normative views

Other Notable Themes

We discussed how their group came to build its IAM and Energy models. Originally this was a transferred model from a larger modelling group that they then developed further. The demands of producing a national NDC then required them to split off their nation in the existing IAM. Two successor models were then developed out of this due to the efforts of PhD students. This way gradually, more system elements are being included in the model, like biodiversity etc.

The participant was fond of detailed anecdotes, so the interview is not full of questions from the interviewer!

Participant:	**29- Grisedale**
Category:	Climate
Description	Senior veteran climate scientist, now working more on models for policy evaluation

Conceptualisation as a whole

Throughout the interview the participant generally characterised uncertainties as the spread around some output. They had a limited conception of uncertainty and did not see to include qualitative uncertainties within this.

The models used for policy evaluation were not firmly categorised as models by the participant but rather "*more of an interpretive tool than a model for actually exploring uncertainty directly*".

Types of Uncertainty and Distinctions

The participant identified aleatoric and epistemic uncertainty.

They described how they had primarily been focussed on aleatoric uncertainties in trying to quantify the changes of the risks of extreme weather events. It appeared as if the participant was talking about these aleatoric uncertainties as really existing variables in the underlying system.

Epistemic uncertainty was described as 'varying parameters and models'. They quickly began to talk about Bayesianism as the appropriate framework to understand these uncertainties. They described how examining epistemic uncertainties had been a trend in the 2000s, but there were always disagreements over how to specify a prior correctly.

When questioned about the relationship between human decisions and epistemic uncertainty they said that human decisions are not epistemic. They did not elaborate further about human decisions, but they said that epistemic uncertainties are things with definite values that we do not know, as opposed to aleatoric uncertainties.

They also identified several 'definitional ambiguities' in the work they are currently doing about definitions of things like current levels of warming, but believed that this wasn't really a kind of uncertainty:
And so, you might get the impression that different groups are reporting different present-day levels of global warming, when in fact, they're just reporting different things. So that's not really an uncertainty, that's just a definitional ambiguity. It helps to be much clearer about those things. The community hasn't been that consistent in the past, in part because there wasn't any need. Until the Paris Agreement we weren't really in the business of trying to pin down the global average surface temperature to within a 10th of a degree. But we are now, because we have these very nearby climate targets.

Scenarios were conceptualised as possible outcomes that one can assign probabilities to. Whereas trajectories are those which one can assign probabilities to.

Influences on uncertainty handling

They described how examining epistemic uncertainties had been a trend in the 2000s, but there were always disagreements over how to specify a prior correctly. They said this has been a decades long argument that was never really resolved.

The policy system and 'things we actually want to know' was described as being more linearly related to observables. Which apparently makes posing questions easier.

In their policy models they start by looking at the implications of the IPCC uncertainty ranges. The IPPC has played a role in shaping uncertainty handling but has failed to clarify things due to the need for consensus. In observational chapters there are frequentist Cis, and bayesianism in forecast chapters. "*I think there's a cottage industry has grown up in arguing about whether these uncertainty intervals should be 'likely', 'very likely' or whatever. And again, you've got to step back and ask yourself, "does it really matter?" And in most cases, it doesn't.*"

We discussed the different tribes of Bayesians: objective, subjective, formal subjective, pragmatic etc. Individual modellers were described as varying in their adherence to the dogma of the individual schools.

Normative views

The participant said that they only work probabilistically with climate models, and not policy models. They mentioned that other groups around the world had used policy models probabilistically.

We discussed as some length the way that one should use scenarios. For example: "*Unfortunately, although everybody says this is true. And everybody sort of says, "Oh, yes, no, no, we never regard scenarios as probabilistic". Because we now have so many scenarios, I mean, in AR5 there were basically four scenarios that everyone focused on. But now there's dozens and dozens of scenarios. And it's very difficult to deal with that many without starting to treat them as a sample. And so, an awful lot of nonsense is getting generated at the moment, based on misinterpreting the available scenarios as some kind of probabilistic representation of possible futures.*" The participant was very much of the category of people that believe that probabilities should not be attached to scenarios. They want there to be many fewer scenarios that the climate science community deals with "*I think even four was probably too many, most people focused on the two extreme ones, a sort of high scenario and a low scenario. And, we'd probably have no need maybe three scenarios: a sort of Paris extension scenario, a two-degree scenario and a 1.5-degree scenario.*"

They believed that there was wated effort trying to refine certain probabilities in IPCC reports as at the end of the day these are not decision relevant.

Other Notable Themes

The participant was somewhat sceptical about what kinds of information could be gleaned from IAMs, especially those that optimise as the objective function has a strong role in determining scenario outcomes. "*it's a bit pointless to argue about whether the model is right or wrong; the questions you should ask is whether or not it's useful for the question or trying to answer.*"

Participant:	**30- Glaramara**
Category:	Climate
Description	Climate scientist. Heavily involved in MIPS. More of model user than developer.
Background	Physics background.
Methods discussed	PPEs, ICEs, MMEs, MIPs
Types	Chaotic Uncertainty / Internal Variability, Structural Uncertainty, Observational uncertainty, Bugs in code

Conceptualisation as a whole

Uncertainty was very linked to the relationship the models have to reality: *And probably the most basic way of assessing uncertainty with a model is asking yourself, "Does it match with observations of what I'll call the observable world?" So that's a question that we would love to be able to answer. That's one of the hardest things to show because of lots of different reasons. But we don't have as many observations as we'd like. We have a lot of have observations especially compared to the past, but it's hard. And a lot of times you find that you just get bogged down in the details.*

Chaos was also important for them as it was one of the things that got them interested in climate modelling in the first place.

Types of Uncertainty and Distinctions

They distinguished between uncertainty as it exists comparing models with observations and the various ensemble approaches of running models. *I don't know if you need to write. I don't know if this is going too fast. But that's another there's the first measure of uncertainty in terms of that is compared to observations, then there's this idea of ensembles. How does this sort of same experiment with the same settings compare when you just change.*

When asked about types they said that uncertainty due to chaotic systems was one type of uncertainty. This as related to internal variability. When asked about internal variability they noted that it depended on the situation the extent to which the internal variability of the model system could be paralleled with the climate system. For example, grid boxes produce variability. *And so, any kind of variability that you see in the model, I think we have to be careful not to just immediately attribute that to reality. But there's a lot of effort that goes into trying to determine what types of variability in the model are, what we'd say 'real' and what types are 'not real'.*

They also identified structural uncertainty. This was related to the choices that a modeller makes when they build a model (like what processes to do in what order).

Structural uncertainty and internal variability were contrasted to a lack of understanding of observations.

They also identified bugs in computer code as a type of uncertainty.

Their conceptualisation of scenarios was very specifically about the sets of scenarios that are used in the CMIP process. They admitted to being foggy on the definition.

Influences on uncertainty handling

The participant said how the understanding of uncertainty in the observational community was different to that in the model community.

They were very involved in some of the MIPs. They saw this as really looking at topical uncertainties. One interesting consideration for MIPs was the choice of variables that one collects as all the outputs from climate models would fill up all the world's archiving space.

We talked about exploring parameter space and how an issue was that even if you do observational studies, you can still end up with issues as you can't be sure that the parameters will be valid everywhere. Their response to a lot of uncertainty was trying to base things in 'physically-based reasoning'.

MMEs were not related so much to structural uncertainty. Instead, this could be explored with modular code and so on.

Perhaps the most interesting part of the conversation was a discussion we had about how the different roles of modellers come into play. The participant described three kinds of people interacting with models:

- People who download the model data and extra analysis. They may not even understand who developed the model if they are downloading CMIP data.
- People who run the models
- People who build the models

Each of these will have a different understanding of uncertainty.
I think that people that are only downloading data, you probably have the whole full range of uncertainty understandings from "they don't know the first thing about uncertainty" to in the case of somebody who's downloading the data for a study of a bunch of different models. But they've also worked with building models, they probably have a great understanding of uncertainty.

Yeah [the model builders] deal with structural things, but they'll have the best awareness of the faults of the model, and of the limits of the model, they understand the limits of the model. And they also understand how often it happens that they change something that they think is going to do one thing and it doesn't do that thing. It doesn't have the impact that they thought it would. And they have the best understanding of how often people change one small thing and they think it's not going to matter, and it does matter. It does change things. So that's the kind of uncertainty the modellers are very familiar with.

Other Notable Themes

Participant:	**31- Bleaberry**
Category:	
Description	Junior IAM modeller who is most involved in the climate side
Background	Engineer
Methods discussed	Prime Analysis, Monte Carlo Sensitivity Analysis
Types	Risk Vs Uncertainty; Normative framework choice
Conceptualisation as a whole	
Note: A bit of the start of the interview (about 2 mins) was lost due to a recording error.	
Types of Uncertainty and Distinctions	
In the bit of the interview missing, they clearly mention risk vs uncertainty as I follow up on it later on. They also see the choice of normative framework as another kind of uncertainty. They understood scenarios to be a form of model output.	
Influences on uncertainty handling	
The clearest influence on them was their supervisor who had pioneered a number of techniques that they were then using. They had little awareness outside of their own institution. They were familiar with DMDU, however. Technically, they described how some models were too aggregated to deal with some issues like impacts. They also cannot represent shocks well. They felt that climate scientists were more advanced in terms of techniques for integration of different models. *They started earlier than to put this kind of very big intercomparison exercises. And to write papers led by a very broad range of different researchers from different institution comparing the results and various…. My impression is that even when you read the papers from the beginning of the year 2000, etc. It was more often the case since then in climate science than in the IAM stuff. It's really based on an impression.* Also, within climate they noted that the variables are a lot more commensurable with each other and interpretation was easier. *Whereas if you look at the full range of the IAMs, some have even some not represented all, like macro economy things. So, there's no point in comparing, like, the evolution of GDP if the model takes that as something exogenous. On the other hand, if the technologies are not well represented .... I don't know.*	
Normative views	
Other Notable Themes	
Like other participants they noted that a lot of people just do very simple sensitivity analyses. They were optimistic about improving the uncertainty around low carbon technologies. Pessimistic about modelling the impacts of climate change due to the differences of impacts in different sectors.	

Participant:	**32- Dollywaggon***
Category:	Climate
Description	Senior Climate scientist with an interest in uncertainty and MMEs. Used to develop, now model operator.
Background	Physics Undergrad. Climate Physics PhD.
Methods discussed	Bayesian Methods, MCMC, Large Ensembles, MMEs, MIPs
Types	Initial condition uncertainty, Parametric, Structural Uncertainty; Unknown-unknowns; Deep uncertainty

Conceptualisation as a whole

Very multifaceted.

Types of Uncertainty and Distinctions

Their explanation of the types was very H&S and is very neatly summarised by them:

Dollywaggon: *Well, I mean, the climate modelling community often separates the initial condition uncertainty, so that the noise in the system, which you can explore with large ensembles using the same model. And then the parametric uncertainty which climateprediction[.net] is the most famous if effort in doing that. And then we often call structural uncertainty, basically the differences you get from comparing a UK model with NASA model or something. But of course, that's kind of an arbitrary way of separating thing is largely driven by practical considerations of how you produce those ensembles, right? You just ask everyone to contribute. And what you get is something that easily separates into that.*

They also talked about the partition between parameters and structure is not obvious as you can have parameters that are like binary switches turning on and off bits of model structure.

Influences on uncertainty handling

They started getting interested in uncertainty when they started thinking about projections.

They characterised different disciplines as handling uncertainty in different ways:

- Physicists like simplicity and don't want their models to be any more complicated than they need to be
- Mathematicians and statisticians are comfortable making very strong assumptions and then doing very rigorous analysis on the back of that
- Economists don't like uncertainties at all and don't bother much *And if they start to use computer models, or if they start to use observations and actual real-world applications, then many would say " it's not proper economics, right?" So, for instance, there is no they have these A journals, right at the highest level of journals in economics, where they have to publish to get tenure. There is not a journal in environmental economics, there simply isn't. So, if you go down to the real world, environmental problems, and you look at actual data and real-world problems, that's not even worth considering in a top journal.*

They described three limitations to the application of Bayesian methods

- Models are too complex to do lots of MCMC. There are too many free parameters, and you have to rely on emulators
- One has to make prior assumptions, and no one can agree on what these should be
- One can't comprehensively sample structural assumptions

The participant said that some see uncertainty as a necessary evil; but they were motivated by the requirements of decision-making.

This academic was more doing reanalysis these days. And they described how they looked at the simulations at hand and decided to ask what kinds of questions they could answer.

Some who do big PPEs might actually be more interested in the computational challenge. Different sub fields deal with uncertainty in different ways. Like observational people. We ended up talking about the division of labour in the same way as with Glaramara. They thought that some within subfields wanted to converge on a 'single best model'. But they were more interested in using different models for different tasks.

The IPCC cycle was a double edge sword. On the one hand it pushes people to prematurely do model releases. On the other hand, it allows intercomparison as everyone releases at once. The demands of publishing and funding were also not in tune with the requirements of long-term model development. The ECMWF was held up as a forward-thinking example.

We talked about how ICEs had improved. But also, how parametric and structural uncertainty remained as the models got more complex in step with the increased in HPC.

Dollywaggon: *And it's because the models are so complex, and they get even more complex. Some sometimes I doubt whether that's the right way of doing things. It's getting harder and harder to make progress, because there's so many things happening at the same time. And we've seen that with many models now in the latest release cycle that they come up with all these new features, and the models do crazy stuff.*

They talked about how it became more challenging to interpret uncertainty from black-box models like emulators and ML models.

We discussed scenarios and the different interpretations and approaches. In the Netherlands they have long done this. Scenario thinking hasn't been prevalent in climate, but Sutton and Howkins are pushing it.

Normative views

Other Notable Themes

Like Glaramara they also described how physically based reasoning was a way out of a situation of not knowing anything.

But I think these are some mostly arguments based on the physical understanding intuition and expert judgment. And often, it's not possible to do it in a strictly formal way, like you would be able to do in a Bayesian method where you specify priors and so on. Because simply, in a practical sense, it cannot be done. Either you don't have a model or it's too expensive to run.

Like others they also talked about the allure of just doing a perfunctory sensitivity analysis. Some are pushing for high resolution approaches in their models. But we are far away from that in HPC terms.

We finished the interview chatting about covid. Optimistic about PPEs, thermodynamics; pessimistic about dynamics and structural uncertainty

Participant:	**33- Harterfell**
Category:	Energy
Description	Leader of a largeEnergy Modelling Group; previously model developer but mainly using other off the shelf models
Background	Energy Engineering background
Methods discussed	Scenario Analysis, Multi Model approaches, Model soft-linking, Sensitivity Analysis
Types	Scenario Uncertainty/Data uncertainty, Epistemic Uncertainty/ Model limitations, Unknowns (Micro, Institutional and Macro)

Conceptualisation as a whole

A broad understanding of uncertainty. Mainly from a non-numerical and epistemic point of view.

Types of Uncertainty and Distinctions

They very helpfully have something of a pre-mulled-over spiel about how they understood uncertainty (they talked for 22 minutes!). They identified a number of levels of uncertainty:

- The uncertainty that comes from using singular scenarios. This can be ameliorated by using more scenarios and more model runs. You can also improve this by going from deterministic to multi-model approaches. These multi runs shed light on uncertainties in data inputs.
- Epistemic Uncertainty. This is also associated with the modelling paradigm and the assumption of a benevolent dictator. This is also associated with the modelling capability. The challenge of parameterising behaviour was also mentioned.

So, to address some of the uncertainties as associated with the modelling construct itself, if you like, or the limitations of the modelling framework, we can use other models to help. And that can be as I say, to help try and understand sort of aspects related to behaviour and also areas where the model is weak. So, looking at things at high resolution for example.

- The final uncertainty related to all the unknown things that couldn't be modelled. The participant subdivided these into a macro level (things like political developments), institutional level (regulation or grid operators and micro (local participation in grids).

They acknowledged the different meanings of scenario. They seemed to be tools for revealing differences.

Influences on uncertainty handling

They started off talking about how they had gotten into the field interested in the lack of good data for decision-making on energy. Thy talked about using off the shelf models as they came ready with a community of users. They have gradually expanded the domains they are interested from energy to economy to environment and now to society.

They felt that there weren't many efforts to deal with these third kinds of uncertainties. This was associated with disciplinary arrogance. *To my mind that's the bigger challenge in terms of those uncertainties, I think are very significant. And I don't think we've even ... in some cases I don't I'm not sure that we've even recognised their importance. If you look at the evolution of the IPCC reports, over time, certainly in the past AR5 there was an increased recognition of what's happening in society, sorry, a recognition of the importance of what's happening in society. But I'm not seeing that yet translating into kind of much real activity in the modelling community, if you like. There's a disciplinary arrogance, there are many challenges.*

They gave a really interesting anecdote about when they had been invited to give a presentation to the transitions community on their energy modelling. Here is a bit of it:
So, the so the first response, I got to giving what I would consider a normal Energy Systems Modelling presentation was "Well this is madness!" That narrow linear approach of GDP leading to a certain energy service demand, and then we meet that- there's so many factors and uncertainties. And so, uncertainty does come into those discussions. But it's even more fundamental than a discussion on uncertainty. It's a discussion on the approach being same daft.

We talked about the different demands that policy stakeholders might have for scenarios. Different stakeholders will have different nuanced understandings of what kinds of information they want. We talked about how some researchers had pretty naïve views about how to make policy impact.

They said that uncertainty was more values when funders were funding pure research versus consultancy work.

The theme reoccurred where uncertainty is a secondary thought when you are just trying to get a model running. And so, as a modeller matures, they have more intellectual and time scope to understand the importance of this.

We also covered how the group one is in and the model one has may affect your uncertainty analysis.

Normative views

Other Notable Themes

They were optimistic about dealing with some of the data uncertainties better. They were pessimistic about the unknown societal uncertainties that are difficult to represent in the models.

Participant:	**34- Pavey**
Category:	Climate
Description	Senior climate scientist and modeller who has published on uncertainty topics

Conceptualisation as a whole

Uncertainty was generally described as the spread around an estimate. The participant varied as to whether they considered uncertainty to be a property of the model system or of the natural world.

Types of Uncertainty and Distinctions

The participant clearly identified the following kinds of uncertainty:

- Forcing uncertainty- uncertainty in emissions and forcing
- Model uncertainty (a term they said they hated).

Interviewer: *What is it about the term model uncertainty that sounds unsatisfactory to you?*
Pavey: *Well, the models are not uncertain. What is uncertain is the behaviour of the real world which is which is in this context, it's response to forcing associated with changes in greenhouse gases or solar radiation or whatever it may be.*

The participant said they preferred to think in terms of forcing and response: "*That the, the term I prefer is.... I like thinking about forcing and response; it's a classic physics kind of framing. So, forcing uncertainty and response to uncertainty are the terms that I find most useful. And when we when we talked about model uncertainty, we really meant response uncertainty.*"

- Internal variability: the variability that we would see if we lived in a stationary climate

The participant described these and similar terms existing for a long time in the literature.

Scenarios were conceptualised as plausible self-consistent storylines about what could happen.

The participant described 'structural uncertainty as the uncertainty associated with the assumption that that your model structure is adequate. This was described as a flavour of model uncertainty and as being unrelated to parametric uncertainty. This was creating a demand for certain kinds of risk-based information.

Influences on uncertainty handling

The participant said that they had done a lot of work towards quantification of uncertainty in climate science. Though they thought on reflection this was counterproductive as climate prediction is not like numerical weather prediction. They attributed this trend to the fact that some parts of climate science are an out-growth of meteorology.

This trend of treating scenarios this way probabilistically was described as not universal. The participant compared the approaches of the UK climate projections and the Dutch national climate assessment, which used more of a storyline approach.

They described a rapid change occurring where governments were being less dominant as consumers of climate information and financial sector organisations were becoming more prominent.

Different groups, or rather individuals representing different groups, were described as more or less keen on different methods for uncertainty exploration.

The IPCC was described as being cumbersome and inertial. The siloisation was described as preventing joined up thinking on risk.

Funders were described as being increasingly open to 'narrative-based methods'. Though these narrative methods were likened to scenarios.

Normative views

The participant was worried about the proliferation of 'probabilistic climate projections' that give probabilistic outputs but ignore many other uncertainties.

The multi-model approach from the CMIPs was described as excluding all the 'known- and unknown-unknowns'.

Other Notable Themes

They were pessimistic about the potential for us to ameliorate certain uncertainties to do with impacts. For example, ecosystems impacts.

They noted that we didn't talk about 'worst case scenarios' which is apparently endlessly a topic of discussion.

Participant:	**35- Causey**
Category:	Climate
Description	Climate modeller who has worked in a number of research centres and on a number of models. Developer
Background	Physics undergrad. Then later in life transitioned to climate modelling.
Methods discussed	ICEs,
Types	Internal Variability, Observational Uncertainty, Model Uncertainty (including parameterisation)

Conceptualisation as a whole

They talked about how the observational people, the theory people and the modeller all had different understandings of the word uncertainty.

But due to their proximity to model development it was clear they were not deeply involved in day-to-day UA. *I'm doing a lot of simulation for the IPCC. I'm not doing much of the comparison. I'm more involved in the model development. And I'm not really involved in the intercomparison itself. And sometimes I end up on the publication because I have done [our] part.*

Types of Uncertainty and Distinctions

Internal variability was mentioned as the type of uncertainty of most concern. But they also said that this wasn't really uncertainty per se. It was said to be the internal variability of the climate system. But the way they answered it was unclear if this was considered to be the same of the model system.

There was also the uncertainty associated with repeat model experiments several times, whereas in reality there is only one evolution of the climate system.

Furthermore, they identified uncertainty due to model assumptions: *And I will have also some stuff that are uncertain because I don't know everything about the simulation, I cannot put everything in the model and some stuff can be wrong. And basically, your model what it gives you, it's what you tell the model. It's what you put in the model. When I say this, some people would say "Why?" What you put in the model, it's what you're going to get an answer based on what you put in the model.* They also discussed how this was associated with limited knowledge.

As an example of this kind of uncertainty, we discussed the aerosol indirect effect. From this discussion, it was apparent that this also includes the parameterisation of the model.

They were quite unfamiliar with scenarios.

Influences on uncertainty handling

We talked about where the priorities were for representing uncertainties better. This was said to be limited by the expected cocktail of effort, human capital and funding. The prioritisation was said to be subjective.

Personalities at different modelling centres determined some of the priorities. *But for example, at some point a few years back, [we had] a group that's called the atmospheric working group. And it's what takes the decision about what we include in the atmospheric model. And you add somebody that wanted really to push, he studying aerosol and the dynamical code would be important in the representation of the aerosol. And for a long time, he didn't have any leverage, because he was not in charge. And at some point, he took the position to be able to push his agenda about the dynamical core. And it's because he believed it's very important. And now we are still using this dynamical code that came at that time.*

Different centres tune models in different ways which is significant.
I know for the tuning for example, us, when we tune the model, we will tune compared to pre-industrial condition. E3SM which is another model in the United States, from DOE Department of Energy, they will tune compared to present day. Both ways are defensible. If you tune to pre-industrial, it's because you know that in industrial time, you had more 0 radiative imbalance, but you have less observations. Whereas if you tune to present day, you have the most satellite observations.

The imaginary policymaker who wants the single value also came up.

Normative views

Other Notable Themes

We talked about the different types of modellers. Most of their interactions were in-institute and with other developers.

Pessimistic about cloud feedback uncertainty. Most optimistic about temperature.

Participant:	**36- Carrock**
Category:	Climate, IAM
Description	Climate researcher interested in the interaction of climate and long-term scenarios. 3rd type of modeller (analysis data)
Background	Engineering undergrad, Physics PhD
Methods discussed	PPEs, Sensitivity Analysis, Scenario Analysis
Types	Emissions Uncertainty, Forcing uncertainty; Deep Uncertainty

Conceptualisation as a whole

Uncertainties were very much synonymous with unknown values of things for this researcher.

Their state of knowledge is such that we don't have that pinned down. So, there is a real number, and it certainly varies spatially and temporally, by season and so on, but the models are not well constrained enough to pin that down. So, there's a chain of uncertainty after you go from emissions, it gets pretty.... Yeah, there are observations that constrain the total number of particles in the atmosphere. Satellites and so on, but there's lots of different sources of particles, and they can't tell all of them apart. So that leaves a lot of degrees of freedom to perhaps, come up with the right answer for the wrong reason.

Types of Uncertainty and Distinctions

Some of the types mentioned were topical. For example, aerosol forcing uncertainty.

When asked about types of uncertainty they distinguished uncertainties by whether they could be bounded or not. Reducing these uncertainties was related to data availability. I pushed them on what properties these uncertainties might have, and they went back to examples. Which is interesting as they had some difficulty abstracting the kinds of uncertainty the experience outside of their work.

They understood scenarios to be a kind of tool. Scenario analysis was mean to be useful in situations of deep uncertainty.

Influences on uncertainty handling

They discussed the political context in which they were currently doing integrated assessment. At the moment they are shying away from that term due to the bad rap some of the very aggregated models have and the political perception in their country.

In their modelling they do impacts, but they shy away from the aggregate stuff as their model isn't right for that.

We talked about how they prioritised deciding what uncertainties to explore with a complex model before putting it into a simpler model.

As the researcher was interdisciplinary, I asked about how they saw the climate vs the IAM community understanding uncertainty differently.
But I think it is easy when dealing with, say, a climate model to sort of slip into mistaking the model for reality. And because you have a model that looks a lot like reality, right, it has the same numbers, you can draw maps, you can show how the maps are similar to reality. And you'll even see language in papers "well, our model has shown this." Well, you've shown it in that model. But the caveat is that's only in that model.

They also said that:

- IAMs involve more expert judgement.
-

They said that experience also increased people's awareness of uncertainty.

The participant recommended I read Asimov's Foundation series trilogy in a conversation about the unpredictability of social systems.

They said that local institutions were important and that technical factors determined whether one could do certain kinds of experiments like PPEs. Also, there are different approaches to modularisation such as hard linking, soft linking. The formats of data files etc.
Some of them, for example, have separate land use model that's sort of partially hard coupled to the main model that you just do… So, you can do different scenarios. But it's not like one integrated system. Whereas other models have integrated systems where everything's coupled together. And that changes the type of uncertainty you can look at just mechanically.
This then caused us to discuss how certain models got into the state that they are. The participant said that it was it was likely formed in the interaction between model groups and funders.
And certainly, in our group, we've always had this philosophy. We've had a very definite group philosophy of "We want the simplest representation that we can have that gets the dynamics we need." So, we really wanted to keep that integration there. And we really tried not to put in more detail than we have to. And we've really worked hard toward integrating the different pieces. And we've invested quite a bit in making that integration possible and making that integration deeper in terms of restructuring internal model code, and so on. So, the different pieces talk to each other more readily. So, it takes a lot of resources. So, we want to look at the uncertainties of land, water and energy and how they interact. And so that means we have to have a long-term plan to invest to enable that capability. And we've managed to do that.

Normative views

Other Notable Themes

The topic of perfunctory sensitivity analyses came up again! *And, you know, climate modeller might do some sensitivity experiments to try to understand how sensitive their model is to a parameter. And sometimes they find that, "well, the model is really sensitive to this parameter that I don't have good constraints on." And that's what you hate to see. But it happens sometimes, right?*

They were optimistic at new data sources like remote sensing to help reduce uncertainty. They were more pessimistic about situations where data sources were more dispersed.

Participant:	**37- Hartcrag**
Category:	IAM
Description	IAM Developer in a big IAM team
Background	Masters in Energy, PhD working on the model they work on now
Methods discussed	Monte Carlo, Sensitivity Analysis
Types	Structural uncertainty, calibration uncertainty, parameter sensitivity Uncertainties; socioeconomic vs physical;

Conceptualisation as a whole

They said that uncertainty is quite an umbrella term.

They understood sensitivity to be the sensitivity of mathematical formulations and parameters inside your model.

Types of Uncertainty and Distinctions

They said that scenarios were a kind of projection. They also referred to them as thinking tools.

Scenario uncertainties were contrasted to sensitivity. The latter was described to be something like the model uncertainties and the mathematical uncertainty due to the mathematical formulations and parameters in the model.

When asked explicitly about types of uncertainty they took a thematic approach and said they separate uncertainties in socioeconomic and physical.

Later in the interview, the participant talked about structural uncertainty: *So, kind of you have basically a structural uncertainty which is which is the conceptual structure of your mathematical formulation, then you have calibration uncertainty, then you have parameter sensitivity. And then you have scenario uncertainty. This is really about the future. But the first three elements are really about the past and about the internal model itself.*

Influences on uncertainty handling

Model development pace was dictated by the need to update the SSP scenarios.

They said that normally IAMers are energy and land modellers and less so climate modellers. As the main climate module used is the MAGICC model, they kind of outsource that aspect of development outside the community.

We discussed the uniqueness of their model and institution and how the fact that it ran in simulation mode was different from a lot of other models. The culture at their institution was focused more on physical parameters. This focus, rather than say macroeconomic variables, was partially to ensure the long-term relevance of their projections. This also avoided several definitional ambiguities. In fact, this choice to pursue physical parameters had been the cause of a previous split in the modelling team where a bunch of modellers left.

They described their model and institute being particularly good at 'scenario thinking'. *And that's the scenario thinking. So, I said in the beginning, what a scenario is. And that a scenario is not a prediction, but a tool to understand long term trends and developments. That I think is a line of thinking that that [our institution is] very good at.* Part of the origin of this was their involvement from early on in the IPCC process in making scenarios.

The aggregate indicators were characterised as belonging to 'transitions science'.

Normative views

Other Notable Themes

They were optimistic about natural science uncertainties (interesting as they professed to not being familiar with this part of the model); They were pessimistic about economic uncertainty. They were also perturbed by the assumption of what they called 'liberal socialism' in the model- essentially the benevolent dictator. They wondered whether different political values could be manifested in the models,

Participant:	**38- Redscrees**
Category:	Energy
Description	Experienced Energy Systems Academic
Background	Physics undergrad. Worked in industry and policy. Developed major energy models. Identifies as a systems modeller.
Methods discussed	Monte Carlo, Scenarios, stochastic programming, MGA, designing the model differently, open sourcing of code, limited foresight
Types	Parametric uncertainty, structural uncertainty

Conceptualisation as a whole

They seemed to not believe that there was uncertainty in the model, but that uncertainty was something that could be interacted with using different techniques.

Well, I mean, I'm not sure there are uncertainties in the model - they are there are techniques for trying to gauge uncertainty. Yeah, I suppose like those types of uncertainty whether or not you know, day to day stuff, we know that everything is... we have lots of parameters in the model that we know are uncertain. Monte Carlo is a method of trying to understand the impact of that. I'm just looking for something that somebody wrote. [Pause whilst typing on computer] Yeah, so for example, there was one paper that looked at deterministic and stochastic uncertainty on one axis and endogenous and exogenous uncertainty on the other axis.

It really did seem to be a technique-focussed view of uncertainty analysis.

Types of Uncertainty and Distinctions

Throughout the interview the participant identified the following kinds of uncertainty:

- Parametric uncertainty- which can be explored with Monte Carlo analysis. They conceptualised the individual runs of an MC to be scenarios. When a monte Carlo produces the same result consistently that was seemingly a robust result.
- Structural uncertainty- especially associated with the objective function. This was explored with MGA and by ‘designing the model a bit differently.

The described scenarios as a view of the world and what the world might be in the future.

Occasionally they referred to types of uncertainty by the method that is used to explore them.

Influences on uncertainty handling

We discussed how suitable different kinds of models were to run in Monte Carlo mode. They discussed how different people at their institution were pushing boundaries of different uncertainty analysis techniques.

They also described how some institutions were not that advanced in their handling:
A lot of people just run the models in a more basic way, and they don't have the people. We are a university; a lot of people who use [a model] are at research institutes- they build a model to do some scenarios, they get told to do some scenarios for the government or whatever. We need to do stuff that's novel. And that means pushing the boundaries. One of the boundaries is uncertainty analysis.

They said that monte Carlo was useful as policymakers had heard of it. Some policymakers will just want small numbers of scenarios.

Not really, I don't see many people who are interested in exploring uncertainty. I'm not sure I have a large enough sample to be able to make a useful kind of statement on that anyway. I'm interested in uncertainty and things where I don't see many researchers going" God, I wish we could just do some Monte Carlo on this!" That'd be great to try stochastic. And if it did, we'd probably promote them, but don't tell them that!

On the technical requirements of doing new kinds of uncertainty analysis:
Yeah, all of these points are going to detail and requires a bit of computer science. But nothing as an engineer, or scientist, as a physics person with a bit of computer knowledge couldn't do. It all requires a bit of poking around and a bit of code, maybe writing in GAMMS or something. And then or the shell script type things, being able to move around data and understand how to play with data and such. So, there's a number of things we need to do.

Normative views

They were pessimistic about dealing with the ‘single benevolent all-seeing dictator’ issue.

Other Notable Themes

Appendix G: Declaration Forms

Referencing doctoral candidate's own published work(s) in thesis

Please use this form to declare if parts of your thesis are already available in another format, e.g. if data, text, or figures:

- have been uploaded to a preprint server;
- are in submission to a peer-reviewed publication;
- have been published in a peer-reviewed publication, e.g. journal, textbook.

This form should be completed as many times as necessary. For instance, if a student had seven thesis chapters, two of which having material which had been published, they would complete this form twice.

For Chapter 2

1. **For a research manuscript that has already been published** (if not yet published, please skip to section 2)**:**
   a. **Where was the work published?** (e.g. journal name)
      Futures________________________________
   b. **Who published the work?** (e.g. Elsevier/Oxford University Press)
      Elsevier________________________________
   c. **When was the work published?**
      March 2022___________________________
   d. **Was the work subject to academic peer review?** YES
   e. **Have you retained the copyright for the work?** YES

2. **For a research manuscript prepared for publication but that has not yet been published** (if already published, please skip to section 3)**:**

n/a

3. **For multi-authored work, please give a statement of contribution covering all authors** (if single-author, please skip to section 4)**:**

n/a

4. **In which chapter(s) of your thesis can this material be found?**

Chapter 2: "The Ambiguities of Uncertainty…"

5. **Candidate's e-signature**

[redacted]

Date: **22/06/2022**

6. **Supervisor e-signature:**

[redacted]

Date: **22/06/2022**

For Chapter 7

1. **For a research manuscript that has already been published** (if not yet published, please skip to section 2)**:**

   N/a

2. **For a research manuscript prepared for publication but that has not yet been published** (if already published, please skip to section 3)**:**

   a. **Where is the work intended to be published?** (e.g. journal name)

   Journal not chosen. Possibly Plos ONE_____________

   b. **List the manuscript's authors in the intended authorship order:**

   Luke Bevan, Gregory Milne

   c. **Stage of publication:**

☒ Not yet submitted

☐ Submitted

☐ Undergoing revision after peer review

☐ In press

3. **For multi-authored work, please give a statement of contribution covering all authors** (if single-author, please skip to section 4)**:**

   Luke Bevan: Drafting Sections 1,2,3.3,4,5,6,7. Editing
   Gregory Milne: Drafting Section 3.1,3.2 Editing

4. **In which chapter(s) of your thesis can this material be found?**

   Chapter 7: "Towards an uncertainty framework for epidemiological models"

5. **Candidate's e-signature:**

   [redacted]

   Date: 22/06/2022

6. **Supervisor e-signature:**

   [redacted]

   Date: 22/06/2022

Appendix H: Bibliography

Here I provide a list of books I have read relevant to this thesis over the course of completing my doctoral studies. These books vary in the level of influence they have had on my thinking: some profoundly, some latently and some barely at all. However, I feel it useful to acknowledge them all here.

Title	Author	Reference
On the History of Uncertainty Concepts		
The Empire of Chance: The Napoleonic Wars and the Disorder of Things	Anders Engberg-Pedersen	(Engberg-Pedersen, 2015)
The Emergence of Probability	Ian Hacking	(Hacking, 1975)
The Taming of Chance	Ian Hacking	(Hacking, 1990)
The Empire of Chance	Gerd Gigerenzer et al. (eds.)	(Gigerenzer et al., 1989b)
Against the Gods: The Remarkable Story of Risk	Peter Bernstein	(Bernstein, 1996)
On Uncertainty and Modelling		
Simulating Nature: A Philosophical Study of Computer-Simulation Uncertainties and Their Role in Climate Science and Policy Advice	Arthur Petersen	(Petersen, 2006)
Dialogues Around Models and Uncertainty	Pauline Barrieu (ed.)	(Barrieu, 2020)
Uncertain Futures: Imaginaries, Narratives and Calculation in the Economy	Jens Beckert and Richard Bronk (eds.)	(Beckert and Bronk, 2018b)
The Politics of Uncertainty: Challenges of Transformation	Ian Scoones and Andy Stirling (eds.)	(Scoones and Stirling, 2020)
Cultures of Prediction in Atmospheric and Climate Science	Matthias Heyman et al. (eds.)	(Heyman et al., 2018)
Acting Under Uncertainty: Multidisciplinary Conceptions	George Von Furstenberg (ed.)	(Von Furstenberg, 1990)
Radical Uncertainty: Decision-making for an unknowable Future	John Kay and Mervyn King	(Kay and King, 2020)
The Cunning of Uncertainty	Helga Nowotny	(Nowotny, 2016b)
Climate and Energy Thematic Books		
The Climate Casino: Risk, Uncertainty and Economics for a Warming World	William Nordhaus	(Nordhaus, 2013)
Philosophy of Science Readings		
Theory and Reality	Peter Godfrey-Smith	(Godfrey-Smith, 2003)
Explaining Science: A Cognitive Approach	Ronald Giere	(Giere, 1988)
How the Laws of Physics Lie	Nancy Cartwright	(Cartwright, 1983)

Models as Mediators: Perspectives on Natural and Social Science	Mary Morgan and Margaret Morrison (eds.)	(Morgan and Morrison, 1999)
The Social Construction of What?	Ian Hacking	(Hacking, 2000)
Understanding Scientific Understanding	Henk de Regt	(de Regt, 2017)
Social Studies of Science		
Epistemic Cultures: How the Sciences make Knowledge	Karin Knorr-Cetina	(Knorr Cetina, 1999)
Opening Pandora's Box: A sociological analysis of scientists' discourse	G. Nigel Gilbert and Michael Mulkay	(Gilbert and Mulkay, 1984)
Laboratory Life	Bruno Latour and Steve Woolgar	(Latour and Woolgar, 1979)
Actor network Theory		
Actor Network Theory: Trials, Trails and Translations	Mike Michel	(Michael, 2017)
Reassembling the Social	Bruno Latour	(Latour, 2005)
Mental Models and Metaphors		
Metaphors We Live By	George Lakoff and Mark Johnson	(Lakoff and Johnson, 1980)
Risk Communication: A Mental Models Approach	M Granger Morgan et al.	(Morgan et al., 2002a)
Interview Methodologies		
Interviewing for Social Sciences	Hilary Arksey and Peter Knight	(Arksey and Knight, 1999)
Interviewing in Social Science Research: A Relational Approach	Lee Ann Fujii	(Fujii, 2018)
Thesis writing guides		
How to Write a Thesis	Umberto Eco	(Eco, 2015)
Authoring a PhD	Patrick Dunleavy	(Dunleavy, 2003)
Completing Your Qualitative Dissertation	Linda Bloomberg and Marie Volpe	(Bloomberg and Volpe, 2012)