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Bayesian material flow analysis of the construction aggregate cycle in England

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ABSTRACT

Quantitative analysis of material over their life cycles provides crucial insight into the movement of materials within economies, informing economic and environmental impact assessment, and governmental and industrial interventions. Material Flow Analysis (MFA) for whole material cycles is often hindered by data gaps, limiting its practical value. We apply Bayesian Material Flow Analysis (BaMFA) to quantify England's 2019 construction aggregates (sand, gravel, crushed rock) system, reducing the labour-intensive manual data reconciliation requirement of conventional MFA approaches. Despite industry-reported data describing only 20 % of the system, BaMFA fully quantifies the system, provides novel insights into its supply-demand balance, and highlights opportunities for enhanced resource efficiency and waste minimisation. This includes improved quantification of primary aggregate consumption (142 Mt, 68 % from indigenous sources) and landfilling (20 Mt, 96 % demolition waste). This research demonstrates the potential of BaMFA for quantitative analysis of material systems and evidence-based action for more sustainable and resilient futures.

1. Introduction

Material Flow Analysis (MFA) uses the conservation of mass principle to model stocks, change-in-stocks, and flows of material(s) through the processes that comprise their life cycles, within geographical and temporal boundaries (Graedel, 2019). MFA provides the essential evidence basis for describing and managing how materials are used throughout the economy; for determining their related economic, environmental, and social impacts; and for understanding the effects of government and industry interventions on those impacts and material stocks and flows. In the scientific literature, MFA is often conducted at the national scale as more data is made available by national governments (e.g., British Geological Survey (United Nations Department for Economic and Social Affairs., 2020) and international trade databases (Bide et al., 2022) than by local authorities (e.g., (Staffordshire Country Council, 2022). Material flows through systems are also not usually disaggregated beyond the material class level (i.e., steel, cement, polyethylene) due to the lack of more detailed data.

MFA has been conducted for many elements, substances, and materials (Myers et al., 2019b). Notable applications of MFA include modelling urban resource metabolism (Dijst et al., 2018), identifying opportunities to conserve resources and reduce waste generation for process optimisation (Allesch and Brunner, 2015), and assessing the feasibility of transitions such as the circular economy (Mayer et al., 2019). There is now substantial and increasing interest from government in developing more detailed and current MFA case studies for economically and environmentally important materials, especially those with significant supply risks (e.g., critical minerals) and poor market transparency (e.g., rare earth elements).

The MFA case study presented in this paper focuses on the life cycles

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of raw aggregate materials, such as sand, gravel, and crushed rock. These materials are economically important to the UK economy as they contribute 6 % of the national Gross Value Added (Office for National Statistics (ONS), 2023). The flows of construction aggregates are considerable, with sand estimated to be the second largest anthropogenic flow of natural resources behind water (United Nations Environment Programme, 2019). Such significant movements of materials contribute to environmental impacts, including climate change, biodiversity loss, and land use change arising from extraction, processing, and transport activities. Demand for construction aggregates is rising in line with global population and affluence. Climate change pressures compound the issue, requiring coastal and flood defences, and components essential for the low carbon energy transition (e.g., concrete for windfarm bases) (Tian et al., 2022). However, despite the importance of aggregate materials, complete quantitative understanding of their metabolism and the effects of different interventions is lacking (Schiappacasse, Müller and Wirth, 2019; Torres et al., 2021; Johansson, 2006). Improving understanding of material flows across economies and opportunities to reduce the consumption of construction aggregates holds considerable value from both life cycle impact and supply-and-demand standpoints.

MFA consolidates material stocks and flows data from different sources, e.g., collected by industry or government, and for different parts of the life cycle. Data sources typically employ different methods and motives for collecting such data; inconsistencies are therefore common. Conventionally, inconsistencies in the data for MFA are resolved through manual reconciliation including making assumptions to fill data gaps, until the number of unknowns can be solved using mass conservation equations. Being highly manual makes conventional MFA time-intensive and expensive to apply. Its ad-hoc nature also makes it difficult to communicate clearly what assumptions have been made and what their associated uncertainties are, especially in analyses of large and complex multi-process systems. Consequently, it is unrealistic to use conventional MFA to model systems that are highly complex or include multicomponent flows, despite multicomponent flows occurring in many systems. For example, steel can be disaggregated into many different sub-materials, containing different alloying elements; it would be useful to understand the component flows of iron and the alloying elements separately, to be able to develop Circular Economy strategies for their use and recovery at highest value. Conventional MFA has therefore been limited to relatively simple systems containing material classes and product types with limited disaggregation, hindering a more detailed quantitative understanding of them. This obstructs the optimisation of material systems by undermining downstream activities of MFA studies, such as developing legislation or improved manufacturing processes that can be informed by such understanding.

However, much more information about materials and products is known than that which is reported in official reported statistics and currently used in conventional MFA. Companies know how large their relevant markets are, trade associations know substantial information about the business activities of their members, and there are many experts with knowledge of processes, materials, products, markets, etc. This information can be qualitative or quantitative. Conventional MFA uses little of this information despite its potential to enable significantly increased material and product disaggregation, more accurate stocks and flows values, and reduced, or at least quantified, uncertainties of those values. Hence there exists substantial untapped potential for more comprehensive and reliable quantification of stocks and flows of material cycles, for more reliable and insightful modelling results.

Bayesian MFA (BaMFA) is a recently developed method that can significantly overcome data unavailability issues that exist in conventional MFA (Lupton and Allwood, 2018; Wang et al., 2024). BaMFA uses Bayes' Theorem to estimate stock and flow data, and associated uncertainties, given an incomplete set of data for potentially very large and complex systems. As a consistent computational approach, BaMFA can avoid the ad hoc input data processing of conventional MFA, facilitating faster calculation and more reliable and detailed system analysis – especially where reported data is lacking (see Wang et al., 2024). It also simplifies the process of updating the system with new processes or data. The lower operational costs of BaMFA can thus reduce expenditure for governments and administrative bodies looking to generate quantitative evidence in near real-time for relevant policymaking (e.g., industrial decarbonisation, waste management). Its lower reliance on complete datasets also enables it to be used while restricted to public datasets, which is often a government requirement. For these reasons, BaMFA can enable improved resource efficiency, reductions in CO_2 emissions increased circularity, and reduction of risks in supply chains and national economies.

Several major infrastructure projects have been proposed in England (e.g., HS2, Hinckley Point C, and Thames Tideway Tunnel) that require considerable quantities of construction aggregates. Most construction aggregates in England are from domestic sources, reflecting their high transportation costs relative to their sales prices (British Geological Society, 2019). For the same reason, local supply and acquisition of construction aggregates is most common despite widespread availability. Large-scale infrastructure projects are therefore dependant on local construction aggregate production (e.g., from quarries) to avoid significant, potentially inhibiting, costs associated with long-distance transportation. However, high population-densities make it increasingly difficult to site and approve new quarries, with permit application processes often exceeding ten years (Mineral Products Association, 2022a). This limits capacity to enhance current construction aggregate (supply) infrastructure. Shortcomings must instead be resolved through (i) greater material efficiency, (ii) reduced waste, and (iii) increased recycling; led by informed policymaking. This requires a fuller understanding of construction aggregate material cycles across England (and other regions), which is at present hindered by data gaps.

In this paper, BaMFA is applied to quantify change-in-stocks and flows of the 2019 construction aggregates system in England, UK, to demonstrate the potential of the method, including for characterising the supply-demand balance for these materials (sand, gravel, crushed rock). It provides an overview of the key steps for applying BaMFA alongside the codebase developed to implement it (Wang et al., 2024). The underlying aim of this research is to use a case study to show how BaMFA could provide basic quantitative evidence to understand and strategically analyse resource use, potentially for all resources in the economy. No previous study has attempted the same level of disaggregation for a construction aggregate cycle as that which is presented here.

2. Bayesian material flow analysis

2.1. System diagram

Consistent with traditional MFA, the first step in BaMFA is to define the goal and scope of the study, which involves defining the system boundary in terms of time, space, and reference material (the basis for mass conservation) (Myers et al., 2019a). A system diagram that (usually) shows all the processes, stocks, and flows pertaining to the material (s) (or substances or elements) of interest within the system boundary is then constructed. Each process may also contain a stock that represents storage of the material of interest. The level of disaggregation depends on the level of detail required in the study.

In our BaMFA methodology, processes are disaggregated into 'parent processes', those that contain subprocesses, and 'child processes', those that do not contain subprocesses. This formulation means that the change-in-stocks and flows of parent processes can be defined in terms of the change-in-stocks and flows of their child processes. Therefore, only the change-in-stocks and flows of the child processes need to be defined in the codebase. An illustrative example is provided in Appendix A1, Supplementary Information.

2.2. Modelling

A summary of the BaMFA method applied in this case study is presented here. A full method is provided alongside justification in the precursory publication (Wang et al., 2024).

Bayesian inference has two inputs: (i) 'Prior distributions', $p(\theta)$, described using 'prior data': estimates for all variables of interest (e.g., changes-in-stocks and flows) that reflect the users' beliefs and expert domain knowledge, which are described before observed (e.g., reported) data is considered; and (ii) observed (e.g., industry-reported) data. These input data, Y, are used to calculate posterior distributions, $p(\theta|Y)$, for each variable of interest using Bayes' theorem (Eq. (1)). The variables of interest here in the construction aggregate case study are masses of construction aggregates.

$$p(\theta|Y) = \frac{p(\theta)p(Y|\theta)}{\int p(\theta)p(Y|\theta)d\theta} \tag{1}$$

where $p(\theta)$ is the prior distribution; $p(Y|\theta)$ is the 'likelihood function': the conditional probability, based on observed data, of a specific change-in-stocks or flow quantity at a given point in the defined system; a probability that depends on probabilistic parameters (mean and variance) defined by the BaMFA model; and $\int p(\theta)p(Y|\theta)d\theta$ is the 'marginal probability' of Y: the unconditional (not considering the observed data) probability of a particular change-in-stock or flow quantity at a specific point in the defined system over the entire sample space.

In BaMFA, parameters used to describe the prior distributions of change-in-stocks and flows (e.g., mean, μ_i, and variance, σ_i^2) are estimated based on domain knowledge including expert opinion. In the context of BaMFA, the variance is inversely proportional to confidence in this subjective information. Here specifically, there is low confidence in the subjective information (priors) in this case study, so high variance is allocated. Change-in-stocks variables are assigned normal-distribution priors (Eq. (2)), and flow variables are assigned truncated-normal distribution priors (Eq. (3)) to ensure that flows are always positive. The likelihood function is also assigned a normal distribution.

$$S_i \sim N\left(\mu_i, \sigma_i^2\right) \tag{2}$$

$$U_{j,k} \sim TN\left(\mu_{j,k}, \sigma_{j,k}^2\right) \tag{3}$$

where μ_i and σ_i^2 are the prior mean and variance of the i^{th} change-in-stock variable, S_i, respectively; and $\mu_{j,k}$ and $\sigma_{j,k}^2$ are hyperparameters in the prior that correspond to flow quantities from process j to k for flow variable $U_{j,k}$(Wang et al., 2024).

An important principle in material flow analysis is 'conservation of mass', i.e., that, in a closed system, mass can be neither created nor destroyed as it moves through the system (Brunner and Rechberger, 2005). Conservation of mass is incorporated into the BaMFA codebase as a constraint where the likelihood function is modelled, but the probabilistic nature of Bayesian inference makes achieving perfect mass conservation difficult. Model parameters and calculated variables have ranges of probable values, which are less tractable than deterministic (exact) values. Therefore, we do not enforce perfect mass conservation. This is justified since there will always be some uncertainty in the system definition (i.e., the processes, stocks, and flows defined in the system diagram) or in the data of interest (and prior distribution) (Laner et al., 2016).

As shown in Eq. (1), the prior and likelihood are combined via Bayes' theorem to produce the posterior distribution, which represents a statistically principled combination of subjective prior knowledge and reported values (i.e., observed data), Y, which is the model output (Fig. 1).

2.3. Bayesian material flow analysis codebase

The BaMFA codebase is designed to offer a robust framework for applying BaMFA within defined (by the user) systems. It is written in Python v3.11.7 and operates through the probabilistic programming library 'PyMC'. PyMC allows Bayesian inference to be performed on user-defined probabilistic models using Markov chain Monte Carlo (MCMC) methods. PyMC v5.10.3 and the Jupyter Notebook programming environment are used in the codebase. The Python dependencies are: pymc, arviz, pandas, numpy, math, random, and matplotlib. These details are listed alongside a user guide in 'Appendix A5', Supplementary Information, and as part of the README document in a Github repository alongside a downloadable .yml of the Python environment used (https://github.com/arm319/aggregates_BaMFA_England_2019).

Several Python scripts are presented within this repository, which are responsible for different scripts and aspects of the BaMFA model, including model definition, pre-processing, and output handling. For ease of use, these separate BaMFA scripts are operated through the principal script, 'runaggregatemodel.ipynb'.

The BaMFA model is defined in the script 'model.py'. This script defines the likelihood functions, prior specifications, and the sample function – the procedure through which the posterior data (results) are

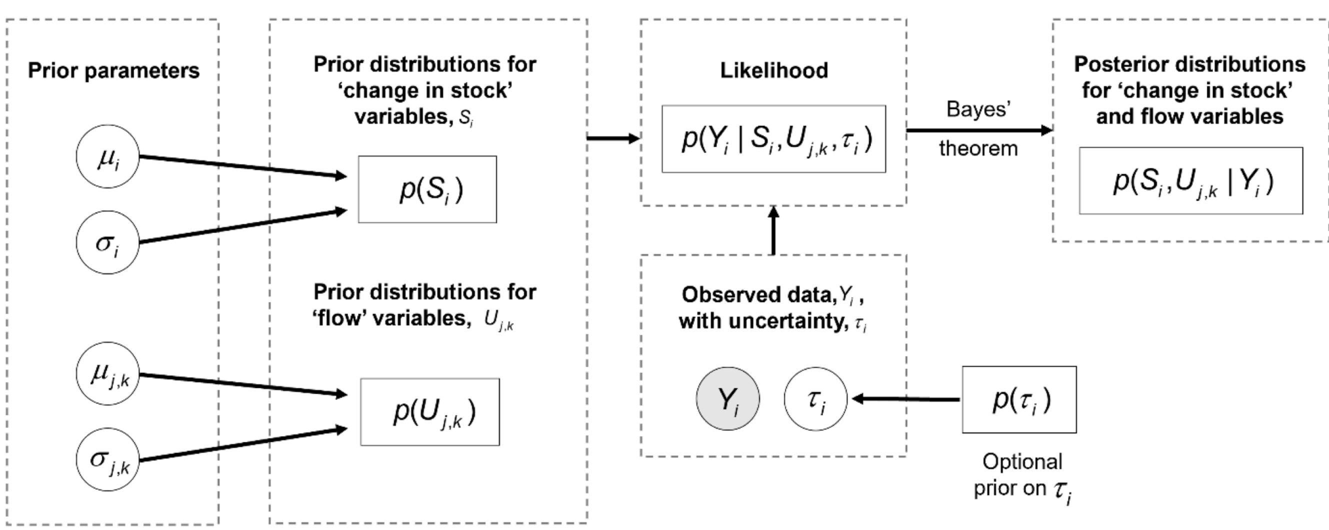

Fig. 1. Schematic of the Bayesian model. The circles represent model parameters where μ_i and $\mu_{j,k}$ are means, σ_i and $\sigma_{j,k}$ are variances, and τ_i is the uncertainty; the grey circle represents an observed datapoint, Y_i. The solid rectangles represent distributions over the variables of interest, and the modelled likelihood. Figure adapted from Wang et al. (2024).

calculated. Here, samples are generated using the 'No-U-Turn Sampler' (NUTS) variant of the MCMC method with 10,000 samples, 2 chains, and additional tuning steps: 2000 tuning samples are used, duplicate samples are recalculated, and the target acceptance rate is set to 0.9 (values between 0.8 and 1.0 are recommended for NUTS) (Xu et al., 2019; Monnahan and Kristensen, 2018). The target acceptance rate is a parameter that influences the sample step size within the sampling space. A larger sample step size explores the sample space more rapidly, increasing the rate of convergence of the model but reduces the accuracy of its calculated posterior distributions.

The prior data and observed data are input separately into the BaMFA model in '.csv' (comma separated values, CSV) format. Four data files are input: prior changes-in-stocks data, prior flows data, observed changes-in-stocks data, and observed flows data. The BaMFA model results including summary statistics (posterior data) are output and stored in '.txt' format (Table S3, Supplementary Data). As BaMFA is probabilistic, posterior data are probability distributions that describe a range of probable change-in-stock and flow quantities; deterministic values can be extracted from the posterior distributions to describe and visualise the construction aggregate system quantitatively. Here, the mean value of each posterior distribution (μ_i) denotes the most likely change-in-stock or flow quantity in each case and is taken as the deterministic result. These data are visualised through 'ppplots.py'. Prior and posterior distributions are plot concurrently for each change-in-stock and flow variable along with their mean values and 95 % high density intervals (95 % HDI), which provide a measure of confidence: how well the calculated results conform to the observed data. These plots are presented in 'Appendix A3' ('A3.1 Stocks', 'A3.2 Flows'), Supplementary Information.

The BaMFA model considers the entire system, handling all constituent parts of the construction aggregates system and their interdependencies simultaneously. Mass conservation being an important example: interdependencies between change-in-stock and flow variables act as simultaneous probabilistic constraints, defined within the code. As the entire system is considered holistically, the posterior distributions represent the parameter values (μ, σ) that collectively best explain the observed data and align with prior beliefs.

2.3.1. Describing the prior and likelihood distributions

Probabilistic distributions are characterised by means, μ, and standard deviations, σ (or variances, σ^2). These parameters are themselves also assigned probability distributions in Bayesian inference, termed hyperparameters, which provide additional information on uncertainty or 'noise' in the model. Sections 2.3.1.1 and 2.3.1.2 describe how these distributions are defined in this case study.

2.3.1.1. Describing the prior distributions. The priors are defined in the model using three parameters: (i) prior mean, (ii) prior mean uncertainty, which represents confidence in the prior mean; and (iii) prior noise, which accounts for variability in the observed data used to inform the prior.

Prior means ($\mu_{stock,i}$, $\mu_{flow,i}$). Prior change-in-stock and prior flow parameters are assigned normal (Gaussian) probability distributions with means $\mu_{stock,i}$ and $\mu_{flow,i}$, respectively. Prior change-in-stock and flow quantity are input into the model through 'Aggregate_Stock_Prior_Simple_V8.txt' and 'Aggregate_Flow_Prior_Simple_V8.txt'. In this case study, the magnitudes of the priors are of most interest; each quantity is rounded up to the power of ten then used as the mean of its corresponding prior distribution.

An additional constraint is imposed on prior flows: prior flows are modelled using a truncated normal distribution with a lower limit of zero, which prevents negative flow quantities. In our BaMFA model, negative flow values do not indicate a reversed flow direction, as they might in typical material flow analyses. Truncation with a lower limit of zero is therefore warranted (Wang et al., 2024).

2.3.1.1.1. Prior mean uncertainty (covariance). Prior mean uncertainties represent confidence in the prior mean. They are standard deviations based on observed change-in-stock and flows data, input through the files 'Aggregate_Stock_Simple_V8.txt' and 'Aggregate_Flow_Simple_V8.txt', respectively. Assigned a default value of 100 initially, prior mean uncertainties are determined by scaling the squared value of the rounded prior mean by the set constant 'covfactor' (here 40.0), with the condition that it cannot be smaller than 0.01 (see 'prior.py'). A covfactor value of 40.0 provides a conservative estimate of the uncertainty, to limit overestimation or underestimation of covariances in the model. Where data is unavailable, the mean and uncertainty are set to 0.01 to ensure that the prior is non-zero.

2.3.1.1.2. Prior noise ($\sigma_{stock,i}$, $\sigma_{flow,i}$). Prior noise is here defined as fixed standard deviations taken directly from the observed change-in-stocks and flows data. Termed 'sigmastocks' and 'sigmaflows' in 'model.py' in the codebase (see https://github.com/arm319/aggregates_BaMFA_England_2019), prior noise values are calculated using a fixed scaling rule: one-tenth of the magnitude of the corresponding observed quantities, with a default minimum value of 0.3. This ensures prior noise is scaled with the observed data while avoiding extreme values. Where observed data is unavailable, prior noise is set to the default minimum value of 0.3. These are fixed values rather than distributions.

2.3.1.1.2.1. Prior noise uncertainty

There is capacity in the model to define prior noise uncertainty, as described below. In this case, prior noise is described as distributions rather than a fixed values (as in 2.3.1.1.3). To reduce computational complexity, prior noise uncertainty is not included in this case study, but this capacity is enabled by setting 'sigmadeterministic' in 'model.py' to zero.

If prior noise uncertainty is included, prior noise for change-in-stock and flow parameters ($\sigma_{stock,i}$, $\sigma_{flow,i}$) are assigned inverse gamma probability distributions (Eq. (4)), a common practice in Bayesian inference.

$$f(\sigma_i|\alpha,\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)}{\sigma_i}^{-\alpha-1}\exp\left(-\frac{\beta}{\sigma_i}\right) \tag{4}$$

where $f(\sigma_i|\alpha,\beta)$ denotes the probability density function of a standard deviation (i.e.,$f(\sigma_i)$) given the hyperparameters α and β; $\alpha(>0)$ is the 'shape parameter' , which influences the shape of the inverse gamma distribution; $\beta(>0)$ is the 'scale parameter' , which determines its spread; and $\Gamma(\alpha)$ is the gamma function evaluated at α, which normalises the distribution. For positive integers: $\Gamma(\alpha) = (\alpha-1)!$ Smaller values of αsignify that there is a lower concentration of data distributed about the mode of $f(\sigma_i|\alpha,\beta)$.

Accordingly, the parameters α and β are defined in 'prior.py': These parameters represent prior beliefs of the defined system and as such serve as starting points for the BaMFA model, refined while it is run. α is set as 4, which is suitable for weakly informative priors (Gao, 2018) while β is a scaled parameter determined using the observed changes-in-stocks and flows data.

2.3.1.2. Describing the likelihood distributions. In Bayesian analysis, likelihoods are scalar values calculated assuming the underlying observed data (Y_i) follows a normal distribution. Eq. (5) shows the likelihood function:

$$P(Y_i|\mu_i,\sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}}\exp\left(-\frac{(Y_i-\mu_i)^2}{2{\sigma_i}^2}\right) \tag{5}$$

where Y_i is an observed change-in-stock or flow, μ_i, is the corresponding prior mean, the predicted value; and σ_i is the corresponding prior standard deviation (noise). The likelihood describes how likely an observe a quantity is, at a specific point in the model, given the predicted value (prior mean) and its uncertainty (prior noise). For example, if an observed flow, $Y_{flow,i}$, is 10 Mt, its corresponding prior mean, $\mu_{flow,i}$, is 5 Mt, and if the prior noise, $\sigma_{flow,i}$, is 0.5, the likelihood function is

1.255×10^{-22}. Such a small value denotes a low likelihood.

3. Construction aggregates case study

3.1. System definition

Figs. 2a-f describe the 2019 construction aggregates system for England, UK, that is the subject of the case study presented here. Here, construction aggregates include crushed rock, gravel, sand, and secondary aggregates such as recycled concrete aggregate. The system is split into six main parts typically used to define material systems (Morley et al., 2022), each representing a key stage in the life cycle of construction aggregates: reserves, extraction, aggregate processing and production, manufacture of upstream products, use, and waste management. Each of these processes is disaggregated into more specific processes to fully represent the complexity of the system. A simplified version of the system is shown in Fig. 2a. Greater detail, including the compositions of stocks and flows (typically sand, gravel, crushed rock, recycled construction and demolition waste), is provided through process flow diagrams (Figs. 2b-f) and a comprehensive mass balance (Table S1, Supplementary Data) of the input data. Modelling was performed for the fully disaggregated system.

3.2. Stocks and flows data

The spatial region England and the timeframe 2019 were chosen for this case study as substantial high-quality stocks and flows data are available for this system, notably from the Aggregate Minerals Survey for England and Wales (Mankelow et al., 2021). Further data for marine dredged aggregates were collected from the Crown Estate (The Crown Estate Licenses, 2017) and for recycling and inert wastes from Mineral Products Association (MPA) reports (Mineral Products Association, 2022c, 2019). Information from these sources provide the observed data, Y_i, for the BaMFA model (see Eq. (2)). The collated data for the fully disaggregated material system are presented in Table S1, Supplementary Data.

3.2.1. 2019 construction aggregates data for England, UK

Despite the UK having one of the most developed systems for planning and monitoring supplies of aggregates in the world (Gunn et al., 2008), less than 20 % of the change-in-stock and flow variables within the modelled system (Figs. 2b-f) could be described using available 2019 construction aggregates data. Most of the observed data pertained to trade: import/export and the production and manufacturing stages (Fig. 2c, Fig. 2d), reflecting the high availability of sales data for aggregates in England (Mankelow et al., 2021). The data regarding 'waste generation' and 'recycling' of aggregates from industry reports (Mineral Products Association, 2022a) lacked the level of disaggregation required to be directly used within the defined system (Fig. 2) without further processing. To use these data, we estimated what portion of UK data is attributable to England and extrapolated to the 2019 reference year (explanations are provided in Table S5, Supplementary Data).

To increase information input into the BaMFA model, expert opinion and domain knowledge were used to define parameter values (e.g., μ, σ) for the prior distributions ($p(\theta)$) of each change-in-stock and flow variable. Such information was solicited via a workshop with attendance from construction aggregate experts in organisations including the British Geological Survey, Mineral Products Association, Construction Products Association, British Aggregates Association, and the Infrastructure and Projects Authority. This workshop specifically focussed on gathering information pertaining to change-in-stock and flow variables absent in the observed data for the 2019 construction aggregate system in England. We also sought domain knowledge on 'ratio data' to disaggregate flows into different aggregate types and account for process efficiencies. Key assumptions obtained from this workshop include a 1:9 extracted materials to product ratio for the 'Extraction and Processing/Production' process; 82 % of construction aggregates within the UK being extracted, used, and recycled in England; and a 70:30 ratio for

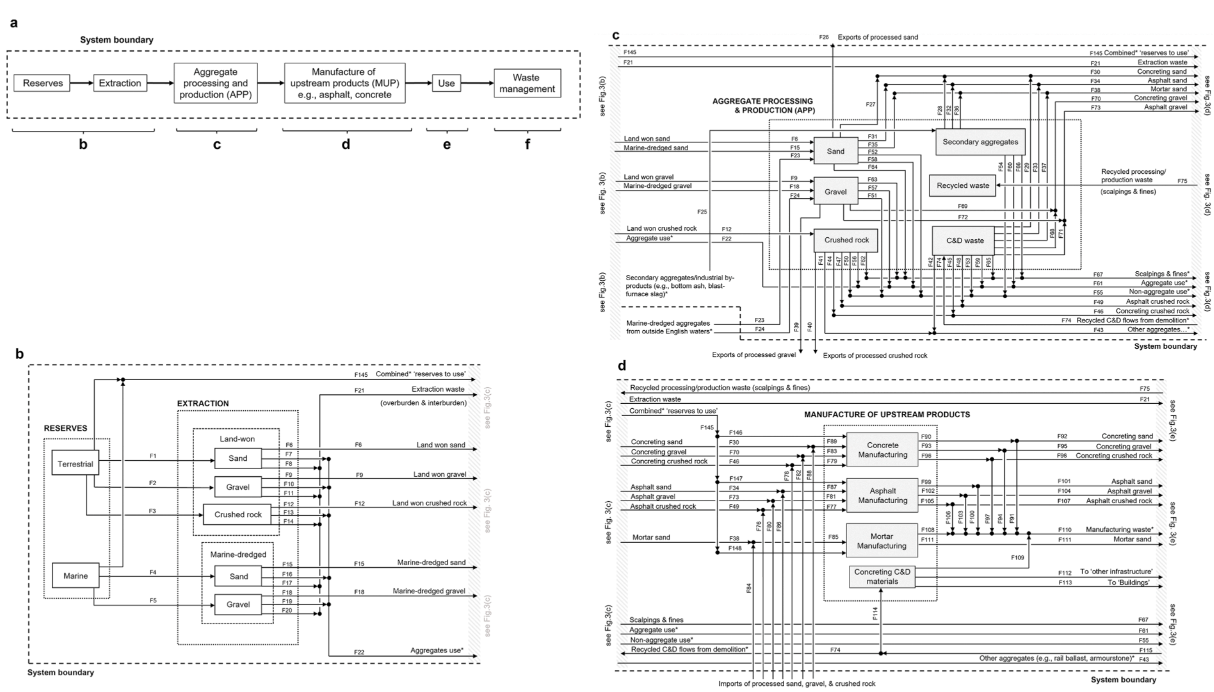

Fig. 2. System diagrams for the 2019 construction aggregates system in England, UK, comprising (**a**) a simplified system diagram showing the main stages of the system, which is disaggregated and described in greater detail in five parts: (**b**) 'reserves' and 'extraction', (**c**) 'aggregate processing and production (APP)', (**d**) 'manufacture of upstream products (MUP)', 'use', and (**f**) 'waste management'. The arrows represent flows of aggregates between processes (white boxes: parent-, child-, or sub-processes) or material stocks (grey boxes) and the direction of flow: origin → destination. The nodes (●) indicate where arrows branch or merge, the dashed line is the system boundary, 'C&D' stands for 'construction and demolition', and the asterisk (*) indicates a flow comprising several materials – as described in Table S2, Supplementary Data.

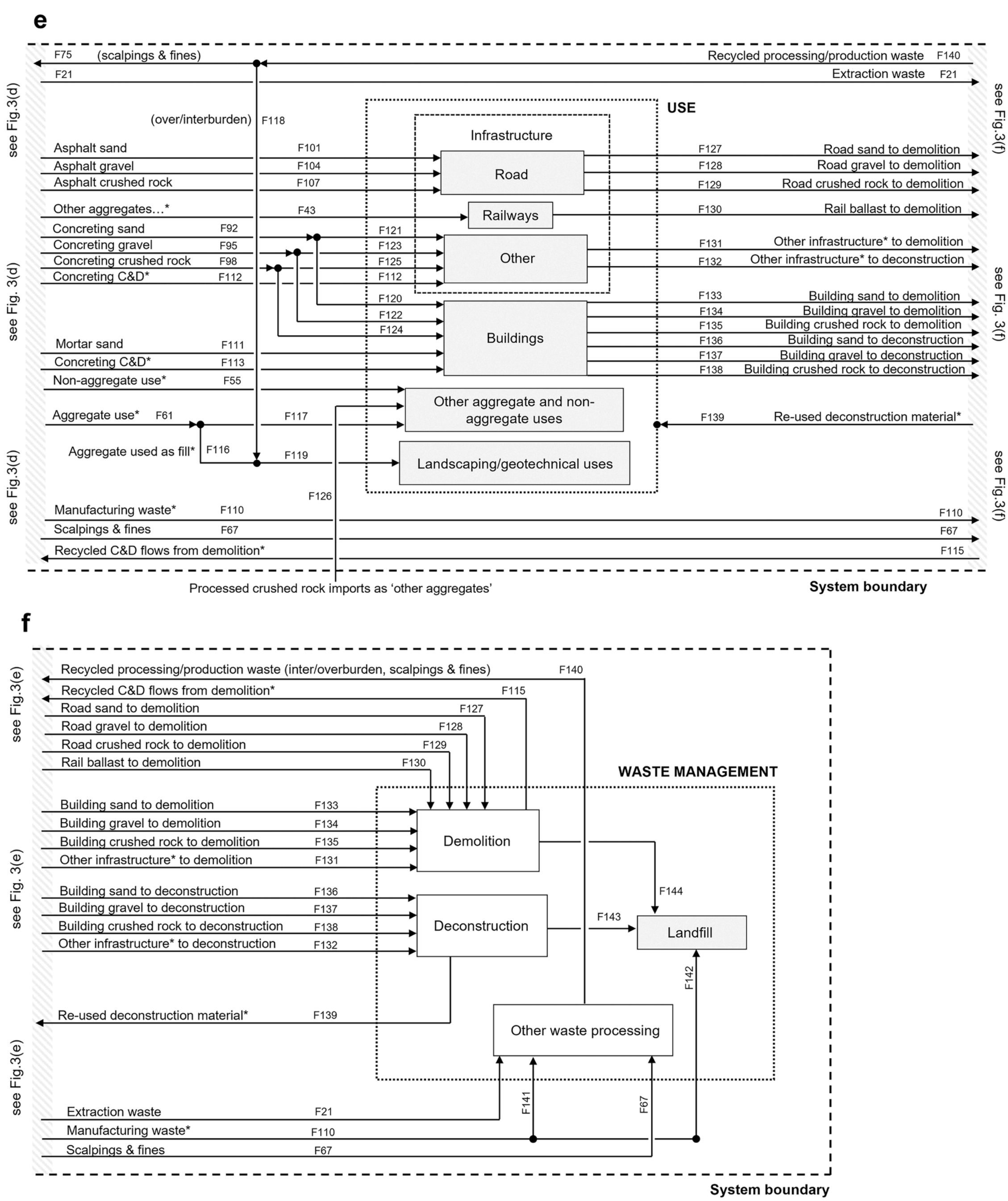

Fig. 2. (*continued*).

land-won and marine-dredged sand and gravel. The full dataset of prior distributions, annotated with the data sources and assumptions used, are provided within 'Flows_prior' and 'Stocks_prior' worksheets in the Supplementary Data file.

4. Results and discussion

Key results for the modelled 2019 construction aggregate system are presented in Table 1; the full data are provided in Tables S2 and S3 in the Supplementary Data file. Table 1 describes material use and disposal or re-use of construction aggregates in England in 2019, comprising the sum of extraction from terrestrial and marine reserves, imports of secondary aggregates (industrial by-product), and imports from outside England. Presented in Table 1 are (i) measures of production: the quantities of aggregates used in the manufacture of concrete, asphalt, and mortar; and the quantities of sand, gravel, and crushed rocks exported across the defined system; (ii) measures of aggregate use within the defined system (another considerable data gap prior to the application of the BaMFA model (Fig. 3a)); and (iii) measures of circularity within the defined system (i.e., the quantities of aggregates sent to landfill and recycled within the defined system).

Fig. 3a shows the observed (e.g., reported) construction aggregate change-in-stocks and flows data input into the BaMFA model, showing that observed data describes only 20 % of the defined system. Where observed data are unavailable, processes are omitted. Fig. 3a attests the need for more reported change-in-stocks and flows data. Especially downstream, where extraction drives direct environmental impacts from land use change (Ogundana and Afolalu, 2024), and at end-of-life (waste management), where materials can re-enter the economy. A more comprehensive understanding of end-of-life changes-in-stocks and

Table 1
Summary of key results for the 2019 construction aggregate system for England, UK, by material: sand, gravel, crushed rock, construction and demolition (C&D) waste, overburden and interburden, scalpings and fines, concrete, asphalt, and mortar.

Summary of key BaMFA results		Material	Quantity (1000 tonnes)
Extraction	From terrestrial reserves within English waters	Land-won sand	19,793
		Land-won gravel	20,419
		Land-won crushed rock	74,520
		Total land-won	**114,732**
	From marine reserves within English waters	Marine-dredged sand	7556
		Marine-dredged gravel	8746
		Total marine-dredged	**16,302**
		Total extracted	**132,807**
Imports	Internally sourced [a]	Secondary aggregates	1965
	Externally sourced [b]	Primary sand	455
		Primary gravel	684
		Primary crushed rock	9851
		Total imported	**12,955**
Manufacture	of…	Concrete	48,858
		Asphalt	5883
		Mortar	2848
		Total manufactured	**57,589**
Use [c]	Construction	Sand	39,177
		Gravel	11,906
		Crushed rock	23,564
		C&D waste	13,970
		Total construction use	**88,616**
	Other use	Sand	10,061
		Gravel	16,667
		Crushed rock	46,861
		C&D waste	16,112
		Total other use	**89,701**
		Total used	**178,317**
Exports		Sand	27
		Gravel	34
		Crushed rock	47
		Total exported	**108**
Landfill		**Total landfill** [d]	**19,613**
Recycle/re-use	From 'Demolition' [e]	C&D materials	42,676
	From 'Deconstruction' [f]	C&D materials	1592
	From 'Other waste processing' (OWP)	Overburden/ interburden	20,783
		Scalpings/fines	71
		Total recycled	**65,122**

[a] Industrial by-products
[b] from outside English waters
[c] as distinguished in Figs. 3e and 4b.
[d] $18,848\times10^3$ tonnes from demolition, 765×10^3 from Manufacturing (see Fig. 3e).
[e] $13,905\times10^3$ tonnes to 'Concreting C&D materials' (see Fig. 3b), and $28,771\times10^3$ tonnes to 'C&D waste' (see Fig. 3b).
[f] to 'Other aggregate and non-aggregate use' (see Fig. 3b).

flows is particularly important for circular economy transitions.

Fig. 3b on the other hand shows the results of the BaMFA model and is substantially more detailed. In comparing Figs. 3a and 3b, the significant potential of the BaMFA method is clear; material cycles can be more comprehensively described, facilitating greater understanding and more informed intervention, even where change-in-stocks and flows data are previously greatly limited or unavailable. The data contained in Fig. 3 are provided in Supplementary Data ('Sankeyknown', 'Sankey2019') and numerically in Tables S2 and S3.

A comprehensive understanding of supply-demand dynamics of construction aggregates requires that the entire supply chain is quantified. This case study is the first to do this at a national level. It is difficult to draw country-level conclusions due to the importance of local construction aggregate supply. However, planning for aggregate provision in the UK relies on data from previous sales (A. Gunn et al., 2008). By providing this data where it currently lacks, the quantitative results of this case study (Table 1 and Supplementary Data) can therefore contribute to improved life cycle efficiency; several opportunities for which are identified from the results (Table 1). These relate to material extraction and end-of-life where, through this case study, considerable data gaps were identified:

The construction aggregate system in England is reliant on indigenous primary production. 68 % of materials serving as input into the construction aggregate system for England in 2019 are primary aggregates (extracted, imported), with secondary aggregates (e.g., industrial by-product) and recycled aggregates making-up the remaining 32 % (21 % as construction and demolition materials, 10 % as overburden/ interburden, and 1 % as secondary aggregates). These values suggest a slightly lower reliance on primary aggregates for construction in England in 2019 than reported (Mineral Products Association, 2022c): 71 % primary aggregates, and 29 % secondary and recycled (predominantly 'down-cycled') aggregates.

Totalling 142 Mt, England's demand for primary aggregates represents an important environmental issue. On a global scale and often in the absence of effective regulation, demand for primary aggregate extraction from rapidly developing cites drives unsustainable terrestrial and marine land use changes; directly, through transformation and occupation, as well as indirectly, through secondary drivers of land use change including environmental feedback effects (e.g., soil and seabed degradation, disruptions to nutrient cycling). Terrestrial extraction, the greatest contributor here, often takes place in densely populated urbanised areas. Compounding this, the extraction and transportation of primary aggregates drives direct emissions of CO_2. The resultant embodied CO_2 within built infrastructure derived from these materials is substantial (91 $MtCO_2$-eq $year^{-1}$ (Drewniok et al., 2023)). So too, therefore, is the opportunity to improve resource efficiency as this mature building stock is developed.

A further benefit to reducing primary aggregate demand is financial and relates to the UK 'aggregate levy', which effectively taxes the extraction of both land-won and marine-dredged sand, gravel, and rock (UK Government, 2017). By reducing primary aggregate extraction within the modelled system, a saving of £2 M Mt^{-1} could be made. However, while it is possible to substitute primary aggregates in some applications, thereby reducing their extraction (Bakare et al., 2023; Li et al., 2023; Russo and Lollini, 2023), the effects of complete primary aggregate substitution in many applications are not yet understood. Furthermore, aggregates from higher ordinal levels (secondary, tertiary) of suitable quality and type must be available to supplement primary aggregate use. Reducing primary aggregate use is therefore contingent on aggregates re-entering the economy at end-of-life.

The BaMFA case study calculated that a significant quantity (20 Mt) of construction and demolition waste, and manufacturing waste is sent to landfill and its value lost. 20 Mt of construction and demolition waste, and manufacturing waste represents a potential embodied carbon cost of up to 2×10^9 t CO_2-eq. (Wang et al., 2022), and through UK 'landfill tax', currently £97 t^{-1} (Jofre-Monseny and Sorribas-Navarro, 2024), a potential financial cost of up to £1.9 billion. Many of the landfilled materials can be recycled but are wasted due to inadequate consideration of potential markets. Considerable opportunity for reuse therefore exists, a longstanding aim of UK government and corporate policy (e.g., Resources and Waste Strategy for England (Department for Environment, Food and Rural Affairs, 2018), UK Environment Act (HM Government, 2021)), Material Products Association sustainability roadmap (Mineral Products Association, 2022b)). However, recovery rates for construction and demolition wastes are already high in England, reportedly exceeding 90 % (Department for Environment, Food and Rural Affairs, 2018). Capacity for improvement towards achieve near-complete

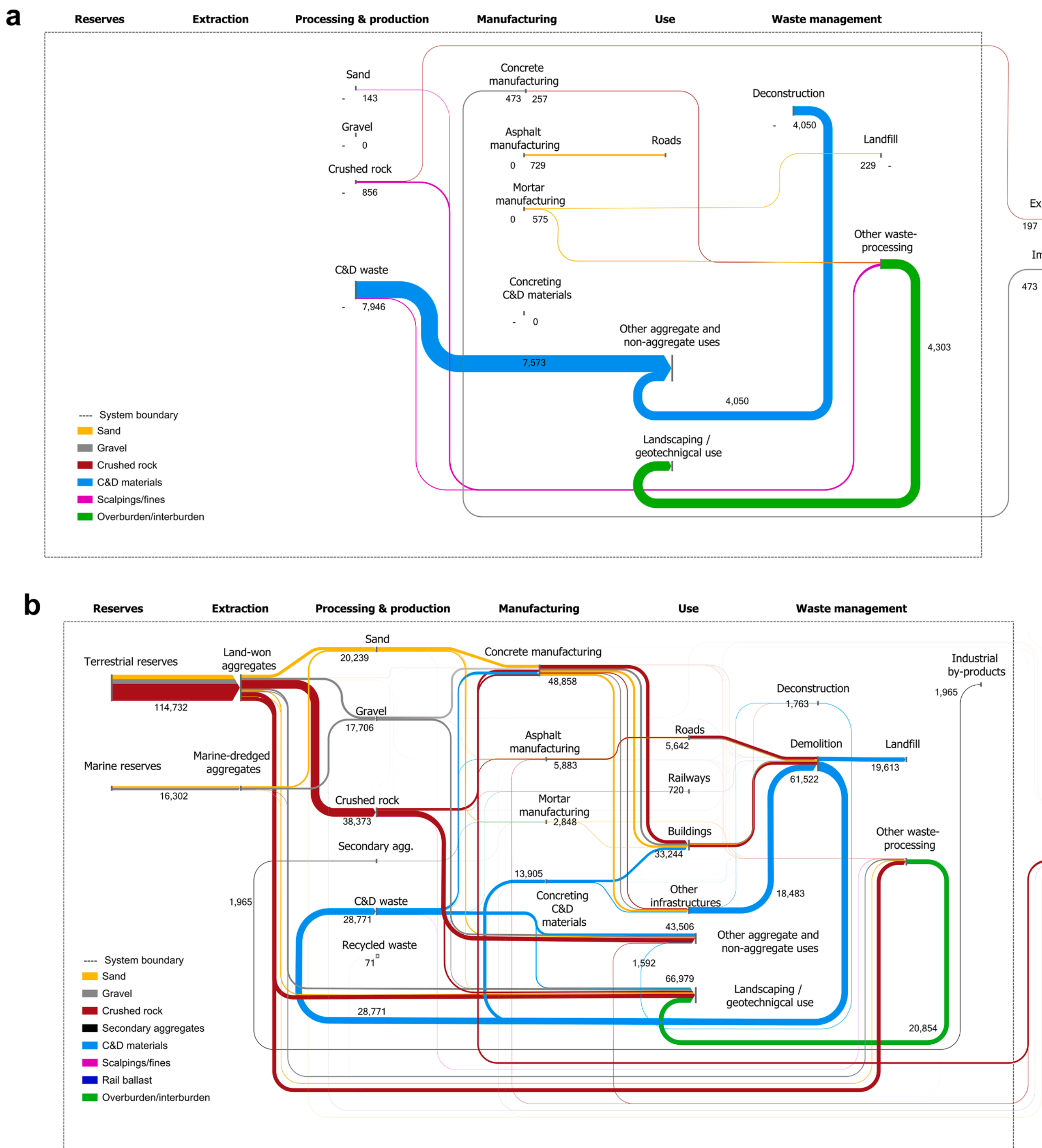

Fig. 3. Sankey diagrams showing (a) the observed (i.e., reported) data for the 2019 construction aggregates system in England, UK, and (**b**) the calculated flows for the 2019 construction aggregates system in England, UK, by material type (see legend, inset). Undefined variables in the observed data are omitted to better convey how well the reported data and BaMFA results describe the modelled system in (a) (~20 %) and (b) (100 %). Quantities are in 1000 tonnes. A dash (-) represents 'no quantity'. Full data are provided in Tables S2 and S3, Supplementary Data. The worksheets 'Sankeyknown' and 'Sankey19' contain the data used to produce Figs. 3a and 3b, respectively. The mean of absolute mass imbalances is 9.7×10^{-2} Mt. The relative mass imbalance across the modelled system is 0.02 % (see Appendix 7, Supplementary Information).

recovery is currently limited by expense and practicality.

We expect that the disposal of some (e.g., hazardous) construction and demolition waste is inevitable but also that the current lack of understanding around waste flows and hence material availabilities, which our paper produces results on, limits market opportunities. To move towards national circular economy and carbon-emission targets, such as the UK's Net Zero Government Initiative, and the EU's 2050 long-term strategy on climate action, the low rates of building material re-use that identified here should be increased. By re-using materials, the production of new infrastructure materials (e.g., steel, concrete, bricks) and their associated greenhouse gas emissions (Akbarnezhad and Xiao, 2017) can be avoided.

To effectively track the reduction of construction and demolition waste, the UK government could implement several key indicators. Including waste diversion rates, which measures the percentage of waste diverted from landfills to recycling or reuse, alongside reuse rates and the reduction in primary aggregate use, which would help measure material re-use (which can be more sustainable than recycling) and the decrease in demand for new primary aggregates. To alignment with UK Net Zero initiatives, carbon emissions per mass of material processed, and those avoided through substituting primary materials with recycled materials, should also be followed. Finally, the generation of construction and demolition waste per unit of GDP as an indicator would provide information on the decoupling of construction and demolition waste generation from economic growth, in support of a more material efficient economy.

4.1. Towards a more comprehensive understanding of material systems

Despite construction aggregate systems and their ancillary processes being well studied and purportedly well defined, reported change-in-stocks and flows data describe only 20 % of the modelled construction

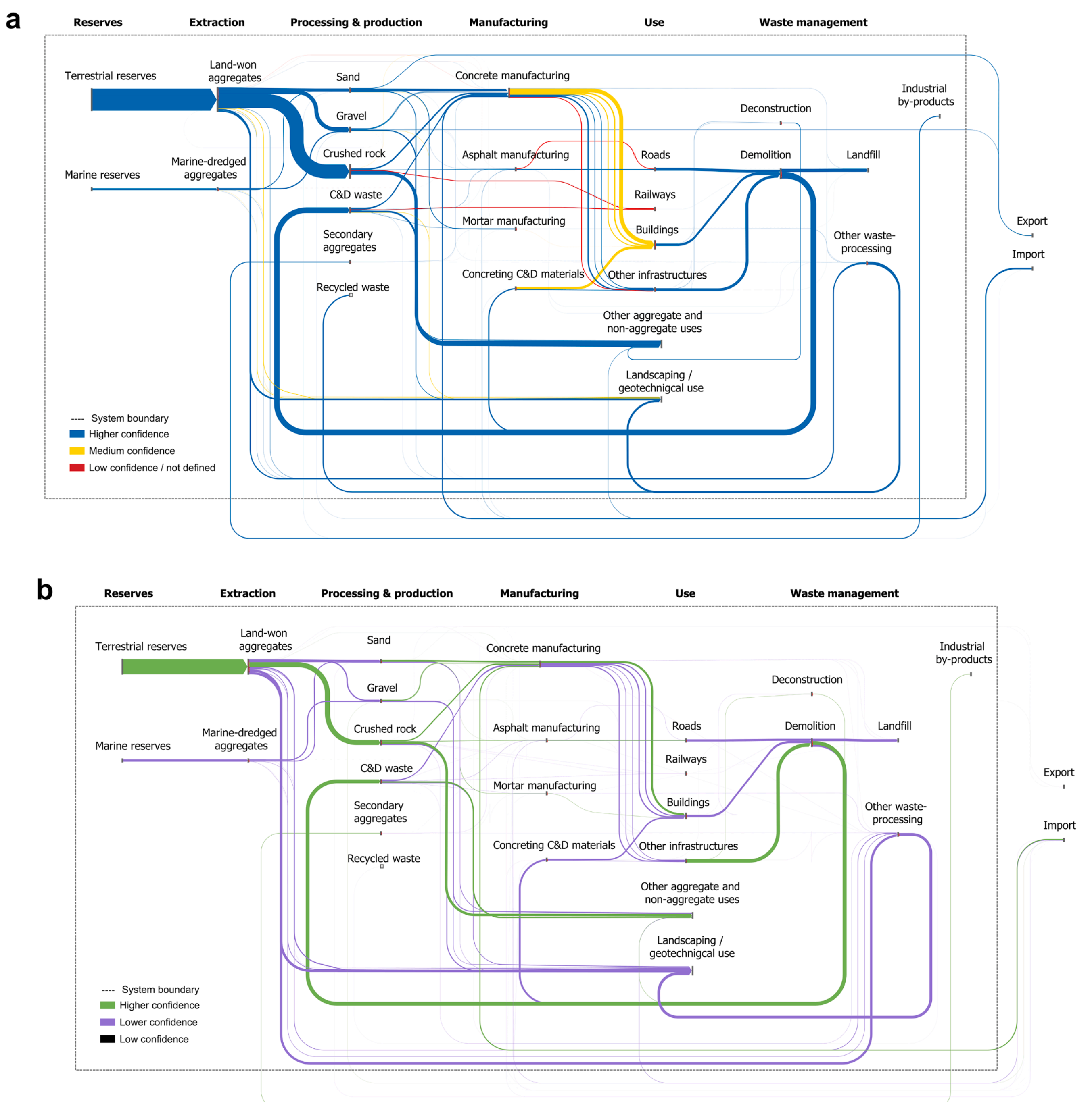

Fig. 4. Sankey diagrams showing (**a**) confidence levels in the prior flows (the data input into the BaMFA model) where blue denotes ‘higher confidence’ (the prior value is considered plausible), amber denotes ‘medium confidence’ (the prior value is considered reasonably plausible), and red denotes ‘low confidence’ (the prior value is not strongly supported). Low confidence priors are omitted from the prior dataset input into the BaMFA model. (**b**) describes confidence levels in the posterior flows (the results calculated by the BaMFA model) based on calculated HDI (confidence ranges), where green denotes ‘higher confidence’: $\frac{|HDI_{97\%}-HDI_{3\%}|}{\mu_{flow,i}} \leq 1$, black denotes ‘low confidence’: $\frac{|HDI_{97\%}-HDI_{3\%}|}{\mu_{flow,i}} >> 1$, and green denotes ‘lower confidence’ between the two: $\frac{|HDI_{97\%}-HDI_{3\%}|}{\mu_{flow,i}} > 1$. Full data are provided in Tables S5 and S7, Supplementary Data.

aggregate system (Fig. 3a). Reported data on the 'use' and 'waste management' life cycle stages are most lacking. This finding reflects a wider issue relating to the collection and dissemination of materials data, which limits our understanding of material cycles and our capacity to assess them. At the global scale, the lack of data regarding sand supply is in particular noted by the UN Environment Program as a significant barrier for the sustainable supply of construction materials (United Nations Environment Program (UNEP), 2022).

More informative priors and comprehensive 'observed data' produce more reliable BaMFA results. The more limited and less informed data are at input, the greater uncertainty that is introduced into the model and subsequently into the results. A combination of uninformed 'vague priors' and 'informative priors', based on reported data and expert knowledge, are used in this case study. The use of vague priors reflects the lack of suitable published data, particularly in the 'use' life cycle stage. Consequently, many of the posteriors calculated in this case study possess broad HDIs (see 'Appendix A3', Supplementary Information, and Fig. 4) and can be improved. To do this, i.e., narrow their HDIs, the prior and likelihood distributions that are inputs into the BaMFA model here should be improved. This requires more accurate and complete data at input. Given change-in-stocks and flows data were most lacking in the 'use' life cycle stage, their corresponding priors are likely the greatest source of uncertainty within this BaMFA case study. Their quantification is therefore a priority.

More generally, accurate empirical assessment of any material or substance, including construction aggregates, requires a greater quantitative understanding of their use from cradle-to-grave and across different temporospatial scales. As well as improving our understanding of material systems, BaMFA can help to optimise the efficiency of data collection. Through BaMFA and the aggregation of requisite data, deficiencies (e.g., poor quality or missing data, and low granularity) in stocks and flows data can be identified, and data collection practices refined. This would facilitate targeted action for quantifying material life cycles, enabling rapid, informed systematic improvements. For example, in the case study presented, flows data between extraction and upstream processing, and around deconstruction are found to be most deficient. To more efficiently reduce uncertainty across the material cycle, addressing these deficiencies should be prioritised, e.g., by collecting more observed data for these flows.

4.2. BaMFA model convergence

In Bayesian modelling, convergence is the point at which the sample space has been sufficiently explored and the posterior distributions are stable and consistent. Divergences are instances where exploration of the sample space is impaired, resulting in unreliable inferences and/or inaccurate estimates (Betancourt, 2018). This may be due to complex sample-space geometries or sub-optimisation (e.g., of model parameters) within the BaMFA model. Failure to explore parts of the sample area can produce biased or unreliable model parameters, and hence unusable posterior data, warranting recalculation. The acceptable level of divergence is context specific; here, a total number of divergences less than 5 % of the total sample size is considered a practical threshold of acceptability (Betancourt, 2018). In the case study reported here, the BaMFA model converged with 311 divergences across 24,000 samples. This is equivalent to 1.3 % of the sample size and is thus acceptably low. The runtime was approximately 40 minutes.

4.2.1. Uncertainty analysis

The BaMFA model generated functional posterior distributions for 146 changes-in-stocks and flows comprising the modelled construction aggregates system, across nine process stages (see Table A1, Supplementary Information). Convergence was confirmed through the Gelman-Rubin statistic (r-hat) ('Table S3', Supplementary Data) (Vehtari et al., 2021). These posterior distributions are visualised in 146 plots in 'Appendix A3', Supplementary Information. In each plot, corresponding prior and posterior distributions are presented together alongside their mean values, and their high-density intervals (HDI 95 %), which describe credible intervals (i.e., range of quantities) for each change-in-stock or flow. A larger HDI range indicate greater uncertainty (lower confidence) for an estimated change-in-stock or flow. However, HDI ranges do not categorise posterior distributions as explicitly precise or imprecise. Determining whether an HDI range is acceptable requires consideration alongside other metrics, such as the Gelman-Rubin statistic, standard deviation, or the 'Monte Carlo standard error of the standard deviation' (MCSE SD), which are presented for this case study in Table S3, Supplementary data. Contextual factors including data quality, model parameters and stakeholder priorities also inform HDI evaluation.

Fig. 4 visualises the confidences in the prior and posterior data. Fig. 4a describes confidences in prior flows, reflecting the strengths and weaknesses of the underlying domain knowledge. Fig. 4b describes confidences in posterior flows based on HDI data (Eq. (5)), which quantifies relative uncertainty (scale independent).

$$\frac{|HDI_{97\%} - HDI_{3\%}|}{\mu_{flow,i}} \tag{6}$$

Full data are provided in Tables S5 and S7, Supplementary Data.

Marginal distributions represent the uncertainty of a single variable, which is an individual change-in-stock or flow here. We present the marginal priors and posteriors calculated here in 'Appendix A3', Supplementary Information ('A3.1 Stocks', 'A3.2 Flows') alongside their corresponding HDIs and mean values ($\mu_{stock,i}$,$\mu_{flow,i}$), since by plotting the prior and posterior marginal distributions together, the two can be contrasted. Individually, a wider marginal distribution indicates higher uncertainty, with a greater range of possible values. Here, a narrower posterior distribution indicates uncertainty at input was reduced. Conversely, wider posterior distributions indicate uncertainty at input has persisted or increased.

Probability values or '*p*-values' complement marginal distributions because they provide greater insight into prior and posterior uncertainties. In statistics, *p*-values describe the probability of observing the calculated change-in-stocks or flows values if the null hypothesis were true, i.e., through random sampling. Rejecting the null hypothesis represents a reliable posterior. A *p*-value less than 0.05 ($p < 0.05$) typically indicates strong evidence against the null hypothesis, whereas a *p*-value greater than 0.05 ($p > 0.05$) typically indicates insufficient evidence to reject the null hypothesis. However, BaMFA does not include hypothesis testing in the same way. Instead, posterior checks are used to scrutinise the model's ability to make reasonable predictions (compared to known, i.e., observed, data). In BaMFA, a *p*-value around 0.5 indicate the posteriors match the known data, which is desirable; whereas *p*-values around 0 or 1 indicates potential issues with the model (Held and Ott, 2018). *p*-values are calculated for change-in-stocks data, flows data, and conservation of mass conditions through 'ppplots.py' (see 'Appendix A6', Supplementary Information). Figure A2, Supplementary Information, shows that the calculated posteriors largely match the known data, indicating that the model made reasonable predictions and produced reliable results. Some high *p*-values exist ($n = 6$), which are attributed to high uncertainty associated with uninformed (vague) priors, but these represent only a small portion (4 %) of the total results.

5. Perspectives

Several aspects set BaMFA apart from conventional MFA. Through BaMFA, missing data can be estimated, with evaluation of the uncertainty of input and output data, as well as relationships between observed variables (e.g., recycling rates) and latent factors like aggregate supply and demand. BaMFA also provides a rapid and repeatable means of generating mass balances and visualisations through an updatable codebase, offering a less time-intensive alternative to conventional MFA. Conventional MFA relies on manual data reconciliation, making it a slower and more laborious process. Nevertheless, the accuracy of results in both methods depends on the validity of the assumptions made to achieve mass balance or convergence.

Through BaMFA, this case study has improved understanding of the construction aggregates system in England, UK, by estimating unavailable data. Changes-in-stocks and flows across the modelled construction aggregate system were quantified, including where data was previously lacking (unreported or unavailable). The resulting posterior data have additional value in 'sequential Bayesian inference', where posteriors from one study are used as priors in a subsequent case study. Conceptually, a more informed and comprehensive description of the modelled system at input, i.e., in the prior, will generate more accurate predictions of change-in-stocks and flows in the posterior. By using BaMFA to populate a database of 'posteriors-turned-priors', more reliable analyses can be performed while data collection and data optimisation is being completed. Iteration of this process over the long-term would lead to the establishment of a posterior-turned-priors dataset that represents the state of quantitative knowledge of a material system and is a practical way to accumulate data that minimises onerous data management effort. We expect it would enable substantially more comprehensive descriptions of the physical economy than previously possible.

Although applied here to model the 2019 construction aggregates system for England, UK, the BaMFA method is versatile and highly adaptable. BaMFA can be applied to any material (e.g., metals, textiles), substance (e.g., water, carbon), or process – single or multi-component – and across any temporal or spatial scale. BaMFA is not restricted to improving understanding or process optimisation in the present; it enables prospective future analyses, which is valuable for policymaking and scenario modelling. Resource supply and demand scenarios, such as 'business as usual' – continued historical demand – or forms of enhanced demand (e.g., to satisfy climate targets) or increased circularity (e.g., to satisfy circular economy targets), can be scrutinised to identify areas of uncertainty, where data is lacking, and opportunities for optimisation and intervention, including material substitution and operational change. This study enhances understanding of national construction aggregate demand, but supply-demand dynamics of construction materials are complex and have a significant spatial component; local production and supply vary unevenly at the national-scale. Variation at the local scale should be considered if future work is undertaken.

Similarly, the potential (life cycle) impacts of interventions can be assessed and compared by adding complementary data onto quantified mass stocks and flows, facilitating more informed action. Of particular interest are climate change, species diversity and human health, and 'value added' (finance, productivity, employment) (Kołodziejczak, 2020; Jakub, Viera and Eva, 2015). Finally, the method can be extended to perform 'dynamic Bayesian MFA', which models the evolution of stocks and flows over time to better understand the probable trajectories of material supply and demand across defined systems.

6. Conclusion

This paper presented the BaMFA method and its application to quantify in detail the life cycle of construction aggregates in England in 2019. We showed that this method can model the change-in-stocks and flows of construction aggregates in England in 2019 despite significant data gaps and without high manual data input – both important limitations of traditional MFA approaches. Although industry-reported data describe only 20 % of the system, the BaMFA method, aided by input (prior values) from construction aggregate domain experts, generated quantitative change-in-stocks and flows for the entire system. Our case study demonstrates the potential of the BaMFA method to improve quantitative understanding of material (and other substance) life cycles in any number of contexts, across temporal and spatial scales. In modelling the change-in-stocks and flows of different construction aggregates, it is also demonstrated that the BaMFA method is not restricted to single-component systems. Regarding data and data collection, the BaMFA method combines different data classification systems and disaggregated resource-specific data, while also identifying previously unknown data issues for targeted data collection. By identifying deficiencies in data and thus data collection practices, the collection of suitable (quality, scope) and underreported data can be optimised. As such, the multidisciplinary value of the BaMFA method exceeds the context of MFA.

Through this case study, the 2019 construction aggregate system for England is now much more comprehensively quantified (see Figs. 3a and 3b). Prior to this study, data on 'use' and 'waste management' were particularly limited. It is now shown that 89 Mt of construction aggregates were used for construction, contributing to infrastructure and building stocks, and 90 Mt were used for other purposes including landscaping. A considerable quantity (65 Mt) of secondary aggregates were recycled and used within the system, but there is further opportunity to increase circularity: 20 Mt of construction and demolition waste were landfilled, representing an avoidable cost of £1.9 billion and 2×10^9 tonnes of CO_2-eq. emissions. The significant demand for primary aggregate demand in England in 2019 (142 Mt) presents similar opportunity for economic and environmental improvement. This consumption of primary aggregates represents a £284 million cost and considerable environmental burden which can be mitigated through greater economic circularity. A critical requisite for identifying and actioning such economic and environmental improvements is further advancing material system understanding through BaMFA, which demands ongoing collection and collaborative sharing of material systems data.

CRediT authorship contribution statement

Adam R. Mason: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Tom Bide:** Writing – review & editing, Supervision, Investigation, Data curation. **Junyang Wang:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **John Morley:** Writing – review & editing, Visualization, Resources, Investigation. **Mohit Arora:** Writing – review & editing, Methodology, Conceptualization. **Alperen Yayla:** Writing – review & editing, Visualization, Validation, Software, Methodology. **Julia A. Stegemann:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Rupert J. Myers:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

The BaMFA codebase used in this case study is available through the accompanying online Github repository.

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2025.108135.

Data availability

Data is provided in the Supplementary Data file on Zenodo: https://zenodo.org/records/13,830,002 , and the codebase developed and used is available on GitHub, as detailed within the manuscript.

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