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CORE-D: county resolution energy demand projections for multi-scale modelling and multi-level governance dialogues in Kenya

Neve Fields^{a,*}, Michelle Akute^b, Leonhard Hofbauer^c, Martin Mutembei^d, Anne Nganga^d, Mark Howells^{a,e}, Ed Brown^a^a STEER Centre, Department of Geography and Environment, Loughborough University, Loughborough, United Kingdom^b Energy and Petroleum Regulatory Authority, Nairobi, Kenya^c UCL Energy Institute, University College London, London, United Kingdom^d Strathmore Energy Research Centre (SERC), Strathmore University, Nairobi, Kenya^e Centre for Environmental Policy, Imperial College London, London, United Kingdom

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ABSTRACT

County-level energy planning within Kenya is becoming increasingly important and relevant following the evolving governance system and energy planning responsibilities. This paper presents county-resolution energy demand projections alongside the underlying energy demand models in support of both integrated national planning, and county energy planning. The County-REsolution energy system Demand models (CORE-D) introduce a new methodological approach to overcome historic energy planning barriers. It is based on a spatial disaggregation of whole energy system demand modelling through downscaling to produce individual county demand models, facilitating the future incorporation of county level data, priorities, and plans for demand assessment. CORE-D can support county energy planning processes by enabling the development of, and facilitating stakeholder discussion on, energy demand projections under various county-level scenarios. In providing a consistent framework for energy demand analysis across all counties the approach particularly supports a coherent integration of county plans to national-level analyses and policy processes. This paper, through presenting baseline national projections at various scales, alongside demonstrative scenarios for Kilifi county which align county projections to existing nationally employed modelling methodologies, provides a foundational tool for subsequent stakeholder-driven enhancements, capacity building exercises, integration of richer and updated datasets, and robust decision-making analyses. The models, and methodologies, have been developed through collaboration with both county and national stakeholders within Kenya.

1. Introduction

The Kenyan Energy Act of 2019 devolves energy planning functions to Kenya's forty-seven county governments through the creation of individual county energy plans (CEP), to be integrated into national scale planning following compliance with the integrated national energy planning (INEP) framework [1]. Alongside CEP development, the Kenyan government has current evolving and ongoing initiatives, such as the Integrated National Energy Plan (INEP) and National Energy Policy 2025–2034 [2] which have identified multi-level governance and planning county-to-national dialogues as a key priority for future development within the energy sector. This multi-level governance approach to energy planning has posed two main problems within

Kenya of (a) limited resources and capacity within county governments, and (b) national level models containing limited consideration for sub-national governments. Subsequent energy modelling analysis within Kenya has therefore typically contained limited-to-no consideration for multi-scale governance [3].

County energy planning development within Kenya has faced many challenges preventing the development and publication of individual CEPs due to a lack of available data, resources, priority, and capacity within the energy specific planning teams and departments. Consequently, as of 2023, only six counties had finished their CEP processes (with only three publicly available) and fifteen had begun development, leaving twenty-six counties with no progress on the development of their energy plans. Additionally, of the completed plans, there is a lack of

* Corresponding author.

E-mail address: N.Fields@lboro.ac.uk (N. Fields).<https://doi.org/10.1016/j.rset.2025.100131>

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standardisation and consistent methodology, with various planning approaches having been adopted such as a three-step process in Nakuru, a five-step process in Kitui, and an energy delivery model (EDM) in Kitui and Meru [1]. Additionally, energy modelling tool adoption varies from OnSSET used by Makueni, Kitui, and Narok, to LEAP adopted by Nakuru. As such, the data collected and produced, the modelling inputs, results and insights gained, and the content of CEPs varies across the counties with existing plans and limited-to-no data available for the counties with no progression in their energy plans.

Alternatively, at the national level, energy planning has widely developed and applied various modelling tools, including the OSeMOSYS modelling tool, to aid whole energy system planning, including through conducting integrated flexibility assessment [4], developing the national cooking transition strategy [5], and assessing green hydrogen development pathways [6]. As a result, the current energy modelling landscape within Kenya remains fragmented, with great inconsistencies in county resolution data and across county and national modelling efforts, making both county energy planning procedures and county-national dialogue a challenge.

The developed methodology employed within this study involves the creation of county-resolution energy demand projections (CORE-D) for Kenya, which can be used for (a) county planning procedures and scenario analysis in isolation and (b) integrated into national and regional level modelling tools as demand inputs. The models and projections produced provide a basis for an accessible and synergised demand analysis approach across the counties, with a consistent set of data requirements and produced energy demands, subsequently facilitating a standardised integration to national level models. This leads to a bi-directional modelling dialogue where national stakeholders can provide feedback and input into the development of county level demand projections, alongside county stakeholders integrating their needs and priorities. Such a method captures the multi-scale governance within Kenyan energy planning and facilitates dialogue between national and county levels.

Through the development of open-sourced energy demand projections, county-specific data can be represented, allowing the capturing of county specific context, needs, and priorities within their energy sectors, and enabling the integration of such projections produced into future national level modelling. Additionally, through employing a downscaling approach, historic barriers to county scale energy modelling of data availability can be overcome, allowing the integration of both downscaled data in instances of data unavailability, and existing county scale data where accessible. The adoption of the open-source, free, and accessible demand modelling tool MAED is used as a simple tool which is accessible to non-experts, facilitating easy uptake in resource strained planning units, allowing for seamless future updating of the models in instances of greater data availability. Additionally, MAED demand projections are already adopted and integrated into national power planning by the Least Cost Power Development Planning Team [7], and such development for county level projections will further synergise county and national planning.

Energy demand is an integral, yet often overlooked, component of energy modelling and planning more broadly, with projections forming the main driving parameter for future resource and supply allocation [8]. Typically, energy modelling studies focus on supply optimisation or simulation with little focus placed on demand projection formulation [9]. Energy demand forecasts are therefore typically reduced to basic projections which link base year aggregate energy consumption with a singular driving parameter such as total GDP or total population. Despite this, energy demand estimates, particularly for electricity demand, have potential wide reaching and costly impacts, with under estimation leading to black outs and supply gaps, and over estimation leading to financial losses and grid instability [10]. By focusing solely on energy demand, this study looks to demand projections in more detail, developing in depth whole energy system projections to be used for capacity building efforts, studies, and planning at multiple geographical

resolutions and sectoral scales, responding to and capturing the characteristics of energy planning processes in the Kenyan devolved governance system.

A related study explored the development of a framework for improved representation of county energy system and planning priorities at a national scale, through developing a disaggregated national whole energy system OSeMOSYS model to represent multi-level governance through both national and county level representation [11]. Additionally, this article directly builds on an accompanying data-in-brief which highlights the data used within this study alongside a detailed and extensive description of the methodological process employed within this study including the novel downscaling approach developed [12].

As such this study specifically focuses on demand projections which, whilst also being used in isolation for county level analysis and capacity building, can facilitate national and county bi-directional dialogues. CORE-D therefore produces demand projections in a consistent format relevant to national scale energy models and could be used as demand input parameters for supply optimisation via model soft linking. Additionally, the study aims to provide zero-order baseline demand models, utilising best available data, as capacity building tools overcoming historic barriers to both county energy planning and wider integrated national energy planning in Kenya, demonstrating a possible method for producing multi-level modelling dialogues. Therefore, the novel contributions of this study are:

- (1). The development of a downscaling approach to overcome barriers to data availability and achieve county-resolution energy data.
- (2). The production of forty-seven open-source county energy demand models and baseline county, regional, and national projections for Kenya.
- (3). The production of tools to support county level capacity building efforts and overcome historic barriers to county energy planning of resource availability and capacity.
- (4). The production of county energy demand baseline projections in a standardised format to facilitate multi-scale modelling via model soft linking.
- (5). Facilitate bi-directional energy dialogues via consistent data requirement, allowing subsequent stakeholder-driven enhancements, integration of richer and updated datasets, and robust decision-making analyses.

2. Background

In recent years, a growing number of studies have looked at energy modelling to inform energy system planning in Low- and Middle-Income Countries (LMICs) and within Kenya specifically. Common trends, themes and challenges across such studies are identified by several articles [9,13–20], including a recent review of energy modelling studies specifically looking at Kenyan case studies [21]. A review of integrated energy systems modelling in Sub-Saharan Africa by Musonye et al. [13] discovered a lack of authorship by relevant Sub-Saharan African (SSA) institutions and stakeholders, identifying a need for increased capacity building efforts within such counties. Similar conclusions on unequal authorship outside of SSA are highlighted by Blimpo et al. [19]. Akpahou et al. [17] examine modelling studies for development and find that historically, energy modelling tools have failed to fully capture SSA's unique features and respond to the specific needs of energy planning within the region. A further review on challenges in energy system modelling by Fodstad et al. [18] examined spatial resolution in modelling studies and found that many studies either neglect to outline information on their spatial resolution or use single node region models with little studies assessing multi-scale modelling. When examining the modelling research landscape in Kenya, Fields et al. [21] find data availability, and model scope are the main challenges to modelling

research within the region. They also identify increased geographical resolution as a main future research direction within Kenyan energy modelling. Subsequently, this research aims to address such identified challenges and future development areas for research within Kenya, with a novel production of energy demand projections at increased geographical resolutions, supporting multi-scale modelling efforts and facilitating bi-directional energy modelling dialogue, via accessible open-source data and modelling produced using a replicable methodology.

2.1. Energy modelling with Kenyan applications

Energy modelling tools have wide application within literature examining Kenyan case studies in recent years, ranging in geographical scope from national [4,6,22–26] to county [27–31], and local resolutions [32–38]. Single mode national model studies include Kehbila et al. [25] who apply the LEAP model to examine potential GHG mitigation pathways, assessing the projected emissions from existing Kenyan energy plans and examining alternatives. Lubello et al. [6] develop a national whole energy system OSeMOSYS model to explore the role of green hydrogen for fertiliser and steel industries under various scenarios. Fields et al. [24] use OSeMOSYS to examine various clean energy transition pathways for Kenya's power sector under rapidly intensifying demand, examining various existing energy targets and policies as scenarios. Carvalho et al. [26] featured an increased spatial granularity within their national SWITCH model, capturing the forty-seven counties as 'load zones' to explore low carbon pathways for Kenyas power sector.

Numerous studies within Kenya have applied a soft-linking methodology to examine energy system development. Kihara et al. [4] link the capacity expansion model (CEM), OSeMOSYS, with the production cost model (PCM), FlexTool, to examine potential grid issues under high variable renewable energy sources. Additionally, soft-linking methodologies have been employed with the specific aim of achieving increase spatial and temporal resolutions within studies. Moksnes et al. [23] soft link OnSSET and OSeMOSYS modelling tools to investigate electrification pathways for Kenya, with the aim of capturing both the spatial and temporal dynamics of the two models. Similarly, Millot et al. [22] develop the OSeMOSYS-FlexTool soft-linking framework outlined in Kihara et al. [4] to include geospatially explicit descriptions of variable renewable energy to enhance power system model planning. Additionally, Moksnes et al. [39] develop a novel modelling workflow called 'GEOSemOSYS' which enables the linking of geospatial data with the OSeMOSYS to achieve increase spatial and temporal resolution in optimisation models. A synthesis of the main characteristics of each selected national modelling study is reported in Table 1.

2.2. Spatial resolution and multi-scale modelling

Various energy modelling reviews have identified increased geographical resolution within the captured models, and the integration of multi-scale modelling considerations, as the main challenges, or development pathways for future studies [3,40–44]. Additionally, it is consistently concluded across studies assessing the impact of increased spatial granularity that such model development can produce varying

results to singular node models, often producing a lower cost overall solution, and locational shifts in the installed capacity [43,45]. For example, Rauner et al. [46] examine spatial patterns of German power system demand at different scales, concluding that a spatial dissonance emerged in studies which used levelized cost of electricity (LCOE) produced results based on economic optimality of single power plant ownerships rather than levels of local power demand. Serpe et al. [47] use the case study of a capacity expansion model for the US to examine the impact of varying spatial resolutions on energy system projections and solve times, concluding that higher resolution models produced different projected energy mixes to lower resolutions, and allowed for higher fidelity analysis. Brinkerink et al. [48] assess the implications of spatial resolution on a global electricity systems model through four spatial scenarios of regional (271 nodes), national (172 nodes), continental (6 nodes), and global (1 node), and conclude that model results varied across the scales, with increased resolution leading to a decreased required renewable capacity.

As such, there has been a trend in research to increase spatial scales within modelling studies, primarily with national models moving beyond singular nodes to an increased resolution. Brandes et al. [49] increase the spatial resolution of their energy model for Germany by extending the model from a singular node to multiple nodes for each of the ten administrative states, to capture the grid exchanges between regions within Germany. Siala & Mahfouz [50] identified a lack of correlation between distribution of data and administrative divisions in European country-level optimisation studies and developed a clustering methodology to optimise expansion planning which accounts for defined regions in an energy system. Clustering methods are also seen in case studies of the North Sea region [44], and Germany and Spain [51].

Whilst comparatively scarce to studies examining increased spatial granularity, research has also focused on capturing multi-level governance arrangements underpinning energy systems [3]. Particularly prevalent are case studies looking to multi-scale governance in Denmark. Alberg et al. [52] develop a methodology for local and national energy system interaction based on allocating shares to the local systems which requires individual balancing and does not consider import or export opportunities. An alternative approach was developed in an additional study by Alberg et al. [53] which models imports and exports from surrounding grids as an additional single technology. However, both approaches take single local systems in isolation, with limited interaction or illustration of how such local systems sit or interact with the national system. Thellufsen & Lund [54] develop a model using EnergyPLAN for better local action and national coordination, measuring the electricity balance between local and national energy systems via adding an additional parameter within the local energy models of 'excess electricity'. Such a framework balances the local and national integration, allowing the modelling of electricity supply that can be imported and exported on an hourly basis.

2.3. MAED modelling

The Model for the Analysis of Energy Demand (MAED) has had wide application to case studies globally of varying geographical, temporal, and sectoral resolutions [55]. An outlined description of the MAED

Table 1

An overview of the key characteristics of the identified existing Kenya national modelling studies.

Study	Reference	Year	Model	Geographical Coverage	Spatial Resolution	Soft-Link
Carvalho et al	[26]	2017	SWITCH	National	County (47 nodes)	No
Moksnes et al	[23]	2017	OSeMOSYS & OnSSET	National	Sub-National (geospatial)	Yes
Kehbila et al	[25]	2021	LEAP	National	National	No
Fields et al	[24]	2023	OSeMOSYS	National	National	No
Kihara et al.	[4]	2024	OSeMOSYS & FlexTool	National	National	Yes
Millot et al	[22]	2024	OSeMOSYS & FlexTool & GIS	National	Sub-National (20 geospatial clusters)	Yes
Moksnes et al	[39]	2024	GEOSemOSYS (GIS & OSeMOSYS)	National	Sub-National cells (40 by 40 km clusters)	Yes
Lubello et al	[6]	2025	OSeMOSYS	National	National	No

model can be found in the methodology section below (Section 3), alongside the model manual [56]. Whilst the MAED model has not been applied to any Kenyan case studies in existing academic literature, there have been multiple applications in Sub-Saharan Africa including Cameroon [57], Rwanda [58], Sierra Leone [59], and Tanzania [60]. Geographical scales vary across MAED applications from city [61], to provincial [62], and national [63]. Additionally, sectoral and energy type coverage also differs across existing studies, from examining households [64] and manufacturing [65] sectors in isolation, to modelling electricity demand [66–68], and whole energy systems [69, 70]. Temporal modelling periods examined within MAED studies also vary from six years [63] to forty years [69]. Additionally, numerous studies have soft linked the MAED model with capacity expansion models such as MARKAL [71], MESSAGE [57], LEAP [72], and OSeMOSYS [73] where MAED demand projection outputs are used as demand input figures for supply optimisation. This diverse applications of the MAED model suggest that it has high utility for vast case study application due to its flexible and easy methodology and could provide an interesting tool for development for Kenyan case studies. Additionally, MAED's methodology is already used within national Kenyan energy planning, with the least cost power development plan (LCPDP) developing an excel based energy demand projection based on MAED principles [7]. Critically, as MAED is already used for modelling in practice within Kenya, subsequent development of MAED models to respond to the needs of Kenyan energy planning processes (in this case energy devolution and integrated national energy planning) will widen the applicability of such research on the ground. Therefore, this research seeks to develop existing MAED application, aligning county demand projections to national demand planning methodologies and structures, facilitating integrated national energy planning and bi-directional county-national modelling dialogues in line with Kenyan energy policy priorities.

3. Methodology

This section outlines the methodological workflow developed for the data collection and manipulation employed, and subsequent county energy demand models and projections created. The county demand models are created using MAED. MAED is an open-sourced bottom-up whole energy system simulation modelling tool developed by the International Atomic Energy Agency (IAEA), which produces disaggregated annual energy demand projections. MAED offers a flexible methodology where the user can define the geographical and sector aggregation scales captured, allowing the modelled to be uniquely tailored to the case study being examined. Fig. 1 outlines the most basic structure of the MAED energy models (and the structure employed within this study), with further disaggregation for the sectors facilitated at the user's discretion depending on data availability and the purpose of the energy model development and study. MAED derives the demand

projections through combining energy intensities for the various defined sectors per energy type (motive power, thermal, and electricity use) and fuel types (solar thermal, biomass, traditional fuels, fossil fuels and electricity) with socio-economic driving factors (population growth rates, GDP growth rates, urbanisation rates and sectoral shares of GDP). Household energy demand is projected using population driving factors (such as population growth rates, urbanisation rates, household size) whereas all economic sectors (agriculture, construction, mining, manufacturing, and services) are projected using economic driving factors (GDP growth rates, sectoral shares of GDP). The model produces both final and useful energy demand per sector and fuel type. More in depth information on the model structure and methodology can be found in the published handbook [56].

MAED was chosen as the modelling tool due to the national Least Cost Power Development planning unit in Kenya, utilising the same methodology to produce their own national scale demand projections for the power sector [7]. As such, by synergising county demand methods and projections in line with those currently utilised by national planning units, CORE-D can better facilitate modelling dialogues and county-national integrated modelling. Additionally, MAEDs 'simple' methodology, overcomes historic barriers to county energy planning within Kenya such as data availability, time, and resource capacity within planning units [1,74,75]. The models basic structure, with the option for further sectoral resolution manipulation, is not data intensive, requiring socio-economic data which is widely reported globally from census and economic reports, with the option to capture increased resolutions in cases where data-availability is higher. Additionally, the model only requires a minimum single base-year data collection, which can be chosen based on the best available data for the case study, overcoming barriers of limited and intermittent data and for planning units with restricted resources. Alongside this, the MAED models were developed specifically as a capacity building and educational resource due to the availability of free online courses and training material which can aid the user in learning how to create their own basic model and produce their own demand projections [76,77], alongside in person capacity building training opportunities and online troubleshooting and support [75]. CORE-D employs a novel downscaling methodology to overcome historic barriers to county data availability, in order to gain county resolution energy balances. Such methodology involves a three-step process of: (a) collecting raw data from national energy balances, (b) processing the national energy balance to align with the structure required for MAED, and (c) disaggregating national energy demand proportional to county Gross County Product (GCP) and population data. Energy consumption for the economic sectors (agriculture, construction, mining, manufacturing, and services) was disaggregated equivalently to the individual counties sectoral economic contribution to the national sectoral GDP. Similarly, household energy consumption was disaggregated equivalently to the percentage of the total national population residing in each individual county. An illustrative

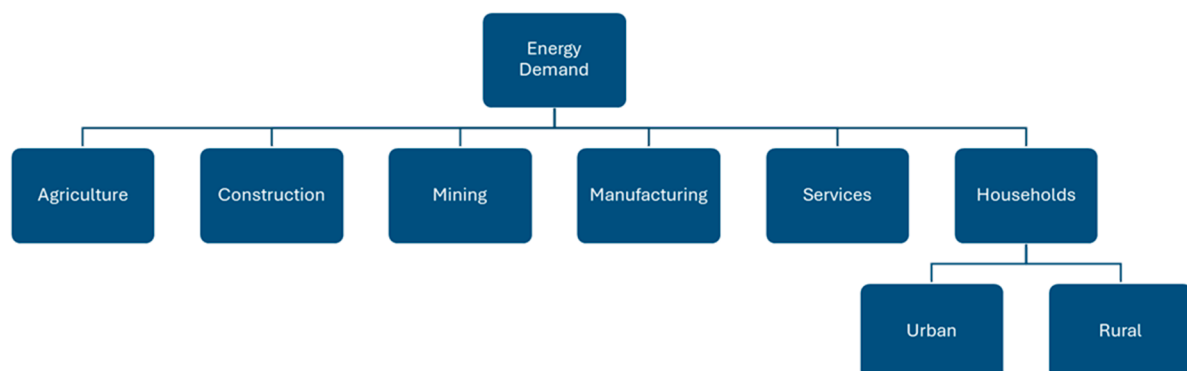


Fig. 1. An illustrative overview of the most basic energy demand model structure within the Model for the Analysis of Energy Demand [12].

representation of the downscaling methodology employed using a case study of Kilifi County can be found in Fig. 2.

An in-depth overview of the downscaling methodology developed and applied within this study is outlined in an accompanying data-in-brief [12]. The energy demand models in this study were created and published in such a way to facilitate easy uptake by academics, planners, and policy makers to allow further model development in the future. All the models are published on the free Zenodo repository (for example Wajir County [79]), with individual data notes explaining the methodology, data and model development steps, excel file data templates to allow easy updating of data in the future, and the MAED model zip files for all 47 counties. As such, the MAED models can easily be uploaded onto the MAED user interface and used for further study in the future. Consequently, MAED is used to overcome barriers to uptake in counties with low capacity and prior modelling experience, with opportunities for further model uptake and development in the future.

3.1. Approach

This study develops individual whole energy system demand models for all forty-seven counties in Kenya, producing a baseline demand projection from 2023 to 2070, with the years from 2019 to 2023 as a calibration period using historic report socio-economic and demand data, taking the total modelling period from 2019 to 2070. This long-term modelling period is in line with the national whole energy system (WESM) OSeMOSYS optimisation modelling period used by in-county national planning teams as an attempt to align national and county modelling initiatives to better facilitate modelling dialogues [11]. The authors acknowledge that the base year of 2019 is becoming outdated, and whilst it is kept to coincide with current national modelling practices and is used alongside further calibration years of 2020–2023, it is expected that both WESM and subsequently CORE-D will revise the modelling period in the upcoming year to accommodate model and data updates.

The workflow to develop the county models can be broken down into six key steps illustrated in Fig. 3. The model workflow can be categorised as: 1) collecting datasets, 2) data processing and manipulation, 3) configuring the model inputs, 4) performing model runs, 5) results analysis, with an optional step of 6) results processing into model parameter inputs. The steps can be split into two halves, with step 1–3 involving the model preparation, and steps 4–6 involving the model running [12].

3.1.1. Model preparation

The primary phase of the workflow involves model preparation, with the first step being the collection of data. Three types of data were collected based on data availability and accessibility and were ranked in priority order as: (a) county data – either county resolved national data or data collected and produced directly from existing county energy

plans or wider planning efforts, (b) national data sets with no processing or downscaling, and (c) processed national resolution data which has been downscaled to a county resolution via a methodology developed by the authors. Data were collected via best-available website, reports, and databases from both national and international organisations alongside existing models and academic articles. A full overview of the collected data, and the downscaled methodology employed, can be found in the associated data article [12]. Once the county and national data was collected, and processed where necessary (step 2), the data was then manually inputted into forty-seven independent MAED models for each of the counties (step 3).

Baseline model parameters included consistent economic sectoral configuration across the modelling period, GCP growth gradually declining at an annual rate of 0.05 %, and a steady 0.5 % urbanisation rate across the modelling period. Individual county priorities, plans, and contexts were not integrated at this stage of the study. This is due to a lack of county data, and as 26 counties are yet to start their county energy plans, data availability particularly in relation to county targets and development priorities, remains poor and fragmented. Alongside this the aim of this research is not to provide an in-depth production and analysis of county demand projection scenarios but instead to (a) explore methods to facilitate integrated national energy planning, (b) align methodologies and demand projection structures from both national and county resolution energy planning, and (c) to produce baseline models as capacity building tools and to overcome historic barriers of county energy planning of limited resources. A full overview of the baseline scenario assumptions can be found in [12].

3.1.2. Model running

Following the undertaking of the steps outlined in the primary model preparation phase, the second phase of running the model was undertaken starting with scenario performance (step 4). Due to the time scales, and demonstrative nature of this primary research study, only one zero-order basic baseline scenario was performed for each of the county models. The model runs produced simple demand projections from 2019 to 2070 and were intended to provide an example of baseline modelling results and outcomes which could be produced through applying the data and methodology outlined in this article. Results analysis was conducted following the production of the baseline projections, including an assessment of the multi-scale nature of the modelling results from both geographical and fuel type scope. An exploration of the results through analysis (step 5) and processing (step 6) in more detail will be explored in Section 4.

4. Results and discussion

The created energy demand models and subsequent projections produced can be utilised to support energy planning efforts across scales within Kenya, considering different geographic, sectoral and fuel foci. All demand projections produced can increase the modelling resolutions

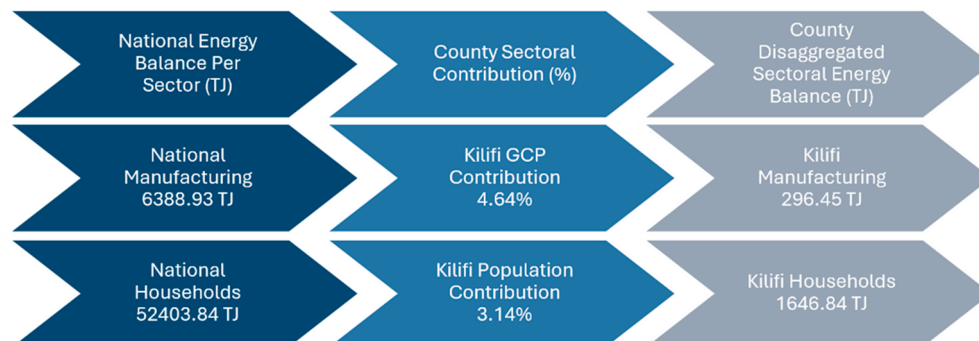


Fig. 2. The downscaling methodology used to obtain county resolution energy balances from the national energy balance data for 2019 for Kilifi County [78].



Fig. 3. An illustration of the five step (with an optional sixth step) methodological workflow to produce county energy demand projections.

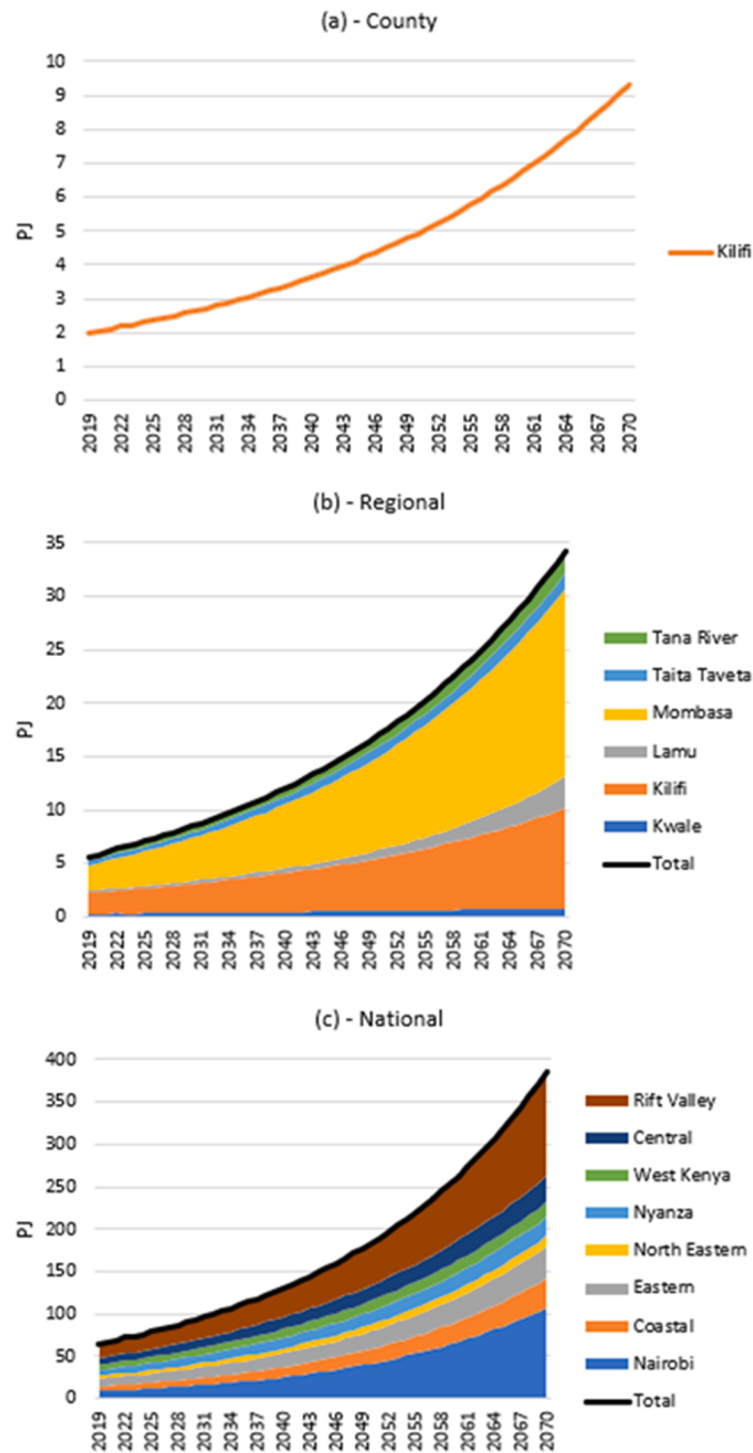


Fig. 4. An illustrative example highlighting the range of potential multi-geographical scale demand projections (PJ) to be produced from 2019–2070 with (a) a baseline demand projection for Kilifi county, (b) a baseline regional demand projection for the coastal region disaggregated by county, (c) a baseline national demand projection for Kenya disaggregated by region.

from singular nodes for optimisation or simulation modelling inputs (whether geographical or sectoral) to explore a more detailed and subsequently representative energy model. Geographical, sectoral and fuel type scope can be picked by the user based on the modelling research aims and objectives and what is most relevant to the case study being examined. Such resolutions could include electricity demand projections for the coastal region of Kenya, rural cooking demand projections for Kilifi County, or national scale whole energy system demand projections with a county geographical and six sector resolution. The following subsections (4.1 – 4.2) provide baseline, singular scenario, multi-scale results to be gained from applying the MAED models produced. Additionally, subSection 4.3. provides an illustrative comparison of three possible demand scenarios for Kilifi County utilising the collected data and subsequent model developed.

4.1. Multi-Geographical scale modelling

The demand projections produced can be used for various multi-scale geographical resolution modelling. Whilst the initial MAED models produce all demands in a standard county resolution format, the user can self-aggregate the demand to multiple resolutions and therefore could be used as modelling demand inputs for a variety of Kenyan contexts. For example, national demand projections could be produced at three resolutions (national, regional, and county) providing flexibility for the model user to utilise the demand resolution most appropriate to their research and/or computer processing capacity. In cases where 47 demand node representation is infeasible due to technological limitations, the user can self-aggregate the produced county demands to their desired resolution.

Fig. 4 provides an example of possible multi-geographical scale demand modelling projections produced. In the baseline projections, demand for Kilifi County will increase from 1.99PJ in 2019 to 9.3PJ in 2070. For the total coastal region, demand is seen to increase from 5.63PJ in 2019 to 34.21PJ in 2070 and national demand increases from 64.11PJ in 2019 to 384.61PJ in 2070. Therefore, in the baseline projections, Kilifi County demand forms 35.3 % of the total coastal region demand, and 3.1 % of total national demand in 2019. This changes to 27.19 % of the total coastal regional demand, and 2.42 % of the total national demand in 2070.

Such a methodology could be especially useful for energy planning, particularly for power providers who operate with regional electricity management and distribution. However, care should be taken when adopting regional forecasts to align utility region boundaries with the geographical scope included in county boundaries. Additionally, the development of individual county projections which account for the needs and priorities of county plans and development goals can then be aggregated to a national scale and integrated into a national energy optimisation model with individual county demand inputs. Thus, helping to facilitate county-to-national modelling dialogues and multi-level energy governance planning through aligning modelling methodologies and demand projections produced and utilised by planners. Therefore, county planning, through demand projections, whilst undertaken separately to national level optimisation models, can also feed into such models as input parameters facilitating multi-level governance dialogues within energy models.

4.2. Multi-Sectoral resolution modelling

Similarly, the demand models produced can also be tailored to varying sectoral resolutions aside from assessing the whole energy system together, to focusing on a specific fuel type or sub-sector. Kenya has a variety of plans and strategies which have explicit connections to energy, such as the cooking transition strategy [5], the least cost power development plan [7], and the slum upgrading and prevention strategy [80], alongside the national energy policy [2]. The methodology utilised provides flexibility in producing energy demands at multiple sectoral

scales. As such, sector resolution can be varied responding to energy governance structures of the case study, for example as household energy usage remains a core part of county energy planning jurisdictions it could be most relevant to have household demand remain at a county level, whereas manufacturing policy and production may be most relevant to be represented at a national level. Due to the fluid nature of CORE-D model, the sectoral resolution of demand projections can therefore change in response to continued developments in county energy planning mandates and increased county responsibilities. Similarly, as the demand projections produced in MAED are already disaggregated by fuel type, CORE-D provides the opportunity to assess electricity demand, additionally at various geographical scales, in isolation.

Fig. 5 provides an example of possible multi-sectoral scale demand modelling projections produced using CORE-D by focussing on household energy demand. In the illustrative baseline household projections produced for Kilifi County, demand increases from 1.64PJ in 2019 to 3.36PJ in 2070. For the coastal regional total household demand, an increase is seen from 4.01PJ to 11.99PJ in 2070 and for total national household demand from 52.03PJ in 2019 to 160.75PJ. Subsequently, Kilifi household demand forms 40.89 % of the coastal regional total household demand, and 3.15 % of the total national household demand in 2019. Alternatively, in 2070 Kilifi household demand forms 28 % of the total coastal region household demand, and 2.09 % of the total national household demand in 2070. Alongside this, household demand forms 82.41 % of Kilifi county's total energy demand in 2019, decreasing across the modelling period to form only 36.13 % in 2070. For the Coastal regional demand, household energy forms 71.4 % of the total in 2019, rapidly decreasing to 35.1 % in 2070. This trend is also seen at the national level, with household energy forming 81.14 % of total energy demand in 2019 and reducing to 41.8 % by 2070.

4.3. Demand projections

Alongside providing an opportunity for the representation of multi-geographical scale, and multi-sectoral resolution within energy demand, the CORE-D demand models can also be used to analyse future demand projections under varying possible future scenario conditions.. Whilst an in-depth energy demand projection assessment for Kilifi utilising CORE-D would require extensive stakeholder engagement and co-creation, initial MAED results can provide insights to show how CORE-D could be used for county case studies in isolation and as capacity building tools for further data integration, alongside feeding into the regionally and nationally aggregated demand as previously illustrated [81].

Two further illustrative future scenarios, alongside the baseline projection, are developed for Kilifi and subsequent projections produced compared. Such scenarios form a baseline, higher, and lower scenario coinciding with baseline, vision and low scenarios employed by the national LCPDP demand scenarios [7,82]. Such ambitious and reserved demand scenarios are consistently conducted in demand assessments to provide a range of possible demand to be considered for uncertainty analysis [8,9,15]. Subsequently, the higher 'ambitious' scenario illustrates a potential future where GCP, population, and urbanisation growth rates are higher than the baseline scenario. Additionally, the lower 'reserved' scenario illustrates a potential future where GCP, population, and urbanisation growth rates are lower than the baseline scenario. Despite conducting and publishing their CEP [81], Kilifi County energy plan contains no whole energy system demand projections, nor any data on base year energy balances or total county demand. As such, validation can't yet be undertaken from comparing MAED county demand results to existing CEPs. An overview of the scenario constraints inputted to produce the projections are outlined in Table 2.

An illustration of the demand projections produced from 2019 to 2070 are shown in Fig. 6. Under all three modelled scenarios, total energy demand is expected to increase significantly across the modelling

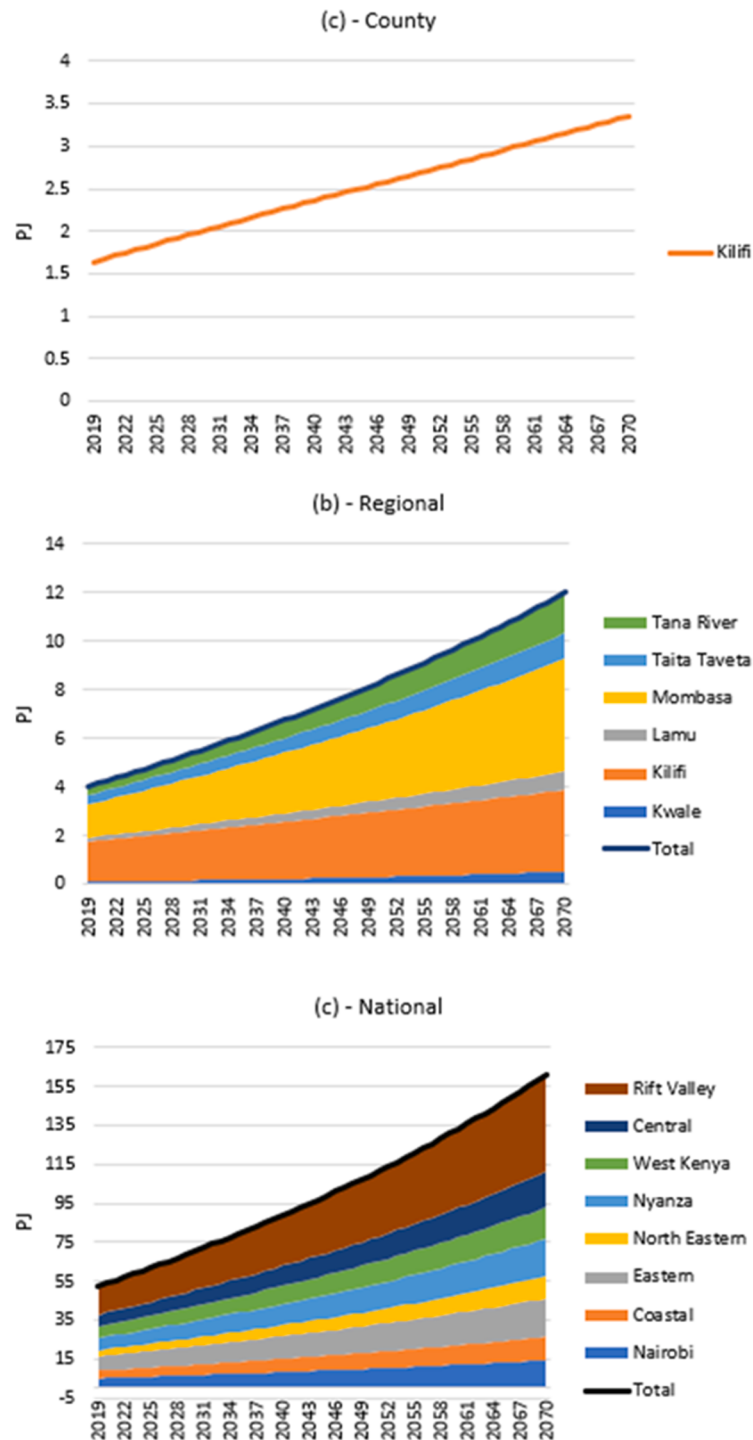


Fig. 5. An illustrative example highlighting the range of potential multi-sectoral scale demand projections (PJ) to be produced from 2019–2070 with (a) a baseline household demand projection for Kilifi county, (b) a baseline regional household demand projection for the coastal region disaggregated by county, (c) a baseline national household demand projection for Kenya disaggregated by region.

period. The baseline demand produced increases from 1.99PJ in 2019 to 9.27PJ in 2070. Comparatively, the demand in 2070 reaches 11.82PJ in the high scenario and 7.82PJ in the low scenario, a total range of 4PJ. This subsequent range of demand projections produced across the scenarios can be used as input parameters for supply optimisation analysis, particularly through providing a demand uncertainty range to be studied by robust decision making (RDM) techniques [83]. Whilst the scenarios developed within this article form basic future development pathways, they illustrate potential outputs which can be gained through

application of the CORE-D models. Future research can be conducted to develop the development scenarios further, to capture a more detailed representation of county social and economic development goals, alongside energy system expansion priorities.

4.4. Limitations and future developments

As indicated previously, this article offers an exploratory look into the county energy demands produced and a discussion into the potential

Table 2

Constraints for Kilifi County's Gross County Product (GDP) %, Population Growth % and Urbanisation %, across the three illustrative modelled scenarios of baseline, low, and high across the projection period of 2023–2070.

Gross County Product %						
	2023	2030	2040	2050	2060	2070
Baseline	6.87	6.52	6.02	5.52	5.02	4.52
Low	6.87	6.38	5.68	4.98	4.28	3.58
High	6.87	6.66	6.36	6.08	5.76	5.46
Population change %						
	2023	2030	2040	2050	2060	2070
Baseline	1.91	1.7	1.4	1.18	1.06	0.96
Low	1.91	1.63	1.28	1.04	0.83	0.81
High	1.91	1.86	1.71	1.67	1.66	1.65
Urbanisation %						
	2023	2030	2040	2050	2060	2070
Baseline	29.1	32.6	37.6	42.6	47.6	52.6
Low	29.1	31.9	35.9	39.9	43.9	47.9
High	29.1	33.3	39.3	45.3	51.3	57.3

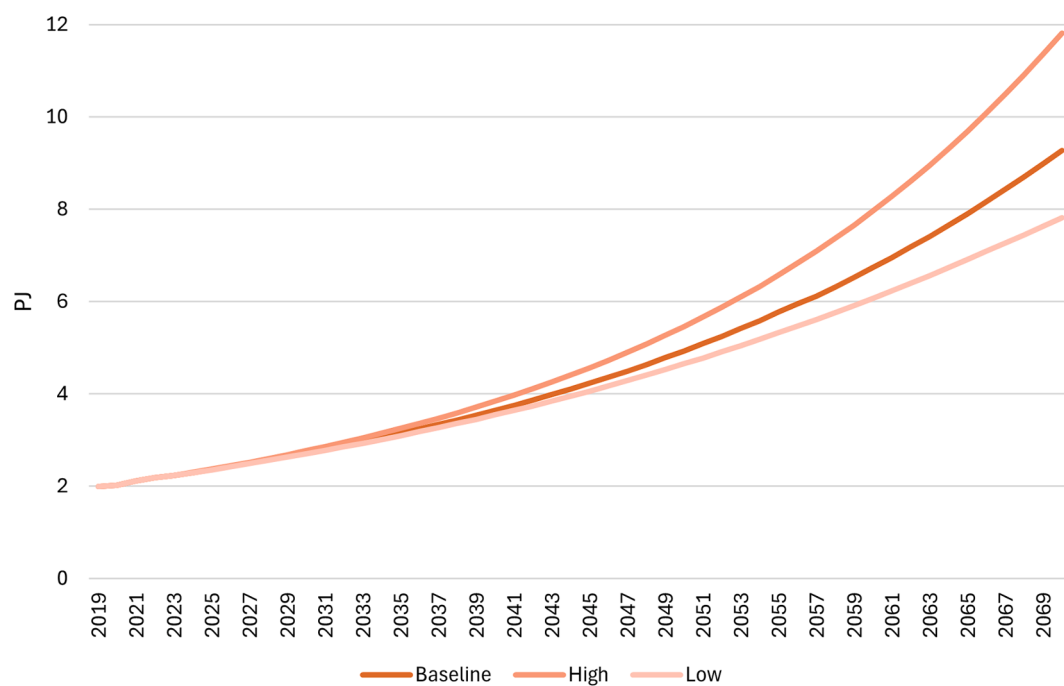


Fig. 6. Total whole energy system demand forecast from 2019 to 2070 across the three modelled scenarios for Kilifi County, with 2019–2023 as the calibrated base years.

multi-scale applications from such projections and therefore does not offer in depth scenario development and subsequent results analysis. Instead, this paper serves as a starting point in which further development of the CORE-D models, through subsequent stakeholder-driven enhancements, capacity building exercises, integration of richer and updated datasets, and robust decision-making analyses can follow. Therefore CORE-D is not the final product, and further integration of additional county-level datasets, priorities, and visions, following the future production of additional CEPs is needed to refine assumptions used within the model. The current version of CORE-D has therefore limited readiness for detailed county scale scenario analysis and subsequently such a study has not been performed within this paper.

A main area of interest for future development of the demand projections is the integration of additional datasets. The expansion of data to be more inclusive and representative to the energy needs of communities within Kenya is a priority for further development, particularly capturing explicit energy demand profiles for Gender and Social Inclusion (GESI), resilience and climate adaptation considerations. Such further developments could include additional disaggregation of the

household sectors by household type (informal versus formal settlements), or demographic characteristics (gender of household head, age of household head). Under the current MAED structure and interface, such disaggregated typologies remain challenging to capture and would require further extensive development to the model code and additional data collection and manipulation.

Engaging county, and national, stakeholders is essential for such future developments, including data collection and further model enhancements for CORE-D. Strengthening partnerships and model co-production with county stakeholders is crucial through collaborative data sharing and collection, alongside capacity building and knowledge sharing. Establishing strong collaborative partnerships with stakeholders will guarantee that CORE-D continues to integrate the most up-to-date and accurate data and remain relevant and representative of current planning priorities and processes within Kenya. Further model development could also include opportunities for collaboration, capacity building, model co-production and scenario analysis for individual county case studies, enhancing the integration of county characteristics, priorities and visions into CORE-D results.

Further, there is currently no way to run multiple counties at once or disaggregate a national model to county resolutions within the MAED interface, and so CORE-D instead relies on 47 separate MAED models. This can prove time consuming for cases where the user is interested in national, or regional, scale projections with county resolutions. However, this does allow for additional flexibility for the user to choose which counties they are interested in and reduces the intensity for technologies which would struggle to run a high-resolution national model. The future development of a data pipeline through a script which manually takes the MAED excel results files and converts the data into demand modelling inputs for optimisation models such as OSeMOSYS will further facilitate seamless multi-scale modelling and governance dialogues from county to national scales and will reduce time for the user. Such soft-linking approaches would allow the county resolution demand projections to be used not only for demand modelling and analysis but also be integrated into supply modelling as a key parameter input.

5. Conclusion

In conclusion, CORE-D presents novel county resolution whole energy system demand models for Kenya, overcoming historic barriers to county and multi-scale modelling of resource and data unavailability. It offers a potential solution to supporting multi-level governance dialogues and integrated national energy planning within Kenya, forming a basis for accessible and consistent data inputs and demand analysis across counties. Through aligning demand methodologies at the county scale to existing national energy planning, CORE-D facilitates bi-directional dialogues from integrated modelling techniques, allowing consistent demand information to feed into national models. Additionally, the methodology offers flexibility in scales depending on research aims, from varying geographical, sector and fuel type detail. Through the creation of forty-seven individual models for each of the counties, CORE-D can capture the unique features of each county's energy sectors alongside capturing individual county energy priorities and needs, thus creating projections which are more representative than national scale projections which omit regional differences. Therefore, CORE-D provides free and accessible resources which can be used to support energy planning processes within Kenya, responding to the changing policy landscape of devolved and integrated energy planning, enabling the future development of enhanced demand projections under varying scenarios to county energy planning. Additionally, it facilitates the integration of county resolution demand projections into national and regional scale energy supply models and analysis. Finally, CORE-D provides a capacity building and educational tool, overcoming historic barriers to county energy planning in Kenya of limited resources and capacity.

Data availability

Links to data repository are available in the paper and in the Supplementary files. This work follows the U4RIA guidelines which provide a set of high-level goals relating to conducting energy system analyses in countries. This paper was carried out involving stakeholders in the development of models, assumptions, scenarios and results (Ubuntu/Community). The authors ensure that all data, source code and results can be easily found, accessed, downloaded and viewed (retrievability), licensed for reuse (reusability), and that the modelling process can be repeated in an automatic way (repeatability). The authors provide complete metadata for reconstructing the modelling process (reconstructability), ensuring the transfer of data, assumptions and results to other projects, analyses and models (interoperability), and facilitating peer-review through transparency (auditability).

CRedit authorship contribution statement

Neve Fields: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michelle Akute:** Writing – review & editing, Conceptualization. **Leonhard Hofbauer:** Writing – review & editing, Methodology, Conceptualization. **Martin Mutembei:** Investigation. **Anne Nganga:** Investigation. **Mark Howells:** Supervision. **Ed Brown:** Supervision.

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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