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To cite this article: Giacomo Falchetta *et al* 2021 *Environ. Res. Lett.* **16** 074038

IOP Publishing Environ. Res. Lett. 16 (2021) 074038 https://doi.org/10.1088/1748-9326/ac0cab

ENVIRONMENTAL RESEARCH
LETTERS

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OPEN ACCESS

RECEIVED
29 July 2020

REVISED
16 June 2021

ACCEPTED FOR PUBLICATION
18 June 2021

PUBLISHED
8 July 2021

LETTER

The M-LED platform: advancing electricity demand assessment for communities living in energy poverty

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Keywords: electricity access, energy demand, rural development, bottom-up energy modelling, sub-Saharan Africa, water-energy-food-environment nexus

Supplementary material for this article is available online

Abstract

Globally about 800 million people live without electricity at home, over two thirds of which are in sub-Saharan Africa. Planning electricity access infrastructure and allocating resources efficiently requires a careful assessment of the diverse energy needs across space, time, and sectors. Because of data scarcity, most country or regional-scale electrification planning studies have however assumed a spatio-temporally homogeneous (top-down) potential electricity demand. Poorly representing the heterogeneity in the potential electricity demand across space, time, and energy sectors can lead to inappropriate energy planning, inaccurate energy system sizing, and misleading cost assessments. Here we introduce M-LED, a Multi-sectoral Latent Electricity Demand geospatial data processing platform to estimate electricity demand in communities that live in energy poverty. The platform shows how big data and bottom-up energy modelling can be leveraged together to represent the potential electricity demand with high spatio-temporal and sectoral granularity. We apply the methodology to Kenya as a country-study and devote specific attention to the implications for water-energy-agriculture-development interlinkages. A more detailed representation of the demand-side in large-scale electrification planning tools bears a potential for improving energy planning and policy.

1. Introduction

Electricity is a direct input to virtually every economic sector. An abundant, affordable, and reliable provision of power is a necessary condition for human livelihoods to prosper. This involves the achievement of nearly all the United Nations' Sustainable Development Goals (SDGs) [1, 2]. Recent statistics on electricity access show that globally just under 800 million people (about 10% of the global population) live without electricity access, more than two-thirds of which are in sub-Saharan Africa (SSA) [3]. Even in areas reached by electricity infrastructure, significant unmet demand can persist [4–6] because consumers cannot afford appliances, the service, or because electricity services are not fully available.

In the context of energy planning to eliminate energy poverty, assessing the long-run electricity demand is crucial [7]. The choice of the most efficient electricity supply option and the size of the local generation capacity and storage system strongly depend on the assumed local demand. In turn, this demand is defined both by the hourly load curve and its peaks, and by the total energy consumption. An inadequate or generic formulation of this potential demand can lead to inefficient budget allocation and electricity infrastructure sizing [8]. Moreover, enabling services for the community and productive uses of electricity beyond household (HH) needs—such as energy use in agriculture, small businesses, and healthcare and education facilities—is crucial to unleash local economic development and ensure the financial sustainability of energy access investments [9]. While substantial uncertainty persists over the structural welfare impacts of electrification programs [10], there is robust evidence of the positive effect of electricity provision on time spent by HH members in income-generating activities [11–14]. In turn—provided a set of conditions is satisfied—the electricity input might improve the income of the whole community [15].

The link between the target demand and electricity supply planning becomes very evident when carrying out country or regional scale studies with geospatial electrification models (GEMs). GEMs are data-intensive computer-based tools that can support policymakers in the integrated evaluation of the most suitable and cost-effective technology for providing universal electricity access [16–28]. Thanks to growing data collection and management facilities, bottom-up techno-economic electrification analysis has become widely available (e.g. the Global Electrification Platform and the World Resources Institute's Energy Access Explorer). Differently from approaches based on linear programming, GEMs do not aim at locally optimising energy systems for specific communities. Their main characteristic is that they allow to identify—country or region-wide—the technology with the lowest local levelized cost of electricity for providing electricity access at each settlement, along with the generation capacity and investment requirements. Besides electricity demand, the cost-optimal set-up depends on the local energy resources and infrastructure. Most GEM-based studies have concluded that decentralised energy solutions will play a prominent role in guaranteeing that SDG 7.1.1 (the universal electricity access target) is met in SSA. For instance, the Africa Energy Outlook 2019 [29] argues that mini-grids and stand-alone systems will serve 30% and 25% of those gaining access, respectively.

Yet, most GEM-based literature has been strongly supply-side oriented [23]. Efforts have focused mainly on modelling residential energy services and have so far exhibited limited capacity of accounting for the electricity demand from services and productive uses driven by the presence of farms, small businesses, commercial activities, healthcare, and educational facilities. In these studies, the residential demand itself has mostly been calibrated with regional average residential electricity consumption levels of urban and rural consumers [20, 27, 28, 30], with little within-country heterogeneity. Archetypical demand targets include e.g. values for SSA from the World Bank Multi-Tier Framework (MTF) [31] or generic per-capita consumption levels defined by decision makers under a medium-run time horizon (usually 2030, the SDGs target year).

Tables SI1 and SI2 (available online at stacks.iop.org/ERL/16/074038/mmedia) summarise the main characteristics of existing GEMs or electricity needs assessments in terms of the demand characterisation. The two tables highlight that several gaps persist in demand estimation, as no previous published study adopted a comprehensive multi-sectoral, bottom-up, high spatio-temporal resolution, open-source methodology. This is consistent with the findings of [7] and [23]. Thus, while substantial advances have been made in supply-side modelling of electricity access, a literature gap remains when it comes to evaluating how big data and bottom-up energy modelling can be together leveraged to represent the potential demand for electricity with high spatio-temporal and sectoral granularity.

To provide a more granular representation of the demand-side in large-scale electrification planning tools, here we introduce the open-source Multi-sectoral Latent Electricity Demand (M-LED) geospatial data processing platform. M-LED is designed to estimate the electricity demand in communities living in energy poverty and expand the level of insight that can be drawn with GEMs by allowing for a more granular representation of energy services that can empower communities in the context of electrification planning. The key novelty of the platform is its multi-sectoral, bottom-up, high spatio-temporal resolution evaluation, which altogether advances the state-of-the-art on latent electricity demand characterisation. Latent (or potential) demand refers to the electricity that would be consumed if the infrastructure (power generation, transmission, and distribution) and socio-economic conditions (income and appliances) were met.

2. Materials and methods

2.1. The M-LED platform

The M-LED platform is an open-source, bottom-up toolkit designed to characterise power requirements across different sectors. M-LED combines openly available geospatial information, modelling instruments, and scenario analysis to support a sectoral-inclusive electrification planning. Residential, health, and education load profiles are computed following a probabilistic distribution starting from field campaign or literature-validated appliance ownership and use patterns. Agricultural (irrigation and crop processing) and micro enterprises loads are assessed combining techno-economic modelling and literature estimates.

Figure 1 offers an overview of the workflow, which is divided into thematic modules for each of the three sectors of power requirements identified: (a) residential; (b) services; (c) productive. Three additional blocks of the figure describe: (d) the platform outputs; (e) the module for estimating the economic implications of meeting the agricultural electricity needs; and (f) the potential integration of M-LED outputs with existing supply-side electrification

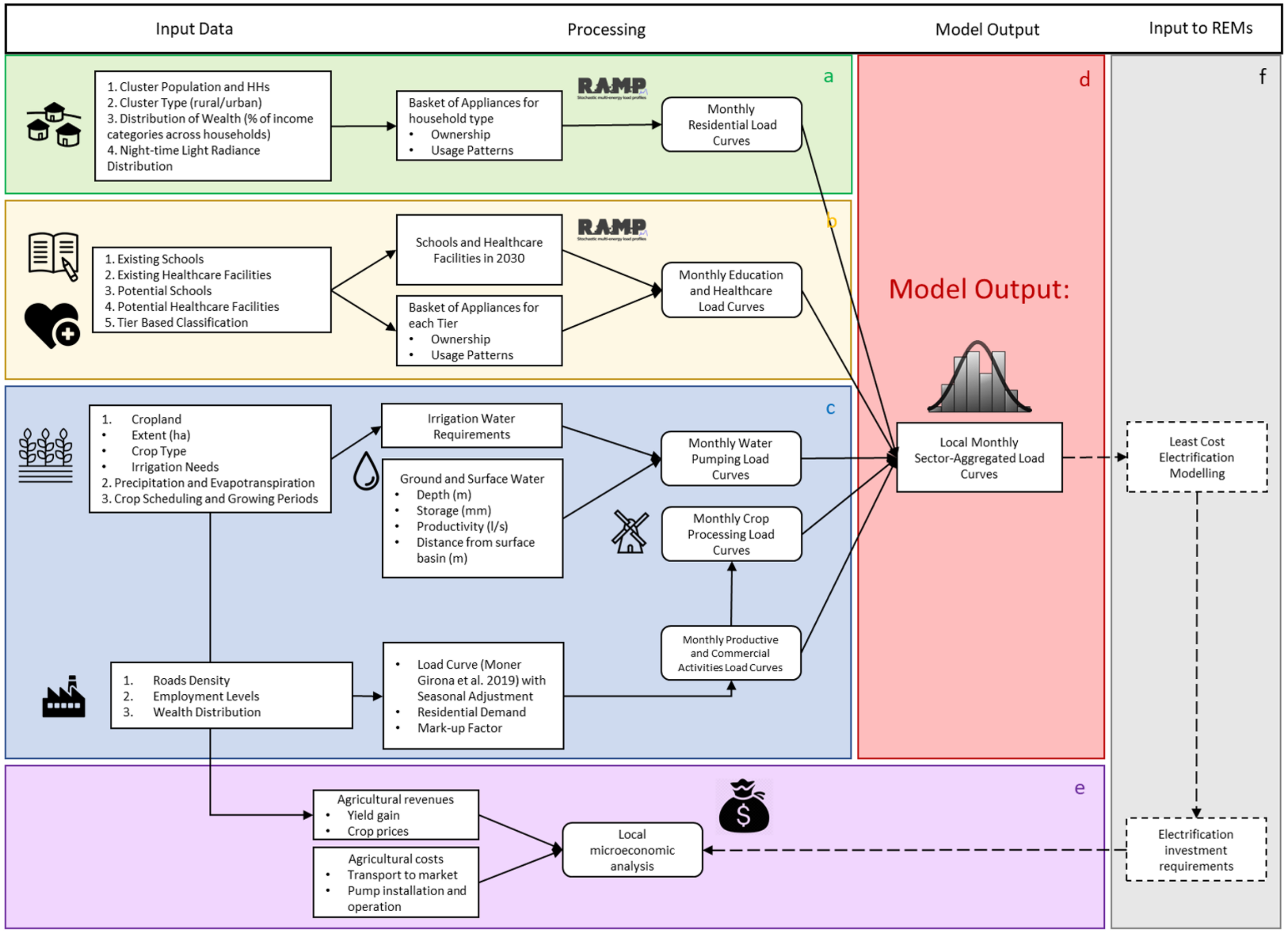

Figure 1. Conceptual framework of the M-LED platform. (a) Assessment and generation of residential demand load curves for each population cluster; (b) assessment of healthcare and educational demand; (c) assessment of productive activities demand: agricultural loads for irrigation and crop processing, micro enterprises and commercial demand; (d) M-LED Output: load curves with monthly level seasonality at 1 h resolution for cluster and sector -specific detail; (e) assessment of costs and revenues due to increased agricultural productivity; (f) the produced output is designed to be fed in geospatial electrification models for more accurate energy planning.

models. Detailed figures presenting the methodology of each module are found in section 2 of the paper. All modules of M-LED are based on an array of open-source Geographic Information System algorithms written in R and Python.

The input data considered in the application presented in this paper and their sources are openly accessible and reported in table SI3. The data processing procedure collates (a) publicly available spatially explicit information with (b) additional information from the field. The publicly available category data consist of (a) socio-demographic information (gridded population and urbanisation data; subnational wealth and employment information from Demographic and Health Surveys (DHS) surveys; nighttime lights data; city accessibility data; administrative boundaries); (b) agriculture-related data (gridded cropland extent and yield estimates; crop calendar; agroclimatic zones data; surface and groundwater availability and characteristics; crop processing energy requirements; historical climate data); (c) service-sector data (healthcare and educational facilities location and characteristics). A field campaign provides an added value for ensuring that the design of the baskets of appliances for residential and service customers is coherent with current appliance use patterns. As a result of the data-intensiveness of the platform, an extensive discussion of the uncertainty implications is found in section 5.3.

Based on a bottom-up approach, M-LED generates electricity demand load curves rendered at a one hour time step. Then, M-LED derives the monthly (seasonal-varying) load curves and yearly-aggregated consumption levels. The outputs consist of georeferenced layers for the estimated currently unsupplied electricity demand within population clusters (detailed in the SI-A1) generated from a set of residential, productive activities, and services. The key added value of the M-LED methodology is that its outputs allow carrying out supply-side planning of electricity access systems according not only to the energy resource availability but also to the specific local community and productive load profiles, including daily, weekly, and seasonal variation, which can significantly affect system design [32].

The methodology described in the following sections has a general validity and is therefore applicable to any area facing an electricity access gap. For the applicative example, we select Kenya as a country-case study to provide a proof-of-concept of the implementation of M-LED. The selection is driven by (a) the abundancy of data and geospatial information compared to most of SSA countries and (b) by the a large number of electricity planning studies carried out applying different tools and assumptions [5, 20, 21, 25, 33], and thus the significant opportunities for better understanding the impact of a multi-sectoral, bottom-up electricity demand modelling approach.

2.2. Residential electricity demand

Residential electrification plays a crucial role for human wellbeing, for instance by enabling telecommunications, conserving food, indoor air circulation and cooling, and night-time activities. In fact, most electrification efforts and targets, including SDG 7.1.1, focus on bringing electricity to all households. To estimate residential demand, M-LED exploits the Remote-Areas Multi-energy systems load Profiles (RAMP) model [34], which supports the creation of stochastic, seasonal-heterogeneous electricity demand profiles. The underlying stochastic process lies in the structure of the bottom-up model adopted for load profile generation, for a more detailed characterization the reader can refer to SI-A2.

To efficiently tailor electrification infrastructure, it is necessary to distinguish among different HH types, which will consume electricity differently according to their opportunity of having access to different electrical appliances. To estimate HH demand in a flexible way, the M-LED framework (figure 2(A)) is designed to ensure a large degree of heterogeneity in residential power demand. We construct $5 \times 2 = 10$ archetypical types of households (five in urban areas, and five in rural settlements) defined by electrical appliance ownership and use patterns. In the context of this paper, the appliance baskets considered are designed starting from a systematic screening of the literature [35–42] about electricity consumption in SSA countries and parametrised based on data from recent field visits in Kenya by the authors and their team (2019). The empirical screening provides the rationale to compile tables of appliances and usage patterns for each HH type. A total number of 22 appliances is selected and modelled across 11 dimensions (table 1).

To account for seasonality of the load, the climate variability is considered. In the specific case of Kenya, the months of January and December are considered the hottest in the country, while June and July the cooler. Fans and air conditioning systems are hence modelled accordingly. June and July are assumed to have no use of such appliances, and the other months gradually increase their use up to a full use in the months of January and December. Given the proximity to the equator of Kenya, in this country study dusk and dawn times are considered to not vary significantly enough to justify seasonal variation of time of use of appliances and lights. The entire set of modelled appliances, users and user types with relative parameters are reported in supplementary file F1.

The RAMP model is used to simulate for each of the ten user classes a representative sample of $n = 100$ households (to ensure sufficient stochasticity effects).

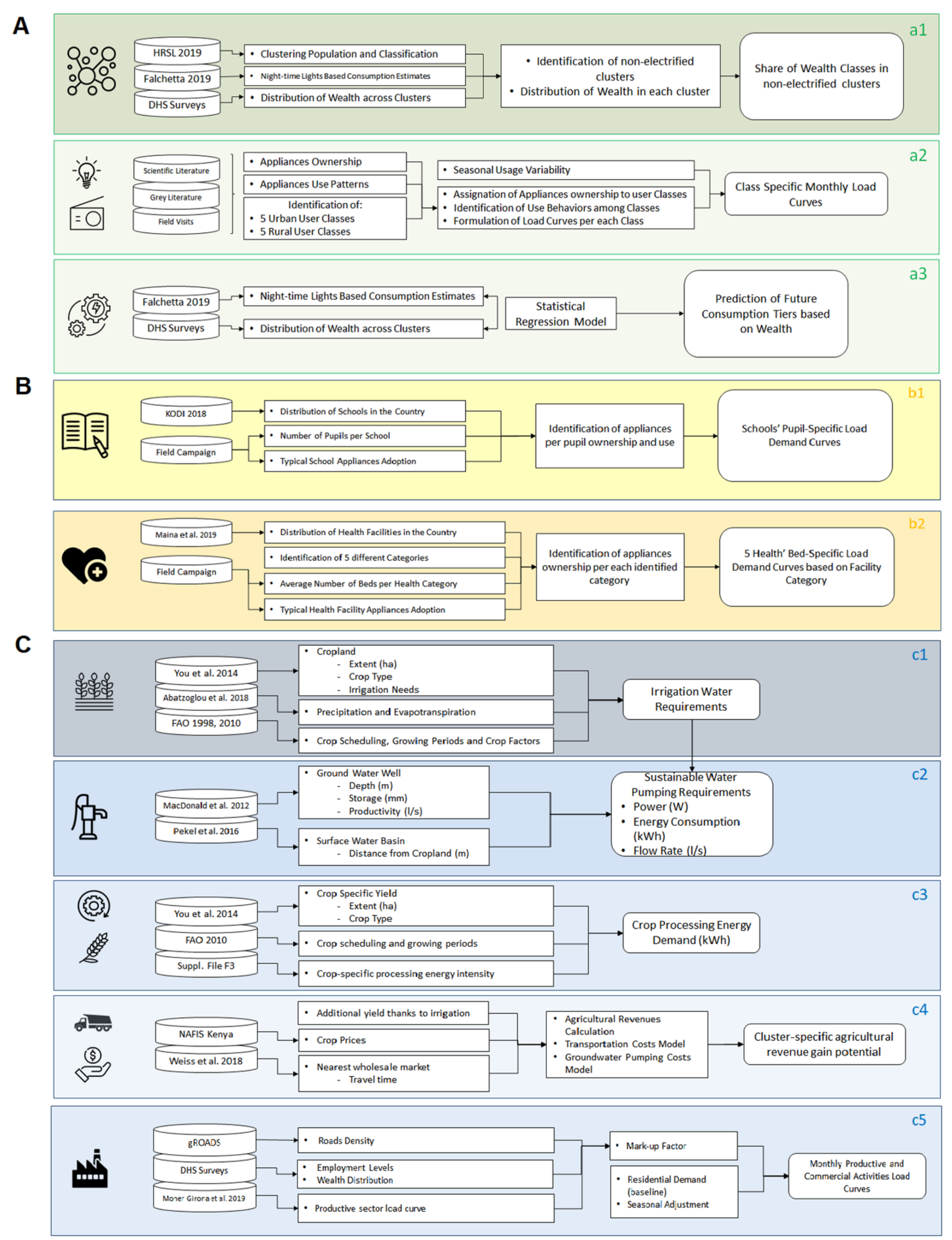

Figure 2. Schematic framework of the methodology and data sources underlying the Kenya case study. (A) Estimation of residential electricity demand. (a1) Generation of population clusters; (a2) estimation of residential electricity demand; (a3) parsing of residential demand to population clusters. (B) Estimation of healthcare and education services electricity demand. (b1) Education electricity demand; (b2) healthcare electricity demand. (C) Workflow of the agricultural sector and of the micro enterprises and commercial electricity demand estimation. (c1) Estimation of Irrigation requirements; (c2) estimation of electricity requirement for water pumping; (c3) estimation of electricity needs for crop processing; (c4) agricultural revenues calculation. (c5) Micro enterprises and commercial electricity demand estimation. Abbreviations: HRSL = high resolution settlement layer; DHS = Demographic and Health Surveys; gROADS = Global Roads Open Access Data Set. KODI = Kenya Open Data Initiative; FAO = Food and Agriculture Organization; NAFIS Kenya = National Farmers Information Service of Kenya. See table SI1 for data details and sources.

For each user sample, RAMP generates 12 month-specific load curves (in W), at a minute time-step for 365 d, from which the total energy consumption can be easily calculated (in kWh).

To match the simulated electricity demand profiles with each population cluster detailed we evaluate the statistical association between the distribution of the population with electricity access across

Table 1. Dimensions considered in the stochastic demand assessment.

Dimension	Description	Range (unit)
Ownership	Category of User that owns the appliance	User Type
Number of appliances per user	Number of that specific appliance owned by the user	0–22 (−)
Appliance power	Nominal power of the specific appliance, allows for a random variability in a defined range for thermal appliances	0–1000 (W)
Number of daily functioning windows	Number of time 'windows' in which the appliance is used during the day	1–3 (−)
Window start and end times	Hours of start and end of time windows in which the appliance can be used	00:00–23:59
% variability of window start and end times	Percentage of allowed random variation of the length of the usage windows	0–100 (%)
Daily functioning time	Total amount of time that the appliance is used during one day	0–1440 (minutes)
% of random variability of daily functioning time	Percentage of allowed random variation of the total daily time of use	0–100 (%)
Minimum time the appliance is kept on after switch-on event	Minimum amount of time the appliance stays on after has been switched on	0–1440 (minutes)
Percentage of occasional use	Probability that the appliance is used on a single day	0–100 (%)
Weekends or weekdays use	Allows to constrain the usage of the appliance only in weekdays or in weekends periods	we/wd/none

electricity access tiers (based on validated, satellite-derived data on the prevalent tier of electricity access at each pixel [43] and with reference to the World Bank MTF [31]) and the type of settlement (urban or rural [44]), the local population density and the distribution of wealth within of SSA countries (based on HH survey data from the DHS surveys [45]). Then, based on the regression results, we allocate each demand profile archetype to HH without access to electricity enclosed in each cluster. The process assumes that in the future households without access to electricity will be distributed among the electrification tiers based on the same proportion of households that today benefit from electricity in the administrative unit within which each cluster falls. For more details on the matching of demand profiles to each cluster, refer to SI-A3.

2.3. Healthcare and education services electricity demand

A large number of healthcare and education facilities also face significant constraints in their activity because they are unable to operate appliances that are crucial for guaranteeing the wellbeing and development prospects of local population [46, 47]. In M-LED, the services electricity demand is modelled (figure 2(B)) in a similar fashion to the residential: we design baskets of appliances ownership and use tiers of each category of facility (reported in supplementary file F2). Scientific [48, 49] and grey [50] literature on the theme exists, but is often generic and usually scarce when it comes to SSA.

To tailor the application presented in this paper to the specific country-study, a field campaign was conducted in primary schools and rural healthcare facilities of Kenya to perform surveys and empirical observations of the appliance ownership and use, energy consumption. Based on these observations, we could construct the consumption patterns of health and education facilities in RAMP and allocate it to the (latent) demand of clusters where similar facilities are located. Information on operational healthcare facilities in Kenya is based on open-data on the location and characteristics of public[7] healthcare facilities [51]. Similarly, open-data for the position and size of schools is retrieved [52].

We classify healthcare facilities into five tiers combining results from the observations and the facility type explicated in the original dataset [51]. Once information about the location and typology of healthcare and education facilities is compiled, we calculate the density of facilities of each tier in each cluster. Based on this information, we estimate the total local sectoral demand exploiting the monthly load demand profiles calculated with RAMP. The seasonality of school facilities is indeed dependent on the national school calendar[8], and has been modelled accordingly. A detailed discussion on classification methodology is available in the SI A-4.

2.4. Agricultural sector demand: the relevance of the WEF nexus (Water, Energy, Food security)

Currently in SSA more than 90% of total cropland is rainfed [53], with this figure standing at about 95% in Kenya [54]. Remarkably, currently 85% of the global population without electricity access is concentrated

[7] To date there is no comprehensive publicly available dataset of private healthcare facilities in sub-Saharan Africa.
[8] https://publicholidays.co.ke/school-holidays/2020-dates/

in rural areas [3]. Together with the lack of fertilisation, the unmet irrigation water demand implies a situation of sub-optimal production, in what has been defined the yield gap [55, 56]. Moreover, the bulk of the production is either for subsistence purposes or it is sold to unprocessed wholesale markets. This is because of the lack of crop processing facilities in most small and medium farm businesses [57, 58], because of the lack of energy supply to power those plants, as well as due to market accessibility. To enable growing agriculture productivity and profitability, the provision of energy is necessary [59–62], along with the purchase of machineries and infrastructure.

The M-LED geospatial analysis estimates the energy requirements to enable artificial irrigation and raw crop processing (figure 2(C)). Agricultural land, hydroclimatic factors, and cropping patterns information is conveyed in a set of agroclimatic equations to estimate daily irrigation water requirements in each cluster. The input data and estimation procedure are described in SI-A5. Then, a groundwater pump model estimates the required power and flow rate of the pump as a function of the groundwater dwell characteristics and of the irrigation requirements (SI-A6). An extensive literature review of crop processing energy requirements in the context of developing countries is carried out (results in table SI4). Based on this review the energy requirements are associated to crop-specific cropland extent and average yield in each cluster, as discussed in SI-A7.

In addition, M-LED can identify hotspots where investment can be prioritized to onset rural development. As an example, we demonstrate that the platform can estimate the increase in the revenues from the potential boost in the per-hectare yield due to artificial irrigation, which in turn might compensate for the low ability-to-pay for energy services of rural dwellers [63]. In our analysis, we consider a recent database of wholesale prices for a basket of crops in Kenya relative the location of each wholesale market. Prices are multiplied to the local potential for yield increase of each crop, net of transportation and total (installation, operation, and maintenance) pumping costs, as detailed in SI-A8.

2.5. Micro enterprises and commercial electricity demand

The provision of electricity can foster small entrepreneurial activities such as small shops, mini-markets, handcraft and telecommunication services retail [64–66] which can represent a significant leverage for broader socio-economic development [67] and be anchor customers for financing electrification projects. In the context of developing countries microenterprises are defined as small businesses employing few people, generally HH-related, and with a limited turnover. Modelling the residual productive demand from microenterprises with a bottom-up approach is challenging because of the lack of granular country or region-wide data, which makes it impossible to model at an appliance or facility level. Proxy estimation approaches have been introduced in previous studies [21, 25]. Here we build on the estimated residential demand as a base layer and calculate a multiplier factor to derive the yearly productive demand on top of given residential demand (figure 2(C)). As detailed in the SI-A9, we carry out a principal component analysis to create a composite index based on relevant drivers of productive activities (road density, accessibility, employment levels and wealth distribution, visualised in figure SI6). The composite index is used to define the local residential demand multiplier factor, ranging between +30% and +60% (similarly to [21]).

The baseline load curve (share of demand at each hour of the day over the total daily demand) of micro productive activities is assumed to follow the same path of that described in Moner-Girona *et al* [22] for Kenya, which in turn is derived from field metered data. A seasonal variation is imposed on the baseline load curve, so that each monthly curve follows the same monthly relative mark-up observed in the residential demand. Equation SI13 describes this procedure algebraically.

3. Results

3.1. An applicative example for Kenya: granular electricity demand estimates

This section illustrates the resulting spatially-explicit sectoral electricity latent demand generated for Kenya with the M-LED platform. The estimated demand encompasses multiple dimensions: sectoral granularity; monthly seasonality in the demand; hourly profile; and spatial distribution of the demand.

Figure 3 shows the geographical distribution of yearly sectoral latent electricity demand density (MWh yr^{-1} km^{-2}). The original results are at a polygonal cluster-dependent resolution; here to ensure a more immediate understanding, they are plotted on a 1×1 km grid. White pixels identify areas with either no population or no sectoral electricity demand, such as natural parks, protected areas, or cropland (for sectors different from agriculture). The results show that substantial heterogeneity is observed in the residential and commercial and micro-enterprise sectors: both are highly correlated with population density, with significantly higher demand in south-western Kenya. Yet in some areas (e.g. in northern Kenya) commercial and micro-enterprise demand is comparatively lower than the residential demand because of lower employment and market accessibility. Irrigation and crop processing electricity demand are concentrated in the agricultural districts in the south-west of Kenya, while healthcare and education demand are more scattered across the country, although with higher density in higher density populated areas. Healthcare facilities are highly sparse

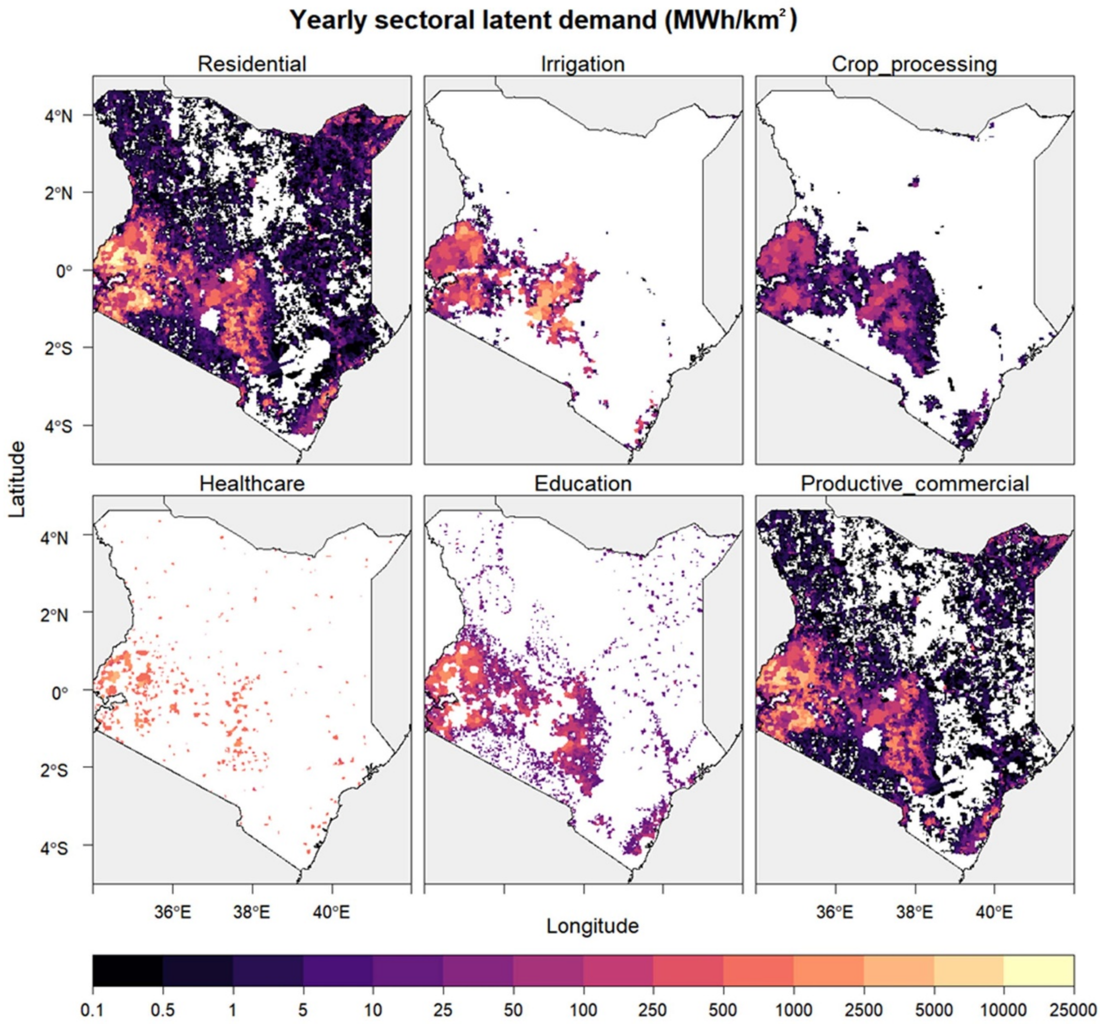

Figure 3. Sectoral demand loads estimated for each population clusters. Maps of Kenya representing: (i) the estimated annual residential demand (per pixel) for households that require electrification (MWh yr^{-1} km^{-2}); (ii) the total healthcare and education demand (per pixel) for facilities requiring electrification (MWh yr^{-1} km^{-2}); (iii) the water pumping and crop processing demand (per pixel) (MWh yr km^{-2}); (iv) the micro-enterprise and commercial activities electricity demand (per pixel) (MWh yr^{-1} km^{-2}).

but at the same time exhibit a high demand density, while schools are relatively more distributed but less electricity intensive.

Figure 4 depicts the hourly load demand profiles across sectors and compare the loads in each month of the year. Residential demand shows a curve profile with three peaks, during wake-up, lunch, and evening times. A similar polymodal distribution characterises commercial and micro-enterprise demand. Most of the seasonality is explained by the variation in the use of air circulation and cooling appliances, since residual uses are rather invariant throughout the year given the proximity of Kenya to the equator. Educational centres show variation in months of year and term breaks with energy demand bimodal distribution with peaks in the morning and in the afternoon. Healthcare results show relatively little seasonal variation, with unimodal normal distribution with a peak at midday for healthcare. Agricultural-related activities show high seasonal variance in the monthly profiles, but the load of the irrigation and crop processing curves is however flat throughout the energy use windows, 5–9 am and 9–11 pm for irrigation and 6 am–6 pm for crop processing machinery.

Figure 5 summarises the yearly aggregated latent demand across sectors in Kenya and its repartition among the eight regions of Kenya. The country-wide aggregation shows that the supply requirements are unevenly split into the residential (at about 1.5 TWh yr^{-1}, or 48% of the total 3.1 TWh yr^{-1}), commercial activities and micro-enterprises (nearly 0.75 TWh yr^{-1}, about one quarter of the total), healthcare (about 0.22 TWh yr^{-1}, or 7%), education (0.18 TWh yr^{-1}, 5.7%), irrigation (0.42 TWh yr^{-1}, 13.5%), and crop processing sectors (about 0.07 TWh yr^{-1}, only about 2%). Additional

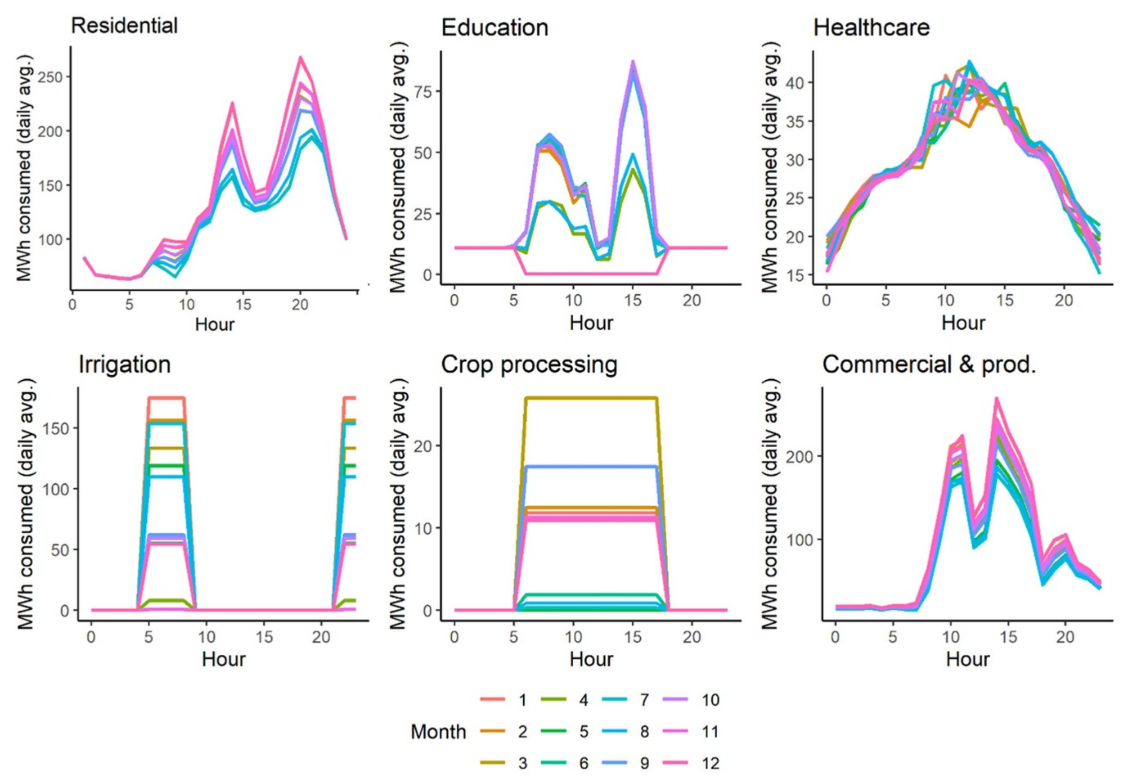

Figure 4. Demand loads per sector generated by the M-LED methodology. Hourly load profiles (MW) are compared for each month of the year per each sector (typical daily load per population cluster averaged at country-level).

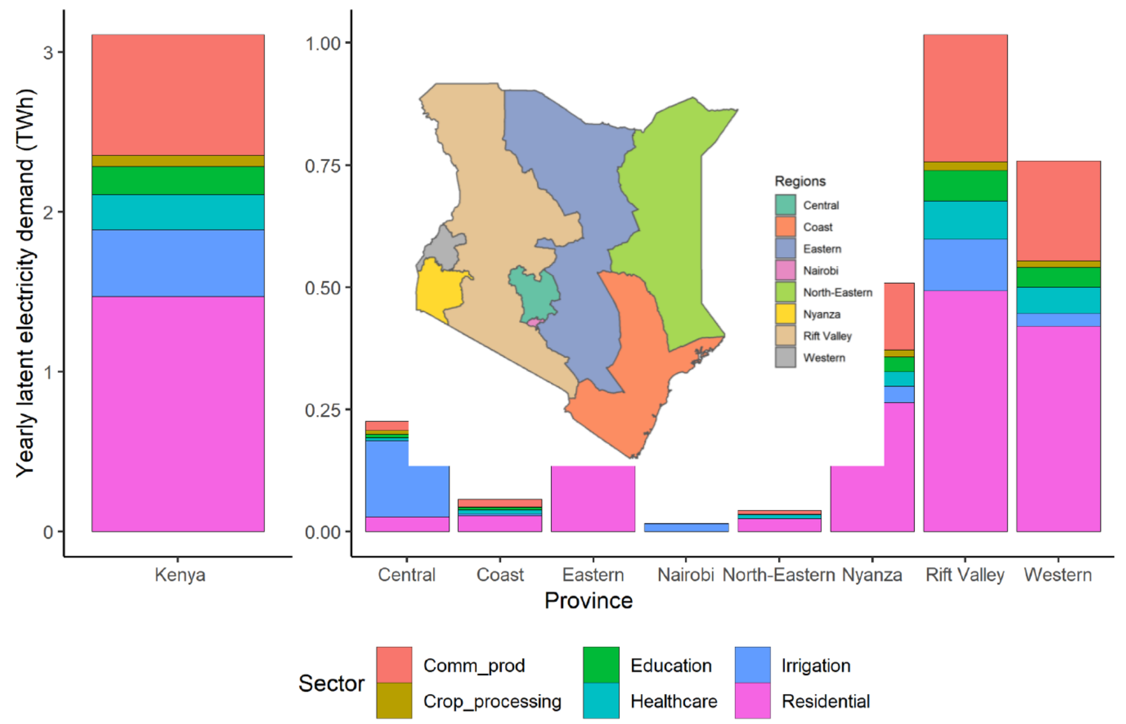

Figure 5. Regional sectoral demand in Kenya estimated with the M-LED methodology. Total annual latent electricity demand (TWh yr^{-1}) by region and country-level. Each electricity demand is divided by sector: residential, commercial (Comm_prod), agriculture (crop processing and irrigation), education and health infrastructure).

insights are drawn when considering the repartition of those aggregate energy requirements across the eight main regions of Kenya, as well as the shares of each sector within each region. The Rift Valley region is the region with the largest latent demand (about one third of the total latent demand), driven mainly by the residential and productive sectors; it is followed by the Western region (about 25% of the country latent demand), with a similar repartition. Notably, in the Central region irrigation latent energy is by far the first sector (>two thirds of the total).

3.2. Potential economic returns estimation

On top of the detailed latent electricity demand results, the M-LED platform enables an analysis of the potential economic returns from the agricultural sector thanks to artificial irrigation. These results (reported and commented in the SI-B) reveal an untapped revenue potential (net of transportation and groundwater pumping costs) of about $4.9 billion/year (about 5% of the 2019 Kenyan GDP). This suggests significant economic potential that in many areas may quickly pay back the investment in electrification when properly accounted by decision makers in the cost-benefit analysis and supported by policies stimulating improved land management and fertilisation. Yet, it must be remarked that additional relevant dimensions that might affect the results of the analysis in the future include the price change of products owing to crop processing and local value creation and the efficiency gains in transport from improved road or rail transportation and logistics.

4. Discussion

4.1. Planning-oriented implications

A detailed formulation of electricity demand is a crucial factor in energy access planning. This is also reflected in the outcome of supply-side electrification models. In this paper we have introduced M-LED, a new, open-source, flexible platform for generating electricity demand curves based on a multi-sectoral bottom-up device-based approach. We have then applied the platform to the country-study of Kenya as an applicative example. We have thus addressed the research question of how big data and bottom-up energy modelling can be together leveraged to represent the potential demand for electricity with high spatio-temporal and sectoral granularity.

The application provided an array of insights, the crucial ones being that planning electricity access based on residential demand only is likely to underestimate the total demand of settlements (and chiefly in rural areas), confirming similar recent claims in the literature [21]. Accounting for healthcare, education, commercial and micro-enterprise, and agricultural energy uses implies a more than doubling of the estimated yearly potential demand *vis-à-vis* residential only (country-wide). This mark-up is even greater in agriculture-intensive rural areas where energy uses for irrigation and crop processing might be significant higher in relative terms.

In the scope of our country-study of Kenya, the analysis reveals that the non-residential sectors considered constitute a very relevant share of the total potential electricity demand in areas electricity access deficit. In aggregated terms, they account for $\sim$53% of the yearly latent electricity demand, or 1.65 TWh yr^{-1}. The ratio between residential and non-residential demand is even more pronounced in the Central region, where although the HH electricity access levels are already quite high, agriculture-related activities require significant electricity input which today is largely missing. Additionally, in population-dense areas productive and commercial demand also has a significant impact on the final regional demand. Another novel insight is offered by our hourly and seasonal-variant formulation of sectoral load curves, which might have a significant impact on the optimisation of energy systems, in particular when paired with variable renewable energy supply curves.

Finally, as demonstrated by our analysis, while planning energy solutions which can comprehensively enable agricultural uses might increase the required power capacity and upfront investment, it might also render them economically attractive. This is because of the significant reduction in the payback time of those investment that could be achieved if the local agricultural productivity and profitability grows [68]. Today most smallholder farmers currently sell their production to few large processing plants or supply it directly to wholesale markets, where crops are shipped abroad for overseas processing in more efficient and larger-scale plants. The transition from rainfed to artificially irrigated agriculture through surface or groundwater electrical pumping thus provides a relevant example of how an electricity input could dramatically boost rural productivity. Moreover, generating value added through local crop processing [68] and retaining it among farms would considerably boost local socio-economic prospects, with the potential to set a positive feedback involving the entire local rural community.

4.2. Comparison of the estimated demand with previous studies

A systematic comparison of our results with previous demand estimates found in the literature (in most cases used to parametrise geospatial supply-side electrification models) is not straightforward. This is because of the differences in both how this demand is formulated (e.g. yearly sectoral consumption in kWh or representative day load curves in W) and how it is parsed to settlements (urban/rural, poor/non-poor). Nonetheless, several insights can still be drawn.

As reported in figure 6 our results, even based on a substantially different approach from other studies, do not fall distant from other works' results in terms of estimated total yearly consumption at the HH level. In the M-LED platform application for Kenya we estimate average urban and rural residential electricity demand of 62 and 840 kWh HH^{-1} yr^{-1}, respectively. Yet, it must be remarked that—while informative—these values alone mask the heterogeneity in the electricity demand that characterises our methodology. The

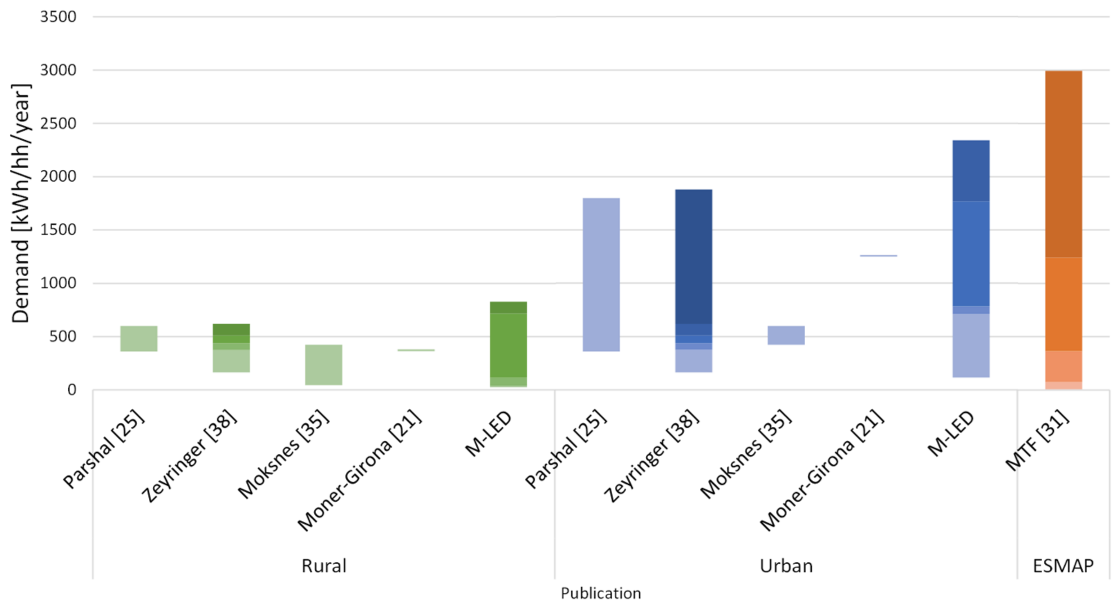

Figure 6. Comparison of the harmonised estimated potential electricity demand of non-electrified households in Kenya. The Tiers of the World Bank—ESMAP (Energy Sector Management Assistance Program) MTF (Multi-Tier Framework) are also reported as reference on the left of graph. Multiple stacked bars on a single publication represent different scenarios or tiers of users with different levels of electricity consumption. The plot gives hence a range of electricity consumption considered for Urban and Rural users. The different shades of colour in the columns represent the range of values of electricity consumption per scenario (every publication considers a different number of scenarios).

SI-B2 reports a more detailed comparative account of our results with previous published studies, including productive and services sectors demand.

This comparison suggests that the detailed characterisation of our study leads to significant differences with previous studies. Firstly, including productive sectors in our characterisation increases notably both the total load of settlements and the productive-to-residential demand ratio. Secondly, it leads to a larger spread in the residential demand between urban and rural areas. Yet, when encapsulating activities such as artificial irrigation and crop processing, the gap in the demand between settlement types is reduced.

On the other hand, a visual comparison of demand maps suggests that the spatial distribution of demand hotspots is identified similarly through different approaches, provided sectors additional to the residential demand are considered. This is because the key non-residential demand drivers considered in these studies are often similar and highly correlated among each other, such as population density, urban/rural prevalence, poverty density or wealth distribution, and the geographical position of service and productive infrastructure and of crop fields. Yet, studies focussing on achieving universal electrification based on residential demand only flatten the heterogeneity in the demand. For instance, by setting a top-down rural demand, they significantly underestimate the demand of rural settlements.

4.3. Data uncertainty and modelling limitations

Irrespective of the large amount of work involved in the development of the M-LED platform and in the formulation of its assumptions, limitations remain.

The M-LED platform is open-source and fully customisable to let the user define the bulk of the input data sources (both for the Kenya case study presented in this paper and for future applications), including technical and economic parameters, the devices ownership and usage patterns, and the overall infrastructure. Yet, the data-intensiveness (table SI3) of the analysis implies growing uncertainty over the reliability of the database, as (despite a careful data selection and wrangling) some sources such as infrastructure and facilities location and characteristics might be outdated or biased.

For instance, gridded population data products are based on census data downscaling based on dasymetric methods applied on building footprint data [69], which can result in systematic undercounting of certain population groups [70]. Electricity access is estimated with nighttime lights, which has own limitations [6, 43]. Cropland information is limited by quality of official data and downscaling methods [71]. Groundwater availability maps are produced by interpolating a set of *in-situ* measurements under given hydrological constraints [72]. Moreover, the water and agricultural analysis relies on the assumption of an optimal irrigation scheduling (as described in [73]) and local crop processing based on current cropping patterns. Healthcare and education facility databases have their own data availability and quality limitations [51].

Furthermore, while the appliance ownership and use baskets considered in the Kenya application are designed after a careful literature screening supported by field campaign experience of the authors, residual cultural, service, and economic heterogeneity might not be captured in the analysis.

Thirdly, a limited number of sectors is considered, as a number of productive activities are not explicitly modelled and simply fall within the generic residual productive and commercial activities.

Overall, the output of the M-LED platform is suitable for informing policymakers in their infrastructure decisions and prioritisation strategies. Nonetheless, local detailed assessments with field visits are required to precisely assess the needs (including future evolution of the load) of specific identified communities and design the power generation and distribution infrastructure necessary to supply electricity to households and other customers.

5. Conclusion

We have introduced the M-LED, a M-LED geospatial data processing platform to estimate electricity demand across space, time, and energy sectors in communities that live in energy poverty. The application to the country study of Kenya shows how big data and bottom-up energy modelling can be together leveraged to represent the sectoral potential demand for electricity with high spatio-temporal granularity.

Our results are potentially beneficial for policy makers, researchers, consultants, and other stakeholders involved in the electrification planning. For instance, the results could contribute to the prioritisation decisions for the allocation of limited governmental funding by leveraging consumers who are likely to have the greatest impact on increasing economic growth thanks to the provision of electricity to existing productive activities or attracting private investments in the most productive areas.

It must be remarked that this paper has focused on the demand estimation methodology. Yet, future functionalities, currently in the design stage, will link the high-resolution hourly, seasonal, and sectoral demand estimates into an array of electricity supply planning models. The new functionality will allow to carry out an independent assessment for several electrification planning models and understand the significance of considering the new multi-sectoral and seasonal dimensions as opposed to conventional top-down demand characterisations.

We encourage further research on the topic and improvements to the state of the M-LED platform introduced at the time of the writing of this paper. A better characterisation of potential industrial demand and a dynamic formulation of demand (with intertemporal growth based on income and other determinants) represent potential first-order improvements.

Code and data availability

The M-LED platform source code and the accompanying documentation are available at https://github.com/giacfalk/MLED. An archive containing all the data inputs for replicating the Kenya analysis is available on Zenodo at https://zenodo.org/record/3980355.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.3980355.

Acknowledgments

Financial support from the European Commission H2020 funded project LEAP-RE (Long-Term Joint EU-AU Research and Innovation Partnership on Renewable Energy), Grant Number 963530 is gratefully acknowledged. We also thank Paolo Cornali and Su-Min Choi for their assistance in the research process.

Conflict of interest

The authors declare no competing financial interests.

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