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TOPICAL REVIEW

Latent demand for electricity in sub-Saharan Africa: a review

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Abstract

Universal access to electricity is an essential part of sub-Saharan Africa's path to development. With the United Nations setting Goal 7 of its sustainable development goals to be universal access to clean, reliable and affordable electricity, substantial research efforts have been made to optimize electricity supply based on projected demand in sub-Saharan African (SSA) countries. Our study reviews the literature on electricity demand, with a specific focus on latent demand (i.e., electricity demand that would exist if the necessary techno-economic conditions were met) in SSA. We found that out of 57 electricity demand papers reviewed, only 3 (5%) incorporated latent demand in their electricity demand projections. Furthermore, majority of the literature on electricity consumption and demand estimation in SSA use econometric models to identify determinants of electricity consumption and project future demand. We find that population density, urbanization, household income, electricity price, market value of crops and availability of natural resources to be significant determinants of electricity consumption in SSA. We conclude the review by proposing a methodology, and providing an initial proof of concept, for more accurately projecting latent demand in sub-Saharan Africa. Incorporating latent demand in electrification models would help inform energy sector stakeholders (e.g., investors and policymakers) about which sectors and geographic locations hold potential for wealth creation via electricity access.

1. Background & motivation

With a rapidly growing population and increasing rate of urbanization, the region of sub-Saharan Africa (SSA) will need to expand access to affordable and reliable electricity to achieve sustainable development. Some studies have highlighted that sustainable development goals (SDGs) are inter-linked citing that access to clean, reliable and affordable energy (SDG 7) will be crucial to attaining other SDGs, such as improved healthcare (SDG 3), quality education (SDG 4), sustainable cities (SDG 11) and overall human development (McCollum *et al* 2018). As a result, researchers have developed many geospatial electrification models (GEMs) to determine least-cost pathways towards attaining universal access (i.e., 100% access) to electricity in SSA. For example, Korkovelos *et al* (2019) developed an open-source GEM to help policymakers in Malawi to identify last-mile communities (i.e., communities that would receive access to electricity last) and the least-cost electricity supply option for them. Another study, Moner-Girona *et al* (2019), used a least-cost electrification model to determine rural areas in Kenya where the potential for deploying renewable decentralized energy systems was being underestimated or unaccounted for in the Rural Electrification Masterplan of Kenya. Many other models have been developed to guide energy policymakers in SSA in planning for universal access (Kemausuor *et al* 2014, Ohiare 2015, Mentis *et al* 2017, Moner-Girona *et al* 2019, Lee *et al* 2019, Nock *et al* 2020). A key in the success of these electricity planning models is proper estimation of future electricity demand.

While these least-cost GEMs are essential for informing development pathways to achieve affordable access to electricity, their outcomes are heavily dependent on input assumptions regarding future electricity demand. This is because GEMs are designed to identify least-cost or otherwise optimal strategies to serve the demand profiles that the user has identified. To project electricity demand, researchers have traditionally used tiered frameworks (Mentis *et al* 2017, Korkovelos *et al* 2019), regression-based models (Gabreyohannes 2010, Adom *et al* Bekoe 2012) or made assumptions about demand growth based on GDP and population growth rates (Kemausuor *et al* 2014). Importantly, relatively few models or analyses explicitly consider or account for latent electricity demand. Interestingly, in a recent review of optimization models used for rural electrification research, latent demand for electricity was not addressed in any of the publications reviewed (Akbas *et al* 2022).

In economics literature, latent demand is described as demand for a product or service that cannot be satisfied by any existing product or service due to resource constraints (Richardson and Crompton 1988, Zax 1997, Freel *et al* 2012, Clifton and Moura 2017). In the electrification literature, latent electricity demand is often defined as the demand for electricity that would be present if accessible infrastructure and adequate techno-economic conditions to supply electricity were available (Fabini *et al* 2014, Afful-Dadzie *et al* 2017, Falchetta *et al* 2020, Poblete-Cazenave and Pachauri 2021). In this paper we focus on the electricity-based definition of latent demand. Latent demand is inherently difficult to quantify because there is uncertainty about how consumers will respond to enhanced electricity access (Poblete-Cazenave and Pachauri 2021). For example, even when the power grid is expanded it is unclear whether the local population will be able to afford the electrical appliances.

Furthermore, there are dynamic interactions between access and demand that are difficult to predict and may evolve over time. For example, electricity access may support economic development or wealth creation, which in turn may further increase demand. Enhancing methodologies for estimating latent demand would help grid utility companies improve their cost recovery due to better estimation of demand and associated revenue streams. It would also enable minigrid companies to develop more accurate estimates of revenue streams, thus enhancing their chances of creating economically viable business models to aid electrification in rural regions that are not connected to the grid and therefore potentially have very high latent demand. Given that demand is the key input for supply-side electricity planning models that are used to inform energy sector stakeholders, accurate estimates of latent demand would enable these stakeholders to better prioritize infrastructure investments and plan development more efficiently. For example, Afful-Dadzie *et al* (2017) used a mixed-integer linear program to show the economic impact of unserved demand in over a 20 years time horizon (i.e., 2016 to 2035). The authors found that increasing budget allocation for energy access from 1.25% to 1.5% of Ghana's GDP would reduce the opportunity cost of unserved demand by US$123 million over those 20 years. Here the authors define latent demand (i.e., unserved demand) as the 'loss of economic activity' due to a lack of electricity supply (Afful-Dadzie *et al* 2017). A major takeaway from this study was that annual savings (up to 1.75% of GDP) by the Government of Ghana could provide the necessary budget to attain 95% electricity access in the country.

Quantifying latent electricity demand is a two-fold challenge. First there is the need to estimate demand under the assumption that sufficient reliable and affordable electricity supply is available to serve all electricity demand in the region (residential, commercial, industrial, agricultural etc). Second, assuming there is sufficient supply to meet the projected demand there is a risk that the system may have been over or under built when the actual demand is realized. Overestimating demand results in energy systems being oversized, and governments not being able to recover their costs. Load overestimation in the design of photovoltaic (PV) minigrids systems results in an additional capital cost of $2 to $6 per daily kilowatt-hour of demand overestimated (Louie and Dauenhauer 2016). As such, the cost borne by minigrid end-users who tend to be lower income populations is prohibitive. The African Minigrid Developers Association (AMDA) highlighted that low consumption of electricity supplied by minigrids has eroded the bankability of many minigrid business models (AMDA 2020). On the other hand, underestimating demand results in low reliability of electricity supply (Louie and Dauenhauer 2016), difficulty achieving the universal access target, and unrealized revenue streams (Afful-Dadzie *et al* 2017). Thus, even if some end-users are provided with a reliable and affordable supply of electricity, underbuilding the electricity system could result in an unreliable power system for some users during periods where demand exceeds available supply. In short, underestimation of latent demand can be self-fulfilling as power systems are designed to serve predicted demand levels. If latent demand is underestimated or not considered in system planning, it will likely be left unserved in the future. Hence, better demand estimation methods (i.e., those that consider latent demand) will be vital to increasing electricity access in SSA.

Improving methodologies for estimating latent demand and incorporating the resultant estimates into system planning models can increase electricity access and generate economic growth in a cost-efficient manner. Hence, *the goal of this paper is to lay out a framework for estimating current, and projecting future, latent electricity demand in SSA countries*. In this paper, we begin by reviewing the existing latent demand literature. Then, we delve into the various factors that affect electricity consumption as well as general electricity consumption trends for newly electrified populations in SSA. We conclude by laying out the general framework for methods that can be used to quantify latent demand and discuss avenues for future work.

2. Methods

Our review encompasses a total of 56 papers on demand estimation and prediction in SSA. In conducting this literature review we identified relevant papers using a combination of web databases and key word searches. The Google Scholar and Web of Science databases were the primary sources for the review process. To identify the relevant studies, we used key words and phrases including 'determinants of electricity consumption in SSA', 'demand prediction', 'demand forecasting', 'latent demand estimation', 'electricity usage patterns', and 'electricity consumption patterns for newly connected users'. In the review process, we focused on english-speaking journal articles, and included all papers published between January 1, 2000 and October 10, 2021. This wide time frame maximizes the coverage. We also included additional papers based on the identified studies' reference lists. While there were several qualitative and quantitative papers on electricity in SSA, we identified 56 papers that discussed or studied demand estimation techniques and electricity consumption in SSA. Our goal is to highlight how different demand estimation techniques impact electrification planning and analyses in SSA. Thus, in our review of latent demand papers, we excluded papers that use electrification tiers or a tiered characterization of demand, due to limits in their estimation technique technical detail and flexibility. We also chose to not review literature related the supply-side of electricity access, meaning that capacity planning models in SSA are typically excluded from our review.

A key factor is demand estimation is determining drivers of electricity consumption within different sectors of the economy. A common technique used to investigate determinants of electricity consumption to identify key determinants of electricity demand is autoregressive distributed lag (ARDL) models. ARDL models are time-series regression models used to estimate a time-variant dependent variable with time-variant explanatory variables. Specifically, an ARDL model seeks to predict present values of the dependent variable using past values of the dependent variable as well as present and past values of the explanatory variables. The past values of the dependent variable (i.e., the lagged values of the dependent variable) are used to characterize the 'sluggish' response of the dependent variable to changes in the explanatory variables (Bentzen and Engsted 2001). Our review on determinants of electricity consumption included 48 studies that used ARDL models in SSA, which we discuss in the next section. While such ARDL models may not be able to explicitly predict electricity load over a time horizon, they show the correlation between various variables and electricity consumption, which may be helpful for understanding consumption patterns among electricity customers in SSA.

3. Results

3.1. Findings from literature on latent demand

Due to the lack of electricity consumption and demographic data publicly available in SSA, accurately estimating and projecting future demand for electricity in the sub-continent is extremely challenging. Hence, researchers have developed various regression-based models to predict demand for electricity in SSA. However, these regression or econometric approaches often fail to capture how electricity consumption may be impacted by changes in available infrastructure or other factors. Nonetheless, in this section, we review the extant literature on demand forecasting in general to show the relative lack of studies estimating latent demand and to provide context for a proposed method to quantify latent demand. In our review, we classified existing literature on electricity demand and consumption estimation into three categories, studies that use survey data to predict electricity demand with regression, studies that use meter data to train regression models to estimate/predict demand, and studies that use deterministic models (i.e., perfect forecasting) to quantify demand. Table shows the classification of these methods of quantifying electricity demand.

First, researchers have carried out surveys among households in SSA to predict demand using demographic characteristics and appliance usage patterns. These research papers pointed out that surveys for predicting electricity demand need to take more accurate inventories of appliances. They also revealed that existing electricity customers are unable to realistically predict the appliances they would purchase in the short-term (Hartvigsson and Ahlgren 2018). Finally, using a combination of regression approaches may help energy sector supply-side stakeholders better understand and predict their customer base's usage patterns.

One study sought to determine the accuracy of energy-use surveys in predicting consumption among rural minigrid customers (Blodgett *et al* 2017). For their analysis, they compared survey-predicted electricity consumption to actual measured consumption of customers in Kenya. The survey predictions resulted in an average customer consumption error of 426 Wh per day per customer on an average customer consumption of 113 Wh per day. Their study demonstrates that customers systematically underestimated their

Table 1. Approaches to estimating and predicting electricity demand/consumption in SSA. Here we find that a majority of studies (95%) exclude latent demand from their analysis.

Demand type	Method	References	Number of studies
	Survey-data-driven regression models	(Blodgett *et al* 2017), (Hartvigsson and Ahlgren 2018)	2
	Meter-data-driven approaches (regression & longitudinal)	(Obok Opok *et al* 2008), (Tchuidjan *et al* 2014), (Louie and Dauenhauer 2016), (Tartibu 2018), (Allee *et al* 2021)	2
Estimate/prediction assumes perfect ability to forecast (latent demand excluded)	Autoregressive (ARDL) & other econometric models on electricity consumption	(Pihl 2000), (Abebaw 2007), (Ziramba 2008), (Amusa *et al* 2009), (Gabreyohannes 2010), (Neelsen and Peters 2011), (Sillah 2011), (Adom *et al* 2012), (Adom *et al* 2012), (Wesseh and Zoumara 2012), (Ubani 2013), (Remigios 2014), (Adom 2015), (Bekele *et al* 2015), (Iyke 2015), (Jones *et al* 2015), (Danmaraya and Hassan 2016), (Inglesi-Lotz and Pouris 2016), (Johnson 2016), (Keho 2016), (Sama and Tah 2016), (Sekantsi *et al* 2016), (Bah and Azam 2017), (Khobai *et al* 2017), (Kwakwa 2018), (Sekantsi and Timuno 2017), (Elfaki *et al* 2018), (Ateba *et al* 2018), (Kwakwa 2018), (Sarkodie and Adom 2018), (Adjei Kwakwa and Adusah-Poku 2019), (Kimutai *et al* 2019), (Samu *et al* 2019), (Taale and Kyeremeh 2019), (Ali *et al* 2020), (Bonkaney 2020), (Jawneh and Manneh 2020), (Onisanwa and Adaji 2020), (Tesfamichael *et al* 2020), (Twerefou and Abeney 2020), (Adusah-Poku *et al* 2021), (Bohlmann and Inglesi-Lotz 2021), (Gafa and Egbendewe 2021), (Guefano *et al* 2021), (Merlin and Chen 2021)	48
	Deterministic approaches (i.e., assuming perfect forecast)	(Ofetotse *et al* 2021)	1
Latent demand included	Deterministic approaches (i.e., assuming perfect forecast)	(Fabini *et al* 2014), (Afful-Dadzie *et al* 2017), (Falchetta *et al* 2020)	3

electricity consumption and failed to accurately state the duration and times of usage of their appliances (Blodgett *et al* 2017).

Another study found that surveys focused on eliciting an accurate inventory of current and future appliances from customers produced more accurate predictions than surveys utilizing demographic information as indicators of demand (Hartvigsson and Ahlgren 2018). They quantified the accuracy of their survey results by comparing daily load profiles from meter data to load profiles predicted using appliance ownership data. Hence, future household surveys need to focus on collecting an accurate inventory of appliances in the household. Given the error associated with survey-based predictions of electricity demand, researchers have studied survey approaches to load estimation for minigrid developers in SSA (Williams *et al* 2019). They conclude that using a random-forest regression in tandem with a Least Absolute Shrinkage and Selection Operator (LASSO) model would enable developers to identify their high-end customers, determine the most relevant determinant of electricity consumption, and more accurately predict electricity demand. More data on appliances in non-residential settings need to be collected to more robustly predict overall demand for electricity.

Although the studies discussed above (Blodgett *et al* 2017, Hartvigsson and Ahlgren 2018) used electric appliances ownership data to predict electricity demand, we determined that electric appliances should not serve as a driver quantifying latent demand for a few reasons. First, although these appliances help predict residential demand for electricity, the accuracy of responses to surveys with appliance inventories varies widely and would consequently skew the results of latent demand estimation (Williams *et al* 2019). Second, the broad range of types of appliances used in the SSA household would require each of these appliances to be identified

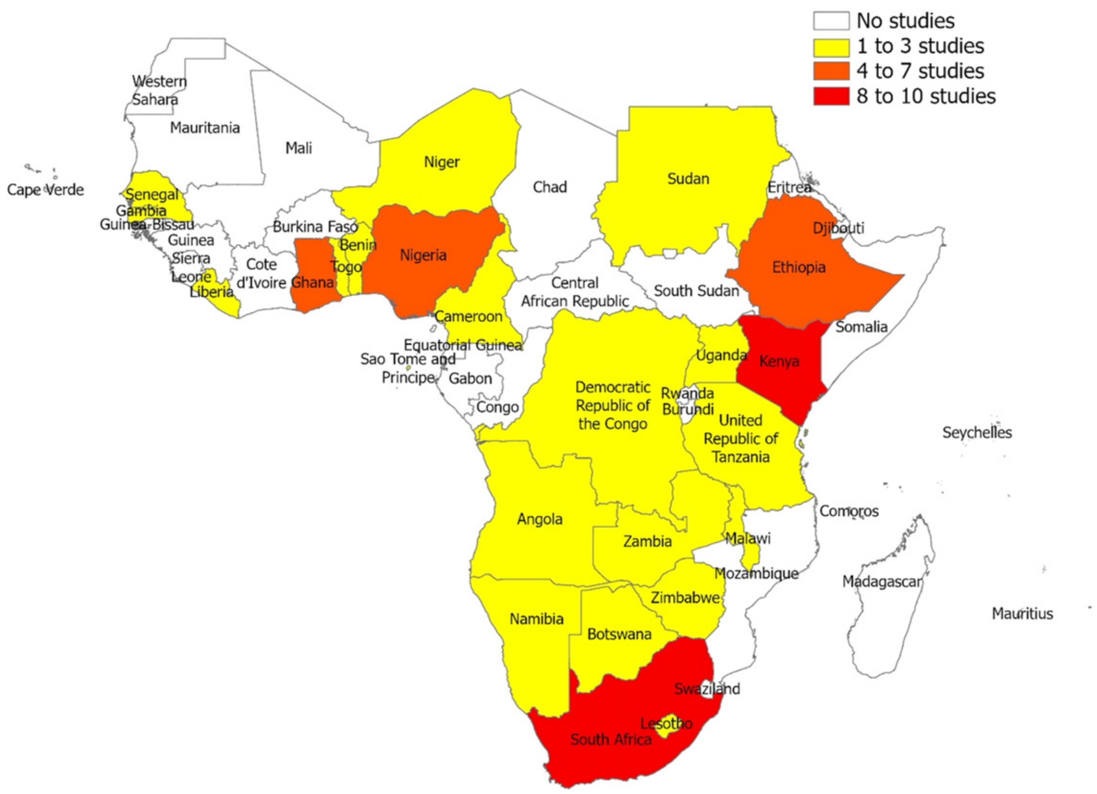

Figure 1. Spatial distribution of electricity consumption or demand studies in SSA. Based on our review, there is a lack of demand studies in parts of West and Central Africa. It is important to note that we focused on studies that attempted to estimate country-level demand, and therefore that collectively investigated electricity demand across the entire subcontinent were not included. Additional data sourced from Louw *et al* (2008), Solarin and Shahbaz (2013), Niger MTF Household Survey (2018), Mulenga *et al* (2019), Hongyun and Radwan (2021).

as a predictor in a regression model, which may require use of more complex models such as the LASSO model. Third, given that the studies that use the ARDL model show correlation between appliances as determinants of consumption and electricity demand, one cannot infer causality from them. Hence, there is causal uncertainty pertaining to appliances as predictors of electricity demand.

The second approach to estimating demand uses historical and current meter data to forecast electricity demand. Three different demand prediction models were investigated in one study to determine which model predicted with the least amount of error (Allee *et al* 2021). They used three different machine learning models, namely an ordinary least squares model, a random forest model and a LASSO model, to predict electricity demand for minigrid customers in Tanzania. The best of the three models (i.e., the LASSO model) predicted daily customer-level load profiles with a median absolute error of 66%, the lowest error margin of the demand forecasting models explored in our review.

Another challenge in quantifying latent demand for electricity in SSA that needs to be considered is the dynamic interaction between demand and access, which may evolve over time. Access to electricity may cause wealth creation (from increased productivity), which may in turn, increase demand for electricity (Poblete-Cazenave and Pachauri 2021). As such, it is essential for researchers to also study how demand for electricity may have evolved for newly connected customers in SSA. Given the relative lack of publicly available data on electricity in SSA, we only found one study that investigated how demand evolved over time for newly connected customers. According to the longitudinal study electricity demand is declining for newly connected customers in Kenya (Fobi *et al* 2018). Using monthly electricity bills of 136 000 utility customers in Kenya, Fobi *et al* (2018) showed that the median newly connected customer tends to rapidly increase consumption until about a year of connection, after which consumption plateaus and eventually starts to decline. Furthermore, they found that electricity consumption among customers that were connected after 2009 tended to peak much sooner than customers that were connected before 2009. This shows that more recently connected customers consume less electricity than earlier customers even after these earlier customers' consumption levels off. Specifically, the median 2009 customer consumed about twice the electricity of the median 2014 or 2015 customer. Furthermore, the authors found that this trend applies to both rural and urban customers, with urban customers generally consuming 50% more electricity than their rural counterparts. Hence, the increase in number of new rural customers in Kenya due to its national electrification plan could ultimately lead to an overall decrease in electricity consumption growth over time because of the increasing proportion of rural electricity customers with relatively less purchasing ability/income than their urban counterparts. Although neither Allee *et al* (2021) nor Fobi *et al* (2018) predicted latent demand for electricity, their results show that a latent demand prediction model would need to consider decreasing electricity consumption from new rural customers, and the LASSO model should be studied more since it has the lowest mean absolute error of all the demand prediction models in this review.

The existing literature specifically on predicting latent demand for electricity using a deterministic approach (i.e., assuming perfect forecast) in SSA is limited. In this review, we only found three studies that developed methods for quantifying and predicting latent demand for electricity. Fabini *et al* (2014) developed a predictive model for mapping latent residential demand for electricity, which they call induced demand using data from the Kenya Integrated Household Survey, Demographic and Health Survey (DHS), Society for International Development and Kenya National Bureau of Statistics (SID-KNBS), the researchers used a *k*-nearest neighbor regression model to cluster households according to ownership or use of various appliances, fuels, building materials and other resources. They estimated demand under two scenarios: (1) current levels of electricity access and (2) expanded access to areas without electricity. In their methodology, they used the difference between the total ownership metric (i.e., appliances currently owned by residents and those that residents are projected to purchase) and the current ownership metric to quantify the latent demand for electricity. Their study found that latent demand was highest in unelectrified areas of Kenya in closest proximity with either the transmission network or an existing/planned minigrid. In essence, this application of their model implicitly quantified latent demand for electricity in Kenya.

Another study, Afful-Dadzie *et al* (2017), used a mixed-integer linear program to show the economic impact of unserved demand in over a 20 years time horizon (i.e., 2016 to 2035). In their paper, Afful-Dadzie *et al* (2017) stress that the literature on latent demand is limited, and that no techniques have been established for estimating latent demand for electricity. As such, assuming that electricity supply taxes in Ghana were designed to sufficiently correct market failure (i.e., compensate individuals with unserved demand), they estimated latent demand by running a regression on electricity supply taxes over a ten-year time horizon.

The last study we found that included latent demand, Falchetta (2021), developed the multi-sectoral latent electricity demand (M-LED) platform to enable planners explicitly quantify latent demand with high spatial resolution as well as from non-residential sectors. To our knowledge, their study is the first to attempt quantifying latent demand from commercial and industrial (C & I), agricultural, school, and healthcare sectors. Using a variety of data sources from Kenya, the authors used the remote areas multi-energy systems load Profiles model (Lombardi *et al* 2019) to create stochastic energy demand profiles for the aforementioned sectors, in addition to the residential sector. To incorporate heterogeneity in residential demand profiles, the researchers developed ten archetypical types of residential consumers based on appliance ownership and usage patterns. Aggregating the predicted load profiles from each of the sectors, researchers can use their model to develop more accurate least-cost electrification plans.

Based on our review, we conclude that the number of electricity demand or consumption studies across the SSA subcontinent varies widely from country to country, with a large gap in countries spanning the Sahara desert region. Figure 1 indicates that a relatively large number of studies are related to Kenya and South Africa, while no studies were identified for others such as Burundi and Sierra Leone. Hence, future work in demand prediction or estimation should use 'demand-study-poor' countries as case studies to assist these countries on their path towards universal electrification. Equally important is the need for governments and research institutes in these countries to incentivize data collection and storage to facilitate researchers' efforts to forecast electricity demand.

3.2. Identifying drivers of electricity consumption and latent demand

To quantify latent demand, it is essential to determine the factors that drive both latent demand and electricity consumption. From our literature search we have found that majority of studies on determinants of electricity consumption used an ARDL model to predict electricity consumption in a country. According to the literature reviewed, some of the key determinants of electricity consumption include population, gross domestic product (GDP), education, employment and use of diesel as an energy source. We summarize these findings in table 2.

Given that a higher population density results in more economic, social and other productive activities (such as education and healthcare), **population density** was identified as a main driver of both latent demand and electricity consumption in SSA (Amusa *et al* 2009, Adom *et al* Bekoe 2012, Ubani 2013, Falchetta 2021). Regarding latent demand, a study of latent demand for electricity in Kenya determined that population density (defined as people per square kilometer) was a significant driver of latent demand in the residential, healthcare and commercial sectors (Falchetta 2021). They used MWh per square kilometer (MWh m^{-2}) as their metric for latent demand for electricity. As a result, their finding aligns with the general intuition that areas with higher populations would generally require access to more services, such as hospitals, that require electricity

Table 2. Summary of drivers of electricity demand and their respective data sources.

	Electricity demand drivers	Source(s)	Data
Socio-economic drivers	Education	Shahbaz *et al* (2019)	MTF household survey; MLED Github repository
	Electricity price	Luhangala *et al* (2022), Al-Bajjali and Shamayleh (2018), Loi and Ng (2018), Ye (2018), Latif (2015), Inglesi-Lotz (2014)	Kenya open data initiative, other national sources
	Employment rate	Ubani (2013), Narayan and Smyth (2005)	MTF household survey, (Shirley *et al* 2019)
	Export diversification	Shahbaz *et al* (2019), Observatory of Economic Complexity (2019)	Observatory of economic complexity, other national sources
	Household income/average income	Narayan and Smyth (2005), Ubani (2013), Loi and Ng (2018), Williams *et al* (2019)	MTF survey, DHS StatCompiler
	Industrial output	Ubani (2013)	No data found
	Population density/population/household size	Falchetta (2021), Al-Bajjali and Shamayleh (2018), Loi and Ng (2018)	World bank, UN, gridded population dataset
	Real GDP (as economic output) or GDP per capita (as income)	Al-Bajjali and Shamayleh (2018), Ubani (2013), Narayan and Smyth (2005), Shahbaz *et al* (2019)	World bank data catalog
Natural-resource-related drivers	Urbanization	Falchetta *et al* (2020)	Global electrification platform
	Average residential/commercial water consumption	Al-Bajjali and Shamayleh (2018)	Rwanda HH survey includes access to water
	Market value of crops	A2EI Report (2019), E4I Report (2020), Falchetta *et al* (2020)	Kenya open data Initiative
	Resource availability (extractable natural resources, cropland, etc)	Falchetta *et al* (2020)	MAPSpam, Kenya open data Initiative
Infrastructure-related drivers	Accessibility (road accessibility and proximity to market)	HarvestChoice & IFPRI (2016), A2EI Report (2019), Falchetta *et al* (2020), IFPRI (2020)	Global electrification platform, harvard dataverse
	Electrification rate (including existing demand in healthcare facilities)	Maina *et al* (2019), Falchetta *et al* (2019), Falchetta (2021)	MLED Github repository
	Public facilities	Snow *et al* (2019)	Snow *et al* (2019)
	Prevalence of diesel systems	E4I Report (2020), A2EI Report (2019), Williams *et al* (2019)	Integrated household survey, MTF household survey

consumption (Narayan and Smyth 2005, Amusa *et al* 2009, Adom and Bekoe 2011, Ubani 2013, Al-Bajjali and Shamayleh 2018, Loi and Ng 2018). Given that **urbanization** was classified geographically by population density in their study, they found that urbanization was a driver of latent demand in Kenya. Studies, such as Ubani (2013) and Al-Bajjali and Shamayleh (2018), used ARDL models with causality direction tests that showed that not only was there a statistically significant correlation between population and electricity consumption (in kWh) but there was a unidirectional causality from population density to electricity consumption.

Given the focus on socioeconomic development in SSA, the relationship between electricity consumption and economic output has been studied at length in the extant literature. GDP is the most commonly used metric for economic output in the literature. Although a plethora of studies have shown a positive relationship between GDP and electricity consumption, the direction of causality between the two variables remains unclear

Table 3. Summary of price elasticity of electricity in extant literature from a select group of countries.

Country	Price elasticity	Source
United States	−0.1	Burke and Abayasekara 2018
Singapore	[−0.05, −0.37]	Loi and Ng 2018
Canada	[−0.1, −0.096]	Latif 2015
South Africa	−1.35	Anderson 2004
South Africa	[−0.95, −1]	Inglesi-Lotz 2014
South Africa	−0.89	Ye *et al* 2018

(Narayan and Smyth 2005, Ubani 2013, Al-Bajjali and Shamayleh 2018, Shahbaz *et al* 2019). Latif (2015) identified four hypotheses about the relationship between GDP and electricity consumption. First, the neutrality hypothesis posits that there is no relationship between the two variables. Second, the conservation hypothesis suggests that a unidirectional causal relationship exists from GDP to electricity consumption. Hence, electricity conservation programs would not affect economic output per this hypothesis. Third, the growth hypothesis states that increased consumption of electricity increases GDP. Fourth, the feedback hypothesis suggests that a bidirectional causal relationship exists between GDP and electricity consumption (i.e., the two variables jointly cause each other at the same time). Hence, although a statistically significant correlation exists between GDP and electricity consumption (in kWh), the uncertainty in the direction of causality prevents GDP from being deemed as a driver of demand. Future work should investigate alternative indicators of economic activity at a high spatial resolution and determine their relationship with electricity consumption.

Extant literature on electricity consumption identified **electricity price** as a significant driver of demand. Researchers have typically found an intuitive negative relationship between electricity price and consumption. Regression-based methods that were used to predict electricity consumption based on price and other factors also determined the price elasticity of demand for electricity (Inglesi-Lotz 2014, Latif 2015, Loi and Ng 2018, Ye *et al* 2018, Al-Bajjali and Shamayleh 2018). These sources found that demand for electricity is relatively price inelastic. Given that many households in SSA have use alternative fuels to power activities, such as kerosene lanterns, we hypothesize that electricity would be relatively more price elastic than in other developed nations (Luhangala *et al* 2022). The reasoning behind this hypothesis is that these alternative fuels may act as substitutes for electricity in these households, making consumers relatively more sensitive to electricity prices. Table 3 summarizes the price elasticity of electricity that has been identified by various studies across some select countries. It is important to note that the Burke and Abayasekara (2018) study summaries the findings of a number of different studies that identified electricity price elasticities for the United States, whereas the other studies are single analyses for a given country. The literature summarized in table 3 appears to support our hypothesis since South Africa has a greater magnitude of elasticity than those of the United States, Canada and Singapore, however more research is needed to be conclusive.

Income is another predictor of electricity consumption investigated widely in the existing body of literature. Across both developed and developing countries, researchers found that there is a positive correlation between average income and electricity consumption (Narayan and Smyth 2005, Ubani 2013, Loi and Ng 2018). The positive relationship between income and electricity stems from wealthier individuals purchasing more appliances for usage in their households. While studies such as Loi and Ng (2018) used income at the household level as a predictor, other studies like Ubani (2013) used GDP per capita as a metric for income. Although both metrics of income resulted in the same trend and revealed that electricity is income elastic across developed and developing countries, household level income may be a more accurate predictor of consumption. The aggregate nature (i.e., low resolution and multi-sectoral) of GDP per capita prevents regression models from properly depicting the relationship between household income and electricity consumption. As a result, future work should use more granular income data for predicting latent demand, such as disposable income per household, instead of using GDP per capita. Furthermore, Williams *et al* (2019) recommend that surveys developed to estimate electricity demand should consider using other customer attributes, such as mode of transportation, as proxies for income to reduce the biases and errors that may result from having household heads elicit their income.

In our review, we also identified that **employment rate** was a driver of both latent demand and electricity consumption. A study showed that in parts of northern Kenya where population was relatively denser, low employment rates resulted in lower levels of latent demand for electricity in the commercial and micro-enterprise sectors (Falchetta 2021). Furthermore, another study identified that there was a statistically significant relationship between employment rate and electricity consumption in Nigeria (Ubani 2013). However, given that neither analysis controlled for income at the household-level, it is unclear whether there is an income effect that plays a role in the relationship between employment rate and electricity consumption. Analysis

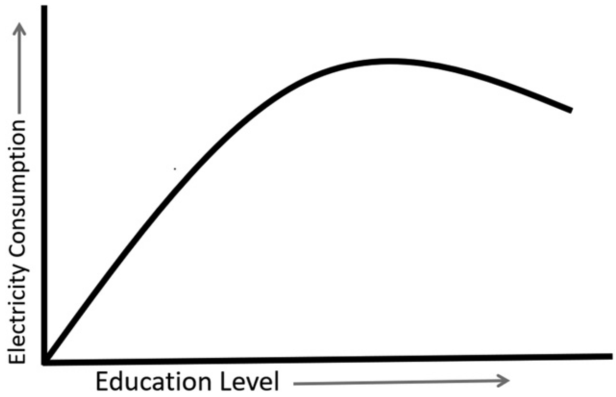

Figure 2. Hypothesis of the relationship between education and electricity consumption similar to that of the Kuznets curve in environmental policy theory. We avoid using units to quantify either education or electricity consumption since the goal of this visualization was to illustrate the concept being conveyed in our hypothesis.

from Narayan and Smyth (2005) showed a neutral relationship between employment and electricity consumption. Additionally, in their review of drivers of electricity consumption, Jones *et al* (2015) found that of the two papers that investigated employment as a predictor of electricity consumption, neither study found the relationship to be statistically significant.

Education is a predictor of electricity consumption that has not been researched as extensively as other predictors such as income and price. One study showed that the education sector was a substantial source of latent demand for electricity because of its unserved energy service requirements in both rural and urban parts of Kenya (Falchetta 2021). Alternatively, regression analysis from Shahbaz *et al* (2019) showed that education was negatively correlated with electricity consumption in the United States. They argued that individuals with higher levels of education in the United States were more conversant with energy efficient appliances and the need for energy conservation and thus all else equal, consumed less electricity than their counterparts with lower levels of education. In line with the Kuznets curve in environmental policy, we hypothesize that higher levels of education may lead to higher consumption rates until a certain level of education is attained by the population in a region. Figure 2 illustrates this hypothesis conceptually using a curve similar to the Kuznets curve described in (2015). Given that our hypothesis suggests that consumption would only decline and not return to its initial level, our curve differs somewhat from the Kuznets curve in that it is not a smooth parabola which has its final value equal to its initial value.

A review of electricity consumption literature indicated that the relationship between education and electricity consumption was unclear in the literature with two sources finding a positive relationship, one source finding a negative correlation, and two sources finding no correlation (Jones *et al* 2015). As such, future work would need to use data sources such as the Integrated Household Surveys of countries in SSA, which contain education levels in the survey questions, to determine the relationship between the two variables.

We also identified that **availability of natural resources** and agricultural factors like **market accessibility** and the **market value of crops cultivated** in an area are drivers of latent demand in SSA. Regarding the availability of natural resources, countries that are endowed with extractable minerals require electricity to power their refining factories. As a matter of fact, some SSA countries have historically invested in building electricity generation capacity to power the refining of such minerals (Adusah-Poku and Takeuchi 2019). Studies have shown that the agricultural sector (from irrigation to post-harvest activities) hold great potential for productive uses of electricity in SSA ((Banerjee *et al* 2017), (Borgstein *et al* 2020), (Van-Hein Sackey 2021)). As such, the availability of arable land as a resource would serve as an indicator of latent demand for electricity. Since most countries in SSA primarily sell their agricultural produce with little or no processing, the market value of the crop cultivated and accessibility to a market serve as drivers of latent demand (E4I, 2020, Falchetta 2021). Using the market value of crops as a predictor of latent demand would provide further insight into the impact that productive uses of electricity in agriculture have on electricity system planning. The E4I report showed that some diesel systems used for post-harvest processing could be replaced with electric systems, which is a potential source of latent demand (E4I 2020). However, this report also pointed out that for such a substitution to occur, electric post-harvest processing systems would need to improve their overall output in terms of quantity of food processed per hour. This is specifically true in the case of grain mills, since the electric milling machine studied relied on solar power, its intermittent nature required customers to mill grain at culturally unconventional times which was undesirable. Aside from these reports, literature on the relationship between these agricultural drivers and electricity consumption is limited.

Because diesel and electricity are potential substitutes for many services, the **prevalence of diesels systems** may be a driver latent electricity demand provided that electric appliances can either outperform their diesel counterparts or reduce costs. Studies, such as Williams *et al* (2019), identified the use of diesel as an energy source in households as a strong predictor of electricity consumption. Our reasoning is that energy consumption in households with such diesel systems can be representative of the household's latent demand given their potential to switch from diesel to electric systems. Al-Bajjali and Shamayleh (2018) also identified **average water consumption** (among households and businesses) as a statistically significant predictor of electricity consumption in Jordan. The relevance of their finding lies in the fact that Jordan is the second most water-scarce country (UNICEF 2017). More data on water consumption in varying contexts (urban and rural) would need to be collected in SSA countries to determine whether the validity of water consumption as a predictor extends to SSA. It is possible that the statistical significance of average water consumption as a predictor depends on the quality of water infrastructure in the country, and thus, its suitability as a predictor of electricity consumption could vary widely from country to country.

Since governments in SSA have been creating national plans for development and economic growth, we considered that industrial and macro-level economic activities, specifically export diversification and industrial output, may be potential drivers for latent demand. One study identified **export diversification** as a driver of energy demand in the United States on a national level (Shahbaz *et al* 2019). Export diversification, for the context of the paper, was defined as the increase in the number of different types of exportable products (Shahbaz *et al* 2019). Their regression-based study identified a negative relationship between export diversification and energy demand due to the manufacture of more energy efficient products. Future work may seek to investigate the potential effect of economies in SSA investing more in manufacturing and natural resource processing on electricity consumption. Although endowed with an abundance of natural resources, countries in SSA tend to export these natural resources more than they process them. As such, leadership in some countries (such as Rwanda and Nigeria) have stated a need to invest in building infrastructure to process these natural resources. An ARDL study of electricity consumption in Nigeria found **industrial output** to be a statistically significant driver of demand for electricity (Ubani 2013). Similar to GDP, utilizing national industrial output as a predictor would not contribute to a geographically granular latent demand estimation model (i.e., for a cluster of businesses or manufacturing plants in a given area for each country). Table 2 summarizes the drivers of electricity consumption found in the literature and their respective data sources.

3.3. Potential barriers for satisfying latent demand

In an ideal latent demand forecasting scenario (i.e., a model is developed to accurately forecast latent demand in SSA) there would still be some barriers that would hinder customers from accessing electricity to serve their entire demand. First, the lack of published grid expansion plans from state-owned utility companies in SSA threatens the commercial viability of off-grid systems. Suppose, for example, that latent demand was perfectly projected in a geographical location and that the planners determined that an off-grid system was the least-cost supply option. In this case the financial risk for off grid investments would be increased by a lack of a publicly available grid expansion plan. Without awareness of the grid expansion plan, minigrid developers would be at risk of future grid encroachment displacing their customers, and therefore, causing financial loss. Thus, even with perfectly forecasted demand models, investments in infrastructure needed to serve latent demand may be hindered by lack of transparency and the financial risk each developer is willing to take on.

Second, the lack of policy regulating interaction between the grid utility and minigrid developers as well as lack of financial incentives such as feed-in tariffs or cost-reflective tariffs for off-grid systems would impede the deployment of off-grid energy systems in SSA. The importance of preventing grid encroachment from increasing the financial risk of investing in off-grid systems due to competition cannot be overstated. This is because even if latent demand models were improved and integrated into electricity planning models, current policy and regulatory frameworks often limit the commercial viability of off-grid systems, creating a barrier to universal electricity access.

Lastly, due to the poor grid reliability in many SSA countries there is a lack of trust in the capability of the electric utility to supply consistent power, leading many households and industries have invested in off-grid systems for backup power generation (Taneja 2014). As a result, the ultimate consumption of electricity from microgrids or national grid connections may still be lower than the demand levels estimated by improved forecasting models. Thus, it is imperative that SSA countries rebuild trust in the local communities and industries.

3.4. Data availability for quantifying latent demand

The lack of data availability for electricity access research in SSA is a potent limiting factor in forecasting latent demand. Given the initial focus by the international community on ensuring residential access to electricity, a myriad of household surveys is available, such as the Integrated Household Survey and the Multi-tier Tracking Framework (MTF) Household Survey (World Bank 2019). These surveys contain relevant demographic information about residential electricity customers in SSA, inventories of appliances, and socioeconomic information. While the availability of data from these surveys can be helpful for projecting latent demand, there is a lack of meter data showing electricity consumption over time for these residential customers. Utility companies in SSA deem meter data to be proprietary information, and as such, tend to be unwilling to publish such data. However, once the utility companies have anonymized the meter data and taken other steps to protect the privacy of the customers, they could share the data via public data platforms such as Zindi or openAfrica.

Furthermore, with the exception of countries like Kenya and South Africa, we did not find any data publicly available about electricity consumption for non-residential purposes in other countries in SSA. Beyond the percentage of existing demand from each sector that can be found on national websites, it is challenging to find high-resolution data to spatially locate geographic areas with various forms of non-residential demand (i.e., education, healthcare, commercial, industrial, etc). As such, simplifying assumptions would need to be made in order to estimate latent demand from these sectors, such as those made in Falchetta (2021) for the agriculture sector in Kenya. For example, given that the cropland extent dataset was at a higher resolution than the rainfed area dataset from MapSPAM, Falchetta *et al* assumed a homogenous distribution of cropland for each crop in each pixel in the downscaling process. The availability of high-resolution data would facilitate research efforts to study productive uses of electricity in SSA. Increased use of smart meters by electricity customers would enable utility companies and minigrid developers to collect data on consumption and determine consumptions patterns that may influence future decision-making. Especially in the case of industrial customers who are resorting to small-scale solar PV systems and diesel generators as backup sources for the grid, utility companies can determine the opportunity cost of poor grid reliability, observe usage patterns and plan accordingly (Taneja 2018).

Nonetheless, some data sources for residential demand, agricultural activity and cropland data and economic growth were identified and are summarized in table 2. The Kenya Open Data Initiative is a repository containing granular data from various sectors in Kenya, including healthcare, education, and local government. The website also contains socioeconomic data on metrics such as the poverty gap. The MTF household survey organized by the World Bank contains a plethora of demographic information as well as some appliance inventory for households in many countries in SSA. National statistics, such as GDP, urbanization and population can also be found on the World Bank Data Catalog. The Global Electrification Platform (GEP) serves as both a tool and data source for least cost electrification in SSA. GEP uses a geospatial electrification model known as the Open-Source Spatial Electrification Toolkit (OnSSET) to determine the least-cost pathway to universal electrification in SSA countries by 2030. As such, the website hosting the tool contains datasets for each country that provide a wide range of spatial data (such as distance from high voltage or medium voltage transmission lines, global horizontal irradiance, wind speed, proximity to a hydropower plant and planned grid network among others) at a high resolution. MapSPAM is a data source containing datasets pertaining to agriculture globally. The MapSPAM datasets are generated from the SPAM model which uses a cross-entropy approach to determine disaggregated crop distribution worldwide.

It is important to note that data availability varies greatly across the sub-continent. Whereas nations such as Kenya have relatively more data available from various sectors, other countries have little data publicly available. Hence, any model that aims to project latent demand for electricity in SSA would need to make a host of simplifying assumptions to estimate demand in certain countries.

4. Recommended methods for quantifying latent demand and future work

A more explicit approach to estimating current and projecting future latent demand for electricity in SSA is a crucial tool for determining the commercial viability of energy system deployment. While one study developed an implicit approach to map induced demand for residential electricity, they neglect to indicate the magnitude of latent demand across different sectors that would exist in their future scenario (Fabini *et al* 2014). While there is a relative abundance of ARDL models being used to predict electricity consumption (table), there is a need to develop more that are driven by consumption data. The drivers of electricity consumption identified in these ARDL studies can be used to inform data collection for a robust latent demand projection model. The M-LED platform developed by Falchetta (2021) could be used as a starting point for modeling latent demand in SSA. Their methodology uses a variety of data sources from each sector, such as population clusters, distribution of wealth, potential schools to be constructed, existing cropland and irrigation requirements and road density. An advantage of using the M-LED platform is that Falchetta (2021) states all the data sources used in their analysis and have made the data publicly available. Given that they (i.e., the researchers) collected their own data directly or indirectly for certain sectors, their database provides a wealth of information for other researchers. Fabini *et al* 2014 used these data to create stochastic load profiles at a cluster resolution using a set of assumptions. A cluster is defined as a group of households, which may range from as few as two households to as many as tens of thousands of households. The current version of the M-LED platform uses the remote areas multi-energy systems load profiles model to process appliance-based classification of households into minute-specific load profiles for a 365 day period. M-LED considers the impacts of climate variability in Kenya by modeling cooling appliance loads based on seasonal temperature patterns. A field campaign was carried out to survey households, schools and healthcare facilities to validate these model results. For the agriculture and enterprise sectors, Falchetta (2021) performed technoeconomic analysis and literature sources (in the absence of adequate data) to estimate latent demand for electricity. Future work could use climate integrated assessment models to predict general weather patterns (within the context of climate change) in the near future to improve the accuracy of the latent demand forecasting.

Due to the relative availability of data in Kenya, we would recommend that Kenya be used as the first case study for any model developed to estimate latent demand. Replicating results from Falchetta (2021) would lend perspective to the type of data that needs to be collected for data-poor countries, and model assumptions that may need reconsideration. When modeling latent electricity demand in a data-poor country, using a framework based on the methods of Ponce de Leon Barido *et al* (2017) may prove practical. The authors scaled the data from multiple sources (to ensure that each variable was within the same order of magnitude) and used the scaled data to create two indices for each ward (the smallest administrative division) in Kenya. The first index is for *natural capital*, which consists of soil quality and potential, cropland availability and number of waterbodies in proximity. The second index is for *infrastructure capital*, which consists of population density, availability of first- and second-tier roads, presence of electricity infrastructure and access to education, trade, healthcare and financial services. The authors then generate a composite micro-enterprise development index, which is the summation of these two indices. Although the goal of their analysis was to determine opportunities for wealth creation in Kenya post-electrification, a similar approach can be used to make first pass estimates of latent demand in data-poor countries.

To develop this framework, future work could replicate the analysis for Kenya found in Ponce de Leon Barido *et al* (2017) and compare the results with those replicated from Falchetta (2021). After this replication of Ponce de Leon Barido *et al* (2017), one can then create a training dataset containing the components of natural and infrastructure capital, the demand drivers identified in table 2, and latent demand from the M-LED platform. The training dataset could then be used to train a LASSO regression model to predict latent demand for electricity in Kenya. The LASSO model is a regression model that determines the most significant predictors of a dependent variable in addition to predicting the dependent variable itself. Having collected appropriate data for other data-poor countries, one can then apply the LASSO model to predict latent demand in such countries throughout SSA. Finally, using some of the geospatial datasets mentioned previously (such as MapSPAM), one can geospatially determine latent demand in SSA. Such an analysis would provide stakeholders with broad insights into the geographic areas with high potential for new energy system deployment to serve latent demand, even in data-poor countries. To acknowledge the dynamic interaction between access and latent demand (i.e., access resulting in increased demand), future work should consider incorporating access to electricity over time as a lagged predictor of latent demand. Figure 3 summarizes our proposed approach to quantifying latent demand in SSA countries.

5. Application of proposed framework

Here we present an application of the first steps of our proposed framework to Kenya to demonstrate the training dataset phase of the data-rich country for predicting latent demand for electricity in SSA. The initial steps of our proposed framework are as follows: (1) collect the necessary input data, (2) determine sector specific latent demand using a deterministic model, and (3) map the spatial distribution of latent demand at a sub-national level, (4) run the trained regression analysis model. Using a deterministic latent demand model, M-LED (Falchetta *et al* 2020), and the necessary input data (e.g., population and sector data) shown in figure 3, we estimated latent demand across residential, education, commercial, health and agricultural sectors in Kenya (Fabini *et al* 2014, Afful-Dadzie *et al* 2017, Falchetta *et al* 2020, Poblete-Cazenave and Pachauri 2021). We then feed this into the regression model (LASSO). The value of this analysis is being able to highlight how stakeholders can address latent demand in different sectors, and where to target their investments for electric system expansion (e.g., grid extension or mini-grid investments may vary by sector).

5.1. Latent demand by sector

The latent demand in a country will vary by sector. These variations can stem from different population densities in areas surrounding those sectors, and expected end-use appliances. In figure 4, we show the annual latent

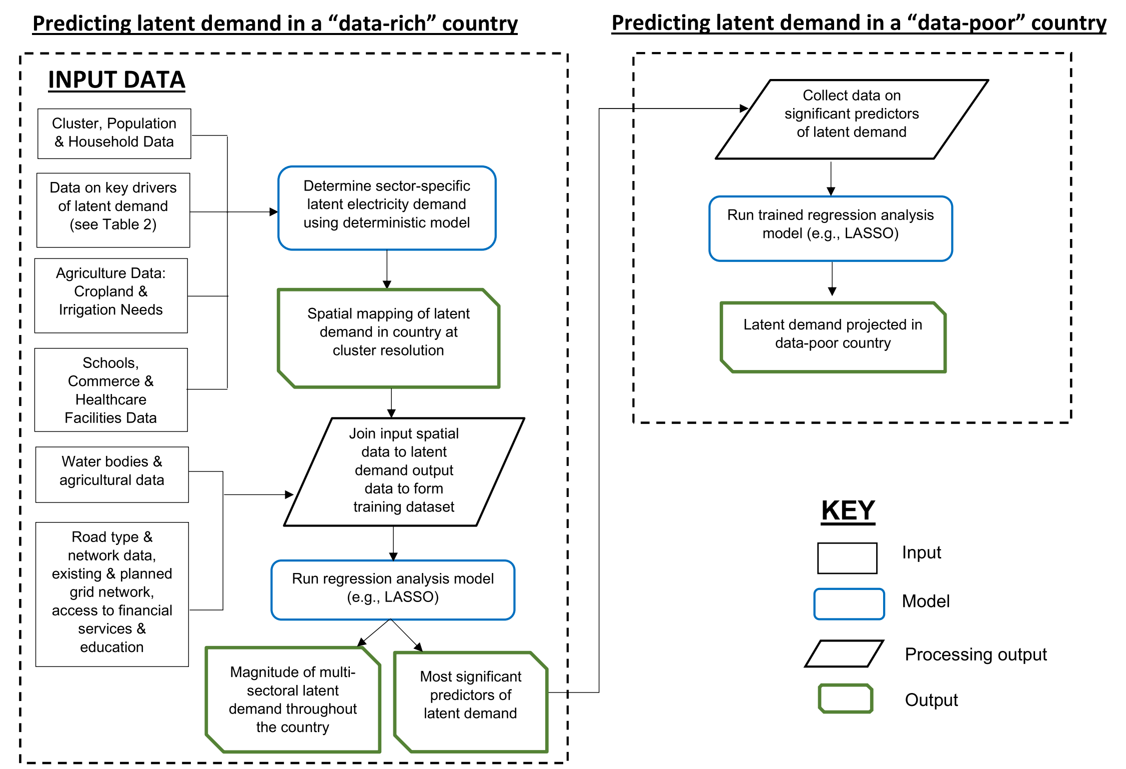

Figure 3. The steps for quantifying latent demand. An initial latent demand dataset would need to be created to train a LASSO regression latent demand model for a relatively data-rich country in SSA, which would determine the most significant predictors of latent demand. Researchers can then collect data on these drivers of latent demand to further train the model to predict latent demand in these data-poor countries.

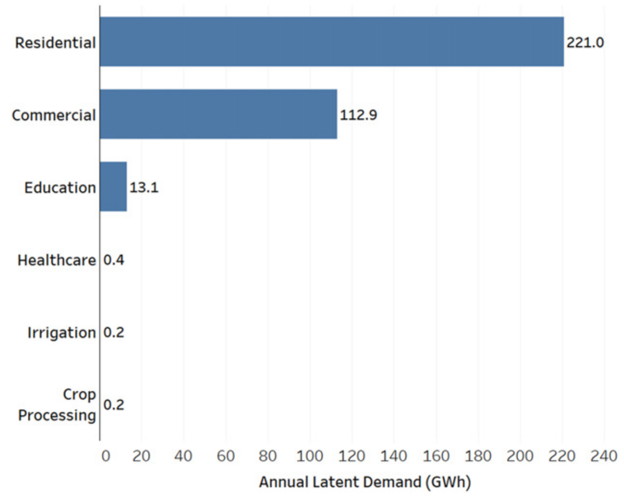

Figure 4. Annual latent demand for Kenya by sector. Here we see that the education and residential sectors have the highest amounts of annual latent demand.

demand estimates from the deterministic model (M-LED) for the residential, education, commercial, healthcare, and agricultural sectors. When investigating the overall sector-wise latent demand in Kenya, we find that highest amounts of latent demand occur in the residential (221 GWh) and commercial (113 GWh) sectors (see figure 4). In the residential and commercial sectors, latent demand is mainly driven by increasing demand for high-end household appliances (i.e., air conditioners) and higher populations in urban parts of the country. The latent demand in the education sector is primarily due to the rising need for education infrastructure to serve Kenya's rural populations, and the demand for high-end appliances for tertiary institutions.

While certain sectors can have high amounts of total latent demand, we find large spatial variability across the country (see figure 5). In investigating the spatial distribution of latent demand by sector, we find that the highest regional levels of latent demand in the education, health, crop processing and irrigation sectors are

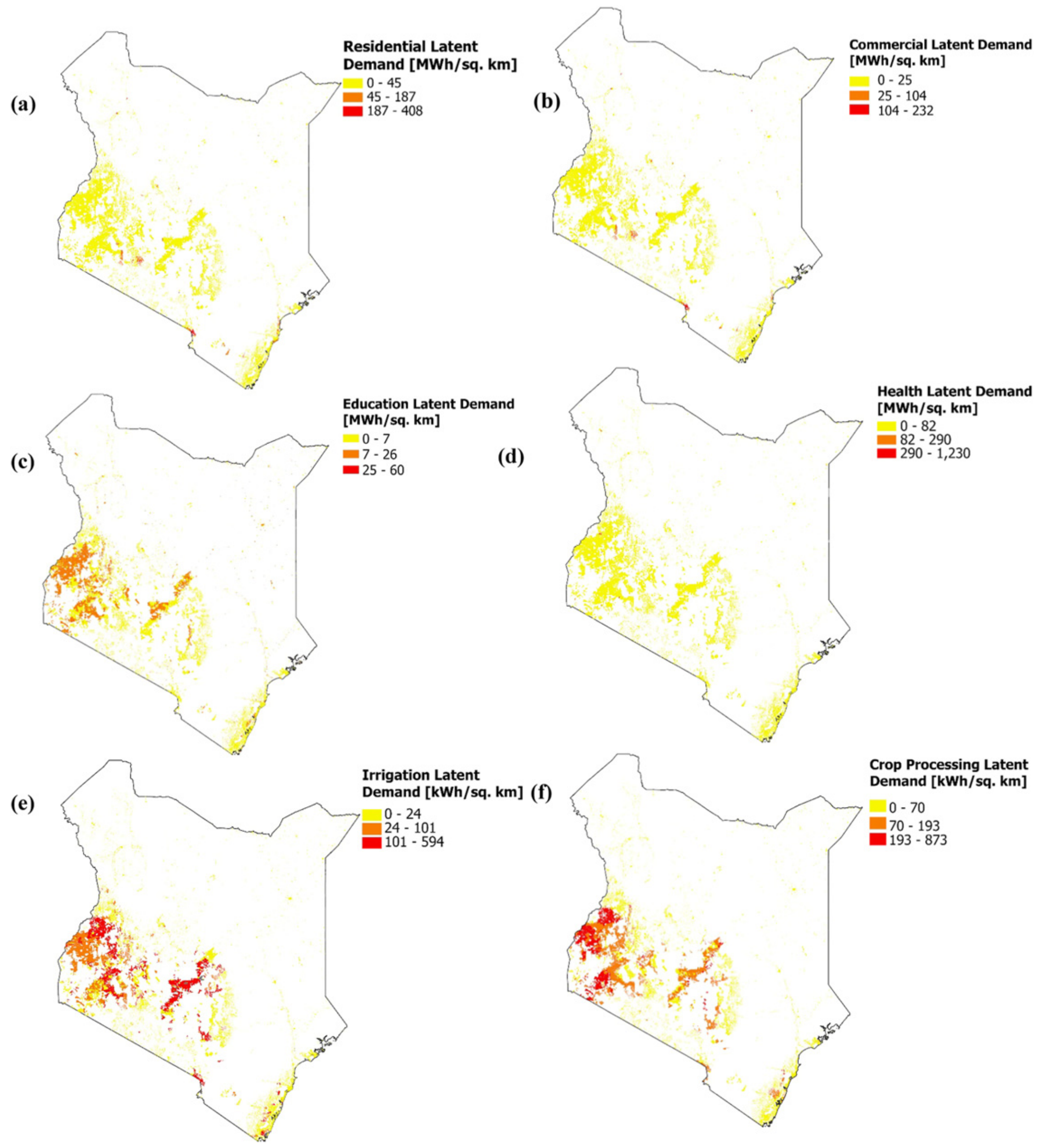

Figure 5. The spatial distribution of annual latent demand in Kenya for the (a) residential, (b) commercial, (c) education, (d) health, (e) irrigation, and (f) crop processing sectors. We find that the residential (a) and commercial (b) sectors had the single locations with the maximum amounts of latent demand in Kenya. The health (b) and education (a) sectors had their highest latent demand from western Kenya, while the agricultural sector (i.e., crop processing (c) and irrigation (d)) had the lowest amount of latent demand. Note that the units for (a)–(d) are in MWh km^{-2}, while (e) and (f) are in kWh km^{-2}.

located in the western part of Kenya. The western part of Kenya is known to have a peri-urban population, with a relative abundance of cropland and higher population density (World Resources Institute 2001, Jayne and Muyanga 2012). As such, we infer from our results that population density and abundance of cropland are significant predictors of latent demand within the education, health and agriculture (i.e., crop processing and irrigation) sectors. Thus, electricity system planners should strongly consider a national productive use program that prioritizes productive use activities in western Kenya due to the potential latent demand for agriculture, health and education in that region.

Figure 5 shows that the residential and commercial sectors had the single locations with highest amounts of latent demand in the urban environment of Mombasa in southern Kenya. This is likely due to the latent demand for high-end appliances (such as air-conditioning and large-scale computing) that businesses in Kenya require to be productive. Hence, future appliance inventory survey work should focus on identifying the power rating, quality, and type of devices used in the commercial sector in Kenya, which would improve the accuracy of demand predictions in urban areas. Furthermore, due to the potential latent demand in the commercial sector, utility companies and Kenya's electricity system planners should consider coordinating with business owners

Table 4. Summary of LASSO regression results for latent demand prediction in Kenya. A (∗) indicates that the variable was not a significant for predicting latent demand, and was dropped from the model.

Independent variable	Coefficient
Intercept	−43 941.75
Population	+135.86
Travel time to market	∗
Electrification rate	∗
Surface water distance	∗
Groundwater depth	∗
Cropland	+191.42
Total observations: 1040	

in the sector to fuel electricity development. It is possible that high users in the commercial sector could cross-subsidize other lower demand sectors (e.g., healthcare and crop production) and rural environments, thus creating more affordable electricity access.

Additionally, based on existing, least-cost, rural electrification literature, stakeholders interested in meeting latent demand in the residential and commercial sectors may want to consider investing in either extending Kenya's grid network or building larger capacity minigrid systems (Afful-Dadzie *et al* 2017, Akbas *et al* 2022, Kemausuor *et al* 2014. Korkovelos *et al* 2020, Mentis *et al* 2016, 2017 Moner-Girona *et al* 2019).

5.2. Latent demand by sector

Here we provide a proof-of-concept of the regression model in our proposed framework, using a subset of our original input data to create a training dataset for a regression model. The input data used are population, travel time to market (i.e., market accessibility), cropland, education sector demand, healthcare demand, and current electrification rate. Summary statistics of our input data can be found in appendix A. We use the LASSO regression model due to its effectiveness for determining the most significant independent variables in a analysis when multicollinearity (i.e., when two or more predictor variables are highly correlated to each other) may be present. The form of LASSO regression is shown in equation (1)

$$\mathrm{LD}_i = \beta_0 + \beta_1 * p_i + \beta_2 * tt_i + \beta_3 * er_i + \beta_4 * sfw_i + \beta_5 * gwd_i + \beta_5 * cr_i + \varepsilon_i. \qquad (1)$$

Here LD is the latent demand at location i, β is the coefficient of the predictor variables, p is the population at location i, tt is the travel time from location i to the nearest market with up to 50 000 people in hours, er is the electrification rate expressed as a fraction at location i, sfw is the distance from surface water in meters of location i, gwd is the average depth of groundwater in meters at location i, cr is the hectares of cropland available for farming at location i, and ε is the error term associated with estimating latent demand in location i within the regression.

The regression results are illustrated in table 4. From the regression analysis we deduce that of the predictor variables, both population and cropland availability were the most significant drivers of latent demand in Kenya. Our results are consistent with the fact that the agriculture sector accounts for about 24% of the GDP in SSA (Banerjee *et al* 2017), and an increasing population corresponds with increasing demand for electricity services (Kanagawa and Nakata 2008). Based on the positive values of the coefficient, we can infer that controlling for all other variables, an additional hectare of cropland in Kenya would increase latent demand by 191 kWh per year while each additional person to the population would increase latent demand by 136 kWh per year.

5.3. Extension to data-poor countries

The above analysis demonstrates the data gathering, collection, and the classification of significant latent demand predictors using a data-rich country (i.e., Kenya). The next steps of our proposed framework would involve collecting data on the significant predictors of latent demand for a data-poor country, which in this case is cropland availability and population. The results of our analysis are in line with our literature review results which showed that cropland and population were predictors of latent demand in SSA. Population data collection efforts should be at a granular resolution (i.e., sub-county level) to ensure that the data is useful in predicting latent demand. Cropland data collection is mainly done via satellite imagery, and thus may require partnerships with research institutions with such technology. We note that despite having a relatively substantial amount of data on Kenya, it can be computationally intensive to scale each sector-based spatial dataset used in the deterministic latent demand model to the same resolution for use as training data. As such, researchers should consider the resources required, specifically computational power, to perform this data-intensive analysis.

6. Conclusion

This paper first reviewed existing literature on methodologies to identify drivers of electricity demand, and more specifically to estimate latent demand, and then outlined a framework for including latent demand in energy planning studies in SSA. Most existing literature is focused on developing and applying econometric models (such as ARDL) to broadly forecast electricity demand. However, the econometric models reviewed in this paper do not explicitly capture latent demand in their estimation of electricity demand. As explained in this paper, the absence of latent demand in these demand estimations prevents SSA countries from adequately prioritizing infrastructure investments and maximizing economic productivity from electricity access. In order to specifically quantify latent demand, a shift towards methods driven by high-resolution household and commercial-level meter data will be essential. Although large gaps in data availability and demand studies exist across SSA, data-based approaches that use survey data and meter data to create predictive models may be helpful. As such, it is essential for research institutions and governments in SSA countries to incentivize the collection of data to facilitate energy-related research.

Based on our review, we conclude that although GDP is commonly identified as a statistically significant predictor of demand, the direction of causality between GDP and electricity consumption remains unclear. This makes recorded GDP an imperfect predictor of latent demand because the presence of latent demand may also imply that a region also has unrealized economic potential. From our review, we identify population density, urbanization, price, household income and market value of crops cultivated as key potential drivers of electricity demand. Furthermore, the reviewed literature also supports our hypothesis that electricity is relatively more price elastic in SSA countries than developed nations, due to the prevalent use of non-electric fuels (e.g., kerosene and diesel) to power essential services, such as lighting and phone charging; however, more analysis is needed to draw firm conclusions. As a result, it is difficult accurately project latent demand without understanding the tariff structures that consumers who are currently underserved will face when their access and consumption levels increase.

Additionally, we show that some demand drivers, such as education, export diversification and industrial output, need to be studied further to create a multi-sectoral latent demand model that accommodates productive uses of electricity from sectors beyond agriculture (i.e., education, healthcare, commercial). Such a multi-sectoral estimation of latent demand would help inform stakeholders about which sectors may hold potential for wealth creation via electrification. Furthermore, we acknowledge the need for any projection of latent demand to consider the dynamic interaction between access and latent demand. Specifically, latent demand estimation methodologies need to consider the fact that increasing electricity access generate wealth, which in turn may further increase demand for electricity. As such, future work on latent demand may need to perform scenario analysis to consider how demand evolves with increasing access to electricity in SSA.

Lastly, we propose a framework for quantifying latent demand in SSA countries. As a proof-of-concept, we create a partial dataset for Kenya (i.e., population, electrification rate, existing education and health sector demand, cropland availability, and travel time to market) and apply these data to predict latent demand across several key sectors. Of the predictor variables used, we find that cropland availability and population were the most significant predictors of latent demand in Kenya. As such, we recommend that data collection efforts in data-poor countries prioritize collecting data on cropland availability and population. Future work ought to consider the computational resources required to predict latent demand using the entirety of the potential input data streams identified in the framework. We also acknowledge that it is essential to collate the remaining input data not used in our dataset (i.e., road type and network, access to financial services, and the location of waterbodies) into a single training dataset to more meaningfully determine the error margins of the correlation coefficient estimates and infer which other variables may be significant determinants of latent demand.

This approach would enable researchers to quantitatively identify the most important drivers of latent demand, and predict latent demand in data-poor countries while helping to fill the gap in electricity-demand-related data in SSA. We also stress that an enabling policy environment is essential to support the commercial viability of energy systems that are intended to serve latent demand. Improving predictions for latent demand would significantly contribute to existing literature by stepping beyond supply-side optimization to identify opportunities for wealth creation via electrification in SSA. Importantly, electrification models that explicitly account for latent demand could ultimately enable investors and other energy sector stakeholders to identify areas where the energy infrastructure would spur economic growth leading to fastest achievement of the universal electricity access target and national development goals.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Appendix A. Data summary table for LASSO regression analysis

See (table 1).

Table A1. Summary statistics of input data for training dataset used to quantify latent electricity demand in Kenya.

Variable	Mean	Standard deviation	Min	Max
Latent demand (kWh)	333 955	2705 332	0	53 260 815
Surface water distance (m)	248 077	432 104	0	1000 000
Groundwater depth (m)	5.87	13.79	0	75
Cropland availability (ha)	174.74	1284.58	0	21 501.04
Population	2535	11 709	0	181 550
Travel time to market (hours)	18.18	43.62	0	448.29
Electrification rate [fraction from 0 to 1]	0.43	0.32	0	1.00
Total number of observations: 1040				

ORCID iDs

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