



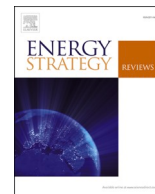
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Long-term spatially explicit electricity demand scenarios for rural electrification: The case of Ethiopia

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ABSTRACT

Access to electricity remains a significant developmental challenge in Sub-Saharan Africa. To address this, national electrification planning must account for both the temporal evolution and spatial heterogeneity of electricity demand, reflecting local socioeconomic realities and climatic conditions. This study aims to project long-term, spatially explicit electricity demand for households, productive users, and community institutions in Ethiopia. It also assesses the potential impact of rising temperatures on future electricity demand. Regression models are used to predict temporal changes in electricity demand, while the Open-Source Spatial Electrification Tool (OnSSET) is used to examine the spatial demand dynamics across population settlements. Three scenarios—Business-as-Usual (BAU), High Economic Growth (HEG), and Rapid Urbanization (RU)—are developed to explore different development pathways from 2021 to 2050. The results show that, compared to the base year (2021), national electricity demand could increase by 176 % under the BAU, 219 % under the HEG, and 285 % under the RU by 2050. The most substantial increase in electricity demand is projected to come from households, followed by productive users. Significant spatial variations are evident, with household demand ranging from Tier 1 to Tier 4. Moreover, while projected temperature increases total national demand by only 0.53 % at national level, it can increase local demand by up to 22.6 %. These findings highlight that national averages or household-only models fail to capture the significant spatial and sector-specific variations in electricity demand. Therefore, high-resolution, multi-sector demand projections are essential for designing cost-effective and equitable electrification pathways.

1. Introduction

Access to reliable and affordable electricity is a fundamental prerequisite for socioeconomic development. However, many developing countries in the Global South struggle to provide universal electricity access [1]. The International Energy Agency (IEA) projects that approximately 660 million people globally will still lack electricity access by 2030 [2]. Addressing this gap in a cost-effective manner requires electrification strategies tailored to the socioeconomic, geographic, and demographic realities of unelectrified areas [3].

A key component of such planning is the projection of future electricity demand at appropriate spatial and temporal scales. For developing countries experiencing rapid rural development, infrastructure expansion, and population growth, long-term, spatially explicit demand projections are essential to ensure electrification solutions are cost-

effective and responsive to local needs [4]. In particular, settlement-level projections enable planners to design solutions that reflect the diverse energy requirements of different communities [5].

Historically, nationwide electrification studies have employed simplified approaches to project electricity demand. These studies classify settlements into broad rural and urban categories and assign typical consumption levels based on the Multi-Tier Framework (MTF). For example, Mentis et al. [6] assigned a Tier 3 demand level (170 kWh/person/year) for rural populations and a Tier 4 demand level (350 kWh/person/year) for urban areas in Nigeria by 2030. Similarly, Mentis et al. [7] projected that rural and urban demand in Ethiopia would reach Tier 3 (150 kWh/person/year) and Tier 4 (300 kWh/person/year), respectively, by 2030. Ouedraogo [8] also projected that the urban population in Cameroon would reach Tier 5 and the rural population Tier 3 by 2035. Bissiri et al. [9] applied weighted average tier

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allocations. They assigned Tier 4 and Tier 5 to the urban population and Tier 2 and Tier 3 to the rural population under different demand scenarios in Burkina Faso and Côte d'Ivoire. These studies oversimplify the spatial heterogeneity in electricity demand across urban, peri-urban, and rural settlements,¹ potentially leading to misaligned electrification strategies. This simplification arises from a predominant focus on supply-side optimization, with relatively little emphasis on formulating demand projections.

Efforts to address this limitation have led to the development of more disaggregated modeling approaches. Dagnachew et al. [10] have disaggregated household (HH) electricity demand across Sub-Saharan Africa (SSA) into five income-based tiers using the MTF in both rural and urban areas. In addition, Korkovelos et al. [11] introduced a highly spatially disaggregated HH demand methodology for Malawi. They differentiated MTF-based HH demand into nine categories by integrating gridded GDP and poverty level data. These advances enable electrification strategies to be tailored to the unique geographic and economic contexts of different regions.

Rural electrification planning should also incorporate the electricity needs of productive users (PUs) and community institutions (CIs), including health centers, education facilities, places of worship (POWs), and government offices [12–14]. These non-household consumers can have electricity demands comparable to those of HHs at the local level. For example, Hartvigsson et al. [13] reported that PUs accounted for approximately 25 % of the customer base in off-grid mini-grids. Similarly, Wassie and Ahlgren [14] noted that HHs and CIs together contribute to around 60 % of the load supplied by a mini-grid and recognized that PUs drive rural electrification benefits. Dagnachew et al. [15] further highlighted that demand from home-based small businesses in SSA could increase HH electricity consumption by up to 50 %. Including PUs and CIs is therefore essential to capture the diversity of electricity needs and support the design of electrification solutions capable of driving broader socioeconomic development.

However, identified studies relevant to nationwide or regional electrification planning in SSA have primarily focused on HHs electricity demand, with less attention given to PUs and CIs [6,7,10,11,16]. Most recently, Sahlberg et al. [17] conducted a nationwide least-cost geospatial electrification planning study for Ethiopia. While their study modeled long-term spatially explicit electricity demand projections from 2018 to 2070, it only considered HH demand. Conversely, national energy planning studies typically provide long-term aggregated projections for multiple sectors. These include HHs, industrial, commercial, agriculture, and public services [18–21]. However, these projections lack the necessary spatial detail required for effective settlement level electrification strategies [11].

Furthermore, rising ambient temperatures due to climate change are expected to increase future electricity demand, particularly in tropical regions [22,23]. As temperatures rise, residential cooling energy demand for air conditioning is projected to increase by up to 150 % by 2050 [24]. Many regions across Africa experience between 4000 and 5000 cooling degree days (CDDs²) annually. This exceeds the levels experienced in major cooling demand centers such as the United States (3,150) and China (1,100) [25]. Currently, approximately 700 million people in Africa live in climates requiring substantial cooling. This figure is expected to rise to approximately 1.5 billion by 2050 [26]. The Intergovernmental Panel on Climate Change (IPCC) reported that global temperatures are rising by about 0.2 °C per decade. This trend is expected to further intensify cooling-related electricity demand [27]. Despite these clear indicators, most existing electrification planning studies have not incorporated the influence of spatially varying and

temporally rising temperatures into demand projections.

However, none of the aforementioned studies have provided long-term spatially explicit electricity demand projections that encompass HHs, PUs, and CIs while also factoring in the influence of ambient temperatures [6,7,10,11]. The confluence of these identified methodological gaps limits the ability of policymakers and planners to develop cost-effective electrification strategies. Thus, this study aims to develop and apply a long-term spatially explicit electricity demand projection model to investigate sectoral and geographic variations in demand under different future development scenarios. It also investigates the influence of rising and spatially varying ambient temperatures on future electricity demand evolution. By doing so, the study seeks to support the development of nationwide least-cost electrification pathways that ensure equitable and sustainable electricity access for all. Specifically, the following research questions are addressed.

- How will future demand for electricity differ across development pathways and consumer groups?
- How does electricity demand evolve across different geographical settlements?
- How and to what extent does a rise in temperature influence the evolution of the electricity demand?

1.1. Novelty of the research

This study makes three key contributions to nationwide electrification planning in developing countries. First, it provides long-term electricity demand projections for key consumer groups in rural areas, including HHs, PUs, and CIs. Unlike previous studies, which relied on HH demand and broad rural–urban classifications, this research projects the electricity demand of these user types at national and high-resolution settlement levels [6–8]. This enables a detailed understanding of demand heterogeneity, which is essential for designing tailored and inclusive electrification strategies. Second, different development pathways and socioeconomic variables, such as urbanization, GDP growth, and electricity access, are incorporated into the demand modeling. By doing so, it captures a broader and more realistic range of plausible future scenarios. This enables policymakers and planners to evaluate various feasible development trajectories and design flexible, adaptive electrification plans. Third, this study incorporates spatial temperature variation and projected ambient temperature rise into electricity demand projections. This is particularly relevant for SSA, where rising ambient temperatures are expected to increase electricity demand in many climate-vulnerable settlements. This factor has often been overlooked in earlier demand studies. By simultaneously considering diverse consumer groups, different development pathways, and climatic influences, the study enables the design of cost-effective and locally tailored electrification strategies, thereby supporting actionable strategic planning.

2. Methodology

2.1. Study approach

An integrated approach, incorporating both spatial and temporal demand analysis, is adopted to investigate long-term electricity demand development pathways. The analysis covers three key demand sectors: households (HHs), productive users (PUs), and community institutions (CIs), which together represent the primary drivers of rural electricity demand. Temporal projections are developed using historical electricity consumption data, enabling the study to capture long-term trends and patterns over time. The spatial dimension is analyzed using georeferenced locations of individual consumers and settlements, enabling a detailed assessment of how electricity demand varies across different communities and local contexts. To explore a range of plausible futures

¹ The term 'settlement', also known as cluster, is used to describe a range of inhabited places, from a small group of homes to a village or entire urban area.

² CDD is an indicator of how warm a location is, and calculated by comparing daily temperatures against a base temperature, typically set at 18 °C.

and capture uncertainties in future demand, three scenarios are developed: Business-as-Usual (BAU), High Economic Growth (HEG), and Rapid Urbanization (RU). Each scenario incorporates projections of key demand drivers, including population growth, GDP growth, urbanization, and rural electrification rate. These drivers are selected based on their empirical relevance in energy demand projections for developing countries [4,28].

The study further evaluates the potential influence of rising temperatures on future electricity demand. To quantify its effect, spatial temperature data, along with global warming projections, are incorporated into the demand projection model [27,29]. The model provides total national, and sector-wise spatially explicit projections of electricity demand. The latter can be used as an input to inform nationwide least-cost electrification planning. An overview of the research framework for developing long-term spatial demand scenarios, including data inputs, modeling steps, and expected outputs, is provided in Fig. 1. The subsequent subsections describe the methodological components in greater detail.

2.2. Model selection

To analyze both the temporal and spatial dynamics of electricity demand, this study employs a combined modeling framework. This integrated approach is applied over a multi-period horizon from 2021 to 2050, offering a long-term perspective. Models were selected based on their strengths and suitability for addressing the challenges of projecting electricity demand in developing countries.

For temporal projections, a multiple linear regression (MLR) model is utilized. The MLR model is selected for its ability to link electricity demand to multiple socioeconomic and demographic factors [30]. This enables the development of scenario-based and sector-specific forecasts, which are essential for understanding the impact of different policy or economic pathways on future demand. The MLR model is widely used in developing countries, where historical data may be limited [31].

Suganthia and Samuel [32] conclude in their review of 12 energy demand forecasting models that regression analysis is preferable for electricity demand forecasting in these contexts due to its effectiveness with limited data and interpretability. These models have been successfully applied in various countries for both short-term and long-term electricity demand forecasting [33]. It systematically establishes a statistical relationship between electricity demand and its key drivers in a transparent and reproducible manner [21,34]. Scenario analysis is used to outline possible pathways for demand evolution and to project each demand driver, while regression analysis enables the systematic integration of these drivers into the demand projection.

For the spatial analysis, the Open-Source Spatial Electrification Tool (OnSSET) is employed. OnSSET was chosen for its proven capability to support nationwide high-resolution, settlement level demand modeling and analysis [11,35]. It integrates population data with georeferenced information on PUs and CIs, enabling detailed spatial mapping of electricity needs. Furthermore, it supports scenario-based analysis, enabling evaluation of alternative development pathways [17]. The open-source nature of OnSSET also ensures transparency, reproducibility, and flexibility, making it suitable for nationwide electrification studies [36]. The methodology combines the MLR model for temporal projections with OnSSET for spatial analysis. This produces both aggregate national electricity demand projections and spatially explicit, sector-wise demand at the settlement level.

2.3. Case study area description

This paper uses Ethiopia as a case for the study. Ethiopia was chosen due to its unique demographic, economic, and energy sector characteristics. The country has a large and rapidly growing population, exceeding 120 million people, with more than 78 % residing in rural areas [37]. This demographic reality contributes to Ethiopia having one of the world's largest electricity access deficits in absolute terms, with about 55 million people lacking electricity access as of 2021. This figure

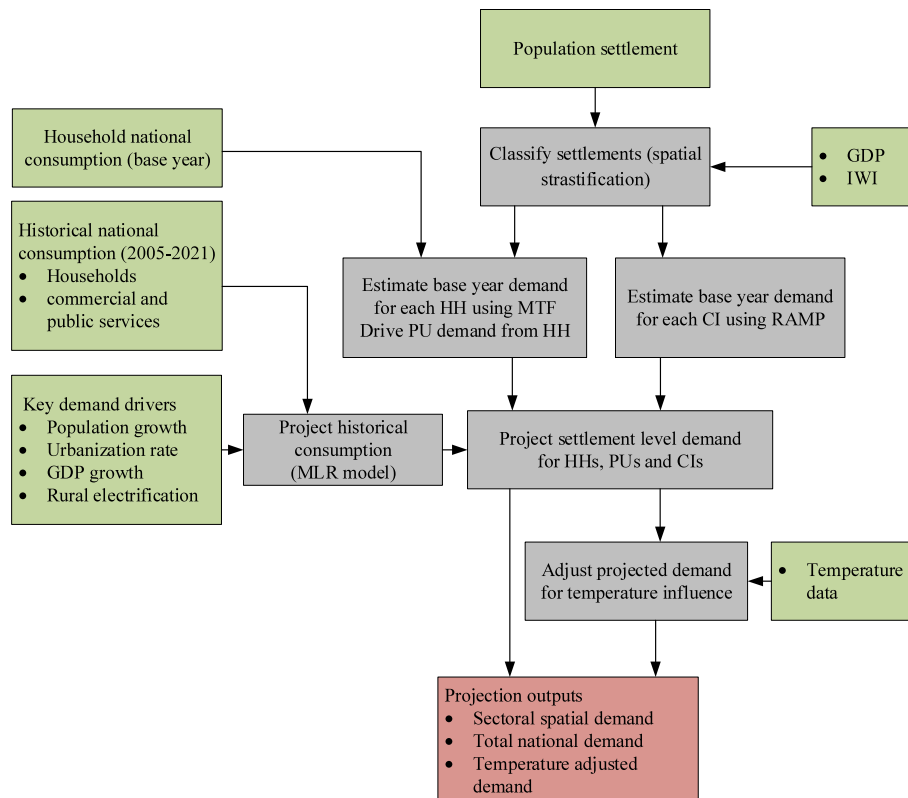


Fig. 1. Flowchart of the study approach, where colors indicate the input data (green), processing steps (grey), and outputs (red).

ranks Ethiopia third globally after Nigeria and the Democratic Republic of Congo [35,38]. Furthermore, the country's per capita electricity consumption is below 100 kWh/year, which places it among the lowest worldwide [39,40]. There are also pronounced regional disparities in access, ranging from nearly 99.9 % in Addis Ababa and surrounding areas to less than 20 % in pastoral regions such as Somali and Afar [41–43]. The government of Ethiopia launched the National Electrification Program II (NEP II) in 2019, aiming for universal access by 2025 [44]. However, the latest reports show that national access is still below 55 % [45], indicating a significant gap between policy targets and current conditions.

Furthermore, the country's rapid economic growth, urbanization, and industrialization have led to notable increases in electricity demand across key sectors. For instance, consumption in the residential sector increased by 662 % from 2005 to 2021, with average annual growth rate (AAGR) of 13.54 %. The commercial and public service sector saw a 347 % increase (with an AAGR of 9.8 %) over the same period [46]. Fig. 2 shows the growth in electricity demand and electricity access in Ethiopia from 2005 to 2021. The aforementioned factors combined make Ethiopia an exemplary case for this study. Insights from this case study are transferable to other SSA countries facing similar electrification challenges.

2.4. Demand profiling at settlement level

The high-resolution electricity demand analysis builds on the population settlements of the study area delineated previously by Ref. [47]. These settlements are identified using a methodology that converts high-resolution raster population data into vector-based population clusters/settlements [48]. Each cluster is characterized by several attributes, including the total population count, classification as urban, or rural, and an electrification status determined by the presence of night-time lights as a proxy for electricity access.

To understand how electricity demand varies across settlements, this study employs a spatial stratification approach. The stratification is based on the relative economic status of each settlement. In this context, economic status refers to the wealth of residents in a settlement compared to others in the country. Electricity use and access are closely linked to economic development. Thus, the analysis relates electricity consumption to relative settlement economic status [49], with wealthier settlements expected to have higher electricity demand than those with lower economic status [11]. This economic stratification approach addresses a key limitation in current electrification planning. Existing studies often use a simple rural-urban classification, which does not capture economic differences within regions. By contrast, this approach accounts for intra-regional economic heterogeneity. Two complementary geospatial datasets, average Gross Domestic Product and the

International Wealth Index, are used to quantify the relative economic status of each settlement.

- **Gross Domestic Product (GDP):** The mean GDP values for each population settlement were derived from the high-resolution GDP data developed by Kummu et al. [50]. These datasets provide global, gridded GDP estimates for selected years (1990, 2000, and 2015). The authors combined available subnational GDP values with spatially interpolated GDP values and national average GDP to derive GDP estimates for the whole world at a spatial resolution of 30 arcseconds (approximately 1 km² at the equator). This fine-grained representation allows for detailed analysis of economic disparities at the sub-national level. The spatial GDP data for the study country is shown in Fig. 3 a).
- **International Wealth Index (IWI):** The IWI serves as a strictly comparable asset-based measure of household wealth, and mean values for each population settlement are calculated using high-resolution village-level poverty maps developed by Lee and Braithwaite [51]. The index takes into account ten assets and living conditions, including five consumer durables (television, refrigerator, phone, bicycle, and car), access to two public services (water and electricity), and three housing characteristics (number of bedrooms, floor material quality, and toilet type). Machine learning algorithms are employed, integrating geospatial data sources such as OpenStreetMap features, day-time satellite imagery, nighttime luminosity, and High-Resolution Settlement Layer population data. This approach enables the estimation of wealth levels at the village level (1 square mile or 1.6 × 1.6 km² spatial resolution) for 25 SSA countries. The IWI for the case study country is shown in Fig. 3 b).

Economic stratification of settlements is achieved by applying the Jenks natural breaks method to both GDP and IWI values, as outlined by Khavari et al. [49]. Using this method, GDP and IWI values are each categorized into five classes. Such a classification method is well-suited for data with clear clusters, where the values within each group are more similar to each other than to the values in other groups. Table 1 presents the classification scheme applied to the GDP and IWI values.

After classifying the gridded GDP and IWI data into five classes, these two economic status indicators are combined into a single composite value (Equation (1)).

$$C_i = 0.5 * GDP_i + 0.5 * IWI_i \quad (1)$$

Where C_i is the combined value of GDP and IWI for settlement i . This composite value captures the economic status of each settlement and is subsequently used to correlate economic status and electricity demand at the settlement level (see details in sections 2.5.1 and 2.5.3).

2.5. Electricity consumer groups

2.5.1. Household

The World Bank's Energy Sector Management Assistance Program (ESMAP) Multi-Tier Framework (MTF) categorizes households into tiers based on their minimum daily electricity consumption and service quality attributes. Access to energy is measured across a spectrum of levels, from level 0 (Tier 0) (without access) to level 5 (Tier 5) (the highest level of access). The tiers for daily consumption start at Tier 1 (12 Wh) and go up to Tier 5 (more than 8219 Wh) [52] (see Appendix Table B 1). The annual electricity demand for HHs is then calculated by aggregating the daily demand over 365 days.

The study correlates HH demand categorization by MTF (Tiers 1 to 5) with settlement economic status, as determined by the C values (ranging from 1 to 5) obtained using Equation (1) [11]. The spatial HH electricity demand is estimated by assuming that all HHs within a given settlement have the same electricity demand. Households in settlements with a C value of 5 are assigned Tier 5, indicating that higher electricity demand

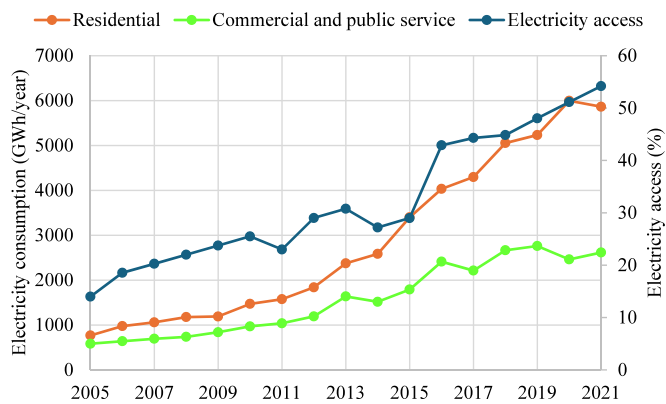


Fig. 2. Trends in electricity access and consumption across residential, and commercial and public service sectors in Ethiopia (2005–2021) (data source: World Bank [45] and the IEA [46]).

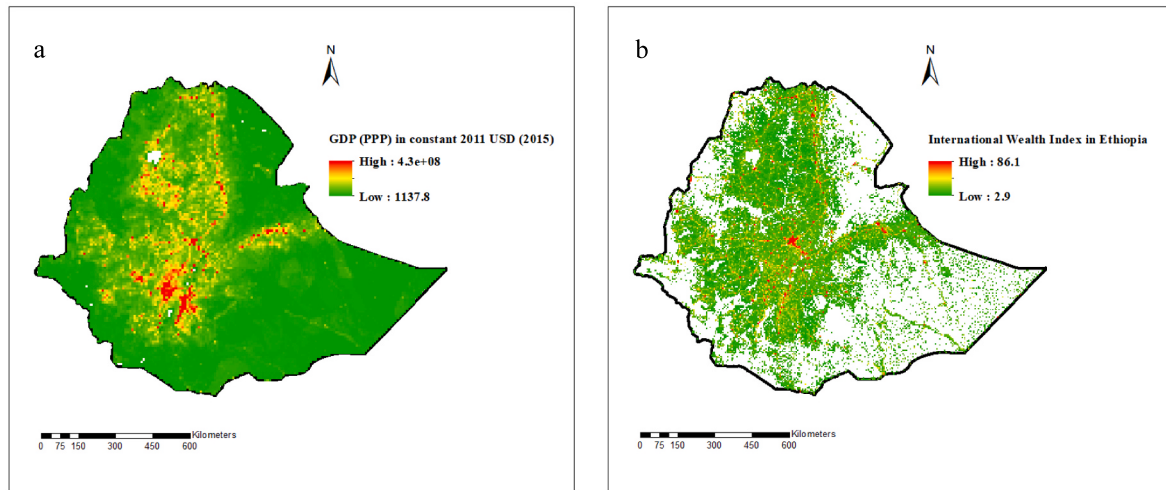


Fig. 3. High resolution spatial economic indicators in Ethiopia. a) The GDP for the year 2015 at a spatial resolution of 1 km², expressed in constant 2011 international US dollars. GDP values range from 1137.8 USD to 4.3 million USD per grid cell [50]. b) The IWI at a grid size of 1.6 × 1.6 km², where household-level wealth index ranges from 2.9 to 86.1 in 2021 [51].

Table 1
GDP and IWI classification scheme for settlement stratification.

GDP	GDP classification	IWI	IWI classification
$GDP_{min}(nb1) \leq GDP < nb_2$	1	$IWI_{min}(nb1) \leq IWI < nb_2$	1
$nb_2 \leq GDP < nb_3$	2	$nb_2 \leq IWI < nb_3$	2
$nb_3 \leq GDP < nb_4$	3	$nb_3 \leq IWI < nb_4$	3
$nb_4 \leq GDP < nb_5$	4	$nb_4 \leq IWI < nb_5$	4
$GDP \geq nb_5$	5	$IWI \geq nb_5$	5

*nb-natural breaks.

is associated with a relatively better economic status. Conversely, HHs in settlements with a C value of 1 are assigned to Tier 1, reflecting lower electricity demand linked to relatively poorer economic status. For HHs in settlements with C values between 1 and 5, a linear interpolation is applied between Tier 1 (38.7 kWh/HH/year) and Tier 5 (3000 kWh/HH/year), as shown in Equation (2).

$$E_i^{HH} = \frac{E_{T_5} - E_{T_1}}{4} \times (C_i - 5) + E_{T_5} \quad (2)$$

Where E_i^{HH} represents the annual electricity demand per HH for HHs in settlement i , and E_{T_1} and E_{T_5} represent the annual electricity demand per HH of Tier 1 and Tier 5, respectively. To determine the total HH electricity demand for each settlement, the MTF-based HH consumption is first converted into per capita terms by factoring in the national average HH size, as shown in Equation (3). The projected HH size for each year is provided in Table 2. The total annual HH electricity demand for each settlement is then determined using Equation (4).

$$E_i^{PC} = \frac{E_i^{HH}}{HH \text{ size}} \quad (3)$$

$$E_i^{total} = Pop_i \times E_i^{PC} \quad (4)$$

Where E_i^{PC} is the annual electricity demand per capita for settlement i . E_i^{total} represents the total annual HH electricity demand for settlement i , and Pop_i is the total population for settlement i .

2.5.2. Household-based productive use

This study also considers household-based small businesses as a proxy for productive use (PU). In rural areas, most PUs are informal and home-based or closely tied to residential activities. Given that the focus of this study is rural areas, PUs are grouped under the HH category. This

Table 2
Growth rates and projected values of key electricity demand drivers for each scenario.

Scenarios	Drivers (%)	Growth rates and projected values		
		2030	2040	2050
BAU	GDP growth rate	6	5	4
	Population growth rate	2.1	1.9	1.8
	Urban population	26.9	32.7	39.1
	Rural electricity access	61.2	85.5	100
HEG	GDP growth rate	11	8	6
	Population growth rate	2.1	1.9	1.8
	Urban population	26.9	32.7	39.1
	Rural electricity access	61.2	85.5	100
RU	GDP growth rate	6	5	4
	Population growth rate	2.1	1.9	1.8
	Urban population	29.2	40.1	56.9
	Rural electricity access	61.2	85.5	100
Average national HH size (people/HH)		4.7	4.6	4.5

grouping enables the model to better reflect the socioeconomic and spatial realities of rural electricity consumption. In addition, there is a lack of georeferenced data for identifying the locations of PUs across the study area. Consequently, the electricity demand of PUs is modeled as a proportion of HH demand, guided by empirical evidence from prior studies. In Tanzania, approximately 25 % of mini-grid customers use electricity for PUs [13]. Similarly, in Ethiopia, PUs account for over 50 % of total annual electricity consumption despite representing only a quarter of the customer base [14]. Further regional data from Mozambique indicates that PUs contribute over 26 % of daily electricity consumption in the grid-connected rural town of 16 de Junho [53]. A broader assessment across SSA suggests that PU could potentially increase HH electricity demand by up to 45 % in a high-uptake scenario, with a more conservative estimate indicating an increase of 25 % [15].

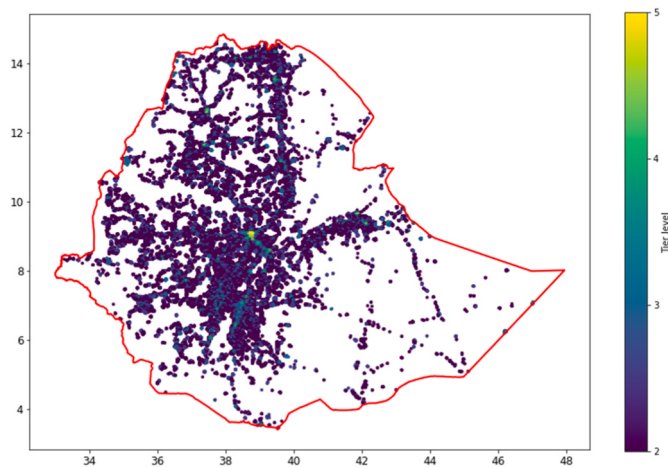


Fig. 4. Methodological basis for identifying settlements with potential for PU. Spatial distribution of HHs with electricity demand at or above Tier 2, which serves as the threshold for estimating PU electricity demand in the study methodology. The horizontal and vertical axes represent longitude and latitude, respectively, and the color bar indicates tier levels from tier 2 to 5.

In light of this, the present study presumes that HHs with electricity demand at or above Tier 2 (73–365 kWh/HH/year) are more likely to engage in PU activities. Therefore, the study conservatively estimates that PU demand equals 25 % of HH demand for HHs in Tier 2 or higher [15,53]. Fig. 4 shows HHs identified with electricity demand above Tier 2, which serves as the basis for estimating the demand of PUs in the study area.

2.5.3. Community institutions

In this consumer group, the annual electricity demand is estimated for four community institutions (CIs), namely health and education facilities, places of worship (POWs), and government offices [5]. These institutions have different electricity demands depending on their location, whether in rural or urban areas. Urban institutions serve larger populations and are thus equipped with a greater number of electrical appliances, resulting in higher electricity consumption. Therefore, separate demand estimations are conducted for rural and urban CIs using the Remote-Areas Multi-energy systems load Profiles (RAMP) model [54]. It is an open-source, bottom-up stochastic tool designed to generate high-resolution load profiles for remote and off-grid areas based on appliance-level data. RAMP requires a relatively small set of input parameters, including rated power, number of units, availability windows, duty cycles, and random variation factors, to produce per-minute load profiles [55]. It is particularly effective for modeling diverse energy needs (e.g., lighting, appliances, water heating, cooking) using limited, interview-based data, which is often characterized by high uncertainty [55]. Its flexibility in handling appliance-level characteristics makes RAMP especially suitable for estimating the electricity demand of CIs. The appliance-specific parameters used for this analysis were adapted from previous studies conducted in Mozambique, where data were collected through direct field-based surveys [12] (see Appendix Table B 2-Table B 5).

A key methodological challenge in spatial demand estimation of CIs was the limited availability of georeferenced data on their locations. Georeferenced locations for health facilities were obtained from the Humanitarian Data Exchange (HDX) website [56], and for education facilities from the Ethiopian Ministry of Education (MOE³) [57]. However, the georeferenced locations of POWs obtained from HDX and

OpenStreetMap (OSM) were limited and did not represent the full coverage of these institutions. Additionally, georeferenced data on government offices were not accessible through any public dataset provider. Due to this lack of georeferenced data, it is assumed that each village and town in Ethiopia has at least one POW and one government office. Georeferenced information from Ref. [58] shows 23,957 villages and towns across the country. This approach may underestimate counts in denser settlements and overestimation in sparsely populated areas. For CIs located outside the population settlements delineated by Ref. [47], a proximity-based method was used to assign them into the nearest population settlement [59]. This approach ensures that all CIs are included in the spatial analysis of electricity demand.

The spatial electricity demand of CIs was estimated by linearly interpolating between rural and urban demand levels using the composite C value calculated in Equation (1). CIs located in settlements with a C value of 5 were assigned the highest (urban) CI electricity demand, while those in settlements with a C value of 1 were assigned the lowest (rural) demand. For settlements with C values between 1 and 5, a linear interpolation was applied, as shown in Equation (5). The spatial distribution of CIs' electricity demand across the study country is illustrated in Fig. 5.

$$E_i^{CI} = \frac{E_{CI}^{urban} - E_{CI}^{rural}}{4} x(C_i - 5) + E_{CI}^{urban} \quad (5)$$

Where E_i^{CI} is the annual electricity demand of a CI in settlement i , E_{CI}^{urban} and E_{CI}^{rural} are the annual electricity demands of CIs in urban and rural areas, respectively.

2.6. Scenarios

Three scenarios are developed to explore various potential future development pathways and their respective impacts on electricity demand. The BAU scenario serves as a baseline and assumes current trends in key drivers of electricity consumption remain unchanged. Conversely, the HEG and RU scenarios explore alternative pathways by applying different growth rates to key drivers. Each scenario incorporates projections of four key demand drivers: annual population growth rate, percentage of the population living in urban areas, annual GDP growth rate, and the level of rural electricity access. Historical data for these drivers, sourced from the World Bank, are available up to 2021 [60]. Therefore, 2021 is used as the base year for projecting electricity demand up to 2050, with all growth rates calculated relative to the 2021 values. Historical electricity consumption data is obtained from the IEA [46]. Table 2 summarizes the assumed growth rates and projected values for each scenario.

2.6.1. Business as usual scenario

The BAU scenario assumes that key drivers (population growth rate and percentage of urban population) follow United Nations projections. For rural electricity access, the scenario extrapolates historical trends observed between 2005 and 2021, projecting 100 % rural access by 2046 [45]. Projections of future GDP growth rates are based on the most up-to-date available data, including historical trends from the World Bank, IMF predictions up to 2028 and a recent study [19]. Consequently, GDP growth rates of 6 %, 5 %, and 4 % are projected to 2030, 2040, and 2050, respectively. This gradual decline in GDP growth rate accounts for the expected decreasing tendency of the GDP growth as the economy matures [61].

2.6.2. High Economic Growth scenario

The HEG scenario envisages a GDP growth rate faster than the baseline. This assumption draws on Ethiopia's strong economic performance, which has seen an average growth rate of nearly 11 % per year since 2004, alongside a reduction in extreme poverty—from 55 % in 2000 to 34 % in 2011 [62]. Over the past 15 years, the country has

³ MOE stands for Ethiopian Ministry of Education, responsible for the governance and policies of education.

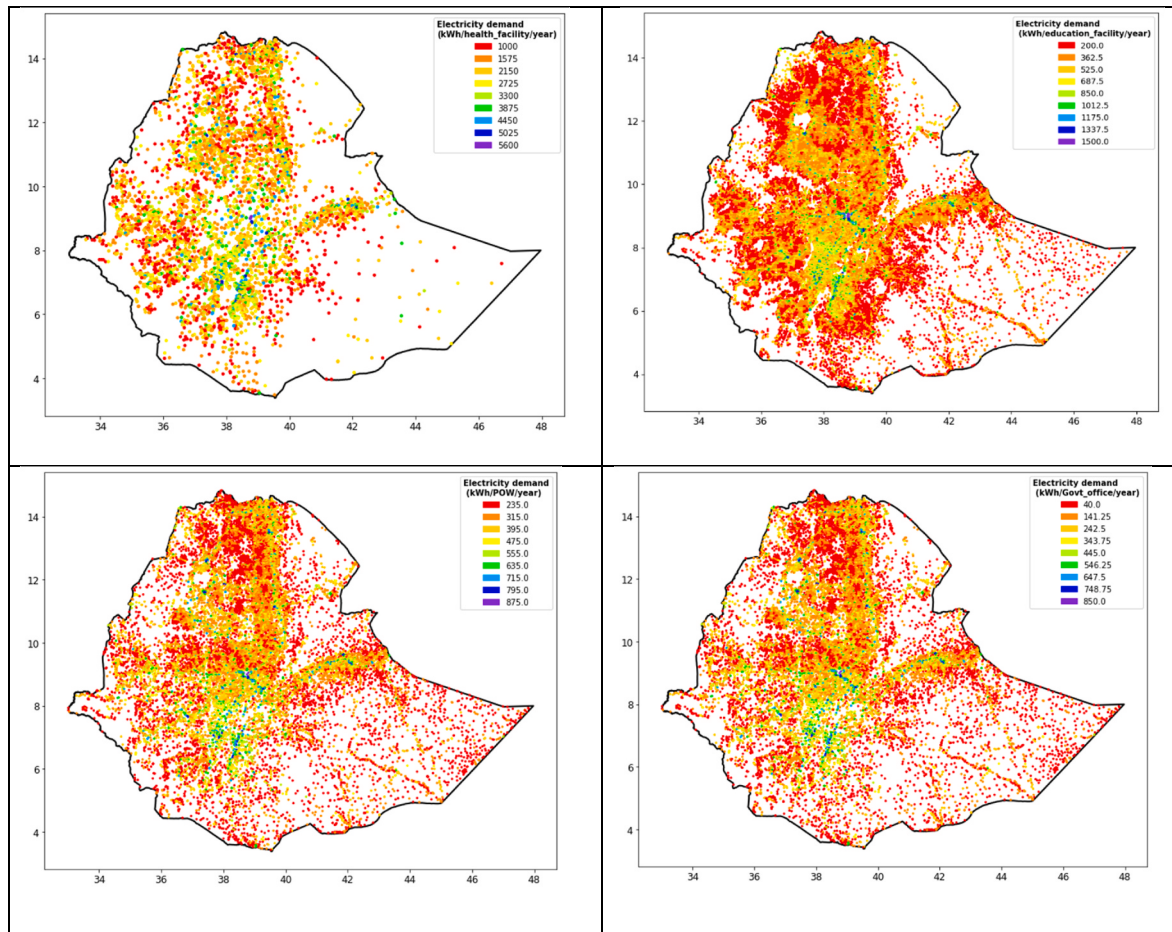


Fig. 5. Methodological demonstration of the base year electricity demand for key CIs in Ethiopia: (a) Education facilities (top left), (b) Health facilities (top right), (c) Places of worship (bottom left), and (d) Government offices (bottom right). The spatial distribution illustrates how CI demand is allocated based on settlement economic status (C values), with demand interpolated between rural and urban CI consumption levels established through RAMP modeling.

experienced an AAGR of nearly 10 %, mainly driven by public infrastructure investments [63]. The HEG scenario is grounded in the government's economic policies and reforms, such as the 2019 Home-Grown Economic Reform Agenda which runs from 2020/21 to 2029/30 and aims to transition the economy to a market-oriented system, attract foreign direct investment (FDI) and boost private sector growth. Building on the country's development goals, the HEG scenario projects average annual GDP growth rates of 11 %, 8 %, and 6 % for the years up to 2030, 2040, and 2050, respectively [19].

2.6.3. Rapid urbanization scenario

The RU scenario assumes a faster pace of urbanization than the BAU scenario. Ethiopia's recent history shows an urbanization rate above the SSA average of 4.8 % in 2021, with annual rates ranging between 4.09 % and 5.25 % from 2005 to 2021 [37]. This scenario is based on the assumption that ongoing and future policy interventions will further increase the pace of urbanization.

Several key factors contribute to this scenario. First, the government's Growth and Transformation Plan (GTP II) includes targeted investments in urban infrastructure, housing, and job creation, all of which are expected to stimulate rural-to-urban migration. This migration is driven by the pursuit of better employment opportunities, improved living conditions, and greater access to services such as education and healthcare [64]. Second, Ethiopia's demographic profile—characterized by a rapidly expanding and youthful population, will further contribute to urban growth. The increasing demand for housing, jobs, and urban services is projected to stimulate the expansion of urban

centers. Given these dynamics, the RU scenario assumes an average annual urbanization growth rate of 5 % throughout the projection period (2021–2050).

2.7. Electricity demand projection model

The MLR model projects future national electricity demand on the basis of historical relationships between the dependent variable (electricity demand) and a set of independent variables (demand drivers). The general mathematical form of the MLR model is expressed in Equation (6).

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (6)$$

- Where, D is the dependent variable (representing electricity demand), β_0 is the y-intercept of the regression line, $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients for the independent variables $X_1, X_2, \dots, X_n$ (the demand drivers), ε is the error term.

The model is applied to project the national electricity demand of each consumer group by incorporating the growth rates of key demand drivers (rural electricity access levels, GDP per capita and urbanization) specific to each scenario, as outlined in Table 2. To build the model, historical national consumption data for households, as well as commercial and public services (from 2005 to 2021) were obtained from the IEA [46], as illustrated in Fig. 2. To project the electricity demand of HHs, the model establishes a correlation between the historical national

consumption of HHs and the key drivers under each scenario. Additionally, the model is validated by cross-referencing the base-year projection for HHs with actual historical electricity consumption data. PU electricity demand projections are derived from HH projections, as described in section 2.3.2.

CIs, such as health centers, schools, churches, and government buildings, which are considered in this study, are categorized as part of the public services group within IEA statistical data [46]. However, the IEA does not report electricity consumption for public services separately from commercial activities; instead, both are combined under the “commercial and public services” category, making it difficult to derive distinct growth trends for this sub-category. In the absence of a historical growth trend for public services alone, the growth rate for the aggregated commercial and public services sector is adopted as the most appropriate proxy for projecting CI demand. This assumption is made under the premise that, in a developing country, particularly in rural areas, commercial activity and public services tend to grow alongside overall economic development, urbanization, and population growth, thereby exhibiting broadly similar energy demand trends. Nevertheless, it is acknowledged that the actual growth rate for CIs may differ from that of the combined commercial and public services sector, which represents a limitation given the constraints on available data. The MLR equation used in the demand projection is represented by Equation (7).

$$D = \beta_0 + \beta_1(\text{Rural electricity}_{\text{access}}) + \beta_2(\text{GDP}_{\text{percapita}}) + \beta_3(\text{Urban population}_{\text{percentage}}) + \varepsilon \quad (7)$$

2.8. Influence of temperature variation on electricity demand

This paper further examines the effects of spatial temperature variation and projected temperature rise due to climate change on future electricity demand. Due to its diverse geography, Ethiopia has a wide range of local climates, from cooler highlands to hotter lowland areas. The long-term average temperature ranges from 8.8 °C in the highlands to 33.8 °C in the lowlands [29]. Empirical evidence from various contexts indicates a strong positive correlation between ambient temperature and electricity demand. For example, in Jordan, average electricity demand increased by approximately 11 % due to elevated temperatures between 2007 and 2016 [65]. Similarly, studies in India and Texas have shown that a 1 °C increase in ambient temperature above a 24 °C baseline results in a 2 % and 4 % increase in electricity demand, respectively [23].

To assess the potential effect of this in Ethiopia, the study used spatial temperature data from the Global Solar Atlas [29], as depicted in Fig. 6. The model incorporates a temperature sensitivity factor that increases total electricity demand by 2 % for every 1 °C rise above a 24 °C baseline (Equation (8)).

$$E_{\text{total}}(T) = \begin{cases} E_{\text{total}}, & T < 24^\circ\text{C} \\ E_{\text{total}} * (1 + 0.02 * (T - 24)), & T \geq 24^\circ\text{C} \end{cases} \quad (8)$$

Where $E_{\text{total}}(T)$ represents total electricity demand considering the effect of spatial temperatures, E_{total} is the baseline total demand without considering the effect of temperature, and T is annual mean daily temperature at 2 m.

Furthermore, to provide a forward-looking perspective on temperature-driven demand, the analysis incorporates temperature rise projections over the study horizon. These projections are sourced from the IPCC reports, which predict an average global temperature rise of about 0.2 °C per decade [27]. For each projection year and settlement, the mean daily temperature is incremented by this decadal change before applying the sensitivity factor. Incorporating both spatial and temporal temperature variation in this way enables the identification of settlements most vulnerable to warming-driven demand growth and quantifies the incremental demand attributable to climate change over time.

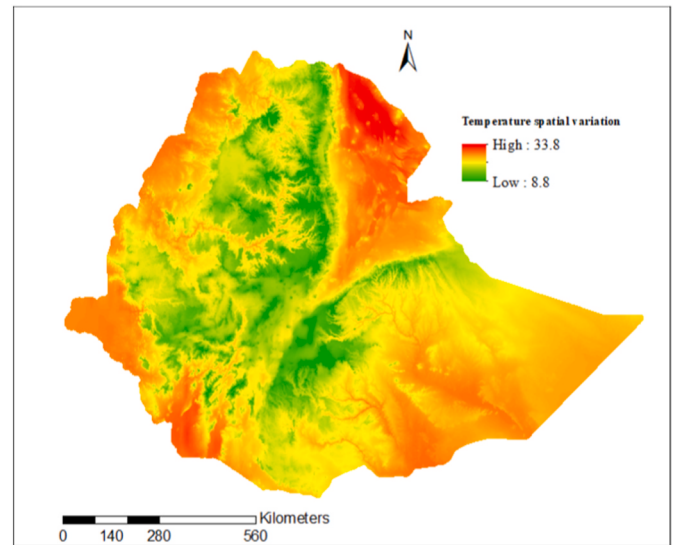


Fig. 6. Long-term average of daily air temperatures in Ethiopia (1994–2018), measured at a height of 2 m above the ground with a resolution of 30 arc-seconds [29].

3. Results and analysis

3.1. Total electricity demand projections under different scenarios

The three scenarios were applied to generate long-term electricity demand projections. The total national projections show substantial electricity demand growth under all scenarios: by 2050 compared to the base year (2021), electricity demand increases to 20,400 GWh (a 176 % increase) under BAU, to 23,600 GWh (219 %) under HEG, and to 28,500 GWh (285 %) under RU. This represents a 40 % increase under RU compared to BAU, and a 16 % increase compared to HEG. The total national projections result in an AAGR of 3.6 %, 4.1 %, and 4.8 % over 2021–2050 for BAU, HEG, and RU, respectively.

In terms of per capita electricity consumption at national level, BAU shows an increase from 70 kWh in 2014 to 106 kWh by 2050, while HEG and RU increases to 122 kWh and 148 kWh, respectively. These results indicate that Ethiopia will experience an increase in both total and per capita electricity demand over the projection period. Fig. 7, shows the demand growth trends under each scenario.

3.2. Electricity demand by consumer group

The analysis of total national electricity demand projections by consumer group (HHs, PUs, and CIs) reveals disparities in total demand

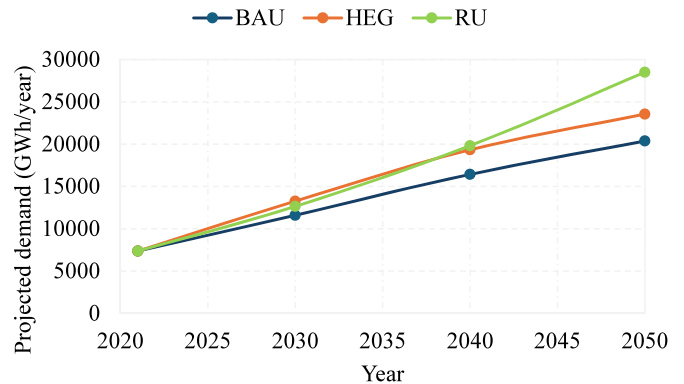


Fig. 7. Projected total electricity demand in Ethiopia (2021–2050) under three scenarios.

and growth rates across sectors. HHs represent the largest share of total electricity demand throughout the projection period. However, its AAGR is slightly lower than CIs. Under the BAU, the projected AAGRs are 3.6 % for both HHs and PUs, while CIs show a higher growth rate of 4.3 %. The HEG scenario predicts AAGRs of 4.1 % for HHs and PUs, and 4.3 % for CIs over the same period. The RU scenario exhibits the highest demand growth among the three scenarios, with AAGRs of 4.8 % for HHs and PUs, and 5.8 % for CIs. The higher growth rate for CIs is due to their low electrification levels in the base year. As electrification expands, CIs electricity demand increases, resulting in higher AAGRs compared to HHs. To validate the model for the base year, the projected result was compared with the actual historical consumption for HHs. The model predicts a demand that is 1.5 % higher than the actual historical consumption in the base year, as shown in Fig. 8. The coefficient of determination (R^2) values for the MLR models exceed 0.97, indicating strong explanatory power of the selected demand drivers. Table 3 summarizes the projected electricity demand by consumer groups across these scenarios.

3.3. Spatial demand analysis

3.3.1. Households

A spatial analysis of HH electricity demand shows an increase in consumption tiers between 2021 and 2050. In 2021, only 54.2 % of HHs had electricity access, leaving approximately 11.4 million HHs without access. Of those electrified HHs, around 11 % were in Tier 1 (basic electricity access). This proportion is expected to increase to approximately 17 % by 2030 and further increase to 25 % by 2050 due to the electrification of unelectrified HHs. The share of HHs with Tier 2 was around 27 % in 2021 and is projected to reach about 23–39 % by 2050. Conversely, HHs in Tier 3, which represented the majority (61 %) of electrified HHs in 2021, are expected to decline to 37–47 % by 2050. This decline is due to newly electrified HHs entering lower consumption tiers (Tiers 1 and 2). It is worth noting that HHs with Tier 4 and above were entirely absent in 2021. However, Tier 4 begins to emerge by 2030 in the HEG and RU scenarios, and by 2040 in the BAU scenario, reaching between 0.08 % and 11 % by 2050.

Fig. 9 illustrates the evolution of HHs electricity demand under the three scenarios. In the BAU scenario, there is a considerable increase in the proportion of HHs falling within Tiers 1 and 2, accompanied by a decline in the proportion of Tier 3. This contrasts with the HEG and RU scenarios, where the rise in the share of HHs in Tiers 1 and 2 is less compared to the BAU scenario, and the share of Tier 3 is relatively higher. In the HEG scenario, the share of Tier 4 HHs grows from nonexistent in 2021 to 5.06 % by 2050. The RU scenario exhibits the largest increase in Tier 4 HHs, with 11.31 % of HHs falling into this category by 2050.

Given that the RU scenario represents the highest increase in

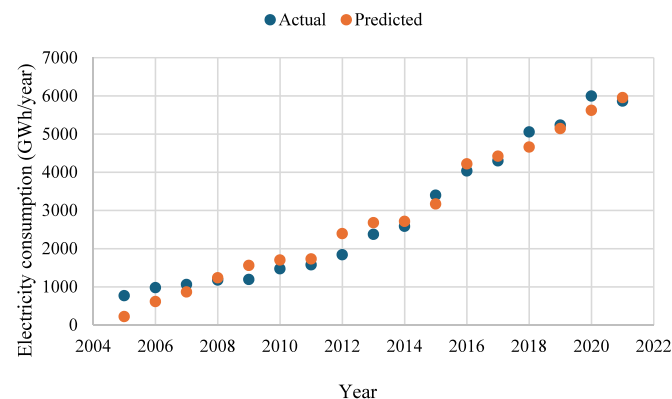


Fig. 8. Regression model validation – actual vs. predicted HH consumption for the years 2005–2021.

Table 3

Projected electricity demand by consumer group and scenario.

Scenarios	Consumer groups	Electricity demand (GWh/year)				AAGR 2021–2050 (%)
		2021	2030	2040	2050	
BAU	HH	5863	9221	13070	16196	3.6
	PU	1465	2304	3264	4044	3.6
	CI	39	71	102	131	4.3
HEG	HH	5863	10557	15389	18738	4.1
	PU	1465	2637	3843	4679	4.1
	CI	39	73	105	134	4.3
RU	HH	5863	10054	15751	22645	4.8
	PU	1465	2512	3933	5654	4.8
	CI	39	80	130	201	5.8

electricity demand by 2050, the spatial analysis of demand focuses on this scenario. The spatiotemporal analysis reveals three key findings as shown in Fig. 10. First, the analysis highlights the progressive electrification of HHs that previously lacked electricity access. As rural electricity access expands, projected to reach 100 % by 2046, many settlements transition to higher demand levels. This leads to an increase in total electricity demand. Second, for HHs that were already electrified, there is also a shift toward higher demand tiers over time. As can be seen from the zoomed sample inset, HHs in settlements with lower demand tiers in 2021 are likely to move toward higher tiers by 2050.

Third, a closer examination of Fig. 10 reveals a large number of HHs in the north-central, central, and south-central regions are expected to transition from Tier 1 consumption levels to higher consumption tiers (Tiers 2 and 3) between 2021 and 2050. In contrast, many HHs in peripheral areas, particularly in the Northeast and Southeast regions, are projected to remain in Tier 1 or shift modestly to Tier 2 during the same period. This regional disparity demonstrates how HH electricity demand varies across the country, depending on local population dynamics, economic factors, and urbanization development.

3.3.2. Productive use

The electricity demand projections for PU at the settlement level show distinct spatial patterns over the projection period (2021–2050), with higher growth in the RU scenario. The percentage provided in this analysis is based solely on settlements with PUs. In 2021, most of these settlements (96.16 %) had a demand of less than 1 GWh, indicating limited energy use in many areas. A smaller proportion of settlements (3.2 %) fell within the demand range of 1–10 GWh, while only a minimal 0.1 % of settlements exceeded 100 GWh in demand. By 2050, the proportion of settlements with demand below 1 GWh is expected to decrease to 90.72 %, while those in the 1–10 GWh range is expected to increase to 8.54 %. Higher demand categories, such as 10–25 GWh, 25–50 GWh, and over 100 GWh, are also expected to see slight increases. Fig. 11 shows the spatial variation and changes in PU electricity demand over time between 2021 and 2050. Settlements labeled as "No PU" correspond to HHs with Tier 1 electricity demand that do not contribute to PU. In contrast, settlements with higher electricity access, GDP, and IWI scores show greater PU electricity demand.

3.3.3. Community institutions

The electricity demand for CIs under the RU scenario also shows higher demand growth across settlements with CIs. Thus, the spatial analysis of CIs demand focuses on this scenario. As with the PUs, the percentages in this analysis are based only on settlements with CIs. In 2030, 63 % of the settlements with CIs have total demand below 1000 kWh. However, by 2050, this proportion is expected to fall to 38 % as more settlements move into higher demand categories. The proportion of settlements with moderate electricity demand (1000–3000 kWh) is projected to grow from 27 % to 46 %, while those with high demand (over 5000 kWh) are expected to rise from 5 % in 2030 to 9 %.

By 2030, electricity demand from CIs may contribute, on average, a

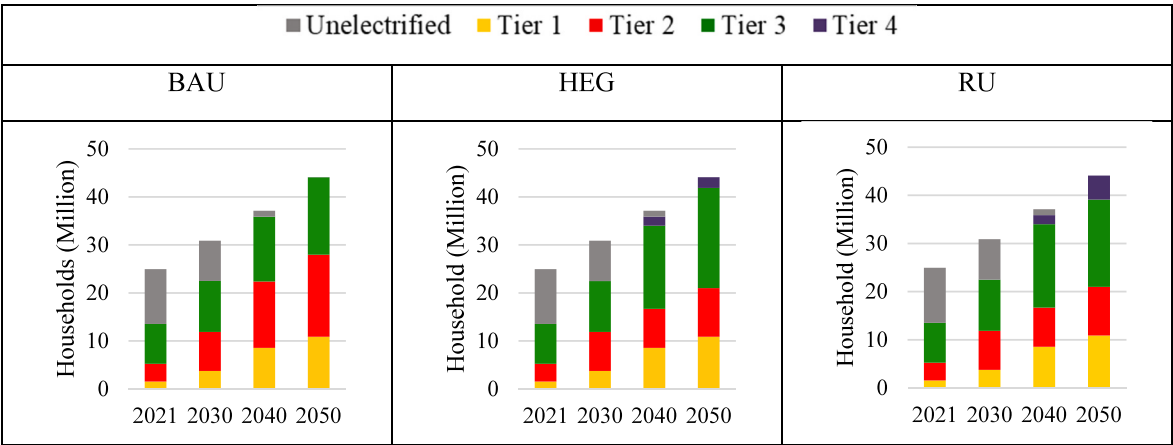


Fig. 9. Evolution of HH electricity demand tiers under three scenarios for the years 2021, 2030, and 2050. Access to electricity is projected to be fully achieved after 2040, which is displayed in the figure as unelectrified in grey.

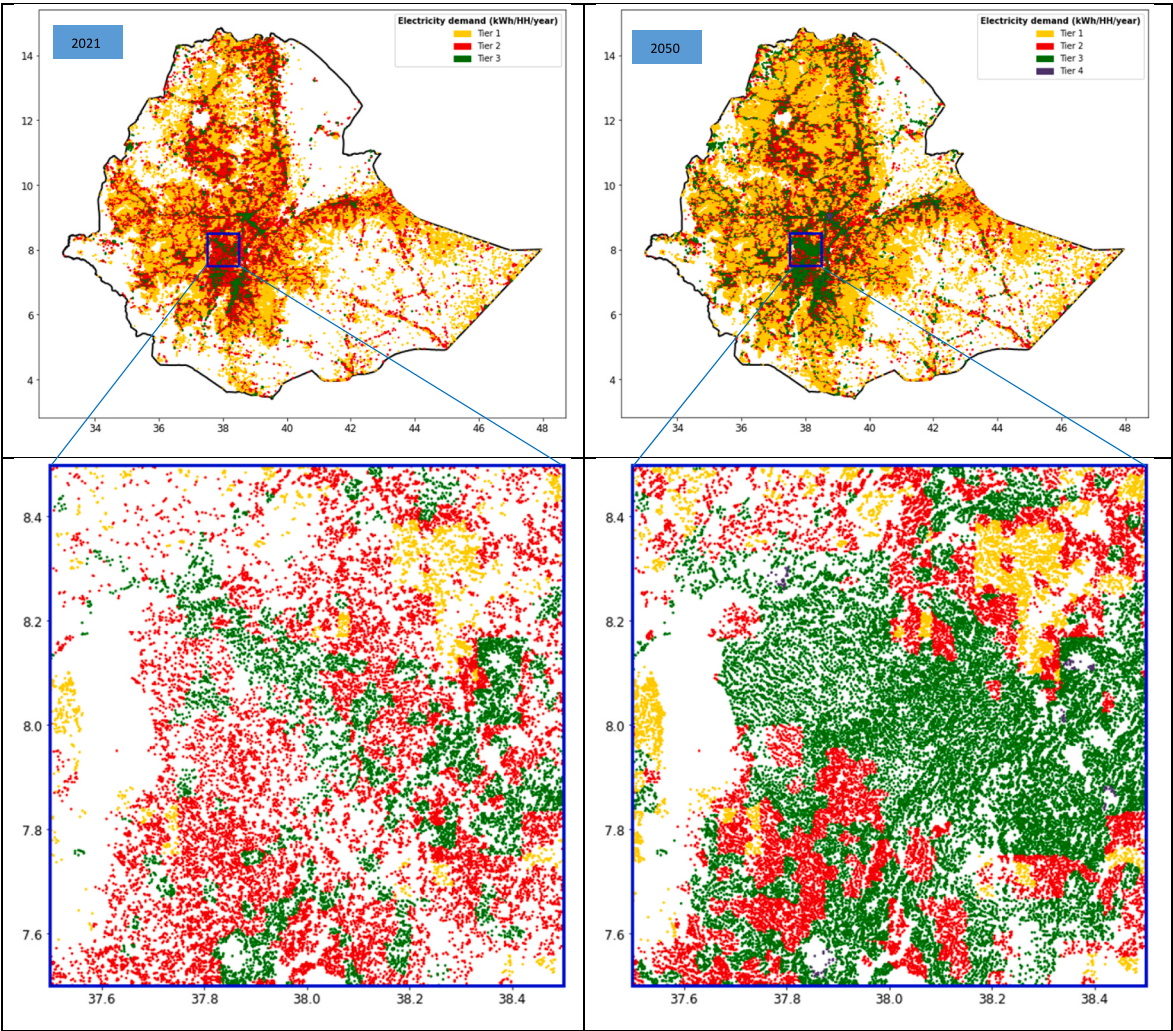


Fig. 10. Spatial variations in HH electricity demand under the RU scenario, comparing the base year (2021) with projections for 2050. In the base year, HH demand ranges from Tier 1 to Tier 3, while by 2050 demand is projected to increase with some settlements reaching Tier 4.

31 % increase in settlement level electricity demand in settlements where these institutions are located. This contribution is projected to rise to 46 % by 2050. This high contribution is primarily attributed to the assumption that every village and/or town includes at least one POW

and one government office. The distribution of HHs across population settlements varies widely, with a larger proportion of CIs located in settlements with smaller populations. This distribution explains their disproportionately higher contribution of CIs to the electricity demand

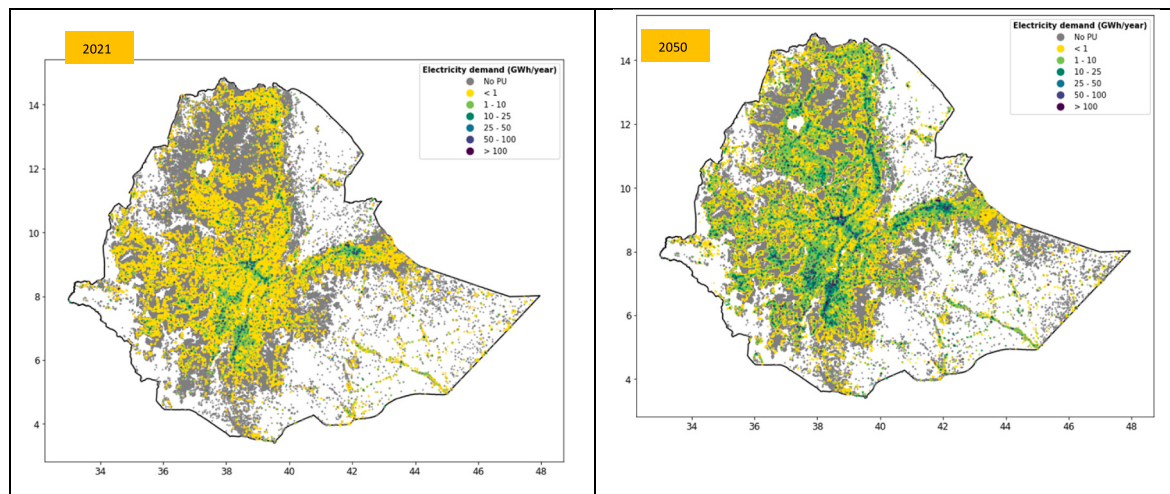


Fig. 11. Spatial variations in electricity demand for PUs under the RU scenario, comparing the base year (2021) demand with projections for 2050. Areas shaded in grey represent settlements where the electricity demand of HHs remains below Tier 2, indicating that there are no PUs in these settlements.

in these settlements. The spatial distribution of CIs electricity demand, as shown in Fig. 12, aligns with the patterns observed for HHs electricity demand in Fig. 10. Settlements with higher HHs demand tend to have greater CIs electricity demand, while settlements with lower HHs demand show relatively lower or no CIs demand.

3.4. Electricity demand due to rising temperature

The analysis on the effect of rising ambient temperature on electricity demand indicates a gradual increase in additional electricity demand over time. Nationally, temperature-driven additional demand is expected to be approximately 0.49 % by 2030 and 0.53 % by 2050 across the three scenarios.

Although the national impact remains relatively small, certain regions are expected to experience more significant increases in electricity demand due to higher temperatures. Regions with yearly average daily temperatures exceeding 24°C—such as the arid and semi-arid lowlands of Afar (Northeast) and Somali (Southeast), parts of Amhara (Northwest), and Benishangul-Gumuz (West), and the peripheral areas—are projected to see higher electricity demand driven by rising temperatures. Using the population growth rates presented in Table 2, the study projects that the population residing in these hotter regions will reach 13 million by 2030 and 20.2 million by 2050. In settlements of these regions, electricity demand is projected to rise by up to 21.8 %–22.6 % between 2030 and 2050 as a result of temperature increases. These

projections are illustrated in Fig. 13, which highlights the settlements expected to be most affected by rising temperatures.

4. Discussion

This study projects Ethiopia's long-term electricity demand from 2021 to 2050 under three scenarios (BAU, HEG, and RU). All scenarios show significant growth, with the RU scenario displaying the highest increase, 40 % above BAU by 2050. This large increase in demand can be attributed to rapid urbanization of previously rural areas, population growth, an increase in electricity-intensive economic activities, expansion of urban infrastructure, and adoption of energy-intensive appliances such as cooking stoves, air conditioners, and refrigerators [66]. These findings are consistent with previous studies, which showed that rapid urbanization of rural areas leads to a substantial increase in energy consumption [67–69]. The RU scenario's higher demand growth highlights the importance of urbanization in electrification planning.

Compared to previous studies carried out for Ethiopia, the results of this study show both alignment and divergence in terms of growth rates. These differences can be attributed to differences in the socioeconomic assumptions, time-horizon, sectoral coverage, and the methods of projections (e.g. regression [4], Low Emissions Analysis Platform (LEAP) [19,20,70]). Table 4 provides a comparative overview of the relatively limited set of long-term electricity demand projections available for Ethiopia.

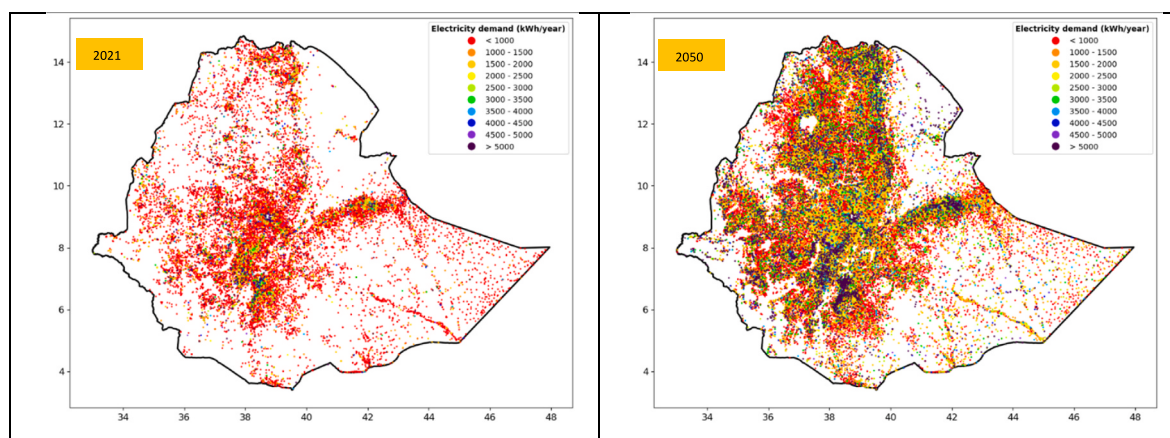


Fig. 12. Spatial variations of electricity demand for CIs under the RU scenario, comparing the base year (2021) with 2050 projections. The highest demand for CIs is observed in areas that align with roads, cities, and densely populated regions.

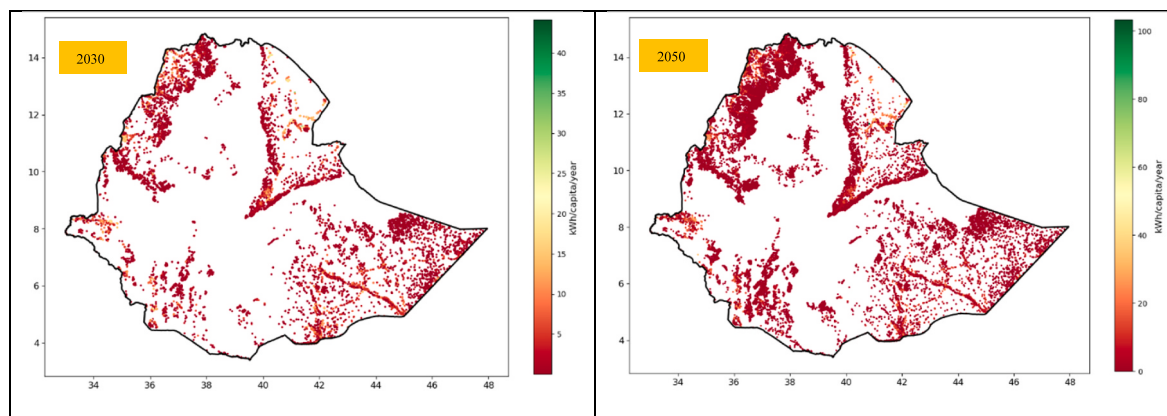


Fig. 13. Additional electricity demand due to projected temperature rise in the RU scenario for the years 2030 and 2050. By 2050, the impact of rising temperatures is expected to extend into central northern regions, indicating a broader geographical spread of temperature-driven demand.

The AAGR projected for HH electricity demand in this study closely matches the projections reported by Pappis et al. [4]. This is likely due to their use of similar methodological approaches, including the use of the OnSSET model for spatial demand estimation and comparable assumptions regarding population growth and electricity access levels. The AAGR for HHs projected by Mondal et al. [20] until 2030 aligns with this study's projection of 5.1–6.8 % for the same period. In contrast, Gebremeskel et al. [19] reported higher AAGRs for the HH sector up to 2050. This is likely due to their optimistic assumptions regarding electrification and appliance uptake, as well as urbanization targets (60–80 % by 2050 compared to the more conservative range of 39.1–56.9 % in this study).

The total electricity demand AAGR projected in this study (5.2 %–6.8 %) closely aligns with the findings of Pappis et al. and, to a lesser extent, with Senshaw [70]. Again, Gebremeskel et al. [19] report higher growth rates for total demand through 2050. The highest total electricity demand growth rates reported in previous studies are predominantly attributable to sectors such as industry, agriculture, transport, and services, and in some cases also account for exports and technical losses [4, 19, 20, 70]. These sectors are not the primary focus of the present study, which is limited to HHs, PUs, and CIs—sectors most relevant for rural electrification planning. As such, the projections herein do not capture the full scope of national demand growth with broader sectoral coverage. This distinction is important for interpreting differences in projected growth rates and absolute demand levels.

Compared to other developing countries, the demand projection for Ethiopia in this study appears relatively moderate. The electricity demand in Pakistan grows at 8.35 % AAGR until 2050 [21], considerably higher than Ethiopia's 3.6 %–4.8 % AAGRs. Similarly, studies in Kenya projects AAGR of 1.8 %–10 % until 2040, exhibits a broader range compared to Ethiopia [71, 72]. Rwanda's AAGR of 6.6 %–7.2 % exceeds this study's AAGR, despite a smaller absolute demand [73]. In contrast, Sierra Leone's projected AAGR from 2019 to 2040, ranging between 3.9 % and 5.7 % [74], aligns closely with Ethiopia's, a more comparable electricity demand growth between these two countries. Such cross-country comparisons illustrate the diverse electricity demand

growth across different nations, driven by their unique economic, demographic, and policy contexts. Furthermore, this study's projection for total electricity demand growth in Ethiopia, ranging from 4.3 % to 5.3 % AAGR until 2040, aligns consistently with the IEA's estimated 4.6 % AAGR for SSA for the 2012–2040 period [75].

Findings from the sectoral demand projections indicate that HH electricity demand remains the primary source of energy consumption. This is in agreement with previous studies, which reported that the HH sector accounted for 88 % of Ethiopia's total energy consumption in 2018 [39]. However, Yalew's [39] estimate includes more energy sources, including biomass, the main energy source in rural areas. Therefore, the HH sector's share of electricity consumption may be lower than both Yalew's estimate and this study's projections. The dominance of HH electricity demand in this paper is due to the methodological approach, where PUs are considered direct derivatives of HH demand. CIs contribute a smaller share to overall electricity demand. This may be due to the assumption that each town or village has only one CI facility, which could result in an underestimation of the actual number of such facilities, particularly in densely populated areas.

A key finding of this research is the spatial variations in electricity demand. Central regions, characterized by higher population densities, relatively higher local economies, and lower poverty rates, are projected to see higher electricity demand growth. Most settlements in these regions are already electrified, which may further increase demand growth by facilitating the adoption of electricity-dependent appliances and economic activities. In contrast, peripheral regions, particularly in the Northeast and Southeast, where poverty rates are higher and local GDP is relatively low, are expected to experience slower electricity demand growth. Limited access to electricity, and sparse populations in these areas are likely to keep demand low over the coming decades. The lower household wealth and less diversified local economies in these regions may hinder their ability to adopt electricity-intensive activities, further limiting demand growth. While the study considers important socioeconomic factors, such as local GDP and poverty levels, it does not explore other variables that may influence spatial demand, such as household income.

The analysis of HH electricity demand reveals a trend towards higher demand tiers (Tiers 3 and 4) over time. This accords with the findings of Sahlberg et al. [17]. While their study anticipates a higher population share in Tiers 1 and 2 until 2030 (Ambition and Big Business scenarios) and up to 2050 (Slow Down), this study shows that Tier 3 demand will continue to dominate until 2050, with a growing share of Tier 2 and Tier 4 demand. The results showing varied demand (Tiers 1 to 4) across regions differ from projections by Mentis et al. [6, 7], who anticipated that all rural areas would reach Tier 3 (150 and 170 kWh/person/year in Ethiopia and Nigeria, respectively) and all urban areas would reach Tier 4 (300 and 350 kWh/person/year in Ethiopia and Nigeria respectively).

Table 4
Comparison of electricity demand projections for Ethiopia.

Studies	Time-horizon	AAGR (%)	Source
Household	2018–2065	4.2	Pappis et al. [4]
Household	2012–2030	7.6	Mondal et al. [20]
Household	2018–2050	8.5	Gebremeskel et al. [19]
Total demand	2018–2065	4.9	Pappis et al. [4]
Total demand	2018–2050	6.0–8.4	Senshaw [70]
Total demand	2018–2050	7.2	Gebremeskel et al. [19]
Total demand	2012–2030	9.7	Mondal et al. [20]

by 2030. Similarly, Ouedraogo [8] projected that urban settlements in Cameroon would reach Tier 5 consumption (1796 kWh/household/year) by 2035, while rural settlements would reach Tier 3 (530 kWh/household/year). However, the results indicate that a significant proportion of the population, particularly in rural areas, will likely remain in the lower tiers (Tiers 1 and 2) even beyond 2030.

Although PUs and CIs represent a smaller portion of national electricity demand, their contribution is expected to grow, particularly at local levels. The demand for PUs, which is tied to HH electricity demand, is projected to increase alongside the growth of HH demand. CIs demand is projected to grow at a higher AAGR, due to the low levels of electricity access in the base year. Spatial analysis shows that in settlements where CIs are present, their average contribution to local electricity demand is expected to reach 46 % by 2050. This high contribution at the local level can be attributed to many CIs being located in settlements with relatively few HHs among the 809,087 total settlements in Ethiopia delineated by Ref. [47]. In such areas, the smaller number of HHs amplifies the share of electricity demand from CIs. This is supported by studies in Benin, where health and education facilities alone are projected to increase national residential demand by up to 23 % by 2030 [76].

The analysis of electricity demand due to temperature variations across regions and projected temperature rise reveals that, while the impact at national level remains relatively small, the effect at local level is considerable, particularly in lowland regions such as Afar and Somali. In these regions, electricity demand is projected to rise by 21.8 %–22.6 % between 2030 and 2050 due to rising temperatures. These findings are strengthened by a previous study in Ethiopia [77], which reported a 22 % increase in electricity consumption during the hotter, dry season. As highlighted in Ref. [22], such temperature-driven demand growth shows the need to incorporate the effect of temperature into long-term energy planning, at least at local levels.

This study makes several methodological and analytical contributions to nationwide geospatial rural electrification planning. Firstly, many energy modeling studies primarily focus on supply-side optimization or simulation while giving relatively little attention to demand projection formulation, often relying on oversimplified assumptions. In contrast, this study focuses on electricity demand and provides electricity demand projections at settlement level using high-resolution gridded GDP and International Wealth Index data. This granular approach represents a substantial improvement over previous nationwide electrification planning studies that relied on oversimplified rural-urban binary classifications [6–9]. This approach is crucial for capturing spatial heterogeneity in electricity demand, preventing supply-demand mismatches, and supporting cost-optimal resource allocation. The study's findings of significant spatial heterogeneity in electricity demand, with HH demand ranging from Tier 1 to Tier 4 across settlements, directly validate its argument against uniform rural-urban electrification approaches. Secondly, this paper integrates electricity demand from three key sectors, including HHs, PUs, and CIs. This offers a more realistic representation of electricity needs in rural and peri-urban areas, contrasting with prior nationwide electrification planning studies that focused solely on residential demand [6,7,10,11,17]. The inclusion of PU and CI demand is particularly important for developing economically sustainable rural electrification solutions. These demands often drive local economic development and can improve the financial viability of electricity infrastructure investments through higher load factors and revenue generation potential.

The incorporation of spatially explicit ambient temperature data and IPCC-based temperature prediction into the electricity demand projections is another unique methodological contribution. By identifying the specific vulnerable regions and quantifying the expected demand increase, the study provides a clear imperative for capacity planning to include additional generation capacity. However, this factor has been overlooked in previous electrification planning studies despite its critical relevance for SSA, where many regions experience substantial CDDs annually and face increasing temperature extremes due to climate

change.

Despite these significant contributions, there are several limitations which are noteworthy. First, the study's scope is limited to HHs, PUs, and CIs, which are deemed most relevant for rural electrification planning. However, this focus means the study excludes other significant demand sectors that contribute substantially to national electricity consumption, such as large-scale industry, mining, and agricultural processing. Consequently, the total national demand projections do not capture the full scope of national demand growth and are not comparable to comprehensive energy demand projections. Second, while the inclusion of PUs is a strength, the method of estimation introduces uncertainty. The estimation of PU electricity demand relies on a fixed proportional relationship with HH demand, assuming PU demand equals 25 % of household demand for households at or above Tier 2 access levels. While this proxy is based on empirical evidence from a study in Ethiopia and SSA countries, this approach may not adequately capture the heterogeneous nature of productive activities across different settlements. Consequently, this proxy could underestimate demand in urban and peri-urban areas where more energy-intensive enterprises or diverse productive activities are prevalent.

Third, the modeling of CIs faces dual limitations related to both baseline demand estimation and growth rate projections. The base-year demand estimates rely on appliance usage parameters adapted from field surveys conducted in Mozambique [12]. However, the actual appliance usage patterns, economic conditions, service delivery standards, and institutional capacity in Ethiopia may differ from those in Mozambique despite both countries face similar low access and GDP per capita among other things. This could potentially introduce biases in the demand estimates for CIs in Ethiopia. Moreover, the growth rate projections for CIs are derived from the projection of "commercial and public services" sector data, due to the absence of historical CI-specific consumption data. However, the aggregated growth rate derived from the combined "commercial and public services" sector may not reflect the electricity demand evolution of CIs. This is because public services may have different growth rates compared to commercial subsectors, as different sub-sectors within a broad category often exhibit distinct growth dynamics.

Fourth, the use of the MLR model for demand projection also presents limitations. While this model provides interpretability and computational efficiency, it may oversimplify the complex, often nonlinear relationships between electricity demand and its socioeconomic drivers such as GDP, urbanization, and electricity access. The long-term projection horizon (2021–2050) further compounds these uncertainties, as future economic, political, and technological developments could fundamentally alter demand patterns in ways not captured by historical relationships used in the model. Fifth, the spatial demand estimates depend on the quality and resolution of the underlying input datasets, including gridded GDP, IWI, and temperature data. In areas where these datasets are outdated, incomplete, or interpolated, the reliability of projections may be reduced.

Finally, the modeling of temperature-induced demand is based on a linear relationship that assumes a 2 % increase in electricity consumption for every 1 °C rise above a 24 °C baseline. This linear assumption may oversimplify the actual demand response, as it does not account for potential non-linear peaks. The model also does not consider variations in appliance ownership, such as the presence or absence of air conditioning units, which can substantially influence temperature-sensitive demand. These limitations collectively suggest that while the study provides valuable insights for electrification planning, the results should be interpreted as indicative rather than precise projections.

5. Conclusion

This study presents long-term, spatial projections of Ethiopia's electricity demand from 2021 to 2050. It provides both total national and high-resolution spatial electricity demand for three key sectors

relevant to rural electrification planning, under three alternative development scenarios. The study also integrates spatially explicit ambient temperature data and projected temperature rise into the electricity demand projections.

The results show significant growth in demand in all considered scenarios. The RU scenario results in the highest increase, up to 285 % by 2050 compared to the 2021 baseline. This is a 40 % increase over the BAU scenario. This highlights the influence of urbanization on Ethiopia's electricity future. The HEG scenario also projects a large increase in demand (219 %), driven by accelerated economic development. Sectorally, HHs remain the dominant consumer group, but CIs can contribute up to 46 % of local demand where present by 2050.

The spatial analysis uncovers significant geographic disparities in electricity demand evolution. Central regions of Ethiopia, with higher economic status and population density, are projected to transition toward higher consumption tiers (Tiers 3 and 4), while peripheral areas in the Northeast and Southeast are expected to remain at lower demand levels (Tiers 1 and 2). This spatial heterogeneity underscores the limitation of traditional, uniform rural-urban demand classifications. Furthermore, the study uniquely quantifies the impact of rising ambient temperatures on electricity demand. While projected temperature increases contribute only 0.53 % to total national demand, they may increase local demand by up to 22.6 % between 2030 and 2050, thereby validating the necessity of spatially explicit modeling.

Three key policy implications can be drawn from the findings of this study. First, since household electricity demand is projected to range from Tier 1 to Tier 4 across different settlements, and community institutions are expected to contribute up to 46 % of local demand by 2050, Ethiopia's National Electrification Program should be guided by settlement-level, multi-sector demand projections. This approach will be crucial for selecting appropriate electrification solutions, correctly sizing generation capacity, and ensuring investments are aligned with the diverse consumption realities of each region. Second, the RU scenario projects demand in 2050 to be 40 % higher than under the BAU. This underscores the critical need to prioritize early infrastructure, generation, and productive-use support in fast-growing towns and peri-urban areas to meet rising electricity needs. Third, substantial

temperature-driven demand is projected in hot lowland areas (such as Afar, Somali, and Benishangul-Gumuz), potentially reaching up to 22.6 % by 2050. Therefore, electrification planning must integrate local climate differences when designing networks and selecting supply technologies for these regions.

Future research should focus on conducting primary field surveys to better characterize productive use of electricity and community institutions, including sector-specific consumption profiles and growth patterns across different settlement types. Future research should also extend spatial electricity demand projections to include the agricultural sector, which represents a substantial yet underexplored component of rural energy demand in developing countries. Additionally, nationwide least-cost electrification planning should be based on multi-sectoral, spatially differentiated demand as it enables technology selection and sizing decisions based on realistic electricity demand projections.

Credit author statement

Adugnaw Lake Temesgen (ALT): Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Visualization, **Yibeltal T. Wassie (YTW):** Supervision, Writing – review & editing, **Getachew Bekele (GB):** Supervision, Writing – review & editing, **Erik O. Ahlgren (EOA):** Supervision, Writing – review & editing.

Declaration of competing interest

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

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Appendix A. Geospatial datasets used in the analysis

Dataset	Type	Source
Population settlements	Vector	Temesgen et al. [47]
Administrative boundaries	Vector	GADM [78]
Villages and towns	Vector	Geofabrik [58]
Health facilities	Vector	HDX [56]
GDP	Raster	Kummu et al. [50]
IWI	Raster	Lee and Braithwaite [51]
Temperature	Raster	Global Solar Atlas [29]

Appendix B. Electricity demand estimation basis

Table B 1
Multi-tier household electricity demand [52].

MTF daily consumption levels (Wh per HH)	Adapted annual electricity demand (kWh per HH)
$12 \leq \text{Tier 1} < 200$	38.7
$200 \leq \text{Tier 2} < 1000$	219
$1000 \leq \text{Tier 3} < 3425$	807.5
$3425 \leq \text{Tier 4} < 8219$	2125
$\text{Tier 5} \geq 8219$	3000

Table B 2

RAMP configuration parameters for health facilities in urban and rural areas [12].

Urban							
Appliances	Quantity	Power (W)	Operating time range [h]	Random window variation (%)	Functioning cycle [h]	Total operating hours [h]	Random time variation (%)
External light	15	25	16–24	20	3	3	20
Internal light	36	20	8–12,14–24	20	3	12	20
Phone charger	10	5	0–24	20	0.5	5	20
Sterilizer	2	1500	6–22	20	0.5	1	20
TV							
PC							
Fridge	2	250	0–24	20	0.5	–	20
Rural							
External light	3	25	16–24	20	3	3	20
Internal light	7	20	8–12,14–24	20	3	12	20
Phone charger	10	5	0–24	20	0.5	5	20
Sterilizer	2	1500	6–22	20	0.5	1	20
Fridge	2	250	0–24	20	0.5	–	20

Table B 3

RAMP configuration parameters for rural and urban school [12].

Urban					
Appliances	Quantity	Power (W)	Operating time range [h]	Functioning cycle [h]	Total operating hours [h]
External light	4	25	17–06	1	12
Internal light	18	20	7–17	0.5	4
PC	13	50	7–17	0.5	4
TV	3	60	7–17	0.5	2
Rural					
External light	2	25	17–06	1	12
Internal light	4	20	7–17	0.5	4

Table B 4

RAMP configuration parameters for government offices [12].

Urban							
Appliances	Quantity	Power (W)	Operating time range [h]	Random window variation (%)	Functioning cycle [h]	Total operating hours [h]	Random time variation (%)
External light	5	20	16–18	0	1	1	30
Internal light	9	15	16–18	0	1	1	30
Phone charger	4	5	8–18	0	1	5	20
Fridge	2	70	8–18	0	1	3	0
Electronics	5	100	8–18	0	1	5	20
Rural							
External light	2	20	16–18	0	1	1	30
Internal light	3	15	16–18	0	1	1	30
Phone charger	2	5	8–18	0	1	5	20

Table B 5

RAMP configuration parameters for places of worship in urban and rural areas [12].

Urban							
Appliances	Quantity	Power (W)	Operating time range [h]	Random window variation (%)	Functioning cycle [h]	Total operating hours [h]	Random time variation (%)
External light	5	25	17–06	0	1	12	0
Internal light	20	25	18–22	0	1	4	0
TV	1	100	16–21	0	1	4	0.2
PC	3	50	16–21	0	0.5	3	0.2
Rural							

(continued on next page)

Table B 5 (continued)

Urban							
Appliances	Quantity	Power (W)	Operating time range [h]	Random window variation (%)	Functioning cycle [h]	Total operating hours [h]	Random time variation (%)
External light	2	25	17–06	0	1	12	0
Internal light	4	25	18–22	0	1	4	0

Data availability

Data will be made available on request.

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