Addis Ababa University

College of Technology and Built Environment

School of Electrical and Computer Engineering

Long-Term Least-Cost Electrification Pathways For Ethiopia: A Geospatial Modeling Approach

High-Resolution Spatial Analysis to Bridge the Electricity Access Gap

Doctoral Thesis

Adugnaw Lake Temesgen

A dissertation submitted to the Graduate School of Electrical and Computer Engineering in partial fulfillment of the requirement for the Degree of Doctor of Philosophy (PhD) in Electrical Engineering (Electrical Power Engineering).

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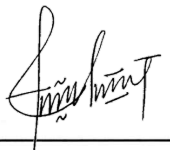

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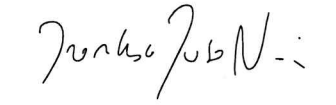

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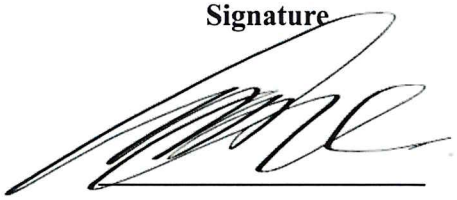

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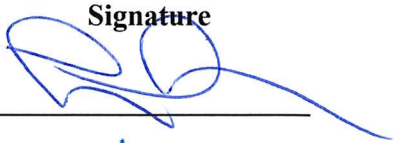

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Declaration

This PhD dissertation is the product of my original and independent work and any material used from other sources has been properly attributed and cited in the text.

Abstract

In 2015, the United Nations adopted the Sustainable Development Goals (SDGs) to guide global development efforts towards 2030. Among these, SDG 7 aims to "ensure access to affordable, reliable, sustainable, and modern energy for all by 2030." Electricity is essential for the development of many sectors, including households, health and education facilities, and productive enterprises. Yet, as of 2022, approximately 685 million people worldwide remained without electricity access, nearly 83% of whom lived in Sub-Saharan Africa, where only about half the population was electrified. In this region, rapid population growth and dispersed settlements further complicate the challenge. Achieving universal electricity access necessitates strategies tailored to the unique context of each population settlement, accounting for settlement distribution, economic activities, and resource availability. To this end, policymakers and planners increasingly employ geospatial and techno-economic assessments to inform energy policies and national electrification targets.

However, geospatial electrification models require large volumes of reliable georeferenced data, from infrastructure locations to electricity consumers, which are often limited or unavailable in many developing countries. This paucity of spatial information, combined with several methodological limitations, can undermine model outcomes. These limitations include: low-resolution data that mask settlement-level variations; simplified demand assumptions that overlook local socio-economic realities; and short-term planning horizons that fail to capture dynamic, long-term investment pathways.

In response, this thesis develops and applies a geospatial framework using the Open-Source Spatial Electrification Tool (OnSSET) to produce phased, least-cost electrification pathways for Ethiopia through 2050. The research is guided by three specific objectives: (1) To analyze how and to what extent geospatial factors affect the feasibility of extending the national power grid to unelectrified settlements. This objective is pursued by conducting a geospatial analysis that quantifies the spatial constraints of grid extension based on factors such as distance from road and substation, terrain slope, elevation, and land cover. The results indicate that geospatial factors may increase grid extension costs by 2.3% to 29% across Ethiopia.

The second specific objective is (2) To develop long-term, spatially disaggregated electricity demand projections for rural electrification planning. Existing literature offers limited insights into spatial heterogeneity in electricity demand, reducing its applicability to spatial electrification planning. This objective is pursued by projecting the electricity demand of households, productive users, and community institutions. Alternative scenarios are developed by considering electricity demand growth in rural areas of developing countries under different drivers of demand, such as population growth, urbanization, rural electricity access, and economic growth, using a multiple regression model. OnSSET is employed to spatially disaggregate electricity demand, using high-resolution data on mean gridded GDP and the International Wealth Index to classify settlements by economic status. The scenario results generate aggregate national electricity demand projections and also show how demand is expected to evolve over time for each consumer group within each settlement. The results show that electricity demand is spatially heterogeneous, with projected household demand ranging from Tier 1 to Tier 4.

The final objective is (3) To explore long-term, least-cost electrification technology mix dynamics and evaluate investment needs to enhance electricity access in rural areas. A geospatial optimization model is developed using OnSSET to determine the optimal electricity supply option that provides electricity at the lowest levelized cost of electricity (LCOE) under varying demand and grid generation cost scenarios. The model integrates spatially disaggregated electricity demand, georeferenced existing grid infrastructures, renewable energy resources (solar, wind, and hydro), geospatial cost penalty factors, and techno-economic parameters. The model identifies the least-cost option for each settlement by comparing the LCOE of grid extension, mini-grid (solar, wind, and hydro), and standalone photovoltaic systems. The results reveal a dynamic technology mix that shifts over time: grid extension can be the least-cost solution for over 82% of the population planned to be electrified by 2030, with its share declining by 2050, while mini-grids become the least-cost option for about 26% of the population. This integrated, geospatial modeling, data-driven approach informs cost-effective, sustainable, and equitable electrification strategies tailored to Ethiopia's diverse regional contexts.

Keywords: Electrification pathways, electricity demand projections, Ethiopia, geospatial modeling, OnSSET, SDG 7, techno-economic assessment.

List of appended papers

The thesis is based on the following appended papers:

Paper I **Adugnaw Lake Temesgen**, Yibeltal T. Wassie and Erik O. Ahlgren, Assessing subnational electricity access using high-resolution datasets: A case study of Ethiopia, 2023 IEEE PES/IAS PowerAfrica, Marrakech, Morocco, 2023, pp. 1-5, doi: https://doi.org/10.1109/powerafrica57932.2023.10363249.

Paper II **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, and E. O. Ahlgren, Analyzing grid extension suitability: A case study of Ethiopia using OnSSET, Energy Strategy Reviews, vol. 52, pp. 101292–101292, Mar. 2024, doi: https://doi.org/10.1016/j.esr.2023.101292.

Paper III **Adugnaw Lake Temesgen**, Basilio Z. S. Tamele, and Erik O. Ahlgren, A high-resolution analysis of electricity demand for informed electrification planning, 2024 IEEE PES/IAS PowerAfrica, Johannesburg, South Africa, pp. 1–5, Oct. 2024, doi: https://doi.org/10.1109/powerafrica61624.2024.10759429.

Paper IV **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, Getachew Bekele, and Erik O. Ahlgren, Long-term spatially explicit electricity demand scenarios for rural electrification: The case of Ethiopia, Energy Strategy Reviews, vol. 62, pp. 101931– 101931, November. 2025, doi: https://doi.org/10.1016/j.esr.2025.101931.

Paper V **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, Getachew Bekele, and Erik O. Ahlgren, Long-term least-cost geospatial electrification planning to bridge the electricity access gap: The case of Ethiopia, Environmental Research: Infrastructure and Sustainability [*Under review*].

Adugnaw Lake Temesgen is the principal author of all papers. Professor Erik O. Ahlgren contributed by providing conceptual ideas, feedback on methodology and discussions, and editing of all papers. Dr. Getachew Bekele contributed by providing feedback, discussions, reviewing and editing papers IV and V. Dr. Yibeltal T. Wassie contributed by providing support in conceptualization, methodology development, discussions, reviewing, and editing paper I, II, IV and V. Basilio Z. S. Tamele contributed with discussion and reviewing of paper III.

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List of Abbreviations

AAGR	Average Annual Growth Rate
AC	Air Conditioning
AfDB	African Development Bank
AICD	Africa Infrastructure Country Diagnostic
API	Application Programming Interface
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BAU	Business as Usual
BPR	Base-to-Peak Ratio
CDD	Cooling Degree Day
CF	Capacity Factor
CI	Community Institution
CIESIN	Center for International Earth Science Information Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DEM	Digital Elevation Model
DRC	Democratic Republic of the Congo
EEU	Ethiopian Electric Utility
EEP	Ethiopian Electric Power
EOG	Earth Observation Group
ESMAP	Energy Sector Management Assistance Program
FDI	Foreign Direct Investment
FDRE	Federal Democratic Republic of Ethiopia
GADM	Global Administrative Areas
GAUL	Global Administrative Unit Layers
GDP	Gross Domestic Product
GEE	Google Earth Engine
GEP	Grid Extension Penalty
GHI	Global Horizontal Irradiance
GHSL	Global Human Settlement Layer
GIS	Geographic Information System

GISEle	GIS for Electrification
GoE	Government of Ethiopia
HEG	High Economic Growth
HH	Household
HRSL	High-Resolution Settlement Layer
HV	High-Voltage
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
IWI	International Wealth Index
LCOE	Levelized Cost of Electricity
LV	Low-Voltage
MAUP	Modifiable Areal Unit Problem
MG	Mini-grid
MILP	Mixed-Integer Linear Programming
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MTF	Multi-Tier Framework
MV	Medium-Voltage
NASA	National Aeronautics and Space Administration
NEP	National Electrification Plan
NOAA	National Oceanic and Atmospheric Administration
NTL	Nighttime Light
O&M	Operations and Maintenance
OnSSET	Open-Source Spatial Electrification Tool
OSM	OpenStreetMap
POW	Places of Worship
PPP	Purchasing Power Parity
PV	Photovoltaic
PU	Productive Use(r)
RAMP	Remote-Areas Multi-energy Systems Load Profiles

REM	Reference Electrification Model
RU	Rapid Urbanization
SA PV	Standalone Photovoltaic
SDG	Sustainable Development Goal
SEforALL	Sustainable Energy for All
SHS	Solar Home Systems
SSA	Sub-Saharan Africa
T&D	Transmission and Distribution
UN	United Nations
VIIRS	Visible Infrared Imaging Radiometer Suite

List of Units

Category	Unit	Description
Power	kW	kilowatt (1 watt x 10^3)
	kWp	kilowatt-peak
	MW	Megawatt (1 watt x 10^6)
	GW	Gigawatt (1 watt x 10^9)
	TW	Terawatt (1 watt x 10^{12})
Energy	kWh	kilowatt-hour
	GWh	Gigawatt-hour
	TWh	Terawatt-hour
Light intensity	$\mu W \cdot cm^{-2} \cdot sr^{-1}$	Microwatts per square centimeter per steradian
Monetary	USD	US dollar
	USD million	1 US dollar x 10^6
	USD billion	1 US dollar x 10^9
	USD/kW	US dollars per kilowatt
	USD/kWh	US dollars per kilowatt-hour
Length	m	meter
	km	kilometer (1×10^3)
Area	km^2	square kilometer

1. Introduction

1.1. Background

Modern energy, particularly electricity, is essential for sustainable socio-economic development. In 2015, the United Nations (UN) adopted 17 interconnected Sustainable Development Goals (SDGs) to guide global development efforts through 2030 [1]. Among these, SDG 7 aims to "ensure access to affordable, reliable, sustainable, and modern energy for all by 2030." This goal is closely interlinked with other goals, exhibiting synergies or trade-offs with around 85% of all SDG targets [2]. Such interconnection underscores the critical role of SDG 7 in enhancing welfare across all scales, from the household to the national level.

Electricity is a critical form of energy that powers nearly all functions of modern society, ranging from essential household functions to large-scale industries [3]. It powers basic household activities such as lighting, cooking, and refrigeration. In countries where traditional biomass remains prevalent, access to electricity can reduce indoor air pollution and its associated health risks [4]. It can also reduce the amount of time spent on the collection of firewood, a burdensome task dominantly undertaken by women and children [5], [6]. Additionally, electricity access supports essential public services such as healthcare and education. It also enables commercial activities and boosts agricultural productivity through irrigation and agro-processing, thereby fueling broader economic development [7]. The cyclical relationship between energy consumption and economic growth is described by the feedback hypothesis, which states that increased energy use stimulates economic growth and, in turn, further increases energy demand [8]. In view of this, electrification is understood to be a critical driver for sustainable rural development [9].

Electrification refers to the provision of electricity to households or communities that previously lacked access to it. Achieving universal electrification in a cost-effective manner requires an integrated strategy that combines centralized grid extension, mini-grids (MGs), and standalone (SA) systems [10], [11]. To support such planning, geospatial electrification models have been developed to enable evidence-based policy and decision-making [12]. These models combine population distribution, energy resources, and infrastructure with techno-economic data to determine the least-cost electrification technology for each settlement [13].

1.1.1. Overview of electricity access in the world

Global efforts to expand electricity access have made considerable progress in recent years. According to the International Energy Agency (IEA), the number of people without access to electricity decreased from 1.14 billion in 2010 to approximately 685 million in 2022 [14]. This corresponds to a rise in electricity access from 84% to 91%. However, progress has been uneven across regions, with some areas achieving near-universal electrification while others continue to lag significantly behind. As of 2022, electricity access reached 99% in Latin America and the Caribbean, 98% in Southeast Asia, and 92% in the Middle East and North Africa [15]. These regions have made substantial strides in providing electricity to their population, largely because of improved infrastructure, better financing mechanisms, and coordinated efforts between governments and international organizations.

In contrast, Sub-Saharan Africa (SSA) has a considerably lower rate of electrification, with only 52% of its population having access to electricity in the same year [16]. This access deficit is especially evident in rural areas, where efforts to bring electricity face challenges owing to high costs, challenging terrain, and sparse population. The IEA has also projected that if current trends continue, approximately 660 million people, or around 8% of the global population, will still lack access to electricity by 2030, with 85% of them living in SSA [14]. This highlights the considerable challenge of achieving universal electricity access on a global scale. Moreover, the global community has not made sufficient progress toward achieving universal access to clean cooking by 2030. It is estimated that 2.1 billion people still rely on polluting fuels and technologies for cooking [17]. The widespread use of traditional biomass fuels in SSA and parts of Asia not only limits access to modern energy but also contributes to severe health impacts, including more than 3 million premature deaths annually attributable to household air pollution [4]. Fig. 1 shows the global distribution of electricity access as a percentage of the population in 2022.

Beyond basic electricity access, disparities in per capita electricity consumption highlight the profound inequalities among nations. Although the global average electricity consumption was approximately 3,500 kWh/year in 2022, substantial disparities exist between developed and developing nations. In the least developed countries such as Burundi, Chad, South Sudan, Yemen, and Ethiopia, consumption is less than 100 kWh/year. Conversely, at the upper end of the spectrum,

nations such as Qatar, Kuwait, and Iceland demonstrate per capita consumption exceeding 15,000 kWh, highlighting profound global inequality in energy utilization [18].

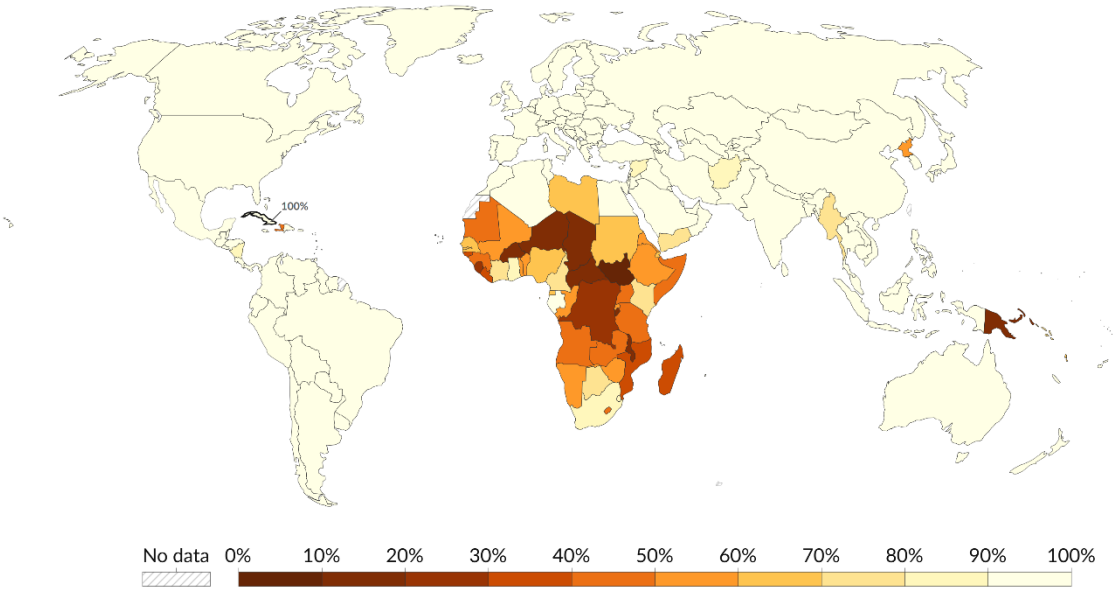

Fig. 1. Global electricity access in 2022, as a percentage of the total population [16].

Another critical aspect of global electricity access is the urban–rural disparity. The SDG 7 tracking report indicates that electricity access in urban areas increased from 96% in 2010 to 98% in 2022, while electricity access in rural areas grew from 73% to 84% over the same period [14]. Despite this progress, disparities in rural-urban access range from a mere 0.3 percentage points in Tunisia to a significant 88.4 percentage points in Equatorial Guinea [15]. Fig. 2 shows the top ten countries with the largest disparities as of 2022, with Equatorial Guinea showing the widest gap (88 percentage points) and Angola the smallest among them (69 percentage points). In countries such as the Democratic Republic of the Congo (DRC), Chad, Equatorial Guinea, and Burundi, the proportion of rural households with access to electricity is less than 2%. The challenge of extending electricity to these rural areas, described as the “last-mile” challenge, involves significantly higher per-connection costs [19].

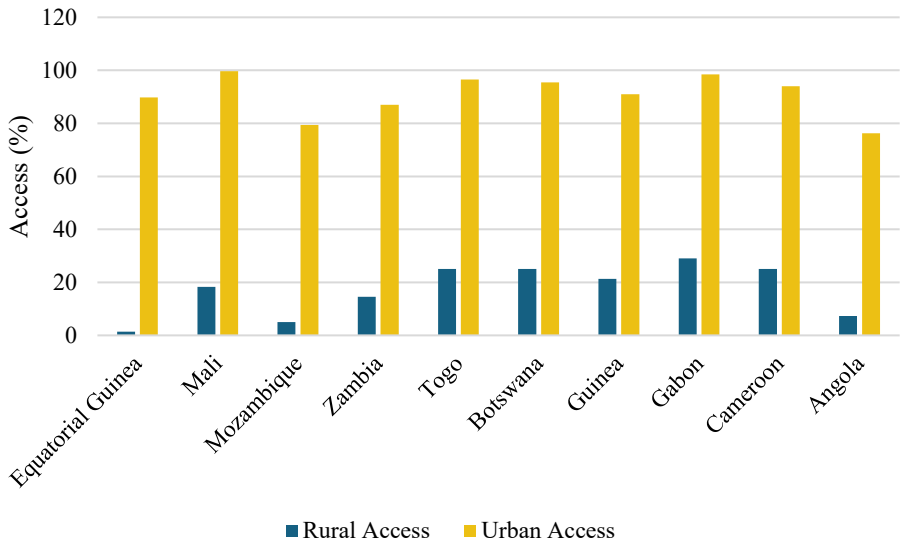

Fig. 2. Countries with the highest rural-urban electricity access disparity in the world in 2022 [15].

1.1.2. Electricity access and consumption trends in Ethiopia

Ethiopia, the second most populous country in Africa with over 120 million people, exemplifies the challenges associated with electrification. Approximately 78% of its population lives in rural areas where electricity access is low and electrification efforts face the greatest challenges [20]. Its national energy mix is overwhelmingly dominated by traditional biomass, which accounts for over 90% of total energy consumption, while electricity constitutes a mere 2% of total energy use [21]. As of 2021, approximately 55 million people in Ethiopia lack electricity access, making it one of the countries with the largest number of people without access globally, after Nigeria (86 million) and the DRC (76 million) [22], [23]. The urban-rural disparity is pronounced, with urban areas having an access rate of 94.3%, compared to only 42.8% in rural areas in 2021 [24], [25]. Regional inequalities are also evident, with electricity access ranging from nearly 99.9% in Addis Ababa and surrounding areas to less than 20% in pastoral regions such as Somali and Afar [26], [27], [28]. Even where households are connected, the electricity supply is unreliable, with frequent blackouts and load shedding exacerbating the country's energy challenges [29].

Per capita electricity consumption in Ethiopia remains among the lowest in the world, at less than 100 kWh/capita/year. This figure is significantly below the African average of 500 kWh and SSA average of 484 kWh [30], [31]. From 2005 to 2021, residential electricity consumption grew by

662%, with an average annual growth rate (AAGR) of 13.5%, whereas the commercial and public service sector grew by 347% (9.8% annually) [32]. These figures reflect rapid demand growth from a very low base, underscoring the scale of Ethiopia's energy poverty. These trends, as illustrated in Fig. 3b, highlight the growth in electricity demand and access to electricity in the country.

Ethiopia's electrification efforts have been guided by the National Electrification Program (NEP 2.0), launched in 2019, which serves as the government's action plan for achieving universal access nationwide [33]. The plan aims to achieve universal access by 2025, with 65% of households to be connected to the national grid and 35% to be served by off-grid solutions such as solar home systems (SHS) and MGs. This integrated approach envisions connecting nearly all of the population residing within 25 km of existing grid lines via grid expansion over the medium to long-term, while remote settlements are served by off-grid systems [22], [33]. Notwithstanding these ambitious objectives, population growth has outpaced the capacity for new grid connections. The country adds approximately 410,000 new households annually, but only about 220,000 new households are connected to the grid each year. This mismatch has widened the access gap, especially in rural areas [34]. The latest reports show that national access remains below 55% (see Fig. 3a) [25]. This gap between targets and actual progress provided the basis for the scenarios and long-term analysis developed in this thesis.

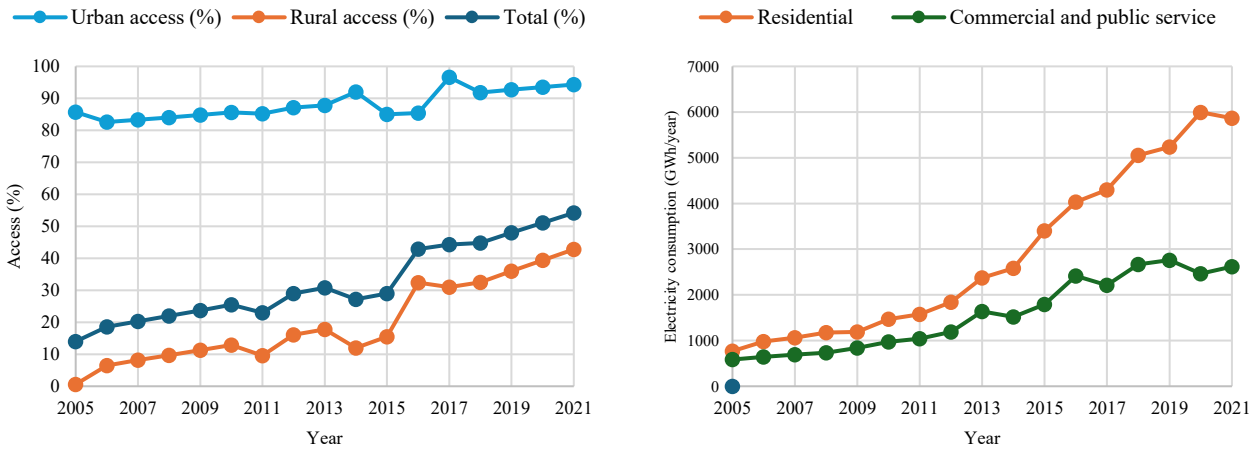

Fig. 3. a) Trends in electricity access in urban, rural, and national access in Ethiopia (left) [25], and b) national electricity access trends and consumption across residential, and commercial and public service sectors in Ethiopia (2005–2021) (right) [25], [32].

1.2. Problem statement

The challenge of limited electricity access in rural areas of developing countries is further compounded by a lack of context-specific electrification plans [35]. Traditionally, grid extension has been considered as the primary pathway to expand electricity access [33], [36]. However, this approach is constrained by geospatial and demographic realities in rural areas. On one hand, from the demand side, rural settlements often have low electricity consumption and high geographic dispersion, which undermines the economic viability of grid-based solutions [37]. On the other hand, from the supply side, the feasibility and cost of grid expansion are strongly influenced by a range of geospatial factors [38]. These include the distance of settlements from substations and road networks, slope and elevation of terrain, and land cover types [10], [39]. These factors directly increase project costs: longer transmission lines raise capital expenditures and energy losses, while rugged terrain and challenging land cover (e.g., water bodies, dense forests) escalate construction, logistics, and maintenance costs [10], [36], [40], [41]. However, a few prior studies do not account these additional costs when evaluating grid extensions [42], [43], [44]. This oversight may lead to an underestimation of the cost of grid extension compared to when all spatial complexities are considered [7], [35]. This leads to a systematic bias in favor of grid extension over potentially more cost-effective, decentralized alternatives such as MGs or standalone (SA) systems.

Even when geospatial factors are included, their influence is diminished by the use of low-resolution population data, which obscures settlement-level heterogeneity [13], [29], [45]. Since geospatial analysis is fundamentally contingent on the resolution of population datasets to identify settlement locations and sizes, low resolution limits the ability to reflect local realities [46]. This reliance on low-resolution data leads to the Modifiable Areal Unit Problem (MAUP), meaning the results can change depending on how the geographic data is grouped or scaled [47]. Higher levels of aggregation smooth out critical variations, thereby underestimating location-specific cost multipliers [48]. Consequently, relying on low-resolution data can lead to an underestimation of grid extension costs. This reinforces a bias toward centralized electrification options that may not be a technically or economically optimal solution [13], [29].

Another drawback of many nationwide electrification studies, as highlighted in the scientific literature, is their predominant focus on supply-side optimization (e.g., technology selection,

investment requirements), while giving little emphasis to the projection of spatial electricity demand [7], [13]. Consequently, spatial demand is often modeled with simplistic, uniform assumptions across all rural and urban households (HHs), applying standardized consumption targets, as defined by the Multi-Tier Framework (MTF) to both categories [29], [49], [50]. However, this approach overlooks the wide variation in electricity consumption that exists within these categories and neglects the electricity needs of productive use(r)s (PUs) and community institutions (CIs) [10], [19], [51], [52]. Such simplifications limit the ability to capture the actual sectoral demand and its evolution over time [53], [54]. In addition, another critical, yet often underexplored, dimension in demand projection is the temperature-driven energy needs. This is particularly relevant in SSA, where rising ambient temperatures are expected to increase electricity demand in climate-vulnerable settlements due to cooling requirements [55], [56].

Furthermore, most existing geospatial electrification studies relatively rely on short planning horizons and provides only a snapshot of the least-cost technology mix for a target year, such as 2030, in line with SDG 7 [13], [29], [57]. Notably, studies have found that 83% of rural electrification studies adopt a planning horizon of ten years or less [58]. However, single target year and short planning horizons are incapable of capturing the dynamic evolution of electricity access pathways, wherein the optimal solution for a given settlement shifts over time in response to demand growth and declining technology costs [59]. For instance, SA systems may be optimal in the short term, but as demand increases and infrastructure expands, MGs or grid extension may become more cost-effective [60]. Consequently, a single-year and short-term planning cannot inform phased, long-term investment strategies required to navigate the multi-decade transition to universal access without risking stranded assets.

Ethiopia's abundant renewable energy resources, including hydropower, wind, and solar irradiation as well as its extensive grid network, contrast sharply with its widespread energy poverty [33], [60]. If this vast energy potential is properly developed and effectively harnessed, Ethiopia could achieve universal electricity access and sustain its long-term socio-economic development.

Therefore, developing an electrification plan that integrates high-resolution population data, existing grid infrastructure, renewable resources, spatiotemporal demand dynamics, and geospatial cost penalties over a long-term dynamic horizon is essential to ensuring that electrification

strategies are cost-effective, sustainable, and contribute to achieving national goals for universal electricity access.

1.3. Research objectives

The main objective of this thesis is to develop and apply a geospatial modeling framework to formulate long-term least-cost electrification pathways for Ethiopia, with a particular emphasis on rural contexts. The study investigates the optimal mix of electrification technologies suitable for diverse geographic and socio-economic contexts, thereby contributing to evidence-based policymaking for achieving universal electricity access. This overarching objective is pursued by addressing the following three research objectives (ROs).

Objective 1: To estimate the share of the population with electricity access at subnational and national levels using nighttime light (NTL) data and to analyze the influence of geospatial factors to grid extension in Ethiopia (RO1) (**Papers I-II**). These access and suitability estimates set the baseline for the demand and supply analysis.

This objective addresses the following research questions.

- How can the level of access to electricity be determined at subnational and national levels from NTL data, and how does it compare to the national statistics?
- How do the seasonal trends and temporal patterns of NTL vary between different states at the subnational level?
- How and to what extent do geospatial factors influence the suitability of grid extension across population settlements?

Objective 2: To develop long-term, spatially explicit electricity demand projections for rural electrification planning (RO2) (**Papers-III and IV**). In response to the identified limitation of simplistic rural-urban demand dichotomies, this objective develops a multi-sectoral spatial demand projection. The resulting spatial demand projections were subsequently employed to evaluate settlement-level least-cost supply options.

This objective is guided by the following research questions.

- 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 electricity demand?

Objective 3: To explore long-term, least-cost electrification technology mix dynamics and evaluate investment needs to bridge the electricity access gap in rural areas (RO3) (**Paper V**). Building on the findings from the preceding objectives, this culminating objective addresses the central research goal of identifying optimal long-term electrification pathways under different scenarios.

This objective seeks to answer the following questions.

- What are the least-cost electrification options, and how do their relative shares change under different scenarios of electricity demand and grid generation costs?
- How does the viability of grid and off-grid solutions change across geographical locations and over time?
- How do investment requirements for each electrification technology evolve over the planning horizon?

1.4. Significance of the study

This research addresses key challenges in electricity access planning, particularly in a country like Ethiopia. Here, the coexistence of vast renewable energy potential (solar, wind, and hydro) with significant gaps in rural electricity access means that the lack of a long-term electrification strategy can lead to inefficient investments and unsustainable solutions, resulting in financial burdens for both the government and rural communities. Thus, a comprehensive understanding and strategic planning of rural energy systems is essential for achieving universal electricity access in a cost-effective and sustainable manner.

This research is particularly important due to its focus on developing long-term rural electrification strategies and an in-depth evaluation of the cost-optimal technology mixes and investment needs based on local resource availability, spatio-temporal electricity demand, and techno-economic

parameters. Developing a long-term national rural electrification plan is an important part of the modeling and planning work that provides a rational basis for informed decision-making. It enables policymakers to establish the policy direction and develop a clear program-roadmap for achieving universal energy access.

The outcomes of the long-term electrification scenarios generated in this research offer quantitative targets for the optimal technology mix needed towards achieving universal electricity access in Ethiopia (directly benefits SDG 7 and co-benefits SDG 13). These results inform decisions on when, where, and how much to invest in electricity supply technologies across diverse rural settlements. This geospatial electricity access planning ensures (i) sufficient supply options to meet the projected demand across regions, (ii) optimized technology placement based on geospatial suitability, (iii) flexibility to accommodate future evolution in demand, and (iv) cost-effective investment strategies that minimize stranded assets and ensure equitable energy access.

This research addresses a critical knowledge gap in the development and application of electrification modeling tools by providing a practical framework for spatially explicit analysis and contributing to local capacity building. The developed framework can be used by energy planners and researchers to explore electrification pathways at both regional and national levels. Moreover, the study is adaptable to other developing countries facing similar electrification challenges. In such cases, the developed methodologies and insights can be transferred and adapted accordingly.

1.5. Contents of papers in the thesis

The main scientific contributions of this work, which are used to address the ROs, are outlined below. The ROs are addressed through five academic papers appended to this thesis. Their content and connections to each RO are expanded below. A summary of the relations between each paper and its corresponding RO is provided in Table 1.

Paper I

> **Adugnaw Lake Temesgen**, Yibeltal T. Wassie and Erik O. Ahlgren, Assessing subnational electricity access using high-resolution datasets: A case study of Ethiopia, 2023 IEEE PES/IAS PowerAfrica, Marrakech, Morocco, 2023, pp. 1-5, doi: https://doi.org/10.1109/powerafrica57932.2023.10363249.

Content: It focuses on assessing electricity access at subnational and national levels in Ethiopia. It leverages high spatial resolution datasets, specifically NTL imagery, WorldPop population counts, and administrative boundaries (level 1), to provide better estimates. The paper compares NTL-derived national electrification rates with the World Bank national statistics and highlights discrepancies in electricity access among regions at the subnational level. This paper provides insights for RO1.

Paper II

> **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, and E. O. Ahlgren, Analyzing grid extension suitability: A case study of Ethiopia using OnSSET, Energy Strategy Reviews, vol. 52, pp. 101292–101292, Mar. 2024, doi: https://doi.org/10.1016/j.esr.2023.101292.

Content: This paper develops a relative grid extension suitability map across Ethiopia using the OnSSET (Open-Source Spatial Electrification Tool) model. It delineates population settlements/clusters using HRSL population data and identifies electrified and unelectrified population using annual median Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) NTL, and as urban or rural based on population density and settlement size. The study identifies geographic areas where the extension of the existing national grid is most suitable, semi-suitable, and less suitable based on a composite assessment of geospatial factors, including terrain, distance from road and substation, and land cover types. These geospatial factors aggregately could raise grid extension investment costs by 2.3% to 29% across Ethiopia, emphasizing that distance from substations significantly contributes to the grid extension spatial cost penalty. The generated population settlements were used in subsequent studies, and grid extension penalties were also used in Paper V. This paper contributes to addressing RO 1 and lays the foundation for ROs 2 and 3.

Paper III

> **Adugnaw Lake Temesgen**, Basilio Z. S. Tamele, and Erik O. Ahlgren, A high-resolution analysis of electricity demand for informed electrification planning, 2024 IEEE PES/IAS PowerAfrica, Johannesburg, South Africa, pp. 1–5, Oct. 2024, doi: https://doi.org/10.1109/powerafrica61624.2024.10759429.

Content: It offers a high spatial resolution analysis of electricity demand in Ethiopia, targeting demand of HHs and CIs. The HH demand is assessed through the MTF, while the electricity needs of CIs, including health facilities, educational institutions, place of worship and government offices, are estimated using the Remote-Areas Multi-energy systems Load Profiles (RAMP) stochastic model. The paper highlights regional variations in electricity demand across the country, identifying patterns of demand and the heterogeneity of electricity needs at the local level. Its findings underline the necessity of tailored electrification solutions that address specific demand characteristics of various settlements to ensure cost-effective electrification strategies. This paper provides insights into RO2.

Paper IV

> **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, Getachew Bekele, and Erik O. Ahlgren, Long-term spatially explicit electricity demand scenarios for rural electrification: The case of Ethiopia, Energy Strategy Reviews, vol. 62, pp. 101931– 101931, November. 2025, doi: https://doi.org/10.1016/j.esr.2025.101931.

Content: Paper IV delves into long-term projections of electricity demand in Ethiopia, considering three different scenarios: Business-as-Usual (BAU), High Economic Growth (HEG), and Rapid Urbanization (RU). The study incorporates spatial and temporal dynamics in electricity demand projections for three key consumer groups in rural areas, including HHs, PUs, and CIs, as well as factoring in the influence of temperature rise on electricity demand. The results indicate a substantial rise in electricity demand by 2050 under all scenarios, with the RU scenario seeing the largest increase in demand. Significant spatial variations in demand are evident, with household demand ranging from Tier 1 to Tier 4. The paper also highlights the importance of considering spatial disparities in demand for effective electrification planning. This paper lays the foundation for answering ROs 2 and 3.

Paper V

> **Adugnaw Lake Temesgen**, Yibeltal T. Wassie, Getachew Bekele, and Erik O. Ahlgren, Long-term least-cost geospatial electrification planning to bridge the electricity access gap: The case of Ethiopia, Environmental Research: Infrastructure and Sustainability [*Under review*].

Content: Paper V develops a long-term geospatial electrification strategy for Ethiopia, focusing on identifying a cost-optimal energy access solution at the settlement level. The study evaluates and compares multiple electrification technologies, including grid extension, MGs (hydro, solar PV, and wind), and SA PV systems. By integrating high spatial resolution data on population distribution, existing infrastructure, renewable energy resources, and spatially disaggregated electricity demand projections, the paper identifies the least-cost electrification solutions at time-steps between 2021 to 2050. The findings directly contribute to answering RO3.

Table 1. The relation between each research objective and appended paper.

Research Objective (RO)	**Paper**				
	Paper I	**Paper II**	**Paper III**	**Paper IV**	**Paper V**
RO1: To estimate the share of the population with electricity access at subnational and national levels using nighttime light (NTL) data and to analyze the influence of geospatial factors to grid extension in Ethiopia	■	■			
RO2: To develop long-term, spatially explicit electricity demand projections for rural electrification planning			■	■	
RO3: To explore long-term, least-cost electrification technology mix dynamics and evaluate investment needs to enhance electricity access in rural areas					■

Other publications not included in this thesis

While the research presented in this thesis draws only on the five papers, the author has engaged in, and contributed to, other academic publications during the course of this PhD journey. These works are listed below.

I. **Adugnaw Lake Temesgen**, G. Bekele, V. C. Broto, and Y. Mulugeta, "A comprehensive exploration of renewable energy education landscape in Ethiopian public universities," *IEEE PES/IAS PowerAfrica*, Johannesburg, South Africa, pp. 1–5, Oct. 2024, doi: https://doi.org/10.1109/powerafrica61624.2024.10759497.

II. **Adugnaw Lake Temesgen** and Getachew Bekele, "GIS-based assessment of economically feasible off-grid mini-grids in Ethiopia," *Discover Energy*, vol. 5, no. 1, May 2025, doi: https://doi.org/10.1007/s43937-025-00073-9.

III. Mulualem G. Gebreslassie, Getachew Bekele, Solomon T Bahta, Akatew H Mebrahtu, Amare Assefa, Fana F Nurhussien, Dawit Habtu, **Adugnaw Lake**, Vanessa Castan Broto, and Yacob Mulugetta., "Developing community energy systems to facilitate Ethiopia's transition to sustainable energy," Energy Research & Social Science, vol. 117, pp. 103713–103713, Aug. 2024, doi: https://doi.org/10.1016/j.erss.2024.103713.

IV. B. Z. Salvador, J. Ntaganda, **A. L. Temesgen**, A. J. Tsamba, and E. O. Ahlgren, "Investigating Households and Productive use Electricity Demand Patterns in Rural Mozambique," 2024 IEEE PES/IAS PowerAfrica, Johannesburg, South Africa, pp. 01–05, Oct. 2024, doi: https://doi.org/10.1109/powerafrica61624.2024.10759452.

1.6. Thesis outline

The outline of the remainder of this dissertation is as follows:

Chapter 2 provides a review of the literature on geospatial electrification planning. It covers the reconceptualization of electricity access metrics, methods for electricity demand estimation, technology options, a comparative analysis of planning models, a synthesis of case studies, and the planning and implementation challenges of rural electrification programs.

Chapter 3 examines current electricity access levels at national and subnational scales using NTL data, and evaluates the influence of geospatial factors, such as terrain, land cover, and infrastructure proximity, on the suitability and cost of grid extension.

Chapter 4 focuses on developing long-term settlement level demand projections for key rural electricity consumers, including households, productive uses, and community services under alternative development scenarios. It also examines the potential effects of temperature rise in future electricity demand in Ethiopia. The results are validated by comparing them against existing studies, with a discussion on the reasons for any deviations and the strengths of the followed approach.

Chapter 5 addresses the core objective of the dissertation by investigating long-term, least-cost electrification options at settlement level. It integrates the findings from Chapters 3 and 4, including grid extension spatial cost penalty factors and electricity demand scenarios, to propose optimal strategies for achieving improved electricity access in Ethiopia. This involves determining the most cost-effective mix of electrification technologies (e.g., grid extension, MGs, SA system s) to meet projected demand under low and high grid generation cost scenarios.

Chapter 6 summarizes the main findings of the work presented in this dissertation. It also presents the conclusions, key contributions, highlights the limitations of the study, and identifies topics for future research in the field of geospatial electrification planning.

2. Geospatial rural electrification planning: A literature review

This chapter reviews existing studies relevant to the scope of the thesis. It focuses on the reconceptualization of electricity access metrics, electricity demand estimation and projection, technology choices, geospatial electrification planning models, case studies, planning and implementation challenges that shape rural electrification programs.

2.1. Reconceptualizing electricity access

A fundamental question within the energy access literature is the very definition of "access": *what does it truly mean to have access to electricity?* Traditionally, electricity access has been measured using a simplistic binary indicator. This approach classifies a population as either connected or not, considering a household electrified as long as any kind of connection is present, regardless of its quality, reliability, or capacity. However, this metric fails to capture critical dimensions of electricity service, particularly its quality, reliability, and availability [5]. This phenomenon is evident from real-world scenarios where a household may have power but for only a few hours a day, or experience frequent and unpredictable outages that limit its practical value [61].

In response to these shortcomings, the World Bank's Energy Sector Management Assistance Program (ESMAP), in collaboration with its partners, introduced the MTF for measuring energy access [62]. The MTF defines access based on multiple attributes, including capacity, duration, reliability, quality, affordability, legality, and safety [63]. This multidimensional approach provides a more realistic assessment of electricity services. It classifies households' electricity use into tiers ranging from Tier 0 (no access) to Tier 5 (full access) [34]. Within this framework, a household is considered to have basic electricity access if it reaches at least Tier 1 [19]. Tier 1 supports basic services such as task lighting and phone or radio charging. More specifically, Tier 1 corresponds to approximately 12 Wh/HH/day, alongside a minimum of four hours of supply during the evening [61].

2.2. Electricity demand estimation and projection

Estimating and projecting electricity demand is crucial for effective rural electrification planning, as it determines technology choice, generation capacity, and investment requirements [10]. Studies have emphasized that electrification outcomes are highly sensitive to assumptions about future

demand. A large-scale sensitivity analysis by Korkovelos et al. [10] identified that electricity demand is the single most influential driver of both total investment needs and supply technology mix. Similarly, Mentis et al. [45] showed that as household electricity consumption rises, the least-cost electrification strategy shifts from decentralized to centralized systems. At a low demand level (Tier 1), SA systems are the dominant solution, accounting for 80% of new connections, while grid extension accounts for the remaining 20%. At a higher consumption level (Tier 5), grid extension becomes the most viable option for 78% of new connections, while the share for MGs and SA systems diminishes to 16% and 6%, respectively.

Despite this sensitivity, the most common approach in countrywide geospatial studies has been the use of simplified, MTF-based per-capita consumption targets. These targets are often assigned uniformly across all urban and rural settlements. For instance, Mentis et al. [13] projected Nigeria's 2030 demand by assigning fixed values of 170 kWh/person/year (Tier 3) for rural areas and 350 kWh/person/year (Tier 4) for urban areas. Comparable urban-rural demand approaches have been applied in electrification studies of Ethiopia [29], Cameroon [49], Burkina Faso and Côte d'Ivoire [50], among others. In such cases, total demand is derived by multiplying projected population, estimated using national urban and rural demographic growth rates, by fixed per capita consumption values corresponding to assumed access tiers [10]. This approach regards electricity demand as a fixed, exogenous parameter, thereby limiting its capacity to capture demand as a dynamic outcome influenced by endogenous processes such as economic development, urbanization, and evolving service needs. Crucially, a single per-capita estimate fails to capture the substantial heterogeneity in income levels, economic activities, and spatial settlement patterns that exists not only between but also within urban and rural areas.

In response to these limitations, a growing body of research has proposed more spatially and socio-economically disaggregated demand modeling approaches. Dagnachew et al. [64] have disaggregated household (HH) electricity demand across SSA into five income-based tiers using the MTF in both rural and urban areas. In addition, Korkovelos et al. [10] and Khavari et al. [47] introduced a highly spatially disaggregated HH demand methodology. They differentiated MTF-based HH demand into nine categories by integrating gridded GDP and poverty level data. These approaches enable more realistic modeling of demand variations and enable electrification strategies to be better tailored to the unique economic contexts of different settlements [59], [65].

While recent advancements have introduced more disaggregated models for household demand, a significant component of local electricity needs remains overlooked in many nationwide studies. This includes PUs and CIs, which represent a substantial portion of local electricity consumption [19]. PU refers to any application of electricity that generates income or enhances productivity, such as small-scale manufacturing (welding, carpentry) to retail services (refrigeration, lighting for shops). Community loads, meanwhile, encompass public institutions such as schools, health clinics, and administrative buildings [7].

These consumer groups function as essential anchor loads that improve the economic viability of capital-intensive decentralized systems like MGs [66]. Hartvigsson et al. [51] found that PUs accounted for approximately 25% of the customer base and 44% of the operator's income in an off-grid MG in Tanzania. Similarly, Wassie and Ahlgren [52] reported that PUs and CIs together contribute to around 60% of the load supplied by a MG, despite representing only a quarter of the customer base in rural Ethiopia. In a study of Kenya, Falchetta et al. [67] showed that the non-residential sectors contributed approximately 53% of the total yearly latent electricity demand in areas lacking electricity access. Dagnachew et al. [68] further estimated that demand from home-based small businesses in SSA could increase HH electricity consumption by up to 50%.

To capture these diverse demand components, several studies have employed bottom-up, end-use modeling approaches grounded in community-level surveys [19], [41], [69]. These surveys collect data on appliance ownership, usage frequency, daily usage patterns, and other relevant details. To capture uncertainties associated with consumer behavior, stochastic tools such as the Remote-Areas Multi-energy Systems Load Profiles (RAMP) model have been introduced [70]. RAMP enables the generation of realistic, high-resolution (in minute) load curves from limited, interview-based datasets, thereby bridging the gap between data scarcity and the need for detailed demand profiles [71], [72].

Furthermore, ambient temperature is an additional but underexplored factor that influences electricity demand. Studies have shown a strong correlation between rising ambient temperatures and increased electricity consumption, particularly driven by the need for space cooling and refrigeration [55]. For example, in Jordan, average electricity demand increased by approximately 11% due to elevated temperatures between 2007 and 2016 [73]. Similarly, studies in India and

Texas have shown that a 1°C increase in ambient temperature above a 24°C baseline resulted in a 2% and 4% increase in electricity demand, respectively [56].

2.3. Energy supply options for rural electrification

The literature emphasizes that no single technology can universally deliver cost-effective electricity access [45], [49], [60]. Instead, a mix of grid extension, MGs, and SA systems is becoming increasingly the most effective approach, with the optimal choice depends on local contexts and national policy objectives [29].

2.3.1. Grid extension

Grid extension has long been regarded as the archetypal mode of electrification, particularly in countries with established national utilities and significant centralized generation capacity [36]. It involves expanding bulk power systems via high-voltage (HV) and medium-voltage (MV) transmission and distribution networks to reach unelectrified areas [38]. The primary advantage of grid is its capacity to provide electricity for a wide spectrum of uses, ranging from basic household lighting to heavy industrial loads [29], [36]. With respect to its cost-effectiveness, however, it is highly dependent on a combination of geospatial and socio-economic factors. Studies have shown that areas with high population density, short distances to existing grid infrastructure, and concentrated electricity demand are best suited for this approach due to economies of scale [11], [13], [38]. In such contexts, grid extension offers lower costs per connection and reduces technical losses. Conversely, in sparsely populated or remote regions, the economic viability of grid extension diminishes significantly. National utilities often find it economically unviable to serve these areas due to a combination of high capital cost per connection, low energy demand, dispersed settlement patterns, and increased transmission losses over long distances [74]. Szabó et al. [75] emphasized that grid extension can be the least-cost choice when anticipated electricity loads are substantial enough to justify new infrastructure. Similarly, other studies emphasize that, given the large upfront capital requirements, large positive effects must be evident to justify such investments [76]. Moreover, grid extension is characterized by long planning and construction timelines, which can delay progress toward universal access goals, particularly in challenging or remote areas [77].

2.3.2. Mini-grids

Mini-grids (MGs) have emerged as a critical solution for providing electricity to communities where grid extension is neither technically nor economically feasible [78]. Their capacities range from a few kilowatts to several megawatts, making them suitable for areas with moderate population and economic growth [3], [79]. MGs integrate a centralized power source, such as solar photovoltaic (PV), diesel, or hydropower, with a distribution network to serve multiple customers within a specific area [41]. The rapid uptake of MGs from 2010 to 2022 was driven by large cost declines in core components and optimization in system performance. The price of PV solar panels, for example, declined by 89% during that period. Also, the prices for small wind turbines decreased by 49% to 64% [80]. These developments, coupled with advancements in battery energy storage systems, have enhanced the reliability and dispatchability of MGs [81], [82]. This has made renewable-based MGs economically viable in a growing number of contexts. Their level of service is of a quality appropriate not only for fulfilling the basic needs of household appliances but also for supporting productive activities such as milling, welding, refrigeration, or irrigation pumping and community loads like schools and health clinics [83], [84], [85]. Their deployment is undertaken by various stakeholders, including public utilities, private firms, communities, and public-private partnerships [86], [87].

2.3.3. Standalone systems

In contrast, standalone photovoltaic (SA PV) systems are a small scale, household level solution designed to provide basic energy services in remote, sparsely populated areas [13]. These systems are most commonly solar PV based, usually coupled with small battery storage. SA systems generally range up to a few hundred watts, sufficient to power essential loads such as lights, phone chargers, radios, and small appliances [3]. Their relatively low cost and simple installation make SA systems the first point of access to electricity for many remote, low-income families. While they can reliably power basic appliances and improve quality of life, their efficacy in fostering broader development has been questioned due to their high unit cost of electricity and low service level. Their limited capacity, in particular, often restricts economic development and productive use opportunities [88]. Therefore, SA systems are best understood as a transitional solution. They serve the most remote population with low electricity demand, acting as a bridge until MGs or grid extensions become viable as demand grows.

2.4. Geospatial electrification planning models

To navigate the complex trade-offs between electrification options, a range of geospatial electrification models have been developed [13]. These models identify the optimal mix of technologies for a given region based on a key metric such as the levelized cost of electricity (LCOE) [89]. Unlike optimization tools such as HOMER, which optimizes the configuration of an energy system for a single settlement, geospatial electrification models are designed to evaluate thousands of settlements simultaneously [45]. To do so, these models integrate the spatial dimension of critical factors such as population distribution, renewable energy resources, existing infrastructure (such as roads and grid lines), and other geographic information with key cost-related indicators, including technology costs, fuel prices, and specific energy access targets [10]. By processing these combined datasets, the models identify the optimal mix of electrification options, ranging from grid extension to MGs and SA systems, that provide electricity at the lowest LCOE while meeting projected demand [29]. Several geospatial electrification models have been developed and applied to support least-cost rural electrification planning at local, national, and sub-continental scales. Some of the most prominent models include IntiGIS, GEOSIM, Network Planner, Reference Electrification Model (REM), Open-Source Spatial Electrification Tool (OnSSET), and GISELe (GIS for Electrification).

IntiGIS

IntiGIS is a modular framework developed by gTIGER, built on the SOLARGIS platform and implemented as a plug-in within the ArcGIS environment [90]. The model was designed to compare grid extension with decentralized options such as SA systems (solar PV, wind, diesel), MGs (diesel and hybrid configurations such as PV-diesel and wind-diesel) [91]. To perform its analysis, IntiGIS requires geospatial data on consumer locations, renewable resource availability, and a set of techno-economic parameters for each technology, discount rates, and component lifetimes [90]. The principal strength of IntiGIS lies in its flexibility and its design as a rapid assessment tool, capable of quickly comparing energy supply options and performing sensitivity analyses [92]. Although the tool is freely distributed, its dependency on proprietary ArcGIS software has constrained its widespread adoption, thereby limiting its visibility in the broader academic community [10].

GEOSIM (Geographic Simulation for rural electrification)

GEOSIM is a commercial/consultancy-oriented suite developed by IED Solutions [93]. It operates on the Manifold GIS platform and provides a modular, GIS-centered methodology for stepwise rural electrification planning, from settlement mapping and demand forecasting to network design and techno-economic ranking of alternatives [10]. Its core objective is to generate optimized electrification scenarios that prioritize socio-economic impact, a feature that distinguishes it from models focused solely on cost minimization [19]. The model first identifies and prioritizes "Development Poles", settlements with high socio-economic potential, and their surrounding "hinterlands" [94]. After this strategic prioritization and a subsequent demand, the model determines the least-cost supply option among grid extension, diesel, wind, biomass, hydro MGs, and SA PV systems [92]. However, a significant limitation noted in comparative analyses is its lack of capability to simulate solar-based hybrid MGs [95].

Network Planner

Network Planner (NP) is a web-based tool developed at Columbia University's Earth Institute/Sustainable Engineering Lab for planning from the community to national scale [96], [97]. NP evaluates and identifies the least-cost options among grid extension, solar, and diesel MGs, and SA PV systems [42], [98]. NP integrates demographic, techno-economic, and geospatial data to generate cost-optimized electrification scenarios within a defined planning horizon [35]. The tool's grid-routing relies on a minimum-spanning-tree (MST)–based heuristic applied cluster-by-cluster to interconnect settlements with radial feeders [7]. The tool's simple interface and low data requirements make it suitable in data-scarce environments. However, NP lacks support for other technologies such as wind or hydro MGs, limiting its applicability in areas with diverse renewable energy resources [43], [99].

Reference Electrification Model (REM)

The REM is a high-resolution tool developed by the Massachusetts Institute of Technology (MIT) and Universidad Pontificia Comillas [100]. REM is designed to identify the least-cost electrification option by optimizing SA systems, MGs, and grid extension [101]. A key distinction of REM is its high spatial resolution approach; rather than operating at the aggregated village or settlement level, it models electrification at the level of individual consumers and buildings [102].

REM clusters individual consumers to minimize total system cost and then designs MV/low-voltage (LV) networks, producing least-cost on-grid/off-grid configurations given inputs such as building locations, resource and topography layers, demand, and costs [103]. The model's high temporal resolution is another distinguishing feature; it conducts hourly demand simulations and can differentiate between critical and deferrable loads [36]. This enables a more detailed reliability analysis and a better assessment of the integration of variable renewable energy sources, aligning its capabilities more closely with detailed dispatch models [90]. However, this granularity comes at the cost of immense data and computational requirements. It requires extensive input data, including geo-tagged household coordinates, detailed hourly load profiles, and high-resolution topographical data, which are often unavailable in many developing countries. This, combined with its proprietary nature, restricts its applicability and adoption within academic and open-access planning frameworks.

OnSSET (Open-Source Spatial Electrification Tool)

OnSSET is an open-source, Python-based model developed at KTH's Division of Energy Systems Analysis in collaboration with multiple partners [13], [29]. It is one of the most widely used geospatial tools in academia and by international organizations such as the IEA and World Bank [104]. OnSSET leverages a combination of geospatial, socio-economic, and techno-economic data to identify the least-cost technology option for each settlement based on a predefined access target and planning horizon [11], [45]. The tool identifies the least-cost electrification option—be it grid extension, MG (solar PV, wind, hydro, or diesel), or SA system (SA PV or diesel)—to satisfy the electricity demand for a given location [10], [105]. The model also determines the generation capacity and associated investment requirements under alternative scenarios [13], [46]. The tool's open-source architecture and accessibility via GitHub have greatly facilitated its adaptation to diverse contexts, making it a preferred tool for both academic and policy applications [71], [106]. This accessibility and flexibility have led to its widespread adoption in a multitude of national contexts [13], [29]. Its ability to integrate multiple open-source data sources and its robust scenario analysis capabilities for countrywide electrification have made it a preferred tool for both research and policy development [49].

GISEle (GIS for electrification)

GISEle is a more recent addition to the suite of geospatial electrification tools. It is an open-source, Python-based framework developed at Politecnico di Milano (Energy4Growing) [19]. It covers three core steps of rural electrification: (1) selecting between on- and off-grid via optimization, (2) sizing hybrid microgrids (PV, wind, hydro, diesel, and batteries) under multi-year planning, and (3) designing MV distribution [89]. It clusters settlements with density-based clustering (DBSCAN), builds cost-weighted graphs of the terrain, and derives least-cost feeders using Dijkstra with Steiner-tree/MST approximations. Furthermore, GISEle enhances its modeling capabilities by integrating hourly resolution electricity demand data such as that provided by the RAMP model. The tool also interfaces with the Soil and Water Assessment Tool (SWAT) to facilitate the sizing of hydropower systems [41]. GISELe's strength is its algorithmic rigor and open availability, making it attractive for detailed network design studies. However, its focus on localized network design limits its applicability for national-level strategic planning.

2.4.1. Comparison of prominent models

This section provides a comparative overview of some of the most widely used or up-to-date geospatial electrification planning models. These include GEOSIM, Network Planner, REM, OnSSET, and GISEle. While all geospatial electrification models address the fundamental question of where grid and off-grid solutions are most cost-effective, they differ considerably in their underlying methodologies, data requirements, technology scope, spatial resolution, and accessibility, making them suitable for different planning contexts [90]. Table 2 provides a comparative summary of these models based on key criteria: input platform, spatial resolution, grid-extension methodology, off-grid technology scope, and others.

Table 2. Comparative overview of selected electrification planning models

Criteria	**GEOSIM**	**Network Planner**	**REM**	**OnSSET**	**GISEle**
Platform	GIS-based software (Manifold)	Web-based portal	Web/Python	QGIS plugin + Python	Python
Spatial resolution	Local demand centers/ development poles	Local demand centers	Individual households/buildings	Population clusters	Population clusters

Geographical /spatial Coverage	Local, national	Local, national	Local, national	Local, national, regional	Local, subnational
Grid-extension algorithm	Based on distance to substations, demand size, investment budgets, and available energy on the grid	Minimum spanning tree (graph theory)	MILP & heuristic	Tree-search with locality-sensitive hashing	Steiner-tree/Dijkstra (graph theory)
Off-grid options	SA PV and MGs based on hydro, solar, wind, biomass and diesel	Solar PV (SHS), solar PV MGs, diesel MGs	SA PV, solar PV MGs, diesel MGs	SA (PV, diesel), MGs (solar PV, wind, hydro, diesel)	MGs (solar PV, wind, hydro, diesel), hybrid systems
Geospatial cost penalties	None	None	Terrain penalties	Includes terrain, substation and road distance, and land cover cost	Includes terrain, road distance, and land cover cost.
Time-step	Single time-step	Single time-step	Single time-step	Multi-time steps	Single time-step
Data & computational intensity	Medium	Low	Very High	Medium-High	Medium-High
Accessibility	Proprietary	Free (non-open-source code)	Proprietary	Free and open-source code	Free and open-source code
Main outputs	Identification and ranking of priority "development poles", estimated electric demands least-cost optimized technologies (grid network and decentralized solutions)	Estimated demand, least-cost optimized solutions, a map of the projected MST-based grid network (MV or LV lines) and	Optimal generation mix and network layout for grid and off-grid MGs, total cost breakdowns, generation and storage specifications	Least-cost electrification options, capacity and investment requirements	Least-cost electrification options, capacity and investment requirements, designed network topology for both LV distribution and MV grid connection

		detailed cost breakdowns			
Limitations	Limited studies in the academic and scientific community	It does not support evaluating wind or hydro mini-grids	Requires extensive input data, and significant computational resources	Does not capture temporal variability of demand and supplies, does not model electric networks	Limited studies in the academic and scientific community; Limited scalability

2.5. Geospatial electrification planning case studies

A growing body of case studies demonstrates the application of geospatial models to local and national electrification planning. Kemausuor et al. [7] applied the NP tool to 2,600 unelectrified communities in Ghana over a 10-year planning horizon. The model used geospatial, socio-economic, demographic, and cost data to identify the cost-optimal technology option for each community. With a base scenario that included a 100% penetration rate and an average household demand of 150 kWh/year for communities with population under 500, the analysis found that grid extension was the optimal solution for more than 85% of communities in each region. Off-grid technologies were recommended for the remaining communities. The authors explain the high share of grid extension due to the extensive pre-existing grid network coverage over the country.

Similarly, the NP model was used for a nationwide analysis in Nigeria over a 17-year planning period, from 2013 to 2030 [35]. The model used demographic, socio-economic, and geospatial data from all 774 local government areas, with an assumed average household demand of 330 kWh/year. The nationwide analysis yielded an even more grid connection outcome. The results reveal that by 2030, 98% of unelectrified communities would be best served by grid extension, with only 2% suited for MGs. The author attributes the dominance of grid extension in this context to high population density.

The REM was applied on a case study area (65 km x 40 km) that is assumed to be representative of rural areas in many SSA countries [36]. This study, also over a 10-year horizon, operated at the individual consumer level, analyzing 52,709 distinct buildings with unique hourly demand profiles

for 17 different customer archetypes. The study's least-cost plan determined that grid extension was the optimal solution for 51% of consumers, with MGs and SA systems being more suitable for the remaining 17% and 33%, respectively. The comparatively higher share of off-grid solutions reflects the model's fine-grained spatial resolution and explicit incorporation of terrain slope and elevation into network routing cost calculations.

The OnSSET model was applied to conduct a nationwide least-cost electrification analysis for Nigeria with a planning horizon of 2030 [13]. The analysis incorporated population distribution, the locations of existing and planned transmission networks and power plants, and renewable energy resources, such as solar, wind, and mini/small hydro potential. Urban and rural electricity access targets were set at 350 kWh/capita/year and 170 kWh/capita/year, respectively. The results showed that grid extension was the lowest-cost option for approximately 85.6% of the newly electrified population in Nigeria, with MGs accounting for about 14.3% and SA systems for just 0.3%. A similar study in Ethiopia projected an even more centralized outcome, with grid extension serving 93% of new connections, MGs 5%, and SA systems just 1% [29]. Both studies relied on low-resolution population data (2.5 km resolution), which tends to bias results in favor of grid extension by under-representing dispersed rural settlements.

To address the limitations of low-resolution, raster-based analysis, recent studies using OnSSET have shifted toward using vector-based population clusters derived from high spatial resolution raster data. For example, Korkovelos et al. [10] used this methodology in a universal electrification analysis for Malawi. Their results diverged markedly from the low-resolution raster-based outcomes: off-grid solar PV systems emerged as the least-cost option for 67.4% of the total population, while grid extension was optimal for only 32.6%.

The GISEle was used in a case study of the Namanjavira region in Mozambique, an area of approximately 2600 km², which is currently unelectrified and well-suited for greenfield planning analysis [41]. The analysis produced an electrification plan comprising six microgrids and two larger interconnected grids linked to the planned national HV network. A key insight from the study was the substantial effect of incorporating detailed spatial analysis into cost estimation. Specifically, the inclusion of internal distribution network costs and penalty factors reflecting terrain morphology such as slope and distance from road infrastructure, resulted in significant cost increases, in some cases by up to 200 % compared to estimates that omitted these parameters.

2.6. Electrification planning and implementation challenges

Despite methodological advances, electrification planning continues to face multiple challenges. Among the main barriers, particularly in developing countries, are the lack of adequate, reliable georeferenced data and a shortage of skilled human resources to perform the required analysis [10]. Critical datasets such as the location and extent of existing power grid infrastructure, current electrification status, electricity demand, and socio-economic indicators are either outdated, incomplete, or entirely unavailable [3]. As a result, planners often rely on proxies derived from nighttime lights, population density, or remotely sensed datasets. While these proxies can bridge data gaps and guide technology selection processes, their accuracy is limited by the quality of underlying assumptions and input data. The compounding effect of this data paucity leads to uncertainty propagation in modeling, hampering the ability to plan and monitor electrification at national scales [13].

Implementation bottlenecks further constrain progress. Many national utilities lack the financial and institutional capacity to execute grid extension plans. For example, in Ethiopia, utilities have historically lacked coordinated technical and planning functions for a countrywide, least-cost connections rollout, and have struggled with streamlined supply chain networks and efficient commercial processes, all of which are critical for supporting a large-scale electrification program [26]. Off-grid developers face policy uncertainty, limited access to finance, and unpredictable demand patterns [104], [107]. Regulatory inconsistencies such as overlapping concessions, inadequate tariffs, or unclear licensing processes also deter private sector participation.

Moreover, the success of electrification interventions depends on their integration with broader development goals. Without complementary investments in productive use, social services, and local capacity building, even technically optimal electrification plans may fail to deliver its full development potential [108].

3. Analyzing grid extension suitability and assessing electricity access

3.1. Introduction

Given the high investment costs associated with grid infrastructure, expansion must be carried out strategically to maximize impact and cost-efficiency. Prioritizing population settlements, where to extend the central grid, is therefore essential to ensure that limited resources are directed toward the most viable areas [38]. Achieving this prioritization requires a spatially informed assessment of the factors influencing grid expansion.

As highlighted in the problem statement in Chapter 1, the techno-economic feasibility of grid extension is highly site-specific and influenced by a plethora of geospatial factors [38], [45]. These factors include proximity to substations and roads, terrain slope, elevation, and land cover types [10], [41]. In this regard, grid extension[1] suitability refers to the comparative viability of extending the national grid to different settlements, which can be quantitatively assessed by evaluating the grid extension penalty (GEP). The GEP is a spatially heterogeneous composite metric that quantifies the additional cost incurred per unit of grid extension length. High GEP values are indicative of higher extension expenses and, consequently, reduced suitability for grid extension, whereas lower values signify better suitability.

In parallel with the suitability analysis, it is crucial to establish a baseline of current electrification status to plan for future connections. This chapter develops such a baseline by estimating electrified and unelectrified population using NTL imagery [109], [110]. NTL data provide a relatively high spatial resolution and inexpensive way to capture the presence or absence of electricity across vast territories [111], [112]. Leveraging these datasets makes it possible not only to estimate current electricity access but also to investigate variations across regions and settlements.

Therefore, in line with the first objective of this thesis, this chapter estimates the share of the population with electricity access at subnational and national levels in Ethiopia and examines the cost impacts of key geospatial factors on the suitability of extending the national grid.

[1] The terms “grid extension” and “grid expansion” are used interchangeably.

3.2. Study approach

A causal comparative research approach was used to analyze the relationships and levels of influence of various geospatial factors on grid extension suitability in Ethiopia. This approach identifies the extent and nature of cause-and-effect relationships between explanatory variables (geospatial factors) and the outcome variable (grid extension suitability) [113]. The overall methodology is structured into three phases: data acquisition, data processing, and comprehensive data analysis and visualization. A simplified flowchart of this methodological approach is presented in Fig. 4. Based on GEP, a spatial grid extension suitability map was developed, visually depicting the distribution of areas categorized as most suitable, semi-suitable, and least suitable for grid-based electrification.

3.3. Modeling tool selection

The selection of an appropriate energy modeling tool depends on the specific questions that need to be answered and the available data. Among the geospatial electrification planning tools in the preceding review (section 2.4), OnSSET stands out for its open-access, flexible, and scalable framework. Unlike GEOSIM, which is limited by its reliance on proprietary GIS platforms and insufficient treatment of solar-based MGs, OnSSET is open-source and supports a wide range of electrification technologies, including grid extension, MGs (solar PV, wind, hydro, and diesel), and standalone systems [10], [93]. Network Planner, while accessible and user-friendly, lacks support for key renewable options such as hydro and wind MGs, making it less suitable for regions with diverse energy resources [43], [99]. It also does not account for terrain-related costs in grid extension [69]. Though REM is methodologically advanced and capable of high-resolution, customer-level analysis, it is not freely available. It also requires extensive data and computational resources, which restricts its use in large-scale, data-constrained contexts [36].

OnSSET's strengths are further reinforced by its extensive documentation and widespread application in the literature, as well as its adaptability to different country contexts and planning horizons [10], [106]. All these attributes make OnSSET the preferred choice for carrying out a nationwide spatial analysis of electrification pathways in Ethiopia in this thesis.

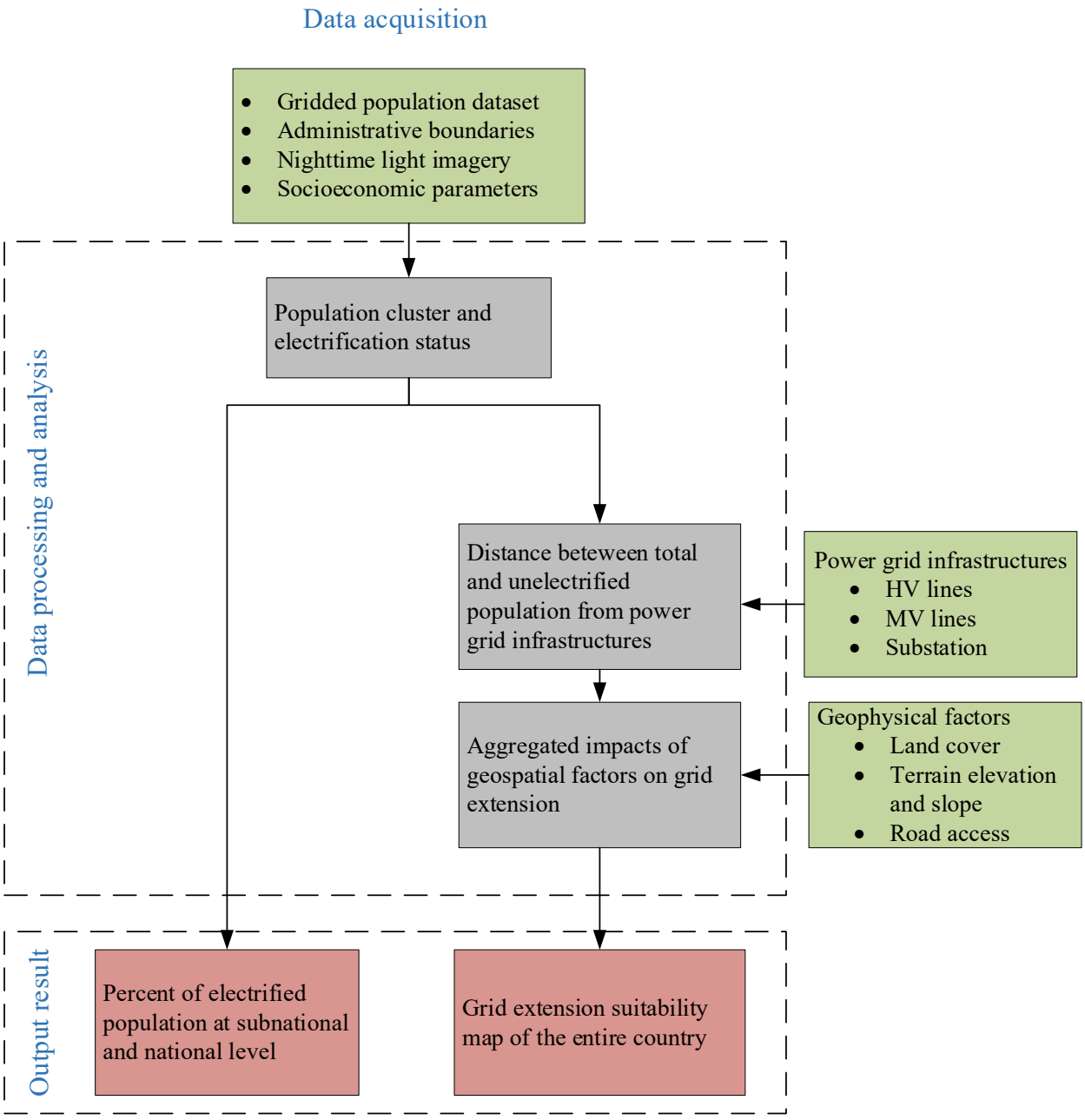

Fig. 4. Flowchart of the methodological approach. Diagram color shows: green “input data”, gold and gray “data process” and red “results of the analysis”.

3.4. Data acquisition

The study incorporates a variety of recently available, open-source GIS and non-GIS datasets. These datasets were obtained from open-source platforms. The specific datasets and their characteristics are detailed in the subsequent subsections and summarized in Appendix Tables A1-A3 and Table C4.

3.4.1. Gridded population dataset

The gridded population dataset is used to generate population clusters, also known as population settlements. These settlements are the smallest geospatial units used for analysis [75]. There are various free, open-source gridded population datasets available, like the Global Human Settlement Layer (GHSL), WorldPop, and the High-Resolution Settlement Layer (HRSL). The HRSL was used as it has demonstrated greater prowess in recognizing the footprints of built-up areas and buildings in both urban and rural settings compared to GHSL and WorldPop [46], primarily owing to its higher resolution of approximately 30 m (1 arc-second) grid size and its integration of subnational census data with high spatial resolution (0.5 m) satellite imagery [46], [114]. Since the most recent population data from the 2020 census was unavailable, population data from 2018 was used and adjusted to reflect the total population in 2020. This dataset is a collaborative product of Meta (formerly Facebook) Connectivity Lab and Columbia University's Center for International Earth Science Information Network. Fig. 5 shows Ethiopia's 2018 HRSL population distribution, categorized to differentiate between densely and sparsely populated areas.

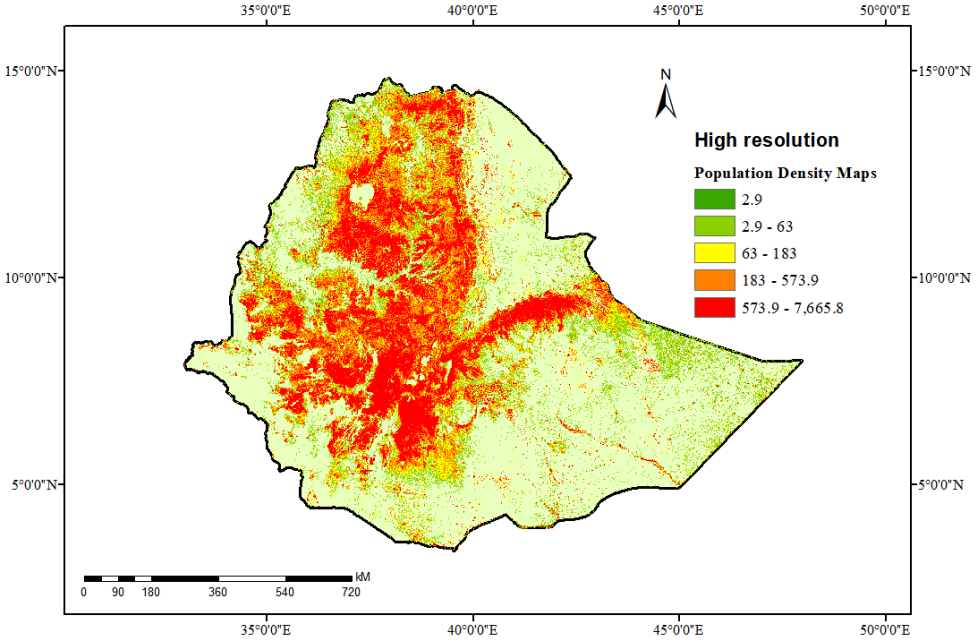

Fig. 5. Population distribution in Ethiopia (at a resolution of 30 m) based on HRSL 2018 raster data [114].

3.4.2. Nighttime light imagery

Nighttime light satellite imagery was employed in conjunction with population data to estimate the electrification status of settlements and, consequently, subnational and national electrification rates, following the approach proposed by Falchetta et al. [109]. This methodology has demonstrated effectiveness in previous research endeavors [115], [116], [117], [118]. The satellite imagery dataset was sourced from the National Oceanic and Atmospheric Administration (NOAA) and comprises cloud-free composite VIIRS NTL (NOAA/VIIRS/DNB/MONTHLY V1/VCMSLCFG). Given that satellites capture lights from various sources, the NTL data was processed using a noise filter adapted from Falchetta et al. [109] to remove background noise and other non-electricity sources. This analysis was conducted on the Google Earth Engine (GEE) platform, a cloud-based geospatial data analysis tool [110].

To identify the electrification status, we processed annual median composites of NTL using a range of five different lower-bound noise floor scenarios: 0.25, 0.27, 0.28, 0.30, and 0.35 $\mu W \cdot cm^{-2} \cdot sr^{-1}$. The result of each noise floor scenario was compared to the World Bank's reported electrification

rate to determine the threshold that provides the best alignment. Any pixel with a radiance value below its noise filter threshold was subsequently masked and set to zero. This process effectively removes background noise, ensuring that only light emissions strongly correlated with electricity access are retained for analysis. Fig. 6 displays the NTL composite, filtered using 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$, for the case study country. Furthermore, the Google Earth Engine (GEE) API, utilized with Python, facilitates the analysis of seasonal trends and temporal patterns of NTL radiance across the 11 administrative regions of Ethiopia from 2016 to 2020.

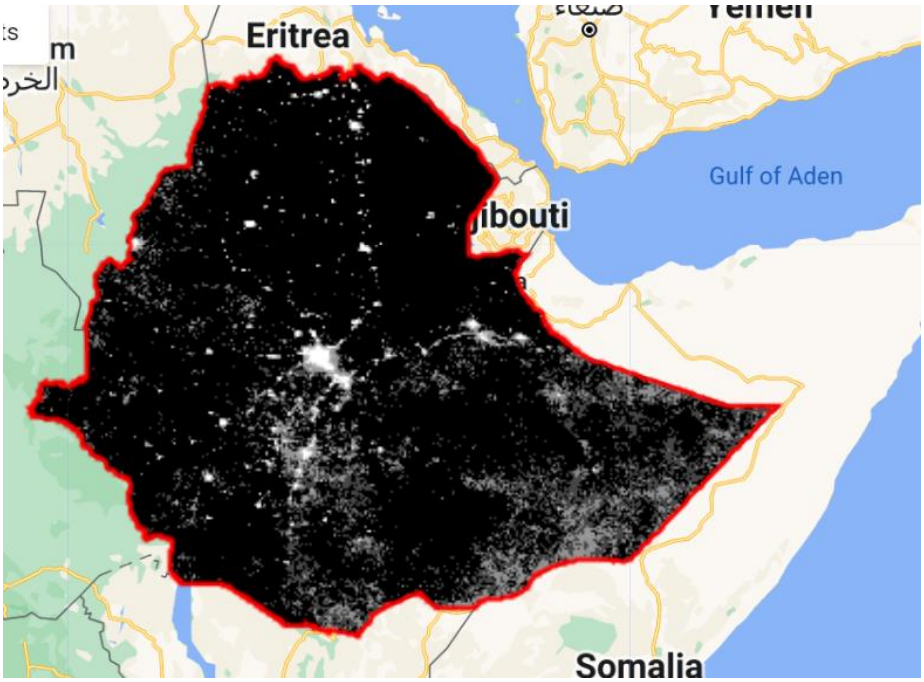

Fig. 6. Annual NTL composite in Ethiopia, filtered using 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$.

3.4.3. Administrative boundaries

Administrative boundaries were instrumental in delimiting the analysis to the study area and for extracting NTL data from the NOAA VIIRS satellite. This ensured that only NTL data within the administrative boundaries were accounted for in the analysis. It also ensured that clusters were contained within boundaries, thus limiting the cluster's maximum area [119]. The entire country territory (Level 0) was applied for clipping the annual NTL raster data, while the first-level administrative boundaries (Level 1) were employed for generating the population clusters and for the estimation of electricity access at the subnational level. Level 0 was obtained from the Global

Administrative Areas (GADM) version 4.0, which provides administrative boundaries using the WGS84 datum coordinate reference system [120]. Level 1 administrative boundaries were incorporated from two authoritative sources: the GADM [120] and the Food and Agriculture Organization (FAO)/Global Administrative Unit Layers (GAUL) V.1/2015 [121]. Specifically, GADM administrative units were utilized for the estimation of electricity access at the subnational level. Conversely, GAUL administrative units were used to analyze seasonal trends and temporal NTL variations at the subnational level.

3.4.4. Power substation

To examine the spatial relationship between the unelectrified population and existing power grid infrastructure, publicly accessible georeferenced datasets of substations were used as input data. These datasets were primarily obtained from Energydata.info, an open data platform established by the World Bank and its partners to address data gaps in the energy sector [122]. Energydata.info sources its data from multiple reliable and verified sources, including Africa Infrastructure Country Diagnostic (AICD), OpenStreetMap (OSM) contributors, and the World Bank project archives [123]. The data used for the case study country was updated in 2017. However, as this data is outdated, we obtained the latest data from Ethiopian Electric Power (EEP[2]) and Ethiopian Electric Utility (EEU[3]) for paper V analysis (see Chapter 5).

3.4.5. Land cover

To evaluate the suitability of different land cover types for grid extension, the MODIS/Terra + Aqua Type MCD12Q1 Version 6 land cover dataset was employed, obtained from Earth Data [124]. This dataset provides global land cover information at a resolution of 500 m [125]. Land cover classification values, ranging from 1 to 17, were derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data [106]. Fig. 7 illustrates the land cover distribution in Ethiopia in 2020, categorized based on the MODIS/Terra + Aqua data.

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[2] Ethiopian Electric Power owns and operates the national power grid with all high-voltage power transmission lines above 66 kV including electrical substations and almost all power plants.
[3] Ethiopian Electric Utility engages in the business of distributing and selling electrical energy in accordance policies and priorities of the government.

A reclassification approach [45], detailed in Appendix Table A2, was used to assess the suitability of different land cover types for grid extension. This approach integrates the Analytic Hierarchy Process to determine the weight of each land cover type in terms of grid extension suitability. Land cover types such as open shrublands, cropland/natural vegetation mosaics, savannas, grasslands, and barren areas are considered highly suitable for grid extension. In contrast, water bodies and permanent wetlands are considered the least suitable for such expansion due to the significant engineering challenges and costs associated with construction in these environments.

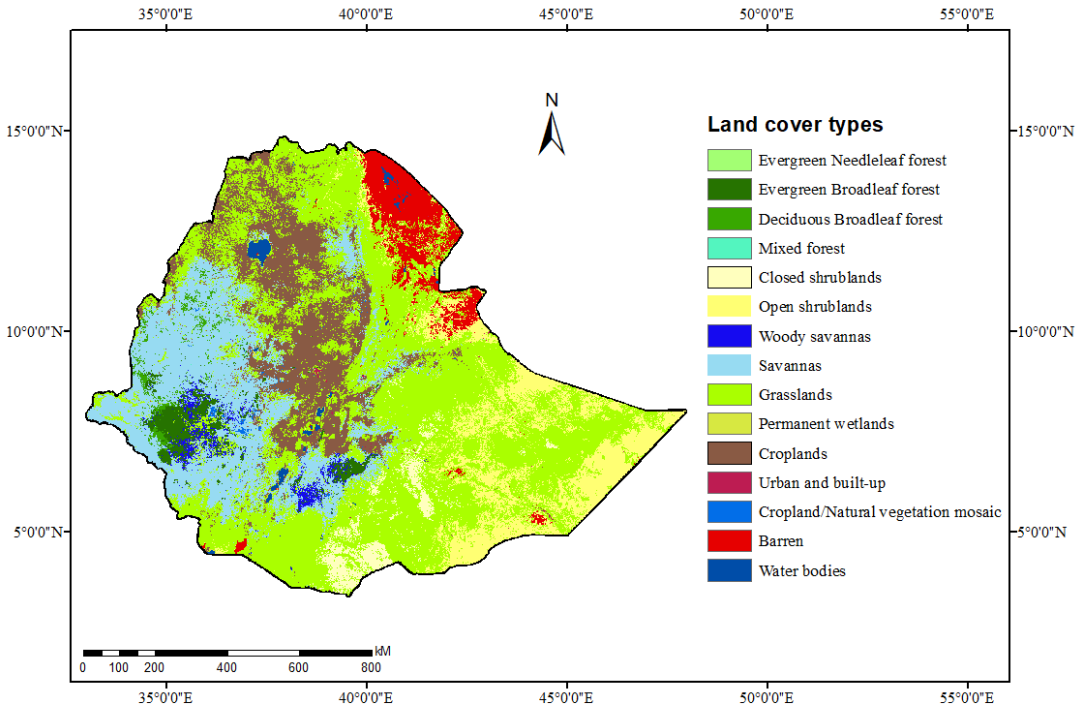

Fig. 7. MODIS/Terra + Aqua land cover types in Ethiopia in 2020 [125].

3.4.6. Elevation and terrain slope

To evaluate how elevation and terrain slope influence the suitability of grid extension, the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM) elevation dataset was utilized [94]. This dataset is a collaborative product of the Japanese Ministry of Economy, Trade and Industry and NASA. It is generated from stereo-pair images captured by the Terra satellite and provides global elevation data at a spatial resolution of approximately 30 meters horizontal posting at the equator [126]. The OnSSET GIS extraction

model subsequently leverages this elevation information to derive a map of terrain slope, a sub-product of the Digital Elevation Model (DEM).

3.4.7. Road access

The impact of road infrastructure access on grid extension suitability was evaluated by assessing the proximity of settlements to different road types such as major roads, highways, primary roads, and secondary roads [40], [94]. The criterion for road scale was that it should at least allow for the use of pickup trucks, ensuring practical accessibility for construction and maintenance [10]. The road data was obtained from the OpenStreetMap project via Geofabrik's server, which provides daily updates, ensuring the most current representation of the road network [127]. Proximity to roads gives ease of access and the reduction of costs related to private property rights, thereby enhancing grid extension suitability.

3.5. Data processing

3.5.1. Population clusters and electrification rate

While gridded population raster datasets are useful for indicating population density at predefined spatial resolutions, their pixelated nature is unable to capture the actual shape or size of settlements. Therefore, this work transforms the pixelated raster population data into vector-based (polygons) population clusters to create more realistic geospatial units for analysis [105]. The "Clustering method" developed by Khavari et al. [46] was employed to do so. Generating population clusters and identifying current electrification status relied on three key GIS datasets: the gridded population raster layer, the annual median NTL imagery raster, and the administrative boundaries vector layer [106].

All raster cells that are adjacent to one another (8-connected neighbors) are merged together to form a single cluster polygon [105]. The size and shape of each cluster are dynamically determined by the spatial distribution of the population and administrative boundaries. Each resulting cluster is attributed with unique characteristics, including population count, electrification status, and an urban/rural classification based on Eurostat thresholds [46]. Through this process, the pixelated population of Ethiopia was divided into 809,087 distinct clusters.

After applying noise filtering to the VIIRS NTL data, a spatial mask is created. A population pixel is classified as "electrified" if it meets two specific criteria: (1) its population density is greater than zero, and (2) its NTL radiance value exceeds the lower-bound noise threshold [10], [29], [106]. The number of electrified people is then determined by summing the individuals within each cluster fulfilling the electrified criteria. This granular approach enables the assessment of electricity access at a cluster level, providing information that is difficult to obtain through conventional methods [105]. For each administrative region (Level 1 administrative unit), the total electrified population is calculated by summing the population values of all settlements classified as electrified within that region. The percentage of the population with electricity access for each region is then derived by dividing the total electrified population by the total population of that region. Electrification rate can be computed using Equation 1.

$$Electrification\ rate = \frac{\sum_{i=1}^{n} ElectrifiedPop_i}{\sum_{i=1}^{n} Pop_i} x100\% \quad (1)$$

Where n represents the total number of clusters, i is an index that represents each population cluster ($i = 1 \ldots n$), and Pop_i is the population living in each cluster.

3.5.2. Seasonal and temporal analysis of NTL

To explore the temporal dynamics in electricity usage patterns across Ethiopia, monthly NTL radiance values were extracted for each administrative region for the period between 2016 and 2020, utilizing the GEE in Python [103]. From the VIIRS image collection, only the average radiance band was filtered for each state, and a consistent lower-bound noise floor of 0.25 μWcm-2sr-1 was applied to ensure that only lights originating from electricity sources were considered. The geometries of the different states/administrative regions were obtained from the FAO/GAUL/2015/level1 feature collection via the GEE API [102]. The nighttime image collection was then reduced to these defined regional geometries, and the mean radiance value for each state was calculated for each monthly observation. Finally, the data was structured using the Pandas library, and plots were generated for each state, illustrating the trend in average radiance over time. This analysis provides critical insights into socio-economic activity patterns, the reliability of electricity supply, and the potential impact of seasonal events such as holidays or climatic conditions on electricity consumption.

3.5.3. Aggregate effects of geospatial factors

The aggregate effect of geospatial factors on grid-extension suitability were estimated using Equation 2. This equation also facilitated the evaluation of the weighted contribution of each individual geospatial factor to the total grid extension suitability score. Prior to this calculation, the input parameters for each geospatial factor were classified on a scale between 1 and 5, with higher values indicating more suitable conditions. For example, areas along existing road networks are assigned the lowest weight (highest suitability score), translating the relative ease and lower cost of line deployment in those areas. The weight assigned to each geospatial factor represents its relative importance in determining the GEP. The default weights provided by OnSSET were adopted, given their extensive usage by the Global Electrification Platform in analyzing electrification strategies for 58 countries, many of which are in SSA, including Ethiopia [128]. However, it is acknowledged that the Analytic Hierarchy Process could alternatively be employed to determine the weight assigned to each factor [45].

The GEP multiplier for each settlement was calculated using Equation 3 [106]. This equation quantifies the additional cost (penalty factor) incurred while constructing electric lines across areas characterized by high slope angles, unsuitable land cover, greater distances from substations, longer road distances, or high elevation [10], [13], [29]. This factor acts as a multiplier on HV and MV costs, providing a more realistic, location-specific assessment of the techno-economic viability of grid extension.

$$\begin{aligned} Combined\ classification \\ = (0.30 * slope\ angle + 0.20 * land\ cover\ suitability \\ + 0.20 * substation\ distance + 0.15 * road\ distance \\ + 0.15 * elevation\ height\ ) \end{aligned} \tag{2}$$

$$GEP = 1 + \frac{e^{(0.85*|1-Combined\ classification|)} - 1}{100} \tag{3}$$

The GEP is a crucial factor in the optimization of the grid extension process, as it directly estimates the additional cost (penalty) of extending the grid to unelectrified settlements. From a geospatial supply-side perspective, settlements with low GEP values are deemed more suitable for grid extension, whereas those with high GEP values are considered less suitable due to the higher associated costs. To visually represent this information, the GEP values were mapped, and

settlements were categorized into three classes of suitability, most suitable, semi-suitable, and less suitable, based on their quantile distribution of GEP values. This spatial representation provides decision-makers with a clearer understanding of areas where grid expansion would face high extra cost from a supply-side perspective.

3.6. Results and analysis

3.6.1. National level electricity access

To estimate the electrification rate in 2020, five different noise filter floors were applied to the NTL data, aiming to minimize the discrepancy between the estimated electricity access and the World Bank report. Table 3 presents the estimated access to electricity obtained from these filters, which varied from 69.1% at the lowest noise filter value (0.25 $\mu W \cdot cm^{-2} \cdot sr^{-1}$) to 24.6% at the highest noise filter value (0.35 $\mu W \cdot cm^{-2} \cdot sr^{-1}$).

Table 3. Nationally estimated electricity access at different noise threshold floors.

NTL data noise floor ($\mu W \cdot cm^{-2} \cdot sr^{-1}$)	Estimated electricity national access	Urban and rural access respectively	Compared to the national statistics from World Bank
0.25	69.1%	98.7% and 61.4%	Overestimated (+18%)
0.27	51.3%	97% and 39.3%	Overestimated (+0.2%)
0.28	44.1%	96% and 30.4%	Underestimated (-7%)
0.30	33.8%	93.4% and 18.2%	Underestimated (-17.3%)
0.35	24.6%	88.4% and 8.1%	Underestimated (-26.5%)

Fig. 8 provides a visual representation of the distribution of electrified and unelectrified population at the cluster level. Blue areas indicate the electrified population, while yellow areas correspond to the unelectrified population.

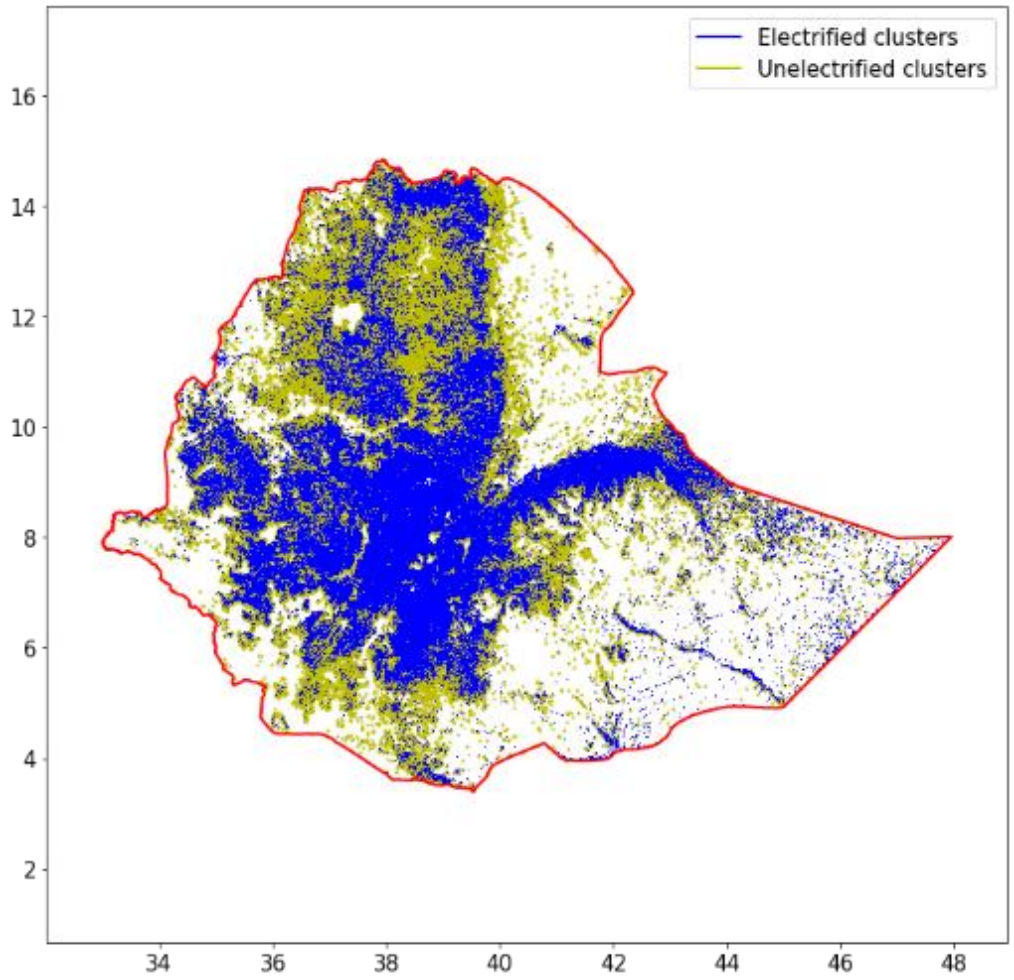

Fig. 8. OnSSET-based electricity access, applying 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ lower bound noise floor, resulting in an estimated electricity access of 51.3%.

The results indicate that a noise floor of 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ provides national electrification rate estimates just 0.2 points above the World Bank's 2020 figure of 51.1%. In contrast, a noise floor of 0.28 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ underestimates electrification rates by 7%. This highlights the critical importance of selecting an appropriate noise floor when using NTL data for estimating electricity access. Additionally, a noise floor of 0.30 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ or higher can provide better accuracy for urban areas, while 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ or higher yields better results for estimating access in rural areas.

3.6.2. Subnational electricity access

Fig. 9 presents estimated subnational electrification rates (%) in 2020 for the 9 regional states and 2 administrative cities. These results were compared with electricity access (% of population) available in the Government of Ethiopia (GoE) NEP 2.0 report for five specific regional states/administrative cities. The subnational electrification estimates generally align with the GoE NEP 2 report, though variations were observed in certain regions. For instance, Addis Ababa's electrification estimate of 100% closely corresponds to the GoE NEP 2's 99.9% rate. While Amhara's 41.8% estimate falls below GOE NEP 2's 51.3%, the correlation is still evident. Conversely, the model's estimates for Oromia (69.20%) and SNNP (71.49%) surpass the GOE NEP 2 rates of 63.3% and 37.9%, respectively. The discrepancy in Tigray is notable, with the analysis estimate at 61.08% compared to the GoE NEP 2's 87.7%. For the Somali region, the model indicates a substantially higher electrification rate than previously reported. According to a report by the African Development Bank (AfDB), the electricity access rate in the Somali Regional State in 2020 was below 20%[4] [26], [27].

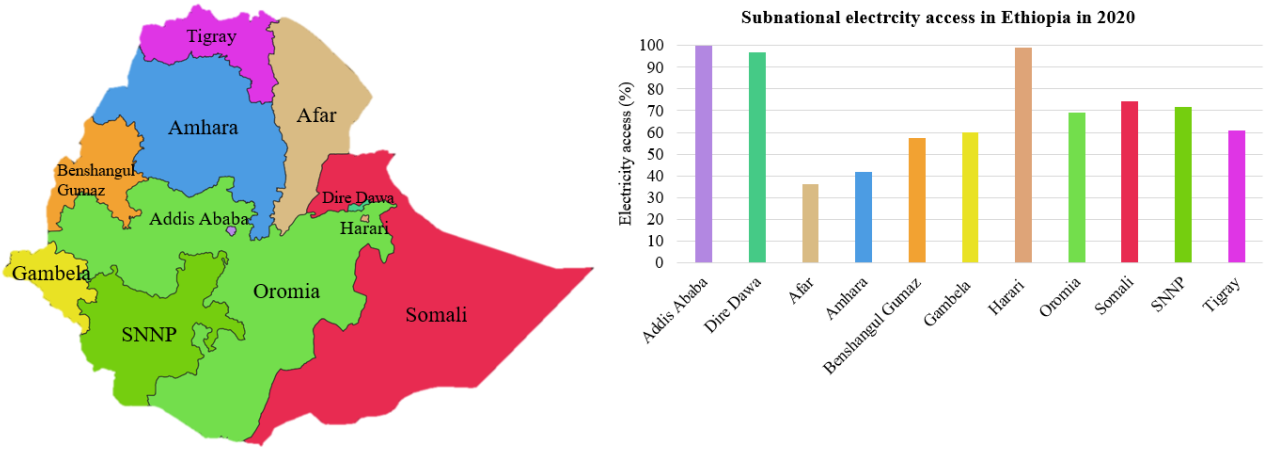

Fig. 9. Estimated access to electricity at subnational level.

[4] This and its discrepancy explanation is described in the corrigendum of paper II. Initially, we only validated those administrative regions such Addis Ababa, Amhara, Oromia, SNNP, and Tigray which are found in NEP 2.0 report.

3.6.3. Subnational temporal and seasonal trends of NTL

Fig. 10 depicts the mean radiance trends across Ethiopian states between 2016 and 2020. A distinct seasonal pattern is evident across most states, characterized by pronounced peaks in nighttime radiance occurring between November and February. This period coincides with Ethiopia's dry season, which is also the primary post-harvest period for its majority-agrarian economy. This confluence of increased disposable income reduced agricultural labor demands, and major cultural and religious festivals (such as Ethiopian Christmas and Epiphany) likely drives the observed increase in electricity consumption for lighting and social activities. Conversely, lower radiance values are consistently observed during the rainy season, spanning from June to September. In light of this, the reduction is likely a consequence of decreased outdoor activities and potential interference from cloud cover, which can attenuate light detection by the satellite sensor. Regional variations in these seasonal cycles are also apparent. States such as Tigray, Amhara, and Oromia exhibit a more pronounced seasonal cycle, with a marked increase in NTL during the months of October to January. In contrast, regions like Gambella, Benishangul-Gumuz, and Somali display relatively flatter radiance profiles, indicating lower baseline access levels and minimal seasonal variation in electricity usage patterns.

Beyond seasonal fluctuations, the NTL data from 2016 to 2020 also reveal distinct inter-annual temporal patterns across different states. Addis Ababa, for instance, demonstrates a steady increase in nighttime lights throughout the period, with only a minor decrease observed in 2018. In this period, Ethiopia experienced power rationing due to a combination of factors, including drought impacting hydropower generation and a growing demand for electricity. The Somali state, while showing less pronounced dry and wet season differences, consistently exhibits a peak in NTL in December. States like Oromia, Amhara, and Tigray have experienced a gradual increase in nighttime lights over time, indicative of broader economic growth and development. Conversely, regions such as Benishangul-Gumuz and Gambella have remained relatively stable or experienced fluctuations, potentially signaling economic stagnation or shifts in population size and activity.

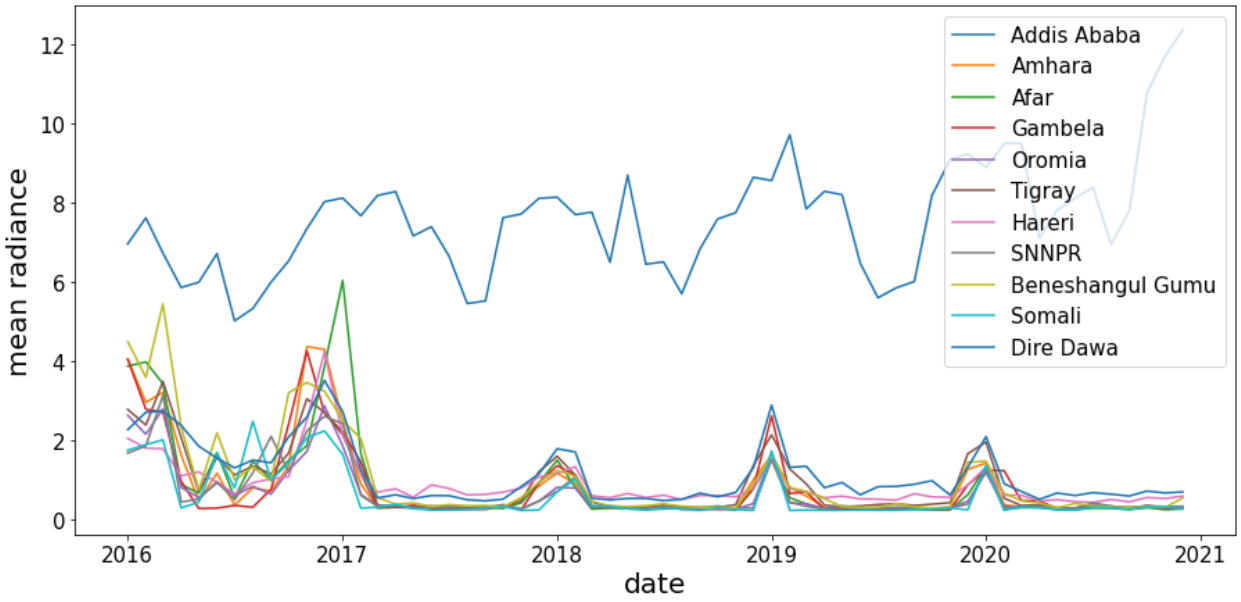

Fig. 10. Monthly mean radiance in each state for the years 2016 to 2020.

3.6.4. Grid extension suitability and penalty

Fig. 11 illustrates the relative contribution of the five geospatial factors to grid extension suitability. The findings indicate that terrain slope is the most significant contributor to grid extension suitability, accounting for a substantial 40.8% of the total score. This prominence is largely attributable to the fact that the vast majority of settlements in Ethiopia (94%) have terrain slope of less than 10°. Land cover emerges as the second most significant factor, contributing to the suitability of grid extension to unelectrified settlements. This is because croplands, grasslands, and savannas cover the majority of settlements in Ethiopia, and according to the suitability classification outlined in Appendix Table A2, grasslands, and savannas were classified as the most suitable and croplands were classified as semi-suitable for grid extension.

In stark contrast, the distance from the substation contributes the least to the overall suitability score, accounting for only 5.7%. This minimal contribution is due to the fact that only a very small fraction of settlements falls under the most suitable class for substation proximity, while the vast majority (97%) are found in the least suitable class. Consequently, the distance from existing substations is the primary driver of the GEP multiplier and the most significant limiting factor for grid extension in Ethiopia.

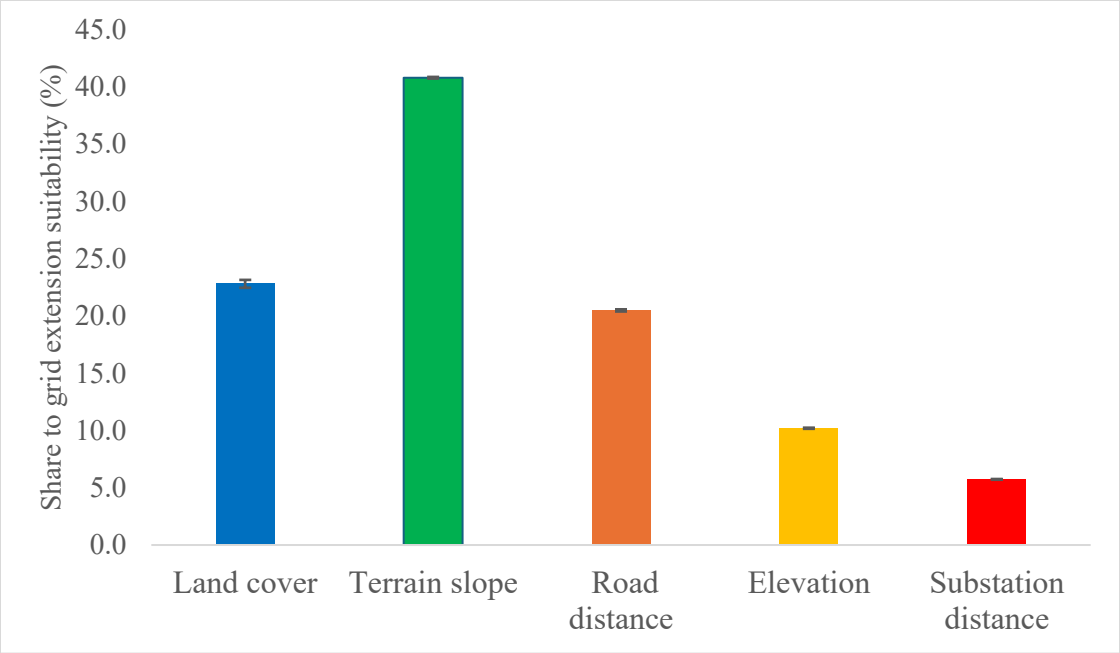

Fig. 11. The contribution of each geospatial factor to the grid extension suitability.

The aggregate impact of these five geospatial factors on grid extension costs was evaluated by calculating the GEP multiplier. The analysis demonstrates that the combined influence of these factors could increase the cost of grid extension across unelectrified settlements in Ethiopia by an average of 8.6%, with a range spanning from 2.3% to 29%. This GEP multiplier is applied directly to the transmission and distribution (T&D) capital expenditure (see Chapter 5). This level of variance in the GEP values is a consequence of location-specific factors, implying that the cost of grid extension is highly dependent on the unique conditions of each settlement. The GEP multiplier thus serves as an inverse indicator of grid extension suitability. Settlements with a lower GEP value are more suitable for grid extension, while those with a higher GEP value are less suitable from a geospatial supply-side perspective.

Fig. 12 provides a spatial representation of the GEP multiplier, illustrating the relative suitability/challenges of extending the grid network across the country. The GEP values are classified into 3 quantiles. Settlements with a GEP value below the 1/3 quantile (green) are deemed most suitable, those in the range between 1/3 and 2/3 quantiles (yellow) are semi-suitable, and those in the upper 2/3 quantile (red) are unsuitable due to the high penalty cost involved. The most suitable class of settlements requires lower investment costs, whereas the less suitable class incurs high investment costs. This spatial representation highlights a significant variation in the

distribution of grid extension suitability across the country. Notably, proximity to electrified settlements is not the sole determinant of grid extension suitability; areas near electrified settlements may be unsuitable due to other geospatial factors, while some remote areas may be semi-suitable due to favorable local topography, suitable land cover, and convenient road access.

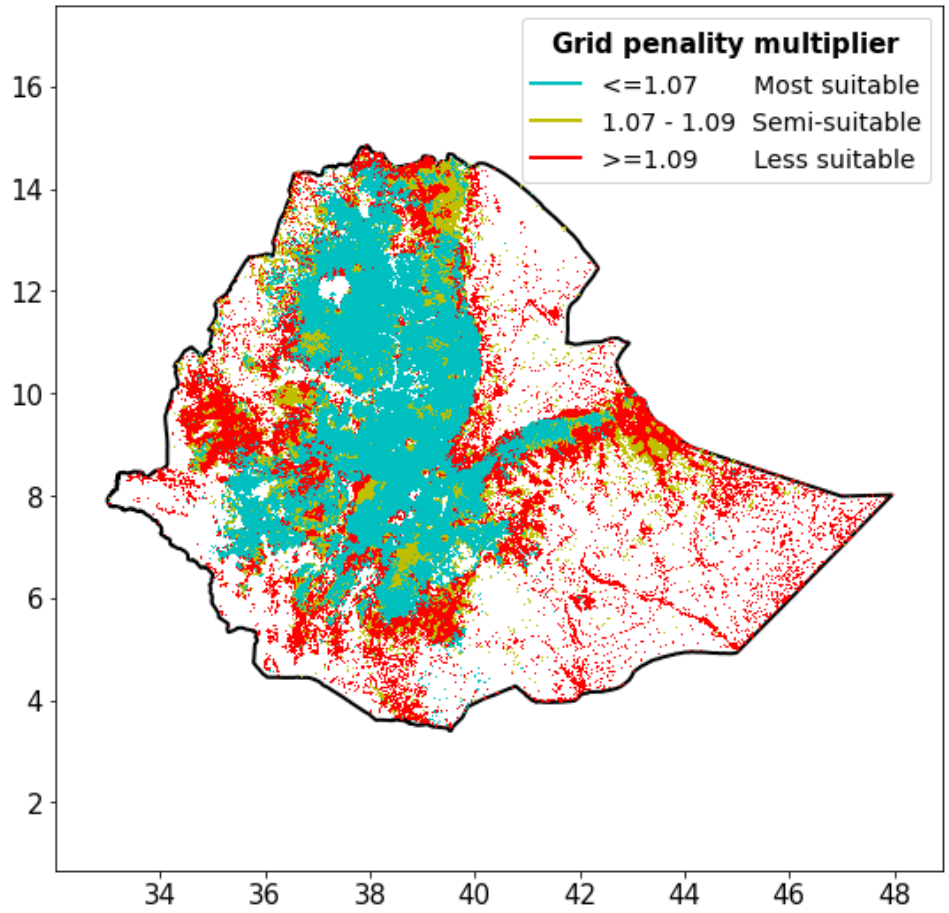

Fig. 12. Grid extension penalty (GEP) map, where green, yellow, and red colors represent the most suitable, semi-suitable, and less suitable settlements, respectively.

3.7. Discussion

The findings show that grid extension suitability in Ethiopia is spatially heterogeneous, a critical insight that must inform strategic electricity access planning. The electrification rate estimation using the NTL imagery and population data indicates that for a lower bound noise filter of 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$, the estimated electricity access rate closely aligns with the World Bank report, with a +0.2% margin of error. However, a 0.35 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ noise floor leads to larger discrepancies

with a -26.5% margin of error. This result is in line with earlier studies [46], [109], which similarly underestimated electrification rates in Ethiopia by 26.8% and 20%, respectively. It is worth noting that the use of a noise floor less than 0.35 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ in estimating electrification rate resulted in estimates higher than those reported in previous studies by Falchetta et al. [109] and Khavari et al. [46]. The underestimation of the electrification rates, when lower bound noise floors of above 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ are used, could be due to low levels of nighttime illumination in the country [109].

Several factors may contribute to these observed discrepancies between NTL-derived estimates and the World Bank's statistics. Firstly, the processing algorithms employed by NOAA's Earth Observation Group (EOG) for generating VIIRS NTL data may involve over-smoothing or over-filtering, potentially removing low average monthly light intensities that are indicative of electrification but are mistakenly classified as temporary light or outliers [129]. Secondly, the limitations of the VIIRS sensor itself must be acknowledged. NTL data is best suited for detecting outdoor lighting; for indoor lighting to be captured, considerable light leakage or high-intensity lighting is required, which is often not the case in rural households with low consumption levels [115]. This can lead to underestimations, particularly in areas dominated by off-grid solar solutions. This is compounded by a temporal bias, as the VIIRS satellite's overpass occurs at approximately 1:30 a.m. local time, a time when most household activity has ceased, further decreasing the chance of detecting light. The sensitivity of the chosen noise filter threshold is also a critical factor; even minor adjustments can significantly impact the resulting access estimates, leading to either overestimation (by including non-electrified areas) or underestimation (by excluding genuinely electrified areas). Thirdly, the overestimation by the World Bank observed in 2016 and 2017 could potentially be attributed to the broader adoption and widespread use of off-grid solutions. For example, the sale of approximately four million off-grid solar devices between 2015 and 2017, leading to a penetration rate of 20% by 2017, may have significantly contributed to overall increase in access [109]. Such as solar lanterns and SHSs, which contribute to World Bank report but may not be captured by the VIIRS satellite sensors.

Among the investigated geospatial factors, terrain slope and land cover emerge as the most significant contributors to the suitability of grid extension to unelectrified settlements. The high suitability of terrain slope is largely due to the fact that the majority of Ethiopian settlements are

located on relatively flat terrain (less than 10° slope). Similarly, the prevalence of settlements in suitable land cover types such as cropland, grassland, and savanna areas further enhances grid extension feasibility. Conversely, the distance from existing substations contributes the least to grid extension suitability, primarily because a vast majority of settlements are located far from substations, making this a significant limiting factor for grid extension in Ethiopia.

The aggregate impact of geospatial factors, quantified by the GEP multiplier, reveals that grid extension costs can increase by an average of 8.6% (ranging from 2.3% to 29%) depending on the location. This aligns with comparable studies that have shown GEP multipliers escalating grid extension investment costs by up to 30% [45]. The finding suggests that a combination of challenging geography and a grid-intensive extension strategy is likely to lead to high electrification costs. Therefore, to avoid such high costs, policy decisions should be targeted at either prioritizing areas with low GEP for grid extension or choosing alternative off-grid solutions in geographically challenging regions. The substantial impact of these geospatial factors underlines their critical role in grid extension planning, as neglecting them can lead to significant cost underestimations and inefficient electrification strategies. As a result, the EEU and the GoE should integrate these factors into their planning frameworks, moving beyond a traditional focus solely on proximity to existing infrastructure. This quantification of the GEP provides a critical, empirically derived input that challenges the viability of grid-centric planning and directly informs the supply-side cost calculations in the final optimization model presented in Chapter 5. However, before evaluating supply options, it is essential to first understand the demand side of the equation, which the next chapter addresses in detail.

4. Long-term spatially explicit electricity demand scenarios

4.1. Introduction

Electricity demand projection is one of the key aspects in regard to rural electrification planning, as it determines technology selection and investment requirements. Thus, long-term spatially explicit electricity demand projections are essential for designing least-cost electrification pathways that address the unique needs of diverse regions and communities [95]. Such projections enable planners to account for geographic, socio-economic, and climatic heterogeneity across urban and rural areas. High-resolution mapping of demand enables the targeting of infrastructure investments to areas with the greatest need and potential impact. This approach reduces the risk of under- or over-sizing generation and distribution assets. Future electricity demand in developing countries is influenced by factors such as GDP per capita, urbanization, and overall economic development [59], [130]. Scenario-based projections capture the uncertainty in demand projection by exploring a range of plausible futures. This approach models a more realistic, evolving demand scenario that accounts for gradual increases in electricity consumption over time. These dynamic scenarios translate socio-economic trends into quantitative estimates of future electricity demand. This approach facilitates analysis of how different development pathways, such as high economic growth or rapid urbanization, could shape electricity demand at the national level. These national trends must be translated into local contexts. Additionally, demand projections for rural areas must consider the needs of key consumer groups, including households (HHs), productive use(r)s (PUs), and community institutions (CIs).

This chapter also explicitly incorporates the impact of rising ambient temperatures on future demand. A warming climate can be a critical driver of future energy consumption, with the demand for air conditioning (AC) rising rapidly as society adapts to climate extremes. Globally, residential AC cooling energy demand is expected to increase by 150% by 2050 [131]. This trend is dire in Africa, where many regions already face extreme heat. The continent's vulnerability to heat stress is underscored by the fact that many regions already experience between 4,000 and 5,000 cooling

degree days (CDDs[5]) annually. Its CDDs exceed the levels experienced in major cooling demand centers such as the United States (3,150) and China (1,100) [132]. This trend will drive the uptake of cooling technologies. It is estimated that approximately 700 million people in Africa currently live in climates requiring substantial cooling, a figure projected to rise to 1.5 billion by 2050 [133].

Thus, this chapter 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, this work seeks to support the development of nationwide least-cost electrification pathways that ensure equitable and sustainable electricity access for all.

4.2. Methodological approach

An integrated approach, incorporating both spatial and temporal demand evolution, is adopted to investigate electricity demand development over a multi-period horizon, spanning from 2021 to 2050. A multiple linear regression (MLR) model is used to project aggregate electricity demand based on key socio-economic drivers over time. The MLR model was chosen for its capacity to relate electricity demand with multiple socio-economic and demographic factors, thereby facilitating scenario-based and sector-specific projections [134]. While relatively simple, MLR has been widely applied in developing countries with limited long-term historical data [135]. It quantifies the relationship between electricity demand and its key drivers in a transparent manner [136], [137]. While scenario analysis provides conceptual pathways for demand evolution and projections of each demand driver, regression analysis facilitates the systematic integration of each demand driver into demand projection. To explore a range of plausible futures and capture uncertainties in long-term projection, the study develops a Business as Usual (BAU) reference scenario, along with two alternative scenarios, High Economic Growth (HEG) and Rapid Urbanization (RU), to project future electricity demand. Each scenario incorporates projections of key demand drivers, namely population growth, economic growth, urbanization, and rural

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

electrification rate. These drivers were selected based on their empirical relevance to energy demand projections in developing countries [59], [130].

For the spatial demand analysis, the OnSSET model is employed [10], [22]. It integrates population data and georeferenced information on PUs and CIs, enabling detailed spatial mapping of electricity needs. We therefore couple a temporal regression model with a spatial disaggregation to produce settlement-level, sector-specific demand over time. Furthermore, spatial temperature data, along with global warming projections, are incorporated into the demand projection model to account for the anticipated increase driven by global warming [138], [139]. An overview of the research framework for developing long-term spatial demand scenarios, including data inputs, modeling steps, and outputs, is illustrated in Fig. 13. The subsequent subsections describe the methodological components in greater detail.

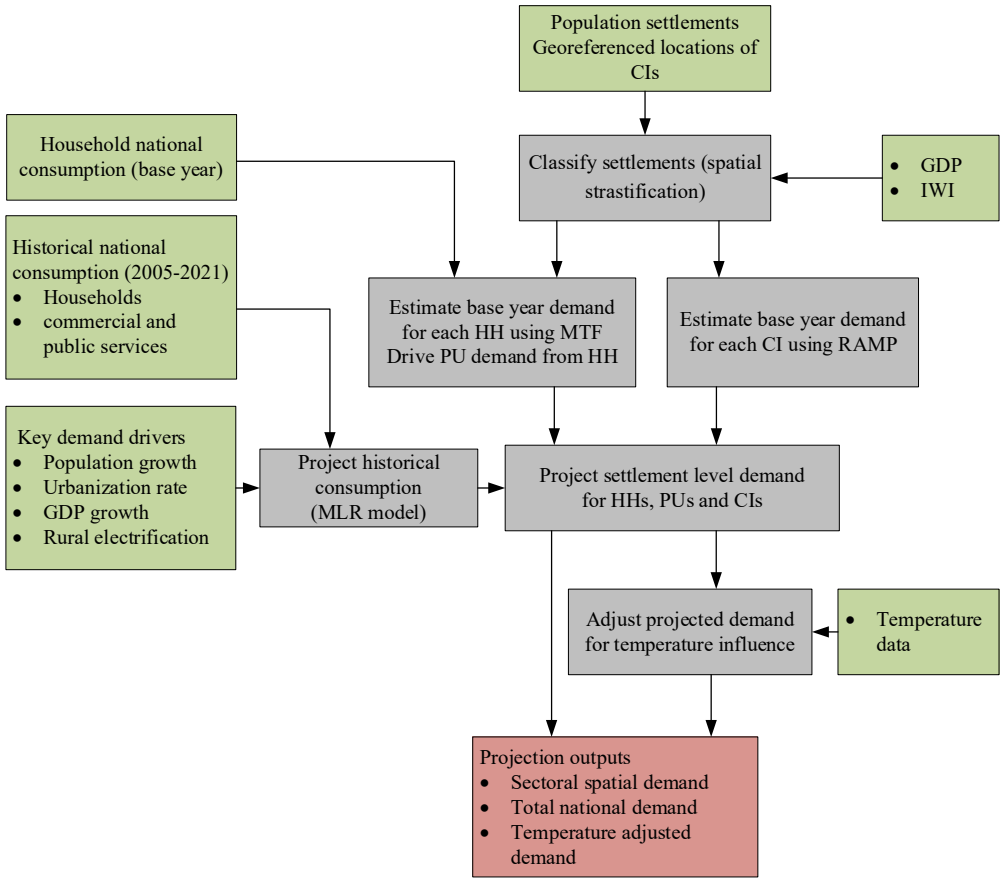

Fig. 13. Flowchart of the study approach. Colors indicate the input data (green), processing steps (gray), and outputs (red).

4.3. Demand profiling at settlement level

Building upon the population settlements identified in Chapter 3, this chapter employs a spatial stratification approach to assess variations in electricity demand across these settlements. Relative economic status is used as the basis for stratification. In this context, a settlement's economic status refers to the relative wealth of its residents compared to others within the country. The analysis is based on a correlation between electricity consumption and economic status [47], with wealthier settlements expected to exhibit higher electricity demand than those with lower economic status [10]. Two complementary geospatial datasets—average Gross Domestic Product (GDP) and the International Wealth Index (IWI)—are used.

The mean GDP values for each settlement were derived from the high-resolution GDP data developed by Kummu et al. [140]. 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 subnational level. The spatial GDP data for the study country is shown in Fig. 14a.

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 [141]. 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 x 1.6 km² spatial resolution) for 25 SSA countries. The IWI for the case study country is shown in Fig. 14b.

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. [47]. 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 4 presents the classification scheme applied to GDP and IWI values.

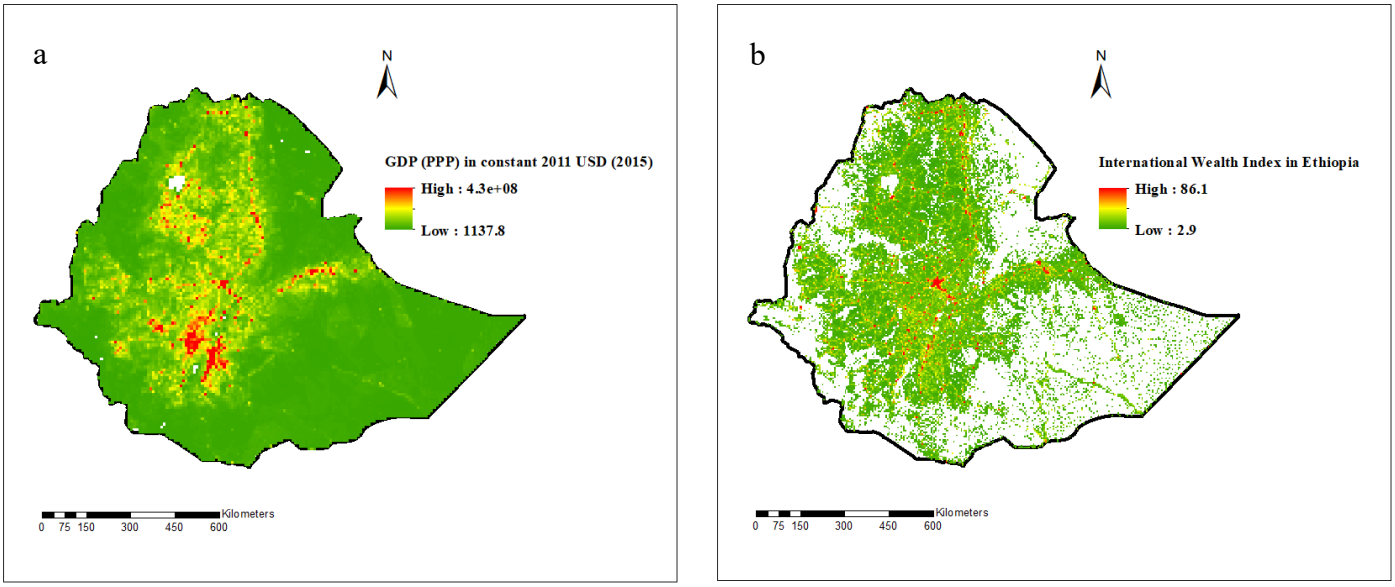

Fig. 14. High-resolution spatial economic indicators in Ethiopia. a) The GDP for the year 2015 at a spatial resolution of 1 km², expressed in constant 2011 international US dollars. GDP values range from 1,137.8 USD to 4.3 million USD per grid cell [140]. b) The IWI at a grid size of 1.6 x 1.6 km², where household-level wealth index ranges from 2.9 to 86.1 in 2021[141].

Table 4. GDP and IWI classification scheme for settlement stratification.

GDP	GDP classification	IWI	IWI classification
$GDPmin(nb1) \leq GDP < nb_2$	1	$IWImin\ (nb1) \leq IWI < nb2$	1
$nb_2 \leq GDP < nb_3$	2	$nb2 \leq IWI < nb3$	2
$nb_3 \leq GDP < nb_4$	3	$nb3\ \leq IWI < nb4$	3
$nb_4 \leq GDP < nb_5$	4	$nb4 \leq IWI < nb5$	4
$GDP \geq nb_5$	5	$IWI \geq nb5$	5

*nb- natural breaks

After classifying the gridded GDP and IWI data, the two indicators are combined to create a composite proxy for electricity demand potential. This composite value, representing the relative economic status of each settlement, is calculated using equal weighting factors (0.5), as shown in Equation 4.

$$C_i = 0.5 * GDP_i + 0.5 * IWI_i \quad (4)$$

Where C_i is the combined value of GDP and IWI for settlement i. The resulting composite index provides a score from 1 to 5 for each settlement, serving as a proxy for its electricity demand potential. A score of 1 indicates the lowest economic status and demand potential, while a score of 5 represents the highest.

4.4. Electricity consumer groups

4.4.1. Households

Household demand is modeled using the MTF, which defines tiers of electricity consumption corresponding to distinct levels of energy service. 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 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, annual electricity demand is determined by linearly interpolating between Tier 1 (38.7 kWh/HH/year) and Tier 5 (3000 kWh/HH/year), as shown in Equation 5. While the relationship between economic status and consumption may exhibit non-linearities, linear interpolation provides a transparent and computationally feasible method for disaggregating demand nationwide, capturing the essential trend of rising consumption with increased economic status.

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

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 6. The projected HH size for each year is provided in Table 5. The total annual HH electricity demand for each settlement is then determined using Equation 7.

$$E_i^{PC} = \frac{E_i^{HH}}{HH\ size} \quad (6)$$

$$E_i^{total} = Pop_i\ x\ E_i^{PC} \quad (7)$$

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.

4.4.2. Household-based productive use

Household-based small businesses are modeled as a proxy for PUs. In rural areas, PUs are often part of the informal economy, a significant business activity in developing countries, with enterprises that are home-based or closely tied to residential activities. Thus, PUs are grouped under the HH category to better reflect the socio-economic and spatial realities of rural electricity consumption. In addition, there is a lack of georeferenced data 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, approx. 25% of a MG's customers use electricity for PUs [51]. Similarly, in Ethiopia, PUs account for over 50% of total annual electricity consumption despite representing only a quarter of the customer base [52]. 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 [142]. 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% [68].

In light of this, HHs with electricity demand at or above Tier 2 (73–365 kWh/HH/year) were assumed to engage in productive activities. Therefore, the electricity demand of a PU is estimated to be 25% of that of a household in these higher tiers [68], [142]. Fig. 15 shows HHs identified with electricity demand above Tier 2, which serves as the basis for estimating the demand of PUs in the study area.

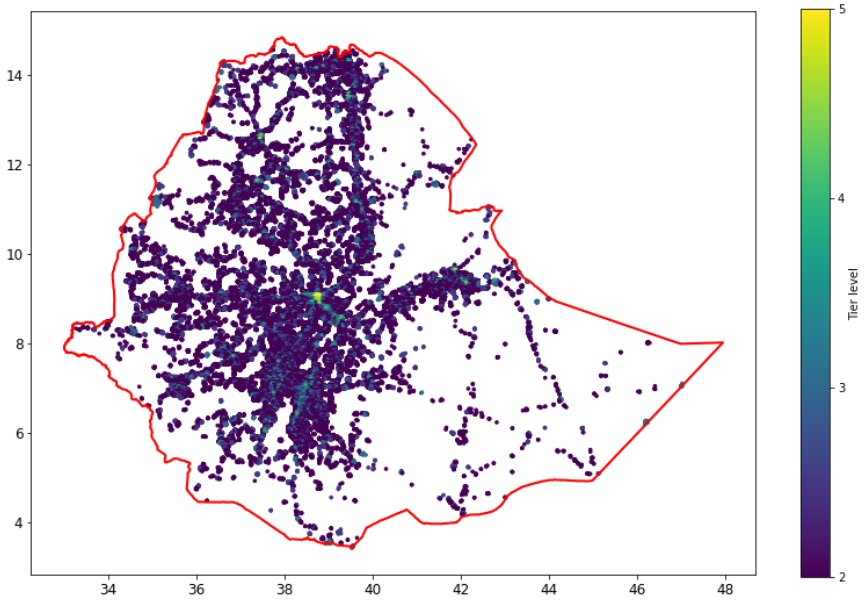

Fig. 15. Methodological basis for identifying settlements with potential for PU. Spatial distribution of HHs with electricity demand at or above Tier 2, which serves as the threshold for estimating PU electricity demand in the study methodology. The horizontal and vertical axes represent longitude and latitude, respectively, and the color bar indicates tier levels from tier 2 to 5.

4.4.3. Community institutions

For this consumer group, electricity demand was estimated for key community institutions (CIs), including health centers, education facilities, places of worship (POWs), and government offices [65]. These social institutions have different electricity demands depending on their location, whether in rural or urban areas. Urban institutions serve larger population and are thus equipped with a greater number of electrical appliances, resulting in higher electricity consumption. Therefore, separate demand estimations were conducted for rural and urban CIs using the RAMP model [72]. The model requires a relatively small set of input parameters, including rated power of appliances, number of units, operating time and windows, usage cycles, and random variation factors [70]. The appliance-specific parameters used for this analysis were adapted from a previous study in Mozambique, where data were collected through direct on-field surveys [19] (see Appendix Table B1 to B5).

A key challenge in estimating the spatial demand of CIs is the limited availability of georeferenced data on the locations of these institutions. Georeferenced data for health facilities was obtained

from the Humanitarian Data Exchange (HDX) website [143], and georeferenced data for education facilities was obtained from the Ethiopian Ministry of Education (MOE[6]) [144]. However, the georeferenced locations of POWs obtained from HDX and OpenStreetMap (OSM) were limited and did not represent the full extent of these institutions. Additionally, georeferenced data on government offices was not accessible through any public dataset provider. In the absence of georeferenced datasets for these institutions, it is assumed that each village and town in Ethiopia accommodates at least one POW and one government office. Georeferenced information from [145] shows 23,957 villages and towns across the country. While this assumption ensures a baseline provision of community services is modeled nationwide, it may result in underestimation in denser urbanized settlements.

For CIs located outside the population settlements delineated by [38], a proximity-based method was used to integrate those CIs into the nearest population settlement [71]. This approach links each CI to the closest population settlement, ensuring 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 4. 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 8. The spatial distribution of CIs' electricity demand across the study country is illustrated in Fig. 16.

$$E_i^{CI} = \frac{E_{CI}^{urban} - E_{CI}^{rural}}{4} x(\, C_i - 5) + \; E_{CI}^{urban} \qquad (8)$$

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.

[6] MOE stands for Ethiopian Ministry of Education, responsible for the governance and policies of education.

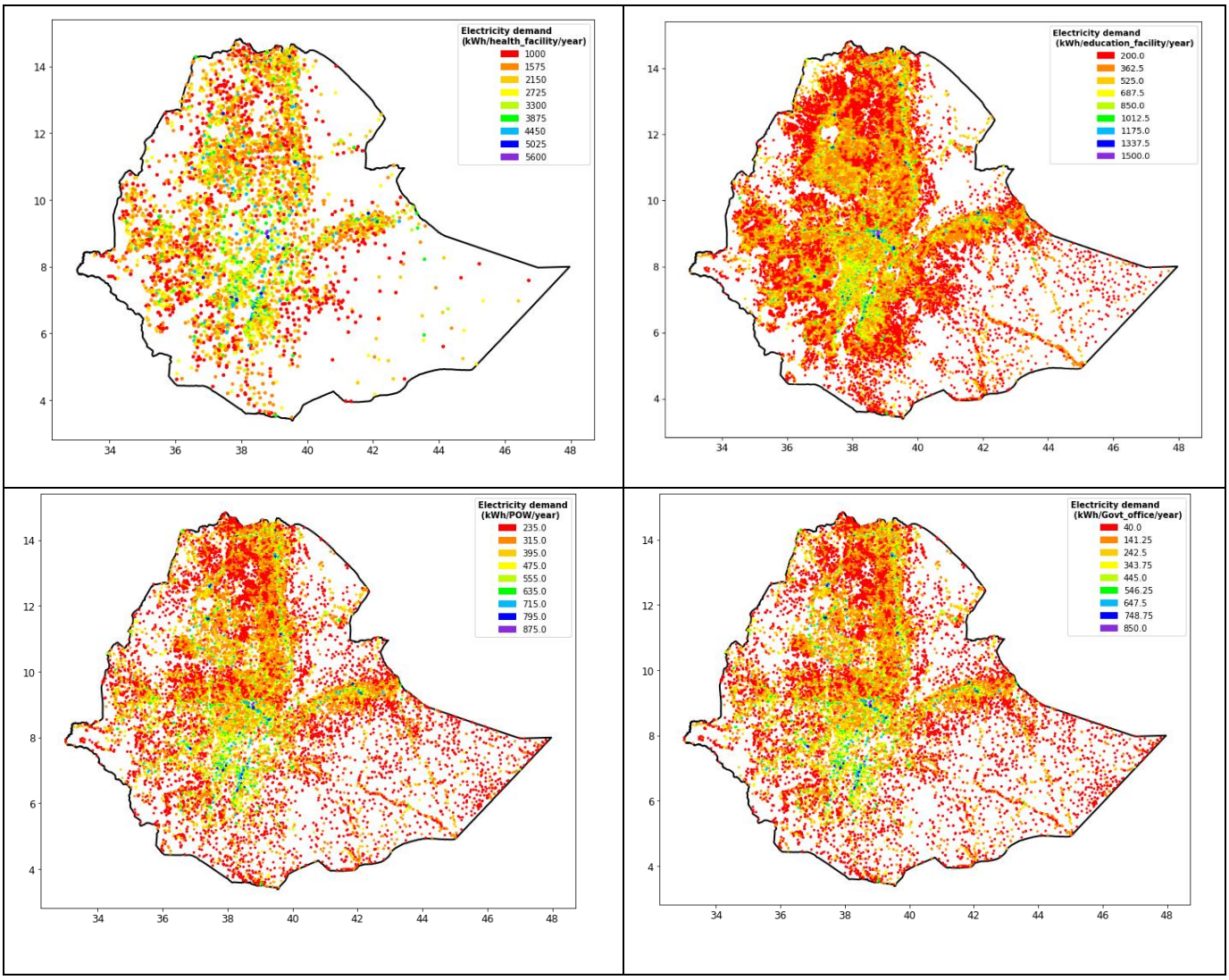

Fig. 16. Methodological demonstration of the base year electricity demand for key CIs in Ethiopia: (a) Education facilities (top left), (b) Health facilities (top right), (c) Places of worship (bottom left), and (d) Government offices (bottom right). The spatial distribution illustrates how CI demand is allocated based on settlement economic status (C values), with demand interpolated between rural and urban CI consumption levels established through RAMP modeling.

4.5. 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 that projects forward the current trends of key drivers without assuming major policy or economic shifts. In contrast, the HEG and RU scenarios explore alternative pathways by applying different growth

rates to these drivers. In each scenario, four key drivers of electricity demand are projected or taken from projecting sources. These are the annual population growth rate, the percentage of the population living in urban areas, the 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 [146]. 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 [32]. Table 5 summarizes the assumed growth rates and projected values for each scenario.

4.5.1. Business as Usual Scenario

The BAU scenario assumes the drivers of electricity demand, including the annual population growth rate and percentage of urban population, follow the projection of the UN. Based on historical trends of rural electrification rate from 2005 to 2021 [25], this scenario extrapolates that 100% rural access will be achieved by 2046. Projections of future GDP growth rates are based on a combination of the most up-to-date available data, including historical trends from the World Bank, IMF predictions up to 2028, and a recent study [147]. Based on this, GDP growth rates of 6%, 5%, and 4% are projected for the years leading up to 2030, 2040, and 2050, respectively. This gradual decline in GDP growth rate reflects the principle that economic growth tends to slow as an economy matures [148].

4.5.2. High Economic Growth Scenario

In the HEG scenario, we envision a GDP growth rate that is greater than the baseline. This assumption is predicated on Ethiopia's strong economic outcomes that show an average growth rate of about 11% per year since 2004, and a decrease in extreme poverty rates—from 55% in 2000 and 34% in 2011 [149]. Over the past 15 years, the country has experienced an AAGR of nearly 10%, mainly due to public infrastructure investments [150]. The assumptions in the HEG are founded on the government's economic policy and reforms, such as the 2019 Home-Grown Economic Reform Agenda, which runs from 2020/21 to 2029/30 and aims to move the Ethiopian economy to a market-oriented economy, attract foreign direct investment (FDI) and develop the private sector. Taking these into consideration, the HEG scenario set out an average annual GDP growth of 11%, 8% and 6% to 2030, 2040, and 2050, respectively [147].

4.5.3. 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 [20]. 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 [151]. 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).

4.6. Electricity demand projection model

The MLR model projects future electricity demand on the basis of historical relationships between the dependent variable (electricity demand) and a set of independent variables (demand drivers). The general form of the MLR model is expressed in Equation 9.

$$D = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \quad (9)$$

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

The model projects the electricity demand of households, and commercial & public services sectors, based on the growth rates of key drivers (rural electricity access levels, GDP per capita, urban population percentage) specific to each scenario, as outlined in Table 5. Historical consumption data for households, as well as commercial and public services (from 2005-2021),

were obtained from the IEA [32]. To project the electricity demand of HHs, the model establishes a correlation between the historical 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 4.4.2.

CIs such as health centers, schools, churches, and government buildings are categorized as part of the public services group within IEA statistical data [32]. 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 this demand projection is represented by Equation 10.

$$D = \beta_0 + \beta_1(Rural\ electricity_{access}) + \beta_2(GDP_{percapita}) + \beta_3\left(Urban\ population_{percentage}\right) + \varepsilon \qquad (10)$$

Table 5. 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

4.7. Influence of temperature on electricity demand

The effects of temperature on future electricity demand is further examined. The spatial temperature data was obtained from the Global Solar Atlas [139], as depicted in Fig. 17. The long-term average temperature ranges from 8.8°C in the cooler highlands (central area) to 33.8°C in the hotter lowlands (Northeast, East, and Southeast regions) [139], [152]. The model incorporates a temperature sensitivity factor that increases the projected baseline demand by 2% for every 1°C increase in yearly average daily temperature (T) above a 24°C threshold (Equation 11).

$$E_{total}(T) = \begin{cases} E_{total}, & T < 24°C \\ E_{total} * (1 + 0.02 * (T - 24)), & T \geq 24°C \end{cases} \quad (11)$$

Where $E_{total}(T)$ represents total electricity demand considering the effect of spatial temperatures, and E_{total} is the baseline total demand without considering the effect of temperature.

Furthermore, to provide a forward-looking perspective on temperature-driven demand, temperature rise projections over the projection period is incorporated. These projections are sourced from the Intergovernmental Panel on Climate Change (IPCC) reports, which predict an average global ambient temperature rise of about 0.2°C per decade [138]. 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.

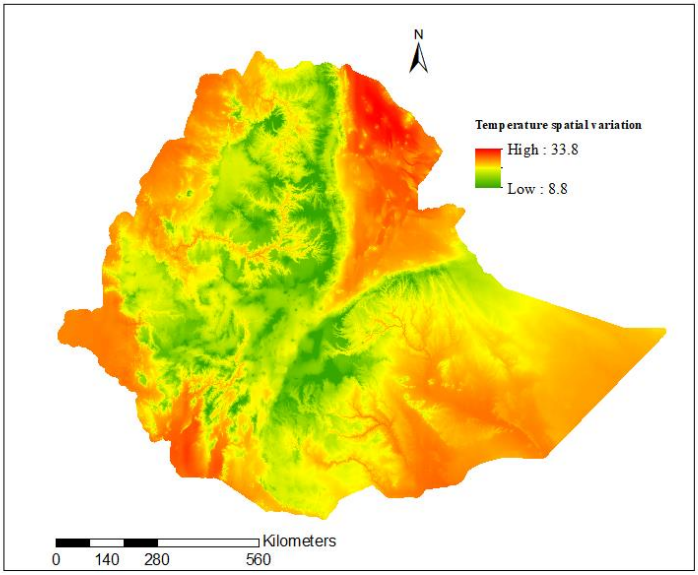

Fig. 17. Long-term yearly average daily air temperatures in Ethiopia (1994–2018), measured at a height of 2 m above the ground with a resolution of 30 arcseconds [139].

4.8. Results and analysis

4.8.1. Total electricity demand projections under different scenarios

The projections show substantial growth in electricity demand levels under all scenarios: by 2050 relative to the 2021 baseline, total electricity demand increases to 20,400 GWh (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 projections result in an AAGR of 3.6%, 4.1%, and 4.8% for BAU, HEG, and RU, respectively.

In per capita terms, BAU shows an increase from 70 kWh in 2014 to 106 kWh by 2050, while HEG and RU increase to 122 kWh and 148 kWh, respectively. These results indicate that Ethiopia is projected to have growth in both total and per capita electricity demand over the projection period. Fig. 18 shows the demand growth trends under each scenario.

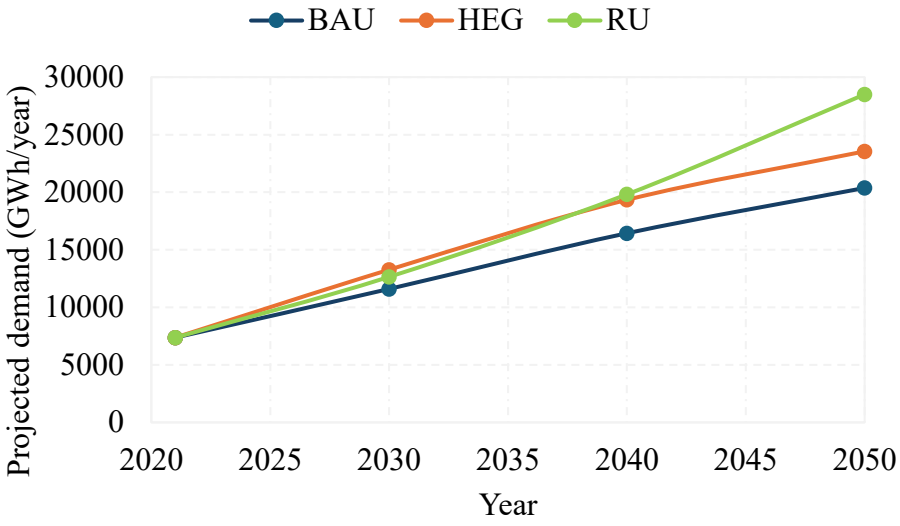

Fig. 18. Projected total electricity demand in Ethiopia (2021–2050) under three scenarios.

4.8.2. Electricity demand by consumer group

The analysis of electricity demand projections by consumer group (HHs, PUs, and CIs) reveals disparities in total demand 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 results in 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. We validated the regression model by comparing its predictions (2005–2021) against the actual historical consumption for HHs. The model fits well, as shown in Fig. 19. The coefficient of determination (R^2) value for the MLR models exceeds 0.97, indicating strong explanatory power of the selected demand drivers. Table 6 summarizes the projected electricity demand by consumer groups across these scenarios.

Table 6. 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

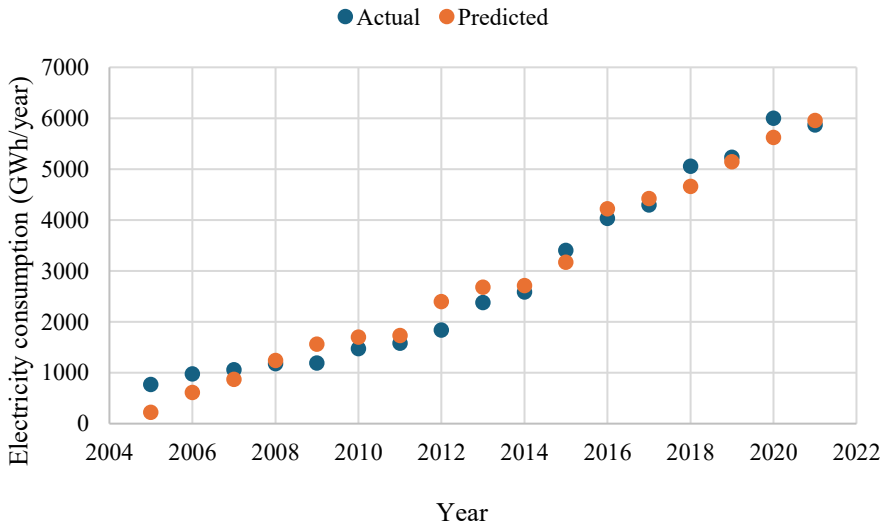

Fig. 19. Regression model validation, actual vs. predicted HH consumption for the years 2005–2021.

4.8.3. Sectoral spatial demand

4.8.3.1. 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 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 approx. 17% by 2030 and further increase to 25% by 2050. This is due to newly electrified HHs starting at lower tiers rather than a decrease in consumption among existing users. 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). 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. 20 illustrates the evolution of HHs' electricity demand under the three scenarios. In the BAU, 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 is in contrast to 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 results in the largest increase in Tier 4 HHs, with 11.31% of HHs falling into this category by 2050.

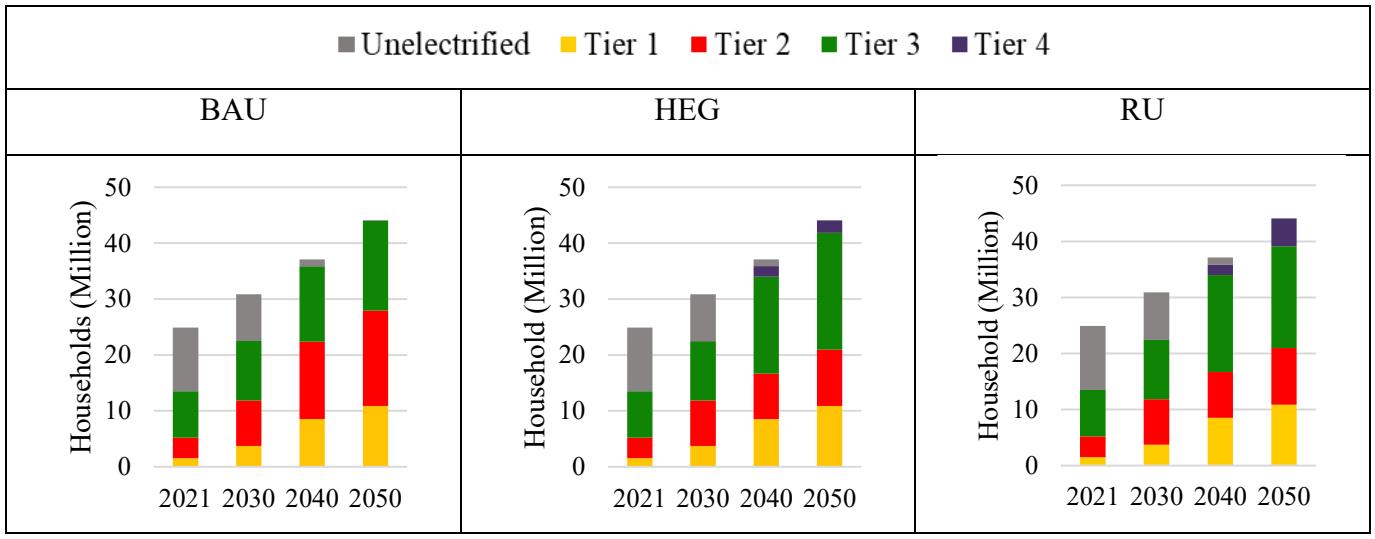

Fig. 20. Evolution of HH electricity demand tiers under three scenarios for the years 2021, 2030, and 2050. Access to electricity is projected to be fully achieved after 2040, which is displayed in the figure as 'unelectrified' in gray.

Given that the RU scenario represents the highest increase in electricity demand by 2050, the spatial analysis of demand focuses on this scenario. The spatiotemporal analysis reveals three key

insights as shown in Fig. 21. 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 enlarged inset map, HHs in settlements with lower demand tiers in 2021 are likely to move toward higher tiers by 2050.

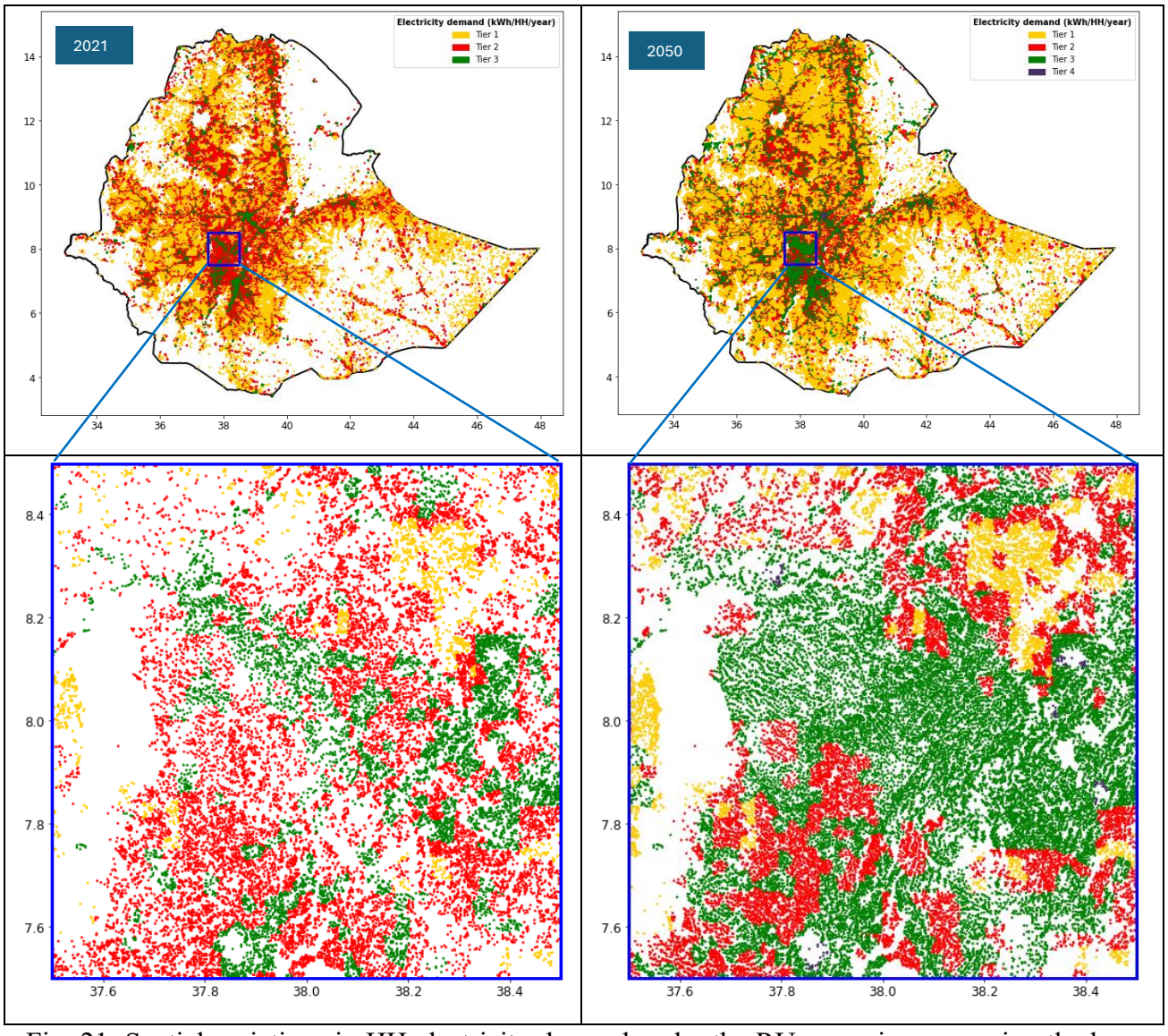

Fig. 21. Spatial variations in HH electricity demand under the RU scenario, comparing the base year (2021) with projections for 2050. In the base year, HH demand ranges from Tier 1 to Tier 3, while by 2050 demand is projected to increase with some settlements reaching Tier 4.

Third, a closer inspection of Fig. 21 demonstrates a sizable number of HHs in the north-central, central and south-central regions of the country, are expected to transition from Tier 1 to Tiers 2 or 3 between 2021 and 2050. In contrast, many HHs in more peripheral areas (north-east and south-east) regions are expected to stay in Tier 1 or move marginally to Tier 2 over the same period. The regional differences demonstrate geographic variation across the national spectrum of HH electricity demand, driven by local population dynamics, economic factors, and urbanization development.

4.8.3.2. 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 fraction of settlements (3.2%) fell within the demand range of 1 to 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. 22 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.

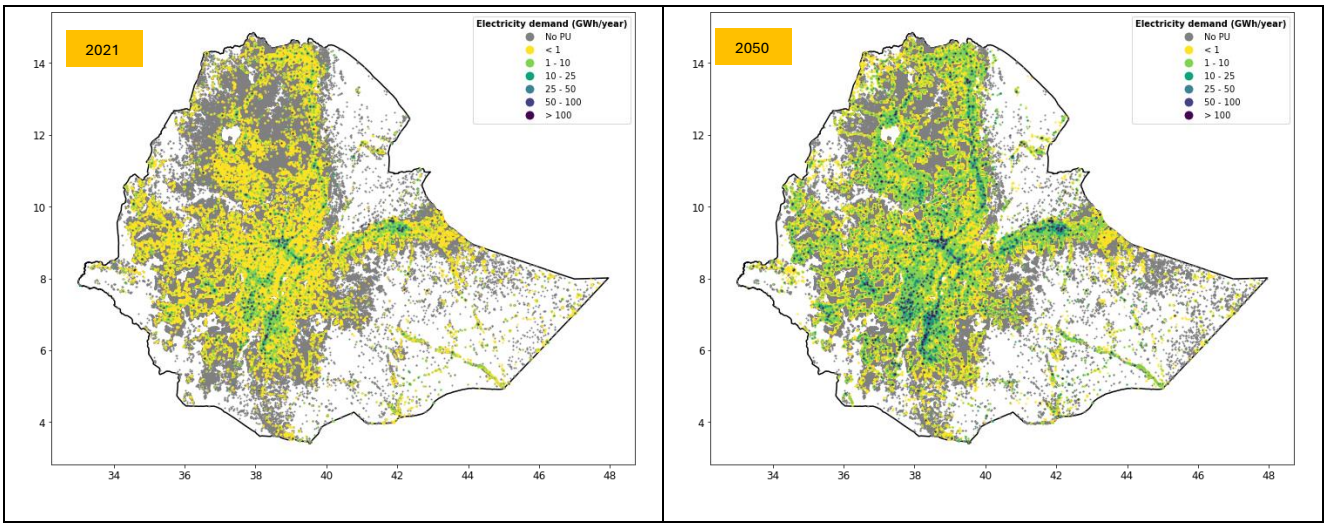

Fig. 22. Spatial variations in electricity demand for PUs under the RU scenario, comparing the base year (2021) demand with projections for 2050. Areas shaded in gray represent settlements where the electricity demand of HHs remains below Tier 2, indicating that there is no PUs in these settlements.

4.8.3.3. 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 had relatively low electricity demand, with total demand per settlement below 1,000 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 (1,000–3,000 kWh) is projected to grow from 27% to 46%, while those with high demand (over 5,000 kWh) are expected to rise from 5% in 2030 to 9%.

By 2030, electricity demand from CIs may contribute, on average, to a 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 substantial 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 population. This spatial distribution explains their disproportionately higher contribution of CIs to the electricity demand in these settlements. The

spatial distribution of CIs electricity demand, as shown in Fig. 23, aligns with the patterns observed for HHs electricity demand in Fig. 21. 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.

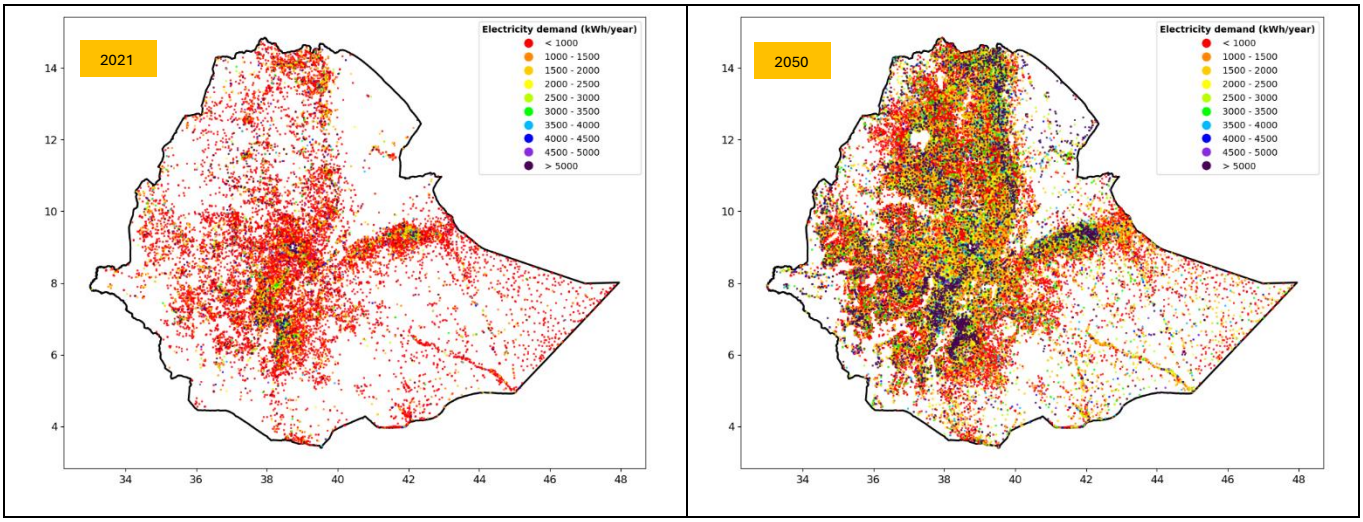

Fig. 23. Spatial variations of electricity demand for CIs under the RU scenario, comparing the base year (2021) with 2050 projections. The highest demand for CIs is observed in areas that align with roads, cities, and densely populated regions.

4.8.4. 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, the additional demand attributed to temperature rises and spatial temperature considerations in electricity demand projections is expected to be approx. 0.49% by 2030 and 0.53% by 2050 across the three scenarios.

Even though the national effect is modest, certain regions are more likely to experience a larger demand for electricity due to the anticipated temperature rise. Some of these areas are the hot and semi-arid lowlands of Afar (Northeast) and Somali (Southeast), Amhara (Northwest), Benishangul-Gumuz (West), as well as peripheral areas. As a result of the expected ambient temperature rise within these regions, electricity demand may increase by up to 21.8% to 22.6% between 2030 and 2050. It is estimated that 13 million people will live in these areas by 2030 and 20.2 million by 2050 (based on the population growth rates presented in Table 5). Fig. 24 shows the settlements that are expected to be the most affected due to the temperature increase.

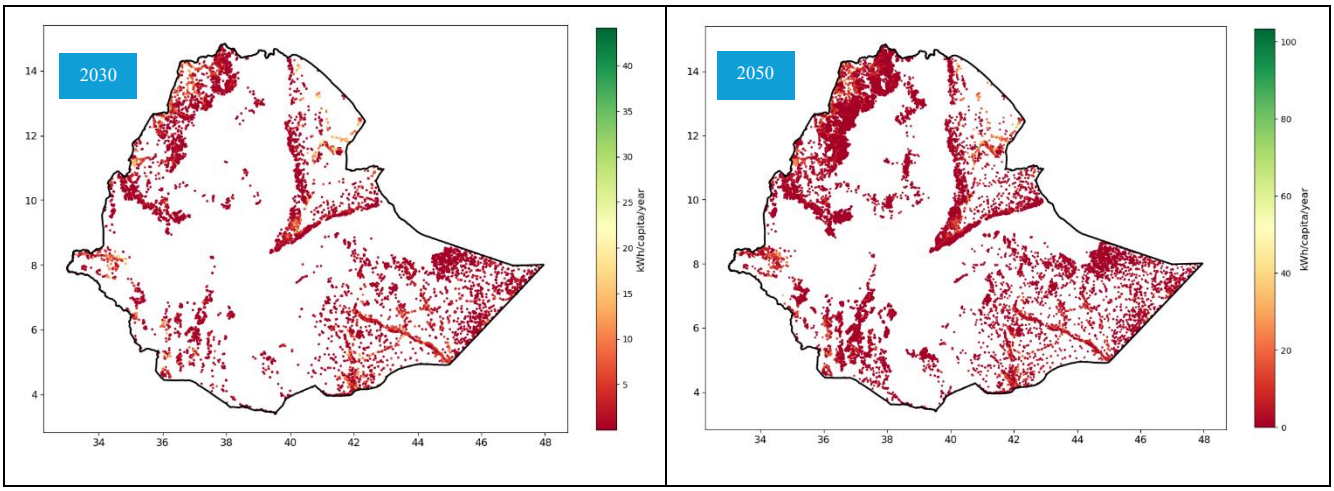

Fig. 24. Additional electricity demand due to projected temperature rise in the RU scenario for the years 2030 and 2050. By 2050, the impact of rising temperatures is expected to extend into central northern regions, indicating a broader geographical spread of temperature-driven demand.

4.9. Discussion

Spatial electricity demand is projected for Ethiopia over 29 years from 2021 to 2050, using three scenarios (BAU, HEG, and RU). All scenarios show significant growth, with the RU scenario displaying the highest increase, 40% above BAU by 2050. These results are consistent with previous studies, which showed that rapid urbanization of rural areas leads to a substantial increase in energy consumption [153], [154], [155]. This high demand growth in the RU scenario as compared to the other two scenarios, highlights the importance of urbanization in electricity access planning.

Compared to previous studies carried out for Ethiopia, the results show both alignment and divergence in terms of growth rates. These differences can be attributed to differences in the socio-economic assumptions, time-horizon, sectoral coverage, and the methods of projections (e.g., regression [59], Low Emissions Analysis Platform (LEAP) [21], [147], [156]). Table 7 provides a comparative overview of the relatively limited set of long-term electricity demand projections available for Ethiopia.

The AAGR projected for HH electricity demand closely matches the projections reported by Pappis et al. [59]. 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. [21] until 2030 aligns with our projection of 5.1–6.8% for the same period. In contrast, Gebremeskel et al. [147] 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 our more conservative range of 39.1–56.9%).

The total electricity demand AAGR projected (5.2% to 6.8%) closely aligns with the findings of Pappis et al. and, to a lesser extent, with Senshaw [156]. Again, Gebremeskel et al. [147] report higher growth rates for total demand through 2050. It is important to note that the highest total electricity demand growth rates reported in previous studies are largely driven by sectors such as industry, agriculture, transport, and services, and in some cases also account for exports and technical losses [21], [59], [147], [156]. 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, our demand projection for Ethiopia appears relatively moderate. The electricity demand for Pakistan grows at 8.35% AAGR until 2050 [136], considerably higher than Ethiopia's 3.6% to 4.8% AAGRs. Similarly, studies in Kenya projected AAGR of 1.8% to 10% until 2040, indicates a broader range compared to Ethiopia [157], [158]. Rwanda's AAGR of 6.6% to 7.2% exceeds the projected AAGR for Ethiopia, despite a smaller absolute demand [159]. In contrast, Sierra Leone's projected AAGR from 2019 to 2040 ranges between 3.9% and 5.7% [160], aligns with our projections for Ethiopia. This shows 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, the projection for total electricity demand growth for Ethiopia, ranging from 4.3% to 5.3% AAGR until 2040, agrees with the IEA's estimated 4.6% AAGR for SSA for the 2012-2040 period [161].

Table 7. Comparison of electricity demand projections for Ethiopia.

Studies	Time-horizon	AAGR (%)	Source
Household	2018-2065	4.2	Pappis et al. [59]
Household	2012–2030	7.6	Mondal et al. [21]
Household	2018-2050	8.5	Gebremeskel et al. [147]
Total demand	2018-2065	4.9	Pappis et al. [59]
Total demand	2018-2050	6.0-8.4	Senshaw [156]
Total demand	2018-2050	7.2	Gebremeskel et al. [147]
Total demand	2012–2030	9.7	Mondal et al. [21]

Findings from the sectoral demand projections indicate that HH electricity demand remains the primary source of energy consumption. This is in agreement with past studies, which reported that the HH sector accounted for 88% of Ethiopia's total energy consumption in 2018 [30]. However, Yalew's [30] 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 our 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 is likely attributable to the modeling 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 that electricity demand vary spatially. Central regions, characterized by higher population densities, relatively higher local economies, and lower poverty rates, are projected to see higher growth in electricity demand. Most settlements in these regions are already electrified, which further increases 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 growth in electricity demand. Limited access to electricity, and sparse population 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 socio-economic 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. [60]. 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), our projection shows that Tier 3 demand will continue to dominate until 2050, with a growing share of Tier 2 and Tier 4 demand. Our findings of varied demand (Tiers 1 to 4) across regions challenge the projections by Mentis et al. [13], [29], 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) by 2030. Similarly, Ouedraogo [49] projected that urban settlements in Cameroon would reach Tier 5 consumption (1,796 kWh/HH/year) by 2035, while rural settlements would reach Tier 3 (530 kWh/HH/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 out of the 809,087 total settlements in Ethiopia delineated by [38]. 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 [40].

The assumption that PU demand is 25% of HH demand for tiers 2 and above is a simplification. It is a conservative but necessary first-order approximation in the absence of granular, nationwide

PU data for Ethiopia. This proxy represents a significant methodological step beyond models that omit PU entirely, thereby providing a more realistic baseline estimation.

Furthermore, the analysis of electricity demand due to temperature spatial 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% to 22.6% between 2030 and 2050 due to rising temperatures. These results are substantiated by a previous study in Ethiopia [54], which reported a 22% increase in electricity consumption during hotter, dry season. This seasonal variation is strongly linked to cooling needs as consumption is observed to be lower during the cooler, rainy season when less power is required for space cooling. As highlighted in [55], such temperature-driven demand growth shows the need to incorporate the effect of temperature into long-term energy planning, at least at local levels.

5. Long-term least-cost geospatial electrification planning

5.1. Introduction

The final stage of electrification modeling involves identifying the supply options that meet projected electricity demand at the lowest possible cost [13], [95]. However, selecting the cost-optimal[7] electrification solution for a given location requires careful consideration of a wide range of parameters, all of which are spatial in nature. These include locally available energy resources (e.g., solar, wind, hydro), proximity to existing infrastructure (such as power networks, substations, roads), electricity demand, land cover, and topography [60]. Grid extension costs, for instance, are particularly sensitive to geospatial characteristics such as proximity to roads and substations, land cover type, elevation, and slope. These factors can collectively increase initial investment requirements by as much as 30%, irrespective of projected demand levels [38], [45]. Similarly, the viability of off-grid electrification solutions, particularly renewable MGs, is heavily dependent on the availability of sufficient local energy resources, including solar radiation, wind speeds, and nearby river flows. Given this spatial complexity, electricity access planning must integrate multiple dimensions: energy supply potential, demand evolution, and techno-economic parameters.

This chapter aims to explore electrification strategy that: (1) identifies least-cost technology mix for each population settlement nationwide under various scenarios; (2) maps the spatial and temporal evolution of these technology choices, revealing where and when different solutions become optimal; and (3) quantifies the total investment required and its allocation over time.

5.2. Methodology

The OnSSET framework is used to identify the optimal technology mix for Ethiopia over a multi-decade planning horizon (2021-2050). The model estimates, analyzes, and visualizes the least-cost options for achieving electricity access goals [11]. The analysis builds on the delineated population settlement and geospatial factors influencing grid extension determined in Chapter 3 and the

[7]Cost-optimal refers to an approach that minimizes the expense of delivering electricity to end users and is used interchangeably with ‘least-cost’ throughout this paper.

electricity demand projections developed in Chapter 4. In this chapter, the OnSSET model extracts and integrates existing grid infrastructure, renewable energy resource data and a set of techno-economic parameters to evaluate electrification options for each settlement in the study area [60]. For each of Ethiopia's 809,087 settlements, the model determines which technology, grid extension, mini-grid systems (hydro, wind, or solar PV), and SA PV systems, can meet projected demand at the lowest LCOE at every time step in the planning horizon. The technology that provides the lowest LCOE is selected as the least-cost option in each settlement [4]. An overview of the methodology used is outlined in Fig. 25 and detailed in subsequent sections.

5.2.1. Model development

Building on the OnSSET platform, nationwide electrification is modeled over a 29-year planning horizon, spanning from 2021 to 2050. The model is set up in three time-steps: 2021–2030, 2030–2040, and 2040–2050. This work employs a myopic modeling approach to identify the optimal electrification pathways [60]. The least-cost technology identified in the previous time-step serves as the starting point for the next, and so on [10], [162]. This myopic approach allows the model to capture the dynamic evolution of technology choices for each of the 809,087 settlements in response to two key evolving factors: (1) the growth in electricity demand as projected in the scenarios from Chapter 4, and (2) the projected decline in technology capital costs at each time step.

For settlements electrified in previous time-steps, the model can choose to either increase the capacity of the existing technology or transition to a more cost-effective alternative to meet growing demand. It assumes a logical, unidirectional technology progression (SA PV → MG → Grid). Technology transitions are possible only if the new option offers a lower LCOE than the capacity expansion of the existing system. Settlements electrified by MGs can transition to grid connections if economically justified but are not allowed to revert to SA PV technologies [10].

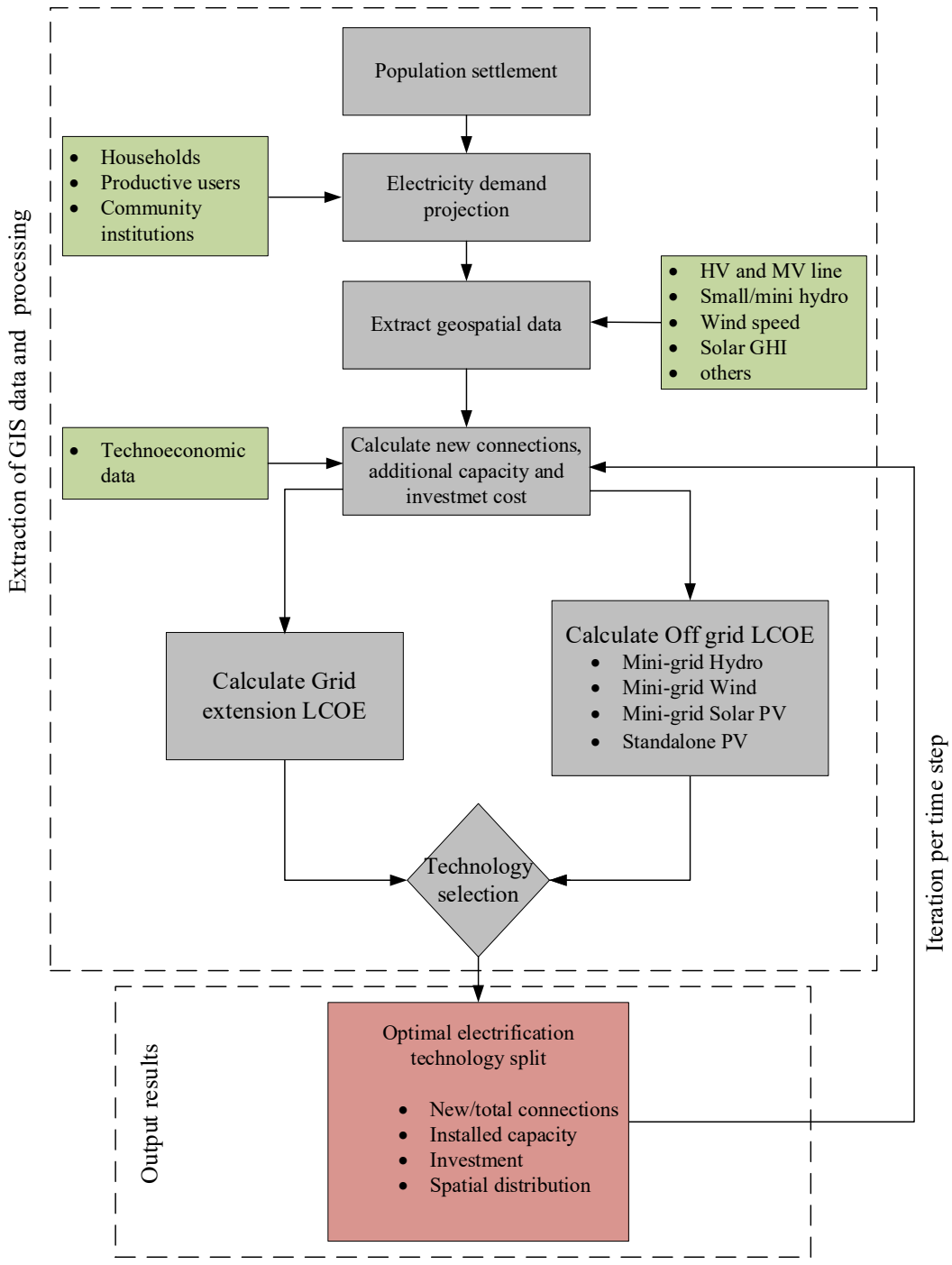

Fig. 25. Integration of geospatial data, demand projections, and optimization processes to derive electrification recommendations. The diagram shows light green "input data," gray "data process," and red "results of the analysis".

This progression reflects the practical realities of energy access in rural areas, where people start using SA PV systems before MGs are deployed or the national grid arrives. A critical consideration

in this progression is ensuring that MG investments are not rendered obsolete by future grid arrival. The model assumes MGs are technically compatible with the central grid and continue operating in parallel after interconnection, allowing their generation and distribution assets to serve until the end of their operational lifetimes.

5.2.2. Identifying grid-electrified settlements

To establish a baseline for electrification planning, the analysis classified population as either electrified (1) or unelectrified (0) in the base year (2021) [10]. Satellite-derived NTL imagery, particularly when combined with population data and grid network proximity, has emerged as a valuable proxy for assessing the electrification status of settlements [5]. A GIS-based multicriteria heuristic that integrated several spatial datasets was employed to do so. Specifically. the classification integrated spatial data on population distribution, locations of existing LV transformers, NTL intensity, and national grid access statistics.

The classification was based on the assumption that settlements located within a certain distance of the existing LV transformer infrastructure should correspond to the nationally reported grid-electrified population figure. As a result, it was found that settlements within 1 km of an LV transformer, with a NTL intensity above 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ and population over 650 is equal to the grid-electrified population of the country (national grid access of 40.4% in the base year, derived from extrapolations of World Bank ESMAP [53] and AfDB data [26]).

5.2.3. New connections and additional capacity

The number of new connections at each time-step is determined by national access targets. It is assumed that the electrification progresses linearly over time. That is, the national access level was set at 72% by 2030, 96% by 2040, and 100% by 2050. These targets are derived based on the projection of historical electricity access development.

To prioritize which settlements should be electrified at each time-step, while meeting these national targets, the OnSSET model employs a prioritization algorithm [10]. Initially, priority is given to settlements that are already electrified but require new connections due to population growth. Subsequently, unelectrified settlements can be prioritized based on criteria such as investment cost per capita for new connections or the travel time to large cities [106], [163]. In this thesis,

unelectrified settlements are ranked in ascending order of investment cost per capita. By doing so, resources can be allocated more efficiently. The resulting technology rollout in one period serves as the starting point for the subsequent time-step's analysis.

For electrified settlements, new connections were calculated as the difference between the current and previous time-step population. For previously unelectrified settlements, the entire population is assumed to be newly connected in the respective time-step. New connection at each settlement is thus calculated as expressed in Equation 12. The electricity demand associated with these new connections is then determined using Equation 13.

$$N_{conn,t} = \begin{cases} Pop_t - Pop_{t-1}, & if\ electrified \\ Pop_t & if\ unelectrified \end{cases} \quad (12)$$

$$E_{new,t} = E_{pc,t}\ x\ N_{conn,t} \quad (13)$$

Where, $N_{conn,t}$ is the number of new connections at time t, Pop_t and Pop_{t-1} represent total population in a settlement at the current and previous time-steps, respectively. $E_{pc,t}$ denotes per capita electricity demand (kWh/capita/year) at time-step t.

In addition to the demand from new connections, the electricity demand of the population who have already electricity access is also expected to increase over time, which is determined using Equation 14. Therefore, the total additional electricity demand for each settlement at every time-step is the sum of the demand from new connections and the incremental demand, as shown in Equation 15. The study's 29-year planning period exceeds the operational lifetimes of most electricity supply technologies (except for grid extension and hydropower). Thus, when technology reaches the end of its operational lifetime, the model accounts for the demand it previously met and adds it to the settlement's total demand for the current time-step. Only additional demand is considered for technologies that are still operational. Thus, the total demand for the settlement at each time-step is given by Equation 16.

$$\Delta E_t = \left(E_{pc,t} - E_{pc,t-1}\right)\ x\ \left(Pop_t - N_{conn,t}\right) \quad (14)$$

$$E_{add,t} = E_{new,t} + \Delta E_t \quad (15)$$

$$E_{tot,t} = \begin{cases} E_{add,t} + E_{met,t} & Exp_t < t \\ E_{add,t} & otherwise \end{cases} \quad (16)$$

Where ΔE_t is incremental demand at time t, $E_{add,t}$ is additional demand at time t, $E_{tot,t}$ is total demand of a settlement at time t, and $E_{met,t}$ is demand previously met by technologies until their expiration year (Exp_t). This approach ensures that expired technologies do not leave settlements without electricity.

To avoid stranded investments, existing infrastructure such as MGs or SA PV systems are assumed to operate until they reach the end of their operational lifespan, even if a settlement transitions to a new technology such as the grid. During transitions, the new technology is sized only for $N_{conn,t}$. The installed capacity required to meet the total settlement demand is calculated as shown in Equation 17.

$$C_{inst,t} = \frac{E_{tot,t}}{H_{yr} \; x \; CF \; x \; BPR \; x \; (1 - L_{dist})} \quad (17)$$

Where, $C_{inst,t}$ is installed capacity at time t, H_{yr} is hours per year, CF is the capacity factor, which differs depending on the supply source, provided in Table C1 and C2, and BPR is the base-to-peak ratio (see assumed values in Table 9). L_{dist} represents distribution losses in transmission and distribution lines, and the assumed values are presented in Table C3.

5.2.4. Investment cost

The investment cost for electrification at each time-step is calculated as the sum of generation capacity costs and the associated transmission and distribution (T&D) infrastructure costs. This is mathematically represented as in Equation 18.

$$I_{cost,t} = C_{inst,t} \; x \; cap_{cost,t} + td_{cost} x \; PF \quad (18)$$

Where $I_{cost,t}$ is the investment cost at time t, $Cap_{cost,t}$ represents the technology-specific capacity cost (USD/kW) at time t, and td_{cost} represents the transmission and distribution infrastructure cost, and PF is a grid penalty factor that adjusts td_{cost} for geographical and logistical complexities.

The cap_{cost} varies by technology type. For SA PV systems, it includes the cost of solar panels, inverters, and batteries for individual household systems. In the case of MGs whether powered by solar, wind, or hydro, Cap_{cost} accounts for the cost of centralized generation equipment and the associated installation costs. For grid extension, it represents the average cost of adding or upgrading existing grid generation capacity.

The td_{cost} also varies depending on the technology. SA PV systems incur no ttd_{cost} as they operate independently at the household level without network infrastructure requirements. In contrast, MGs require a localized distribution network to deliver electricity from a central generation point to individual users. This includes the cost of LV distribution lines, transformers, and end-user connection costs. Grid extension involves a more complex and capital-intensive infrastructure, and thus td_{cost} includes the upfront capital costs for HV and MV transmission lines, substations, transformers, LV lines, and end-user connection costs.

To reflect the real-world difficulties of building grid infrastructures, the model incorporates a grid extension penalty (GEP) factor that adjusts the td_{cost} for grid extension. As detailed in Chapter 3, section 3.5.4, this GEP is a composite metric that quantifies the additional costs incurred due to geospatial constraints such as challenging terrain, land cover, and distance from existing infrastructure [38]. Consequently, the model applies this location specific penalty to provide a more realistic estimate of td_{cost}.

5.2.5. LCOE

The LCOE is used as a key metric for comparing the relative cost-effectiveness of different electrification technologies [50]. It represents the final cost of electricity required for the overall system to breakeven over the project lifetime [74]. To put it another way, LCOE represents the unitary cost (USD/kWh) of electricity generated over a technology's operational lifetime, accounting for all capital expenditures, operational and maintenance costs, and fuel expenses where applicable. For each settlement and technology at each time-step, the LCOE is calculated by dividing total discounted lifetime costs by total discounted electricity generation, as given by Equation 19.

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_{cost,t} + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \quad (19)$$

Here, $I_{cost,t}$ is the upfront investment cost derived from Equation 18, $O\&M_t$ is the operations and maintenance cost expressed as a percentage of the capital cost. F_t is the fuel cost, which represents the grid generation cost (in USD/kWh) for grid extension technologies and is zero for off-grid technologies. E_t denotes the electricity generation, r is the discount rate, and n is the technology's lifespan.

5.2.6. Least-cost electrification technology split

The OnSSET model identifies the least-cost electrification technology for each settlement by comparing the LCOE of all available technologies. To do so, at each time-step, the model first identifies the lowest LCOE among off-grid technologies (hydro MG, wind MG, solar MG, and SA PV systems) for each settlement [60]. This is then compared to the LCOE of connecting the settlement to the centralized grid. The technology with the lowest overall LCOE is recommended as the least-cost solution. This process is repeated iteratively throughout the planning horizon, enabling the model to adapt technology choices as costs and demand evolve over time. As a result, each settlement is dynamically assigned the most economically viable electrification option throughout the planning horizon.

5.2.7. Scenarios

The planning of future electrification in rural areas without electricity is challenged by uncertainties in demand growth and grid generation costs (average national cost of grid electricity in USD/kWh). To address these uncertainties, the analysis incorporates multiple scenarios, exploring a set of potential pathways that describe how future electrification strategies might be developed based on different demand evolutions and grid generation costs [59].

Grid generation costs can be influenced by factors such as technological advancements, economies of scale, and the national energy mix [10]. To account for this, the least-cost electrification technology selection for each demand pathway described in chapter 4 is analyzed under two grid generation cost assumptions: Low Grid Generation Cost (LGGC) and High Grid Generation Cost (HGGC), as shown in Table 8. By combining the three demand growth pathways (BAU, HEG and

RU, described in detail in section 4.5) with the two grid generation cost scenarios (LGGC and HGGC), six integrated scenario combinations are established: BAU–LGGC, BAU–HGGC, HEG–LGGC, HEG–HGGC, RU–LGGC, and RU–HGGC. These combinations enable the assessment of least-cost electrification strategies under a wide range of plausible futures.

Grid generation cost assumptions are informed by the work of Sahlberg et al. [60] and Pappis et al. [59], who employed a soft-linked OnSSET and OSeMOSYS to calculate centralized grid electricity generation costs in Ethiopia, focusing on medium- to long-term planning. Their analysis optimized grid capacity expansion, incorporating residential demand alongside industrial, commercial, and public service loads from 2018 to 2070 [60]. The rationale for using these costs lies in the disparity between demand scales: the projected national demand of currently unelectrified areas is significantly lower than the national demand modeled by Pappis et al. [59], which includes significant industrial and commercial loads. Therefore, the additional demand from unelectrified regions is unlikely to change the national average grid generation costs.

5.2.8. Data and assumptions

5.2.8.1. GIS data

The developed geospatial electrification planning model processes various GIS data, in the form of both vector (shapefiles) and raster data layers. These data include existing grid infrastructure, renewable energy resources, and relevant geographical features [19]. A complete list of the GIS data used along with their corresponding sources, is provided in Appendix Table A1.

The analysis incorporates georeferenced grid infrastructure data such as HV and MV transmission lines, substations, and distribution transformers. The collected HV lines include voltage levels between 45 kV and 500 kV. The total length of HV lines is approximately 16,397 km in the study area, as determined through QGIS-based analysis. Similarly, in the study area, MV lines consist of 15 kV and 33 kV networks. The total length of these MV lines is approximately 61,575 km. The model also incorporates the locations of 152 substations and 42,184 distribution transformers. These grid infrastructure data were obtained from EEP and EEU. The geographical distribution and spatial extent of the existing grid infrastructure across Ethiopia are shown in Fig. 26.

The model's assessment of supply-side options incorporates spatial data for renewable energy resources, including solar irradiance, wind speed, and hydropower potential. Solar irradiance data is used to assess the suitability of solar MGs and SA PV systems. For this purpose, Global Horizontal Irradiance (GHI) data was sourced from the Global Solar Atlas [139]. Wind MGs potential is evaluated using wind speed data from the Global Wind Atlas at a height of 100 m [164]. This data is then adjusted to a height of 55 m using the logarithmic wind profile method embedded within the OnSSET model [165]. This adjustment accounts for the variation in wind speed with height due to changes in surface friction. MG wind systems were modeled based on the Vestas V44 turbine (600 kW), commonly used in small-scale wind turbines [166], [167]. For hydro MGs, data on small and mini-hydro potential, ranging from 0.01 to 10 MW, were acquired from Energydata.info [122]. This potential was determined through a high-resolution GIS-based assessment that combined digital elevation models, river network data, and mean runoff volumes to estimate discharge and head across perennial river networks [168].

Additional geospatial layers incorporated into the model include land cover classifications, road network data, and topographic variables such as elevation and slope. These factors are particularly important for adjusting the cost of grid extension through the application of a topographic penalty factor [38]. All GIS data inputs are then extracted for each population settlement using the OnSSET_GIS_Extraction_notebook [106].

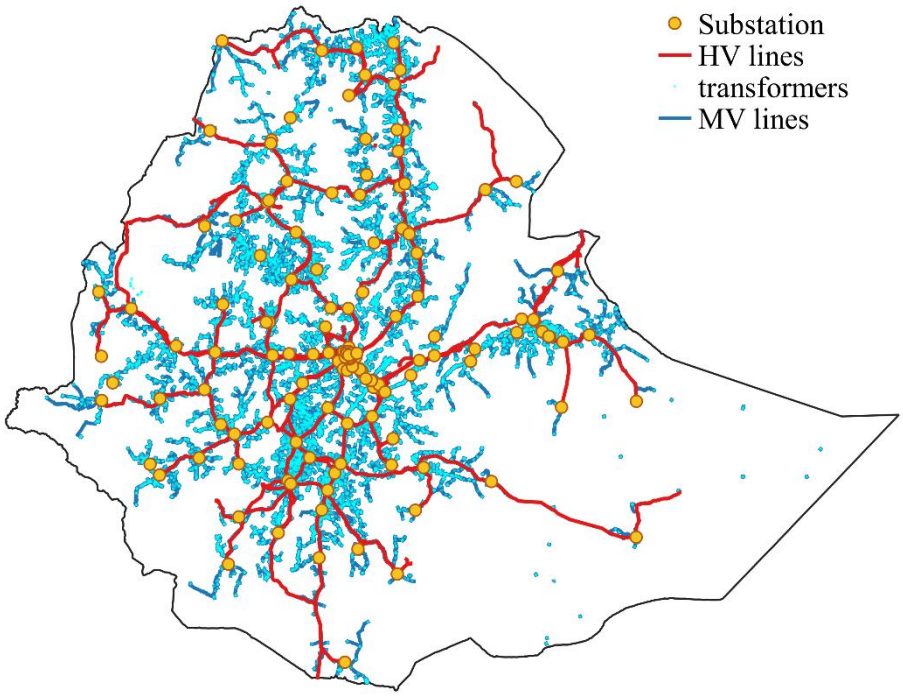

Fig. 26. Existing HV and MV lines, substations, and transformers georeferenced data.

5.2.8.2. Techno-economic data

The techno-economic parameters used in this analysis are drawn from an extensive review of peer-reviewed studies, particularly Ethiopia-focused electrification studies [3], [45], [60], [163], [169]. Grid generation and capital costs were derived from Sahlberg et al.'s Ethiopia-specific projections across multiple time-steps [60]. Grid transmission and distribution costs were compiled from various sources, including the Global Electrification Platform [169], Mentis et al. [45], and Korkovelos et al. [3]. These costs are assumed to remain constant throughout the analysis period (Table C3).

Baseline costs for solar PV MGs were established by averaging the capital costs of 10 operational MGs, deployed in Ethiopia, with capacities ranging from 175 to 550 kWp [54]. Projections from the ESMAP indicate a 25% reduction in solar hybrid MG capital costs per kW between 2020 and 2030 owing to technological advancements [78]. Accordingly, the model applies a stepped cost reduction: 2.5% annual decline (2021-2030), followed by 1.5% annual reduction (2030-2050), to account for continued learning curves and innovations in solar technology.

For wind MG, hydro MG, and SA PV, the capital costs for the first time-step (2021–2030) are drawn from [49], [163], and [169]. Wind MGs costs are projected to decline by 1% annually, in line with global trends for small-scale wind systems [170]. Hydro MG costs are assumed to remain constant throughout the analysis period, given its status as a mature technology with no expected significant cost reductions. Similar to solar MGs, a 1.5% annual cost reduction is applied to SA PV systems. Table C1 (off-grid) and C2 (grid) summarize these techno-economic parameters, detailing capital costs, capacity factors, and technology lifetimes across the analysis horizon.

Table 8. Grid generation costs for 2030, 2040, and 2050 [59], [60].

Grid generation cost (USD/kWh)	**2021–2030**	**2030–2040**	**2040–2050**
Grid (High)	0.19	0.20	0.23
Grid (Low)	0.08	0.09	0.1

5.2.8.3. Key modeling assumptions

The geospatial electrification model is guided by a set of assumptions that define both the baseline conditions and the model's temporal evolution. A list of the key modeling assumptions is presented in Table 9.

A particularly important consideration pertains to the role and limitations of SA PV systems. Although these solutions can deliver basic electricity access, their limited capacity cannot support the medium- and high-power appliances required for productive uses, such as refrigeration, food processing, or mechanical loads, which are essential for long-term economic development [171]. Recent studies, such as Stevanato et al. [88], have highlighted that SHS-based electrification, despite being a low-cost solution, due to limited capacity results in missed economic development opportunities. Thus, their research introduced the concept of shadow costs to quantify the economic losses incurred due to the inability of SHS systems to support high-power appliances required for income-generating activities. Their work highlights that treating SHS as equivalent to grid or MG solutions in electrification planning significantly underestimates the broader development impacts.

Building upon these findings, a phased approach is adopted to progressively limit the deployment of SA PV systems to sparsely populated households, in line with previous findings [78], [172]. In the short term (up to 2030), SA PV remains unrestricted to allow rapid expansion in remote areas where grid or MG infrastructure may not be feasible. However, SA PV systems are restricted to settlements with fewer than 50 households between 2030 and 2040. In the long-term, from 2040 to 2050, the threshold is further reduced to settlements with fewer than 30 households. This modeling choice reflects a development-oriented perspective that, while SA PV is vital for initial energy access, national long-term strategy should aim to provide energy levels sufficient for economic growth and improved livelihoods, which often requires the capacity of mini-grids or the central grid. Thus, this phased deployment strategy ensures that higher-demand settlements gradually shift toward MGs or grid extensions, capable of supporting community development and economic productivity.

Table 9. Key modeling assumptions [10], [163].

Modeling Parameters	**Assumptions**
Base year urban population	22%
Base year grid access	40.4%
Base year population	120,283,026
Discount rate	10%
Base-to-peak (BPR)	BPR is assumed to be 0.8 for grid, 0.85 for MG hydro, wind and PV, and 0.9 for SHS

5.3. Results and analysis

5.3.1. Least-cost electrification technology mix

The results reveal that the optimal electrification technology mix changes over time and is strongly influenced by grid generation costs (Fig. 27). Under the LGGC scenario, grid extension emerges as the dominant least-cost solution in the initial phase (2021–2030), serving over 82% of the total population targeted for electrification and accounting for over 67% of new connections across all demand pathways (BAU, HEG, RU). The dominance of grid extension in the early years of the planning horizon can be attributed to two primary factors. First, the model prioritizes settlements with the lowest per-capita investment requirements, which are those settlements with high electricity demand and larger population. Second, there are extensive grid networks already in place in Ethiopia, and the proximity of a high proportion of population to existing grid infrastructure. Our analysis reveals that over 73% of the total population resides within 5 km of MV lines, while 83% is located within 5 km of both HV and MV grid lines, allowing most settlements to be reached at a relatively low cost of grid extension, given the short distances. Among those who are expected to be electrified by 2030, more than 85% are currently located within 5 km of the grid lines.

However, the grid extension share gradually declines during 2030-2040 as electrification expands to remote areas. By 2050, while grid remains the dominant least-cost option, its share of the total electrified population slightly declines to 78.8% under the LGGC-BAU compared to 2030 levels, with similar marginal declines in the LGGC-HEG (79.5%) and LGGC-RU (79.7%) pathways. MGs become increasingly cost-effective in remote areas, growing from approximately 1.3-1.5% in 2030 to 12-13% by 2050 across all demand pathways. SA PV serves the lowest-demand population, with its share decreasing from about 16% in 2030 to 7.8% by 2050.

In the HGGC scenario, by contrast, higher grid generation costs reduce the competitiveness of grid extension and alter the optimal technology mix. The grid extension share drops by 5.2-5.5 percentage points by 2030 and 12.8-13.1 percentage points by 2050 compared to LGGC. Conversely, MGs see a substantial increase, electrifying approx. 7% of the total population by 2030 and growing to around 26% by 2050 across all demand pathways. SA PV maintains a similar share to that observed in the LGGC scenario.

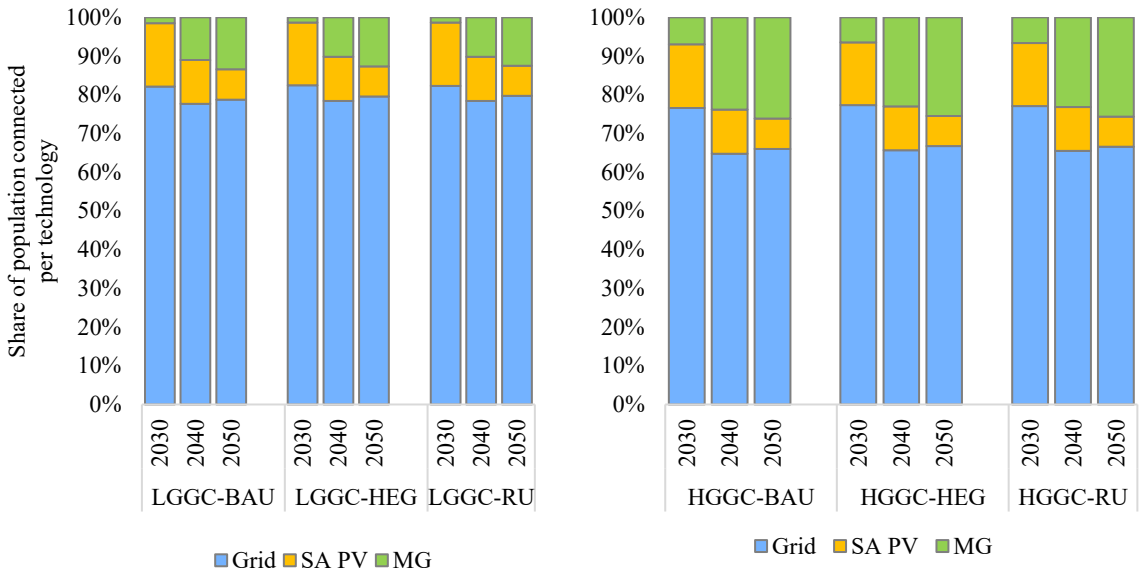

Fig. 27. Share of total population per technology under the LGGC (left) and HGGC (right) scenarios for the three demand pathways (BAU, HEG, and RU) for 2030, 2040, and 2050.

5.3.2. Spatial distribution and temporal evolution of electrification options

The optimal electrification technology varies considerably across the grid generation cost scenarios and evolves over time (Figs. 28 and 29). The maps use a color-coded scheme to indicate the least-cost technology for each settlement: grid (blue), MG PV (red), SA PV systems (yellow), MG wind (brown), MG hydro (green), along with unelectrified settlements (gray).

Under the LGGC-RU scenario, in 2030 (Fig. 28A) shows that grid extension emerges as the dominant cost-optimal solution in settlements with relatively high electricity demand and unelectrified population, averaging 394 kWh/HH/year and 614 people per cluster. Notably, 85% of new connections in 2030 are located within 5 km of existing grid (HV or MV) lines. In contrast, SA PV systems are optimal for low population density and low-demand clusters, averaging 17.5 kWh/HH/year and 151 people per cluster, while MG PV fills an intermediate niche, serving moderate demand clusters predominantly located beyond 10 km from the grid (60% of newly electrified population by MG PV). MG hydro and wind solutions show a competitive advantage only in specific geographic areas with suitable resource conditions. By 2050 (Fig. 28B), MG PV may become an increasingly cost-optimal solution, replacing many previously SA PV-designated

areas and expanding into previously unserved settlements, particularly in the northeastern and southeastern regions.

A detailed study of a zoomed-in 274 km² area, located 120 km from the capital Addis Ababa (Fig. 28C), shows SA PV emerge as the least-cost option for 18% of newly electrified settlements in the inset area by 2030, even within close proximity (0.5–5.4 km) to existing grid lines. This finding, which may appear counterintuitive, is driven by specific local conditions: low electricity demand (4-153 kWh/HH/year), small population clusters (35–412 individuals), and favorable solar resources (GHI > 6.2 kWh/m²/day). The analysis further reveals that MG PV can also be the least-cost option for 7% of newly electrified settlements at distances of 1.2–2.5 km from the grid under similar solar conditions. By 2050 (Fig. 28D), all of the SA PV systems would be phased out, with half of their served population transitioning to grid connection and the other half to MG PV systems. Notably, MG PV's share expands substantially, reaching 52% of newly electrified settlements and competing with grid extension even in areas within 0.5-5.4 km of existing infrastructure. This detailed case shows that local conditions can make decentralized solutions economically preferable to grid extension, even under scenarios with low grid generation costs. This challenges the traditional assumption that grid proximity is the sole determinant of the optimal electrification strategy.

In contrast, the HGGC-RU scenario shows how higher grid generation costs reshape the spatial distribution of optimal electrification technologies. By 2030 (Fig. 29A), MG PV systems can be the least-cost option in areas previously designated as grid-optimal under the LGGC-RU scenario. This shift is particularly evident in the changing spatial relationship between MG PV installations and existing grid infrastructure. Only 35% of the newly electrified population served by MG PV is situated beyond 10 km from existing grid lines, compared to 60% under the LGGC-RU scenario. This indicates that MG PV is becoming more competitive even in areas close to the grid. By 2050 (Fig. 29B), MG PV further expands, not only displacing SA PV systems in remote locations but also emerging as the optimal solution in settlements that would have been grid-connected under the LGGC-RU scenario.

A detailed analysis of the same zoomed-in area provides compelling evidence of this shift. By 2030, SA PV systems remain the least costly option in the same settlements as in the LGGC-RU

scenario, but the share of MG PV rises to 62% (Fig. 29C). This represents a 55-percentage point increase compared to the MG PV share under the LGGC-RU scenario. MG PV continues to dominate in 2050 (Fig. 29D), representing a 52-percentage point increase over the LGGC-RU scenario. Notably, several of these MG PV systems appear in settlements where grid extension would have been the least costly option under the LGGC-RU scenario.

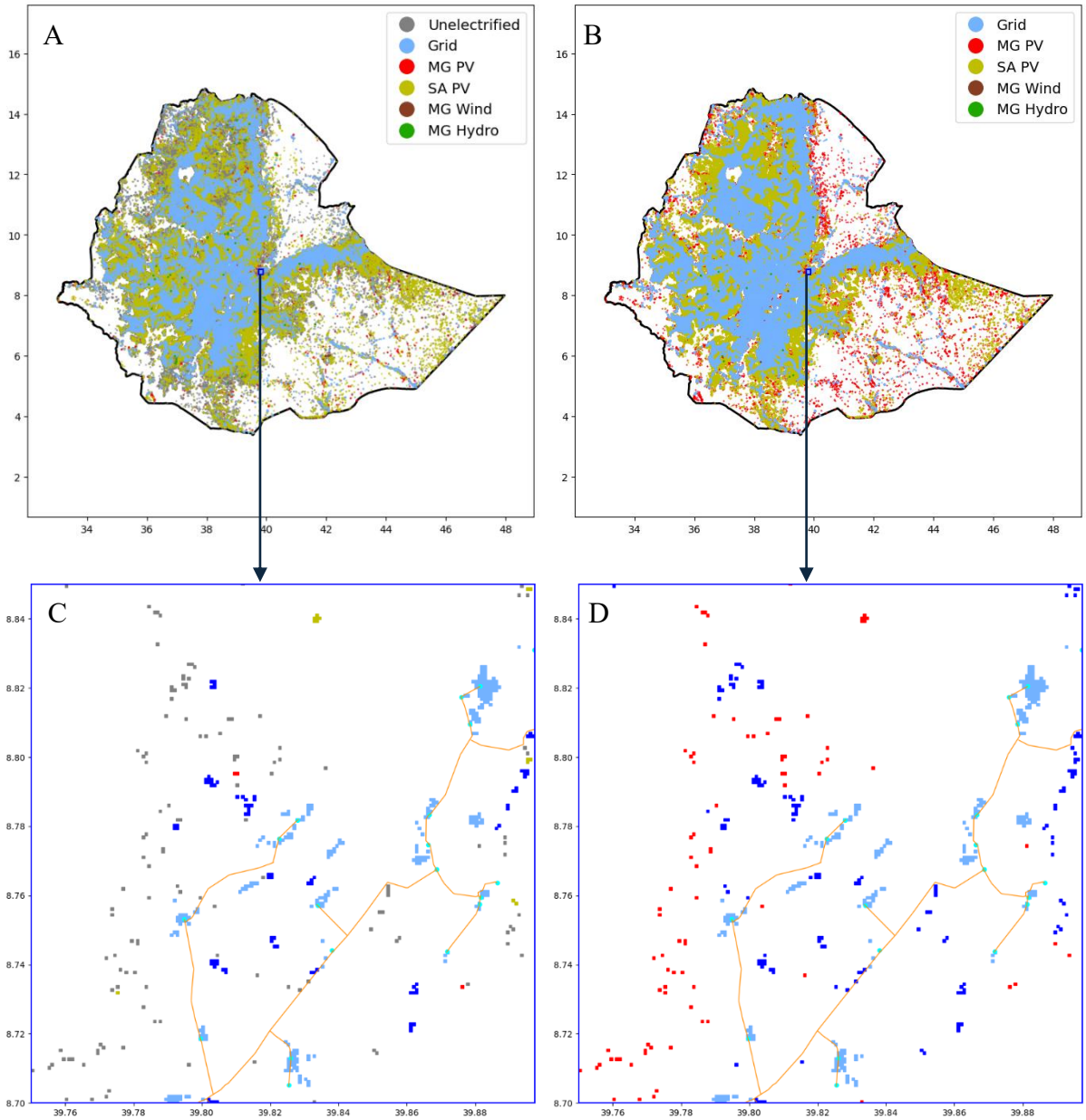

Fig. 28. Spatial distribution of the least-cost electrification technology under the LGGC-RU scenario for 2030 (A) and 2050 (B). Figures C and D provide zoomed-in views of the blue box in Figures A and B, respectively. Color coding: Dark blue represents newly grid-extension

recommended settlements, light blue represents already grid-electrified settlements in the base year, gray represents unelectrified areas, red represents settlements recommended for MG PV, dark orange represents MV lines, and green represents transformer locations.

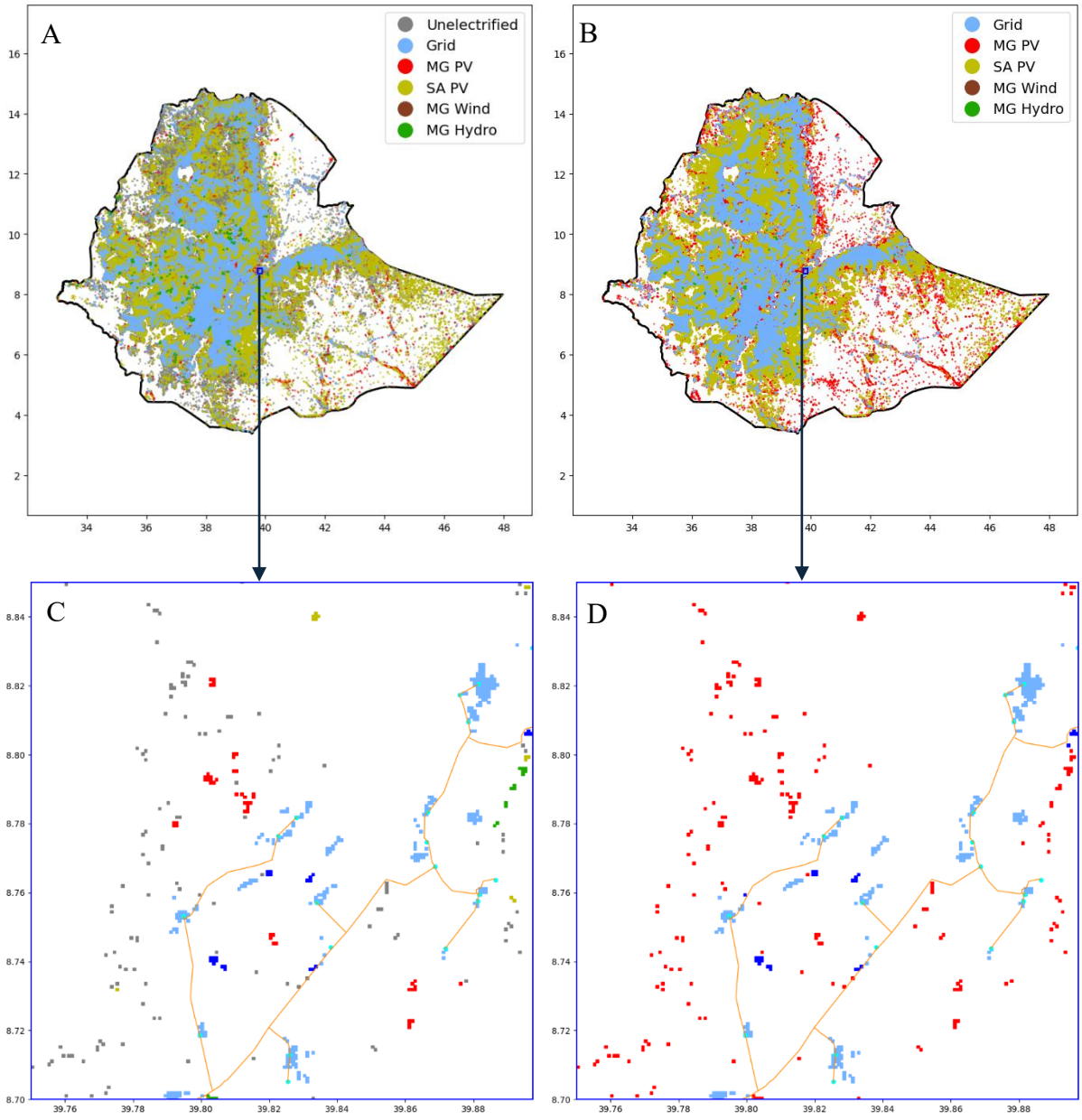

Fig. 29. Spatial distribution of the least-cost optimization technology in Ethiopia under the HGGC-RU scenario for 2030 (A) and 2050 (B). Figures C and D provide zoomed-in views of Figures A and B, respectively.

5.3.3. Investment requirements

Discounted to the base year, the total investments are estimated to range between 5.2–5.6 billion USD under the LGGC scenarios and 6.2–6.8 billion USD under the HGGC scenarios over the whole modeling horizon. This implies an average investment of approx. 5.9 billion USD over the 29 years, translating to around 0.2 billion USD per year. The transition from LGGC to HGGC scenarios increases total investment requirements by 21%, representing a significant burden for an already capital-constrained country. The investment requirements can be disaggregated into two main categories. First, new electrification in previously unelectrified settlements demands 3.4 to 3.5 billion USD under LGGC scenarios and 3.7 to 4.0 billion USD under HGGC scenarios. Second, additional capacity needs in already electrified settlements require 1.8 to 2.1 billion USD under LGGC scenarios and 2.5 to 2.9 billion USD under HGGC scenarios.

The distribution of investment by technology evolves over time. In the LGGC scenario, grid extension's share decreases from 93-94% in 2030 to 67-75% by 2050, while MG PV increases from 3-4% to 24-32%. More notably, under the HGGC scenario, grid extension investment declines from 81-83% to 37-41%, as MG PV rises from 14-16% to 59-62% over the same period. SA PV maintains a minimal share (1-3%) across all scenarios and years. These trends reflect the changing cost-effectiveness of different electrification solutions throughout the planning period. The relatively low contribution of SA PV suggests that, given the assumptions provided, it is found to be a cost-effective solution for those with low demand. This translates to a reduced generation capacity, which in turn results in lower investment requirements compared to grid extensions and MGs. For each of the three demand pathways, the discounted investment requirements by technology under the LGGC and HGGC scenarios are shown in Fig. 30. A spatial analysis of discounted investment per new connection reveals disparities across scenarios and over time (Fig. 31). Under the LGGC-HEG scenario, the national average investment cost per capita is estimated at approx. 37 USD in 2030, decreasing to 29 USD by 2050. In contrast, the HGGC-HEG scenario results in a 14% increase in average per capita investment cost in 2030 and a 24% increase by 2050 compared to the LGGC-HEG scenario.

Fig. 30. Discounted investment requirements by electrification technology type for each demand pathway under the LGGC (left) and HGGC (right) scenarios.

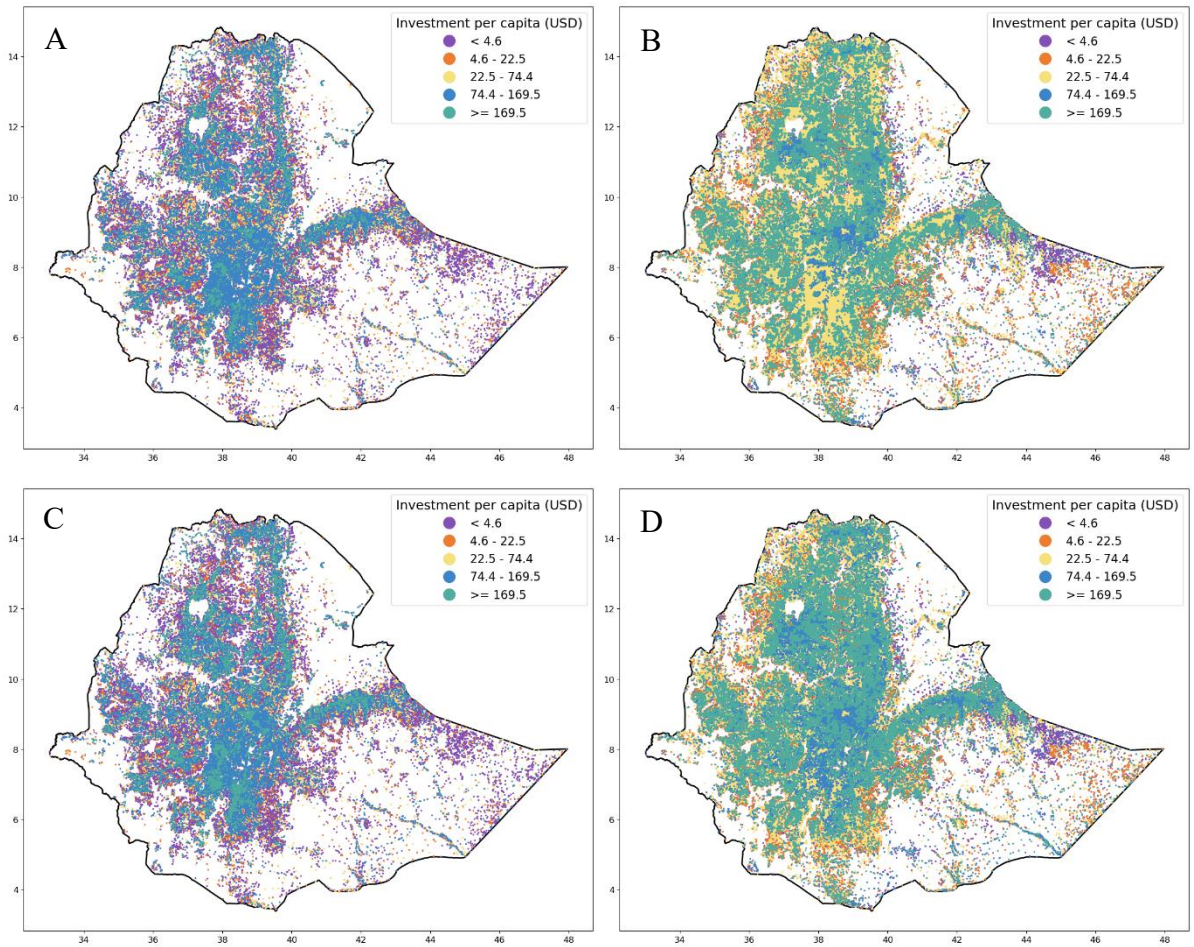

Fig. 31. Spatial variation in investment cost per new connection under the LGGC-HEG (A and B) and HGGC-HEG (C and D) scenarios, showing costs in 2030 (A and C) and 2050 (B and D).

5.4. Discussion

The cost-optimal electrification strategies and their associated investment costs under different demand evolution and grid generation cost scenarios are explored. A geospatial modeling framework that utilizes high-resolution geospatial data and settlement-level demand projections is employed. This approach provides a detailed understanding of the spatial and temporal dynamics of least-cost electrification technology mixes for 809,087 settlements across Ethiopia over a 2021-2050 planning horizon.

The results show that grid extension is the least-cost option for the majority of Ethiopia's population across all developed scenarios. This outcome is likely due to the spatial proximity of the population to the national grid (more than 83% of the population live within 5 km of MV or HV grid networks and more than 92% live within 10 km). However, the grid's share slightly declines as electrification target approaches universal access, and grid expands to remote, low-demand settlements. These results align closely with official government estimates, which indicate that 75–80% of the population lives within 5 km of existing lines and around 90% within 10 km [33].

However, if grid generation comes at a higher cost, there is a significant potential for MG deployment [60]. Under the High Grid Generation Cost (HGGC) scenario, the share of the population served by grid declines to 66% by 2050, while MGs increase to 26%. This finding is consistent with projections from similar studies in East Africa, which estimate an MG share of 4–37% by 2030 [173]. The shift toward MGs is driven by two key trends: the increasing marginal cost of extending the grid to remote locations, and the assumed annual decline in solar technology capital costs. Spatial analysis reveals that technology choice is not only a function of distance to the grid but also of local demand and settlement characteristics. The model identified settlements where SA PV and MG PV systems are the least-cost solution—even when located within 0.5–5.4 km of existing grid lines. This is driven by specific local conditions, including low electricity

demand (4–191 kWh/HH/year) and small population clusters (35–412 people), which make the per-connection cost of grid extension economically unjustified despite the physical proximity.

The impact of different electricity demand pathways on the optimal technology mix is also analyzed. In view of this, despite considerable differences in aggregated electricity demand across the BAU, HEG and RU pathways, the comparative analysis shows minimal changes in the optimal technology mix. The settlement level demand in these pathways may not be sufficient to surpass the economic thresholds that would favor a transition between SA PV, MG, or grid connection. However, incorporating demand from PUs and CIs alters the optimal technology mix. In the LGGC scenario, the grid extension share increases, while the share of SA PV systems declines, and MGs see a marginal increase. This shift is accompanied by an increase in total investment of up to 21.7%, rising from 2.6 to 3.2 billion USD in 2030 under the LGGC-HEG scenario. The HGGC scenario shows similar trends: grid share and MGs increase, while SA PV decreases, and investment up by 24.1% (e.g., from 3.0 billion to 3.8 billion USD in 2030 under HGGC-HEG), due to MGs and grid expansion.

Comparing our findings with existing literature requires careful consideration of methodological differences, including scope (total population vs. new connections), geographic focus (national vs. regional), and data resolution. Our finding of 67.4–68% grid extension share for new connections by 2030 (under LGGC) falls between a higher grid extension share reported for Nigeria (86%) [13] and Bolivia (76.2%) [71], and a lower relative share of 55% found for Cameroon [49]. The discrepancy with Mentis et al. [13] may be attributed to their use of lower-resolution population data (2.5 km), potentially overestimating grid viability in comparison to our high-resolution population data (30 m), which better captures rural settlement heterogeneity [174]. The role of SA PV systems for new connections in our analysis (29.3–29.7%) exceeds that reported for Bolivia [71]. However, our results show more conservative off-grid deployment compared to studies in Malawi (67.4% off-grid PV for total population) [10] and parts of Nigeria (58.8% MG PV for new connections) [90]. These differences likely reflect variations in existing grid infrastructure coverage, resource availability, specific cost assumptions, population density, and policy contexts.

Our finding of a 67-68% grid extension share for new connections by 2030 (under LGGC) is significantly lower than the 89% projected for Ethiopia by Mentis et al. [29]. This divergence can be attributed to key methodological advancements in this thesis. First, the use of high-resolution

(30 m) population data, compared to lower spatial resolution (e.g. 2.5 km) used previously, allows for a better representation of rural settlements. Second, our analysis incorporated actual, georeferenced grid infrastructure data, including HV and MV lines, as well as the locations of substations and transformers, sourced from the EEP and EEU, rather than relying on outdated data from open-source platforms. Third, our granular demand model, which projects and incorporates varying HH demand levels ranging from Tier 1 to Tier 4, capturing greater spatial heterogeneity. Mentis et al., on the other hand, applied uniform electricity demand: Tier 3 for all rural areas and Tier 4 for urban areas. Moreover, our results indicate that off-grid technologies (SA PV and MGs combined) can serve no more than 34% of the population, even in the scenario most favorable to off-grid solutions (HGGC). This contrasts with Dalla Longa et al. [175], who found that off-grid technologies could provide least-cost electricity to as much as 70% of the Ethiopian population by 2050. A possible explanation for this difference is that Dalla Longa et al. considered only HV grid lines, whereas our analysis includes both HV and MV lines in the grid extension evaluation.

Our findings underscore that a more realistic representation of local conditions, enabled by high-resolution spatial data, significantly shifts model outcomes toward decentralized solutions. This suggests that previous studies relying on lower-resolution data may have overestimated the relative share of grid extension. To the best of our knowledge, such an insight was reported only by Bhattacharyya and Palit [174] and Isihak [176] who observed that models that use data at a granular level tend to favor off-grid technologies, while aggregated data often bias results toward grid-based approaches. Moreover, while many studies focus on achieving universal access by 2030, it is critical that modeling efforts with longer timelines are undertaken to understand how the system should evolve over time. Doing so can inform policies and regulations that guide investments toward the best long-term electricity supply mix and ensure the sustainability of the chosen electrification pathway.

6. Conclusions, contributions and future work

6.1. Conclusions

This thesis aimed to develop and apply geospatial modeling approaches to support long-term, integrated electrification planning towards achieving universal electricity access in Ethiopia. As part of this thesis, the influence of key geospatial factors on grid extension suitability were analyzed, and nighttime light combined with population data were used to assess electrification rates at subnational and national levels. It also developed long-term, spatially disaggregated electricity demand projections for major rural electricity consumers, including households, productive users, and community institutions. Additionally, a long-term, least-cost electrification pathway analysis that integrated spatially disaggregated electricity demand projections with geospatial cost penalties and renewable resource data was conducted to identify cos-optimal electrification technology mixes (grid extension, MGs, and SA PV systems) over a multi-decade horizon (2021-2050).

The findings from the five interconnected studies that constitute this thesis, three journal articles and two conference papers, show that a high-resolution, data-driven, and integrated approach is critical for identifying cost-effective, sustainable, and equitable electrification pathways suited to Ethiopia's diverse regional contexts. The results provide a multi-decade (2021–2050) investment roadmap that adapts to evolving electricity demand and declining technology costs, thereby enabling the development of phased investment strategies. The findings underscore that the optimal choice between grid extension, mini-grids, and standalone systems is not a simple function of distance, but a complex interplay of local demand, resource availability, population density, geospatial constraints, and grid generation costs. Achieving a cost-effective, sustainable, and equitable transition to universal electricity access in Ethiopia requires a dynamic, spatially differentiated strategy that embraces a mix of grid, mini-grid, and standalone solutions. However, it is important to note that our models do not project a single "best" pathway to universal electricity access but rather provide alternative scenarios to explore.

The research objectives posed in Chapter 1 is addressed as follows.

RO1: To estimate the share of the population with electricity access at subnational and national levels using nighttime light (NTL) data and to analyze the influence of geospatial factors to grid extension in Ethiopia

The analysis shows that combining noise-filtered NTL data with high-resolution population datasets provides a good proxy for estimating electrification rates at national and subnational levels. Applying a lower-bound noise filter of 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$ to the NTL imagery, provides a national electrification rate of 51.3% in 2020, closely matching the World Bank's reported 51.1%. The analysis of electricity access at the subnational level highlights significant regional inequalities across Ethiopia's 11 administrative regions. It ranges from nearly universal access in urban centers like Addis Ababa (close to 100%) to less than 40% in pastoral regions such as Afar. While the model's estimates often align with government reports, notable variations exist. For instance, the estimate for Amhara (41.8%) is below the official figure (51.3%), whereas estimates for Oromia (69.2%), Somai (74%) and SNNP (71.5%) are higher than reported.

The study also quantified the aggregate cost impact of five key geospatial factors, including terrain slope, elevation, land cover, distance from substation and road on the feasibility of grid extension as Grid Extension Penalty (GEP). The findings show that these factors increase the cost of grid extension by a national average of 8.6%, with location-specific penalties varying from as low as 2.3% in favorable areas to as high as 29% in geographically challenging settlements. Terrain slope and land cover are major contributors to grid extension suitability largely because most settlements are situated on relatively flat terrain with suitable land cover types. The results also show that distance to substations is the primary limiting factor, as most settlements are far from existing infrastructure, making grid rollout more costly.

RO2: To develop long-term, spatially explicit electricity demand projections for rural electrification planning

The long-term projections under three different scenarios, Business-as-Usual (BAU), High Economic Growth (HEG), and Rapid Urbanization (RU), reveal significant growth in total electricity demand. The Rapid Urbanization (RU) scenario projects the highest demand, reaching

28,500 GWh by 2050. This represents a 285% increase from the 2021 baseline and is 40% higher than the BAU scenario.

Furthermore, the analysis provides quantitative evidence against the use of over-simplified dichotomy between rural-urban consumption targets, a common practice in many nationwide electrification planning studies. The high-resolution model reveals spatial heterogeneity in demand. By 2050, HH electricity demand is projected to vary from Tier 1 to Tier 4 across the country. Central regions, characterized by higher economic activity, are projected to experience robust demand growth, while more remote, peripheral areas are likely to remain in lower consumption tiers for the foreseeable future. The analysis also addresses a critical omission in many previous studies by explicitly modeling the demand of PUs and CIs. These consumer groups, while often representing a smaller portion of national demand, are identified as essential "anchor loads" that can enhance the economic viability of rural energy systems and drive local economic development. The result shows that in settlements where CIs are present, they may contribute up to 46% of the local-level electricity demand by 2050. Finally, the research also incorporates the impact of climate on demand, finding that while the national effect is modest (0.49% to 0.53% by 2050), the local impact is considerable, with demand potentially increasing by 21.8% to 22.6% in settlements where average annual temperature is above 24 °.

RO3: To explore long-term, least-cost electrification technology mix dynamics and evaluate investment needs to enhance electricity access in rural areas

The results show that the least-cost technology mix evolves dynamically over time and is sensitive to the cost of centralized grid power. Under a Low Grid Generation Cost (LGGC) scenario, grid extension is the dominant least-cost solution in the initial phase of electrification, serving over 82% of the population targeted for electrification by 2030. On average, grid is the least-cost solution in settlements with over 390 kWh/household/year electricity demand and located within 5 km of existing power grid infrastructures. However, its relative share declines in the long term as the grid reaches progressively more remote and sparsely populated areas where the geospatial cost penalty is higher and demand is low. In contrast, MGs become increasingly cost competitive over time. Under a High Grid Generation Cost (HGGC) scenario, MGs emerge as the least-cost option for approximately 26% of the population by 2050. Standalone Photovoltaic (SA PV)

systems consistently maintain their niche role as the optimal solution for the most dispersed populations with the lowest levels of demand.

This high-resolution analysis also challenges the definition of the 'last mile' as being determined solely by geographic distance. The model identified instances where SA PV and MG PV systems are the least-cost solutions for settlements with low demand (e.g., 4–191 kWh/HH/year) and small populations (e.g., 35–412 people), even when those settlements are located within 0.5–5.4 km of existing grid lines. This finding demonstrates the necessity of using geospatial analysis to create more heterogeneous plans that account for diverse local contexts. The finding that decentralized solutions can be cost-optimal even within 5 km of the grid suggests a need to revise the National Electrification Program's (NEP 2.0) grid-centric connection targets. A more flexible, technology-agnostic approach based on settlement-level techno-economics should be adopted.

6.2. Contributions

The main contributions of the thesis to the existing research on integrated geospatial electrification planning systems are presented as follows.

Contribution 1: Overcoming aggregation bias with high spatial resolution modeling.

A key methodological contribution of this thesis is the development and application of a high spatial resolution geospatial modeling that addresses the aggregation bias in low spatial resolution modeling framework. Low spatial resolution population datasets generate large clusters that tends to smooth out local variations and influences key modeling parameters. This smoothing effect underestimates the true cost of grid extension and overstate its competitiveness within least-cost technology mixes. In contrast, this thesis employs high spatial resolution (30 m) population data to delineate over 800,000 vector-based (polygons) population settlements across Ethiopia. This granularity enables a better representation of population settlements, population sizes, captures the details (e.g., maximum nighttime light intensity, land cover types,), and spatial relationships to infrastructures. This higher spatial resolution analysis provides a more realistic cost assessment for grid extension compared to previous national studies that used coarser data, thereby improving the relevance of model outputs for practical decision-making.

Contribution 2: A spatiotemporal and multi-sectoral demand modeling.

This thesis develops and applies a long-term (to 2050) demand projection model that maps future electricity needs nationwide. This is a significant improvement over the simple, one-size-fits-all consumption goals based only on whether an area is urban or rural, which are often used in existing studies. The model's strength lies in combining three critical elements necessary for realistic planning in developing countries. First, it develops a spatially explicit demand model that, for the first time in this context, disaggregates demand for households, community institutions, and productive users. Second, its use of socio-economic dynamics projects demand under multiple development scenarios, directly linking future electricity demand to national growth trajectories in urbanization and economic growth. It uses gridded Gross Domestic Product (GDP) and International Wealth Index (IWI) for spatial electricity demand modeling. A granular understanding of how demand evolves across geographical space and time is critical for sizing infrastructure and selecting the appropriate technology portfolio for diverse local contexts. Third, the model integrates spatial and temporal temperature dynamics to assess temperature-driven demand evolution. Together, these features provide a more realistic foundation for infrastructure sizing and investment planning.

Contribution 3: A long-term, phased analytical approach for strategic investment.

This work advances beyond a single, short-term, target-year analysis (e.g., 2030) by adopting a long-term, multi-timestep framework that captures the dynamic evolution of least-cost technology mixes over three decades (2021-2050). This approach provides policymakers on *when* and *where* to prioritize different technologies, enabling phased investment strategies that can adapt to changing electricity demand and technology costs. This dynamic perspective is essential for minimizing the risk of stranded assets and ensuring that short-term investment decisions align with long-term, least-cost pathways. In doing so, the thesis addresses a major gap in existing planning studies, which often provide single end-year snapshots rather than a roadmap of the transitional journey required to achieve universal access.

6.3. Future work

While this thesis advances geospatial electrification modeling, there remain several limitations, which can be opportunities for future work. While this dissertation included PUs and CIs beyond HHs in demand projections, the analysis relied on proxies and assumptions due to data scarcity. Therefore, a critical area for future research is the collection of primary field data through surveys to capture better load profiles and demand trajectories of diverse rural enterprises and institutions. Integrating higher-quality, bottom-up data would enhance technology selection, infrastructure capacity sizing, and better estimates investment needs.

Furthermore, the agricultural sector, a major component of rural economies, was not included in the demand projections due to a lack of georeferenced agricultural datasets. Future work could build on this dissertation and incorporate the electricity demand for agricultural activities such as irrigation and agro-processing to provide a more holistic representation of rural energy needs and strengthen the policy relevance of geospatial electrification analysis.

The OnSSET model provides robust spatial cost comparisons but is limited in its temporal granularity. Current capacity sizing is based on annual electricity demand and does not reflect seasonal or diurnal variations in both demand and renewable resource availability. A significant advancement would be to increase the model's temporal resolution. This would involve integrating hourly or daily load profiles and corresponding renewable resource data into the capacity sizing and LCOE calculations, thereby enabling a better assessment for selecting optimal electrification technologies.

Furthermore, the current version of the OnSSET model does not assess the associated costs of non-served energy (loss of load) for SA systems, which can lead to an incomplete cost comparison with more reliable options. Future research efforts should develop and integrate reliability and service quality metrics into the optimization framework. This would mean costing outages for every economic assessment of the available technology alternatives, leading to an assessment that adequately embodies the economic and societal appreciation of dependable power.

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Appendices

This appendix consolidates the key datasets, parameters, and results from the research presented in this thesis. It provides a comprehensive reference for geospatial data, socio-economic factors, techno-economic model parameters, and key findings used and generated throughout the study.

Appendix A. Geospatial and socio-economic datasets

This section details the GIS datasets and socio-economic parameters used for the analysis, including their type, sources, resolution, and purpose within the models.

Table A1: Input GIS datasets

Dataset	Data type	Spatial resolution	Description	Data source
Population	Raster	30m	High-resolution spatial identification and quantification of inhabited areas in the base year (2018). This data is critical for determining settlement locations and population density, essential for estimating electricity demand.	Meta Connectivity Lab and Columbia University [177]
Administrative boundaries	Polygon	-	National and subnational administrative boundaries, used to delineate regions for electrification planning	GADM V.4.0 (2018) [120]
Nighttime light	Raster	~500m (around equator)	Nighttime light intensity data, used as a proxy for existing electrification levels	VIIRS DNB (2020) [129]
(HV, MV substation and transformers)	Line/point shapefile	-	Georeferenced data on existing transmission and distribution lines, substations and transformers, crucial for assessing grid extension potential.	EEP and EEU
Land cover	Raster	~500 m	Land cover used to assess grid extension suitability.	MODIS Land Cover Product

				(MCD12Q1) V6 (2020) [125]
Terrain elevation and slope	Raster	30m	High-resolution elevation and slope data used to assess grid extension suitability.	GDEM (NASA and Japan Space Systems, 2019) [126]
Roads	lines	-	This helps determine grid extension suitability	Geofabrik (2022) [127]
Mini/small hydro	Polygon	-	Potential sites for mini/small-scale hydropower installations, used for off-grid energy planning.	Energydata.info [122]
GHI	Raster	250m	To assess the solar PV MG and SA PV systems	Global Solar Atlas [139]
Wind speed	Raster	250m	Wind speed data at 100m were used to assess wind energy potential for mini-grid systems	Global Wind Atlas [164]

Table A2: Geospatial factors classification and weights [106], [128].

Geospatial factor	Weight	Suitability index				
		5 (suitable)	*4*	*3*	*2*	*1(unsuitable)*
Slope (degree)	30%	0-10	10.1-20	20.1-30	30.1-40	>40
Land cover [a]	20%	7,9,10,14,16	2,4	1,3,5,12,13,15	6,8	11,17
Distance to substation (km)	20%	0	0.5	1	5	>10
Distance to road (km)	15%	0	5	10	25	>50
Digital elevation (m)	15%	<500	500-1000	1000-2000	2000-3000	>3000

[a] Further classification can be obtained at https://lpdaac.usgs.gov/products/mcd12q1v006/.

Table A3: Major socio-economic parameters of the study area [25], [31], [178], [179]

Parameters	Unit	Year	Study base year value

Population	Million persons	2020	114.96
Population growth	Percent	2030	2.2
Average household size, urban	People	2030	4.4
Average household size, rural	People	2030	5.2
Urban ratio start year	Percent	2020	21.7
Urban ratio end year	Percent	2030	26.9
Total electricity access	Percent	2020	51.1
Urban electricity access	Percent	2020	93.2
Rural electricity access	Percent	2020	39.4

Appendix B. Electricity demand estimation

This section details the methodology and parameters used to estimate household and institutional electricity demand.

Table B1: Multi-tier household electricity demand [62], [171].

MTF daily consumption levels (Wh/HH/day)	Adapted annual electricity demand (kWh/HH/year)	Indicative appliances powered
$12 \leq Tier\ 1 < 200$	38.7	Task lighting, plus phone charging, or radio
$200 \leq Tier\ 2 < 1000$	219	As Tier 1, plus general lighting, fan, and television
$1000 \leq Tier\ 3 < 3425$	807.5	As Tier 2, plus refrigerator, food processor, water pump, and rice cooker
$3425 \leq Tier\ 4 < 8219$	2125	As Tier 3, plus washing machine, iron, hairdryer, and microwave
$Tier\ 5 \geq 8219$	3000	As Tier 4, plus air conditioner, water heater, and electric cooker

Table B2: RAMP configuration parameters for health facilities in urban and rural areas [19].

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 B3: RAMP configuration parameters for rural and urban schools [19].

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 B4: RAMP configuration parameters for government offices [19].

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 B5: RAMP configuration parameters for places of worship in urban and rural areas [19].

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							
External light	2	25	17-06	0	1	12	0
Internal light	4	25	18-22	0	1	4	0

Appendix C. Techno-economic parameters and model assumptions

This provides a detailed breakdown of the techno-economic parameters used to model various electrification technologies, including costs, efficiencies, and other key assumptions.

Table C1:Techno-economic input parameters of off-grid generation technologies [49], [163], [169]

Technology	Capital cost (USD/kW)			Capacity factor (%)*	Lifetime (years)
	2021–2030	2030–2040	2040–2050		
Hydro MG	3000	3000	3000	50	30
Solar PV MG	2920	2482	2043	17-28%	20
Wind MG	3750	3375	3000	24-48%	20
SA PV systems					
- < 20 W	9620	8177	6734	17-28%	15
- 20 – 50 W	8780	7463	6146	17-28%	15
- 50—100 W	6380	5423	4466	17-28%	15
- 100 – 1000 W	4470	3800	3129	17-28%	15
- > 1 kW	6950	5908	4865	17-28%	15

*Capacity factors for wind and solar technologies are calculated based on the annual resource availability in each settlement by the OnSSET model.

Table C2: Grid generation capacity capital costs [59], [60].

Grid	2021–2030	2030–2040	2040–2050
Grid generation capacity capital cost (USD/kW)			
Grid (High)	4577	5624	2393
Grid (Low)	3196	2364	2285

For grid, 100% capacity factor is considered and lifetime 30 years.

Table C3: Transmission and distribution costs in the model [3], [45], [169]

Parameter	Value	Unit
HV line (69-132 kV)	53000	USD/km
MV line (11-33 kV)	7000	USD/km
LV line (0.2-0.4 kV)	4250	USD/km
HV to MV substation (1000 kVA)	25000	USD/unit
MV to LV substation (400 kVA)	10000	USD/unit

Service transformer (50 kVA)	4250	USD/unit
Additional connection cost per household connected to grid	150	USD/HH
Additional connection cost per household connected to MG	125	USD/HH
Additional connection cost per household connected to SA	0	USD/HH
Grid transmission and distribution losses	12	%
Mini-grid distribution losses	5	%
O&M costs of distribution for Grid and MG	2	% of capital cost/year

Table C4: Other model parameters [25], [45], [179]. All parameters were used only in Paper I, except for the lifetime values, which were also applied in Paper V.

Parameter	Value	Unit
Annual new grid connection limit	534,000	HHs/year
Annual grid generation limit	389	MW/year
Discount rate	8	Percent
Lifetime	30	years

Appendix D: Published/submitted articles

Paper I

2023 IEEE PES/IAS PowerAfrica

Assessing subnational electricity access using high-resolution datasets: A case study of Ethiopia

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***Abstract*—Access to electricity is essential for economic and social development, yet nearly half of the population in Ethiopia lacks basic electricity. However, national level reporting of electrification rates makes it difficult to identify areas with limited access. To address this, this study aims to estimate subnational and national level electricity access using nighttime light and gridded population data with Google Earth Engine and compare the results with the national electrification rate reported by the World Bank. The study findings reveal a considerable disparity ranging from 28.2% in 2016 to 0.6% in 2020 between the estimated national-level electricity access rate and the data reported by the World Bank for the period 2016-2020. The results further reveal that significant differences exist in electricity access among states, with Addis Ababa having almost 100% access to electricity in all years. In contrast, Afar and Somali states had the lowest access rates in 2016. Despite an overall increase in access across all states, there was a decreasing trend in mean nighttime light radiance from 2016 to 2020. These findings provide valuable insights for policymakers and stakeholders in identifying areas where interventions are needed to improve access to electricity and to plan electrification programs effectively.**

***Index Terms*—access, electrification, night light, subnational**

I. Introduction

In order to identify where local, national, and international efforts can be directed to achieve the Sustainable Development Goals (SDG7), it is imperative to have up-to-date and harmonized information on electrification progress, particularly spatially explicit data [1]. In the quest for achieving universal electricity access, it is often assumed that we have accurate knowledge of the population segments that have access to electricity, as well as those that do not. However, such information is often scarce or inaccurate. This creates a significant challenge in designing and implementing effective electrification strategies.

Traditionally, electricity access levels at the national level are determined using household surveys and census data [2]. While these methods are reliable, they are expensive, time consuming, and often have limited geographic coverage [3]. Nighttime light data has emerged as a promising and reliable tool for estimating the level of electricity access at different spatial scales [1], [4]. It can capture the presence or absence of electricity access at high resolution and is also relatively inexpensive and easy to obtain [5].

To estimate the level of electrification, researchers have taken advantage of the correlation between nighttime light output and electricity at regional and national levels [3], [6]. This method involves analyzing satellite imagery to identify areas with high and low levels of nighttime light emissions, which can then be used to estimate the level of electrification by combining it with population data [4], [6]–[8].

It is crucial to investigate variations in access at the subnational level to enhance the effectiveness of local-scale electrification plans [4]. Such data can help identify areas where access to electricity is limited and is essential when planning electrification programs.

Two recent studies have been done to estimate the level of electricity access in SSA [1], [7]. The first used nighttime light data, population data, land cover, and administrative boundaries to identify areas with/without access to electricity at the subnational and national levels. The study found that the estimates of electrification rates derived from nighttime light data were generally consistent with national statistics in some countries. However, there were some discrepancies in certain regions. The second study showed that the use of stable nighttime light data in conjunction with the High-Resolution Settlement Layer (HRSL) population improved the accuracy of electricity access estimates [7].

Despite the efforts made by these and a handful of other previous studies to estimate electricity access levels, their estimates were found to be over or underestimated when compared to the national electrification rate compiled by the World Bank [1], [7]. The reason is that these studies overlooked the country-specific lower-bound noise filter threshold and instead used a uniform threshold across all SSA countries.

Thus, the objective of this study is to accurately estimate the electricity access level at subnational and national levels in Ethiopia. The study also aims to compare estimates of electricity access levels derived from nighttime light data with existing national statistics. In light of this, the paper seeks to answer the following research questions:

- How can the level of access to electricity be determined at subnational and national levels from nighttime light data, and how does it compare to the national statistics?

- How do the seasonal trends and the temporal patterns of nighttime lights vary between different states at the subnational level?

II. Methodology

The research methodology involves several steps, starting from data acquisition (nighttime light, gridded population, and administrative boundaries) and estimation of electricity access level at both the subnational and national levels to the comparison of the estimated level of electricity access with the national level statistics compiled by the World Bank. The aim of the comparison is to assess the accuracy of electricity access rate estimations using satellite nighttime light data. Seasonal trends and temporal patterns of nighttime lights were also analyzed to gain insights into how these patterns vary across regions and over time.

This study uses the Google Earth Engine (GEE) API with JavaScript to process nighttime light data and identify lights that originate from electricity sources. Subsequently, the processed nighttime light data is combined with gridded population and level 1 administrative boundaries to determine electricity access at the subnational level for the period from 2016 to 2020. The study also utilizes GEE with Python to analyze the seasonal trends and temporal patterns of nighttime light across the different regions for the same period.

A. Overview of study area

This study uses Ethiopia to showcase the application of the methodology. Ethiopia was selected due to its significant electricity access deficit and being the second most populous country in Africa. According to the World Bank, only 51.1% of Ethiopia's 114 million+ inhabitants (of which 93.2% is living in cities and 39.4% in rural areas) had access to electricity in 2020 [9]. Although achieving universal access to electricity is close to a reality in urban areas, the majority of the rural population still lacks access to it. With the current pace of electrification, it is unlikely that the country can meet the SDG7 target by 2030.

Furthermore, Ethiopia still has one of the lowest electricity consumption levels in SSA. In 2018, the average per capita electricity consumption in Ethiopia was 83 kWh, while in the same year, the average per capita electricity consumption in SSA and the African continent were 484 kWh and 500 kWh per capita, respectively [10].

B. Data Sources

Nighttime light (raster): In this study, the nighttime light (NTL) data is obtained from the National Oceanic and Atmospheric Administration (NOAA) Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) monthly composite dataset (MONHTLY_V1) through the GEE API for the period between 2016 to 2020 [5], [11]. This dataset provides a monthly composite of global nighttime lights with a high spatial resolution (500 meters around the equator).

Gridded population (raster): The use of nighttime light data in combination with gridded population datasets has been used to estimate electricity access at both subnational and national levels [1] and to map urbanization patterns [12]. This study used a gridded population dataset obtained from the open-access hub of the WorldPop project [13]. The dataset is derived from national censuses, household surveys, and satellite imagery, and it provides estimates of population count and density for every 100x100 meter pixel in the study area. The dataset used in this study is the unconstrained and United Nations-adjusted version covering 2016-2020.

Administrative boundaries (vector/polygon): We utilized administrative boundaries to limit the spatial extent of our analysis to the study area. Level 1 administrative boundaries from both the Global Administrative Areas Database (GADM) V.4.0 [14] and the Food and Agriculture Organization (FAO)/Global Administrative Unit Layers (GAUL) V.1/2015 [15] were incorporated. Specifically, GADM administrative units were used while estimating access to electricity at the subnational level. GAUL administrative units were used during the seasonal trends and temporal nighttime light variation analysis. The attributes of all input datasets used for the analysis are tabulated in Table I. In this case study, the subject country encompasses a total of 9 states and 2 city administrations, as shown in 1.

C. Estimating access to electricity at subnational and national level

Our first step in estimating access to electricity was to apply a noise filter to the nighttime light data, adapted from Falchetta et al. [1]. In order to filter nighttime light data on GEE, we first had to establish the lower bound noise floors. This was achieved through manual testing of different thresholds and a visual inspection of small villages, to ensure that already electrified settlements were not overlooked as shown in Fig. 2 and 3. Specifically, 0.17 μWcm^{-2} sr^{-1} was used for 2016 and 2019, 0.23 μWcm^{-2} sr^{-1} for 2017 and 2018, and 0.25 $\mu Wcm^{-2}sr^{-1}$ for 2020. The appropriate filtering threshold for nighttime light data varies between the years because the amount of noise in the data can change over time.

The noise filter replaces any values below thresholds with 0, effectively eliminating the noise from the nighttime light data.

Fig. 1. Level 1 administrative regional states of Ethiopia.

TABLE I
INPUT DATASETS

Dataset	Data source	Data type	Spatial resolution	The year used in analysis
Population	WorldPop population count [13]	Raster	30m	2016-2020
Administrative boundaries	GADM V.4.0 [14] and FAO/GAUL V.1/2015 [15]	Vector/polygon	poly-lines	2018 and 2015
Nighttime light	VIIRS DNB nighttime lights [11]	Raster	500m (at the equator)	2016-2020

Fig. 2. Filtered nighttime light of 2016 using 0.17 $\mu Wcm^{-2}sr^{-1}$ lower bound noise floor.

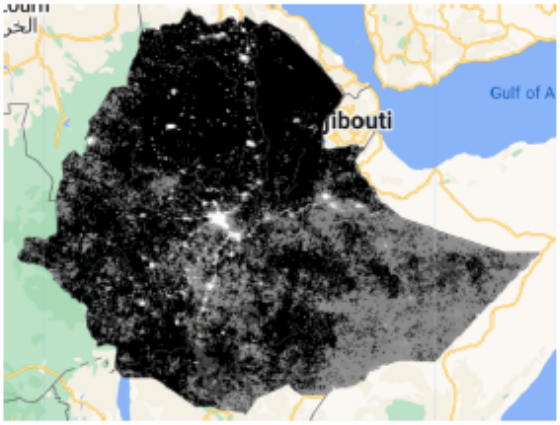

Fig. 3. Filtered nighttime light of 2020 using 0.25 $\mu Wcm^{-2}sr^{-1}$ lower bound noise floor.

Secondly, we masked the population data to exclude areas with no population and no nighttime light. The mask was applied to filter the population density data so that only pixels where there is both population and nighttime brightness above the threshold are retained. This gives the population data with access to electricity.

Next, the masked population with nighttime light above the threshold within each region is summed up using level 1 administrative units. By doing so, we were able to obtain the total population with access to electricity in each administrative region/state.

In the final step, we summed up the total population data, again using level 1 administrative boundaries. This step enabled us to obtain the total population in each administrative region. Access to electricity in each state (subnational level) was then calculated by dividing the entire population with access to electricity by the total population in each level 1 administrative unit. This calculation provided an estimate of the percentage of the population with access to electricity at the subnational level.

Subsequently, to determine access to electricity at the national level, we aggregated the subnational estimates of access to electricity. Precisely, we summed up the total population with access to electricity across all administrative regions and divided it by the total population of the country to obtain the national estimate of access to electricity.

D. Analyzing seasonal trends and temporal patterns in nighttime lights

To analyze the temporal and seasonal trends of nighttime light data at subnational level, we employed VIIRS data and GEE API in Python Notebook [16]. From the VIIRS image collection, we filtered out only the average radiance band for each state and applied 0.25 $\mu Wcm^{-2}sr^{-1}$ lower bound noise floor to obtain only lights from electricity. The date range for the analysis is set from January 2016 to December 2020. The geometries of the different states/administrative regions in Ethiopia are obtained using the GEE API from the FAO/GAUL/2015/level1 feature collection [15]. Then we reduced the nighttime image collection to regions defined by the geometries of the different states and calculated the mean radiance value for each state for each date. Finally, the data is structured using the Pandas library, and a plot is generated for each state showing the trend in average radiance over time.

III. RESULT AND ANALYSIS

A. Access to electricity at subnational level

Fig. 4 shows the access to electricity at the subnational level (level 1 administrative unit or state) in Ethiopia from 2016 to 2020. This figure illustrates a general trend of increasing

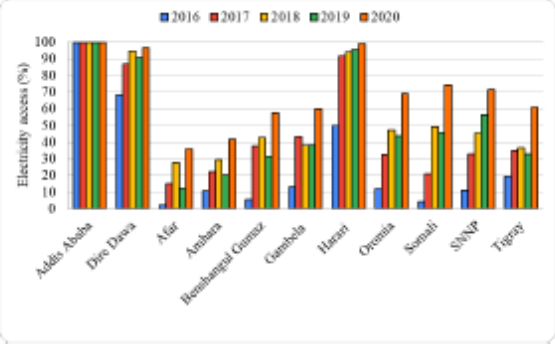

Fig. 4. Estimated access to electricity at the subnational level between 2016-2020.

access to electricity across all states in the study period. However, there are also significant differences in the access to electricity between states. Addis Ababa had almost 100% access to electricity in all years, while Afar and Somali had the lowest electricity access.

The difference in access to electricity between states can be attributed to several factors, including geographic location, economic development, and government policies. For example, Addis Ababa, being the capital city, has a higher level of economic development and therefore receives more government attention compared to other states, resulting in 100% access to electricity. In contrast, states like Afar, remotely located from major economic hubs with sparsely populated areas, have lower access to electricity largely due to the high cost of infrastructure development and low population density.

B. Access to electricity at the national level

Table II presents the comparison between estimated national electrification rates using nighttime and high-gridded population data, and electrification rates reported by the World Bank from 2016 to 2020. The results show that the estimated electrification rates were lower than the World Bank data for all years except for 2020, where it was higher. The discrepancy between the two datasets ranges from 28.2% in 2016 to as little as 0.6% in 2020. In 2016, the difference between the World Bank electrification rate (%) and the estimated electrification rate (%) is 28.2%, and even with a lower noise filter, the difference remains considerable.

There could be several reasons for the disparity between the estimated electrification rates and the World Bank data. One reason could be the accuracy of the World Bank data itself. If these data are not accurate, then it will be difficult to correlate with our findings. Another reason could be that the low average monthly light intensity might have been removed as outliers (considered as temporary light) when calculating stray and cloud-filtered nighttime light by the Earth Observation Group (EOG) [11]. This exclusion of low light intensity may have contributed to underestimating the electrification rate.

Another factor that may have affected the estimation is the choice of the lower noise filter threshold. Using a lower

TABLE II
BOTTOM-UP ESTIMATED ELECTRIFICATION RATE, WORLD BANK ELECTRIFICATION DATA, AND THEIR MISMATCH

Year	2016	2017	2018	2019	2020
Estimated electrification rate (%))	14.7	32.5	44.3	42.5	64.1
World Bank data (%)	42.9	44.3	44.9	48.1	51.1
Mismatch (%) (Estimated - World Bank)	-28.2	-11.8	-0.6	-5.6	+13

threshold may overestimate electrification rates by including areas that are not actually electrified while using a higher threshold may underestimate the rates by excluding areas that are actually electrified.

A study [6] also raised a concern that the NOAA VIIRS sensor may not detect electricity availability in smaller villages without outdoor lighting or in electrified villages that do not emit enough light to be captured by the sensor. Moreover, the sporadic or short-term use of lights, or turning off the lights before 1:30 AM when the VIIRS sensor takes recordings, could also hinder accurate detection of nighttime light data.

C. Seasonal and temporal patterns of nighttime light in different states of Ethiopia

Fig. 5 indicates seasonal and temporal patterns of the nighttime light data from 2016 to 2020 in all states of Ethiopia. The seasonal patterns in nighttime lights vary between different states. Generally, the months of November to February are associated with higher nighttime lights across all states, likely due to the holiday season and increased economic activity. However, some states exhibit more pronounced seasonal changes than others. For instance, the states of Tigray and Amhara have a marked increase in nighttime lights during the months of October to January, while the state of Oromia shows a more gradual increase during the same period. Gambella and Somali states exhibit more pronounced seasonal changes in nighttime light patterns than others did.

The nighttime light data from 2016 to 2020 also show temporal patterns in different states. In the state of Addis Ababa, there has been a steady increase in nighttime lights

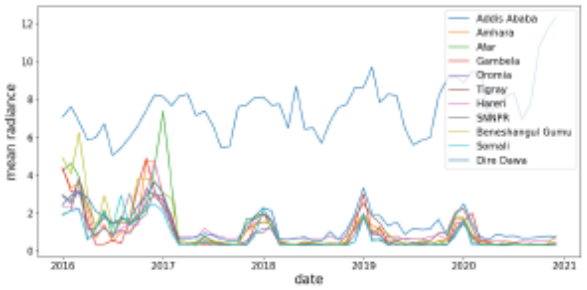

Fig. 5. Monthly mean radiance in each state for the years 2016 to 2020.

from 2016 to 2020, with the exception of a small decrease in 2018. On the other hand, in the state of Gambela, there has been a fluctuation in nighttime lights, with a sharp decrease in 2017 followed by an increase in 2018 and a decrease in 2019.

In contrast, in the state of Somali, the difference between the dry and wet seasons is less pronounced, and the peak in nighttime lights occurs in December. Some states such as Oromia, Amhara, and Tigray have experienced a gradual increase in nighttime lights over time, indicating overall economic growth and development. On the other hand, other states such as Benishangul-Gumuz and Gambela have remained relatively stable or experienced fluctuations in nighttime lights, indicating possible economic stagnation or fluctuations in population size and activity.

The spike in the nighttime mean radiance could have resulted from various factors, such as the implementation of new electrification programs or the widespread adoption of solar home systems among rural households in recent years. For instance, the sale of approximately four million off-grid solar devices between 2015 and 2017 and a penetration rate of 20% in 2017 may have contributed to the observed fluctuation in radiance [1].

The outcomes of this research hold significant potential for various stakeholders. Governments and policymakers can utilize these findings to formulate targeted strategies for enhancing electricity access, considering the specific regional disparities highlighted. Investors could identify areas with high potential for electricity expansion, informed by the subnational disparities identified. Electricity companies could use this data to prioritize their infrastructure development, ensuring better coverage in regions with limited access. Ultimately, these findings provide valuable insights to guide informed decision-making and resource allocation toward achieving more equitable and sustainable electrification.

IV. Conclusion

Using nighttime satellite imagery, gridded population, and administrative boundaries data provides a promising alternative approach to estimating electrification rates at different spatial scales as well as season and temporal changes.

The results of our study however indicate a significant disparity between the estimated national-level electrification rate and the data reported by the World Bank in Ethiopia for the period 2016-2020, with the discrepancy ranging from 28.2% in 2016 to 0.6% in 2020. Various factors may contribute to the lack of a better estimation, including the accuracy of the World Bank data, the inability of the NOAA VIIRS sensor to detect indoor light, the possibility that the light being used is not visible from outside, and turning off the lights before 1:30 AM when the VIIRS sensor takes recordings.

The study also finds that, despite the overall increasing trend in electricity access at the subnational and national levels from 2016 to 2020, there are significant disparities in access between states. The findings further indicate that the seasonal patterns in nighttime lights vary between the different states, with the months of November to February generally associated with higher nighttime lights across all states. Likewise, the temporal patterns in nighttime lights experience a steady increase over time in some states, while others exhibit fluctuations or remain relatively stable.

The study highlights that electricity access level estimation using nighttime light data could be an alternative approach for guiding electrification decision-making. However, efforts are needed to improve data quality and accuracy to ensure the reliability and effectiveness of the method. Thus, further studies are needed to refine the methodology and improve the accuracy of estimates.

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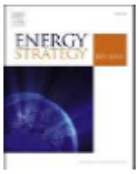

Analyzing grid extension suitability: A case study of Ethiopia using OnSSET

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ABSTRACT

Several geospatial factors influence the suitability of national power grid expansion, especially in remote areas. Since previous studies have neither explicitly examined the level of influence of these factors nor provided a clear spatial representation of their impact, this paper examines how geospatial factors (distance from substation and road, terrain slope, elevation, and land cover) influence grid extension suitability to unelectrified settlements in the context of Ethiopia. Open-access and remote-sensing datasets are used together with OnSSET geospatial modeling analysis methodology. A spatial grid extension suitability map is developed to display areas that are most suitable, semi-suitable, and less suitable for grid extension. Results show that terrain slope is the most significant contributor to grid extension suitability, accounting for 40.8 % of the total score. The findings reveal that the geospatial factors studied, aggregately, might increase the total investment cost of grid extension by 2.3 %–29 % across Ethiopia. The results also show that 45 % and 85 % of Ethiopia's population live within 10 km distance from high-voltage and projected medium-voltage lines, respectively. The study underscores that rather than focusing exclusively on distances from existing grid infrastructures, it is important to take into account the aforementioned geospatial factors affecting investment costs for grid extension planning.

1. Introduction

Access to electricity is a fundamental pillar for socioeconomic development, underscored by the United Nation's (UN's) Sustainable Development Goal 7 (SDG7) to ensure affordable and reliable energy for all by 2030 [1]. Electricity access significantly influences living standards, education, healthcare, and agricultural productivity [2], but 759 million still lacked basic electricity access in 2019, predominantly in Sub-Saharan Africa (SSA), where over half the population lacks electricity access [3] in contrast to the UN's goal of universal energy access and projected economic growth [4]. In light of this, the imperative to extend electricity access to underserved population figures prominently in the policy agendas of many developing countries. However, the pathways to achieve this goal diverge, primarily revolving around grid extension and off-grid systems.

The de facto electrification strategy is to expand existing national power grids and transmission networks [5], supported by initiatives such as Power Africa [6]. [1]Grid expansion refers to the construction of additional transmission lines to meet the increasing electricity demand. The feasibility of grid-based electrification relies on the correlation between existing grid coverage and population distribution [7]. The distance from households to the nearest grid connection point significantly impacts electricity transmission costs for two reasons: longer transmission lines entail higher capital costs, and also energy losses, for a given connection [8]. Thus, proximity to the grid typically translates to lower connection costs [9].

On the demand side, grid extension-based electrification pathways often face challenges from low electricity consumption by settlements [10]. This can be attributed to several factors, including low population density, sluggish economic growth, and low-income levels of residents: leading to limited demand for electricity. Consequently, the levelized cost of electricity ([2]LCOE) for grid-based electrification tends to be high, making it economically less viable.

Grid extension suitability is also affected by various [3]geospatial

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[1] In this paper, the terms "grid extension" and "grid expansion" are used interchangeably.

[2] The levelized cost of electricity (LCOE), represents the average cost per unit of electricity generated that would be required to recover the costs of building and operating a generating plant over its lifetime. LCOE is used for investment planning and to compare different methods of electricity generation on a consistent basis.

[3] The term "geospatial" in this paper refers to information that is directly related to specific geographic locations.

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factors, including but not limited to, access to roads, land cover, and topography [8]. For instance, road distance guides electrification choices in Directorate General of Energy (DGE) – Energy Division (Togo) [11]. Additionally, higher elevations entail greater expenses for construction and transportation [12]. Notably, these geospatial elements, including distance from power grid, can account for a significant portion of the initial investment cost, with estimates reaching up to 30 % [12].

Grid extension suitability in this study refers to the comparative suitability of extending the grid to different settlements, assessed by evaluating the grid extension penalty (GEP) and LCOE. GEP represents extra costs per unit grid extension length due to supply-side factors (distance from substation and road, terrain, elevation and land cover). LCOE covers total electricity costs, including capital and operating expenses. High GEP or LCOE values indicate higher extension expenses, while low values indicate better suitability for grid extension.

Moreover, the dependency of geospatial analysis outcomes on the resolution of utilized datasets bears crucial significance [13]. Notably, employment of lower-resolution datasets can potentially undermine the accuracy of the GEP multiplier and, thus, possibly result in a skewed preference for grid extension as a more favorable electrification approach. This underscores the necessity of embracing finer-scale data to capture the intricate dynamics of geospatial factors accurately.

In this context, the study by Mentis et al. [14] holds significance. The authors conducted geospatial planning studies to determine the least-cost electrification mix in Ethiopia for universal electricity access. Employing a population grid with a spatial resolution of 2.5 × 2.5 km, their findings indicate that grid extension was the cost-effective choice for nearly 89 % of the newly electrified population by 2030 for the base case scenario (for the electricity access targets 50 (rural)-300 (urban) kWh/capita/year). Similarly, Korkovelos et al. [8] undertook a comparable analysis, utilizing high-resolution population data (30 × 30 m grid size) in Malawi. Their emphasis on detailed data capture was geared towards accurately accounting for the characteristics of settlements, thereby yielding more precise estimations of grid extension suitability. Their work showed, under the baseline scenario, that by 2030 off-grid PV emerged as the least-cost option for 67.4 % of the population and grid extension only for the remaining 32.6 %.

Furthermore, although previous studies [8,12,14–16] have made strides towards factoring in geospatial parameters, none of them has illuminated the precise spatial influence of these factors on individual unelectrified settlements. Additionally, they have not probed into the cumulative weight of these factors, nor have they delineated the specific contributions of each factor to the overall suitability of grid extension. This gap in comprehensive spatial representation hampers effective settlement prioritization for grid expansion, potentially leading to inefficiencies in electrification initiatives and undermining larger-scale national strategies and investments.

Addressing the problems, therefore, requires grid-based electrification planning that is grounded on comprehensive and thorough understanding of the various geospatial factors and their influence on the suitability of grid-extension to unelectrified settlements. This will enable the government and other stakeholders to make informed electrification planning decisions. The main objective of this paper is, thus, to examine how various geospatial factors influence the suitability of grid extension, specifically in the context of areas where the population lacks access to electricity. With this objective, the paper seeks to answer the following research questions.

- How is the unelectrified population distributed in relation to the national power grid infrastructures?
- How and to what extent do geospatial factors influence the suitability of grid extension to unelectrified population settlements?
- How does the suitability of grid expansion, in terms of LCOE, vary across unelectrified settlements as electricity demand target changes?

This study is novel in two ways. Firstly, it methodologically complements previous studies on electrification planning [5,8,12,14–17] by incorporating the projected medium-voltage lines, high-resolution populations, and nighttime light data into the modeling, particularly for grid-based electrification planning. Secondly, unlike earlier studies, it explicitly investigates how geospatial factors affect grid-extension suitability across various demand levels (electrification tiers), thus contributing to the understanding of this relationship amidst other influences.

This research employs Ethiopia as a case due to its size (area of 1.1 million km^2), sizable (population over 114 million people) and considerable gaps in electricity access (only 51.1 % had access to electricity in 2020 [18]). The country also has a pronounced rural-urban disparity with only 39.4 % of the rural population having access to electricity compared to 93.2 % in urban areas. These statistics underscore the challenges the country faces in achieving universal electricity access. The Government of Ethiopia (GoE) launched the second National Electrification Plan (NEP 2.0) in 2019, targeting universal access by 2025, with 65 % through the grid and 35 % via off-grid solutions [19]. As of 2019, the government reported providing electricity to 33 % of its population through grid expansion and 11 % through off-grid solutions [19,20]. Notably, electricity tariffs in Ethiopia were subsidized at around 0.0187 USD/kWh from 2005 to 2017, rising to 0.0765 USD/kWh in 2021 [21]. Despite these relatively affordable tariffs, a major barrier to electricity access lies in the high connection fee, which amounts to USD 150 per household connection, relative to the low household income [20]. This last-mile connection cost is a key economic factor that inhibits wider access, particularly in SSA [22]. A related barrier is the high cost of electrical appliances such as CFL/LED lights, that are subject to 25 % import duty and 15 % VAT taxes [20].

The remainder of this paper is organized as follows. Section two details the methodology employed, including the choice of modeling tool and the techniques used for obtaining and processing input data. This methodology is then applied to the case country under investigation. The results are then presented and analyzed in the Results and Analysis section. Section four provides a discussion of the results together with the novelty of the developed methodology and the strengths and weaknesses of the paper. The final section presents the major conclusions drawn from the research with the answers to the research questions posed at the outset of the research.

2. Methodology

2.1. Research approach

It is evident from the introductory section that well-informed grid extension planning requires a comprehensive understanding of the influence of several factors including geophysical factors, population density, and level of electricity demand [8,14–16]. Therefore, in this study, a causal comparative research approach is applied to analyze the relationships and level of influences of the various geospatial factors on grid extension suitability in unelectrified areas of Ethiopia. Causal research, also known as causal-comparative research, identifies the extent and nature of cause-and-effect relationships between two or more variables [23]. It is typically used to determine the influence of changes in explanatory variables on the outcome variable, in this case, the influence of geospatial factors and the level of electricity demand on grid expansion suitability. In this study the approach is divided into four phases: modeling tool selection, data acquisition, data processing, and data analysis and visualization. The following subsections provide description of each phase. Fig. 1 shows a simplified flowchart of the methodology and steps followed.

2.2. Modeling tool selection

The selection of an appropriate energy-modeling tool depends on the

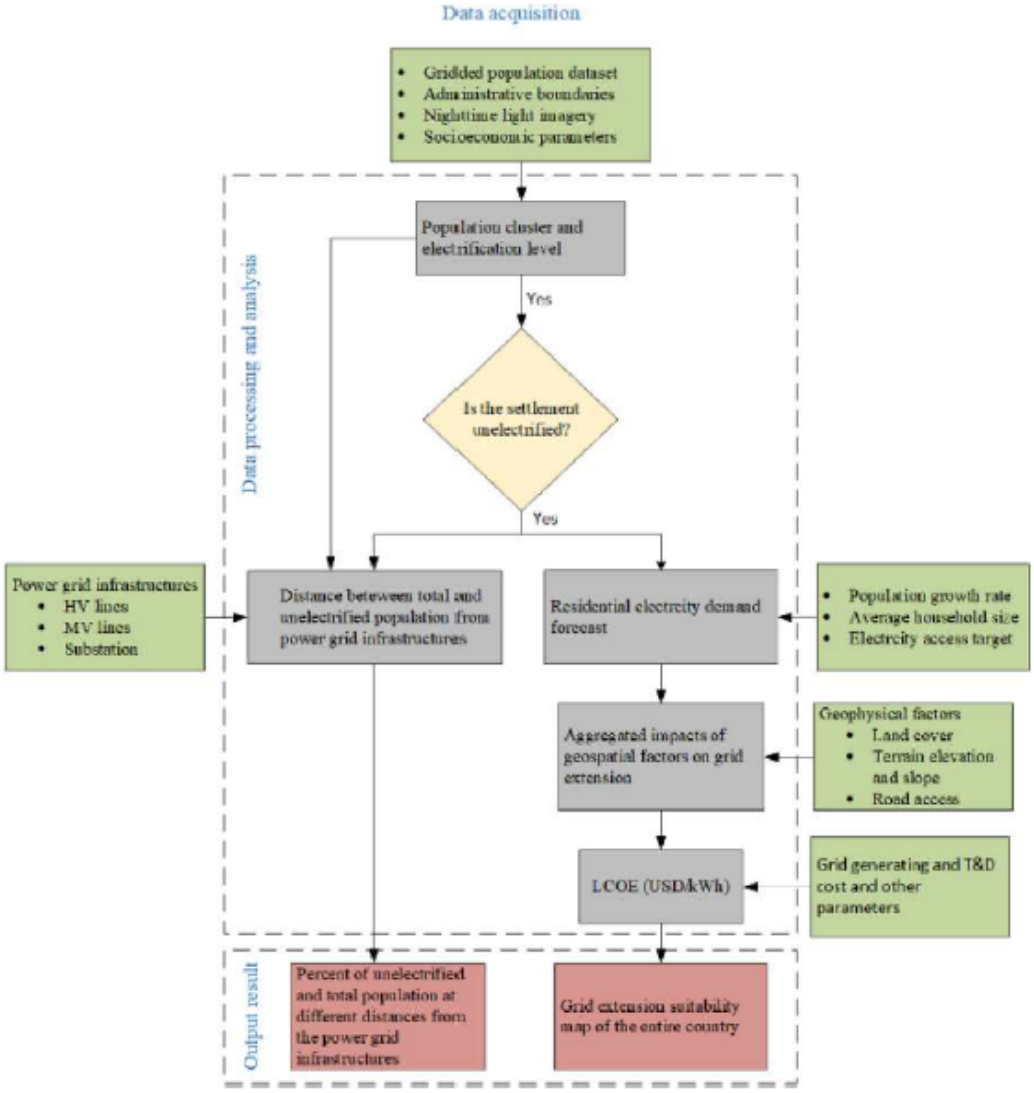

Fig. 1. Flowchart of methodological approach. Diagram color shows: olive green "input data", gold and grey "data process" and red "results of the analysis".

specific questions that need to be answered and the available data. For this particular study, the OnSSET (Open-Source Spatial Electrification Toolkit) was chosen for several reasons. Firstly, it is an open-source platform [24], making it easily accessible from the GitHub repository and customizable to tailor specific research needs. Secondly, the tool supports nationwide spatial analysis, which meets the study's objective of examining the factors that affect grid extension suitability across unelectrified settlements in the entire country. The modeling tool is programmed to determine the extent of influence of geospatial factors and identify areas that are suitable, semi-suitable, and unsuitable for grid extension. This modeling tool is applied to Ethiopia.

Thirdly, in contrast to traditional energy modeling tools, such as TIMES, MESSAGE, and OSeMOSYS, OnSSET has the unique capability of accounting for topography-related costs in grid extension-based electrification pathways [15]. Traditional energy supply models typically lack this capability of accounting for location-specific peculiarities [25]. Fourthly, OnSSET is thoroughly documented in the literature [8] and on the developers' website [26]. All these qualities make OnSSET a preferred choice for nationwide spatial analysis of electrification efforts, particularly in developing countries like Ethiopia with diverse terrain and varying degrees of access to electricity.

2.3. Data acquisition

The second step in conducting this study is to acquire the necessary input GIS datasets and other parameters presented in Appendix Tables A1, A2, A3, A4, and A5. The datasets used in this study are obtained from open-source platforms. These datasets are further discussed in detail in the following subsections.

2.3.1. Gridded population dataset

The gridded population dataset serves as the basis for generating population clusters/settlements [17]. This data is used to determine where populations are situated within the study area's territory. There are various free, open-source gridded population datasets available, like the Global Human Settlement Layer (GHSL), WorldPop, and the

High-Resolution Settlement Layer (HRSL). This study used HRSL as it has demonstrated greater prowess in recognizing the footprint of built-up areas/buildings in both urban and rural settings than GHSL and WorldPop population dataset [27], owing to its resolution of approx. 30 m (1 arc-second) grid size and the use of subnational census data together with high-resolution (0.5 m) satellite imagery [27,28]. However, since the most recent population data from the 2020 census were not available, population data from 2018 were utilized and adjusted to reflect the total population in 2020. This raster dataset is produced by a joint venture between Meta (formerly Facebook) Connectivity Lab and Columbia University's center for International Earth Science Information Network (CIESIN). Fig. 2 discloses Ethiopia's 2018 HRSL population. It is divided into five categories that differentiate between densely and sparsely populated areas.

2.3.2. Nighttime light imagery

We utilized nighttime light (NTL) imagery in conjunction with population data, following the approach proposed by Falchetta et al. [29], to estimate electrification status of settlements and, consequently, the national electrification rate. This methodology has demonstrated effectiveness in previous research [30–34]. The satellite imagery dataset was sourced from the National Oceanic and Atmospheric Administration (NOAA) and comprises cloud-free composite VIIRS nighttime lights (NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG). As the satellite detects and gathers nocturnal light from a variety of sources, including lights from fires, flares, the sun and moon, boats, and blooming effects surrounding major cities, the best result of electricity rate estimation is obtained by using a dataset that has been cleaned of such noise [14].

To reduce short-term fluctuations and enhance data quality, we generated the 2020 annual composites of NTL from the VIIRS-DNB straylight-corrected monthly composite images utilizing the Google Earth Engine (GEE) platform, which is a cloud-based computing platform that allows users to analyze geospatial data based on Earth science data [34]. Following the approach by Falchetta et al. [29], we processed annual median composite scenarios using five different lower-bound noise floors: 0.25, 0.27, 0.28, 0.30, and 0.35 $\mu W\ cm^{-2} \cdot sr^{-1}$. These values represent the minimum intensity below which any light is considered noise or ephemeral. This ensures that only electricity-generated light is included in our analysis. We tested various noise floors in an effort to identify the one that offered the most precise estimation of Ethiopia's national electrification rate in comparison to the World Bank's reported electrification rate. Fig. 3 displays the NTL composite for the case study country. The data in this figure represents the annual median radiance, and it has been filtered using a threshold of 0.27 $\mu W \cdot cm^{-2} \cdot sr^{-1}$. Additionally, Appendix Figure A1 provides further insights into nighttime light variations using both the minimum threshold (0.25 $\mu W\ cm^{-2} \cdot sr^{-1}$) and the maximum threshold (0.35 $\mu W\ cm^{-2} \cdot sr^{-1}$). These thresholds provide insights into variations in nighttime light levels within the case study country.

The population density map (Fig. 2) aligns closely with the processed nighttime light (NTL) map (Fig. 3), highlighting a strong correlation between population density and NTL intensity. Higher population density corresponds to brighter NTL, signifying greater electrification, while lower population density areas exhibit dimmer or no NTL, indicating lower electrification levels. This connection emphasizes NTL's effectiveness as a proxy for assessing electricity access where detailed data may be limited.

2.3.3. Administrative boundaries

The administrative boundaries were used to extract the nighttime light data from the NOAA VIIRS satellite data and delimit the analysis to the study area. By doing this, only the nighttime light data inside the administrative boundaries is accounted for in the analysis. This also ensures that the population cluster is contained within these boundaries, thus limiting the maximum area of the cluster [35]. In this study, the entire country territory (level 0) was applied for clipping the annual nighttime light raster data, and the first-level administrative boundaries (level 1) were employed for generating the population cluster. Both datasets were obtained from the Global Administrative Areas (GADM) version 4.0. The GADM gives high-resolution administrative boundaries

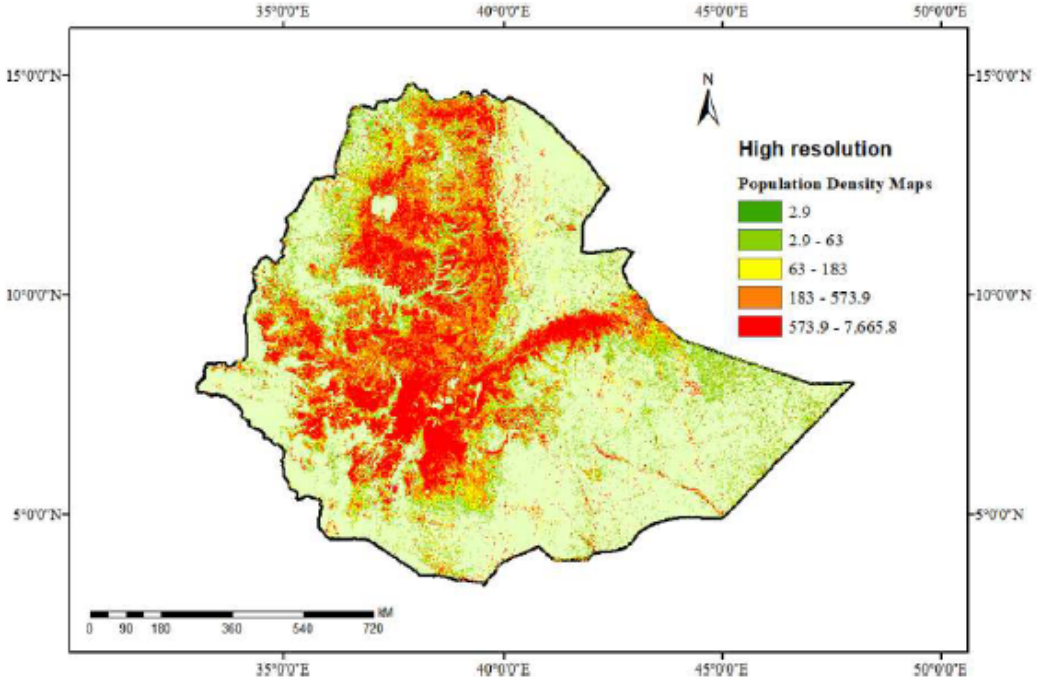

Fig. 2. Population distribution in Ethiopia (at a resolution of 30 m) based on HRSL 2018 raster data [28].

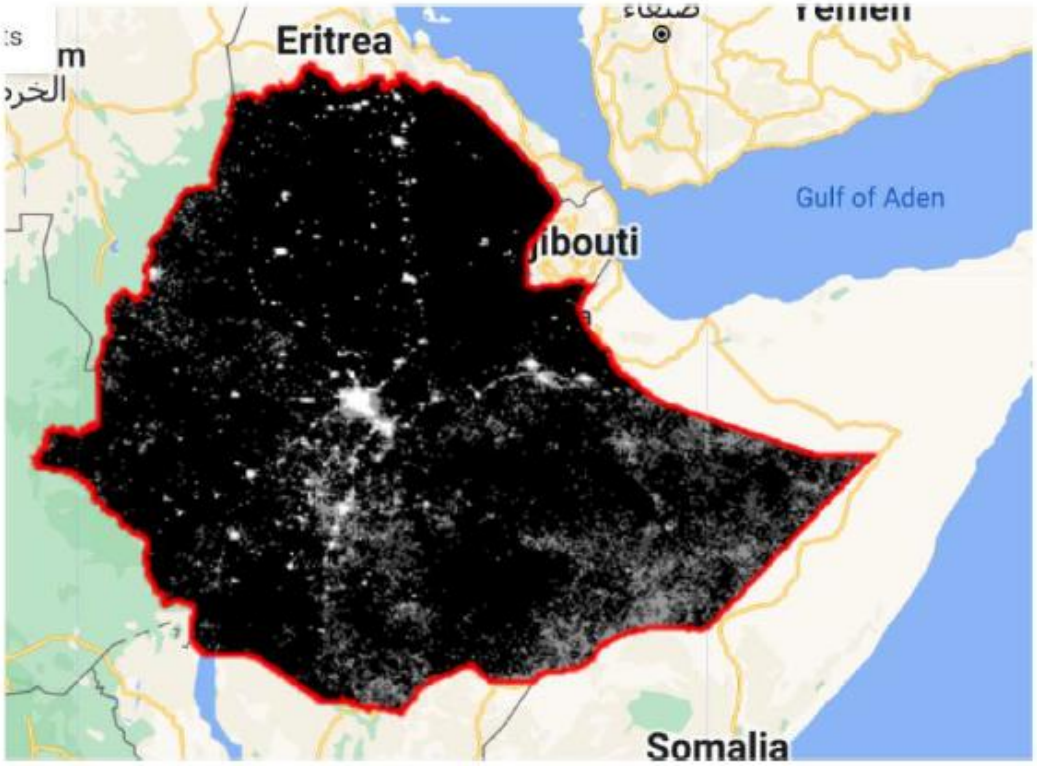

Fig. 3. Annual NTL composite in Ethiopia, filtered using 0.27 μW $cm^{-2} \cdot sr^{-1}$.

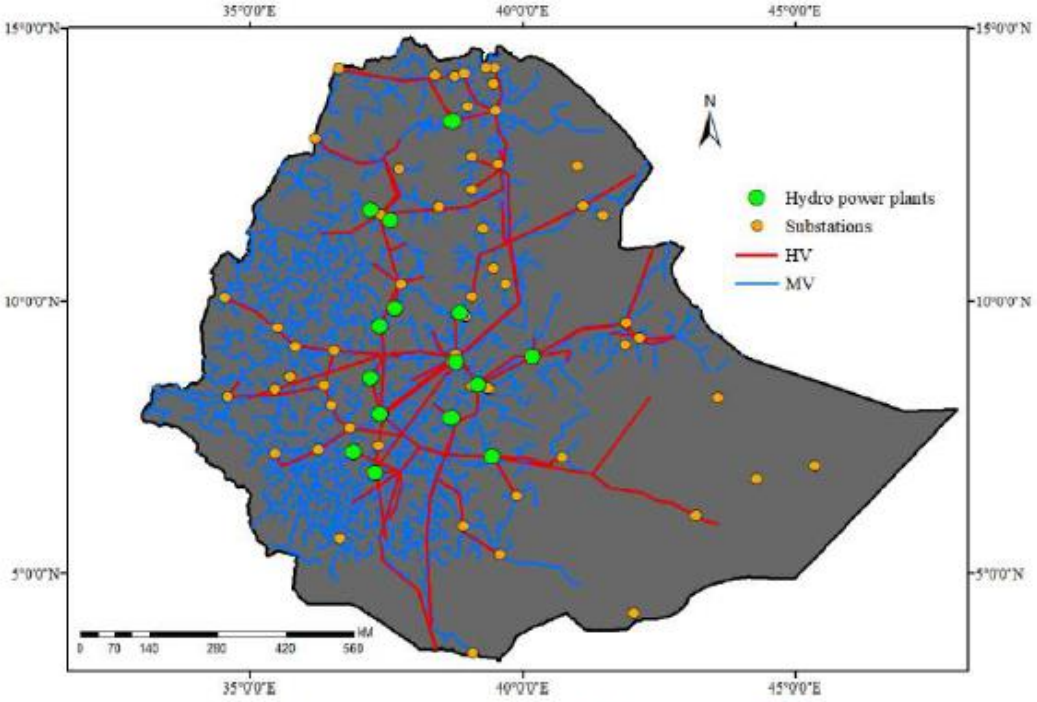

Fig. 4. Existing HV and projected MV lines, and substations in Ethiopia [37,40].

at different levels using the WGS84 datum coordinate reference system and longitude/latitude [36].

2.3.4. Power grid infrastructures

The spatial distribution of the existing power grid infrastructures was used in order to examine where the unelectrified population lives in relation to it. To that end, publicly accessible georeferenced datasets of High Voltage (HV) transmission lines, projected Medium Voltage (MV) lines, and substations, were used as input data. These datasets can be obtained from Energydata.info, an open data platform created by the World Bank and its partners with the aim of filling a data gap in the energy sector [37]. The Energydata.info portal sources its data from multiple reliable and verified sources, such as Africa Infrastructure Country Diagnostic (AICD), OpenStreetMap (OSM) contributors, and World Bank projects archive and IBRD maps, and international organizations [38]. The data used for this case study was updated in 2017.

It is worth noting that the availability of these datasets varies by country and the type of infrastructure. In specific instances, such as the case study area, the MV lines dataset is unavailable on the energydata.info platform. Consequently, we sourced this information from the Gridfinder web application [39]. This application uses machine learning and publicly available datasets, such as nighttime data and MODIS land cover data to drive MV network distribution lines. The Gridfinder Tool estimates the MV lines by utilizing a many-to-many variant of Dijkstra's algorithm and integrating road networks as a cost function. The algorithm aims to predict distribution networks based on the assumption that lines tend to follow roads [39]. Fig. 4 displays the HV, projected MV lines, and substations in the study country.

The red lines signify HV lines linking remote hydropower plants (depicted in green) to substations (highlighted in orange). The blue lines, on the other hand, depict the distribution of the projected Medium Voltage (MV) lines within cities and towns. These substations encompass both HV to MV converters and diesel-based units.

2.3.5. Land cover

To evaluate the suitability of land cover for grid extension, we employed the MODIS/Terra + Aqua Type MCD12Q1 Version 6 land cover dataset, obtained from Earth Data [41]. This dataset provides global land cover information at a resolution of 500 m [42]. Maps were created using data from the Moderate Resolution Imaging Spectroradiometer (MODIS), and land cover classification values were made based on a range of 1–17 [26]. Fig. 5 shows the land cover in Ethiopia in 2020, classified into different categories based on the MODIS/Terra + Aqua data. When calculating the GEP, the OnSSET GIS extraction model reclassifies these values, with corresponding weights listed in Table A2.

This study utilized a reclassification approach [12], detailed in Appendix Table A2, to assess the suitability of different land cover types for grid extension. This method integrates the Analytic Hierarchy Process to determine the significance (weight) of each land cover type in terms of grid extension suitability. Notably, land cover types like open shrublands, cropland/natural vegetation mosaics, savannas, grasslands, and barren areas are deemed highly suitable for grid extension, while water bodies and permanent wetlands are considered the least suitable for such expansion.

2.3.6. Elevation and terrain slope

To assess the influence of elevation and terrain slope on the suitability of grid extension [11], the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM) elevation dataset is used. This dataset, produced by the Japanese Ministry of Economy, Trade, and Industry and NASA, uses stereo-pair images from the Terra satellite to generate a digital elevation model with a horizontal resolution of 15 m [8,43]. The OnSSET GIS extraction model then utilizes this information to create a map of terrain slope, a sub-product of DEM, which is used to identify restriction zones and determine the suitability for grid extension.

2.3.7. Road access

The impact of road infrastructure access (major roads, highways,

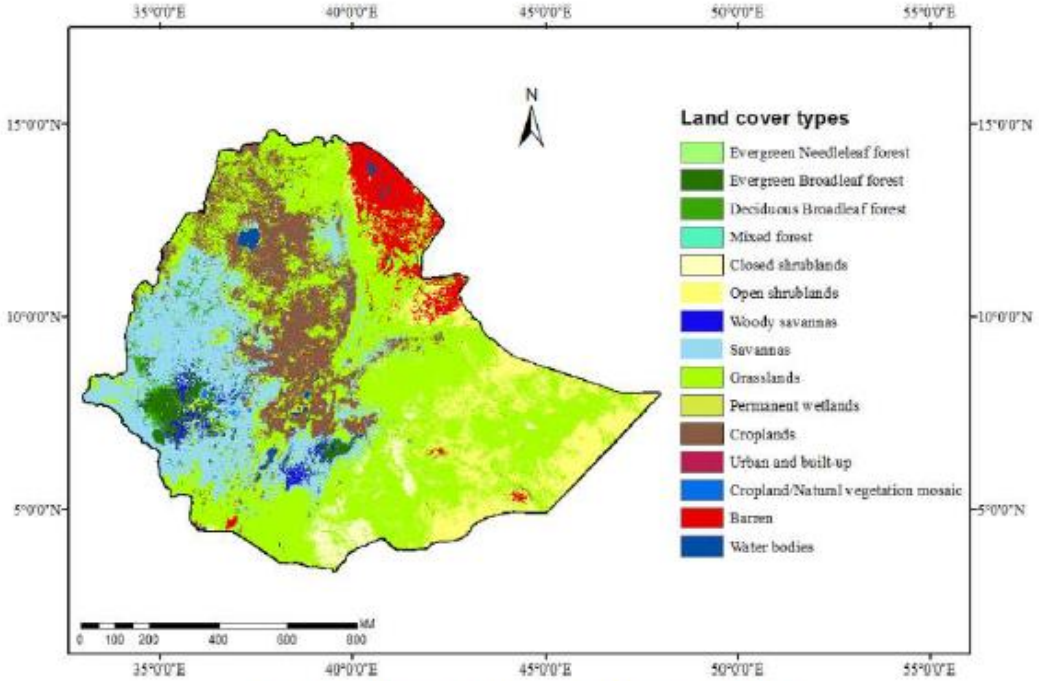

Fig. 5. MODIS/Terra + Aqua land cover types in Ethiopia in 2020 [42].

primary, and secondary roads) on the grid extension suitability is assessed by evaluating its proximity to roads [9,11]. The road scale should at least allow for the use of pickup/trucks [8]. The road data used in this study is obtained from the OpenStreetMap project via Geofabrik's server, which is updated daily [44].

2.4. Data processing

2.4.1. Population cluster and electrification rate

At this stage, the population clusters are generated, and distribution of electrified and unelectrified settlements are identified. A population cluster also known as a settlement is a geospatial unit representing human settlements formed by contiguous groups of people, which serves as a basis for the analysis. Population clustering in this context is a technique for converting high-resolution raster population data into vector-based population clusters with unique characteristics indicating population, electrification status, and urban-rural categorization [45]. The following three GIS datasets are utilized to generate the population cluster and ascertain the current electrification status [26]; more information about the datasets is given in Appendix Table A1.

- Gridded population dataset (raster layer)
- Nighttime light imagery (annual median nighttime light (raster)), cleaned from background, biomass burning, cloud cover, stray and aurora light
- Administrative boundaries (vector layer)

To establish population clusters for analysis, researchers have several options available. Two common methods include using the PopCluster QGIS plugin developed by KTH-dES [35] or the Clustering method written in Python developed by Khavari et al. [27] and available on the GitHub repository [45]. Both methods allow the user to set a threshold for the population layer below which is counted as zero. Alternatively, the second method allows to set thresholds for both the population layer and the nighttime light. It also allows users to calibrate population data using "start year" (base year) population figures. At the end of this process, the population clusters are polygonized within the inner administrative border to ensure that the clusters do not spill over into different administrative territories, enabling leaders and policymakers to focus on a specific area/region [27].

In this study, the Clustering method [27] was used. The simplified

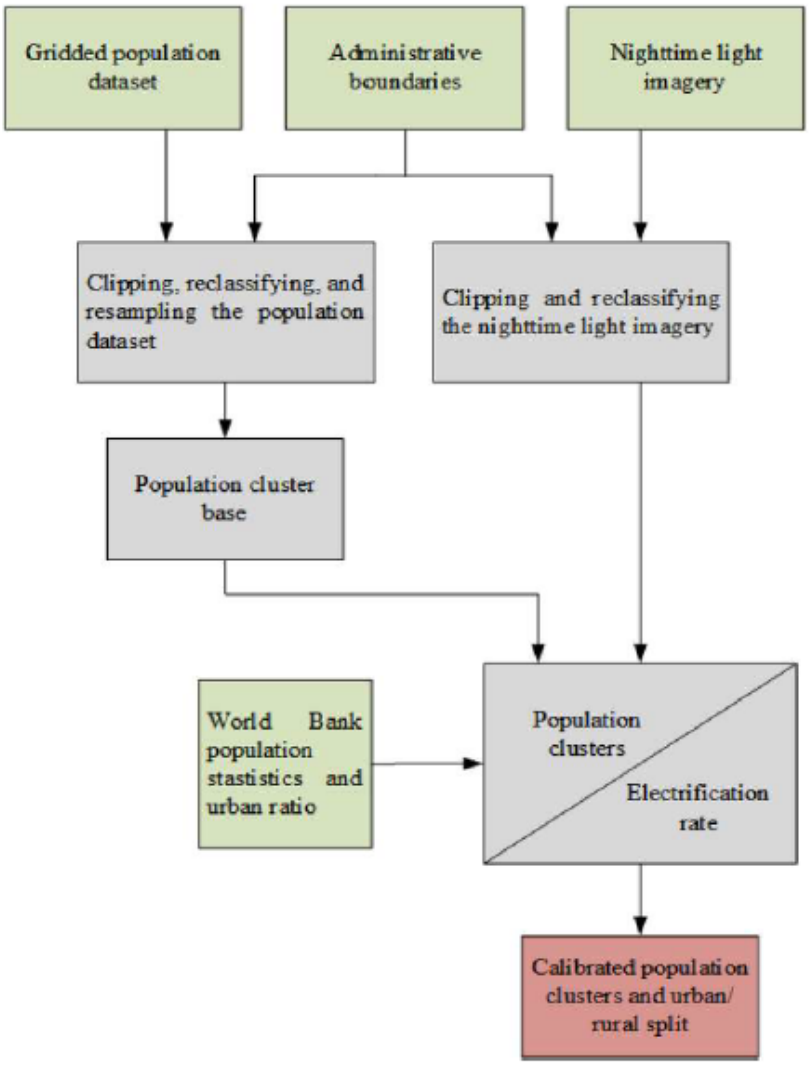

Fig. 6. The simplified population clustering process diagram, adopted from Ref. [27].

steps of the process are depicted in Fig. 6. A threshold of zero was used for both the population and nighttime light data in the analysis. The population raster dataset (a raster with cell size of 30 m) is resampled to produce an output raster with cell size of 90 m [45]. Clusters are created by multiplying a resampled population with rasterized disaggregated administrative boundaries and then converting the resulting raster layer into polygons, each polygon representing a cluster. The size of the clusters is determined by the population's spatial distribution and administrative boundaries. Each cluster denotes a specific region/-location. The Clustering method allowed us to analyze the demographic composition of each cluster, including the number of people, their electrification status, and the urban/rural split.

In order to detect already electrified populations, OnSSET uses a heuristic approach utilizing a combination of spatial nighttime light brightness and population datasets to identify lit clusters and classify them as electrified (1) or unelectrified (0) [8], [14], [26]. Specifically, a settlement is considered as electrified if it fulfills the criteria of having a population density of at least 1 person per square kilometer and a nighttime light brightness value exceeding the minimum threshold described in Section 2.3.2. Then the number of electrified people is determined by summing the population with the count of individuals within each cluster who inhabit areas where light sources are detected, signifying those with access to electricity [45]. This enables us to assess access to electricity at a cluster level, information that is often difficult to obtain. The rate of access to electricity at the national level for the year 2020 is then computed with equation (1). The Clustering method relies on thresholds used by Eurostat to classify settlements into urban and rural areas [27].

$$\text{Access to electricity at national level} = \frac{\sum_{i=1}^{n} Electrified\ population\ in\ each\ cluster_i}{\sum_{i=1}^{n} Population\ in\ each\ clusters_i} x\,100\% \quad (1)$$

where i and n represent the population cluster.

Accordingly, the pixelated population of Ethiopia was divided into 809,087 clusters by the OnSSET Clustering method. This was accomplished by merging eight adjacent grid cells of the HRSL population dataset.

2.4.2. Distance from the power grid

The OnSSET grid extension algorithm begins by identifying all population settlements within the study area. Each settlement and power grid infrastructure (HV line, projected MV line, and substation) is denoted by its x and y position coordinates. The algorithm then iteratively traverses a subset of the tree nodes using Locality-Sensitive Hashing (LSH) to identify the nearest HV line, projected MV line, and substation to each settlement [8]. LSH is a method for approximating the nearest neighbor search problem in high-dimensional spaces. It works by creating a hash table of the data points, and then using the hash values to quickly identify points that are likely to be close to the target point.

Once the nearest power grid infrastructure (HV line, projected MV line, or substation) is identified for a population settlement, the algorithm uses the coordinates of both the settlement and the power grid infrastructure to calculate the distance between them. This allows the algorithm to determine the proportion of unelectrified and total population in relation to the grid infrastructure by computing the ratio of the sum of unelectrified population to the total population of the country and the ratio of the total population located at various distances from the grid infrastructure to the total population of the country, respectively.

2.4.3. Residential electricity demand

Population projections for 2030, along with different electricity access targets, referred to as "tiers," are used to determine future residential electricity demand scenarios. We used the current average electricity consumption per household in Ethiopia, approx. 335 kWh/year [46,47], as a benchmark to adapt two consumption tiers. From the Global Tracking Framework [48], we adapted tier 1 (38.7 kWh/household/year) and tier 3 (803 kWh/household/year), which are lower and higher than Ethiopia's average consumption, respectively. These tiers are assumed to be applied uniformly across the country. Initially, two separate access tiers were considered for urban and rural areas. However, the author notes that the urban areas of the country have nearly achieved electricity access, allowing for the use of a single, uniform tier without sacrificing any important information. The electricity demand for unelectrified settlements is calculated by multiplying the target electricity access tier by the projected population for the year 2030, taking into account the average household size in rural and urban areas.

2.5. Data analysis and visualisation

At this phase, the suitability of grid extension to unelectrified settlements was evaluated by analyzing the GEP and LCOE. Accordingly, a spatial grid extension suitability map showing the distribution of areas most suitable, semi-suitable and least suitable for grid-based electrification is developed.

2.5.1. Aggregate effects of geospatial factors

The combined and weighted contribution of geospatial factors to grid extension suitability is estimated through Equation (2). Using this equation, we also evaluated the weighted contribution of each geospatial factor to the total grid extension suitability score. The input parameters were first classified between 1 and 5, with higher values indicating more suitable conditions, as shown in Table A2. The weight assigned to each geospatial factor represents the importance of that feature in determining the grid expansion penalty (GEP). The default weights provided by OnSSET were adopted in this study based on their extensive usage by the Global Electrification Platform in analyzing electrification strategies for 58 countries, many of which are SSA countries including Ethiopia [49]. However, the Analytic Hierarchy Process can be used to determine the weight assigned to each factor [12]. The GEP multiplier for each settlement is calculated using Equation (3) [26]. This equation calculates the grid penalty to increase the grid cost in areas with high slope angles, unsuitable land cover, higher substation distance, higher road distance, or high elevation, [8,14,15].

$$\begin{aligned} Combined\ classification = (&0.30 * slope\ angle + 0.20 \\ &* land\ cover\ suitability + 0.20 \\ &* substation\ distance + 0.15 * road\ distance \\ &+ 0.15 * elevation\ height\ ) \end{aligned} \quad (2)$$

$$Grid\ expansion\ penalty\ (GEP) = 1 + \frac{e^{(0.85*|1-Combined\ classification|)} - 1}{100} \quad (3)$$

The GEP is a crucial factor in the optimization of the grid extension process, as it estimates the additional cost (penalty) of extending the grid to unelectrified settlements. Settlements with high GEP values are considered less suitable for grid extension due to their higher penalty, while those with low GEP values are more suitable. To visually represent this information, the GEP was then mapped and settlements were categorized into three classes of suitability (most suitable, semi-suitable, and less suitable) based on their GEP values, using quantiles. This map may provide decision-makers and energy companies with a better understanding of areas where grid expansion would be relatively feasible from the supply side perspective.

2.5.2. LCOE

The LCOE for each population settlement was calculated using a cost model following Nerini et al. [50] and Mentis et al. [12]. The LCOE calculation takes into account both supply and demand side factors including capital expenses, operating costs, and expected project lifespan. In the LCOE calculations, we considered three key parameters interlinked with costs: I) the targeted level of electricity demand expressed in kWh/household/year; II) population density, quantified in households/km2; III) local grid connection specifics, encompassing the distance from the nearest grid (km), translatable into wire costs and the average national cost of grid electricity ($/kWh). Details of the cost model are given in the Appendix Table A4 and Table A5. Based on the LCOE values, settlements are classified into three suitability categories as most suitable, semi-suitable, and less suitable. Settlements with a low LCOE value were deemed most suitable for grid extension while those with an intermediate LCOE value were considered semi-suitable, and settlements with a high LCOE were considered less suitable. Finally, the data analysis results are presented in maps, graphs, and figures for better understanding and easier visualization.

It is evident from the detailed description of the methodology section that this study is based on high-quality and multiple datasets to the greatest extent possible, including high-resolution population datasets, NTL datasets, varying demand levels; and as many robust and relevant data analysis methods as possible, including GEP, LCOE, and visual-spatial representations.

Table 1
Geospatially estimated electricity access at different noise threshold floors.

NTL data noise floor ($\mu W \cdot cm^{-2} \cdot sr^{-1}$)	Estimated electricity national access	Urban and rural access respectively	Compared to the national statistics from World Bank
0.25	69.1 %	98.7 % and 61.4 %	Overestimated (+18 %)
0.27	51.3 %	97 % and 39.3 %	Overestimated (+0.2 %)
0.28	44.1 %	96 % and 30.4 %	Underestimated (−7%)
0.30	33.8 %	93.4 % and 18.2 %	Underestimated (−17.3 %)
0.35	24.6 %	88.4 % and 8.1 %	Underestimated (−26.5 %)

The results indicate that a noise floor of 0.27 $\mu W\ cm^{-2} \cdot sr^{-1}$ provides the best estimate, with a slight overestimation of the national electrification rate by 0.2 % compared to the World Bank's reported rate of 51.1 % for Ethiopia. In contrast, a noise floor of 0.28 $\mu W\ cm^{-2} \cdot sr^{-1}$ underestimates electrification rates by 7 %. The study highlights the importance of selecting an appropriate noise floor when using NTL data for estimating access to electricity. Additionally, the study suggests that using a noise floor of 0.30 $\mu W\ cm^{-2} \cdot sr^{-1}$ or higher can provide better accuracy in determining access to electricity in urban areas, while a noise floor of 0.27 $\mu W\ cm^{-2} \cdot sr^{-1}$ or higher yields better results for estimating access in rural areas.

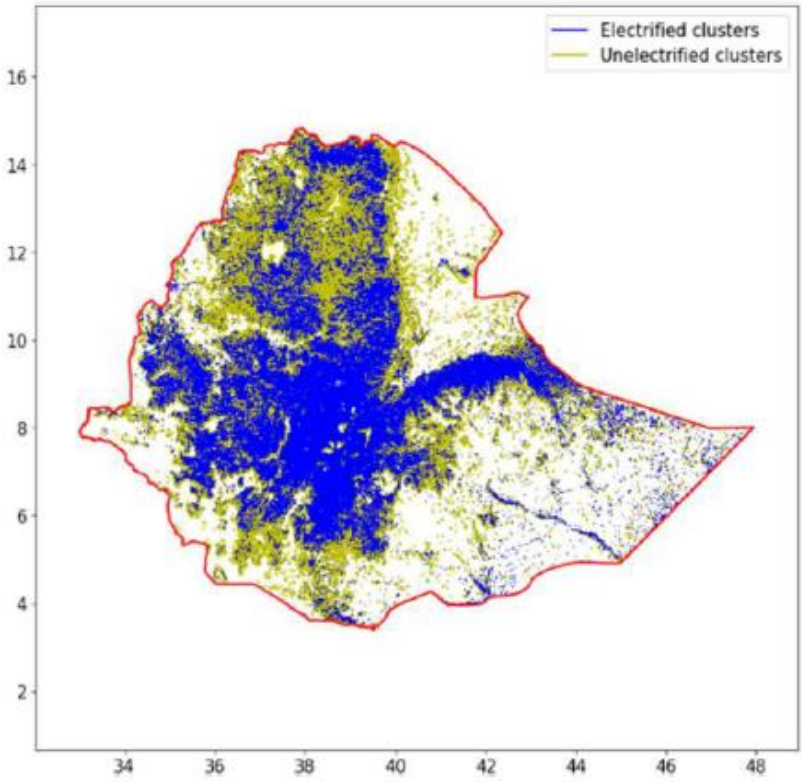

Fig. 7. OnSSET based electricity access, applying 0.27 $\mu W\ cm^{-2} \cdot sr^{-1}$ lower bound noise floor, resulting in an estimated electricity access of 51.3 %.

3. Results and Analysis

3.1. Geospatially estimated electrification rate

Fig. 7 provides a visual representation of the distribution of electrified and unelectrified populations at the cluster level, as determined by the methodology described in section 2.4.1. The blue areas indicate the electrified population, while the yellow areas correspond to the unelectrified population. To accurately estimate the electrification rate, the study applied five different noise filter floors to find the noise floor that minimizes the discrepancy between the estimated access to electricity and the World Bank report, as explained in section 2.3.2. Table 1 presents the estimated access to electricity obtained from these filters, which varies from 69.1 % at the lowest noise filter value (0.25 μW $cm^{-2}{\cdot}sr^{-1}$) to 24.6 % at the highest noise filter value (0.35 μW $cm^{-2}{\cdot}sr^{-1}$).

Fig. 8 shows the subnational electrification estimates of the 11 regional states/administrative regions. These results are compared with the regional electricity access rates available in the GoE NEP 2.0 report, specifically for the five regional states. The subnational electrification estimation results generally align with the GoE NEP 2 report (see Figure A3.2 in [20]), with variations observed in specific regions. For instance, Addis Ababa's perfect electrification estimate of 100 % closely corresponds to the GoE NEP 2's 99.9 % rate. While Amhara's 41.8 % estimate falls below GoE NEP 2's 51.3 %, a correlation is still evident. Conversely, our model's estimates for Oromia (69.20 %) and SNNP (71.49 %) surpass the GoE NEP 2 rates of 63.3 % and 37.9 %, respectively. The Tigray variation is notable, with our estimate at 61.08 % compared to the GoE NEP 2's 87.7 %. These comparisons highlight the model's insights and the significance of using diverse sources for comprehensive assessments.

3.2. Power grid infrastructures proximity to population settlements

The results of the study presented in Section 2.4.2 indicate that a significant portion of Ethiopia's population resides in close proximity to power grid infrastructure. Specifically, Fig. 9 shows that 85 % of the population lives within 10 km of the projected medium-voltage (MV) transmission lines, while 45 % of the population lives within the same distance of the high-voltage (HV) lines. Combining the two figures reveals that 87.7 % of the population lives within 10 km of either HV or the projected MV lines. Additionally, the study shows that almost all electrified population in Ethiopia is located within 5 km of existing grid lines, while nearly all the unelectrified populations are located within a 25 km from existing grid lines. These findings have important implications for the planning and prioritization of electrification projects in Ethiopia, particularly with regards to extension of the power grid.

Unfortunately, this study did not include off-grid electrification solutions such as mini-grids due to lack of reliable nationwide data. As a result, the geographic overlap between the grid and off-grid systems, as well as the distribution of Ethiopia's population relative to these off-grid power generation and distribution systems are not analyzed in this study.

Limited access to data on MV lines presents a challenge in assessing their contribution to electrification planning. However, the inclusion of projected MV lines in our analysis improves the understanding of the

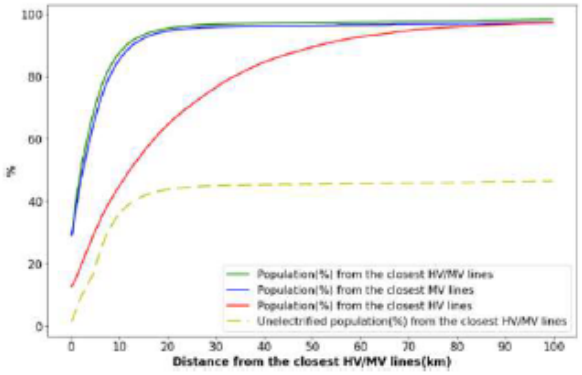

Fig. 9. Share of the population as a function of distance from the closest HV/projected MV line. The total share of the unelectrified population is 48.7 %.

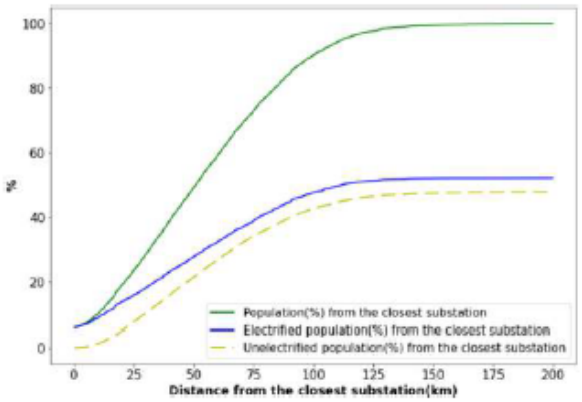

Fig. 10. Share of the population as a function of distance from the closest substation. The total share of the unelectrified population is 48.7 %.

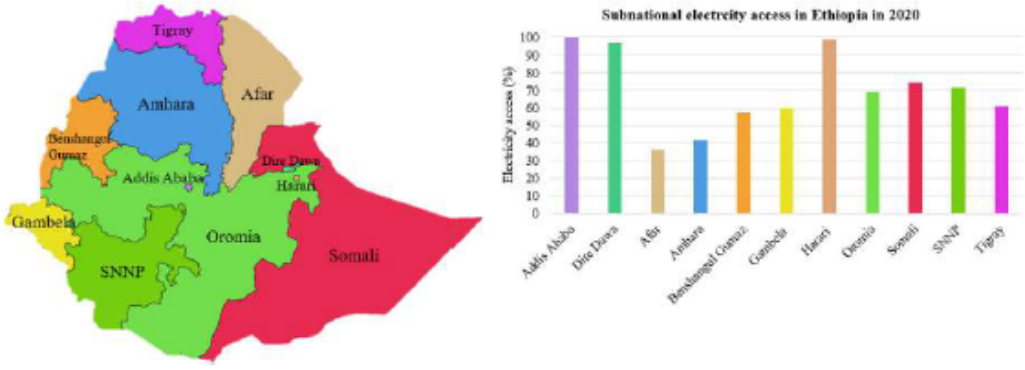

Fig. 6. Estimated access to electricity at subnational level.

distribution of the total and unelectrified population in relation to the existing grid infrastructure. This strengthens the robustness of our findings and provides a clearer picture of the proportion of the population residing in close proximity to the grid. In addition, the use of high-resolution population data (30 m) enhances the accuracy of our analysis, enabling the identification of areas without access to electricity at a finer resolution.

Fig. 10 presents the percentage of the total and unelectrified population within different distances from the closest substation. The results reveal that more than 90 % of the total population and nearly all the electrified population are located within 100 km of the nearest substation. Furthermore, almost all the unelectrified population is located within 125 km of the nearest substation.

3.3. Grid extension suitability and penalty

Fig. 11 illustrates the relative contribution of the five geospatial factors to the grid extension suitability, as determined from equation (2) in section 2.5.1. The results indicate that terrain slope contributes the most to the grid extension suitability, accounting for 40.8 % of the total score. This is because the majority of settlements in Ethiopia, 94 %, have a terrain slope of less than 10°, which is considered the most suitable class in this study, as presented in Table A2 in the Appendix. In contrast, the distance from the substation contributes the least (5.7 %) to the suitability score. This is because only a small fraction of the settlements falls under the most suitable class, which indicates that the distance from the substation has a high contribution to the GEP multiplier, resulting in a significant impact on the capital cost of grid extension.

The impact of the five geospatial factors on grid extension costs was evaluated by calculating the GEP multiplier using Equation (3). According to the analysis results, the combined impact of these factors could raise the cost of grid extension across unelectrified settlements in Ethiopia by an average of 8.6 %, ranging from 2.3 % to 29 % depending on the location. The variability in GEP values across settlements is likely due to location-specific factors, implying that the cost of grid extension may vary based on the specific conditions of the settlement. The GEP multiplier is also used as an indicator of the suitability of grid extension, as a penalty is the inverse of suitability. Settlements with a lower GEP value are more suitable for grid extension, while those with a higher GEP value are less suitable. Fig. 12 presents a spatial representation of the GEP multiplier. The figure shows the relative suitability of extending the grid network across the country. Settlements with a GEP value below 1/3 quantile (green) are deemed most suitable for grid extension, those with a GEP value in the range between 1/3 and 2/3 quantiles (yellow) are semi-suitable, and those with a GEP value in the upper 2/3 quantile (red) are unsuitable for grid extension due to the high penalty cost involved.

The most suitable class of settlements requires lower investment costs than other settlements, while the less suitable class of settlements would incur high investment costs. There is a significant variation in the distribution of grid extension suitability across the country.

The semi-suitable locations are distributed throughout the country. It is worth noting that proximity to electrified settlements is not the only determining factor for grid extension suitability. There are areas near electrified settlements but not suitable for grid extension due to other geospatial factors than just distance. On the other hand, there are also areas that are semi-suitable for grid extension despite being far from electrified settlements. This is due to other factors, such as favorable local topography, suitable land cover, and convenient road access.

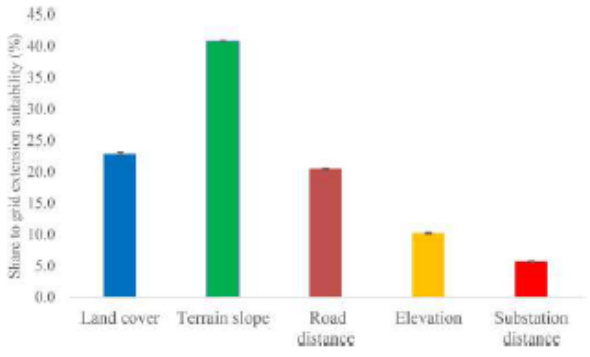

Fig. 11. The contribution of each geospatial factor to the grid extension suitability.

3.4. Grid extension suitability in terms of LCOE

Fig. 13 presents the findings of the geospatial analysis using the LCOE as a primary metric for grid extension suitability. The LCOE was calculated for two distinct electricity access targets: tier-1 (38.7 kWh/household/year) and tier-3 (803 kWh/household/year) as adapted from the World Bank's Global Tracking Framework [48]. The results shown by the two maps in Fig. 13 provide a comprehensive visual representation of the regions that are most suitable (green), semi-suitable (yellow), and less suitable (red) for grid extension for both access targets.

Semi-suitable locations are scattered across the country. Fig. 13 also shows that as the demand target increases from tier-1 to tier-3, the proportion of people falling under the most suitable category increases by 13 %. Conversely, the proportion of people falling under the less suitable category decreases by 62 % as the demand shifts from tier-1 to tier-3.

4. Discussion

4.1. Distribution of the total and unelectrified population in relation to the grid

Approximately 87.7 % of Ethiopia's population resides within 10 km of the HV or projected MV grid lines, with 85 % within the 10 km distance of the projected MV lines. Our findings also show that almost the entire unelectrified population (48.7 % of the total) resides within 25 km of power grid lines. This finding is in agreement with the Ethiopian government's NEP 2.0 report, which states that 90 % of the population lives within 10 km distance from the existing MV lines [20]. A study by Arderne et al. [39] using nighttime light data to map power system networks calculated that 97 % of the world's population is located within 10 km from an MV line. The authors, however, noted that this estimate varies greatly among regions and income levels, with SSA having the highest proportion of individuals beyond 10 km from an MV line. Our results suggest that the distribution of unelectrified population within a reasonably short (10 km) distance from HV/the projected MV lines could make grid extension viable, considering other factors and available capital.

4.2. National electrification rate estimation using geospatial analysis

The electrification rate estimation using the NTL imagery and population data shows that for a lower bound noise filter of 0.27 μW $cm^{-2}{\cdot}sr^{-1}$, the estimated electricity access rate is relatively accurate with +0.2 % margin of error compared to the World Bank report. However, a 0.35 μW $cm^{-2}{\cdot}sr^{-1}$ noise floor leads to larger discrepancies with a −26.5 % margin of error. This result is in line with earlier studies [27,29], which similarly underestimated electricity access rate in Ethiopia by 26.8 % and 20 %, respectively. It is worth noting that the use of a noise floor less than 0.35 μW·$cm^{-2}{\cdot}sr^{-1}$ in estimating electrification rate resulted in estimates higher than those reported in previous studies by Falchetta et al. [29] and Khavari et al. [27]. The underestimation of the electricity access rates, when lower bound noise floors of above 0.27 μW $cm^{-2}{\cdot}sr^{-1}$ are used, could be due to several factors, including under

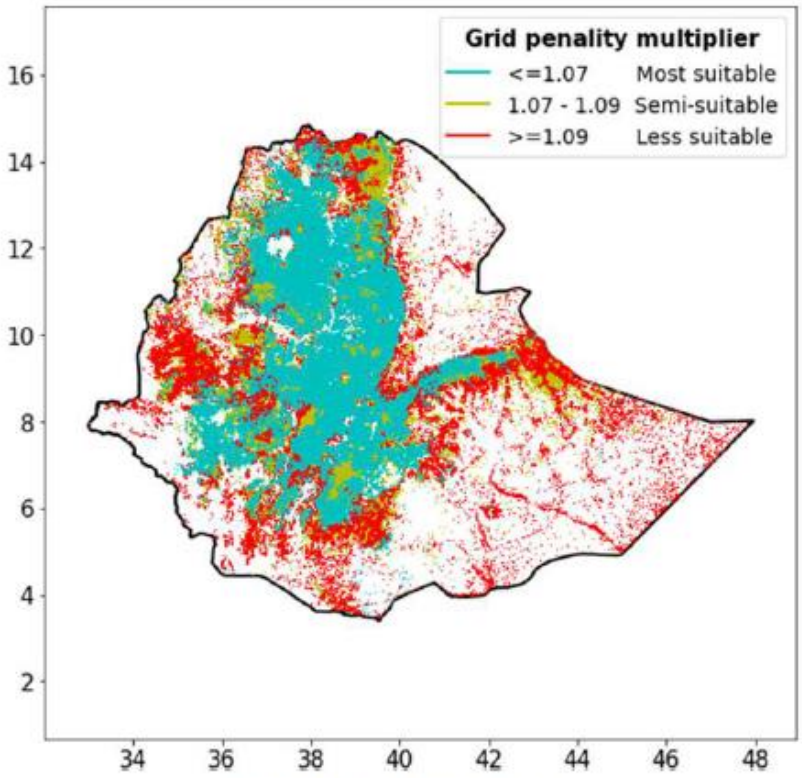

Fig. 12. Grid extension penalty (GEP) map.

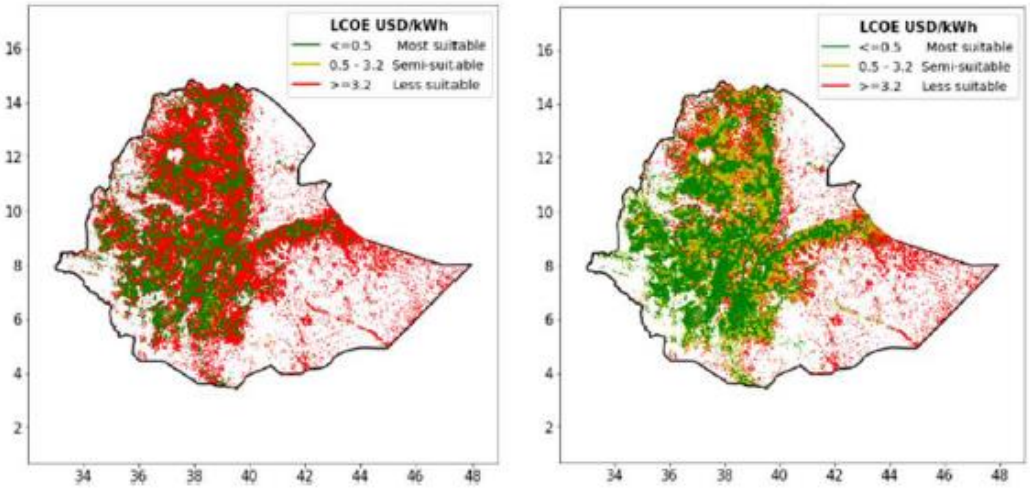

Fig. 13. Relative grid extension suitability in Ethiopia for two different electricity demand targets (tiers): 38.7 kWh/household/year (left) and 803 kWh/household/year (right).

detection of standalone solutions such as solar-home-systems (SHS), or low levels of lighting in highly distributed communities [29]. The method's reliability is indicated by its alignment with the World Bank's data, affirming its practical application potential.

4.3. The influence of geospatial factors on grid extension suitability

Our findings show that among the considered geospatial factors, terrain slope and land cover contribute the most to the suitability of grid extension to unelectrified settlements (see Fig. 11). Terrain slope has the most significant contribution to the grid extension suitability or contributes the least to the GEP multiplier, compared to the other four

geospatial factors. Land cover is the second significant factor that contributes to the suitability of grid extension to unelectrified settlements. This is because the majority of settlements in Ethiopia are located in cropland, grassland, and savanna areas and according to the suitability classification outlined in section 2.3.5, grasslands, and savannas were classified as the most suitable and croplands were classified as semi-suitable for grid extension.

The distance from existing substations, in contrast, contributes the least to the grid extension suitability, accounting for 5.7 % of the total suitability score. This is due to that only a minuscule fraction of settlements falls under the most suitable class, while the vast majority of settlements (97 %) are found in the least suitable class of distance from substations. Thus, the distance of settlements from existing substations plays a crucial role in increasing or decreasing the GEP multiplier and is perhaps the primary limiting factor for grid extension in Ethiopia.

According to the results presented in section 3.3, the combined impact of the five geospatial factors can result in a substantial rise in the investment cost by up to 29 %, depending on the location. This unequivocally illustrate the critical role of geospatial factors in grid extension planning; neglecting them can lead to nearly 30 % cost increases. A comparable study [12] showed that the GEP multiplier could escalate the grid extension investment cost by 30 %.

4.4. Novelty and significance of the study

This study introduces several novel aspects to the field. Firstly, it methodologically complements prior studies [8,14–17] which have implicitly considered geospatial factors in grid extension planning, especially in the context of grid vs. off-grid electrification. However, these studies, except [16], have used lower-resolution population datasets with a spatial resolution of 1 sq. km. This reliance on lower-resolution data can lead to an underestimation or misrepresentation of geospatial factors due to the complexities present at finer scales. Consequently, critical nuances in grid extension suitability might be overlooked, potentially resulting in suboptimal investment choices and inefficiencies in electrification planning. With finer spatial granularity (30 m for terrain, 500 m for land cover, and 30 m for population distribution), we are able to capture intricate local variations that impact grid-extension suitability. By leveraging such high-resolution datasets, our study minimizes the risk of overlooking critical geospatial factors, ultimately contributing to more effective and accurate electrification planning.

Secondly, this study stands out by incorporating not only HV lines but also the projected MV lines and substations into the modeling process, unlike the studies referenced as [14,15], and [17]. These studies primarily focused solely on HV lines when evaluating electrification planning in Nigeria, Ethiopia, and SSA, respectively. This comprehensive inclusion of multiple voltage levels and infrastructure elements enhances the accuracy of our electrification planning analysis. It allows us to capture a more nuanced representation of the grid network and its potential extensions, leading to more robust and precise planning outcomes. Thirdly, this study breaks new ground by explicitly analyzing the spatial impact of geospatial factors on grid-extension suitability, factoring in diverse energy demand targets or electrification tiers.

Although the research employed Ethiopia as a case study, the robustness of the methodology applied and the datasets and analyses employed make the findings generalizable and applicable to other developing countries that have sizable populations without access to electricity. In addition to its scientific contribution, this study offers valuable insights to decision-makers, government bodies, and utility companies, guiding investment decisions towards areas with the highest potential for benefiting from grid extension. This targeted approach enhances the overall resource efficiency of electrification efforts.

4.5. Limitations of the study

One limitation pertains to the reliance on open-access datasets, which might not consistently capture the most up-to-date information. This reliance on open-access datasets could potentially introduce limitations in terms of data accuracy, affecting the precision of the study's findings and conclusions. A particular noteworthy limitation within this context pertains to our use of the Gridfinder Tool for assessing population proximity to MV (Medium Voltage) lines. It is important to acknowledge that predictive tools like Gridfinder, relying on remote sensing techniques and publicly available datasets, such as nighttime data and MODIS land cover data, to establish MV network distribution lines, may not achieve the same level of reliability as data directly sourced from utility companies. This discrepancy is evident when considering the contrast between the relatively low nightlight imagery in Ethiopia and Gridfinder's estimates of densely distributed MV lines in the west of Addis Ababa, as illustrated in Fig. 4. This could potentially affect the accuracy of the grid extension suitability analysis conducted using the LCOE for each settlement. However, this does not affect the grid extension suitability analysis solely based on geospatial factors.

Besides, the study does not take into account off-grid solutions such as SHSs and mini-grids in accelerating the electrification in remote areas. Grid extension feasibility might not fully represent the complete electrification landscape. By excluding consideration of off-grid solutions, the study might not capture the potential contributions of these alternative approaches to rapidly expand electrification in remote and underserved areas. In addition, the study's scope is confined to the economic viability of grid extension and does not address other challenges (political, regulatory, socio-cultural factors, etc.) that often significantly influence large-scale electrification projects.

Moreover, a noteworthy limitation of the study pertains to its reliance on nighttime satellite imagery, collected at 1:30 a.m. local time when many rural households may not have their interior lighting switched on, thereby remaining invisible from an external perspective. This limitation can result in the underestimation of actual electricity use in rural areas, especially for activities such as indoor lighting, refrigeration, or electricity for irrigation, which might not be detectable by the satellite sensors. This can lead to the omission of actual electricity use in the estimation. A previous study [30] also highlighted this challenge, indicating that the NOAA VIIRS sensor's capability to detect electricity availability might be compromised in areas with minimal or absent outdoor lighting. Even in cases where electrified villages emit subdued light, the sensor's sensitivity may not be sufficient for accurate detection. This potential challenge influences the accuracy of electrification rates estimation. The study underscores the need for a nuanced understanding of the limitations inherent in the use of nighttime imagery for electrification assessment and acknowledges the potential for discrepancies in the results due to these constraints. Additionally, the accuracy of electrification estimation is also contingent upon the noise filter applied to the nighttime light imagery, which can inadvertently affect the identification of electrified areas.

5. Conclusions and future work

This paper investigates how and to what extent geospatial factors (distance from substation and road, terrain slope, elevation, and land cover) influence grid expansion suitability in Ethiopia. Using high-resolution nighttime light (NTL) imagery and population data with the OnSSET methodology, the research examines the proportion of the country's population in relation to the power grid infrastructures and the suitability of extending the grid to unelectrified areas.

The findings show that a significant portion of the population resides near the existing power grid lines, with 87.7 % living within a 10 km distance from a high-voltage lines and/or projected medium-voltage line, and 85 % residing within a 10 km distance from the projected medium-voltage lines. Nearly all unelectrified population (about 49 % of

the total) lives within 25 km of power grid lines. This proximity suggests the potential cost-effectiveness of grid extension-based electrification.

The study finds that the combined impact of the five geospatial factors (GEP multiplier) increases grid extension costs by 2.3 %–29 %, depending on location. Terrain slope and land cover are the factors contributing the most to the suitability of extending the grid to unelectrified settlements, while distance from substations contributes the least to the grid extension suitability. This emphasizes the necessity of considering geospatial factors for accurate and efficient grid extension planning. Neglecting these factors could lead to cost underestimations and ineffective electrification strategies. Consequently, the Ethiopian Electric Utility (EEU) and Government of Ethiopia (GoE) should integrate these factors in planning, moving beyond the conventional focus on proximity to existing infrastructure. Incorporating spatial analyses of grid extension suitability enhances planning efficacy.

Furthermore, the study demonstrates that grid extension suitability, gauged by LCOE, highlights the need to consider both electricity demand and population when assessing grid extension feasibility. This underscores the significance of geospatial factors in grid planning and informs priority areas for extension or off-grid solutions. This approach optimizes costs and expedites electricity access in unelectrified regions. Future research could explore demand estimation, cost-effective alternatives, and investment strategies for universal electrification.

CRediT authorship contribution statement

Adugnaw Lake Temesgen: Conceptualization, Methodology, Software, Validation, Formal analysis, Conceptualization, Methodology, Software, Validation, Formal analysis. Yibeltal T. Wassie: Supervision, Writing – review & editing, Supervision, Writing – review & editing. Erik O. Ahlgren: Supervision, Writing – review & editing, 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.

Data availability

Data will be made available on request.

Appendix. All the input GIS datasets, parameters and variables used in this paper are listed below

Table A1
Input GIS datasets.

Dataset	Data source	Data type	Spatial resolution	Temporal coverage	The year used in analysis
Population	HRSL (High Resolution Settlement Layer) [28]	Raster	30 m	2003–2020	2018
Administrative boundaries	GADM administrative areas V.4.0 [36]	Vector/polygon	–	2018–2022	2018
Night-time light	VIIRS DNB night-time lights [51]	Raster	~500 m (at equator)	2012–2021	2020
HV and substation	EnergyData.info [37]	Vector/polygon	–	2012–2017	2017
MV lines	gridfinder.org [40]	Vector/polygon	–	~2020	2020
Land cover	MODIS Land Cover Product (MCD12Q1) V6 [42]	Raster	~500 m	2001-	2020
Terrain elevation and slope	GDEM (NASA and Japan Space Systems) [43]	Raster	30 m	2009–2019	2019
Roads	Geofabric [44]	Vector/lines	–	~2018	2018

Table A2
Geospatial factors classification and weight [26,49].

Geospatial factor	Weight	Suitability index				
		5 (suitable)	4	3	2	1 (unsuitable)
Slope (degree)	30 %	0–10	10.1–20	20.1–30	30.1–40	>40
Land cover [a]	20 %	7,9,10,14,16	2,4	1,3,5,12,13,15	6,8	11,17
Distance to substation (km)	20 %	0	0.5	1	5	>10
Distance to road (km)	15 %	0	5	10	25	>50
Digital elevation (m)	15 %	<500	500–1000	1000–2000	2000–3000	>3000

[a] Further classification can be obtained at https://lpdaac.usgs.gov/products/mcd12q1v006/.

Table A3
Major socioeconomic parameters of the study area [18,46,47,52].

Parameters	Unit	Year	Study base year value
Population	Million persons	2020	114.96
Medium population growth	Percent	2030	2.2
High population growth	Percent	2030	2.5
Average household size, urban	People	2030	4.4
Average household size, rural	People	2030	5.2
Urban ratio start year	Percent	2020	21.7
Urban ratio end year	Percent	2030	26.9
Total electricity access	Percent	2020	51.1
Urban electricity access	Percent	2020	93.2
Rural electricity access	Percent	2020	39.4

Table A4
Grid generating and T&D cost. Sources [12,50,53–56].

Parameter	Value	Unit
HV line (69–132 kV)	53000	USDkm^{-1}
MV line (11–33 kV)	7000	USDkm^{-1}
LV line (0.2–0.4 kV)	4250	USDkm^{-1}
HV to MV substation (1000 kVA)	25000	USD/unit
MV to LV substation (400 kVA)	10000	USD/unit
Service transformer (50 kVA)	4250	USD/unit
Generating cost	0.09	USDkWh^{-1}
Additional connection cost per household connected to grid	150	USD/HH
T&D losses	7–29	% of capital cost/year
O&M costs of distribution	2	% of capital cost/year

Table A5
Other model parameter. Sources [12,18,52].

Parameter	Value	Unit
Annual new grid connection limit	534,000	Households/year
Annual grid generation limit	389	MW/year
Discount rate	8	Percent
Lifetime	30	years

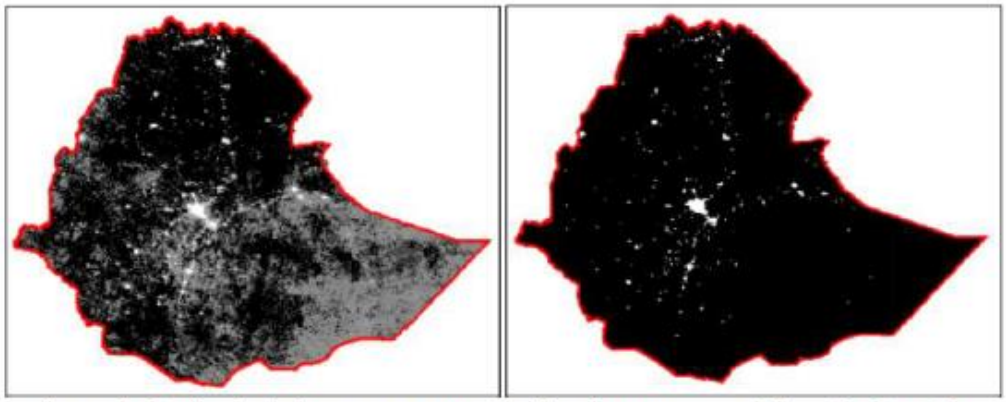

Fig. A1. Filtered nighttime light of 2020 using 0.25 μWcm-2sr-1 (left) and 0.35 μWcm-2sr-1 (right) lower bound noise floor.

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Paper III

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A high-resolution analysis of electricity demand for informed electrification planning

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***Abstract*—Electrification planning necessitates a nuanced understanding of electricity demand. However, previous studies have largely overlooked regional differences and relied on a one-size-fits-all approach to demand estimation. This study aims to examine the spatial distribution of electricity demand across households and community institutions in a developing country context, using Ethiopia as a case for the study. The study employed a multifaceted approach: household demand was estimated using the Multi-Tier Framework (MTF), while the demand for community institutions (healthcare, education facilities, places of worship, and government offices) was estimated using the Remote-Areas Multi-energy systems load Profiles (RAMP) stochastic model. The spatial distribution was visualized using the OnSSET methodology. The findings reveal significant demand heterogeneity, with 64% of households falling within Tier 1 and Tier 2 demand levels assuming all households have electricity access, but 61.3% of currently electrified households exhibit Tier 3 in 2020. Additionally, community institutions exhibited electricity demand patterns, with health facilities requiring the highest average demand (around 2,100 kWh/year), followed by education facilities (400 kWh/year). Insights from these high-resolution demand assessments can inform the selection of cost-optimal electrification technologies (e.g., grid extension, mini-grids, standalone systems) based on the demand patterns of specific communities at local level in Ethiopia.**

Keywords*— *community, electricity demand, electrification, geospatial, household, spatial

I. Introduction

Access to reliable and affordable electricity remains a critical challenge for millions of people residing in rural areas worldwide [1]. According to the United Nations Development Programme (UNDP), approximately 800 million people, predominantly in Sub-Saharan Africa, lack basic electricity access [2]. Electrifying these vast, sparsely populated areas presents a unique set of challenges that traditional approaches cannot address. Effective electrification strategies require a nuanced understanding of the diverse needs and energy demands of each community.

Thus, assessing the electricity demand of unelectrified communities is an initial and essential step of electrification planning that can guide decisions regarding suitable electrification approaches, whether deploying off-grid systems, or extending the national grid [3].

Understanding electricity demand becomes even more crucial in light of the heterogeneity in electricity consumption patterns across regions of a country. Factors such as population density and economic activities have a notable impact in shaping demand. Overlooking these variations can lead to significant shortcomings in planning. Traditional electrification planning approaches often fail to capture these spatial variations, potentially leading to over-investment or under-investment in electrification technologies [4].

Thus, understanding the spatial variations in electricity demand is crucial for designing cost-effective electrification strategies [5]. Effective planning that considers these variations optimizes resource allocation, ensuring that infrastructure investments meet current and future energy needs of each community.

However, several previous studies have limited their focus to just two demand levels based on the rural-urban divide [6], [7], [8] and poverty rate [9]. Such approaches provide a very broad picture and overlooks the diverse socio-economic factors that can influence consumption patterns within both rural and urban settings. Additionally, other studies employ a uniform electricity demand for the entire nation [10] failing to capture the significant variations in demand that exist across different regions.

Furthermore, previous studies often focused primarily on household (HH) electricity demand [11],[12]. While household demand is undoubtedly crucial, it is however also important to consider the electricity needs of community institutions (CIs), such as health centers, education facilities, places of worship (POW) and government offices, and productive uses (PUs), e.g., household based businesses. In particular PUs may have comparable demands as HHs but also CIs may locally be important in particular in rural contexts.

Since there is very little information on CI demand and its relation to HH demand, this study specifically focuses on assessing the spatial electricity demand of HHs and CIs at a high spatial resolution. The inclusion of CIs in the demand assessments is critical for two reasons. First, neglecting these institutions can lead to underestimating total electricity needs at local level, resulting in unreliable power supplies that ultimately hinder their operations. Second, understanding their specific energy needs allows policymakers to tailor electrification strategies, ensuring reliable access to power for essential services in these critical institutions.

Thus, this study aims to explore high-resolution electricity demand patterns , with a specific focus on households and community institutions. It seeks to delineate the spatial heterogeneity (variation across locations) of electricity demand within each consumer category, thereby fostering the understanding of demand patterns across diverse regions.

This study addresses the following research question:

- How does the electricity demand vary across high-resolution spatial scales?

II. Methodology

This section details the methodology and data used to assess spatial variations in electricity demand across the study area. Ethiopia, with its significant unelectrified population and diverse socio-economic landscape and regional electricity access disparities, serves as an ideal case to explore challenges faced by developing countries in electrification planning [13]. We leverage the geospatial data and economic indicators to develop a high-resolution picture of electricity needs across the study area. A summary of the datasets such as Population settlements, Administrative boundaries, Villages and towns, and Health facilities used in this study is provided in Table III. The following steps were undertaken to analyze spatial variations in electricity demand:

a) Identifying settlements and electrification status: We built upon existing research to identify population settlements and electrified populations within the study area [14]. The term 'settlement' is used to describe a range of inhabited places, from a small group of homes to a village or entire urban areas.

b) Classification of settlements by economic status: Settlements are assigned numerical values ranging from 1 to 5, reflecting their economic status and poverty level. The rationale behind this classification lies in the established correlation between electricity consumption and economic status/living standards. Settlements with higher economic status typically exhibit greater electricity demands compared to those with lower status. To capture variations in economic status and poverty levels, two key datasets were utilized:

- **Mean gridded Gross Domestic Product (GDP):** This dataset provides estimates of GDP at a spatial resolution of 30 arc-seconds, which corresponds to approximately 1 kilometer at the equator, allowing for a more nuanced understanding of economic conditions at a finer geographic scale [15].
- **International Wealth Index (IWI)**: This data source provides valuable insights into patterns and disparities of poverty at sub-national and community levels at 1.6 x 1.6 km² resolution across sub-Saharan African countries. This high-resolution poverty data is sourced from [16].

To classify settlements by economic status, we adapted the approach proposed by Korkovelos et al. [17]. This method employs Jenks natural breaks (nb) classification to classify both IWI and GDP data into five distinct classes (see Table I). This classification method is particularly effective for data exhibiting clear clusters, meaning the values within each group are more similar to each other than to values in other groups [18]. This approach allowed us to estimate relative electricity demand levels within the study area at high resolution.

TABLE I. CLASSIFICATION OF GDP AND IWI FOR SPATIAL DEMAND

GDP	GDP classification	IWI	IWI classification
nb1 $\leq GDP <$ nb2	1	nb1 $\leq IWI <$ nb2	1
nb2 $\leq GDP <$ nb3	2	nb2 $\leq IWI <$ nb3	2
nb3 $\leq GDP <$ nb4	3	nb3 $\leq IWI <$ nb4	3
nb4 $\leq GDP <$ nb5	4	nb4 $\leq IWI <$ nb5	4
$GDP \geq$ nb5	5	$IWI \geq$ nb5	5

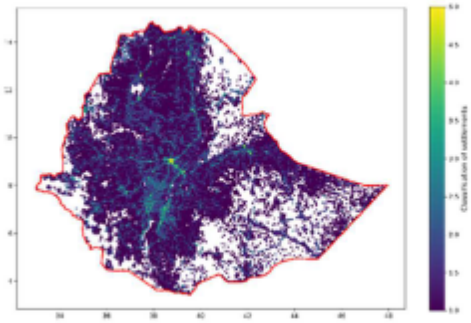

Fig. 1. Classification of settlements based on gridded mean GDP and IWI combined.

After classifying settlements into five classes, we combined GDP and IWI information using (1) to generate a single combined value that reflected the combined influence of both factors [17]. Settlements categorized as Class 1 are expected to exhibit the lowest electricity demand, while those in Class 5 are likely to have the highest demand, as illustrated in Fig. 1.

$$GDP\_IWI_{in\ settlement_i} = 0.5xGDP_{in\ settlement_i} + 0.5xIWI_{in\ settlement_i} \quad (1)$$

B. Household electricity demand

To estimate household electricity demand within the study area, we utilized data from the World Bank's Energy Sector Management Assistance Program (ESMAP) Multi-Tier Framework (MTF) [4]. This framework categorizes HH electricity consumption into Tiers based on minimum daily and annual consumption levels. As shown in Table II, MTF categorizes household (HHs) consumption into 5 Tiers, ranging from Tier 1 (basic energy access) to Tier 5 (high consumption levels).

However, this categorization lacks specificity regarding the population distribution within each Tier for a given location. To address this limitation and account for the heterogeneity of HH electricity demand, we linked the MTF HH consumption categorization to the settlement classification shown in Fig. 1. Settlements in class 1 correspond to Tier 1 demand, while class 5 corresponds to Tier 5 demand. Intermediate classes represent linear interpolations between Tiers 1 to 5. This method enables the spatial variation of HH electricity demand distribution across the MTF Tiers, thereby capturing electricity consumption variations within the study area.

TABLE II. HOUSEHOLD ELECTRICITY DEMAND CLASSIFICATION

Daily consumption (Wh/household)	Tier classification
$12 \leq Demand < 200$	Tier 1
$200 \leq Demand < 1000$	Tier 2
$1000 \leq Demand < 3425$	Tier 3
$3425 \leq Demand < 200$	Tier 4
$Demand \geq 8219$	Tier 5

C. Community institutions' electricity demand

While the MTF is a valuable approach for classifying HH electricity demand, it is not directly applicable to community institutions (CIs) such as health centers, schools, places of worship (POW), and government (Gov't) offices. To address this gap, this study employed the RAMP (*Remote-Areas Multi-energy Systems Load Profiles*) stochastic model [3], [19].

RAMP enables the estimation of electricity demand for various CIs, accommodating the difference between rural and urban settings [19]. We assessed the daily electricity load profiles for each CI type in both rural and urban contexts by adapting the appliance-level parameters from reference [3]. These profiles offer an overview of the electricity consumption patterns throughout a typical day, as depicted in Fig. 2. Subsequently, we computed the annual electricity demand for each CI category (rural and urban) based on their respective daily load profiles.

For spatial distribution analysis, georeferenced data for health facilities (totaling 5176) was obtained from [20]. However, for other facilities, due to limited georeferenced data availability, we conservatively assumed that each village and town accommodates at least one of these facilities. This resulted in the identification of 23,957 villages and towns across Ethiopia [21], forming the basis for spatial analysis of electricity demand distribution in education facilities, POW, and government offices in the study region. To conduct this analysis, we classified each facility using (1) and then interpolated between rural and urban electricity demand.

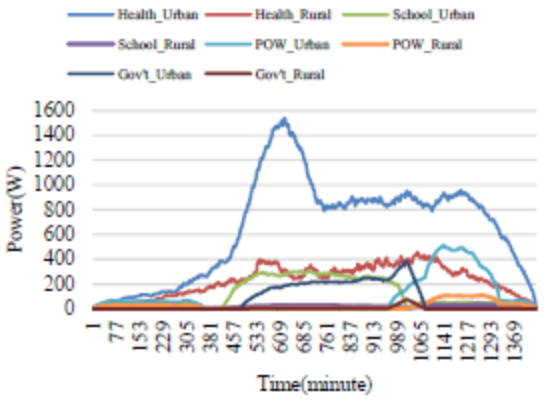

Fig. 2. Load profiles of community institutions' electricity demand derived using RAMP stochastic model.

TABLE III. GEOSPATIAL DATASETS USED IN THE ANALYSIS

Dataset	Type	Source
Population settlements	Vector	Temesgen et al. [14]
Administrative boundaries	Vector	GADM [22]
Villages and towns	Vector	Geofabrik [21]
Health facilities	Vector	HDX [20]
GDP	Raster	Kummu et al. [15]
IWI	Raster	Lee et al.[16]

III. RESULTS AND ANALYSIS

A. Household electricity demand

Fig. 3. presents the spatial variation of household (HH) electricity demand and distribution of population across different Tier levels in 2020. The study finds that the largest share of the population (39%) falls within Tier 2 of electricity consumption, followed by 36% in Tier 3 as shown in Fig. 4. The smallest proportion, accounting for just 21% of the population, falls within Tier 1 electricity demand. However, when examining only the electrified population, a different picture emerges. The majority of electrified households (61.3%) then falls within Tier 3 electricity demand. These results emphasize the necessity of granular-level electricity demand assessment for cost-optimal electrification planning strategies.

B. Community institutions' electricity demand

Fig. 5. presents the spatial distribution of electricity demand for CIs (health facilities, schools, POW, and Gov't offices). Health facilities exhibit a large range of electricity demand, spanning from 1000 to 5600 kWh/year on a national scale. Out of the 5176 health facilities considered, a substantial portion (25%) has an electricity demand of around 1575 kWh/year, which falls into the second-lowest electricity demand category within this consumer group. Conversely, a smaller proportion (8.4%) exhibit the highest demand (around 5600 kWh/year). Similarly, schools demonstrate a wide range of electricity demands, ranging from 200 to 1500 kWh annually. Likewise, POW and Gov't offices show varying electricity requirements, ranging from 235 to 875 kWh/year and 40 to 850 kWh/year, respectively.

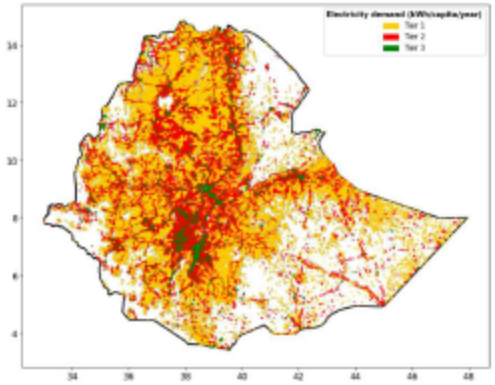

Fig. 3. The spatial distribution of HH electricity demand classified into Tiers in 2020.

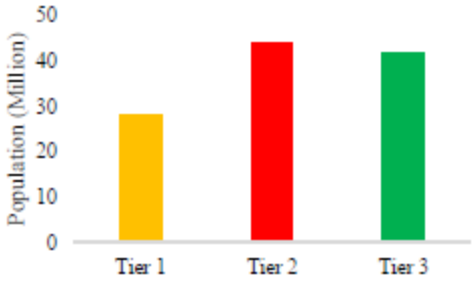

Fig. 4. Distribution of household electricity demand Tiers in 2020.

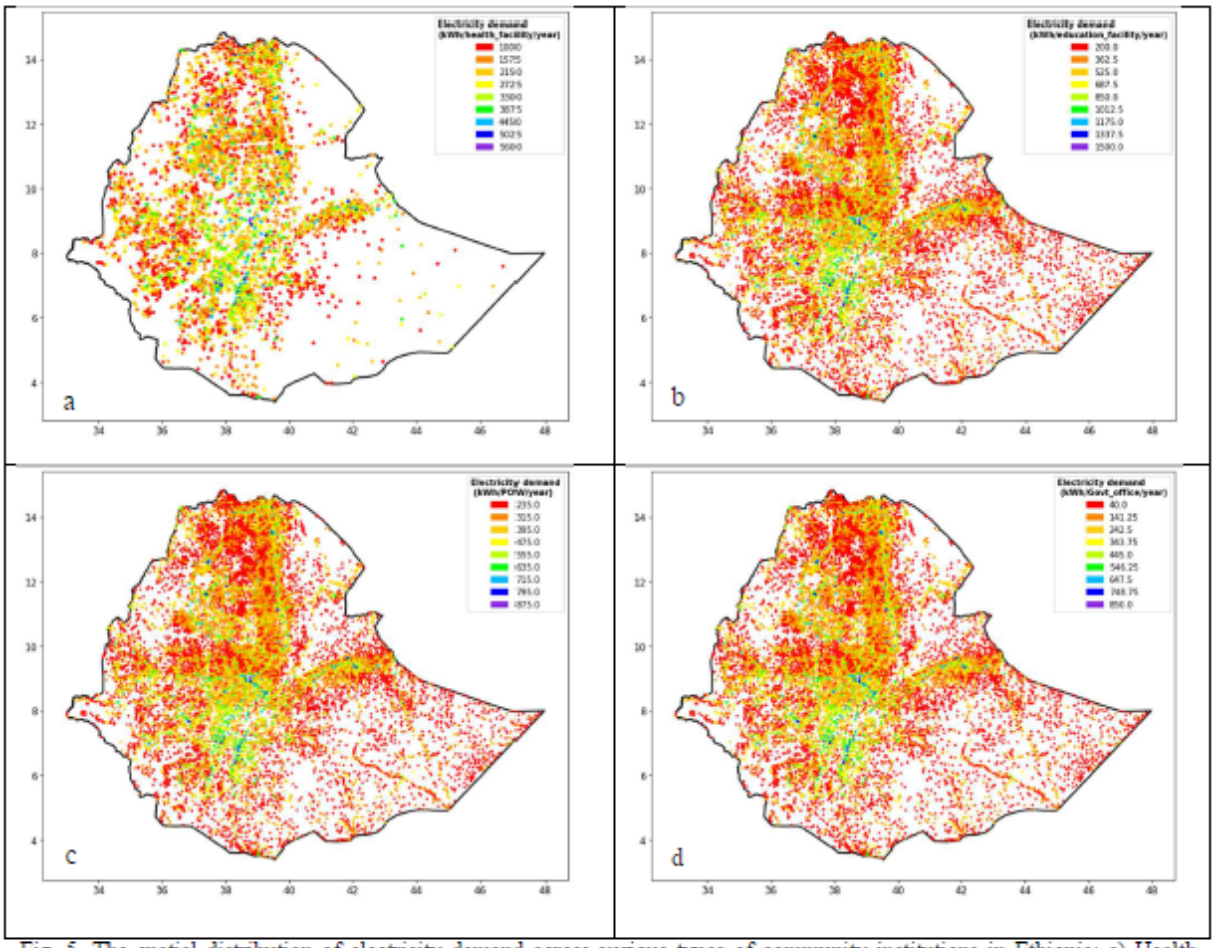

Fig. 5. The spatial distribution of electricity demand across various types of community institutions in Ethiopia: a) Health facilities b) Education facilities c) Places of worship d) Government offices.

Upon analyzing settlements accommodating these institutions, it is noted that 34% exhibit the lowest electricity demand levels—around 40 kWh/year for Gov't offices, 200 kWh/year for education facilities, and 235 kWh/year for places of worship. Conversely, less than 1% of settlements requires the highest electricity demand, reaching around 850 kWh/year for government offices, 875 kWh/year for places of worship, and 1500 kWh/year for education facilities.

Fig. provides an overview of electricity demand distribution across CIs. It illustrates the minimum, first quartile (25th percentile), median (50th percentile), third quartile (75th percentile), maximum, and any outliers in the electricity demand within each CI. Health facilities emerge as the highest consumers, with an average demand of approximately 2,100 kWh per facility annually. Education facilities, on the other hand, exhibit a notably lower average demand compared to health facilities, averaging around 400 kWh per facility annually. POW and Gov't offices demonstrate the lowest levels of electricity demand. POWs typically require an average of 340 kWh per year. Similarly, Gov't offices exhibit a modest average demand of 175 kWh per year.

At a national level, the number of CIs is very small compared to the number of HHs and their total electricity demand is only a fraction of the HH demand. However, the picture changes at the local level. Here, even though the number of HHs is much higher than CIs, the electricity demand of a large share of the HHs is so small, a substantial share of HHs (64% in 2020) are falling within the lowest demand tiers (Tier 1 and 2), that locally the CI demand may become essential. Further, since HHs in many communities are scattered this leads to low connection rates. In contrast, CIs are often clustered in specific areas. For this reason, along with their potentially higher energy needs (spanning Tiers 1 to 5 in the same year), may make them essential for local electrification planning efforts.

IV. Discussion

Our findings challenge the binary assumptions of Mentis et al's. [6] energy access targets for Ethiopia by 2030, where rural areas are assigned Tier 3 and urban areas Tier 4. Our result shows that there are HHs still show Tier 1 and Tier 2 demand. Relying on such oversimplified binary assumptions for electrification planning could lead to over- or under-sizing of supply.

Thus, spatially explicit electricity demand assessments are key for tailoring electrification strategies to local and national needs, enabling cost-effective infrastructure deployment. Identifying high-demand areas helps prioritize investments in grid extensions or large-scale renewables, ensuring sustainable and equitable electrification strategies.

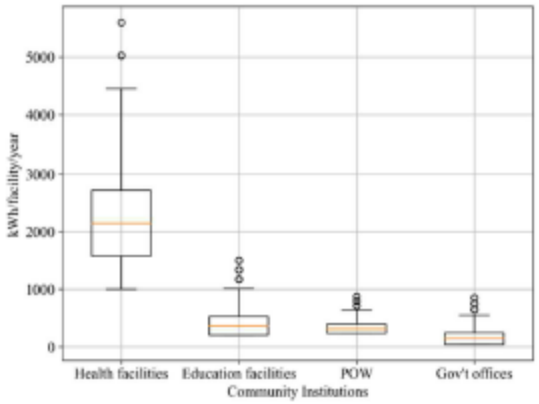

Fig. 6. Distribution of electricity demand across different CIs.

V. Conclusions

This study explores electricity demand at high spatial resolution. The study employs the Multi-Tier Framework (MTF) to estimate household (HH) demand, the Remote-Areas Multi-energy system load Profiles (RAMP) stochastic model to estimate community institution (CI) demand, and OnSSET to reveal the spatial heterogeneity in electricity demand. We used Ethiopia as a case for the study. Our findings reveal significant heterogeneity in electricity demand across the study area, both within HHs and CIs, as well as across these sectors. Assuming all HHs have access to electricity, Tier 2 is most prevalent. However, among electrified HHs (in 2020), Tier 3 is more prevalent. Among CIs, health facilities shows the highest consumption followed by education facilities, places of worship, and government offices.

Findings of high-resolution electricity demand assessments could play an important role in informing electrification strategies both at both local and national levels. Locally, such assessments aid in tailoring electrification technology capacities to suit contextual needs, while nationally, they facilitate the efficient deployment of electrification infrastructure, ensuring optimal resource allocation for achieving universal electricity access. By bridging the gap between local needs and national planning, spatial electricity demand assessments can contribute to the realization of sustainable and inclusive electrification efforts for all.

Future research should extend beyond the current scope and also encompass productive use of electricity. Additionally, investigating the spatiotemporal evolution of electricity demand is essential to understand evolution over time and variations across regions, aiding in the development of adaptive energy infrastructures.

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Paper IV

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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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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

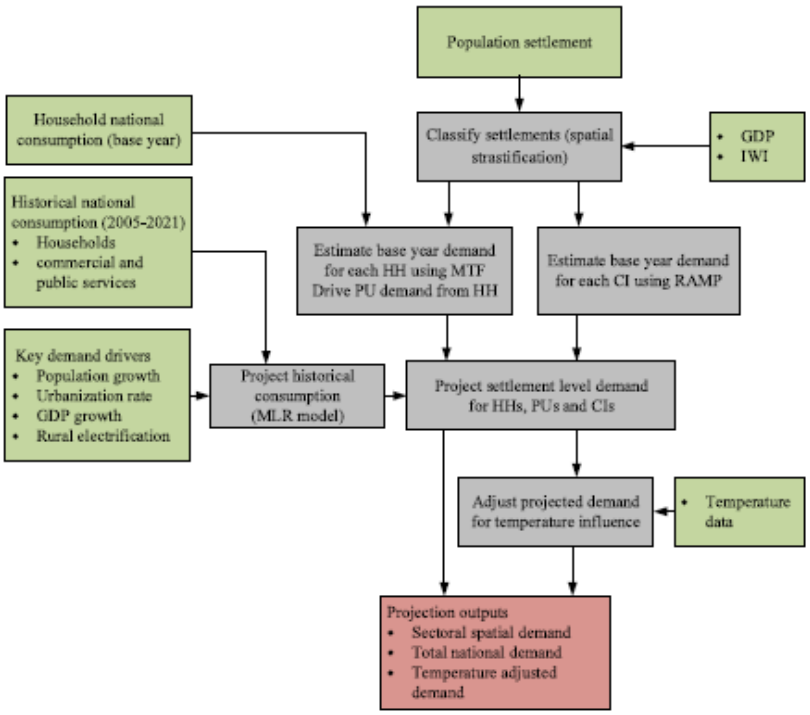

Fig. 1. Flowchart of the study approach, where colors indicate the input data (green), processing steps (grey), and outputs (red).

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.

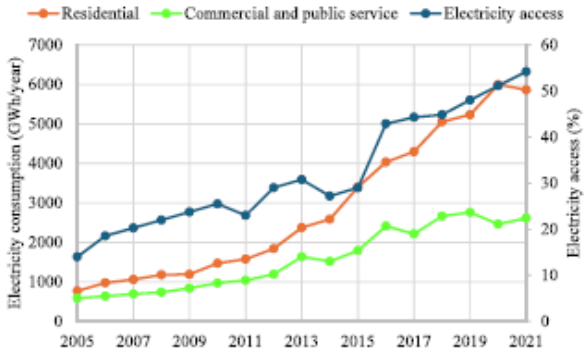

Fig. 2. Trends in electricity access and consumption across residential, and commercial and public service sectors in Ethiopia (2005–2021) (data source: World Bank [45] and the IEA [46]).

- **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 km^2 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 km^2 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

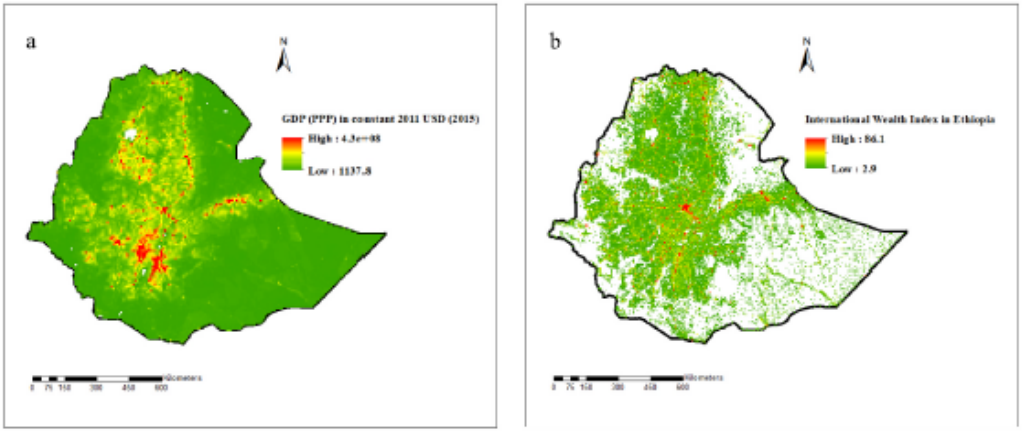

Fig. 3. High resolution spatial economic indicators in Ethiopia. a) The GDP for the year 2015 at a spatial resolution of 1 km^2, expressed in constant 2011 international US dollars. GDP values range from 1137.8 USD to 4.3 million USD per grid cell [50]. b) The IWI at a grid size of 1.6 × 1.6 km^2, where 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
$GDPmin(nb1) \leq GDP < nb_2$	1	$IWImin\ (nb1) \leq IWI < nb2$	1
$nb_2 \leq GDP < nb_3$	2	$nb2 \leq IWI < nb3$	2
$nb_3 \leq GDP < nb_4$	3	$nb3 \leq IWI < nb4$	3
$nb_4 \leq GDP < nb_5$	4	$nb4 \leq IWI < nb5$	4
$GDP \geq nb_5$	5	$IWI \geq nb5$	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).

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

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).

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

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

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].

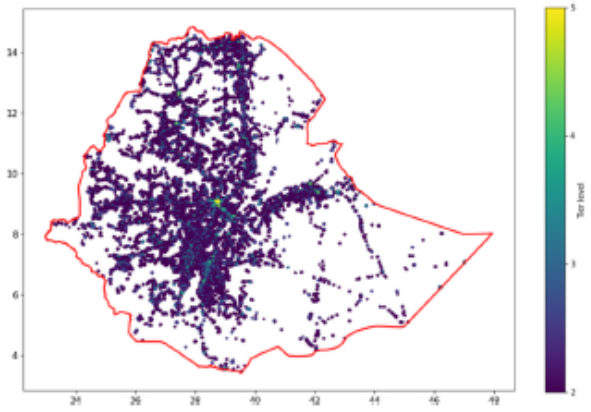

Fig. 4. Methodological basis for identifying settlements with potential for PU. Spatial distribution of HHs with electricity demand at or above Tier 2, which serves as the threshold for estimating PU electricity demand in the study methodology. The horizontal and vertical axes represent longitude and 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 (MOE[3]) [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.

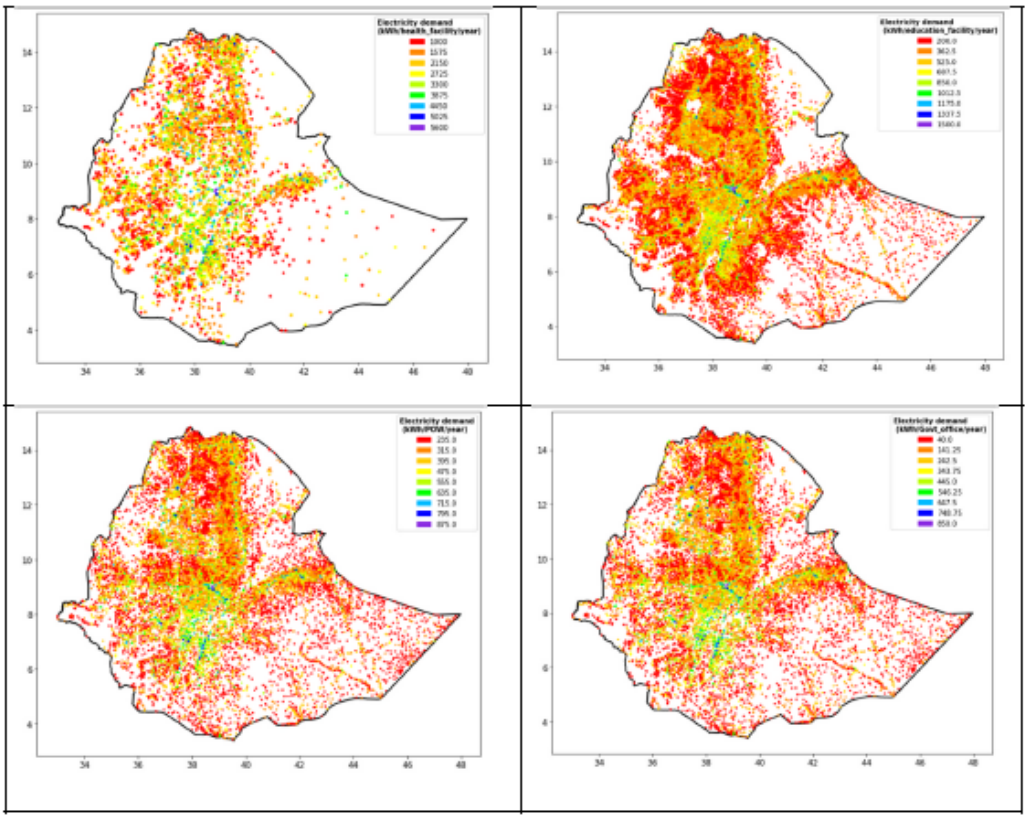

Fig. 5. Methodological demonstration of the base year electricity demand for key CIs in Ethiopia: (a) Education facilities (top left), (b) Health facilities (top right), (c) Places of worship (bottom left), and (d) Government offices (bottom right). The spatial distribution illustrates how CI demand 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 urbanisation 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).

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

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

$$D = \beta_0 + \beta_1\left(Rural\ electricity_{access}\right) + \beta_2\left(GDP_{percapita}\right) + \beta_3\left(Urban\ population_{percentage}\right) + \varepsilon \quad (7)$$

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)).

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

Where $E_{total}(T)$ 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.

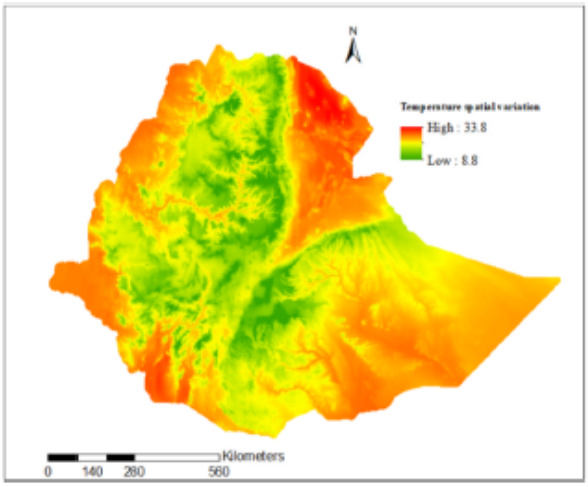

Fig. 6. Long-term average of daily air temperatures in Ethiopia (1994–2018), measured at a height of 2 m above the ground with a resolution of 30 arc-seconds [29].

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

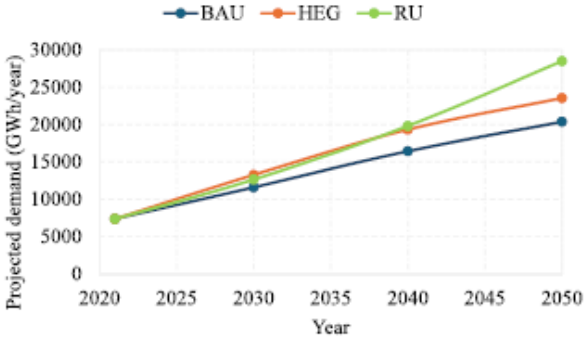

Fig. 7. Projected total electricity demand in Ethiopia (2021–2050) under three scenarios.

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 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.

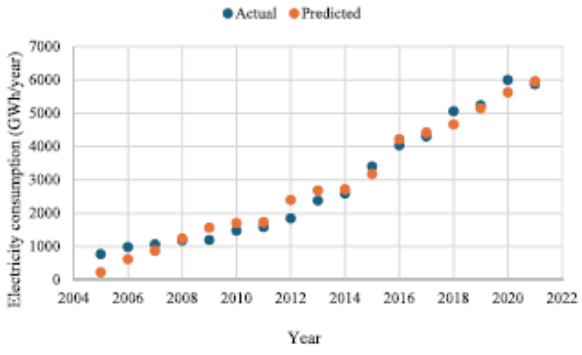

Fig. 8. Regression model validation – actual vs. predicted HH consumption for the years 2005–2021.

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

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

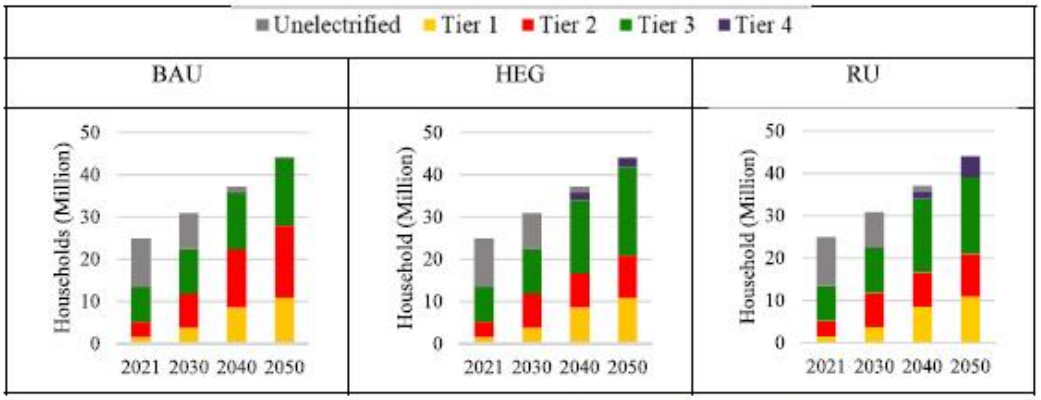

Fig. 9. Evolution of HH electricity demand tiers under three scenarios for the years 2021, 2030, and 2050. Access to electricity is projected to be fully achieved after 2040, which is displayed in the figure as unelectrified in grey.

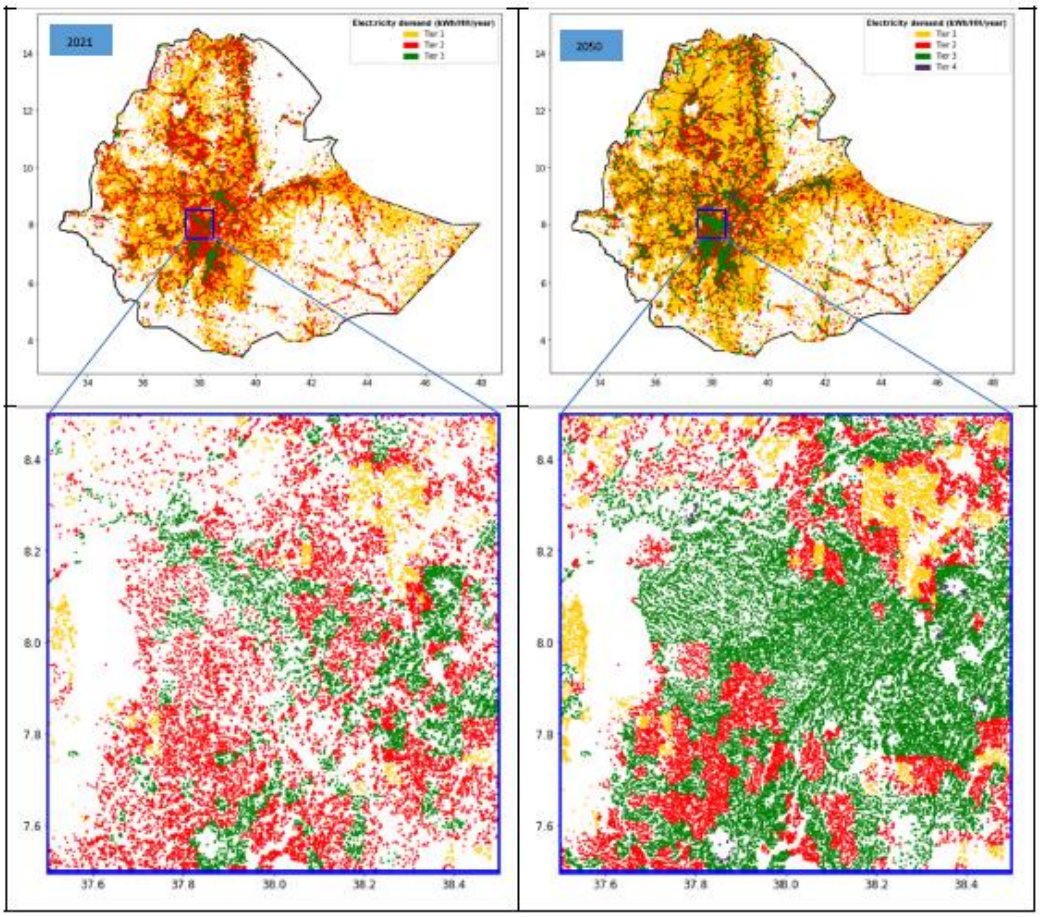

Fig. 10. Spatial variations in HH electricity demand under the RU scenario, comparing the base year (2021) with projections for 2050. In the base year, HH demand ranges from Tier 1 to Tier 3, while by 2050 demand is projected to increase with some settlements reaching Tier 4.

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

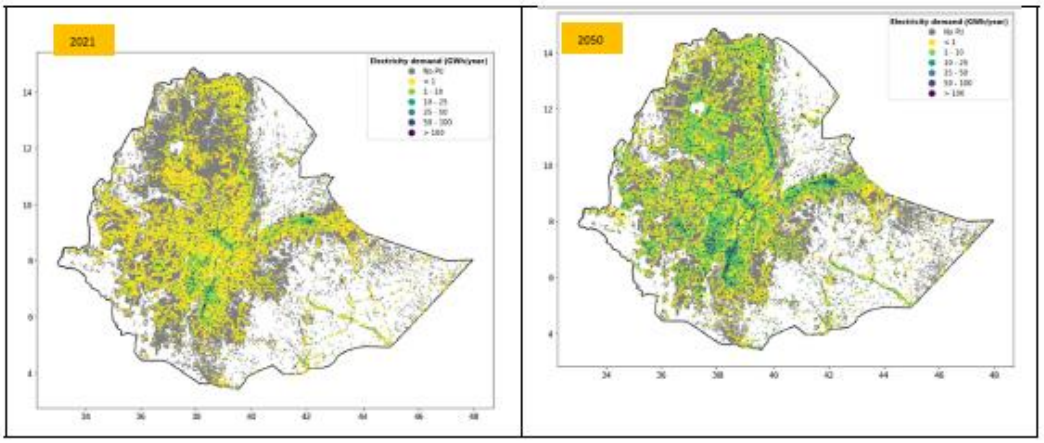

Fig. 11. Spatial variations in electricity demand for PUs under the RU scenario, comparing the base year (2021) demand with projections for 2050. Areas shaded in grey represent settlements where the electricity demand of HHs remains below Tier 2, indicating that there are no PUs in these settlements.

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.

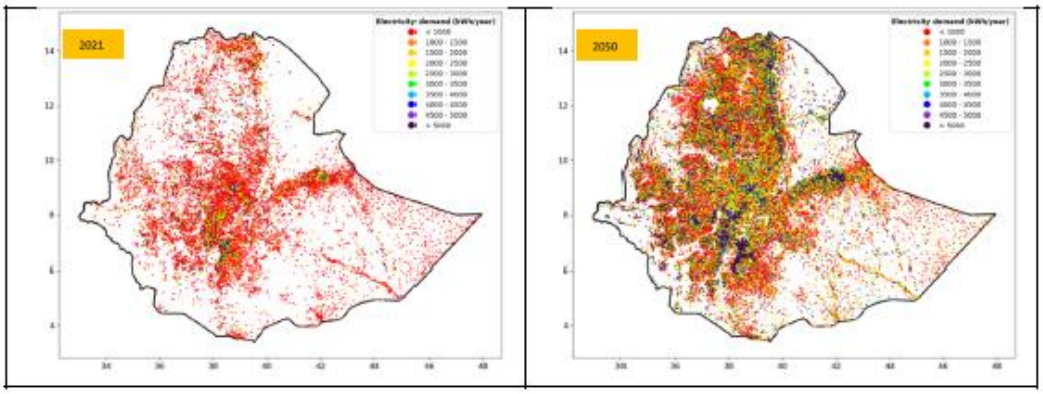

Fig. 12. Spatial variations of electricity demand for CIs under the RU scenario, comparing the base year (2021) with 2050 projections. The highest demand for CIs is observed in areas that align with roads, cities, and densely populated regions.

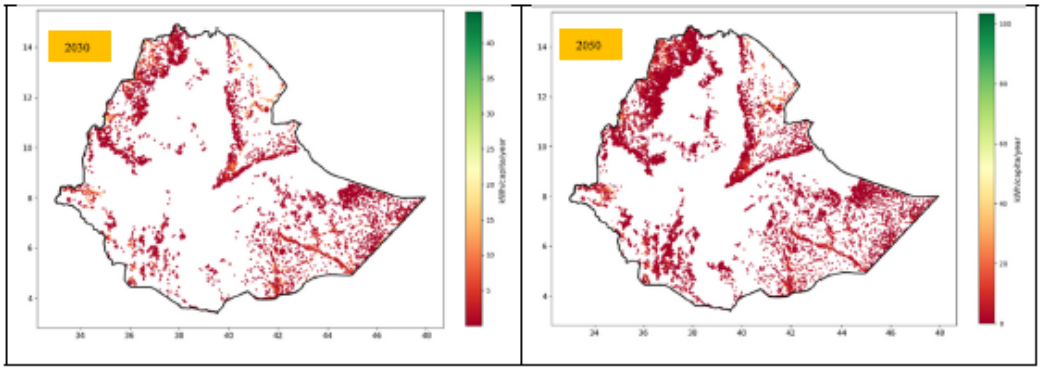

Fig. 13. Additional electricity demand due to projected temperature rise in the RU scenario for the years 2030 and 2050. By 2050, the impact of rising temperatures is expected to extend into central northern regions, indicating a broader geographical spread of temperature-driven demand.

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].

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]

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)

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)
$12 \leq$ *Tier* 1 $<$ 200	38.7
200 $\leq$ *Tier* 2 $<$ 1000	219
1000 $\leq$ *Tier* 3 $<$ 3425	807.5
3425 $\leq$ *Tier* 4 $<$ 8219	2125
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							

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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Paper V

Long-term least-cost geospatial electrification planning for improved electricity access: The case of Ethiopia

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Abstract

Expanding electricity access cost-effectively requires strategies that account for the local realities of demand, infrastructure, and resource availability. Many existing studies often utilize binary urban-rural categorizations and overlook productive and institutional loads. This study aims to develop a long-term electrification plan at the settlement level, identifying the least-cost solutions among grid extension, renewable mini-grids (MGs), and standalone solar (SA PV) systems. Using the Open-Source Spatial Electrification Tool (OnSSET), the analysis is based on a myopic optimization across three periods: 2021–2030, 2030–2040, and 2040–2050. Multiple scenarios are developed to explore variations in electricity demand and grid generation costs. Results show that under a low grid generation cost (LGGC) scenario, grid extension can be the most cost-effective solution for over 82% of the population by 2030, although its share declines slightly over time. Under a high grid generation cost (HGGC) scenario, MGs become competitive for about 26% of the population by 2050. SA PV emerge as the least-cost option for over 16% of the population in both scenarios by 2030 but become less competitive in later periods. National average investment cost per capita is estimated to reach 37-42 USD in 2030 and decrease to 29-36 USD by 2050. The study reveals significant spatial heterogeneity in optimal technology selection, influenced by demand, population density, resources, and grid proximity. These findings highlight the need for (a) integrated national electrification planning that combines grid expansion with MGs deployment while gradually phasing out SA PV, and (b) a shift from a singular focus on grid extension towards location-specific, and demand-responsive electrification strategies.

Keywords: Electricity access; Geospatial electrification; Off-grid; OnSSET; Rural electrification; Sub-Saharan Africa

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1. Introduction

Global electricity access has improved considerably over the past decade. The number of people living without electricity has reduced by nearly half, dropping from 1.14 billion in 2010 to around 685 million in 2022 [1], [2], [3]. This progress, representing a 40% increase in access, is a significant step toward achieving global development goals. However, access remains uneven across regions. In particular, in Sub-Saharan Africa (SSA), rapid population growth has outpaced electrification efforts [4]. Current projections indicate that if progress continues at its present pace, approx. 660 million people, predominantly residing in SSA, will still lack electricity in 2030, thereby jeopardizing the achievement of the United Nation's Sustainable Development Goal 7 (SDG 7) [3].

The persistent challenge of expanding electricity access, particularly in rural areas, is primarily driven by economic constraints and dispersed rural settlement patterns [5]. These factors render traditional grid extension highly challenging due to the substantial per capita investment requirements [6]. In response, many countries have adopted integrated electrification strategies that combine both on-grid and off-grid solutions (e.g., mini-grids (MGs) and standalone photovoltaic (SA PV) systems) [7]. Nevertheless, identifying the most cost-optimal[1] electrification solution for any given location requires careful consideration of a multitude of spatial factors. These include the availability of local energy resources, proximity to existing infrastructure, prevailing electricity demand levels, population density, land cover characteristics, and topography [8]. Grid extension costs, for instance, are particularly sensitive to geospatial characteristics, such as proximity to roads and substations, land cover type, elevation, and slope, all of which can collectively increase initial investment requirements by as much as 30%, independent of electricity demand levels [9], [10]. Similarly, the viability of off-grid electrification solutions, particularly renewable MGs, is heavily dependent on the availability of sufficient local energy resources, including solar radiation, wind speeds, and nearby river flows.

To navigate this complexity and determine the most cost-effective mix of electrification technologies, geospatial electrification models have become valuable tools [5], [9], [11], [12].

[1]Cost-optimal refers to an approach that minimizes the expense of delivering electricity to end users and is used interchangeably with 'least-cost' throughout this paper.

These models leverage Geographic Information Systems (GIS) to integrate diverse geospatial datasets with technoeconomic parameters. This integration enables least-cost analysis that compares grid extension with off-grid alternatives. As a result, these models can provide optimized recommendations for each location at the lowest overall cost [13]. Additionally, these electrification planning tools are essential for identifying the most cost-effective technology mixes and informing investment decisions, and shaping policy frameworks [14].

Despite their potential, existing geospatial models and technology selection studies often have critical limitations. Many of these studies rely on uniform electricity demand assumptions based on a binary rural-urban categorization for an entire country [6], [13], [15], [16]. Other studies even applied a single demand level across all SSA countries [9], [17]. This oversimplification may lead to misaligned supply capacities and local demand [18]. While some studies [12], [19], incorporate spatially variable demand informed by local economic indicators (e.g., GDP and poverty levels), they only target residential demand and neglect demand from productive uses (PUs) and community institutions (CIs).

In addition, the spatial resolution of input data significantly impacts cost assessments and technology recommendations. Low-resolution data can mask important spatial features such as settlement patterns, terrain, land cover, and proximity to existing infrastructure. This may result in an underestimation of grid extension costs and a bias towards grid-based solutions. For example, studies relying on a population grid with the spatial resolution of 2.5 km have identified grid extension as the least-cost option for 86% of new connections in Nigeria and 89 to 93% in Ethiopia [6], [13]. In contrast, high-resolution data captures fine-scale settlement distributions and environmental constraints, resulting in a more realistic representation of rural geographies and cost assessment. In this regard, a study in Malawi [12], which utilized high-resolution population data (30 m), found that off-grid PV systems were the least-cost electrification solution for 67.4% of the total population, while grid extension was optimal for the remaining 32.6%.

Moreover, many geospatial electrification studies have considered a single-time-step approach, resulting in only a snapshot solution for a specific end year of analysis (e.g., 2030, in line with SDG7) [6], [13], [20], [21]. However, this approach's lack of iterative and incremental planning limits its ability to support the phased development of electricity infrastructure over the long term

[22]. To better capture the dynamic nature of electrification, it is important to adopt a myopic modeling approach that considers sequential decision-making over time. This approach provides deeper insights into the rollout processes and better aligns with investment cycles, institutional capacities, and evolving socioeconomic conditions [23].

Addressing these gaps requires developing electrification plans that incorporate: (i) spatially disaggregated demand projections, not only from HHs but also from PUs and CIs, while factoring in the effect of local climate conditions and rising temperatures on electricity demand; (ii) high-resolution geospatial datasets that accurately reflect local conditions; and (iii) iterative, time-stepped modeling approaches that align with real-world investment cycles and policy timelines. In light of these, this study aims to conduct long-term rural electrification planning through geospatial analysis and identify the least-cost electrification technology for each population settlement, explicitly accounting for spatially disaggregated demand from HHs, PUs, and CIs, along with warming climate influences. Specifically, the study seeks to address the following questions:

- What are the least-cost electrification options, and how do their relative shares change under different scenarios of electricity demand and grid generation costs?
- How does the viability of grid and off-grid solutions change across geographical locations and over time?
- How do financial investment requirements for each electrification technology evolve over the planning horizon?

Novelty of the research

This study introduces a novel approach to electrification planning through three key contributions. First, it employs high-resolution geospatial analysis along with spatially disaggregated electricity demand projections based on HHs, PUs, and CIs sectors. This enables a more realistic assessment of electrification options. Second, this study adopts a myopic optimization approach that produces phased electrification pathways and corresponding investments, which is closer to reality. This approach reveals how the optimal technology mix evolves both spatially and temporally, supports the strategic timing of investments, and importantly, considers path dependencies where decisions made in one period impact options in the next. Third, the overarching novelty of this research lies in the synergistic integration of these components into a holistic methodology where spatial

constraints inform costs, detailed demand shapes system sizing, and dynamic optimization guides adaptive infrastructure rollout.

2. Methodology

The methodology consists of three interconnected key phases, namely model selection and development, spatial electricity demand projection, and evaluation of least cost electrification options. The model selection and development are done considering nationwide spatial planning for rural electrification, while the spatial electricity demand projection is assessed through spatial representation and relevant scenarios. A key aspect of this study's geospatial methodology is the identification of the least-cost electrification technology at the settlement level. A spatially explicit approach is essential for considering the diverse aspects of rural electrification planning, particularly those related to the geographical features and local energy resources of the study area [24]. An overview of the methodology used in this study is outlined in Figure 1 and detailed in subsequent sections.

2.1. Model selection

The selection of an appropriate rural electrification modeling tool was guided by the need to address specific planning questions, spatial details, and input data availability. Several electrification planning tools are available in the literature, including GEOSIM, Network Planner, the Rural Electrification Model (REM), and the Open-Source Spatial Electrification Toolkit (OnSSET). Each model presents unique capabilities and limitations with respect to spatial resolution, technology flexibility, and input data requirements.

GEOSIM is an integrated geospatial tool developed using proprietary GIS software (Manifold) designed to optimize energy service delivery across large-scale territories for rural electrification planning [8]. It introduces a socioeconomic planning approach that prioritizes settlements based on land-use classifications and development potential, using a conceptual framework of "Development Poles" and "hinterlands" [38]. Following this initial assessment and once demand forecasting for the planning horizon is complete, the model evaluates electrification options including grid extension and decentralized systems based on diesel, wind, biomass, and

hydropower [29]. However, GEOSIM lacks support for solar-based mini-grids—a significant omission given the importance of solar resources in many rural contexts [27]. Moreover, its reliance on proprietary software limits accessibility, reproducibility, and adaptability across different planning environments [39]. Network Planner, a free web-based tool, which minimizes a cost function to determine the least cost electrification and the layout of the corresponding grid extension network for unserved demand centers [26]. It focuses on grid extension, SHS, solar MGs, and diesel generators [27]. Yet, it lacks support for wind or hydro MGs, reducing its applicability in regions with varied renewable resources [28].

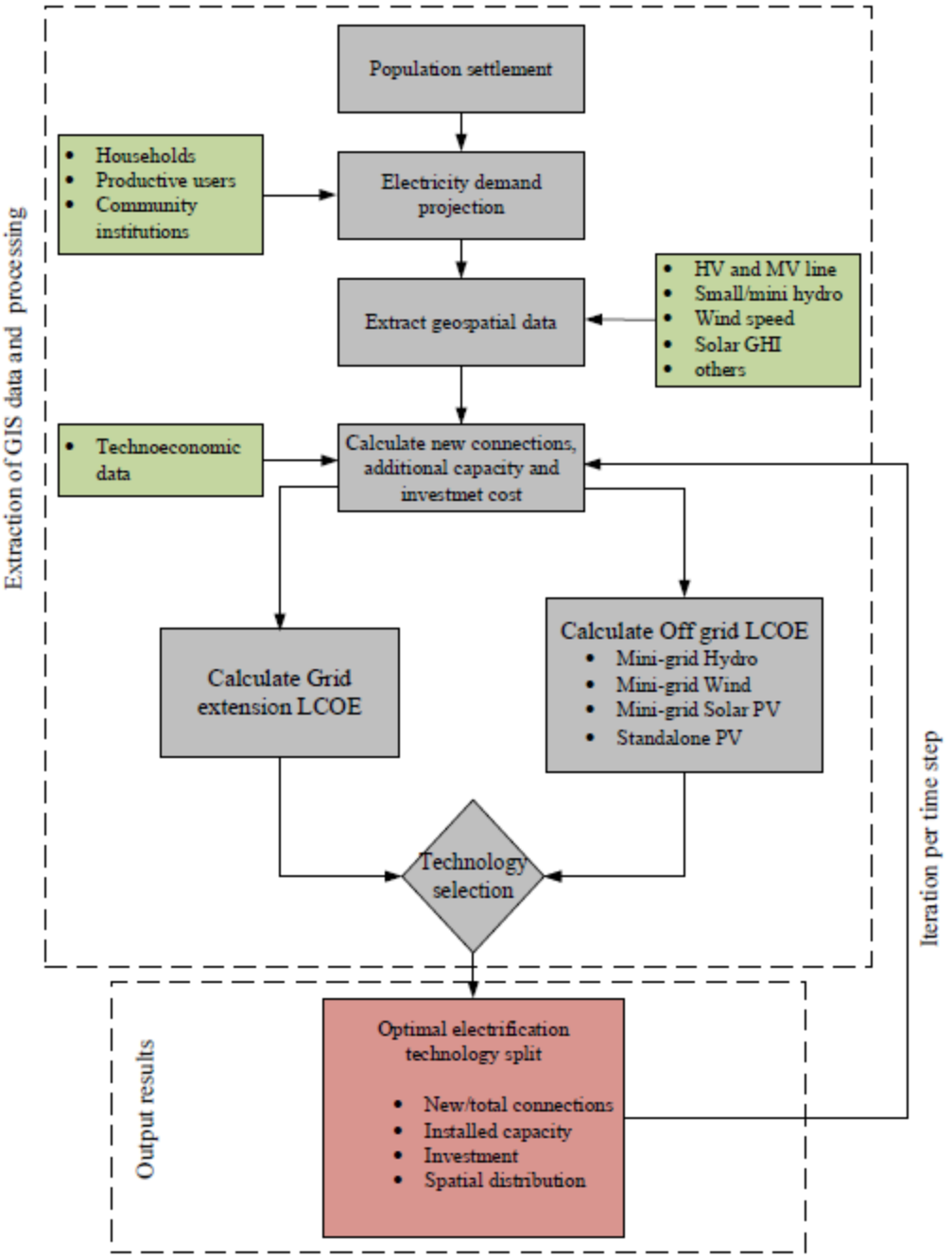


Figure 1: Workflow of the geospatial electrification analysis in this paper using OnSSET. Colors indicate input data (green), processing steps (gray), and outputs (red).

REM is a tool used for optimizing detailed engineering designs for electrification plans. It integrates geospatial data, electricity demand, and technology costs [29]. It compares grid connections, solar MGs, and SA PV systems at the individual customer level [20].

However, it requires extensive input data, such as georeferenced building footprints, demand profiles, and is computationally intensive [14]. Additionally, its non-open-source nature limits transparency, adaptability, and reproducibility [30]. These constraints make REM better suited for localized or high-resolution planning exercises than scalable national applications in data-constrained contexts. OnSSET is a GIS-based tool developed to identify the least-cost electrification option(s) among seven electrification solutions: centralized grid extension, mini-grids (solar PV, wind, diesel, or hydropower), and standalone systems (solar PV, diesel) [9], [12], [13]. It integrates a wide array of spatial data, including infrastructure, terrain, energy resource maps, and population distributions, to determine the least-cost electrification solution at the settlement level while achieving targeted national electricity access [6], [9]. Furthermore, OnSSET's open-source design ensures transparency, reproducibility, and adaptability for diverse case studies [31]. For these reasons, the authors chose OnSSET as the modeling framework for this study.

2.2. Model development: OnSSET

Building on the OnSSET tool, this study models rural electrification analysis over a 29-year planning horizon, spanning from 2021 to 2050. The model is set up in three timesteps: 2021–2030, 2030–2040, and 2040–2050. This stepwise approach, based on myopic optimization, considers evolving demand, technology cost trends, and policy shifts over time [8]. At each time step, the model identifies the least-cost supply and necessary generation capacity, along with the associated investment costs for each settlement. The least-cost technology identified in the previous time step serves as the starting point for the next, and so on [12], [32].

For settlements electrified in previous time steps, the model allows either expanding the capacity of the current technology or switching to a more cost-effective alternative as demand increases. The model assumes unidirectional progression of technology, starting with SA PV systems, transitioning to MGs, and eventually to a centralized grid (SA PV → MG → Grid). Technology transitions are possible only if the new option offers a lower LCOE than the capacity expansion of the existing system. Settlements electrified by MGs can transition to grid connections if economically justified but are not allowed to revert to SA PV technologies [12]. This progression

reflects the practical realities of energy access in rural areas, where people start using SA PV systems before MGs are deployed or the national grid arrives.

2.3. Generating population settlements

The first step in the modeling process is to generate population settlements[2], which are the smallest spatial units used in the analysis. Settlements were created by combining a High-Resolution Settlement Layer (HRSL), nighttime light (NTL) imagery, and administrative boundaries (see details [10]). The HRSL provides high-resolution (approx. 30 m) gridded population estimates, while the NTL data offers a proxy for electrification status. Administrative boundaries were used to constrain the analysis within the study area's spatial extent. The HRSL raster data were subsequently aggregated into polygon settlements by merging adjacent cells (8-connected neighbors) into a single settlement using the clustering algorithm developed by Khavari et al. [33]. This resulted in 809,087 settlements in the study area. Each generated settlement is characterized by population size (inhabitants), area (km^2), average NTL intensity, and classification as rural or urban based on population size and density thresholds [33].

2.4. Identifying grid-electrified settlements

Once the population settlements were created, they were classified as either electrified (1) or unelectrified (0) in the base year (2021), to establish a baseline for electrification planning [12]. This classification employed a GIS-based multi-criteria heuristic, drawing upon spatial data on population distribution, existing low-voltage (LV) distribution transformers, and NTL intensity, in conjunction with national grid access statistics.

The classification was based on the assumption that settlements located within a certain distance of the existing LV transformer infrastructure should correspond to the nationally reported grid-electrified population figure. As a result, it was found that settlements within 1 km of an LV transformer, with a NTL intensity above 0.27 $\mu W\ cm^{-2}\ sr^{-1}$ and population over 650 is equal to the grid-electrified population of the country (national grid access of 40.4% in the base year, derived

[2] 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.

from extrapolations of World Bank ESMAP (2018) [34] and African Development Bank (AfDB) (2020) data [35]).

2.5. New connections and additional capacity

The number of new connections at each time step is determined by national access targets. In this study, it is assumed that the electrification progresses linearly over time. That is, the national access level was set at 72% by 2030, 96% by 2040, and 100% by 2050. These targets are derived based on the projection of historical electricity access development.

The OnSSET model employs a prioritization algorithm to determine which settlements should be electrified at each time step, while meeting national access targets [12]. Initially, priority is given to settlements that are already electrified but require new connections due to population growth. Subsequently, unelectrified settlements are prioritized based on criteria such as investment cost per capita for new connections or the travel time to large cities [31], [36]. In this study, unelectrified settlements are ranked in ascending order of investment cost per capita.

For electrified settlements, new connections were calculated as the difference between the current and previous time-step populations. For previously unelectrified settlements, the entire population is assumed to be newly connected in the respective time step. New connections at each settlement are thus calculated as expressed in Equation 1. The electricity demand associated with these new connections is then determined using Equation 2.

$$N_{conn,t} = \begin{cases} Pop_t - Pop_{t-1}, & if\ electrified \\ Pop_t & if\ unelectrified \end{cases} \quad (1)$$

$$E_{new,t} = E_{pc,t}\ x\ N_{conn,t} \quad (2)$$

Where, $N_{conn,t}$ is the number of new connections at time t, Pop_t and Pop_{t-1} represent total population in a settlement at the current and previous time-steps, respectively. $E_{pc,t}$ denotes per capita electricity demand (kWh/capita/year) at time-step t.

In addition to the demand from new connections, the electricity demand of already electrified people is also expected to increase over time (Equation 3). Therefore, the total additional electricity

demand for each settlement at every time step is the sum of the demand from new connections and the incremental demand (Equation 4). The study's 29-year planning period exceeds the operational lifetimes of most electricity supply technologies (except for grid extension and hydropower). Thus, when a technology reaches the end of its operational lifetime, the model accounts for the demand it previously met and adds it to the settlement's total demand for the current time step. Only additional demand is considered for technologies that are still operational. Therefore, the total demand for the settlement at each time-step is given by Equation 5.

$$\Delta E_t = (E_{pc,t} - E_{pc,t-1})\, x\, (P_t - N_{conn,t}) \qquad (3)$$

$$E_{add,t} = E_{new,t} + \Delta E_t \qquad (4)$$

$$E_{tot,t} = \begin{cases} E_{add,t} + E_{met,t} & Exp_t < t \\ E_{add,t} & otherwise \end{cases} \qquad (5)$$

Where ΔE_t is incremental demand at time t, $E_{add,t}$ is additional demand at time t, $E_{tot,t}$ is total demand of a settlement at time t, and $E_{met,t}$ is demand previously met by technologies until their expiration year (Exp_t). This approach ensures that expired technologies do not leave settlements without electricity.

To avoid stranded investments, existing infrastructure operates until their lifespan ends, even if a settlement transitions to a new technology such as the grid. During transitions, the new technology is sized only for $N_{conn,t}$. The installed capacity required to meet the total settlement demand is calculated as Equation 6.

$$C_{inst,t} = \frac{E_{tot,t}}{8760\, x\, CF\, x\, BPR\, x\, (1-L_{dist})} \qquad (6)$$

Here, $C_{inst,t}$ is installed capacity at time t, CF is the capacity factor, which differs depending on the supply source (provided in Table A2 and A3), and BPR is base-to-peak ratio (Table 3). Distribution losses reflect the percentage of energy lost during transmission and distribution, and the assumed values are presented in Appendix Table A4.

2.6. Investment cost

The investment cost for electrification at each time step is estimated as the sum of generation capacity costs and the associated transmission and distribution (T&D) infrastructure costs, as shown in Equation 7.

$$Investment_{cost,t} = C_{inst,t}\, x\, cap_{cost,t} + td_{cost} x\, PF \qquad (7)$$

Where $Cap_{cost,t}$ represents the technology-specific capacity cost (USD/kW) and td_{cost} represents the transmission and distribution infrastructure cost, and PF is a grid extension penalty factor that adjusts td_{cost} for geospatial factors. The total investment cost over the planning horizon is then computed as the discounted sum of the annual investment costs at each time step, using the base year as the reference.

The capacity cost (cap_{cost}) varies by technology type. For SA PV systems, it includes the cost of solar panels, inverters, and batteries for individual household systems. In the case of MGs, whether powered by solar, wind, or hydro, Cap_{cost} accounts for the cost of centralized generation equipment and the associated installation costs. For grid extension, it represents the average cost of adding or upgrading existing grid generation capacity.

The td_{cost} also varies depending on the technology. SA PV systems incur no td_{cost} as they operate independently at the household level without network infrastructure requirements. In contrast, MGs require a localized distribution network to deliver electricity from a central generation point to individual users. This includes the cost of low-voltage (LV) distribution lines, transformers, and end-user connection costs. Grid extension involves a more complex and capital-intensive infrastructure, and thus td_{cost} includes the upfront capital costs for high-voltage (HV) and medium-voltage (MV) transmission lines, substations, transformers, LV lines, and end-user connection costs.

To reflect the real-world difficulty of grid infrastructure deployment in diverse geographic contexts, a penalty factor (PF) is applied to the td_{cost} for grid extension. This PF is calculated based on a composite geospatial index derived from five critical variables: terrain slope, elevation, land cover type, distance to the nearest road, and distance to the nearest substation [10]. Each variable is classified into suitability classes and weighted according to its influence on construction

costs. Higher terrain slope, elevation, dense vegetation, and greater distance from existing infrastructure increase the PF, thereby increasing the estimated T&D costs [10], [37]. Conversely, settlements located in favorable environments with flat terrain, close proximity to roads, and near substations experience minimal cost penalties.

2.7. LCOE

The LCOE is used for comparing the relative cost-effectiveness of various electrification technologies in rural electrification planning [38]. It represents the per-unit cost (USD/kWh) of supplying electricity, accounting for all costs incurred over a technology's operational lifetime [21]. For each settlement and technology at each time step, the LCOE is calculated by dividing the total discounted investment cost by the total discounted electricity generation as Equation 8.

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_{cost,t} + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \quad (8)$$

Here, $I_{cost,t}$ is the upfront investment cost derived from Equation 7, $O\&M_t$ is the operations and maintenance cost expressed as a percentage of the capital cost. F_t is the fuel cost, which represents the grid generation cost (in USD/kWh) for grid extension technologies and is zero for off-grid technologies. E_t denotes the electricity generation, r is the discount rate, and n is the technology's lifespan.

2.8. Least cost electrification technology split

The OnSSET model assigns the least-cost electrification technology to each settlement by comparing the LCOE values of all available technologies. To do so, at each time step, the model first identifies the lowest LCOE among off-grid technologies (hydro MG, wind MG, solar MG, and SA PV systems) for each settlement [8]. This is then compared to the LCOE of connecting the settlement to the centralized grid. The technology with the lowest overall LCOE is recommended as the least-cost solution. This process is executed iteratively over the planning horizon, allowing the technology choice to evolve over time. As a result, each settlement is dynamically assigned the most economically viable electrification option throughout the planning horizon.

2.9. Scenarios

Planning future electrification, especially in rural areas without electricity, is challenged by uncertainties in demand growth and grid generation costs (average national cost of grid electricity in USD/kWh). To address these uncertainties, different demand evolution and grid generation cost scenarios can be developed [12], [39].

2.9.1. Electricity demand scenarios

Future spatial electricity demand is projected at the settlement level based on HHs, PUs, and CIs (see details in [40]). These projections are driven by key socioeconomic factors, including population growth, GDP growth, urbanization rates, and rural electrification rates. To account for potential variations in these drivers, three scenarios are developed, namely Business-as-Usual (BAU), High Economic Growth (HEG), and Rapid Urbanization (RU). The baseline scenario (BAU) assumes that the key drivers of electricity demand continue to evolve in line with historical trends observed between 2005 and 2021, resulting in moderate demand growth. The HEG scenario reflects higher demand driven by higher GDP growth than the BAU, while the RU scenario accounts for higher demand growth due to faster urbanization compared to the BAU.

Each scenario is modeled using multiple linear regression (MLR), which incorporates the assumptions of key demand drivers (Equation 10). Additionally, the demand projection model incorporates the spatially heterogeneous influence of temperature and global warming projections to account for increased electricity demand in warmer climates.

$$D = \beta_0 + \beta_1(Rural\ electricity_{access}) + \beta_2(GDP_{percapita}) + \beta_3(Urban\ population_{percentage}) + \varepsilon \qquad 10$$

Where D represents electricity demand, β_0 is the y-intercept of the regression line, β_1, β_2,..., β_n are the coefficients for the demand drivers, and ε denotes the error term.

2.9.2. Grid generation cost scenarios

In addition to electricity demand, future grid electricity generation cost is a critical factor in determining the optimal electrification strategies [39]. This cost can be influenced by factors such

as technological advancements, economies of scale, and the national energy mix [12]. To account for this, two potential scenarios for grid generation cost are considered in this study: Low Grid Generation Cost (LGGC) and High Grid Generation Cost (HGGC), as shown in Table 1.

By combining the three demand growth pathways with the two grid generation cost scenarios, six integrated scenario combinations are established: BAU–LGGC, BAU–HGGC, HEG–LGGC, HEG–HGGC, RU–LGGC, and RU–HGGC. These combinations enable the assessment of least-cost electrification strategies under a wide range of possible futures.

3. Case description, data, and assumptions

Ethiopia was chosen as a case for the study due to its low electricity access, significant rural-urban population disparity, and abundant but underutilized renewable energy resources.

3.1. Case description

Ethiopia faces significant challenges in electricity access, with only 54.2% of the population having access as of 2021. In rural areas, accounting for approx. 78% of the population, this drops to 42.8% [41]. Subnational analysis reveals significant disparities in electricity access among states, with Addis Ababa having almost 100% access, while Afar and Somali lag far behind [42]. Despite abundant renewable energy potential, the country's per capita electricity consumption remains critically low at approx. 100 kWh/year, among the lowest globally [43], [44].

Ethiopia's electrification efforts are guided by the National Electrification Plan (NEP 2.0), launched in 2019, which outlines a roadmap to achieve universal electricity access by 2025 [45]. The plan sets specific targets, aiming for 65% of the population to be connected to the national grid and 35% to rely on off-grid solutions, including solar home systems (SHS) and MGs. By 2030, NEP 2.0 envisions that 96% of households to be connected to the grid, and 4% to be supplied by off-grid technologies [45]. Despite these goals, population growth, adding approx. 410,000 new households yearly, outpaces grid connections, which only connect around 220,000 new households annually, widening the access gap, particularly in rural areas where grid expansion remains

economically challenging [46]. Moreover, the grid supply falls short of demand, resulting in load shedding, and blackouts [13].

3.2. Data and assumptions

3.2.1. GIS data

The developed geospatial electrification planning model processes various GIS data, in the form of both vector (shapefiles) and raster data layers. These data include existing grid infrastructures, renewable energy resources, and relevant geographical features [47]. A complete list of the GIS data used in the study, along with their corresponding sources, is provided in Appendix Table A.

The analysis incorporates georeferenced grid infrastructure data, such as HV and MV transmission lines, substations, and distribution transformers. The collected HV lines include voltage levels between 45 kV and 500 kV. The total length of HV lines is approx. 6,397 km in the study area, as determined through QGIS-based length analysis. Similarly, in the study area, MV lines consist of 15 kV and 33 kV networks. The total length of these MV lines is approx. 61,575 km. The model also incorporates 152 substations and 42,184 distribution transformers. These grid infrastructure data were obtained from Ethiopia's Electric Power (EEP[3]) and Ethiopia's Electric Utility (EEU[4]). The geographical distribution and spatial extent of the existing grid infrastructure across Ethiopia are shown in Figure 2.

The spatial data for renewable energy resources include solar irradiance, wind speed, and hydropower potential. Solar irradiance data is used to assess the suitability of solar MGs and SA PV systems. For this purpose, Global Horizontal Irradiance (GHI) data was sourced from the Global Solar Atlas [48]. Wind energy potential is evaluated using wind speed data from the Global Wind Atlas at a height of 100 meters [49]. This data is then adjusted to a height of 55 meters using the logarithmic wind profile method embedded within the OnSSET model [50]. MG wind systems

[3] Ethiopian Electric Power owns and operates the Ethiopian national power grid with all high voltage power transmission lines above 66 kV including all attached electrical substations and almost all power plants within the national power grid.
[4] Ethiopian Electric Utility is a public enterprise that engages in the business of distributing and selling electrical energy in accordance with economic and social development policies and priorities of the government.

were modeled based on the Vestas V44 turbine (600 kW), commonly used in small-scale wind turbines [51], [52]. For hydro MGs, data on small and mini-hydro potential, ranging from 0.01 to 10 MW, were acquired from Energydata.info [53]. This potential was determined through a high-resolution GIS-based assessment that combined digital elevation models, river network data, and mean runoff volumes to estimate discharge and head across perennial river networks [54].

Additional geospatial layers incorporated into the model include land cover classifications, road network data, and topographic variables such as elevation and slope. These factors are particularly important for adjusting the cost of grid extension through the application of a topographic penalty factor [10]. All GIS data inputs are then extracted for each population settlement using the OnSSET_GIS_Extraction_notebook [31].

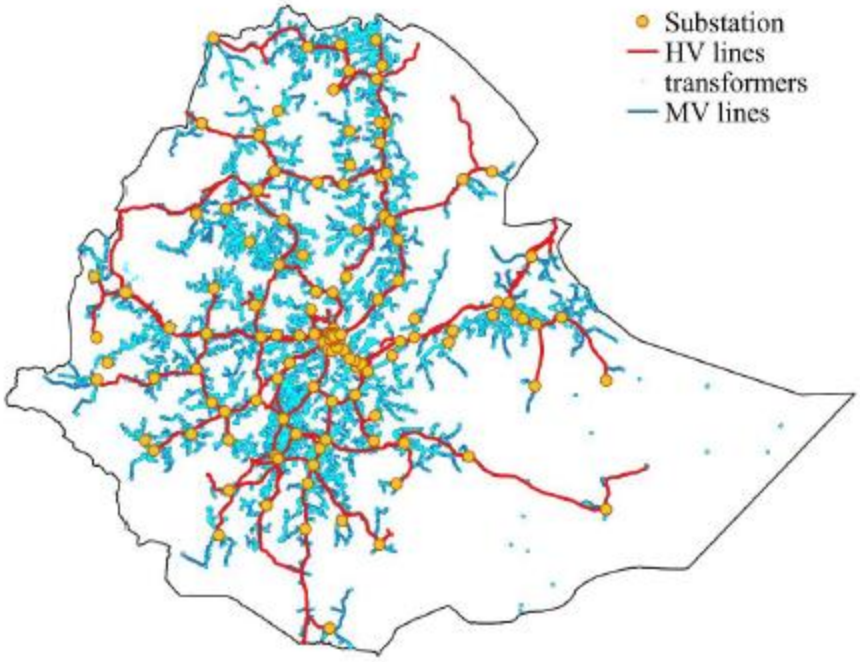


Figure 2: Existing HV and MV lines, substations, and transformers georeferenced data.

3.2.2. Technoeconomic data

The technoeconomic parameters used in this analysis are drawn from an extensive review of peer-reviewed studies, particularly Ethiopia-focused electrification studies [8], [9], [36], [55], [56]. Grid generation and capital costs, were derived from Sahlberg et al.'s Ethiopia-specific projections

across multiple time steps [8]. Grid transmission and distribution costs were compiled from various sources, including the Global Electrification Platform (GEP) [55], Mentis et al. [9], and Korkovelos et al. [56]. These costs are assumed to remain constant throughout the analysis period.

Baseline costs for solar PV MGs were established by averaging the capital costs of 10 operational MGs, deployed in Ethiopia, with capacities ranging from 175 to 550 kWp [57]. Projections from the Energy Sector Management Assistance Program (ESMAP) indicate a 25% reduction in solar hybrid MG capital costs per kW between 2020 and 2030 owing to technological advancements [7]. Accordingly, the model applies a stepped cost reduction: 2.5% annual decline (2021-2030), followed by 1.5% annual reduction (2030-2050), to account for continued learning curves and innovations in solar technology.

For wind MG, hydro MG, and SA PV, the capital costs for the first time step (2021–2030) are drawn from [16], [36], and [55]. Wind MGs costs are projected to decline by 1% annually, in line with global trends for small-scale wind systems [58]. Hydro MG costs are assumed to remain constant throughout the analysis period, given its status as a mature technology with no expected significant cost reductions. Similar to solar MGs, a 1.5% annual cost reduction is applied to SA PV systems. Tables A2 (off-grid) and A3 (grid) summarize these technoeconomic parameters, detailing capital costs, capacity factors, and technology lifetimes across the analysis horizon.

Grid generation cost assumptions are informed by the work of Sahlberg et al. [8] and Pappis et al. [39], who employed a soft-linked OnSSET and OSeMOSYS to calculate centralized grid electricity generation costs in Ethiopia, focusing on medium- to long-term planning. Their analysis optimized centralized power generation by accounting for residential, industrial, commercial, and public service electricity demand across various national development scenarios from 2018 to 2070 [8]. The rationale for adopting these costs lies in the significant difference in demand levels. The projected national demand of currently unelectrified areas in this study is significantly lower than the national demand modeled by Pappis et al., which includes industrial and commercial loads. The additional demand from unelectrified regions is unlikely to change the national average grid generation costs. Therefore, the generation cost scenarios used in this study are derived directly from these long-term national projections.

Table 1: Grid generation costs for 2030, 2040, and 2050 [8], [39].

Grid generation cost (USD/kWh)	2021–2030	2030–2040	2040–2050
Grid (High)	0.19	0.20	0.23
Grid (Low)	0.08	0.09	0.1

3.2.3. Electricity demand projection

The aggregated electricity demand under each scenario (BAU, HEG, RU) is shown in Table 2. The annual average growth rate (AAGR) for electricity demand between 2021 and 2050 is projected to be 3.6% under BAU, 4.1% under HEG, and 4.8% under RU. These growth rates translate to cumulative increases in national demand of 176%, 219%, and 285%, respectively, over the modeling horizon (2021-2050).

Table 2: Projected electricity demand under three scenarios for 2030, 2040, and 2050, including the influence of temperature. The base year (2021) consumption is 7,400 GWh.

Scenario	Projected demand (GWh)			Growth rate (2021-2050)	AAGR (%)
	2030	2040	2050		
BAU	11,700	16,500	20,500	176%	3.6
HEG	13,300	19,400	23,700	219%	4.1
RU	12,700	19,900	28,700	285%	4.8

3.3. Key modeling assumptions

The geospatial electrification model in this study is guided by a set of assumptions that define both the baseline conditions and the model's temporal evolution. A list of the key modeling assumptions is presented in Table 3.

A particularly important consideration pertains to the role and limitations of SA PV systems. Although SA PV solutions can deliver basic tiers of electricity access, they lack the capacity to support productive uses essential for long-term economic development. A recent study by

Stevanato et al. [59], has highlighted that while SHS offer a cost-effective electrification solution, their limited capacity results in missed economic development opportunities. Stevanato et al. introduced the concept of shadow costs to quantify the economic losses incurred due to the inability of SHS systems to support high-power appliances required for income-generating activities. Their findings indicate that treating SHS as equivalent to grid or MG solutions in electrification planning significantly underestimates the broader development impacts.

Building upon these findings, this study adopts a phased approach to progressively limit the deployment of SA PV systems to sparsely populated households, in line with previous findings [7], [60]. In the short term (up to 2030), SA PV remains unrestricted to allow rapid expansion in remote areas where grid or MG infrastructure may not be feasible. However, as the electrification network expands and alternative solutions become more viable, SA PV systems are restricted to settlements with fewer than 50 households between 2030 and 2040. In the long term, from 2040 to 2050, the threshold is further reduced to settlements with fewer than 30 households. This strategy ensures that larger settlements gradually shift toward MGs or grid extensions, capable of supporting community development and economic productivity.

Table 3: Key modeling assumptions [12], [36].

Modeling Parameters	**Assumptions**
Base year urban population	22%
Base year grid access	40.4%
Base year population	120,283,026
MV and LV lines	MV can be extended only up to 50 km and LV up to 0.8 km
Discount Rates	10%
Base-to-peak (BPR)	BPR is assumed to be 0.8 for grid, 0.85 for grid MG hydro, wind and PV, and 0.9 for SHS

4. Results and analysis

This section presents the cost-optimal rural electrification pathways for Ethiopia from 2021 to 2050 based on outputs from the OnSSET model. It analyzes the optimal technology mix, grid extension, MGs, and SA PV systems, and examines their spatial distribution, temporal evolution, and corresponding investment requirements under varying demand growth pathways (BAU, HEG, RU) and grid generation cost assumptions (LGGC, HGGC).

4.1. Least-cost electrification technology mix

The results reveal that the optimal electrification technology mix changes over time and is strongly influenced by grid generation costs (Figure 3). Under the LGGC scenario, grid extension emerges as the dominant least-cost solution during the initial phase (2021–2030), serving over 82% of the total population and accounting for over 67% of new connections (Table B1) across all demand pathways (BAU, HEG, RU). The dominance of grid extension in the early years of the planning horizon is attributed to two key factors. First, the model prioritizes settlements with the lowest per-capita investment requirements, which are those settlements with high electricity demand and larger population. Second, there are extensive grid networks already in place in Ethiopia, and the proximity of a high proportion of population to existing grid infrastructure. Our analysis reveals that over 73% of the total population resides within 5 km of MV lines, while 83% is located within 5 km of both HV and MV grid lines. Among those who are expected to be electrified by 2030, more than 85% are currently located within 5 km of the grid lines.

However, the grid extension share gradually declines as electrification expands to remote areas. By 2050, while grid remains the dominant least cost option, its share of the total electrified population slightly declines to 78.8% under the LGGC-BAU compared to 2030 levels, with similar marginal declines in the LGGC-HEG (79.5%) and LGGC-RU (79.7%) pathways. MGs become increasingly cost-effective in remote areas, growing from approx. 1.3-1.5% in 2030 to 12-13% by 2050 across all demand pathways. SA PV serves the lowest-demand populations, with its share decreasing from about 16% in 2030 to 7.8% by 2050.

In contrast, under the HGGC scenario, higher grid generation costs reduce the competitiveness of grid extension and alter the technology mix. Grid extension share drops by 5.2-5.5 percentage points by 2030 and 12.8-13.1 percentage points by 2050 compared to LGGC. Conversely, MGs see a substantial increase, electrifying approx. 7% of the total population by 2030 and growing to around 26% by 2050 across all demand pathways. SA PV maintains a similar share to that observed in the LGGC scenario.

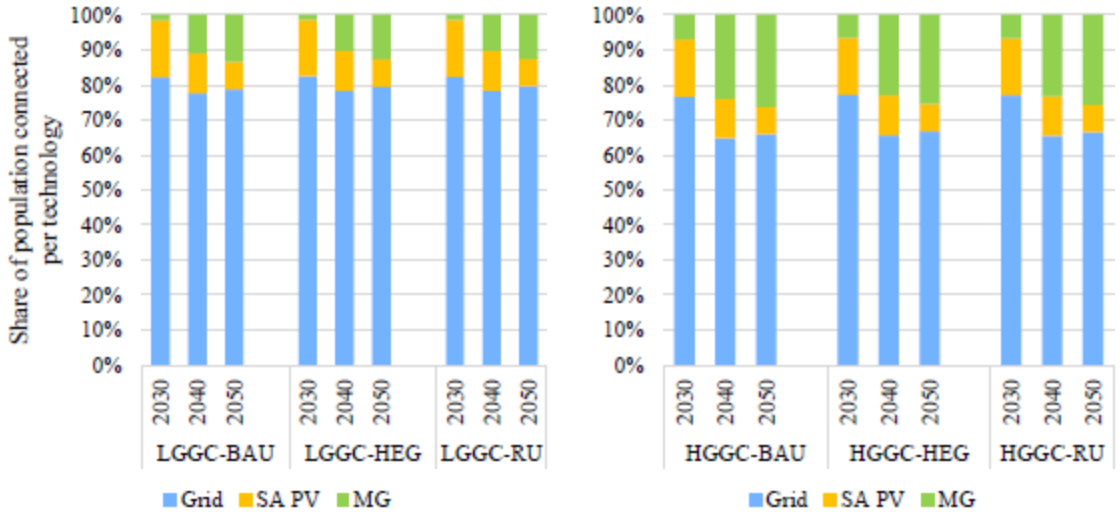


Figure 3: Share of total population per technology under the LGGC (left) and HGGC (right) scenarios for the three demand pathways (BAU, HEG, and RU) for 2030, 2040, and 2050.

4.2. Spatial distribution and temporal evolution of electrification options

The optimal electrification technology varies considerably across geographical areas and evolves over time (Figures 4 and 5). The maps use a color-coded scheme to indicate the least-cost technology for each settlement: grid (blue), MG PV (red), SA PV systems (yellow), MG wind (brown), MG hydro (green), along with unelectrified settlements (gray).

In 2030, under the LGGC-RU scenario (Figure 4A), grid extension emerges as the dominant cost-optimal electrification solution, particularly in settlements with relatively high electricity demand and unelectrified populations, averaging 394 kWh/HH/yr and 614 people per cluster. 85% of new connections in 2030 are located within 5 km of existing grid (HV or MV) lines. In contrast, SA PV systems are optimal for low population density and low-demand clusters, averaging 151 people

per cluster and 17.5 kWh/HH/yr, while MG PV fills an intermediate niche, serving moderate demand clusters predominantly located beyond 10 km from the grid (60% of newly electrified population by MG PV). MG hydro and wind solutions are only competitive in specific geographic areas with suitable resource conditions. By 2050 (Figure 4B), MG PV may become an increasingly cost-optimal solution, replacing many previously SA PV-designated areas and expanding into unserved settlements, particularly in the northeastern and southeastern regions.

A detailed analysis of a zoomed-in 274 km² area, located 120 km from the capital Addis Ababa, shows SA PV emerge as the least-cost option for 18% of newly electrified settlements by 2030 (Figure 4C), even within close proximity (0.5-5.4 km) to existing grid lines. This can be attributed to specific local conditions: low electricity demand (4-153 kWh/HH/year), small population clusters (35-412 individuals), and favorable solar resources (GHI > 6.2 kWh/m²/day). The analysis further reveals that MG PV can also be least cost option for 7% of newly electrified settlements at distances of 1.2-2.5 km from the grid under similar solar conditions. By 2050 (Figure 4D), all of the SA PV systems would be phased out, with half of their served population transitioning to grid connection and the other half to MG PV. Notably, MG PV's share increases to 52% of newly electrified settlements and competes with grid extension even in areas within 0.5-5.4 km of existing infrastructure.

In contrast, the HGGC-RU scenario shows how higher grid generation costs reshape the spatial distribution of optimal electrification technologies. By 2030 (Figure 5A), MG PV systems can be the least cost option in areas designated as grid-optimal under the LGGC-RU scenario. This shift is particularly evident in the changing spatial relationship between MG PV installations and existing grid infrastructure. Only 35% of newly electrified population by MG PVs are situated beyond 10 km from existing grid lines, compared to 60% under the LGGC-RU scenario. By 2050 (Figure 5B), MG PV further expands, not only displacing SA PV systems in remote locations but also emerging as the optimal solution in settlements that would have been grid-connected under the LGGC-RU scenario.

A detailed analysis of the same zoomed-in area provides compelling evidence of this shift. By 2030 (Figure 5C), SA PV systems remain the least costly option in the same settlements as in the LGGC-RU scenario, but the share of MG PV rises to 62%. This represents a 55-percentage point

increase compared to the MG PV share under the LGGC-RU scenario. MG PV continues to dominate in 2050 (Figure 5D), representing a 52-percentage point increase over the LGGC-RU scenario. Notably, several of these MG PV systems appear in settlements where grid extension would have been the least costly option under the LGGC-RU scenario.

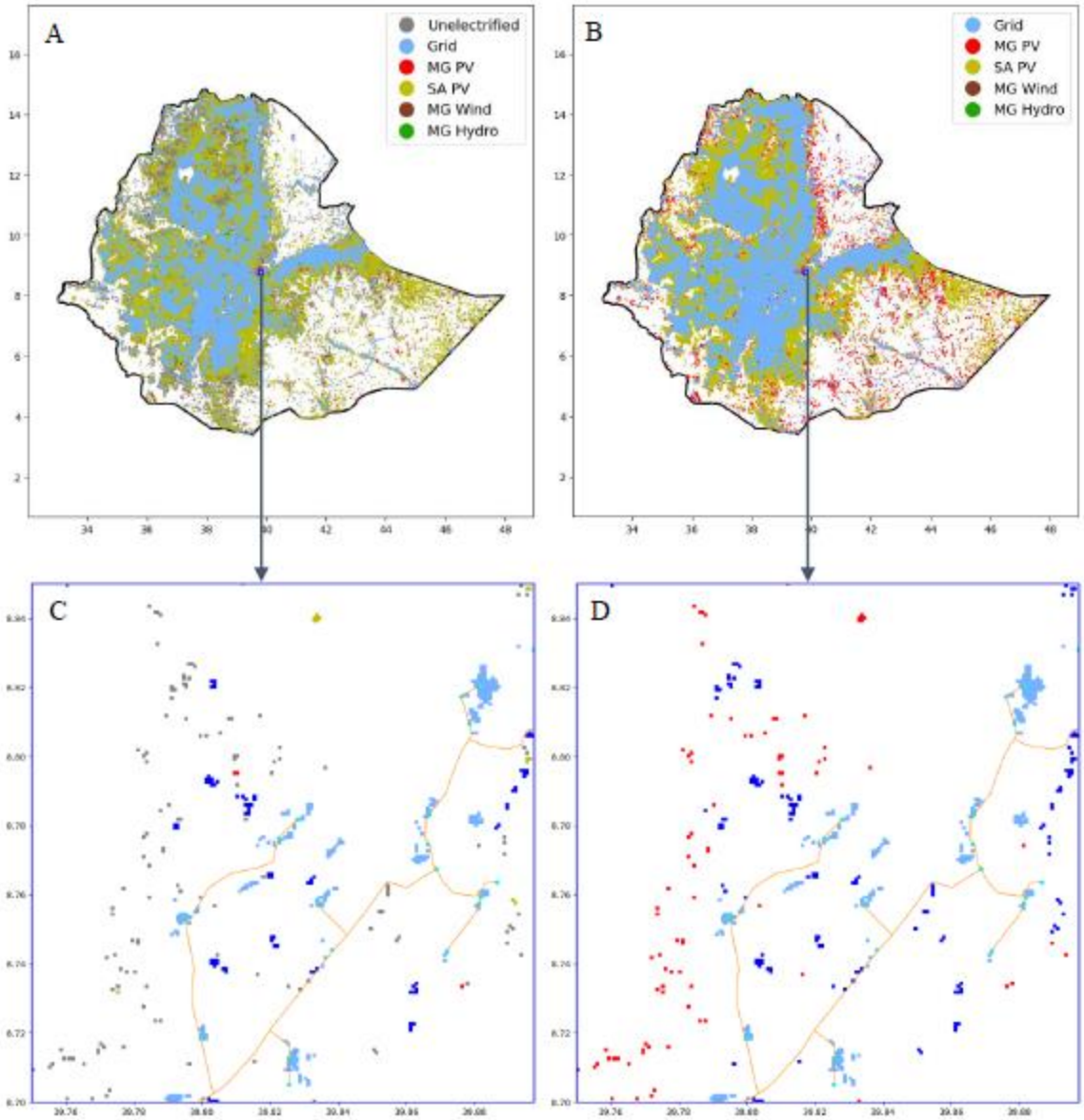


Figure 4: Spatial distribution of the least-cost electrification technology under LGGC-RU scenario for 2030 (A) and 2050 (B). Figures C and D provide zoomed-in views of the blue box in Figures A and B, respectively. Color coding: dark blue represents newly grid extension recommended

settlements, light blue represents already grid-electrified settlements in the base year, gray represents unelectrified areas, red represents settlements recommended for MG PV, dark orange represents MV lines, and cyan represents transformer locations.

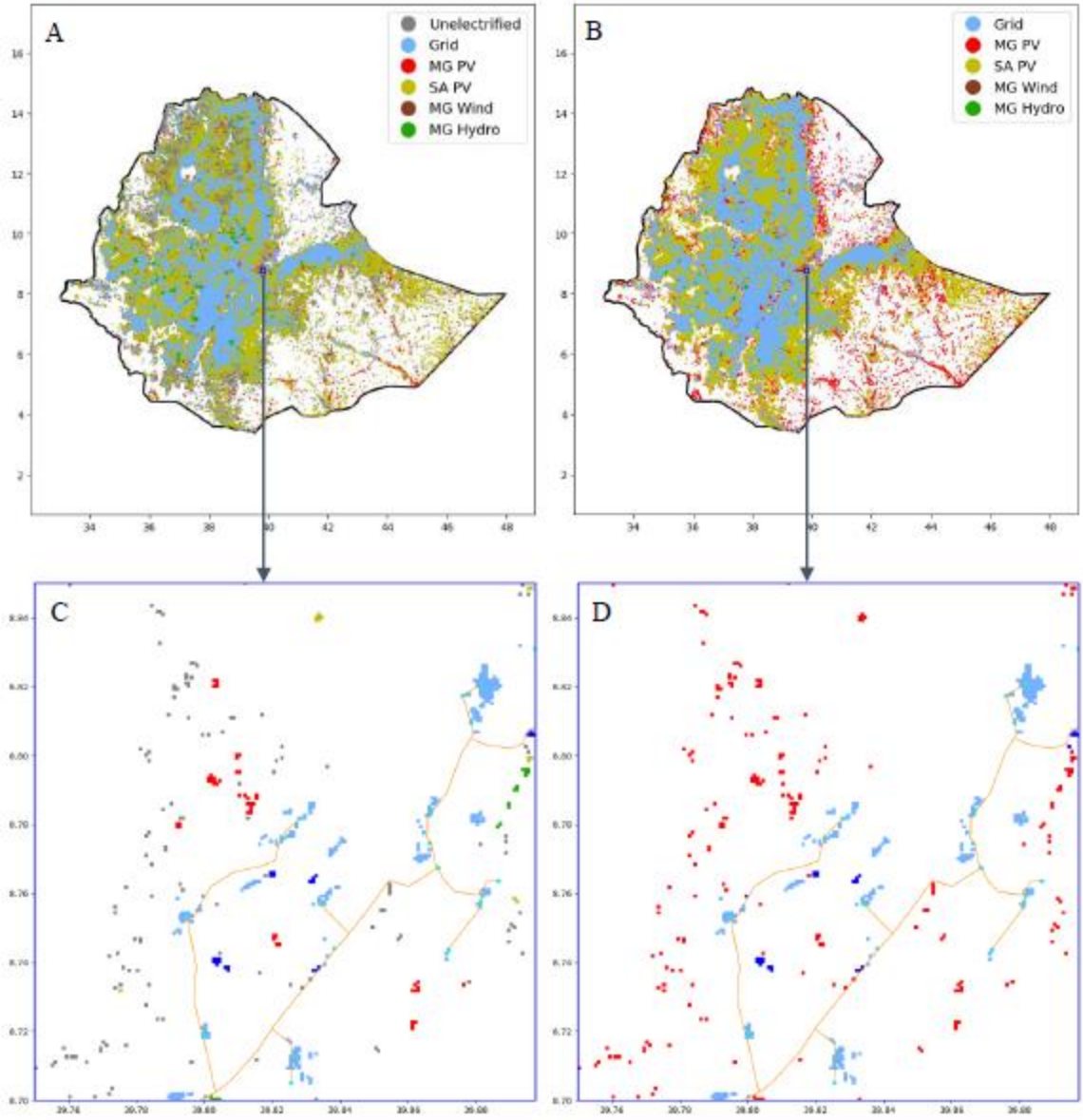
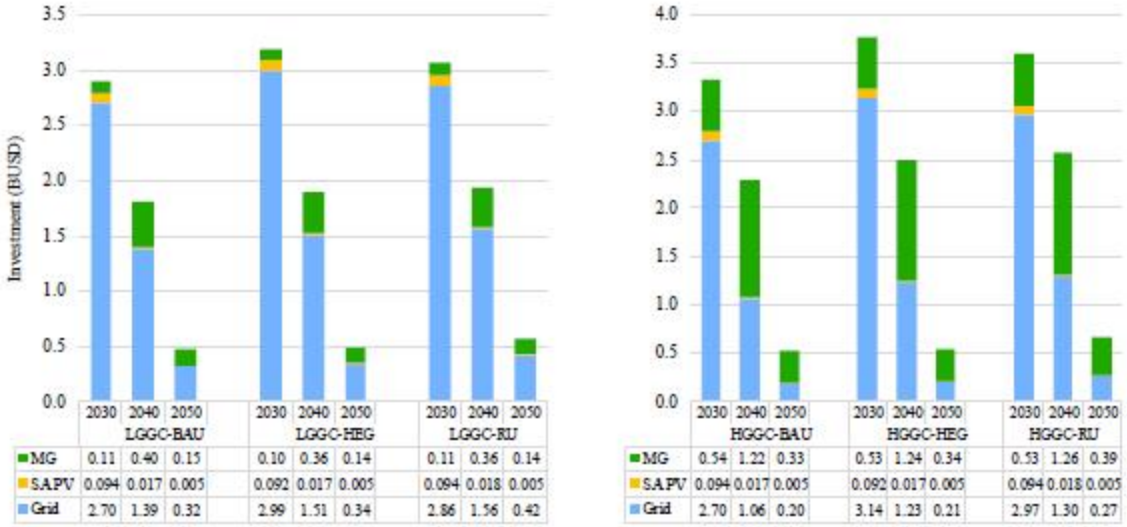


Figure 5: Spatial distribution of the least-cost optimization technology in Ethiopia under HGGC-RU scenario for 2030 (A) and 2050 (B). Figures C and D provide zoomed-in views of Figures A and B, respectively.

4.3. Investment requirements

Discounted to the base year, the total investments are estimated to range between 5.2–5.6 billion USD under the LGGC scenarios and 6.2–6.8 billion USD under the HGGC scenarios over the whole modeling horizon. This implies an average investment of approx. 5.9 billion USD over the 29 years, translating to around 0.2 billion USD per year. The transition from LGGC to HGGC scenarios increases total investment requirements by 21%, representing a significant burden for an already capital-constrained country. The investment requirements can be disaggregated into two main categories. First, new electrification in previously unelectrified settlements demands 3.4 to 3.5 billion USD under LGGC scenarios and 3.7 to 4.0 billion USD under HGGC scenarios. Second, additional capacity needs in already electrified settlements require 1.8 to 2.1 billion USD under LGGC scenarios and 2.5 to 2.9 billion USD under HGGC scenarios.

The distribution of investment by technology evolves over time. In the LGGC scenario, grid extension's share decreases from 93-94% in 2030 to 67-75% by 2050, while MG PV increases from 3-4% to 24-32%. More notably, under the HGGC scenario, grid extension declines from 81-83% to 37-41%, as MG PV rises from 14-16% to 59-62% over the same period. SA PV maintains a minimal share (1-3%) across all scenarios and years. These trends reflect the changing cost-effectiveness of different electrification solutions throughout the planning period. The relatively low contribution of SA PV suggests that, given the assumptions provided, it is found to be a cost-effective solution for those with low demand. This translates to a reduced generation capacity, which in turn results in lower investment requirements compared to grid extensions and MGs. For each of the three demand pathways, the discounted investment requirements by technology under the LGGC and HGGC scenarios are shown in Figure 6. A spatial analysis of discounted investment per new connection reveals disparities across scenarios and over time (Figure 7). Under the LGGC-HEG scenario, the national average investment cost per capita is estimated at approx. 37 USD in 2030, decreasing to 29 USD by 2050. In contrast, the HGGC-HEG scenario results in a 14% increase in average per capita investment cost in 2030 and a 24% increase by 2050 compared to the LGGC-HEG scenario.



	2030	2040	2050	2030	2040	2050	2030	2040	2050
	LGGC-BAU			LGGC-HEG			LGGC-RU		
MG	0.11	0.40	0.15	0.10	0.36	0.14	0.11	0.36	0.14
S.APV	0.094	0.017	0.005	0.092	0.017	0.005	0.094	0.018	0.005
Grid	2.70	1.39	0.32	2.99	1.51	0.34	2.86	1.56	0.42

	2030	2040	2050	2030	2040	2050	2030	2040	2050
	HGGC-BAU			HGGC-HEG			HGGC-RU		
MG	0.54	1.22	0.33	0.53	1.24	0.34	0.53	1.26	0.39
S.APV	0.094	0.017	0.005	0.092	0.017	0.005	0.094	0.018	0.005
Grid	2.70	1.06	0.20	3.14	1.23	0.21	2.97	1.30	0.27

Figure 6: Discounted investment requirements by electrification technology type for each demand pathway under the LGGC (left) and HGGC (right) scenarios.

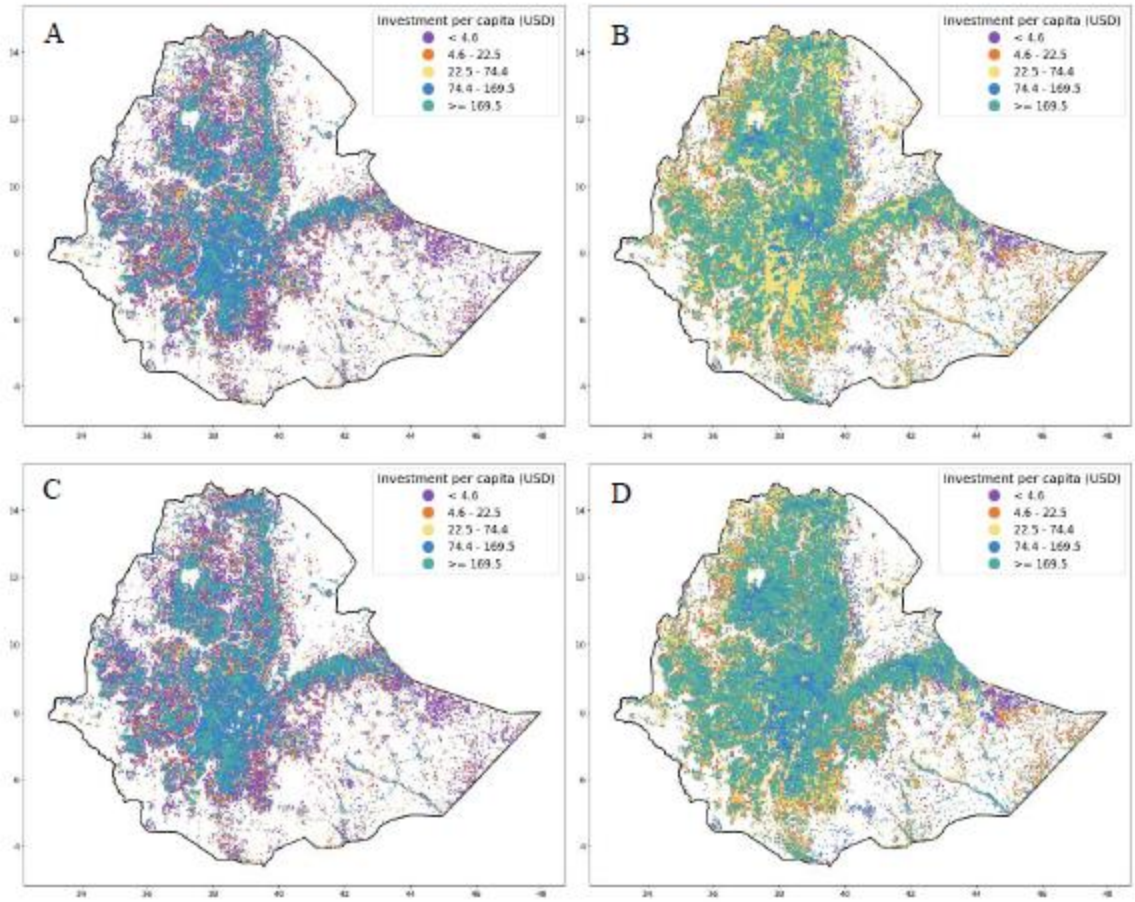


Figure 7: Spatial variation in investment cost per new connection under the LGGC-HEG (A and B) and HGGC-HEG (C and D) scenarios, showing costs in 2030 (A and C) and 2050 (B and D).

5. Discussion

This study explores optimal electrification strategies and their associated investment costs under different demand evolution and grid generation cost scenarios. The study employs a geospatial modeling framework that utilizes high-resolution geospatial data and settlement-level demand projections. This approach provides a detailed understanding of the spatial and temporal dynamics of least-cost electrification technology mixes across the study area over a 2021-2050 planning horizon.

The results show that grid extension is the least-cost option for the majority of Ethiopia's population across all developed scenarios. This outcome is likely due to the spatial proximity of the population to the national grid (more than 83% of the population lives within 5 km of MV or HV grid networks and more than 92% live within 10 km). However, the grid's share slightly declines as electrification target approaches universal access and grid expands to remote, low-demand settlements.

However, if grid generation comes at a higher cost, there is a large space for MGs [8]. Under the High Grid Generation Cost (HGGC) scenario, the share of the population served by grid declines to 66% by 2050, while MGs increase to 26%. These findings are consistent with similar studies in East Africa projecting a 4–37% MG share by 2030 [61]. The shift toward MGs is driven by two key trends: the increasing marginal cost of extending the grid to remote locations, and the assumed annual decline in solar technology capital costs. Spatial analysis reveals that technology choice is not only a function of distance to the grid but also of local demand and settlement characteristics. In areas even within 0.5–5.4 km of grid lines, SA PV and MG PV systems were identified as least-cost solutions for settlements with low population (35–412 people) and minimal electricity demand (4–191 kWh/HH/year), where the high per-connection cost renders grid extension economically unjustified despite physical proximity.

The study also analyzes the impact of different electricity demand pathways on the optimal technology mix. Despite considerable differences in aggregated electricity demand across BAU, HEG and RU pathways, the comparative analysis shows minimal changes in the optimal technology mix. The settlement level demand in these pathways may not be sufficient to surpass the economic thresholds that would favor a transition between SA PV, MG, or grid connection. However, incorporating demand from PUs and CIs alters the mix. In the LGGC scenario, grid extension share increases, while the share of SA PV systems declines, and MGs see a marginal increase. This shift is accompanied by an increase in total investment of up to 21.7%, rising from 2.6 to 3.2 billion USD in 2030 under the LGGC-HEG scenario. The HGGC scenario shows similar trends: grid share and MGs increase, while SA PV decreases, and investment up by 24.1% (e.g., from 3.0 billion to 3.8 billion USD in 2030 under HGGC-HEG), due to MGs and grid expansion.

Comparing our findings with existing literature requires careful consideration of methodological differences, including scope (total population vs. new connections), geographic focus (national vs. regional), and data resolution. Our finding of 67.4–68% (LGGC, 2030) of new connections via grid extension falls between the higher grid extension rates reported for Nigeria (86%) [6] and Bolivia (76.2%) [62], and the lower rate of 55% found in Cameroon [16]. The discrepancy with Mentis et al. [6] may be attributed to their use of lower-resolution population data (2.5 km), potentially overestimating grid viability in comparison to our high-resolution population data (30 m), which better captures rural settlement heterogeneity [63]. The role of SA PV systems for new connection in our analysis (29.3-29.7%) exceeds than that of Bolivia [62]. However, our results show more conservative off-grid deployment compared to studies in Malawi (67.4% off-grid PV for total population) [12] and parts of Nigeria (58.8% MG PV for new connections) [20]. These differences likely reflect variations in existing grid infrastructure coverage, resource availability, specific cost assumptions, and policy contexts.

Our findings diverge from earlier Ethiopia-specific studies that suggested higher grid extension shares (89% for new connections), Mentis et al. [13]. The lower share identified in this study reflects the influence of higher spatial resolution and more granular demand modeling. While Mentis et al. applied uniform electricity demand, Tier 3 for all rural areas and Tier 4 for urban areas by 2030, our study incorporates varying HH demand levels ranging from Tier 1 to Tier 4, capturing greater spatial and socioeconomic heterogeneity. Moreover, our results show off-grid

deployment (SA PV and MGs collectively) can serve not more than 34% of the population even in the most off-grid leaning HGGC scenario compared to Dalla Longa et al. [64], who reported off-grid technologies could serve 70% of the Ethiopian population by 2050. One possible reason could be Dalla Longa et al. only considering HV grid lines, whereas our study includes both HV and MV lines in the grid extension analysis.

Our findings underscore that a more realistic representation of local conditions, enabled by high-resolution spatial data, significantly shifts model outcomes toward decentralized solutions. This suggests that previous studies relying on lower-resolution data may have overestimated the role of grid extension. To the best of our knowledge, such trend was only reported by Bhattacharyya and Palit [63] and Isihak [15] who observed that models that use data at granular tend to favor off-grid technologies, while aggregated data often bias results toward grid-based approaches.

This study makes methodological contributions to rural electrification planning by integrating high-resolution spatial data, disaggregated electricity demand projections, and dynamic optimization. First, the use of HRSL population data (at 30 m resolution) to delineate population settlements, which forms the smallest spatial unit, better captures the realities of population distribution, The high-resolution population data enables a better spatial assignment of additional geospatial information, including terrain slope and elevation, proximity to roads and the electrical grid, renewable resource availability, and NTL intensity. This integrated, high-resolution geospatial base reduces spatial averaging effects, reflects local realities and allows the selection of electrification technologies that match local contexts. Second, electrification technology selection is informed by spatially disaggregated (using poverty and GDP maps) demand projections that account for HHs, PUs, and CIs. These projections also account for temperature impacts in warmer climates, with electricity demand increasing by 2% per 1°C rise above a 24°C baseline [40]. These spatially disaggregated electricity demands differ from many previous studies that relied solely on HH demand projections, and broad rural-urban classifications.

Despite its strengths, this study has limitations that warrant careful consideration when interpreting and applying the results. The reliability of the findings relies on the representativeness of the input data, much of which comes from publicly available geospatial datasets and remote sensing sources. Additionally, the temporal resolution of certain datasets may not align with the study's multi-year analysis, potentially introducing some degree of generalization. There are also limitations related

to the OnSSET modeling framework. Although OnSSET is effective for comparing the LCOE across various technologies at a national level, its technology capacity sizing is based on annual electricity demand and does not account for temporal variations like seasonal or daily electricity demand patterns and changes in renewable resource availability. Furthermore, the capital cost assumptions for different technologies are subject to uncertainties. In addition, although the research examines both low and high grid generation cost scenarios, future grid generation costs may differ due to unforeseen developments. Future electricity demand also presents uncertainties. The study incorporates three demand pathways, but demand may evolve differently, affecting the optimal electrification strategies and investment needs.

6. Conclusion

Optimizing national electrification strategies requires identifying technology solutions tailored to geographic, demographic, and economic contexts, a critical challenge for many developing countries like Ethiopia. Determining an appropriate mix and spatial deployment of grid extension versus off-grid systems is central to cost-effective rural electrification. This study employed OnSSET, a GIS-based tool to integrate high-resolution geospatial data, disaggregated electricity demand projections (from households, productive uses, and community institutions), and technoeconomic parameters in order to investigate cost-optimal electrification pathways for Ethiopia from 2021 to 2050. By analyzing different scenarios with varying demand growth and grid generation costs (Low Grid Generation Costs – LGGC and High Grid Generation Costs–HGGC), the research compared grid extension, MGs, and SA PV systems.

The findings reveal significant spatio-temporal dynamics in the optimal technology mix. In the initial phase (to 2030), grid extension emerges as the most cost-effective solution for a substantial majority (over 82% of the population under LGGC), particularly for settlements, on average, with over 600 people, over 390 kWh/household/year electricity demand, and located within 5 km of existing infrastructure. However, its relative share slightly decreases as electrification reaches more remote, sparsely populated areas (to approx. 79–80% by 2050 under LGGC). Under HGGC scenarios, the optimal technology mix shifts markedly. Higher costs reduce the attractiveness of extending the grid even in areas that are relatively proximate to existing lines, thereby boosting the competitiveness of decentralized solutions, particularly solar PV MGs. By 2050, MGs may

serve up to 26% of the population, while SA PV systems, although initially competitive (serving over 16% of the population in early phases), contribute a diminishing share over time. Our findings underscore that the utilization of high-resolution spatial data tends to increase the modeled share of decentralized solutions.

The research also highlights the importance of demand assessment beyond households. Incorporating electricity demand from productive uses and community institutions increases the relative share of grid extension by up to 6.8 percentage points while concurrently increasing overall investment requirements (up to 7.9%). Furthermore, the analysis confirms that while grid proximity is influential, local factors—such as population density, specific demand levels, renewable resource availability, and geographical constraints such as terrain, are decisive in determining the least-cost solution, sometimes favoring off-grid options even near existing lines.

Investment analysis further substantiates the spatio-temporal evolution of technology choices. Investment requirements over the whole modeling period are estimated to be between 5.17–5.54 billion USD under the LGGC scenarios and 6.12–6.8 billion USD under the HGGC scenarios. Over 50% of the investment is required in the initial stage (by 2030) when high-demand areas require substantial capacity additions. In the latter years of the planning horizon, investment requirements decline considerably, reflecting both the reduced size of the remaining unelectrified population and the compounding effects of a 10% annual discount rate applied to future expenditures.

This study underscores the necessity of dynamic, integrated, and spatially explicit electrification planning. Achieving cost-effective and sustainable universal electricity access necessitates strategies that adapt over time, leveraging a portfolio of technologies tailored to specific local conditions and responsive to evolving demand profiles, technology costs, and national grid economics. The use of high-resolution data and sectoral demand modeling, as employed in this study, provides crucial insights for developing such nuanced and effective national electrification roadmaps.

Credit Author Statement

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Appendix

Table A1: Input GIS datasets

Dataset	Data type	Spatial resolution	Description	Data source
Population	Raster	30m	High-resolution spatial identification and quantification of inhabited areas in the base year (2018). This data is critical for determining settlement locations and population density, essential for estimating electricity demand.	Meta Connectivity Lab and Columbia University [65]

Administrative boundaries	Polygon	-	National and subnational administrative boundaries, used to delineate regions for electrification planning	GADM V.4.0 (2018) [66]
Night-time light	Raster	~500m (around equator)	Night-time light intensity data, used as a proxy for existing electrification levels	VIIRS DNB (2020) [67]
(HV, MV substation and transformers)	Line/point shapefile	-	Georeferenced data on existing transmission and distribution lines, substations and transformers, crucial for assessing grid extension potential.	EEP and EEU
Land cover	Raster	~500 m	Land cover used to assess grid extension suitability.	MODIS Land Cover Product (MCD12Q1) V6 (2020) [68]
Terrain elevation and slope	Raster	30m	High-resolution elevation and slope data used to assess grid extension suitability.	GDEM (NASA and Japan Space Systems, 2019) [69]
Roads	lines	-	This helps determine grid extension suitability	Geofabric (2018) [70]
Mini/small hydro	Polygon	-	Potential sites for mini/small-scale hydropower installations, used for off-grid energy planning.	Energydata.info [53]
GHI	Raster	250m	To assess the solar PV MG and SA PV systems	Global Solar Atlas [48]
Wind speed	Raster	250m	Wind speed data at 100m were used to assess wind energy potential for mini-grid systems	Global Wind Atlas [49]

Table A2: Technoeconomic input parameters of off-grid generation technologies used in the model [16], [55], [36]

Technology	Capital cost (USD/kW)			Capacity factor (%)*	Lifetime (years)
	2021–2030	2030–2040	2040–2050		
Hydro MG	3000	3000	3000	50	30
Solar PV MG	2920	2482	2043	17-28%	20
Wind MG	3750	3375	3000	24-48%	20
Standalone (SA) PV systems					
- < 20 W	9620	8177	6734	17-28%	15
- 20 – 50 W	8780	7463	6146	17-28%	15
- 50—100 W	6380	5423	4466	17-28%	15
- 100 – 1000 W	4470	3800	3129	17-28%	15
- > 1 kW	6950	5908	4865	17-28%	15

*Capacity factors for wind and solar technologies are calculated based on the annual resource availability in each settlement by the OnSSET model.

Table A3: Grid generation capacity capital costs used in the model [8],[39].

Grid	2021–2030	2030–2040	2040–2050
Grid generation capacity capital cost (USD/kW)			
Grid (High)	4577	5624	2393
Grid (Low)	3196	2364	2285
Additional grid connection cost (USD/ HH)	150	150	150

For grid, 100% capacity factor is considered and lifetime 30 years.

Table A4: Transmission and distribution costs in the model [56], [9], [55]

Parameter	Value	Unit
HV line (69-132 kV)	53000	USDkm^{-1}
MV line (11-33 kV)	7000	USDkm^{-1}
LV line (0.2-0.4 kV)	4250	USDkm^{-1}
HV to MV substation (1000 kVA)	25000	USD/unit

MV to LV substation (400 kVA)	10000	USD/unit
Service transformer (50 kVA)	4250	USD/unit
Additional connection cost per household connected to grid	150	USD/HH
Additional connection cost per household connected to MG	125	USD/HH
Additional connection cost per household connected to SA	0	USD/HH
Grid transmission and distribution losses	12	%
Mini-grid distribution losses	5	%
O&M costs of distribution for Grid and MG	2	% of capital cost/year

Table B1: The share of newly electrified population by each technology.

Scenarios	Technology	% new connection in each year		
		2030	2040	2050
LGGC-BAU	Grid	67.4	66.5	83.2
	SA	29.8	23.0	8.1
	MG	2.8	10.5	8.6
LGGC-HEG	Grid	68.0	68.1	84.1
	SA	29.6	23.0	8.1
	MG	2.4	8.9	7.8
LGGC-RU	Grid	67.8	68.2	84.7
	SA	29.7	23.0	8.1
	MG	2.5	8.8	7.2
HGGC-BAU	Grid	57.4	42.8	71.3
	SA	29.8	23.0	8.1
	MG	12.7	34.2	20.6
HGGC-HEG	Grid	58.7	43.9	71.5
	SA	29.6	23.0	8.1
	MG	11.8	33.1	20.4
HGGC-RU	Grid	58.2	43.9	71.4
	SA	29.7	23.0	8.1
	MG	12.1	33.1	20.5