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Long-term least-cost geospatial electrification planning to bridge the electricity access gap: the case of Ethiopia

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Abstract

Expanding electricity access cost-effectively requires strategies that account for spatial heterogeneity in demand, resource availability, and proximity to infrastructure. However, many existing studies oversimplify electrification planning by applying binary rural–urban categorizations and neglecting productive and institutional electricity loads. This study developed a long-term electrification plan at the settlement level, utilizing the Open-Source Spatial Electrification Tool to identify the least-cost solutions among grid extension, mini-grids (MGs), and standalone photovoltaic solar (SA PV) systems. Settlements were delineated by aggregating the high-resolution settlement layer (∼30 m resolution) and then enriched it with georeferenced resource data (solar irradiation, wind speeds, hydropower potential) and existing grid networks. Using a myopic optimization approach across three distinct periods (2021–2030, 2030–2040, and 2040–2050), the study analyzed multiple scenarios developed by combining varying electricity demand and grid generation costs. Under a low grid generation cost scenario, grid extension is the least-cost option for more than 82% of the population by 2030, though its share declines slightly in later periods. Under a high grid generation cost scenario, MGs become competitive for about 26% of the population by 2050. SA PV systems emerge as the least-cost option for over 16% of the population in both scenarios by 2030 but become less competitive in later periods. The findings emphasize the need for integrated national planning that combines grid expansion with MG deployment, while gradually phasing out SA PV systems. This approach accelerates the deployment of solutions tailored to local contexts, directly contributing to the achievement of Sustainable Development Goal 7.

1. Introduction

Global electricity access has improved, with the number of people lacking it reduced considerably over the past decade [1–3]. However, access remains uneven across regions. In particular, sub-Saharan Africa (SSA) has experienced rapid population growth that has outpaced electrification efforts [4]. Projections indicate that if progress continues at its current pace, approx. 660 million people, predominantly residing in SSA, will still lack electricity by 2030. This shortfall jeopardizes the achievement of the United Nations' 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 make traditional grid extension challenging because of substantial per capita investment requirements [6]. In response, many countries have adopted integrated electrification strategies that combine on-grid and off-grid solutions (e.g. mini-grids (MGs) and standalone photovoltaic (SA PV) systems) [7]. Nevertheless,identifying the most cost-optimal[3] electrification solution for any given location requires careful consideration of a multitude of spatial factors. These factors include local energy resource availability, proximity to existing infrastructure, prevailing electricity demand levels, population density, land cover types, and topography [8, 9]. Grid extension costs, for instance, are sensitive to geospatial characteristics, such as proximity to roads and substations, land cover type, elevation, and slope. These factors can collectively increase grid extension investments by as much as 30%, independent of electricity demand levels [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 speed, and nearby river flow.

To navigate this complexity and determine the most cost-effective mix of electrification technologies, geospatial electrification models have become valuable tools [9, 11–13]. These models leverage geographic information systems (GISs) to integrate diverse geospatial datasets with technoeconomic parameters [14]. This integration enables least-cost analysis that compares grid extension with off-grid alternatives. These models can provide optimized recommendations for each location at the lowest overall cost [15]. Additionally, electrification planning tools are essential for identifying cost-effective technology mixes, informing investment decisions, and shaping policy frameworks [16].

However, existing geospatial electrification planning studies have critical limitations. A key limitation lies in the way spatial electricity demand is represented. Many countrywide electrification planning studies rely on uniform electricity demand assumptions based on a binary rural–urban categorization [6, 15, 17, 18]. These studies have assigned uniform consumption targets, based on the multi-tier framework, to both categories without accounting for variations in local economic and climatic conditions. Other studies have even applied a single demand level across all SSA countries [9, 19]. This oversimplification may lead to misaligned supply capacities and local demand [20, 21]. Even when spatial demand variation is considered, many existing studies focus only on residential demand, neglecting productive use (PU) and community institution (CI) loads that influence system sizing and economic viability [13, 22].

In addition, the spatial resolution of input data significantly affects 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 [23]. 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 a spatial resolution of 2.5 km have identified grid extension as the least-cost option for 86% of new connections in Nigeria and 89%–93% in Ethiopia [6, 15]. In contrast, high-resolution data captures fine-scale settlement distributions and environmental constraints, resulting in a more realistic representation of rural geography and cost assessment. In this regard, a study in Malawi [13], 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 SDG 7) [6, 15, 24, 25]. However, the lack of iterative and incremental planning in this approach limits its ability to support the phased development of electricity infrastructure over the long term [26]. 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 aligns better with investment cycles, institutional capacities, and evolving socioeconomic conditions [27].

Addressing these gaps requires developing electrification plans that incorporate: (i) spatially disaggregated demand projections, not only from households (HHs) but also from PUs and CIs, while factoring in the effect of local climate conditions on electricity demand; (ii) high-resolution geospatial datasets that better 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?

[3] 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.

- 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 in a given region. 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 and 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 comprises three interconnected key phases, namely model selection and development, spatial electricity demand projection, and evaluation of least-cost electrification options. 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 [28]. 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 (REM) tool was guided by the need to address specific planning questions, spatial details, and data availability. Several electrification planning tools are available in the literature, including GEOSIM, Network Planner, the REM, and the Open-Source Spatial Electrification Toolkit (OnSSET). Each model has unique capabilities and limitations with respect to spatial resolution, technology flexibility, and data requirements.

GEOSIM is an integrated geospatial tool developed using proprietary GIS software (Manifold) designed to optimize large-scale energy service delivery [13]. 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' [29]. Following this initial assessment and once demand is forecasted for the planning horizon, the model evaluates electrification options, including grid extension and decentralized systems based on diesel, wind, biomass, and hydropower [30]. However, GEOSIM lacks support for solar-based MGs, a significant omission given the importance of solar resources in many rural contexts in SSA [31]. Moreover, its reliance on proprietary software limits its accessibility, reproducibility, and adaptability [32]. Network Planner is a free, web-based tool that determines the least-cost grid extension layout and electrification options [33]. It considers grid extension, SA PV, solar MGs, and diesel generators [34]. However, it does not support wind or hydro MGs, limiting its use in diverse renewable resource areas [35].

REM is a tool used to optimize detailed engineering designs for electrification plans. It integrates geospatial data, electricity demand, and technology costs [36]. It compares grid connections, solar MGs, and SA PV systems at the individual customer level [24]. However, it requires extensive input data, such as georeferenced building footprints and demand profiles, and is computationally intensive [16]. Additionally, its non-open-source nature limits transparency, adaptability, and reproducibility [37]. These constraints make REM better suited for localized or high-resolution planning exercises than for 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, MGs (solar PV, wind, diesel, or hydropower), and standalone systems (solar PV, diesel) [9, 13, 15]. It integrates a wide array of spatial data, including infrastructure, terrain, energy resource maps, and

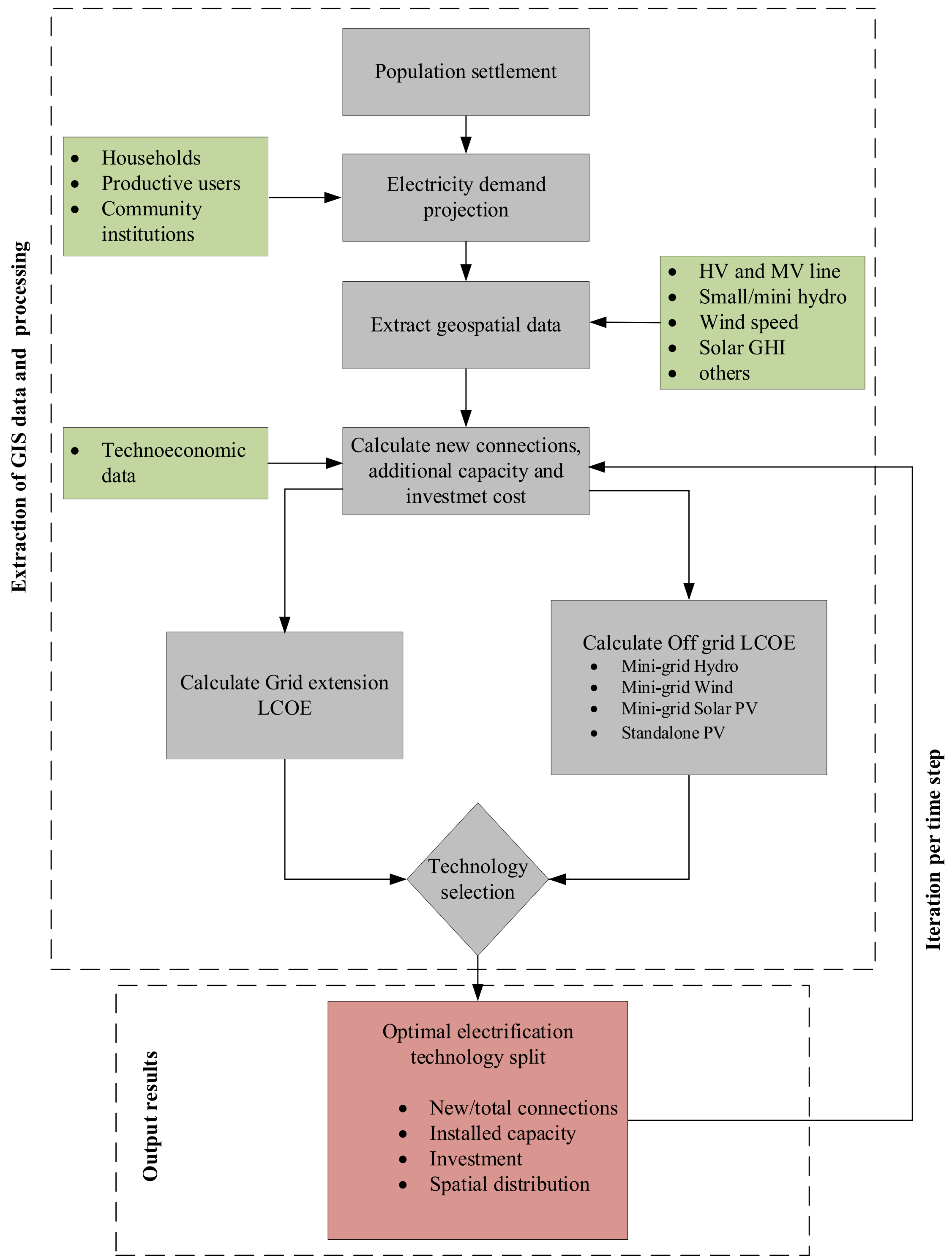


Figure 1. Workflow of the geospatial electrification analysis in this paper using OnSSET. Colors indicate input data (green), processing steps (gray), and outputs (red).

population distributions, to determine the least-cost electrification solution at the settlement level while achieving targeted national electricity access [6, 9]. Furthermore, the open-source design of OnSSET ensures transparency, reproducibility, and adaptability to diverse case studies [38]. Due to its comprehensive technological coverage, ability to perform nationwide settlement-level analysis, well-documented guidelines on the developer's website, and open-source nature, 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, from 2021 to 2050. The model is set up in three time steps: 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 step, and so on [13].

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 [13]. 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[4], 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 (approximately 30 m) gridded population estimates, while the NTL data offers a proxy for electrification status. Administrative boundaries were used to constrain the analysis to the spatial extent of the study area. The HRSL raster data was 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* [39]. 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 [39].

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 [15]. This classification employed a GIS-based multi-criteria heuristic, drawing on spatial data on population distribution, existing low-voltage (LV) distribution transformers, and NTL intensity, in conjunction with national grid access statistics [13].

The classification was based on the assumption that settlements located within a certain distance of the existing LV transformer infrastructure 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 μW cm^{-2} sr^{-1} and a population over 650 is equal to the grid-electrified population at national level (national grid access of 40.4% in the base year, derived from extrapolations of the World Bank Energy Sector Management Assistance Program (ESMAP) (2018) [40] and African Development Bank (AfDB) (2020) data [41]).

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 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 [13]. 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 travel time to large cities [38, 42]. 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-steps. 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),

[4] 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.

$$N_{\text{conn},t} = \begin{cases} \text{Pop}_t - \text{Pop}_{t-1} & \text{if electrified} \\ \text{Pop}_t & \text{if unelectrified} \end{cases} \tag{1}$$

$$E_{\text{new},t} = E_{\text{pc},t}\, x\, N_{\text{conn},t} \tag{2}$$

where, $N_{\text{conn},t}$ is the number of people in the settlements that require 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. $E_{\text{pc},t}$ 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 hydro MGs). 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 a settlement at each time-step is given by equation (5),

$$\Delta E_t = \left(E_{\text{pc},t} - E_{\text{pc},t-1}\right) x \left(\text{Pop}_t - N_{\text{conn},t}\right) \tag{3}$$

$$E_{\text{add},t} = E_{\text{new},t} + \Delta E_t \tag{4}$$

$$E_{\text{tot},t} = \begin{cases} E_{\text{add},t} + E_{\text{met},t} & \text{Exp}_t < t \\ E_{\text{add},t} & \text{otherwise} \end{cases} \tag{5}$$

where ΔE_t is incremental demand at time t, $E_{\text{add},t}$ is additional demand at time t, $E_{\text{tot},t}$ is total demand of a settlement at time t, and $E_{\text{met},t}$ 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 infrastructures operate 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 $N_{\text{conn},t}$. The installed capacity required to meet the total settlement demand is calculated as equation (6),

$$C_{\text{inst},t} = \frac{E_{\text{tot},t}}{8760 \times \text{ CF } \times \text{ BPR } \times (1 - L_{\text{dist}})}\,. \tag{6}$$

Here, $C_{\text{inst},t}$ is installed capacity at time t, CF is the capacity factor, which differs depending on the supply source (provided in tables A2 and A3), and distribution losses (L_{dist}) reflect the percentage of energy lost during transmission and distribution (T&D), and the assumed values are presented in appendix table A4. BPR refers to the base-to-peak ratio (see table 3).

The BPR is a measure of the flatness of the load profile, defined as the ratio of the average load (base) to the peak (maximum) load over a given period. A higher BPR indicates a flatter, more stable load profile, while a lower BPR indicates greater variability and higher peaks relative to the base load. Since generation infrastructure must be sized to meet the peak demand, in each settlement it is estimated by dividing the average annual energy ($E_{\text{tot},t}$) by BPR (see [13]).

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 T&D infrastructure costs, as shown in equation (7),

$$\text{Investment}_{\text{cost},t} = C_{\text{inst},t}\, x\text{cap}_{\text{cost},t} + td_{\text{cost}} x \text{ PF} \tag{7}$$

where $\text{Cap}_{\text{cost},t}$ represents the technology-specific capacity cost (USD/kW) and td_{cost} represents the T&D 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 HH 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 HH level without any 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 costs of LV distribution lines, transformers, and end-user connections. 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, 43]. Conversely, settlements located in favorable environments with flat terrain, close proximity to roads, and near substations incur minimal cost penalties.

2.7. LCOE

The LCOE is used for comparing the relative cost-effectiveness of various electrification technologies in rural electrification planning [44]. It represents the per-unit cost (USD/kWh) of supplying electricity, accounting for all costs incurred over a technology's operational lifetime [25]. 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),

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{I_{\mathrm{cost},t} + \mathrm{O\&M}_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_{\mathrm{tot},t}}{(1+r)^t}}. \tag{8}$$

Here, $I_{\mathrm{cost},t}$ is the upfront investment cost derived from equation (7), $\mathrm{O\&M}_t$ 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. $E_{\mathrm{tot},t}$ 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 (the average national cost of grid electricity in USD/kWh). To address these uncertainties, different demand evolution and grid generation cost scenarios can be developed [13, 45].

2.9.1. Electricity demand scenarios

Future spatial electricity demand at the settlement level is calculated as an aggregate of three essential load components, including HHs, PUs, and CIs (see details in [46]). 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.

Table 1. Grid generation costs for 2030, 2040, and 2050 [8, 45].

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

Each scenario is modeled using multiple linear regression (MLR), which incorporates the assumptions of key demand drivers (equation (9) [46]. Additionally, the demand projection model incorporates spatial temperatures and global warming projections to account for increased electricity demand in warmer climates.

$$D = \beta_0 + \beta_1 \left(\text{Rural electricity}_{\text{access}}\right) + \beta_2 \left(\text{GDP}_{\text{percapita}}\right) + \beta_3 \left(\text{Urban population}_{\text{percentage}}\right) + \varepsilon \quad (9)$$

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 [45]. This cost can be influenced by factors such as technological advancements, economies of scale, and the national energy mix [13]. 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 selected as the case for this study due to a confluence of factors, including low electricity access, significant rural–urban population disparity, and abundant but underutilized renewable energy resources that make it a compelling environment for achieving universal electricity access.

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% [47]. This leaves about 55 million people lacking electricity access, making it one of the countries with the largest number of people without access globally, after Nigeria (86 million) and the Democratic Republic of Congo (76 million) [48]. Additionally, the country's 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 [49, 50]. The per capita electricity consumption also remains critically low at approx. 100 kWh yr^{-1}, placing it among the lowest globally [51, 52]. The challenge is further compounded by significant regional disparities in access. While the capital, Addis Ababa, has nearly 100% access, pastoral regions such as Afar and Somali lag far behind [53].

Ethiopia's electrification efforts were guided by the National Electrification Plan (NEP 2.0), launched in 2019, which outlined a roadmap to achieve universal electricity access by 2025 [54]. 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 SA PV systems and MGs. By 2030, NEP 2.0 envisions that 96% of HHs to be connected to the grid, and 4% to be supplied by off-grid technologies [54].

However, the latest reports show that national access (% of population) is 55.4% [47]. This gap between policy targets and current conditions is the core premise for the scenarios and long-horizon analysis that follow. Population growth, adding approx. 410 000 new HHs yearly, outpaces grid connections, which only connect around 220 000 new HHs annually, widening the access gap, particularly in rural areas where grid expansion remains economically challenging [55]. This gap between targets and realities is a core premise for the scenarios and long-horizon analysis that follow. Moreover, the grid supply falls short of demand, resulting in load shedding and blackouts [15].

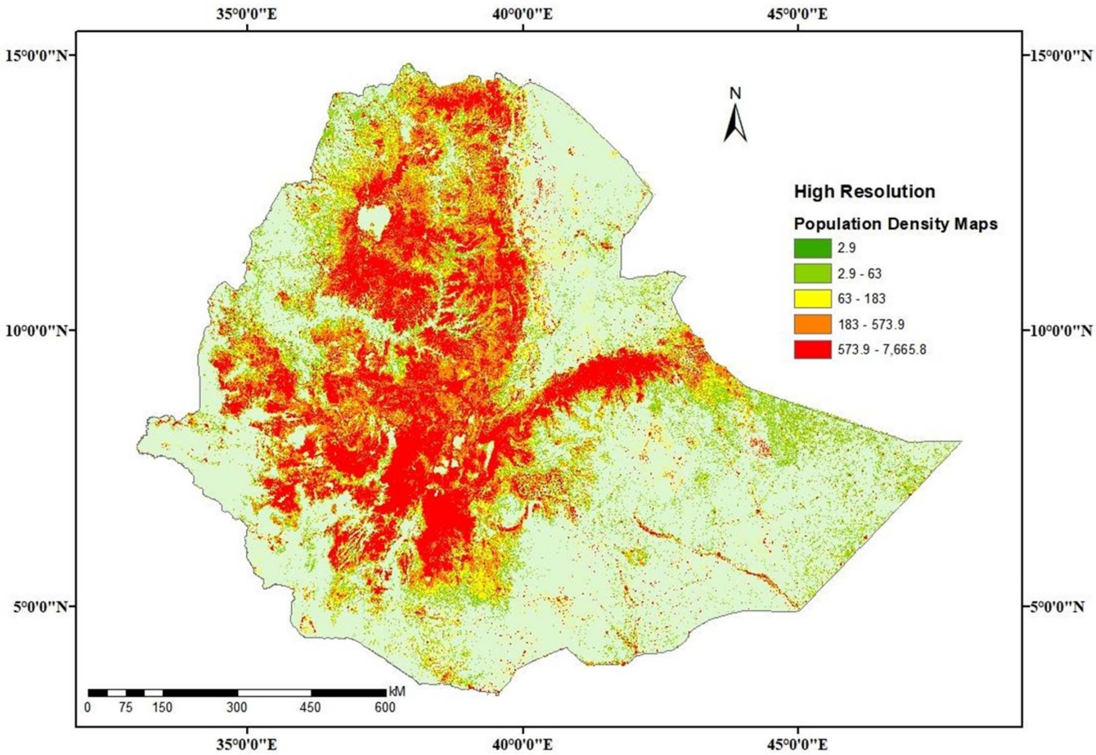


Figure 2. Population distribution in Ethiopia (at a resolution of 30 m) based on HRSL 2018 raster data [10]. Reproduced from [10]. CC BY 4.0.

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 population density, existing grid infrastructures, renewable energy resources, and relevant geographical features [56]. Figure 2 shows Ethiopia's 2018 HRSL population. A complete list of the GIS data used in the study, 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 approx. 6397 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[5]) and Ethiopia's Electric Utility (EEU[6]). The geographical distribution and spatial extent of the existing grid infrastructure across Ethiopia are shown in figure 3. The appearance of some transformers being disconnected from the main powerlines, particularly in the southeastern part of the country, is attributed to two main reasons: data fragmentation and local power sources. The geospatial data compiled by the utilities (EEP and EEU) for the distribution network might be fragmented or incomplete. In addition, certain transformers in the region are associated with local off-grid supply systems that operate independently of the national grid network.

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 [57]. Wind energy potential is evaluated using wind speed data from the Global Wind Atlas at a height of 100 m [58]. This data is then adjusted to a height of 55 m using the logarithmic wind profile method

[5] 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.

[6] 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.

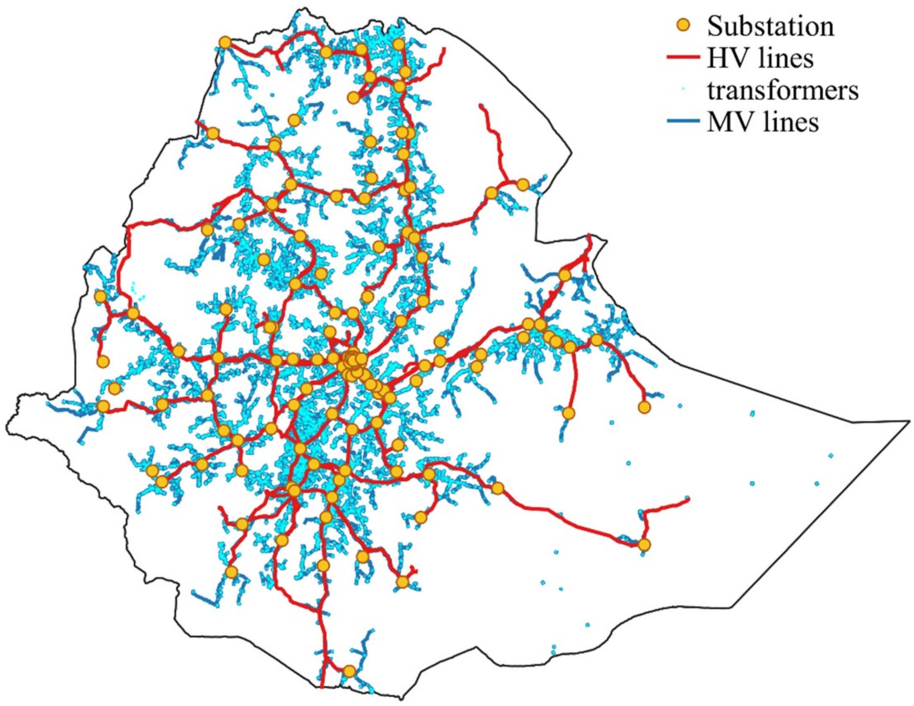


Figure 3. Existing HV and MV lines, substations, and transformers georeferenced data.

embedded within the OnSSET model [59]. MG wind systems were modeled based on the Vestas V44 turbine (600 kW), commonly used in small-scale wind power generation [60, 61]. For hydro MGs, data on small and mini-hydro potential, ranging from 0.01 to 10 MW was acquired from Energydata.info [62]. 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 [63].

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 PF [10]. All GIS data inputs are then extracted for each population settlement using the OnSSET_GIS_Extraction_notebook [38].

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, 42, 64, 65]. Grid generation and capital costs were derived from Sahlberg *et al*'s Ethiopia-specific projections across multiple time steps [8]. Grid T&D costs were compiled from various sources, including the Global Electrification Platform (GEP) [64], Mentis *et al* [9], and Korkovelos *et al* [65]. 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 [66]. Projections from the 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 [18, 42], and [64]. Wind MG costs are projected to decline by 1% annually, in line with global trends for small-scale wind systems [67]. 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, operation and maintenance (O&M), and technology lifetimes across the analysis horizon. The model uses system-level and technology-specific capital cost, O&M, and operational lifetime parameters derived

Table 2. Projected electricity demand under three scenarios for 2030, 2040, and 2050, including the influence of temperature. The base year (2021) consumption is 7400 GWh [46].

Scenario	Projected demand (GWh) 2030	2040	2050	Growth rate (2021–2050)	AAGR (%)
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

from recent electrification planning studies in Ethiopia and SSA [10, 18, 64]. Component-level lifespans, such as the shorter life of batteries, are handled by incorporating their replacement costs into the O&M costs, which are then annualized over the system's operational lifetime.

Grid generation cost assumptions are informed by the work of Sahlberg *et al* [8] and Pappis *et al* [45], who employed soft-linking 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. The distinction between the two scenarios is driven by three main underlying parameters: the assumed grid generation capacity capital costs (see table A3), different discount rates, and varying projections for electricity demand evolution. Specifically, the LGGC scenario utilizes a 10% discount rate and predicates higher annual electricity demand growth, whereas the HGGC scenario applies a 20% discount rate and assumes annual electricity demand growth [45].

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).

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 PUs essential for long-term economic development. A recent study by Stevanato *et al* [68], has highlighted that while SA PV 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 SA PV systems to support high-power appliances required for income-generating activities. Their findings indicate that treating SA PV 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 HHs, in line with previous findings [7, 69]. This strategy ensures that larger settlements gradually shift toward MGs or grid extensions, capable of supporting community development and economic productivity.

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 HHs between 2030 and 2040. In the long term, from 2040 to 2050, the threshold is further reduced to settlements with fewer than 30 HHs. Recent innovations, however, such as mesh-grid configurations, have shown promise in extending the capability of SA PV systems to support higher-power appliances.

Table 3. Key modeling assumptions [13, 41].

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 SA PV

The chosen BPR values are justified by the distinct characteristics of the load profiles and consumer behavior associated with each technology's service [38]. The national grid has the lowest BPR (0.8) due to its diverse, aggregated load and high, less-controllable peak demands; MGs have an intermediate BPR (0.85) due to localized loads and moderate peak variation; and SA PV have the highest BPR (0.9) because of user-enforced load management and highly limited power availability, resulting in a flatter, more predictable consumption pattern.

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 4). 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 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.

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 5(A)), 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^{-1} 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

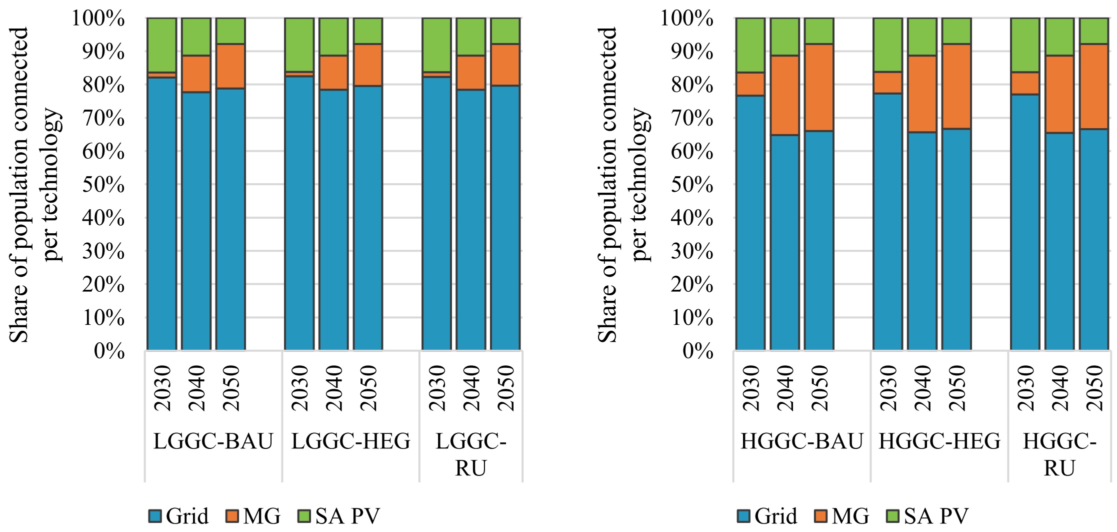


Figure 4. Share of total population per technology under the LGGC (left) and HGGC (right) scenarios for the three demand pathways (BAU, HEG, and RU) for the periods 2030, 2040, and 2050.

17.5 kWh HH yr^{-1}, 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 (5B), 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 km^2 area, located 120 km from the capital Addis Ababa, shows SA PV systems emerge as the least-cost option for 18% of newly electrified settlements by 2030 (figure 5(C)), even within close proximity (0.5–5.4 km) to existing grid lines. 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 5(D)), 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 results in a different spatial distribution of optimal electrification technologies. By 2030 (figure 6(A)), 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 6(B)), 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 6(C)), 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 6(D)), 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.

4.3. Investment requirements

Discounted to the base year, the total investments are estimated to range between 5.2 and 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 investment requirements can be disaggregated into two main categories. First, new electrification in previously unelectrified settlements demands 3.4–3.5 billion USD under LGGC scenarios and 3.7–4.0 billion USD under HGGC scenarios. Second,

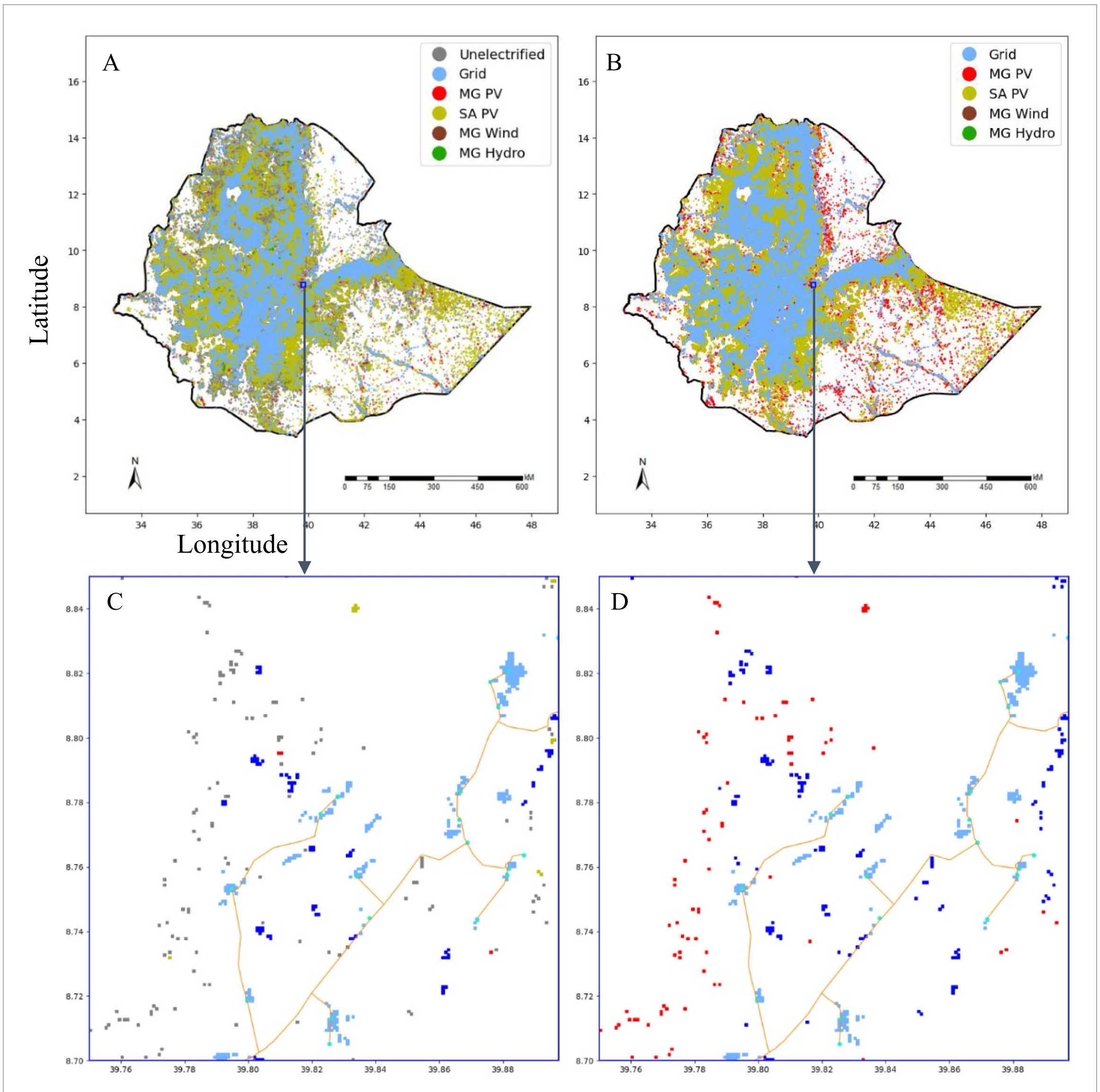


Figure 5. Spatial distribution of the least-cost electrification technology under LGGC-RU scenario for the periods 2030 (A) and 2050 (B). Figures C and D provide zoomed-in views of the blue box in Figures A and B, respectively. Color coding: dark blue represents newly grid extension recommended settlements, 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.

additional capacity needs in already electrified settlements require 1.8–2.1 billion USD under LGGC scenarios and 2.5–2.9 billion USD under HGGC scenarios.

The distribution of discounted investment by technology evolves over time (figure 7). 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.

The total cost for grid extension is composed of generation capacity costs (USD/kW) and the associated T&D infrastructure costs. The T&D component includes upfront capital costs for HV, MV, and LV transmission lines, which are calculated using cost per unit length (USD/km). It also includes unit costs for substations and transformers (USD/unit), and a fixed cost per HH (USD/HH) for the final end-user connection. This is also adjusted by a geospatial PF to reflect the real-world difficulty of deployment based on geographic and environmental characteristics.

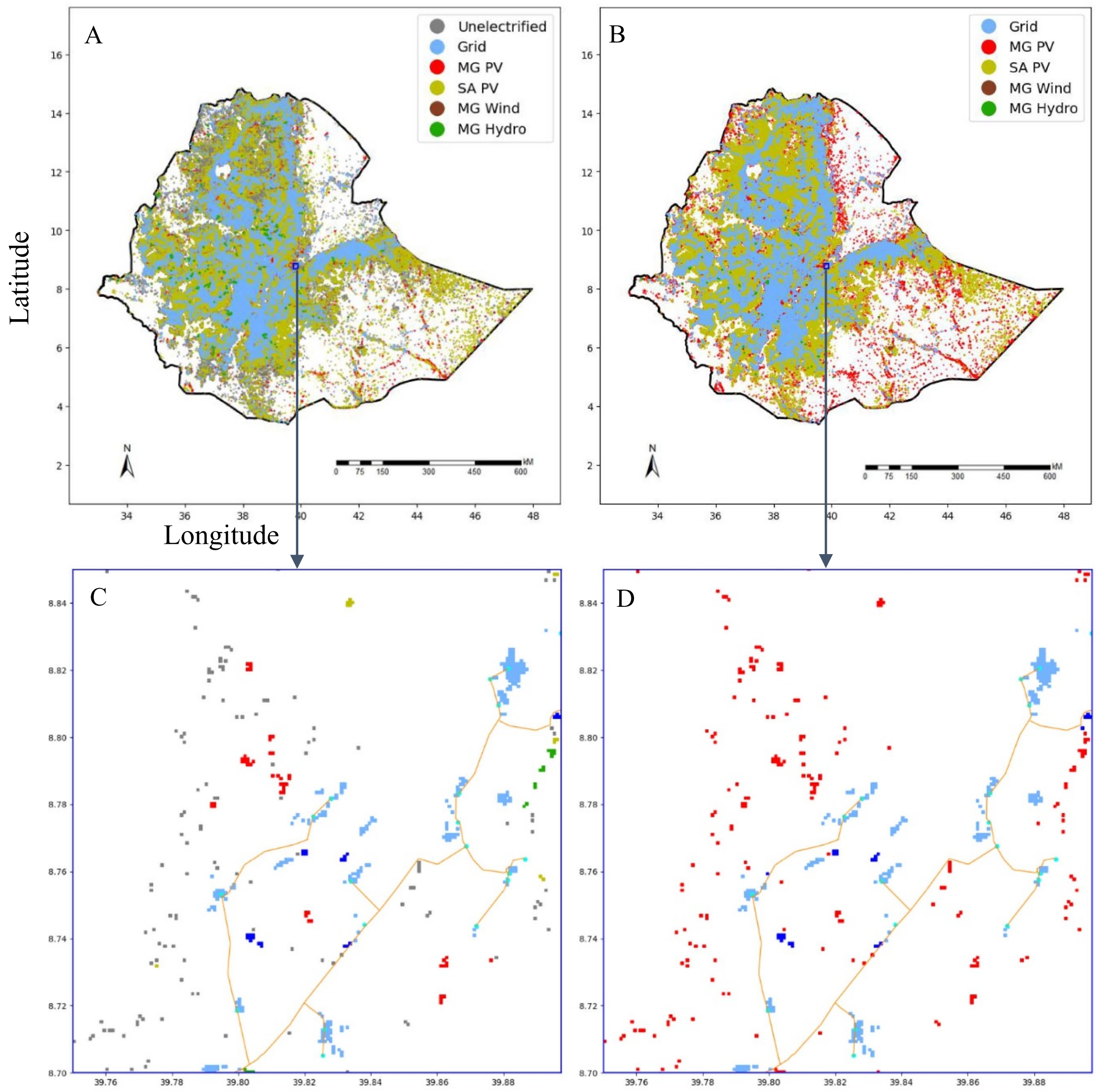


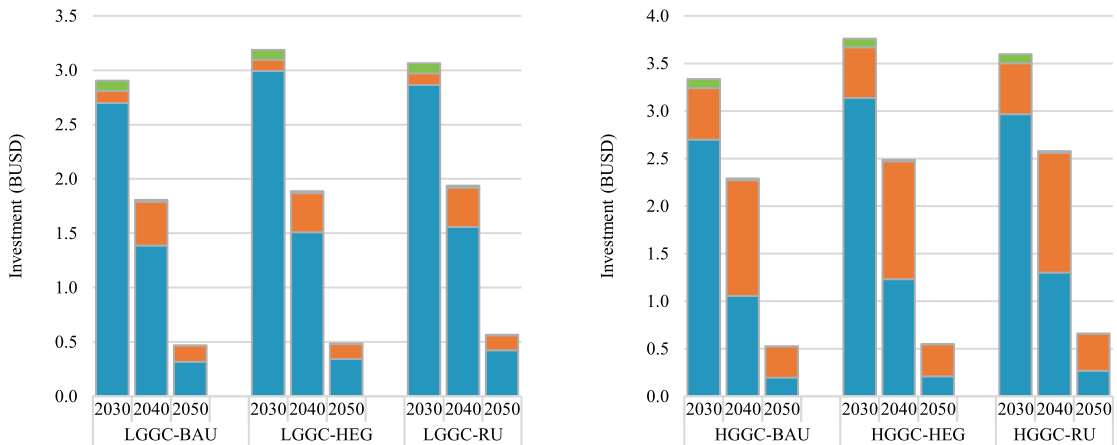
Figure 6. Spatial distribution of the least-cost optimization technology in Ethiopia under HGGC-RU scenario for the periods 2030 (A) and 2050 (B). Figures (C) and (D) provide zoomed-in views of figures (A) and (B), respectively.

A spatial analysis of discounted investment per new connection reveals disparities across scenarios and over time (figure 8). Under the LGGC-HEG scenario, the national average discounted 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 discounted per capita investment cost in 2030 and a 24% increase by 2050 compared to the LGGC-HEG scenario.

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, particularly by 2030. 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 (averaging 614 people and 394 kWh HH yr^{-1}). Second, there are extensive grid networks already in place in Ethiopia, and the proximity of a high proportion of population to existing grid



	LGGC-BAU 2030	LGGC-BAU 2040	LGGC-BAU 2050	LGGC-HEG 2030	LGGC-HEG 2040	LGGC-HEG 2050	LGGC-RU 2030	LGGC-RU 2040	LGGC-RU 2050
SA PV	0.09	0.01	0.00	0.09	0.01	0.00	0.09	0.01	0.00
MG	0.11	0.40	0.15	0.10	0.36	0.14	0.11	0.36	0.14
Grid	2.70	1.39	0.32	2.99	1.51	0.34	2.86	1.56	0.42

	HGGC-BAU 2030	HGGC-BAU 2040	HGGC-BAU 2050	HGGC-HEG 2030	HGGC-HEG 2040	HGGC-HEG 2050	HGGC-RU 2030	HGGC-RU 2040	HGGC-RU 2050
SA PV	0.09	0.01	0.00	0.09	0.01	0.00	0.09	0.01	0.00
MG	0.54	1.22	0.33	0.53	1.24	0.34	0.53	1.26	0.39
Grid	2.70	1.06	0.20	3.14	1.23	0.21	2.97	1.30	0.27

Figure 7. Discounted investment requirements by electrification technology type for each demand pathway under the LGGC (left) and HGGC (right) scenarios for the periods 2030, 2040, and 2050.

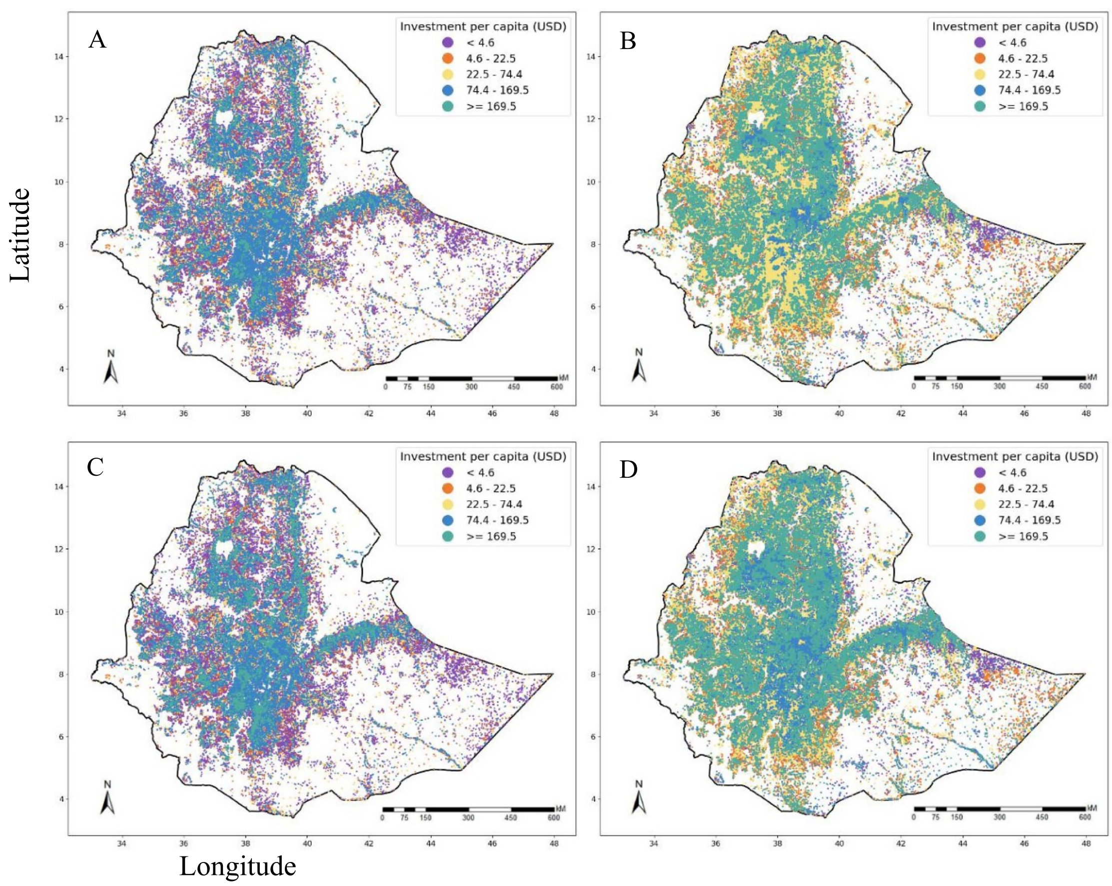


Figure 8. Spatial variation in investment cost per new connection under the LGGC-HEG (A) and (B) and HGGC-HEG (C) and (D) scenarios showing costs in 2030 (A) and (C) and 2050 (B) and (D).

infrastructure (more than 83% of the population lives within 5 km of MV or HV grid networks, and more than 92% live within 10 km). The grid connection in this phase minimizes T&D line costs, securing its least-cost advantage.

As the national access target moves toward universal coverage by 2050, all settlements previously identified as having the highest per capita investment requirements are expected to be electrified.

Simultaneously, the assumed declining cost of off-grid solutions contributes to grid share declining slightly over time. For instance, Solar PV MG capital costs are assumed to have a 30% reduction in capital costs over the period, falling from 2,920 USD/kW to 2043 USD/kW. This MG cost decline, along with the assumed increasing grid generation costs, drives the temporal shift in the optimal technology mix by 2050. Under LGGC, the grid's share declines slightly to approximately 79%–80% by 2050, while MGs capture the most expensive-to-reach settlements, increasing their population share from under 2% to 12%–13%.

However, if grid generation comes at a higher cost, there is a large space for MGs [8]. Under the 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 [70]. 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 existing grid but also of local resource availability, demand, settlement size, and geographical constraints. For instance, 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 and favorable solar resources (GHI > 6 kWh m^{-2} d^{-1}), low population (35–412 people) and minimal electricity demand (4–191 kWh HH yr^{-1}). In these situations, the high per-connection cost of grid extension renders it economically unjustified despite physical proximity. The inclusion of geospatial factors, such as distance from substation and road, terrain slope, elevation, and land cover, is crucial because these factors increase the T&D costs for grid extension by a range of 2.3%−29% across Ethiopia [10]. This detailed, settlement-level modeling of spatial heterogeneity, facilitated by high-resolution data (like the 30 m population density map), is what allows the results to significantly shift toward decentralized solutions.

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. The transition from LGGC to HGGC scenarios increases total investment requirements by 21%, representing a significant burden for an already capital-constrained country.

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. The study's 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%) [71], and the lower rate of 55% found in Cameroon [18]. 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 [72]. The role of SA PV systems for new connections in our analysis (29.3%–29.7%) exceeds than that of Bolivia [71]. However, our results show more conservative off-grid deployment compared to studies in Malawi (67.4% off-grid PV for total population) [13] and parts of Nigeria (58.8% MG PV for new connections) [24]. 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* [15]. 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* [73], 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. The results of this study also suggest a significant divergence from Ethiopia's NEP 2.0 targets, which aim for near-universal grid access (96% grid and 4% off-grid solutions) by 2030 [54]. The least-cost analysis, even under the financially favorable LGGC scenario, finds a substantially different optimal mix by that year, suggesting up to 83% grid and 17% off-grid solutions. Notably, the results under HGGC scenario by 2050 (67% grid and 33% off-grid solutions) align more closely with the NEP 2.0's earlier target for 2025 (65% grid and 35% off-grid).

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 a trend was only reported by Bhattacharyya and Palit [72] and Isihak [17], who observed that models that use data at a granular level tend to favor off-grid technologies, while aggregated data often biases 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 form the smallest spatial unit, better captures the realities of population distribution. This 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 [46]. 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 need 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. While our technoeconomic parameters are derived from Ethiopia-specific studies [8, 9, 64] and operational solar MG project data, they represent point estimates that may not fully capture ongoing market dynamics. Capital costs for mature technologies, such as hydro MGs, are assumed to remain constant over the planning horizon, without explicitly modeling inflation, currency depreciation, or changes in import tariffs. While plausible cost escalation could increase absolute investment requirements, the limited share of hydro MGs in the least-cost solution space implies that such uncertainty would have a negligible influence on national-level technology allocation outcomes. In addition, although the research examines both low and HGGC scenarios, future grid generation costs may differ due to unforeseen developments in fuel prices, technological breakthroughs, or policy shifts. 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. The MLR used for demand projections (equation (9)) relies on limited predictors, which may underrepresent the spatial heterogeneity in economic activity across Ethiopia. Specifically, the model does not incorporate the elasticity of electricity demand to income, shifts in appliance ownership, or specific industrial growth patterns, which could lead to non-linear demand surges not captured here.

Additionally, the assumed unidirectional progression (SA PV → MG → Grid) may be refined by considering interconnected MGs (IMGs) as an intermediate state between isolated MGs and centralized grid connection. While this study models MGs as isolated systems, Wu *et al* [74] highlight that clustering neighboring MGs with complementary load profiles can deliver important techno-economic benefits. Wu *et al*'s analysis of three clustered MGs in Ethiopia's Southern Nations, Nationalities, and Peoples' region demonstrated that while overall system net present cost increased by 6.4% due to interconnection infrastructure, the system benefited from substantial component-level savings: PV capital costs fell by 30.1%, battery costs by 44%, and converter costs by 34.1% compared to operating the same villages as isolated MGs. Critically, the largest village in their cluster experienced a reduction in LCOE from 0.109 USD/kWh to 0.108 USD/kWh (approximately 1%), while simultaneously achieving improved reliability through reduced unmet load (from 7.1% to 6.3%) and better utilization of renewable resources. If we conservatively assume that clustering could reduce MG PV LCOE by 1% (based on Wu *et al*'s

Ethiopia-specific finding for the largest village), this could increase the share of MGs. Assuming a 20% cost reduction for MG PV, we estimate the MG share under LGGC could increase from 12% to approximately 19%–20% by 2050, with similar proportional increases under HGGC scenarios.

Moreover, this study treats electrification as a purely technoeconomic optimization, and thus, it does not explicitly model or quantify the broader development and climate co-benefits associated with the expansion of renewable-based solutions. While the electrification technologies considered are renewable-based, including the grid, which is predominately supplied by hydro, wind and geothermal in Ethiopia, the positive impacts on other SDGs such as job creation (SDG 8), improved health outcomes from reduced indoor air pollution (SDG 3), enhanced educational opportunities (SDG 4), and climate change mitigation (SDG 13) are not calculated or assessed within the scope of this analysis. Moreover, governance and grid reliability constraints that heavily affect real-world feasibility are not taken into account. The model also assumes unconstrained investment flows and neglects implementation lags. The transition from MG to grid extension is determined purely by LCOE. Critical non-economic considerations, such as social acceptability, service quality, and reliability of the current service remain unexamined. In reality, customer willingness to transition often depends on the perceived service reliability and the social acceptance of the new provider, factors not accounted for in this strictly cost-based optimization.

Implementation bottlenecks further constrain electrification 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 [41]. Off-grid developers face policy uncertainty, limited access to finance, and unpredictable demand patterns [5, 26]. Regulatory inconsistencies such as overlapping concessions, inadequate tariffs, or unclear licensing processes also deter private sector participation. Finally, the study's focus on technoeconomic optimization means that the broader implications of electrification strategies for land use and environmental consequences are not analyzed within the current scope.

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 HHs, PUs, and CIs), 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 (LGGCs and HGGCs), 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 HH yr^{-1} electricity demand, and settlements 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. The 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 HHs. Incorporating electricity demand from PUs and CIs 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), as 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.

The findings from this detailed geospatial analysis carry substantial policy implications that can guide strategic decision-making in Ethiopia's national electrification program. The core result—that the optimal technology mix is highly sensitive to local conditions, demand profiles, and economic parameters—challenges uniform, top-down policy approaches. The finding that off-grid solutions can be cost-optimal even within 5 km of existing grid infrastructure suggests a need to revise NEP 2.0, which currently targets grid extension for all communities within a 25 km radius of the existing network. In the short term (up to 2030), grid extension efforts should prioritize settlements meeting specific criteria: populations exceeding 600 residents, demand above 390 kWh HH yr^{-1}, and location within 5 km of existing grid lines. Simultaneously, SA PV systems should serve as interim solutions for sparsely populated areas with fewer than 150 residents and low average demands of 18 kWh HH yr^{-1}. In the medium term (2031–2040), electrification efforts should increasingly incorporate solar MGs, particularly in settlements with annual HH demand above 185 kWh and strong solar resources (average daily GHI of 5.8 kWh m^{-2}). Although this study models MGs as isolated systems, emerging evidence suggests that IMG approaches can reduce component level costs by reducing generation redundancy, sharing storage capacity, and smoothing demand through complementary load profiles. Policy frameworks for this period should therefore begin to explicitly support IMGs as a potentially more cost-effective and scalable alternative to isolated MG deployment. In the long term (to 2050), new SA PV systems should be limited to settlements with demand below 4.8 kWh/HH/year, while ensuring larger settlements receive grid or MG connections capable of supporting productive electricity uses crucial for sustained economic growth.

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. Overall, the study provides a data-driven, long-term, and spatially explicit modeling framework for identifying cost-optimal electrification pathways and phased investment strategies tailored to Ethiopia's diverse local realities. In doing so, it directly contributes to SDG 7 and co-benefits toward SDG 13.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

Data preprocessing available at https://doi.org/10.1088/2634-4505/ae5556/data1.

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Appendix

Table A1. Input GIS datasets.

Dataset	Data type	Spatial resolution	Description	Data source
Population	Raster	30 m	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 [75]
Administrative boundaries	Polygon	—	National and subnational administrative boundaries, used to delineate regions for electrification planning	GADM V.4.0 (2018) [76]
Night-time light	Raster	~500 m (around equator)	Night-time light intensity data, used as a proxy for existing electrification levels	VIIRS DNB (2020) [77]
(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) [78]
Terrain elevation and slope	Raster	30 m	High-resolution elevation and slope data used to assess grid extension suitability.	GDEM (NASA and Japan SpaceSystems, 2019) [79]
Roads	Lines	—	This helps determine grid extension suitability	Geofabric (2018) [80]
Mini/small hydro	Polygon	—	Potential sites for mini/small-scale hydropower installations, used for off-grid energy planning.	Energydata.info [62]
GHI	Raster	250 m	To assess the solar PV MG and SA PV systems	Global Solar Atlas [57]
Wind speed	Raster	250 m	Wind speed data at 100 m were used to assess wind energy potential for mini-grid systems	Global Wind Atlas [58]

Table A2. Technoeconomic input parameters of off-grid generation technologies used in the model [18, 42, 64].

	Capital cost (USD/kW)				
Technology	2021–2030	2030–2040	2040–2050	Capacity factor (%)[a]	Lifetime (years)
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

[a] 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, 45].

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 [9, 64, 65].

Parameter	Value	Unit
HV line (69–132 kV)	53 000	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)	25 000	USD/unit
MV to LV substation (400 kVA)	10 000	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.

		% new connection in each year		
Scenarios	Technology	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

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