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National electricity planning in settings with low pre-existing grid coverage: Development of a spatial model and case study of Kenya

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ABSTRACT

We develop a spatial electricity planning model to guide grid expansion in countries with low preexisting electricity coverage. The model can be used to rapidly estimate connection costs and compare different regions and communities. Inputs that are modeled include electricity demand, costs, and geographic characteristics. The spatial nature of the model permits accurate representation of the existing electricity network and population distribution, which form the basis for future expansion decisions. The methodology and model assumptions are illustrated using country-specific data from Kenya. Results show that under most geographic conditions, extension of the national grid is less costly than off-grid options. Based on realistic penetration rates for Kenya, we estimate an average connection cost of \$1900 per household, with lower-cost connection opportunities around major cities and in denser rural regions. In areas with an adequate pre-existing medium-voltage backbone, we estimate that over 30% of households could be connected for less than \$1000 per connection through infilling. The penetration rate, an exogenous factor chosen by electricity planners, is found to have a large effect on household connection costs, often outweighing socio-economic and spatial factors such as interhousehold distance, per-household demand, and proximity to the national grid.

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1. Introduction

The International Energy Agency estimates that 1.6 billion people worldwide have no access to electricity. In Sub-Saharan Africa (SSA), fewer than 10% of rural households have electricity connections, and many rural social institutions, including schools and health clinics, also lack access.¹ Governments of countries in SSA are now emphasizing the critical role that electricity services play in human development, and this emphasis has coincided with a greater awareness of the suitability of off-grid options for remote, rural populations. Given the increasing population densities of many rural areas, planners need tools to make rapid assessments of the cost-effectiveness of grid expansion and other technology options without having to undertake multi-year rural electrification studies. A model that combines basic information on electricity demand and costs with geographic variability in population density and other factors can demonstrate how different settlement patterns affect the costs of each technology option and help planners prioritize areas for grid expansion.

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Energy planners often spend substantial time and resources to obtain reasonably accurate estimates of electrification costs in particular administrative units or regions. This includes assessing whether grid or off-grid options are more suitable and establishing levels of financial support for national, district, or local contributions. Engineering studies that estimate costs by producing a "bill of materials" needed for an electrification project typically require detailed assessments that incorporate the physical location of each structure to be electrified. Depending on the scope of the project, this might include a large number of households, institutions, and other infrastructure. The expense of acquiring this level of detail can be prohibitively high, precluding rapid, yet informed, planning and policy decisions.

In this paper, we combine insights from engineering and planning to develop a methodology for electricity planning that incorporates detailed spatial information, allowing for rapid comparison of technologies while providing reasonably accurate cost estimates. The methodology preserves spatial granularity to the smallest spatial unit at which data are generally available. In the case of Kenya, this was a "sublocation," which typically represents 5000 to 10,000 people in an area smaller than 15 km².

The methodology can guide national policy decisions by helping planners compare different regions, select appropriate areas for grid expansion and application of other technologies, estimate costs, and set reasonable electrification targets and

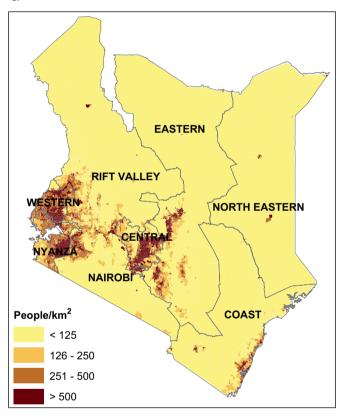
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¹ Excluding South Africa.

timelines. The methodology can also help to determine the appropriate public sector contribution to electrification as countries shift from state-dominated power systems to private ownership and market-driven investment (World Bank, 2002; Rufin et al., 2003; Victor and Heller, eds., 2006; Modi et al., 2006).

We apply the methodology to the case of Kenya, a country of 36 million, the bulk in the western portion of the country that includes the dense and sprawling city of Nairobi and high-density rural regions in the Western and Nyanza provinces (Fig. 1). More than half the population resides in 3% of Kenya's land area and lives at densities of more than 500 people/km², and over 90% of the population lives at densities higher than 125 people/km². We find, given the high density of many rural regions and the current

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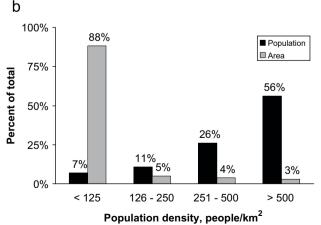


Fig. 1. Kenya's population distribution. (a) Population density, computed as the ratio of sublocation population to sublocation area. The sublocation is the smallest administrative unit in Kenya. (b) Percent of total population that resides in sublocations with specified population density ranges. The percent of the total area of the country at each specified population density range is also shown.

electricity demand and cost structure in Kenya, national grid expansion tends to be more cost-effective than off-grid options.

1.1. Electricity planning in SSA

In SSA, most urban centers have electricity access, but rural coverage is uneven and inadequate. In such cases, there are several alternative frameworks to guide planning. These include integrated rural development (electricity is treated as a component of infrastructure development), area coverage (quickly reach as many customers in a particular area as possible), grid extension (prioritize households close to the grid), isolated generation (evaluate local generation sources in remote regions), and intensification (focus on adding connections in electrified areas) (Munasinghe, 1988). Regardless of which approach is chosen, a first step is to understand where people live and how best to reach them given existing infrastructure; this suggests distribution planning as the natural starting point for a national analysis.

Geographic information systems (GIS), a powerful tool for analyzing information on where and how people live, can be used to improve peoples' access to services and markets. For this reason, GIS systems are being employed in development planning in SSA in a range of sectors, including electricity planning efforts. A recent Ugandan study, for example, mapped energy demand centers and developed a ranking system to prioritize locations based on the number of households and institutions (Kaijuka, 2007). This study used maps to visualize the distribution of households and institutions, but did not incorporate spatial information into a planning model. Therefore, we distinguish our approach from planning efforts that use GIS solely as an organizational or visualization tool.

Efforts to further develop grid electricity infrastructure in SSA face a range of financial, technical and institutional challenges including lack of access to capital, poor coordination across sectors and institutions, and high levels of poverty resulting in low ability to pay for services (Haanyika, 2006). Moreover, electrification by itself has not always lived up to the touted development benefits (World Bank Independent Evaluation Group, 2008). Addressing these issues is mostly beyond the scope of this paper. Instead, we ask: What is the most cost-effective way to reach the target population regardless of projected impacts on development. We do make some accommodation for ability to pay by adjusting electricity demand levels based on poverty data and utility company estimates, but this is done exogenously and does not factor into the definition of cost-effective.

1.2. Background on Kenya's power sector

In 1997, Kenya's vertically integrated electricity industry was split into the Kenya Electricity Generation Company (KenGen) and Kenya Power and Lighting Company (KPLC), with the Energy Regulatory Commission responsible for industry supervision. Both companies are now publicly traded on the Nairobi stock exchange, but the government remains the majority shareholder. KPLC, which owns and operates the national transmission and distribution system, purchases electricity from KenGen and Independent Power Producers (IPPs). KenGen generates about 80% of the electricity consumed in Kenya, approximately 62% of which comes from hydropower, 26% from fossil sources, and 12% from geothermal plants in the Rift Valley (Kenya Electricity Generation Company (KenGen), 2008). Most hydro stations are located along the Tana River and its tributaries, with thermal plants (diesel and natural gas) in Nairobi and Mombasa. In 2007, KPLC's effective system capacity of 1045 MW had attained a peak of 976 MW (KPLC, 2007a).

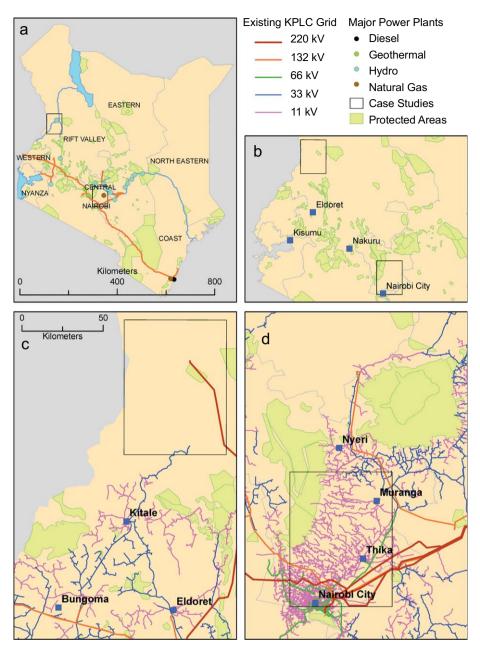


Fig. 2. Kenya's national electricity grid as of October 2007. (a) High voltage transmission network. (b) Outlines of areas of detail shown in subfigures c and d. (c) Detailed view of an area for grid extension in the western part of the Rift Valley. (d) Detailed view of an area for infilling around Nairobi.

KPLC's high-voltage transmission network connects the major urban centers of Nairobi, Mombasa, Nakuru, Eldoret and Kisumu (Fig. 2). These cities, along with the agriculturally productive rural areas around Mount Kenya, have better medium-voltage (MV) coverage than other parts of the country.² In these areas, the penetration rate (defined as the percentage of households with a

grid connection) can reach 30%. In other rural areas – home to three-quarters of Kenya's population – existing lines are insufficient and penetration rates remain below 10% and sometimes much lower. Much of the north and east of the country is arid, and there are no grid lines.

Approximately 12% of Kenya's 8 million households were connected to the KPLC national grid as of October 2007, with some additional households connected to KPLC's mini-grids in Lamu and Garissa and other locally managed mini-grids. Another 2–4% of households have access to an alternative source of electricity.³ Most of these households have a battery-based system (BBS), and some BBS systems are connected to solar PV cells. Although Kenya

² KPLC maintains a digitized and georeferenced version of its high- and medium-voltage distribution network (220, 132, 66, 33 and 11 kV lines), last updated in October 2007. The data were received directly from KPLC as AutoCAD files and then converted to shapefiles. In addition to existing grid lines, the dataset included 33 and 11 kV grid lines under construction. These lines were digitized by the Ministry of Energy as part of the 1996/97 Rural Electrification Master Plan. Most have now been built and thus were considered part of the existing distribution network. Original KPLC data were cleaned and simplified to create a continuous medium-voltage network passing through demand nodes representing sublocations that currently have access to electricity.

³ World Bank (2006) estimated a 14.5% national electrification rate for Kenya when households with access to any kind of electricity services were included.

has one of the most developed PV markets in East Africa, knowledge on effective use and long-term maintenance is not widely understood leading to frustrations with PV systems including variation in power availability and short battery life.

Between June 2006 and October 2007, KPLC added nearly 170,000 new customers, reaching a total of 971,038 connections (Muhammad, 2007). Considering that there were just 67,000 new connections between 2005 and 2006, and fewer than 50,000 in each previous year (KPLC, 2007b), this represented unprecedented growth and was achieved largely through a rapid connection program managed by foreign executives brought in at the government's behest. As part of the coverage expansion, KPLC connected a backlog of tens of thousands of households on waiting lists, indicating strong demand for electricity despite the high connection prices charged by KPLC.

Ambitious targets laid out in Sessional Paper No. 4 (as cited in World Bank, 2006) call for a 20% household electrification rate by 2010 and a 40% rate by 2020. Kenya's population is growing by approximately 2.3% per year, adding close to 200,000 households each year. To meet the targets, Kenya will need to connect well

over this number of customers on an annual basis. Achieving the Millennium Development Goals (MDGs) will also require a focus on connecting all schools, health institutions and other social infrastructure, with deployment of decentralized technologies in more remote and sparsely populated areas.

Several recent documents have addressed Kenya's plans for increasing electricity coverage. These include the Least Cost Development Plan of KPLC (2007a), Project Prospectus of the Ministry of Energy (2007) and a World Bank (2006) study on rural electrification in Kenya. The last of these studies provides institutional context for coverage expansion as well as a discussion of financing and policy options.

Our work is distinguished from previous efforts in its spatial approach to electricity planning, and its effort to bridge the gap between engineering and planning. Traditionally, engineers have been concerned with technical requirements and costs of rural power whereas planners have focused on the need for geographic coverage, equity, and rural development. Our model combines analytical techniques from both disciplines to create a mutual understanding across their different perspectives.

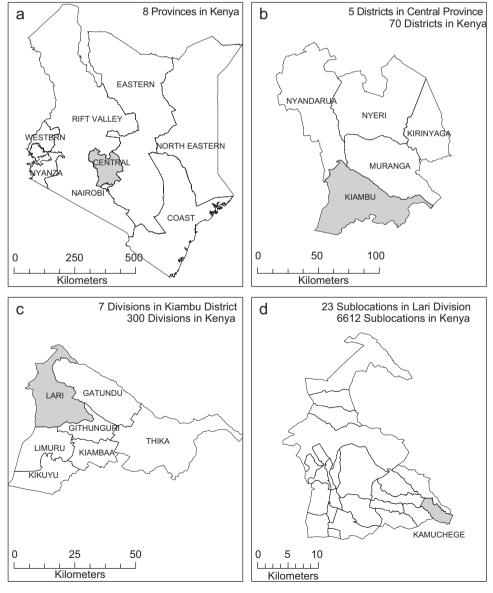


Fig. 3. Administrative units of Kenya and their typical geographic extent. (a) Provinces. (b) Districts. (c) Divisions. (d) Sublocations.

2. Spatial electricity planning and costing model

Our model determines the least-cost technology - either grid electrification or an off-grid alternative - to connect each population center, which we refer to as a demand node. To rapidly provide reasonable cost estimates, the model reduces the computational complexity from millions of households to several thousand demand nodes, generally allowing the smallest political administrative unit in a country to be used (e.g. village, department or sublocation depending on the country's political organization). This allows for the incorporation of detailed demographic and socio-economic data often available at a much higher spatial resolution than the province or district, while still permitting rapid planning by aggregating households. In the model, we represent each of Kenya's 6612 sublocations as a discrete demand node.⁴ The average sublocation is less than 15 km², though some sparsely populated sublocations are many times larger and dense sublocations tend to be less than $10 \,\mathrm{km}^2$ (Fig. 3).

The model is not meant to replace detailed engineering analyses of grid roll out, including load-flow analysis, which would be needed as part of the implementation process, so it cannot be used as a stand-alone implementation tool.⁵ Instead the model can be used to guide electrification planning within Ministries, Rural Electrification Agencies and donor organizations.

2.1. Comparison of technology costs

Our model first estimates the cost of achieving a target level of penetration in each demand node. We compare the cost of grid electrification to two possible decentralized, off-grid technologies: (1) diesel mini-grids with low-voltage (LV) distribution lines and secondary medium-voltage lines if needed; and (2) standalone solar photovoltaic (PV) systems for households combined with a diesel generator in the market center to meet productive demand.⁶ In both the grid electrification and diesel mini-grid scenarios, MV line is defined as power distribution line at a voltage of 33 or 11 kV and LV line is defined as distribution line at a voltage lower than 500 V. Although micro-hydro and wind power are other viable options in some parts of Kenya, solar PV and diesel were chosen because their costs are reasonably well understood, and because they could be implemented in any part of the country.⁷

We develop a demand model to estimate the additional domestic, productive and institutional consumption within each node based on the number of households and institutions to electrify, and their unit demands, and include a coincidence factor

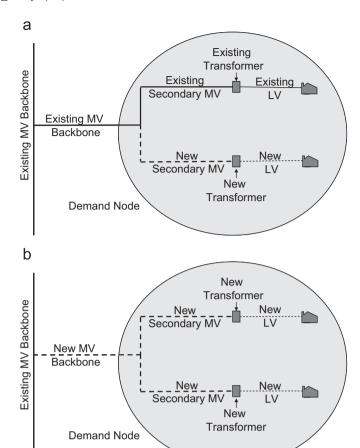


Fig. 4. Nomenclature assigned for national grid extension architecture. (a) Infilling in demand nodes with existing MV line. (b) Grid extension in demand nodes without existing MV line. Note that each demand node represents a sublocation.

to account for different user peaks associated with different activities occurring at different times.⁸ We then estimate the net present value of the 10-year discounted capital and maintenance costs for each technology option based on the unit costs of appropriately sized equipment.⁹

⁴ Kenya has 6612 sublocations represented by 6783 polygons. The original georeferenced file obtained from the Columbia Earth Institute contained a greater number of polygons, but was cleaned to remove duplicate data. Some sublocations are represented by multiple polygons; in this case, the total population of the sublocations was apportioned to the polygons based on relative area. Only sublocations with population greater than 0 were used in the model. These sublocations are represented by 6737 polygons.

⁵ We chose a cost minimization approach rather than a benefit maximization approach because tabulation of costs is more straightforward and objective compared with assessing location-specific benefits in SSA. Results of the model could be incorporated into a full cost-benefit analysis.

⁶ In the solar PV plus diesel option, individual solar PV systems are used to electrify individual households and institutions while a diesel generator is used to meet productive demand. Linking solar PV systems through LV distribution lines is not considered attractive because the benefits from scale economies are insignificant compared to the cost of the wire.

 $^{^7}$ According to the International Small-Hydro Atlas, there are six micro-hydro (<10 MW) plants in Kenya, with a total capacity of 13.64 MW, and half of Kenya's potential hydropower capacity of 6000 MW is located on small rivers where additional micro-hydro plants could be developed (IEA, 2009). Therefore, although they are not considered in this paper, decentralized micro-hydro plants could play an important role in the expansion of Kenya's electricity sector.

⁸ The coincidence factor indicates the percentage of total demand that occurs during peak hours. It accounts for the fact that different user peaks associated with different activities and equipment occur at different times. Note that in the case of infilling, we assume that productive and institutional demands are already met, so we include only the cost of connecting additional households. In unconnected nodes, we include an estimate of the cost of meeting productive demand and connecting social institutions including schools and health centers.

⁹ Technologies are compared based on total aggregate demand for a demand node (sublocation). We compare technologies over a 10-year time horizon regardless of when each sublocation is connected. This means that if an area is connected only in year 9 of the 10-year horizon, the underlying technology choice is still based on 10 years of system operation rather than a single year of system operation. Projected peak demand incorporates 10 years of population growth, but not economic growth. In all cases, the cost of the technology includes transportation and installation of equipment. In the case of grid extension, capital costs cover MV line and transformers, poles, LV line to connect households and institutions, and indoor household equipment such as wire and lamps; costs do not include generation and high-voltage transmission, reinforcement of the existing distribution network, or institutional capacity building. The diesel minigrid cost structure is similar to national grid extension but includes the cost of an appropriately sized diesel generator for the community. Solar PV plus diesel capital costs include solar panels and batteries for domestic demand and a diesel generator for productive demand. Note that since the decentralized options are stand-alone systems of distribution, costs associated with generating electricity using solar PV and/or a diesel generator are included. In the case of grid extension, generation costs are included indirectly through the cost of MV electricity purchases.

This technology comparison step permits the identification of demand nodes where national grid extension is the most costeffective technology option. Costs of grid extension are broken up into two major elements (Fig. 4). The first component is the cost of extending an MV line from an existing distribution network to an MV-to-LV transformer. We refer to this component as extension of the MV backbone. The second component is the cost of connecting households and institutions within the demand node, including the cost of secondary MV line internal to the node, MV-to-LV transformers, LV line and internal household wiring. This component covers costs internal to the node, which for brevity we refer to as the "internal cost." Estimation of the internal cost takes into account the spatial area of the demand node and average interhousehold distance, both of which affect the amount of secondary MV line, as well as LV line and transformers, required to connect households within the node. 10 The internal cost also includes a tariff representing cost recovery of generation and transmission expenses. 11 Splitting the costs into these two components makes sense from a practical standpoint since many countries are considering the franchisee model, with concessions limited to one or more demand nodes building out from the backbone.

In nodes that have an existing MV backbone, increasing the penetration rate through additional grid connections is generally more cost-effective than the decentralized options. New connections in these nodes are referred to as *infilling*, and our estimate of internal cost includes an evaluation of whether additional secondary MV line is needed to support the new connections. Utilities, through practice, have already recognized areas with an MV backbone as economically viable for grid expansion, and sometimes refer to this mode of extension as "intensification" in contrast with "extensification" in cases where new MV backbone is needed.

In nodes with no existing MV backbone, we first compare the costs of the two decentralized options and identify the lower cost off-grid technology. Note that in principle this comparison can be carried out for decentralized options other than those considered here. We then compare the cost of the identified decentralized technology with the internal cost of grid electrification. If the decentralized option is the lower cost choice even before considering the cost of extending the MV backbone, then clearly this location is not viable for grid extension. However, if the internal cost is lower than the decentralized option, then the difference in cost provides a decision metric, MVmax, defined as the maximum length of MV backbone that would be cost-effective to build such that the overall cost of grid extension is equal to the lower cost decentralized option. The metric is node specific and provides a simple estimate of how far the existing MV backbone can be extended to reach this node.

2.2. Grid extension algorithm and grid compatibility

The computed *MVmax* metric, along with the location of demand nodes relative to one another and the existing grid, can

then be used to identify all the grid compatible nodes. If extension of the national grid is the cheapest way to electrify a demand node, it is defined as grid compatible.¹³

The grid extension algorithm is based on Kruskal's minimum spanning tree (Nesetril et al., 2001 translation of Boruvka, 1926). Boruvka's work was motivated by a contemporary problem in Czechoslovakia: economic construction of power networks to connect cities. The basic problem is: Join n points in a given space such that any two points are either joined directly or by means of some other points and the total length of the network is the shortest possible (Nesetril et al., 2001).

We relax the constraint that *all* points must be connected to allow for the existence of alternative technologies that do not require networking. Instead, we connect only the points (demand nodes) for which networking is the most cost-effective option. The algorithm searches over the whole space and selects connections by moving from the shortest possible connection to the longest possible connection. Small demand nodes that might be passed over in an algorithm that adds connections by moving sequentially outward from the existing grid can become grouped into larger demand hubs that become part of the extended grid (Fig. 5). This may increase the total number of nodes classified as grid compatible.¹⁴

Two relations drive our algorithm:

the algorithm.

- (1) For each non-connected demand node, n, connect if $distance_{n,g} \leq MV_{\max_n}$ and the connection does not created loop where $distance_{n,g}$ is the distance between node n and the closest point on the grid, g, where the closest point might be part of the existing grid or a node previously connected by
- (2) For each newly connected group of nodes $MV\max_k = MV\max_i + MV\max_i distance_{i,j}$ where $distance_{i,j}$ is the distance between nodes i and j. $MV\max_k$ is the adjusted $MV\max$ value for a demand group containing nodes i and j.

The algorithm is an example of combinatorial optimization where the objective is to find the least-cost electricity network given existing grid lines and a set of unconnected demand nodes. A recent paper applied similar techniques to the design of autonomous village-level power systems, ultimately using a combination of a minimum spanning tree and simulated annealing process to find a solution (Lambert and Hittle, 2000). Compared with our algorithm, the Lambert and Hittle approach is more detailed and computationally expensive, so it is better suited to analysis of small, sub-national areas.

3. Modeling electricity demand and costs in Kenya

Demand nodes and electrification costs were modeled for Kenya using demographic and poverty data along with unit

¹⁰ An adjustment factor is applied to account for the fact that electricity grid lines normally follow roads, and another countervailing factor accounts for clustering of population within the geographic area represented by the demand node

node.

11 The model does not account for reinforcement of the existing network or institutional costs associated with supporting a large number of additional connections.

¹² The digitized, georeferenced version of KPLC's grid that we had access to did not allow us to precisely determine the number of existing connections, if any, in each demand node (sublocation). Therefore, we assumed that any sublocation with existing MV line has at least some household connections. As utilities obtain increasingly detailed georeferenced data, this assumption could be modified. Using the model, we verified that in demand nodes with existing MV lines, additional grid electrification is cheaper than off-grid alternatives.

¹³ At present, we do not model lines of varying voltages, feeder lines, or reinforcement of the existing grid, nor do we consider generation or transmission needs to support the scale-up in distribution. The amount of line needed to connect the node is proxied by the straight-line distance between the demand node and the closest connection point on the grid.

¹⁴ Given this search pattern, the algorithm will generate mini-grids, i.e. sets of nodes that are connected to one another but that are not connected to the main network. Therefore, the program includes an option to clean out all mini-grids below a threshold number of connections defined by the user.

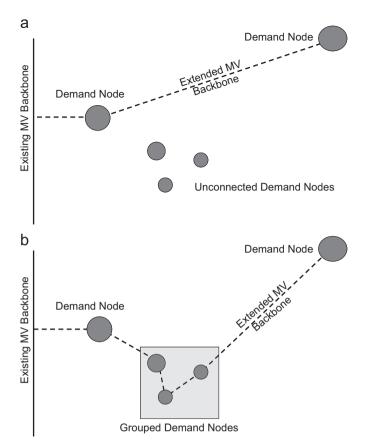


Fig. 5. Algorithmic grouping of demand nodes. (a) Schematic illustrating a sequential algorithm where nodes are not grouped. (b) Schematic illustrating the algorithm in this study, where nodes can be grouped.

demand and cost data obtained from a variety of sources. Since the sublocation was selected as the geographic unit for demand nodes, all data were obtained at or disaggregated to this spatial resolution.

3.1. Demand categories

In Kenya, household energy demand varies with income and population density, with higher-income and more densely-populated sublocations tending to have higher demand. Therefore, sublocations were classified into four demand categories, each with different household and productive demand levels (Table 1). These categories replace the more traditional distinctions between urban, peri-urban and rural electrification and were developed through consultations with KPLC. Since much of Kenya's population is not nucleated into settlements, and since sublocation boundaries are not aligned with urban/rural boundaries, the demand classification was considered the most accurate method for estimating household demand in different parts of Kenya.

The classification was developed from population and poverty data. Population data collected by Kenya's Central Bureau of Statistics as part of a 1999 Census were projected forward to the base year of 2007 assuming an annual population growth rate of 2.3%. Sublocations with a population density below the median

Table 1Classification of sublocations into four demand categories.

Demand category	Population density (people/ km ²)	Poverty rate (%)	Household demand ^a (kWh/hh/ year)	Productive demand ^b (kWh/hh/ year)
Sparse, poor	<256	> 54	360	50
Sparse, non-poor	<256	< 54	600	100
Dense, poor	>256	> 54	360	75
Dense, non-poor	>256	< 54	1800	340

^a Household demand covers all energy consumed inside the home to power light bulbs, radios, TVs, etc.

of 256 people/km² were classified as low density and other sublocations as high density.

Poverty data were obtained from the Center for International Earth Science Information Network (CIESIN) at Columbia University at a spatial resolution of locations, which is one geographic level above sublocations. The Foster, Greer, and Thorbecke head-count index, which gives the proportion of each location's total population counted as poor, was selected as a poverty indicator. All sublocations in each location were assumed to have the same headcount index. Kenya's sublocations were classified into non-poor (<54% of the sublocation's population living below the poverty line, the median value) and poor. Sublocations with missing data were classified as poor.¹⁶

About 25% of sublocations were assigned to each of the four demand categories, but a greater share of the population is concentrated in dense sublocations (Fig. 6).

3.2. Modeling total demand and technology requirements within each node

Total peak demand for each node was estimated by summing up all household, productive and institutional demands and setting the coincidence factor equal to 75%. Household and productive demand estimates were based on the demand category. Institutional demand was estimated from data supplied by Kenya's Ministry of Education and Ministry of Health on the distribution of schools and health centers and their average energy consumption. Annual demand for each institution was assumed to range from 360 kWh/year for a small clinic to 15,000 kWh/year for a boarding school.¹⁷

¹⁵ Population data were obtained from the Columbia Earth Institute, though the original source was Kenya's Central Bureau of Statistics (CBS). The population growth rate of 2.3% was obtained from the World Bank's World Development Indicators database. No distinction was made between urban and rural population growth. The base year used for projection was 1998, the year for which residency was established by the CBS.

^b Productive demand covers all energy consumption associated with productive infrastructure and market centers. This may include water pumps, agroprocessing equipment, mills and small businesses. To obtain the total productive demand in a sublocation, the numbers in this table should be multiplied by the total number of households in the sublocation. 100% of households in all electrified sublocations are assumed to have access to electricity for productive use, but this does not include any major or specific industrial demand.

¹⁶ Most data for the Northeast province were missing, but there was little missing data in the other provinces.

¹⁷ Assumed annual electricity consumption for health and educational institutions: clinic – 360 kWh/year, dispensary – 600 kWh/year, health center – 2400 kWh/year, primary school (day) – 1200 kWh/year, secondary school – 2400 kWh/year, boarding school – 15,000 kWh/year. Hospitals were not included because they were assumed to already have adequate access to electricity. The distribution of health centers across sublocations was based on Ministry of Health standards for the number of institutions needed to serve a population of a given size. The distribution of schools was based on the Ministry of Education's data on the number of schools in each division. The Ministry of Education has undertaken a school-mapping project to identify the geographic location of each school and collect data on access to basic services, including electricity access, but these data were not available in time for incorporation into the present work. Kenya has approximately 16,000 primary schools and 6000 secondary, boarding and specialized schools. Most primary schools and around half of the secondary schools do not have electricity. Around 20,000 health institutions – mostly smaller

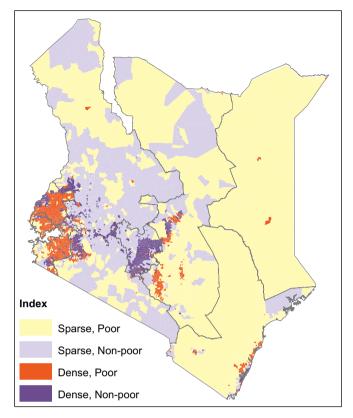


Fig. 6. Distribution of demand categories obtained from density and poverty indices developed for Kenya.

Whenever possible, the spatial location of the demand node was mapped to a known township, market center, or trading center within the sublocation; otherwise the centroid of the sublocation was used to represent the location of the demand node within Kenya.¹⁸

To estimate the technology requirements for grid electrification, we first assumed that 50% of the demand node's spatial area would need to be within range of an MV-to-LV transformer. ¹⁹ This reflects the tendency of population to cluster into settlements, rather than to spread out evenly across a sublocation, though clustering of households is fairly weak in Kenya.

We assumed that each MV-to-LV distribution transformer could cover a radius of 300 m. Since distribution grids frequently follow roads, this assumed range is smaller than the typical range of a MV-to-LV transformer. Transformer range allows one to then

(footnote continued)

clinics and dispensaries – are needed to ensure adequate health coverage in Kenya. Based on World Bank (2006), most dispensaries and around 30% of existing health centers do not have access to electricity. In our model, all health and educational institutions in a sublocation with existing MV lines were assumed to have access to electricity, and other institutions were assumed to lack electricity.

¹⁸ In some cases, data on the locations of population centers available from the Solar and Wind Energy Resource Assessment (SWERA) database could be used to identify the locations of townships, market centers and/or trading centers. In cases where multiple townships, market centers and/or trading centers could be identified within the same sublocation, the largest center was selected to represent the demand node, with largest defined according to a hierarchy with city > municipality > township > market center > trading center > lodge. In cases where there were multiple centers with the same classification, the one closest to the sublocation's centroid was selected. In cases where the SWERA data could not be used to identify a demand node, the centroid of the sublocation was used.

used.

¹⁹ Note that the 50% figure is an assumption that would otherwise have to be computed based on population settlement patterns in the country.

estimate the number of transformers and corresponding length of secondary MV line needed in the demand node.

An estimate of the length of LV line needed to connect each household (or other point of demand such as a school or clinic) to the closest MV-to-LV transformer requires the specific geographical layout of households within a demand node. If households are tightly clustered, then the LV line length would be smaller as compared with a situation where households are spaced uniformly apart. To characterize the nature of household spatial distribution, an "inter-household distance" is defined that represents the length of LV line needed for each household. In this paper, we have assumed that inter-household distance is equal to the average distance between households in a demand node, assuming that households are equally spaced over 20% of the sublocation's total area. In a companion paper we have discussed the issue of estimating inter-household distance (Zvoleff et al., 2009).

3.3. Modeling unit costs for each technology

Detailed cost estimates for each component of each technology were developed during consultations with KPLC and others between January and November 2007. We compared the capital and recurrent costs of three technologies: (1) national grid extension, (2) diesel mini-grids, and (3) individual solar PVs combined with a diesel generator. Unit costs were derived from listed market prices for MV line, LV line, transformers, diesel generators, solar panels and batteries. Market prices for grid extension and diesel mini-grids were obtained from KPLC. Local experts were consulted to refine solar PV costing. Cost estimates for individual components of each technology are summarized in Table 2. Costs do not include the extensive institutional capacity building that would be associated with a rapid scale-up in electricity coverage. Also, note that costs are constantly changing, and many of the unit costs have gone up since the data were gathered for this paper.

4. Model evaluation using a 100-node test region

We first evaluated the model's ability to guide policy decisions by testing it on a $10\,\mathrm{km} \times 10\,\mathrm{km}$ test region with 100 demand nodes. A total population of 25,000 were allocated unevenly across the nodes to capture natural demographic variation in population density. For simplicity, the following assumptions were made: productive and institutional demands were assumed to be 0 and population growth was assumed to be 0. We also assumed that there was no existing national grid. We used the test region to investigate the impact of a range of geographic and policy factors on the model's estimation of household connection costs and MV backbone length. Descriptions of test scenarios, and the results for each scenario, are summarized in Table 3.

In the base scenario, the target penetration rate was assumed to be 100% resulting in an average connection cost of \$1784 and 9.5 m of new MV backbone per household, both of which are reasonable results given unit cost assumptions and population distribution. Since the penetration rate is a key exogenous policy variable, we next tested the impact of lower penetration rates on average connection costs. Decreasing the target penetration rate has two main effects. The primary effect is an increase in the average household connection cost since infrastructure costs – and particularly MV line – are spread over fewer households. A secondary effect is that the number of demand nodes for which grid electrification is more cost-effective than a decentralized option is reduced, resulting in a smaller national grid (Fig. 7). In the test region, 83 of the nodes were grid compatible when the

Table 2Capital and recurrent costs for each technology (USD)

Capital and recurre	ent costs for each tec	ennology (USD).							
National grid exter	nsion: demand node	connection costs ^a							
Peak demand at no Capital (USD)	ode		MV line (per km) ^b MV/LV 3 ϕ transformer Installation (per transformer)	<4 kW 14,098 1507 746	< 12 kW 14,098 1507 746	<20 kW 14,098 1507 746	<40 kW 14,098 2627 2612	<80 kW 14,098 2638 2612	Per l 39
T		Transformer maintenance Transformer lifetime MV line maintenance	10 years	al capital cost					
National grid exter	nsion: household con	nection costs							
Peak demand per l Capital (USD)			LV line (per km) ^c New connection Household equipment ^d	< 50 W 10,611 149 82	< 75 W 10,611 149 94	<175 W 10,611 149 154	<400 W 10,611 149 232	< 1 kW 10,611 149 367	Per k' 367
Recurrent (USD/year) (all levels of peak demand)		Billing and O&M Electricity	O&M-LV lines a Electricity purc	Billing (per hh per year) O&M-LV lines and equipment Electricity purchase Distribution losses			3% of capital cost 0.04 per kWh (wholesale)		
Diesel mini-grid									
Diesel generator costs Capital (USD)	Generator Installation Civil engineering Fuel tank	1000 per kV A with 25% of generator c 1667 1741	n a power and scaling factor of 0.6 ost	54					
Recurrent (USD/ year)	Generator maintenance Fuel	5% of generator co.	st and lifetime of 5 years						
Mini-grid network costs		All capital and recudistribution lines,	irrent costs are the same as for na and lighter load.	tional grid extension w	ith the exception of tech	nical losses, which are a	assumed to be 2% reflect	ing the smaller netwo	rk size, short
Solar PV+Diesel ge	nerator ^e								
Solar PV-peak den Capital (USD)	Panel and f Batteries	ixing amps, accessories	<50 W < 300 45 150 22 150 22	5	< 175 W 900 450 450	< 400 W 2400 1200 1200	<1 kW 6000 3000 3000	Per kV 6000 3000 3000	N
Recurrent (USD/year) O&M 5% of capital cost; lifetimes—panel (20 years), battery (3 years), balance (10 years)									
Diesel engine All capital and recurrent costs are			s are the same as for a	diesel generator, but the	generator is sized base	ed only on productive d	emand.		

^a Cost assumptions for national grid extension and diesel mini-grids were finalized following meetings with KPLC in Nairobi in October/November 2007.

^b Three-phase conductors of 75 mm² are assumed for MV line extension and a cost of 14,908 USD/km was derived from an average of the unit costs for 33 and 11 kV conductors since the model does not explicitly distinguish between 33 and 11 kV line. The cost also includes overhead of 35% to cover transport and other administrative costs, as suggested by KPLC.

^c An average of the costs for single-phase conductors and three-phase conductors of 50 and 100 mm².

d Includes labor cost (45 USD for loads up to 50 W), wires (22 USD), and lamps/light bulbs (15 USD).

e Solar PV systems are used to electrify individual households and a diesel generator is used to meet productive demand. Note that solar PV output is limited by daily solar radiation and Kenya has an estimated 2000 h of sunlight per year, on average. Linking solar PV systems through LV distribution lines is not considered attractive because the benefits from scale economies are insignificant compared to the cost of the wire.

f Sizing of systems takes into account the efficiency of panels as well as the losses in batteries and converters.

Table 3Comparison of population coverage, average connection cost, and network length in 100-node test region.

Scenario description	Number of nodes and population covered	Average household connection cost	MV network length
Base: population of 25,000 randomly distributed across 100 demand nodes, each of which represents a discrete spatial area. The total area is $100 \mathrm{km^2}$, so the average population density is $250 \mathrm{people/km^2}$. Households are assumed to have 4 people and electricity demand of $500 \mathrm{kWh/year}$. The target penetration rate is 100% . There is no existing electricity grid.	83 nodes (99% of pop)	\$1,784/hh	59 km (9.5 m/hh)
In the scenarios below, all assumptions are the same as for the base, except as noted percentage	ges shown compare each scenario	to the base	
(1) Varying household demand: per-household demand at each node is randomly assigned to 250, 500, 1000 or 2000 kWh/year.	86 nodes (pop –1%)	+6%	+4% (+5%)
(2) Equal population at each node: population of 25,000 evenly distributed across 100 demand nodes, each of which represents a discrete spatial area.	95 nodes (pop -4%)	+22%	+12% (+16%)
(3) 75% target penetration rate: target penetration rate is 75%.	80 nodes (pop -25%)	+35%	-4% (+28%)
(4) 50% target penetration rate: target penetration rate is 50%.	75 nodes (pop -50%)	+108%	-11% (+80%)
5) 25% target penetration rate: target penetration rate is 25%.	54 nodes (pop -75%)	+314%	-30% (+199%)
(6) Nucleated population: population is assumed to be concentrated into 50% of the area represented by each demand node, lowering the inter-household distance.	89 nodes (pop -1%)	-20%	+3% (+3%)
(7) Low capital cost for solar PV: the capital cost of solar PV is reduced by 50%.	50 nodes (pop −6%)	-14%	-31% (-26%)
(8) Existing grid in center: there is an existing electricity grid connecting two demand nodes in the middle of the area. One of the connected demand nodes represents the largest demand center.	83 nodes (no change)	No change	+1% (+1%)
(9) Existing grid in corner: there is an existing electricity grid connecting two demand nodes in the corner of the area. The connected demand nodes represent relatively small populations.	83 nodes (no change)	No change	No change
(10) Sequential algorithm, existing grid in center: there is an existing electricity grid connecting two demand nodes in the middle of the area. One of the connected demand nodes represents the largest demand center. New connections are selected using a sequential algorithm.	98 nodes (no change)	+4%	+14% (+13%)
(11) Sequential algorithm, existing grid in corner: there is an existing electricity grid connecting two demand nodes in the corner of the area. The connected demand nodes represent relatively small populations. New connections are selected using a sequential algorithm.	98 nodes (no change)	+4%	+13% (+12%)
(12) Sequential algorithm, low target population: there is an existing electricity grid connecting two demand nodes in the corner of the area. The connected demand nodes represent relatively small populations. New connections are selected using a sequential algorithm. The target population is one-half of the population reached in the base scenario.	77 nodes (pop –48%)	+24%	-13% (+70%)

penetration rate was 100%, but only 54 were compatible when the penetration rate was reduced to 25%, and the average connection cost more than tripled. However, all the high-population nodes were still incorporated into the grid, so the 75% reduction in population coverage was primarily due to the reduction in penetration rate rather than the reduction in the number of nodes covered.

We also tested the impact of population clustering within the demand nodes, which reduces inter-household distance and thus the amount of LV line needed to connect each household. As expected, the average connection cost was reduced for lower inter-household distances. The resulting network also changed so a slightly different set of nodes were grid compatible in this scenario. The new network required more MV backbone per household, primarily because a few nodes requiring a lot of MV backbone became grid compatible when their inter-household distances were reduced.

If the cost of an off-grid alternative such as solar PV is reduced, the geographic area in which grid extension is the most cost-effective technology is reduced. In a test scenario, when the capital cost of solar PV was cut in half, the number of grid compatible nodes dropped from 83 to 50. Since the connected

nodes tended to be the ones with the lowest grid costs, the average connection cost in grid compatible nodes dropped by 14%. As with the previous scenarios, the change in the population connected to the grid was small relative to the change in average connection costs.

Test scenarios also revealed that our algorithm is not very sensitive to the location of the existing grid, even though any existing lines are always incorporated into the expanded network. This is primarily because the characteristics of demand nodes, including total electricity demand and population density, have a stronger effect on network expansion than the location of demand nodes in space.

Finally, we compared the performance of our algorithm with the performance of a sequential algorithm that searches for new connections step-by-step by moving outward from the existing grid. We confirmed that the sequential algorithm tends to connect more nodes to reach the same level of population coverage, resulting in higher average connection costs and a longer MV backbone per household. Overall, our approach appears to be an improvement over a sequential approach to electricity planning, and our model captures the effects of a range of geographic and policy factors that affect grid expansion and costs.

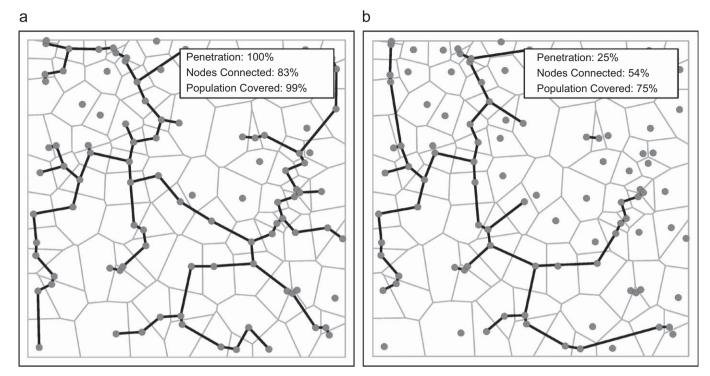


Fig. 7. Comparison of computed grid extension for two different penetration rates using a 100-node test region. No pre-existing grid was assumed for these illustrative examples. (a) Least-cost connected network if a 100% penetration rate is assumed for each connected note. (b) Similarly, a network where each connected node is assumed to have a 25% penetration rate.

5. National grid extension case study of Kenya

We applied the model to the problem of grid extension in Kenya to test its performance at a national scale, and to explore how connection costs are related to Kenya's human geography. We also identified opportunities for lower cost grid extension. We assumed a base year of 2007 and a time horizon of 10 years.

We compared two scenarios: full penetration and realistic penetration (Table 4). In the full penetration scenario, we assumed 100% penetration in every connected demand node. In the realistic penetration scenario, we assumed a 65% penetration rate in dense, non-poor demand nodes and a 30% penetration rate elsewhere based on consultations with KPLC. In the realistic penetration scenario, the assumed penetration rates are considered a basic indicator of the number of households in each demand category with the ability to pay for an electricity connection.

The computed results for the realistic penetration scenario show that 5565 out of the total 6737 demand nodes would be connected to the national grid, where each demand node represents a sublocation in Kenya. In this scenario, 41% of the households in the country, or about 4.1 million households, would be grid connected within 10 years. Note that these figures include the \sim 1 million households that are already connected to the grid and account for population growth over the 10-year time horizon. The number of new households connected to the grid is 3.1 million. The number and percentage of households that would be connected in each demand category, along with the national totals, is shown in Table 5. As expected, coverage of densely populated demand categories is higher than coverage of sparsely populated demand categories.

The assumed penetration rates constrain the maximum number of connections possible in each demand node, explaining why only 41% of total households in Kenya are covered in the realistic penetration scenario. However, 93% of all households are located within sublocations where grid electrification is the most cost-effective option. This indicates that in the long-term, if the

Table 4Assumed penetration rates for national grid extension scenarios in Kenya.

Demand category	Current pene	tration rate	Target penetration rate (all demand nodes)		
	Demand nodes without existing MV lines (%)	Demand nodes with existing MV lines (%)	Realistic penetration scenario (%)	Full penetration scenario (%)	
Sparse, poor	0	10	30	100	
Sparse, non-poor	0	10	30	100	
Dense, poor	0	10	30	100	
Dense, non-poor	0	30	65	100	

relative costs of technologies remain the same, grid electrification is likely to be the most cost-effective technology for much of Kenya's population.

The average cost per household for grid-electrification is shown in Table 6 to be \$1907. The total capital cost of connecting all 3.1 million new households in this scenario is approximately \$6 billion. These estimates are based on unit costs of infrastructure at the time data were gathered. Unit costs can change as material costs change, and with supply chain development that can come with intensified procurement. Moreover, since the model includes multiple approximations, these numerical estimates must be treated with the appropriate caution. The breakdown across MV backbone, MV secondary lines, and LV lines, averaged across all households is shown in the last column of Table 6. Nationally the costs of distribution from the last transformer, which include LV lines and household connection equipment, represent the largest component of the costs (66% of the total). This result suggests that lowering the cost of the LV distribution system - perhaps through single-phase lines, altered standards, or bulk procurement - could

 Table 5

 Summary of population coverage for realistic and full penetration scenarios.

Demand category	Total in Kenya	Grid compatible ^a	
		Realistic penetration	Full penetration
Sparse, poor			
Demand nodes	1843	1109	1371
Households (millions)	1.625	0.351	1.348
Households (% of category)	100%	22%	83%
Sparse, non-poor			
Demand nodes	1518	1135	1291
Households (millions)	1.448	0.373	1.348
Households (% of category)	100%	26%	93%
Dense, poor			
Demand nodes	1819	1781	1796
Households (millions)	3.249	0.975	3.249
Households (% of category)	100%	30%	100%
Dense, non-poor			
Demand nodes	1557	1540	1544
Households (millions)	3.726	2.422	3.726
Households (% of category)	100%	65%	100%
Total	1.		
Demand nodes	6737 ^ь	5565	6002
Households (millions)	10.048	4.120	9.671
Households (% of category)	100%	41%	96%

^a In both scenarios, all grid compatible households are assumed to be connected over a 10-year period beginning in 2007 and ending in 2017. The numbers presented in this table include pre-existing connections in addition to new household connections.

Table 6Summary of connection costs for realistic penetration scenario.

	Infilling	Grid extension	Total
Number of households (millions) Total costs (millions USD)	2.070	1.005	3.075
MV backbone	_	123	123
MV secondary lines	659	1118	1847
LV lines and HH equipment	2580	1316	3895
Total	3239	2627	5866
Average cost per household (USD)			
MV backbone	_	123	40
MV secondary lines	318	1183	601
LV lines and HH equipment	1246	1309	1267
Total	1564	2615	1907
Percent of average cost			
MV backbone	_	5%	2%
MV secondary lines	20%	45%	32%
LV lines and HH equipment	80%	50%	66%

have a significant impact on reducing the costs of grid electrification. The importance of lowering the LV line costs is especially important to note in the case of infilling nodes, where 80% of the average capital cost per household is associated with LV line and household equipment compared to 50% in grid extension nodes.

Fig. 8 shows how the total capital cost for each of the scenarios varies with the total number of households covered. The marginal cost of connecting additional households rises as households in more costly demand nodes are reached, and this causes the

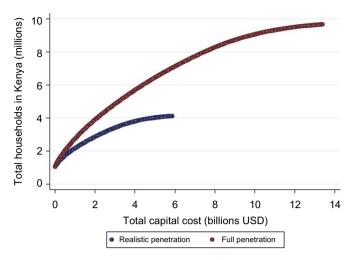
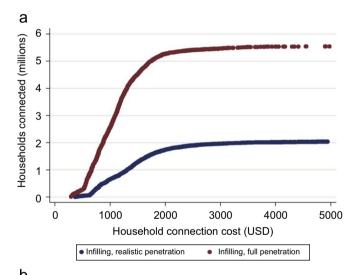


Fig. 8. Total number of households that could be connected at each capital investment level. Note that curves begin above 0 because there are already approximately 1 million households connected in Kenya. Capital costs are shown for realistic and full penetration scenarios.



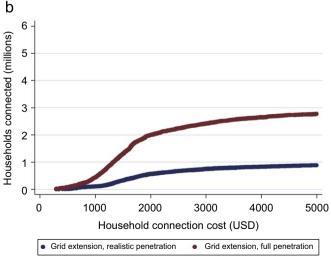


Fig. 9. The number of grid compatible households that could be connected shown cumulatively for each level of household connection cost. (a) Infilling type household connections in the realistic and full penetration scenarios. (b) Grid extension type household connections in the realistic and full penetration scenarios.

^b Kenya's 6612 sublocations are represented by 6737 demand nodes.

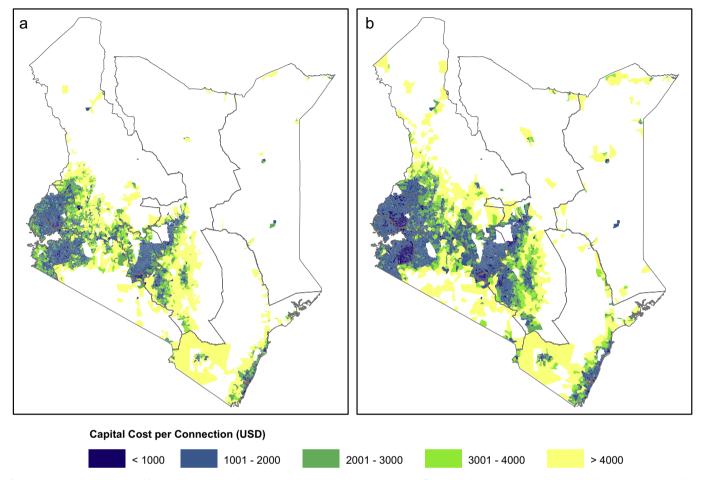


Fig. 10. Capital cost per household connection, averaged by sublocation (demand node) and shown for each sublocation that is grid compatible in Kenya. (a) Realistic penetration scenario. (b) Full penetration scenario.

average per-household connection cost to increase. In the realistic penetration scenario, the first million households can be connected for approximately \$0.8 billion, the next million for \$1.4 billion, and the final 1.1 million for \$3.7 billion. This effect becomes more pronounced in the full penetration scenario, where 8.7 million new households could be connected for \$13.4 billion, but 6.5 million households (75% of the total 8.7 million) could still be connected for just half of that (\$6.7 billion).

In the full penetration scenario, the higher target penetration rate for connected nodes both reduced the average connection cost and increased the number of grid compatible nodes. In this scenario, 424 additional demand nodes were covered and 96% of the population was connected at an average cost of \$1552 per household. The average connection cost was reduced because the cost of MV distribution infrastructure was spread over a larger number of households. This resulted in grid electrification being the most cost-effective technology in many additional demand nodes that require substantial MV backbone to reach. These results suggest that in cases where there is a fixed budget for a national connection program, the highest number of households can be reached by focusing on lower cost demand nodes first, and by connecting a high percentage of the households in each of these nodes (i.e. by moving toward full penetration in each connected demand node).

The situation in Kenya is characterized by substantial existing MV infrastructure in high-density areas, but low penetration rates. In such a case, there is a cost advantage to focusing on infilling opportunities, where existing infrastructure and

relatively low inter-household distances reduce electrification costs.²⁰ Fig. 9 shows that in the realistic penetration scenario, over 30% of infilling households, but only 10% of grid extension households, have a connection cost of under \$1000. In the full penetration scenario, 46% of infilling households and 14% of grid extension households have a connection cost of under \$1000.

There is considerable spatial variation in the average household connection cost. Fig. 10a shows the spatial distribution of costs for the realistic penetration scenario, and Fig. 10b shows the distribution for the full penetration scenario. These figures confirm the attractiveness of connecting peri-urban areas around Nairobi as expected, but it is noteworthy that low-cost connection opportunities also exist in the poorer rural areas of the Western and Nyanza provinces. Knowledge of spatial variation in costs can be used to identify network branches with the lowest average connection costs. This information may be useful to planners who must select a subset of the grid compatible demand nodes to include in a scale-up program constrained by a fixed budget or time horizon, or designed to meet a target electrification rate. However, since prioritization within small regions depends on the level of connectedness one level higher, utilities must consider plans for overall network evolution when focusing on smaller regions.

²⁰ Although infilling areas also tend to have higher per-household electricity demand, which is associated with slightly higher internal costs, this is outweighed by these other factors.

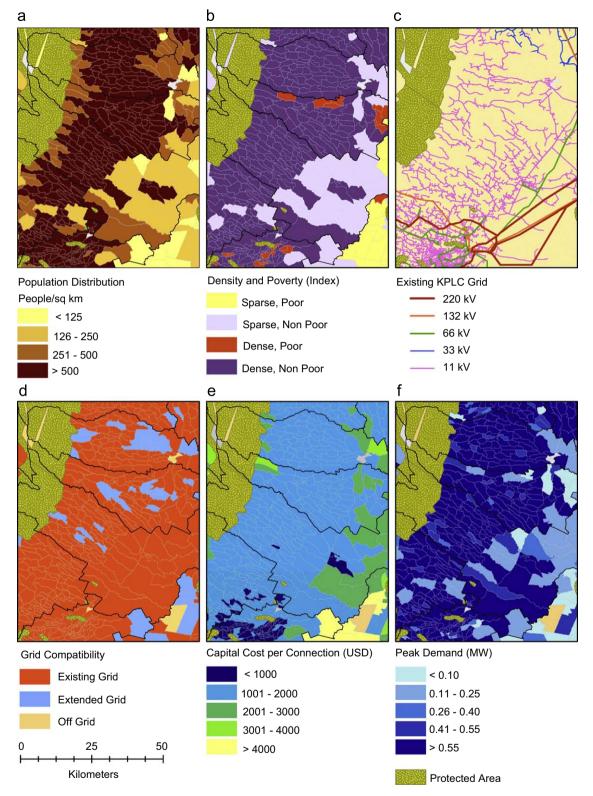


Fig. 11. Assumptions and results shown for infilling-type connections for a section of Kenya near Nairobi. (a) Population distribution. (b) Demand categories. (c) Existing electricity grid. (d) Grid compatible sublocations. (e) Average per-household connection cost. (d) Additional peak demand.

Figs. 11 and 12 compare and contrast two different regions of Kenya, one a densely populated region near Nairobi (Fig. 11), and the other a sparsely populated region in the western part of the Rift Valley (Fig. 12). These regions are also shown as insets in Fig. 2. Figs. 11a, b, and c show the key inputs into the model, illustrating the high density, low poverty and extensive existing

infrastructure that characterize this area. The results shown in Figs. 11d and e confirm that grid electrification is indeed the lowest cost option for this region, and that average household connection costs are relatively low. In contrast, in the sparsely populated western Rift Valley region, grid compatibility is in the vicinity of the existing MV network shown at the bottom of

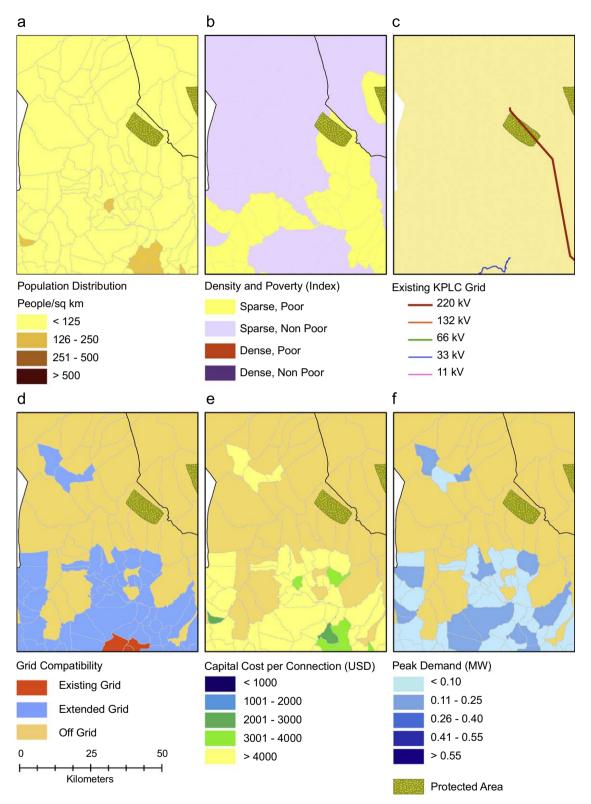


Fig. 12. Assumptions and results shown for grid extension-type connections for a section of Kenya in the western Rift Valley. (a) Population distribution. (b) Demand categories. (c) Existing electricity grid. Note that the transmission line that ends near the protected area is a high-voltage spur from a power plant. (d) Grid compatible sublocations. (e) Average per-household connection cost. (d) Additional peak demand.

Fig. 12c. Fig. 12d reveals that, while grid extension is the most cost-effective technology in some sublocations, much of the region is best served by off-grid technology. Even in grid compatible areas, the average connection cost usually exceeds \$4000 per household.

Analysis of different regions within Kenya also highlights differences in how new connections may affect peak demand on the network (Figs. 11f and 12f). Sparser rural areas not only have fewer households, but also tend to have lower demand per household and are often connected at a lower penetration rate,

both of which are reflected in our realistic scenario. This means that additional peak demand will tend to be lower in sparser areas compared with dense, infilling areas. In either case, upgrades to the existing network may be needed to support the additional demand. Fully accounting for network upgrades and transmission costs may increase household connection costs more in some places than in others, so electricity planning efforts should consider whether there are opportunities to connect additional households without upgrading the existing MV distribution network or increasing the generation capacity.

6. Conclusions, policy outcomes and further research

Meeting national electrification targets in Kenya, and elsewhere in SSA, requires a substantial and rapid increase in electricity access. The tools developed in this paper can help planners estimate investment costs and financing requirements to support electrification programs and identify opportunities for cost-effective grid expansion. Incorporation of spatial information at a geographic resolution of small administrative units (e.g. sublocations in Kenya) allows for comparison of costs within and across regions without the computational expense of treating each household as an individual demand node. Inclusion of high-resolution socio-economic data can help to identify grid expansion opportunities in impoverished regions that may be eligible for specialized financing programs.

We found that the penetration rate, an exogenous variable chosen by planners, often had a greater effect on average connection cost than inter-household distance, per-household demand, and proximity to the national grid. This suggests that planners should intensify regional connection programs.

Further research is needed to more fully incorporate generation costs associated with different technology options. Opportunities to expand Kenya's renewable generation capacity should be evaluated as part of comprehensive electricity planning efforts. Kenya's abundant supply of hydro and geothermal resources warrants particular attention to how these resources can be further developed to support expanded access to the national grid, as well as in isolated, off-grid settings. Other alternatives to fossil fuels, including solar thermal and wind power, may also be viable in Kenya. A spatial model that considers the full set of electrification options given the distribution of demand and energy sources would improve electricity planning across Sub-Saharan Africa.

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