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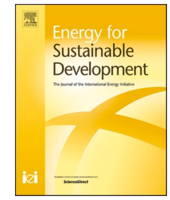

Electricity consumption and its determinants in rural Mozambique – At the edge of the electricity grid

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A B S T R A C T

The lack of reliable data on electricity consumption is one of the main obstacles to selecting the right supply technologies and allocating resources to achieve universal electricity access in sub-Saharan Africa. Using data collected from on-site surveys, this study aims to estimate electricity consumption in rural Mozambique at the edge of the electricity grid and examine the factors that influence it. The consumption is estimated for households, community institutions, and productive users in four different localities. Three of the localities are off-grid and rely largely on Solar Home Systems, while one is a small town and has access to grid electricity. To analyze the determinants of electricity consumption, multiple linear regression models are used. The results show that households account for >62 % of the total electricity consumption. The average household consumption in the grid-electrified town (2.54 kWh/day) is significantly higher than in the off-grid localities (0.04 to 0.24 kWh/day). Furthermore, the load profiles of households in the grid-electrified town and off-grid localities differ significantly. However, productive users consume the most electricity per user in all localities. The regression analysis shows a positive and strong relationship between consumption and appliance ownership, with refrigerators and televisions having the most significant influence in the grid-powered locality, and cellphones and LED lamps having the biggest effect in the off-grid areas. The study demonstrates the substantial spatial and sectoral differences in electricity consumption in rural Mozambique. It also reveals how access to grid electricity, productive use, and appliance ownership shape electricity consumption in rural Mozambique. Understanding these dynamics is thus crucial for accurate demand forecasting and optimal rural electrification planning.

Introduction

760 million people worldwide, mainly in rural areas, did not have access to basic electricity in 2022, with 80 % of them living in Sub-Saharan Africa (SSA) (IEA, 2023). Lack of electricity access electricity deprives rural communities of basic services such as healthcare, education, and communication. It also hinders rural households from starting small businesses, increasing agricultural productivity, and raising incomes; crucial to reducing poverty and improving living standards.

Supply-side infrastructure and capacity have been the main focus of efforts to increase electricity access in most SSA countries. However, little attention is paid to thorough investigation of demand, especially in rural areas (Van-Hein Sackey et al., 2022). Given the low ability-to-pay of rural communities in SSA (Zigah & Creti, 2023), in-depth understanding of the variability of demand across sectors and locations is thus crucial for adopting cost-effective supply solutions since inaccurate demand assessments lead to under- or over-dimensioning of the supply system capacity, resulting in unreliable supply or high investment cost and thus unaffordable electricity tariffs (Hartvigsson et al., 2013). High-quality electricity consumption data is thus essential for demand forecasting and selection of supply technologies.

Demand forecasting in rural areas of developing countries is challenging due to lack of data (Mandelli et al., 2016). In areas with grid-electricity access, consumption data is typically collected in aggregate form leading to unknown load patterns and magnitudes. In areas

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without prior access to electricity, life with electricity is unknown (Manuel & Victorino, 2020). In the absence of historical data, researchers often employ alternative methods for estimating demand including use of data from other locations, assumptions based on previous experiences, or surveys in the location to be electrified (Kakar et al., 2018; Oladeji & Sule, 2015). Hartvigsson and Ahlgren (Hartvigsson & Ahlgren, 2018) compared load profiles of rural households in Tanzania based on consumer surveys and metered data. The two methods performed well in estimating peak loads, but the survey approach resulted in an underestimation of the load and capacity factors with errors of 48–117 %, which was attributed to lack of sufficient data on electrical appliances and time of use. Similarly, using simple electrical load surveys, Oladeji and Sule (Oladeji & Sule, 2015) and Harijan and Kumar (Kakar et al., 2018) estimated electricity demand in unelectrified villages in Nigeria and Pakistan, respectively. Pandyaswargo et al. (Pandyaswargo et al., 2020), estimated electricity demand in off-grid villages in three Asian countries using interview-based surveys to develop future demand growth scenarios. This evidence suggests that simple survey methods may provide a rough demand estimate but over-or-under estimate the peak load as they are often based on an assumed (hypotethical) number of household (HH) appliances and their operation hours. In reality, appliance usage vary during the day impacting total load, peak load and system dimensioning.

Despite considerable efforts to increase rural electricity access in SSA, including policy, programs and projects, there are still large electricity access differences between urban and rural areas. In 2022, >85 % of the urban population in SSA had access to electricity, but access in rural areas was still below 10 % (IEA, 2023). The electricity access in the region is expected to growth by about 30 % by 2030 due to rapid urbanization and population growth, putting further pressure on already limited resources (IEA, 2023). Thus, studies estimating electricity demand should consider differences between urban and rural areas.

Analysis of spatial demand variations is critical for appropriate technology selection and resource allocation (Zhang et al., 2011) since it helps electrification planners identify grid capacity limits, determine grid-extension cost-effectiveness, prioritize infrastructure investments, and improve system stability (Moksnes et al., 2024). A study of rural and peri-urban microgrid sites in Honduras (Few et al., 2022) showed that rural areas show higher peak loads and seasonal variations due to agricultural activities, while in urban areas tailoring and workshops determine loads. Understanding spatial demand variations in SSA contexts is thus essential for decentralized systems deployment (Aryanpur et al., 2021; Moksnes et al., 2024). Yet, little is known about spatial rural demand variability. This also applies to the special conditions characterizing rural areas where some localities are grid-connected while others are not, what we here refer to as the edge of the electricity grid.

Most rural SSA electricity demand studies have focused on the residential sector, paying less attention to productive use (PU) despite PU playing a major role in determining electricity consumption and thus for optimal electrification pathways (Hartvigsson et al., 2021). Recent investigations in rural Ethiopia (Wassie, Ahlgren, 2023a) show that underestimation of PU demand led to mini-grid undersizing, resulting in 13 h daily load-shedding.

There is also lack of knowledge about sectoral demand variations and factors influencing demand in rural SSA (Van-Hein Sackey et al., 2022). While urban area demand drivers are well-established, there has not been adequate research on factors determining rural area demand (Dokas et al., 2022). Studies, mostly on grid-electrified HHs, indicate influence by several factors, including sociodemographics, dwellings, local climatic conditions and stock of appliances (Blimpo et al., 2020; Khanna & Rao, 2009; Wassie, Ahlgren, 2023b). Others found that rural HHs continue to rely on firewood (Khanna & Rao, 2009) and that demand determinants vary between HHs and businesses (Wassie, Ahlgren, 2023b). Knowledge of demand drivers is thus crucial for power supply system planning (Wassie, Ahlgren, 2023b).

Thus, the overall aim of this study is to explore electricity consumption at the edge of the electricity grid and identify the factors influencing consumption. Specifically, it seeks to address the following questions:

1) How does electricity consumption vary across different rural localities?
2) How does electricity consumption vary between sectors (HHs, PUs, institutions)?
3) What are the main factors affecting rural electricity consumption?

The study does this by using data collected through on-site surveys in four rural localities in one district in rural Mozambique. It contributes to the growing body of research on electricity consumption estimation in rural areas of developing countries, and offers a unique perspective by spatially disaggregating electricity consumption, allowing for better informed decision-making and design of localized generation systems. Another novel aspect is that the electricity consumption estimation is based on data acquired from in-depth on-site interviews and observations regarding the actual quantity and wattage of appliances used by end-users, as well as their operating hours.

Methodology

Given that the aim of this study is to assess the spatial and sectoral dimensions of electricity consumption - including households (HHs), community institutions (CIs) and productive uses (PUs) - and to identify the key factors influencing electricity consumption in rural localities, a comprehensive methodological approach that could combine these aspects was necessary. The methodological approach used to conduct the study thus consists of five main steps, namely: (i) site visit and information gathering, research design and preparation of data collection tools, (ii) quantitative and qualitataive data collection, (iii) estimation of electricity consumption, (iv) spatial and sectoral analysis of demand, and, (v) analysis of the factors affecting electricity consumption. Common methods for estimating electricity demand include stochastic models, deterministic models and regression analysis (Herraiz-Cañete et al., 2022; Mandelli et al., 2016), each differing in terms of accuracy, data and time requirements, complexity, cost, and resource intensity. Due to the lack of historical consumption data and the need for more accurate demand estimates, deterministic models were used in this study to estimate the baseline (present) electricity consumption of the study HHs, CIs and PUs. Compared to stochastic models, deterministic models yield more accurate energy demand estimates, especially when backed by primary data from on-site quantitataive surveys and when estimation is done for a short period of time (Herraiz-Cañete et al., 2022; Mandelli et al., 2016). Additionally, regression models were employed to examine the major factors influencing electricity consumption.

Fig. 1 illustrates the methodological approach and the processes followed. The four rural localities selected to explore the spatial influence on electricity consumption are located in one district and include one grid-connected and three off-grid, at varying distance to the grid-connected locality.

Description of the case study site

This study is carried out in Mapai-Sede district,[1] Gaza province, Mozambique. Since detailed information about the district was not available, first the site was visited, to establish contact with local authorities, and obtain permission to conduct the research. Mapai-Sede is located at latitude −22.850036, longitude 31.962329. The district consists of four localities: 16 de Junho (the district's capital and major town), Mapai River, Mepuzi, and Chidulo. 16 de Junho lies along the

[1] Mapai-Sede is geographicaly an administrative post within entire Mapai district, but is considered to represent a district for the purposes of this study.

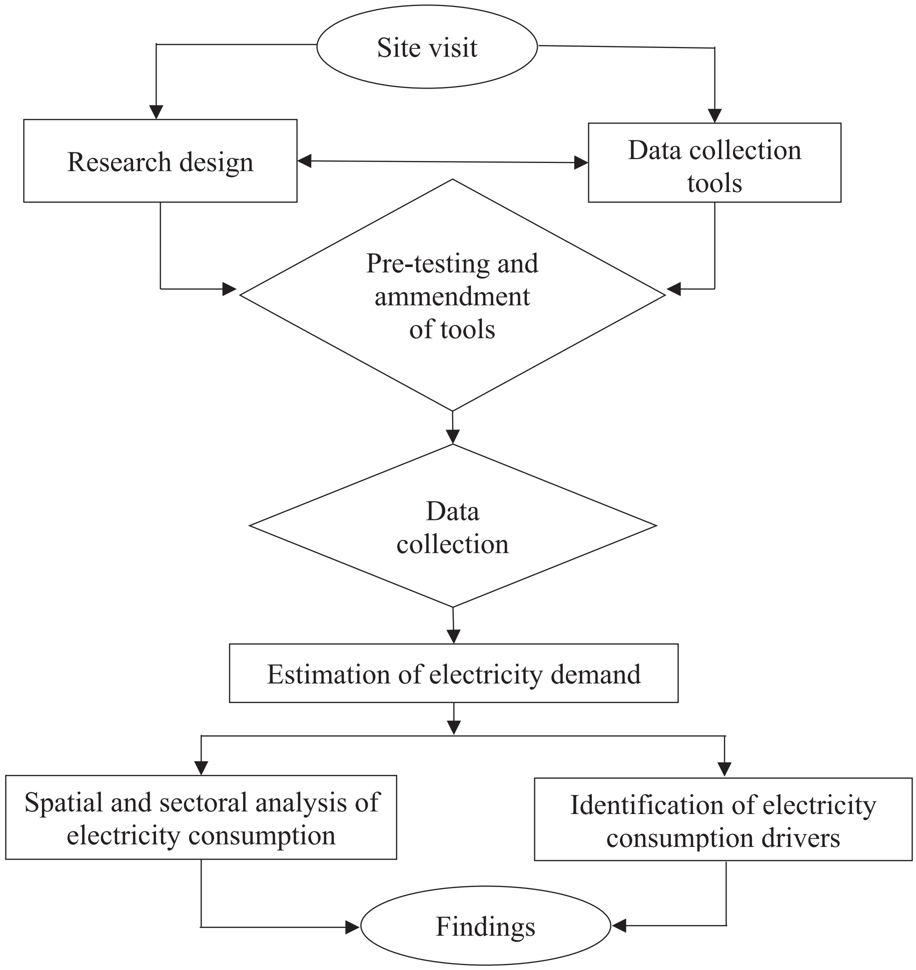

Fig. 1. The methodological approach and processes followed in the study.

main road and railway line and is connected to the national grid, but the other three localities are off-grid. To better understand the effect of the degree of rurality on demand for electricity, the study is conducted in all four localities, see Fig. 2. Mapai River is the closest locality to 16 de Junho, while Chidulo is the farthest. Mapai River and Mepuzi are located on margin of Limpopo river and agriculture is the major income generating activity, while Chidulo is characterized by dry climate with charcoal production dominating as family income source.

The population of Mapai-Sede is estimated to be 26,109 inhabitants, with a density of only 3.32 inhabitants per square kilometer. The population is concentrated in 16 de Junho (almost 50 %). Mapai-Sede has 4747 HHs in total, of which 53 % are in 16 de Junho, 23 % in Mapai River, 15 % in Mepuzi and 9 % in Chidulo. The climate is arid to semi-arid, with an average annual rainfall of 365 mm. The annual average temperature is 23.8 °C, with a maximum of 33.5 °C (October to March) and a minimum of 18.8 °C (June and July) (INE, 2023).

16 de Junho is where the main infrastructures of the government are located. Following the grid-electrification it has experienced rapid urbanization. Access to grid electricity and existence of a variety of public services has made 16 de Junho a preferred place for residence, commerce, and tourism. In the three off-grid localities people depend mostly on solar home systems (SHS) and pico-solar home systems (PSHSs), small PV systems designed to power one to three compact LED lamps, charge phones, and/or power radios (Peters & Sievert, 2016). The PSHSs are sold locally by a Maputo-based company through the pay-as-you-go model. The flexible payment scheme makes PSHSs affordable and enables HHs to gradually acquire electricity supply (Yadav et al., 2019). In few cases where off-grid HHs also run businesses, we found SHSs with 150–400 Wp capacity. In addition to HH use, PV systems are used for water pumping telecom antennas, and by hospitals, bars, and kiosks. Overall, the electricity access analysis suggests that electricity demand in Mapai-Sede will likely continue to grow, enhancing public services and business activities. Table 1 presents population data and the distance between the off-grid localities and 16 de Junho.

Sample selection and sample size determination

A multi-stage stratified random sampling approach was used to select sample respondents for the study. First, electricity end-users (both those connected to the grid and those with private PV systems) in the district were identified with the help of local administrations. Second, the main electricity end-uses, and user groups/sectors in the four localities of the district were identified based on data gathered from the site visit and discussions with local energy offices. These end-user groups include households (HHs), community institutions (CIs), and productive users (PUs). Third, all end-users identified in each locality were classified into one of the three groups based on the main purpose for which electricity is used. This was essential to create a reasonably homogeneous group of end-users such that a random sampling might yield a representative sample. Once a complete list of all end-users in each sector was created, the sample size required for the study at district level was determined using Cochran's sample size determination formula as (Royall, 1970):

$$n = \frac{\frac{Z^2 * p * (1-p)}{e^2}}{1 + \left(\frac{Z^2 * p * (1-p)}{N * e^2}\right)} = 274 \quad (1)$$

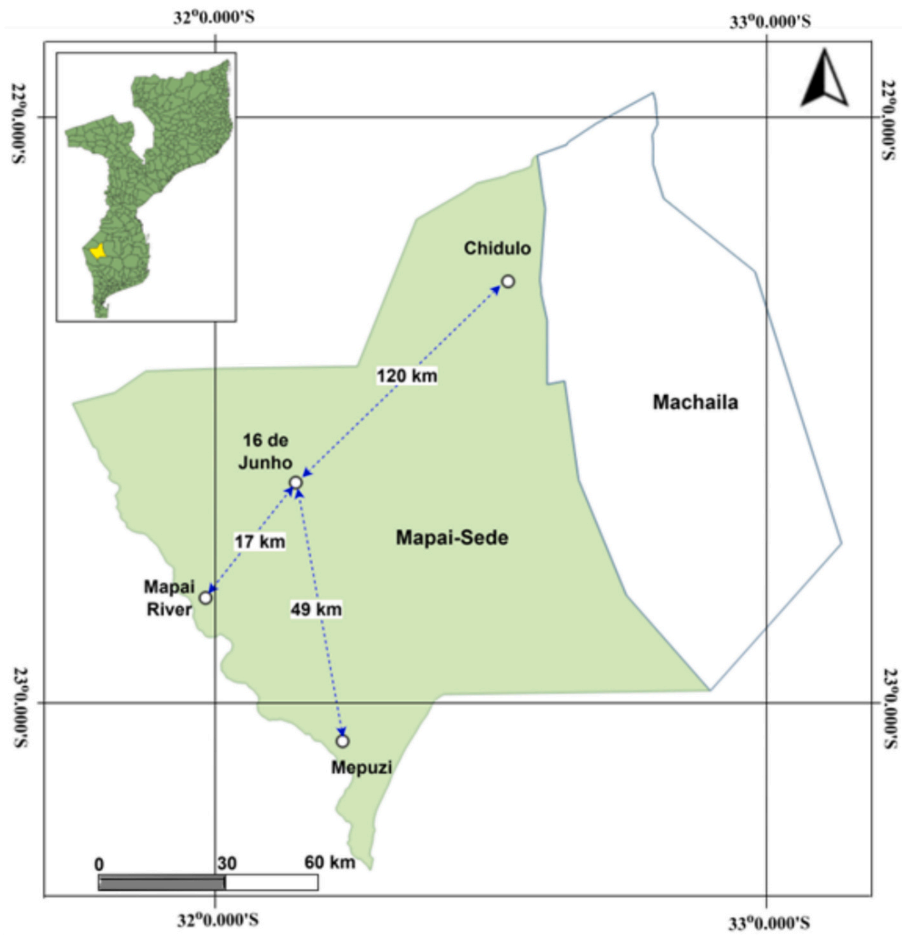

Fig. 2. The geographical location of Mapai-Sede and the four study localities.

Table 1
Population and number of HHs in each locality of Mapai-Sede in 2022[1].

	D_o (km)	Men	Women	Total Pop.	No. HHs	% HHs
16 de Junho	0	5530	8300	13,831	2515	53
Mapai River	17	2799	3103	5902	1073	23
Mepuzi	49.2	1801	2128	3929	714	15
Chidulo	120	1153	1294	2447	445	9
Total		**11,283**	**14,825**	**26,109**	**4747**	**100**

D_o- distance from the capital town (16 de Junho) of Mapai-Sede; Pop-population.

[1] Data obtained from the Mapai-Sede district administration.

Table 2
Distribution of surveyed samples in each study locality by sector.

Consumer group (sector)	Spatial distribution				
	16 de Junho	Mapai River	Mepuzi	Chidulo	Total
Households (HHs)	47	21	26	31	125
Community institutions (CIs)	24	7	7	7	45
Productive users (PUs)	26	5	4	6	41
Total	97	33	37	44	211

where: n is the required sample size, p is the proportion of end-users expected to have access to electricity (25 %), e is the margin of error (5 %), Z is 1.96 for alpha 0.05 (i.e., 95 % confidence level) and N is total number of HHs, PUs and CIs in the district (roughly 5200).

Fourth, the calculated district-level total 274 samples were distributed to the four study localities based on the population size of each locality, using a method called population proportion sampling. Fifth, the sample sizes allotted to each locality were further divided among the three end-user categories according to their respective proportions in the total end-user population. Finally, a simple lottery method was used to randomly select sample end-users in each category in each locality. Table 2 reports the final sample sizes in each locality by sector. Table 2 shows that we were only able to collect data from 211 out of the 274 samples, partly because the respondents were not present at home when the survey was being conducted. Of the total 211 samples surveyed, 59 % are HHs, 22 % are CIs, and 19 % are PUs. Appendix A provides a detailed report of the different types of end-users surveyed in each sector.

Data collection

In the grid-connected locality, attempts to collect metered historical data on electricity consumption failed due to the use of prepaid meters. These devices only provide the total electricity consumption since their installation, without recording detailed consumption patterns over time. On other hand, electricity is purchased via cellphones with mobile payment systems, without receipts being issued. Since historical data on electricity consumption was not available in the district, a bottom-up approach was used to collect data for the study. This approach is predicated on collecting data at the local or individual end-user level, then aggregating the data to look for trends and patterns (Ferrari et al., 2019; Herraiz-Cañete et al., 2022). In order to achieve this, a semi-structured survey questionnaire with a detailed format for quantyfying the appliances used by sample respondents, their operating hours and duration, was prepared and then pretested using a pilot on-site survey with five to ten respondents from each sector in November 2022, following the guidelines proposed by (Abu Hassan et al., 2006; van Teijlingen & Hundley, 2002). The purpose of the pilot survey was to determine whether the questionnaire was capable of capturing the required data to address the research questions, and whether the format was comprehensive enough and convenient for each end-user group. Following the pilot survey, the questionnaire was amended, and final data collection carried out during December 2022 through in-person surveys with the sample HHs, CIs and PUs. To ensure accuracy and quality of the data collected and ensuring adherence to key ethical guidelines,[2] the surveys were administered through face-to-face interviews with individual respondents by the lead author and two trained data collectors.

To control and minimize bias from various sources, several measures were taken throughout the research process. To control selection bias, a stratified random sampling technique was applied where all three major end-user groups were proportionally represented in the total sample. To control response bias, the survey questions were designed and arranged in such a way that they do not point towards a specific answer or lead to biased responses. Another step made to avoid response bias due to unclear questions was the in-person interview technique. To minimize non-response bias, the survey was scheduled to coincide as nearly as feasible with the respondents' spare time. In cases where end-users were unable to accurately tell the rated power and time of use of appliances, the trained data collectors read the rated power and recorded the duration of use of each appliance. This was necessary to reduce measurement errors. Furthermore, in-depth interviews, field observations, and repeated measures–where respondents are systematically asked the same question in different ways–were used to cross-validate the responses obtained and assess the internal consistency (reliability) of the data collected. The form was written in Portuguese, but the interview was conducted in the local language (Xichangana).

The data collected from the surveys and interviews include the type, quantity, and rated power of appliances, the time frame (period) the appliances are used over the 24 h, and the duration of each appliance's use over the day (operating time). Appendix B presents the various types of pico-PV systems utilized in off-grid areas of Mapai-Sede, and Appendix C details the electrical loads of different appliances identified in the four localities. In addition, to examine the factors influencing electricity consumption, data on the demographic and socioeconomic characteristics of HHs including monthly income, income sources, other energy sources, type and number of buildings, age and gender of the HH-head, and family size were collected.

Electricity consumption estimation

The electricity consumption estimation is based on appliance ownership and daily operating duration data gathered from the in-depth interviews and on-site observational studies. This bottom-up estimation method requires comprehensive data on five important variables: appliance type, rated power, daily operating period (in hours), sector type and number of end-users (Moksnes et al., 2024). In each locality, daily electricity consumption for every sampled user is calculated, and average consumption per user per day is estimated for each sector. Aggregate daily consumption by sector is calculated as:

$$E = \sum_{k=1}^{S} \sum_{j=1}^{U} \sum_{i=1}^{N} n_i {}^* P_i {}^* t_i \tag{2}$$

where E is the aggregated electricity consumption (kWh/day); n_{i} is the number of appliances of i-type; P_{i} is the rated power (W) of appliance i-type; and t_{i} is the operating period (hours) of the appliance i-type; $i = 1, 2, 3, \ldots, N$ is the total number of appliances for each specific user; $j = 1, 2, 3, \ldots, U$ is the total number of users' in a sector; $k = 1, 2, 3, \ldots, S$ is the total number of sectors in a specific subregion is sectors; $i, j, k \in \mathbb{N}$.

Appendix C provides estimated daily electrical loads. Data on appliance rated power and daily operating time are utilized to create peak loads of HHs, PUs and CIs.

Sectoral and spatial analysis of electricity consumption

To understand how electricity consumption varies across sectors and locations, the graphical analysis approach is used (Hlawatsch et al., 2013; Knaflic, 2015). Its advantage is that it improves readability of the estimated consumption while also facilitating comparisons of differences in estimated values across locations and sectors (Abu Hassan et al., 2006). Accordingly, the share of different appliances to the and total electricity consumption are compared. Aggregated sectoral consumption for different locations is compared to investigate how the degree of rurality affects the electricity consumption.

Seasonal electricity consumption variations were not considered due to limited seasonal climate (mainly temperature) variations in the region.

Analysis of factors affecting households electricity consumption

To investigate the factors affecting HHs electricity consumption, a multiple linear regression (MLR) model is used. Several econometric/statistical models can be used to analyze the determinants of electricity consmption (Bekele et al., 2015; Bhattacharyya & Timilsina, 2010; Chapala et al., 2020; Louw et al., 2008). The MLR is one of the most commonly used models to analyze factors influencing electricity consumption. Since the district capital and the three off-grid localities have different sources of electricity, two separate MLR analyses are performed.

Dependent variable is the monthly electricity consumption of HHs in kWh. The independent (predictor) variables include HH-head age and gender, HH monthly per capita income, number of dwellings, monthly firewood and charcoal use, number of lamps, number of televisions (TVs), number of radios, number of refrigrators, number of cellphones and distance from 16 de Junho (see Appendix D). The analysis was done using R software v.4.3.3. The general form for a MLR model can expressed as shown in Eq. (3)

$$y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \varepsilon \tag{3}$$

where y is the dependent variable (HH's monthly electricity consumption); β_0 is the intercept or the predicted consumption if all the factors (independent variables) considered are zero; $\beta_1, \beta_2, \ldots, \beta_{\mathrm{n}}$, are the coffecients for the predictor variables, $X_1, X_2, \ldots, X_{\mathrm{n}}$; and ε is the error term.

The MLR allows identification of factors of significant impact for electricity consumption levels, as well as strengths and directions of these relationships. It was assumed that there is a no relationship between independent variables. The accuracy and significancy of the MLR was measured based on R-squared (R^2) and F-statistic. Due to the lack of historical data on electricity consumption, the input data were collected through a survey.

Results and analysis

Descriptive statistics of demographic and socioecnomic

[2] Guided by five core principles: obtaining informed consent from research participants, explaining the purpose and objectives of the research clearly, safeguarding the confidentiality and anonymity of responses, avoiding any form of coercion of participants, and respecting the privacy of respondents as well as their values, and norms. Initially, written consent was obtained from the local government to conduct research in the region.

characteristics of survey HHs are presented in Table 3. Educational attainment and household size differ considerably between 16 de Junho and the three off-grid localities. Subsistence agriculture (crop and livestock farming) is the main source of livelihood for >90 % in the region (INE, 2023). A significant number of rural HHs also depend on production and sale of charcoal as a major source of income. In contrast, small businesses and non-farm employment are the main sources of income in 16 de Junho. The monthly income of HHs varies seasonally based on the type of income source. 77 % of the sampled respondents in the rural localities earn a monthly gross income of <10, 000 Mozambican Metical (USD 156), while 23 % in 16 de Junho make >20,000 Metical (USD 313).

Energy sources and electricity access

Of the 125 HHs interviewed in the four localities, 85 % depend almost exclusively on firewood for cooking, with the remaining 15 % using both firewood and charcoal in line with earlier studies (Deloitte, 2023; Hartmann & Alessi, 2018; Uamusse, 2019). HHs in 16 de Junho continue to utilize traditional biomass fuels for cooking despite having grid electricity access, possibly since firewood and charcoal are cheaper than electricity (an 80 kg bag of charcoal costed 400 MT (USD 6.50) and a 12 kg bundle of firewood 20 MT (USD 0.31) in 2022). Electricity is thus used only for lighting and cooling. The heavy reliance of HHs in off-grid areas is likely due to the “free” availability of biomass, lack of access to electricity and other cleaner fuels, and the relatively low income of the HHs (Sitoe et al., 2014).

In Mapai-Sede, electricity is supplied by both the main grid and stand-alone PV systems. Since September 2016, 16 de Junho has been connected to the grid. As a result, HHs, businesses and public institutions began receiving grid electricity in 2017. The off-grid localities rely mainly on SHS, pico-SHSs (solar lanterns), battery-powered lanterns, LED lamps, and candles for lighting. According to the Planning and Infrastructure Services of the Mapai-Sede (SDPI), in 2022, 2908 HHs in the district had access to electricity, of which 1500 (52 %) were grid-electrified, and the remainder 1408 (48 %) were mostly supplied by SHS and pico-SHSs (PSHS), see Table 4.

Combining Table 4 and Table 1 data reveals that 60 % of 16 de Junho HHs are grid-connected. According to the survey participants, electricity demand in 16 de Junho has shown low growth over the last five years. The load assessments and in-depth interviews show that HHs, PUs and CIs in 16 de Junho utilize relatively high wattage appliances such as refrigrators, air conditioners and TVs. Despite having grid access, all surveyed HHs primarily rely on firewood for cooking and water heating purposes. In contrast, 56–70 % of HHs in the off-grid localities rely on pico-PVs and SHs, with capacities typically 5–15 Wp.

Table 3
Socio-economic characteristics of survey HHs in the study localities.

Socio-economic characteristics		Localities (sample size)			
		16 de Junho (n = 47)	Mapai River (n = 21)	Mepuzi (n = 26)	Chidulo (n = 31)
Gender of HH-head	Male	30	14	17	21
	Female	17	7	9	10
Average age of the HH-head		40.5	39.8	41.5	42.6
Average education level of HH-head		8.5	4.9	5.1	4.6
Average HH size		4.4	8.4	7.6	8.9
Average monthly income of the HH (in 10^3 Metical*)		11.00	9.29	8.70	7.50

* MT – Metical, the Mozambican currency. In 2022, 1 USD = 63.87 MT.

Table 4
Number of HHs with access to electricity across the four study localities.[1]

	Grid	PV systems	Total
	HH	HH	HH
16 de Junho	1500	N/A	1500
Mapai River	–	602	602
Mepuzi	–	498	498
Chidulo	–	308	308
Total	1500	1408	2908

[1] Primary data obtained from the Planning and Infrastructure Services of the Mapai (SDPI).

Spatial and sectoral variation in electricity consumption

There are clear differences in electricity consumption between the grid-connected 16 de Junho and the off-grid localities. The estimated absolute daily peak load (P_{peak}), average daily consumption per user (E_{av}) and total electricity consumption (E) for all three sectors (HHs, CIs and PUs) are highest in 16 de Junho, and decline with increasing rurality (D_o), see Table 5. The significantly higher electricity consumption by HHs in 16 de Junho compared to the other localities can be attributed to the fact that 16 de Junho is served by the national grid.

A comparison of the average electricity consumption (E_{av}) per user reveals that PUs have the highest consumption, closely follows by CIs, while the HH consumption is much lower in all localities. This clearly shows how important PUs are to the dynamics of rural electricity consumption. Table 5 also unveils that HHs account for the largest aggregated electricity consumption (E) in all four localities, except Chidulo. Interestingly, in the three off-grid localities, the degree of rurality does appear to affect the total consumption (E) for PUs and HHs but not for CIs.

Households (HH)

An analysis of the HH electricity consumption by appliance type across the four localities offers two important insights. First, it shows that the number of appliances utilized by HHs in the grid-connected and off-grid localities differ markedly. Second, it unveils that the share of the various appliances in the HH’s total electricity consumption varies across the four localities, see Fig. 3. In 16 de Junho, refrigerators account for a large percentage of the HH’s daily electricity use, followed by CD/DVD players, TVs, fans, and irons. Since Mapai-sede is a hot district, there is a high demand for electricity for refrigeration and space cooling.

Table 5
Summary of estimated values of daily peak load, total electricity consumption, and average electricity consumption for HHs, CIs, and PUs in the four localities.

Sector	Location	Sample size	P_{peak} (kW)	E (kWh/d)	$E_{av} \pm$ SD (kWh/d)
Households	16 de Junho	47	904.9	3814.8	2.54 ± 2.27
	Mapai River	21	14.2	119.2	0.12 ± 0.07
	Mepuzi	26	23.1	183.6	0.24 ± 0.08
	Chidulo	31	3.0	23.7	0.04 ± 0.05
Community institutions	16 de Junho	24	138.2	1028.6	25.69 ± 37.42
	Mapai River	7	3.5	32.5	2.73 ± 2.95
	Mepuzi	7	1.9	13.3	2.08 ± 2.80
	Chidulo	7	3.2	14.9	1.28 ± 1.28
Productive use	16 de Junho	26	262.1	974.6	25.97 ± 24.83
	Mapai River	5	3.9	37.6	2.86 ± 5.65
	Mepuzi	4	6.4	41.13	3.53 ± 5.59
	Chidulo	6	4.5	53.16	3.32 ± 4.54

P_{peak} – peak load (in kW), E – total electricity consumption (in kWh/day); E_{av} – average consumption (in kWh/day); *SD* - standard deviation of the mean.

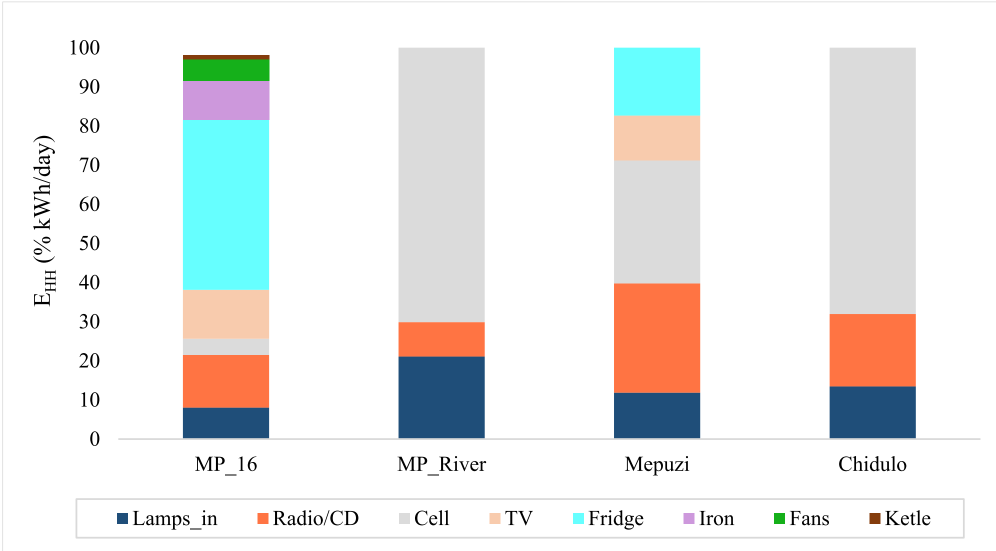

Fig. 3. The estimated percentage share of appliances in the daily electricity consumption of HHs across the four study localities.

During the hot season in particular, cooling fans and air conditioners are used for up to 11 h a day.

In the off-grid areas, lamps, cellphone charging, and radios account for the biggest share of the HH electricity consumption. Few HHs in Mepuzi installed PV systems with capacities between 200 and 400 Wp, and utilize refrigerators and TVs. Access to affordable grid electricity thus plays a major role in determing the electricity consumption of rural HHs.

Another important finding is that the load profiles of HHs in the grid-electrified and off-grid localities are enormously different. The size and distribution of hourly HH loads in the four localities are conspicuously different. Fig. 4 displays that the load curve of HHs in 16 de Junho has a peak load of slightly over 700 W, which occurs at the evening (20:00) accompanied by an early morning mini peak load of around 600 W. The morning peaks are mainly due to ironing and preparation of tea. In contrast, Fig. 5 shows that the peak load in the three rural localities ranges 5 - 35 W and occurs mostly during midday. The differences in load characteristics are direct reflections of the electricity supply source (grid vs stand-alone PV systems), appliance ownership and HH use and economic capability to purchase higher capacity SHS.

Community Institutions (CI)

Fig. 6 displays the percentage of electricity consumed by various community institutions in each of the four localities. In 16 de Junho, government offices are responsible for the largest share (57 %), followed by street lighting (22 %), and schools (13 %). The load survey shows that, aside from computers and other office equipment, air conditioners and fans account for a sizable amount of the electricity consumed by the government offices. In the off-grid localities, the share of electricity consumption of CIs varies between localities. In Mapai River, hostels/state employee residences (63 %), and schools (26 %) make up the largest CI consumption share, while in Mepuzi and Chidulo, health centers (64 %) and churches (32 %) dominate. In all three off-grid localities, health centers are powered by stand-alone PV systems with a minimum capacity of 200W$_p$, but other CIs use PSHS. The small capacity of PSHSs thus limit the electricity consumption to powering small radios, lighting, and charging cellphones, see Table 5.

Productive use (PU)

As reported in Table 5, PUs consume the most electricity per single user in all four localities, but the number and type of PUs varies

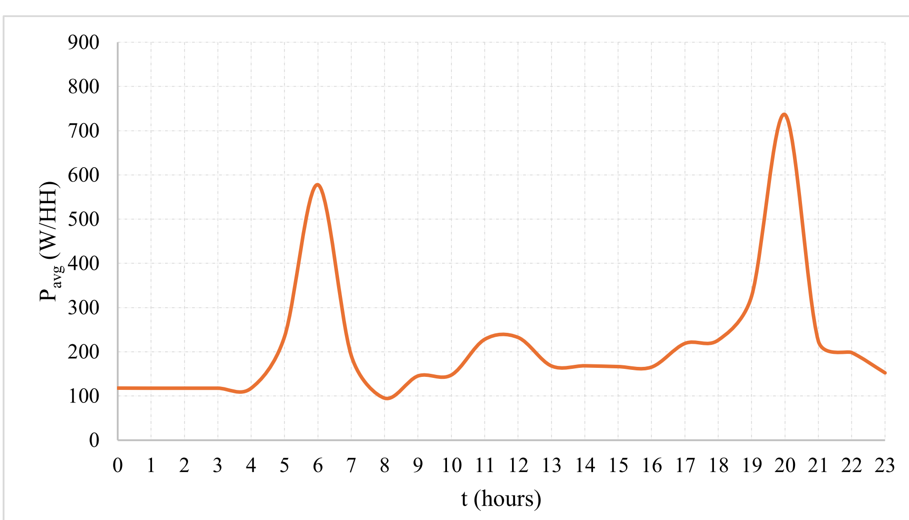

Fig. 4. The estimated average load profile per HH in 16 de Junho. The duty cycle of fridges is assumed to be 0.40, the kettle usage is spread out over time and the electricity consumption of cellphones is the average.

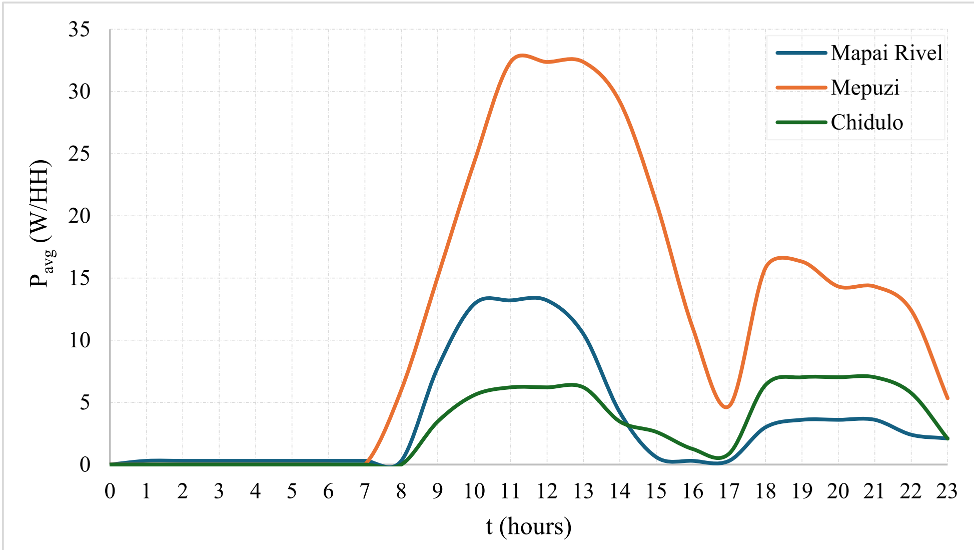

Fig. 5. The estimated average load profile per HHs in off-grid localities of Mapai-Sede.

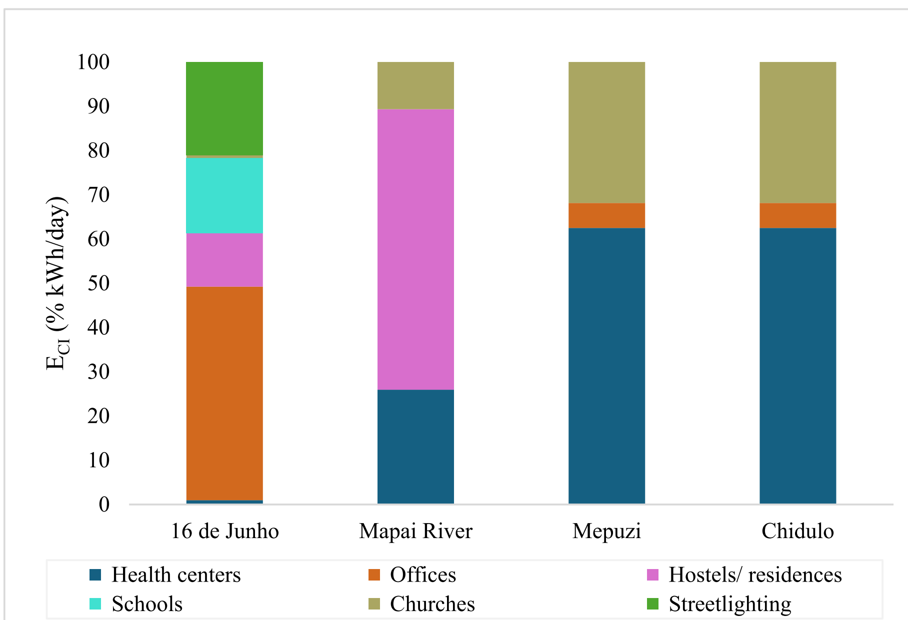

Fig. 6. The estimated percentage share of different services in daily CI electricity consumption.

significantly between 16 de Junho and the off-grid localities Fig. 7. The reason is that PU of electricity in 16 de Junho involves a range of businesses including hotels and guest houses (33 %), kiosks and bars (22 %), grain mills (19 %), water pumping (10 %), and metal-wood workshops and hair salons (16 %). Almost all rooms in hotels and guest houses are equipped with high-wattage appliances such as AC (air conditioners), cooling fans, small refrigerators, and TVs. The air conditioners in particular are power-intensive, resulting in a higher total electricity consumption. In the off-grid localities, water pumping (69 to 88 %) accounts for most of the PU electricity consumption, followed by kiosks, bars and shops (7 to 26 %), and hair salons (2 to 7 %).

In the off-grid localities, water pumping is often conducted using PV systems with a capacity of 1.5 kW_p, while other productive users utilize PSHS or SHS with capacities ranging from 150 to 300W_p. Fig. 7 indicates that the % share of electricity consumption from shops and kiosks in Mapai River is small compared to the other off-grid localities. This is because HHs in Mapai River often shop at 16 de Junho, as such there are not many small shops or bars in Mapai River. By contrast, the % share of electricity consumption for water pumping decreases with the degree of rurality. This is due to the limited access to sufficient capacity PV systems in remote areas.

A comparison of the average daily load profiles of PUs in 16 de Junho and those of PUs in the off-grid areas shows that the load curve of PUs in 16 de Junho oscillates throughout the day, with the peak load occurring in the evening, while the load curve of PUs in the off-grid areas is closely tied to the solar irradiance intensity, with the peak load occurring around midday.

Aggregated electricity consumption by sector

A comparison of the share of the different sectors in the total daily electricity consumption (E) of each locality reveals that the HH sector consumes the most electricity followed by PUs in all four localities,

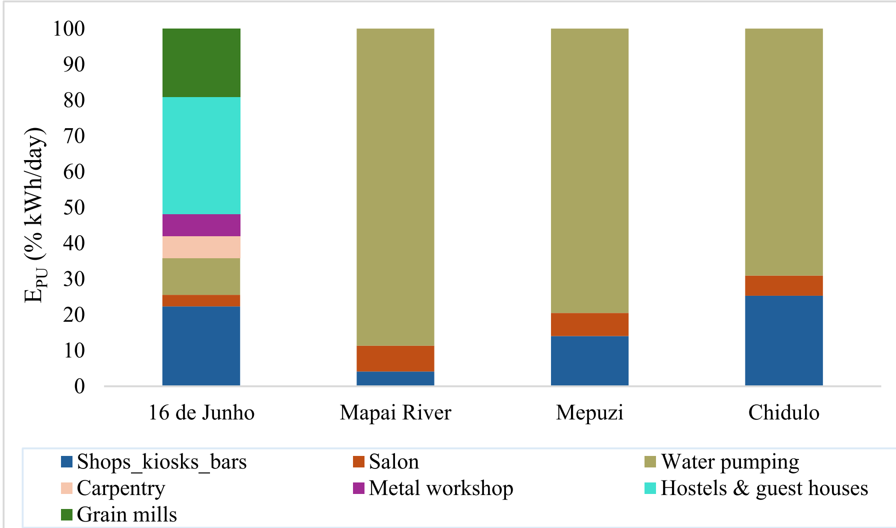

Fig. 7. The estimated percentage share of different services in the daily PU electricity consumption.

except in Chidulo. However, as seen from Fig. 8, in the remotest locality, Chidulo, PUs consume more electricity than HHs. This is explained by the high number of HHs leading to a high aggregate cansumption.

As was shown in Table 5, among the three sectors, CIs account for the lowest aggregate electricity consumption in all four localities and PUs has the highest per user consumption while HHs the lowest. Interestingly, the electricity consumption pattern in Chidulo differs from the other localities with a higher aggregate daily PU demand than that of HHs and CIs, Table 5. There are two possible reasons for this. The first is that Chidulo is the remotest location with poor roads and limited transportation services resulting in HHs depending on locally sold low capacity (below 10 W_p) PSHS. The second is that a few wealthy PUs own PV systems with capacities as large as 200 W_p.

Factors influencing household electricity consumption

Tables 6 and 7 present summary of the results of the regression analysis for the factors affecting HH's electricity consumption in 16 de Junho and off-grid localities, respectively. The overall model F-stats and *p*-values show that both models are statistically significant and have a high goodness-of-fit. The adjusted R^2 in Table 6 suggests that the model explains 73 % of the variation in electricity consumption among HHs in 16 de Junho, whereas the adjusted R^2 in Table 7 indicates that the model explains 89 % of the variance in electricity consumption among HHs in the off-grid areas. The results in Table 6 disclose that the HHs in 16 de Junho with higher monthly per capita income, and higher number of appliances (refrigerators, televisions, radios, and lamps), consume significantly more electricity. The coefficient for per capita income shows that an increase in HH's monthly per capita income by 1000 metical (MT) may increase the HH's monthly electricity consumption by 3 kWh ($p < 0.01$). The largest influence on the electricity consumption of HHs in 16 de Junho, however, comes from appliance ownership.

With respect to charcoal use, the model result suggests that a one ton increase in the HH's monthly charcoal use is linked to a 2.66 kWh decrease in monthly electricity consumption ($p < 0.1$), holding other variables constant.

The coefficients in Table 7: illustrate that HH's electricity consumption in the off-grid localities is positively and significantly influenced by per capita income, and the number of lamps and cellphones the HH owns. A one unit increase in the number of lamps (typically 3 W LED) used by the HH is associated with a 0.45 kWh increase in the HH's monthly electricity consumption. Table 7 also shows that for every

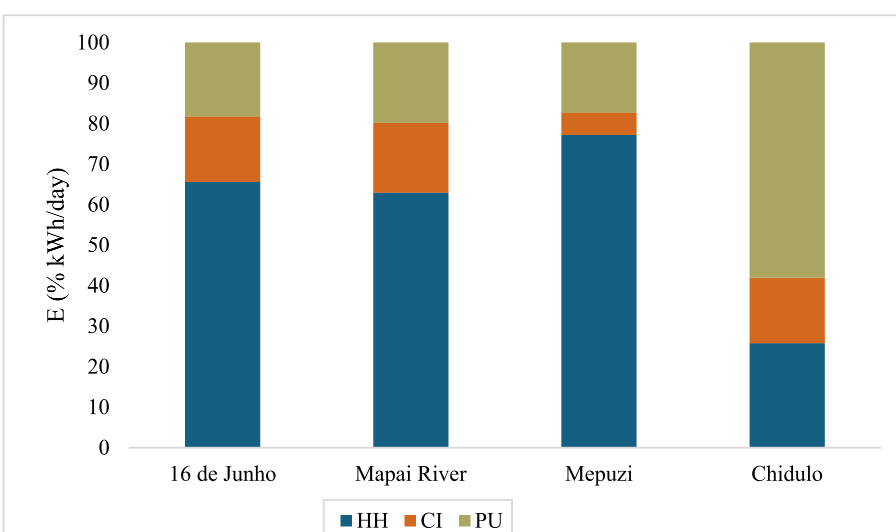

Fig. 8. The estimated percentage share of different sectors in the daily total electricity consumption of each locality.

Table 6
Multiple Linear Regression (MLR) analysis results for households in 16 de Junho.

Call:
lm(formula = E ~ Percapitaincome + Charcoal + NoLamps + NoTVs + NoRadios + NoRefrigirators,
data = Rdata_capital_town).

		No. Observations:		47
		Multiple R-Square:		0.767
		Adjusted R-Square:		0.732
		F-Statistic:		21.90
		p-value:		0.000
Variables	Coeff.	Std. error	t-value	Pr(>|t|)
Intercept	−14.040	11.671	−1.201	0.236
Monthly per capita income (10^3 MT)	3.093	1.172	2.603	0.012**
Monthly charcoal use (ton//HH)	−2.662	1.155	−1.980	0.0550*
No of lamps (unit/HH)	9.105	11.477	2.034	0.048**
No of televisions (unit/HH)	46.535	11.433	4.022	0.000***
No of radios/CD players (unit/HH)	24.848	0.393	2.106	0.041**
No of refrigirators (unit/HH)	77.102	11.856	6.658	0.000***

Signif. level: **p* < 0.1; ***p* < 0.05; ****p* < 0.01.
Residual standard error: 1.159 on 40 degrees of freedom.

Table 7
Multiple Linear Regression (MLR) results for rural households.

Call:
lm(formula = E ~ Distance + Percapitaincome + Firewood + NoLamps + NoCelphones, data = RdataRural).

		No. Observations:		78
		Multiple R-Square:		0.895
		Adjusted R-Square:		0.887
		F-Statistic:		122.3
		P-value:		0.000
Variables	Coeff.	Std. error	t-value	Pr(>|t|)
Intercept	3.682	3.127	1.677	0.097 *
Distance from district capital (km)	−0.122	0.102	−2.031	0.047**
Monthly per capita income (10^3 MT)	1.712	1.059	3.664	0.000***
Monthly firewood use (ton/HH)	−0.103	0.085	−2.584	0.014**
No of lamps (unit/HH)	0.448	0.172	4.814	0.000 ***
No of cellphones (unit/HH)	1.532	0.186	17.783	0.000 ***

Signif. level: *p < 0.1; **p < 0.05; ***p < 0.01.
Residual standard error: 0.7887 on 72 degrees of freedom.

additional cellphone the HH owns, the monthly electricity consumption increase by 1.5 kWh. Distance from the district capital town (market center), and firewood use are negatively and statistically significantly associated with HH electricity consumption. This reinforces the results in Table 5 where HHs in the distant locality of Chidulo have the lowest average electricity consumption.

Discussion

Spatial and sectoral variability of electricity consumption

One of the main findings in the studied rural localities is that HHs account for >62 % of the total daily electricity consumption in three localities, but not in the remotest, and that the share of PUs and CIs is generally similar. The explanation for the high share of the residential sector in the total electricity consumption relates to Mapai-Sede being a rural district and HHs representing the majority of the end-users. However, each PU show a much higher consumption than the HHs in all localities; in line with a recent study in rural Ethiopia (Wassie, Ahlgren, 2023b) finding that HHs accounted for 43 to 60 % of the total electricity consumption followed by PUs (25 to 49 %).

Another major finding is that rural electricity consumption varies significantly across locations, particularly among HHs. The average daily consumption per HH in the grid-connected district capital is more than six times that of the three off-grid (2.54 compared to 0.04–0.24 kWh/day). Degree of rurality also appears to determine consumption as the average daily consumption per HH in the two localities closer to the district capital is higher than that of HHs in the remotest. The daily consumption per PU and CI in the district capital is two-three times higher than that in the three off-grid localities. Such large divergence is also reported in a study on grid-connected rural villages in Mozambique (Uamusse et al., 2020), finding HH consumption ranging from 0.38 to 20.56 kWh/day depending on HH's location and other underlying factors. Location thus seem to determine electricity consumption of rural HHs and businesses in SSA by affecting their access to grid power, income generation opportunities, and access to appliances. This is more evident from the survey data where HHs and businesses in the localities closer to the district capital have easier access to SHS retailers, whilst those in remote locations are unable to do so because of the long distance, poor quality roads and the additional costs that come with these barriers. Electricity consumption in Mapai is found to still be low, with HHs in 16 de Junho falling under Tier 3 of the World Bank's Multitier Framework (MTF) and HHs in the off-grid localities falling under Tier 1 and Tier 2 (ESMAP, 2015; Peters & Sievert, 2016).

A related important finding is the significant difference of HH load profiles between the grid-connected and off-grid localities. In the district capital, a grid-connected small town, the proximity to the main road and the railroad and high concentration of economic and business activities leads not only to a high consumption but also to a different load pattern due to HH utilization of high-wattage appliances such as TVs, refrigirators and air conditioners for as long as they want and can afford. Off-grid HHs with mostly low-capacity pico-PVs can only use these systems to power 1 to 3 LED lamps and charge cellphones for a limited number of hours per day. These findings demonstrate that the availability of power plays a fundamental role in determining the electricity consumption of rural HHs.

Factors affecting household electricity consumption

The regression analysis results reveal that the factors determining HH's electricity consumption in grid-connected and off-grid localities of Mapai-Sede are notably different. While appliance ownership and income are common major drivers in both locations, the type of appliances used are distinctly different between the two locations. Evidently, in rural localities, consumption is influenced by lamps and cellphones, but in 16 de Junho by refrigerators and TVs. Furthermore, load assessment data shows that air conditioners and cooling fans have significantly increased the electricity consumption of productive users in 16 de Junho. This demonstrates how local climate (temperature) affects electricity consumption. Previous studies have also found that space cooling fans and refrigerators have a substantial impact on HH's electricity consumption (IEA, 2019; INE, 2023; Wassie, Ahlgren, 2023b).

Another important finding is that while per capita income is a major influencing factor in both 16 de Junho and off-grid areas, its influence is more pronounced for HHs in 16 de Junho. One possible explanation is that the off-grid HHs are located far from market centers, and hence even when they have adequate disposable income they cannot access higher capacity PV systems. As a result, variations in income among HHs will have little effect on electricity consumption. This was also supported by our on-site surveys where some HHs in Mepuzi and Chidulo who could afford higher capacity SHS depended on pico-SHS which are basically designed only for lighting, and charging cellphones. Our findings support a recent study (Wassie, Ahlgren, 2023b) showing that

HH's electricity consumption in rural SSA is affected more by location, local climate and access to appliances than by income. The significant and negative correlation between charcoal use and electricity consumption in 16 de Junho might be because HHs in 16 de Junho depend more on charcoal for cooking whereas HHs in the off-grid localities rely more on firewood (Bernard, 2012; Kituyi et al., 2001). As a result, HHs with higher charcoal consumption may use less electricity. The takeaway is that HH's electricity consumption in grid-powered and off-grid areas are affected by related but different factors and, hence, a thorough understanding of this dynamics is crucial for informed rural electrification planning and accurate demand forecasting.

One limitation of this study is the lack of validation of the survey data against measured data, which may introduce errors in estimating and predicting future electricity demand. Self-reported information from surveys often fails to fully capture actual electricity consumption patterns. Cross-validating survey data with measured data would have been the most reliable approach to address these limitations.

Contributions and implications

This study contributes by exploring, analyzing and comparing electricity consumption at the edge of the grid, in grid-connected and off-grid localities within one district – a topic less studied in rural areas. Understanding these differences and dynamics is essential for electrification investments, policy decisions and electrification strategies, whether through grid expansion or decentralized off-grid technologies. The significant spatial and sectoral electricity consumption differences have implications for resource allocation, choice of electrification technology and tariff setting. Localities with high HH or PU electricity demand might benefit from grid extension, while low-demand localities might be more cost-effectively served through decentralized technologies.

Conclusions

This study investigates spatial and sectoral variations in rural electricity consumption and the influencing factors. Data were gathered through an on-site survey of end-users (bottom-up approach) in four localities at the edge of the electricity grid, three remote off-grid and one grid-connected, in Mapai-Sede, Mozambique. Multiple linear regression models were used to analyze the factors influencing household electricity demand. The findings show as expected a much higher electricity consumption in the central grid-connected locality than in the off-grid localities. Analysis of electricity consumption across sectors reveals that, in all four localities, HHs account for 62 % of daily total consumption, and that both average daily consumption per user and peak loads in all sectors were manyfolds higher in the grid-connected locality than in off-grid localities. The load profiles of households in the grid-connected and off-grid localities were distinctly different.

The regression analysis shows that HH's electricity consumption in the grid-connected locality is positively and strongly associated with per capita income and the number of refrigerators, space cooling fans and televisions, whereas in the off-grid localities, cellphones and LED lamps dominate. The results imply that, while the factors affecting HH's electricity consumption differ somewhat, appliance ownership remains the most important determinant in both areas.

Overall, this study unveils that electricity consumption in rural Mozambique varies significantly both spatially and sectorally. It also shows that grid connection, productive use, and appliance ownership play an important role in shaping electricity consumption. The study affirms that access to electricity, particularly grid electricity, improves rural economic development, business creation and provision of public services. However, the study does also reveal that electricity consumption in rural Mozambique is still low. Understanding these dynamics is therefore crucial for locally-fit and optimal rural electrification planning. In view of that, the study emphasizes the need for a comprehensive approach to rural electrification and energy planning taking into account spatial, sectoral, and socio-economic variations. By designing strategies and actions taking this complexity into account, policy makers can improve electricity supply.

CRediT authorship contribution statement

Basilio Z.S. Tamele: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Yibeltal T. Wassie:** Writing – review & editing, Supervision, Methodology. **Alberto J. Tsamba:** Supervision. **Erik O. Ahlgren:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. Distribution of sample end-users in each locality by sector

Consumer group	Spatial distribution				
	16 de Junho	Mapai River	Mepuzi	Chidulo	Total
Households	47	21	26	31	**125**
Government Buildings	15	1	1	1	18
Health Centers	1	1	1	1	4
Schools	2	1	1	1	5
Churches	5	4	4	4	17
Street lighting	1	0	0	0	1
Sub-total Community Institutions	**24**	**7**	**7**	**7**	**45**
Mini-shops	3	0	0	0	3
Kiosks	3	2	1	2	8
Bars	3	1	1	2	7

(*continued on next page*)

(*continued*)

Consumer group	Spatial distribution				
	16 de Junho	Mapai River	Mepuzi	Chidulo	Total
Hotels/guest houses	5	0	0	0	2
hair salons	2	1	1	1	5
Metal workshops	2	0	0	0	2
Water supply	3	1	1	1	6
Grain mills	1	0	0	0	1
Carpentry	4	0	0	0	4
Sub-total business	**26**	**5**	**4**	**6**	**41**
Total	**97**	**33**	**37**	**44**	**211**

Appendix B. Pico-PV systems used by off-grid households and small businesses

Appendix C. Estimated daily electric loads (energy services) in different sectors

Sector	Appliances	Locality											
		16 de Junho			Mapai River			Mepuze			Chidulo		
		x	$\overline{x}$	Δx	x	$\overline{x}$	Δx	x	$\overline{x}$	Δx	x	$\overline{x}$	Δx
	Lighting	57	2.59	1.89	18	1.80	1.54	49	6	1.29	15	0.62	0.13
	Radio/CD-DVD	25	0.53	0.50	3	0.30	0.48	6	0.20	0.40	4	0.16	0.38
	Cell	42	1.62	1.28	15	1.50	1.50	44	1.46	1.27	16	0.66	0.76
Households (HHs)	TV	16	0.34	0.47	–	–	–	2	0.06	0.25	–	–	–
($n_0 = 47$; $n_1 = 21$; $n_2 = 26$; $n_3 = 31$)	Fan	18	0.38	0.49	–	–	–	–	–	–	–	–	–
	Fridge	19	0.40	0.49	–	–	–	1	0.03	0.18		–	–
	Iron	21	0.45	0.50	–	–	–	–	–	–	–	–	–
	Kettle	14	0.30	0.46	–	–	–	–	–	–	–	–	–
	Common applian.:												
	Lighting	573	30.11	35.79	25	8.33	3.51	39	6.73	5.81	24	6.00	1.41
	Cooling AC	37	2.18	1.74	–	–	–	–	–	–	–	–	–
	Cooling Fan	40	2.35	3.85	–	–	–		–	–	–	–	–
	Kettle	16	0.9	0.24	–	–	–	–					
	Cellphone	–	–	–	–	–	–	11	3.66	3.51	–	–	–
	Offices:												
	- Computers	40	2.50	2.80	–	–	–	–	–	–	–	–	–
	- Microwave	3	0.19	0.40	–	–	–	–	–	–	–	–	–
	- Photocopy/printer	19	1.06	0.24	–	–	–	–	–	–	–	–	–
Community institutions (CI)	Residences:												
($n_0 = 24$; $n_1 = 7$; $n_2 = 7$; $n_3 = 7$)	- TV, DVD-CD	2	0.33	0.52	–	–	–	–	–	–	–	–	–
	- Microwave	1	0.17	0.41	–	–	–	–	–	–	–	–	–
	- Oven/Stove.	6	1	0.0									
	- Blender	1	0.17	0.41	–	–	–	–	–	–	–	–	–
	- Fridge/ Freezer	6	1	0.0	–	–	–	–	–	–	–	–	–
	Health Center:				–	–	–	–	–	–	–	–	–
	- Lab. Equipment	–	–	–	–	–	–	–	–	–	–	–	–
	- Refrigerator	1	1	0	–	–	–	–	–	–	–	–	–
	- Sterilizer	2	2	0	–	–	–	–	–	–	–	–	–
	Churches:												
	- Sound system	5	1.00	–	3	1.00	–	4	1.00	–	4	1.00	0
	Streetlights:	120	–	–	–	–	–	–	–	–	–	–	–
	Common applian:												
	Lighting	382	25.13	46.71	–	–	–	15	–	–	–	–	–
	Cooling Fans	77	4.00	8.00	–	–	–	–	–	–	–	–	–
	Cooling AC	19	1.00	3.00	–	–	–	–	–	–	–	–	–
	Kettle	78	3.55	8.97	–	–	–	–	–	–	–	–	–
	Shops/kiosks/bars:												
	- Refrigerators	15	1.88	0.35	–	–	–	1	0.25	–	–	–	–
	Carpentry:												
	- Saw	6	1.50	1.29	–	–	–	–	–	–	–	–	–
	- Sender	5	1.25	0.50	–	–	–	–	–	–	–	–	–
Productive users (PU)	- Planer	6	1.50	0.58	–	–	–	–	–	–	–	–	–
($n_0 = 23$; $n_1 = 5$; $n_2 = 4$; $n_3 = 6$)	- Drill	5	1.25	0.50	–	–	–	–	–	–	–	–	–
	Hair Salon:												
	- hair drier	5	1.67	1.53	–	–	–	–	–	–	–	–	–
	- hair cutter	4	1.33	1.15	2	2	–	2	2	–	2	2	–
	- straightener	2	0.67	0.58	–	–	–	–	–	–	–	–	–
	Metal Workshop												
	- Drilling machine	2	1.00	0.0	–	–	–	–	–	–	–	–	–
	- Cutting Machine	3	1.50	0.71	–	–	–	–	–	–	–	–	–
	- Welding Machine	2	1.00	0.00	–	–	–	–	–	–	–	–	–
	Water pumps	3	1	0	1	1	0	2	1	0	1	1	0
	Hostels/G. House												
	- Refrigerators	68	11.33	17.56	–	–	–	–	–	–	–	–	–

x- total number of appliances in the sampled users; $\overline{x}$- the average load per user; Δx- the mean standard deviation; n_1, n_2, n_3, n_4- the sample sizes for 16 de Junho, Mapai River, Mepuze and Chidulo, respectively.

Appendix D. Summary statistics of household parameters based on collected data

Parameters	Off-grid localities (sample, $n = 79$)			District capital town (sample, n = 47)		
	Mean	Min	Max	Mean	Min	Max
Electricity demand, E (kWh/month/HH)	2.848	0.000	10.170	70.14	0.00	267.60
Distance from the capital, D (km)	66.48	17.00	135.00	3.975	0.200	9.000
Gender (0 = Male; 1 = Female)	0.36	0	1	0.33	0	1
Age of the HH head (years)	32	41.400	62.00	40.53	31	65
Level of education of the HH head (years)	4.99	0.000	12.00	8.72	0.00	16
Number of Dwellings (per HH)	7.000	3.835	1.000	3.021	1.000	6.000
Number of rooms (per HH)	7.00	2.00	16.00	5.872	4.000	10.000

(continued on next page)

(*continued*)

Parameters	Off-grid localities (sample, $n = 79$)			District capital town (sample, n = 47)		
	Mean	Min	Max	Mean	Min	Max
HH size (number of occupants/HH)	7.777	1.000	24.000	4.426	1.000	13.000
Per capita income (10^3 MT/month/HH)	1.7614	0.1042	23.6250	3.698	0.080	20.00
Firewood for cooking (10^3 kg/month/HH)	0.090	0.314	1.980	0.2145	0.0000	0.4500
Charcoal for cooking (10^3 kg/month/HH)	0.02886	0.0000	0.36000	0.02667	0.0000	0.0810
Number of lamps (per HH)	3.000	0.000	5.000	4.532	0.000	9.000
Number of Radios (per HH)	0.2025	0.0000	1.000	0.5532	0.0000	1.0000
Number of cellphones (per HH)	1.195	0.000	5.000	1.617	0.000	7.000
Number of Televisions, TV (per HH)	NA	NA	NA	0.3404	0.0000	1.0000
Number of freezers (per HH)	NA	NA	NA	0.4043	0.0000	1.0000
Number of Kettles (per HH)	NA	NA	NA	0.3191	0.0000	1.0000
Number of fans (per HH)	NA	NA	NA	0.383	0.000	1.000

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