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Socio-economic determinants of energy poverty at the household level in Uganda

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Abstract

Access to affordable, reliable, and sustainable energy extends beyond access to electricity. In Uganda, despite a tripling of electricity access between 2013 and 2023, over 90 per cent of households continue to use traditional biomass fuels for cooking, with considerable rural-urban differences. Lack of access to modern energy, as well as inefficiencies in energy use and supply, position households in a state of energy poverty. While research on energy poverty exists in Uganda, it is primarily based on unidimensional, access-based metrics, which understate the composition and extent of energy poverty. Furthermore, research on the socioeconomic determinants of energy poverty in Uganda is scarce. To close this gap, this study explores the socioeconomic determinants of energy poverty at the household level by, first, generating a multidimensional energy poverty index for Uganda. Thereafter, using the obtained index to carry out a national spatial hotspot analysis. The socioeconomic drivers of energy poverty are then estimated using econometric models based on survey data from 472 households. The study's findings, obtained from ordinary least square and logistic regression model estimations, suggest that households with higher income and education, particularly those headed by women, are less vulnerable to energy poverty. In contrast, larger household size and unmet household energy demand exacerbate the vulnerability. The findings reinforce the case for ongoing Government energy access initiatives and welfare support such as the Parish Development Model, while highlighting the need to embed affordability, financial inclusion, and gender mainstreaming as core pillars of energy policy design and implementation.

Keywords: Energy poverty; Multidimensional index; Uganda; Socioeconomic determinants; Hotspot analysis; Gender; Parish Development Model; Sub-Saharan Africa.

JEL codes: Q41; O13; I32; R11

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1 Introduction

Access to energy is imperative for economic development and poverty alleviation. Universal access to affordable, reliable, and sustainable energy services requires expanding electricity access, promoting clean cooking fuels and technologies, improving energy efficiency, and increasing the use of renewable energy (SDG7). While global access to electricity improved to 80% in 2021, Sub-Saharan Africa (SSA) reached only 30%. Moreover, less than 20% of the global population uses renewable energy. This implies that many households do not have adequate access to modern energy, even in cases where they are not completely energy-deficient. This situation is commonly referred to as ”energy poverty” and it has detrimental effects on household livelihoods Churchill and Smyth (2021); Llorca et al. (2020); Thomson et al. (2017).

While energy is fundamental for Uganda's socioeconomic transformation, energy poverty remains widespread across the country. Sustained interventions and significant investment by the Government towards addressing energy shortages led to a tripling of electricity access from 14% in 2013 to 45% in 2021 and a further increase of 60% in the financial year 2023/24. Nonetheless, there were significant divergences between rural areas and urban areas. Access to electricity in the rural area increased from 3% in 2013 to 36% in 2021 while for urban areas, it grew from 56% to 72%.Furthermore, inefficiencies persist in both the supply and demand of energy, with demand projected to surge further as the country's tenfold-growth development strategy accelerates. Additionally, more than 90% of households continue to rely on solid fuels for cooking, reflecting the persistent vulnerability of Ugandans to energy poverty. Over-reliance on solid fuels is not only a health hazard Health Effects Institute (2019), but also generates adverse effects through lost opportunities for education, particularly for women and children, who spend most of the day collecting cooking fuels Khizar et al. (2020). Consequently, improving access to affordable energy is crucial for the country's economic development, social wellbeing, and environmental sustainability, as the energy sector feeds directly into other key sectors of the economy.

A key limitation is that energy poverty in Uganda is still predominantly measured as a unidimensional indicator, most notably electricity access. Indeed, existing research has adopted single measures of energy poverty Nussbaumer et al. (2012a); Munro and Bartlett (2019); Miller and Ulfstjerne (2020); Kay et al. (2021). The exclusion of critical dimensions of deprivation related to affordability, quality, reliability, cleanliness, and adequacy relative to household demand, underestimates both the extent and intensity of energy deprivation.

Although recent studies, such as Ssennono et al. (2021), have begun to adopt multidimensional approaches, empirical evidence on the socioeconomic determinants of household vulnerability remains limited. Little is known about how income, education, employment, household composition, gender dynamics, access to finance, and participation in government programmes interact with energy supply conditions to shape household energy outcomes. It is therefore imperative that empirical evidence on the socioeconomic determinants of multidimensional energy poverty in Uganda be explored, as such evidence is crucial for effective policy design, particularly given that programmes such as Uganda's Parish Development Model (PDM) and ongoing electrification and clean-cooking initiatives require granular data on where energy poverty is most severe, who is most vulnerable, and why. Moreover, the limited availability of gender-disaggregated data hinders effective gender mainstreaming in energy, climate, and social protection policies.

Given this background, the purpose of this study is to close the highlighted gaps and contribute to the body of knowledge on the socioeconomic determinants of energy poverty. The general objective of this study is to examine the socioeconomic determinants and spatial distribution of multidimensional energy poverty at the household level in Uganda in order to inform the design of targeted and effective energy and development policies. The specific objectives are to:

1. Identify spatial hotspots of energy poverty based on a multidimensional energy poverty index.

2. Analyze the socioeconomic determinants of household multidimensional energy poverty using primary data collected from identified hotspot areas; and,

3. Generate evidence-based policy recommendations to support targeted interventions aimed at reducing energy poverty in Uganda.

To achieve these objectives, the study first develops a multidimensional energy poverty index for each of Uganda's sub-regions, then undertakes a nationwide hotspot mapping exercise describing the intensity of energy poverty across the country, and finally examines the socioeconomic characteristics of the most vulnerable areas. The study findings make several contributions. At the policy level, they provide empirical evidence to guide government agencies, development partners, and local authorities in designing targeted, energy access and use interventions. Academically, they contribute to the literature on multidimensional energy poverty by offering a robust analytical framework and empirical evidence from a low-income country context, while also addressing a critical evidence gap on the gendered dimensions of energy poverty in Uganda.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology. Section 4 presents the emprical framework while the spatial hotspot analysis regressions results are in section 5. Section 6 contains the conclusion and policy recommendations.

2 Literature Review

Energy poverty is broadly defined as the inability to access sufficient, affordable, and clean energy for household needs, including lighting, cooking, and heating International Energy Agency (2022). The International Monetary Fund (2022) further emphasises that energy poverty extends beyond electricity access to include the use of inefficient and hazardous traditional fuels such as firewood and charcoal. In Uganda, the majority of households (94%) continue to use solid fuels for cooking, reflecting the persistent vulnerability of Ugandans to energy poverty Uganda Bureau of Statistics (2023). Existing studies indicate that the determinants of energy poverty are multifaceted, spanning affordability, awareness, gender dynamics, energy infrastructure, and policy interventions. Household income is among the most consistently identified determinants. Lower-income households in Uganda rely heavily on biomass fuels, as they cannot afford electricity or cleaner alternatives such as liquefied petroleum gas Kasekende and Ochieng (2021). The cost of grid connection and recurrent electricity bills further restrict access among economically disadvantaged communities.

Educational attainment also influences energy choices and the adoption of modern energy solutions. Tumwebaze et al. (2022) find that households with higher education levels are more likely to transition to cleaner energy sources, owing to greater awareness of the associated health and economic benefits. Conversely, limited educational attainment among rural populations remains a significant barrier to the adoption of sustainable energy solutions. Gender dynamics represent another critical determinant of energy access, particularly in rural areas where women bear primary responsibility for household energy needs. Mukasa and Nabwami (2020) find that women in energy-poor households spend considerable time collecting firewood, significantly curtailing their economic opportunities. Male-dominated household decision-making further compounds this challenge by limiting investment in cleaner energy technologies, reinforcing the gendered dimensions of energy poverty.

Geographical location also plays an important role in shaping energy outcomes. Urban areas generally enjoy relatively better electricity access, while rural households are disproportionately affected by inadequate grid infrastructure and high connection costs Ministry of Energy and Mineral Development (2023). Off-grid solutions such as solar home systems have been promoted to bridge this gap; however, affordability constraints continue to limit their uptake amongst households. The availability of energy infrastructure, including grid extension and renewable energy projects also influence energy access. The Ugandan Government has implemented policies such as the National Energy Policy (2019) to expand electrification; however, progress has been constrained by financial limitations and logistical challenges Ministry of Energy and Mineral Development (2023). Unreliable electricity supply and frequent outages additionally discourage investment in grid connections, undermining the gains made through electrification programmes.

Several policy initiatives have been introduced to address energy poverty in Uganda. The Rural Electrification Strategy aims to increase electricity access through subsidies and private sector engagement, while donor-funded programmes such as the World Bank's Energy for Rural Transformation project have supported off-grid solar solutions World Bank (2023b). Despite these efforts, affordability and infrastructure gaps remain persistent challenges. Taken together, the existing literature highlights the critical role of income, education, gender, geographical location, and infrastructure in shaping energy poverty outcomes in Uganda. However, a number of important gaps remain. First, most existing studies examine these determinants in isolation, with limited attention to how they interact to shape household energy outcomes. Second, the predominant focus on electricity access as a single measure of energy poverty overlooks broader dimensions of deprivation related to affordability, reliability, cleanliness, and adequacy. Third, there is limited empirical evidence on the spatial distribution of energy poverty and the vulnerability of specific household groups.

This study seeks to address these gaps by developing a multidimensional measure of energy poverty, mapping its spatial distribution across Uganda, and examining the socioeconomic determinants of household vulnerability with particular attention to gender and the role of government programmes.

3 Data and Methodology

3.1 Research design

This study adopts a quantitative research methodology to examine the socioeconomic factors that contribute to household energy poverty. First, secondary data from national household surveys, administrative records, and reports from relevant ministries are supplemented with data from international institutions and publicly accessible platforms to construct a Multidimensional Energy Poverty Index (MEPI). Subsequently, a spatial hotspot analysis is performed using the constructed MEPI to determine which geographic regions are most and least vulnerable to energy poverty. Based on these hotspot results, a stratified random sample of 30 households is selected from each of Uganda's 16 sub-regions. To enhance the accuracy and contextual relevance of the sampling process, local community leaders and District Planning Officers are consulted for validation of identified hotspot areas. Finally, econometric modelling is applied to primary data from a household survey conducted among the sampled households to investigate the socioeconomic determinants of energy poverty and assess how these determinants vary across levels of vulnerability.

3.2 Data sources

Guided by the literature, and consistent with empirical evidence that energy access constraints arise from the interaction of demand-side household characteristics and supply-side policy and institutional factors Practical Action (2018), the study combines variables from multiple datasets to identify eleven indicators that capture multidimensional energy poverty. These indicators are broadly classified under two main categories. The sensitivity category captures households' direct exposure to energy-related deprivation, such as lack of electricity, use of traditional fuels, and poor lighting. The adaptive capacity category reflects the structural and institutional capacity of households to cope with and adapt to energy poverty, including access to finance, participation in decision-making, and availability of energy infrastructure. The definitions and data sources for all indicators used to develop the multidimensional measure are summarised in Table 1.

Table 1: Multidimensional Energy Poverty Index: Definitions and Sources

Dimension	Indicator/Measurement	Description	Data Source
Sensitivity	Households without electricity connection (%)	Share of households without access to electricity	Uganda National Household Survey2019/20, UBoS
	Households using firewood as main energy source (%)	Share of households relying primarily on firewood for cooking	Uganda National Household Survey2019/20, UBoS
	Households not using clean energy for lighting (%)	Share of households using non-modern lighting sources	Uganda National Household Survey2019/20, UBoS
	Energy demand index	Estimated total energy demand based on population	Energy Access Explorer
Adaptive Capacity	Households with grid connections (%)	Share of households connected to the national electricity grid	Uganda Bureau of Statistics
	Population with access to finance (%)	Share of population with access to formal or semi-formal financial services	Uganda National Household Survey2019/20, UBoS
	Gender income gap (%)	Difference in average income or earnings between women and men as a share of average income for men	Demographic and Health Survey 2022
	Women's participation in decision-making (%)	Share of women elected as Chairpersons and Councilors at Local Government per district	Women in Local Government, 2019,UBoS
	Energy infrastructure	Availability of infrastructure for electricity and alternative sources of clean energy	Uganda National Household Survey2019/20, UBoS
	Participation in government development programmes (%)	Number of women benefiting from government-supported development programmes	Uganda Women Entrepreneurship programmeme Report FY2021/2022
	Energy supply index	Composite indicator reflecting energy availability and supply adequacy	Energy Access Explorer(open access geospatial platform)

3.3 Construction of the MEPI

The Multidimensional Energy Poverty Index (MEPI) is generated through a structured procedure that consolidates the eleven indicators of energy deprivation shown in Table 1 as follows. Let the households be denoted by $i = 1, \ldots, N$, and let the $K = 11$ indicators be partitioned into two non-overlapping sets: Sensitivity indicators $\mathcal{S}$ and Adaptive Capacity indicators $\mathcal{A}$, such that $\mathcal{S} \cap \mathcal{A} = \emptyset$ and $\mathcal{S} \cup \mathcal{A} = \{1, \ldots, 11\}$. Let x_{ik} denote the raw value of indicator k for unit i. To address differences in measurement scales, all indicators are first normalised using min-max normalisation to ensure that each variable contributes equally to the analysis. With directionality $d_k \in \{+1, -1\}$ where $d_k = +1$ implies higher values indicate higher deprivation, and $d_k = -1$ implies higher values indicate lower deprivation), the normalisation is applied as shown in Equation (1).

$$z_{ik} = \begin{cases} \dfrac{x_{ik} - \min_i x_{ik}}{\max_i x_{ik} - \min_i x_{ik}}, & d_k = +1, \\[2ex] 1 - \dfrac{x_{ik} - \min_i x_{ik}}{\max_i x_{ik} - \min_i x_{ik}}, & d_k = -1, \end{cases} \qquad z_{ik} \in [0, 1]. \tag{1}$$

Principal Component Analysis (PCA) is then applied separately to the sensitivity and adaptive capacity indicators to reduce dimensionality and derive weights based on the relative contribution of each indicator within its respective category. This approach allows each indicator's contribution to be endogenously determined within its domain, while preserving the conceptual distinction between demand-side constraints and supply-side enabling conditions. The dominant component extracted from each domain serves as a summary measure of that dimension.

Let $\mathbf{Z}^{(S)} = [z_{ik}]_{k \in \mathcal{S}}$ and $\mathbf{Z}^{(A)} = [z_{ik}]_{k \in \mathcal{A}}$ denote the normalised data matrices for the sensitivity and adaptive Capacity indicators, respectively. PCA is conducted separately on each matrix. For category $C \in \{S, A\}$, let $(\lambda_m^{(C)}, \mathbf{v}_m^{(C)})$ denote the eigenvalue–eigenvector pair of the correlation (or covariance) matrix of $\mathbf{Z}^{(C)}$, where $\mathbf{v}_m^{(C)} = (v_{km}^{(C)})_{k \in \mathcal{C}}$.
The m-th principal component score for unit i is given by equation (2):

$$PC_{im}^{(C)} = \sum_{k \in \mathcal{C}} v_{km}^{(C)} z_{ik}, \qquad C \in \{S, A\}. \tag{2}$$

Using explained-variance-weighted loadings, indicator weights within each category are defined as in Equation (3),

$$w_k^{(C)} = \frac{\sum_{m=1}^{M_C} \left(\lambda_m^{(C)} \, |v_{km}^{(C)}| \right)}{\sum_{j \in \mathcal{C}} \sum_{m=1}^{M_C} \left(\lambda_m^{(C)} \, |v_{jm}^{(C)}| \right)}, \qquad \sum_{k \in \mathcal{C}} w_k^{(C)} = 1, \tag{3}$$

where M_C denotes the number of retained components in category C.

The sensitivity and adaptive capacity sub-indices are then constructed as shown in Equation (4).

$$SI_i = \sum_{k \in \mathcal{S}} w_k^{(S)} \, z_{ik}, \qquad AC_i = \sum_{k \in \mathcal{A}} w_k^{(A)} \, z_{ik}. \tag{4}$$

Because higher adaptive capacity represents enabling conditions, that is, lower deprivation, the adaptive capacity sub-index is inverted so that higher values consistently imply higher energy poverty, as shown in Equation (5).

$$AC_i^* = 1 - AC_i. \tag{5}$$

The overall MEPI is then computed as shown in Equation (6).

$$MEPI_i = \alpha \, SI_i + (1 - \alpha) \, AC_i^*, \qquad \alpha \in (0, 1). \tag{6}$$

Equal weight is assigned to the sensitivity and adaptive capacity components, setting $\alpha = 0.5$. This weighting choice follows the approach adopted in the multidimensional poverty literature, including Alkire and Foster (2022) and Nussbaumer et al. (2012b), where equal weighting across dimensions is applied in the absence of strong empirical or theoretical grounds for differential weighting. The resulting $MEPI_i$ is subsequently used to generate spatial hotspot maps, enabling the identification of geographic concentrations and intensity of energy poverty across Uganda. The spatial hotspot analysis and maps are presented in section 4.

3.4 Household survey

Based on the spatial hotspot maps, areas spanning the most and least vulnerable regions were selected in order of severity to constitute the study sample. A structured questionnaire is administered to randomly selected households within the sampled hotspot areas to obtain primary data. The target population comprises all households in Uganda, encompassing both rural and urban regions. Given the large population size, a stratified random sample is drawn to ensure both randomness and adequate representation across socioeconomic and geographic groups. The sampling frame is organised around four regions, namely, Central, Eastern, Northern, and Western, which are further divided into 16 sub-regions to ensure comprehensive geographical coverage, as outlined in Table 2.

Table 2: Sampling Frame by Region and Sub-region

Region	**Sub-regions**
Central	Kampala, Buganda South, Buganda North, Buganda West
Eastern	Busoga, Teso, Bukedi, Elgon
Northern	Acholi, Lango, West Nile, Karamoja
Western	Ankore, Toro, Bunyoro, Kigezi

In each sub-region, 30 households are randomly selected, yielding a total sample of 480 households, more than the minimum sample size, determined by the following formula:

$$n = \frac{Z^2 p(1-p)}{e^2}, \tag{7}$$

where n denotes the required sample size, Z is the Z-score corresponding to the chosen confidence level (1.96 for 95%), p is the estimated response proportion (0.5), and e is the margin of error (0.05). While the calculated minimum sample size is approximately 385 households, the sample is expanded to 480 households to enable proportional stratification across the 16 sub-regions and to enhance statistical power.

3.5 Data collection instrument

Primary data is collected using a structured questionnaire comprising predominantly closed-ended questions. The questionnaire captures information on household socioeconomic characteristics, dwelling type, household composition, energy use patterns and sources, access to finance for clean energy, energy demand, income, and expenditure. The questionnaire is administered by trained research assistants under the supervision of the principal and co-investigators.

3.6 Eligibility criteria

The study targets household heads as the primary respondents, given their central role in decision-making on energy access and household socioeconomic conditions. Both male and female adults aged 18 years and above who provide voluntary informed consent are eligible. Consent is demonstrated through the signing of an informed consent form, translated into four local languages. Preference is given to respondents who have resided in the community for at least six months to ensure familiarity with local energy practices and living conditions. Elderly participants aged 65 years and above are included provided they are willing and able to participate. All household heads meeting the inclusion criteria are interviewed regardless of their current energy access status, to enhance the comparability and robustness of the results.

4 Empirical Framework

This study employs Ordinary Least Squares (OLS) regression to examine the socioeconomic determinants of household-level energy poverty. The dependent variable is the household Multidimensional Energy Poverty Index (MEPI), constructed consistently with the district-level index. Specifically, the index incorporates both sensitivity and adaptive capacity dimensions.
The choice of OLS is guided by diagnostic testing on the MEPI which showed that the index has distributional properties and does not have meaningful censoring at the boundaries, rendering it an appropriate and parsimonious estimator for the continuous outcome. The OLS is complemented by a logistic regression estimated on a binary classification of energy poverty status, which serves as a robustness check. This combination is consistent with comparable studies in the literature. Ashagidigbi et al. (2020) similarly use OLS alongside alternative specifications for continuous energy poverty indices in Nigeria, while Compaore et al. (2024) employ logistic regression to examine multidimensional energy poverty determinants in West Africa. The models are estimated separately for the full sample, the male subsample, and the female subsample to examine whether the determinants of energy poverty differ by gender.
The OLS regression model is specified as follows:

$$\begin{aligned} MEPI_i^* = \alpha_0 + \alpha_1 Age_i + \alpha_2 Gend_i + \alpha_3 MStatus_i + \alpha_4 Educ_i \\ + \alpha_5 Occ_i + \alpha_6 Emp_i + \alpha_7 Dwell_i + \alpha_8 Fam_i \\ + \alpha_9 Inc_i + \alpha_{10} Exp_i + \varepsilon_i. \end{aligned} \tag{8}$$

where:

- $MEPI_i^*$ is the Multidimensional Energy Poverty Index score for household i, ranging from 0 (no deprivation) to 1 (maximum deprivation);
- α_0 is the intercept term and α_j ($j = 1, \ldots, 10$) are slope coefficients;
- Age_i is the age of the household head (years);
- $Gend_i$ is the gender of the household head (binary or categorical);
- $MStatus_i$ is the marital status of the household head;

- $Educ_i$ is the highest education level attained by the household head;
- Occ_i is the occupation category of the household head;
- Emp_i is the type of employment (e.g., formal/informal);
- $Dwell_i$ is the dwelling type;
- Fam_i is household size (number of household members);
- Inc_i is household income;
- Exp_i is household expenditure;
- $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$ is the error term.

To examine whether the determinants of energy poverty differ across vulnerability levels, stratified regressions are estimated separately for the male and female subsamples, as described above. The vulnerability segmentation based on MEPI tertiles is used to define the least, moderately, and most vulnerable groups as follows:

$$V_i = \begin{cases} \text{Least vulnerable,} & \text{if } MEPI_i \leq P_{33}, \\ \text{Moderately vulnerable,} & \text{if } P_{33} < MEPI_i < P_{67} \\ \text{Most vulnerable,} & \text{if } MEPI_i \geq P_{67} \end{cases} \tag{9}$$

where P_{33} and P_{67} are the 33rd and 67th percentiles of the MEPI distribution. This segmentation enables the analysis to isolate and compare the socioeconomic characteristics that distinguish households experiencing severe energy deprivation from those with minimal deprivation. Such insights are essential for designing targeted policy interventions that respond effectively to the specific needs of the most at-risk households.

An interaction model is additionally estimated for the full sample, incorporating interaction terms between gender and the continuous socioeconomic variables (age, family size, income, and expenditure) to assess whether the effects of these variables differs significantly between male and female household heads. Also. a reduced model retaining only the variables found to be significant in at least one full-sample specification is estimated as an additional robustness check. The results of these additional models estimated and the diagnostic tests undertaken are presented in the Appendix.

5 Findings

5.1 Spatial hotspot analysis

Figures 1-3 show hotspot maps based on the MEPI and its components that were generated using secondary data. Figure 1 shows the spatial distribution of sensitivity to energy poverty in Uganda. Notably, districts with a large proportion of households without electricity connections, such as Katakwi, Soroti, Serere, Ngora, Kumi, and Bukedea, are also heavily reliant on firewood as their primary energy source. Furthermore, the entire eastern Uganda and certain parts of southwestern Uganda, including Rubanda, Rukiga, Kisoro, and Kanungu, rely heavily on firewood as their main energy source. Additionally, the need for energy in Uganda is widespread rather than region-specific, as indicated by the majority of districts having very high demand and the small number of isolated areas with moderate or lower demand.

The overall sensitivity score indicates that energy poverty is most prevalent in northern, eastern, and certain parts of southwestern Uganda, as well as semi-urban central districts such as Wakiso. Comparatively, low sensitivity is concentrated mainly in the central and parts of western Uganda, particularly in the urban and economically diversified districts. This underscores the existence of differences between rural and urban locations, even in a multidimensional setting. Generally, there is a high correlation between the individual variables and the composite index, suggesting that sensitivity to energy poverty is heightened in areas where there is lack of electricity access, reliance on traditional biomass, and high energy demand coexist.

Figure 2 shows that electricity supply has a significant positive impact on adaptive capacity. Most locations have medium to high adaptability due to grid connections, and the energy supply score shows that adaptability is quite high. However, inadequate access to formal financial services and a lack of diversification into alternate sources of energy limit households' ability to adapt. Furthermore, areas with a significant gender income disparity are associated with greater vulnerability, as women have fewer resources to adopt cleaner and more reliable energy technology and face disproportionate time limitations when collecting energy fuels. Additionally, areas with higher female participation in decision-making and active participation in government development projects have better adaptive potential. Consequently, the resilience ability to energy poverty varies and when these factors are combined, the total adaptive capacity to energy poverty across the country is quite low.

Figure 1: Maps showing sensitivity

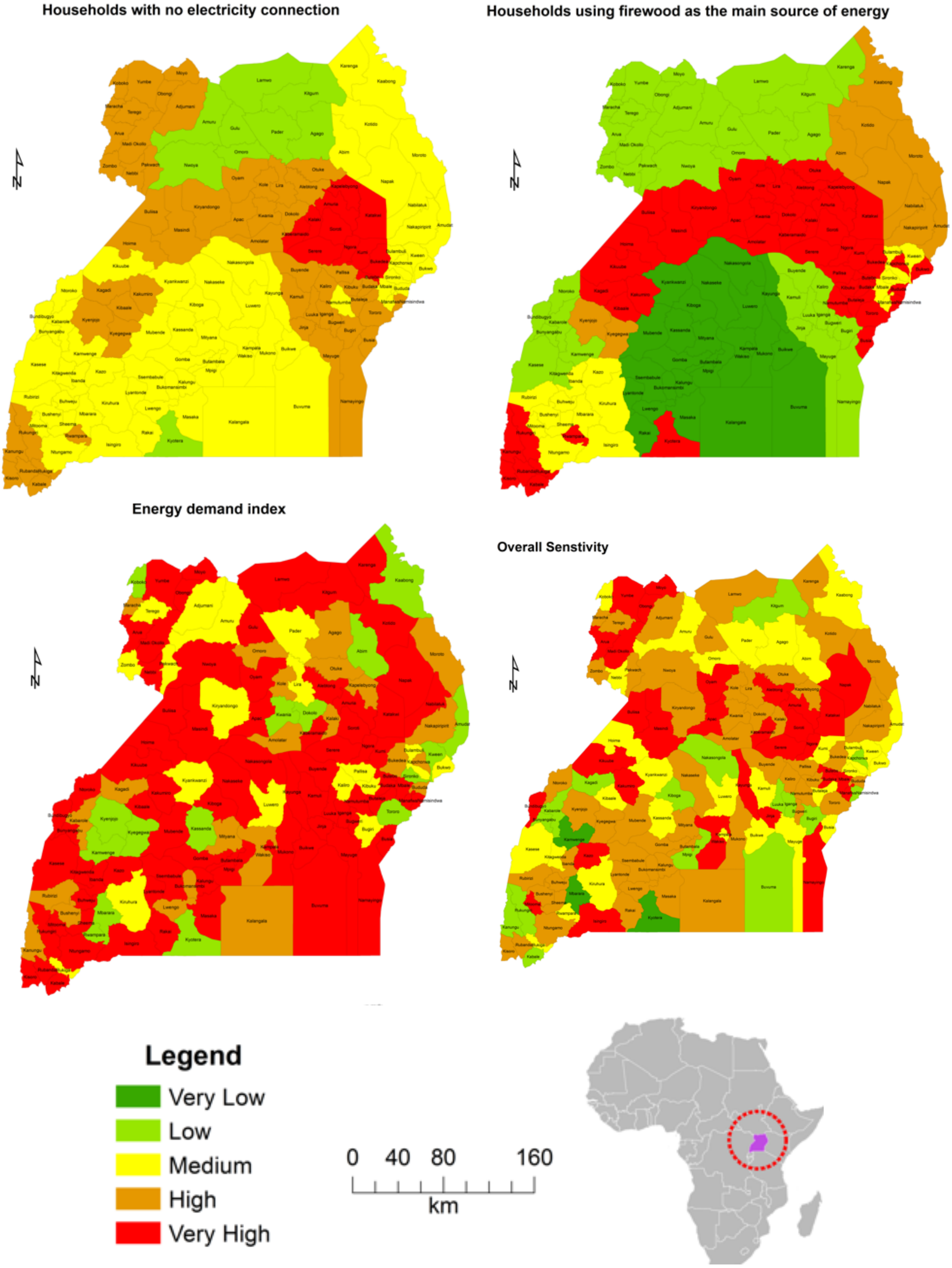


Figure 2: Maps showing Adaptability

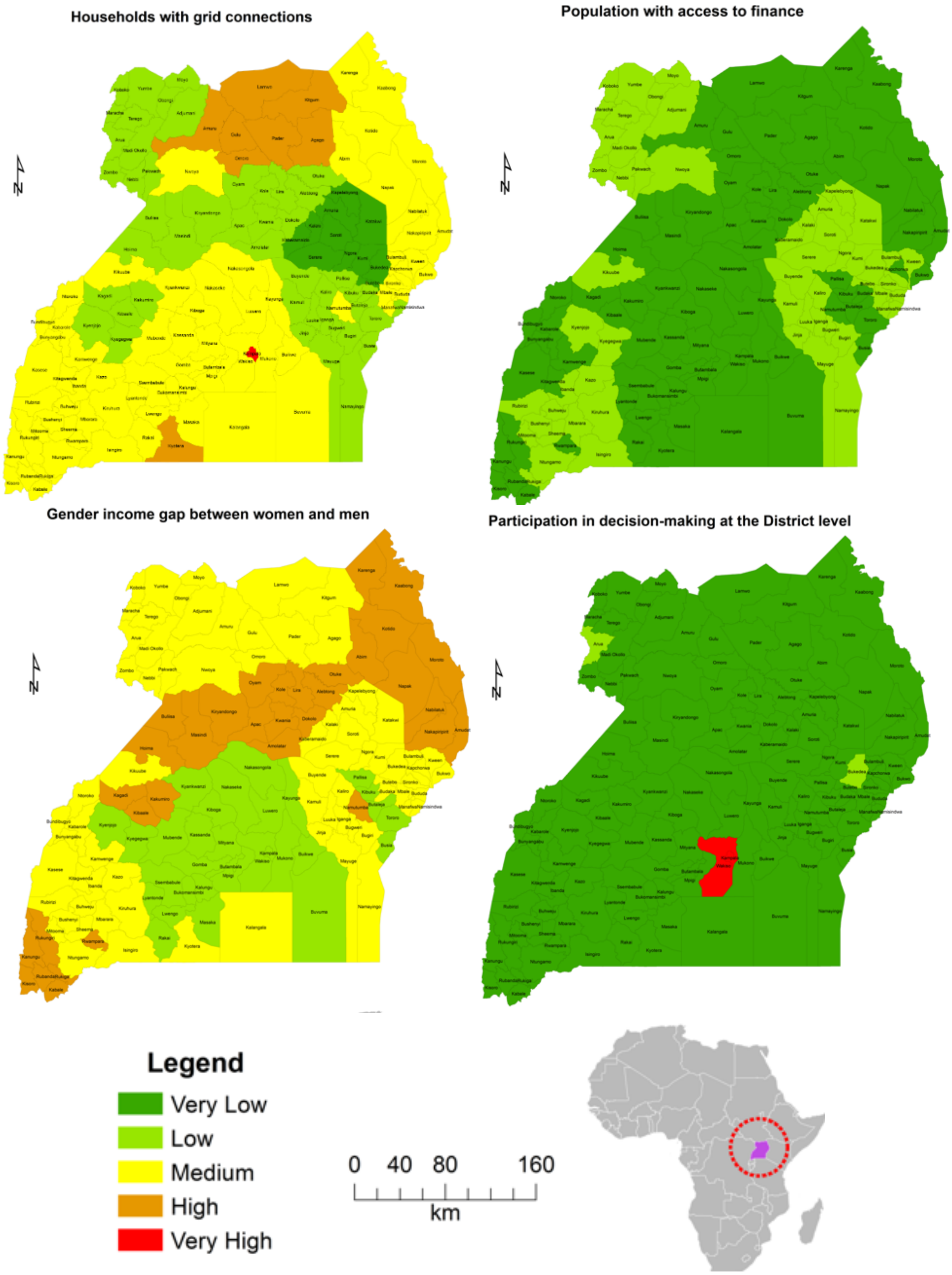
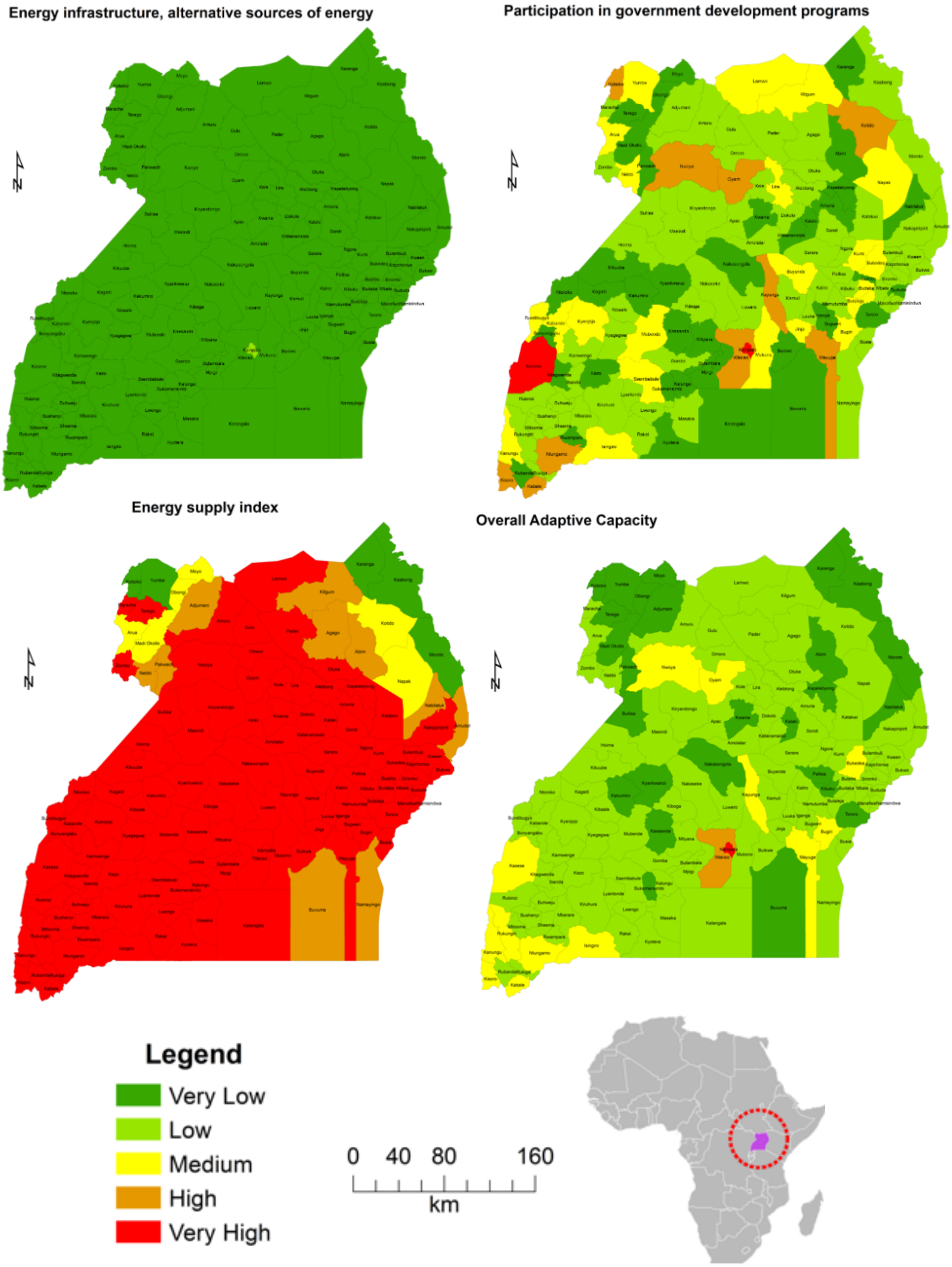
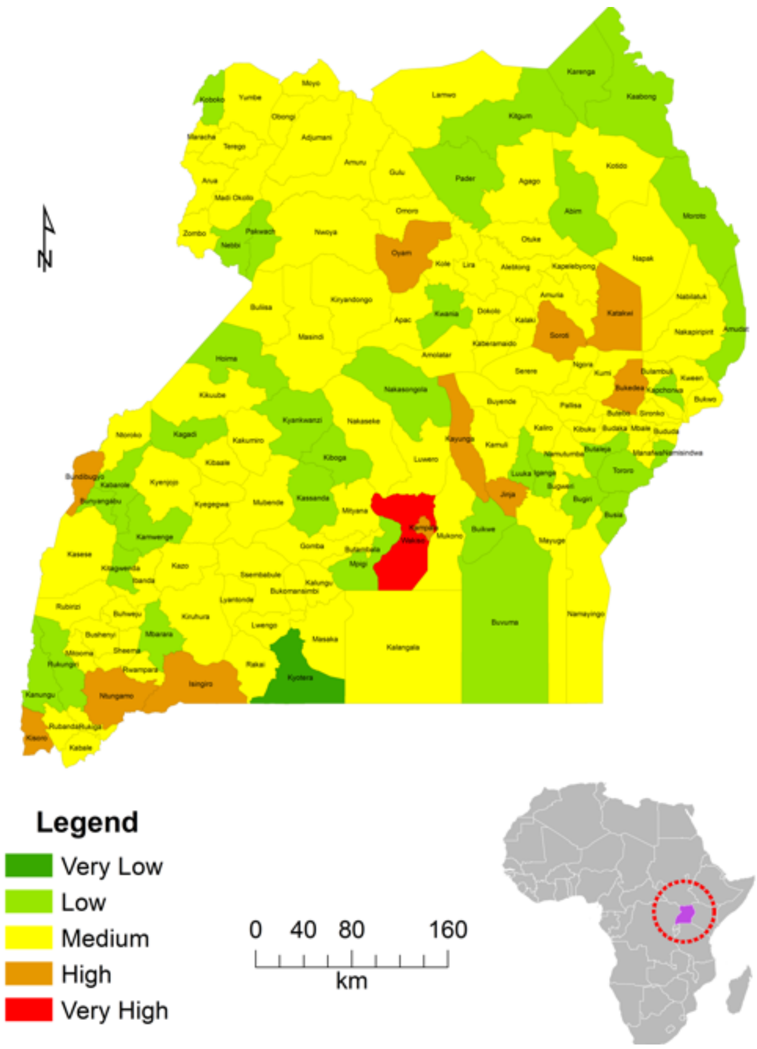


Figure 2: Maps showing Adaptability (continued)



The overall multidimensional metric is used to show the spatial distribution of energy poverty hotspots in Uganda (Figure 3). The hotspots are not evenly distributed, as the map illustrates, with Wakiso district having the highest energy poverty score. Overall, energy poverty scores are high in eleven districts across four regions. These include Bundibugyo, Ntungamo, Isingiro, and Kisoro in the western region; Kampala and Kayunga in the central region; Jinja, Bukedea, Soroti, and Katakwi in the eastern region; and Oyam in the northern region.

Figure 3: Energy poverty hotspots in Uganda



5.2 Regression results

The regression results indicate that multidimensional energy poverty in Uganda is driven by a combination of household-level factors, mainly household size, educational attainment, income, and demand for electricity. These findings hold consistently across alternative model specifications, as presented in Table 2 where the MEPI is the dependent variable. According to the the OLS estimations in Panel A, household size emerges as one of the most consistent determinants of energy poverty. Across the full sample, an additional household member is associated with a 0.004 point increase in the MEPI, a result significant at the 5 percent level. While the magnitude appears small, it is meaningful given that the index is bounded between 0 and 1, and household sizes in the sample vary considerably. This effect remains significant among male-headed households but diminishes in the female subsample, most likely due to the smaller number of female respondents reducing statistical precision.

Occupation type is also positively and significantly associated with higher MEPI scores across several specifications. This finding may seem surprising as one might expect employment to reduce energy poverty. However, the result reflects the occupational profile of the survey respondents, the majority of whom are subsistence farmers. Subsistence farming, despite being a recognised livelihood, rarely generates the cash income or asset accumulation needed to invest in better energy sources or technologies. The result therefore captures a real structural constraint rather than a statistical irregularity.

Education, by contrast, is negatively associated with energy poverty and statistically significant at the 10 percent level in the full sample and female subsample. Households headed by individuals with formal schooling score between 3 and 7 percentage points lower on the MEPI, holding other factors constant. This is consistent with the broader literature, which finds that education increases awareness of cleaner energy options, improves the ability to navigate markets and government programmes, and correlates with higher and more stable incomes over time.

Household income exhibits a negative and highly significant association with energy poverty in both the full and male sub-samples. Higher income reduces energy deprivation by expanding households' purchasing power and their ability to afford modern energy services, from electricity connection fees to cleaner cooking fuels. This reinforces the case for integrating households into the formal economy through programmes such as the Parish Development Model as a prerequisite for sustained improvements in household welfare and energy access.

Energy demand, measured by whether households expressed a desire for a grid connection, is negatively associated with MEPI but falls short of statistical significance. This suggests that stated demand for electricity does not, on its own, predict lower energy poverty once other household characteristics are accounted for. A plausible explanation is that many households want a grid connection but face supply-side barriers such as cost, infrastructure and location that prevent this demand from translating into improved energy outcomes. The OLS model captures these conditional relationships, though its modest overall fit is not unexpected in cross-sectional surveys of this kind, where individual circumstances not captured in the data naturally account for a substantial share of the variation.

Panel B presents results from ordinal logistic regressions, where the MEPI is converted into ranked categories based on tertiles and quartiles. This approach complements the OLS model by allowing the relationship between each determinant and energy poverty to vary across different levels of deprivation, rather than assuming a constant linear effect throughout the distribution. The ordered logit results are similar to the OLS results, suggesting that the key findings are robust and not driven by the choice of a linear specification.

Household size remains positively and significantly associated with more severe energy poverty in the full and male sub-samples. Education continues to show a negative and significant association with higher deprivation, particularly in the female tertile and full quartile specifications. Household income also maintains its negative and significant effect across the full and male tertile specifications, consistent with the OLS findings.

Electricity demand shows more mixed results in the ordinal models. In the tertile specifications, households expressing demand for electricity are associated with higher MEPI categories, while in the quartile specifications the direction reverses and the effect becomes negative and significant. This apparent inconsistency likely reflects variation across deprivation thresholds rather than a genuine contradiction. A reasonable interpretation is that households in the middle range of energy poverty are more likely to actively express unmet demand while the most severely deprived households may lack both access and the awareness or resources to articulate demand. This kind of threshold heterogeneity is what the ordinal logit framework is designed to capture, and the well-identified cut-points across most models support this interpretation. Age, marital status, dwelling ownership, and expenditure are not significant in any specification.

Table 3: Determinants of Energy Poverty (Dependent variable=MEPI

	Panel A: OLS			Panel B: Ordered Logit			
	(1) Full	(2) Male	(3) Female	(4) Tertile:Full	(5) Tertile:Male	(6) Tertile:Female	(7) Quartile
Panel A: OLS							
Age (years)	-0.0005	-0.0006	-0.0007				
	(0.0004)	(0.0005)	(0.0016)				
Household size	0.0041**	0.0046**	0.0023				
	(0.0019)	(0.0021)	(0.0055)				
Log expenditure	-0.0022	-0.0017	-0.0032				
	(0.0039)	(0.0043)	(0.0110)				
Education (=1)	-0.0354*	-0.0186	-0.0697*				
	(0.0210)	(0.0272)	(0.0394)				
Occupation (=1)	0.0407***	0.0278*	0.0907*				
	(0.0142)	(0.0147)	(0.0494)				
Dwelling owner (=1)	-0.0130	-0.0133	-0.0004				
	(0.0207)	(0.0222)	(0.0775)				
Electricity demand (=1)	-0.0220	-0.0034	-0.0753				
	(0.0183)	(0.0188)	(0.0481)				
Tertile Income (earnings)	-0.0017***	-0.0018***	-0.0005				
	(0.0005)	(0.0006)	(0.0018)				
Observations	469	364	105				
Adjusted R^2	0.0449	0.0358	0.0602				
AIC	-564.32	-466.22	-88.76				
BIC	-506.21	-411.66	-51.61				
Panel B: Ordered Logit							
Age (years)				-0.0045	-0.0076	-0.0034	-0.0048
				(0.0066)	(0.0073)	(0.0200)	(0.0068)
Household size				0.0517*	0.0710**	-0.0238	0.0689**
				(0.0282)	(0.0319)	(0.0707)	(0.0294)
Log expenditure				-0.0677	-0.0583	-0.1188	0.0069
				(0.0587)	(0.0670)	(0.1360)	(0.0582)
Education (=1)				-0.4311	-0.2092	-0.9275*	-0.4844*
				(0.2770)	(0.3631)	(0.5041)	(0.2899)
Occupation (=1)				0.4829**	0.4019*	0.8805	0.5051**
				(0.2173)	(0.2418)	(0.5480)	(0.2201)
Owns business (=1)				-0.2619	-0.3324	0.1578	-0.2464
				(0.2273)	(0.2500)	(0.6368)	(0.2285)
Electricity demand (=1)				0.8355***	1.1333***	0.1856	-0.5126**
				(0.2502)	(0.2997)	(0.5131)	(0.2501)
Income (earnings)				-0.0173**	-0.0197**	0.0072	-0.0132
				(0.0088)	(0.0098)	(0.0232)	(0.0087)
Cut 1				-1.1097	-1.2535	-2.2172	-1.7048
				(1.0445)	(1.3264)	(2.4163)	(1.0509)
Cut 2				0.2745***	0.3026***	0.2771*	0.9825***
				(0.0764)	(0.0863)	(0.1652)	(0.0546)
Observations				469	364	105	469
Pseudo R^2				0.0458			0.0267
AIC				1008.04			926.15
BIC				1070.30			988.41

Notes: Robust (HC3) standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Columns (1)–(3) report OLS estimates. Columns (4)–(7) report ordered logit coefficients. Positive = higher vulnerability. Cut 1 and Cut 2 denote threshold parameters. Tertile: Low 0.433 (N=179), Moderate 0.433–0.533 (N=138), High ¿0.533 (N=152). Quartile: Low 0.367 (N=131), Moderate 0.367–0.567 (N=260), High ¿0.567 (N=78).

6 Conclusion and Policy recommendations

Energy poverty in Uganda remains a constraint on inclusive and sustainable growth. Despite increased national electricity access over the past decade, many households continue to rely on biomass fuels for cooking and lack the financial capacity to access or sustain modern energy services. Prior research has relied predominantly on unidimensional indicators, focusing on connections rather than affordability, reliability, and efficient use. This study addresses that gap through a multidimensional framework that identifies where energy poverty is concentrated and the household-level factors that shape it.

The MEPI is constructed from eleven indicators grouped into two conceptual dimensions — sensitivity and adaptive capacity — and weighted using PCA. A spatial mapping exercise identifies twelve high-vulnerability districts, and primary household survey data collected in these hotspot areas are used to estimate OLS, ordinal logistic, and binary logistic regression models across the full sample and gender subsamples. The following key findings emerge.

Energy poverty hotspots are concentrated in Wakiso and eleven further districts spanning all four regions: Bundibugyo, Ntungamo, Isingiro, and Kisoro in the West; Kampala and Kayunga in the Centre; Jinja, Bukedea, Soroti, and Katakwi in the East; and Oyam in the North. High vulnerability in these areas reflects the co-existence of limited supply infrastructure, affordability constraints, and adverse household-level socioeconomic conditions.

With respect to socioeconomic determinants, household income is the single most consistent and significant predictor of energy poverty across all models and specifications, underscoring the centrality of purchasing power in determining energy access outcomes. Occupation type is the most robust structural determinant, with households engaged predominantly in subsistence farming recording significantly higher energy poverty, reflecting their limited capacity to generate savings and investment income. Education reduces energy poverty significantly, particularly among women, and this effect strengthens in reduced-form models, indicating partial suppression in the full-model estimates. Unmet electricity demand predicts higher vulnerability in ordinal specifications, reflecting concentrated unmet demand among the most energy-deprived households. Age, marital status, business ownership, and log expenditure are not significant in any full-sample model. These findings directly inform the policy recommendations that follow.

Household income-enhancing interventions and financial inclusion should be prioritised in hotspot areas as higher household income reduces energy deprivation. Financial inclusion should be extended to the hotspot areas through financial literacy programmes and targeted financial products as these offer a direct pathway to reducing energy deprivation. In particular, affordable instruments such as pay-as-you-go solar financing, and installment-based grid connection schemes can lower upfront cost constraints that limit clean energy adoption among low-income households. By lowering entry barriers to solar home systems and improved cooking equipment, such mechanisms can accelerate the transition to modern energy, especially in rural areas where capital constraints remain binding. Integrating income support with inclusive energy financing frameworks is therefore essential for sustained reductions in multidimensional energy poverty.

Interventions should aim beyond providing connections to promoting integrated programmes that link household energy access with livelihood support. This is based on the finding that occupation type is the most robust structural determinant of energy poverty, with subsistence farmers recording significantly higher deprivation, underscoring that energy poverty is inseparable from livelihood constraints. Households that adopt solar systems or cleaner cooking technologies should be supported to leverage these investments in income-generating activities such as agro-processing and small retail enterprises. This productive-use of energy equipment not only strengthens the economic case for clean energy adoption, contributes to household income and consequently, reduces the risk of households reverting to biomass fuels when incomes fluctuate.

Sector-specific programmes. The consistent finding that subsistence farmers face higher energy poverty calls for sector-specific programmes, including subsidised connections. Household-level interventions should also promote energy efficiency alongside access, including certified efficient lighting, improved cookstoves, and guidance on efficient energy use, since reducing the recurrent cost of energy services is as important as reducing upfront connection costs for households whose incomes are low and irregular.

Investment in girls' education and adult literacy programmes should be sustained particularly in hotspot districts. The finding that education significantly reduces energy poverty among women, robustly across model specifications, underscores the importance of educating women. Therefore, female education should be priotised as it enhances women's capacity to access information, participate in decision-making, and adopt modern energy technologies.

Addressing unmet electricity demand. The ordinal model finding that households with unmet demand for grid connections record higher vulnerability underscores the urgency of the Rural Electrification Strategy. Accelerating last-mile connections in the identified hotspot districts, combined with affordability measures such as subsized tariffs and installment payment schemes, will reduce the gap between demand and access. Where grid extension remains cost-prohibitive, off-grid solar solutions and mini-grids offer a viable alternative and should be promoted alongside strict enforcement of quality standards to protect households from substandard products that undermine trust in renewable energy technologies.

Gender mainstreaming in energy policy. Integrating standardised gender-disaggregated indicators into planning and monitoring frameworks will enable policymakers to recognise the specific constraints women face and develop gender-responsive strategies. Women should be provided with access to energy financing, technical training on clean energy technologies, and opportunities to participate in local energy value chains as distributors or technicians, recognising that empowering women in energy decision-making improves adoption rates and strengthens household welfare more broadly. Notably, the null result on women's autonomous decision-making suggests that decision-making power alone, without accompanying income and resources, is insufficient to reduce energy poverty, an important nuance for programme design that cautions against treating empowerment and resource provision as substitutes.

The hotspot maps provide a direct operational tool for the PDM. While the survey findings indicate 197 recipients of PDM and other government programmes, none had used the facilities to adopt modern energy technology. Therefore, parishes within the identified high-vulnerability districts should be prioritised for energy investment across all seven PDM pillars. The spatial concentration of deprivation across twelve districts spanning all four regions, and the finding that vulnerability reflects the co-existence of income constraints, limited education, and supply-side deficits, confirms that energy poverty cannot be addressed by the energy sector alone.

Overall, this study demonstrates that energy poverty in Uganda is a systemic socioeconomic issue with pronounced gender and spatial dimensions. Addressing it effectively requires coordinated, evidence-based, and spatially targeted action across income support, education, infrastructure, and gender mainstreaming.

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Table 4: Binary Logistic Regression — Above-Median Energy Poverty

	Full Sample	Male	Female	Female + WD
Panel A: Socioeconomic characteristics				
Age (years)	-0.0071	-0.0079	-0.0166	-0.0162
	(0.0073)	(0.0080)	(0.0226)	(0.0228)
Household size	0.0204	0.0298	-0.0136	-0.0258
	(0.0320)	(0.0358)	(0.0844)	(0.0863)
Log(Expenditure)	-0.0819	-0.0955	-0.0410	-0.0509
	(0.0630)	(0.0721)	(0.1468)	(0.1482)
Education[a]	-0.4693	-0.2225	-1.1529**	-1.2199**
	(0.2965)	(0.3908)	(0.5553)	(0.5665)
Occupation[b]	0.4709*	0.3820	0.9116	0.9816
	(0.2502)	(0.2754)	(0.6762)	(0.6876)
Owns business[c]	-0.1790	-0.2480	0.4999	0.5772
	(0.2576)	(0.2865)	(0.7137)	(0.7228)
Dwelling ownership[d]	-0.6308	-0.3865	-2.2354*	-2.3533*
	(0.3899)	(0.4293)	(1.3070)	(1.3327)
Electricity demand[e]	-0.1068	0.1152	-0.6836	-0.6781
	(0.2703)	(0.3205)	(0.5785)	(0.5763)
Income (Earning)	-0.0395***	-0.0422***	-0.0174	-0.0184
	(0.0107)	(0.0121)	(0.0277)	(0.0278)
Panel B: Marital status (ref: Divorced/Separated)				
Married monogamous	-0.0085	-0.6911	0.3711	0.2800
	(0.4775)	(0.9021)	(0.8710)	(0.8835)
Married polygamous	0.2699	-0.5027	1.9176	2.0532
	(0.5590)	(0.9545)	(1.4284)	(1.4486)
Never married	-0.2133	0.0928	-0.9855	-0.9366
	(0.8849)	(1.5621)	(1.3877)	(1.3986)
Widow/Widower	0.0215	-0.6222	0.6068	0.4888
	(0.5344)	(1.6874)	(0.7329)	(0.7539)
Panel C: Gender-specific variable				
Women's decision-making	—	—	—	-0.3459
				(0.5104)
Constant	2.5285**	2.9124*	3.6836	4.2298
	(1.1472)	(1.5201)	(2.8059)	(2.9460)
Panel D: Model fit statistics				
Observations	469	364	105	105
Pseudo R^2 (McFadden)	0.0584	—	—	—
AIC	626.98	—	—	—
BIC	685.09	—	—	—

Dependent variable: Binary indicator equal to 1 if household MEPI exceeds the sample median (0.467), and 0 otherwise. Out of 469 observations, 194 (41.4%) are classified above the median. Coefficients are log-odds. Standard errors in parentheses. A positive coefficient increases the probability of being above the median MEPI. Model fit statistics are reported for the full sample only. Reference category for marital status: Divorced/Separated. WD = women's decision-making variable, included only in the Female + WD specification.

[a] Education: 1 = attended school, 0 = never attended.
[b] Occupation: 1 = named occupation (subsistence farmer, nurse, teacher, etc.), 0 = other.
[c] Owns business: 1 = yes, 0 = no.
[d] Dwelling ownership: 1 = owner-occupied, 0 = other tenure.
[e] Electricity demand: 1 = household wants a grid connection, 0 = no or missing.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 5: Reduced Model Estimates — OLS, Ordinal Logit, and Binary Logit

	OLS			**Ordinal Logit (Tertile)**			**Binary Logit (Median)**		
Variable	Full	Male	Female	Full	Male	Female	Full	Male	Female
Household size (*Fam*)	0.0024	0.0028	0.0009	0.0271	0.0398	-0.0301	-0.0238	-0.0198	-0.0293
	(0.0017)	(0.0019)	(0.0047)	(0.0258)	(0.0289)	(0.0678)	(0.0291)	(0.0322)	(0.0755)
Education (*Educ*)[a]	-0.0383**	-0.0204	-0.0574*	-0.4921**	-0.2030	-0.8961**	-0.5344**	-0.2632	-0.9574**
	(0.0185)	(0.0269)	(0.0331)	(0.2472)	(0.3546)	(0.4098)	(0.2613)	(0.3762)	(0.4473)
Occupation (*Occ*)[b]	0.0442***	0.0331**	0.0902**	0.5101**	0.4639**	0.7282	0.4883**	0.4690*	0.5541
	(0.0137)	(0.0143)	(0.0412)	(0.2099)	(0.2342)	(0.4993)	(0.2336)	(0.2592)	(0.5666)
Electricity demand (*elec_demand*)[c]	-0.0115	0.0115	-0.0849**	0.9413***	1.3095***	-0.0730	0.0224	0.3386	-0.9594*
	(0.0164)	(0.0170)	(0.0412)	(0.2354)	(0.2846)	(0.4521)	(0.2446)	(0.2902)	(0.5136)
Cut-points / Threshold (Ordinal Logit only)									
Cut 0|1	—	—	—	0.3935	0.9941**	-0.7369	—	—	—
				(0.3667)	(0.4901)	(0.6683)			
Cut 1|2	—	—	—	0.2573***	0.2806***	0.2468	—	—	—
				(0.0764)	(0.0863)	(0.1648)			
Constant	0.4779***	0.4488***	0.5159***	—	—	—	-0.1450	-0.6675	0.8634
	(0.0260)	(0.0339)	(0.0522)				(0.3922)	(0.5181)	(0.7589)
Model fit									
Observations	469	364	105	469	364	105	469	364	105
Adj./R^2 / Pseudo R^2	0.0307	—	—	0.0351	—	—	0.0167	—	—
AIC	−566.21	—	—	1001.03	—	—	635.50	—	—
BIC	−545.45	—	—	1025.93	—	—	656.26	—	—

Dependent variables: OLS — continuous MEPI score (HC3 robust standard errors); Ordinal Logit — MEPI tertile category (Low ≤ 0.433; Moderate 0.433–0.533; Hi
to 1 if MEPI exceeds the sample median (0.467), 0 otherwise. Coefficients reported; standard errors in parentheses. Model fit statistics reported for the full samp
$N = 105$.

[a] Education: 1 = attended school, 0 = never attended.

[b] Occupation: 1 = named occupation (subsistence farmer, nurse, teacher, etc.), 0 = other.

[c] Electricity demand: 1 = household wants a grid connection, 0 = no. Note that the sign on electricity demand differs across OLS (negative, insignificant) and orc
reflects threshold heterogeneity: households expressing unmet demand cluster disproportionately in higher deprivation categories in the ordinal specification, where
threshold effects.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 6: Diagnostic Tests and Model Fit Summary

Panel A: Variance Inflation Factors — OLS Full Sample ($N = 469$)

Variable	VIF
Age	1.28
Household size	1.16
Log(Expenditure)	1.07
Education	1.26
Occupation	1.11
Business ownership	1.06
Dwelling ownership	1.20
Electricity demand	1.14
Married monogamous	5.25
Married polygamous	3.09
Never married	1.46
Widow/Widower	3.81
Conventional threshold for concern: VIF > 10	

Panel B: MEPI Distribution by Categorisation Scheme

Scheme	Category	N	Share (%)
Median split	Low (≤ 0.467)	275	58.6
	High (> 0.467)	194	41.4
Tertile	Low (≤ 0.433)	179	38.2
	Moderate (0.433–0.533)	138	29.4
	High (> 0.533)	152	32.4
Fixed cutoffs[d]	Least vulnerable (≤ 0.2)	1	0.2
	Moderately vulnerable (0.2–0.8)	463	98.7
	Most vulnerable (≥ 0.8)	5	1.1

Panel C: Model Fit Comparison across Specifications

Estimator	Sample	N	Adj./R^2/Pseudo R^2	AIC	BIC
OLS	Full sample	469	0.0307	−558.34	−504.39
	Male	364	0.0169	−460.13	−409.47
	Female (no WD)	105	0.0696	−90.66	−56.16
	Female (with WD)	105	0.0598	−88.71	−51.56
OLS (reduced)	Full sample	469	0.0307	−566.21	−545.45
Ordinal Logit	Tertile, full	469	0.0419	1010.01	1068.12
	Quartile, full	469	0.0242	926.48	984.59
	Vi (fixed), full	469	0.2864	77.69	135.80
Ord. Logit (reduced)	Tertile, full	469	0.0351	1001.03	1025.93
Binary Logit	Median split, full	469	0.0349	639.91	693.87
Logit (reduced)	Median split, full	469	0.0167	635.50	656.26

Panel A: VIF computed from the full-sample OLS model with all regressors. All values are well below the conventional threshold of 10, confirming the absence of problematic multicollinearity.
Panel B: The fixed-cutoff (Vi) scheme assigns only 6 households to the extreme categories, confirming that meaningful boundary censoring is absent from the MEPI distribution and that the data-driven tertile scheme is the more appropriate basis for ordinal categorisation.
Panel C: Adj. R^2 reported for OLS; McFadden pseudo R^2 for all other estimators. The OLS reduced model achieves identical adjusted R^2 to the full model (0.0307) while substantially improving AIC and BIC, confirming that the excluded variables contribute no additional explanatory power. The Ordinal Logit Vi model pseudo R^2 of 0.2864 reflects near-perfect fit arising from near-complete concentration of observations in the middle category rather than genuine explanatory power, and should not be interpreted as substantively meaningful. WD = women's decision-making variable.
[d] Fixed cutoffs follow the conventional vulnerability index thresholds of 0.2 (least) and 0.8 (most) applied in the spatial hotspot analysis. The near-complete concentration of observations in the moderate category (98.7%) confirms that these thresholds are not suitable for the regression sample and that data-driven tertiles are preferred.

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