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The role of forest status in households' fuel choice in Uganda

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ABSTRACT

In this study, we investigate how households' choice of energy source is influenced by the status of the local forest resource. We assume that households choose between clean fuels (e.g., kerosene, LPG, solar, and electricity), dirty biobased fuels (e.g., firewood, animal dung, crop residues, and charcoal), and mixed fuels. We integrate socioeconomic data with high-resolution satellite data on forest conditions from the Uganda National Panel Survey. The findings from a random-effects multinomial logit model indicate that households in vegetated areas are 6–7% less likely to rely solely on dirty biobased fuels, and 6–8% more likely to use mixed fuels, compared to those in non-vegetated areas. A larger forest stock is more strongly associated with lower use of firewood than charcoal. A possible explanation for the findings is the presence of policies for forest conservation and enhanced forest property rights, which improve forest conditions and limit opportunities to collect firewood. Given households' dependence on forest-based fuels, such policies could need to be modified to secure households' access to these fuels.

1. Introduction

In developing countries, dirty biobased[1] energy practices (e.g., firewood, animal dung, crop residues, and charcoal) have both negative and positive effects. On one hand, the use of biobased fuels is dangerous to human health and excessive use of forest fuel can undermine the sustainability of forest ecosystems (Chen and Kuo, 2001; Herington et al., 2016; Shankar et al., 2020). The health impacts comprise respiratory infections for children (Edwards and Langpap, 2012; Heltberg, 2005; Jagger and Shively, 2014), a considerable physical burden associated with firewood collection (Foell et al., 2011), and exposure to air pollution among women involved in cooking (Muller and Yan, 2018). Excessive forest fuel extraction has the potential to degrade forests (Manning and Taylor, 2014) and may over time worsen fuel scarcity (Amacher et al., 1993; Baland et al., 2017; Burke and Dundas, 2015; Manning and Taylor, 2014). On the other hand, firewood collection facilitates income generation (Ektvedt, 2011; Kamanga et al., 2009; Kim et al., 2017), and the collection and use of biobased fuels is an important part of culture and daily life (Mazzone et al., 2021).

Compared to dirty biobased fuels, so-called clean energy sources like kerosene, LPG,[2] solar energy, and electricity, have a wider range of applications,[3] are less hazardous to human health, and are easier to use (Stern, 2010). Utilizing such energy sources also lessens the strain on forest health status (Garland et al., 2015; Government of Uganda, 2015). Therefore, it is frequently suggested that initiatives aimed at promoting the transition to clean energy should be encouraged (Lee, 2013; Smith, 2002). Different policy instruments, such as information campaigns advocating improved and more efficient biomass stoves, or subsidy schemes to cover the expenses of the poor for adopting new technology in order to stimulate a fuel switching process, could be used (Heltberg, 2005). Such a transition is argued to be particularly important where fuelwood is an important fuel (Edmonds, 2002; Fisher, 2004; Heltberg et al., 2000) and forest degradation is a serious problem. For any policy program intending to achieve conversion towards clean fuels, or enhanced forest status, it is important to understand how households respond to changes in forest condition (Bandyopadhyay et al., 2011).

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[1] Dirty fuels are also called traditional or inferior fuels in the literature.
[2] Liquefied Petroleum Gas.
[3] For instance, solar energy can be utilized for a variety of tasks, including lighting, cooking, and charging mobile devices. Batteries in mobile phones, however, cannot be charged with firewood.

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Knowledge about these responses is valuable because it improves the understanding of the magnitude of policy interventions required, and how policies could affect forest conditions in different localities.

Evidence on the links between forest degradation, firewood collection, and fuel choice is scant (Heltberg et al., 2000; Pattanayak et al., 2004). Relatively few studies examine the effect of firewood scarcity on fuel choice. These studies measure firewood scarcity in different ways. Some studies make use of economically related scarcity indicators, such as the price of firewood (Alem et al., 2016), the total firewood collection time (Guta, 2012, 2014; Lee et al., 2015; Palmer and MacGregor, 2009), and the average firewood collection time (Heltberg et al., 2000), where the latter two are used as indicators of opportunity costs of firewood. These measures have limitations. For example, the market price of firewood does not fully reflect firewood scarcity because the energy input market is not well-functioning in Africa (Cooke et al., 2008). Heltberg (2005) uses a physical measure, the distance to forests, that indicates households' potential access to collectable firewood. Heltberg et al. (2000) consider both average fetching time, forest access, and forest stock. They measure forest stock as the ratio of the village population number to forest area. A lower ratio then indicates a greater incentive to substitute non-forest fuels, such as animal dung and crop residues, for forest firewood. The other forest related variable, forest access, is measured by the village population number relative to the total area of the village, where higher ratio is expected to induce a larger use of non-forest fuels.

Common to the mentioned studies is that the proxies for firewood scarcity are almost always obtained from self-reported data. Such self-reported data have drawbacks (Burivalova et al., 2015) because they could include measurement errors. When household heads report, for example, the time spent gathering firewood or the distance travelled by each household member, recording and recalling issues may arise. In contrast, Jagger and Kittner (2017) use a different approach, examining the connection between household energy preferences and biomass availability as measured by a satellite-based measurement of land cover change. However, their study is limited to agriculture-driven deforestation in west central Uganda and contains few observations (902 households).

The purpose of this study is to examine the role of forest status in households' fuel choice. We assume that households choose between clean and dirty fuels, or a mix thereof, and hypothesize that households in areas with more forest vegetation use more biobased dirty fuels, in particular firewood and charcoal. To avoid the above mentioned problems associated with self-reported data on firewood scarcity, we use the Enhanced Vegetation Index (EVI)[4] as an indicator of forest status. The EVI is a satellite based measurement of surface vegetation greenness used to reflect variations in forest availability and biomass richness of a forest (Ishtiaque et al., 2016). It is a global-based and widely used index for monitoring vegetation activity (Boles et al., 2004; Soudani et al., 2006; Xiao et al., 2004). Admittedly, measurement errors could still be a potential pitfall associated with remote sensing data (Donaldson and Storeygard, 2016). For example, classification of forest status into non-vegetated, sparsely vegetated, and densely vegetated areas based on such data (Hasanah and Indrawan, 2020) could involve a subjective component. We address this problem by using a continuous measure of the forest status variable as a robustness check.

The analysis is applied to Uganda. This choice is motivated by the country's strong dependence on firewood, in combination with political ambitions to rapidly transit towards cleaner energy. Moreover, disaggregated data on energy utilization is available, and extrapolation of the results to other Sub-Saharan Africa (SSA) countries is relevant because uptake of clean energy and reliability of electricity supply, in particular, is a serious problem in the region at large (Blimpo and Cosgrove-Davies, 2019). The household socioeconomic characteristics and satellite data on forest status are obtained from a three-round panel dataset from the Uganda National Panel Survey (UNPS) collected during 2009/10, 2010/11, and 2011/12 and made available by the Uganda Bureau of Statistics (Uganda Bureau of Statistics, 2009/10, 2010/11, 2011/12). We model households' fuel choice using the random-effects multinomial logit model (REMNLM) under Generalized Structural Equation Modeling (GSEM) that addresses selectivity bias (Baum et al., 2017).

Our paper makes at least two contributions to the literature. First, it employs a spatio-temporally robust measure of firewood scarcity at household level, thereby improving on earlier studies. Also, the use of remote sensing data, which can be linked to field-based household data, allows us to obtain data with high spatial resolution. Second, unlike most previous research on similar topics that typically relies on cross-sectional data (Alem et al., 2016), we use panel data that takes into account socioeconomic, housing, environmental, and weather variables that are not commonly controlled for in earlier studies.

The remainder of the paper is organized as follows. Section 2 provides the context of the study. Section 3 describes the data, and section 4 presents the econometric methods. Section 5 discusses the results, and section 6 concludes.

2. Case study background

This section briefly presents the background regarding the socioeconomic situation, forest status, fuel use, and energy policy targets in Uganda.

2.1. Socioeconomic context

Uganda has a population of about 42 million. Above 15% of the population is between the ages of 0 and 14. Over the period 2009/10 to 2011/12, the percentage of female-headed households is 44%, see Table A.1 in the Appendix. In Uganda, migration is common. Young individuals between 15 and 34 years make up 55% of the movers. Migration could affect landscapes in protected areas. For example, Hartter et al. (2015) document that areas surrounding Kibale National Park in western Uganda have changed from being sparsely settled bushland to a heavily settled subsistence farming landscape due to migration.

The UNPS shows that close to 70% of the working age (14–64 years) group are self-employed in the country. More women than men are unemployed. The majority of men work in paid jobs, whereas the majority of women are self-employed. Most people work within the agriculture and service sectors. Poverty is a persistent problem, and about 10% of the population remained chronically poor during the studied time period (Uganda Bureau of Statistics, 2011/12).[5]

Farming households typically receive land as an inheritance or gift. Of the agricultural households, 34% are involved in crop production, 11% are engaged in livestock rearing, and 10% practice mixed farming. Other households are involved in, e.g., mining and quarrying, manufacturing, and construction. The main crops are bananas, sweet potatoes, and beans and maize. The percentage of farmers raising cattle, goats, sheep, and pigs decreased over the study period, while the percentage of households engaged in poultry farming increased. The latter can be linked to a growing market for local birds and new breeds of chicken. Likewise, the percentage of households rearing small animals increased (Uganda Bureau of Statistics, 2011/12).

Uganda is a diverse country in terms of ethnicity (or tribes), culture and religion. The dominant tribes are Baganda (18.61%), Banyakole

[4] The EVI data is measured based on household locations by enumeration areas in Uganda.

[5] These households are female-headed, polygamous married, and/or led by household heads having no formal education. Geographically speaking, they are mostly located in the country's North.

(9.21%), Langi (8.43%), Basoga (7.18%), Bakiga (6.95%), and Iteso (6.92%). There are 42 indigenous languages, with English and Swahili being official languages (Hamilton et al., 2016), and Christianity and Islam account for about 82% and 14% of the population, respectively (International Religious Freedom Report, 2019).

2.2. Forest status

Uganda's forests include alpine, tropical high- and medium-altitude forests, woodlands, wetland and riparian forests, plantations and trees (Obua et al., 2010). Private and customary land comprise about 70% of the forest, while local governments administer some public forests. Forest reserves are available on public land, and are protected by law. The woodlands are mostly privately owned. Natural forests and shrubs dominate Uganda's vegetation (Bamwesigye et al., 2020). Forest structure and composition varys across the country due to differences in altitude, soil type, drainage, and human activities (Hamilton, 1984). Langdale-Brown et al. (1964) grouped the Ugandan forests into medium altitude–moist-evergreen forest, medium altitude–moist-semi-deciduous forest, and high-altitude forest. The first type of forest is structurally complex and rich in species, including *Peptadeniastrum-Uapaca* (in Ssese islands), *Peptadeniastrum-Albizia-Celtis* (in drier lake shores), and *Parinari excelsa* (in western rift valley). Representative plant species for the medium altitude–moist-semi-deciduous forests are *Celtis-Chrysophyllum* (north of Lake Victoria), *Cynometra-Celtis* (along the western rift), *Albizia-Milicia excelsa* (to the north of Lake Victoria), and *Albizia-Markhamia* (mid-west). The high-altitude forests have fewer species, e.g. *Prunus* moist sub-type, and typically a broken and irregular canopy. These forests are found in south-west Uganda.

Forest degradation is a problem. High population growth leading to increased demand for forest products, and weak governance of settlements and forests contribute to this (Obua et al., 2010). Private and publicly owned forests are both important sources of firewood and charcoal (Khundi et al., 2011), and therefore affected by this demand. In an effort to enhance forest management, Uganda is undergoing a transition to a more decentralized system, where about 70% of the forests are managed by the country's District Forestry Service,[6] while the remaining area falls equally under the National Forestry Authority[7] and the National Wildlife Authority.[8]

2.3. Fuel use

In Uganda, biomass accounts for over 90% of the energy supply (Okello et al., 2013; Turyareeba, 2001), and firewood serves as a primary source of energy in about 89% of the households (Government of Uganda, 2015). Animal dung and crop residues account for 4.8% of the country's primary energy consumption (Okello et al., 2013). Low forest biomass availability in west central Uganda forces households to instead rely on crop residues for cooking, or to collect non-forest based firewood which has a lower quality than forest-based firewood. Based on observed collection time, firewood scarcity in Uganda seems to be increasing over time (Jagger and Kittner, 2017).

Clean energy sources account for less than 10% of total energy consumption: of this, petroleum fuels (e.g., gasoline, diesel fuel, kerosene, fuel oil, aviation fuel, and LPG) make up 7.4%, and electricity 1.1%. Thus, Uganda is one of the countries with the lowest access to electricity in Africa (Okello et al., 2013). It is argued that the national electricity supply has serious reliability problems, which is a challenge to the adoption of new technologies (Blimpo and Cosgrove-Davies, 2019).

2.4. Energy policy targets

The Ugandan government has set a target to reduce national wood consumption by 40% by 2030. In accordance with the UN Sustainable Energy for All initiative, it also aspires to promote access to clean energy services, including access to electricity and modern cooking solutions for all in the same target year (Ministry of Energy and Mineral Development, 2017). In order to achieve these targets, millions of households must acquire LPG stoves, or improved wood and charcoal stoves. Achieving this will be a challenge given the country's annual production capacity of 300,000 clean stoves, their short lifespan, inadequate stove distribution centers, and LPG companies being concentrated in the capital city Kampala (Government of Uganda, 2015).

3. Data and measurements of forest status

The UNPS includes seven survey rounds that span from 2009/10 to 2019/20. The present study makes use of data from three survey rounds: 2009/10, 2010/11, and 2011/12 (Uganda Bureau of Statistics, 2009/10, 2010/11, 2011/12). The inclusion of more recent survey rounds is not possible because data on our chosen indicator for forest status is not publicly available for more recent survey rounds.

The UNPS is suitable for fuel choice analysis in the African context because the survey contains a detailed energy use section. From this section, we use the question "Do you use [list of fuels] for cooking, lighting, and heating?". We elicit whether or not a particular household is using clean energy sources (e.g., kerosene, LPG, solar, and electricity), dirty biobased energy sources (e.g., firewood, animal dung, crop residues, and charcoal), or a mix of those. The UNPS questionnaire asks if households use a specific fuel and the amount consumed in different, relevant units (e.g., kg, liter, or bundle, where the latter applies to firewood). However, the fuel quantities and measurement units are largely missing in the data, and it is not clear how the measurements should be converted into a single uniform unit. Therefore, we do not use such quantitative data in our econometric analysis.

The classification of fuels as being clean or dirty used in this study is based on their effects on health and natural resource conditions (Pachauri and Jiang, 2008). Kerosene, however, is classified as clean in some studies (Alem et al., 2016; Foell et al., 2011; Viswanathan and Kavi Kumar, 2005), and dirty in others (Rahut et al., 2014). In this paper, we place it in the clean category, motivated by the low local environmental impact (Kavi Kumar and Viswanathan, 2007), despite its global impact on climate change.

Throughout the paper, a household is defined as using clean energy if it uses at least one clean energy input but not any dirty fuel. Correspondingly, households defined as using dirty energy use at least one dirty fuel, but not any clean source. Households are categorized as using mixed energy if they use at least one clean and at least one dirty source. Biobased fuels from forests and agricultural land are all included in the dirty energy category. However, as our main purpose is to investigate the effect of forest status on fuel choice, it is also necessary to specifically focus on forest fuels. We therefore also carry out analysis where forest fuels are treated separately from the other dirty fuels, and separately from each other, which is further explained in Section 4 below. The UNPS includes areas from the 2005/06 Uganda National Household Survey (UNHS).[9] There were 34 enumeration areas (EAs) in Kampala District and 72 others[10] in the Central, Eastern, Western, and Northern regions. All UNPS rounds attempt to keep the same households across

[6] A local government unit responsible to mange land and forest resources outside of national parks.

[7] The National Forestry Authority administers central and local forest reserves.

[8] National Wildlife Authority advises on matters pertinent to land use in and off national parks, enforcement of use rights within parks being the major task.

[9] Before UNPS, UNHS surveyed households to measure national poverty in Uganda. Since 1999, it has collected data on 17,450 households in 112 districts.

[10] 58 rural and 14 urban EAs.

survey rounds. The inclusion of Kampala, other urban, and rural areas of all regions ensure representation in the UNPS strata. UNPS randomly selects EAs and households from each EA.

To identify the role of forest status in households' decisions on energy use, we need an indicator of forest viability. Forest biomass is such an indicator. The concept 'biomass' broadly includes both above-ground and below-ground living mass, but most studies focus on above-ground biomass due to the difficulty in collecting data on below-ground biomass (Lu, 2006). Remotely sensed data uses vegetation indices (VIs) to measure forest biomass. The VIs are calculated based on vegetation properties and variations of structural canopy (Huete et al., 2002b; Shen et al., 2010), and can be used for vegetation classification (Huete et al., 1999). The most commonly used VIs are the EVI and the Normalized Difference Vegetation Index, NDVI. The present paper is based on the EVI. The EVI is introduced as an improvement over NDVI by optimizing the vegetation signal where NDVI saturates (Huete et al., 2002a). The EVI removes both atmospheric and background noises simultaneously (Wang et al., 2003), and has proved to perform better than NDVI in many empirical applications (Huete et al., 1999; Liu and Huete, 1995). The value of the EVI falls between 0 (bare ground) and 1 (healthy vegetation). A detailed technical presentation of EVI is provided by Liu and Huete (1995), Huete et al. (1994) and Huete et al. (1997). Forest scientists also use NDVI to differentiate vegetated regions from non-vegetated ones, with an index falling between −1 and +1 (Tucker, 1979). The higher the NDVI value, the greater the density of the forest. While lower values indicate sparse vegetation, negative values commensurate to waterbodies. However, the NDVI estimation is less effective for our purpose since it is very sensitive to fluctuating atmospheric and canopy background conditions (Gao, 1996; Liu and Huete, 1995).

Finally, there is a connection between the socioeconomic data (such as household roster, education, housing conditions, and energy use) and the satellite data on forests from UNPS. These datasets have unique household ID numbers in common. This unique identifier matches the datasets together and makes them ready for analysis. The household-level analysis has an unbalanced panel with 6270 observations in the full sample. The regions, sample households, and forest conditions in Uganda are shown in Fig. 1.

4. Econometric methods

On an aggregate level, the use of forest fuels can lead to a decline in forest status. This should be taken into account by a social planner when deciding on the optimal level of fuelwood extraction. However, for an individual household the same feedback effect from their private fuelwood collection decision is likely to be small or negligible when there are many neighbouring households also collecting fuelwood. In our analysis, we therefore assume that the forest status is exogenous to individual households. In our regressions, the dependent variable is whether the fuel sources of household i at time t are clean ($j = 1$), dirty ($j = 2$) or mixed ($j = 3$). The utility of the i^{th} household from any fuel source category is modeled as:

$$Choice_{ijt} = \theta_j Forest_{it} + X'_{it}\beta_j + \varepsilon_{ijt} \tag{1}$$

where $Choice_{ijt}$ is the category of the chosen fuel by household i at time t into $j = 1, 2, 3$. The variable $Forest_{it}$ is an EVI-based indicator of forest status in the neighbourhood of household i at time t, and θ_j is the coefficient of interest. Following Hasanah and Indrawan (2020), we chose to classify EVI into 3 groups, reflecting the extent of forest status: non-vegetated if $0 \le EVI \le 0.35$ (yes $= 1$), sparsely vegetated if $0.36 \le EVI \le 0.5$ (yes $= 2$), and densely vegetated if $0.51 \le EVI \le 1.0$ (yes $= 3$).

The variable X′ is a vector of other explanatory variables with β_j as the associated vector of coefficients. These are household variables (e.g., education of the household head, age, gender, and family size), economic variables (e.g., land size, livestock size, and wealth measured in terms of consumption spending), housing variables (e.g., number of rooms, independent, shared residence, and other), environmental variables (plain, plateau, and mountainous areas), and weather variables (e.g., mean rainfall and temperature). The inclusion of these variables is motivated by the literature on household fuel choices, and ensures that we minimize estimation bias in θ_j.

We hypothesize that more educated household heads tend to shift from dirty to clean fuels. Higher income is expected to have a similar effect, in accordance with the energy ladder hypothesis (Guta, 2012; Heltberg, 2005). Households with higher expenditures are hypothesized to use more clean or mixed fuels, but less of dirty energy

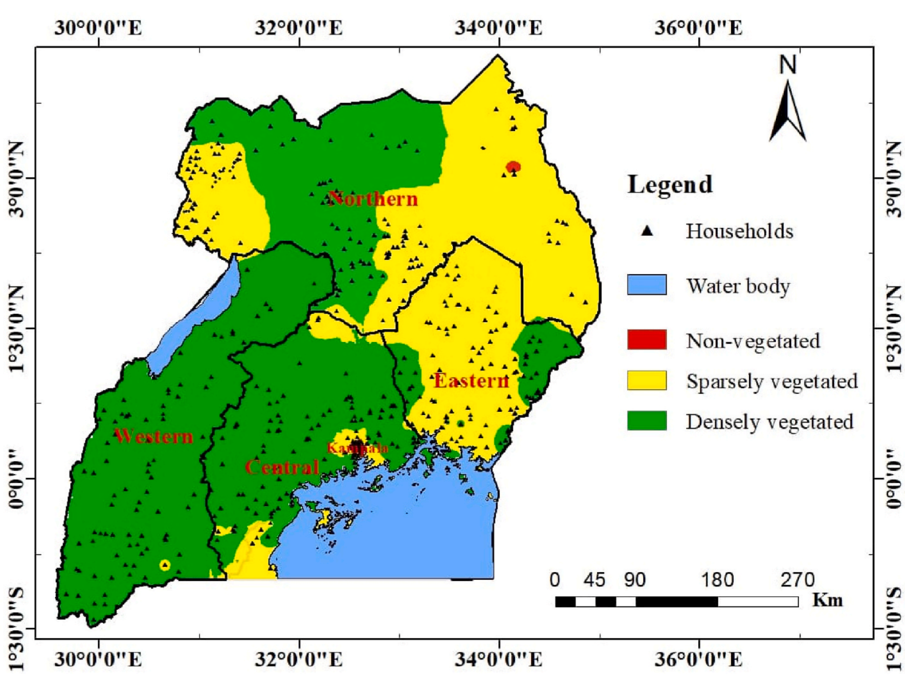

Fig. 1. UNPS regions, sample households, and forest status in Uganda.

(Gebreegziabher et al., 2012; Guta, 2012). The literature reports that larger families use more firewood (Cruz et al., 2020; Ouedraogo, 2006), and less clean fuels and charcoal (Ouedraogo, 2006). Female-headed households will rely more on dirty biobased fuels (Guta, 2012; Ouedraogo, 2006). In addition, households with larger land and livestock holdings could use more dirty biobased fuels (Guta, 2012). Housing factors may affect fuel choice. Heltberg (2005) reports that the number of rooms is positively related to the use of LPG. As observed in Burkina Faso the type of dwelling matters, for example, tenants that share a yard have more limited space for firewood storage facilities (Ouedraogo, 2006). We use environmental landscape factors as control variables in the econometric specifications because they affect the level of infrastructural investments (Yamada and Yamada, 2021), and thus installation of electricity. Weather conditions can also affect energy choice (Auffhammer and Mansur, 2014; Ektvedt, 2011; Mazzone et al., 2021). For example, most firewood in Peru is collected during dry seasons, when agricultural activity is less intense (Ektvedt, 2011). Finally, the variable ε_{ijt} is the random error term, assumed to be independently and identically distributed, and follows type I extreme value distribution.

In spite of the inclusion of control variables, some situations could still result in wrong θ_j estimates in Eq. (1). First, there could be a potential endogeneity problem due to omitted variables bias. We follow the literature and address the problem through the inclusion of a latent variable, $\mathscr{L}_{it}$, in our model (Baum et al., 2017; Nkegbe et al., 2018). $\mathscr{L}_{it}$ is included in each energy equation, and its variance is constrained to one to allow estimation of its magnitude in the equations. Second, the coefficient θ_j could be biased if there are regional characterstics that affect the outcome variables differently across regions. For example, Himbara (1994) shows that investors channel their investment projects towards areas where their ethnic groups are located. There can also be cultural and behavioral differences in fuel use across locations (Cruz et al., 2020; Farsi et al., 2007; Heltberg, 2005; Kim et al., 2017), differences in population density, infrastructural development, resource availability and accessibility, and plants species suitable for firewood use (Jiménez-Escobar et al., 2021) that affect fuel choice. We address these concerns by controlling for region fixed-effects ($ш_R$). The year fixed-effects ($ш_t$) address variations in fuel choice across survey rounds.

Third, Eq. (1) overlooks the unobserved heterogeneity between units entailing within-unit dependence and ignores the independence of irrelevant alternatives (Alem et al., 2016; Skrondal and Rabe-Hesketh, 2014). With the exception of Alem et al. (2016), previous studies that make use of a panel multinomial logit model, such as Guta (2012), do not take these concerns into account. The estimates based on such studies are therefore inconsistent and inefficient (Malchow-Møller and Svarer, 2003). In our study, we use REMNLM (Chen and Kuo, 2001; Malchow-Møller and Svarer, 2003; Rabe-Hesketh et al., 2004) in the GSEM setup to specifically address these issues. This approach allows for a correlation among the residuals for the clean, dirty, and mixed energy equations within the same household, and assumes independent residuals across households. The REMNLM considers survey round (t) at level 1 and household (i) at level 2 to account for the time-invariant unobserved household heterogeneity, α_{ij}.

Addressing the aforementioned problems, Eq. (2) presents the REMNLM equation:

$$Choice_{ijt} = \theta_j Forest_{it} + X'_{it}\beta_j + \mathscr{L}_{it} + ш_t + ш_R + \alpha_{ij} + \varepsilon_{ijt} \tag{2}$$

The multinomial model is given by:

$$P(j|Forest_{it}, X_{it}, \alpha_i) = \frac{exp(\theta_j Forest_{it} + X'_{it}\beta_j + \alpha_{ij})}{\sum_{z=1}^{J} exp(\theta_j Forest_{it} + X'_{it}\beta_z + \alpha_{iz})} \tag{3}$$

After calculation of the sample likelihood for the random-effects model by integrating over the distribution of the unobserved heterogeneity, the Full-Information Maximum Likelihood Estimator (FIMLE) is used.

The precise effect of forest status could differ across different types of dirty fuels. We expect larger availability of forest biomass to be positively associated with the use of wood fuels such as firewood and charcoal. Moreover, charcoal can be potentially transported between regions. The market is well integrated (Branch and Martiniello, 2018) and charcoal is highly traded compared to firewood. We therefore expect the effect of local forest status on firewood to be higher than that on charcoal. We address these differences among dirty biobased fuels by using three alternative definitions of dirty energy, summarized in Table 1. The baseline model, which is reported in panel A of Table 3, and Tables A.3 and A.4 in the Appendix, includes all biobased fuels in the dirty category, below referred to as Dirty-I. In the second case, households are defined as using dirty fuels if they use firewood and, potentially, also other dirty fuels. In the third case, households are defined as using dirty fuels if they use charcoal and, potentially, also other dirty fuels. The last two alternative dirty fuel categories are labeled as Dirty-II and Dirty-III in Table 1. Using these alternative definitions, we are able to specifically identify the role of forest status in firewood and charcoal use. Combinations of clean and dirty fuels are referred to as mixed fuels, and the definition of Mixed-I to III follows from that of Dirty-I to III. Thus, Mixed-I implies that a combination of clean fuels, and fuels included in Dirty-I, are used. The definitions of Mixed-II and III follow the same logic. The non-wood dirty fuels (i.e., crop residues and animal dung) are not directly dependent on forest conditions. However, it could also be relevant to study the specific impact on these fuels because forest policy could lead to switch away from using forest fuels (Heltberg et al., 2000). These estimations are presented in panel C of Table A7.

Some variables in the X'_{it} vector need to be transformed into logarithms to ensure a normal distribution. However, the log is sometimes undefined for the variables land size, number of rooms, tropical livestock unit (TLU), and household head's years of education, which contain cases with zero values. We solve this problem and retain the zero-value observations by applying the inverse hyperbolic sine transformation approach (IHSTA). For any random variable x, the IHSTA becomes $\ln(x + \sqrt{x^2 + 1})$ (Bellemare and Wichman, 2020; Burbidge et al., 1988; Ravallion, 2017).

Table 1
Different definitions of dirty and mixed energy sources used in Table 3, and A.3 and A.4.

Panels	Cases	Any clean used	Any dirty used	Firewood (+other dirty) used	Charcoal (+other dirty) used
Panel A	Clean	X			
	Dirty-I		X		
	Mixed-I	X	X		
Panel B	Clean	X			
	Dirty-II			X	
	Mixed-II	X		X	
Panel C	Clean	X			
	Dirty-III				X
	Mixed-III	X			X

Note: The energy utilization 'cases' are defined as follows. Clean shows the household completely depends on at least one of the clean energy sources in all panels (Any clean used). Dirty-I implies the dirty fuels consisting of both wood fuels (firewood and charcoal) and non-wood fuels (crop residue and animal dung), labeled as 'Any dirty used'. Dirty-II means the household uses firewood or combines it with other dirty fuels (Firewood (+other dirty) used). Finally, Dirty-III indicates the household uses charcoal alone or in combination with other dirty sources (Charcoal (+other dirty used). The definitions of Mixed-I, Mixed-II, and Mixed-III directly follows the definitions of Dirty-I, Dirty-II, and Dirty-III together with clean in each panel, respectively.

Table 2
Summary statistics.

Variable	Panel A: EVI (%)							
	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
	Mean	N	Mean	N	Mean	N	Mean	N
EVI	0.484	1955	0.515	2077	0.509	2238	0.503	6270

Variables	**Panel B: Households location based on forest status (%)**							
	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
Forest status	Mean	N	Mean	N	Mean	N	Mean	N
Non-vegetated	11.71	1955	6.40	2077	6.03	2238	7.93	6270
Sparsely vegetated	44.65	1955	26.53	2077	36.77	2238	35.84	6270
Densely vegetated	43.63	1955	67.07	2077	57.19	2238	56.23	6270

Fuel usage	**Panel C: Households consuming different fuel inputs (%)**							
	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
	Mean	N	Mean	N	Mean	N	Mean	N
Dirty energy								
Firewood	.789	1955	.809	2077	.83	2238	.81	6270
Animal dung	0	1955	0	2077	.004	2238	.001	6270
Crop residue	.09	1955	.089	2077	.09	2238	.089	6270
Charcoal	.298	1955	.266	2077	.252	2238	.271	6270
Clean energy								
Kerosene	.884	1955	.842	2077	.805	2238	.842	6270
LPG	.006	1955	.003	2077	.005	2238	.005	6270
Solar	.009	1952	.018	2077	.019	2238	.015	6267
Electricity	.13	1951	.095	2073	.083	2237	.102	6261

Energy categories (%)	**Panel D: Percentage of households in different energy categories**							
	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
	Mean	N	Mean	N	Mean	N	Mean	N
Clean energy sources	2.61	1955	2.21	2077	1.70	2238	2.15	6270
Dirty energy sources	6.91	1955	10.35	2077	14.83	2238	10.88	6270
Mixed energy sources	90.49	1955	87.43	2077	83.47	2238	86.97	6270

Fuel channels (%)	**Panel E: Percentage of households using different channels for obtaining fuels**							
	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
	Mean	N	Mean	N	Mean	N	Mean	N
Market purchase	25.53	1892	24.64	2029	22.29	2198	24.07	6119
Self-collection	67.65	1892	68.90	2029	71.97	2198	69.62	6119
Purchase and collection	6.82	1892	6.46	2029	5.73	2198	6.31	6119

Table 3
Marginal effects: the role of forest status in fuel choice (non-vegetated being the base category).

Variables	Dependent variable: fuel choice								
	Panel A: Basket of dirty fuels			Panel B: Firewood used			Panel C: Charcoal used		
	Clean (1)	Dirty-I (2)	Mixed-I (3)	Clean (4)	Dirty-II (5)	Mixed-II (6)	Clean (7)	Dirty-III (8)	Mixed-III (9)
Sparsely vegetated	−0.000	−0.061***	0.061***	−0.015**	−0.072***	0.087***	−0.005	−0.040*	0.045*
	(0.005)	(0.012)	(0.014)	(0.006)	(0.015)	(0.017)	(0.017)	(0.021)	(0.025)
Densely vegetated	−0.006	−0.074***	0.080***	−0.020***	−0.090***	0.110***	−0.023	−0.021	0.044**
	(0.005)	(0.013)	(0.014)	(0.006)	(0.017)	(0.018)	(0.014)	(0.015)	(0.020)
Latent variable, L		−2.56e-15**	−2.56e-15**		−5.40e-15**	−5.40e-15**		1.21e-11*	1.21e-11*
		(1.07e-15)	(1.07e-15)		(1.17e-15)	(1.17e-15)		(7.15e-12)	(7.15e-12)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heterogeneity indicators									
Variance (L)		1(constrained)			1(constrained)			1(constrained)	
Variance (equations)	1.18e-07***			4.75e-08**					14.251***
	(7.20e-09)			(3.18e-09)					(4.641)
Observations	6270	6270	6270	5215	5215	5215	1834	1834	1834

Note: The dependent variable is whether or not the household chooses (a) at least one of the clean energy sources but not any dirty fuel inputs in columns 1, 4, and 7; (b) at least one of the dirty energy sources excluding any clean energy in column 2; (c) firewood as a dirty energy but not any other clean energy in column 5, and (d) charcoal as a dirty energy distinct from all clean energy sources in column 8 for cooking, lighting, and/or heating purposes. The definitions of mixed energy I to III in columns 3, 6, and 9 varies depending on the definitions of dirty energy I to III in each panel. The answers are coded as 1 if yes and 0 otherwise for each column in panels A to C. Other controls appear in Table A.2 in the Appendix. Columns 1–9 are REMNLM fitted with GSEM. Robust standard errors clustered at the household level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5. Results and discussion

This section provides the results. It begins with the descriptive analysis, followed by the empirical results.

5.1. Data description: the EVI, energy utilization and energy sources

This sub-section provides a description of the data on EVI and household energy utilization across years, with summary statistics reported in Table 2. The average EVI is 0.5 for the pooled sample with improvements in forest biomass availability between the survey rounds 2009/10 to 2010/11. The average EVI slightly falls during 2011/12 as opposed to the preceeding year. About 56% of the households are located in densely vegetated areas followed by another 36% and 8% being in sparsely and non-vegetated areas, respectively. Households rely on different energy inputs. Close to 84% of the households report using kerosene as a source of energy. Kerosene is commonly used for cooking and lighting in SSA (Karekezi and Kithyoma, 2002). Firewood is used for cooking, heating, and/or lighting purposes by about 79%, 81% and 83% of the households over the three survey rounds. About 27% of the pooled sample households also use charcoal, while the proportion of households using the remaining energy sources is fairly limited, see panel C of Table 2. The huge majority, close to 87%, of the households use mixed fuels. This is followed by about 11% and 2% of the households solely relying on dirty and clean energy sources, respectively (panel D of Table 2).

The number of households self-collecting fuel, mainly in terms of firewood from own land and their villages increases from 68% in 2009/10 to 72% in 2011/12. At the same time, there is a consistent decline over the years in the proportion of households purchasing energy inputs on the market, or combining market purchases and self-collection (panel E of Table 2). The summary statistics of other control variables can be found in Table A.1 in the Appendix. One can note from Table A.1 that the average land size, including both own land and land with user rights, is 4.5 acres for the pooled sample. The presence of own land helps households to grow different biomass fuels and firewood-targeting trees (Cooke et al., 2008). Also, larger land and livestock sizes may provide households with crop residues and animal dung.

5.2. Empirical results

The main empirical results and robustness checks are presented below.

5.2.1. The role of forest status in fuel choice

This sub-section reports the econometric analysis on the role of forest status in households' fuel choice decisions. Table 3 provides the main results in terms of marginal effects[11] estimated by FIMLE.[12] Robust standard errors clustered at the household level are reported. Results for the baseline definition of dirty fuels (Dirty-I) are shown in panel A of Table 3. Columns 2 and 3 show that households switch from dirty to mixed fuels when the forest stock improves. More specifically, households in areas with sparse and dense vegetation are 6–7% less likely to use dirty energy compared to households in non-vegetated areas (see column 2, panel A of Table 3). This is associated with a corresponding increase in the probability of selecting mixed energy sources, as shown in column 3, panel A of Table 3.

As mentioned in section 4, we explore the specific role of forest status in wood fuel choice by using firewood (Dirty-II) and charcoal (Dirty-III) as necessary components in the dirty energy basket. The associated results are presented in panels B and C of Table 3 for firewood and charcoal, respectively. We find that households' use of firewood is likely to be 7–9% lower with sparse and dense vegetation relative to the non-vegetated localities (column 5, panel B of Table 3). Moreover, there is a simultaneous 1.5–2% reduction in the likelihood of exclusively using clean sources (column 4, panel B of Table 3). Together, this leads to a corresponding increase by 9–11% in the probability of using mixed fuels (column 6, panel B of Table 3).

We also look at how forest status affects the use of charcoal. According to the findings, households in sparse vegetation areas have a lower likelihood of using charcoal compared to those in non-vegetated areas (column 8, panel C of Table 3). The use of charcoal is not affected by dense vegetation. The fact that charcoal is more mobile than firewood may account for the weak statistical effect on charcoal use. In addition, charcoal traders commonly give bribes to forest officials (Jagger and Shively, 2015), fostering the mobility of this fuel across localities.The descriptive analysis supports this: we find that 1247 households rely on purchased charcoal, while only 440 households in the entire sample buy firewood. Column 9 shows the impacts of changing forest conditions on using mixed energy are comparable to those available in panels A and B of Table 3.

The negative effect of forest status on choosing firewood as a fuel source is contrary to expectations. It indicates that forest status is not an exclusive determinant of firewood use. There are at least two potential explanations. First, legal or property rights issues affect forest management and use. Obua et al. (1998) show that local communities in Budongo forest reserve in Uganda dislike strict forest management rules. Locals are not provided with licenses to access non-timber forest products and are deprived of the advantages of the timber industry. As a result, people distrust the forest department. Heltberg et al. (2000) also report restrictions on animal and motor-powered firewood transportation in the Sariska Tiger Reserve in northwest India, and note that well-equipped forest guards can reduce locals' ability to gather firewood. Active forest protection therefore reduces dependence on fuelwood. Second, policymakers lack knowledge on causes of forest degradation in Africa (Fairhead and Scoones, 2005; Reenberg, 2012; Rohde et al., 2006). There is a risk that tougher forest resource management regulations will be introduced to improve forest status, such as prohibitions on collecting even dry and fallen woods from forest areas, affecting locals' livelihoods (Barrett et al., 2013; Edstedt and Carton, 2018; Lyons and Westoby, 2014; Reddy and Chakravarty, 1999; Rohde et al., 2006).

Households' possibilities for adaptation to enhanced private property rights and forest conservation policies vary depending on the economic, environmental, and cultural context. One mechanism is to substitute the non-wood dirty fuels for the wood fuels when access to forests is limited,[13] which eases the pressure on natural forests (Heltberg et al., 2000). Households could also opt for new fuelwood species as suggested by the diversification hypothesis (de Albuquerque, 2006). One alternative is exotic species, for which the acceptance could vary depending on the cultural context (Jiménez-Escobar et al., 2021). Food preferences can be flexible and affect the demand for firewood (Mazzone et al., 2021). For example, native species can be preferred for their specific characteristics, e.g., hot flame, less smoke, long-lasting flame and embers, and ease of splitting and lighting (Cruz et al., 2020; Kim

[11] It is important to note that the marginal effects in each panel would always sum up to zero whenever the REMNLM is used. This is so because a higher coeffficent value of a variable in one of the categories of the dependent variable would imply a reduction in the estimates for the other alternatives.

[12] We use separate but correlated random-effects among different energy categories. The estimated variances of the random-effects are statistically significant and highlight the potential importance of common shocks across the fuel choice and forest status circle. These results reveal that the unobserved household heterogeneity component is statistically significant. The coefficient of $\mathscr{L}$ is significantly different from zero in all panels. This confirms that omitted variables would have affected fuel choice if left unaddressed via $\mathscr{L}$ in Eq. (2). The clean energy is a base category when we estimate the effect of $\mathscr{L}$.

[13] Panel C of Table A7 in the Appendix supports this idea.

et al., 2017). Evidence from Kenya demonstrates that households prepare composite meals[14] and have dishes that need less time in response to a lack of firewood (Waswa et al., 2020). There are also different cultural preferences in relation to firewood gathering. The majority of rural Vietnamese households, for example, prefer green branches and whole living trees for firewood purposes compared to dry or dead trees (Kim et al., 2017). Also, households may adapt by collecting firewood from new places, including woodlots, bushes, and gardens, and could receive firewood through welfare programs (Jiménez-Escobar et al., 2021; Kim et al., 2017; Waswa et al., 2020).

Regardless of the variations in the definition of dirty energy depending on the panels, our results consistently show an increase in the use of mixed fuels in the presence of a more viable forest stock. This finding suggests that households show fuel stacking behavior (Burke and Dundas, 2015; Shankar et al., 2020). Such behavior is often found when no single fuel can wholly meet every type of energy need by a particular household (Pillarisetti et al., 2019; Troncoso et al., 2019). We only find that fuel stacking behavior significantly reduces the probability of solely relying on clean energy (column 4, panel B of Table 3) for households that use firewood and are exposed to a higher forest stock. This finding is in line with Choumert-Nkolo et al. (2019), who document that households' probability of connecting to the electricity grid decreases with increasing fuel stacking in Tanzania. Investment costs related to the use of clean energy might explain this.

Table A.2 in the appendix shows the effects of other control variables in the main regression. More educated household heads use more clean energy, but the response is small: a 10% increase in education increases the likelihood of clean fuel consumption by 1% (column 1) to 2% (column 4). Previous research also points to a similar conclusion (Gebreegziabher et al., 2012; Heltberg, 2005). This is so because educated families have a high opportunity cost of time when using dirty energy (Heltberg, 2005). Education has a negative, albeit insignificant, impact on dirty fuel consumption, while earlier literature has shown a significant negative association between education and consumption of firewood (Gebreegziabher et al., 2012; Heltberg, 2005).

Higher wealth encourages mixed fuel use, see columns 3, 6, and 9 of Table A2, while clean fuel use is largely unaffected. In Uganda, the support for fuel stacking behavior therefore seems stronger than for the energy ladder hypothesis. Economic and sociocultural factors explain fuel stacking. Clean fuels have high initial investment costs, such as an electrical installation and purchase of its accessories (Choumert-Nkolo et al., 2019; Mazzone et al., 2021; Muller and Yan, 2018), high transaction costs (Masera et al., 2000) and limited accessibility and reliability (Blimpo and Cosgrove-Davies, 2019; Guta, 2014; Kowsari and Zerriffi, 2011; Shankar et al., 2020). This motivates households to use mixed fuels as an insurance strategy (Louw et al., 2008). Culture (e.g., preferences, cooking patterns, food tastes, feeding habits, and firewood collection traditions) also drive fuel stacking. Households have different preferences for various fuels. For example, kerosene is the least preferred fuel in Ghana since it is time-consuming to use and has less power than firewood (Akpalu et al., 2011). Kenyan households cook firewood saving foods, such as tea and porridge, and githeri – a popular and nutritious food that ideally reduces eating frequency (Waswa et al., 2020). Also, food taste depends on fuel types used to cook it (Akpalu et al., 2011; Masera et al., 2000; Shankar et al., 2020; Winther, 2007). Finally, fuel stacking, including firewood, prevails because firewood resources are mostly available (Cruz et al., 2020) and its collection is seen as an integral part of social life (Louw et al., 2008; Mazzone et al., 2021). The likelihood that mixed fuels could be adopted is significantly associated with female headship (Guta, 2012), family size, the number of rooms (Heltberg, 2005), the size of the land, and rainfall. However, the majority of these factors hinder the adoption of clean fuels.

[14] These meals are intended to lower the daily cooking frequency.

5.2.2. Robustness checks

Our results are robust to a series of sensitivity checks. First, we conduct the same analysis as in Table 3 without using the terrain categories, mean temperature, mean rainfall, and region fixed-effects in Eq. (2). The resulting marginal effects of the estimates of forest status, reported in panels A to C of Appendix Table A.3, are almost similar in both magnitude and statistical significance to those reported in Table 3. Table S1 in the online supplementary material provides the results for other controls. Second, the EVI is treated as a continuous variable, different to the discrete variable levels used above. The EVI has a negative and weakly significant effect on using clean energy. The other magnitudes and statistical significances are otherwise similar to those in Table 3. The results indicate that increases in forest stock decrease the probability of using dirty energy according to the baseline definition (panel A of Table A.4) and firewood (panel B of Table A.4). The probability of choosing mixed fuels increases as shown in panels A to C of Table A.4. Results for additional controls can be found in Table S2 in the online supplementary material.

Third, we use separate random-effect probit models (REPM) for different fuel categories to evaluate the relationship between forest status and fuel choice. Table A.5 depicts the marginal effects estimated by FIMLE. The estimates are comparable to the main results reported in Table 3. The other controls for these models appear in Table S3 in the supplementary material. Fourth, we use the linear probability models (LPM) to show that the effect of forest conditions on energy choices is robust to the main results. Table A.6 presents these results, which are consistent with results reported above. The estimates for other controls can be found in Table S4 in the supplementary material. We finally analyze whether the role of forest stock (continuous form) in fuel choice varies between the rural and urban households, using separate regressions for the rural and urban sample as a fifth robustness check. The results are shown in panels A and B of Table A.7 for rural and urban households, respectively. The conclusions remain unchanged.

6. Conclusions and policy implications

Rural livelihoods depend on forests as a source of energy. Forests are also a key source of income, carbon sequestration and land protection, and are an integral part of day-to-day activities in many communities. This paper investigates the impact of forest status on households' fuel choice after controlling for other covariates. We use the Enhanced Vegetation Index (EVI) as an objective measure of forest status, and combine it with socioeconomic data from the Uganda National Panel Survey (UNPS) collected during 2009/10, 2010/11, and 2011/12. Households are assumed to choose between clean fuels (e.g., kerosene, LPG, solar energy, and electricity), and biobased dirty fuels (e.g., firewood, animal dung, crop residues, and charcoal), or a mix thereof.

The empirical results highlight some major findings. Compared to households in non-vegetated areas, households in sparsely and densely vegetated areas are substantially less likely to utilize dirty biobased fuels in general, and firewood and charcoal in particular. The effect on the use of firewood is bigger and more significant than the effect on the use of charcoal. The fact that charcoal is more commonly transported across regions and supplied on the market than firewood explains this result. The charcoal market is well integrated and more easier to purchase from the market compared to firewood. For example, charcoal traders often come from distant areas and employ agents in small trading centers to buy charcoal on their behalf (Tabuti et al., 2003).

The negative association between increases in forest stock and firewood use could potentially be explained by forest conservation efforts, implemented through legal restrictions, or stronger property rights, where both could support more viable forests while simultaneously reducing possibilities for firewood collection. Given the importance of firewood for households, this raises a concern that firewood collection in forests is overly restricted because of misguided forest protection policies, which might not achieve a sustainable balance between protection and use of the forest resources. On the other hand, when access to forests is restricted, non-wood fuels (such as animal dung and crop residue) could replace firewood and even charcoal. Alternatively, households could adapt by increasing the use of exotic woody plants for firewood consumption. The potential for adaptation depends on the cultural and household level preferences for firewood plant characteristics and harvesting practices.

Improvements in forest biomass are associated with a higher likelihood of using mixed energy sources, i.e., increased fuel stacking behavior. The conclusion holds both when we treat all dirty fuels as a single basket, and for firewood and charcoal separately. Higher household wealth also increases the tendency to use mixed fuels. The literature provides multiple explanations for fuel stacking. For example, clean fuels are generally expensive and their supply is unreliable. Meles (2020) shows that there are frequent power disruptions, which reduces the benefits of having an electricity connection in Ethiopia. LPG cylinder deliveries are frequently late in Mexico, forcing households to wait until the next one or go to town to pick up a full cylinder (Masera et al., 2000). This makes the use of mixed fuels inevitable as a way of ensuring a constant supply of fuels at the household level. Cultural practices and behavioral factors could also motivate fuel stacking. Households use different fuels for cooking different foods because it is generally perceived that food tastes depend on the fuel used to cook the food. People may, for example, have preferences for foods cooked with firewood. In addition, attitudes towards the environment and intergenerational knowledge (e.g., the way someones' relatives cook food) affect fuel choice. These factors make fuel stacking, particularly with firewood use included, appealing. In contrast, the wealth coefficients do not provide strong statistical evidence for the energy ladder concept, i.e., the hypothesis that rising household income leads to a conversion from dirty to clean fuels. Higher wealth does significantly lower the use of dirty fuels, but it does not guarantee the switch to cleaner fuels.

Our results further show that household head education is positively associated with clean fuel adoption, while household head age, female-headed households, and family size are negatively correlated with clean fuel use. Larger livestock herds support the use of dirty fuels since it enhances access to animal dung. The use of mixed fuels is higher in female-headed households, households with more family members, and households with a larger number of rooms, while it is negatively related to the size of livestock. All results are on the overall robust to alternative model specifications and estimation strategies.

Our results have several policy implications. First, the lower possibilities for gathering firewood from protected and private forest areas underscores the necessity for alternative firewood supply, given that many people are still highly dependent on firewood. In this regard, encouraging households to grow early maturing trees could be useful as it would enhance the available firewood resources and ease the strain on the forest stock. Second, provision of modern cookstoves to households in sparsely and densely vegetated areas seems necessary to achieve the targeted access to clean energy sources and the targeted 40% decrease in wood usage aimed for by 2030. Policy makers should acknowledge the benefits associated with fuel stacking at the household level, as long as supply shortages temporarily constrain the use of different fuels. Third, increased access to education for household heads may be crucial for Uganda to reach its energy policy targets. This could be combined with campaigns to raise awareness about the importance of using clean fuels and managing forest resources sustainably. Fourth, policies that increase household wealth, e.g., through income diversification opportunities and the provision of energy subsidies for the poor, can help in financing households' investments in clean energy. Fifth, the increased use of dirty fuels in response to larger livestock holdings could also be counteracted if households are encouraged to produce biogas using zero-grazing techniques. Such a transition is likely to require policies that take into account also local cultural practices related to livestock management. Sixth, when reliance on forest charcoal decreases due to restricted access to forests, policies need to secure a reliable supply of charcoal via proper trading routes and better functioning markets. The creation of charcoal cooperatives with local inhabitants serving on board membership might be beneficial.

Our study has several limitations that should be kept in mind. One is the lack of data on forest property rights, which prohibits us from identifying the role of these rights in forest status and energy choices. For example, using data from Thailand, Chankrajang (2019) reports that extensive community forestry leads to better forest cover. Moreover, our paper does not address the role of institutions, such as the level of democracy, and political accountability of forest authorities and community representatives, in forest status and the use of firewood and charcoal production, as argued by Nygren (2005) to be important for the relationship between the studied outcomes. In addition, the UNPS data on fuel expenditure, fuel quantities, and units for those, are mostly missing. The lack of such data prevent us from assessing the relationships between forest status, fuel choice, and households' energy intensity. Future surveys that include this information could help address these issues and thus provide more complete welfare estimates related to our research question.

CRediT authorship contribution statement

Bahre Gebru: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, reviewing and editing. **Katarina Elofsson:** Supervision, Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, reviewing and editing.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.113390.

Appendix

Table A.1
Summary statistics of other controls.

	Year 2009/10		Year 2010/11		Year 2011/12		Pooled	
	Mean	N	Mean	N	Mean	N	Mean	N
Urban (=1 if yes)	.262	1955	.226	2077	.206	2238	.23	6270
Head age, years	45.927	1955	47.244	2077	47.396	2238	46.888	6270
Female head (=1 if yes)	.51	1955	.529	2077	.296	2238	.44	6270
Family size	6.554	1955	7.258	2077	7.78	2238	7.225	6270
Head education, years	5.52	1955	5.779	2077	5.467	2238	5.587	6270
Number of rooms	2.923	1955	8.733	2077	3.03	2238	4.886	6270
Land size, acres	4.672	1955	5.235	2077	3.571	2238	4.466	6270
Livestock size, TLU	359.651	1955	.844	2077	.781	2238	112.698	6270
Monthly consumption expenditure	286000	1955	235000	2077	227000	2238	248000	6270
Independent residence (=1 if yes)	0.293	1955	0.307	2077	0.316	2238	0.306	6270
Shared residence (=1 if yes)	0.570	1955	0.559	2077	0.552	2238	0.560	6270
Other residence (=1 if yes)	0.137	1955	0.134	2077	0.132	2238	0.134	6270
Plains (=1 if yes)	0.673	1955	0.695	2077	0.705	2238	0.691	6270
Plateaus (=1 if yes)	0.148	1955	0.125	2077	0.114	2238	0.128	6270
Mountains (=1 if yes)	0.179	1955	0.181	2077	0.181	2238	0.180	6270
Mean annual rainfall (mm)	1131.125	1955	1132.657	2077	1128.674	2238	1130.757	6270
Mean annual temperature (mm)	218.352	1955	219.054	2077	219.47	2238	218.983	6270
Central region (=1 if yes)	.332	1955	.303	2077	.282	2238	.304	6270
Northern region (=1 if yes)	.21	1955	.24	2077	.258	2238	.237	6270
Eastern region (=1 if yes)	.219	1955	.247	2077	.239	2238	.235	6270
Western region (=1 if yes)	.239	1955	.211	2077	.221	2238	.223	6270

Note: The analysis is at household-level. All figures in this table are nationally representative according to the UNPS. Consumption expenditure is monthly household expenditure in constant prices after adjusting for regional price variations measured in terms of Ugandan Shilling (UGX). TLU is Tropical Livestock Unit. 1USD ≈3533.80 UGX on August 2021.1 Acre ≈0.405 ha.

Table A.2
Marginal effects: the role of forest status in fuel choice (non-vegetated being the base category): other controls from Table 3.

Variables	Dependent variable: fuel choice								
	Panel A: Basket of dirty fuels			Panel B: Firewood used			Panel C: Charcoal used		
	Clean (1)	Dirty-I (2)	Mixed-I (3)	Clean (4)	Dirty-II (5)	Mixed-II (6)	Clean (7)	Dirty-III (8)	Mixed-III (9)
Urban	−0.000	−0.004	0.004	0.007*	0.005	−0.011	−0.030***	0.003	0.027*
	(0.004)	(0.010)	(0.012)	(0.004)	(0.012)	(0.013)	(0.010)	(0.012)	(0.015)
Head age	−0.000***	0.000	0.000	−0.000***	0.000	0.000	−0.000	−0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Female head	−0.012***	−0.005	0.017***	−0.008**	0.002	0.006	−0.037***	−0.019*	0.056***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.006)	(0.007)	(0.010)	(0.010)	(0.013)
Family size	−0.024***	−0.016***	0.040***	−0.024***	−0.022***	0.046***	−0.061***	0.001	0.060***
	(0.003)	(0.006)	(0.007)	(0.003)	(0.007)	(0.008)	(0.010)	(0.010)	(0.014)
Head education	0.001***	−0.000	−0.001	0.002***	−0.000	−0.002	0.001	−0.000	−0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of rooms	−0.008**	−0.024***	0.032***	−0.010***	−0.017**	0.027***	−0.017*	−0.009	0.026*
	(0.003)	(0.007)	(0.008)	(0.004)	(0.008)	(0.009)	(0.009)	(0.012)	(0.014)
Land size	−0.004**	−0.004	0.008*	−0.006***	−0.001	0.007	−0.005	−0.004	0.009
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)
TLU	0.002	0.010***	−0.013***	0.002	0.010**	−0.012***	0.007	0.001	−0.008
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.007)	(0.008)	(0.010)
Consumption expenses	−0.001	−0.013**	0.013**	0.001	−0.012**	0.011*	−0.014*	−0.008	0.022**
	(0.002)	(0.005)	(0.006)	(0.002)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
Shared residence	−0.001	0.001	0.000	0.007*	−0.006	−0.001	−0.021*	−0.006	0.027*
	(0.004)	(0.010)	(0.011)	(0.004)	(0.016)	(0.016)	(0.011)	(0.012)	(0.016)
Other residence	−0.012***	0.023***	−0.011	−0.014***	0.025***	−0.011	−0.023	−0.037	0.060**
	(0.004)	(0.008)	(0.009)	(0.005)	(0.008)	(0.009)	(0.017)	(0.025)	(0.027)
Plateaus	0.000	0.001	−0.001	−0.000	−0.001	0.001	0.004	0.016	−0.020
	(0.004)	(0.008)	(0.010)	(0.004)	(0.009)	(0.010)	(0.011)	(0.015)	(0.016)
Mountains	0.007	0.004	−0.011	0.004	0.003	−0.008	0.030	0.003	−0.033
	(0.007)	(0.014)	(0.016)	(0.007)	(0.014)	(0.016)	(0.020)	(0.026)	(0.030)
Mean rainfall	−0.000	−0.000***	0.000***	−0.000	−0.000***	0.000***	0.000	−0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean temperature	0.000	0.001***	−0.001***	0.000	0.001***	−0.001***	0.000	0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	6270	6270	6270	5215	5215	5215	1834	1834	1834

Note: The dependent variable is whether or not the household chooses (a) at least one of the clean energy sources but not any dirty fuel inputs in columns 1, 4, and 7; (b) at least one of the dirty energy sources excluding any clean energy in column 2; (c) firewood as a dirty energy but not any other clean energy in column 5, and (d) charcoal as a dirty energy distinct from all clean energy sources in column 8 for cooking, lighting, and/or heating purposes. The definitions of mixed energy I to III in columns 3, 6, and 9 varies depending on the definitions of dirty energy I to III in each panel. The answers are coded as 1 if yes and 0 otherwise for each column in panels A to C. The authors apply IHSTA for land size, number of rooms, TLU, and head education. Monthly consumption expenditure and family size are in logarithmic forms. Rural, male headship, independent residence, and plain terrains are reference groups through out Table A.2. Columns 1–9 are REMNLM fitted with GSEM. Robust standard errors clustered at the household level are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.3
Marginal effects: the role of forest status in fuel choice (non-vegetated being the base category): robustness check 1 excluding some explanatory variables.

Variables	Dependent variable: fuel choice								
	Panel A: Basket of dirty fuels			Panel B: Firewood used			Panel C: Charcoal used		
	Clean (1)	Dirty-I (2)	Mixed-I (3)	Clean (4)	Dirty-II (5)	Mixed-II (6)	Clean (7)	Dirty-III (8)	Mixed-III (9)
Sparsely vegetated	0.002	−0.056***	0.055***	−0.017***	−0.084***	0.102***	0.002	−0.027	0.024
	(0.005)	(0.012)	(0.014)	(0.006)	(0.016)	(0.018)	(0.016)	(0.016)	(0.025)
Densely vegetated	−0.010*	−0.087***	0.097***	−0.028***	−0.124***	0.152***	−0.024	−0.032**	0.056**
	(0.005)	(0.014)	(0.016)	(0.006)	(0.020)	(0.022)	(0.016)	(0.015)	(0.023)
Latent variable, L		3.53e-16	3.53e-16		−3.19e-07	−3.19e-07		−1.37e-14	
		(3.26e-16)	(3.26e-16)		(9.60e-08	(9.60e-08		(8.98e-15	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	No	No	No	No	No	No	No	No	No
Heterogeneity indicators									
Variance (L)		1.0 (constrained)			1.0 (constrained)			1.0 (constrained)	
Variance (equations)	0.582			0.430			1.66e-07***		
	(0.821)			(0.902)			(1.64e-08)		
Observations	6270	6270	6270	5215	5215	5215	1834	1834	1834

Note: The dependent variable is whether or not the household chooses (a) at least one of the clean energy sources but not any dirty fuel inputs in columns 1, 4, and 7; (b) at least one of the dirty energy sources excluding any clean energy in column 2; (c) firewood as a dirty energy but not any other clean energy in column 5, and (d) charcoal as a dirty energy distinct from all clean energy sources in column 8 for cooking, lighting, and/or heating purposes. The definitions of mixed energy I to III in columns 3, 6, and 9 varies depending on the definitions of dirty energy I to III in each panel. The answers are coded as 1 if yes and 0 otherwise for each column in panels A to C. Other controls appear in Table S1 in the online supplementary material. Columns 1–9 are REMNLM fitted with GSEM. Robust standard errors clustered at the household level are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.4
Marginal effects: the role of forest status in fuel choice: robustness check 2 using a continuous variable for forest status.

Variables	Dependent variable: fuel choice								
	Panel A: Basket of dirty fuels			Panel B: Firewood used			Panel C: Charcoal used		
	Clean (1)	Dirty-I (2)	Mixed-I (3)	Clean (4)	Dirty-II (5)	Mixed-II (6)	Clean (7)	Dirty-III (8)	Mixed-III (9)
EVI	−0.034*	−0.376***	0.410***	−0.084***	−0.490***	0.574***	−0.104*	−0.106	0.210**
	(0.019)	(0.058)	(0.063)	(0.025)	(0.076)	(0.082)	(0.062)	(0.067)	(0.085)
Latent variable, L		5.30e-17	5.30e-17		−1.18e-15***	−1.18e-15***		9.34e-07***	9.34e-07***
		(6.30e-16)	(6.30e-16)		(4.44e-16)	(4.44e-16)		(5.88e-07)	(5.88e-07)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heterogeneity indicators									
Variance (L)		1.0 (constrained)			1.0 (constrained)			1.0 (constrained)	
Variance (equations)	9.38e-08***			4.28e-08***			13.845***		
	(5.60e-09)			(2.88e-09)			(4.428)		
Observations	6270	6270	6270	5215	5215	5215	1834	1834	1834

Note: The dependent variable is whether or not the household chooses (a) at least one of the clean energy sources but not any dirty fuel inputs in columns 1, 4, and 7; (b) at least one of the dirty energy sources excluding any clean energy in column 2; (c) firewood as a dirty energy but not any other clean energy in column 5, and (d) charcoal as a dirty energy distinct from all clean energy sources in column 8 for cooking, lighting, and/or heating purposes. The definitions of mixed energy I to III in columns 3, 6, and 9 varies depending on the definitions of dirty energy I to III in each panel. The answers are coded as 1 if yes and 0 otherwise for each column in panels A to C. Other controls appear in Table S2 in the supplementary material. Columns 1–9 are REMNLM fitted with GSEM. Robust standard errors clustered at the household level are reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A.5
Marginal effects: the role of forest status in fuel choice (non-vegetated being the base category): robustness check 3 using random-effect probit models for each fuel type.

Variables	Dependent variable: fuel choice				
	Clean (1)	Dirty (2)	Mixed (3)	Firewood (4)	Charcoal (5)
Sparsely vegetated	0.002	−0.092***	0.087***	−0.057***	−0.033
	(0.007)	(0.016)	(0.018)	(0.015)	(0.026)
Densely vegetated	−0.003	−0.136***	0.136***	−0.100***	−0.020
	(0.007)	(0.017)	(0.019)	(0.016)	(0.025)
Latent variable, L	−0.062**	−0.189***	−0.065***	−0.116***	−0.229***
	(0.031)	(0.458)	(0.003)	(0.025)	(0.009)
Other controls	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A.5 (*continued*)

Variables	Dependent variable: fuel choice				
	Clean (1)	Dirty (2)	Mixed (3)	Firewood (4)	Charcoal (5)
Heterogeneity indicators					
Variance (L)	1.0 (constrained)	1.0 (constrained)	1.0 (constrained)	1.0 (constrained)	1.0 (constrained)
Variance (equations)	2.272***	1.476***	1.496***	1.649***	1.659***
	(0.623)	(0.239)	(0.206	(0.256)	(0.219)
Observations	6270	6270	6270	6270	6270

Note: The dependent variable is whether or not the household purely relies on clean energy sources (column 1), purely chooses dirty fuels (column 2) or depends on the mixtures of clean and dirty fuels (column 3) for cooking, lighting, and/or heating purposes. While the dependent variable in column 4 is whether or not the household chooses firewood as a dirty energy but not any other clean energy, column 5 asks whether charcoal is used as an energy source in the household. The answers are coded as 1 if yes and 0 otherwise. Other controls appear in Table S3 in the supplementary material. Columns 1–5 are REPM fitted with GSEM. Robust standard errors clustered at the household level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.6
The role of forest status in fuel choice (non-vegetated being the base category): robustness check 4 using linear probability models for each fuel type.

Variables	Dependent variable: fuel choice				
	Clean (1)	Dirty (2)	Mixed (3)	Firewood (4)	Charcoal (5)
Sparsely vegetated	0.002	−0.108***	0.105***	−0.054***	−0.034
	(0.013)	(0.021)	(0.024)	(0.015)	(0.025)
Densely vegetated	−0.003	−0.123***	0.126***	−0.069***	−0.018
	(0.013)	(0.020)	(0.023)	(0.012)	(0.025)
Other controls	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes
Observations	6270	6270	6270	6270	6270
R^2	0.095	0.197	0.181	0.229	0.490

Note: All regressions are linear probability models. The dependent variable is whether or not the household purely relies on clean energy sources (column 1), purely chooses dirty fuels (column 2) or depends on the mixtures of clean and dirty fuels (column 3) for cooking, lighting, and/or heating purposes. While the dependent variable in column 4 is whether or not the household chooses firewood as a dirty energy but not any other clean energy, column 5 asks whether the household uses charcoal as an energy source. The answers are coded as 1 if yes and 0 otherwise. Other controls appear in Table S4 in the supplementary material. Robust standard errors clustered at the household level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.7
The effect of forest status on fuel choice: robustness check 5 for rural and urban households, and non-wood fuels.

Variables	Dependent variable: fuel choice						
	Clean (1)	Dirty (2)	Mixed (3)	Firewood (4)	Charcoal (5)	Animal dung (6)	Crop resid (7)
Panel A: Rural households							
EVI	−0.011	−1.935***	1.945***	−1.844***	−0.035		
	(0.044)	(0.160)	(0.166)	(0.158)	(0.119)		
Observations	4827	4827	4827	4827	4827		
Panel B: Urban households							
EVI	−0.007	−0.480***	0.486***	−0.228***	−0.120		
	(0.083)	(0.120)	(0.140)	(0.081)	(0.160)		
Observations	1443	1443	1443	1443	1443		
Panel C: Non-wood fuels							
Sparsely vegetated						0.003**	0.034***
						(0.002)	(0.011)
Densely vegetated						0.000	0.010
						(0.001)	(0.007)
Common covariates							
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is whether a household uses the energy source indicated in the column heading in a given year for cooking, lighting, and/or heating purposes. All regressions are linear probability models. The forest status is continuous in panels A and B but categorical in panel C with non-vegetated as the reference category. The controls (not reported in the Appendix to save spaces) are household head's age in years, female head, family size, head education in years, number of rooms, land size, TLU, and monthly consumption expenses. The authors apply IHSTA for land size, number of rooms, TLU, and head education. Monthly consumption expenditure and family size are in logarithmic forms. Male headship is used as a reference category. Robust standard errors clustered at the household level are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

References

Akpalu, W., Dasmani, I., Aglobitse, P.B., 2011. Demand for cooking fuels in a developing country: to what extent do taste and preferences matter? Energy Pol. 39, 6525–6531. https://doi.org/10.1016/j.enpol.2011.07.054.

Alem, Y., Beyene, A.D., Köhlin, G., Mekonnen, A., 2016. Modeling household cooking fuel choice: a panel multinomial logit approach. Energy Econ. 59, 129–137. https://doi.org/10.1016/j.eneco.2016.06.025.

Amacher, G.S., Hyde, W.F., Joshee, B.R., 1993. Joint production and consumption in traditional households: fuelwood and crop residues in two districts in Nepal. J. Dev. Stud. 30, 206–225. https://doi.org/10.1080/00220389308422311.

Auffhammer, M., Mansur, E.T., 2014. Measuring climatic impacts on energy consumption: a review of the empirical literature. Energy Econ. 46, 522–530. https://doi.org/10.1016/j.eneco.2014.04.017.
Baland, J.-M., Libois, F., Mookherjee, D., 2017. Forest degradation and economic growth in Nepal, 2003–2010. Journal of the Association of Environmental and Resource Economists 5, 401–439. https://doi.org/10.1086/695690.
Bamwesigye, D., Hlavackova, P., Sujova, A., Fialova, J., Kupec, P., 2020. Willingness to pay for forest existence value and sustainability. Sustainability 12, 891.
Bandyopadhyay, S., Shyamsundar, P., Baccini, A., 2011. Forests, biomass use and poverty in Malawi. Ecol. Econ. 70, 2461–2471. https://doi.org/10.1016/j.ecolecon.2011.08.003.
Barrett, G., Brooks, S., Josefsson, J., Zulu, N., 2013. Starting the conversation: land issues and critical conservation studies in post-colonial Africa. J. Contemp. Afr. Stud. 31, 336–344.
Baum, C.F., Lööf, H., Nabavi, P., Stephan, A., 2017. A new approach to estimation of the R&D–innovation–productivity relationship. Econ. Innovat. N. Technol. 26, 121–133. https://doi.org/10.1080/10438599.2016.1202515.
Bellemare, M.F., Wichman, C.J., 2020. Elasticities and the inverse hyperbolic sine transformation. Oxf. Bull. Econ. Stat. 82, 50–61. https://doi.org/10.1111/obes.12325.
Blimpo, M.P., Cosgrove-Davies, M., 2019. Electricity Access in Sub-saharan Africa: Uptake, Reliability, and Complementary Factors for Economic Impact. The World Bank, Washington,DC.
Boles, S.H., Xiao, X., Liu, J., Zhang, Q., Munkhtuya, S., Chen, S., Ojima, D., 2004. Land cover characterization of Temperate East Asia using multi-temporal VEGETATION sensor data. Rem. Sens. Environ. 90, 477–489.
Branch, A., Martiniello, G., 2018. Charcoal power: the political violence of non-fossil fuel in Uganda. Geoforum 97, 242–252. https://doi.org/10.1016/j.geoforum.2018.09.012.
Burbidge, J.B., Magee, L., Robb, A.L., 1988. Alternative transformations to handle extreme values of the dependent variable. J. Am. Stat. Assoc. 83, 123–127. https://doi.org/10.2307/2288929.
Burivalova, Z., Bauert, M.R., Hassold, S., Fatroandrianjafinonjasolomiovazo, N.T., Koh, L.P., 2015. Relevance of global forest change data set to local conservation: case study of forest degradation in masoala national park, Madagascar. Biotropica 47, 267–274. https://doi.org/10.1111/btp.12194.
Burke, P.J., Dundas, G., 2015. Female labor force participation and household dependence on biomass energy: evidence from national longitudinal data. World Dev. 67, 424–437. https://doi.org/10.1016/j.worlddev.2014.10.034.
Chankrajang, T., 2019. State-community property-rights sharing in forests and its contributions to environmental outcomes: evidence from Thailand's community forestry. J. Dev. Econ. 138, 261–273.
Chen, Z., Kuo, L., 2001. A note on the estimation of the multinomial logit model with random effects. Am. Statistician 55, 89–95. https://doi.org/10.1198/000313001750358545.
Choumert-Nkolo, J., Combes Motel, P., Le Roux, L., 2019. Stacking up the ladder: a panel data analysis of Tanzanian household energy choices. World Dev. 115, 222–235. https://doi.org/10.1016/j.worlddev.2018.11.016.
Cooke, P., Köhlin, G., Hyde, W.F., 2008. Fuelwood, forests and community management–evidence from household studies. Environ. Dev. Econ. 103–135.
Cruz, R.S., Medeiros, P., Ferreira Junior, W., Silva, R., 2020. Factors that influence human behavior in fuelwood use and their implications for biocultural conservation. Ethnobiology and Conservation 9, 1–13.
de Albuquerque, U.P., 2006. Re-examining hypotheses concerning the use and knowledge of medicinal plants: a study in the Caatinga vegetation of NE Brazil. J. Ethnobiol. Ethnomed. 2, 1–10.
Donaldson, D., Storeygard, A., 2016. The view from above: applications of satellite data in economics. J. Econ. Perspect. 30, 171–198. https://doi.org/10.1257/jep.30.4.171.
Edmonds, E.V., 2002. Government-initiated community resource management and local resource extraction from Nepal's forests. J. Dev. Econ. 68, 89–115. https://doi.org/10.1016/S0304-3878(02)00007-X.
Edstedt, K., Carton, W., 2018. The benefits that (only) capital can see? Resource access and degradation in industrial carbon forestry, lessons from the CDM in Uganda. Geoforum 97, 315–323.
Edwards, J.H.Y., Langpap, C., 2012. Fuel choice, indoor air pollution and children's health. Environ. Dev. Econ. 17, 379–406. https://doi.org/10.1017/S1355770X12000010.
Ektvedt, T.M., 2011. Firewood consumption amongst poor inhabitants in a semiarid tropical forest: a case study from Piura, northern Peru. Norsk Geografisk Tidsskrift-Norwegian Journal of Geography 65, 28–41.
Fairhead, J., Scoones, I., 2005. Local knowledge and the social shaping of soil investments: critical perspectives on the assessment of soil degradation in Africa. Land Use Pol. 22, 33–41.
Farsi, M., Filippini, M., Pachauri, S., 2007. Fuel choices in urban Indian households. Environ. Dev. Econ. 12, 757–774. https://doi.org/10.1017/s1355770x07003932.
Fisher, M., 2004. Household welfare and forest dependence in Southern Malawi. Environ. Dev. Econ. 135–154.
Foell, W., Pachauri, S., Spreng, D., Zerriffi, H., 2011. Household cooking fuels and technologies in developing economies. Energy Pol. 39, 7487–7496. https://doi.org/10.1016/j.enpol.2011.08.016.
Gao, B.-C., 1996. NDWI—a normalized difference water index for remote sensing of vegetation liquid water from space. Rem. Sens. Environ. 58, 257–266.
Garland, C., Jagoe, K., Wasirwa, E., Nguyen, R., Roth, C., Patel, A., Shah, N., Derby, E., Mitchell, J., Pennise, D., Johnson, M.A., 2015. Impacts of household energy programs on fuel consumption in Benin, Uganda, and India. Energy for Sustainable Development 27, 168–173. https://doi.org/10.1016/j.esd.2014.05.005.
Gebreegziabher, Z., Mekonnen, A., Kassie, M., Köhlin, G., 2012. Urban energy transition and technology adoption: the case of Tigrai, northern Ethiopia. Energy Econ. 34, 410–418.
Government of Uganda, 2015. Ministry of Energy and Mineral Development, Sustainable Energy for All Initiative-Action Agenda (Kampala, Uganda).
Guta, D.D., 2012. Application of an almost ideal demand system (AIDS) to Ethiopian rural residential energy use: panel data evidence. Energy Pol. 50, 528–539.
Guta, D.D., 2014. Effect of fuelwood scarcity and socio-economic factors on household bio-based energy use and energy substitution in rural Ethiopia. Energy Pol. 75, 217–227. https://doi.org/10.1016/j.enpol.2014.09.017.
Hamilton, A.C., 1984. Deforestation in Uganda. Oxford University Press.
Hamilton, A.C., Karamura, D., Kakudidi, E., 2016. History and conservation of wild and cultivated plant diversity in Uganda: forest species and banana varieties as case studies. Plant Diversity 38, 23–44. https://doi.org/10.1016/j.pld.2016.04.001.
Hartter, J., Ryan, S.J., MacKenzie, C.A., Goldman, A., Dowhaniuk, N., Palace, M., Diem, J.E., Chapman, C.A., 2015. Now there is no land: a story of ethnic migration in a protected area landscape in western Uganda. Popul. Environ. 36, 452–479. https://doi.org/10.1007/s11111-014-0227-y.
Hasanah, A., Indrawan, M., 2020. Assessment of tropical forest degradation on a small island using the enhanced vegetation index. In: IOP Conference Series: Earth and Environmental Science. IOP Publishing, 012061.
Heltberg, R., 2005. Factors determining household fuel choice in Guatemala. Environ. Dev. Econ. 10, 337–361. https://doi.org/10.1017/s1355770x04001858.
Heltberg, R., Arndt, T.C., Sekhar, N.U., 2000. Fuelwood consumption and forest degradation: a household model for domestic energy substitution in rural India. Land Econ. 213–232.
Herington, M.J., Reddy, N.H., Rao, R.K., 2016. The Smokeless Village: understanding energy transitions in rural Andhra Pradesh, India. World Development Perspectives 4, 30–32. https://doi.org/10.1016/j.wdp.2016.12.002.
Himbara, D., 1994. The failed Africanization of commerce and industry in Kenya. World Dev. 22, 469–482.
Huete, A., Justice, C., Liu, H., 1994. Development of vegetation and soil indices for MODIS-EOS. Rem. Sens. Environ. 49, 224–234. https://doi.org/10.1016/0034-4257(94)90018-3.
Huete, A.R., Liu, H.Q., Batchily, K., van Leeuwen, W., 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS. Rem. Sens. Environ. 59, 440–451. https://doi.org/10.1016/S0034-4257(96)00112-5.
Huete, A., Justice, C., Van Leeuwen, W., 1999. MODIS vegetation index (MOD13). Algorithm theoretical basis document 3, 295–309.
Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002a. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Rem. Sens. Environ. 83, 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2.
Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002b. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Rem. Sens. Environ. 83, 195–213.
International Religious Freedom Report, 2019. 2019 Report on International Religious Freedom:Uganda. United States Department of State, Office of International Religious Freedom.
Ishtiaque, A., Myint, S.W., Wang, C., 2016. Examining the ecosystem health and sustainability of the world's largest mangrove forest using multi-temporal MODIS products. Sci. Total Environ. 569, 1241–1254.
Jagger, P., Kittner, N., 2017. Deforestation and biomass fuel dynamics in Uganda. Biomass Bioenergy 105, 1–9. https://doi.org/10.1016/j.biombioe.2017.06.005.
Jagger, P., Shively, G., 2014. Land use change, fuel use and respiratory health in Uganda. Energy Pol. 67, 713–726. https://doi.org/10.1016/j.enpol.2013.11.068.
Jiménez-Escobar, N.D., Doumecq, M.B., Morales, D., Ladio, A.H., 2021. Cross-scale analysis of diversification processes in fuelwood use in three contrasting ecoregions of Argentina (Chaco, Pampa and Patagonia): the role of exotic species in subsistence. Ethnobiology and Conservation 10.
Kamanga, P., Vedeld, P., Sjaastad, E., 2009. Forest incomes and rural livelihoods in Chiradzulu District, Malawi. Ecol. Econ. 68, 613–624.
Karekezi, S., Kithyoma, W., 2002. Renewable energy strategies for rural Africa: is a PV-led renewable energy strategy the right approach for providing modern energy to the rural poor of sub-Saharan Africa? Energy Pol. 30, 1071–1086. https://doi.org/10.1016/S0301-4215(02)00059-9.
Kavi Kumar, K.S., Viswanathan, B., 2007. Changing structure of income indoor air pollution relationship in India. Energy Pol. 35, 5496–5504. https://doi.org/10.1016/j.enpol.2007.04.011.
Khundi, F., Jagger, P., Shively, G., Sserunkuuma, D., 2011. Income, poverty and charcoal production in Uganda. For. Pol. Econ. 13, 199–205.
Kim, L.T.T., Nichols, J.D., Brown, K., 2017. Firewood extraction and use in rural Vietnam: a household model for three communes in Ha Tinh Province. Agrofor. Syst. 91, 649–661.
Kowsari, R., Zerriffi, H., 2011. Three dimensional energy profile:: a conceptual framework for assessing household energy use. Energy Pol. 39, 7505–7517.
Langdale-Brown, I., Osmaston, H.A., Wilson, J.G., 1964. The Vegetation of Uganda and its Bearing on Land-Use. The Vegetation of Uganda and its Bearing on Land-Use.
Lee, L.Y.-T., 2013. Household energy mix in Uganda. Energy Econ. 39, 252–261. https://doi.org/10.1016/j.eneco.2013.05.010.
Lee, S.M., Kim, Y.-S., Jaung, W., Latifah, S., Afifi, M., Fisher, L.A., 2015. Forests, fuelwood and livelihoods—energy transition patterns in eastern Indonesia. Energy Pol. 85, 61–70. https://doi.org/10.1016/j.enpol.2015.04.030.

Liu, H.Q., Huete, A., 1995. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Trans. Geosci. Rem. Sens. 33, 457–465. https://doi.org/10.1109/TGRS.1995.8746027.

Louw, K., Conradie, B., Howells, M., Dekenah, M., 2008. Determinants of electricity demand for newly electrified low-income African households. Energy Pol. 36, 2812–2818. https://doi.org/10.1016/j.enpol.2008.02.032.

Lu, D., 2006. The potential and challenge of remote sensing-based biomass estimation. Int. J. Rem. Sens. 27, 1297–1328. https://doi.org/10.1080/01431160500486732.

Lyons, K., Westoby, P., 2014. Carbon colonialism and the new land grab: plantation forestry in Uganda and its livelihood impacts. J. Rural Stud. 36, 13–21.

Malchow-Møller, N., Svarer, M., 2003. Estimation of the multinomial logit model with random effects. Appl. Econ. Lett. 10, 389–392. https://doi.org/10.1080/1350485032000082018.

Manning, D.T., Taylor, J.E., 2014. Migration and fuel use in rural Mexico. Ecol. Econ. 102, 126–136. https://doi.org/10.1016/j.ecolecon.2014.03.012.

Masera, O.R., Saatkamp, B.D., Kammen, D.M., 2000. From linear fuel switching to multiple cooking strategies: a critique and alternative to the energy ladder model. World Dev. 28, 2083–2103. https://doi.org/10.1016/S0305-750X(00)00076-0.

Mazzone, A., Cruz, T., Bezerra, P., 2021. Firewood in the forest: social practices, culture, and energy transitions in a remote village of the Brazilian Amazon. Energy Res. Social Sci. 74, 101980.

Meles, T.H., 2020. Impact of power outages on households in developing countries: evidence from Ethiopia. Energy Econ. 91, 104882 https://doi.org/10.1016/j.eneco.2020.104882.

Ministry of Energy, Mineral Development, 2017. Energy Efficiency Roadmap for Uganda: Making Energy Efficiency Count (Kampala, Uganda).

Muller, C., Yan, H., 2018. Household fuel use in developing countries: review of theory and evidence. Energy Econ. 70, 429–439. https://doi.org/10.1016/j.eneco.2018.01.024.

Nkegbe, P.K., Araar, A., Abu, B., Ustarz, Y., Alhassan, H., Setsoafia, E.D., Abdul-Wahab, S., 2018. Rural Non-farm Engagement and Agriculture Commercialization in Ghana: Complements or Competitors? Partnership for Economic Policy Working Paper.

Nygren, A., 2005. Community-based forest management within the context of institutional decentralization in Honduras. World Dev. 33, 639–655.

Obua, J., Banana, A.Y., Turyahabwe, N., 1998. Attitudes of local communities towards forest management practices in Uganda: the case of Budongo forest reserve. Commonw. For. Rev. 77, 113–118.

Obua, J., Agea, J.G., Ogwal, J.J., 2010. Status of forests in Uganda. Afr. J. Ecol. 48, 853–859. https://doi.org/10.1111/j.1365-2028.2010.01217.x.

Okello, C., Pindozzi, S., Faugno, S., Boccia, L., 2013. Development of bioenergy technologies in Uganda: a review of progress. Renew. Sustain. Energy Rev. 18, 55–63. https://doi.org/10.1016/j.rser.2012.10.004.

Ouedraogo, B., 2006. Household energy preferences for cooking in urban Ouagadougou, Burkina Faso. Energy Pol. 34, 3787–3795. https://doi.org/10.1016/j.enpol.2005.09.006.

Pachauri, S., Jiang, L., 2008. The household energy transition in India and China. Energy Pol. 36, 4022–4035. https://doi.org/10.1016/j.enpol.2008.06.016.

Palmer, C., MacGregor, J., 2009. Fuelwood scarcity, energy substitution, and rural livelihoods in Namibia. Environ. Dev. Econ. 693–715.

Pattanayak, S.K., Sills, E.O., Kramer, R.A., 2004. Seeing the forest for the fuel. Environ. Dev. Econ. 9, 155–179. https://doi.org/10.1017/s1355770x03001220.

Pillarisetti, A., Ghorpade, M., Madhav, S., Dhongade, A., Roy, S., Balakrishnan, K., Sankar, S., Patil, R., Levine, D.I., Juvekar, S., Smith, K.R., 2019. Promoting LPG usage during pregnancy: a pilot study in rural Maharashtra, India. Environ. Int. 127, 540–549. https://doi.org/10.1016/j.envint.2019.04.017.

Rabe-Hesketh, S., Skrondal, A., Pickles, A., 2004. GLLAM manual. In: U.C. Berkeley Division of Biostatistics Working Paper Series, Paper 160. University of California, Berkeley.

Rahut, D.B., Das, S., De Groote, H., Behera, B., 2014. Determinants of household energy use in Bhutan. Energy 69, 661–672. https://doi.org/10.1016/j.energy.2014.03.062.

Ravallion, M., 2017. A concave log-like transformation allowing non-positive values. Econ. Lett. 161, 130–132. https://doi.org/10.1016/j.econlet.2017.09.019.

Reddy, S.R.C., Chakravarty, S.P., 1999. Forest dependence and income distribution in a subsistence economy: evidence from India. World Dev. 27, 1141–1149. https://doi.org/10.1016/S0305-750X(99)00057-1.

Reenberg, A., 2012. Insistent dryland narratives: portraits of knowledge about human-environmental interactions in Sahelian environment policy documents. West African Journal of Applied Ecology 20, 97–111.

Rohde, R.F., Moleele, N., Mphale, M., Allsopp, N., Chanda, R., Hoffman, M., Magole, L., Young, E., 2006. Dynamics of grazing policy and practice: environmental and social impacts in three communal areas of southern Africa. Environ. Sci. Pol. 9, 302–316.

Shankar, A.V., Quinn, A.K., Dickinson, K.L., Williams, K.N., Masera, O., Charron, D., Jack, D., Hyman, J., Pillarisetti, A., Bailis, R., Kumar, P., Ruiz-Mercado, I., Rosenthal, J.P., 2020. Everybody stacks: lessons from household energy case studies to inform design principles for clean energy transitions. Energy Pol. 141, 111468 https://doi.org/10.1016/j.enpol.2020.111468.

Shen, M., Chen, J., Zhu, X., Tang, Y., Chen, X., 2010. Do flowers affect biomass estimate accuracy from NDVI and EVI? Int. J. Rem. Sens. 31, 2139–2149. https://doi.org/10.1080/01431160903578812.

Skrondal, A., Rabe-Hesketh, S., 2014. Handling initial conditions and endogenous covariates in dynamic/transition models for binary data with unobserved heterogeneity. J. Roy. Stat. Soc.: Series C (Applied Statistics) 63, 211–237. https://doi.org/10.1111/rssc.12023.

Smith, K.R., 2002. In praise of petroleum? Science 298, 1847–1848.

Soudani, K., François, C., Le Maire, G., Le Dantec, V., Dufrêne, E., 2006. Comparative analysis of IKONOS, SPOT, and ETM+ data for leaf area index estimation in temperate coniferous and deciduous forest stands. Rem. Sens. Environ. 102, 161–175.

Stern, D.I., 2010. Energy quality. Ecol. Econ. 69, 1471–1478. https://doi.org/10.1016/j.ecolecon.2010.02.005.

Tabuti, J.R.S., Dhillion, S.S., Lye, K.A., 2003. Firewood use in Bulamogi County, Uganda: species selection, harvesting and consumption patterns. Biomass Bioenergy 25, 581–596. https://doi.org/10.1016/S0961-9534(03)00052-7.

Troncoso, K., Segurado, P., Aguilar, M., Soares da Silva, A., 2019. Adoption of LPG for cooking in two rural communities of Chiapas, Mexico. Energy Pol. 133, 110925 https://doi.org/10.1016/j.enpol.2019.110925.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Rem. Sens. Environ. 8, 127–150. https://doi.org/10.1016/0034-4257(79)90013-0.

Turyareeba, P.J., 2001. Renewable energy: its contribution to improved standards of living and modernisation of agriculture in Uganda. Renew. Energy 24, 453–457. https://doi.org/10.1016/S0960-1481(01)00028-3.

Uganda Bureau of Statistics, 2009/10. The Uganda National Panel Survey (UNPS), Basic Information Document (Kampala, Uganda).

Uganda Bureau of Statistics, 2010/11. The Uganda National Panel Survey (UNPS), Basic Information Document (Kampala, Uganda).

Uganda Bureau of Statistics, 2011/12. The Uganda National Panel Survey (UNPS), Basic Information Document (Kampala, Uganda).

Viswanathan, B., Kavi Kumar, K.S., 2005. Cooking fuel use patterns in India: 1983–2000. Energy Pol. 33, 1021–1036. https://doi.org/10.1016/j.enpol.2003.11.002.

Wang, Z., Liu, C., Huete, A., 2003. From AVHRR-NDVI to MODIS-EVI: advances in vegetation index research. Acta Ecol. Sin. 23, 979–987.

Waswa, F., Mcharo, M., Mworia, M., 2020. Declining wood fuel and implications for household cooking and diets in Tigania Sub-county Kenya. Scientific African 8, e00417.

Winther, T., 2007. Rising Electricity Consumption: Driving Forces and Consequences. The Case of Rural Zanzibar. ECEEE, Oslo, pp. 1835–1845.

Xiao, X., Zhang, Q., Braswell, B., Urbanski, S., Boles, S., Wofsy, S., Moore III, B., Ojima, D., 2004. Modeling gross primary production of temperate deciduous broadleaf forest using satellite images and climate data. Rem. Sens. Environ. 91, 256–270.

Yamada, T., Yamada, H., 2021. The long-term causal effect of US bombing missions on economic development: evidence from the Ho Chi Minh Trail and Xieng Khouang Province in Lao PDR. J. Dev. Econ. 150, 102611.