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YSSP Report

Young Scientist Summer Program

Introducing the energy-fertility nexus in population projections: can universal access to modern energy lead to energy savings?

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1 Abstract

In a climate- constrained world, understanding the energy needs to reach universal access to modern energy is critical. This requires making assumptions on future population trajectories, and developments in energy access can affect them. Yet, this feedback has never been accounted for in energy models. Access to modern energy leads to fertility decline as it reduces child mortality, improves health, increases women's access to information, education and employment. In this paper, we assess the household energy requirements to expand energy access while considering the relationship between energy access and fertility, using Zambia as a case study. To do so, we built a micro-simulation model of population projection in which fertility depends on access to modern energy and education level, and projected the electricity and cooking energy needs of the Zambian population to 2050, under different scenarios. We find that while the electricity consumption is higher in the universal access scenario compared to the baseline scenario, total energy demand is 67% lower, partly due to strong decline in the use inefficient traditional cooking fuels. We also find that reduced population growth due to expanded energy access and education accounts for 15% of this reduction in rural areas, and 8% overall. Although the challenge of achieving universal access to modern energy seems daunting, our results suggest that this goal could be co-beneficial to achieving climate goals. Our study also reveals that accounting for the energy-population nexus in energy models will scale down the currently assumed energy needs to ensure decent well-being for all.

Acknowledgements

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2 Introduction

Access to modern energy provides services that are essential to fulfill human basic needs (GEA 2012; McCollum et al. 2018). Yet, in 2019, around 759 million had no access to electricity and 2.6 billion people had no access to clean cooking energy (IEA et al. 2021). Assessing the energy requirements to fulfill this gap is necessary to accurately assess the share of the global carbon budget that needs to be allocated to emerging countries to fulfill the basic needs of their population.

Projecting the energy requirements to eradicate energy poverty requires making assumptions on future population pathways. Traditionally, energy modelers attempting to answer this question use existing population projections, like the UN population projections (UNFPA 2019), or the Shared Socio-economic Pathways scenarios for populations (K. C. and Lutz 2017). However, for a given projection, the population scenario chosen may be inconsistent with the scenario of energy access, resulting in an overestimation or underestimation of population size, and thus energy demand.

This is particularly relevant because energy access, in addition to female education, has been shown to have large effects on fertility decline (Grimm, Sparrow, and Tasciotti 2015 ; Grogan 2016 ; Potter, Schmertmann, and Cavenaghi 2002 ; Peters and Vance 2010; Fujii and Shonchoy 2020; Harbison and Robinson 1985). Particularly for women, access to modern energy leads to less time spent on household chores(Das et al. 2020; Wickramasinghe 2011; OXFAM 2017), lower child mortality(Adaji et al. 2019; Ezzati 2005), better health (Das et al. 2020; IEA 2016; WHO 2014), access to information (OXFAM 2017; Das et al. 2020) and education (Winther et al. 2017), which all contribute to lowering fertility.

Previous empirical studies have quantified the effects of expanded electricity access (Grimm, Sparrow, and Tasciotti 2015 ; Grogan 2016 ; Potter, Schmertmann, and Cavenaghi 2002) and access to modern cooking fuels (Belmin et al., n.d.) on fertility, in various countries. Belmin et al. (n.d.) found, for 42 countries that achieving universal access to electricity by 2040, coupled with expanding education attainment, would result in a total fertility rate 19% lower than in the business-as-usual scenario. However, the resulting population size, necessary to estimate the energy demand, has not been estimated. Population scenarios that are consistent with the SSP framework also have been developed and are based on assumptions of future developments in education attainment (K. C. and Lutz 2017). However, they make no assumptions about how energy access would jointly develop.

Here, we estimate the energy requirements to eradicate energy poverty in Zambia while taking into account the negative effect of access to energy on fertility and population dynamics. To project future population pathways and future energy demand in Zambia, we developed a Micro-Simulation Model (MSM) of population projection that endogenously accounts for the relationship between energy access and fertility. We ran this model from 2015 to 2050 using DHS data of Zambia in 2018 (ICF 2004) to construct the base population. To study the differential effect of various possible energy poverty reduction pathways on population size and energy demand, we used three energy access scenarios. We also used existing education-dependent mortality scenarios and education scenarios. To obtain an estimate of the future energy demand of Zambia's population, we used assumptions on (i) the per capita electricity consumption of those having access to electricity, and (ii) the per capita energy required for cooking, depending on the type of fuel used. We defined modern energy for cooking as any energy derived from electricity, liquefied petroleum gas (LPG), natural gas, kerosene and biogas. All forms of traditional biomass are excluded, namely firewood, charcoal, agricultural crops, animal dung as well as coal. Despite the fact that coal does not require collection, we excluded it from modern fuels because of its particularly negative impacts on health.

We chose Zambia as a case-study because of the data availability and the characteristics of its demography and level of energy access of its population. Zambia is a high-fertility country with most of its population living in rural areas. In 2018 the Total Fertility Rate (TFR), which can be interpreted as the average number of children per women, was 4.63 (UNFPA 2019). The patterns of energy access vary greatly from urban to rural areas. In 2017, 75% of the urban population had access to electricity, while only one tenth of the rural population had access to electricity (Luzi et al. 2019). Zambia's population is highly dependent on charcoal for cooking, in particular in urban areas where it is used by 60.7% of the population. In rural areas, firewood is used by most households (83.6%), followed by charcoal (14.2%). Electricity is the main modern cooking fuel used in Zambia (32.5% of urban households use electricity as a main cooking fuel, 1.9% for rural households)(Luzi et al. 2019). The heavy dependence of Zambia's electricity sector on hydro-power makes electricity supply vulnerable to climate variability and droughts, which caused in 2012 cuts in electricity supply and thereby decline in the use of electricity for cooking (Samboko et al. 2016).

In the following sections we present our methodology to develop the micro-simulation model of population projection built for this analysis. We also present the logistic regression model necessary to predict at each time step the probability for a women to give birth depending on her access to modern energy and her level of education. We then describe the different mortality, education and energy scenarios, as well as the the method used to estimate energy use exogenously. Next, we present our results about different population and fertility outcomes across the different scenarios, as well as the results on electricity and cooking energy demand. We conclude this paper with a discussion about the contribution of population in lowering the energy requirements to reach universal access to modern energy, and the significance of including feedback between energy access and population dynamics in energy models.

3 Methods and data

3.1 Micro-simulation model of population projection

To estimate the energy needs of the population in Zambia under different energy scenarios while accounting for the effect of energy access on population dynamics, we built a dynamic Micro Simulation Model (MSM) model of population projection. MSMs start with a base population and treat each individual independently. Random experiments are used to simulate life events of each individual according to some probabilities of life events to occur. The events we simulate in this study are giving birth, death, getting access to electricity, getting access to modern cooking fuels, and transitioning to a higher education level. These random experiments, or Monte Monte Carlo processes, work as follows: a random number between 0 and 1 is drawn and compared to the probability of the life event to occur (e.g. giving birth). When the random number is inferior to the probability, the event occurs, otherwise it does not occur. The probability of death, and the education and energy transition probabilities are directly derived from the scenarios (see Sections 3.4, 3.5 and 3.6). In contrast, the probability for a women to give birth is derived endogenously at each time step, and depend on the age, energy access, level of education of the women, whether the latter lives in urban or rural area and the time step (Figure 1). The model runs from 2015 to 2045 with five-year time steps.

Micro-simulation models allow to easily run population projections in which the demographic rates can depend on a large number of states (Van Imhoff and Post 1998). Here, fertility depends on age, education, access to electricity, access to modern cooking fuels. With a traditional multi-state cohort component model of population projection, this large number of dimensions would make the estimation of fertility unmanageable.

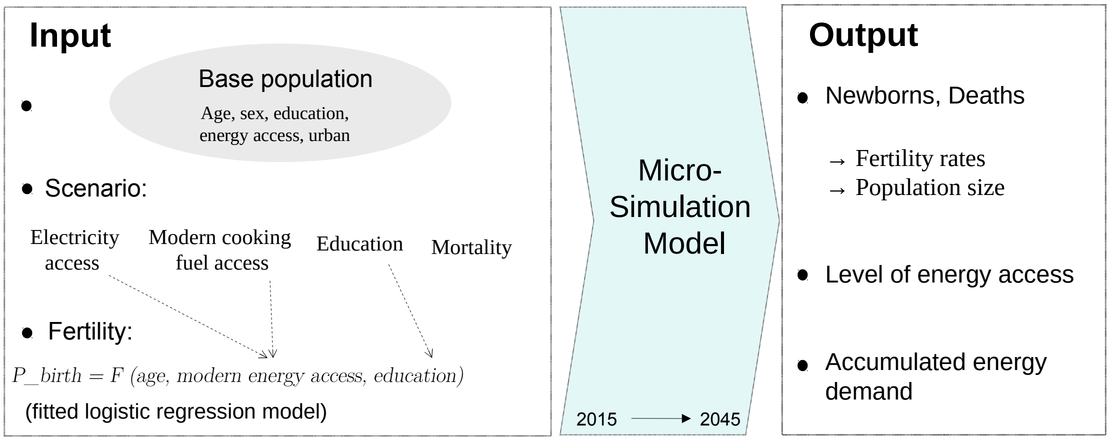

Figure 1: Overview of the Micro-Simulation Model of population projection

3.2 Base population

We used the 2018 Demographic and Health Survey data of Zambia to construct the base population. We used the *Person Recode* of the DHS data (ICF 2004), meaning that all household members are included. This allowed to obtain individuals of both sex and all ages. From the DHS data we kept the following variables: age, sex, individual weight, number of education years, whether the household lives in an urban or rural area, whether the individual has access to electricity and modern cooking fuels, and for children under 18, the number of education years of the mother. From the variable number of education years, we created six categorical variables corresponding to *No education*, *Incomplete primary education*, *Completed primary education*, *Lower secondary education*, *Upper secondary education*, *Post secondary education*). The same categories were used in the mortality and education scenario (see section 3.4, 3.5 and 3.6 on scenarios). Observations with missing values on these variables were excluded, which resulted in a final sample of 58019. The weights were re-adjusted accordingly, so that their sum equals to the sample size.

3.3 Fertility module

In our model, the probability for a woman to give birth is endogenously determined at each time step and for each women of fertile age (between 15 and 49 year old). We used a logistic regression to estimate the parameters allowing to predict the probability for a woman to give birth, depending on her age group (five-year), level of education, whether her household has access to electricity, modern cooking fuels. The dependent variable is whether the women had a birth in the last year. The data used for the regression is a pool of four DHS data for Zambia, for the years 2002, 2007, 2013 and 2018, resulting in 89796 observations. We used the *Individual Recode* of this DHS data, meaning that the samples are only composed of women between 15 and 49 year old. In the regression, we added a parameter corresponding to the year in which the data was collected, allowing to account for the fact that fertility may follow a secular trend. We also added interaction terms between the age group and (i) whether the household has access to electricity, and (ii) whether the primary cooking fuel used by the household is modern. The results of the model are displayed in Table 1 and the logistic regression model takes the form:

$$\log\left[\frac{P(\text{birth}=1)}{1-P(\text{birth}=1)}\right] = \alpha + \sum_{i=1}^{6}\beta_i Agecat_i + \sum_{j=1}^{5}\gamma_j Educcat_j + \theta_0 Elec + \sum_{k=1}^{5}\theta_k Elec \times Agecat_k + \epsilon_0 MCF + \sum_{l=1}^{5}\epsilon_l MCF \times Agecat_l + \eta Year \quad (1)$$

where $P(\text{birth} = 1)$ is the probability that a women gave birth in the past year, $Agecat_{1..6}$ the five-year age group to which the women belong at the time of the survey, $Educcat_{1..5}$ the education group to which the women belong, $Elec$ and MCF are dummy variables taking the value 1 if the women has access to electricity and modern cooking fuels, respectively, and $Year$ is the year of the survey. α is the coefficient for the reference category, which corresponds to age group 15-19, no education, no access to electricity and no access to modern cooking fuel.

Table 1: Results of a logistic regression model that predicts the probability for a women aged 15-49 to have given birth in the past year.

	Gave birth in the past year (Yes/No)
Age group 20-24	0.826^{***} (0.031)
Age group 25-29	0.710^{***} (0.032)
Age group 30-34	0.514^{***} (0.035)
Age group 35-39	0.201^{***} (0.038)
Age group 40-44	-0.558^{***} (0.050)
Age group 45-49	-2.336^{***} (0.113)
Educ group: Incomplete primary	-0.137^{***} (0.031)
Educ group: Primary	-0.227^{***} (0.035)
Educ group: Lower secondary	-0.444^{***} (0.035)
Educ group: Upper secondary	-0.666^{***} (0.043)
Educ group: Post secondary	-0.646^{***} (0.064)
Having access to electricity	-0.661^{***} (0.072)
Having access to modern cooking fuel	-0.547^{***} (0.119)
Year	-0.008^{***} (0.002)
Age group 20-24 X Elec	0.225^{**} (0.090)
Age group 25-29 X Elec	0.265^{***} (0.094)
Age group 30-34 X Elec	0.393^{***} (0.099)
Age group 35-39 X Elec	0.014 (0.119)
Age group 40-44 X Elec	-0.469^{**} (0.207)
Age group 45-49 X Elec	0.065 (0.431)
Age group 20-24 X MCF	0.221 (0.145)
Age group 25-29 X MCF	0.519^{***} (0.145)
Age group 30-34 X MCF	0.606^{***} (0.152)
Age group 35-39 X MCF	0.741^{***} (0.182)
Age group 40-44 X MCF	0.882^{***} (0.294)
Age group 45-49 X MCF	-10.171 (64.550)
Intercept / Reference category	15.031^{***} (3.208)
N	87332
Log Likelihood	-37796.210
AIC	75646.430

P-values: 0.1 > * > 0.05 > ** > 0.01 > ***

All levels of education, whether the woman has access to electricity and whether she has access to modern cooking fuels have a negative effect on the probability of giving birth. The age categories are also all significant, with age groups 20-24 and 25-29 having the strongest effect on the probability of giving birth. Age also interacts with access to energy in a significant way. In particular, the effect of access to both energies seem to have a particularly strong effect in the reference age group 15-19.

3.4 Mortality scenario

The probabilities for individuals to survive to the next time step were taken from projections from the Wittengstein Center for Demography and Human Capital (WIC) open data repository (Lutz et al. 2018). The WIC developed scenarios of mortality, fertility and migration that are consistent with the Shared Socio-economic Pathways narrative (Riahi et al. 2017), widely used in the climate modeling community. Among the SSPs scenario, we used SSP1 which corresponds to a world shifting toward a more sustainable path with low mitigation and adaptation challenges and SSP2 a middle-of-the road scenario. For each scenario, the survival probability depends on the age group and education level of the individual. Following (Marois and KC 2021), the probability of surviving for children under the age of 15 depends on the mother's education level (Fuchs, Pamuk, and Lutz 2010). In this study, we considered neither domestic nor international migration.

3.5 Education scenario

We represent six education groups: *No education*, *Incomplete primary education*, *Completed primary education*, *Lower secondary education*, *Upper secondary education*, *Post secondary education.* Following (Marois and KC 2021), the level of education can only increase or stagnate, and only at certain ages. The education only starts at the age of 15. The education scenario also come from projections from the WIC (Lutz et al. 2018). These projections are represented as proportions of the population being in a given education group. From these proportions, we created probabilities for an individual to transition from one education level to the next higher education level. The transition probabilities from education group 3 to 4, 4 to 5 and 5 to 6 can be written as follows:

$$pe6 = (e6_{t+5} - e6_t)/e5_t$$

$$pe5 = (e5_{t+5} - e5_t \times (1 - pe6))/e4_t$$

$$pe4 = (e4_{t+5} - e4_t \times (1 - pe5))/e3_t$$

There are no transitions between incomplete primary and complete primary education(Marois and KC 2021). The reason is that at the age 15-19, individuals who have not completed primary education or higher are likely to be out of the education system, and to remain at their current education level throughout the rest of their life.

3.6 Energy scenario

The energy scenarios we used represent future trajectories of the proportion of people having access to electricity and having access to modern cooking fuels. Since the energy access is highly different across rural and urban areas, these scenarios are differentiated by urban and rural areas. For both access to electricity and access to modern cooking fuels, we used three scenarios. The first two scenarios are taken from existing projection performed from the bottom up and following the SSP framework (Poblete-Cazenave et al. 2021). We used SSP1 and SSP2. As these scenarios were developed for the whole sub-Saharan Africa, without any distinctions on countries, we applied the absolute percentage increase for sub-Saharan Africa to the initial level of electricity/modern cooking fuel access in Zambia, that we obtained from the DHS data of 2018. The last scenario assumes universal access to both electricity and modern cooking fuel by 2040 with a linear

Table 2: Scenarios used in the projection

Scenario	Mortality	Education	Electricity	Modern cooking fuels
SSP1	SSP1	SSP1	SSP1	SSP1
SSP2	SSP2	SSP2	SSP2	SSP2
Universal	SSP1	SSP1	Universal	Universal

increase in the proportion of the population having access to both forms of energy. Although this scenario requires quite unrealistic percentage increase, in particular in rural areas where access to both forms of energies is very low, this universal access scenario allows to show what would happen in case the sustainable development goals were reached by 2040.

We then derived, from these trajectories, the probability for an agent to get access to electricity, and to get access to modern cooking fuel. Although in reality, a household might use multiple cooking fuels at the same time, or come back to firewood after using mostly modern fuels, in our model the transition can only occur in one direction: from not having access to having access. The formula for the transition probability is written as follows:

$$p_{\overline{elec}-->elec} = (elec_{t+5} - elec_t)/\overline{elec}_t$$

with $p_{noelec-->elec}$ the probability of getting access to electricity, $elec_{t+5}$ the proportion of the population having access to electricity in time step $t+5$ and $\overline{elec}_t$ the proportion of the population not having access to electricity in time step t.

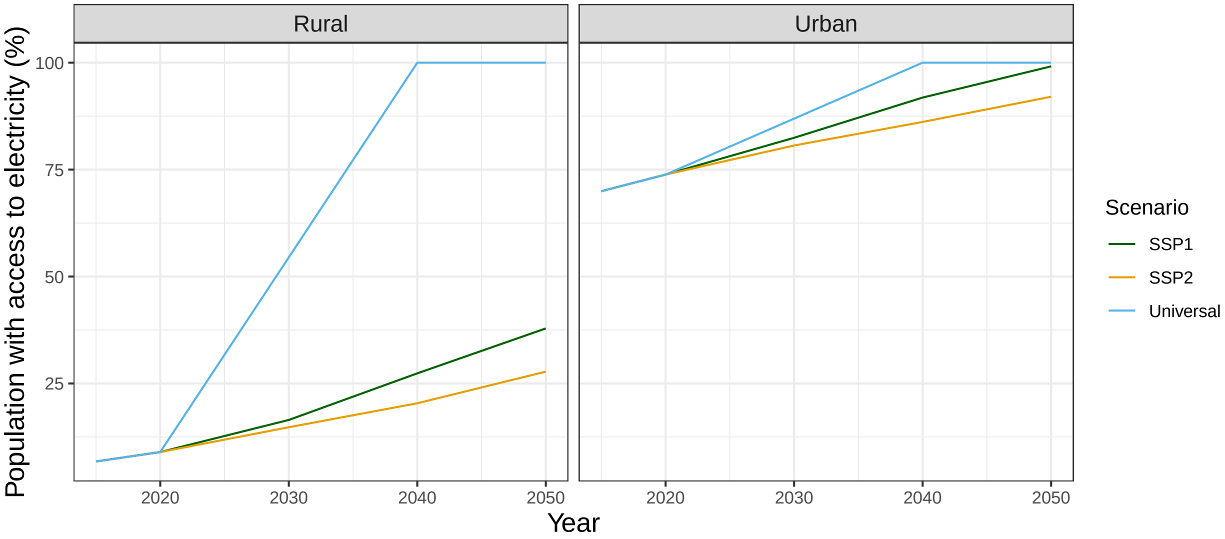

Figure 2: Scenarios of the proportion of the Zambian population having access to electricity in rural (left) and urban (right) areas, from 2015 to 2050.

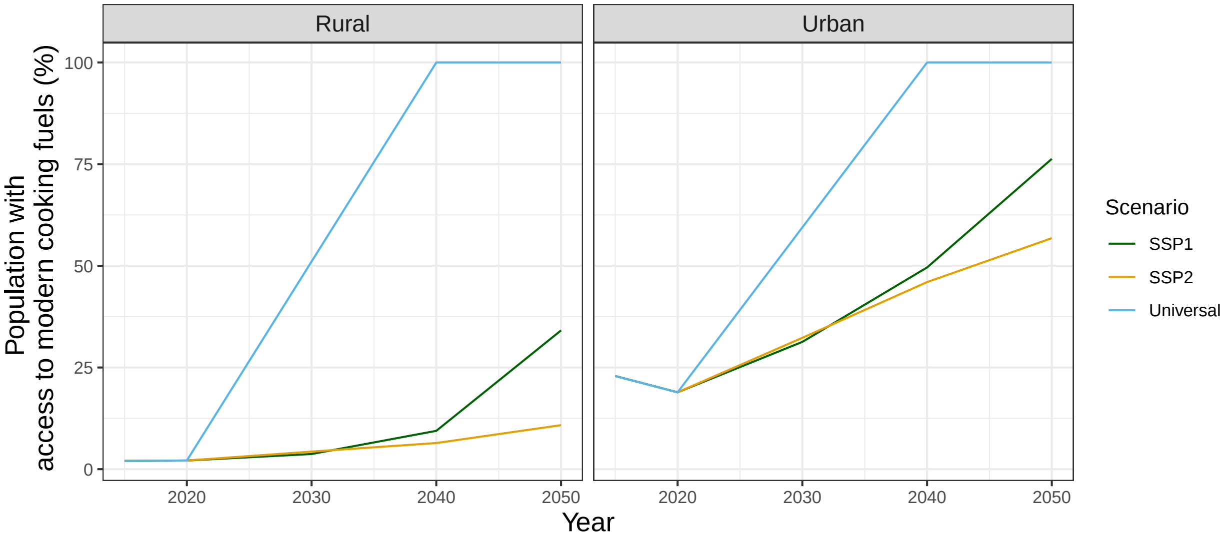

Figure 3: Scenarios of the proportion of the Zambian population having access to modern cooking fuels in rural (left) and urban (right) areas, from 2015 to 2050.

3.7 Estimation of energy use

Electricity

Our model derives the energy use of the Zambian population exogenously. Energy use depends on whether the individual has access to electricity, modern cooking fuels and whether she/he lives in rural or urban area. To obtain estimates of average electricity consumption for rural and urban areas, we used the Multi-Tier Framework (MTF) data of Zambia (Luzi et al. 2019). The Zambian MTF data is a nationally representative survey of 3612 households interviewed in 2017, covering many aspects of energy access and energy use. It provides data on electricity consumption of households connected to the grid who had an electricity bill. For urban areas, to derive the electricity consumption of household having access to electricity, we used the average electricity consumption from the electricity bills, which is 305 kWh/capita/year (SI, Figure 8).

For rural areas, we used an alternative method. The reason for this is two fold: first, the number of household in rural areas having an electric bill is quite small (107 households, see SI, Figure 8). Second, the value on the electric bill does not account for electricity use from off-grid systems, and access to off-grid systems tends to be higher in rural area, and the associated electricity consumption lower (Luzi et al. 2019). Using the MTF data as well, we obtain another estimate of the electricity consumption in rural and urban areas from data on electric appliances present in the household and how long they are used. These estimates are likely to be under-estimated since the usage time was not reported for all electric appliance (only light, TV, radio and fan). We then derived the ratio of electricity consumption between urban and rural areas, that we applied to the value of 305 kWh per capita per year observed in urban areas from the electricity bills. We obtained an estimate of 122 Kwh per capita per year for household having access to electricity in rural areas (SI, Figure 8, yellow bar).

Cooking fuels

Second, to estimate the energy demand for cooking energy, we made two assumptions. The first is that everyone in the population uses the same amount of useful energy for cooking (Daioglou, Ruijven, and Vuuren 2012). We fixed this value at 1GJ/year. Second, supported by the literature (see also Introduction), we assumed that rural households using traditional fuels all use fuelwood, that urban household using traditional fuel all use charcoal, and that all households cooking with modern energy use electricity. We then used efficiency values of 20%, 21% and 75% for respectively fuelwood, charcoal and electricity (Pachauri, Rao, and Cameron 2018 ; IEA 2017). The following formula was used to derive the final energy required for cooking, for each individual:

$$FE_i = UE_i * \frac{1}{thermalEff_{c(i)}}$$

with FE_i the final energy for cooking for women i, UE_i, the useful energy for cooking for women i (the same as everyone else in the population), and $thermalEff_{c(i)}$ the thermal efficiency of the fuel c that women i uses as a main cooking fuel.

3.8 Implementation

The model was implemented in R and follows an Object-Oriented programming style, since micro-simulation models operate at the individual level. Each individual in the the population is an instance of a S4 object. At each time step and for each individual, we simulated successively, through Monte Carlo Processes the following events: reproduction, transition of energy access, transition of education, and death.

4 Results

4.1 Fertility and population size

In our projection model, fertility depends on both level of energy access and level of education, which vary substantially across the different scenarios. We find that under the universal access to energy scenario, the Total Fertility Rate (TFR) of the Zambian population in 2050 reaches 2.12 children per women, which is 31% lower compared to the SSP2 (or baseline) scenario. The TFR under the Universal access scenario is also significantly smaller than the TFR of the SSP2 from IIASA projections (compared with the value of 2045) (Figure 4, panel a). In terms of population size, we find that the projected size of the population in Zambia under the Universal access scenario is 33.5 million, which is 11% lower compared to the SSP2 scenario (Figure 4, panel b). Interestingly, the difference in TFR between the SSP1 and SSP2 scenario does not translate into large population size difference in 2050. This can be due to the fact that in SSP1, fertility does not decline enough to off-set the decline in mortality associated with SSP1 scenario.

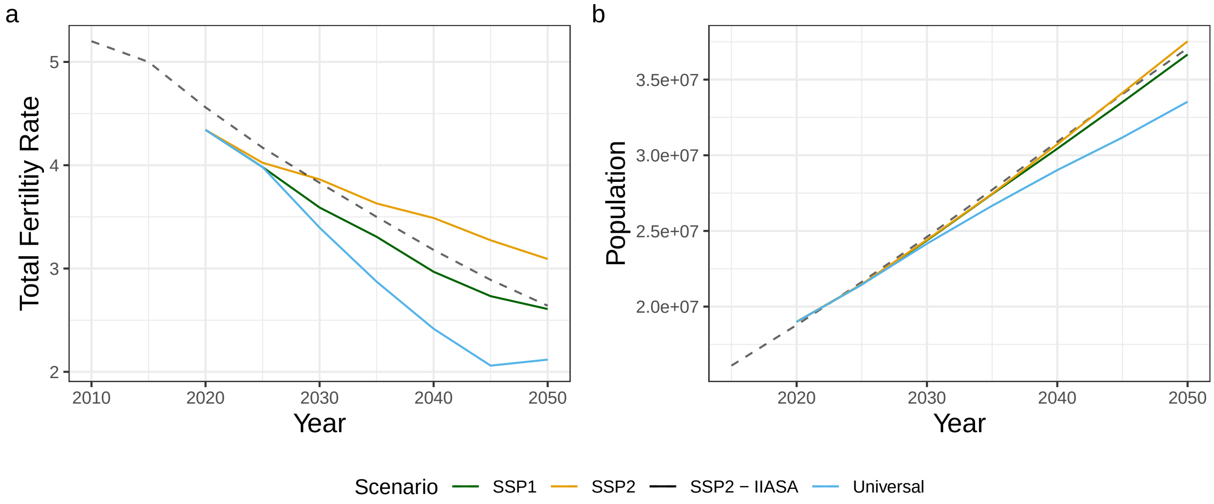

Figure 4: Projected total fertility rate (left) and population size (right) of Zambia under three scenarios of energy access and education attainment. The black dotted line represents the trajectory under the SSP2 scenario developed by IIASA (K. C. and Lutz 2017)

4.2 Energy demand

Electricity demand

We find that under the universal access scenario the contribution of population dynamics to lowering electricity demand is substantial. In rural areas, the electricity demand of the population in Zambia under the Universal access to energy is significantly higher than the electricity demand under the SSP1 and SSP2 scenario, reaching 9081 TJ in 2050 (Figure 5, left). This is explained by the fact the percentage of people having access to electricity increases dramatically in the universal access scenario, and the associated decline in population size does not offset for the electricity demand of the population having newly access to electricity. However, if population size would not have declined in the universal access scenario, the electricity consumption would be much higher. With the population size observed in the SSP1 scenario in 2050 (Figure 4, right) with full access to electricity, the electricity demand would reach 1.0401×10^4 TJ, which is 14 % higher compared to the electricity demand observed in the universal access scenario. The effect of energy access on reducing fertility and stabilizing population growth contributes substantially to lowering the energy demand when all the population has access to electricity.

In urban area, until 2050, electricity consumption under the universal access to energy scenario is higher than in the other scenarios. However, between 2040 and 2050 the growth of electricity consumption becomes lower than in the two other scenarios (Figure 5, right). If these trends would continue in the decade 2050-2060, electricity consumption under the Universal access scenario would likely become lower than in the SSP1 scenario.

The difference in electricity consumption between rural and urban areas is notable. For each scenario, electricity demand remains lower in rural areas compared to urban areas. This reflect recent projections of electricity consumption by rural and urban areas in sub-Saharan Africa, which found that even under a universal access scenario, electricity demand remained lower in rural areas (Dagnachew et al. 2018). In the universal access scenario, however, electricity demand is relatively high, reaching about two third of the demand observed in urban areas in 2050. This can be due to the fact that our model does not yet accounts for urbanization, which results in a relatively large rural population, and thereby large electricity demand.

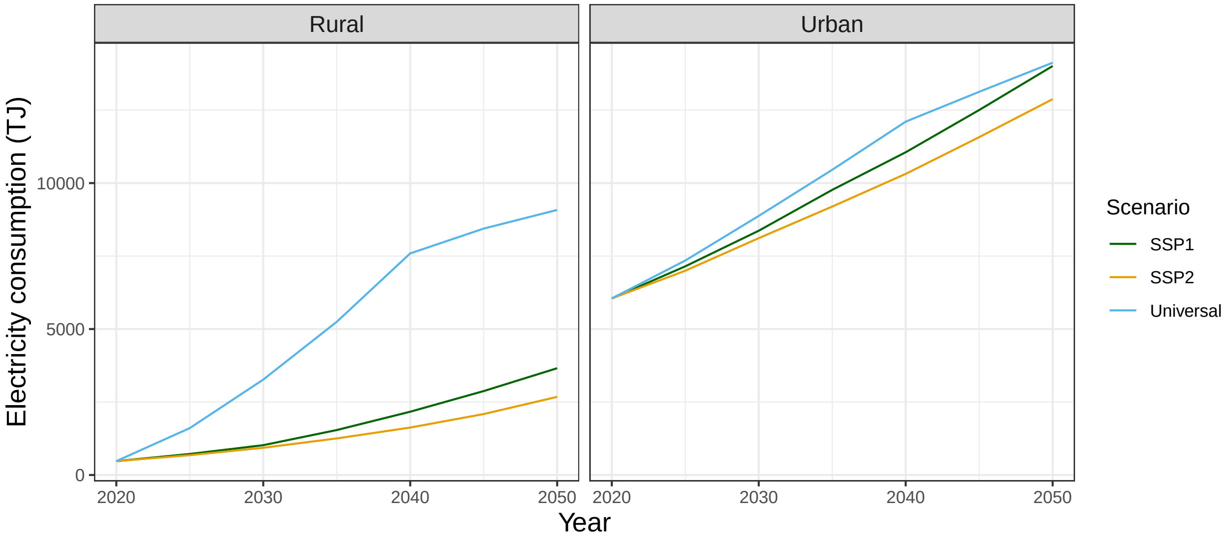

Figure 5: Total electricity demand of the population in Zambia under three scenarios of energy access and education attainment.

Cooking energy demand

We find that in the universal access scenario, the final cooking energy consumption of the population in Zambia is much lower than in the SSP1 and SSP2 scenario. In 2050, in urban areas the final cooking energy demand (both modern and traditional) is only 1.7152×10^4 TJ while it reaches 2.8756×10^4 TJ in the SSP1 scenario. The pattern is similar in rural areas (Figure 6). This saving in energy demand in the universal access scenario is driven by two factors: (i) the gains in efficiency due to the large proportion of the population that shifted to modern cooking fuels, and (ii) the smaller population size in the universal access scenario. In rural areas, the stabilization of population growth arising from expanded energy access contributed to lowering the cooking energy demand by 15% compared to the SSP1 scenario.

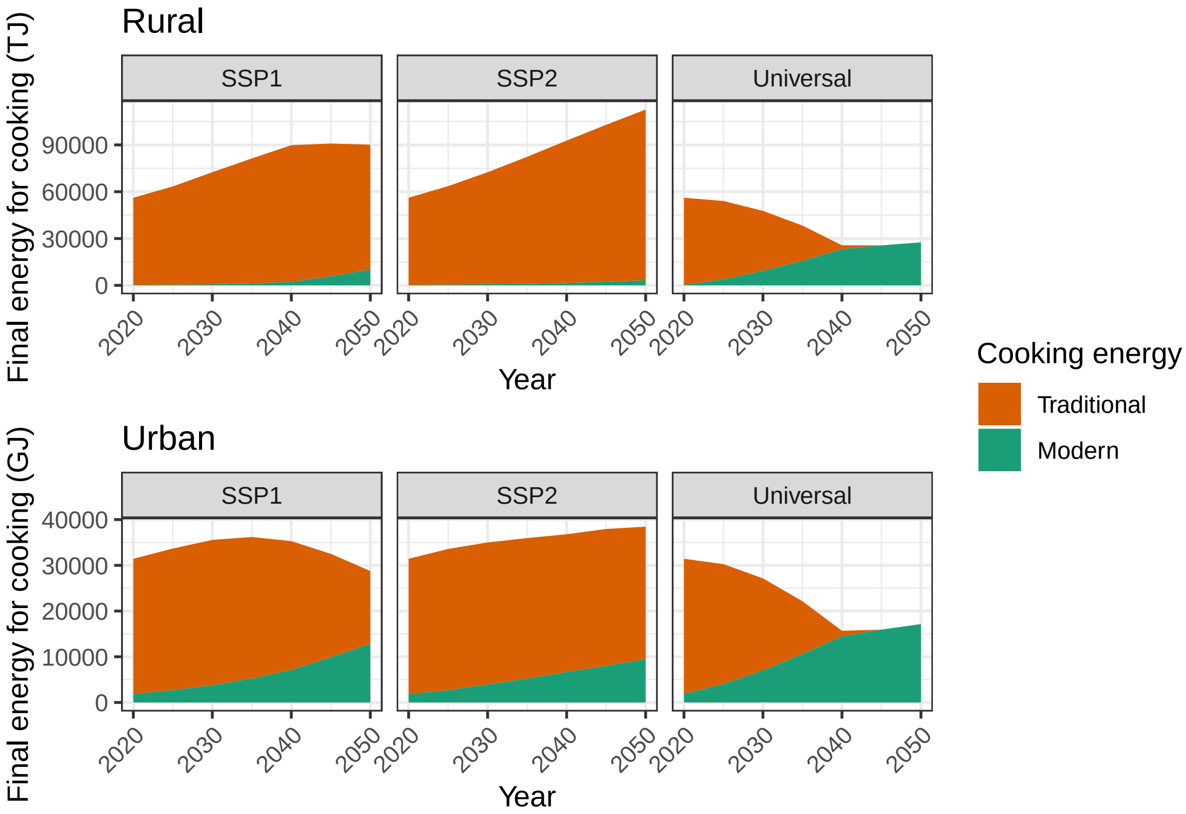

Figure 6: Final cooking energy demand of the rural (top) and urban (bottom) population in Zambia under three scenarios of energy access and education attainment

Total residential energy requirements to reach universal access to modern energy

Combined together, the residential electricity and cooking energy demand is lower in the scenario in which the population reaches universal access to modern energy than in both baseline SSP2 scenario and SSP1 scenario. In the universal access scenario, the total residential energy requirement is 6.7925×10^4 TJ, 3.6649×10^4 TJ in rural area and 3.1276×10^4 in urban area (Figure 7). This is respectively 67%, 88% and 15% lower than in the SSP1 scenario. Lower population growth arising from improved energy access and education contributes substantially to this reduction in rural areas. More specifically, it contributed to lowering the total energy demand by 14% in rural areas, only 1% in urban areas and 8% altogether.

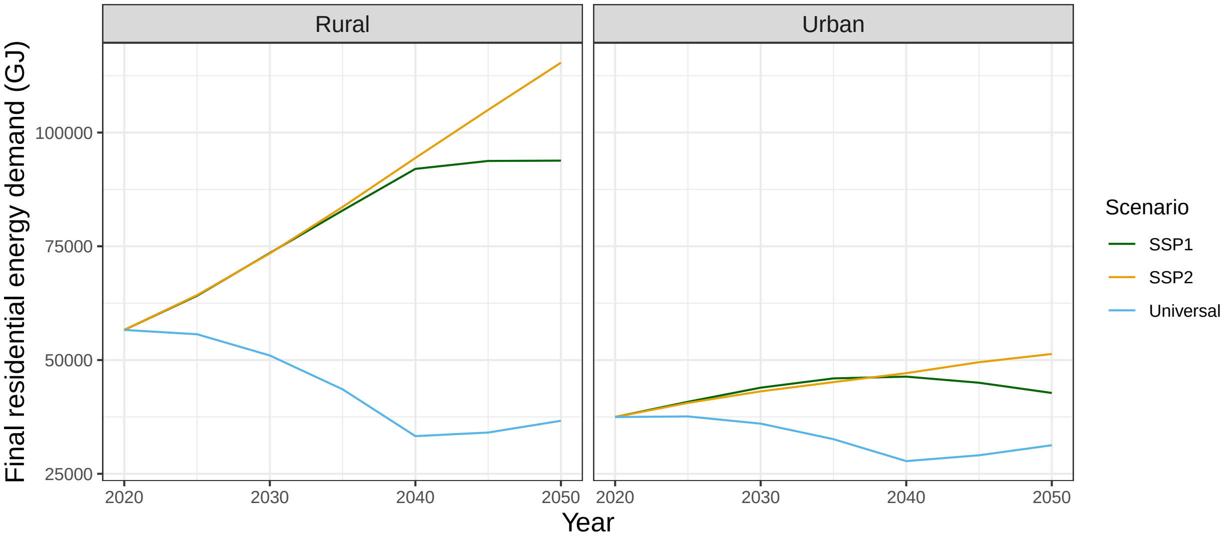

Figure 7: Final residential energy demand of the rural (left) and urban (right) population in Zambia under three scenarios of energy access and education attainment

5 Discussion and conclusions

Our results show that reaching universal access to electricity and modern cooking fuels by 2040 would lead to significantly lower population compared to our baseline scenario. In our Zambian case study, we also find that the projected population size is 10% lower than the SSP2 scenario developed by IIASA (K. C. and Lutz 2017). This middle-of-the-road population scenario is typically used in projection models aiming at estimating the energy and CO2 needs to implement universal access to energy (Dagnachew et al. 2018; Kikstra et al. 2021 ; Rao, Min, and Mastrucci 2019). For example, using the SSP2 population scenario, Kikstra et al. (2021) found that the final energy requirements for decent living in 2050 for Global South regions was 108 EJ yr—1. Our results suggest that such estimate could be significantly lower if a population scenario consistent with the achievement of universal access to energy were used. The same is applicable for the associated carbon costs and investment costs of eradicating energy poverty.

Our results also suggest considerable synergies between achieving SDG 7 on universal access to energy and climate protection goals. The total energy demand is significantly lower in the universal access scenario compared to the SSP1 and SSP2 scenarios. In particular, the net energy demand for cooking is much lower in the universal access compared to the SSP1 scenario, partly due to the efficiency gains from switching a large share of the population to modern cooking solutions. The contribution of the reduction of population growth –resulting from expanded energy access and improved education– on the savings of total energy demand is substantial, particularly in rural areas. Population growth decline contributed to lowering the electricity demand and cooking energy demand both by 15% in rural areas. Considering the potential savings in CO2 associated with this reduction in cooking energy demand, implementing policies to reach universal access to modern cooking fuels would constitute a solution that would maximize improvements in living conditions while mitigating important amount of carbon emissions. Electricity consumption, however, is higher in the universal access scenario than in the baseline scenario, in particular in rural areas. Expanding access to electricity, combined with climate policy encouraging the adoption of renewable energies, could reduce electricity demand under a universal energy access scenario (Dagnachew et al. 2018), and maximize well-being improvements while minimizing the carbon costs of achieving SDG 7 on universal access to modern energy.

Overall, this study demonstrates the importance of taking into account population dynamics when projecting into the future the energy requirements to eradicate energy poverty. The model developed here is, to our knowledge, the first projection model that internalizes the effect of energy access on fertility. This constitutes an important advance towards including the nexus between energy access and population dynamics in energy modeling. However, there are a number of limitations that should be kept in mind when interpreting our results. First, mortality does not depend on energy. This could be problematic as modern cooking fuels uptake is associated with lower child mortality. In our model mortality depends on education attainment. As long as education and energy access follow a similar progression, this limitation would not affect too much the results. But experimenting with scenarios with important differences in energy and education pathways would require taking a closer look at the effect of modern energy on mortality and how it affects the dynamic of the model. Second, although energy consumption is a critical component of our results, we made several simplifications to estimating it, that may require revision in future developments. In particular, better representing the distributional aspects of energy use would be an important addition to the model. A third notable limitation is the way the cooking energy transition is represented. Although a lot of evidence exist on the fuel stacking behavior of energy-poor households (households cummulate different fuels rather than switching from one fuel to another), our model does not represent this characteristic of household energy transition. Those three aspects could be the focus of future developments of this model.

More efforts are needed to incorporate the relationship between energy access and population dynamics into energy models (Kikstra et al. 2021). Such models can reveal novel mitigation solution that are simultaneously beneficial to achieve other SDGs like SDG 7 on energy access, SDG 1 on poverty eradication or SDG 5 on gender equality. While the challenge of rapidly achieving universal access to modern energy may seem daunting, shedding light on the additional climate co-benefits of achieving this goal could help further encourage investments targeted at achieving reliable access to modern energy for all.

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Supplementary Information

5.1 SI 1: Estimation of electricity use

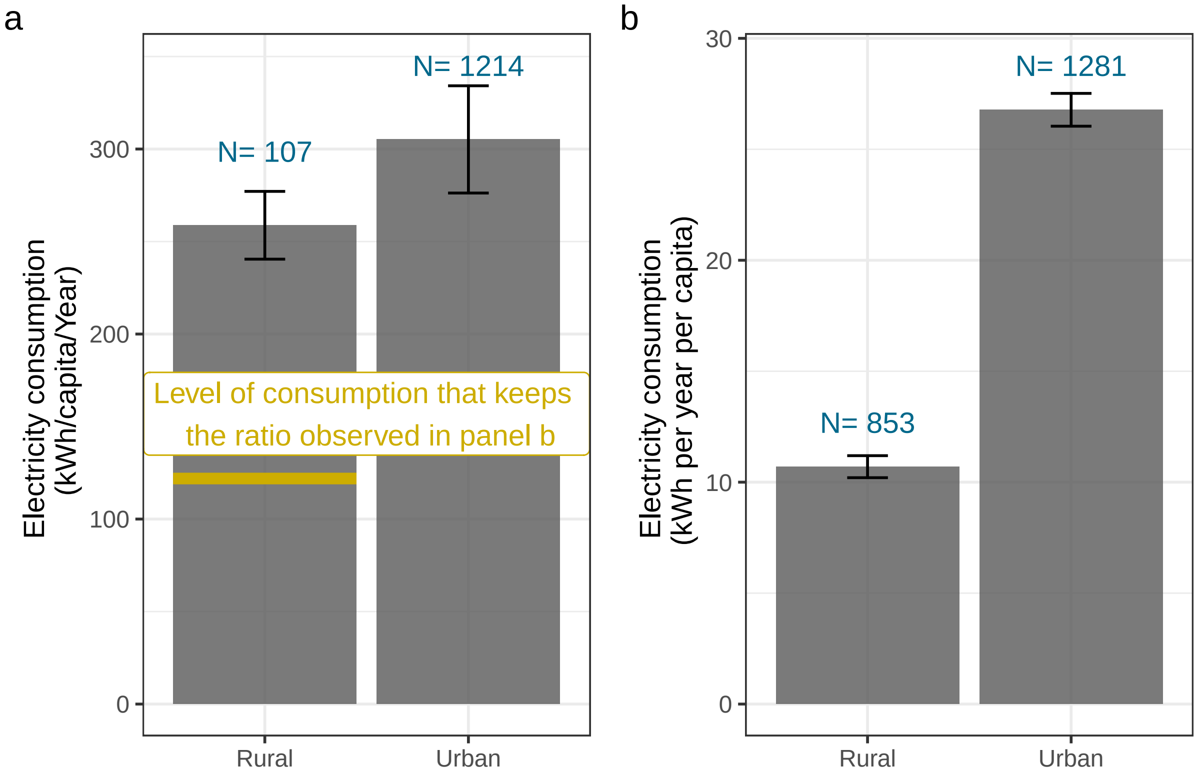

Figure 8: Two estimates of the average per capita electricity consumption in rural and urban areas in Zambia, derived from the Multi-Tier Framework data for Zambia, 2017. On panel a, the estimate come from data of electricity consumption read on electricity bill of households connected to the grid. On panel b, the estimates come from data on electric appliances present in the household. The bars represent the 95% confidence intervals and the numbers in blue are the sample sizes. The yellow bar represents a reconstructed per capita electricity consumption for rural areas, using the ratio betwen urban and rural areas observed in panel b, applied to the electricity consumption in urban areas on panel a.