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The energy-population dividend: Evidence from energy-specific population projections

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Abstract

In a climate- constrained world, understanding the energy required to achieve universal access to modern energy is critical. This requires making assumptions on future population trajectories. Although access to modern energy can affect population dynamics, this feedback has not yet been accounted for in demographic models. Access to modern energy leads to fertility declines as it reduces child mortality, improves health, increases women's access to information, education and employment. In this paper we present a demographic model that endogenizes the effect of increased access to modern energy on population dynamics and estimates the size of this effect on total final energy use by households for the case of Zambia. To do so, we built a microsimulation model to project future population size and composition, accounting for how fertility depends on access to modern energy and education. We used these population projections to then estimate household energy demand of the Zambian population until 2070, under different scenarios. We found that in 2070, while electricity consumption is higher in a universal access scenario compared to a baseline scenario, total energy demand is 29% lower, partly due to a strong decline in the use of inefficient traditional cooking fuels. We also found that reduced population growth due to universal energy access contributes to lowering the energy demand by 56% by 2050, compared to a more limited expansion in energy access, and this contribution increases over time. Although the challenge of achieving universal access to modern energy seems daunting, our results suggest that this could have co-benefits with achieving climate goals. Our study also reveals that accounting for the energy-population dividend in energy models will scale down the currently assumed energy needs to ensure a decent life for all.

1 Introduction

Access to modern energy provides services that are essential for meeting basic human needs (GEA 2012; McCollum et al. 2018). Despite significant progress in global energy access, approximately 675 million people still lacked access to electricity and 2.3 billion people lacked access to clean cooking energy in 2021 (IEA et al. 2023). Projections for achieving universal energy access, especially for fast growing populations, are highly dependent on future demographics. Traditionally, most models used for these projections rely on exogenous population data from independent sources such as the UN (UNFPA 2019), or the Shared Socio-economic Pathways (SSP) (KC and Lutz 2017; KC et al. 2024).

However, there is growing evidence that energy access plays an important role in fertility decline and thereby population dynamics. Studies have shown a link between access to modern energy and fertility decline in low- to middle-income countries (Grimm, Sparrow, and Tasciotti 2015 ; Grogan 2016 ; Potter, Schmertmann, and Cavenaghi 2002 ; Peters and Vance 2010; Fujii and Shonchoy 2020; Harbison and Robinson 1985; Belmin et al. 2022). This decline has been attributed to several factors, including less time spent by girls and women on household chores (Das et al. 2020; Wickramasinghe 2011; OXFAM 2017), lower child mortality (Adaji et al. 2019; Ezzati 2005), improved health outcomes (Das et al. 2020; I. E. A. IEA 2016; WHO 2014), increased access to information (OXFAM 2017; Das et al. 2020) and education (Winther et al. 2017). Given this interplay, accurate modeling of energy access scenarios requires the endogenization of demographic trends. Neglecting this connection might lead to inaccurate energy demand projections, potentially causing misallocation of resources in the pursuit of universal energy access.

Detailed econometric studies for individual countries have quantified the impact of expanded electricity access on fertility(Grimm, Sparrow, and Tasciotti 2015 ; Grogan 2016 ; Potter, Schmertmann, and Cavenaghi 2002). A recent study by Belmin et al. (2022) examined the impact of access to electricity and modern cooking fuels in 44 developing countries. It found that achieving universal access to electricity by 2040, coupled with increasing educational attainment, would result in a total fertility rate 19% lower than in a business-as-usual scenario. The study also demonstrated that the negative effect of energy access on fertility persists even after controlling for education, GDP and other predictors of fertility decline (Belmin et al. 2022).

An early study used the historical correlation between average per capita energy use and population growth in different world regions to model future population size and energy demand (Sheffield 1998). Such an approach could be taken even further by considering critical components of population projections such as age or education. Population scenarios developed within the SSP framework provide valuable population projections that take into account assumptions about future trends in educational attainment (KC and Lutz 2017; KC et al. 2024). Similarly, we suggest that these scenarios would benefit further by taking into account the expansion of energy access. Here, we present a novel, open-source microsimulation demographic model that explicitly incorporates the effects of access to modern energy on fertility. We use this model to analyze four stylized energy transition scenarios, ranging from moderate and partial transitions to rapid and universal adoption of modern energy. Similar to Sheffield (1998), our goal is to quantify the difference in population size and corresponding energy demand attributable to the energy-fertility effect. However, unlike Sheffield (1998), our approach avoids relying on aggregate region-wide correlations. Instead, we develop an explicit microsimulation model to capture individual-level dynamics and the complex interactions between energy access and fertility.

We chose Zambia as a case study because of its demographic characteristics, the status of access to modern energy in the country, as well as the availability of data. Zambia is a high-fertility country with most of its population living in rural areas. In 2022 the Total Fertility Rate (TFR), which can be interpreted as the average number of children per women, was 4.24 (UNFPA 2022). 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, particularly 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 type of modern energy used for cooking in Zambia (32.5% of urban and 1.9% of rural households use electricity as a main cooking fuel) (Luzi et al. 2019). The heavy dependence of Zambia's electricity sector on hydro-power, also makes electricity supply vulnerable to climate variability and droughts, and has caused electricity outages in 2012 and subsequently, a decline in the use of electricity for cooking (Samboko et al. 2016).

2 Methods and data

2.1 Overview

The modeling framework has two components: (i) a microsimulation model of population projection that determines at each time step, the size and the distribution of the population by place of residence (rural or urban), education level, access to electricity and modern cooking fuels, and (ii) an energy calculator that estimates the population's energy demand using disaggregated data on per capita energy consumption and the population projections from the MSM (Figure 1). The analysis is carried out for four scenarios. Each scenario is composed of assumptions on mortality, educational attainment, energy access and urbanization pathways created using the SSP framework (Table 2). The model was implemented in R and operates at the individual level. The validation of the model is presented in the *Validation* section of the Supplementary Information (Supplementary Figure 3-5).

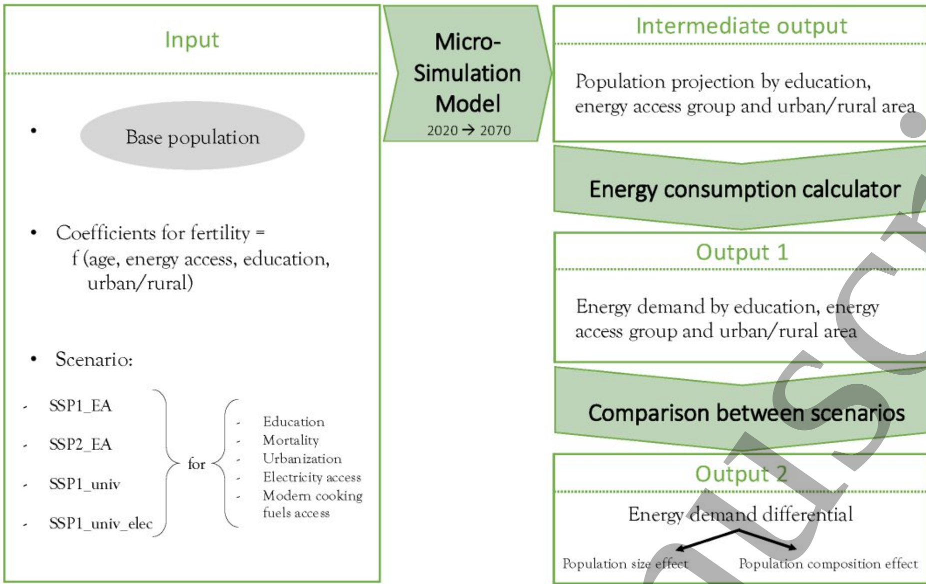

Figure 1: Overview of the modeling framework in two steps: the microsimulation model of population projection and the energy calculator.

2.2 Microsimulation model of population projection

We developed a dynamic microsimulation model (MSM) to project population trends from 2020 to 2070, using five-year time steps. The base population of the model is set to 2015, with scenario data starting in the same year. The first year of simulation results, 2020, represents the first step in the projection. The MSM simulates individual life events such as birth, death, access to electricity and modern cooking fuels, educational attainment, and urbanization. Each individual is treated independently in the model, and events are simulated using Monte Carlo methods. For each potential event for each individual, a random number is drawn from a uniform distribution between 0 and 1. This number is then compared to the predefined probability of the event. If the random number is lower than the probability, then the event will occur for that individual.

The probability of surviving, moving to an urban area, transitioning to a higher education level, and getting access to modern energy are directly derived from the input data (see Section 2.2.3). In contrast, the probability that a woman gives birth is derived endogenously at each time step, and depends on her age, access to modern energy, level of education, and whether she lives in a rural or urban area and the year (see Figure 1 and Table 1). Microsimulation models allow to easily run population projections where demographic rates depend on a large number of states (Van Imhoff and Post 1998). Here, fertility depends on five dimensions. With a traditional multi-state cohort component model of population projection, this large number of dimensions would make the estimation of fertility unmanageable.

2.2.1 Base population

We used the 2018 Demographic and Health Survey data of Zambia to construct the base population. More specifically, we used the *Person Recode* of the DHS data (ICF 2004), in which all members of interviewed households are included in the sample. This allowed for obtaining data on individuals of both sex and all ages. From the DHS data we extracted the following variables: age, sex, number of education years, whether the individual lives in a rural or urban area, whether they have access to electricity and modern cooking fuels, and for children under 18, the number of years of education of the mother and finally the individual survey weight. From the variable number of education years, we created six categorical variables: *No education*, *Incomplete primary education*, *Completed primary education*, *Lower secondary education*, *Upper secondary education*, and *Post secondary education*). Observations with missing values on these variables were excluded, which resulted in a final sample size of 57960 individuals. To ensure representativeness of the base population in terms of education, we calibrated the base population using age-specific, education-specific population distribution data for the year 2015 from the Wittgenstein Center for Demography and Human Capital (WIC) (Lutz et al. 2018) (Supplementary Method 1).

2.2.2 Fertility

In our model, the probability that a woman will give birth is endogenously determined at each time step and for each woman of fertile age (between 15 and 49 years old). We used a logistic regression to estimate the parameters allowing us 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, to modern cooking fuels and whether she lives in a rural or urban area. We chose this set of independent variables as they have been shown to be the most influential in explaining fertility variations (Lutz, Butz, and Samir 2014 ; Belmin et al. 2022 ; Lerch 2017 ; Adhikari, Lutz, and KC 2023). The dependent variable is whether the women gave birth in the last year. The coefficients from the logistic regression model were estimated using a pooled sample of four DHS surveys for Zambia (2002, 2007, 2013 and 2018), resulting in a sample size of 87332. We provide a detailed description of the data and method used for this regression in Supplementary Method 2.

The estimated coefficients for any level of education other than *No education*, having access to electricity, having access to modern cooking fuels, and living in an urban area are all negative and significant, which suggests that these variables might have a strong effect on the probability of giving birth (Table 1). The age categories are also all significant, with age groups 20-24 and 25-29 having the strongest positive effect on the probability of giving birth, relative to the reference age group of 15-19. Age also interacts with access to energy in a significant way. In particular, the coefficients for access to both electricity and modern cooking fuels are particularly strong for the reference age group, and the coefficient for electricity is also strong for the age group 20-24.

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

	Gave birth in the past year (Yes/No)
Age group 20-24	0.829*** (0.031)
Age group 25-29	0.718*** (0.032)
Age group 30-34	0.524*** (0.035)
Age group 35-39	0.209*** (0.038)
Age group 40-44	-0.554*** (0.050)
Age group 45-49	-2.332*** (0.113)
Educ group: Incomplete primary	-0.120*** (0.031)
Educ group: Primary	-0.180*** (0.035)
Educ group: Lower secondary	-0.374*** (0.036)
Educ group: Upper secondary	-0.576*** (0.043)
Educ group: Post secondary	-0.581*** (0.065)
Having access to electricity	-0.516*** (0.073)
Having access to modern cooking fuels	-0.538*** (0.119)
Living in urban area	-0.287*** (0.023)
Year	-0.009*** (0.002)
Age group 20-24 X Elec	0.218** (0.090)
Age group 25-29 X Elec	0.261*** (0.094)
Age group 30-34 X Elec	0.401*** (0.099)
Age group 35-39 X Elec	0.015 (0.119)
Age group 40-44 X Elec	-0.465** (0.207)
Age group 45-49 X Elec	0.081 (0.431)
Age group 20-24 X MCF	0.227 (0.145)
Age group 25-29 X MCF	0.517*** (0.145)
Age group 30-34 X MCF	0.591*** (0.152)
Age group 35-39 X MCF	0.729*** (0.182)
Age group 40-44 X MCF	0.885*** (0.294)
Age group 45-49 X MCF	-10.174 (64.533)
Intercept / Reference category	16.454*** (3.205)
N	87332
Log Likelihood	-37717.040
AIC	75490.080

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

Table 2: Description of scenario components and narrative.

Scenario name	Narrative	Education	Electricity access	Modern cooking fuel access	Urbanization	Displacement of all traditional fuels by 2040
SSP1_EA	Fast development in education and urbanization. Energy access expands, in particular in urban areas. However, universal energy access is not reached by 2040.	Fast (SSP1-IIASA)	Intermediate (SSP1-Poblete Cazenave et al. 2021)	Intermediate (SSP1-Poblete Cazenave et al. 2021)	Fast (SSP1-IIASA)	No
SSP2_EA	Slow development in education and energy access, especially in rural areas. Intermediate urbanization.	Slow (SSP2-IIASA)	Slow (SSP2-Poblete Cazenave et al. 2021)	Slow (SSP2-Poblete Cazenave et al. 2021)	Slow (SSP2-IIASA)	No
SSP1_univ	Fast development in education and urbanization. Universal energy access is reached by 2040. However, despite fast electrification, households continue to use some traditional energy when they get access to modern energy (fuel stacking),	Fast (SSP1-IIASA)	Fast (Universal access by 2040)	Fast (Universal access by 2040)	Fast (SSP1-IIASA)	No
SSP1_univ_elec	Fast development in education and urbanization. Universal energy access is reached by 2040. Contrarily to SSP1_univ, all traditional energy for cooking is displaced by electricity, coherently with the fast electrification happening simultaneously.	Fast (SSP1-IIASA)	Fast (Universal access by 2040)	Fast (Universal access by 2040)	Fast (SSP1-IIASA)	Yes

2.2.3 Scenarios

We created four scenarios that explore different assumptions about mortality, educational attainment, urbanization, and access to modern energy (Table 2 and Figure 2). These scenarios are based on the SSP framework (Riahi et al. 2017), which is widely used in energy and climate mitigation modeling. Among the different SSP scenario assumptions, we used SSP1, which corresponds to a world shifting to a more sustainable pathway with low mitigation and adaptation challenges, and SSP2, which represents a middle-of-the-road scenario. The assumptions about future mortality, educational attainment, urbanization, and access to modern energy come from existing pathways found in the literature that follow the SSP framework. In this paper, we do not consider international migration and domestic migration is reflected in the different urbanization projections for SSP1 and SSP2.

We defined modern energy for cooking as any energy derived from electricity, liquefied petroleum gas (LPG), natural gas and biogas. All forms of traditional biomass are excluded, namely firewood, charcoal, agricultural crops, animal dung as well as coal and kerosene. Although coal and kerosene do not need to be collected, we excluded these from the basket of modern fuels because of their negative health effects.

The first scenario is called *SSP1_EA* (SSP1 with Energy Access) and represents a future with good progress in development, including progress in energy access, especially in urban areas. The second scenario, *SSP2_EA* (SSP2 with energy access), represents a mid-road scenario with limited progress in development and slow progress in energy access. The third scenario, *SSP1_univ*, like *SSP1_EA*, represents a trajectory with good progress in development, but additionally assumes universal access to electricity and modern cooking fuels by 2040. The fourth and final scenario, *SSP1_univ_elec*, is based on *SSP1_univ*, but in addition assumes that traditional fuels are completely replaced by electricity (see sub-Section *Scenario for completely electrifying clean cooking*). The assumptions used to construct these scenarios are described in detail below.

Mortality, education and urbanization assumptions

The mortality, and educational attainment data were taken directly from the WIC open data repository (Lutz et al. 2018). The WIC has developed a set of population dynamics and characteristics scenarios that are consistent with the SSP narratives. We also used urbanization assumptions that follow the SSP framework from the study of Jiang and O'Neill (2017).

A few details are important to note about the mortality and education assumptions. The mortality assumptions are provided by the WIC as survival probabilities. For each scenario, this probability depends on the age group and education level of the individual at the beginning of the period. Following Marois and KC (2021), we assume that the probability of survival for children under the age of 15 depends on the mother's education level (Fuchs, Pamuk, and Lutz 2010). We provide further details on the education assumptions in Supplementary Method 3.

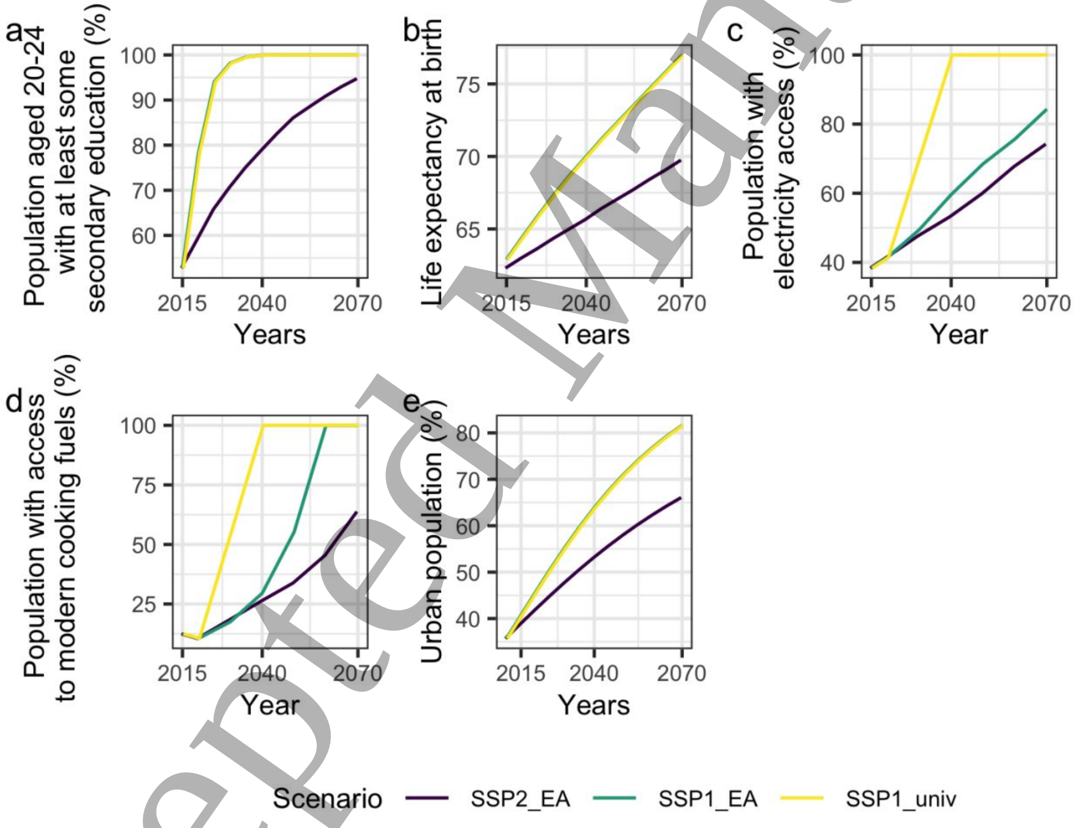

Figure 2: Background changes in education (a), life expectancy (b), access to electricity (c), access to modern cooking fuels (d) and urbanization (e) as input of the microsimulation model. In the case of education, life expectancy, and urbanization, the path for the SSP1_univ scenario is the same as for SSP1_EA, which is why the yellow and green lines overlap in plots a, b, and e (but they were slightly dodged for visibility). On plot c and d, the distinction between rural and urban is not represented but it is taken into account in the model.

Energy access assumptions

The energy access assumptions we used correspond to future trajectories of the proportion of people having access to electricity and having access to modern cooking fuels. These trajectories are differentiated by rural and urban areas, to account for the important difference in energy access levels and shifts over time between rural and urban areas. The first two energy access trajectories, used in the scenarios *SSP1_EA* and *SSP2_EA*, are consistent with energy access projection by Poblete-Cazenave et al. (2021) for the SSP1 and SSP2 pathways for the period from 2020 to 2050, that we adapted to Zambia and further projected until 2070 (Supplementary Method 4). The third energy access pathway we constructed is used in the scenario *SSP1_univ*, which normatively assumes universal access to both electricity and modern cooking fuels by 2040 with a linear increase in the proportion of the population having access to both forms of energy. After 2040 and until 2070, energy access remains universal. Although this scenario requires rapid percentage increases in access levels that are higher than the historical trends, in particular in rural areas where access to both forms of energy is currently very low, this normative scenario shows what would happen if the Sustainable Development Goals were achieved by 2040. From these macro-level energy access assumptions, we then derived the probability for an individual to get access to electricity, and to get access to modern cooking fuels (Supplementary Method 5).

Scenario for completely electrifying clean cooking

In low- to middle-income countries, most households do not use only one type of cooking fuel, but often use multiple fuels, a phenomenon known as fuel stacking (Masera, Saatkamp, and Kammen 2000 ; Price, Barnard-Tallier, and Troncoso 2021). Fuel stacking can be explained by several factors, such as household preferences (e.g. taste, convenience), the availability of devices and resources in local markets (Jeuland et al. 2020 ; Medina et al. 2019), and as a way to secure households against shocks (e.g. electricity outages, LPG shortages).

This phenomenon is also represented in the data we used to estimate energy consumption (see Section 2.3). Households categorized as having access to modern cooking fuels can still have significant charcoal and firewood consumption (Figure 3, first and third columns), with the associated health and well-being costs.

For this reason, we created an additional scenario we referred to as *SSP1_univ_elec*. This second normative scenario reflects a situation in which, in addition to the entire population getting access to electricity and modern cooking fuels as in *SSP1_univ*, all traditional fuel use is displaced by electricity by 2040, in line with the rapid up-scaling of electric capacity occurring concurrently in the country. The scenario was not designed for plausibility, but as a what-if scenario to illustrate the full potential of modelling the nexus between energy access and fertility to reveal reductions in energy demand. To create this scenario, we used the same mortality, education, urbanization and energy access assumptions as in *SSP1_univ*, but we added a new assumption on energy consumption. To do so, we modified the energy consumption data we derived from Baltruszewicz et al. (2021) by converting traditional fuels into the equivalent electricity use, applying conversion efficiency factors of the respective fuels (Supplementary Method 6). Note that the population and fertility trajectories in the *SSP1_univ_elec* scenario are by construction the same as in *SSP1_univ*, because in our modeling framework the energy calculator comes ex-post to the population projection model (Figure 1).

2.3 Energy consumption calculator

The MSM estimates, for four scenarios, the population counts at each time step, broken down by education level, electricity and modern cooking fuel access as well as urbanization level. To derive the energy demand of the simulated population at each time step, we multiplied the number of people in any given category by the average per capita energy consumption of this category.

We used direct final energy consumption data for households in Zambia from Baltruszewicz et al. (2021). This study combines the 2015 Living Condition Measurement Survey (LCMS) for Zambia (Central Statistical Office of Zambia 2015) with a multi-regional input-output model (MRIO) and Zambia's residential energy use from IEA to calculate the total direct, final (based on IEA) and indirect final household energy use (based on MRIO). As said, we here only used direct final energy consumption data from Baltruszewicz et al. (2021).

Since the household survey contains information about the education levels, energy access, location of residence (urban or rural areas), we used this information to calculate the average direct final energy consumption per capita, for households grouped along these variables (Figure 3). Further details on data and procedures are provided in Supplementary Method 7.

Figure 3: Direct final energy use per capita for different combinations of categories in the energy-extended LCMS dataset (Baltruszewicz et al., 2021). NB: the category No Elec-Clean cooking was not represented because there are too few cases.

In the scenarios we kept the level of energy use of the household types shown in Figure 3 constant over time. This is obviously not a realistic assumption. However, our goal was not to model the energy requirements for decent living but to capture the effect of increased access to modern energy on population dynamics and translate this effect into total final energy use by households. If too many variables are changed at the same time this effect cannot be isolated. By holding energy use per household category constant, we can clearly distinguish two energy access related effects on final energy use: the population size effect and the population composition effect. In the scenarios the share of the population with higher education, living in urban areas, and having access to modern energy changes over time and thus the frequency distribution of the energy profiles, shown in Figure 3, changes. Further details on data and procedures are provided in Supplementary Method 7.

2.4 Limitations

The following limitations should be kept in mind when interpreting our results.

In the microsimulation demographic model energy is not a predictor of mortality. This could lead to a small overestimation of the population size in scenarios with rapid improvements in energy access, as child mortality and morbidity in particular declines with expansion of modern energy access (Adaji et al. 2019; Dimitrova et al. 2022). The microsimulation model does not account for the reality of fuel stacking, where energy-poor households often combine different fuel sources rather than switching cleanly from one to another. The model uses a binary variable for access to modern energy. This simplification could lead to an underestimation of the projected population size, as the underlying statistical analysis groups households with access to modern energy but still significant reliance on traditional fuels alongside households with no reliance on traditional energy.

In the energy consumption calculator energy per capita is static for each education/modern energy access/urbanization category, whereas in reality energy consumption has typically increased with more access to modern energy. As explained above this was a deliberate choice, because we want to distill the energy-fertility effect on energy use under stylized conditions.

3 Results

3.1 Population and fertility

We estimated that the population of Zambia in 2070 ranges from 41.5 to 54.6 million, depending on the scenario. In scenarios where the entire population gains access to modern energy and secondary education by 2040 (*SSP1_univ*), we estimated that the population in 2070 is 27% lower than in the baseline scenario (*SSP2_EA*) and 13% lower than in the scenario where the entire population attains secondary education but access to modern energy remains limited (*SSP1_EA*) (Figure 4, panel a). In other words, achieving universal access to modern energy reduces the population substantially compared to a more moderate expansion of energy access (*SSP1_EA*), holding all other modeling parameters (education and urbanization) constant.

The difference in population size is explained by the difference in fertility rates between the three scenarios (Figure 4, panel b). In the *SSP1_univ* scenario, the total fertility rate declines almost exponentially until 2045 to reach 2.3. This corresponds to the rapid achievement of universal access to modern energy by 2040 and universal secondary education by 2030 (Figure 2). The TFR continues to decline but more slowly, to drop to 1.9 in 2070. The decline in the TFR is less dramatic in *SSP1_EA* and *SSP2_EA*. In 2070, it drops to 2.4 in the *SSP2_EA* scenario and to 2.1 in *SSP1_EA*.

The population growth rate declines in all scenarios, from about 3% in 2025 to 1.21% in 2070 under *SSP2_EA* and to 0.69% under *SSP1_EA* (Figure 4, panel c). The population growth rate declines to 0.41% in 2070 under *SSP1_univ*, which is closer to the value projected by WIC under SSP1 (0.34%).

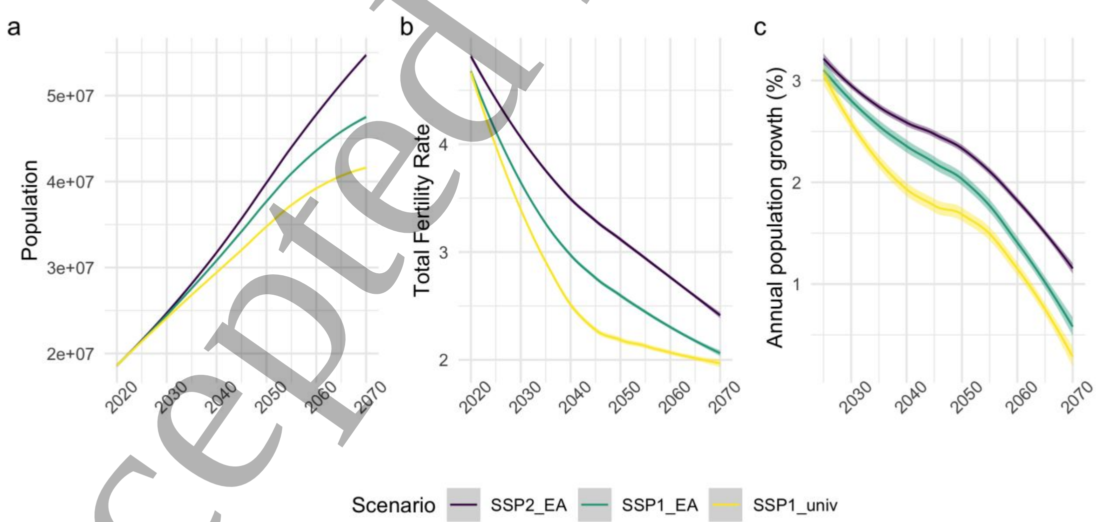

Figure 4: Evolution of the population size (a), total fertility rates (c) and annual population growth (c) in three scenarios. Note that the population and fertility trajectories for the SSP1-univ-elec are exactly the same as in SSP1-univ, by construction.

3.2 Energy demand

Under our scenario assumptions total household final energy demand of the Zambian population in 2070 is estimated to range from 268 to 650 PJ (Figure 5). Under the *SSP1_univ* scenario, energy demand is estimated to be 29% lower than under the *SSP2_EA* and 11% lower than under the *SSP1_EA*. The energy demand reduction is dramatic in the *SSP1_univ_elec* scenario, with demand being 83% and 68% lower than under the *SSP2_EA* and *SSP1_EA* scenarios, respectively.

In contrast to total energy demand, electricity demand increases in all scenarios. In the *SSP2_EA* scenario, which we consider the baseline scenario, electricity demand is estimated to increase in all scenarios. In the baseline scenario, electricity demand in 2070 is estimated to be 8-fold higher than in 2020, reaching 108 PJ. Under both *SSP1_EA* and *SSP1_univ*, demand in 2070 is about 12-fold higher than in 2020, and it is 17 times higher in the *SSP1_univ_elec* scenario, reaching 253PJ (Figure 6). This implies the need for a significant development of the country's installed power generation capacity.

The increase in electricity demand in our model is consistent with model results from the International Energy Agency's Africa Energy Outlook 2019 (IEA 2019). Although this macro-level model does not include the relationship between energy access and population, it provides us with an order of magnitude for changes to electricity demand. They projected electricity demand in sub-Saharan Africa (excluding South Africa) to 2040 under a *Stated Policy* scenario, which simulates a situation in which all current energy policies are implemented, and an *Africa Case* scenario, which reflects a situation with more ambitious goals for sustainability and economic development. They estimate that electricity demand would increase by a factor of 4 compared to 2018 levels under their *Stated Policy* scenario, and by a factor of 8 under their *Africa Case* scenario. These magnitudes are similar to our estimates. We estimated that by 2040, electricity demand could be as little as twice the 2020 level or as much as 10 times the 2020 level, depending on the scenario considered (Figure 6 in the main text).

The share of traditional energy in the energy demand also varies strongly in the different scenarios, and in 2070 it ranges from 82% to 0 % (Figure 5). In the *SSP2_EA* scenario, in 2070 82% of the energy demand is traditional energy, the majority of it being firewood and charcoal. In the *SSP1_EA* scenario, 66% comes from traditional energy, and only 59% in the *SSP1_univ* scenario. It can be surprising that in this scenario, still more than half of the energy demand comes from traditional energy. As explained above by the fact that households use multiple fuels, and even when they get access to one source of modern energy, they continue to use some traditional energy on the side (Figure 3).

In *SSP1_univ_elec*, since all cooking facilities are replaced by electricity by 2040, energy demand from this date onwards is only comprised of modern energy. The share of traditional energy in total household energy demand experiences a small drop around 2035 under *SSP1_univ* and around 2055 under *SSP1_EA*. This coincides with the timing when universal access to modern cooking fuels is achieved, which happens in 2040 under *SSP1_univ*, and in 2055 under *SSP1_EA* (Figure 2).

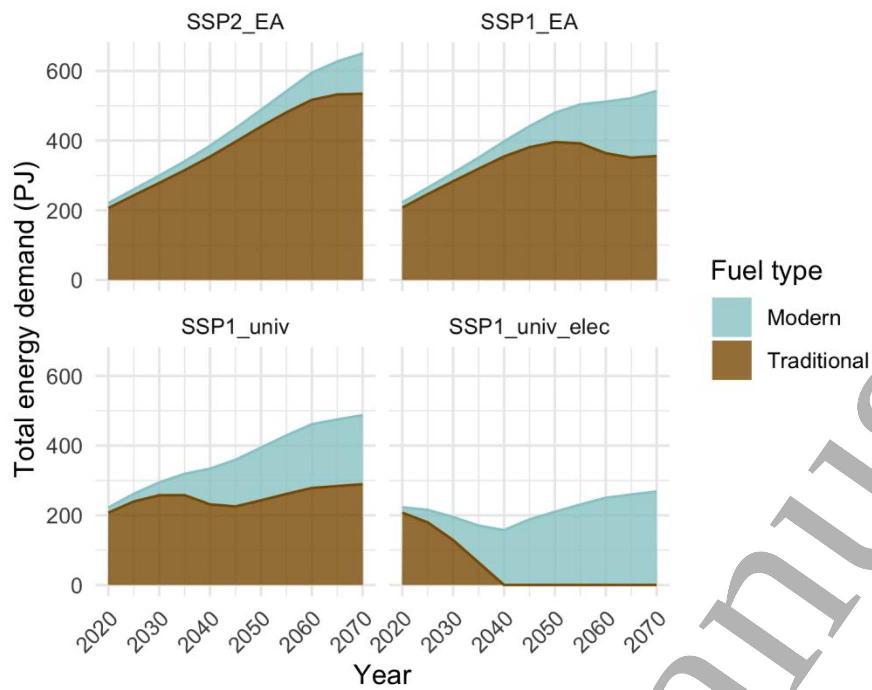

Figure 5: Traditional and modern energy demand in the four scenarios. Traditional energy includes firewood, charcoal, coal, kerosene and paraffin. Modern energy includes electricity, gas, LPG, diesel.

Figure 6: Electricity demand in the four scenarios.

3.3 Decomposing energy demand change by population composition and size effects

Keeping final energy use per capita and population groups constant over the scenario period, now allows us to quantify two effects of the feedback between energy access and demographic change on total residential energy demand in Zambia: the population composition and the population size effect. First, we considered the impact on energy demand of the scenario-driven increase in the share of the population with higher education, living in urban areas, and having access to modern energy. This change in population composition affects energy consumption patterns, since energy consumption per capita differs between groups (Figure 3). Second, we considered the effect of changes in population size, which directly affects energy demand.

To distinguish the "population size effect" from the "composition-efficiency effect", we decomposed the change in energy demand between *SSP1_EA* and *SSP1_univ*, the two scenarios that differ only in terms of the energy access pathway. However, since the education, urbanization and mortality trajectories are identical under these two scenarios, we were able to factor out the "population size effect" alone.

To decompose the change in energy demand, we calculated energy demand for a hypothetical scenario in which the proportion of the population in each education, energy access, and urbanization group in each time step is kept as in *SSP1_univ*, but the population size is as in *SSP1_EA*. This simulates a situation where energy access improves, but the effect of this improvement on population size is not considered. Figure 7 shows the results of this decomposition in both relative (panel a) and absolute (panel b) terms. The blue in the graph represents the composition-efficiency effect and the orange represents the population size effect.

We estimated that the "composition efficiency" effect due to expanded energy access contributes 26% of the reduction in energy demand between *SSP1_EA* and *SSP1_univ* in 2030, and 56% in 2050 (Figure 7). After 2060, this effect contributes 100% to the total change in energy demand. In other words, if the demographic feedback is not taken into account, the energy demand under *SSP1_univ* would be higher than under *SSP1_EA* from 2060 onwards (Figure 7, panel b). Thus, the orange area represents the estimated magnitude of the overestimation of energy demand when the demographic feedback from expanded access to modern energy is not considered.

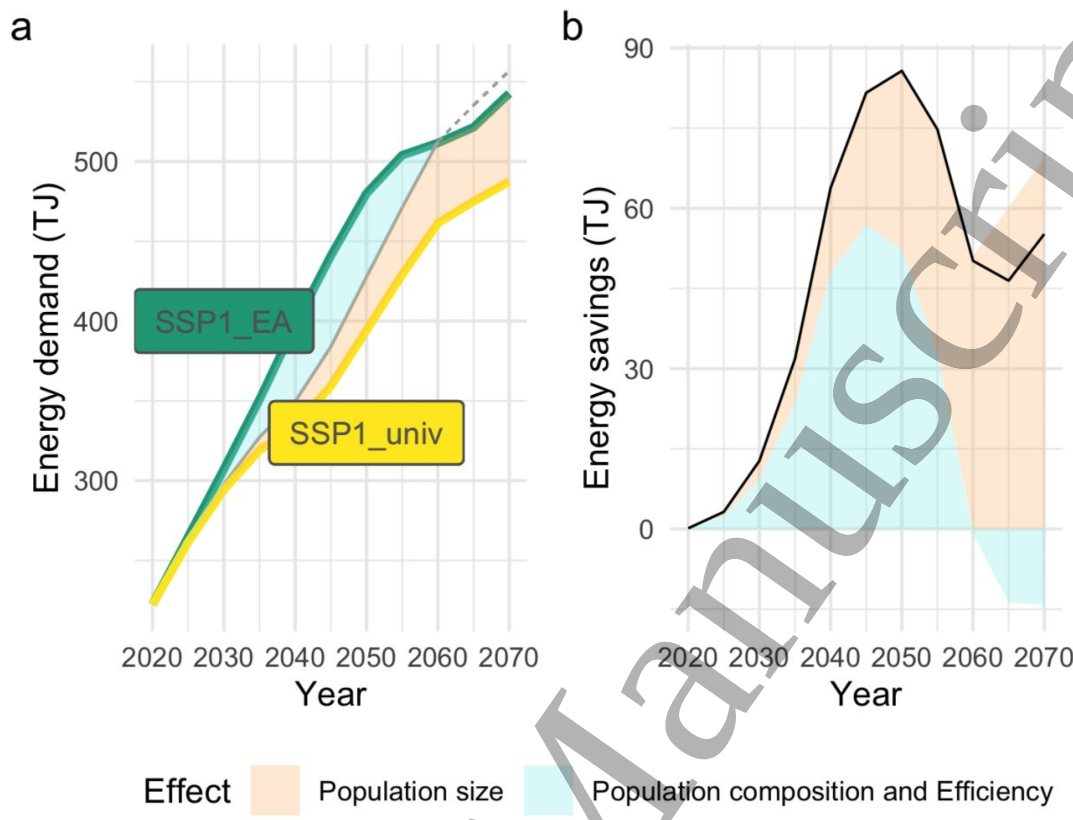

Figure 7: Decomposition of the difference in energy demand in absolute (a) and relative terms (b) between the SSP1_univ scenario (yellow) and the SSP1_EA scenario (green). The orange area corresponds to share of the difference in energy demand due to the population size effect (itself due to expanded energy access). The blue area represents the share of the energy demand difference that is due to the composition-efficiency effect.

4 Discussion and conclusions

Achieving universal access to modern energy is more urgent than ever. It is a necessary condition for improvements in well-being, health, education, gender equality and climate resilience, and recent studies have also shown its significant impact on reproductive health and fertility patterns.

In this article we presented a unique microsimulation demographic model that endogenizes the effect of access to modern energy on fertility decline and applied it to four energy transition scenarios for Zambia. The model is unique in that it includes the link between energy access and fertility decline in a demographic model that accounts for age, sex and education structure of the population. The scenarios used background assumptions from the SSP framework, as it is the most widely used framework in energy modeling. The energy pathways in the *SSP1_EA* and the *SSP2_EA* scenarios were taken from the SSP literature (Poblete-Cazenave et al. 2021). The energy pathways for the *SSP2_univ* and *SSP1_univ_elec* were created by us to demonstrate the demographic and energy use dividends that could be achieved if much more ambitious transition pathways towards modern energy were implemented.

In the *SSP2_EA* scenario, which we interpret as baseline scenario, the projected population of Zambia in 2070 is 54,6 million, however in our *SSP1_univ* and *SSP1_univ_elec* scenarios (which yield per definition the same population projection, see above) the population is 41.5 million, or 23% lower. The population size projected for Zambia in 2070 for the SSP2 scenario from the WIC is 47.1 million people, which is 13% higher than the population size we found in the *SSP1_univ* scenario (41.5 million).

Obviously, population projections are not directly comparable across models due to differences in model design, input data, and methodologies. Therefore, it is the difference in population outcomes between the three energy-population pathways presented here that clearly shows a substantial effect, especially in scenarios with rapid expansion of access to modern energy.

The main contribution of this study is that it quantifies the potential contribution of two modern energy related population effects, the composition effect and the size effect, on aggregate residential energy demand under scenarios of rapid achievement of universal access to modern energy. We have deliberately kept per capita residential energy demand for each demographic group constant in order to be able to clearly quantify these two effects. Thus, the aggregate energy projections should not be interpreted as energy demand projections for decent living in Zambia.

The energy results, presented here, estimate the energy-population dividend that can be expected from a rapid energy transition in Zambia. Household energy demand from all fuels would be 29% lower but electricity demand would be higher when the entire population of Zambia had access to modern energy compared to the baseline. If the entire population of Zambia were to switch to electricity only for household energy, energy demand would be 83% lower. Our study suggests that incorporating the energy-population dividend into all energy models that project energy demand or carbon emissions following the expansion of modern energy access would result in greater economic and political incentives to invest in modern energy access, for example in the frame of carbon credit schemes for clean cookstoves or international emission reductions targets (Supplementary Note 1).

Although not the focus of this paper, this translates into significant differences between the scenarios in terms of greenhouse gas emissions. For example, emissions in the *SSP1_univ* scenario are about halved in 2050 compared to the baseline (Supplementary Method 8, Supplementary Tables 3-6 and Supplementary Figure 2). If combined with climate policies that encourage the deployment of renewable energy, this could further reduce emissions (Dagnachew et al. 2018). This could also enable the decarbonization of sectors other than the residential sector, which are expected to grow as the population develops. For Zambia future research could use our results as benchmark to more realistically represent the complexity of the energy transition at the household level. This could include scenarios of increasing household energy use, variations in its energy mix and reliability, such as e.g. accounting for the quality of the electricity connection or better modeling how the cooking energy transition occurs.

The presented microsimulation demographic model could be applied to many other low-income countries because the energy-fertility nexus is almost universal in high-fertility countries (Belmin et al. 2022). The model could also be improved by endogenizing energy not only for fertility but also for mortality rates and by including modern energy use per capita as an explanatory variable. The latter was the basic idea of Sheffield (1998) who, however, did not develop a demographic model, but used historical correlations between aggregate data for total (i.e. including industrial) energy use per capita and population growth across world regions. Applying similar models to more countries with different energy access, socio-economic and demographic contexts could further strengthen our findings on the importance of the energy-population dividend.

Further efforts are needed to incorporate the relationship between access to energy services and decent living standards and population dynamics into energy models (Kikstra et al. 2021). Such models can reveal novel mitigation solutions that are simultaneously beneficial to achieving other SDGs, such as SDG 7 on energy access, SDG 3 on good health, 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 and development co-benefits of achieving this goal could help further encourage investments aimed at achieving reliable access to modern energy for all.

Data Availability

The DHS data used to produce the base population and the pooled dataset for the regression is publicly available and free of charge at: https://dhsprogram.com/, but access to the data requires a permission from the DHS Program. The WIC data is publicly available at: http://dataexplorer.wittgensteincentre.org/wcde-v2/. The raw energy data may be available upon request. The different data used to calculate greenhouse gas emissions are publicly available (see Supplementary Table 4 for all the data sources). All the available data is located on the companion git repository of this article: https://github.com/camillebelmin/achieving-universal-energy-access.

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Code Availability

The pre-processing and the analysis were carried out in R and Rmarkdown and are fully reproducible. All the code is available on the git repository of this article: https://github.com/camillebelmin/achieving-universal-energy-access.

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