Supplementary information

Achieving universal energy access while reducing energy demand? Evidence from energy-specific population projections

Camille Belmin[123] Peter-Paul Pichler[1] Guillaume Marois [34]
Shonali Pachauri[3] Helga Weisz[12]

Contents

[1] Potsdam Institute for Climate Impact Research, Germany
[2] Humboldt University Berlin, Germany
[3] International Institute for Applied Systems Analysis, Wittgenstein Centre (IIASA, OeAW, University of Vienna), Austria
[4] Asian Demographic Research Institute of the Shanghai University, China

1 Supplementary Methods

Supplementary Method 1: Calibration of the base population

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). Education level is a central variable in the model. However, the DHS data is not a survey specifically meant to create a sample representative of the education distribution in a country. Therefore, our calibration consists of re-weighting the DHS survey weights to ensure that the re-weighted age-education distribution in the base population matches that of the WIC dataset. This also allows avoiding any discontinuity between the education distribution of the base year population and the education distribution in the first time step in our projections. Unfortunately, we could not calibrate the population also in terms of energy access. While the DHS data allows for determining energy access by education, age, and urbanization for the sample, this could only be compared to national energy access indicators distinguishing between rural and urban regions but not the other demographic variables like age or education.

Supplementary Method 2: Fertility regression model

In the microsimulation model (MSM), 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. The dependent variable is whether the women gave birth in the last year.

The data used for the regression is a pool of four Individual Recode files from the DHS data for Zambia, for the years 2002, 2007, 2013 and 2018. This resulted in a sample consisting in 89796 women. Note that here, the resulting data is not a household panel dataset because in DHS data, not the same households are interviewed across waves. In the regression, we added a parameter corresponding to the year in which the data was collected, allowing us to account for the fact that fertility may follow a secular trend. We also added interaction terms between age group and (i) whether the household has access to electricity, and (ii) whether the primary fuel used for cooking by the household is modern. The results of the model are displayed in Table 1 and the logistic regression model takes the form:

$$\log\left[\frac{P(\text{birth}=1)}{1-P(\text{birth}=1)}\right] = \alpha + \sum_{i=1}^{6}\beta_i Agecat_i + \sum_{j=1}^{5}\gamma_j Educcat_j + \delta Urban + \theta Elec + \sum_{k=1}^{5}\theta_k Elec \times Agecat_k + \mu MCF + \sum_{l=1}^{5}\mu_l MCF \times Agecat_l + \eta Year + \epsilon \tag{1}$$

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 woman belonged at the time of the survey, $Educcat_{1..5}$ the education group to which the woman belongs, $Elec$, MCF and $Urban$ are dummy variables taking the value 1 if the woman has access to electricity, modern cooking fuels, or lives in an urban area, respectively, and $Year$ is the year of the survey. α is the coefficient for the reference category, which corresponds to age group 15-19, for those with no education, no access to electricity, no access to modern cooking fuel and living in rural areas.

Supplementary Method 3: Implementation of education pathways

The education projections are represented in the WIC data as proportions of the population being in a given education group: *No education*, *Incomplete primary education*, *Completed primary education*, *Lower secondary education*, *Upper secondary education*, *Post secondary education.* Our MSM also uses the same education categories. In order to use the WIC education projections as the education assumptions in our model, at each time step we reassigned an education category to each individual so that the education distribution of the simulated population matches the education distribution of the WIC projection (Supplementary Figure 3 and 4).

Supplementary Method 4: Adaptation of SSP scenarios for energy access to Zambia

The first two energy energy access trajectories, used in the scenarios *SSP1_EA* and *SSP2_EA* came from 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. These scenarios were developed for the entire region of sub-Saharan Africa, without any distinction at the individual country level. To apply these scenarios to Zambia, we considered the absolute percentage increase in access to electricity (respectively modern cooking fuels) between 2020 and 2030 in sub-Saharan Africa and applied this to the initial level of electricity (resp. modern cooking fuels) access in Zambia, that we determined from the DHS data of 2018. This way we obtained projected values of energy access for Zambia in 2040 and 2050. To obtain energy access values for 2060 and 2070, we assumed the absolute percentage increase between 2040 and 2050 is perpetuated.

Supplementary Method 5: Calculation of probability of transition for modern energy access

From the macro-level pathways for energy access derived adapted from SSP scenarios (see the sub-Section on *Energy access assumptions* in Section 2.2.3 in the main text), we then derived the probability for an individual to get access to electricity, and to get access to modern cooking fuels. Although, in reality, a household might use multiple cooking fuels at the same time or revert back to the use of 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 as follows:

$$p_e = \frac{elec_{t+5} - elec_t}{1 - elec_t}$$

with p_e 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 $1 - elec_t$ the proportion of the population not having access to electricity in time step t. A similar equation defines the probability of getting access to modern cooking fuels.

Supplementary Method 6: Displacement of traditional fuels by electricity in *SSP1_univ_elec*

To create the scenario for completely electrifying clean cooking *SSP1_univ_elec*, 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.

For example, if 10 GJ per capita of charcoal is the estimated energy consumption for a particular population group, and the conversion efficiency of an electric stove is 75% while that of a traditional firewood stove is 12%, we estimated that 10*12/75 = 1.6 GJ per capita of electricity is needed to replace the charcoal use. We sourced the conversion efficiencies from Dagnachew et al. (2020) (Table 1 in the original paper) and from the Global Energy Assessment (GEA 2012).

We assumed a linear rate of displacement of traditional fuels by electricity for the period from 2020 to 2040. In other words, we assumed that in 2020, 0% of traditional fuels are displaced, 25% is displaced in 2025, 50% in 2030, 75% in 2035 and 100% in 2040. After 2040, we assumed that households keep using only electricity for cooking.

Supplementary Method 7: Pre-processing of the energy data

We calculated estimates of average per capita energy consumption for cross-categories along education level, access to energy, and location (urban/rural), using the data output 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 to derive the energy footprint of all households surveyed. Since the household survey contains information about the education level, energy access, location of residence (urban or rural areas), we used this information to calculate the average energy consumption per capita, for households grouped along these variables.

We carried out two pre-processing steps to estimate the average energy consumption for each population group. First, we re-categorized the variables from the LCMS to match those used in the microsimulation model. The original LCMS contains two variables regarding cooking: the main type of energy used for cooking and the main device used for cooking. We first re-categorized these two variables into two categories - modern and traditional (see Supplementary Table 1 to see the full list of fuels and devices and the re-categorization). Then we assumed that a household uses modern cooking fuels if it uses either a modern fuel or a modern stove. In total, we created four population sub-groups of energy access by combining access to modern cooking fuel (or not) and access to electricity (or not). The second variable that we re-categorized is education. In the LCMS, the education categories are specific to Zambia, so we re-categorized them into *No education*, *Primary education*, *Junior secondary education*, *Senior secondary education* and *Post-secondary education* (see Supplementary Table 2 to see the full list of education levels and the re-categorization). In the data there was only one category for primary education. This is in contrast to the WIC data categorization which has two categories for this level. This resulted in five education groups.

In a second pre-processing step, we combined some categories to increase their sample size. Ideally, considering the distinct average per capita energy consumption for 40 sub-groups, corresponding to the combination of 5 education levels, 2 residence locations and 4 energy access groups would have allowed for capturing more of the population heterogeneity in energy consumption. Unfortunately, splitting the data along all 40 categories resulted in samples sizes that were at times too small and combinations that are not very common (e.g., having access to modern cooking fuels but no access to electricity in rural areas for those with post-secondary education) (Supplementary Figure 1). To ensure an adequate sample size, some categories were merged. The categories *No education* and *Primary education* were combined. Then we grouped together all cases corresponding having at the same time *No access to electricity* and *Access to modern cooking fuels* because these cases are very rare across urban and rural areas and across all education levels. This resulted in only one per capita energy consumption value for this category. The estimates of energy consumption per capita for each category considered are presented in Figure 3 in the main text.

Table 1: Categorization of the variables for the main energy type and the main type of stove used for cooking in the Living Condition Measurement Survey Zambia 2015 dataset.

Traditional energy	charcoal purchased, charcoal own produced, collected firewood, purchased firewood, kerosine/paraffin, crop/livestock residues, coal
Modern energy	electricity, gas, solar
Traditional stove	brazier (mbaula), brick/stone stand on open fire, clay stove (mbaula), crop/livestock residues, metal stand on open fire, vehicle tyre rim
Modern stove	stove/cooker, solar, electrictiy, gas, hot plate without stand

NB1: The category “Gas” did not include any differentiation in the input data.
[a] NB2: Although solar energy represents a very small amount of the sample, we did not exclude it from the data.

Table 2: Categorization of education levels in the LCMS dataset for Zambia 2015 into education levels relevant for the micro-simulation

Education level in the LCMS dataset for Zambia 2015	Education level in the microsimulation model
Grade 1, Grade 2, Grade 3, Grade 4, Grade 5, Grade 6, Grade 7	Primary
Grade 8, Grade 9	Junior secondary
Grade 10, Grade 11, Grade 12, 12 A Levels	Senior secondary
Degree, Certificate, Diploma, Masters Degree, Doctorate	Post secondary
NA	No education

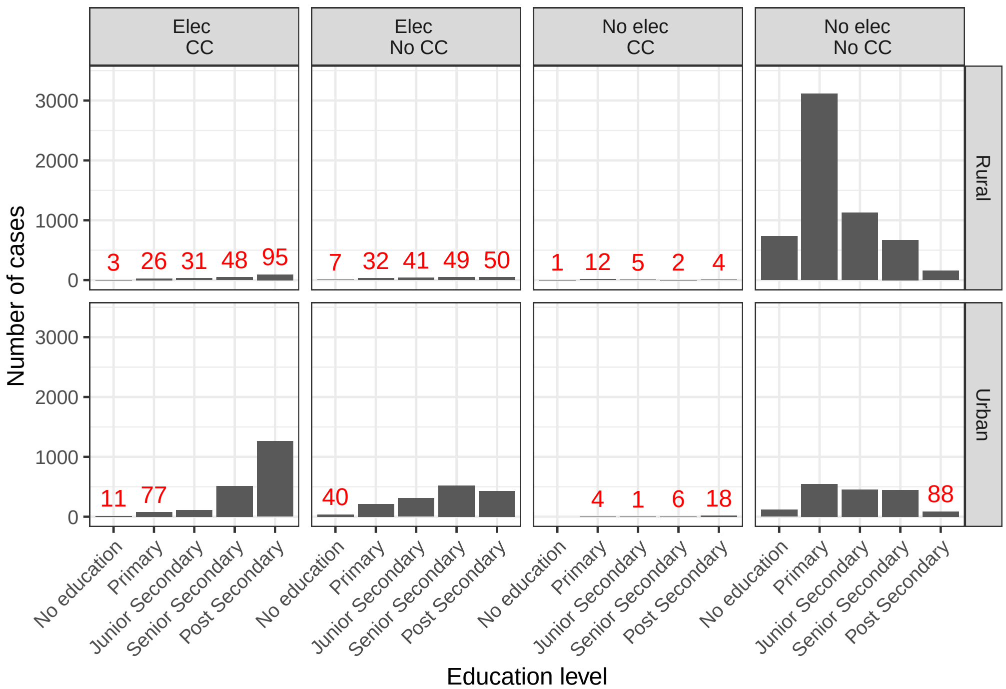

Figure 1: Number of cases in each sub-group of the LCMS dataset for Zambia 2015. The numbers in red show the number of cases for groups with less than 100 cases.

Supplementary Method 8: Calculation of greenhouse gases emissions

We converted household energy use into greenhouse gas emissions using data on emissions factors, fraction of renewable biomass, global warming potential as well as projection of electricity mix for the region sub-Saharan Africa. We here provide details on the calculations. We accounted for the following greenhouse gases: carbon dioxide (CO2), methane (CH4) and nitrous dioxide (N2O), carbon monoxide (CO), Non-Volatile HydroCarbons (NMHC), black carbon (BC) and organic Carbon (OC). The conversion of charcoal and firewood into emissions required to account for the share of non-renewable biomass (Bailis et al. 2015).

For emission factors, whenever possible we used the default emission factors for stationary combustion in the residential and agriculture/forestry/fishing categories from the 2006 IPCC guidelines for national greenhouse gas inventories (IPCC 2006) (see Supplementary Table 3 and 4). When not available, we used the 1996 IPCC guidelines (IPCC 1996), and two other studies from Freeman and Zerriffi (2014) and Zavala et al. (2017).

To convert non-CO2 greenhouse gases into CO2 equivalent, we used values of global warming potential to 100 years from Arias et al. (2021), Reynolds and Kandlikar (2008) and Shindell et al. (2009) (see Supplementary Table 6). To obtain the emission factor of electricity, we needed data on the current and future electricity mix of Zambia. We used data from IRENA (IEA et al. 2021) combined with projection of electricity mix for sub-Saharan Africa from Van Vuuren et al. (2021) to project the electricity mix of Zambia until 2070.

The formula to calculate the greenhouse gas emissions (in CO2e) GHG_i for each type of energy i writes:

$$GHG_i = e_i \times \sum_g cf_{g,i} * GWP_g$$

with:

- e_i, the energy use from energy source i, in GJ (NB: for firewood and charcoal, we only account for the share of energy that is considered non-renewable, see next paragraph),
- $cf_{g,i}$, the emission factor for greenhouse gas g, for energy source i, in kg/GJ,
- GWP_g, the Greenhouse gas Warming Potential to 100 years, for gas g.

Since firewood and charcoal are not a fossil fuels and can be considered as partly renewable, we only converted into greenhouse gas emissions the share of energy use from firewood that can be considered as non-renewable. To account for that, we multiply the energy use for firewood and charcoal by the fraction of non-renewable biomass f_{NRB} (see the two equations below). We took the value for f_{NRB} for Zambia (34%) from the study of Bailis et al. (2015) (see Supplementary Table 5).

$$e_{firewood} = e'_{firewood} \times f_{NRB}$$

with:

- $e_{firewood}$, the energy use from firewood considered non-renewable,
- $e'_{firewood}$, the total energy use from firewood,
- f_{NRB}, the fraction of non-renewable biomass.

For charcoal, we first convert charcoal energy use into the equivalent in firewood energy, by multiplying the total charcoal energy use by two factors. The first factor is 3.6, which is the quantity of firewood (in kg) necessary to produce one kg of charcoal, that we took from Bailis et al. (2015). The second factor is the ratio of calorific value between firewood and charcoal. The formula to obtain the non-renewable energy use from charcoal is the following:

$$e_{charcoal} = e'_{charcoal} \times 3.6 \times \frac{NCV_{firewood}}{NCV_{charcoal}} \times f_{NRB}$$

with:

- $e_{charcoal}$, the energy use from charcoal considered non-renewable,
- $e'_{charcoal}$, the total energy use from charcoal,
- f_{NRB}, the fraction of non-renewable biomass.

Emissions from electricity depend on the way electricity is generated, which depends from one country to the other. To calculate emissions from electricity, we adopted the following steps. First, we calculated the percentage of non-renewable energy in the electricity source mix of Zambia, using 2020 data from IRENA (IEA et al. 2021).

Second, we estimated how renewable energy will develop in the future in Zambia. Since projections specific to Zambia do not exist, we used data from Van Vuuren et al. (2021) to obtain the percentage change in renewable energy source in the electricity mix of sub-Saharan Africa, using the SSP2 projection. We then obtained a percentage of renewable energy in the electricity source mix for Zambia until 2070.

Third, we calculated the average CO2 factor for non-renewable sources of electricity. Finally, we calculated the average CO2 factor of electricity for every 5-year time step using the projected percentage of renewable in the electricity source mix, and the average CO2 factor for non-renewable sources of electricity, as follows:

$$ef_{elec,t} = p_{NRB_{elec,t}} \times \frac{\sum_s ef_{NRB_s}}{S}$$

with:

- $ef_{elec,t}$, the emission factor for electricity in Zambia for timestep t,
- $p_{NRB_{elec,t}}$, the percentage of non-renewable energy in the electricity source mix of Zambia at time step t and
- $\frac{\sum_s ef_{NRB_s}}{S}$, the average emission factor of non-renewable energy source for electricity production in Sub-Saharan Africa, across S sources.

Table 3: Emission factors in kg/GJ for different energy sources and greenhouse gases. Data sources: see Supplementary Table 4.

Fuel	**CO2**	**CH4**	**NO2**	**CO**	**NMHC**	**BC**	**OC**	**SO2**
Coal	97.5	0.300	0.0015	0.9985507	0.0772947	0.1487923	0.1135266	0.0072464
Firewood	112.0	0.300	0.0040	5.0000000	0.6000000	0.0705128	0.1378205	0.0173077
Charcoal	112.0	0.200	0.0010	7.0000000	0.1000000	0.0061017	0.0084746	0.0135593
Kerosene	71.9	0.010	0.0006	0.1289954	0.1152968	0.0006849	0.0009132	0.0006849
LPG	63.1	0.005	0.0001	0.0780127	0.1553911	0.0014799	0.0014799	0.0000000
Gas	56.1	0.005	0.0001	0.0500000	0.0500000	0.0014583	0.0014583	0.0000000
Diesel	74.1	0.010	0.0006	1.0000000	0.2000000	0.0200581	0.0288372	0.0069280
Paraffin	73.3	0.010	0.0006	0.1289954	0.1152968	0.0006849	0.0009950	0.0007463

Table 5: Data for fraction of Non-Renewable Biomass (fNRB), Wood equivalent and Net Calorific Values for different energy sources. Source: Bailis et al. 2015 for fNRB and wood equivalent, IPCC 2006 default, Table 1.2, for NCV.

Fuel	**fNRB**	**Wood equivalent**	**NCV (GJ/t)**
Coal	1.00	NA	20.7
Firewood	0.34	1.0	15.6
Charcoal	0.34	1.9	29.5
Kerosene	1.00	NA	43.8
LPG	1.00	NA	47.3
Gas	1.00	NA	48.0
Diesel	1.00	NA	43.0
Paraffin	1.00	NA	40.2

Table 6: Data for Global Warming Potential to 100 years, for different greenhouse gases, and their source

Gas	**GWP100**	**Source**
CO2	1.0	IPCC AR6
CH4	27.9	IPCC AR6
NO2	273.0	IPCC AR6
CO	2.2	IPCC AR5, Table 8.A.4
NMHC	3.4	IPCC AR4
BC	900.0	Reynolds and Kandlikar 2008
OC	-35.0	Reynolds and Kandlikar 2008
SO2	-30.0	Shindell et al. 2009

Table 4: Data sources for emission factors for different energy sources and greenhouse gases. For all values taken from Freeman and Zerriffi (2014) and Zavala et al. (2017), the values were divided by the corresponding Net Calorific Values found in Table 5. Values: see Supplementary Table 3.

Fuel	**CO2**	**CH4**	**NO2**	**CO**	**NMHC**	**BC**	**OC**	**SO2**
Coal	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
Firewood	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	IPCC 1996 default	IPCC 1996 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
Charcoal	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	IPCC 1996 default	IPCC 1996 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
Kerosene	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
LPG	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
Gas	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	IPCC 1996 default	IPCC 1996 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1
Diesel	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	IPCC 1996 default for road transportation	IPCC 1996 default for road transportation	Zavala et al. 2017, averaged on Table 2	Zavala et al. 2017, averaged on Table 2	Zavala et al. 2017, averaged on Table 2
Paraffin	IPCC 2006 default	IPCC 2006 default	IPCC 2006 default	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1	Freeman and Zerriffi 2014, Table S1

2 Supplementary results

Supplementary Figure 2: Greenhouse gas emissions

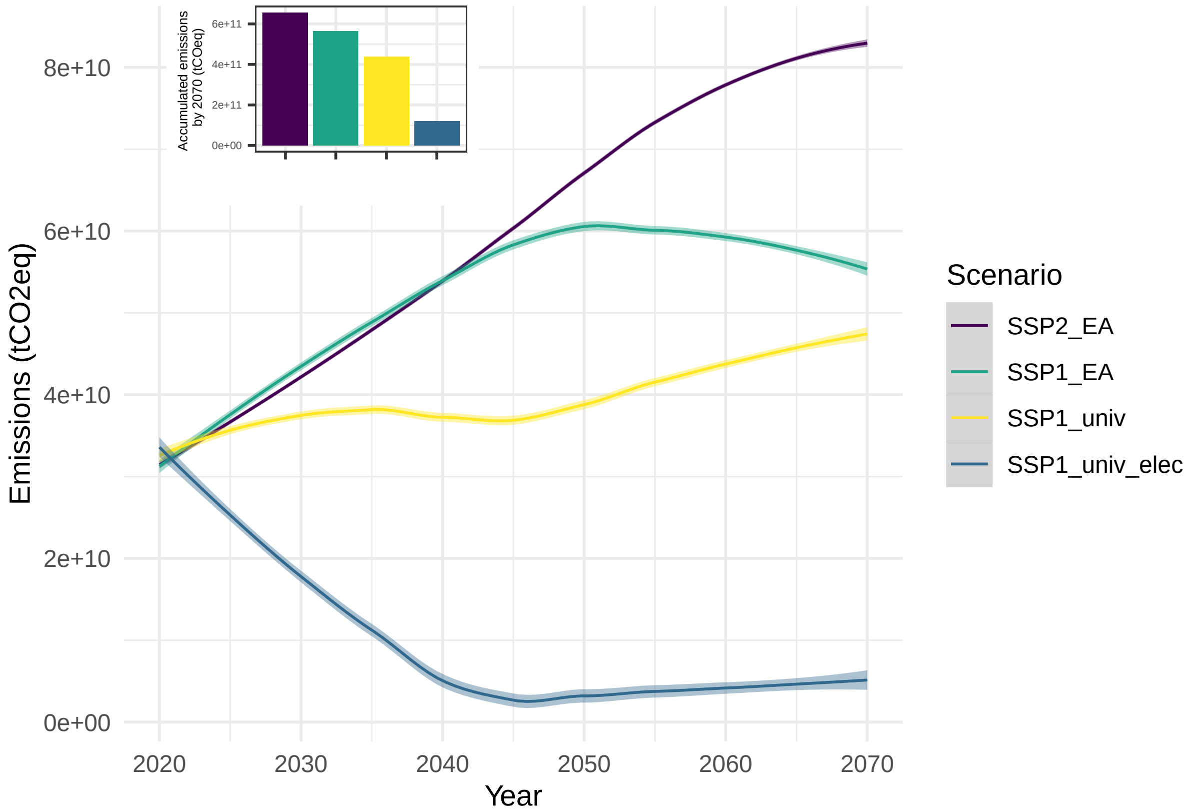

Figure 2: Emissions of the population under four scenarios. Inset: Cummulated emissions in 2070 under four scenarios.

3 Validation

Supplementary Figures 3 and 4: Validation of the education pathways

To validate the microsimulation model, we first verified that the population distribution by education category for the age groups affected by the education transition (from 15 to 30 years old) matched the input data (Figure 2 in the main text). We found that for both scenario SSP1 and SSP2, the model reproduces the educational and age distribution of the WIC projections for the population between 15 and 30 years old, for the entire period from 2020 to 2070 (Supplementary Figure 3 and 4, which shows only the period from 2030 to 2050 for clarity).

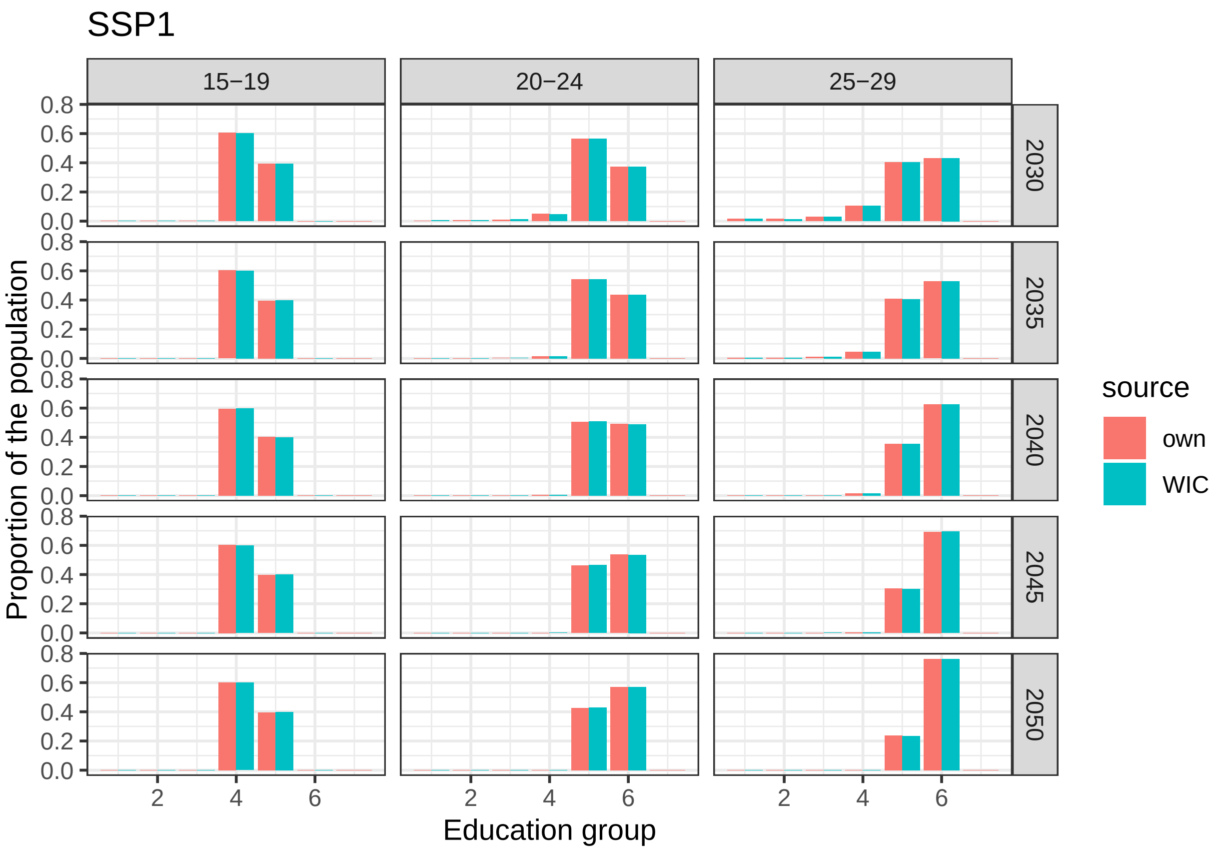

Figure 3: Proportion of the population in three age categories from 2030 to 2050 in the microsimulation, compared with WIC data, for SSP1 scenario.

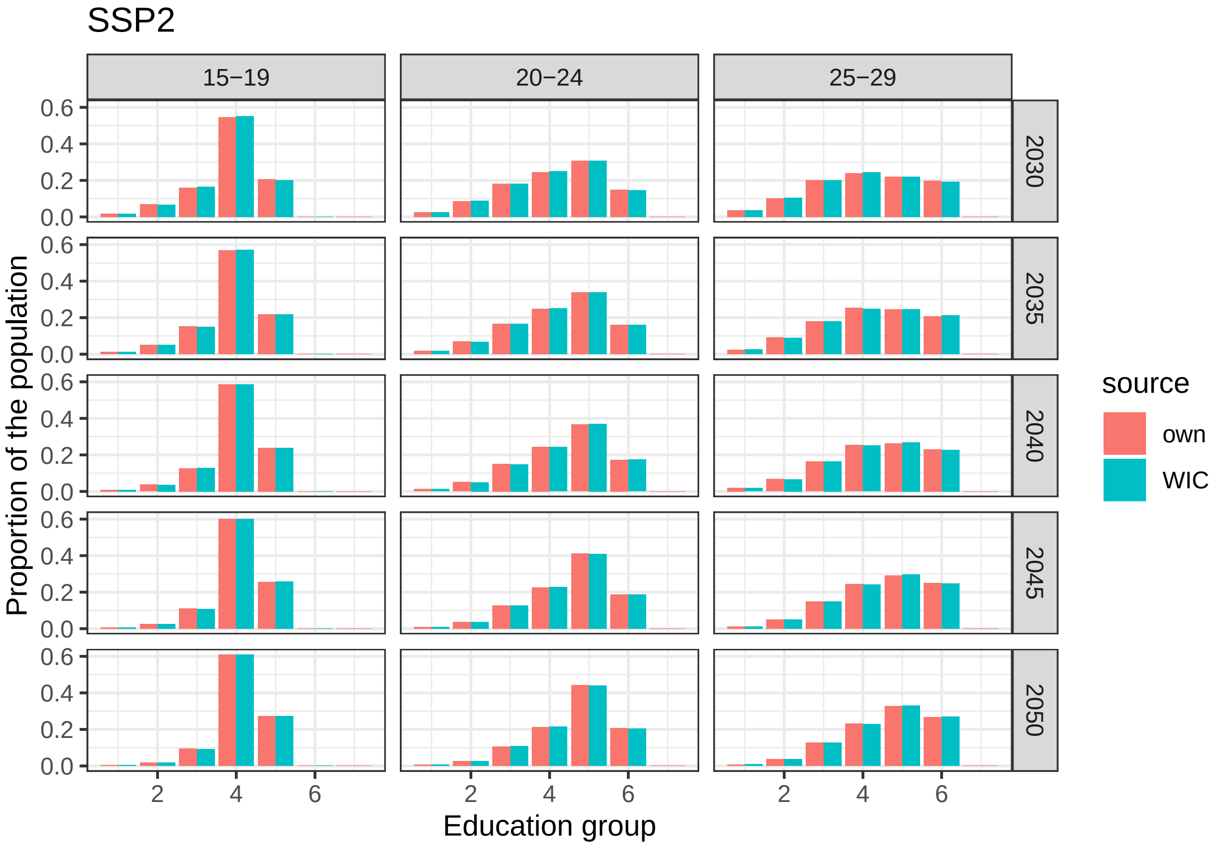

Figure 4: Proportion of the population in three age categories from 2030 to 2050 in the microsimulation, compared with WIC data, for SSP2 scenario.

Supplementary Figure 5: Validation of the microsimulation model

A second step to the validation of the model was to run a simulation of the microsimulation model in which we replaced the fertility module by the age-specific fertility rate projections from the WIC data. We then compared our population projections that we call *SSP1_EA_valid* and *SSP2_EA_valid* with the population projections for the SSP1 and SSP2 scenarios from WIC. We found that our model reproduced the trajectories derived from the WIC macro model (Supplementary Figure 5). However, there are small differences, especially for SSP1 after 2050. This may be because we did not include migration in our model while the projection from WIC do, or because of unavoidable differences in the implementation of the models, one being a micro-level model and the other a macro-level model. However, the similar trends validate the implementation of the microsimulation model.

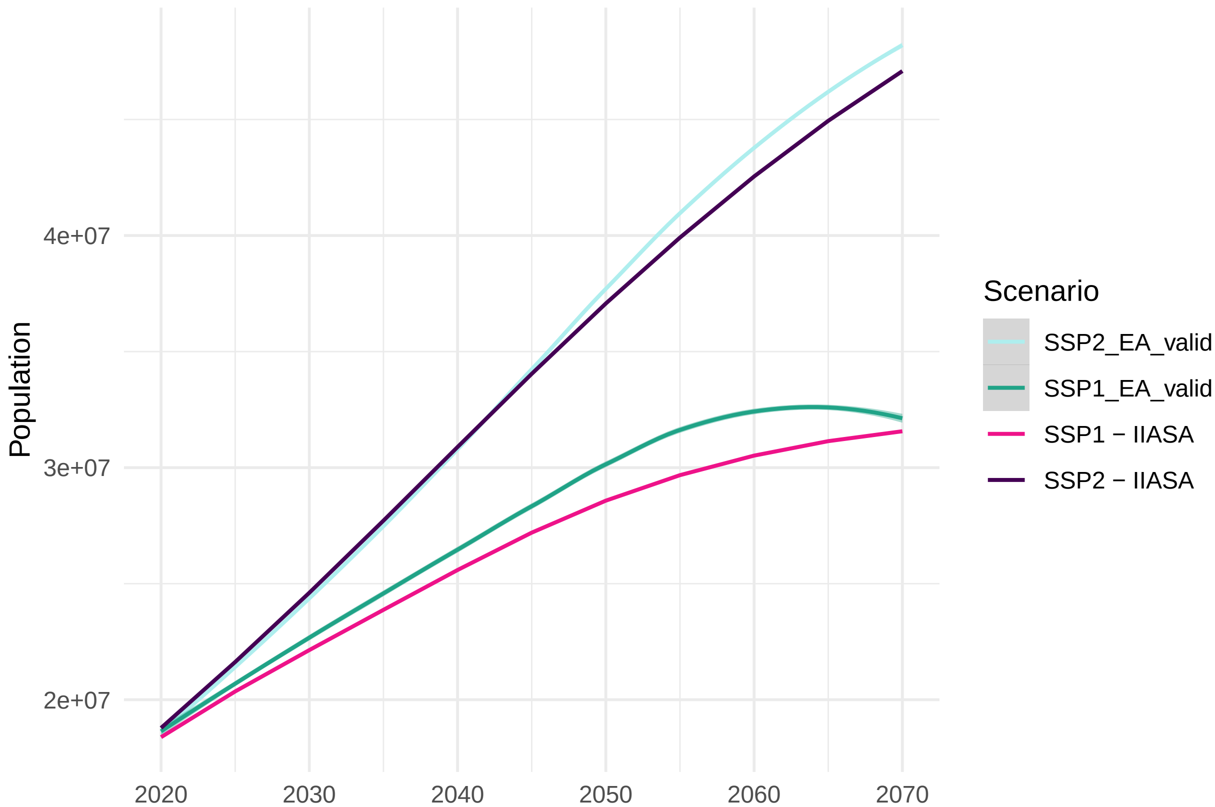

Figure 5: Population pathways from a simulation of the microsimulation model in which the fertility module was replaced by Age-Specific Fertility Rates projections from WIC data, compared with population pathways from the WIC data, for SSP1 and SSP2.

References

Arias, P., N. Bellouin, E. Coppola, R. Jones, G. Krinner, J. Marotzke, N. Vaishali, P. Matthew, G. K. Plattner, and R. Joeri. 2021. "IPCC Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change." Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, SL, Péan, C., Berger, S ….

Bailis, Robert, Rudi Drigo, Adrian Ghilardi, and Omar Masera. 2015. "The Carbon Footprint of Traditional Woodfuels." *Nature Climate Change* 5 (3): 266–72. https://doi.org/10.1038/nclimate2491.

Baltruszewicz, Marta, Julia K. Steinberger, Anne Owen, Lina I. Brand-Correa, and Jouni Paavola. 2021. "Final Energy Footprints in Zambia: Investigating Links Between Household Consumption, Collective Provision, and Well-Being." *Energy Research & Social Science* 73 (March): 101960. https://doi.org/10.1016/j.erss.2021.101960.

Central Statistical Office of Zambia. 2015. "World Bank, Zambia Living Conditions Monitoring Survey 2015. Retrieved from Http://Zambia.opendataforafrica. Org/Ssvcmrd."

Dagnachew, Anteneh G., Andries F. Hof, Paul L. Lucas, and Detlef P. van Vuuren. 2020. "Scenario Analysis for Promoting Clean Cooking in Sub-Saharan Africa: Costs and Benefits." *Energy* 192 (February): 116641. https://doi.org/10.1016/j.energy.2019.116641.

Freeman, Olivia E., and Hisham Zerriffi. 2014. "How You Count Carbon Matters: Implications of Differing Cookstove Carbon Credit Methodologies for Climate and Development Cobenefits." *Environmental Science & Technology* 48 (24): 14112–20. https://doi.org/10.1021/es503941u.

GEA. 2012. *Global Energy Assessment*. Cambridge University Press. https://ideas.repec.org/b/cup/cbooks/9780521182935.html.

IEA, IRENA, UNSD, World Bank, and WHO. 2021. "Tracking SDG 7: The Energy Progress Report (2021)." https://www.irena.org/publications/2021/Jun/Tracking-SDG-7-2021.

IPCC. 1996. "1996 IPCC Guidelines for National Greenhouse Gas Inventories." *Reference Manual* 3.

IPCC. 2006. "2006 IPCC Guidelines for National Greenhouse Gas Inventories." https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol2.html;

Lutz, Wolfgang, Anne Goujon, Samir KC, Marcin Stonawski, and Nikolaos Stilianakis. 2018. *Demographic and Human Capital Scenarios for the 21st Century: 2018 Assessment for 201 Countries*. IIASA.

Poblete-Cazenave, Miguel, Shonali Pachauri, Edward Byers, Alessio Mastrucci, and Bas van Ruijven. 2021. "Global Scenarios of Household Access to Modern Energy Services Under Climate Mitigation Policy." *Nature Energy* 6 (8): 824–33. https://doi.org/10.1038/s41560-021-00871-0.

Reynolds, Conor CO, and Milind Kandlikar. 2008. "Climate Impacts of Air Quality Policy: Switching to a Natural Gas-Fueled Public Transportation System in New Delhi." ACS Publications.

Shindell, Drew T., Greg Faluvegi, Dorothy M. Koch, Gavin A. Schmidt, Nadine Unger, and Susanne E. Bauer. 2009. "Improved Attribution of Climate Forcing to Emissions." *Science* 326 (5953): 716–18.

Van Vuuren, Detlef, Elke Stehfest, David Gernaat, Harmen-Sytze de Boer, Vassilis Daioglou, Jonathan Doelman, Oreane Edelenbosch, Mathijs Harmsen, Willem-Jan van Zeist, and Maarten van den Berg. 2021. "The 2021 SSP Scenarios of the IMAGE 3.2 Model."

Zavala, Miguel, Luisa T. Molina, Tara I. Yacovitch, Edward C. Fortner, Joseph R. Roscioli, Cody Floerchinger, Scott C. Herndon, et al. 2017. "Emission Factors of Black Carbon and Co-Pollutants from Diesel Vehicles in Mexico City." *Atmospheric Chemistry and Physics* 17 (24): 15293–305. https://doi.org/10.5194/acp-17-15293-2017.