Supplementary File: Title: Integrated geospatial modelling for the achievement of universal energy access in Kenya

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Key modelling assumptions

The following section presents the GIS-, socio-economic and techno economic data used in the modelling exercise.

Table S1. GIS data

Dataset	Description	Source used
Population density & distribution	Spatial identification and quantification of the current (base year) population. Sets the basis of the OnSSET analysis and directly connected to the electricity demand.	Global Human Settlement Layer[1,2]
Administrative boundaries	Delineates the boundaries of the analysis.	GADM[3]
Existing and planned MV network	Used to spatially identify currently electrified population, and act as a basis for extension to new settlements.	Energydata[4]
Distribution transformers	Used to spatially identify currently electrified population.	Energydata[5]
Primary substations	Used to assess grid extension suitability, the closer a settlement is to a substation, the easier it is to extend the grid to said settlement.	Energydata[6]
Roads	Used to assess grid extension suitability, the closer a settlement is to a road, the easier it is to extend the grid to said settlement.	OpenStreetMap[7]

Poverty	Poverty across Kenya. Used to derive disaggregated electricity demand in combination with GDP layer.	WorldPop[8]
GDP	GDP per capita (PPP), used in order to derive disaggregated electricity demand in combination with poverty layer.	DRYAD[9]
Elevation	Used to determine terrain slope. Both terrain slope and elevation are used to specify grid extension suitability.	SRTM[10]
Land cover	Classifies Kenya into 17 specific categories. Different categories imply different penalties on the grid extension	MODIS[11]
Night-time lights	Dataset used to identify and spatially calibrate the currently electrified/non-electrified population.	VIIRS[12]
Mini-grid locations	Used to estimate settlement with current electricity access with mini-grids	Energydata[13]
GHI	Provides information about the Global Horizontal Irradiation (kWh/m2/year). Used to identify the suitability of photovoltaic systems.	GlobalSolarAtlas[14]
Hydropower potential	Mini/small hydropower potential. Dataset developed by KTH-dES. Takes into account environmental, social and topological restrictions and provides power availability in each identified point.	Energydata[15]
Travel time	Visualizes spatially the travel time required to travel by motorized transport from any individual cell in Kenya to the closest town with a population of at least 50,000 people.	MalariaAtlasProject[16]
Urban – rural status	Map visualizing urban, rural and peri-urban settlements. Used to determine which settlements are urban and which are rural in the analysis. Areas that have coding of either 30, 23 or 22 are considered urban, while the rest are rural.	GHS-SMOD[1,2]
Walking friction	Time it takes to travel 1 m by foot. Used to determine the least-cost path for collection of manure and biomass. The least-cost path is in turn used to estimate fuel collection times for wood and biogas. For more information on this please refer to Khavari et al.[17]	MalariaAtlasProject[18]
Livestock	Head-counts of buffaloes, cattle, chickens, goats, pigs and sheep. Used to determine the availability of manure. Where manure is available, biogas is available as a stove option. For more information on this please refer to Khavari et al.[17]	Publication[19]
Forest cover	Used to determine the availability and collection time of wood.	Publication[20]
Relative wealth index	Used to determine the relative level of wealth in different settlements. This is in turn used to distribute the minimum wage spatially and estimate a value of time. For more	Publication[21]

	information on this please refer to Khavari et al.[17]	
Temperature	The average temperature in different regions. Used to estimate biogas conversion potentials.	GlobalSolarAtlas[14]

Table S2: Socio-economic data used in analysis

Parameter name	Description	Input
Country_name	Country name	Kenya
Country_code	ISO-2 code of the country	KE
Start_year	Start year of the analysis	2021
End_year	End year of the analysis	2028
Population_start_year	Population in the study area in the start year.	53,000,000[22]
Population_end_year	Population in the study area in the end year.	60,080,000[22]
Urban_start	Urban rate in the start year (1 represents 100%).	0.29[23]
Urban_end	Urban rate in the end year (1 represents 100%).	0.32[23]
Elec_rate	National electrification rate in the start year (1 represents 100%).	0.77[24]
rural_elec_rate	Rural electrification rate in the start year (1 represents 100%).	0.68[24]
urban_elec_rate	Urban electrification rate in the start year (1 represents 100%).	0.98[24]
Mort_COPD	Mortality rate of COPD in the study area	10.12 deaths per 100,000 people per year[25]
Mort_IHD	Mortality rate of IHD in the study area	27.31 deaths per 100,000 people per year[25]
Mort_LC	Mortality rate of LC in the study area	2.55 deaths per 100,000 people per year[25]
Mort_ALRI	Mortality rate of ALRI in the study area	42.81 deaths per 100,000 people per year[25]
Mort_STROKE	Mortality rate of stroke in the study area	10.85 deaths per 100,000 people per year[25]
Morb_COPD	Expected number of cases of COPD in the study area	972.75 cases per 100,000 people per year[25]
Morb_IHD	Expected number of cases of IHD in the study area	933.38 cases per 100,000 people per year[25]
Morb_LC	Expected number of cases of LC in the study area	2.4 cases per 100,000 people per year[25]
Morb_ALRI	Expected number of cases of ALRI in the study area	6,062.08 cases per 100,000 people per year[25]
Morb_STROKE	Expected number of cases of stroke in the study area	518.22 cases per 100,000 people per year[25]
Rural_HHsize	Household size in rural areas	5.8
Urban_HHsize	Household size in urban areas	4.8
Meals_per_day	Meals cooked per person and day	3

infra_weight	Importance of electricity infrastructure when calibrating electrified population. If the weights of this, NTL_weight and pop_weights are the same, equal importance is used.	2
NTL_weight	Importance of nighttime light intensity when calibrating electrified population. If the weights of this, pop_weight and infra_weights are the same, equal importance is used.	1
pop_weight	Importance of population density when calibrating electrified population. If the weights of this, NTL_weight and infra_weights are the same, equal importance is used.	1
Minimum_wage	Minimum wage in the study area	118.78 USD/month*
COI_ALRI	Cost of illness for ALRI	39 USD/case[26]
COI_COPD	Cost of illness for COPD	103 USD/case[26]
COI_LC	Cost of illness for LC	2,431 USD/case[26]
COI_IHD	Cost of illness for IHD	45 USD/case[26]
COI_STROKE	Cost of illness for stroke	3,970 USD/case[26]
VSL	Value of statistical life in the study area	203,671 USD/life**
Discount_rate	Discount rate	0.11*
Cost of carbon emissions	Cost of carbon emissions	51 USD/tonne CO_{2eq}
w_health	Weight of reduced morbidity and mortality in the net-benefit equation.	1
w_environment	Weight of reduced carbon emissions in the net-benefit equation.	1
w_social	Weight of time saved in the net-benefit equation.	1
w_costs	Weight of costs in the net-benefit equation.	1
w_spillovers	Weight of spillovers in the net-benefit equation.	1
Health_spillovers_parameter	The importance of health spillovers	1
fnrb	Fraction of non-renewable biomass harvested	0.611[27]

* Provided by Nuvoni Centre for Innovation Research
** Calculated based on Robinson et al.[28] and Ref. [29]

Table S3: Techno-economic data used

Parameter	Description	Unit	Stoves for which this is relevant for our study
name	The name of the technology.	-	All
inv_cost	The investment cost of	USD	All

	stove		
tech_life	Technical life of stove	Years	All
fuel_cost	Fuel cost	USD/kg (USD/kWh for electricity)	All
energy_content	Energy content of fuel	MJ/kg (MJ/kWh for electricity)	All
pm25	Daily average (24-hour) of particle matter emitted	24-h μg/m^3	All
efficiency	Efficiency of stove	Ratio (between 0 and 1)	All
time_of_collection	Time needed for fuel collection	Hours per day	All
time_of_cooking	Time needed for cooking	Hours per day	All
om_cost	Yearly operation and maintenance cost	USD/year	All
n2o_intesity	Nitrous oxide intensity of the stove in use	kg/GJ	All non-electrical options
ch4_intesity	Methane intensity of the stove in use	kg/GJ	All non-electrical options
bc_intesity	Black carbon intensity of the stove	kg/GJ	All non-electrical options
oc_intesity	Organic carbon intensity of the stove	kg/GJ	All non-electrical options
co2_intesity	Carbon dioxide intensity of the stove	kg/GJ	All non-electrical options
Grid capacity cost	Cost of adding capacity to the grid. Inlcuded in the net-benefit calculation of all stoves relying on electricity	USD/MW	All electrical options

Table S3: Stove shares across Kenya as collected by Nuvoni Centre for Innovation Research.

	Urban	Rural
Improved Charcoal Stove	12.52%	6.49%
Metallic charcoal stove	5.30%	3.94%
Three stone open fire	8.79%	66.11%
Improved firewood stoves	1.89%	8.09%
LPG stove	65.17%	14.4%
Kerosene stove	3.15%	0.57%
Hot Plate	0.00%	0.07%
Electric-Oven	0.14%	0.00%
Electric Hob	0.30%	0.00%
Electric coil stove	0.59%	0.00%
Biogas stove	0.42%	0.27%

OnStove prioritization

Urban prioritization

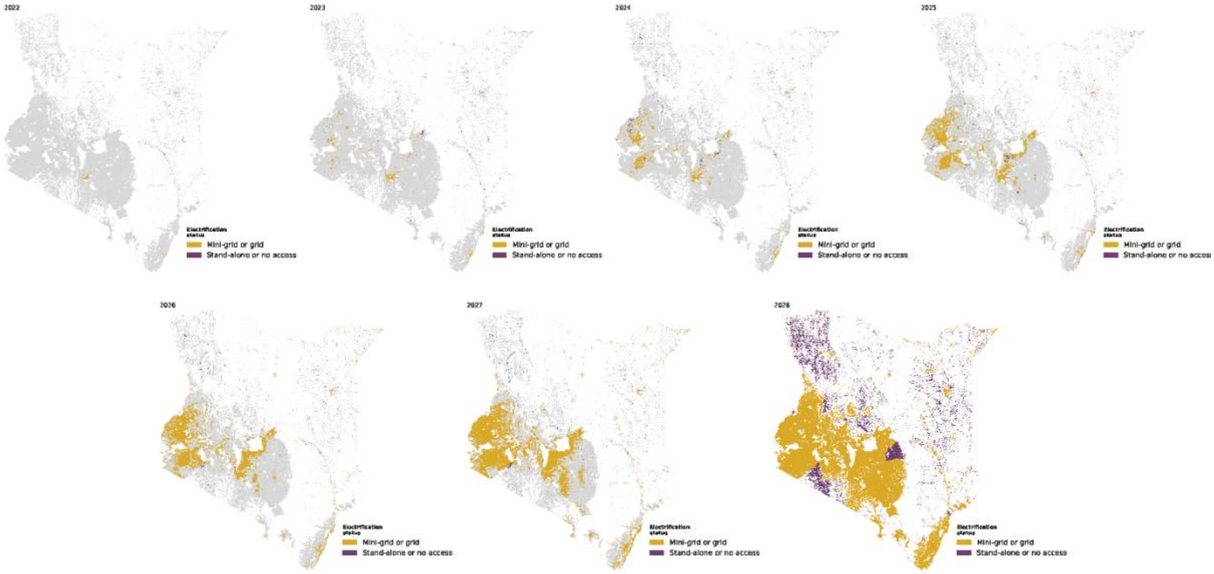

Figure S1. Order of clean cooking access across Kenya when using an urban prioritization. Yellow cells are candidates for electric cooking and purple ones are not. Note that only newly added cell from one year to the next are guaranteed to be assessed. The others are only assessed if the current stove which they use reaches the end of its lifetime.

Highest current costs first

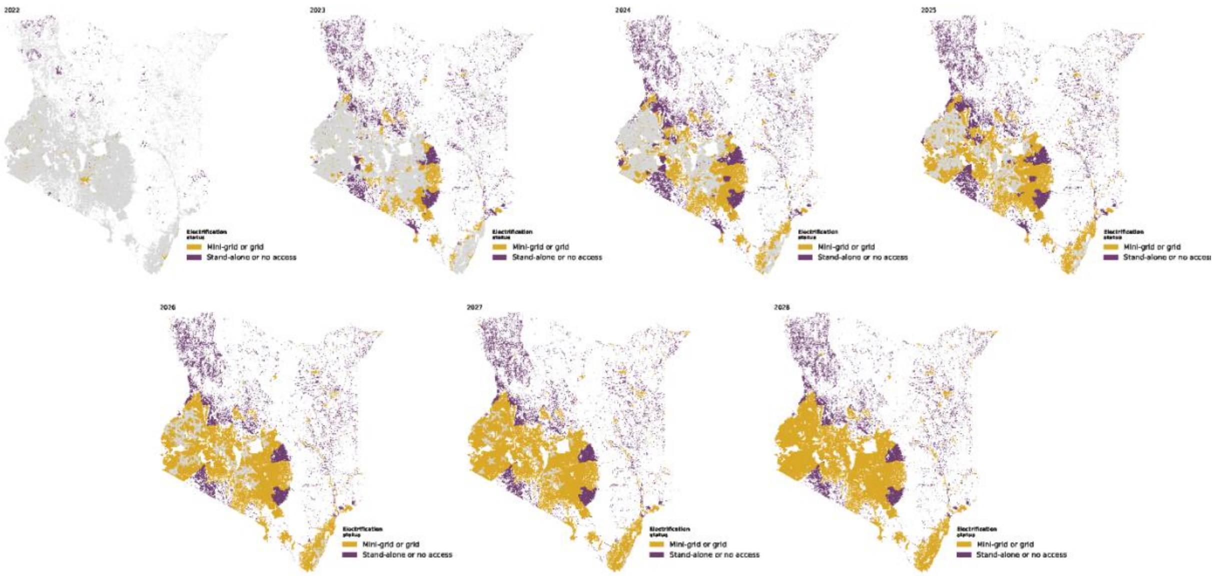

Figure S2. Order of clean cooking access across Kenya when prioritizing based on highest current costs. Yellow cells are candidates for electric cooking and purple ones are not. Note that only newly added cell from one year to the next are guaranteed to be assessed. The others are only assessed if the current stove which they use reaches the end of its lifetime.

Lowest current benefits first

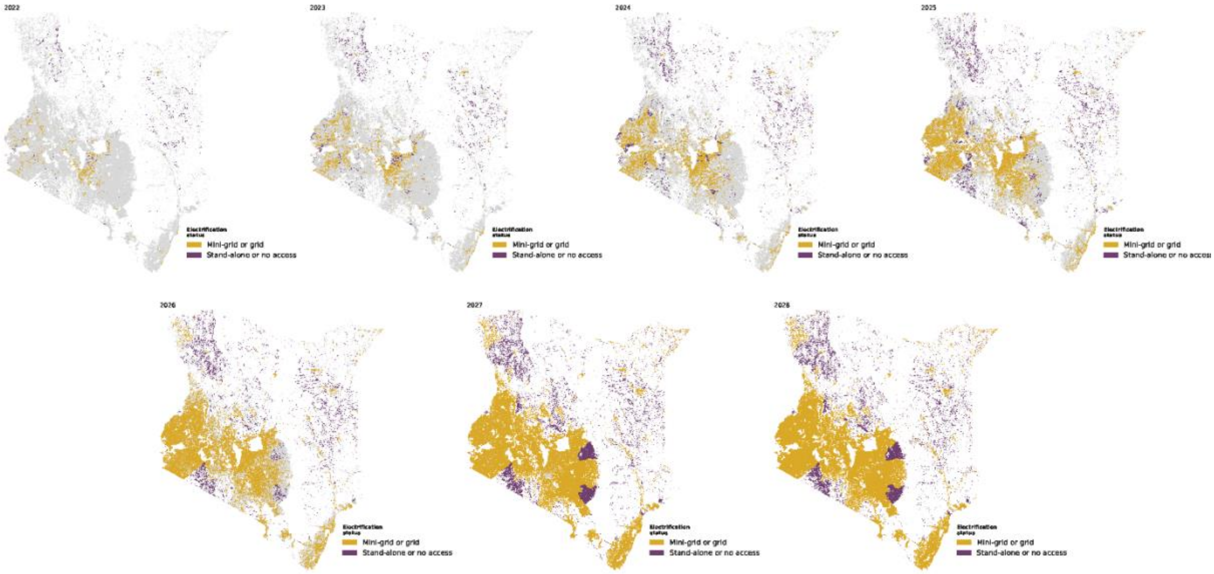

Figure S3. Order of clean cooking access across Kenya when prioritizing based on highest current drawbacks. Yellow cells are candidates for electric cooking and purple ones are not. Note that only newly added cell from one year to the next are guaranteed to be assessed. The others are only assessed if the current stove which they use reaches the end of its lifetime.

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