Spatio-Temporal Projection of Electricity Demand for Previously Un-Electrified Populations

1st Mai ElSayed
School of Energy Systems
LUT University
Lappeenranta, Finland
mai.elsayed@lut.fi

2nd Antti Pinomaa
School of Energy Systems
LUT University
Lappeenranta, Finland
antti.pinomaa@lut.fi

3rd Samuli Honkapuro
School of Energy Systems
LUT University
Lappeenranta, Finland
samuli.honkapuro@lut.fi

***Abstract*—Many countries in Sub-Saharan Africa face a two-fold challenge of achieving universal electricity access and transitioning to a climate-neutral energy sector. Electrification and energy transition modelling for such countries require a high spatio-temporal resolution to capture dispersed populations and enable the assessment of off-grid vs on-grid solutions. This study presents a novel method to disaggregate country-scale socioeconomic indicators and project them under various development scenarios. Based on these disaggregated projections, the residential electricity demand is estimated for all populated cells, including currently un-electrified ones. The resulting high-resolution geospatial datasets serve as a critical input to electrification and energy system modelling tools and can greatly enhance their accuracy compared to country-wide single-point static estimates. Namibia has been used here as an illustrative case study.**

***Index Terms*—Demand projection, Electricity access, Geospatial analysis, Sub-Saharan Africa, Transition pathways**

I. Introduction

One of the central United Nations' (UN) Sustainable Development Goals (SDG) is to reach universal electricity access by 2030 [1]. Globally, over 90% of people have at least basic access to electricity as of 2022 [2]. However, electricity access rates are highly disproportionate across the globe, with almost half of the population in Sub-Saharan Africa (SSA) still lacking basic electricity access [2].

Low electricity access rates in SSA mean that these countries face a two-fold challenge when it comes to the energy transition toward climate neutrality. The first fold is expanding their current power generation and transmission capacities to electrify the entire population, and the second is increasing the share of electricity generated from renewable sources. Since significant capacity expansions are still underway, such countries also stand to benefit from the unique opportunity of leapfrogging fossil-based electricity generation into a renewable-based one [3]. Thus, avoiding the high levels of greenhouse gas (GHG) emissions that current advanced economies produced as part of their socioeconomic development.

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A first and essential step when embarking on the energy transition is the formulation of long-term low-emission development strategies (LT-LEDS) as recommended in the Paris Agreement [4]. To this end, scenario-based energy system models (ESM) are typically used to support policymakers in the design of LT-LEDS related to the energy sector [5]. However, these models often lack the spatial resolution required to capture the challenge of electrifying dispersed populations for the first time. Moreover, most ESMs only include centralised on-grid solutions and do not integrate off-grid ones [6]. Geospatial-based models have been developed to overcome these shortcomings. Earlier attempts focused only on grid extension planning by exploring which population clusters would benefit more from off-grid solutions depending on parameters such as the cluster size and its distance from the grid. A recent study attempted more comprehensive energy transition modelling via soft-linking a geospatial-based electrification planning tool to an ESM [7].

One fundamental input to any ESM is the demand level for different energy carriers, such as electricity. Yet, quantifying and projecting electricity demand remains challenging, especially for previously un-electrified populations. The use of geospatial-based models also introduces an additional challenge. The high spatial resolution used by such models requires that all input data need to be highly resolved as well. So far, electrification planning studies have used static electricity demand estimates for previously un-electrified populations [8]. Some studies use a single estimate for all un-electrified population clusters within a country that stays constant over the modelled transition period, as in [9]. Other studies vary the demand only temporally according to a certain growth rate, as in [10], while others vary it only spatially according to socioeconomic parameters, as in [11]. Furthermore, most of these studies consider only one scenario making them unequipped to tackle the inherent uncertainty in long-term energy planning [8].

Hence, the main goal of this study is to develop a methodology for estimating and projecting electricity demand with high spatio-temporal resolution under various development pathway scenarios. The methodology is tailored for countries with low electricity access rates. The results would enable dynamic geospatial-based modelling of the energy transition in SSA under deep uncertainty. The following sections outline the methodology and the results based on an illustrative case study of Namibia. The implications and limitations of the results are then discussed and the study is finally concluded.

II. Methodologies

This section outlines the general methodology developed to estimate residential electricity demand with a high spatio-temporal resolution under each of the five Shared Socio-economic Pathways (SSP) [12]. All data processing and visualisation for this study have been done using Python to ensure that the methodology is available open-source and open-access (see section V). This methodology can be applied to any region with a dispersed population and a low electricity access rate. In this study, Namibia is used as an illustrative case study for other SSA countries with similar characteristics.

A. Data sources

Five main data sources are used in this study. The first is the population count dataset [13] from the Global Human Settlement Layer developed by the European Commission Joint Research Centre. This is a spatial raster dataset with global coverage spanning the period between 1975 to 2020 in five-year intervals.

The second data source is the global gridded datasets developed by Kummu et al. [14]. These include datasets for total Gross Domestic Product (GDP), GDP per capita, and Human Development Index spanning the period 1990 to 2015 in two different spatial resolutions. The first and second data sources are used for base year calculations, such as population and income level distribution within the study region. The base year used in this study is 2015 as it is the latest year for which both high-resolution sub-national population counts and GDP data are available.

The third data source is the nighttime lights datasets developed by the Earth Observation Group [15]. These include global monthly and annual composites of nighttime lights in 15 arc-second resolution. Nighttime lights are used in this study to determine which populated cells are currently un-electrified.

The fourth data source is the SSP narratives and database developed by IIASA and other contributing modelling teams [17]. The SSPs are potential narratives for how basic socio-economic drivers and their corresponding climate change adaptation and mitigation challenges may develop globally. The SSP database includes annual historical values from 1950 to 2020 as well as projections until 2100 for population, GDP, and education indicators. The highest spatial resolution currently available for these indicators is on a country scale. For the purposes of this study, total population and total GDP projections for Namibia under the five SSPs have been used as the basic socio-economic drivers behind the evolution of electricity demand. Details about the specific datasets used in this study can be found in Table I.

The fifth data source is the energy access Multi-Tier Framework (MTF) developed by the Energy Sector Management Assistance Program of the World Bank [18]. The goal of this framework is to define energy access beyond binary terms. The MTF household electricity access tiers are used in this study to classify the estimated residential electricity demand according to the annual consumption level. Other corresponding aspects to each tier, e.g. power rating, availability and electricity services, can then be used for further analysis beyond the scope of this study.

TABLE I: Input datasets details.

Dataset	Description	Source
Sub-national population count	*Type*: geospatial raster *Spatial extent*: global *Spatial resolution*: 30 arc-sec *Temporal resolution*: 5-year interval for 1975-2030 *Selected year*: 2015 *Unit*: population per grid cell	Global Human Settlement Layer [13]
Sub-national total GDP (PPP)	*Type*: geospatial raster *Spatial extent*: global *Spatial resolution*: 30 arc-sec *Temporal resolution*: annual for 1990, 2000 & 2015 *Selected year*: 2015 *Unit*: constant 2011 international USD	Kummu et al. [14]
Sub-national nighttime lights	*Type*: geospatial raster *Spatial extent*: global *Spatial resolution*: 15 arc-sec *Temporal resolution*: annual for 2012-2023 *Selected year*: 2022 *Version*: VIIRS annual masked average *Unit*: nW/cm$^2/sr$	Earth Observation Group [15], [16]
National population count projections	*Type*: tabular data *Spatial extent*: global *Spatial resolution*: national *Temporal resolution*: annual for 2020-2100 *Selected years*: 5-year interval for 2025-2050 *Model*: IIASA-WiC POP 2023 *Scenarios*: SSP 1-5 *Unit*: million	SSP Scenario Explorer [19], [21]
National total GDP (PPP) projections	*Type*: tabular data *Spatial extent*: global *Spatial resolution*: national *Temporal resolution*: annual for 2025-2100 *Selected years*: 5-year interval for 2025-2050 *Model*: IIASA GDP 2023 *Scenarios*: SSP 1-5 *Unit*: billion constant 2017 international USD	SSP Scenario Explorer [20], [21]

B. Base year calculations

First, the global high-resolution population count [13], total GDP [14], and nighttime lights [16] raster datasets are clipped to the geographical extent of the study region, Namibia. Next, the total GDP and nighttime lights rasters are each aligned to the population count raster using affine transformation to ensure all rasters have consistent grids. Then, the population count raster is vectorised and stored as a GeoDataFrame (GDF) [22] to facilitate further calculations.

The location of currently un-electrified population clusters is determined using the nighttime lights raster. The raster is first sampled to obtain the nighttime light intensity observed for each populated cell. Then, the minimum threshold for light intensity is calibrated such that the resulting electricity access rate corresponds to the latest official figures reported by the World Bank [23]. Each populated cell is then classified as electrified or not based on this calibrated threshold.

Calculating the GDP per capita, hereafter referred to as income level, for each populated cell involves several steps. First, total GDP values are obtained from the total GDP raster and stored in the main GDF using raster sampling. However, total GDP values are not available for all populated cells. To mitigate this problem, the main GDF is split into four subsets based on GDP data availability and electrification status. For electrified and un-electrified subsets with available GDP data, the income level is calculated by dividing the total GDP of each cell i by its population count, as in (1):

$$INC_i = GDP_i / POP_i \tag{1}$$

For the other two subsets, the income level of each cell is estimated using a nearest-neighbour search. In other words, each populated cell with unavailable GDP data takes on the same income level as its nearest neighbour from the corresponding subset based on electrification status. Now that all populated cells have either a computed or an estimated income level, all subsets are recombined into one main GDF.

The goal of this stage is not to obtain the absolute population count and income level of each populated cell. Rather, it is to obtain the relative distribution of these socio-economic parameters across the study region, i.e. Namibia. To this end, all values are normalised. For the population count, the value of each cell is normalised to the sum of all cells, see (2). For the income level, the value of each cell is normalised to the weighted (by population) average of all cells, see (3).

$$nPOP_i = \frac{POP_i}{\sum_{i=0}^{n} POP_i} \tag{2}$$

$$nINC_i = INC_i / \frac{\sum_{i=0}^{n} INC_i \cdot POP_i}{\sum_{i=0}^{n} POP_i} \tag{3}$$

C. Socio-economic indicators projection

The SSP Scenario Explorer [21] is used to retrieve population and GDP developments under each of the SSP narratives. In this study, the time horizon considered is 2025 to 2050 in 5-year intervals. However, annual data until 2100 are available from the SSP Scenario Explorer and can be used to extend and/or enhance the temporal resolution of the results. Based on the population and total GDP projections for Namibia, the national average income level is calculated for each SSP and year.

Since population and income level projections are only available as single-point values for the whole country, they need to be disaggregated on a cell-by-cell basis. Hence, the normalised population and income level values calculated in section II-B are used in combination with the projected total

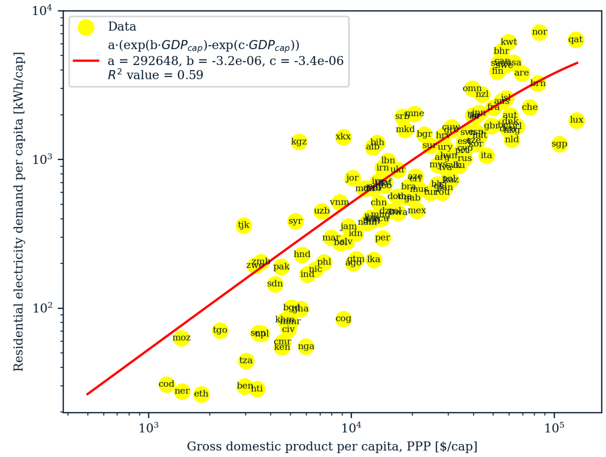

Fig. 1: Residential electricity demand per capita as a function of income level.

population ($totPOP$) and average income level ($avgINC$) of the whole country. To calculate the population count of cell i for year j and SSP narrative n, the following equation is used:

$$POP_{i,j,n} = nPOP_i \cdot totPOP_{j,n} \tag{4}$$

Similarly, the income level of cell i for year j and SSP narrative n is calculated as follows:

$$INC_{i,j,n} = nINC_i \cdot avgINC_{j,n} \tag{5}$$

At this stage, population count and income level data are available for each SSP narrative, year, and cell with a 30 arc-sec spatial resolution. Raster maps of the study region are then generated for each indicator, year, and SSP narrative.

D. Electricity demand estimation

Estimating the electricity demand of each populated cell involves several steps. First, some statistics are gathered for the base year for all countries. The World Bank's DataBank [23] is used to retrieve GDP per capita and electricity consumption per capita across all sectors. The IEA's Energy Statistics Data Browser [24] is used to obtain the fraction of electricity consumed by the residential sector. The correlation between income level and residential electricity demand is then derived using a two-term exponential function (see Fig. 1), similar to the method in [25]. Based on this correlation, the residential electricity demand per capita ($avgRED$) for each populated cell i in year j under SSP narrative n can be estimated using:

$$avgRED_{i,j,n} = a \cdot (e^{b \cdot INC_{i,j,n}} - e^{c \cdot INC_{i,j,n}}) \tag{6}$$

where $a = 292648$, $b = -3.2 \cdot 10^{-6}$, and $c = -3.4 \cdot 10^{-6}$.

The values obtained from (6) are capped to country-specific minimum and maximum thresholds based on the MTF. The MTF assumes a household size of 5 people for each tier's minimum electricity demand level. This is adjusted to the average household size of the study region as retrieved from the United Nation's Population Division household statistics [26], which is 4.2 people per household in Namibia. This adjustment results in a minimum ranging from 1.1 kWh/cap/a

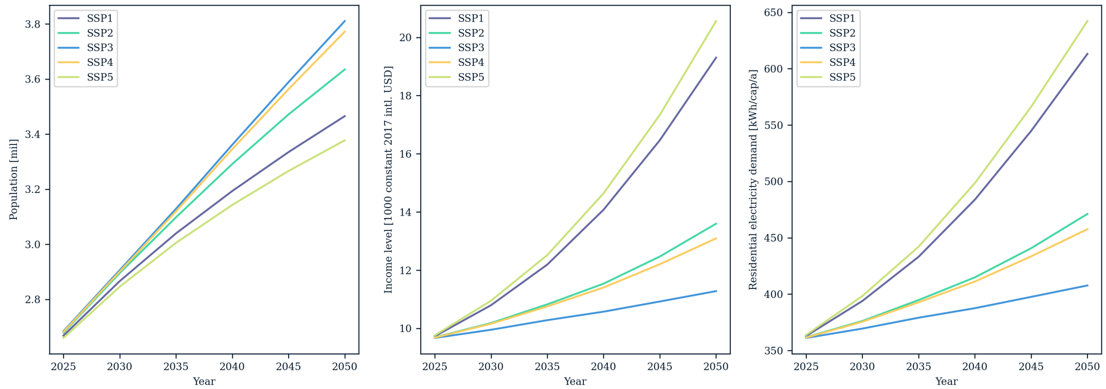

Fig. 2: Development of Namibia's population size (left), average income level (middle), and average residential electricity demand (right) across all scenarios.

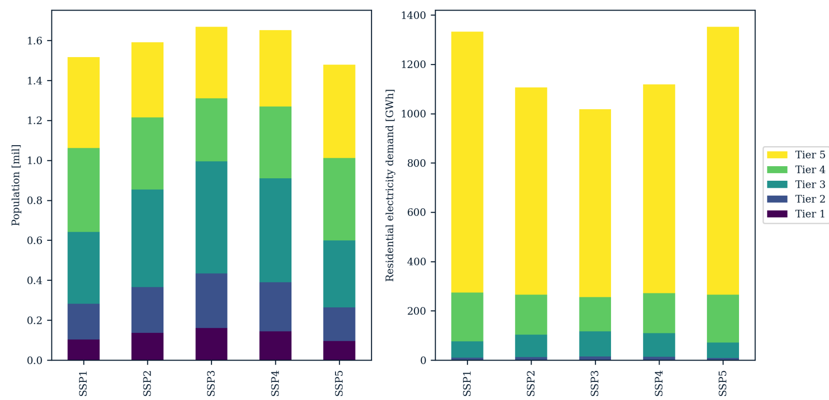

Fig. 3: Breakdown of 2050 population size (left) and projected residential electricity demand (right) by electricity access tier across all scenarios. Values are for currently un-electrified clusters only, not the whole country.

for Tier 1 to 714 kWh/cap/a for Tier 5. To reach universal electricity access, it is assumed that any populated cell should have at least the minimum demand level corresponding to Tier 1. The total electricity demand for cell i in year j under SSP narrative n is calculated as follows:

$$totRED_{i,j,n} = avgRED_{i,j,n} \cdot POP_{i,j,n} \tag{7}$$

Finally, the average residential electricity demand of each cell is classified according to the aforementioned adjusted MTF tiers. Raster maps of average demand, total demand, and MTF tiers can then be generated for each year and SSP narrative.

III. RESULTS

First, it is important to mention the basic characteristics of the SSP narratives to be able to contextualise the results. SSP1 (Sustainability) is characterised by economic growth coupled with reduced reliance on fossil resources, high levels of education resulting in lower fertility rates, and high levels of international cooperation. SSP2 (Middle of the Road) assumes a continuation of current trends and moderate progress in global income convergence. SSP3 (Regional Rivalry) has significantly slower economic growth along with continued reliance on fossil resources, low education levels coupled with higher fertility rates, and low international cooperation levels. SSP4 (Inequality) exhibits a divergence in socio-economic and technological trends between high-income countries and their low-income counterparts. For a medium-income country like Namibia, this means similar but slightly better development trends to those of SSP3 across the different socio-economic indicators. SSP5 (Fossil-fuelled development) has similar socio-economic development trends to SSP1, except that fossil resources fuel this development with complete disregard for environmental impacts.

In Namibia, the population continues to grow across all scenarios but at different rates (see Fig. 2). SSPs 3 & 4 have the highest growth rate, with population reaching 3.81 million people by 2050 under SSP3. On the contrary, SSPs 1 & 5 show a slowing growth rate, with population reaching only 3.38 million people by 2050 under SSP5. Total GDP development exhibits a reverse pattern, where SSPs 1 & 5 show exponential growth while SSP3 has a modest almost linear growth.

The combination of relatively small population size and relatively high total GDP in SSPs 1 & 5 results in rapidly increasing income levels, surpassing 20,000 USD/cap by 2050 under SSP5. In contrast, the average income level under SSP3 only grows to around 11,300 USD/cap by 2050. SSPs 2 & 4 reach higher income levels than SSP3 by 2050, but still fall significantly behind SSPs 1 & 5 (see Fig. 2).

Since the residential electricity demand per capita has been calculated based on income level, it mimics the same developmental trend as that of income levels across different

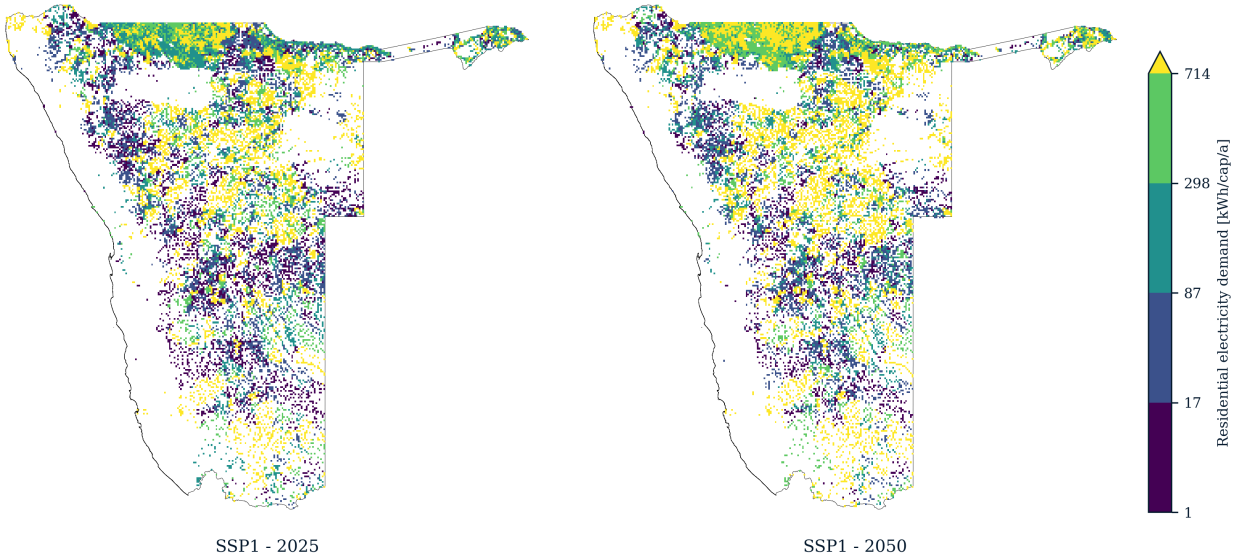

Fig. 4: Spatial distribution of estimated residential electricity demand under SSP1 in 2025 (left) and 2050 (right). Only currently un-electrified clusters are shown here. The spatial resolution has been downsampled by a factor of 5 to enhance visibility.

SSPs. In 2025, it is estimated that the average demand level is 362 kWh/cap/year. By 2050, SSP3 results in only a 13% increase in the demand level while SSP5 results in over 77% increase (see Fig. 2).

Besides the differences in the average level of residential electricity demand, the SSPs also differ in the distribution of electricity access tiers among the population. For currently un-electrified population clusters, as much as 60% of the population would still belong to lower electricity access tiers (1-3) by 2050 under SSP3. In contrast, only 40% would belong to Tiers 1-3 under SSP5 (see Fig. 3). SSP1 shows a similar distribution to that of SSP5. SSPs 2 & 4 lie somewhere in the middle, yet lean more towards the distribution under SSP3.

Despite 40-60% of the population belonging to Tiers 1-3 across the SSPs, the significantly lower annual demand levels of these tiers result in a relatively small contribution to the projected residential electricity demand of currently un-electrified clusters by 2050. Conversely, the high annual demand level corresponding to Tier 5 means that it dominates the total demand across all scenarios (see Fig. 3). Overall, SSPs with higher population shares belonging to Tier 5 have higher residential electricity demand. For example, SSP 5 results in a total demand of 1.35 TWh while SSP 3 results in a 25% lower demand by 2050. In Namibia's case, the influence of a higher income level on electricity demand outweighs that of a lower population size.

The spatial distribution of residential electricity demand levels depends on the distribution of income levels across the country. If all population clusters were electrified, the aggregate demand level of most administrative regions in 2025 would correspond to Tier 4. By 2050, the demand in most regions under SSPs 1 & 5 grows to Tier 5. On the contrary, most regions remain in Tier 4 under SSP 3 throughout the modelled transition period. Fig. 4 shows an example of the spatial distribution of estimated residential electricity demand under SSP 1 in 2025 and 2050.

IV. Discussion & Conclusions

This research presents a first attempt at enhancing the resolution of electricity demand estimates and projections. High-resolution datasets are particularly important for electrification and energy transition planning in countries with low electricity access rates. Existing studies for such countries often use single-point estimates for the entire country or spatially-differentiated but temporally-static estimates. These studies seldom account for different development scenarios as well.

The method developed here delivers highly-resolved geospatial raster maps for vital socioeconomic indicators, such as population count, total GDP, and income level. Based on these disaggregated socio-economic indicators, per capita and total residential electricity demand levels can be estimated. The spatial resolution achieved is 30 arc-seconds ($\sim$1km). This resolution can be downsampled to accommodate different user preferences and modelling resources. The temporal resolution used in this study is based on 5-year intervals up to a specified target year, i.e. 2050. This can be further enhanced to an annual level and extended to 2100 if needed. Finally, this method allows for modelling different scenarios. The SSP narratives have been used in this study as an example, but any other scenario can be easily accommodated. While this method was developed with developing countries in mind, it can be used for any country or study region whenever high-resolution datasets are required. Using the resulting datasets greatly enhances the level of detail of central input assumptions to ESMs, allowing for high-resolution dynamic electrification planning and energy transition modelling of many understudied developing countries.

Nevertheless, the developed disaggregation method has several limitations. First, it is assumed that historical relative distributions of population count and total GDP persist in the future. This can be addressed if further data on sub-regional population growth rates and/or internal migration patterns exist. As for the distribution of total GDP, one of the differentiating assumptions between SSPs is inequality levels. While this has been quantified on an inter-country basis, it has not yet been quantified on an intra-country basis. Finally, it is assumed that only currently populated cells will also be populated in the future. This does not account for the potential expansion of inhabited areas. All of these limitations are intended to be addressed by the authors in future research work.

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V. Appendix

The developed Python workflow and all generated high-resolution maps for the Namibian case study are publicly available on GitHub via the following link: https://github.com/mai-elsayed23/high-res-elec-demand.git.