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Report

Downscaling IAMs results to the country level – a new algorithm

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Abstract

This report presents a new tool for downscaling outputs from Integrated Assessment Models (IAMs) from model-native regions to the country level. The algorithm produces a range of pathways consistent with the underlying IAM-results, based on a range of criteria. Criteria used for the downscaling include historical data, planned capacities, country-available resource in the form of supply cost-curves, quality of governance as well as regional benchmarks based on IAM results. The tool can be used to explore the implications of Paris Agreement compatible pathways for energy systems and CO_2 emissions at the country level and to enhance the regional comparison of IAMs. Finally, results could be used as inputs to other models, to provide national level information consistent with global IAM results.

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1 Introduction

The goal of the Paris Agreement is to limit long-term global temperature change to well-below 2ºC and pursuing efforts to limit it to 1.5ºC. However, as energy and climate policies are not set at the global level, but by individual countries, these countries have developed and submitted their own plans formulated in Nationally Determined Contributions (NDCs) and mid-century net zero emissions strategies. Assessments of future emissions and the effectiveness of climate policies are usually performed with Integrated Assessment Models (IAMs) at the global and world-region level. However, bringing together insights from IAMs with information at the country level has remained difficult, as global models usually provide results for a limited number of world regions.

Several strategies have been developed to overcome this limitation. IAMs have increased regional resolution and added individual countries as native regions to their models. However, this strategy has remained difficult due to complexity of IAMs, solving simultaneously for different modules including energy, economy and climate change. Ex-post downscaling of IAM model output is another strategy. The advantage of applying downscaling techniques is they do not require extensive computational time, since they do not increase the spatial resolution of the IAMs themselves.

Downscaling approaches can provide results according to "heuristic" rules, such as downscaling algorithms (Gaffin et al., 2004; Höhne and Ullrich, 2005) or by using statistical model or simplified versions of energy-system models (Bollen, J.C. et al., 2004.; Carter et al., 2004). The literature so far has focused mainly on GHG emissions, by using algorithm based on IPAT equations[1]
(Ehrlich and Holdren, 1971; van Vuuren et al., 2007). Other downscaling approaches based on conditional modeling can capture the relationship between primary energy and energy related emissions, while minimizing costs (Sferra et al., 2019). However currently there is lack of research on downscaling benchmarks related to the energy sectors such as industry, transportation and residential and commercial.

This report presents a new downscaling tool to explore country level pathways on energy and emissions. The report is organized as follows: chapter 2 introduces the basic principles for the downscaling algorithm. Chapter 3 describes the data used as input for the downscaling tool and the output variables. Chapter 4 describes the methodology; chapter 5 introduces country-level policies and show an application example of the downscaling algorithm. Chapter 6 concludes by summarizing results from the NGFS project and discuss strengths and limitations of the approach.

[1] IPAT (Impact= Population x Affluence x Technology) equations can be used to scale down emissions by using population projections and emission intensity assumptions (e.g., based on some convergence criteria).

2 Basic principles for the new downscaling method

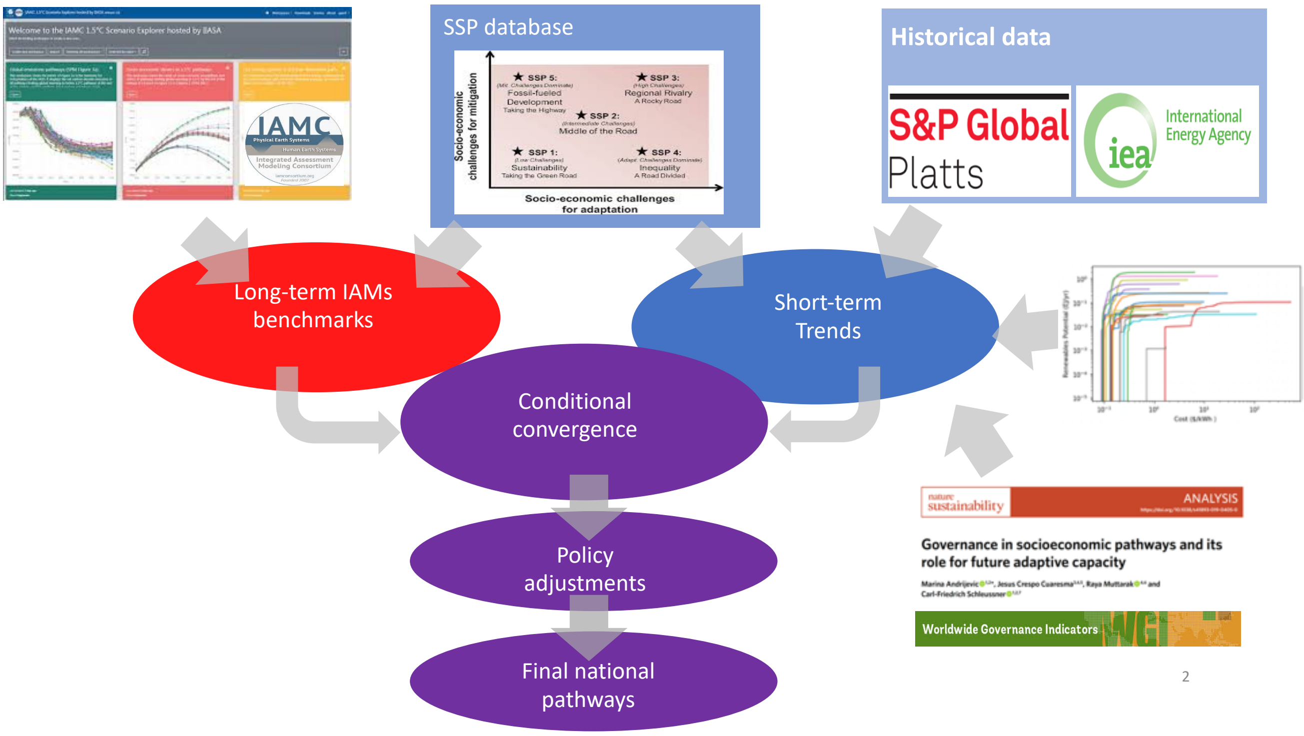


Figure 1 Conceptual framework of the downscaling algorithm. By using a conditional convergence approach, the algorithm combines long term benchmarks from IAMs results with short term extrapolations based on historical data. Socio-economic projections at the country-level are based on the SSP database. Finally, policies are introduced to reflect both Nationally Determined Contributions (NDCs) and long term strategies towards net zero emissions.

As a general principle, the new downscaling approach is based on combining two types of information: 1) observed historical energy data at the country level and 2) regionally aggregated benchmarks from IAMs. In the short-term, downscaled results should be in line with observed data at the country level. In the long-term, energy variables converge towards the regional IAM results and could significantly deviate from the historical data. The downscaling methodology is thus based on two pathways:

- "Short term projections" are based on extrapolation of historic trends;
- "Long term IAMs benchmarks" are based on regionally aggregated IAM results.

We harmonize both pathways so that the sum of country level results within a region coincides with the regional IAM results, where large countries will undertake the biggest adjustments required to match the regional data. Then we create a linear interpolation to converge from the "short term" pathway to the "long-term" pathway between the base year (e.g., tb= 2010) and a future "time of convergence" (tc). The base year is the year after which model scenarios can start to diverge from historical data. However, historical data information can be used until more recent available years (hence beyond the base year) as we do for estimating the final energy demand (please refer to chapter 4, Final energy section).
We assume different times of convergence between the short-term to long term projections, based on the type of scenario, to better reflect the underlying scenario storyline. For example, for scenarios aiming at net zero emissions by 2050 we assume a "fast" convergence, whereas for delayed transition storylines we assume a "slow" convergence across countries.

The definition of slow, medium and fast convergence, differs depending on the type of variables that we downscale: as primary and secondary energy variables (e.g., primary energy consumption by fuel) depends on the availability of energy resources at the country level, a slower timer of convergence is assumed, whereas for final energy variables, we expect a faster convergence of end-use technologies across countries (e.g., for Final Energy|Liquids we expect a similar fuel efficiency of Internal Combustion Engines – ICE – across all countries), hence faster convergence is assumed.

Timing of convergence (tc)	Final energy variables	Primary and secondary energy variables
Slow	2100	2200
Medium	2150	2250
Fast	2200	2300

Table 1: Timing of convergence

Then we calculate some weights that change over time based on the assumptions we made on the timing of convergence *tc*:

$$\varphi_{t,tc} = \frac{t - tc}{tb - tc} \qquad 1)$$

Based on weight $\varphi_{t,tc}$ we generate a pathway $EN_{c,t}$ as a linear combination of short term $EN_Short_{c,t,tc}$and long-term projections $EN\_long_{c,t}, tc$, as in the equation below, for each country *c*, time t and timing of conditional convergence *tc*:

$$EN_{c,t,tc} = \varphi_{t,tc}\, ENlong_{c,t} + (1 - \varphi_{t,tc})\, ENShort_{c,t} \qquad 2)$$

3 Variables

3.1 Input

The downscaling algorithm focuses on energy variables such as Final energy, Secondary energy and Primary energy. To downscale these variables, we use regional input data from Integrated Assessment Models. Many IAMs (Integrated Assessment Models) scenarios are developed on the basis of the so-called SSPs "Shared Socio-economic Pathways" framework. The SSPs have been developed to facilitate the integrated analysis of future scenarios in relation to challenges to mitigation and adaptation (Riahi et al., 2017). SSPs are based on five different narratives ranging from a sustainability storyline (with low challenges for both mitigation and adaptation) to a regional rivalry pathway (with high challenges for both mitigation and adaptation). Those narratives entail some quantitative elements that are available at the country-level, including GDP (Crespo Cuaresma, 2017; Dellink et al., 2017), Population (Samir and Lutz, 2017), and governance indicators (Andrijevic et al., 2020). Our downscaling algorithm uses GDP and population data from baseline scenarios (absent of climate policies) as they are available in the SSP online database[2].
We also use historical data to initialise the country-level variables at the base year. The IEA Energy Balances 2019 (IEA, 2019) provides energy-related historical data for 183 countries and regional aggregates.
In addition, for the electricity sector we additional data such as the PLATTS database (Platts, 2019.) that contains power plants information around the world (including operational, planned and plants under construction). We also use governance indicators (Andrijevic et al., 2020) available at the country level on GitHub repository[3]. Regarding the renewables energy potential availability, we rely on supply-cost curves based on the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)[4] (Gernaat et al., 2021).

3.2 Output

The downscaling tool provides country-level data for final, secondary and primary energy variables as well as energy-related CO_2 emissions.
Final energy variables include energy demand by energy carrier (electricity, liquids, gases, solids, heat, hydrogen) and sectors (transportation, residential and commercial, and industry). Secondary energy variables include information regarding the fuel mix (e.g., coal, natural, gas, oil, renewables etc.) associated to each energy carrier (e.g., liquids, solids, gases etc.).
Primary energy variables provide information regarding the overall energy mix (including energy transformation losses) by also differentiating technologies with and without Carbon Capture and Storage (CCS).
The table below provides a list of variables that will be made available by the downscaling algorithm (based on input data).

[2] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=welcome
[3] https://github.com/marina-andrijevic/governance2019
[4] https://www.isimip.org/

Variables to be downscaled:			
Emissions	**Primary energy**	**Secondary energy**	**Final energy**
Emissions|CO2|Energy	Primary Energy|Biomass	Secondary Energy|Electricity|Biomass	Final Energy
Carbon Sequestration|CCS|Biomass	Primary Energy|Coal	Secondary Energy|Electricity|Coal	Final Energy|Electricity
Carbon Sequestration|CCS|Fossil	Primary Energy|Coal|w/ CCS	Secondary Energy|Electricity|Gas	Final Energy|Gases
	Primary Energy|Coal|w/o CCS	Secondary Energy|Electricity|Geothermal	Final Energy|Heat
	Primary Energy|Fossil	Secondary Energy|Electricity|Hydro	Final Energy|Hydrogen
	Primary Energy|Fossil|w/ CCS	Secondary Energy|Electricity|Nuclear	Final Energy|Liquids
	Primary Energy|Fossil|w/o CCS	Secondary Energy|Electricity|Oil	Final Energy|Solids
	Primary Energy|Gas	Secondary Energy|Electricity|Solar	Final Energy|Industry|Electricity
	Primary Energy|Gas|w/ CCS	Secondary Energy|Electricity|Wind	Final Energy|Industry|Gases
	PrimaryEnergy|Gas|w/o CCS	Secondary Energy|Gases|Biomass	Final Energy|Industry|Heat
	Primary Energy|Geothermal	Secondary Energy|Gases|Coal	Final Energy|Industry|Hydrogen
	Primary Energy|Hydro	Secondary Energy|Gases|Natural Gas	Final Energy|Industry|Liquids
	Primary Energy|Nuclear	Secondary Energy|Liquids|Biomass	Final Energy|Industry|Solids
	Primary Energy|Oil	Secondary Energy|Liquids|Coal	Final Energy|Residential and Commercial|Electricity
	Primary Energy|Oil|w/ CCS	Secondary Energy|Liquids|Oil	Final Energy|Residential and Commercial|Gases
	Primary Energy|Oil|w/o CCS	Secondary Energy|Solids|Biomass	Final Energy|Residential and Commercial|Heat
	Primary Energy|Solar	Secondary Energy|Solids|Coal	Final Energy|Residential and Commercial|Liquids
	Primary Energy|Wind		Final Energy|Residential and Commercial|Solids
			Final Energy|Transportation|Electricity
			Final Energy|Transportation|Gases
			Final Energy|Transportation|Hydrogen
			Final Energy|Transportation|Liquids

Table 2: List of inputs and outputs of the downscaling algorithm.

The next section describes how the energy intensity indicator can be used to make projections of final energy demand.

4 Methodology

The literature (Ehrlich and Holdren, 1971; Fujimori et al., 2017; Gidden et al., 2019, 2018; van Vuuren et al., 2007) usually relies on an IPAT/Kaya decomposition (Alcamo et al., 2000; Hwang et al., 2020; Kaya, 1989) to downscale CO_2 emissions, by multiplying final energy demand by an emissions intensity. According to the IPAT approach, the impact I on emissions can be defined as the product of population *POP*, affluence *A* and Technology *T*:

$$I = POP \times A \times T \tag{3a}$$

Based on the Kaya approach, we assume that affluence and technology refer to energy intensity (defined a final energy divided by GDP) and emissions intensity (defined as emissions divided by GDP) per capita, for each country *c* and time *t*:

$$CO2_{c,t} = \frac{CO2_{c,t}}{FEN_{c,t}} \frac{FEN_{c,t}}{GDP_{c,t}} \frac{GDP_{c,t}}{POP_{c,t}} POP_{c,t} \tag{3b}$$

The same equation can be rewritten as follows:

$$CO2_{c,t} = \frac{CO2_{c,t}}{FEN_{c,t}} FEN_{c,t} \tag{3c}$$

Where:

$$FEN_{c,t} = \frac{FEN_{c,t}}{GDP_{c,t}} \frac{GDP_{c,t}}{POP_{c,t}} POP_{c,t} \tag{3d}$$

We further decompose overall final energy into different energy carriers *e* such as electricity, liquids, gases, solids, heat, hydrogen (equation *3e*) and at the sectorial level *s* including transportation, residential and commercial and industry (equation *3f*)

$$FEN_{c,t,e} = \frac{FEN_{c,t,e}}{FEN_{c,t}} FEN_{c,t} \tag{3e}$$

$$FEN_{c,t,e,s} = \frac{FEN_{c,t,e,s}}{FEN_{c,t,e}} FEN_{c,t,e} \tag{3f}$$

We use this general approach for downscaling the final energy demand to the country level by energy carrier and sector. However, since equation *3f* builds upon the results of equations *3e* and *3d*, the uncertainty associated to those (more granular) energy variables (e.g., Final Energy|Industry|Electricity) increases. In this study we enhance the general IPAT/Kaya approach by explicitly downscaling the fuel mix of each county rather than making a general assumption on an aggregated emissions intensity for all fuels (as in equation 3b). The advantage of this enhanced approach is the possibility to link energy use in each country with energy related emissions. In this manner, the downscaling tool allows for exploring the implication of net zero targets on the energy mix (which would not be possible by using the standard IPAT/Kaya approach). In addition, policies can be included at the country level in order to better represent national developments and long-term strategies (e.g., coal phase out policies or economy-wide emissions targets).

The next sections describe the methodology for downscaling final, secondary and primary energy variables as well as carbon emissions.

4.1 Final energy

In this study we use the energy-part of the Kaya identity approach (equation 3d) to decompose final energy demand in three contributing elements: energy intensity (defined as Final energy consumption divided by GDP), GDP per capita and population.

GDP and population projections are already available at the country level (from the SSP database). In order to calculate total final energy demand based on GDP and Population projections, we need to make assumptions regarding the evolution of the energy intensity in the future. Final energy intensity is a an often-used metric that allows for comparing how energy is used to produce services and final goods (hence GDP) across countries (GEA, 2012.). Higher energy intensities are usually observed in countries with energy abundance, labor shortage and relatively cold winters. This is the case for example of the USA, which had significantly higher energy intensity compared to other developed economies (David and Wright, 1996; GEA, 2012.). Path dependencies in the energy system can lead to lock-in by hindering the convergence of energy intensity to the levels of other economies.

Although energy intensities trajectories might differ across countries, historical data from 1972-2016 suggest an inverse relationship between the level of the final energy intensity (defined as Final energy consumption divided by the GDP) and GDP per capita:

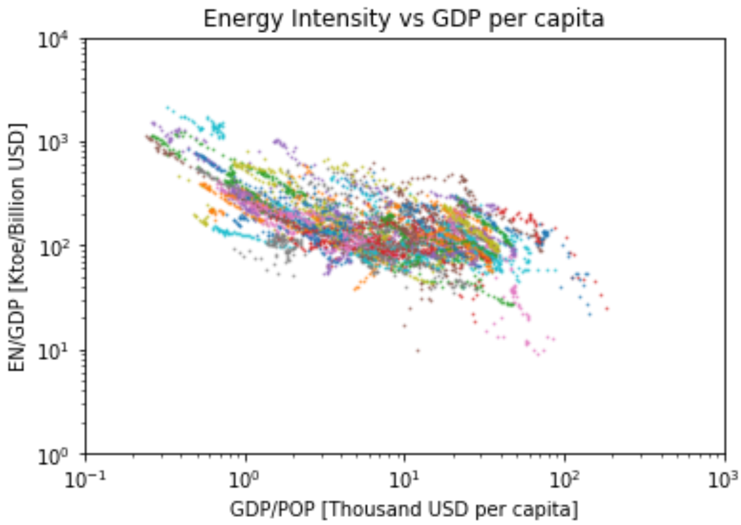


Figure 2: Historical energy intensities (vertical axis) over GDP per capita across countries, from 1972 to 2017 (source of data: IEA international energy balances 2019). One of the reasons behind this pattern is the increasing share of electricity in Final energy use, which for more applications is more efficient than traditional forms of energy (e.g., solid biomass) hence leading to decreasing energy intensities.

The literature suggest that energy intensity can still improve by a factor 10 or more in the very long term (Ayres, 2005; GEA, 2012.; Grubler et al., 2018; Nakicenovic et al., 1998; Nakićenović et al., 1993; Wall, 1977). As a result, we assume that this relationship between energy intensity and income per capita will continue in future long-term scenarios, by using a log-log function[5]:

[5] This assumption might be overruled at later point in time as we will correct those initial pathways to replicate regional IAMs results (please see next section, equation 7)

$$\log\left(\frac{FEN_{c,t}}{GDP_{c,t}}\right) = \beta_c \log\left(\frac{GDP_{c,t}}{POP_{c,t}}\right) + \alpha_c \qquad 4)$$

To this end, we estimate the parameters of the functional form (α and β) based on:

- Historical data at the country level (historical trend extrapolations for each country – the methodology is described in a dedicated sub-section below) or
- Future regional energy intensity based on IAM results (in this latter case α and β would be the same for all the countries j – methodology described in a dedicated sub-section below).

We initialize the energy intensities at the country level based on observed historical energy intensities at the country level, and then converge based on regional information from IAMs.

4.1.1 Long-term IAMs benchmarks

For long term projections, we assume that the energy intensity at the country level will follow the same path (over GDP per capita). Therefore, we estimate a relationship between energy intensity *EI_Long* and GDP per capita, via regression, based on regional IAMs results.

$$EILong_{s,c,t}{}^{*} = \exp\left[\alpha_s + \beta_s log\left(\frac{GDP_{c,t}}{POP_{c,t}}\right)\right] \qquad 5)$$

Then, we calculate the final energy demand at the country level by multiplying the energy intensity by the GDP projections (available at the country level).

$$ENLong_{s,c,t}{}^{*} = EILong_{s,c,t}{}^{*} GDP_{S,c,t} \qquad 6)$$

Based on those calculations, countries with the same level of income per capita will have the same level of energy intensity in a given year. Finally, we harmonize the long-term projections to ensure that the sum of country level results, coincides with the regional IAMs data $EN_{s,R,t}$, in a proportional manner:

$$ENLong_{s,c,t} = \frac{EN_{s,R,t}}{\sum_{c \in R} ENLong_{s,c,t}{}^{*}} \; ENLong_{s,c,t}{}^{*} \qquad 7)$$

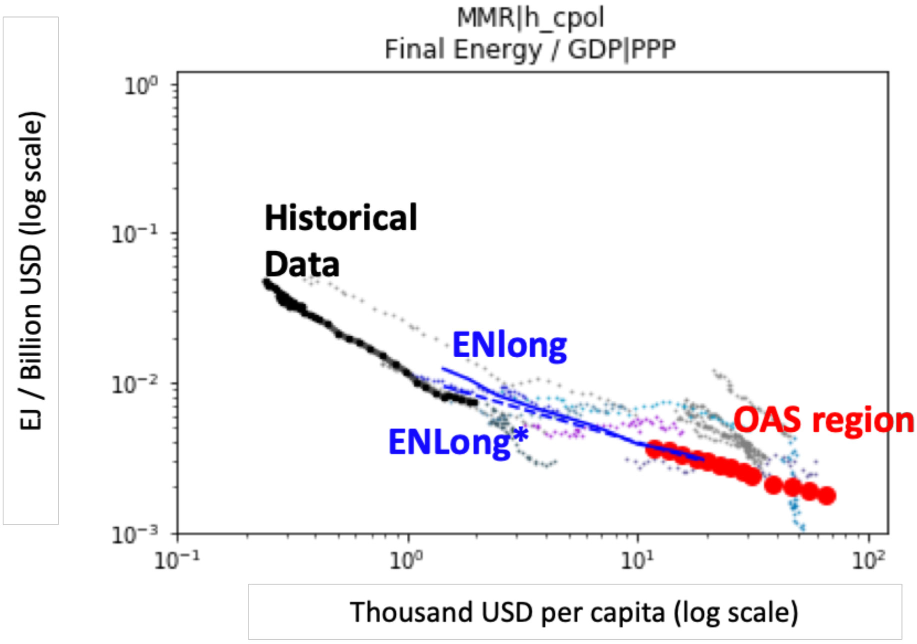


Figure 3: Energy intensity of Myanmar (vertical axis) over GDP per capita. The red line shows the regional MESSAGE model results of the Other Asia region under a current policies scenario (from 2010-2100). The black solid lines show historical data from 1972 to 2017 in Myanmar (source of data: IEA international energy balances 2019), whereas other colored thin dotted lines represent historical data for other countries within the Other Asia region. Grey dotted lines depict historical energy intensities in selected reference countries including China, India, United States of America, Germany, France, Great Britain. The blue lines represent the long-term projections in Myanmar not harmonized (dashed line) and harmonized (continuous line).

4.1.2 Short-term projections

Long term IAMs benchmarks are based on regionally aggregated IAM results. In this section we calculate the short-term projections based on historical trends extrapolations of the energy intensities at the country level. Short-term projections will be then harmonized to match regional IAMs results.
The next two sub-sections describe how the downscaling algorithm 1) merges historical country-level data with regional IAMs results and 2) minimize the adjustments required to match IAMs results during the harmonization process.

4.1.3 Merging historical country-level data with regional IAMs results

In order to provide realistic results at the country-level, historical data should be interpreted and combined with regional IAMs results. For example, we know from historical data that usually the energy intensity increases in the early stages of industrializations and then declines as GDP per capita increases (this pattern is known as 'the hill of energy intensities' (GEA, 2012)). As a result, if we run a regression using the entire historical time series (including when the energy intensity is increasing), we might find a relatively weak directional relationship. At the same time, our estimates might incorporate dynamics that characterize early development stages, and therefore may not represent well expected future developments. To avoid this problem, the algorithm should be able to select the most appropriate starting date of the time series (for example by eliminating data before the 'hill' in the energy intensity).
To this end, the algorithm selects the optimal length of the historical time series (starting from most recent data) by maximizing the r-squared of the regression by the number of observations. This means that the number of historical data observations can be reduced by half only if the r-squared

of the regression will (at least) double. In other words, the algorithm tries to find a relationship that is as long and as stable as possible.
However, it is also important to evaluate historical data in the context of IAMs results and the future scenario storylines. IAMs scenarios or SSPs storylines usually envisage increasing GDP per capita over time, whereas historical data show that in several (a total of 16) countries GDP per capita has declined during the period 1980-2010 (including for example Saudi Arabia, Brunei, Haiti, Venezuela, Zimbabwe etc.). In this case, it might not be entirely appropriate to rely only on historical trend extrapolations (as future income per capita growth might largely differ from the developments observed in the past). For this reason, we add – only for countries with declining GDP per capita – an additional data point (with t=2100) to the historical data series, based on long term projections. By doing so, we combine the historical data information (until the most recent available year) with the energy intensity projections (based on regional IAMs long-term trajectory) in 2100.
For the other countries we rely only on historical data to estimate the parameters of our regression, as in the equation below:

$$ENShort\_hist_{s,c,t} = \exp\left[\alpha_{s,c} + \beta_{s,c} log\left(\frac{GDP_{c,t}}{POP_{c,t}}\right)\right] GDP_{S,c,t} \quad 8)$$

We estimate the parameters by using historical data until 2015. Then, we harmonize the intercept (alpha) to replicate observed data at the base year. Please note that the base year does not necessarily coincide with the most recent available year from historical data.
Finally, we assume that even in the short-term projections, there will be some degree of convergence to long-term projections. We assume some convergence here because (depending on countries) historical data might be limited to a short time series. Another reason is to avoid that major structural break in the economy (e.g., during the 90s, in Former Soviet Union countries) might obscure the historical trends. To overcome these problems, we assume that the degree of convergence depends on the robustness of the historical trends. We assume a slower convergence *max_tc* for historical estimates with a relatively high number of observations and high r-squared, as shows in the graph below:

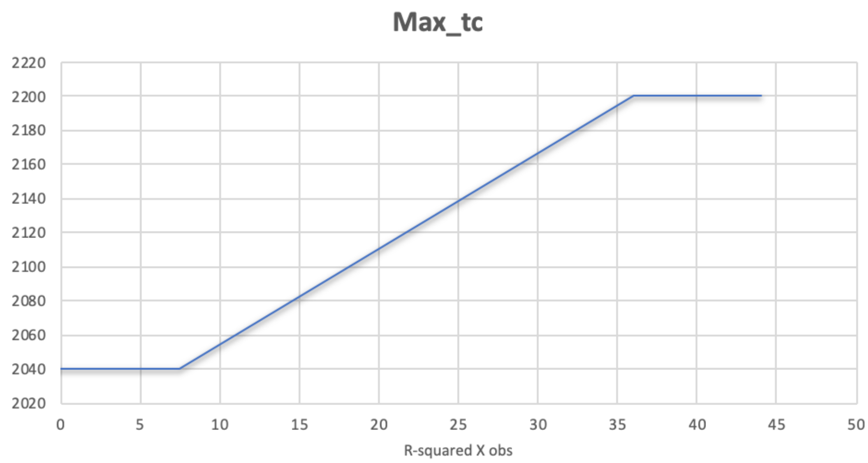


Figure 4: Timing of convergence (Max_tc) as a function of the R-squared multiplied by the number of observations. We assume a convergence in 2040 if r-squared lower or equal than 7.5 (e.g., 25 observations with an r-squared of 0.3) and linearly increases up to 2200 (e.g., 36 observations with and an r-squared equal to 1).

If the slope has an opposite sign compared to the slope based on long-term projections, we assume a faster convergence to the long-term $ENLong_{s,c,t}$ projections, with max_tc equal to 2040. Finally, we compute the weights based on max_tc and the slope of the historical trend regression.

$$\varphi max_t = \left(\frac{t - \max\_tc}{tb - \max\_tc}\right)^{\max{(1,\beta_c)}} \tag{9)}$$

$$ENShort\_conv_{s,c,t}{}^{*} = \varphi max_t \; ENLong_{s,c,t} + (1 - \varphi_{maxt}) \;\; ENShort\_hist_{s,c,t} \tag{10)}$$

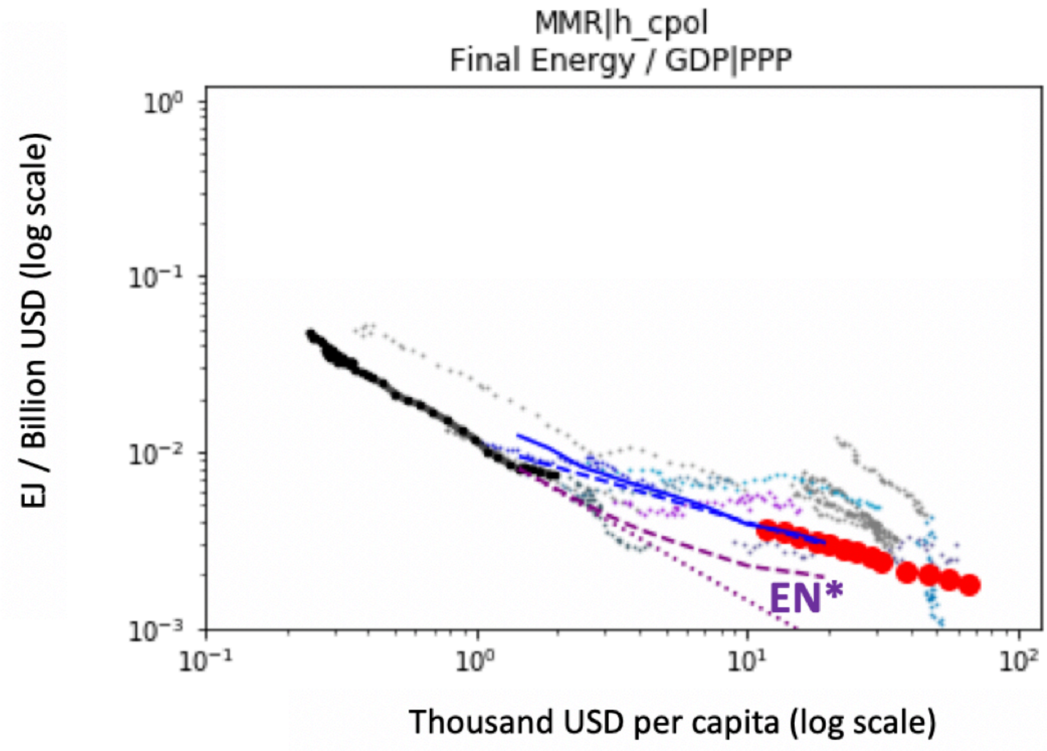


Figure 5: Energy intensity projections in Myanmar under a current policies scenario based on the MESSAGE model. The graph compares historical data (solid black lines) and trend extrapolations (dotted purple line) with future unharmonized projections based on historical data (dashed purple line) and long-term projections based on IAMs benchmarks applied to the country-level (blue line), as well as harmonized projections (continuous blue lines), and the regional energy intensity based on MESSAGE (red dotted line). Other colored dotted lines show the energy intensity of other countries with the Other Asia Region of MESSAGE. Grey dotted lines depict historical energy intensities in selected reference countries including China, India, United States of America, Germany, France, Great Britain.

Please note that based on equation above, we cannot guarantee consistency with regional IAMs results. Therefore, we need to harmonize the results. A simple way to harmonize the results is keeping the same proportions across countries, as we do for the long-term projections:

$$ENShort\_conv_{s,c,t} = \frac{EN_{s,R,t}}{\sum_{c \in R} ENShort\_conv_{s,c,t}{}^{*}} \;\; ENShort\_conv_{s,c,t}{}^{*} \tag{11)}$$

It is possible to improve the results by maximizing the overlap between the 'unharmonized' and 'harmonized' projections. In this manner, smaller countries might continue to follow their historical trends (with some convergence to long term-projections), whereas the bigger countries will make the most of the adjustments required to match regional IAMs results. This can be done by using an integral minimization approach as described in the next section.

4.1.4 Regional Harmonization using an integral minimization approach

This section describes the methodology used to minimize the integral between 'unharmonized' and 'harmonized' projections. We can improve the results (minimize the integral) starting from the smallest to the biggest countries. To illustrate the methodology, we can consider a region made up by three countries: country1 (the smallest country), country2 and country3 (the biggest).
In country 1, we calculate the short-term pathways as a linear combination of 'harmonized' and 'unharmonized' projections, based on a weight (γ), as in the equation below:

$$\begin{aligned} ENShort_{s,c,t} &= \gamma \ ENShort\_conv_{s,c,t}{}^{*} \\ &+ (1-\gamma) \ ENShort\_conv_{sc,t} \end{aligned} \quad 12)$$

If $\gamma \neq 0$, country1 will deviate from the $ENShort_{sc,t}$ (harmonized projections), by creating a delta (mismatch) with the regional IAM results:

$$Delta_{s,c,t} = \sum_{c \in C} ENShort\_conv_{s,c,t}{}^{*} - ENShort_{s,c,t} \quad 13)$$

This delta needs to be compensated by the remaining countries in this region (e.g., country2 and country3). As a result, the subsequent country (e.g., country2) will follow the same approach, but will also partly compensate for the 'Delta' caused by the adjustments made by the previous countries ($c \in C$). The 'Delta' correction is proportional to the relative size of country c (in terms of energy consumption), compared to the size of remaining countries in that region:

$$\begin{aligned} ENShort_{s,c,t} &= \gamma \ ENShort\_conv_{s,c,t}{}^{*} + (1-\gamma) \ ENShort\_conv_{s,c,t} \\ &+ Delta_{s,t} \frac{ENShort\_conv_{s,c,t}}{EN_{s,R,t} - \sum_{c \in C} ENShort\_conv_{s,c,t}} \end{aligned} \quad 14)$$

Finally, the last country in the region (country 3) will compensate for the remaining 'Delta':

$$ENShort_{s,c,t} = EN_{s,R,t} - \sum_{c \in C} ENShort_{s,c,t} \quad 15)$$

Results can be further improved by imposing a maximum correction rate at the country level (in particular in the last country), where any further adjustments required to match regional IAMs results will be allocated equally across all countries. With this approach we minimize the sum of the integrals between the unadjusted $ENShort\_conv_{s,c,t}{}^{*}$ and adjusted ($ENShort_{s,c,t}$) projections across all countries by adequately choosing:

- the parameters γ and
- an 'optimal' country sequence (from small to big countries).

To do so, we employ numerical optimization methods. In the example above, we choose a region with three countries. However, this approach can be applied to a region with *N* countries, where equations 13 and 15 apply to the first and last country respectively, whereas equation 14 applies to all remaining countries. IAMs regions usually contain multiple countries (e.g., up to 50 countries or even more depending on the region chosen). In this context we make two list of countries: big and small. We define the list of 'big' countries as the one with the largest:

- Final energy consumption at the base year,
- cumulative GDP (throughout the century) and
- cumulative Population (throughout the century)

For GDP and population, we use cumulative data (until 2100) as we consider the full-time horizon from 2010 to 2100 (and do calculate the list of big countries for individual time slices). Once we have selected the "big countries", it is important to accurately choose the 'correct' sequence of countries, as the algorithm adjusts countries sequentially. If the sequence of countries is not chosen well, the algorithm might not be able to improve the results (based on the simple proportional adjustment). As a result, we define the optimal sequence of the 'big' countries by using an optimization approach with $\gamma = 0$ and will iteratively change the country order until the sum of integral across all countries is minimized. The sum of integral across countries can be also weighted by using the r-squared of the regression, so that countries with a strong historical trend have a bigger impact in the objective function (to be minimized). We also need to define the correct sequence of the small countries. In principle, the same optimization approach could be used for the 'small' countries as well. However, for large regions (e.g., with 20 countries or more) this would significantly slow down the computational run-time, without leading to major improvements in the final solution. Therefore, we employ the R-squared of the regression as the basis for ranking the list of small countries. In other words, small countries with a robust historical trend should be the first in the list. This would give them the opportunity to follow as much as possible the historical trends (if this minimizes the sum of integral in all countries). Please note that the list of 'small' country could be empty (this is possible for small regions, e.g., made by 3 countries). If all countries are in the 'big' country list, the solution found by the algorithm will be more accurate in terms of integral minimization (as this will be entirely based on an optimization method).

Once we have the optimal sequence of countries, we can determine the optimal correction rate by using an optimization approach. We change γ until we minimize the sum of (weighted) integral across all countries.

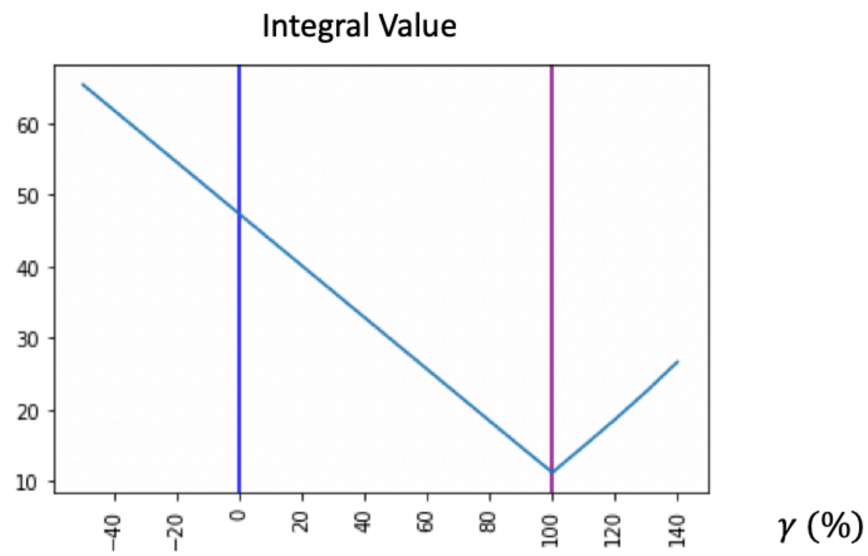


Figure 6: Integral value associated with the correction rate value γ

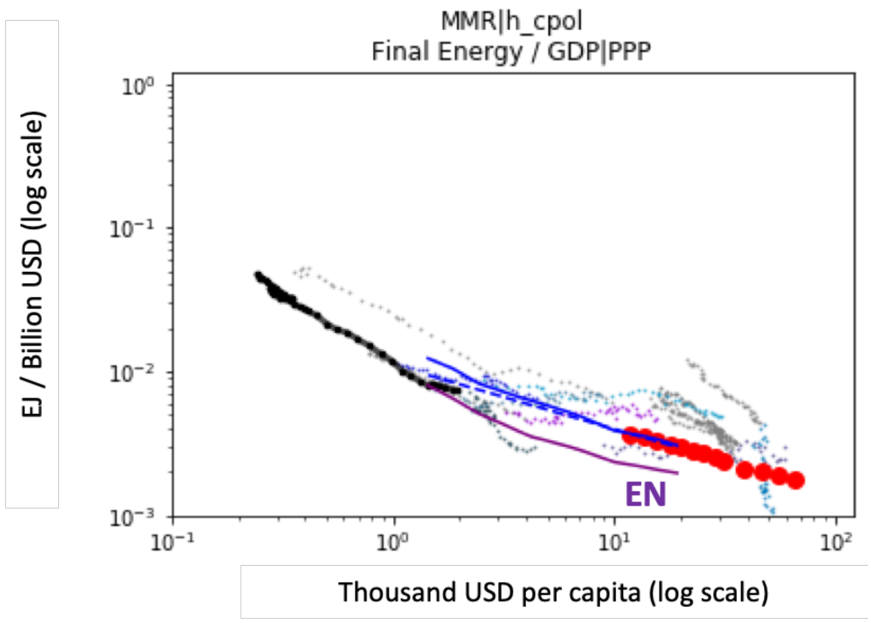


Figure 7: Energy intensity projections in Myanmar under a current policies scenario based on the MESSAGE model. The graph compares historical data (solid black lines) with future harmonized Short-term projections (solid purple line) and long term projections based on regional IAMs benchmarks applied to the country level (solid Blue line), and the regional energy intensity based on MESSAGE (red dotted line). Other colored dotted lines show the energy intensity with other countries with the Other Asia Region of Message. Grey dotted lines depict historical energy intensities in selected reference countries including China, India, United States of America, Germany, France, Great Britain.

4.1.5 Final energy by sectors and energy carriers

This section generalizes the methodology described in the section above, so that it can be applied to final energy demand by energy carriers and sectors. To do so, we replace GDP with a more generic term: *main_sector* (while keeping the relationship with GDP per capita):

$$\frac{ENLong_{s,c,t}{}^{*}}{Main\_sector_{S,c,t}} = \exp\left[\ \alpha_s + \beta_s log\left(\frac{GDP_{c,t}}{POP_{c,t}}\right)\right] \quad 16)$$

$$\frac{ENShort_{s,c,t}{}^{*}}{Main\_sector_{S,c,t}} = \exp\left[\ \alpha_{s,c} + \beta_{s,c} log\left(\frac{GDP_{c,t}}{POP_{c,t}}\right)\right] \quad 17)$$

The generic term main_sector will change depending on the energy carrier and sector that we aim to downscale. The table below provides a list of the 'main_sector' for each energy carrier *e* and sector *s*:

Variables to be downscaled (enshort/enlong):	**Main Sector**
Final Energy	GDP|PPP
Final Energy|Liquids	Final Energy
Final Energy|Transportation|Liquids	Final Energy|Liquids
Final Energy|Buildings|Liquids	Final Energy|Liquids
Final Energy|Industry|Liquids	Final Energy|Liquids
Final Energy|Gases	Final Energy
Final Energy|Transportation|Gases	Final Energy|Gases
Final Energy|Buildings|Gases	Final Energy|Gases
Final Energy|Industry|Gases	Final Energy|Gases
Final Energy|Solids	Final Energy
Final Energy|Transportation|Solids	Final Energy|Solids
Final Energy|Buildings|Solids	Final Energy|Solids
Final Energy|Industry|Solids	Final Energy|Solids
Final Energy|Electricity	Final Energy
Final Energy|Industry|Electricity	Final Energy|Electricity
Final Energy|Buildings|Electricity	Final Energy|Electricity
Final Energy|Transportation|Electricity	Final Energy|Electricity

Table 3: List of variables to be downscaled and main sector reference.

This methodology provides results that are consistent with regional IAMs results, both for long-term and short-term projections. Regarding individual countries, we also need to ensure that sum across energy carriers and sectors is consistent with the (previously downscaled) total final energy demand. As a result, we enhance consistency of results at the country level, by introducing some adjustments to the short-term projections.

To this end, we use an iterative process: we first adjust the energy carriers results proportionally in each country, so that the sum across energy carriers e coincides with total final energy demand *Main_sector*:

$$ENShort_{e,c,t}{}^{*} = ENShort_{e,c,t} \times \frac{Main\_sector_{e,c,t}}{\sum_e ENShort_{e,c,t}} \quad 18)$$

Then we adjust (proportionally) the results for each energy carrier, so that the sum across countries coincides with the regional IAMs results $EN_{e,s,R,t}$:

$$ENShort_{e,c,t} = ENShort_{e,c,t}{}^{*} \times \frac{EN_{e,R,t}}{\sum_c ENShort_{e,c,t}{}^{*}} \qquad 19)$$

We keep on iterating between the two equations above to minimize an objective function, defined as the difference between energy demand by energy carrier and production by energy carrier in all countries:

$$Obj_e = \sum_t \sum_c \left(Main\_sector_{e,c,t} - \sum_f ENShort_{e,c,t,f} \right)^2 \qquad 20)$$

It is possible this iterative process converges to a solution with an error *Obj* value above zero. This difference can be interpreted as trade of secondary energy products across countries[6].We minimize trade to make most of the countries as energy independent as possible (which is often a concern for policy makers) and therefore avoid possible unrealistic trade patterns in the future (e.g., with excessive/unrealistic trade across counties). In other words, the algorithm tries to minimize trade of secondary products across countries, although this might be inevitable if IAMs results assume trade across regions (for example in scenario assuming developing of super grids or other transmission networks). Finally, we employ the same approach to enhance consistency of sectorial energy demand across countries, so that the sum of energy demand across sectors, coincides with total energy demand.

4.1.6 Hydrogen

Hydrogen is a relatively new technology and for this reason there is lack of historical data availability for most countries. In this context, we are not able to estimate a relationship of how hydrogen might evolve over time in relation to income per capita, based on historical data. Therefore, we assume that hydrogen will be used by end-use sectors at a rate proportional to the use of electricity (as indirect electrification with hydrogen is complementing direct electrification for the subsectors in which direct electrification is hard to achieve (Ueckerdt et al., 2021)) and apply this methodology directly to the final range of projections, under the assumption of conditional convergence *tc*. To do so, we calculate a regional benchmark defined as hydrogen divided by electricity demand (from IAMs). Then we calculate hydrogen by multiplying this benchmark by the (previously downscaled) electricity demand *e=EL* at the country level.

$$EN_{e=hydrogen,c,t} = \frac{EN_{e=hydrogen,R,t}}{EN_{e=EL,R,t}} \times \; EN_{e=EL,c,t,tc} \qquad 21)$$

[6] Please note that some IAMs represent trade of secondary energy carriers across different regions.

4.1.7 Heat

For energy demand from heat, we use an approach similar to hydrogen, as heat also complements electricity use. However, as historic data for heat exists, in this case we make the usual distinction between long-term and short-term projections. We calculate long-term projections by using the same approach described for hydrogen, as in the equation below:

$$HeatLong_{c,t} = \frac{Heat_{R,t}}{EN_{e=EL,R,t}} \times \; EN_{e=EL,c,t} \tag{22)}$$

For short term projections, we use the base-year historical data to allocate heat at the country level, without considering the historical relationship with income per capita. First, we calculate the ratio of heat divided by electricity consumption in each country:

$$HtoEL_c = \frac{Heat_{c,t=2010}}{EN_{e=EL,c,t=2010}} \tag{23)}$$

Then, we calculate an index of how this $HtoEL$ ratio dynamically evolves over time based on regional IAMs results:

$$HtoELindexed_{R,t} = \frac{HtoEL_{R,t}}{HtoEL_{R,t=2010}} \tag{24)}$$

We multiply the $HtoEL$ ratio and the dynamic index $HtoELindexed$ by the country-level electricity demand:

$$HeatShort_{c,t}{}^{*} = \; HtoEL_c \times \; HtoELindexed_{R,t} \times EN_{e=EL,c,t} \tag{25)}$$

Finally, we harmonise the results by using a proportional approach[7]:

$$HeatShort_{c,t} = \frac{Heat_{R,t}}{\sum_{c\in R} HeatShort_{c,t}{}^{*}} \; \times \; HeatShort_{c,t}{}^{*} \tag{26)}$$

To conclude, we generate our projections based on the assumptions on the timing of conditional convergence *tc*:

$$EN_{e=heat,j,t,tc} = \varphi_{t,tc} \; Heatlong_{j,t} + (1 - \varphi_{t,tc}) \; HeatShort_{j,t} \tag{27)}$$

[7] In this case we do not need an integral minimization approach, as we do not extrapolate historical trends over time.

4.2 Secondary energy

4.2.1 Liquids, solids, gases

This section describes the methodology for downscaling secondary energy by fuel: coal, oil, gas, biomass, nuclear, solar, wind and geothermal energy, for each energy carrier (e.g., liquids, solids, gases, electricity). As for final energy, we make a distinction between short-term and long-term IAMs benchmarks projections. Then we minimize trade of secondary energy carriers across countries by using the same methodology described for final energy carriers (as we did in the final energy section). Finally, we use a linear combination of short-term and long-term projections, depending on timing of conditional convergence tc. Compared to the final energy results, we adopt a broader range of criteria to determine short-term projections in the electricity sector. Regarding long term projections we use data based on regional IAMs results. Long term projections assume the same fuel composition *f* across countries, based on regional IAMs results $EN_{e,s,R,t,f}$ for each energy carrier *e*.

$$ENLong_{e,c,t,f} = ENLong_{e,c,t} \times \frac{EN_{e,R,t,f}}{\sum_f EN_{e,R,t,f}} \tag{28)}$$

For short-term projections, we calculate the fuel mix of solids, liquids and gases based on historical data at the base year (*t=tb*), as we did for the broader energy carriers:

$$ENShort_{e,c,t,f} = EN_{e,R,t,f} \times \frac{EN_{e,c,t=tb,f}}{EN_{e,R,t=tb,f}} \tag{29)}$$

4.2.2 Electricity

Regarding the electricity sector, we use some additional criteria on top of historical data such as: economic lifetime, governance and supply cost curves. To this end we assume a weight for each criterion *i*, and calculate the short-term projections as a weighted average:

$$ENShort_{e=EL,c,t,f}{}^{*} = \sum_i \omega_{i,f,t} \times ENShort_{e=EL,c,t,f,i} \tag{30)}$$

Where:

$$\sum_i \omega_{i,tmf} = 1 \tag{31)}$$

At the base year, we initialize electricity generation by using the historical data criteria: $\omega_{i=hist,\ t=t0} = 1$. For all the other time periods, we assume the following weights for each fuel ω_f:

	Solar	Wind	Biomass	Hydro	Coal	Gas	Oil	Geothermal	Nuclear
Cost curves	0.35	0.35	0.50	0.50	0.00	0.00	0.00	0.00	0.00
Planned capacity	0.00	0.00	0.00	0.00	0.50	0.50	0.50	0.50	0.00
Historical data	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.85
Governance	0.15	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.15

Table 4: List of criteria for downscaling electricity generation by fuel. Weights add up to 1 for each column.

We harmonize the results proportionally to match regional IAMs data for each fuel:

$$ENShort_{e=EL,c,t,f} = ENShort_{e=EL,c,t,f}{}^{*} \times \frac{EN_{e=EL,R,t,f}}{\sum_c ENShort_{e=EL,c,t,f}{}^{*}} \qquad 32)$$

We update the results dynamically over time to account for path dependencies, starting from the results at the base year. To this end, we compute the difference in IAMs results:

$$ENdiff_{e=EL,R,t,f} = (EN_{e=EL,R,t+1,f} - EN_{e=EL,R,t,f}) \qquad 33)$$

Then, we allocate this difference to the country level (based on a range of criteria), while constraining electricity generation to be always greater than zero:

$$ENShort_{e=EL,c,t+1,f} = Max\left(0, ENdiff_{e=EL,R,t,f} \times \frac{ENShort_{e=EL,c,t,f}}{\sum_f ENShort_{e=EL,c,t,f}}\right) \qquad 34)$$

Finally, we adjust (again) the results again to match regional IAMs and calculate the projections based on our assumptions on conditional convergence *tc*.

$$EN_{e=heat,j,t,tc} = \varphi_{t,tc}\, ENlong_{e=heat,j,t} + (1-\varphi_{t,tc})\, ENShort_{e=heat,j,t} \qquad 35)$$

The sub-sections below describe the methodology to calculate electricity generation based on each of the four criteria *i*.

4.2.2.1 Planned capacity of power plants

Electricity generation can be downscaled based on the remaining economic lifetime criteria of currently operational power plants at the country level, as well as planned capacity additions. Since existing and planned power plants will remain operational until the end of economic lifetime, we use this information as a criterion for the downscaling. Here, we assume that existing and planned power plants at the country level are preferred over building new power plants. Hence, our basic assumption is to minimize stranded assets. This criterion is particularly useful under Paris Agreement compatible pathways, where minimizing future stranded assets (unused power plants capacity) is essential to avoid costly carbon locks-in. Indeed, under 1.5°C scenarios the power sector would need to be fully decarbonized by 2050, whereas the average technical lifetime of fossil-fuel power plant could reach 50 years. In this context the PLATTS database provides detailed information for all different types of power plants across all countries, including the size of power plant, year of construction and expected retirement date. The database also distinguishes between currently operational and new power plants (under construction or planned/announced).
As a first step we calculate the remaining technical lifetime of operational power plants in each country, based on the expected retirement date (for each individual plant). If the retirement date is unknown, we use our own assumptions about technical lifetime reported in the table below:

Type of power plant	Technical lifetime (years)
Coal	50
Gas	40
Oil	30
Geothermal	30

Table 5: Technical lifetime assumptions by type of power plants (if information on retirement date is not available directly from PLATTS database).

Based on this data, we calculate installed capacity at the country level from the base year until the end of the century.

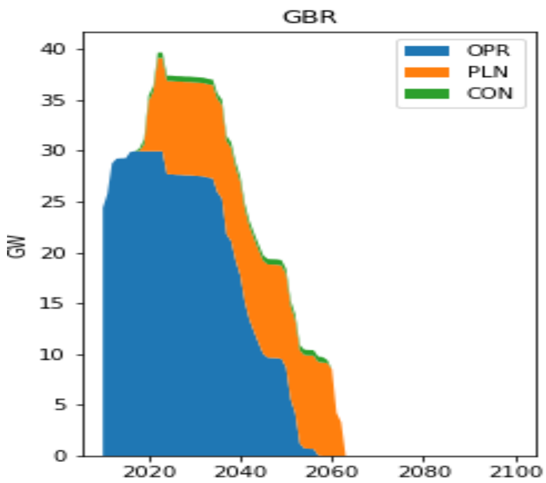


Figure 8 – Projected gas-fired power plants capacity in the United Kingdom by type (operational, planned and under construction).

We calculate the projected capacity by summing up all power plants units (u) for each fuel (f) at the country level. Then we allocate electricity generation (for each fuel) at the country level by using projected capacity as the main determinant:

$$ENShort_{e=EL,c,t,f,i=lifetime} = EN_{e=EL,R,t,f} \frac{\sum_u GW\_installed_{c,t,f,u}}{\sum_{c \in R} \sum_u GW\_installed_{c,t,f,u}} \quad 36)$$

4.2.2.2 Governance

Another criterion that can be used for downscaling is Governance. Governance indicators are available at the country level for different SSP storylines (Andrijevic et al., 2020). Those indicators are used as proxy for downscaling critical technologies such as nuclear power plants. In this case the fuel allocation is based on governance indicators (Gov).

$$ENShort_{e=EL,c,t,f,i=governance} = EN_{e=EL,R,t,f} \times \frac{Gov_{c,t}}{\sum_{c \in R} Gov_{c,t}} \quad 37)$$

The main assumption here is that countries investing in nuclear power plants would require a higher level of governance. Indeed, governance and institutions drive of long-term stability and sustainable growth and stability of nations (Andrijevic et al., 2020). Governance benchmarks assessing present day and future evolution of governance is necessary to assess capacity to invest in critical technologies like nuclear. Governance indicators could be also used to assess countries capabilities to invest in new low carbon technologies such as renewables energy.

4.2.2.3 Supply Cost Curves for renewable energy potential

Supply cost curves are useful tools that illustrate the availability of energy supply at a given costs. Cost curves criteria can be used to allocate electricity generation based on cost minimization and available potential (Gernaat et al., 2021). We use this approach to allocate renewable energy across countries.

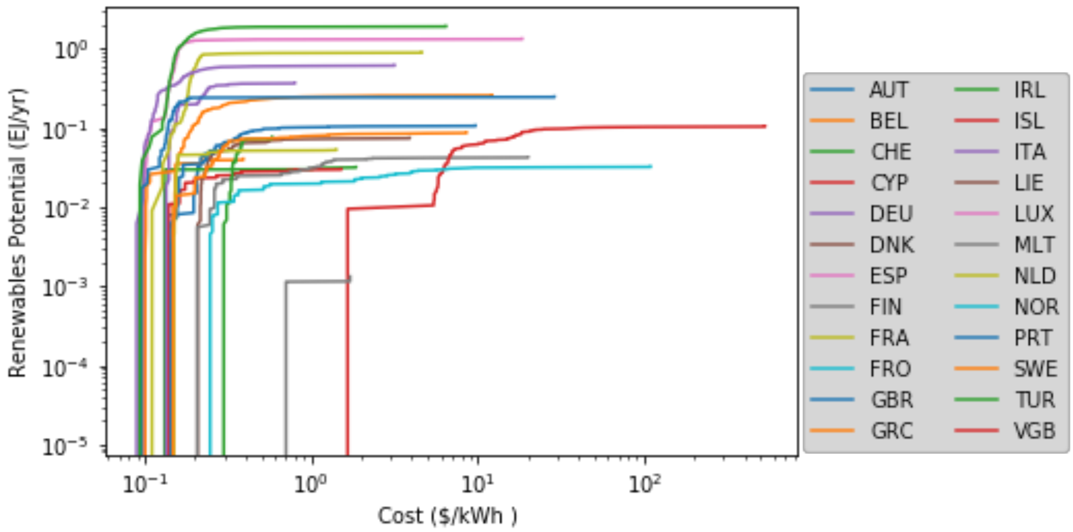


Figure 9: Solar PV Supply cost curves in the WEU region of MESSAGE (source adapted based on Gernaat et al 2021).

To this end, we rank each country by cost and allocate renewables based on the associated potential at the country level:

- First, we calculate the renewables cost associated with the regional production data from IAMs, in each time period.
- Then we allocate the regional production across all countries based on Supply cost curves above.
- Finally, we harmonize the results (in a proportional manner) to make sure that the sum of country level results coincides with regional IAMs results.

Supply cost curves s are widely utilized by researchers and policy makers, as they are simplified tool addressing complex problems. However, supply cost curves provide a static representation of energy availability and costs in each point in time and do not consider path dependency, uncertainty and system-wide interactions.

4.2.2.4 Minimizing electricity trade

We combine all the criteria described above by using a weighted criteria matrix (table four). The downscaling algorithm generate pathways based on simplified rules and does not consider investments required in the electricity grid infrastructure nor. backup capacity in scenarios with high penetration of renewable energy.
As a final step, the algorithm tries to minimize the amount overall trade across all countries, in order to avoid unrealistic patterns in the long term (as energy dependency is often a major concern for policy makers). However, trade across countries might be inevitable if IAMs assume trade across different IAM regions, for example in case of a development super-grid infrastructures across regions. Finally, the tool does not consider bilateral trade across countries but only aggregated electricity trade which is computed as the difference between secondary energy electricity and final energy electricity.

4.3 Primary energy and CO2 emissions

Finally, we calculate primary energy at the country level by multiplying secondary energy results by using a conversion rate. We use the same conversion rate as in regional IAMs results

$$Primary_{e,c,t,f,tc} = Secondary_{e,c,t,f,tc} \times Conv_{e,R,t,f} \quad 38)$$

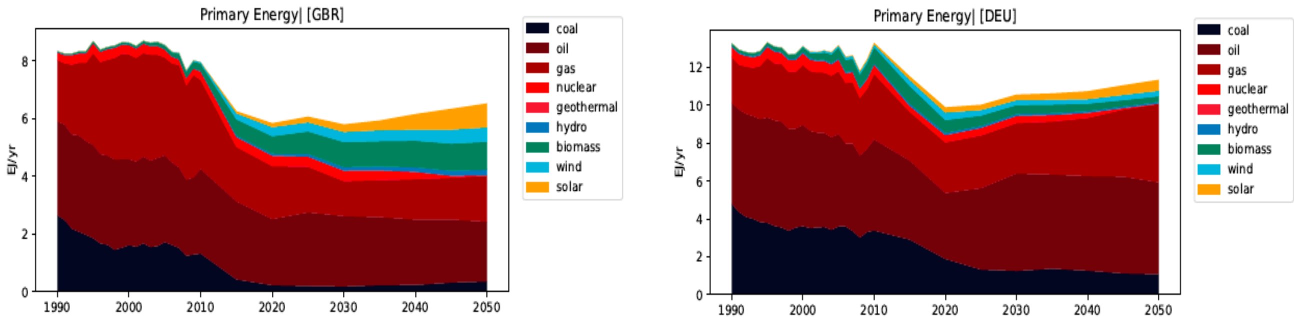


Figure 10: Primary energy by fuel in the United Kingdom and Germany under a current policy scenario (based on MESSAGE model) and comparison with historical data (1990-2009)

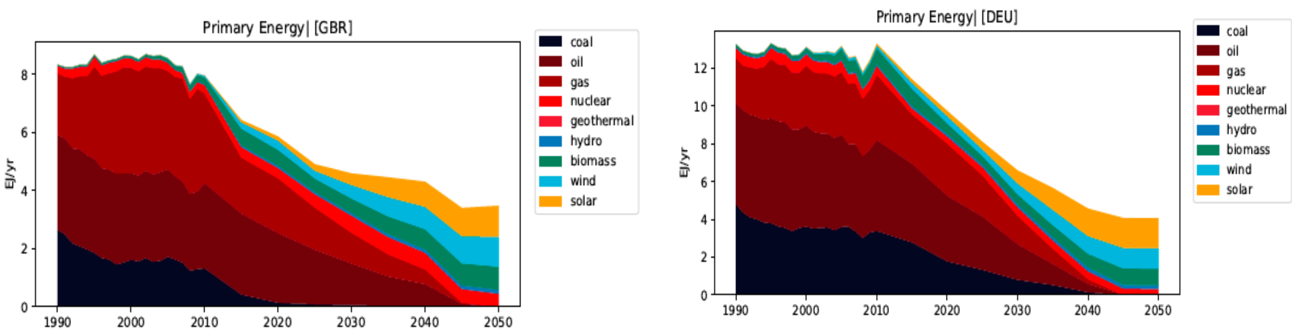


Figure 11: Primary energy by fuel in the United Kingdom and Germany under a 1.5°C pathway (based on MESSAGE model) and comparison with historical data (1990-2009).

In order to calculate carbon emissions, we distinguish between technologies with and without CCS (Carbon Capture and Sequestration) by using the same allocation (within each fuel) of the regional IAMs results.

$$Primary\_CCS_{c,t,f,tc} = Primary_{c,t,f,tc} * \frac{Primary\_CCS_{R,t,f,tc}}{Primary_{R,t,f,tc}} \quad 39)$$

$$Primary\_wo\_CCS_{c,t,f,tc} = Primary_{c,t,f,tc} * \frac{Primary\_wo\_CCS_{R,t,f,tc}}{Primary_{R,t,f,tc}} \quad 40)$$

For Biomass with CCS, we calculate the emission factor by computing the ratio between Carbon Sequestration from Biomass with CCS and Primary energy biomass with CCS at the regional level.

$$EmiFactorBECCS_t = \frac{CCS\_Sequestration\_Biomass_{R,t,f,tc}}{Primary\_CCS_{R,t,f=Biomass,tc}} \quad 41)$$

$$CCS\_Sequestration\_Biomass_{C,t,f,tc_t} = EmiFactorBECCS_t \times Primary\_CCS_{c,t,f=Biomass,tc} \quad 42)$$

Then we calculate CCS sequestration from fossils by using the emissions factors below:

Fuel	Emission factors (Mt CO_2/EJ)
Oil|w/o CCS	67.5
Gas|w/o CCS	56.1
Coal|w/o CCS	95.7

Table 6 – Emissions factors by fuel.

Finally, we harmonize the results to match regional IAMs results:

$$CCS\_Sequestration\_Fossils_{c,t,f,tc}{}^{*} = \sum_{f \in Coal,Oil,Gas} \left(Emi\_factors_f \times Primary\_CCS_{c,t,f,tc}\right) \quad 43)$$

$$CCS\_Sequestration\_Fossils_{c,t,f,tc} = CCS\_Sequestration\_Fossils_{c,t,f,tc_t}{}^{*} \times \frac{CCS\_Sequestration\_Fossil_{R,t,f,tc}}{\sum_c CCS\_Sequestration\_Fossils_{c,t,f,tc_t}{}^{*}} \quad 44)$$

In a similar manner we compute emissions from technologies without CCS:

$$CO2\ emissions\ wo\ CCS_{c,t,f,tc}{}^{*} = \sum_{f=Coal,Oil,Gas} \left(Emi\_factors_f \times Primary\_wo\_CCS_{c,t,f,tc}\right) \quad 45)$$

We harmonize emissions from fossils without CCS so that the sum of country-level results matches regional IAM results. To do so we first calculate regional emissions from technologies without CCS as the sum of total emissions from energy, negative emissions from biomass and the assumed carbon leakage8 from fossil fuels with CCS:

$$
\begin{aligned}
CO2\ emissions\ wo\ CCS_{R,t,f,tc} \\
&= CO2\_total\_emissions\_energy_{R,t,f,tc} \\
&- CCS_{Sequestration_{Biomass}\, e,C,t,f,tc_t} \\
&+ carbon\ leakage \times CCS\_Sequestration\_Fossils_{e,R,t,f,tc_t}
\end{aligned} \qquad 46)
$$

Then we harmonize CO_2 emissions without CCS at the country level:

$$
\begin{aligned}
&CO2\ emissions\ wo\ CCS_{c,t,f,tc} \\
&= CO2\ emissions\ wo\ CCS_{c,t,f,tc_t}^{*} \quad \frac{CO2\ emissions\ wo\ CCS_{R,t,f,tc}}{\sum_c CO2\ emissions\ wo\ CCS_{c,t,f,tc_t}^{*}}
\end{aligned} \qquad 47)
$$

Finally, we compute total emissions from energy as the sum of emissions from technologies without CCS, the amount of CO_2 captured by fossils fuel technologies with CCS multiplied by a carbon leakage (by default set at 10%) and negative emissions from biomass:

$$
CO2_{\ c,t,f,tc} = \begin{matrix} CO2\ emissions\ wo\ CCS_{c,t,f,tc} \\ +carbon\ leakage \times CCS_{Sequestration_{Fossils}\, c,t,f,tc} \\ -CCS\_Sequestration\_Biomass_{c,t,f,tc} \end{matrix} \qquad 48)
$$

[8]By default, we assume that CCS technologies can capture 90% of emissions from burning fuels. The remaining 10% will be released in the atmosphere and we refer to this as "carbon leakage".

5 Policy adjustments

In this section we adjust the carbon emissions and primary energy mix based on current NDC (Nationally Determined Contributions) and the mid-century targets. NDCs are often considered by IAMs (depending on the type of scenario) at a regionally aggregated level. By contrast the downscaling algorithm introduces NDC targets at the country level, in order to enhance realism of country-level pathways. Although NDCs submitted under the Paris Agreement might contain information about targets at the sectorial level, we do only consider here aggregated GHG emissions targets. To do so, we combine Energy related CO_2 emissions from the downscaling algorithm with non-CO_2 emissions using an IPAT approach (Gidden et al., 2019, 2018). Those GHG targets are introduced as soft constraints, as country-level policies might not be fully consistent with underlying IAMs results, depending on scenario/storylines considered. In other words, we assume that countries will try to reach their domestic targets, although these might be only partially achieved (depending on regional policies considered by a given model/scenario).
We introduce policies in three steps, as described below:

- First, we compute total GHG emissions as the sum of total CO_2 emissions, LULUCF emissions and total non-CO_2 gases based on IPCC AR4 Global Warming Potentials. LULUCF and non-CO_2 emissions are downscaled based on (Gidden et al 2018).
- Secondly, we calculate the gap between current total GHG emissions (without policies) and the emissions targets. Then we distribute those emissions targets (for 2030 and 2050) to yearly emissions targets for all time periods (starting from 2015), assuming that they will gradually tighten over time, based on a linear interpolation.
- Thirdly, we assume that countries can fill the emissions gap by either increasing BECCS (Biomass with CCS) or by replacing fossil fuels with renewables. We assume that countries will try to fill 50% of the emissions gap by increasing BECCS (Biomass with CCS). However, the amount of BECCS largely depends on the type of scenario (e.g., BECCS technologies are usually not deployed under a current policy scenario) and by biomass availability. As a result, it might not be possible to meet 50% of the emission gap by increasing BECCS. Therefore, we assume that the remaining emission gap (50% or more) will be met by replacing fossil fuels with renewables.

The graphs below show downscaled carbon emissions from energy in Germany and the United Kingdom under a current policy and a 1.5°C pathway, based on the IAM MESSAGE in comparison with historical data.

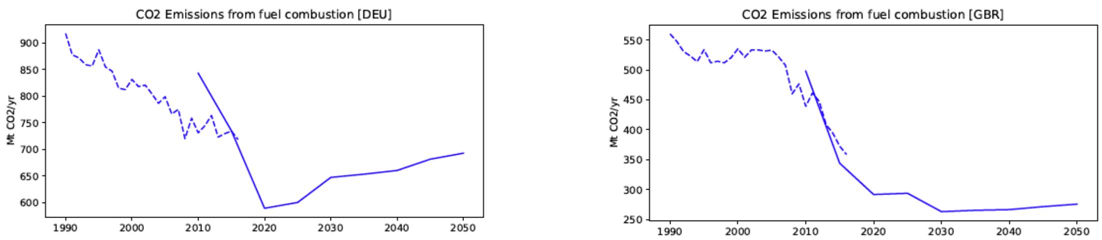


Figure 12: Carbon emissions the United Kingdom and Germany under a current policy scenario (based on MESSAGE model) and comparison with historical data (1990-2009).

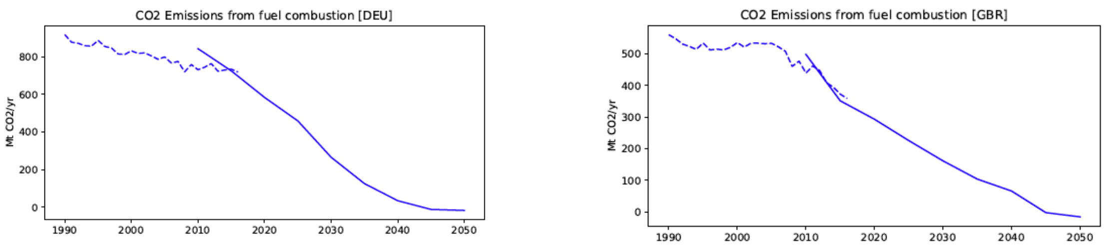


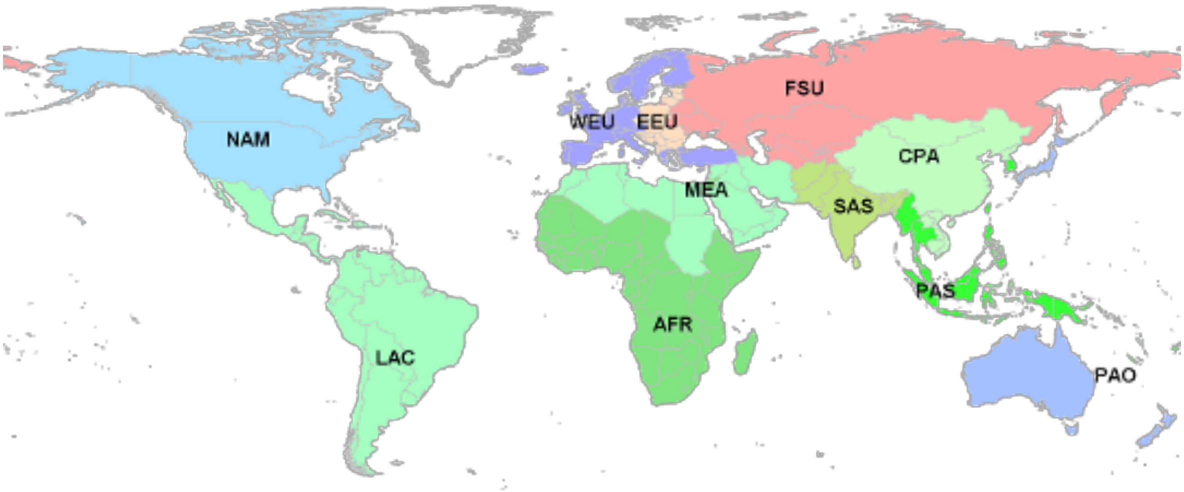
Figure 13: Carbon emissions the United Kingdom and Germany under a 1.5°C pathway (based on MESSAGE model) and comparison with historical data (1990-2009).

This approach allows for generating pathways as consistent as possible with country-level NDCs targets and mid-century net zero strategies. However, the downscaling algorithm adjusts all the primary and secondary energy variables, but do not update the final energy variables, which might introduce some inconsistencies if large policy adjustments are introduced.

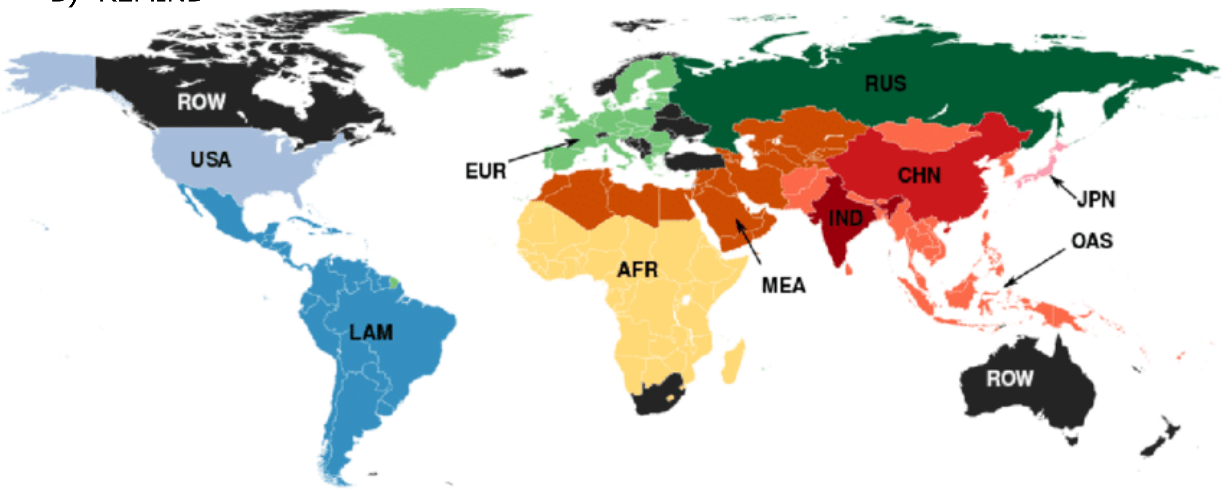
5.1 Application example: aggregating models to common regional definition

In this section, we use the downscaling algorithm to enhance comparisons across IAMs results. To do we downscale results to the country level and re-aggregate the results to the EU28 level. We do this for three models: GCAM, MESSAGE and REMIND.

A) MESSAGE



B) REMIND



C) GCAM

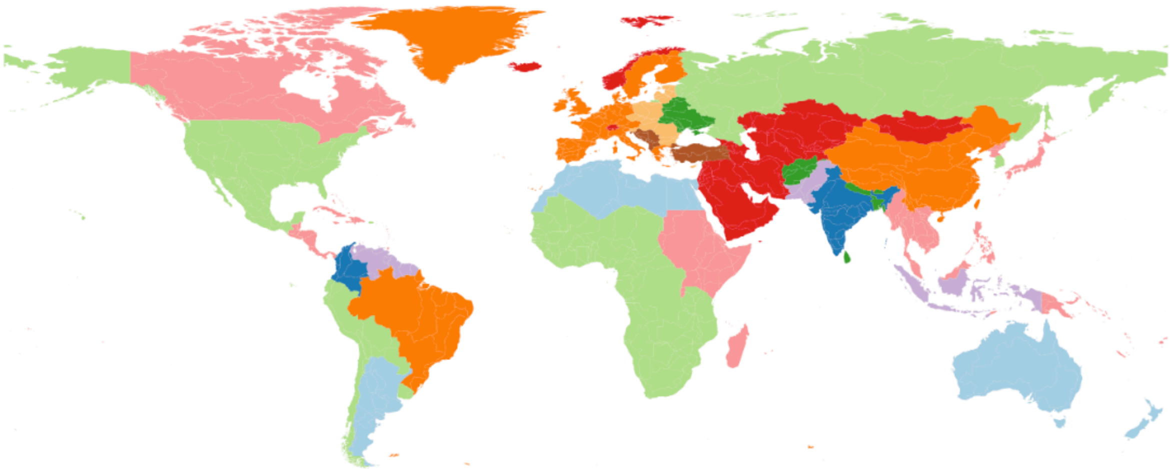


Figure 14 Regional resolution of the MESSAGE (panel A), REMIND (B) and GCAM (C).

The graph below compares Energy related CO_2 emissions for the EU28 regions across different scenarios for all the three models:

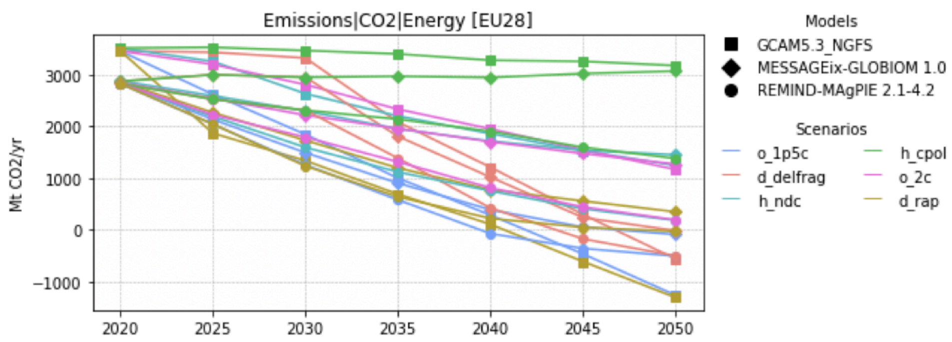


Figure 15 Energy related CO_2 emissions in the EU28 region across model (MESSAGE, GCAM and REMIND) and scenarios: h_cpol (Current policies), h_ndc (Nationally Determined Contributions), d_delfrag (Delayed transition), o_2C (Well-below 2°C), d_rap (Divergent NetZero Policies), o_1p5c (Net zero 2050). Results are based on downscaled pathways at the country level aggregated to the EU28 region.

The graph above shows that projected energy related CO_2 emissions depend on the type of model chosen. For example, under a current policy scenario (h_cpol) the REMIND envisions declining emissions in the EU28, whereas according to MESSAGE and GCAM emission will increase or stabilise over time. This pattern is affected by different assumptions regarding final energy demand, as shown in the graph below:

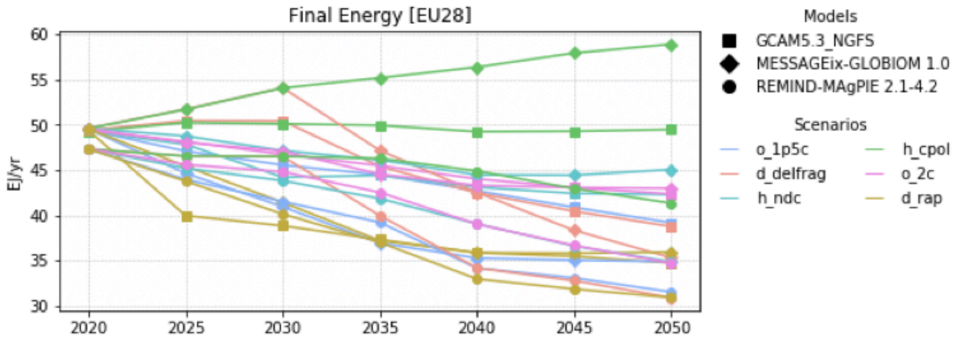
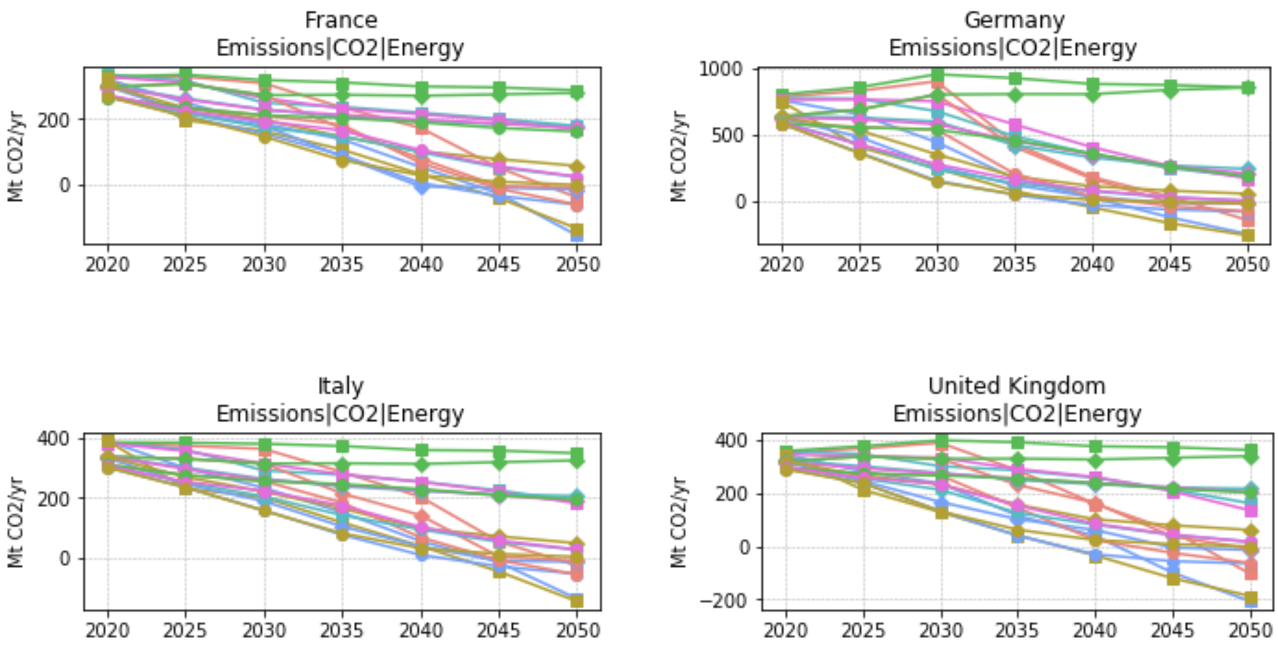


Figure 16 Final Energy in the EU28 region across model (MESSAGE, GCAM and REMIND) and scenarios: h_cpol (Current policies), h_ndc (Nationally Determined Contributions), d_delfrag (Delayed transition), o_2C (Well-below 2°C), d_rap (Divergent NetZero Policies), o_1p5c (Net zero 2050). Results are based on downscaled pathways at the country level aggregated to the EU28 region.

While looking into individual countries, results might also largely differ as shown in the graph below:



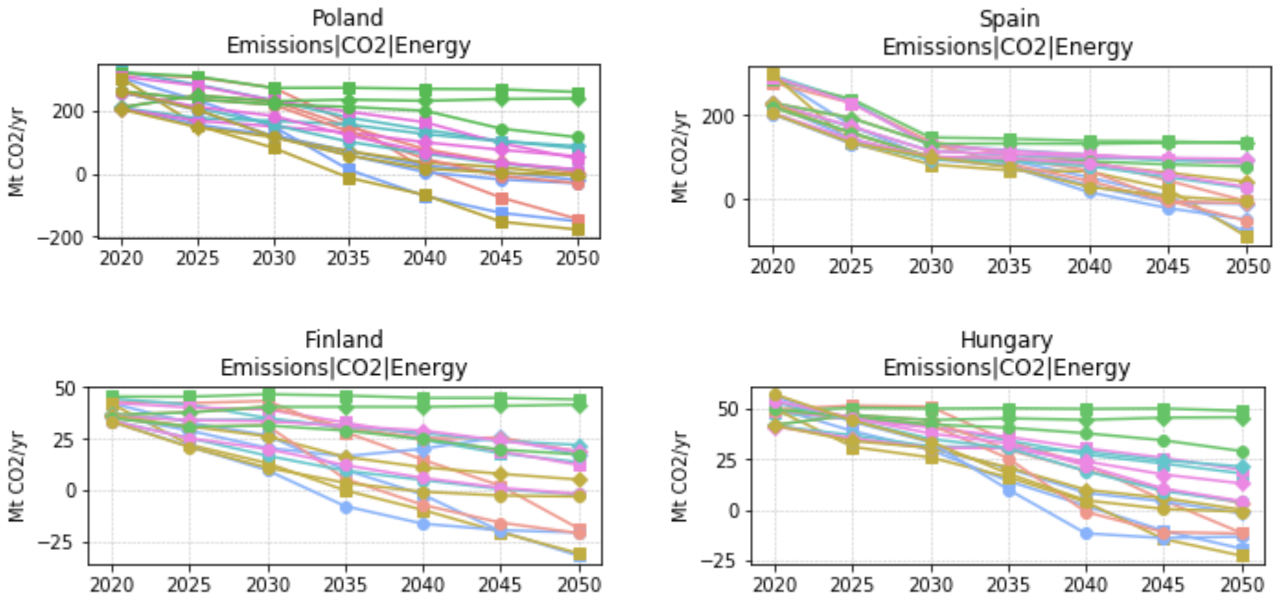


Figure 17 Energy related CO_2 emissions in selected EU28 countries across model (MESSAGE, GCAM and REMIND) and scenarios: h_cpol (Current policies), h_ndc (Nationally Determined Contributions), d_delfrag (Delayed transition), o_2C (Well-below 2°C), d_rap (Divergent NetZero Policies), o_1p5c (Net zero 2050).

Symbol	Definition	Unit
φ	Conditional convergence weights	%
tc	Timing of convergence (e.g., 2100)	Year
t	Time index	Year
tb	Base year	Year
R	Region index	
c	Countries index	-
ec	Energy Carrier index (e.g., liquids, solids, gases)	-
f	Fuel index (e.g., coal, oil gas, etc.)	-
s	Sector Index (e.g., Industry, Transportation, Residential and Commercial)	-
$\boldsymbol{EN}$	Energy Variable (with convergence between short-term and long term projections)	EJ/yr
$\boldsymbol{ENlong}$	Energy Variable: long term projections	EJ/yr
$\boldsymbol{ENShort}$	Energy Variable: short term projections	EJ/yr
FEN	Final Energy	EJ/yr
GDP	Gross Domestic Product	billion US$2005/yr
POP	Population	million
$\boldsymbol{\alpha}$	Offset of regression	-
$\boldsymbol{\beta}$	Slope of regression	-
$\boldsymbol{EILong}^{*}$	Energy Intensity of long-term projections (based on regression)	EJ/billion US$2005/yr
$\boldsymbol{ENShort\_hist}$	Short term projections based on regression	million
$\boldsymbol{\varphi max}$	Convergence weights used in Final Energy for short-term projections (we assume some degree of convergence also in short term projections)	-
$\mathbf{max\_}\boldsymbol{tc}$	Maximum convergence assumed in Final Energy variables for calculating short term projections	-

$\boldsymbol{ENShort\_conv}^*$	Short term projections with some convergence to long term projections (not harmonised to match regional IAM results)	EJ/yr
$\boldsymbol{ENShort\_conv}$	Short term projections with some convergence to long term projections (harmonised to match regional IAM results)	EJ/yr
$\boldsymbol{Delta}$	Deviations (mismatch) with harmonized projections, (introduced by the integral minimization approach) that will be compensated by the biggest countries in the region.	EJ/yr
$\boldsymbol{\gamma}$	Optimal correction rate for short term projections (weight used in the integral minimization approach)	-
Main_Sector	Denominator of the energy benchmark. For example, while computing the Energy Intensity (defined as Energy divided by GDP) benchmark, GDP is the main_sector (denominator of the energy intensity benchmark).	GDP PPP or EJ/yr
Obj	Objective function, defined as the sum of secondary energy trade across countries (to be minimised)	EJ/yr
$\boldsymbol{HeatLong}$	Final Energy|Heat (long term projections)	EJ/yr
$\boldsymbol{HtoEL_c}$	Heat to Electricity ration	%
$\boldsymbol{HtoELindexed}$	Indexed Heat to Electricity ration (base year =1)	-
$\boldsymbol{HeatShort_{c,t}}$	Final Energy|Heat (short term projections)	EJ/yr
$\boldsymbol{\omega}$	Criteria weights used for Electricity downscaling	-
$\boldsymbol{ENdiff}$	Difference between energy consumption in time t+1 and t	EJ/yr
$\boldsymbol{GW\_installed}$	Installed power plants	GW
Gov	Governance indictors	-
$\boldsymbol{Primary}$	Primary energy	EJ/yr
$\boldsymbol{Secondary}$	Secondary Energy	EJ/yr
Conv	Conversion from primary to secondary energy	-
$\boldsymbol{Primary\_CCS}$	Primary energy fuels with CCS (Carbon Capture and Storage)	EJ/yr
$\boldsymbol{Primary\_wo\_CCS}$	Primary energy fuels without CCS (Carbon Capture and Storage)	EJ/yr
$\boldsymbol{EmiFactorBECCS_t}$	BECCS emission factors	Mt CO_2 /EJ
$\boldsymbol{CCS\_Sequestration\_Biomass}$	Carbon Sequestration from Biomass	Mt CO_2 /yr
$\boldsymbol{CCS\_Sequestration\_Fossils}$	Carbon Sequestration from fossils	Mt CO_2 /yr
$\boldsymbol{Emi\_factors}$	Emissions factors by fuels	Mt CO_2 /yr
$\boldsymbol{CO2\ emissions\ wo\ CCS}$	CO_2 emissions from technologies without CCS (Carbon Capture and Storage)	Mt CO_2 /yr
$\boldsymbol{CO2}$	Total energy related emissions (Emissions|CO2|Energy)	Mt CO_2 /yr
$\boldsymbol{carbon\ leakage}$	Capture rate of CCS technologies	%
$\boldsymbol{I}$	Impact on emissions (IPAT equations)	Mt CO_2 /yr
A	Affluence (IPAT equations)	(It depends on chosen indicator)
T	Technology (IPAT equations)	(It depends on chosen indicator)

Table 8 List of parameters

6 Conclusions

We have presented a new downscaling algorithm which provide country-level results based on a range of criteria, such as historical data, planned capacities, supply cost curves and governance. Depending on the criteria, the tool provides results to the country level and therefore can be used to explore the feasibility space of low-carbon emissions pathways in line with the Paris Agreement.

The strength of the downscaling algorithm is the ability to provide country level results within a reasonable computational time, without the need to increase the regional resolution of IAMs, by combining country-level information with regional IAMs results. The tool can be also used to enhance comparisons among IAMs results by using a common regional resolution. Therefore, the tool can be used for harmonising IAMs at the regional level in line with a given scenario/storyline, as harmonisation across models usually is done only at a global space.

However, the downscaling algorithm provides results at the country level by using a set of predefined heuristic rules. The algorithm does not consider all the complex interactions between energy, climate change and the economy, that are captured by IAMs at the regional level. Results from this tool, can be used as boundary constraints for further modeling exercises (for example a country-level CGE – computable general equilibrium model – without a representation of the rest of the world). The downscaling algorithm minimises trade of energy (e.g., electricity) across countries, therefore trying to make all countries as energy independent as possible (to minimise the risk of producing unrealistic trade patterns in the long term).

Finally, the algorithm considers country-level policies (as stated by the NDCs – Nationally Determined Contributions) aiming at stabilising emissions in 2030 and net zero mid-century strategies. To do so, the tool adjusts the primary and secondary energy mix in order to align GHG emissions with those targets. However, those country-level targets are introduced as so called "soft constraints", as they could be eventually overruled by the regional constrains (for example if a given scenario/storyline is not compatible with individual targets at the country level).

7 References

1. Alcamo, J., Roehrl, R.A., Victor, N., 2000. Special report on emissions scenarios (SRES), a special report of Working Group III of the Intergovernmental Panel on Climate Change.
2. Andrijevic, M., Crespo Cuaresma, J., Muttarak, R., Schleussner, C.-F., 2020. Governance in socioeconomic pathways and its role for future adaptive capacity. Nat. Sustain. 3, 35–41. https://doi.org/10.1038/s41893-019-0405-0
3. Ayres, R.U., 2005. Mass, Energy, Efficiency in the US Economy. IIASA Interim Report. IIASA, Laxenburg, Austria: IR-05-034 URL http://pure.iiasa.ac.at/id/eprint/7801/ (accessed 10.8.21).
4. Bollen, J.C., Velthuijsen, J.W., ASE Other Research, 2004 A trade view on climate change policies : a multi-region multi-sector approach.
5. Carter, T.R., FRONZEK, S., BÄRLUND, I., 2004. FINSKEN: a framework for developing consistent global change scenarios for Finland in the 21st century. Fin. Framew. Dev. Consistent Glob. Change Scenar. Finl. 21st Century 9, 91–107.
6. Crespo Cuaresma, J., 2017. Income projections for climate change research: A framework based on human capital dynamics. Glob. Environ. Change 42, 226–236. https://doi.org/10.1016/j.gloenvcha.2015.02.012
7. David, P.A., Wright, G., 1996. The Origins of American Resource Abundance. IIASA Working Paper. IIASA, Laxenburg, Austria: WP-96-015. https://doi.org/10/1/WP-96-015.pdf
8. Dellink, R., Chateau, J., Lanzi, E., Magné, B., 2017. Long-term economic growth projections in the Shared Socioeconomic Pathways. Glob. Environ. Change 42, 200–214. https://doi.org/10.1016/j.gloenvcha.2015.06.004
9. Ehrlich, P.R., Holdren, J.P., 1971. Impact of Population Growth. Science 171, 1212–1217.
10. Fujimori, S., Abe, M., Kinoshita, T., Hasegawa, T., Kawase, H., Kushida, K., Masui, T., Oka, K., Shiogama, H., Takahashi, K., Tatebe, H., Yoshikawa, M., 2017. Downscaling Global Emissions and Its Implications Derived from Climate Model Experiments. PLOS ONE 12, e0169733. https://doi.org/10.1371/journal.pone.0169733
11. Gaffin, S.R., Rosenzweig, C., Xing, X., Yetman, G., 2004. Downscaling and geo-spatial gridding of socio-economic projections from the IPCC Special Report on Emissions Scenarios (SRES). Glob. Environ. Change 14, 105–123. https://doi.org/10.1016/j.gloenvcha.2004.02.004
12. GEA, 2012 Energy Primer. Online Textbook based on Chapter 1 of the Global Energy Assessment (GEA). IIASA, Laxenburg, Austria (September 2014) URL http://pure.iiasa.ac.at/id/eprint/11190/ (accessed 10.8.21).
13. Gernaat, D.E., de Boer, H.S., Daioglou, V., Yalew, S.G., Müller, C., van Vuuren, D.P., 2021. Climate change impacts on renewable energy supply. Nat. Clim. Change 11, 119–125.
14. Gidden, M.J., Fujimori, S., van den Berg, M., Klein, D., Smith, S.J., van Vuuren, D.P., Riahi, K., 2018. A methodology and implementation of automated emissions harmonization for use in Integrated Assessment Models. Environ. Model. Softw. 105, 187–200. https://doi.org/10.1016/j.envsoft.2018.04.002
15. Gidden, M.J., Riahi, K., Smith, S.J., Fujimori, S., Luderer, G., Kriegler, E., van Vuuren, D.P., van den Berg, M., Feng, L., Klein, D., Calvin, K., Doelman, J.C., Frank, S., Fricko, O., Harmsen, M., Hasegawa, T., Havlik, P., Hilaire, J., Hoesly, R., Horing, J., Popp, A., Stehfest, E., Takahashi, K., 2019. Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. Geosci. Model Dev. 12, 1443–1475. https://doi.org/10.5194/gmd-12-1443-2019

16. Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D.L., Rao, N.D., Riahi, K., Rogelj, J., De Stercke, S., Cullen, J., Frank, S., Fricko, O., Guo, F., Gidden, M., Havlík, P., Huppmann, D., Kiesewetter, G., Rafaj, P., Schoepp, W., Valin, H., 2018. A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. Nat. Energy 3, 515–527. https://doi.org/10.1038/s41560-018-0172-6
17. Höhne, N., Ullrich, S., 2005. Emission allowances under the proposal of the" South north dialogue-equity in the greenhouse. Cologne Ger.
18. Hwang, Y., Um, J.-S., Schlüter, S., 2020. Evaluating the Mutual Relationship between IPAT/Kaya Identity Index and ODIAC-Based GOSAT Fossil-Fuel CO2 Flux: Potential and Constraints in Utilizing Decomposed Variables. Int. J. Environ. Res. Public. Health 17, 5976.
19. IEA, I., 2019. World Energy Statistics and Balances, IEA.
20. Kaya, Y., 1989. Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. Intergov. Panel Clim. Chang. Strateg. Work. Group May.
21. Nakićenović, N., Grübler, A., Inaba, A., Messner, S., Nilsson, S., Nishimura, Y., Rogner, H.-H., Schäfer, A., Schrattenholzer, L., Strubegger, M., 1993. Long-term strategies for mitigating global warming. Energy 18, 401.
22. Nakicenovic, N., Nakićenović, N., Grubler, A., Grübler, A., McDonald, A., McDonald, A.T., 1998. Global Energy Perspectives. Cambridge University Press.
23. Platts, S.G., 2019. Platts-World Electric Power Plants Database.
24. Riahi, K., Van Vuuren, D.P., Kriegler, E., Edmonds, J., O'neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Change 42, 153–168.
25. Samir, K.C., Lutz, W., 2017. The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Glob. Environ. Change 42, 181–192.
26. Sferra, F., Krapp, M., Roming, N., Schaeffer, M., Malik, A., Hare, B., Brecha, R., 2019. Towards optimal 1.5° and 2° C emission pathways for individual countries: A Finland case study. Energy Policy 133, 110705.
27. Ueckerdt, F., Bauer, C., Dirnaichner, A., Everall, J., Sacchi, R., Luderer, G., 2021. Potential and risks of hydrogen-based e-fuels in climate change mitigation. Nat. Clim. Change 11, 384–393.
28. van Vuuren, D.P., Lucas, P.L., Hilderink, H., 2007. Downscaling drivers of global environmental change: Enabling use of global SRES scenarios at the national and grid levels. Glob. Environ. Change 17, 114–130.
29. Wall, G., 1977. Exergy-a useful concept within resource accounting. Chalmers tekniska högskola, Göteborgs universitet.