Methodological improvements of Resource Adequacy Assessments

Work package 4
Final Report

Inclusion of climate change impact in RAA

Study on behalf of the
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Inclusion of climate change impact in RAA

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List of Abbreviations

ACER	European Union Agency for the Cooperation of Energy Regulators
CSP	Concentrated Solar Power
ERAA	European Resource Adequacy Assessment
GCM	General Circulation Model
GHG	Greenhouse Gas
LOLE	Loss of load expectation
MTU	Market Time Unit
PECD	Pan-European Climate Database
PV	Photovoltaic
RAA	Resource Adequacy Assessments
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RES	Renewable Energy Sources
TSO	Transmission System Operator

Executive Summary

On the 1st of January 2020, the EU Regulation 2019/943 of the European Parliament and of the Council on the internal market for electricity came into force. In particular, this regulation updated the methodology for (European) Resource Adequacy Assessments (ERAA) to improve it along several dimensions, one of which is the inclusion of climate change impact on adequacy assessment. ACER provided further clarification in its decision by 2nd October 2020 on the ENTSO-E draft methodology for the ERAA, which forms also a basis for national RAA.

As stated in the ACER methodology for ERAA, "*the expected frequency and magnitude of future climate conditions shall be taken into account in the PECD, also reflecting the foreseen evolution of the climate conditions under climate change*". To this effect, three methodological options were proposed by ACER to take climate change into account in RAA:

a. rely on a best forecast of future climate projection
b. weight climate years[11] to reflect their likelihood of occurrence (taking future climate projection into account)
c. rely at most on the 30 most recent historical climatic years included in the PECD

In this report, we describe, examine and compare these options, highlighting their appropriateness and effectiveness by reviewing research papers and methodologies followed by TSOs to reflect climate change in adequacy studies.

First, our literature review suggests that climate change is expected to have an impact on power systems, on both the supply and demand of electricity, but also on adequacy:

- **Impact on power demand and power plants efficiency due to temperature change**: Over the timeframe of the RAA of ten years, climate change is expected on average and depending on location to decrease heating demand and increase cooling demand due to rising temperatures. The direct implication for power systems is that both the shape and volume of electricity demand will be affected. Furthermore, climate change might introduce higher 'volatility' in the trends with more extreme events during both winter and summer seasons compared to the past ~30 years of observed climate data. Temperature increase impact should also be expected on the supply side, namely on thermal capacity by decreasing thermal efficiency as temperature increase. Furthermore, power plants failure rate is correlated with the temperature, which need to be reflected in the adequacy assessments.
- **Impact on hydro production and thermal plant availability due to changes in precipitation**: the conducted literature review indicates a prevalence of projected decrease in hydropower potential. This is the result of changes in precipitation, evaporation that affect the variability and volumes of water available for power plants. Additionally, there is an increased risk of the thermal power plant located along rivers shutdowns during severe droughts.
- **Impact on variable renewables production due to changes in wind speed and solar irradiance levels**: the impact on wind and solar generation is less clear-cut. The findings about wind production are mixed, with diverging results across regions and between studies, suggesting both potential increases and decreases. Concerning PV generation, negligible to small positive effects from changes in irradiance are expected, while temperature increase lowers efficiency.

[1] A climate year defines the weather variables at a specific location for that year (wind speed, irradiance, temperature etc…)

Studies[2] that analyse the impact of climate change on adequacy conclude that climate change would decrease LOLE in cold countries, mainly due to a reduction of heating demand during winter. Conversely, warm countries could see their LOLE increasing due to a higher expected cooling demand over summer. Additional research needs to be conducted in that field, with state-of-the-art RAA studies aiming to provide further insights on the evolution of LOLE with respect to raising temperatures by leveraging climate databases that account for climate change effects.

Second, we discuss the available methods and examples of applications implementing ACER's options.

Finally, we assess the three ACER's options with respect to three criteria: (i) accuracy; (ii) complexity; and (iii) compatibility with other studies.

Overall and albeit more complex, the first option which consists in relying on a projection of future climate appears to be the most promising one out of the three, as it allows to assess the climate change effects on all climate variables used as inputs into power market modelling (temperatures, wind speeds, precipitation and solar radiation) in a consistent way. Variants of this option that aim at reducing its complexity by bypassing GCMs and RCMs should be used in our view as temporary solutions as they do not provide a fully internally consistent dataset with respect to climate variables.

We consider the second option in its generalised formulation, consisting in an adjustment of the historical data to account for the historical climate trends. This option can be quite accurate over the timeframe of the RAA of ten years over which the climate change effect is not expected to be very significant, assuming that historical trends are representative for the next ten years. However, this option may lack consistency between all climate variables obtained through extrapolation.

The third option which consists in relying on the 30 most recent historical climatic years without any refinement or trend correction is the simplest option out of the three since it does not require any additional modelling. However, the last 30 years contain the historical climate trend and using these data directly would most likely result in underestimating the effect of the climate change over the next ten years. Additionally, limiting the dataset to the last 30 years may not be enough to capture rare climate events that could affect adequacy analyses. Considering a longer time horizon might allow to better account for such events statistically.

We thus conclude that ACER's option 1, in its full form (without applying shortcuts) is the most accurate and preferable option for including climate change in RAA, albeit involving quite complex modelling. The use of climate data generated by climate models ensures consistency between climate variables obtained from the model. Furthermore, the complexity of option 1 can be justified by the flexibility of this approach to apply and test in RAA different climate evolution scenarios.

ACER's option 2 considered in the generalised form as adjustment of the historical data to account for the historical climate trends, could still be a reasonably accurate option to address climate change over the time horizon of ten years with little additional modelling efforts. However, this option appears as an intermediary solution rather than a long-term one.

[2] E.g., Harang et al., "Incorporating climate change effects into the European power system adequacy assessment using a post-processing method", 2020 (https://doi.org/10.1016/J.SEGAN.2020.100403)

1. Introduction

In this report, we present, develop, and analyse detailed methodologies for the implementation of the ACER's options to consider climate change in the scope of RAA (Resource Adequacy Assessments).

The objective of RAA is to assess the average number of hours in which a country's electricity demand cannot be met by domestic available resources or via imports through interconnections (Loss of Load Expectation or LoLE). RAA typically relies on a Monte Carlo simulation, which is used to simulate each target year several times with different random inputs to obtain a large sample of results, representative of possible future states of the grid. The objective is thus to obtain a robust outcome in the face of uncertainty. Random inputs include variables dependent on the climate profiles (RES generation, demand) and random outages events derived from available statistics.

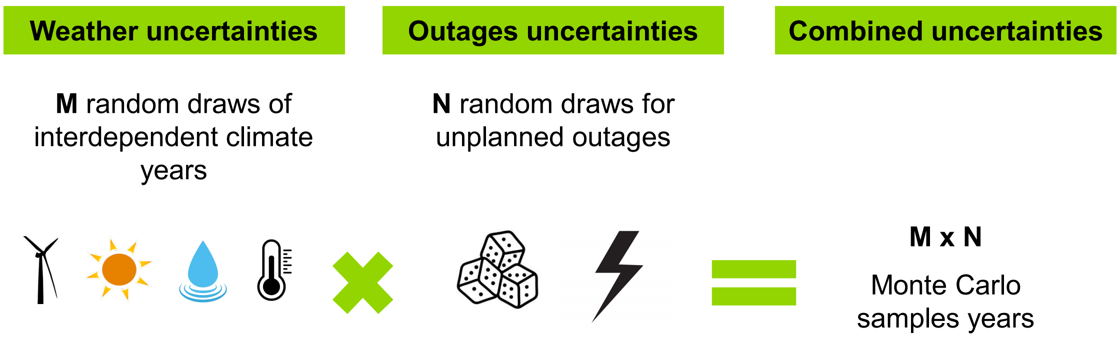

Figure 1. Monte Carlo simulation in ERAA

The ERAA methodology as approved by ACER on the 2nd of October 2020, which is also the basis for national RAA in the EU, aims at ensuring a realistic assessment of resource adequacy, by requiring that the best forecast of the system state will be used to assess as best as possible the overall adequacy of the electric power system to supply current and projected demand levels. As such, it aims to best reflect system development trends, including changes of generation capacity mix, change of demand patterns, network development, trends in market design and others.

One relevant driver for system development trends is climate change. The ENTSO-E methodology for ERAA as approved by ACER thus suggests that the evolution of future climate conditions or climate change should be taken into account in RAA. In its decision on the methodology, ACER suggests[3] three potential options to reflect climate change in the PECD (Pan European Climate Database):

I. Rely on a best forecast of future climate projection;
II. Weight climate years to reflect their likelihood of occurrence (taking future climate projection into account); or
III. Rely at most on the 30 most recent historical climatic years included in the PECD.

The ACER approval also states a minimum spatial and temporal granularity for the input data in RAA, including the variables derived from the climate data:

- The market time unit (MTU) shall be smaller than or equal to an hour; and

[3] Article 4, 1(f)

- The spatial granularity of modelled zones shall be set at least by the smallest level between country and bidding zone.

This report aims to analyse the three suggested options to consider climate change with regards to their respective strengths and weaknesses. The report is structured as follows:

- First, we provide a summary of the relevant existing literature on climate change impact on power markets in general and on adequacy in particular.
- Second, we provide detailed descriptions of possible methodologies for implementing ACER's proposed options in ERAA, based on the academic literature and the applied studies (e.g. performed by TSOs). We further map analysed methodological alternatives to ACER's proposed options.
- Finally, we evaluate the strengths and weaknesses of the ACER's proposed options and the extent to which they can appropriately reflect future climate change in Resource Adequacy Assessments, their explanatory power, and uncertainties that they may have. In this assessment we also rely on the academic discussion during the workshop held on 21 September 2021.

2. Literature research on impact of climate change on adequacy and power markets

In this section, we present an analysis and summarise the main findings of the available academic literature on the inclusion of climate change effects in power markets modelling. We distinguish two types of research:

- Assessing climate change impacts on the elements of power systems in general, and
- Assessing the impacts of climate change on adequacy.

The key takeaways of this literature review can be summarised as follows:

- Climate change is expected on average and depending on location to have a clear impact on power demand through increasing temperature, in particular, by decreasing heating demand in winter and increasing cooling demand in summer. The impact of temperature increase should also be expected on thermal capacity, decreasing thermal efficiency.
- Precipitation will also be affected, decreasing the hydropower potential and water available for hydro power plants. In addition, there is an increasing the risk of power plant shutdowns during droughts, especially on power plants located along rivers.
- The impact on wind and solar generation is less clear-cut. The findings about wind production are mixed, with diverging results across regions and between studies, suggesting both potential increases and decreases. Concerning PV generation, negligible to small positive effects from changes in irradiance are expected, while temperature increase lowers efficiency.
- Overall, climate change is expected to decrease LOLE due to lower demand over winter. However, in warm countries LOLE may increase because of higher summer demand.
- Power plants failure rate is correlated to temperature, which might make it necessary to adjust the power plant fleet to climate change in order to meet security of supply standard when taken into account in adequacy assessments.

2.1 Assessing climate change impacts on power systems in general

Several studies assess more generally the impact of climate change on energy systems, underlying the regional differences in the impacts that could arise from climate change, and providing insights that can broadly be sorted in three categories: (i) impacts on the supply side; (ii) impacts on the demand side; and (iii) other impacts. The three sections below distil the main findings of the literature review in these three categories.

2.1.1 Impacts on the supply side

Energy production is expected to be affected by climate change. Indeed, renewable energy sources which are dependent on climate variables will be impacted by changes in precipitation, temperature, wind speed and solar irradiation: this is the case for solar, wind and hydro assets. As underlined by Cronin et al. (2018)[4], the literature shows differences between impact studies which are mainly due to two factors: (i) the climate projections used as inputs to

[4] Cronin et al. (2018), Climate change impacts on the energy system: a review of trends and gaps, NIH (https://doi.org/10.1007/s10584-018-2265-4)

the impact models; and (ii) the impact model assumptions. Therefore, any impact should be viewed in light of this uncertainty as additional research is necessary in this field. For solar assets, although an increase in temperature decreases the efficiency of photovoltaic panels, it is expected to be offset by slightly higher levels of irradiance that would increase solar production. Furthermore, CSP output (Concentrated Solar Power systems) is expected to increase as the efficiency of CSP plants increases with temperature.

The impacts of climate change on wind resources are mixed – results diverge across regions and between studies. In Europe, both an increase and a decrease in generation is reported in several studies. Pryor et al. (2020) indicate in their paper[5] that the climate change impact on wind power generation is highly uncertain as it is very hard to predict whether wind speed will increase or decrease, at either global or regional scales. Therefore, results from studies should be seen in light of this uncertainty.

Impacts on hydro assets are also mixed and highly dependent on the regions, as precipitation are either expected to increase or decrease differently per location. The meta-analysis conducted by Yalew et al. (2020) indicate a prevalence of projected decrease in hydropower potential in the studies they reviewed. This is the result of changes in precipitation, evaporation that affect the variability and volumes of water available for power plants. T.H. van Vliet et al. (2016)[6] also highlight a decrease in usable hydropower plant usable capacity due to climate change in their study.

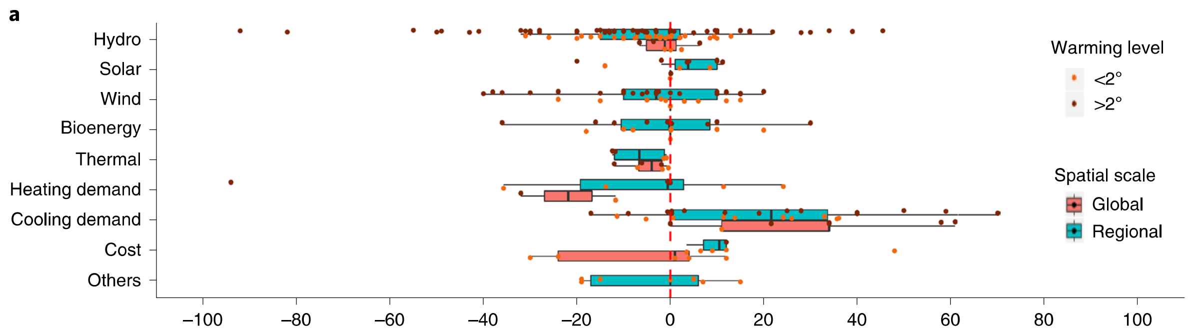

Figure 2 Climate change impact on energy systems per warming level and regional level[7]

Another expected impact will be on thermal power plants which might see their cooling systems affected by temperature changes. Thermal generation efficiency might decrease and the risk of power plant shutdowns during droughts may increase. The largest impacts are expected on power plants located along rivers: plants located along the same river may experience highly correlated shutdowns. Additionally, plants relying on biomass or biofuels could see an impact on their combustible.

2.1.2 Impacts on the demand side

Impacts of climate change are also expected on the demand side, mainly from temperature changes that will affect both the shape and the overall volume of power demand. Indeed, changes in temperature affect heating and cooling requirements. Material changes in cooling requirements are expected to shift peak power consumption from winter to summer in some regions and might affect optimal transmission planning and peak-generation capacity in Eu-

[5] Pryor et al., "Climate change impacts on wind power generation", Nature Reviews, earth & environment, 2020 (https://doi.org/10.1038/s43017-020-0101-7)

[6] . T.H. van Vliet et al. (2016), "Power-generation system vulnerability and adaptation to changes in climate and water resources", Nature Climate Change (https://doi.org/10.1038/nclimate2903)

[7] S. G. Yalew, et al., "Impacts of climate change on energy systems in global and regional scenarios", Nature Energy, 2020 (https://doi.org/10.1038/s41560-020-0664-z), p4

rope. Overall, it is expected that heating demand will decrease while cooling demand will increase, with an overall net impact highly dependent on the region and that could be small overall as both effects combined compensate each other.

Wenz et al. (2017)[8] highlight the expected regional differences in impacts of climate change in Europe. They notably report that the average daily peak load and overall electricity consumption could increase by 3% to 7% in Portugal and Spain, while decrease by 2% to 6% in northern Europe for countries such as Sweden and Norway. Figure 3 below details additional results under two RCP scenarios (Representative Concentration Pathway): (i) RCP 4.5; and (ii) RCP 8.5. These two scenarios intend to capture how concentration in GHG emissions in the atmosphere will change in the future as a result of human activities. The number corresponds to the radiative forcing values in the year 2100 (respectively 4.5 W/m^2 and 8.5 W/m^2).

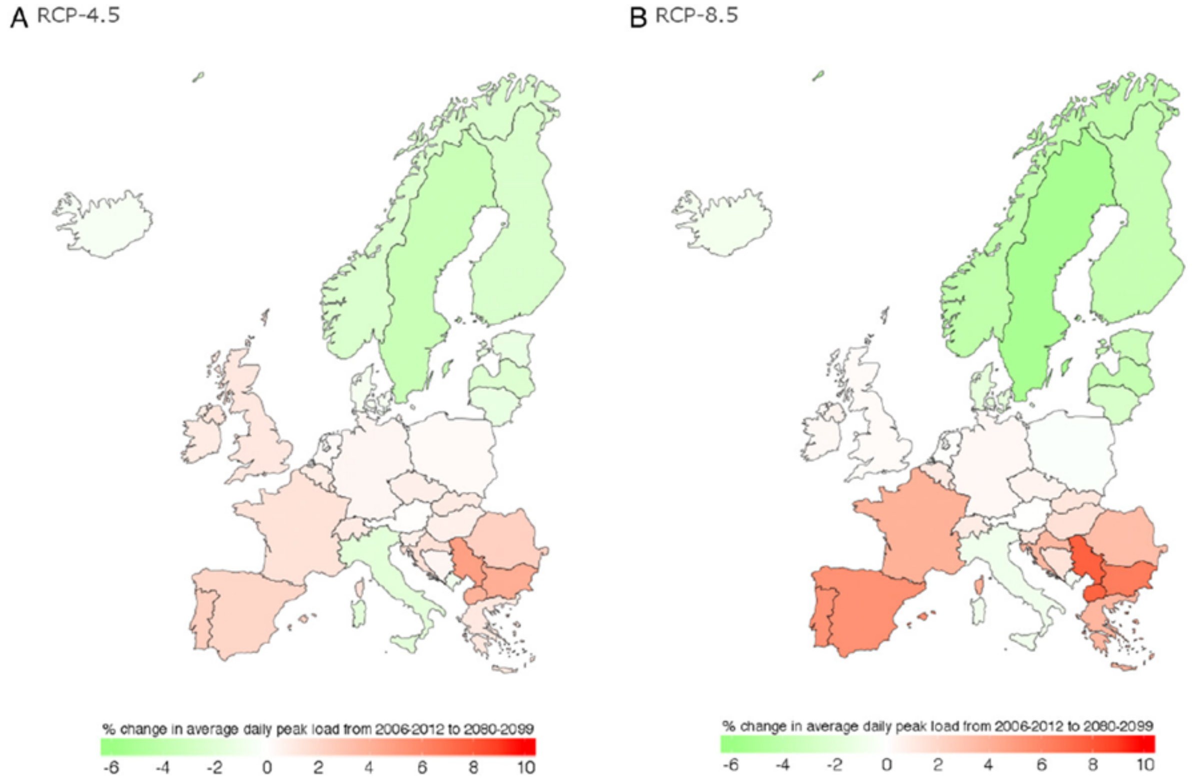

Fig. 4. Percentage change in average daily peak load from 2006–2012 to 2080–2099 for projected daily maximum temperatures under mitigated (*A*) and unmitigated (*B*) climate change. While daily peak load decreases in northern European countries, it increases in southern and western European countries. This trend is most pronounced for a scenario of unabated climate change (RCP-8.5, *B*) but still holds for a scenario of mitigated climate change (RCP-4.5, *A*). Table 1 provides data on all countries and the three RCPs, as well as on different planning horizons until 2100.

Figure 3 Percentage change in average daily peak load in Europe from 2006-2012 to 2080-2099[9]

Kozarcanin et al. (2019)[10] further highlight the impact of a temperature increase due to climate change on cooling and heating demand for power systems and the regional differences that are expected in their article “21st Century Climate Change Impacts on Key Properties of a Large-Scale Renewable-Based Electricity System”.

[8] Wenz et al., “North South polarization of European electricity consumption under future warming.”, 2017, PNAS (https://doi.org/10.1073/pnas.1704339114)

[9] Wenz et al., “North-south polarization of European electricity consumption under future warming”, 2017 (https://doi.org/10.1073/pnas.1704339114),p5

[10] Kozarcanin et al. (2019), “ 21st Century Climate Change Impacts on Key Properties of a Large-Scale Renewable-Based Electricity System“, ScienceDirect (https://doi.org/10.1016/j.joule.2019.02.001)

2.1.3 Other impacts

Indirect impacts might materialise as well on top of direct supply and demand impacts. Seleshi G. Yalew et al. (2020)[12], in their meta-analysis “Impacts of climate change on energy systems and regional scenarios”, underline that cross-sectoral competition for resources might arise from climate change, giving the example of water for producing electricity with hydropower, cooling thermal power plants, irrigation and manufacturing. They also highlight possible material changes in investment expenditures to adapt to climate change, namely on cooling and heating infrastructures.

Impacts are also expected on transmission and distribution infrastructure as highlighted by Fant et al. (2020)[11] with transmission and distribution costs expected to rise as lifespan of installations is reduced with higher temperatures.

Figure 4 below summarises impact on energy systems across the three categories explored in this chapter: (i) supply; (ii) demand; and (iii) others. This figure was extracted from Seleshi G. Yalew meta-analysis.

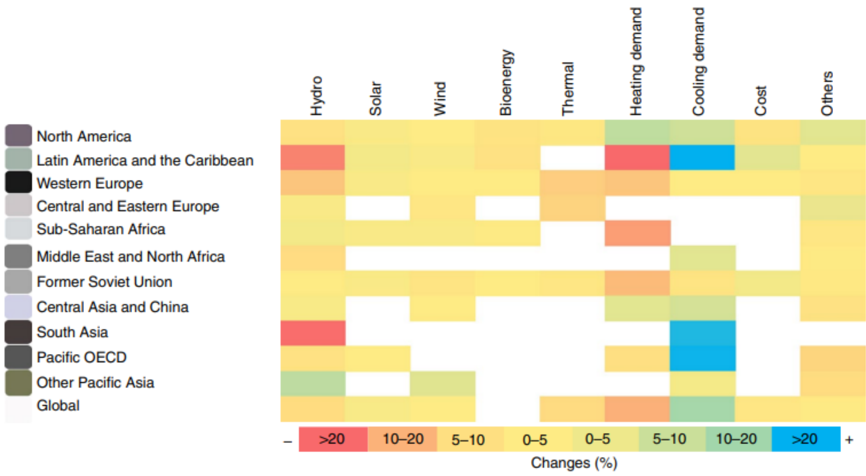

Fig. 4 | Climate change impacts on energy systems averaged across studies, presented per region from results of the reviewed studies. Cells with a red background represent large decreases. Cell colours transitioning from yellow to orange indicate slight decreases. Cells with a blue background represent large increases, and colours transitioning from yellow to blue indicate slight increases. Blank spaces in cells represent ‘no studies’ in the associated regions and energy systems, indicating that some regions are in clear need of more studies relative to others.

Figure 4 Climate change impacts on energy systems[12]

2.2 Assessing the impact of climate change on adequacy

Several studies directly address the impact of climate change on electricity system adequacy. In particular, three papers stand out, which are described below. The key takeaways of this analysis are:

- On average LoLE is expected to decrease due to lower demand over winter. However, significant differences between countries are expected, with LoLE increasing in warm countries due to expected increase in consumption over summer;
- Wind and solar production are not expected to change much;

[11] Fant et al. (2020), “Climate change impacts and costs to U.S. electricity transmission and distribution infrastructure”, Elsevier (https://doi.org/10.1016/j.energy.2020.116899)

[12] S. G. Yalew, et al., “Impacts of climate change on energy systems in global and regional scenarios”, Nature Energy, 2020 (https://doi.org/10.1038/s41560-020-0664-z), p5

- With power plants failure rates being correlated to temperature, climate change will negatively impact adequacy, as additional capacity will be required to ensure security of supply targets when taken into account in the modelling.

2.2.1 First study: "Incorporating climate change effects into the European power system adequacy assessment using a post-processing method" by Harang et al.

In this study, Harang et al. (2020)[13] introduce an approach to include the effects of climate change overt the short-term (5-10 years) into European adequacy studies and discuss its advantages and limitations. Essentially, the approach relies on modifying existing profiles based on the impact of climate change derived from a GCM (General Circulation Model).

The methodology used the following four steps, as described in the hybrid approach in 3.2.1:

1. Gather existing datasets for temperature projection. In this article, the temperature evolution was derived from the EURO-CORDEX climate simulation based on RCP8.5 and the demand profiles were taken from ENTSOE's PEMMB (Pan European Market Modelling Database).
2. Compute existing profiles temperature sensitivity curves, that is how demand evolves at different temperature level (see Figure 12). Run a regression and compute the coefficients of the regression.
3. Deduct the new loads based on regression coefficients and the temperature shift of the temperature projection.
4. Run an adequacy study with the new profiles computed

Results of this analysis show a non-negligible impact on adequacy in the MAF model 2025. Indeed, in the simulation in which only the power demand was adjusted to take into account climate change, the average LOLE in the EU decreased by 59% and the unserved energy by 30% relative to a scenario that does not take into account climate change. This average value encompasses large geographical differences with some market nodes that see their LOLE increasing (for instance Turkey and Cyprus by 60% and 112% respectively) and other that see their LOLE decreasing (for instance Austria). Figure 5 provides additional simulation results analysed in this paper.

[13] Harang et al., "Incorporating climate change effects into the European power system adequacy assessment using a post-processing method", 2020 (https://doi.org/10.1016/J.SEGAN.2020.100403)

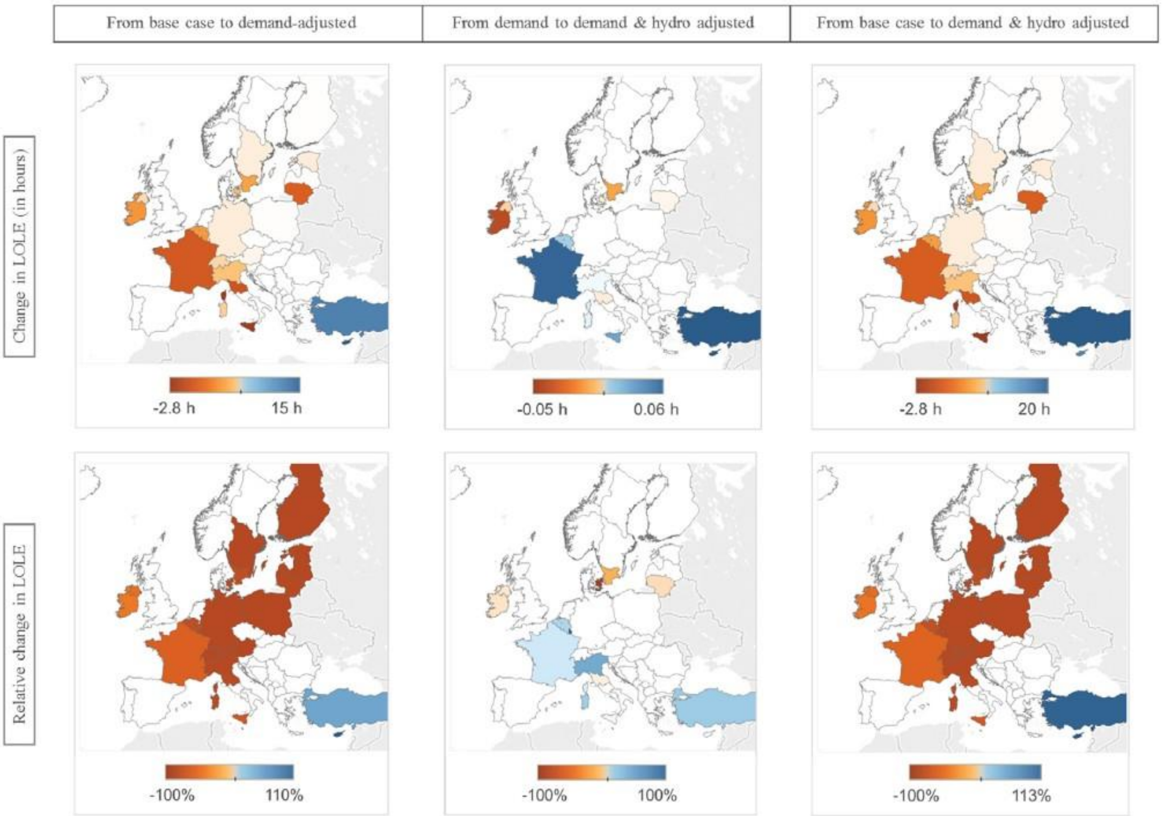

Figure 5 Change in LOLE in models MAF2025 (the base case); MAF2025 (demand CC affected) and MAF2025 (demand and hydro CC affected)[14]

While simpler to put in place than more advanced techniques that rely on GCM, downscaling and synthetic patterns, this methodology also present some caveats as shift in frequency and magnitude of extreme events is not considered. Contrary to using outputs from GCMs directly, assumptions have to be made on the effect of climate change on target variables such as electricity demand or hydro generation, which might introduce significant errors and biases.

2.2.2 Second study: "Meteorological conditions leading to extreme low variable renewable energy production and extreme high energy shortfall" by K. Van der Wiel et al.

In this study, K. van de Wiel et al.(2019)[15] investigate energy shortfalls resulting from varying weather conditions, with energy shortfalls being defined as the residual load, that is the difference between demand and renewable production. The study focuses on the modelling of the situations of the extreme energy shortfalls that may lead to the adequacy issues, that is, situations when low renewable production coincides with high demand.

This analysis is based on a very large ensemble simulation from two climate models giving 3x2000 years of simulated weather conditions. From this data are derived daily wind and so-

[14] Harang et al., "Incorporating climate change effects into the European power system adequacy assessment using a post-processing method", 2020 (https://doi.org/10.1016/J.SEGAN.2020.100403), p7

[15] K. van der Wiel, "Meteorological conditions leading to extreme low variable renewable energy production and extreme high energy shortfall", 2019 (https://doi.org/10.1016/j.rser.2019.04.065)

lar generation, as well as the power demand. Such large sampling allows to capture the frequency of extreme events both on the demand side and on the renewable production side. The flowchart of their modelling is described in Figure 6 below.

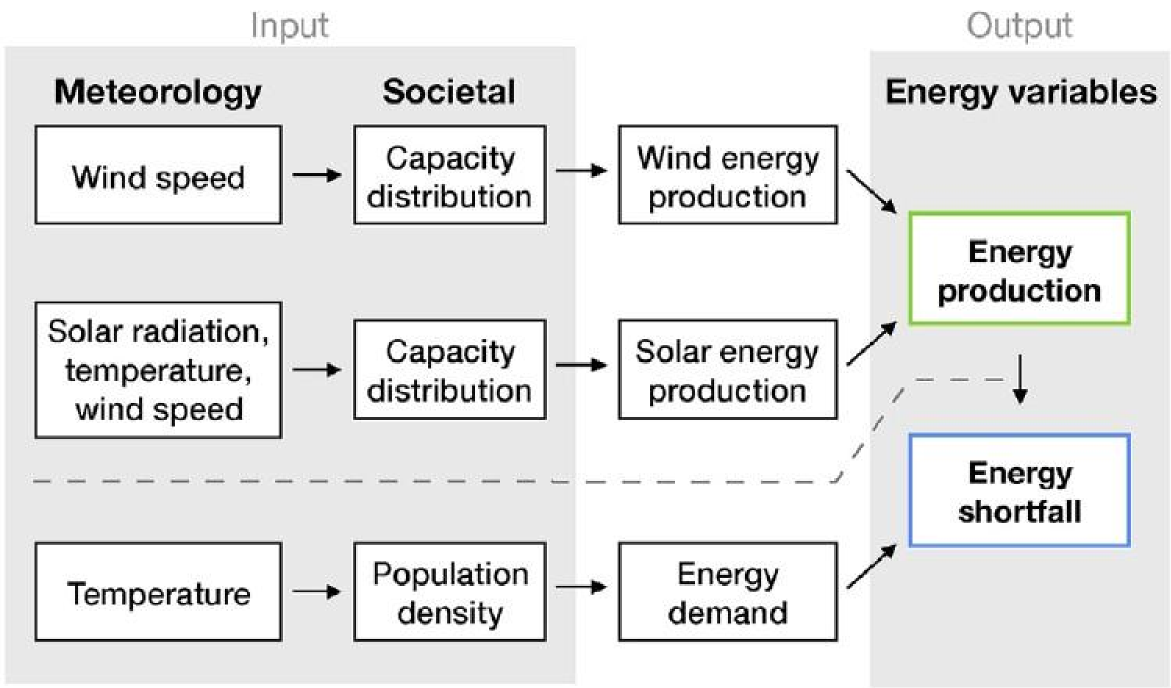

Figure 6 Methodology followed to estimate energy shortfalls[16]

To model the impact of climate change on energy shortfalls, the authors ran two simulations, one scenario without climate change impact used as a benchmark, and another one with a 2C° projected increase in temperature relative to pre-industrial levels.
The paper finds that both wind and solar production do not change much in response to climate change both in mean terms and variability terms (standard deviation). Energy demand is expected to decrease in the winter season (less heating needed) resulting in lower energy shortfalls in winter. K. Van der Wiel et al.(2019) report that their model is not very sensitive to high temperatures and that summertime demand does not change in these simulations. Changes in occurrences of extreme energy shortfall events are in line with decreased wintertime energy demand and thus decrease as well in the modelling. It is underlined in the paper that the energy demand model used assumes a historical (2006–2015) relationship between temperature variations and electrical consumption that will very likely change due to future changes in electrical consumption and power system design.

2.2.3 Third study: "Resource adequacy implication of temperature-dependent electric generator availability" by Murphy et al.

In this paper, Murphy et al. (2020)[17] analyse the impacts of temperature on outages rates and their correlation and show how this impacts resource adequacy in the PJM power market (Pennsylvania-Jersey-Maryland). They underline that at both very cold and very hot temperatures, PJM's fleet is less available than on average, which has a substantial impact on

[16] K. van der Wiel, "Meteorological conditions leading to extreme low variable renewable energy production and extreme high energy shortfall", 2019 (https://doi.org/10.1016/j.rser.2019.04.065), p3

[17] Murphy et al. (2020), "Resource adequacy implication of temperature-dependent electric generator availability", Elsevier (https://doi.org/10.1016/j.apenergy.2019.114424)

adequacy assessment results. Indeed, current resource adequacy assessments typically assume that generator failures are both independent and invariant to ambient conditions. However, they demonstrate in their paper that extreme temperatures are a driver of correlated failures, which increase capacity procurement between 0.5% and 1.5% when accounted for in resource adequacy assessments (in scenarios in which temperature increases by one and two degrees respectively). To conduct this analysis, generators' forced outage rate was modified to depend on ambient temperature rather than fixing it at an average value in an open-source resource adequacy tool (RECAP). The model was calibrated to find the capacity required to limit the frequency of loss-of-load events to once in 10 years over a 11-year horizon, consistent with PJM adequacy assessment approach.

3. Methodology options to address climate change in ERAA

In this section, we provide a detailed description of the potential implementation methodologies of the three options proposed by ACER as well as the information and input data that would be needed, and the modelling effort that would be required to implement these options.

Adequacy assessments model the weather-related uncertainties affecting renewable power production and power demand as well as outages affecting power plants.

Not accounting for climate change is a problem, because adequacy of power system is typically affected by weather events, such as periods of very high demand due to cold temperature or periods of very low renewable production due to the absence of wind or solar production, or combinations of such events, which may lead to energy shortfalls.

The crux of adequacy modelling is to properly forecast the weather impact on power markets, by correctly assessing average conditions, as well as occurrences of severe weather events that drive the adequacy situations. Accounting for the occurrence of the severe events is tricky because, by nature, these events are rare. Any estimation of their frequency is uncertain, and a very large data sample is required to reduce sampling uncertainty. It is generally considered that 30 years is enough to represent the mean climate in the scientific community depending on the location,[18] but it would not necessarily be enough to be representative of extreme events. Furthermore, the lack of representativeness of 30 years cannot necessarily be solved by adding additional historical weather years, as this may increase the overestimation of cold waves in a context where the climate is expected to warm up. Finally, only accounting for changes in averages might not be sufficient to assess adequacy appropriately as adequacy issues might arise from severe weather events such as heat waves or cold waves that affect the volatility of underlying distributions rather than average values.

The overall process of going from climate data to power markets input data is described in the figure below. Weather data from climate database feeds into algorithms to convert them into production or demand data. For instance, wind speed is used to derive onshore wind production patterns.

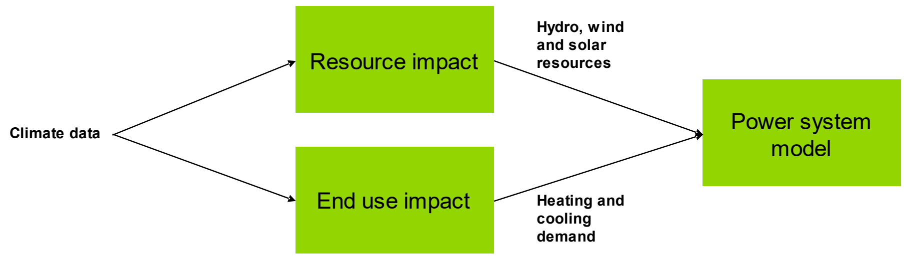

Figure 7 From climate data to power market data

Two factors need to be jointly addressed to ensure accuracy of the adequacy forecast:

- **Impact of the year-to-year weather variation assuming the same climate conditions.** Even in the absence of climate change, weather conditions vary significantly

[18] NASA.gov (https://www.nasa.gov/mission_pages/noaa-n/climate/climate_weather.html), workshop conducted on the 21st of September 2021

from one year to another. The adequacy assessment needs to be able to correctly account for such variation and to accurately represent the probability and magnitude of occurrence of severe weather events independently of climate change; and

- **Impact of the climate change.** The climate change further impacts the year-to-year variation of weather, changing both the average and the variance of the weather variables. To the extent climate change impacts the occurrence and magnitude of severe weather events, this could have an impact on adequacy assessment.

As of today, the climate data used as input in the overall process typically does not consider climate change, as it is in general either based on historical data or reanalysed historical data. The data available typically covers the last 30+ years.

For example, one can use the solar irradiation, wind and temperature data over a number of historical years and then apply these patterns to a forecast year (e.g. 2025) to simulate the range of resulting demand and RES production profiles. Such demand and RES production profiles would reflect the historical year-to-year weather variation. The historical climate data also reflects the climate change dynamics over the time period covered by the historical data, however, it may not be able to correctly reflect the expected evolution of the climate in the future and hence, would not properly account for the latter factor.

In the rest of the section, we present a range of methodologies of deriving the climate data for RAA addressing these two factors. In particular, we start from the approaches that derive the climate data from Global Circulation Models as well as various intermediate options and provide examples of such implementation. Finally, we map the available approaches to the three ACER's proposed options.

3.1 Deriving climate data from General Circulation Model

The first methodology for deriving climate data consists in creating synthetic climate year data using a combination of GCMs (General Circulation Model) and RCMs (Regional Climate Model). We describe this general approach below.
The methodology to go from a GCM to power market model inputs essentially relies on four main steps described in Figure 8 and further detailed below.

Methodology overview

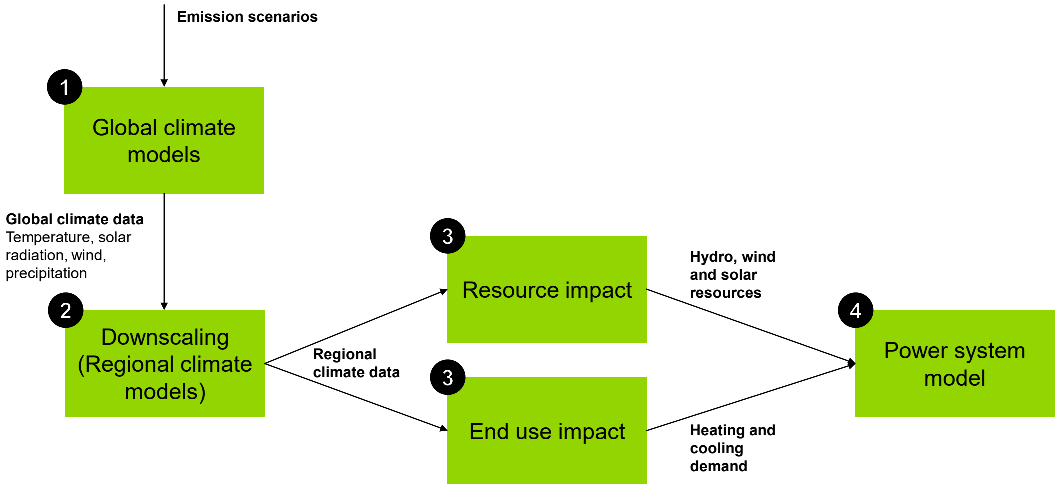

Figure 8 using future climate projection - methodology overview

Step 1: General Circulation Models
The evolution of climate variables is typically projected via General Circulation Models (GCM) which emulates physical interactions between climate variables. These complex models include a wide array of effects ranging from atmospheric chemistry to ice sheet dynamics and provide as an output a projection of climate variables that can be used as inputs in power market studies. Due to the complexity of these models and to the limitation of computing power, the earth is divided into small areas across the height and the depth of the atmosphere and oceans. This simplification is done to calculate the state of the climate and its evolution in each area such as temperature, air pressure, humidity, wind speed, etc. The size of these areas is typically referred as “spatial resolution”. On average, doubling the spatial resolution of a GCM increases tenfold the amount of computing power necessary to run the model in the same amount of time. Similarly, a compromise must be made on the time resolution of the model, that is how often it will compute the state of the climate system.

GCMs typically take as input the GHG concentration of the atmosphere as climate change depends on it to a large extent. As such, various trajectories of global warming and more generally climate variables evolution can be modelled in response to different radiative forcing evolutions such as given by the IPCC (Intergovernmental Panel on Climate Change) scenarios (RCP 4.5, RCP8.5 etc.). RCP scenarios (Representative Concentration Pathway) intend to capture how GHG and aerosol emissions in the atmosphere as well as land use will change in the future as a result of human activities. The number corresponds to the additional radiative forcing values in the year 2100 (respectively 4.5 W/m^2 and 8.5 W/m^2), that is the difference between the energy flowing into the atmosphere from sunlight that is absorbed by the earth and the one that is reflected back into space. The higher this number, the higher the warming effect.

Outputs from GCMs can be extremely valuable to assess the impact of climate change on power markets. Indeed, it is expected that both the production side and the demand side will be affected by the evolution of climate variables, with changes of wind speed, irradiation and water flow patterns affecting the production of hydro and thermal power plants, as well as to a lesser extent wind and solar. It will also be the case on the demand front with temperature affecting the level of demand, as less heating or more cooling will be required to adapt to temperature changes.

Step 2: Downscaling
While GCMs provide an internally consistent set of inputs for power market models, taking into account climate evolution and associated variables, they typically lack the granularity required for power market studies. Indeed, not only inputs need to be geographically tailored to a specific power market zone, but they also need to be fed at hourly granularity into power market models to accurately dispatch power plants and emulate the proper functioning of the market. As aforementioned, compromise have to be made to store the outputs of GCM runs, and thus, although they are run natively with timesteps around some tens of minutes, it is not possible to store the outputs at the granularity required for power market modelling. Thus, a substantial amount of re-processing is required to downscale the output data of GCMs to the required spatial and time granularity of power market models. This process is both costly and imprecise as resampling outputs from a GCM to a more granular geographical and time resolution requires to make proxies and assumptions that may introduce significant errors in the process. The downscaling is typically done via Regional Climate Models (RCM). Regional modelling is also called dynamical downscaling. However, since Regional Climate Models are still models, they again have biases which need to be adjusted, and the temporal resolution of the stored outputs may not fit the requirements either. Statistical techniques designed to bias adjust and downscale global or regional climate model outputs are also available. There are however ways to calibrate the model to ensure a given level of accuracy, namely by calibrating it against historical data to ensure that model outputs are as close as possible as real observations

Steps 3 and 4
The combination of the GCM, the regional downscaling and the bias adjustment can provide the climate data necessary for the adequacy modelling. As discussed above, the wind and solar radiations need to be converted into electric generation variables and temperatures are converted into the demand. This is typically done through functions that output generation based on the technology considered and weather data inputs. For instance, in the case of solar power plants, irradiance is used as one of the main inputs to create solar power generation time series among other parameters that include plant efficiency, and additional technical characteristics of the plants.

Finally, a power market model is run with the data series created in step 3, allowing to model the impact of climate change.
Below we present two examples of the approach based on GCMs used in the recent adequacy analyses: Elia and ENTSO-E.

3.1.1 ELIA's 2022-2032 adequacy study example

In its latest adequacy study, the Belgian TSO ELIA implemented an approach relying on a future climate projection done by Météo-France. The climate database produced by Météo-France can be classified in the synthetic climate years with constant climate category as it consists in multiple potential and equiprobable realisations of a specific target year.
The methodology followed by ELIA consists in three main steps summarised below.

First, Météo-France uses its climate model (ARPEGE-Climat) to generate 200 synthetic climate years with equiprobable rate of occurrences for a target year (for instance 2025) under an RCP scenario (either RCP4.5 or RCP8.5):

- To do so, the climate model is first run with conditions typical of an historical year. Then, the outputs are calibrated against observations to mitigate the biases of the model and to ensure that the synthetic climate years outputted by the model and adjusted are statistically coherent with the historical ones
- Then, synthetic climate years are generated for the target year (for instance 2025) based on future possible evolutions (RCP pathways, ocean surface temperatures reconstructed to be representative of the target period) and bias adjusted.

Second, outputs from Météo-France climate model undergo two main transformations to generate electricity production time series:

- Climate values are aggregated at country level for power market modelling purposes
- Then, these aggregated values are converted into electricity production time series following RTE's methodology. Essentially, RTE derived so-called "transfer functions" by technologies that take weather variables as input, and output electricity production time series. To create these functions, RTE compared historical meteorological data with historical load factor series and determined the transfer functions based on a statistical learning process. This was done per area and per technology. It is worth noting that the transfer functions also take into account technological improvement. This process is described in Figure 9.

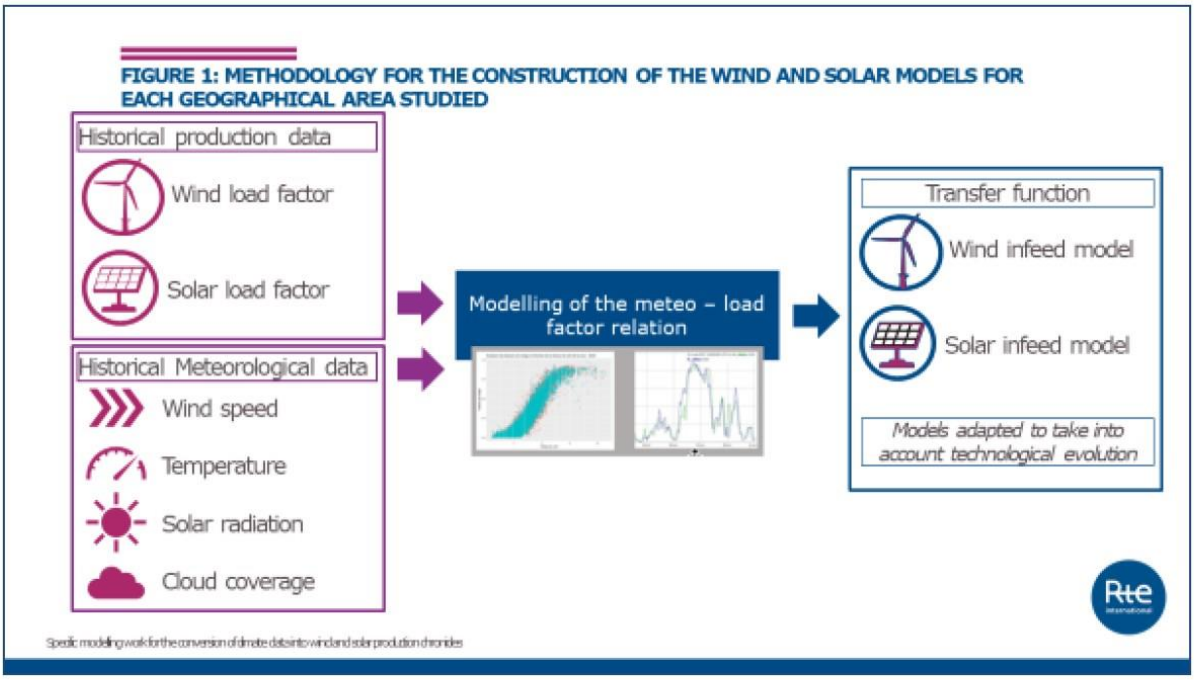

Figure 9 Meteorological data conversion - ELIA/RTE[19]

Third, outputs of step 2 (artificially generated production series) are used in power market modelling. It is worth noting that the 200 series generated only focus on a specific year (in this example 2025), which are deemed representative for a few years around the target year. Indeed, computing 200 synthetic times series for each target year would be an extremely heavy process requiring tremendous amount of data, model calibration and computing power. Besides, it does not take into account all sources of climate variability.

3.1.2 ENTSO-E PECD (Pan European Climate Database) 4.0 roadmap

Over the past few years, ENTSO-E has been significantly improving the underlying data that feeds into their modelling to properly integrate the impact of weather on power markets. The data fed into the modelling of ENTSO-E comes from the PECD (Pan European Climate Database), which is currently being reviewed to integrate climate change considerations into it. Figure 10 describes the current PECD roadmap presented during the expert discussion panel that we conducted at the end of September 2021, further detailed below.

[19] From "representation of the effects of climate on the electrical system: modelling wind and solar generation",p2, (link)

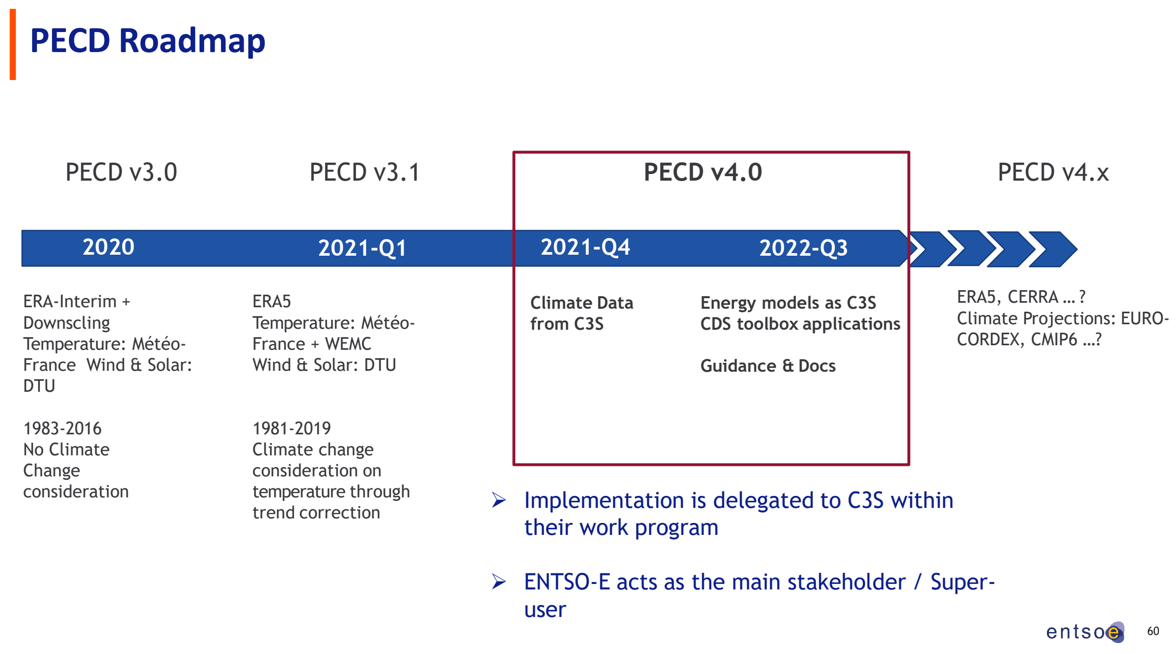

Figure 10 PECD roadmap[20]

In particular, the upcoming PECD v4.0 approach planned to be introduced in 2022 aims at improving the way climate change is considered into the modelling by integrating: (i) several climate projections from several climate models; and (ii) several greenhouse gases emissions scenarios. Climate data from the Copernicus Climate Change Service (C3S) will be used for the PECD V4.0.

3.2 Alternative methodologies

In this section, we present other approaches to integrate the effect of climate change in power markets, that do not follow the general approach described in section 3.1 above.

3.2.1 Hybrid approach

An alternative methodology to using outputs of a GCM model, downscaling them with regional models, applying bias adjustments and then computing new production patterns via conversion algorithms consists in a hybrid approach where the outputs of the GCM model are used to calibrate already existing production/load datasets. This gets rid of step 2 and 3 in Figure 8.

Harang et al. (2020)[21] explore this option in their article “incorporating climate change effects into the European power system adequacy assessment using a post-processing method”. Indeed, a post-processing approach can be used to account for the effects of climate change on existing hourly load factor or demand time series derived from historical data. The overall methodology is described in Figure 11. This approach consists of two main steps:

- **Step 1**: Analysis of the weather dependency of existing power market data series

[20] From workshop conducted on the 21st of September 2021

[21] Harang et al., “Incorporating climate change effects into the European power system adequacy assessment using a post-processing method”, 2020 (https://doi.org/10.1016/J.SEGAN.2020.100403)

In this first step, the historical relationship between weather variables and existing production or load timeseries is analysed to create a function that describes how they change with respect to weather variables.

- **Step 2:** Modification of original production/load series
  The functions obtained from step 1 are used with climate change projections to modify the original timeseries, and therefore embed the impact of climate change in these.

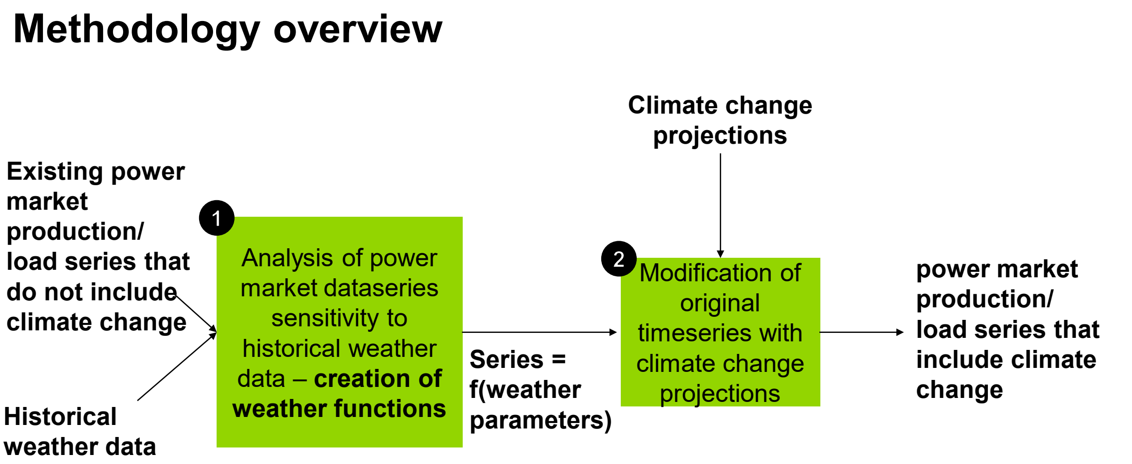

Figure 11 Hybrid approach methodology overview

Load data series example

In their article, Harang et al. (2020) describe how a temperature shift is applied to existing load timeseries by computing the temperature sensitivity curve of the original load series.

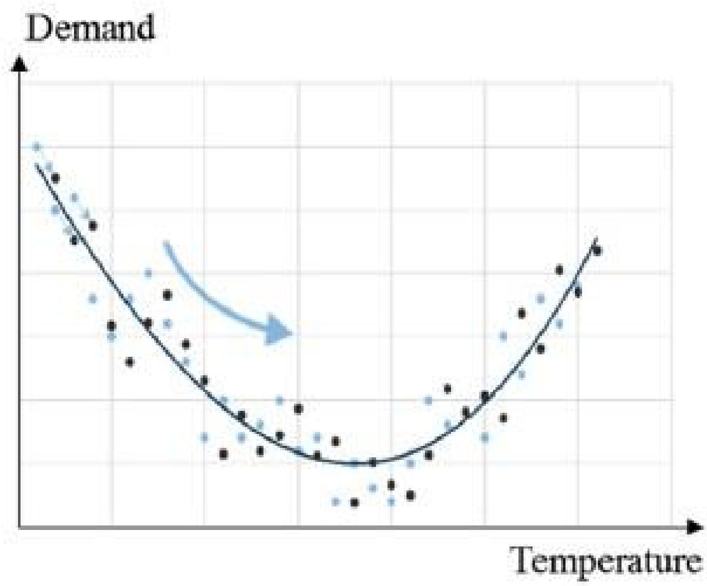

Figure 12 demand sensitivity to temperature[22]

The power demand sensitivity to temperature was computed, and from this were derived coefficients used to move up or down each point of the original timeseries according to projected temperature changes due to climate change. This is illustrated by Figure 12 above. By shifting the temperature, a new load curve can be derived, consistent with the original curve

[22] Harang et al., "Incorporating climate change effects into the European power system adequacy assessment using a post-processing method", 2020 (https://doi.org/10.1016/J.SEGAN.2020.100403), p7

which does not take climate change effects into account, which can therefore be used as a counterfactual.

Reprofiling and scaling methods have the advantage to be easier to implement, and to build upon existing datasets, but require making strong assumptions. From a technical standpoint, these hybrid methods appear easier to implement while integrating some effects of climate change in power market modelling. However, because they only modify existing time series, they typically fail at integrating changes in occurrences of extreme events since these remain as in the original data series. A possible way to go around this shortcoming was studied by Parey et al. (2019), presented in the next section.

3.2.2 Estimating the frequency of extreme events

Against the backdrop of climate change, the frequency of severe weather events is expected to change.

Parey et al. (2019)[23] explore how occurrences of extreme events could be estimated (integrating climate change) in their article "Generating a set of temperature time series representative of recent past and near future climate". It is argued in this article that due to the rarity of extreme weather events which impact security of supply, a very large data sample is required to reduce sampling uncertainty. Parey et al. (2019) propose a methodology to expand outputs from GCMs (either in a single model configuration or multi-model ensembles) to produce a significantly larger ensemble of temporal evolutions and thus estimate more correctly occurrences of rare events.

This much larger set of data is generated artificially by using a stochastic weather generator, which is then used to identify changes in the frequency of the most severe heat waves or cold waves. Typically, weather generators have been used for pricing derivatives in the energy sector. Weather generators typically include the impact of climate change by using Change Factors (CFs) derived from GCMs or RCMs, which express changes between a baseline climate and future projections. Change factors are applied to the statistics of the observed time series to produce projected time series, which are then used to calibrate the weather generator. However, in their study, Sylvie Parey *et al.* rather combined the trends in temperature mean and standard deviation extracted from climate model projections with the stochastic generator outputs to compute future temperature timeseries.

The importance of the climate model choice is highlighted in the paper, as it affects materially the outcomes of the simulation. In particular, it was found that the intensity of very severe cold waves was reduced by a factor two on average across several models, with a large deviation of results (one model estimating a division by a factor 5 and another one projecting almost no change). Similarly, the intensity of very severe heat waves was found to increase by a factor 4 on average with one model going up to a factor 10.

Such a technique could be used as an intermediary solution to derive probabilities of extreme weather events with respect to climate change, and to weight existing production/load data series with extreme events in the Monte Carlo adequacy assessment so that they are picked more or less often. Such a methodology would however carry an inherent drawback: the physical structure / patterns of extremes might be different in the future from what they were in the past, making the method less robust than using a projection from a GCM.

[23] Parey et al. (2019), "Generating a set of temperature time series representative of recent past and near future climate", Frontiers in environmental science

3.2.3 Approaches relying on statistical forecast of the climate variables

Approaches that do not use future climate projections can be developed from the existing historical data by analysing how climate change has already affected this data in the past and by extrapolating the historical trends into the future. For example, the PECD V3.1 from ENTSO-E is a good methodological example of only relying on existing data series (re-analysed historical data), and not using any climate model's future projections. Instead, trends are extrapolated from the existing data, which already likely encompasses near-term effects of climate change.

PECD V3.1

The PECD (v3.1) takes into account climate change through temperature trend correction[24] and does not rely on anything else than already available time series.

Essentially, this methodology consists in computing linear trends using the available data, which is then applied to forecast years. Climate change affects climate variables trends in two main ways: (i) changes in mean; and (ii) changes in variance. A linear trend is therefore computed for both the mean and the variance on historical data and then extrapolated to future periods. Once the linear trend is computed, the extrapolation can be performed on the original time series, by following these steps: (i) de-trend the original timeseries with respect to temperature; (ii) select randomly or based on a criterium individual years out of the original timeseries; (iii) adjust the variance of the selected year based on the "target" year (e.g., 2025) based on their estimated variance (linearly extrapolated from historical analysis); and (iv) add the appropriate trend based on the target year (mean trend). To avoid mapping issues, each year in the 1981-2019 dataset was adjusted to 2025, which means that years further in the past are subject to larger trend adjustments than recent years.

The figure below illustrates the process of de-trending the existing data with respect to temperature to obtain a temperature neutral profile, and of applying the projected temperature effect of a target year in the future. Two main parameters are estimated to conduct this adjustment: mean evolution and variance evolution. The mean gives the overall trend of the forecast, while the variance will give the deviation from the mean, or in other words the volatility of the series. First, the original timeseries are detrended, and trends are computed for the mean and the variance. Once this is done, a regression is performed on the trends of the mean and the variance to extrapolate them into the future (see Figure 13).

[24] ENTSO-E use of Pan European Climate Database (PECD), from Copernicus Climate Change Service

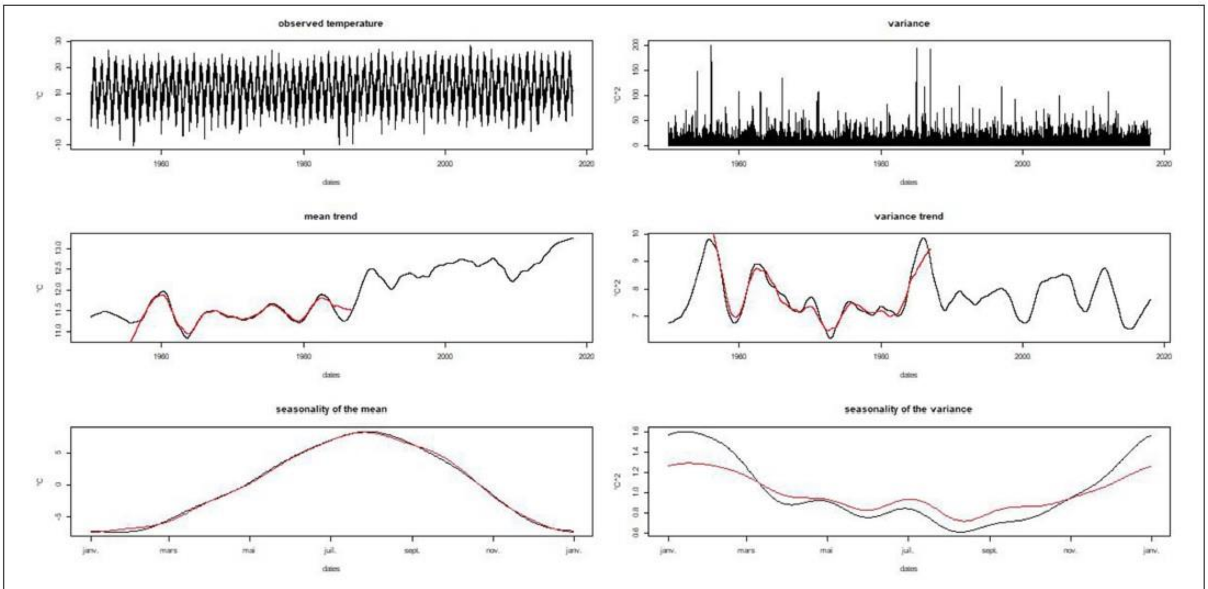

FIGURE 2 | Observed indicator from 1950 to 2017 (top left panel), non-parametric trend in mean (middle left panel), seasonality of the mean (bottom left panel), evolution of the variance (top right panel), non-parametric trend in variance (middle right panel), and seasonality of the variance (bottom right panel). Black curves are for the total period and red curves for period 1955–1986.

Figure 13 mean and variance trends from temperature series[25]

In a second step, the original de-trended series are adjusted to reflect the projected mean and variance obtained from the extrapolation in the first step. For example, considering that one wants to model 2030 with a 2006 weather year, one would adjust the mean and the variance of the de-trended 2006 pattern to the projected variance and mean of 2030. An example of result from this process is shown in Figure 14.

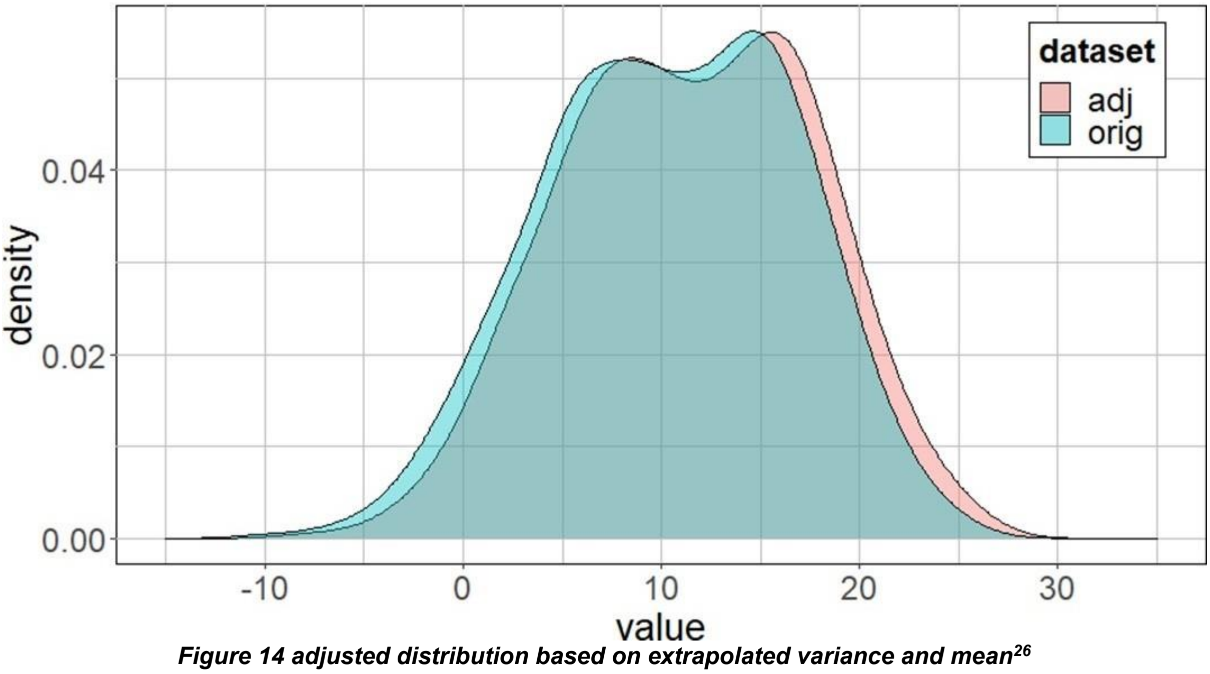

Figure 14 adjusted distribution based on extrapolated variance and mean[26]

[25] P7 from Parey et al. “Generating a set of temperature time series representative of recent past and near future climate”, published on 28 june 2019 (doi: https://doi.org/10.3389/fenvs.2019.00099)

[26] From workshop conducted on the 21st of September 2021

3.3 Classification of the ACER's options to consider climate change

ACER introduced three options to consider climate change in the ENTSO-E methodology for ERAA published on the 2nd of October 2020:

i. *rely on a best estimate of future climate projection*

ii. *weight climate years to reflect their likelihood of occurrence (taking future climate projection into account)*

iii. *rely at most on the 30 most recent historical climatic years included in the PECD*

We classify in the table below how the techniques identified in this chapter fit with ACER's options. We understand that ACER's options were proposed with no specific link to the approaches that have been developed later. It may thus make sense to generalise ACER's Option 2 and consider it to be a general approach to adjust the historical data in some way to account for the historical climate trends.

	Example	**Comment**
ACER Option 1	• General GCM approach (Illustrated by ELIA's adequacy approach) • ENTSO-E PECD v4.0	All these methodologies use future climate projections from GCMs and RCMs seem to fall into this category as they aim to use the best estimate of the future climate projection.
ACER Option 2	• Parey et al. (2019) • ENTSO-E PECD v3.1 • Hybrid approach	ACER's Option 2 can be considered as a general approach to adjust the historical data in some way to account for the historical climate trends. This can be e.g. • Via weighting the historical years (more recent years being weighted higher). Methodology by Parey et al.(2019) could be used to estimate probabilities of occurrences of severe weather events, and weight the weather years selection in Monte Carlo simulations for ERAA. Or • Via correction based on historical trends, such as extrapolations of mean and variance changes in temperature from existing datasets. Via a hybrid approach (post-processing approach) that can be used to account for the effects of climate change on existing hourly load factor or demand time series derived from historical data.
ACER Option 3	• PECD v3.0	This methodology only relies on existing datasets without altering them with respect to climate change.

4. Appropriateness of ACER's options to address climate change in RAA

In this section, we compare the advantages and drawbacks of the three methodologies described in Section 3, by assessing to what extent the options proposed by ACER can appropriately reflect future climate change in Resource Adequacy Assessments. To do so, an analysis of their strengths and weaknesses, explanatory power and associated uncertainties was conducted. This assessment largely relies on observations obtained from: (i) the overview of the existing literature to date; and (ii) inputs from experts obtained during the workshop conducted on the 21st of September 2021 (See the summary in the Annex).

The table below describes in more detail the advantages and drawbacks of the three envisioned methodologies by assessing them across three dimensions:

(i) **Accuracy:** This criterion aims at measuring how well climate change is taken into account by the methodology.

(ii) **Complexity:** This criterion aims at assessing the modelling efforts required to put in place that methodology; and

(iii) **Benchmarking ability:** The third criterion aims at assessing whether this methodology can easily be used to benchmark several scenarios of climate change

The table below presents the assessment of each of ACER's Options against these three criteria, considering ACER's Option 2 in a generalised way as the approach to adjust the historical data in some way to account for the historical climate trends.

	ACER Option 1 **Rely on a best forecast of future climate projection**	**ACER Option 2** **Adjust the historical data in some way to account for the historical climate trends.**	**ACER Option 3** **Rely at most on the 30 most recent historical climatic years included in the PECD**
Accuracy	+ Climate variables used as inputs for power markets (temperature, wind speed, precipitation and solar radiation) are fully internally consistent thanks to GCMs, which model the physics of climate change. + Allows to capture the impact of climate change across all relevant dimensions: (i) mean changes; (ii) variance changes; and (iii) occurrences of extreme weather events. Results for the first few years of the projection might not be as accurate as recently observed historical data due to modelling errors/inaccuracies (i.e., necessary downscaling of outputs of GCMs might introduce additional biases and modelling errors/inaccuracies.) However, robust calibration against historical data should ensure a good level and transparent level of accuracy.	Allows to capture the impact of climate change across one dimension only (e.g., occurrences of extreme events only or applying the trends to reflect mean and variance changes due to temperature) without ensuring consistency between all climate variables + Good accuracy for the next decade as the weather is not expected to change drastically in the next ten years, but rather over longer horizons. - Applying the historical climate trends or weighting historical climate years assumes that past trends will be representative of the future with respect to temperature, which might not be the case and will not address the changes in mean and variance of existing time series.	Could still be quite accurate for short-term forecast as weather is not expected to change drastically over the coming years. However, the historical data already captures the climate changes over the past 30 years and using such data without correction may bias the projection. - Does not allow to capture the impact of climate change on mean, variance and frequency of extreme events changes. - Limiting the dataset to the last 30 years may not be enough to capture rare climate events. Frequency of events might not be accurately modelled. However, taking too many historical years could lead to underestimating the impact of climate change in this approach.
Complexity	- Complex modelling required due to the need of one or several GCMs and subsequently RCMs. Modelling effort is high, both in terms of computing power necessary to run the different models (GCMs, RCMs) but also in terms of input data required and data processing. Possibility to reduce complexity by applying post-processing methods but reducing accuracy as changes in extreme events frequency would not be reflected	+ Statistical adjustment for the historical trends is a relatively simple option relying on existing datasets, extrapolating the historical trends into the future. Assessing the weights of the climate years to reflect their future likelihood is more complex requiring large sample of weather years through to capture accurately occurrences of severe events.	+ Simplest option out of the three as it relies on existing datasets and does not involve additional complex climate modelling or any additional data processing.
Benchmarking ability	+ Ability to run several scenarios of climate change, allowing for easy comparison between scenarios and to create benchmarks.	- Running several climate change scenarios would be more difficult and less consistent than in option 1 as different weights/adjustments of the historical series will have to be done to run different climate change scenarios	- This option does not provide the possibility to take into account alternative scenarios of climate change

Overall and albeit more complex, the first option which consists in relying on a best estimate of future climate projection appears to be the most promising one out of the three, as it allows to assess the climate change effects on all climate variables used as inputs into power market modelling (temperatures, wind speeds, precipitation and solar radiation), and to run different climate change scenarios, ensuring full consistency between input timeseries used in power market modelling. Indeed, this methodology allows to capture: (i) mean changes of weather parameters; (ii) variance changes of other relevant weather parameters (precipitation, wind and solar radiation); and (iii) changes in frequency of extreme weather events. However, both the variable consistency and the future changes are dependent on the chosen climate model. Identifying the best estimate for the projection is not an easy task since a large number of climate models exists with different strengths and weaknesses. Variants of this option that aim at reducing its complexity by bypassing GCMs and RCMs could be used in our view as temporary solutions as they do not provide a fully internally consistent dataset with respect to climate variables.

We consider the second option in its generalised formulation, consisting in an adjustment of the historical data to account for the historical climate trends. For example, detrending methodologies which consist in extrapolating trends of impact of temperature from historical data allow to capture the main impact of climate change on the power sector of the mean and the variance of the temperature. This approach can be quite accurate over the timeframe of the RAA of ten years over which the climate change effect is not expected to be very significant, assuming that (i) there are no trends break compared to historical trends; and (ii) frequency of extreme events is representative in the historical climate years available. This option may also lack consistency between all climate variables obtained through extrapolation.

The third option which consists in relying on the 30 most recent historical climatic years included in the PECD without any refinement or trend correction can also be relevant for short-term projections. It is the simplest option out of the three since it does not require any additional modelling and existing datasets can be used as they are. However, using such an approach would rely on the hypothesis that the weather is not expected to change much over the coming years compared to the average of the last 30 years and that the existing dataset is therefore representative of the forecast years. However, the last 30 years contain the climate trend and using these data directly with no adjustment for this trend would most likely result in underestimating the effect of the climate change over the next ten years. On the other hand, limiting the historical dataset to the last 30 years may not be enough to capture rare climate events. However, taking too many historical years could lead to underestimating the effect of climate change by using this approach.

Therefore, we conclude that ACER's Option 1, in its full form (i.e. relying on Global Climate Models (GCM), Regional Climate Models (RCM) and bias adjustment, without applying shortcuts) is the most accurate and preferable option for including climate change in RAA, albeit involving quite complex modelling. The use of climate data generated by climate models ensures consistency between climate variables obtained from the model. Furthermore, the complexity of Option 1 can be justified by the ability of this approach to benchmark alternative scenarios of climate change.

ACER's Option 2 considered in the generalised form as adjustment of the historical data to account for the historical climate trends, could still be a reasonably accurate option to address the climate change over the time horizon of ten years with little additional modelling efforts.

Literature

We list below the articles and documents that have been reviewed in this report:

- L. A. Wenz, et al., “North–south polarization of European electricity consumption under future warming. Proc. Natl. Acad. Sci., 2017 (https://doi.org/10.1073/pnas.1704339114)
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- Fant et al. (2020), “Climate change impacts and costs to U.S. electricity transmission and distribution infrastructure”, Elsevier (https://doi.org/10.1016/j.energy.2020.116899)

Appendix

Meeting minutes: Workshop WP4, 21 September 2021

Date and time:	21.09.2021
Place:	Online
Participants (Institution):	**Research team**: Fabien Roques, Dmitri Perekhodtsev, Anton Burger (Compass Lexecon), Christian Nabe, Karoline Steinbacher, Konstantin Staschus (Guidehouse), Robert Diels, Martin Lienert, Marcel Brodhof (r2b) **External experts**: Dr Blanka Bartók (BBU), Dr Laurent Dubus (RTE/ENTSO-E), Laurens Stoop (Univ Utrecht), Dr Matti Juhani Koivisto (DTU), Dr David Brayshaw (University of Reading), Dr Hagen Koch (Potsdam Institute for Climate Impact Research), Dr. Jan Wohland (ETH Zurich), Dr Alberto Troccoli (World Energy & Meteorology Council), Dr Luke Lavin (NREL) and Dr Laura Manz (Guidehouse) **Pentalateral Forum steering lead:** Benedikt Günter, Simeon Hagspiel, Jan Hensmans, Eppie Pelgrum. **Pentalateral Forum members**

The key takeaways of the discussion session are listed below:

- Concerns were raised about the data quality outputted by GCMs when compared to historical data. Jan Wohland (ETH Zurich) mentioned that within 10 years you might be better off to just using historical data, and that climate change signal will be relatively small. David Brayshaw (Univ. of Reading) also suggested that the trend over 5 to 10 years due to the amount of greenhouse gas increases is relatively modest.
- Caution was raised about relying entirely on historic data, as using 30 years of recent history to look five to ten years into the future may introduce biases. Indeed, the earlier part of the record consist of data from 30 years ago which ultimately consist in a transient record over these 30 years.
- Matti Kovisto (DTU) mentioned that one option could be to use 20 of historical years in combination with scaling of the historical data with temperature, maybe even with mean wind speeds. However, it would be hard to model the correct representation of extreme events.
- Alberto Troccoli (WEMCO) argued that the longest possible record of historical data should be used: “even if you go back to the 60s and you know you got this very cold periods because those are part of the statistics of the climate we know and although they are unlikely to recur.”
- Thermal generation is one of the challenging aspects of considering climate change in RAA. Indeed, accounting for correlation of temperature effect on outage rates of thermal plants is tricky. European rivers which host a number of thermal power plants. One needs to be very careful and account for these correlations in the Monte Carlo simulations.