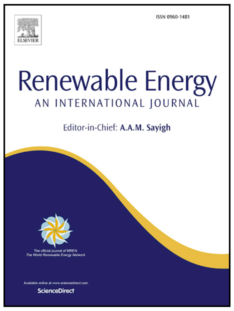

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Quantifying the sensitivity of European power systems to energy scenarios and climate change projections

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Highlights

- Future climate affects European power systems simulated with EURO-CORDEX models
- Significant climate uncertainty in key power system properties (demand, renewables)
- Climate uncertainty exacerbated in renewable-intensive power system scenarios
- Spatio-temporal and multi-model aggregation masks complex patterns of change
- Better understanding of climate uncertainty in power system design is needed

Abstract

Climate simulations consistently show an increase in European near-surface air temperature by the late 21st century, although projections for near-surface wind speeds and irradiance differ between models, and are accompanied by large natural variability. These factors make it difficult to estimate the effects of physical climate change on power system planning. Here, the impact of climate change on future European power systems is estimated.

We show for the first time how a set of divergent future power system scenarios lead to marked differences in Europe's total energy balance (demand-net-renewable supply) by 2050, which dominate over the uncertainty associated with climate change (~50% and ~5% respectively). However, within any given power system scenario, national power systems may be subject to considerable impacts from climate change, particularly for seasonal differences between renewable resources (e.g., wind power may be impacted by ~20% or more). There is little agreement between climate models in terms of the spatio-temporal pattern of these impacts, and even in the direction of change for wind and solar. More thorough consideration of climate uncertainty is therefore needed, as it is likely to be of great importance for robust future power system planning and design.

Keywords: Demand, wind power, Solar PV, climate change, uncertainty, scenarios

1 - Introduction

To meet carbon reduction targets, energy systems across the globe are changing their power systems rapidly to incorporate low-carbon generation. Substantial growth in the amount of installed wind and solar power generation has been seen in both advanced and developing economies (IEA, 2018). Large changes in electricity demand are also expected due to electrification of heating and transport, economic development, and changes in thermal comfort requirements (Isaac and Van Vuuren, 2009, IPCC, 2011). Collectively these changes lead to a growing sensitivity of supply and demand to meteorological conditions.

This large increase in weather sensitivity is also occurring at a time of rapid global climate change. It is well established that global and regional temperatures are increasing and will continue to increase with human-induced climate change, resulting in increasing electricity demand for residential cooling (IPCC, 2014, Mideksa, and Kallbekken, 2010). However, there is less certainty in the response of near surface wind speeds and surface solar radiation, two key meteorological variables for renewable power generation (IPCC, 2013). How these meteorological changes impact the characteristics of wind and solar power production is also less well known (IPCC, 2015). Europe is a particular region of interest due to the large amount of wind, solar and hydropower presently installed and planned, alongside the uncertainty regarding future European climate projections (Stoker et al. 2013; Gonzalez et al 2019). In the European Union, 17.5% of energy consumed in 2017 was from renewable sources (EUROSTAT, 2019), with an aim of at least 32% renewable energy consumption by 2030 (EU Commission, 2014). The sensitivity of the European power system to climate is also likely to increase significantly, given the renewable capacity increases planned to meet the 1.5°/2° degree Paris agreement targets and multiple countries' aims for "net-zero" emissions by 2050 (e.g. the UK; CCC, 2019, and France; HCplC 2019).

Recent studies investigating the impact of climate change on demand concur that annual heating-induced demand is likely to reduce, whereas cooling-induced demand is likely to increase (Mirasgedis et al. 2007, Isaac and van Vuuren 2009, Golombek et al. 2011, Mideksa and Kallbekken, 2012, Damm et al. 2017, Auffhammer et al. 2017, Spinoni et al. 2018, Arnell et al. 2018). However, the realised trend is likely to depend strongly on a broader picture of socio-economic and technological change (e.g., Boßman and Staffell 2015, Kavvadias et al. 2019). By contrast, studies of climate change impacts on renewable generation potential are far less consistent. For wind, some studies find moderate reductions in projected wind power generation over Europe (Barstad et al, 2012, Tobin et al. 2016, Tobin et al. 2019) particularly in summer (Moemken et al. 2018) while others find increases (Cradden et al. 2012, Hueging et al. 2013). Changes in the inter-annual and seasonal variability of wind power generation are also found across Europe (Hueging et al. 2013, Weber et al 2018). For solar photovoltaic (PV) power generation potential there is a similarly inconsistent climate change response: Jerez et al. (2015) suggest a reduction in solar PV potential across all of Europe, with largest reductions over Scandinavia, whereas other studies find that solar PV potential generally increases in Central-Southern Europe and decreases in Northern Europe, with an overall increase across Europe (Wild et al. 2015, Müller et al. 2019).

The previously discussed studies have shown potential impacts of climate change on electricity demand, wind and solar PV generation. A key limitation is that they are focussed on a single electricity variable and do not directly consider the integrated impact of climate change on power systems through simultaneous changes in demand and both wind and solar power generation. Recently, several integrated power system impact studies have emerged for individual countries or regions. Many of these have focussed on quantifying the role of “present-day” inter-annual clima te variability (Bloomfield et al. 2016, Staffell and Pfenninger 2018, Collins et al. 2018, Drew et al. 2019, Wohland et al. 2019). There are, however, relatively few studies which address long-term (decadal scale) climate projections at continental scale.

Bloomfield (2017) investigated the impact of climate change on demand and wind power generation for the United Kingdom using a single global climate model, showing that with a quadrupling of CO2 emissions moderate reductions in annual demand are seen with little change in wind power generation. Tobin et al. (2018) studied the vulnerabilities of wind, solar, hydro and thermoelectric power generation across Europe under three different climate scenarios. In each case, the most consistent response across several climate models came from the temperature-sensitive aspects of the power system, primarily through demand (alongside consequences for the cooling efficiency of thermoelectric power generation). Although Tobin et al. (2018) rigorously analyse the weather-dependent power system components they do not compare different economic scenarios to benchmark the magnitude of the climate induced response. Kozarcanin et al. (2019), using six climate models, calculated power system infrastructure metrics (relating to transmission, storage and the total volume of electricity generation) based on a single Europe-wide power system model incorporating wind, solar and demand. They demonstrated that for most of these metrics, the impacts of 21st century climate change are modest relative to the magnitude of present-day inter-annual variability. Elsewhere, in the US, Craig et al. (2019) showed that although optimal power system design in Texas is potentially impacted by climate change through changes in wind and solar generation, the sign and magnitude of the changes – particularly in individual component technologies - are very dependent on the choice of climate model.

The aim of this study is therefore to understand the sensitivity of possible future European power systems to both the choice of power system scenario and the potential impacts of climate change (including identifying the roles of emission scenarios and climate model uncertainty). Although previous studies have addressed various individual components of this problem to a limited extent, this is the first study to examine the impact of all these sources of change and uncertainty simultaneously. Having an understanding of the relative magnitude of both of these types of uncertainty (i.e., power system scenario and climate change projection) is important for future policy design in highly weather-dependent systems, for which the magnitude of the climate uncertainty has been shown to be increasing (Bloomfield et al., 2016). To do this the following three aims are addressed:

- Firstly, we investigate the impact of climate change, within a chosen power system scenario, on relevant surface climate indicators and weather-dependent power-system components: i.e., the extent to which a given future power system scenario is affected by climate change and uncertainty.
- Secondly, we investigate the extent to which these impacts of climate change and uncertainty can be understood in terms of differences between technologies (i.e. the amount of installed wind and solar power generation) and geographic location.
- Finally we investigate if the gross operating characteristics of different high-level European energy policy scenarios (e.g. 100% renewable vs. large amounts of carbon-capture and storage) are strongly impacted by climate change, making comparisons to the previous two aims.

This study makes use of country-level time series of meteorological variables, electricity demand, and wind and solar power generation from the Copernicus Climate Change Service (C3S) European Climate Energy Mixes (ECEM) project (Troccoli et al. 2018). As well as addressing the questions defined above, this paper also illustrates the potential use of ECEM data to motivate further investigation by the energy systems research community. The analysis presented here can be replicated and extended using this publicly available and easy-to-use dataset.

The paper is structured as follows. Section 2 describes the ECEM dataset in detail and introduces the modelling framework and energy system scenarios used for the analysis. Section 3 begins by showing the impact of climate change on a fixed present-day energy system, for a series of power system relevant climate variables (section 3.1), followed by demand (section 3.2), wind power generation (section 3.3) and solar power generation (section 3.4). Following this, a combined system approach is taken to assess how the uncertainty in the climate change projections is impacted when demand and wind/solar power are analysed together with increasing levels of renewable generation (section 3.5). A storyline-based approach, to understanding system uncertainty (which explores contrasting but equally plausible scenarios) is then presented based on a comparison of two contrasting model responses (section 3.6). Finally, the impact of near-future (to 2065) climate change on the choice of energy policy scenario is investigated (section 3.7). The latter analysis enables context to be given to the magnitude of the climate uncertainty that is presented in the previous results sections. The paper concludes in section 4 with a discussion of the main sensitivities explored in this study and their implications for energy-climate research and policy.

2 - Methods and Data

2.1 - The ECEM climate and energy dataset

The data used in this study is taken from the C3S ECEM demonstrator (ECEM 2020, Troccoli et al. 2018; Goodess et al. 2019). They are derived from two underlying sources of climate data. Firstly, a bias-adjusted reanalysis (ERA-Interim, Dee et al. 2011; see Jones et al. 2017 for bias adjustment methodology) spanning the period 1979-2016; and secondly, regionally downscaled climate model projections covering the period 2006-2100.

For the projections, two emissions scenarios are included (Representative Concentration Pathways RCP4.5 and RCP8.5), for a set of six EURO-CORDEX global-regional climate model pairs (i.e., a global climate model is downscaled using a regional climate model over a limited spatial domain). The choice of climate models and emissions scenarios are described in detail in Bartok et al. (2019), but in summary, the subset of six EURO-CORDEX models selected is considered to provide a plausible representation of present-day European climate, while the inter-model range is intended to span a range of plausible climate change responses of the wider 11-member EURO-CORDEX set.

For each climate model and emissions scenario, seasonal and annual-mean near-surface temperature, near-surface wind speed, surface solar radiation, electricity demand, onshore wind power capacity factor and photovoltaic (PV) solar power capacity factor data are downloaded from the ECEM website. In our analysis, energy systems without significant storage are considered (i.e. energy generated from wind and solar PV must be prioritised and used to meet demand as soon as it is generated). Due to the more complex operating characteristics of hydropower generation, it is excluded from this analysis, and therefore reference to “renewables” is restricted to wind power and solar PV generation. Other aspects of present day power systems that may be impacted by climate change (either directly or indirectly depending on the relationship to meteorological variables) are: offshore wind power (see section 2.1.2 for the motivations for this choice), the efficiency of thermal power plants and transmission lines, availability of water for thermal cooling, availability of biomass resources, deep geothermal, concentrated solar power, and the potential for use of current and future energy storage. Wind and PV solar power are amongst the fastest growing renewable sources and this is why they have been considered. Moreover, it is by assessing individual demand, wind and solar power generation components, as well as at their aggregate values, that it is possible to better plan for the others (e.g. those listed in the previous paragraph). This type of assessment has previously been implemented in Bloomfield et al., (2016) to quantify the impacts of present day climate variability on a power system with various levels of wind power generation.

Future work with an increasingly developed dataset could begin to explore the impact of climate change on a more “complete” power system perspective. This is currently beyond the scope of this work. A full description of how the two renewable energy variables are created from the meteorological variables and validated is given in Saint-Drenan et al. (2018) and Dubus et al. (2017a, 2017b) but a brief description of each conversion model is provided below.

2.1.1 - Demand model

Daily electricity demand is modelled in two stages using a Generalised Additive Model (GAM) approach. The long term changes in demand (due to socio-economic and technological factors such as changes in population) and the daily weather-dependent residuals are modelled separately. Meteorological variables included in the modelling of the weather-dependent residuals include near-surface temperature, surface solar irradiation, relative humidity and wind speed. The two components can then be re-combined to get a modelled time-series of an individual country's demand.

For most of this paper, fixed demand data available from the ECEM Demonstrator is used. This therefore isolates the component of demand associated with physical changes in climate (see section 2.2.1 and Figure 1 for further definition). To compare the impact of climate change to the impact of policy-based decisions on European power systems, we use demand data modelled using five contrasting e-Highway20501 scenarios, (evolving scenarios; see section 2.2.2 and Figure 1 for further definition). The evolving demand data is used in Section 3.6 to understand the impact of climate change on high level policy choices.

2.1.2 - Wind power model

National wind power capacity factor is calculated first at each individual bias-adjusted reanalysis grid box (by extrapolating near-surface winds to a constant hub-height of 100 m and then converting them through a standard wind power curve), assuming a simplified homogeneous distribution of wind farms. The capacity factor is then aggregated to country level using a geographical averaging procedure that takes into account the cosine of the latitude, to account for the different areas of grid boxes. The national level wind energy generation is calculated by multiplying the capacity factor by the nationally-installed capacity as appropriate (see Figure 1 for the two possibilities of fixed or evolving installed wind power capacity scaling that are used). Note that, for future scenarios with increased wind capacity, it is assumed that the distribution of wind farms within the country is also homogeneous, giving the same weight to each individual model grid point regardless of how the wind farm distribution may have evolved.

In the ECEM project only onshore wind farms were considered due to bias-adjusted wind speed data only being available for these sites. Before bias correction the reanalysis data was interpolated onto a 0.5 degree grid (to be comparable with the observations used for bias correction), resulting in a general smoothing of the data. At this somewhat coarse resolution in some countries it is challenging to discriminate between grid points where wind power generation would or would not be permitted, hence the decision to apply a homogenous distribution of wind farms.

It is has previously shown that offshore wind power capacity factors are generally higher, and less variable than onshore wind power capacity factors (Drew et al., 2015) which could influence the results of this study. The chosen wind power model does however perform favourably over Europe, when compared to other state-of-the-art reanalysis-derived energy products (see Troccoli et al., 2018 for comparison of country-level mean capacity factors).

2.1.3 - Solar power model

Solar PV production is estimated first on a grid cell basis using a physical model of capacity factor. The meteorological inputs for the model are surface irradiance and 2 m temperature, as well as solar zenith angles. These are then passed through an empirical solar power curve to give a resultant solar power capacity factor at each grid box. The capacity factors are aggregated to country scale using a homogenous distribution of solar PV production across each country, as there is no comprehensive geographical data on installed solar PV capacity available spanning the whole of Europe. The characteristics of the PV modules included within the empirical model (e.g., module orientation, module power curves) are estimated using statistical techniques (see Saint-Drenan et al. (2018) for further technical details of the methodology). The national capacity factors are then scaled by the nationally installed capacity as appropriate (see Figure 1 for the two possibilities of fixed or evolving installed solar power capacity scaling that are used). For future scenarios with increased solar PV capacity, it is assumed that the distribution of solar PV within the country remains homogeneous.

The impact of using a homogenous distribution of solar PV capacity within each country is discussed at length in Saint-Drenan et al. (2018), by comparing it's performance against a models with detailed information on the spatial distribution of PV plants in France and Germany. There, it is noted that model performance is not significantly degraded by an assumption of uniform spatial distribution for these countries where spatial capacity data is readily available. It is, however, expected that solar PV would tend to be installed in regions that experience the largest number of hours of sunshine (typically the southern latitudes of each country) and the homogeneous spatial distribution assumption therefore provides a conservative estimate of future potential PV generation (and is particularly noticeable for countries with a larger latitudinal range, such as Norway and Sweden).

2.2 – Energy system evolution

Future electricity production depends on both the weather conditions and the socio-technological evolution of demand and generating capacity, including the energy mix. To differentiate between these two drivers, the analysis is organised in two steps. First, the contribution of climate change and variability is isolated by considering a “fixed” power system configuration (i.e., the background demand-trend associated with socio-economic drivers is removed and installed renewable capacities are held fixed at 2015 levels; the fixed scenarios in Figure 1). Secondly, the complete ECEM future electricity system projections are analysed. Changes in demand and renewable generation from the second step are therefore associated with changes in the physical climate and an evolving energy system scenario (i.e., socio-economic drivers of demand, increased renewable generation capacity; the evolving scenarios from Figure 1).

2.2.1 – Step 1: Fixed demand and generation capacity portfolios

A fixed power-system, whereby the installed capacities and the background demand level is held constant, isolates the impacts of climate on the output energy variables (see Figure 1a-c). Here, two fixed systems are considered, one corresponding to the “present-day” system (circa 2015), and a second based on the European Reference scenario (EUREF, Capros et al., 2016) installed wind and solar capacities in 2050. The EUREF scenario is believed to be a highly plausible future energy pathway at the time of writing. A key point to note is that, in each case, the fixed power system scenario (whether for 2015 or 2050) is applied across the whole of the climate time-series (i.e., from 1979-2065) for each of the RCPs.

The break-down of installed wind and solar power by country for each of the fixed scenarios is shown in Figure 2. A possible fixed future demand dataset has not been used in this study, as the analysis is focused around the impact of increasing renewable capacity on changes in residual-load. Due to the large volume of data which has been analysed (six climate models, 2 RCP scenarios, 26 countries) from here on we focus on the European-total response (i.e. the sum of all countries) and four representative case-study countries. These are chosen to be geographically diverse and to have contrasting levels of installed wind and solar capacity in 2015. Details of the selected case-study countries are given in Table 1.

To demonstrate the impact of climate change on the fixed energy systems, results are displayed as differences between two 20-year time periods (1980-2000 and 2045-2065). An annual and seasonal breakdown of the differences is given for the European total and the four representative case-study countries. To assess the confidence in the results shown in sections 3.1-3.5 the change between the two 20 year periods is bootstrapped. To do this a randomly selected 1 year block of data is taken from each of the 20-year time periods from which the difference between these two sampled periods can be found. 2000 samples are taken to provide an estimate of how dependent the results are on the particular 20 years that were present in the original sample.

2.2.2 – Step 2: Evolving generation capacity portfolios

To compare the magnitudes of future climate and future energy system uncertainty (section 3.6) a set of evolving generation scenarios are required (see Figure 1d-f). Evolving energy projections are available from the ECEM project, based on five different scenarios from the European e-Highway2050 (2015) project. These energy scenarios were developed to span a diverse range of possible future energy pathways. Details of European demand, wind power and solar power capacities for each of the e-Highway scenarios are given in Table 2 and are compared to the more recent EUREF scenario (this was not available during the ECEM project, hence it not being included as an evolving scenario). The values of installed capacity for each renewable type are specified in the e-Highway2050 (2015) scenarios at only three snapshots in time: 2030, 2040 and 2050. Therefore, to create the future energy system simulation, the capacities were interpolated in linear increments each year between these snapshots (and also in the period between 2015 and 2030).

3 - Results

3.1 - Impact of climate change on European surface weather

Figure 3 shows the impact of climate change on the European-averaged 2m temperature, 10m wind speed and surface irradiance. There is an increase in 2m temperatures in the future period (2045-2065 compared to 1980-2000), which is exacerbated in the higher RCP scenario, and is clearly seen in all seasons (Figure 3a).

All of the climate models agree in the sign of the temperature response, although the magnitude of the response is sensitive to the choice of climate model. Similar results are seen in all the individual case-study countries (see Figure S1). The sampling uncertainty on the change in 2m temperature (assessed using a bootstrapping approach and represented by the black bars on the individual climate model simulations) is largest in winter, and of comparable magnitude to the mean difference between RCP4.5 and RCP8.5.

The response to climate change is far less clear for near-surface wind speeds (Figure 3b). The multi-model annual-mean response is close to zero for both RCPs, but some models suggest moderate, statistically significant increases in annual mean wind speeds while others suggest reductions. The sampling uncertainty is much larger than for surface temperature and is largest over smaller spatial scales (compare Figure 3b with Figure S2). Climate models suggesting increases in RCP4.5 tend to also suggest increases in RCP8.5 and vice versa, suggesting that the inter-model differences are not simply due to sampling of internal variability. Overall, however, the impact of climate change on European annual-mean near surface wind speeds is very sensitive to the choice of climate model, with different models showing contrasting responses.

The annual-mean response of European surface irradiance to climate change is a ~1 Wm-2 increase in RCP4.5 and ~1 Wm-2 decrease in RCP8.5. However the individual climate models exhibit a vast array of responses (Figure 3c) with some models having a drastically different response to climate change to the other models, emphasising the danger of relying on either an ensemble-mean climate response or a single model for impact assessments. High levels of sampling uncertainty and differences between models are also seen in the individual case-study countries (Figure S3), suggesting spatial variations are being averaged out in the European total.

3.2 - Impact of climate change on electricity demand in a fixed present-day power system

To isolate the role of climate change and climate uncertainty in driving changes in power system behaviour, the “fixed” power system scenario approach is adopted here, as described in Section 2.2.1. Figure 4a shows the multi-model mean percentage change in European demand between 1980-2000 and 2045-2065 under a fixed 2015 power system. Across Europe there is a ~1% reduction in annual demand which is slightly larger in RCP8.5 than RCP4.5. The seasonal breakdown of this response shows that in winter, spring and autumn a reduction in mean demand of ~2% is seen. In contrast, an increase in demand of ~1.5% is seen in summer. In both cases larger responses are seen for RCP8.5 than RCP4.5. The modest response in annual mean demand therefore occurs as a response to strongly compensating seasonal signals.

Comparing the responses in individual models and their associated sampling uncertainties confirms that the sign of change is robust across all models. These responses are also consistent with the 2m temperature responses (Section 3.1) insofar as warmer temperatures lead to a reduction in demand for heating in cooler seasons and increased demand for air conditioning, and more general cooling needs, in summer (consistent with Damm et al. 2017 and Tobin et al. 2019).

The modest climate change response in demand over the whole of Europe, however, masks considerable geographical diversity (Fig 4b to e). In Sweden a reduction in demand is seen in the annual mean (~3%) and in each season (~5%), although the reduction is smallest in summer. In contrast, Italy experiences increased annual-mean demand due to larger increases in summer (~5%) and autumn (~1%) than the reductions seen in other seasons. In Romania and Germany, the signs of the change in each season are the same as for Europe as a whole, however in Germany the percentage changes are much smaller. These differences in the temperature-driven response of demand between individual countries reflect the complex mixture of different temperature sensitivities between the demand models used in each country: for example, the relative share of electric vs. gas-based heating or the relative size of the residential sector. The differences also reflect the background meteorological conditions prevailing and the non-linear nature of the demand model: for example, a climate-change induced 1°C increase in winter temperature may lead to less heating demand if it corresponds to a change from 8°C to 9°C, but the same 1°C increase may have less impact if it corresponds to a change from 16°C to 17°C.

3.3 - Impact of climate change on wind power generation in a fixed present-day power system

The mean changes in European wind power generation between 1980-2000 and 2045-2065 are shown in Figure 5 for Europe and the four case-study countries, assuming a fixed 2015 power system. The European annual multi-model mean response to climate change is a ~1% reduction in generation, with a slightly smaller response in RCP8.5 than RCP4.5 (Figure 5a). However, unlike demand there is considerable spread across the individual climate model simulations (up to ± ~8%), and the individual models do not even agree on the sign of the change. When the change is examined seasonally this uncertainty is exacerbated, particularly in summer. There is large sampling uncertainty, with differences between samples of years being greater than the sign of the projected change.

This large range of model responses and large sampling uncertainty is further exacerbated in each of the four individual country case-study countries (Figures 5b to d). For example, Italian summer wind power generation is projected to increase under RCP8.5 by >30% in two models (one not shown on the graph because of the scale). However, ~10% reductions are seen in three other models, and no change is seen in the remaining model. This is consistent with previous studies that show large uncertainty in the sign and magnitude of the response of wind power generation to climate change when comparing multiple models (e.g. Reyers et al. 2016, Tobin et al. 2019).

The first model in the six-model set (left hand point on each bar in Figure 5) has a very different response when compared to the rest of the models (consistent with the results for European wind speeds; Figure 3). The inclusion of this model within the 6-member ensemble (which we note are all chosen as plausible future climate projections; Bartok et al. 2019) emphasises that reliance on an ensemble-mean response to climate change can lead to misleading results.

In summary, while the impact of climate change on wind power generation appears relatively small when looking at the ensemble mean response, this masks the differing responses of individual models, which is exacerbated by spatial and temporal averaging. In contrast to electricity demand, the sampling uncertainty associated with natural climate variability is very large for wind power generation compared to the impact of climate change.

3.4 - Impact of climate change on solar power generation in a fixed present-day power system

For the fixed present-day power system, the percentage multi-model mean change in European solar power generation is similar to that seen for demand (compare Figure 4 and Figure 6). Across Europe there is a ~1% reduction in solar generation in the multi-model mean, which is larger in RCP8.5 than RCP4.5. However, again this relatively modest change occurs as the product of competing responses seasonally, geographically, and across different climate models. Large mean reductions (3-5%) are seen in winter and spring, with moderate increases in summer and autumn. In contrast to the results for European demand, the individual models have a large range of responses (±5%). The changes are robust to sampling uncertainty within each climate model but are inconsistent across the multi-model ensemble. This again emphasises the potential dangers of using either an individual model or ensemble-mean for impact studies, as both result in a lack of range of potential climate response.

The responses from individual case-study countries are not all similar to the European total response. Sweden and Germany see reductions in the multi-model mean annual solar generation, which are consistent with projected increases in precipitation and cloudiness (Kjellström et al. 2010). In Romania there is a ~1% increase in the multi-model mean solar generation in RCP4.5, but a ~1% reduction in RCP8.5, whereas only very small changes are seen for Italy. There is a large model spread around each of these responses, although within each model, the sampling uncertainty is small (in contract to the corresponding wind power generation results from Figure 5). The solar PV model uses both surface solar irradiance and 2m temperature. The trends observed here are then explained by the changes in both weather variables. A decrease in irradiance means a decrease in solar power generation, while increases in air temperature also lead to a reduction in solar power generation, as solar panel efficiency decreases for higher temperatures.

3.5 - Impact of climate change on residual-load in present-day and future power systems

Although the response of individual technologies is useful for scientific understanding and to inform the planning of solar and wind farms it is beneficial for decision makers to view the compound response of the weather-dependent energy system to climate change. For this reason, the impact of climate change on European level residual-load (i.e. demand minus wind and solar PV) is presented here.

Figure 7a shows the European-level response of residual-load to climate change, assuming the fixed 2015-like present-day power system. Almost all models agree with each other on the sign of the response. However, the spread between the climate models is larger than for demand only (compare Figure 7a and Figure 4a). This is due to the large model spread in the wind power and solar power responses to climate change (Figures 5 and 6). The contribution of wind and solar PV generation also makes the changes more sensitive to sampling uncertainty.

In Figure 7a the total installed capacities of wind and solar PV are modest compared to the scale of total European demand. Figure 7b, however, shows how climate change would affect a power system with much higher renewable capacities (i.e. the fixed 2050-like power system, see Section 2.2.1). Increasing the installed wind and solar capacity across Europe results in a moderate increase in the multi-model mean response of residual-load to climate change. This has the same sign as for the present-day system, but with much larger spread between the individual models (with models now often disagreeing on the sign of the multi-model mean response), and much larger sampling uncertainty. This suggests that for future power systems with high renewables penetration, there is considerably less certainty in the potential impacts of climate change, due to our limited understanding of the future responses of near-surface wind speeds and surface solar radiation to climate change.

3.6 A storylines-based approach to climate uncertainty in energy systems

One of the key challenges in studies which assess the uncertainty of future climate projections is how these results can be used by decision makers. To achieve this goal, results should be communicated in an easily digestible way. A possible way to do this is to reduce the number of simulations and look for coherence between model responses through a storylines-based approach (Shepherd et al. 2018, Shepherd et al. 2019, Zappa 2019). The approach can strengthen decision-making by allowing the user to work backward from a particular vulnerability, question or decision point, for example "How much residual-load will be required over Europe by 2050?" A storyline is therefore presented here that discusses the European total climate response by comparing two climate models exhibiting grossly different model responses.

Figure 8 shows the multi-model mean change in residual-load between 1980-2000 and 2045-2065 for RCP8.5. The multi-model mean response is a ~2% reduction in residual-load, associated with a ~5% reduction in winter and ~5% increase in summer. However, examining the individual model simulations shows that no individual climate model exhibits a response that is similar to the multi-model mean. Two contrasting responses are shown in Figure 8 (these correspond to the first and fifth individual climate models indicated in the bar charts in Figures 3-7). Model 1 suggests a much more marked reduction in residual-loads than the multi-model mean, with these reductions occurring preferentially in winter. By contrast, Model 2 suggests increases in annual-mean residual-load over much of western Europe with the strongest signal in summer.

A key point to emphasise is that, in the absence of any reason to discount one or more of these climate models, each of these scenarios should be considered equally plausible estimates of future climate. Moreover, as all climate models frequently share many elements of code, they cannot be considered as unbiased estimators. This means that, although it is difficult to detect a change in residual-load "signal" due to anthropogenic future climate change, it is still possible to identify plausible scenarios of future changes in residual-load that might occur. This raises a fundamental question regarding the purpose of climate information in power system planning: should future power system design be robust to the signal of climate change, or the wider plausible range of climates it might face? The former approach is well suited to avoiding false-alarms (falsely identifying a climate change signal) but suffers from missed-warnings – i.e., it ignores possible outcomes because they cannot be reliably detected (Shepherd, 2019).

3.7 - Impact of climate change on high-level energy system policy choice

The widely differing power-system pathway scenarios outlined in Table 2 show that there are a broad range of plausible policy choices which could be taken to meet carbon reduction targets. These differences can be expected to lead to significant differences in projected renewable generation and consequent implications for residual-load.

Figure 9 shows the contrast between the magnitude of the impact of physical climate change to 2065 (and its attendant uncertainty – due to choice of climate model and emissions scenario), and the gross differences that are produced by these high-level policy choices. The “Fossil and Nuclear” energy scenario (see Table 2) is not included in Figure 9 due to its very low relevance to current energy policy, however this scenario is included in Figure S4 for completeness. A key result is that, after 2025, there is almost no overlap between the climate realisations produced under different energy system scenarios. The differences between individual climate model realisations and between different RCP scenarios for the same energy scenario are very small compared to the differences produced by the energy scenarios themselves. This shows that, while the choice between these high-level power system planning pathways is important for climate mitigation, levels of European total energy variables that will result are not themselves strongly influenced by the choice of these two emissions pathways. Viewed in this way, the uncertainty in power system behaviour associated with climate change is perhaps rather modest. We do however note that the RCP scenarios available from the ECEM data are not strong mitigation scenarios (such as RCP 2.6). The inclusion of this scenario would lead to greater distinction between the climate change scenarios. This conclusion does not, however, mean that the impact of physical climate change, including changes in extreme events, can be safely neglected. This is because eventually the future power system will be just one amongst all possible options or scenarios.

4 Conclusions

Power systems are in a rapid period of change as countries around the world seek to decarbonise their economies. Power systems in Europe are faced with complex and profoundly different scenarios concerning the gross configuration of a future ~2050 power system, from highly renewable to fossil-intensive. These power system changes also occur against a changing climate which may itself strongly impact on renewable resources and demand. This study has shown, for the first time, the extent to which gross aspects of national and European renewable supply and demand are affected by both physical climate change and the choice of power system pathway. We note that in this study we have not reproduced the behaviour of a real power system but rather the availability of renewable energy within a set of potential system pathways to meet demand.This work has been made possible by the creation of multiple constituent

European energy systems realisations available from the ECEM project. Novel highlights from this study are as follows:

- The gross characteristics of European-total annual-average supply-demand balance in future power systems are dominated by policy-level questions around power system design.

- Significant climate impacts are, however, found within any given energy pathway, particularly at sub-continental and sub-annual scales.

- Averaging climate change responses over multiple climate models leads to small mean energy responses, which are not representative of individual climate model trajectories, or potential future energy system uncertainty. Adopting a storyline-based approach – whereby multiple plausible future climate scenarios are identified to test system design – may therefore be a more appropriate strategy for addressing future climate risk.

- Aggregating over multiple models leads to a relatively modest average signal but this leads to two important questions of how this “aggregate result” should be interpreted. Firstly, there is an issue concerning the role of multi-climate-model averaging. Taking the multi-climate-model mean boosts the “signal” when seeking to identify the response to a particular level of climate forcing (see, e.g. Hueging et al. 2013, Devis et al. 2018 for wind power generation and Damm et al. 2017 for demand). The concept is that the random effects of sampling natural low-frequency variability and uncorrelated model error “noise” cancel to produce a better estimate of a forced climate-change “signal”. However, if it is assumed that each individual model projection is an equally plausible estimate of the future climate, then it is clear that for any given RCP climate forcing scenario there are a wide range of possible future climates that may occur. It is therefore prudent to assess power system performance against this whole range of possible future climates, rather than narrowing this range into a single “multi-model average” realisation. Moreover, it is important to recall that climate models share many common components and model development heritage, and this therefore implies that errors in the individual climate model may not be independent.

- Secondly, it is important to define what constitutes a meaningful change in climate. It has been suggested that the impact of climate change on power system design is modest (or can even be neglected completely) because it is smaller than recent historical year-to-year variations in climate (e.g., Ravestein et al. 2018, Kozarcanin et al. 2019). It must, however, be remembered that even the most naïve interpretation of a shift in the mean climate implies that the whole year-to-year distribution shifts by the same amount. When seeking to quantify climate change impacts as complex as those in power system design and planning, even modest shifts in the mean may lead to significant consequences. Furthermore, this naïve accounting neglects other potentially important shifts in the distribution, such as changes in the tails leading to disproportionally more frequent and/or severe extremes.

- In the analysis discussed above, through utilising the ECEM datasets, six EURO-CORDEX regional climate models applied to two commonly-used climate forcing scenarios (RCP4.5 and 8.5) have been considered. Clearly, the results presented from this type of study are always limited by the number of climate models and climate forcing scenarios that it is possible to include. The analysis, however, leads to the identification of important questions concerning how this kind of result should be interpreted. In particular, the lack of consistency between climate models may be taken to suggest either a relatively weak forced response to climate change, or as a wide range of possible climate futures that must be adequately prepared for. It is therefore suggested that an important avenue for further research is how to more thoroughly incorporate climate uncertainty in power system design and planning. Approaches such as emergent constraints (Smith et al. 2019), robust climate sampling (Hilbers et al. 2019) and combining probability distributions (Clemen et al. 1999, Lichtendahl et al. 2013) may help to make this challenging problem more conceptually and computationally tractable.

In conclusion, acknowledging the magnitudes of the uncertainty in future climate (be that mitigation pathway or the set of climate models used to make the projection) compared to the choice of future power system pathway is of crucial importance for decision makers planning future national decarbonisation strategies. The realisation that a multi-model mean climate response (commonly used to reduce the volume of information presented) masks the subtleties of the individual model response could have drastic impacts for future decarbonisation strategies. Finally, it is important to acknowledge that a larger installed capacity of wind and solar generation results in a greater degree of climate uncertainty, relative to the uncertainty in the choice of power system pathway.

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Captions:

Figure 1: Schematic showing how meteorological data (e.g. 2m temperature, 10m wind speed, surface solar radiation or weather-driven capacity factor) can be combined with an energy scenario to create either evolving (top) or fixed (bottom) demand or renewable generation. The first column in both types of experiment shows the relevant climate model data (with solid and dashed lines indicating the RCP4.5 and RCP8.5 scenarios). The middle columns show how this climate model data can then either be combined with a fixed (top) or evolving (bottom) time series of installed generation. The combination of this installed capacity data with the meteorological input results in the time evolving or

fixed energy data (third column) incorporating either changes in both climate and energy system structure (evolving) or just changes in climate (fixed).

Figure 2: Installed wind power (blue) and solar power (yellow) capacity for a 2015 (bright colours) and 2050 (faint colours) power system. Data taken from the EUREF scenario (Capros et al. 2016). Countries are described using the ISO alpha-2 codes. Note Bosnia and Herzegovina (BA), Switzerland (CH), Montenegro (ME), Republic of North Macedonia (MK) Norway (NO) and Serbia (RS) are not included in EUREF but are included within the ECEM datasets.

Figure 3: The impact of climate change on European-averaged annual-mean, and seasonal mean (a) 2m Temperature (b) 10m wind speed (c) Surface Irradiance. Changes are calculated as the difference between 2045-2065 mean and 1980-2000 mean. Coloured bars show the multi-model mean for each RCP scenario, and individual models are shown by black points with the black bars showing 2 standard deviations of the change (calculated using a bootstrapping technique; see section 2.2 for further details)

Figure 4: The impact of climate change on annual-mean and seasonal electricity demand (difference between 2045-2065 mean and 1980-2000 mean) using the fixed present-day (2015) power system scenario. Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the black bars showing 2 standard deviations of the change based on a bootstrapping technique (see section 2.2 for further details).

Figure 5: The impact of climate change on annual-mean and seasonal mean wind power generation (difference between 2045-2065 mean and 1980-2000 mean), using the fixed present-day (2015) power system scenario. Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the black bars showing 2 standard deviations of the change based on a bootstrapping technique (see section 2.2 for further details).

Figure 6: The impact of climate change on annual-mean and seasonal mean solar power generation (difference between 2045-2065 mean and 1980-2000 mean), using the fixed present-day (2015) power system scenario. Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the black bars showing 2 standard deviations of the change based on a bootstrapping technique (see section 2.2 for further details).

Figure 7: The impact of climate change on annual-mean, and seasonal-mean residual-load (difference between 2045-2065 mean and 1980-2000 mean). Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by symbols with black points with the error bars showing two standard deviations of the change based on a bootstrapping technique (see section 2.2 for further details). The top plot is for the fixed 2015 power system and the bottom is for the fixed 2050 power system (see Figure 2 for details of the installed renewable capacities).

Figure 8: The impact of climate change on annual-mean, winter-mean and summer-mean changes (columns) in residual-load for each European country. These are shown as the difference between 2045-2065 mean and 1980-2000 mean (yellow bars in

Figures 3-7). Rows show the multi-model mean response (average over the six climate models) and two example models, which are the models from the first and fifth bars in Figures 3-7.

Figure 9: Annual-mean European total residual-load, Demand (load), Wind power generation (WP), and solar power generation (SP) time series for the six climate models (individual lines), two RCP scenarios (solid vs dashed lines showing RCP4.5 and RCP8.5 respectively) and four plausible e-highway2050 scenarios used in the ECEM project (for all five e-Highway2050 scenarios see Supplementary Figure S4). The bends in 2040 and 2020 are associated with the availability of projection pathways from e-Highway2050 (see Section 2.2.1).

Table 1: Details of Demand, Wind Power and Solar power generation for the four chosen case-study countries for 2015. WP+SP refers to the total of wind power and solar power generation produced for each country.

Table 2: Details of gross power system properties in 2050 in the EUREF scenario (Capros et al., 2016) and five of the e-highway2050 scenarios (e-Highway2050 2015) properties, in terms of installed wind power generation (WP) solar power generation (SP) and annual-mean demand (D)

Figure S1: The impact of climate change on annual-mean and seasonal-mean 2m temperatures (difference between 2045-2065 mean and 1980-2000 mean). Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the error bars showing 2 standard deviations of the change (based on 1000 bootstrapped samples; see Figure 4 caption for more details).

Figure S2: The impact of climate change on annual-mean, and seasonal-mean 10m wind speed (difference between 2045-2065 mean and 1980-2000 mean). Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the error bars showing 2 standard deviations of the change (based on 1000 bootstrapped samples; see Figure 4 caption for more details).

Figure S3: The impact of climate change on annual-mean and seasonal-mean surface irradiance (difference between 2045-2065 mean and 1980-2000 mean). Coloured bars show the multi-model mean for each RCP scenario, and individual models are given by black points with the error bars showing 2 standard deviations of the change (based on 1000 bootstrapped samples; see Figure 4 caption for more details).

Figure S4: Annual-mean European total residual-load, Demand (load), Wind power generation (WP), and solar power generation (SP) time series for the six climate models (individual lines), two RCP scenarios (solid vs dashed lines showing RCP4.5 and RCP8.5 respectively) and five e-highway2050 scenarios used in the ECEM project. The bends in 2040 and 2020 are associated with the availability of projection pathways from e-Highway2050 (see Section 2.2.1).

Footnote 1:

e-Highway2050 was a research project funded by the 7th Framework Programme of the European Commission with the aim of developing a methodology for the construction of long-term scenarios for the pan-European transmission network for the period 2020-2050. More information can be found here (https://www.entsoe.eu/outlooks/ehighways-2050/) and here (https://www.dena.de/en/topics-projects/projects/energy-systems/e-highway2050/)

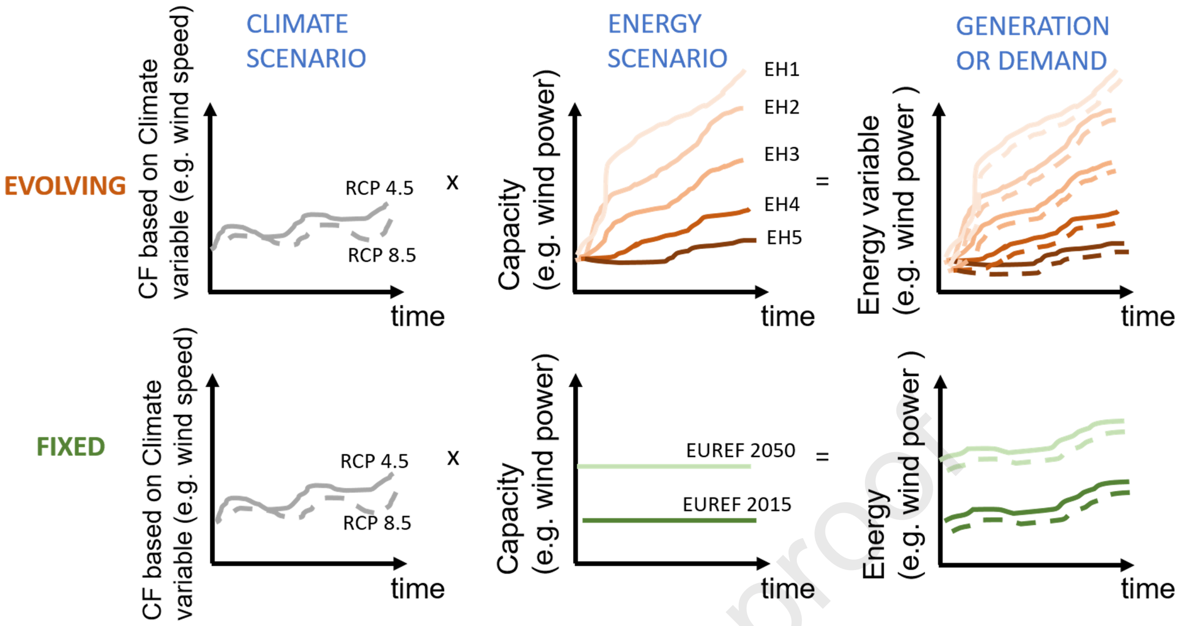
Table 1: Details of Demand, Wind Power and Solar power generation for the four chosen case-study countries for 2015. WP+SP refers to the total of wind power and solar power generation produced for each country.

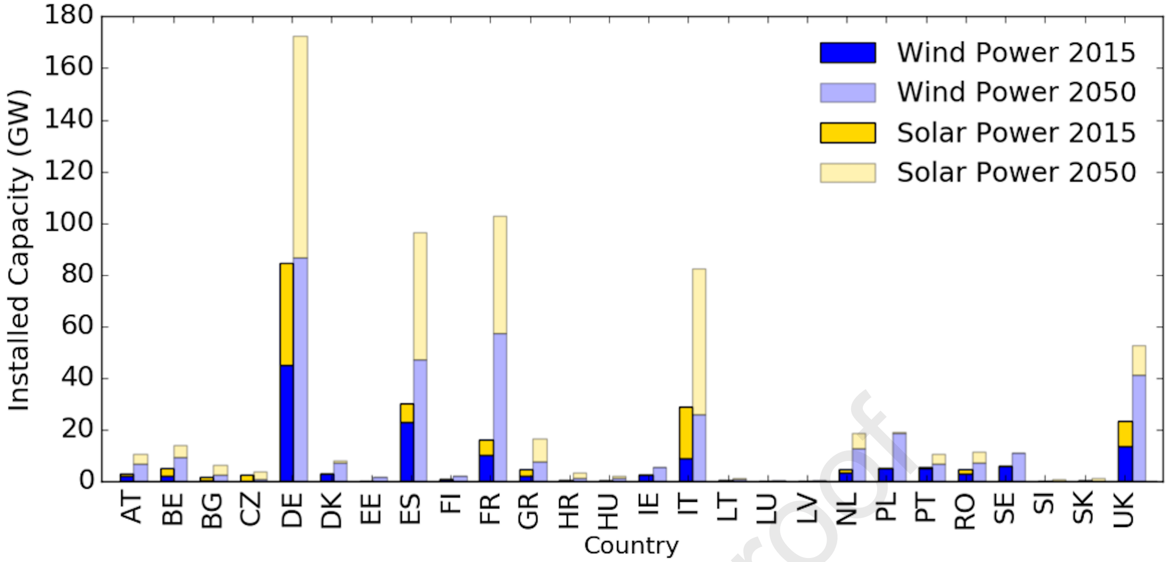
Country (Fig. 2 country code)	Annual demand (TWh)	Total installed Wind and Solar capacity (GW)	Ratio of installed Wind:Solar power	Rationale for choosing country as a case-study
Sweden (SE)	139	6	98:2	Northern, small WP+SP, mostly wind
Romania (RO)	54	5	62:38	Eastern, large WP+SP, mostly wind
Germany (DE)	487	85	53:47	Central, large WP+SP, wind and solar
Italy (IT)	296	28	32:68	Southern, large WP+SP, mostly solar

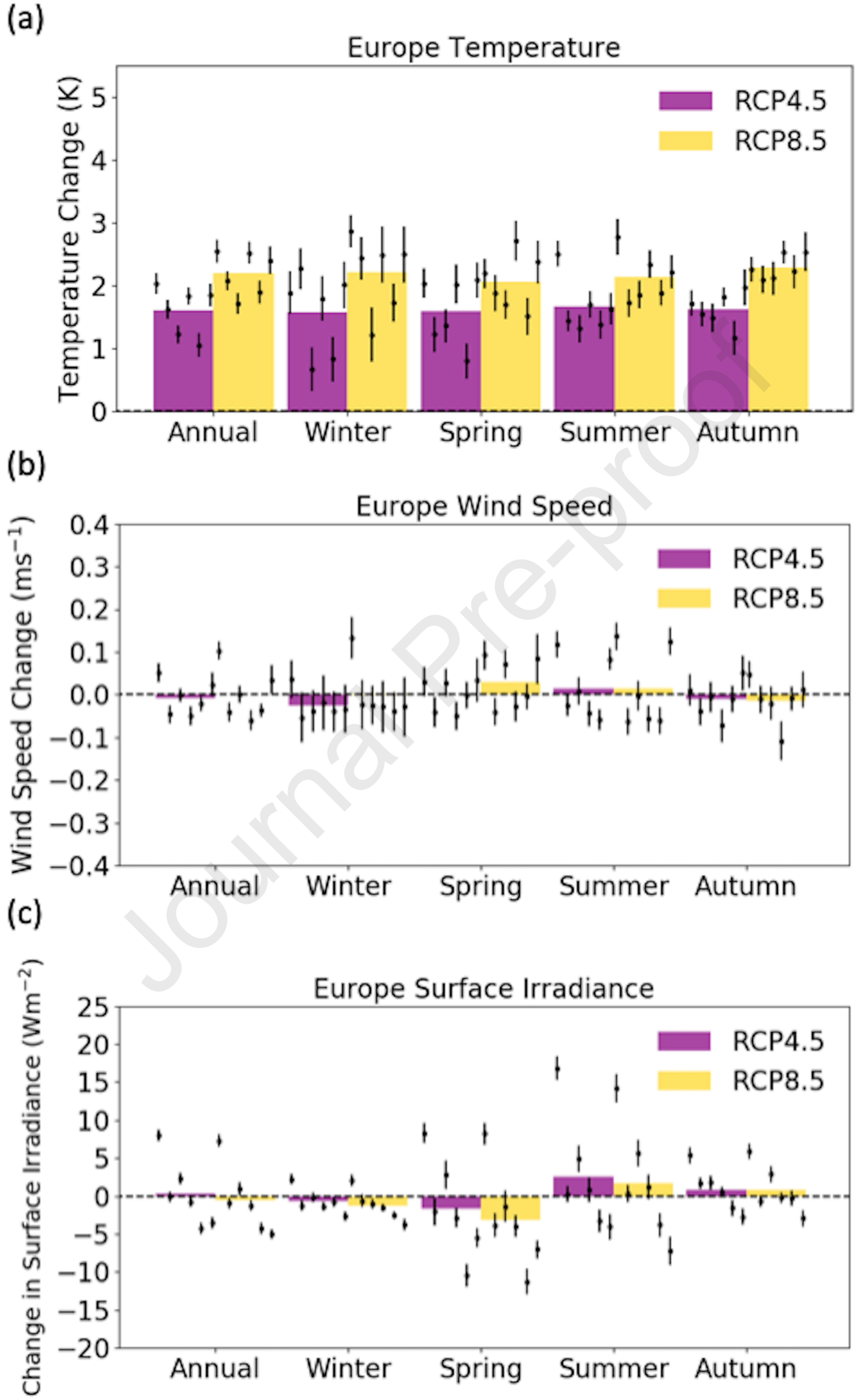
Table 2: Details of gross power system properties in 2050 in the EUREF scenario (Capros et al., 2016) and five of the e-highway2050 scenarios (e-Highway2050 2015) properties, in terms of installed wind power generation (WP) solar power generation (SP) and annual-mean demand (D)

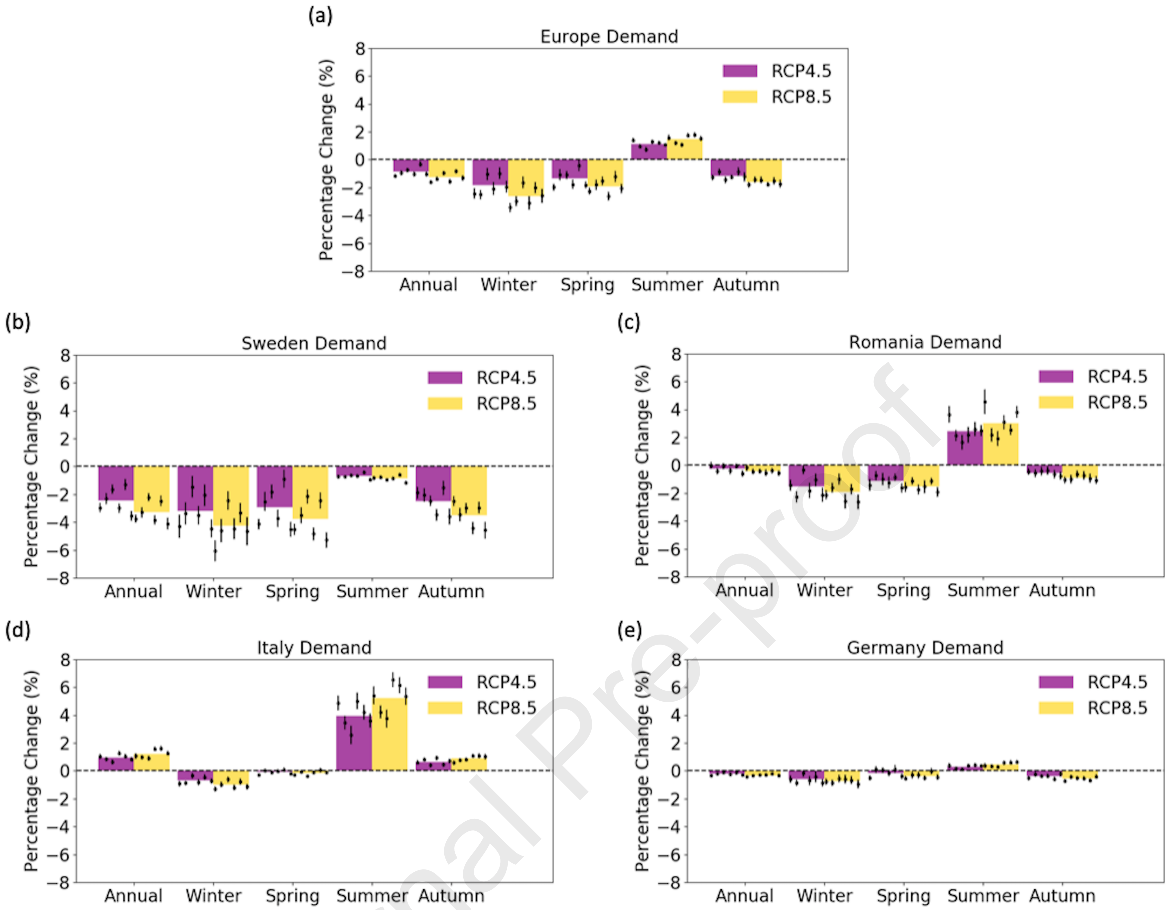
2050 statistics	EUREF	Fossil and Nuclear	Small and Local	Big and Market	Large Scale RES	100% RES
European Total WP (GW)	317	303	387	512	813	874

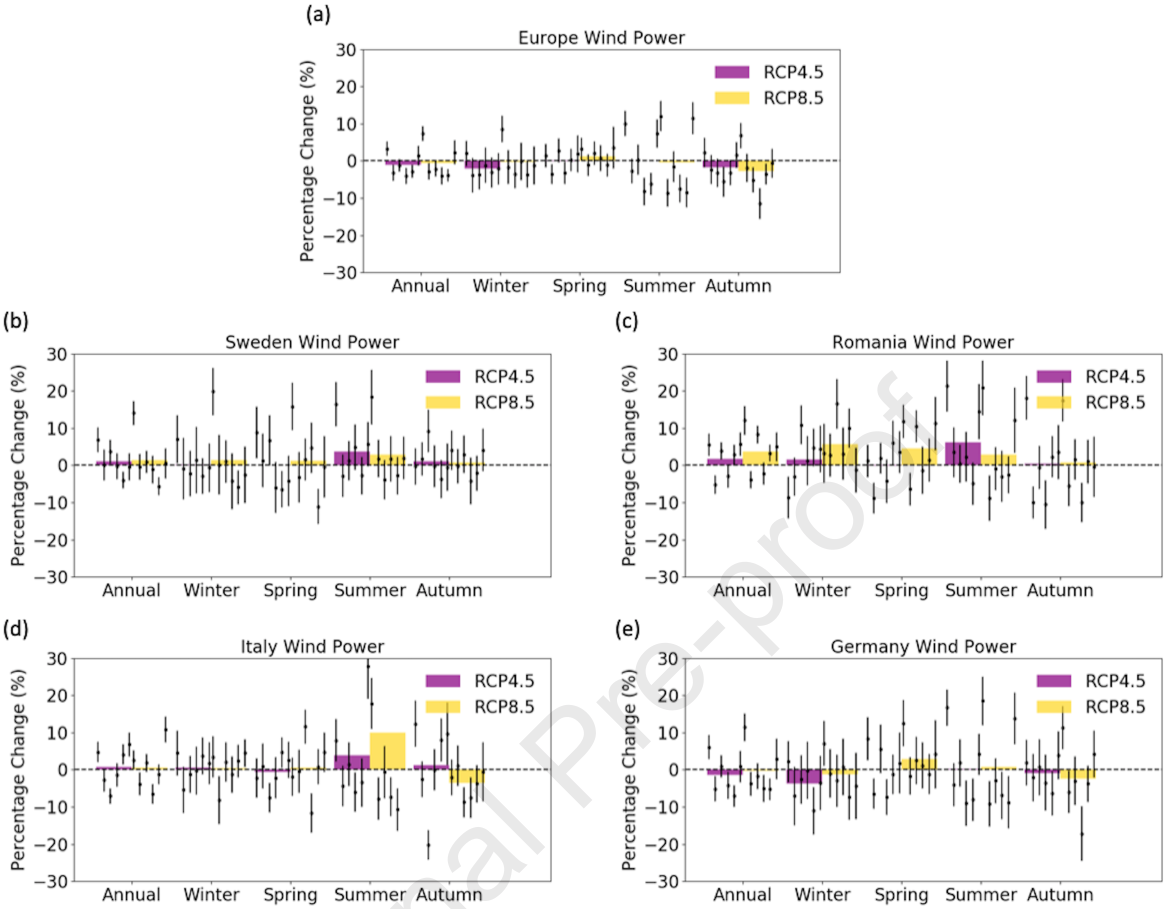
SP (GW)	247	189	573	278	241	662
D (TWh)	4250	4705	3186	4280	5195	4277

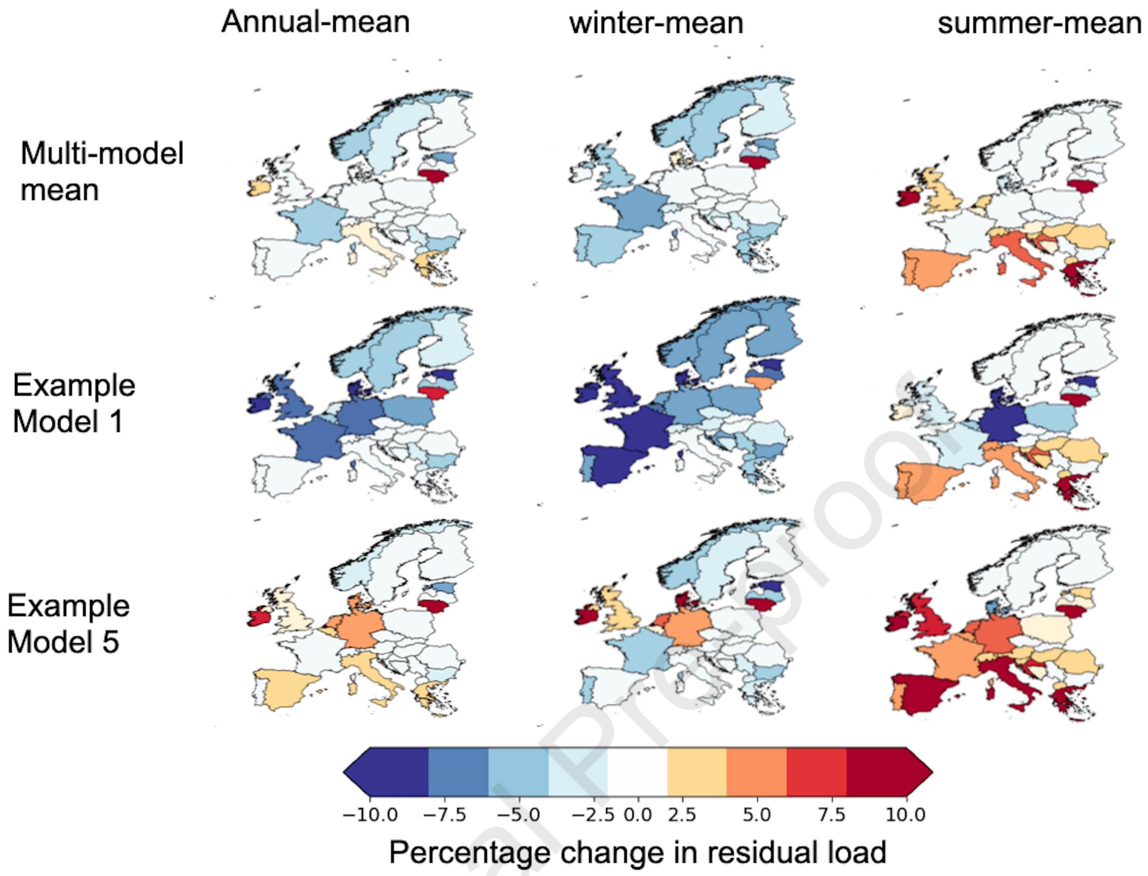

CLIMATE SCENARIO
ENERGY SCENARIO
GENERATION OR DEMAND
EVOLVING
CF based on Climate variable (e.g. wind speed)
RCP 4.5
RCP 8.5
x
Capacity (e.g. wind power)
EH1
EH2
EH3
EH4
EH5
=
Energy variable (e.g. wind power)
time
FIXED
CF based on Climate variable (e.g. wind speed)
RCP 4.5
RCP 8.5
x
Capacity (e.g. wind power)
EUREF 2050
EUREF 2015
=
Energy (e.g. wind power)
time

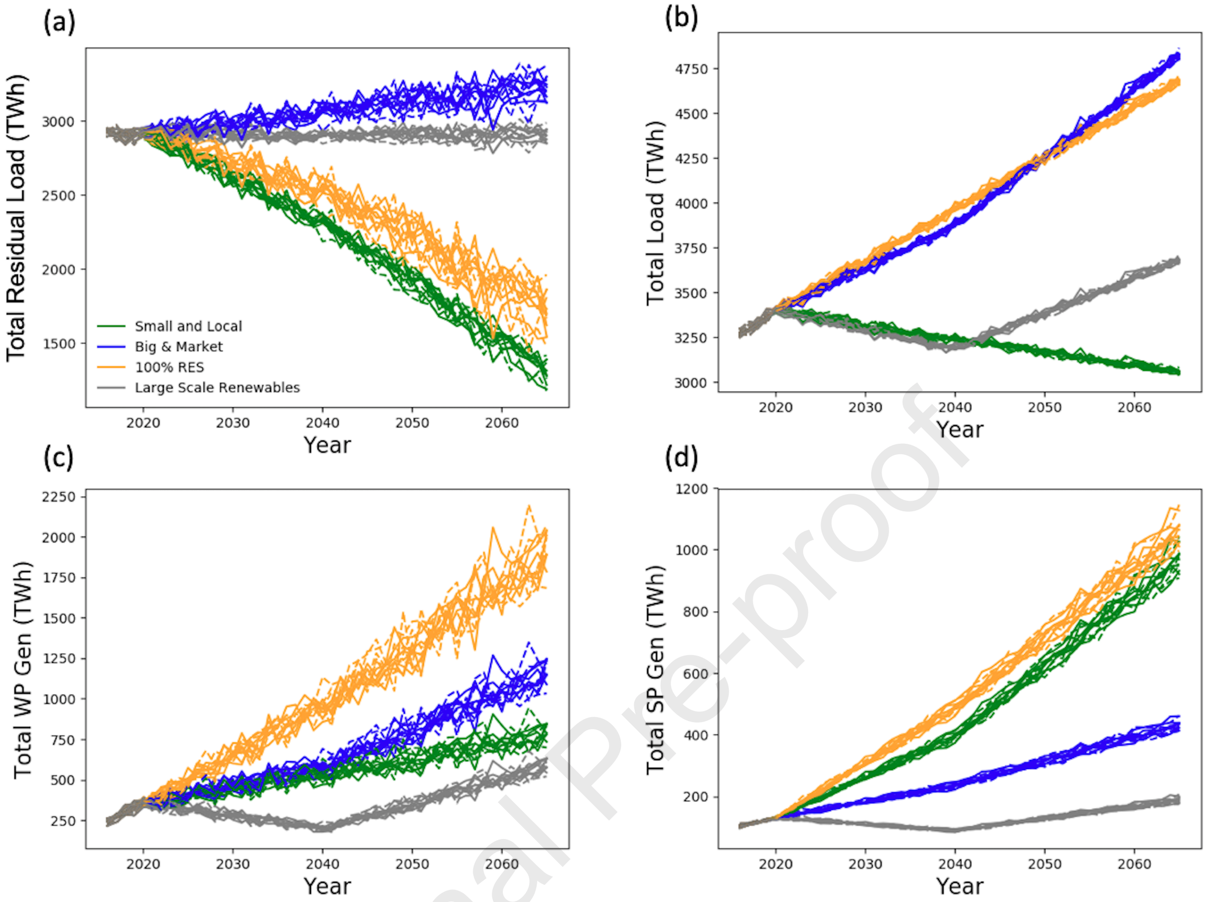

Installed Capacity (GW)
0
20
40
60
80
100
120
140
160
180
Wind Power 2015
Wind Power 2050
Solar Power 2015
Solar Power 2050
AT
BE
BG
CZ
DE
DK
EE
ES
FI
FR
GR
HR
HU
IE
IT
LT
LU
LV
NL
PL
PT
RO
SE
SI
SK
UK
Country

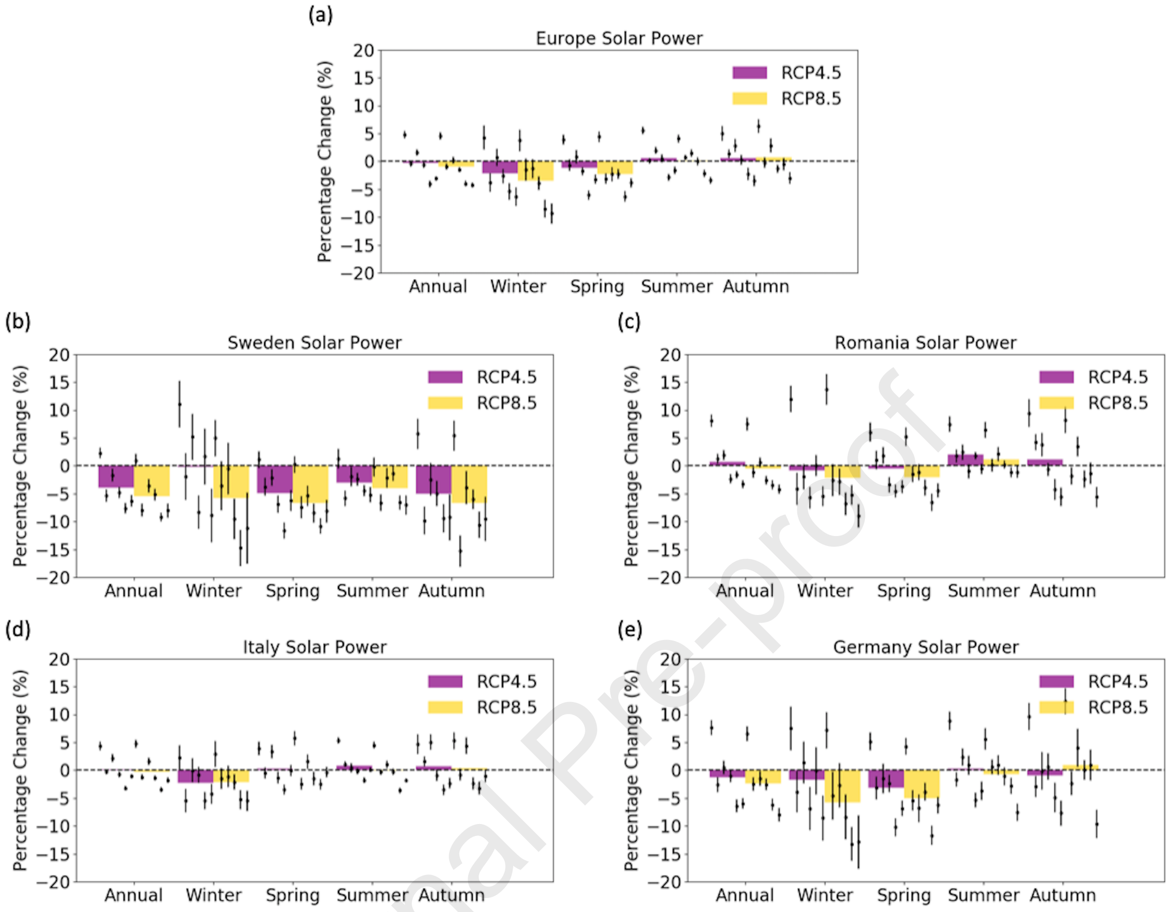

(a)
Europe Temperature
Temperature Change (K)
0
1
2
3
4
5
RCP4.5
RCP8.5
Annual
Winter
Spring
Summer
Autumn
(b)
Europe Wind Speed
Wind Speed Change (ms^{-1})
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
RCP4.5
RCP8.5
Annual
Winter
Spring
Summer
Autumn
(c)
Europe Surface Irradiance
Change in Surface Irradiance (Wm^{-2})
25
20
15
10
5
0
−5
−10
−15
−20
RCP4.5
RCP8.5
Annual
Winter
Spring
Summer
Autumn

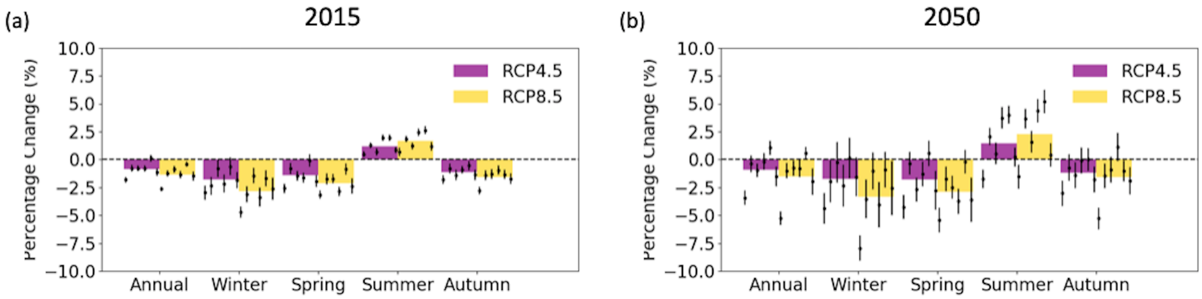

(a)
Europe Demand
(b)
Sweden Demand
(c)
Romania Demand
(d)
Italy Demand
(e)
Germany Demand
Percentage Change (%)
8
6
4
2
0
−2
−4
−6
−8
Annual
Winter
Spring
Summer
Autumn
RCP4.5
RCP8.5


(a)
Europe Wind Power
(b)
Sweden Wind Power
(c)
Romania Wind Power
(d)
Italy Wind Power
(e)
Germany Wind Power
RCP4.5
RCP8.5
Percentage Change (%)
30
20
10
0
−10
−20
−30
Annual
Winter
Spring
Summer
Autumn


Annual-mean
winter-mean
summer-mean
Multi-model mean
Example Model 1
Example Model 5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
Percentage change in residual load


(a)
Total Residual Load (TWh)
3000
2500
2000
1500
2020
2030
2040
2050
2060
Year
Small and Local
Big & Market
100% RES
Large Scale Renewables
(b)
Total Load (TWh)
4750
4500
4250
4000
3750
3500
3250
3000
2020
2030
2040
2050
2060
Year
(c)
Total WP Gen (TWh)
2250
2000
1750
1500
1250
1000
750
500
250
2020
2030
2040
2050
2060
Year
(d)
Total SP Gen (TWh)
1200
1000
800
600
400
200
2020
2030
2040
2050
2060
Year


(a)
Europe Solar Power
(b)
Sweden Solar Power
(c)
Romania Solar Power
(d)
Italy Solar Power
(e)
Germany Solar Power
Percentage Change (%)
20
15
10
5
0
−5
−10
−15
−20
Annual
Winter
Spring
Summer
Autumn
RCP4.5
RCP8.5


(a)
2015
(b)
2050
Percentage Change (%)
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
RCP4.5
RCP8.5
Annual
Winter
Spring
Summer
Autumn

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: