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47 Keywords separated by ' - ': Climate change - Electricity demand - Energy - Electricity consumption - Extreme events - Adaptation

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Impact of climate change on Spanish electricity demand

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Keywords Climate change · Electricity demand · Energy · Electricity consumption · Extreme events · Adaptation

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1 Introduction

Climate change poses great challenges to the energy sector, which in turn is a major driver of strategies to deal with climate change (Mideksa and Kallbekken 2010; Auffhammer and Mansur 2014; Cronin et al. 2018). On the mitigation side, there is an urgent need to decarbonize the electricity grid and reduce energy consumption per capita, because electricity and heat production is the economic sector with the highest share of greenhouse gas (GHG) emissions worldwide (Edenhofer et al. 2014). On the adaptation side, the contribution of a reliable energy supply to food production, water treatment or acclimatization to a warmer climate is vital for the resilience of the economy (European Union Energy Initiative Partnership Dialogue Facility 2017). Hence, the need to balance supply and demand has become an important policy concern in a context of a projected growth in global energy consumption.

To effectively design the future low-carbon power system, electricity grid planners must consider future changes in electricity demand, which depends on a wide range of factors. The key role of socio-economic and meteorological conditions as the main drivers of electricity demand has been widely reported (Apadula et al. 2012; Cassarino et al. 2018; De Felice et al. 2013; Lam et al. 2008; Psiloglou et al. 2009; Sailor and Muñoz 1997; Suganthi and Samuel 2012). However, these drivers may dominate at different timescales (Giannakopoulos and Psiloglou 2006; Hor et al. 2005; Mirasgedis et al. 2006). On the one hand, the socio-economic aspects control low-frequency variability, which is related to changes in population, income or energy-intensive industries. On the other hand, the day-to-day variability of electricity demand is strongly influenced by changes in meteorological conditions (Bessec and Fouquau 2008; Henley and Peirson 1997). For instance, increases in cloud cover enhance lighting demand, relative humidity affects the efficiency of air conditioning and cooling fans and wind speed influences the surface heat transmission of walls and roofs (Arens and Williams 1977; Hor et al. 2005; Maia-Silva et al. 2020). However, temperature stands out as the main meteorological driver of electricity demand, causing similar non-linear responses across countries with a diversity of socio-economic conditions (Bessec and Fouquau 2008; Damm et al. 2017; Wenz et al. 2017). The occurrence of warm and cold temperatures raises electricity consumption because of the use of cooling and heating appliances. In fact, the energy required to cool or heat a building is usually quantified using weather-based indices such as cooling degree days (CDDs) and heating degree days (HDDs), which depend on the outdoor temperature above or under a temperature range known as thermal comfort (American Meteorological Society 2021).

Based on the demand–temperature relationship and the ongoing global warming, climate change is expected to alter the regional patterns of electricity demand. Previous analyses have projected future increases in CDDs and decreases in HDDs (Bertoldi and Atanasiu 2007; Mideksa and Kallbekken 2010; McFarland et al. 2015; Spinoni et al. 2018; Shi et al. 2018). This implies that the demand for cooling will grow while the demand for heating will drop. Hence, the net change in the electricity demand will depend on changes in the regional temperature distribution. There has been a considerable amount of literature on the impact of climate change on regional electricity consumption for different areas around the globe. Trotter et al. (2016) found a relevant contribution of weather variables and associated uncertainty to the path of electricity demand over the 2016–2100 periods in Brazil. Hadley et al. (2006) reported that the added expenditures on electricity due to the rise in CDDs overweight the savings related to the reduction in HDDs for most locations in the USA. Bartos et al. (2016) and Auffhammer et al. (2017) also projected significant increases in the intensity and frequency of US peak events. The occurrence of these extreme demand periods is a major issue since they may cause energy shortages and raise the cost of electricity for consumers (Strengers 2012; Lee et al. 2020).

In Europe, Wenz et al. (2017) estimated that the contribution of future warming to total European consumption will be almost zero owing to a north-south polarization. While electricity demand is projected to decrease in northern Europe, it will increase in southern and western European countries. Bloomfield et al. (2021) also reported small changes in annual mean demand as a response to seasonal compensations, with decreases of demand in winter, spring and autumn partially counterbalanced by an increase in summer. In fact, the annual peak load of 19 out of the 30 countries considered by Wenz et al. (2017) could experience a shift from winter to summer before the end of the twenty-first century. This poses challenges to the energy conversion plans of these countries as well as to the development of effective mitigation and adaptation strategies that can cope with the projected rise in energy demand while meeting the objectives of the Paris Agreement (Schleussner et al. 2016; Rose et al. 2017).

In this paper, we provide the first quantitative analysis of the seasonal shift of electricity demand extremes in peninsular Spain (hereafter referred to as Spain) for different time horizons and levels of warming. Unlike previous studies, the countrywide assessment is complemented with estimates at the local scale to uncover regional differences. This is crucial for the implementation of efficient regulations to manage future extreme events of electricity demand. For this purpose, daily series of pseudo-electricity demand has been generated from observed and simulated temperature datasets for the entire twenty-first century.

The paper is structured as follows. Section 2 describes the datasets and methodology used to establish the current electricity demand–temperature relationship in Spain and to generate future series of pseudo-demand from temperature projections. Sections 3 and 4 present the analysis of the impact of future warming on the daily distribution of electricity demand and on the seasonal occurrence of extreme demand days. Section 5 summarizes the main findings and implications of this work.

2 Data and methods

2.1 Electricity demand data

We have used daily data of electricity demand in Spain for 2007–2015 from Red Eléctrica de España (REE) (https://www.ree.es/es) (last access: February 2021). Despite the data availability beyond 2015, the study period is limited until this year to match the temperature observations introduced below. This countrywide series is based on daily accumulated totals from hourly records and encompasses all sources of energy consumption, including commercial, industrial and residential economic sectors.

2.2 Temperature data

We have used two different temperature datasets from the Spanish Agencia Estatal de Meteorología (AEMET): an observational-based grid (Herrera et al. 2016; Kotlarski et al. 2017) and a model-based local dataset (Petisco de Lara 2008) (http://www.aemet.es/es/

serviciosclimaticos/cambio_climat/datos_diarios?w=0) (last access: February 2021). The former has been used to establish the countrywide electricity demand–temperature relationship, while the latter has been employed to generate recent past (1961–2000) and future (2006–2100) local series of pseudo-electricity demand at 374 weather stations, following the procedure described in Section 2.5.

The gridded dataset has been generated by blending observations from ~ 2500 quality-controlled stations over Spain for the period 1971–2015. It provides daily minimum and maximum temperatures at the 20-km horizontal resolution, which have been averaged to obtain daily mean temperatures for each grid cell and day. Figure S1 displays the mean temperatures for 1971–2015. A spatial average over all grid cells has been applied to calculate countrywide daily mean temperature series for 2007–2015, which will be used to derive the electricity demand–temperature relationship.

Local series of simulated daily temperature were available from a statistical downscaling of general circulation model (GCM) simulations participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). This method is based on circulation analogues as described in Section S1 of Supplement (more details can be found in Petisco de Lara 2008). The dataset provides both daily minimum and maximum temperatures, which have been averaged to compute the daily mean temperature for each station, and subsequently countrywide spatial averages. Table 1 lists the 14 GCMs with downscaled data available for the periods and scenarios used in this study. Some GCMs are provided by the same institution with modifications in the land model (ACCESS1-0 vs ACCESS1-3), carbon cycle components (MIROC-ESM vs MIROC5, CMCC-CESM vs CMCC-CM) or atmospheric resolution (MPI-ESM-LR vs MPI-ESM-MR). This ensemble provides a representative sample to quantify the uncertainty in the simulated series of temperature and the associated pseudo-demand. The term ensemble mean will refer to the average of a given variable for all GCMs in Table 1, with different measures of statistical dispersion (e.g. standard deviation, interquartile range, 10th–90th percentile range) representing the ensemble spread.

The simulated daily mean temperature series cover the recent past (1961–2000) and the twenty-first century (2006–2100), following the corresponding historical runs and future projections under the 8.5 W/m^2 Representative Concentration Pathway (RCP8.5, hereafter) scenario, respectively (one simulation per model and experiment). This scenario of high GHG

Q4 **Table 1** CMIP5 models and modelling groups included in this study

Institute ID	Model version	Atmospheric resolution (Lon × Lat, levels)
CSIRO/BOM, Australia	ACCESS1-0	192 × 145, L38
=	ACCESS1-3	192 × 145, L38
BCC, Beijing, China	bcc-csm1-1	128 × 64, L26
BNU, Beijing, China	BNU-ESM	128 × 64, L26
MOHC, Exeter, UK	HadGEM2-CC	192 × 145, L60
INM, Moscow, Russia	inmcm4	180 × 120, L21
AORI/NIES/JAMSTEC, Japan	MIROC5	256 × 128, L40
=	MIROC-ESM	128 × 64, L80
MRI, Tsukuba, Japan	MRI-CGCM3	320 × 160, L48
MPIM, Hamburg, Germany	MPI-ESM-LR	192 × 96, L47
=	MPI-ESM-MR	192 × 96, L95
CMCC, Bologna, Italy	CMCC-CESM	96 × 48, L39
=	CMCC-CM	480 × 240, L31
CNRM, Toulouse, France	CNRM-CM5	256 × 128, L31

emissions (Riahi et al. 2011) allows us to quantify changes in electricity demand for different levels of countrywide warming that may be relevant for policy-makers. While warming is usually expressed relative to pre-industrial levels (Edenhofer et al. 2014), here they have been computed relative to the historical period 1961–2000. To do so, we have first calculated the warming evolution by subtracting the Spanish mean temperature simulated for the 1961–2000 period from all 31-year running means within the 2006–2100 RCP8.5 simulation. Next, we have identified the 31-year periods when the mean warming is the closest to some predefined targets (from 1 to 4 °C at 0.5 °C intervals). Note that the same warming level can be achieved at different periods depending on the model. This is illustrated in Figure S2, where the warming evolution is represented for each model. Finally, the 31-year periods with the same level of Spanish warming in all models have been grouped to derive multi-model ensemble means for that target.

2.3 Electricity demand detrending

As stated in the introduction, socio-economic factors must be taken into account to establish a reliable relationship between electricity demand and temperature. Since the end of the last century, Spain experienced an important economic and demographic growth until 2008, leading to a marked increase in electricity demand. That was followed by reduced consumption levels during a period of decline in economic activity and a recovering trend since 2015 (REE 2019). Similar evolutions have been reported for other European countries (Apadula et al. 2012; Slini et al. 2014). Socio-economic factors are also key to understand the weekly cycle of electricity demand, which shows a pronounced drop at the weekend, especially on Sundays, associated with low activity during non-working days (Figure S3). These considerations stress the need to remove major socio-economic effects from the electricity demand series before uncovering its relationship with temperature.

For the removal of long-term trends in electricity demand, we followed the methodology developed by Thornton et al. (2016), which requires continuous time series. Accordingly, we have used the Fourier transform to construct an evolving background series that captures both the low-frequency variability and changing the annual cycle of daily electricity demand during 2007–2015. To avoid spurious effects from periods of low activity, we first replaced the electricity demand of Saturday/Sunday with the adjacent Friday/Monday values, as well as that of bank holidays and holiday periods (Easter, August and Christmas) by linearly interpolated values from the adjacent non-holiday days (see Thornton et al. 2016 for details). Next, we used a second-order Fourier fit with smoothed harmonic parameters to represent the annual cycle of each year. This background (blue line in the top panel of Figure S4) was removed from the corrected time series of electricity demand (red line in the same panel). The difference was then added to a repeating mean annual cycle (blue line in the bottom panel of Figure S4). The result is a time series of detrended demand (red line in the bottom panel of Figure S4). More details on the detrending method are provided in Sections 3 and 4 of Thornton et al. (2016).

2.4 Daily temperature and electricity demand relationship

Figure 1 shows the scatterplot of daily electricity demand (D) vs observed mean temperature for Spain (T), using the original (left panel) and detrended (right panel) series of electricity demand for 2007–2015. Removing socio-economic factors (Section 2.3) decreases the large spread in the original series, leading to a more constrained D–T relationship. We note that

Fig. 1 (right panel) excludes weekends, bank holidays and holiday periods to avoid double counting the data used for the correction of these days' demand in the previous section. As expected, the highest loads are related to both winter cold and summer warm extremes due to the use of electricity heating and air conditioning appliances, respectively. Conversely, mild temperatures of spring and autumn reduce electricity consumption because of their proximity to thermal comfort. Overall, spring temperatures are colder than those in autumn, but the associated demand is similar. The contribution of the length of daytime to the D–T relationship seems to be small compared to that of heating and cooling activities, as the relationship does not change for different seasons within the same temperature ranges. This effect might be relevant in regions at higher latitudes than Spain, where the seasonal variability of day length is large (e.g. Johnsen 2001).

We then compute the non-linear response curve by fitting the data with a least squares cubic polynomial. The fit $\widetilde{D}(T)$ (solid black line) is characterized by a minimum load value at around 17 °C and increasing values toward the tales. The U-shape function resembles that found in previous studies evaluating the D–T relationship in Spain (Valor et al. 2001; Pardo et al. 2002; Blázquez et al. 2013), with a steeper slope at high temperatures than that at low temperatures. Thus, the sensitivity of electricity demand is higher for the temperature range associated with the use of cooling than with that of heating devices. This asymmetry is partly explained by the use of non-electric heating systems (e.g. furnace or natural gas) in winter. Other southern European countries such as Greece or Italy, with comparable seasonal temperature cycle and economic development, show similar asymmetric responses (Bessec and Fouquau 2008; Damm et al. 2017; Mirasgedis et al. 2006; Wenz et al. 2017) despite experiencing different temperature ranges. Both low and high-temperature slopes are approximately linear, allowing the extension of the fitted function beyond the range of temperature

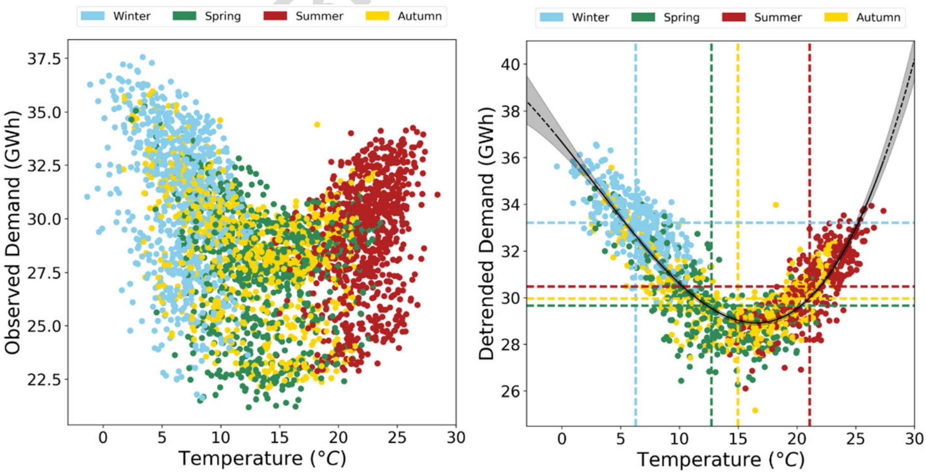

Fig. 1 Left panel: Scatterplot of daily average temperature (°C) and average electricity demand (GWh) in Spain for the period 2007–2015, coloured by season. Right panel: as left but for detrended electricity demand considering only working days. Vertical and horizontal dashed lines represent the seasonal means of temperature and electricity demand, respectively. Full details of the detrending methodology are given in Section 2.3. We obtain the response function using a least squares polynomial fit of degree 3 (solid black line). The dashed black line represents the extension of the fit beyond the observational temperature range. Grey shading indicates the uncertainty of the fit at the 95% confidence level determined through a 10,000-trial bootstrap resampling of n bivariate pairs (temperature, detrended demand), where n is the sample size

observations (dashed black line). This linear behaviour outside the observed distribution agrees with the findings by Wenz et al. (2017), who reported that the normalized electricity load–temperature relationship has the same functional form for 35 European countries, including Spain. The fit is robust to bootstrap resampling with replacement, despite the expected increases in uncertainty (grey shading) toward undersampled temperature ranges. This non-parametric method minimizes the influence of the strong autocorrelation of temperature and electricity demand time series for small lags on the calculation of that uncertainty. Additional analyses provided in Section S2 of the Supplement have confirmed that the residuals of the fit (i.e. vertical difference between the points and the black line in Fig. 1) are not affected by significant trends or changes in the residual variance (heteroscedasticity).

2.5 Pseudo-demand time series

The observed D–T relationship has been employed to generate daily pseudo-demand time series D_p until the end of the twenty-first century based on the countrywide temperature projections for Spain described in Section 2.2. The procedure has been carried out on a daily basis and for each model separately, assuming a stationary relationship between temperature and electricity demand given by $\widetilde{D}$. The simplest way to proceed would take $D_p = \widetilde{D}(T_m)$, with T_m being the simulated absolute temperature for a given day of the recent past (1961–2000) or the future (2006–2100). However, this approach ignores the characteristic patterns of electricity demand in Spain (e.g. the decrease during August summer holidays; top panel of Figure S6). This would affect the quantification of seasonal shifts and their times of emergence. Therefore, we adopted a relative approach, based on the estimation of daily departures in $\widetilde{D}$ from the climatological cycle of detrended electricity demand in observations, $\overline{D}_o$. Accordingly, the pseudo-demand series is computed as:

$$D_p = \overline{D}_o + \Delta\widetilde{D} \tag{1}$$

where $\overline{D}_o$ is the observed climatological mean for a given calendar day during the 2007–2015 period (the overbar represents temporal average) and $\Delta\widetilde{D}$ is the temperature-induced change in demand for that day. Similarly, $\Delta\widetilde{D}$ is estimated from the corresponding temperature change in the observed D–T distribution:

$$\Delta\widetilde{D} = \widetilde{D}(T) - \widetilde{D}\left(\overline{T}_o\right) \tag{2}$$

With $\overline{T}_o$ being the observed climatological mean temperature for that calendar day (bottom panel of Figure S6). Taking $\widetilde{D}(T) = \widetilde{D}(T_m)$ in (2) would implicitly assume a reasonable representation of the observed temperature distribution in the models. However, systematic biases in the annual cycle of temperature are common in GCMs and regional downscaling exercises (Jacob et al. 2013) and would cause unrealistic estimates of $\Delta\widetilde{D}$. To avoid this, daily simulated temperature anomalies ΔT_m are added to the climatological mean temperature of observations instead: Q6

$$\Delta\widetilde{D} = \widetilde{D}\left(\overline{T}_o + \Delta T_m\right) - \widetilde{D}\left(\overline{T}_o\right) \tag{3}$$

With $\Delta T_m = T_m - \overline{T}_m$ and $\overline{T}_m$ being the historical (1961–2000) mean temperature of the model for the given calendar day. This approach corrects the climatological bias of the model since $\overline{T}_o + \Delta T_m = T_m - (\overline{T}_m - \overline{T}_o)$ so that we only assume realistic simulations of temperature variability. The resulting pseudo-demand series can have a slight unintentional weekly cycle stemming from $\overline{D}_o$ (see Figure S6). Although this would add some realism to the D_p series, which also accounts for the reduced demand during holiday periods, the presence of weekly variations is not expected to affect the seasonal patterns (and shifts) of electricity demand.

The methodology has been tested in observations, by replacing T_m with T_o in (3) and comparing the resulting D_p from (1) with the actual D_o for the period 2007–2015. These observed and modelled time series are shown in Figure S7. Note that the pseudo-demand time series does not try to reproduce the observed demand but represents the demand that would have occurred given the observed temperatures while keeping some characteristic patterns during traditional holiday periods. Despite this, it is able to capture the climatological annual cycle of observations and the occurrence of the upper extremes but ignores certain socio-economic factors such as economic cycles or the reduced demand on weekends. About 72% of the high extremes (defined as the 90th percentiles) of both series occur simultaneously or within a day's difference. The mean absolute error between both series is 1.96 GWh, which is approximately 0.6 standard deviations of D_o, and the root mean square error is close to 2.45 GWh (8.5% of the mean demand). Moreover, the reconstructed series is significantly correlated with the observed one (R = 0.62, p value<0.01). The performance of the model is somewhat worse than that of Thornton et al. (2016) for the UK (0.5 standard deviations of D_o and R = 0.80), probably because of different demand patterns in these countries. Despite this, the method reproduces the observed seasonality of electricity demand and captures satisfactorily the occurrence of the upper extremes, which are the main focus of this study. The overall agreement evidences that these aspects of the observed electricity demand are largely determined by temperature.

3 Distribution changes and seasonal shift of electricity demand extremes

The daily series of pseudo-demand are herein used to explore the evolution of Spanish electricity demand patterns under the RCP8.5 scenario. Figure 2 displays the multi-model electricity demand distributions conditioned on the level of Spanish warming. The first two boxes represent the distributions reproduced from observed (2007–2015, red) and simulated (1961–2000, blue) temperatures. Models display a reasonably good agreement with observations, but also a slight overestimation of the upper tail of the distribution, even when the modelled distribution is obtained from an earlier and colder period. This may indicate model biases in extreme temperatures but also a larger spread resulting from the large sample size of models (40 years × 14 models) compared to that of observations (9 years). The remaining boxes correspond to different levels of warming with respect to the 1961–2000 period.

Overall, warming induces an increase in electricity demand. It is also accompanied by a widening of the distribution, increasing the occurrence and severity of extreme electricity demand days. These distributions are significantly different at the 95% confidence level for all temperature bins, as determined through the two-sample Kolmogorov-Smirnov test (e.g. Wilks 2011). Even though the median (solid green lines) remains largely unaffected, the mean (dashed green lines) increases with regional warming (e.g. 3.4% for a 4 °C warming). The lower and upper tails of the distribution also show divergent trends. While the 10th percentile (bottom of the whiskers) barely changes, the

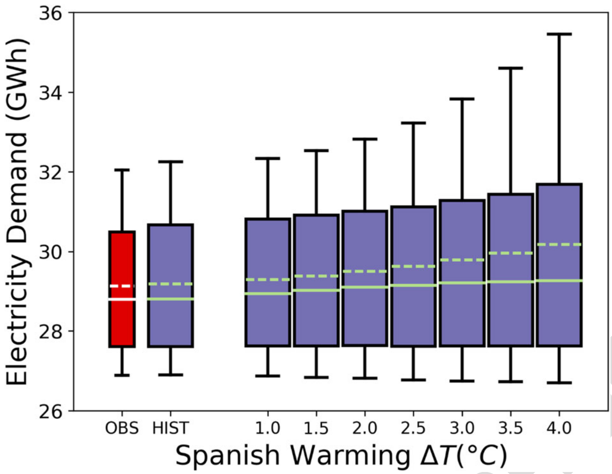

Fig. 2 Boxplots of the daily electricity demand derived from observed (red) and modelled (blue) temperatures in Spain. Observational data have been evaluated for 2007–2015, whereas the statistical downscaling of GCM simulations considers the interval 1961–2000 as the historical period (HIST) and different degrees of regional warming during 2006–2100. The boxes extend from the lower (Q1) to the upper (Q3) quartile values of the data, with solid and dashed horizontal lines indicating the position of the medians and means, respectively. The whiskers extend from the boxes to show the range of the data between the 10th and 90th percentiles. All distributions derived from modelled temperatures are significantly different at the 95% confidence level (determined through the two-sample Kolmogorov-Smirnov test)

90th percentile (top of the whiskers) exhibits a stronger build-up than the mean values (~ 10% for 4 °C warming). The small changes in the lower tail of the distribution can be explained by the similar frequency of days within the range of comfort regardless of the warming considered. Spring and autumn projected temperatures often remain within this range, while warming pushes winter temperatures within the range of comfort, moderating the pseudo-demand as opposed to summer (Figure S8). As winter and summer (spring and autumn) are the seasons with the highest (lowest) current electricity demand (Fig. 1), the change in the upper tail suggests that the increase in electricity demand associated with the rise in days requiring cooling overcompensates the drop caused by the reduction in days requiring heating. Therefore, the highest load days would eventually occur in summer instead of winter, reversing the present-day pattern of electricity demand.

This is also supported by Fig. 3, which displays the evolution of the seasonal frequency of occurrence of electricity demand extremes (defined as the 90th percentiles of the daily electricity demand for each year) until the end of the twenty-first century, using the historical and RCP8.5 simulations. For the 1961–2000 periods, the highest frequency is found in winter, but extreme demand days in summer start to outnumber those in winter by the early twenty-first century. Indeed, more than 90% of the extremes would occur in summer by the mid-century under RCP8.5. The summer frequency peak occurs in July due to the high temperatures and the holiday drop of electricity demand in August (see Section 2.5). The seasonal shift of the extreme electricity demand days from winter to summer has important implications for the energy system operations. Since energy planners seek an acceptable balance between demand and supply, a seasonal change of the former might alter the current optimal energy mix due to the large inter-seasonal variability of renewables. This issue will be further discussed in Section 5.

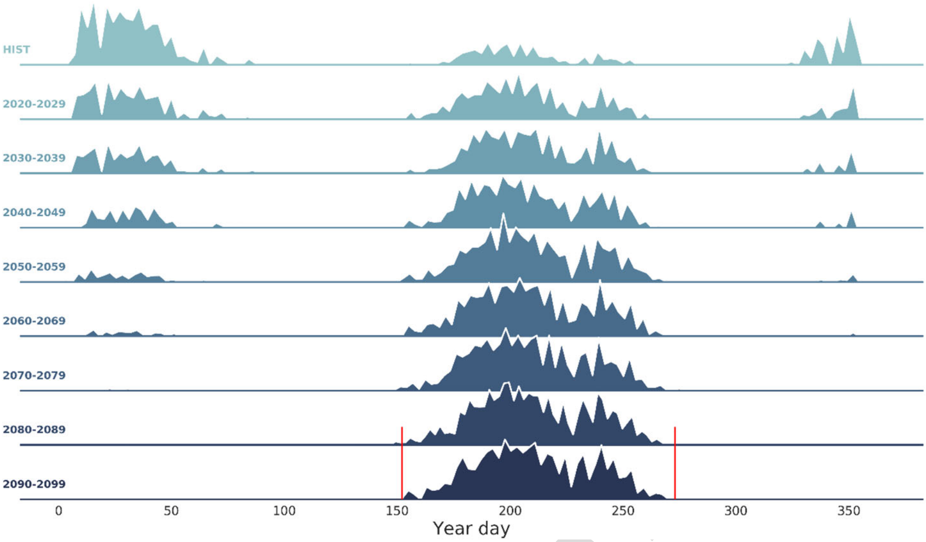

Fig. 3 Probability density function of extreme electricity demand days (above the 90th percentile of the distribution of daily demand in each year) for the 1961–2000 historical period (HIST) and for each decade from 2020 to 2099. The x-axis represents the day of the year and the red vertical lines delimit the extended summer from June to September

To quantify future changes in the seasonal patterns of electricity demand, we have computed the frequency ratio of extreme electricity demand days between the extended summer (June–September) and the entire year. In the following, we will refer to this ratio as the *summer extreme demand ratio* (SEDR). A SEDR value above (below) 0.5 indicates more (less) electricity demand days in the extended summer than in the rest of the year. Figure 4 shows SEDR as a function of the projected warming, considering the multi-model ensemble mean (black squares) and each model individually (coloured circles). Like observations (blue star), historical simulations (left black square) are characterized by relatively low frequencies of high electricity demand days during the extended summer (SEDR well below 0.3). Nevertheless, the observed SEDR for 2007–2015 (~ 0.16) does not overlap with the spread of the multi-model ensemble for the 1961–2000 period, as indicated by the uncertainty boxes around the ensemble mean (~ 0.23 ± 0.03). Although both periods are asynchronous, this result suggests that models overestimate the number of extreme electricity demand days in summer, in line with the reported overestimation of summer temperatures and extremely hot days over western Europe in CMIP5 models (Cattiaux et al. 2013). Despite this, SEDR shows a clear increase in the level of regional warming at a remarkable rate. Some models project that the seasonal shift in SEDR (i.e. SEDR > 0.5) would already occur for a 1 °C warming. However, the critical SEDR threshold of 0.5 is embedded within the associated uncertainty range of model projections, which means that the seasonal shift is not detected with confidence for that level of warming. A more detailed assessment indicates that the emergence of the critical SEDR threshold is detected at the 90% confidence level for a Spanish warming of 1.1 °C (not shown). This steep rise continues until a 3 °C warming is reached. At this point, most of the extremes occur during the extended summer, and consequently, SEDR hardly changes with additional warming, leading to decreases in the inter-model spread.

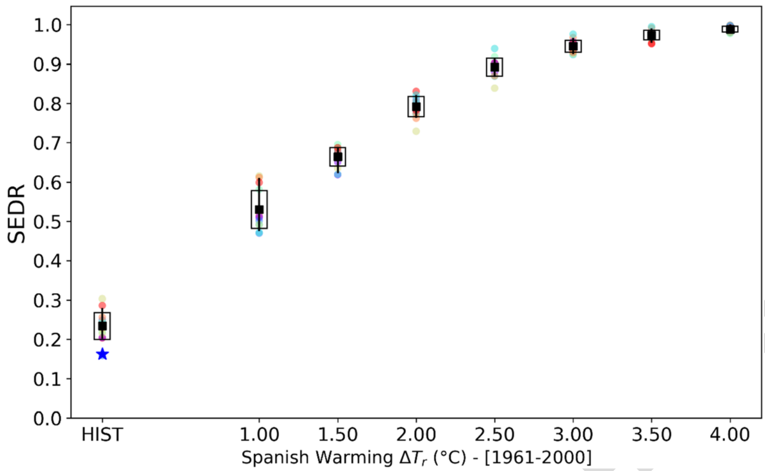

Fig. 4 Projected values of summer extreme demand ratio (SEDR) (y-axis) for different degrees of regional warming (x-axis) with respect to the period 1961–2000 (HIST). Black squares depict the model ensemble means, the boxes represent the model ensemble spread (mean ± standard deviation) and the black lines extend from the 10th to the 90th percentiles. Coloured circles represent each ensemble member. Blue star shows the SEDR value derived from electricity demand reproduced from observed temperatures for the period 2007–2015

The increase in SEDR relates to winter and summer warming, as both contribute to concentrate extreme demand days during summer. To better understand the contribution of the warming in different seasons to the SEDR increase, we have repeated the analyses shown in Fig. 4 but considering only the projected warming in the extended winter (December–March, left panel of Figure S9) and extended summer (right panel of Figure S9). For that purpose, we have computed the seasonal cycles of warming with respect to the 1961–2000 period for the 31-year intervals corresponding to each level of warming. Then, these seasonal cycles have been used to remove the warming from the simulated temperatures except for the winter and summer days, respectively. The resulting SEDR values allow us to evaluate the influence of seasonal warming on the seasonal shift of electricity demand. Overall, SEDR increases with both summer and winter warming, indicating a positive contribution of both seasons to the change of this ratio. However, this rise is substantially higher under summer warming than under winter warming. This can be explained by the rapid evolution of summer temperatures out of the levels of thermal comfort under the projected warming.

The projected warming rates are subject to uncertainties associated with the future evolution of anthropogenic GHG emissions and with the sensitivity of GCMs to this forcing. Therefore, the time when these changes become apparent will depend on the scenario and model considered. To estimate this time horizon (TH), we have used the RCP8.5 scenario as a worst-case outcome since this is relevant for the design of roadmaps in adaptation strategies. We define a simple estimate of TH in the multi-model ensemble as the first 31-year interval when SEDR has significantly exceeded 0.5 (considered as the period when the 10th percentile of the multi-model ensemble lays above that threshold). The TH is found for the 31-year interval between 2018 and 2048. This time range seems to be consistent with the recent trend of observed electricity demand, which only shows 2 years (2015 and 2016) with annual maxima during summer months since records began (REE - https://www.ree.es/es/datos/demanda/evolucion) (last access: February 2021). If we consider a threshold of 0.7 to compute TH, the resulting interval is delayed until 2038–2068. According to these results, electricity demand patterns could abruptly change in a few decades, revealing the need for implementing adaptation measures in the current planning strategies of the future electricity system. However, under a more optimistic scenario such as RCP4.5 (equivalent to 4.5 W m^{-2} radiative forcing in the year 2100), the 0.7 thresholds would not be reached until 2063–2093, as inferred from the 11 out of the 14 GCMs with available RCP4.5 simulations. This evidences the great uncertainty and dependence of TH on the global socio-economic pathway and associated GHG emissions.

4 Spatial variability of electricity demand changes

In the previous section, we have quantified the influence that climate change could exert on the temporal patterns of national electricity demand. As different climatic zones can be found in Spain (Kottek et al. 2006), here we examine the spatial variability of projected electricity demand changes within the country. For this purpose, we have computed SEDR from simulated temperature data at each weather station in the historical period (Fig. 5a) and for different levels of Spanish warming (Fig. 5c-f). Due to the lack of local electricity demand data, this analysis has been carried out using the countrywide D–T relationship for all sites considered. Although regional socio-economic conditions such as population density modulate this relationship, with this idealized approach, we can interpret the influence that different local temperature responses associated with the same level of Spanish warming could exert on electricity demand. As expected, historical SEDR values present regional differences. The highest values are found in northeastern Spain and, to a lesser extent, central and southwestern Spain, where more than 30% of extreme pseudo-demand days occur in the extended summer. This is explained by the large variability of simulated summer temperatures there (Figure S10, right), which implies a substantial occurrence of temperature extremes. On the other hand, SEDR presents the lowest values (below 0.2) near the northern coast along the Bay of Biscay as well as in southeastern Spain, even when the latter is among the warmest regions of Spain (Figure S10, left). These regions exhibit low variability of summer temperatures (Figure S10, right), supporting that historical SEDR is more affected by the day-to-day variability than by the mean value of local summer temperature. However, the projected temperature changes are substantially higher for the mean (Figure S11, left) than for the standard deviation (right), suggesting a greater contribution of the former to future SEDR changes.

Local increases in SEDR vary across the country and so do local warming rates. According to the regional projections, the highest summer warming will occur in northeastern and central Spain and the lowest one in other northern regions, these regional differences exceeding 1.5 °C for 4 °C of Spanish warming (Figure S11, left). Due to this spatial heterogeneity, the spatial pattern of the projected SEDR is not stationary and evolves with the level of Spanish warming. For 1 °C and 2 °C (Fig. 5 c and d), the spatial pattern of SEDR resembles that described for the historical period, with the highest values in northeastern and central Spain. However, for a 4 °C warming (Fig. 5f), SEDR approaches 1 everywhere, even for regions experiencing lower warming than the rest of the country. In this case, the largest growth of SEDR with respect to historical values occurs in northwestern and southeastern Spain as these are the regions with the lowest historical values. These are also the regions that would experience the latest reversal in the seasonal pattern of electricity demand (Fig. 5b). That shift might not be detected until around 2035–2040 in southestern Spain as well as 2040–2060 along the northern and northwestern coasts. Overall, the SEDR increase is clear over all sites and thus supports the

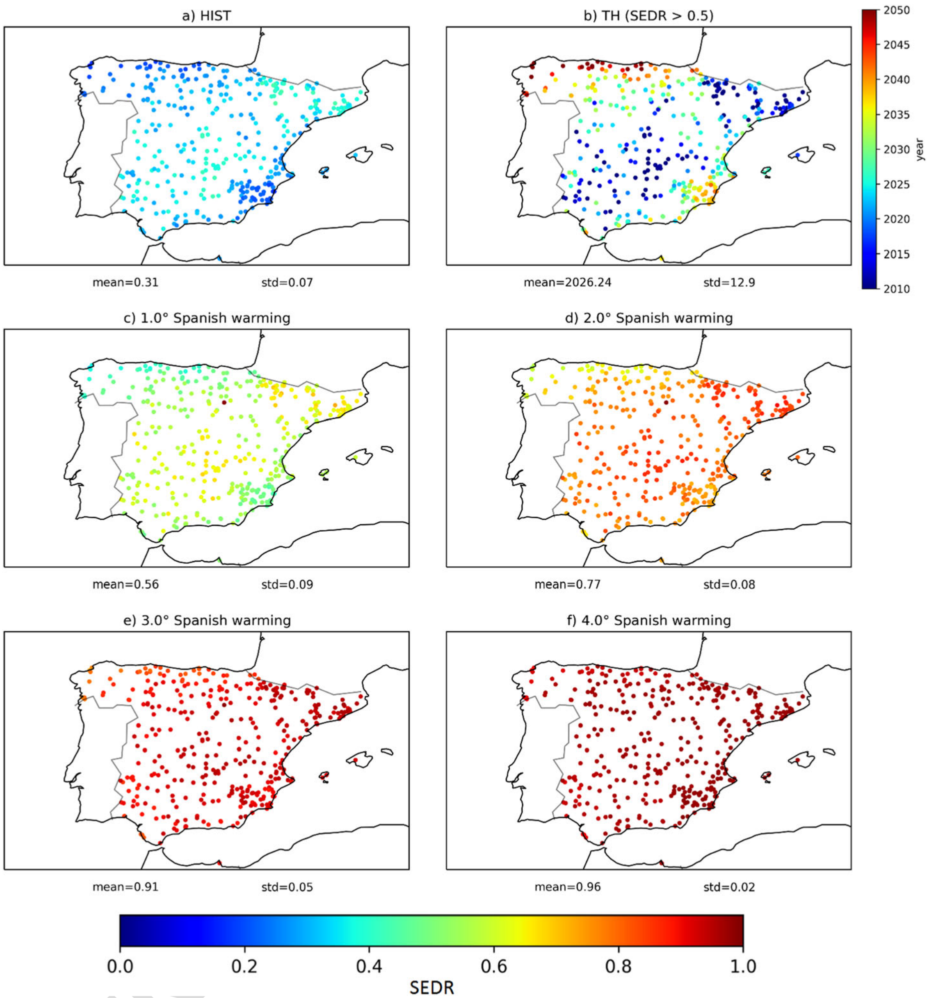

Fig. 5 Composites of SEDR for the 1961–2000 historical period of the statistical downscaling of GCM simulations (**a**) and for 31-year windows with 1, 2, 3 and 4 °C average Spanish warming with respect to that period (**c**–**f**). Panel **b** shows the composite of the time horizon (TH) when SEDR significantly exceeds 0.5 at the 90% confidence level, indicating a seasonal shift in the occurrence of extreme demand days

findings observed for the whole country. When averaged over all sites, the resulting evolution of SEDR and the inter-model variability are in line with the countrywide results reported in Fig. 4.

5 Discussion and concluding remarks

In this work, we have quantified for the first time the changes of electricity demand patterns in Spain for different time horizons and levels of warming, with a focus on projected seasonal shifts. Although the results are built on the evaluation of a specific country, the implications discussed here could be common to other countries where similar seasonal changes in the annual peak load are also expected (e.g. Portugal or Italy). Furthermore, this work highlights the importance of analysing the impact of climate change on the energy system on a seasonal basis. In particular, we have found that, despite the minor warming effects on the median values of daily electricity demand, the mean values as well as the frequency and severity of extreme electricity demand days are expected to increase significantly in Spain. The implications of the intensification of electricity demand extremes are notable, as the electrical power system network is mostly designed based on the highest load day of the year in order to guarantee the electricity supply at all times and therefore avoid power outages. Thus, the electricity system would have to increase the peak capacity needed during future extreme demand periods. Moreover, the required increase in generation capacity would involve a high imbalance with electricity demand during non-extreme days, therefore reducing the efficiency of the electricity grid.

We have also shown a seasonal shift of these extreme electricity demand days from winter to summer. In recent decades, the highest load values have mostly occurred in winter, but the decrease of cold days in this season together with the increase of warm days in summer is triggering a seasonal shift. Wenz et al. (2017) reported that this seasonal shift may be commonplace in numerous European countries by the end of the twenty-first century. Our results indicate that the change in Spain is outstanding, with more than 90% of extreme electricity demand days of the year being projected in summer for warming above 3 °C. Since these events will be related to extreme heat, there could be side issues that jeopardize the electricity infrastructure (e.g. water shortage for nuclear plants or efficiency losses in electricity transmission) (Mideksa and Kallbekken 2010). Hence, this result should be considered by energy planners to ensure power supply and improve the effectiveness of the energy system. The renewable energy generation capacity in Spain has increased by more than 8500 MW since 2009, reaching 46.7% of the total capacity by 2018. Wind and hydroelectric power resources are the major contributors to the renewable pool (above 80%), while solar-based technology is limited to shares below 15% (REE 2018). The seasonal cycle of wind power production is characterized by a winter maximum and a summer minimum, whereas hydroelectric generation is higher in winter and spring than in summer and fall (Garrido-Perez et al. 2020; Gómez-Calvet et al. 2018; REE 2018). Hence, the projected seasonal shift of load extremes indicates the need to increase the presence of solar energy systems in the future energy mix, as their seasonal generation maximum occurs in summer. This is in line with the objectives of the last Spanish National Integrated Plan of Energy and Climate (PNIEC 2021). It would decrease the power system stress both in summer and in winter, because the Spanish peak demand events are associated with high-pressure systems and positive anomalies of incoming solar radiation in these seasons (Bloomfield et al., 2020).

The evaluation of the changes in the seasonal pattern of Spanish demand caused by climate change also reveals that the induced seasonal shift in peak demand and the associated adverse effects will be felt already for low levels of warming. We have identified this seasonal shift at the 90% confidence level for a Spanish warming around 1.1 °C with respect to 1961–2000. This corresponds to a global warming of around 1.5 °C considering a pre-industrial baseline (see Section S3 in Supplement for the equivalence between Spanish and global warming), coinciding with the target established by the Paris Agreement. However, the projected warming is not homogeneous within the country. While Spain is warming up faster than the global mean (Figure S12), there are some Spanish regions that might be exposed to higher warming than others. The identification of the most vulnerable regions to changes in demand patterns is useful for electricity management. In particular, power plant locations should ensure effective transmission lines that minimize the losses due to transport and distribution of electricity (Doukas et al. 2011). Given the present-day national-wide relationship between temperature and electricity demand, our results show that northwestern Spain would undergo delayed seasonal shifts (i.e. for higher levels of warming) as compared to other regions due to the lower projected warming. However, for the highest levels of national warming, they would also experience the highest increase of extreme electricity demand days in summer, mainly because these extremes have not historically occurred during summer in this region.

Despite the clear impact of climate change on Spanish electricity demand, there is still some uncertainty about the point at which these changes will occur due to some limitations of our approach. First, global climate model simulations tend to overestimate summer temperatures and extremely hot days over Western Europe (Cattiaux et al. 2013). This results in a slight overestimation of the number of extreme electricity demand days in summer. Therefore, the estimated changes in electricity demand might occur somewhat later than estimated here. Second, the computation of electricity demand projections and the subsequent analyses have been carried out under the assumption of a stationary relationship between electricity demand and temperature in Spain. This approach neglects possible structural changes that may alter the electricity demand–temperature relationship. As an illustration, a growth in average income could raise the penetration of air conditioning in residential buildings to keep indoor temperatures at a comfort level (Davis and Gertler 2015). In fact, the penetration of air conditioning in Spain rose from 14.9% in 2000 to 55.3% in 2008 (Fernández Boneta and Sebi 2012). This could substantially increase electricity consumption in the residential sector (Jakubcionis and Carlsson 2017). The transition from internal combustion engines to electric vehicles may also play a role in the electricity demand–temperature relationship, affecting the projected seasonal shift because of the currently higher motor fuel combustion in summer than in other seasons (CORES 2018). On the other hand, as the use of natural gas for residential heating is fairly widespread (around 32% in 2011) (IDAE 2011), an electrification of heating systems would mean a strong increase in the winter electricity demand. These potential infrastructure changes could alter the shape of the electricity demand–temperature response curve, accelerating or decelerating the seasonal shift of demand extremes from winter to summer. The methodology used in this study could be refined to account for these effects and improve future projections of electricity demand over different regions of the globe.

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Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by J.M.G.P. The first draft of the manuscript was written by J.M.G.P. and D.B. All authors commented on previous versions of the manuscript. The funding acquisition was obtained by C.O. All authors read and approved the final manuscript.

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Code availability Available upon request.

Declarations

Conflict of interest The authors declare no conflict of interest.

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