A copula-based assessment of renewable energy droughts across Europe

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ARTICLE INFO

ABSTRACT

Meeting carbon-reduction targets will require thorough consideration of climate variability and climate change due to the increasing share of climate-sensitive renewable energy sources (RES). One of the main concerns arises from situations of low renewable production and high demand, which can hinder the power system. We analysed energy droughts, defined as periods of low energy production (wind plus solar generation) or high residual load (demand minus production), in terms of two main properties: duration and severity. We estimated the joint return periods associated with energy droughts of residual load and power production. We showed that moderate winter energy droughts of both low renewable production and high residual load occur every half a year, while summer events occur every 3.6 and 2.4 years (on average). As expected, the occurrence of energy droughts tends to decrease with the degree of the severity of the energy drought, and moderate and extreme energy droughts showed longer return periods for most countries. In general, we found a large variability across Europe in summer, with some countries (e.g. Italy) being more sensitive to energy droughts. Our results highlight the relevance of sharing RES during prolonged periods of low production and high demand.

1. Introduction

A rapid decarbonisation of the energy system is required to mitigate the effects of climate change [1]. Europe is expected to reach a climate-neutral economy with large reductions in green house emissions to at least 80% below 1990 levels by 2050 [2]. This ambitious plan towards a low-carbon power system is influenced by a changing climate, not only on the production side but also on the demand side as heating and cooling patterns are changing as a result of rising temperatures e.g. [3,4]. Balancing variable energy supply and demand might become a major concern in the design of renewable power systems, due to a strong sensitivity to weather and climate variability. In particular, wind and solar power installed capacities have rapidly grown over the past years [5] and they are expected to be important contributors to the European renewable power system. However, their fluctuating nature represents a challenge for renewable energy production as both sources are directly dependent on weather conditions with a high spatio-temporal variability [6–8].

As a result of the dependency of renewable energy sources (RES) on meteorological variables that are strongly time-variable, balancing the RES generation and energy consumption is a key concern, since electricity demand must be continuously matched by electricity supply

to avoid blackouts [6]. The residual load (or net load) is the imbalance between RES and the energy demand (sometimes called load), and is defined as the difference between the energy demand and the energy production [6,9,10]. In an optimal situation, wind and solar capacities might be adjusted to maintain balance between electricity demand and energy production at all time-scales [6]. However, even with theoretically adequate installed capacities of wind and solar, the variability of RES and of demand, which is highly dependent on temperature, could result in periods of positive residual load (hereinafter referred to as RL), during which the demand exceeds the production, or in periods of negative RL with a surplus of RES generation [11].

The effects of RES variability and the strong dependence on weather conditions have become the subject of recent studies that examine periods of low production by RES [12,13]. In particular, extended periods of low wind production, which have been termed *dunkelflauten* (from the German dunkel: absence of light, and Flaute: absence of wind [5,14] can be challenging during demand peaks [5]. While previous studies have examined the fluctuations of wind power linked to the large-scale atmospheric circulation over Europe e.g [15,16], emerging literature focuses on the analysis of prolonged periods of low RES production. [13] characterised periods of low production from RES,

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referred to as "energy production droughts", which were identified as consecutive days of energy production below a fixed threshold for each RES (i.e. wind, solar and hydropower). Similarly, they identified "energy supply droughts" as periods of high residual load. They found a large variability in the energy droughts between renewable sources and the considered European regions, and showed a large decrease in the frequency and duration of the energy droughts when the power system used a mix of energy sources, rather than relying on just renewable generation. Following this approach, [8] assessed the complementarity between solar and wind power in Poland, where energy droughts of wind power generation were more frequent than those of solar resources. This study also highlighted that the presence of local hybrid energy production systems (such as solar and wind) would reduce the variability of the renewable energy production. [14] quantified the occurrence of low onshore wind power generation in Germany using 40 years of reanalysis data. They found that low-wind-power events are less frequent in winter than in summer, but that the maximum duration was evenly distributed throughout the year.

Another recent study analysed the mismatch between energy supply and demand in California and the Western Interconnect [17]. The authors quantified the occurrence of energy droughts of renewable production when daily wind and solar power was less than half of the climatological mean. Recently, [18] examined the climatology and synoptic conditions linked to extreme reductions of wind and solar production at weekly time-scales over western North America. They identified co-variability between wind droughts and higher than average solar power, due to the seasonal cycle and synoptic conditions, which highlights the need for energy-sharing resources (i.e. energy mix).

Despite the increasing attention received by the so-called *energy droughts* in the recent literature, there is no clear established definition of energy supply droughts. Furthermore, quantitative frequency analyses on RES droughts are limited. Energy droughts (hereinafter referred to as ED) can be included within a multivariate framework in which their main characteristics, such as duration and severity, are dependent on each other. Copulas have become very popular for multivariate frequency analyses [19,20], as they allow for the joint simulation of different univariate distribution characteristics (e.g. duration and severity). Within the energy transition context, a comprehensive frequency analysis of ED is particularly important for evaluating the potential risks of power generation highly dependent on weather conditions. Thus, motivated by the successful application of copulas in meteorological and hydrological drought analyses, here we propose a bivariate copula-based approach to model the dependence between the two main features of the ED: duration and severity.

The remainder of this paper is organised as follows. Section 2 introduces the data used during this study. Also in Section 2, the energy-conversion models are summarised. Section 3 includes the ED definition and a description of the copula modelling procedure. The results are presented in Section 4, and Section 5 concludes our study with a general discussion and conclusions.

2. Data

We use daily time series of hourly European electricity demand, solar and wind power at country level for 27 countries (Table S1). The data sets, created by [21], are a reconstruction of energy indicators (i.e. energy demand, wind and solar power), based on the ERA5 reanalysis product [22] that covers the period 1979–2019. This data set corresponds to 3-hourly time series aggregated at a daily time step per indicator and per country.

The data is available from the Reading Research and Data Repository (http://dx.doi.org/10.17864/1947.227) and it has been used in previous studies [9,23]. In the following section, we briefly summarise the methods used for the weather-to-energy conversion data. Interested readers are referred to [9] for further details of the models construction and validation.

2.1. Energy demand

The electricity demand was reconstructed based on a multiple linear regression model trained with observed national demand, in giga (10^9) watts (GW), corresponding to two complete years (2016–2017), extracted from the ENTSOe transparency platform [24]. The regression model uses both weather-dependent and human-behaviour-dependent predictors e.g. the day-of-the-week and long-term socioeconomic trends, [21]. The weather-dependent model parameters are heating-degree days (HDDs) and cooling-degree days (CDDs). A heating-degree day occurs when a country-average 2 metre temperature falls below 15.5 degrees (the threshold at which residential heating is required) whereas a cooling-degree day occurs when a country-average 2 metre temperature is above 22 degrees and energy is required for residential cooling. Within the model, 2 metre temperatures are the only weather-dependent variable that contributes to fluctuations in demand. This style of multiple-linear regression based modelling is common in the literature e.g. [7,13,25].

As we are mainly interested in the meteorological impacts, here we use the weather-dependent model version that neglects the human behavioural factors, as in [9]. Thus, in this weather-dependent model version the predictors representing human behaviour (e.g. the weekday and socioeconomic predictors) are neglected in order to highlight the weather dependence further details can be found in [9].

2.2. Wind and solar power

Wind power capacity factors were obtained from a physical model that uses bias-adjusted wind speeds (using the Global Wind Atlas as the 'truth') at an altitude of 100 metres above ground from the ERA5 reanalysis [9]. Calibrated wind speeds are then passed through a power-curve to convert to wind power capacity factors. Different power-curves are used for different grid cells of the underlying climate data set: three turbine classes are retained, Class 1, 2 and 3. The choice of the turbine class per grid cell is dependent on the long-term average wind power generation. The three different turbine curves allow the maximum potential to be extracted from each grid-cell's wind speeds. Country-level wind power generation is calculated by weighting each grid box by the amount of wind power installed there (in the reference year 2017).

Solar power capacity factors were modelled following the empirical formulation of [26], using 2 metre temperature and incoming surface solar radiation as inputs. The solar power capacity factors were calculated at each grid point and then aggregated to national level assuming a uniform distribution of solar panels across the country (as at the time of model creation there was not available data on panel locations). Both wind and solar power data sets captured the overall behaviour of the national wind and solar power generation well (see [9] and references therein for further details).

The capacity factors (expressed in %) obtained from both wind and solar power models were used to calculate the daily national wind and solar power production, for which we used as the baseline the installed capacity of wind and solar corresponding to 2017 for each country(see Supplementary Fig. S1) [9,23]. Additionally, we performed further sensitivity analyses with differing installed capacities: doubling and tripling the current installed capacities either for wind or solar (alternatively) and assuming that the locations of the wind farms are kept the same as in 2017. Results from these experiments are summarised in the supplementary material. As these experiments aim to provide further context on the impact of changing installed capacities, for illustrative purposes only the results of a representative number of Europe countries are shown in the supplementary material. Unless noted, the main results presented in the following sections assume the installed capacity of the reference year (i.e., 2017).

Short name	Description	Threshold
LWS	Low wind and solar production	<10th
RL	Residual load (demand - wind and solar production)	>90th
Demand	Electricity demand	>90th

3. Methods

3.1. Energy droughts: event definition

We begin our analysis by defining ED events using a threshold-level based approach. An ED of low production is identified as an episode or period of time during which the energy production of renewable sources (i.e. wind and solar) is below the 10th percentile of the total generation (also referred to here as LWS) over the period of study 1979–2019. An ED of the residual load (i.e. demand minus wind and solar production, here also referred to as RL) occurs when the residual load exceeds the 90th percentile of the distribution of residual load. For comparison, we additionally analyse ED of high electricity demand, defined as instances when the demand exceeds the 90th percentile of the distribution of the electricity demand. Table 1 summarises the events definition.

While the main results will focus on episodes of low renewable production, high residual load and high demand, similar frequency analyses were also conducted on the individual renewable energy sources (see Section 4.1). Threshold-based approaches typically assume independent observations, and thus, declustering extreme values is often applied to assure independence of events. Here, energy droughts that are separated by at least two days are treated as independent events. Declustering events reduces the number of extreme events compared to the original series. We used a clustering window of 2 days as a good compromise from a weather perspective, to cluster events co-occurring with the same weather system, but also from a modelling perspective, as we obtain a sufficient number of events for our modelling purposes. Then, we estimate the main characteristics of ED: (1) the duration, D (days), which is defined as the consecutive days below or above the selected threshold values and (2) the severity, S (GW) defined as follows:

$$S = \sum_{i=1}^{D} \frac{|(E_i - E_{th})|}{\sigma} \tag{1}$$

where E_i is the energy quantity (i.e., production, residual load or demand) for the days during a particular event, E_{th} is the threshold value and σ is the standard deviation of the corresponding energy distribution (i.e., production, residual load or demand). Standardising the severity values allows us to provide a better comparison of ED across countries due to the large variability, in terms of residual load, demand and renewable production (i.e., see Fig. S1).

As shown in previous studies [9,10], peaks of energy demand and low production show a strong seasonal variability. Therefore, the frequency analyses presented here are performed separately for two extended seasons: winter (October–March, ONDJFM) and summer (April–September, AMJJAS). Please note that the ED are defined based on absolute threshold values (i.e. considering the entire distribution throughout the year), and we then perform the frequency analysis for winter and summer.

3.2. Copula analysis

Copulas [27] are flexible tools to describe the joint behaviour of multiple variables and have been successfully applied in frequency analysis, multivariate modelling, simulation and prediction [19,28]. Recently, the use of copulas has rapidly grown to examine dependence

structures that exist between complex inter-correlated variables in many different areas, including hydrology, climate science or energy applications [29]. This methodology has gained popularity in the context of drought analysis [20,30]. In a bivariate case, a copula is a joint distribution function that characterises the dependence between two random variables independently from their marginal distribution functions [27]. For two random variables X and Y with marginal distribution functions $F_X(x) = P(X \leq x)$ and $F_Y(y) = P(Y \leq y)$ respectively, a copula function can be used to construct their joint cumulative distribution function as follows

$$F_X Y(x, y) = P(X \leq x, Y \leq y) = C(F_X(x), F_Y(y)) \tag{2}$$

where C is the copula of the transformed random variables $U = F_X(X)$ and $V = F_Y(Y)$, with the marginals U and V being uniformly distributed on the interval [0,1]. According to Sklar's theorem, if the marginal distributions are continuous, then the copula function C is unique [31]. The main advantage of using copula functions is the flexibility to model the dependence between multiple variables with different univariate marginal distributions. Interested readers can refer to [19,27] for more information about copulas and their applications.

ED are mainly characterised by duration and severity, which are typically dependent on each other. Prior constructing the copula models, we examined the strength of the relationship between the duration and severity in terms of the Kendall's τ coefficient. Then, we applied the copula analysis to model the joint distribution of the duration (D) and the severity (S) separately for each country, season and ED from low production, high residual load and high demand. The main procedure of the copula analysis conducted here can be summarised as follows: (1) estimating the marginal distributions of the duration and the severity; (2) selecting the most appropriate copula; (3) constructing the joint distributions and (4) estimating the return period of both, duration and severity exceeding a given threshold.

To model the joint distributions, it is necessary to transform the random variables (D and S) to uniformly distributed marginals [0,1], which can be accomplished by calculating the normalised ranks (non-parametric estimation) or by modelling the marginals with parametric distributions parametric estimation; [32]. Here, we adopted the parametric method and several distributions including log-normal, gamma, exponential and GEV were tested to fit the marginal distributions of S and D. For simplicity, we treated the duration as a continuous variable, similarly to previous studies [33,34]. The Kolmogorov–Smirnov test is selected as a goodness-of-fit test to evaluate the fit of the marginal distributions, which are estimated using maximum likelihood estimation (MLE).

After the marginal specification, the copula parameters were estimated using MLE and the most appropriate copula model was selected based on the Aikaike information criterion AIC. The goodness-of-fit was additionally tested using the Cramer–von Mises test [35]. Then, the joint distributions derived from the copula allowed us to estimate the joint probability that a particular event will occur. Among the possible events used in the literature [36] that correspond to specific hazard scenarios [37], a critical condition affecting the power system might occur when both the duration and the severity of the ED production or residual load exceed a certain value. In this case, the joint probability of exceedances of both D and S over a fixed threshold is expressed as:

$$P(D > d, S > s) = 1 - F_D(d) - F_S(s) + C(F_D(d), F_S(s)) \tag{3}$$

where F_D and F_S are the marginal distributions of duration and severity, respectively, C is the copula expressed in Eq. (2), and d and s are the two given thresholds.

Once the joint probability is derived from the copula, we assess the power risks through the associated joint return period. The return period is a measure of the expected recurrence interval of a hazard event [38], in our case, energy droughts, and can be defined as the
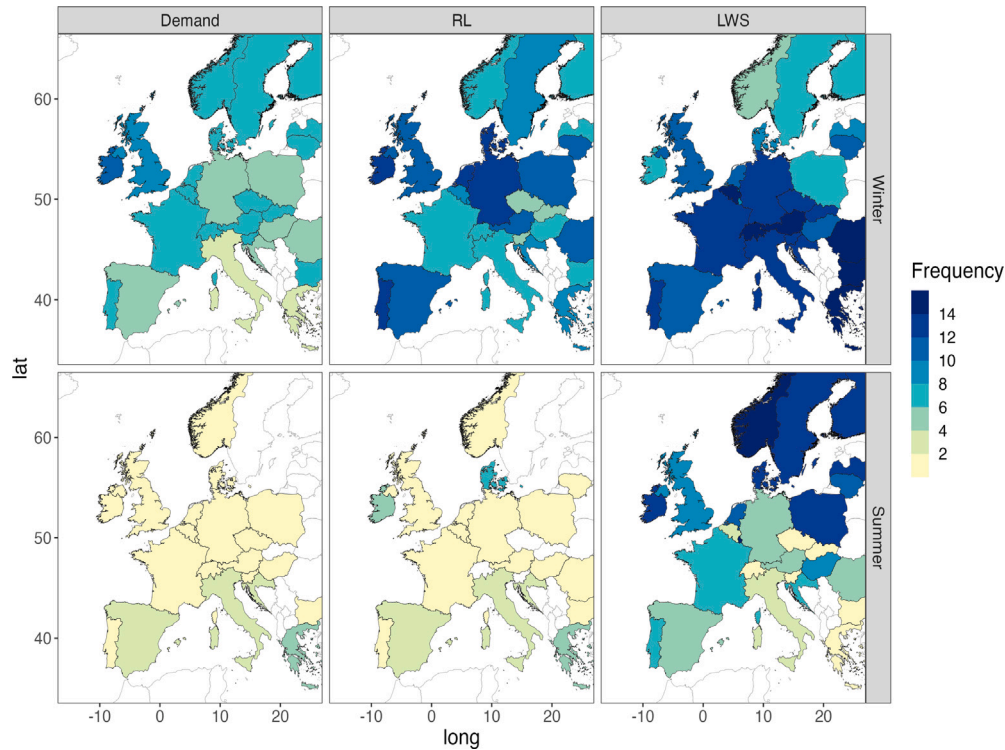
Fig. 1. Frequency of ED (events per season) for each country and each ED of demand, residual load (RL) and low wind and solar production (LWS) calculated for the summer and winter during the period of study 1979–2019 for each country. White areas within the countries of study indicate no ED.

Table 2

Classification of ED according to different threshold levels of both duration (D) and severity (S).

Class of ED	Joint probability
Moderate	$P(d_{75th} < D \leq d_{90th}, s_{75th} < S \leq s_{90th})$
Severe	$P(d_{90th} < D \leq d_{95th}, s_{90th} < S \leq s_{95th})$
Extreme	$P(D > d_{95th}, S > s_{95th})$

inverse of the expected frequency of the event. In the bivariate case, the return period is estimated as follows:

$$T = \frac{\tau}{P(D > d, S > s)} \qquad (4)$$

where τ is the average inter-arrival time (in years) of successive ED (i.e. total number of years divided by the total number of ED) and P is the joint probability derived from the copula analysis (Eq. (3)). This approach is commonly used to assess meteorological and hydrological droughts [19]. Let d_q and s_q denote the q-th percentile of the marginal distribution of the duration and severity, respectively. We select three threshold values, $q = 75$, 90, and 95 percentiles, to define several classes of ED, for which the return periods were estimated. Table 2 summarises the classification of ED. Please note that the percentiles are defined locally, i.e. for each country and season, as the copulas are applied separately for each case. We tested fixed thresholds (e.g., 2, 4 days for the duration), but given the high variability of load and amount of installed capacity across countries (see Fig. S1), local percentiles are more suitable for comparing ED across the European countries.

We further examined empirically the joint return periods by counting the number of events for which both S and D exceed the selected thresholds. The empirical method is straightforward, but it requires long time series for very extreme events, which is less of an issue when a parametric copula approach is implemented [39].

4. Results

Before starting the bivariate copula analysis to model the dependence between the main characteristic of ED, we examined their frequency, duration and severity separately for each country and season. In addition to the ED of low production, demand and residual load, we further assessed the events of the individual sources (i.e. wind and solar separately) as well as the corresponding demand-net-individual RES: demand-net-wind, defined as the demand minus wind power, and demand-net-solar, defined as the demand minus solar power. Thus, we begin this section by presenting a frequency analysis of the energy droughts, followed by the dependence analysis between duration and severity of ED through the copula models.

4.1. Frequency analysis of ED

Fig. 1 illustrates the total number of ED per year calculated for each country and for each ED of demand, wind and solar production and residual load. Note that the frequency analysis is performed separately for each season, and therefore the total number of ED corresponds to events per season. The frequency of ED of low production is generally larger in winter (11.4 events per year on average) than in summer (7.6 events per year on average). However, significant variability in the occurrence of low production events exists across the countries. While in most countries, the occurrence of ED of low production decreases in summer, the number of ED of low production in summer is comparable or higher than in winter for a few countries (e.g. Poland, Norway, Sweden, Latvia). This is explained by the small amount of installed solar capacity in those countries (Fig. S1). Therefore the droughts of low production are mainly driven by wind speed, which is reflected in the large frequency of ED of wind in summer, as shown in Fig. 2 for the individual wind source. The strong seasonality of solar power generation explains the reduced number of solar generation droughts in
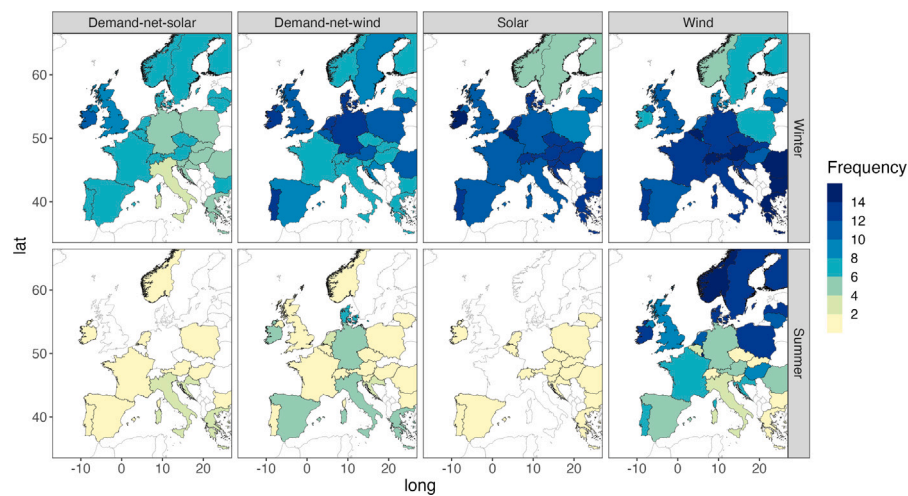
Fig. 2. Frequency of ED (events per season) for each country and each ED of individual sources: demand-net-wind, demand-net-solar, wind power and solar power, calculated for the summer and winter during the period of study 1979–2019 for each country. White areas within the countries of study indicate no ED.

Fig. 3. Maximum duration (days) of ED of demand, residual load (RL) and low wind and solar production (LWS) calculated for the summer and winter during the period of study 1979–2019 for each country. White areas within the countries of study indicate no ED.
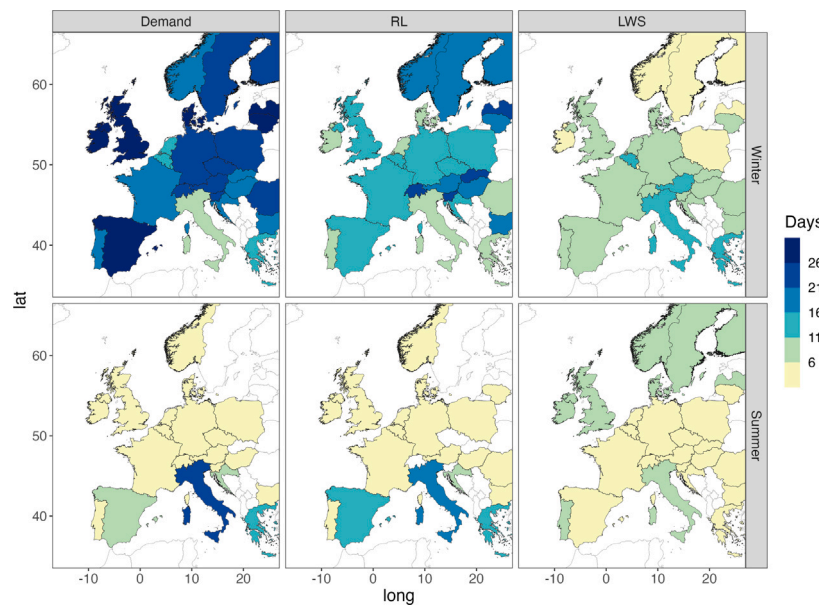
summer over Europe (Fig. 2). Moreover, the sensitivity analysis with an increasing amount of solar power capacity installed (e.g., with double and treble values with respect to the baseline scenario) showed that the ED of low production in summer are generally reduced comparing with the current scenario (i.e., 2017) for a number of selected countries, such as Germany, the UK, France and Portugal (see Supplementary Fig. S2). As the solar capacity is increased, fewer energy production droughts occur in summer and more in winter, when the solar generation significantly decreases due to short day length. On the contrary, when increasing wind capacities, overall, fewer production droughts occur in winter and more in summer (Fig. S2). Similar pattern is observed in the ED of the residual load in summer, when the demand is typically low. Due to the higher demand in winter, changes in the installed capacity (particularly solar capacity) have a much smaller effect on the number of residual load droughts (Fig. S2).

The lowest frequency of ED of demand and residual load is observed in summer (0.81 and 1.6 events per year on average) due to the electricity demand patterns (i.e. low demand during the warmer months). The number of ED of demand and residual load is substantially higher in winter (6.37 and 11.4 events per year on average). Also in winter, it can be observed that a higher number of ED of residual load occur than ED of demand in some countries (e.g., Germany, UK), which can be explained by a lower renewable production in winter. Despite the reduced occurrence of ED of demand and residual load in summer, a number of countries experienced more than 100 high demand and residual load events over the 41 year period. In the case of the northern countries, such as Denmark or Ireland, this can be attributed to the low amount of installed capacity of solar power, which leads to a high demand-net wind (see Fig. 2) that results in higher residual load (driven mostly by wind production). The number of ED of demand and residual load in the southern countries (e.g. Spain, Greece, Italy) is associated with the increasing use of air conditioning that results in demand peaks in summer [9,25]. Those countries also tend to experience the longest ED of residual load (~15 days) compared to the rest of the countries in summer (Fig. 3). Consistently with the seasonal patterns and with the weather dependence of both production and demand, overall, the maximum duration of energy droughts is larger in winter than in summer. The longest lasting ED correspond to the
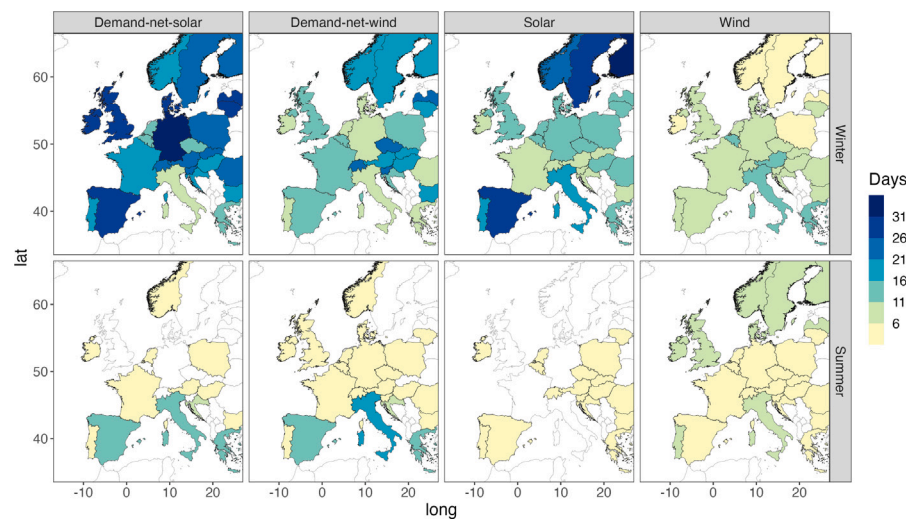
Fig. 4. Maximum duration (days) of ED of individual sources: demand-net-wind, demand-net-solar, wind power and solar power, calculated for the summer and winter during the period of study 1979–2019 for each country. White areas within the countries of study indicate no ED.

winter demand (21.8 days on average), following by the ED of residual load (15.6 days on average). When increasing the current installed wind capacities, the ED of residual load are generally shorter in winter (∼ 6 days on average when trebling the installed wind capacities), which is in agreement with more wind power generation in winter. With higher wind power installed capacities, the ED of residual load are mainly driven by the amount of wind power production, which might also explain the similar or larger durations of energy droughts in some countries during the summer (see Fig. S3). A contrasting seasonal pattern is found when increasing the current amount of solar installed capacities: shorter ED of residual load are found in summer (than those in the current scenario), while little change is observed in winter. It is worth mentioning that the time series of the winter demand and residual load generally show less variability compared to the time series of wind and solar production. Moreover, as shown in Fig. 1, ED of low production are more frequent than ED of residual load and demand, thus we could expect longer ED of demand and residual load and shorter ED low production. The mean duration of ED also showed the seasonality of events, particularly in winter, when RL ED last on average for 2.3 days, compared to ED of low production that last 1.4 days (not shown). Most European countries experience peak demands in winter, when the renewable production is also strongly influenced by seasonality (e.g. shorter daylight hours and reduced incoming solar radiation resulting in decreased solar power generation) and weather patterns e.g. persistent high-pressure systems associated with below normal wind speed that lead to decreasing wind power generation, [13,23]. The ED of individual sources, more specifically the ED of solar and demand-net-solar are considerably shorter in summer than in winter due to their seasonality (i.e. more incoming surface radiation in summer) (Fig. 4). The longer duration events will provide the greatest challenges for energy system balancing.

The severity of ED of demand, residual load and low production is higher in winter in most of the central and northern European countries (Fig. 5), which is consistent with more frequent and longer-lasting events in winter compared to summer (Fig. 1). Similar results are observed when examining the ED of individual sources, wind and solar, separately (Fig. 6). The severity of wind and solar ED is generally larger in winter, as is the severity of the demand-net-wind and the demand-net-solar. Exceptions are found in the southern countries, such as Italy, where the most severe ED of residual load, in terms of both duration and severity, occur in summer, which is expected as a result of summer peaks demand. Also in Italy, it can be observed that the most severe demand-net-wind and the demand-net-solar events occur in summer. As stated above, this is explained by the higher summer ED

of demand accompanied by low wind production (Fig. 1), which result in high demand-net wind (i.e. demand minus wind generation, see Fig. 2). Moreover, in the case of Italy, the lower installed solar capacity (compared to other countries) (see Fig. S1) explains more severe ED of residual load summer, in terms of duration and severity, which highlights the importance of the temporal complementarity i.e., availability of sources in time, [40] between renewable sources in regions within an energy mix, as shown in previous studies [7,13]. Overall, for winter ED of residual load, we notice lower severity values when increasing the wind power capacities (relative to the baseline installed capacity scenario), while in summer, lower severity ED of residual load occur under a potential installed capacity scenario with higher solar installed capacities (Fig. S4).

4.2. Bivariate return periods of ED

An important step in the copula analysis is the fitting of the marginal distributions. Here, exponential and generalised extreme value (GEV) distributions are identified as the most appropriate to represent the duration and the severity for most countries for the ED corresponding to the low production, high residual load and demand (see Supplementary Tables S2, S3, and S4). The results from the copula selection process indicated that the Joe copula was best suited to capture the relationship between the duration and the severity in most cases (see Supplementary Tables S5, S6 and S7). The parameter of the copula functions represents the dependence structure between the drought duration and the severity. For each ED (i.e., low production, residual and demand), we tested the strength of the relationship between the duration and the severity through the Kendall's τ correlation coefficients (Fig. S5). Similarly to the copula parameters (see Tables S5, S6 and S7) that indicate the dependence between two variables, higher correlations between the duration and the severity were generally observed in winter, particularly for the duration and severity corresponding to the ED of demand and residual load, while a lower correlation was found in summer. Higher correlation values between duration and severity suggest that the most severe events are those that last longest, while lower correlation values, as in summer, suggest that there are severe events that do not last for a long time. This points out the risks of ED in winter when European countries experience high demand. Nevertheless, it can be noted that the dependence between D and S is particularly strong in summer in a few countries (e.g. Italy, Greece.), where the ED of residual load seem to be more severe than in winter, as a result of higher summer demand (e.g., more cooling days), which is consistent with the frequency analysis presented above.

Fig. 5. Severity of energy droughts of demand, residual load (RL) and low wind and solar production (LWS) for the summer and winter during the period of study 1979–2019 for each country. Please note the change of the scales due to the large variability between the loads and production. The long names of the country acronyms are displayed in table S1.

Fig. 6. Severity of energy droughts of individual sources: demand-net-wind and wind power, and demand-net-solar calculated for the summer and winter during the period of study 1979–2019 for each country. The long names of the countries acronyms are displayed in table S1. Please note the change of the scales due to the large variability between the demand-net quantities and the production.

Given the dependence between the drought characteristics, the joint return periods are crucial to assess the potential risks associated with ED. Therefore, we calculated the joint return periods corresponding to three classes of ED (see Table 2). Furthermore, the empirical joint return periods were estimated directly from the number of observed events, and can be used to assess the robustness of the fitted copulas. Fig. 7 shows the joint return periods for moderate ED for demand, residual load and low production (Table 2). As stated in Section 3.2, the

classification of ED is based on local percentiles due to the high variability across countries in terms of solar and wind installed capacities as well as in terms of loads. As expected, moderate EDs are more frequent in winter than in summer. In winter, ED of demand show slightly larger return periods everywhere, occurring once every 0.98 years than the ED of residual load that occur once every 0.67 years, while the ED of low production are generally more frequent (every 0.58 years). It is worth noting that only a few countries are affected by moderate ED of demand and residua load in summer (Fig. 5). These events tend to
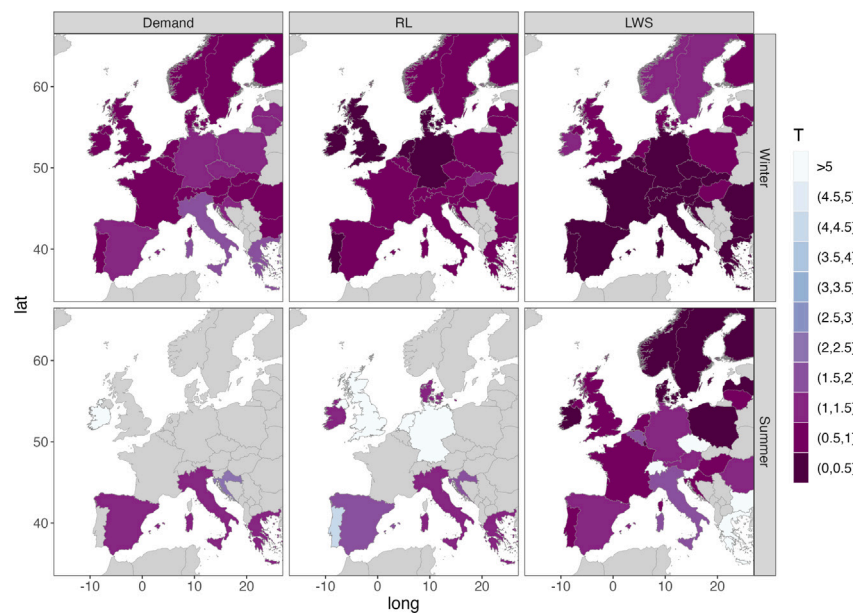
Fig. 7. Joint return periods (T) expressed in years corresponding to moderate ED (Table 2) of demand, residual load (RL) and low wind and solar production (LWS) for both extended seasons, summer and winter. Grey colours indicate countries where the copulas were not applied due to the limited number of ED.

occur most frequently in countries such as Italy, Greece or Denmark, due to the summer peak demand or as a result of a low production (e.g. low wind power generation in summer drives the ED of low production, and thus, higher RL, in those countries with low solar installed capacities). Similar patterns of return periods were obtained when counting the number of moderate ED empirically(Fig. S6), which indicates a reasonably good agreement between both methods.

Severe energy droughts (i.e. exceeding the 90th percentile of the marginal distributions of D and S) are relatively frequent in winter (on average, every ∼ 1.6 years) compared to summer (on average, every ∼ 8–9 years)(Fig. 8). While in winter, the return periods are very similar across Europe, we found a large variability across countries in summer. For example, in some countries (e.g. Norway, the UK, Ireland) severe ED of low production occur very often, every 2–3 years, compared to countries that experience summer severe ED of low production less than once every 10 years. Such variability in summer return periods across countries was also found in the empirical return periods. However, we also noticed larger differences when comparing the empirical return periods and the return periods from the copulas than for the moderate ED in summer (Fig. S7). The differences are likely due to bias in the empirical estimates because the number of observed events is small.

As expected, the return periods increase with the severity of the ED, and extreme energy droughts occur less often throughout the year (in Fig. 9). Similarly to moderate and severe ED, extreme ED are more frequent in winter. Overall, similar values were found for the different countries, with slightly larger return periods of ED of residual load (every ∼3.5 years) than ED of low production, which tend to occur more often (every ∼2.9 years). The variability across countries in terms of return periods notably increases in summer, particularly in the case of low production. Some countries (e.g. the UK, Denmark) seem to experience extreme ED of low production quite often (every ∼2–4 years), while in other countries (e.g. Switzerland, Poland) extreme ED of low production appear to be more rare (every >30 years). The empirical return periods obtained for winter show in general a good agreement with the return periods derived from the copulas (Fig. S8). Larger differences were found when comparing the summer return periods and in general, the empirical method underestimated the frequency of extreme ED (i.e. larger return periods). This might be explained by the fact that the empirical approach has limitations when interest is on rare events, as it might be the case with extreme ED [39,41].

Overall, the sensitivity analysis with differing installed capacities showed largest return periods for the summer ED of low production when increasing the amount of solar power installed. For example, countries such as Germany, Italy or France showed return periods ∼10 years when doubling the installed solar capacities and >20 years when trebling the installed solar capacities (e.g., see return periods for severe ED in the Supplementary Fig. S9). In contrast, a higher amount of installed wind power lead to larger return periods in winter (Fig. S9). In the case of winter ED of residual load, we noticed little impact on the return periods when increasing either wind and solar capacities (Fig. S9). This is likely due to the higher winter demand that result in high residual load.

5. Discussion

Characterising periods of peak demand and periods of low power generation is crucial to address energy security concerns arising from the increasing share of renewable sources in the European energy supply. Renewable energy sources (RES), particularly wind and solar, are intermittent due to their strong weather dependence. Thus, the fluctuating power generation in periods of low production and high demand represents a major challenge for balancing energy supply and demand. Previous studies that analysed the so-called energy droughts e.g. [8,13,18] suggested that the complementary behaviour of existing wind and solar power would reduce periods of low energy production in systems with both renewable sources compared to systems with a single source.

A multivariate frequency analysis is essential to better understand the relationship between the characteristics (duration and severity) of the energy droughts, and thus to provide further insights into the risks associated with energy droughts across European countries. We proposed a copula-based approach to examine the relationship between the duration and the severity of periods of low production of wind and solar power and high demand and residual load. We examined the risks of several types of energy droughts classified based on local percentiles of the duration and severity. Such an energy drought analysis could be further extended by accounting for how strongly operational planners actually rely on a given renewable resources. This can be achieved by considering capacity credit calculations that are used by planners as a measure of how strongly they can rely on a renewable resource during
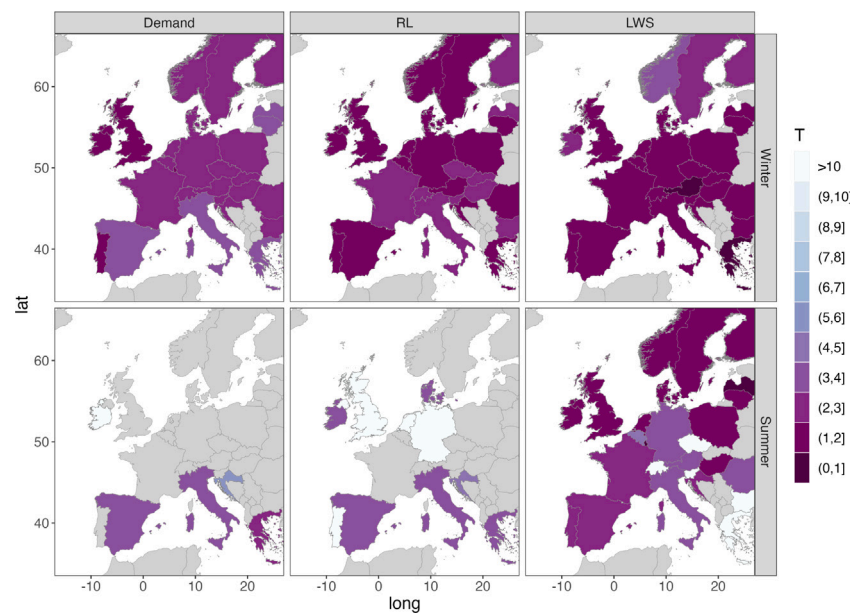
Fig. 8. Joint return periods (T) expressed in years corresponding to severe ED (Table 2) of demand, residual load (RL) and low wind and solar production (LWS) for both extended seasons, summer and winter. Grey colours indicate countries where the copulas were not applied due to the limited number of ED.
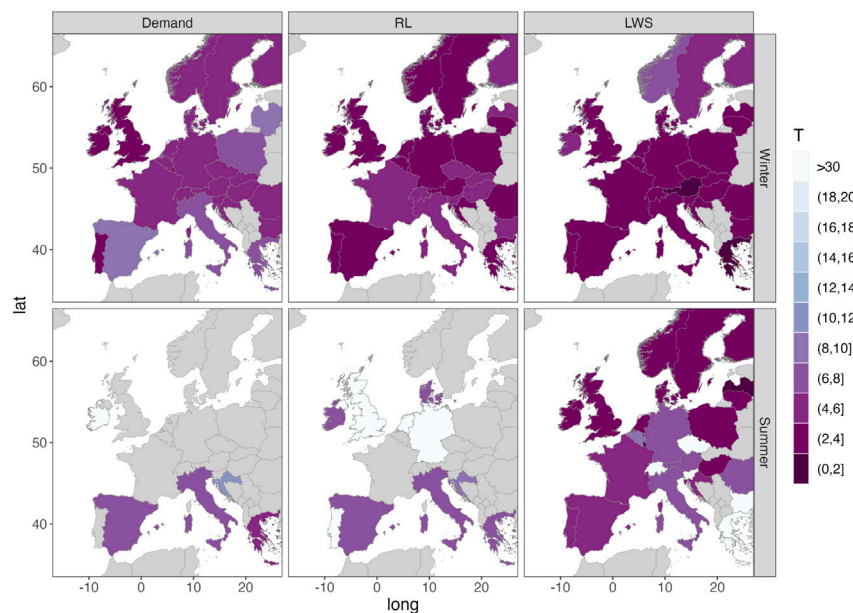

Fig. 9. Joint return periods (T) expressed in years corresponding to extreme ED (Table 2) of demand, residual load (RL) and low wind and solar production (LWS) for both extended seasons, and winter. Grey colours indicate countries where the copulas were not applied due to the limited number of ED.

high load periods [42]. For instance, when wind exhibits a low capacity credit, (e.g. in the order of 10%–15%) [42], an actual drought would only occur if the resource availability falls below this capacity credit.

In contrast to the previous studies that addressed the issue of energy droughts e.g [8,13,14], here we presented a multivariate frequency analysis in order to provide a better understanding of the energy droughts on the basis of the dependence structure of their main features: duration and severity. Our approach is similar to the copula-based assessments presented in the literature to analyse meteorological droughts by using well-known meteorological drought indices, such as standardised precipitation index or standardised precipitation evapo-transpiration index) e.g. [19,33]. In this work, the energy droughts were defined based on a threshold approach, and declustered to assume independence of events. Therefore, we acknowledge that a different

window to decluster events might have an impact on the results presented here. Overall, the clustering window could be related to the time scale used to define the energy droughts (e.g., hourly, sub-daily, daily) and to operational and maintenance aspects of power generation. As daily data was used to define energy droughts, a clustering window of 2 days allowed us to investigate a sufficient number of independent events likely associated with the same weather system.

This analysis based on daily data might potentially be extended by investigating the links of energy droughts with large-scale atmospheric patterns that can lead to long-lasting or more severe energy drought events. However, future research could assess energy drought using hourly time series, which would be particularly valuable to assess the capacity credit of wind power generation (i.e. its ability to provide generation during peak demand events).

Our study assumes a baseline power scenario of solar and wind power installed capacities representative of the present-day power system (i.e., 2017). As stated in the introduction, wind and solar installed capacities are rapidly growing in most of European countries. Thus, it is expected that changing the installed capacities will have an impact on the results presented here. The sensitivity analysis performed for increasing installed capacities (either solar or wind) pointed out the relevance of the temporal complementarity of renewable sources within the same region, as a result of the strong weather dependence of the renewable energy sources. Overall, as the wind capacity increases the frequency of energy production droughts in winter decrease, while an opposite seasonal behaviour is found when increasing solar capacities that result in fewer energy production droughts in summer when solar generation is usually higher. We showed that with a higher amount of wind power installed the winter energy droughts of power production would be generally less severe and generally shorter, while less severe summer energy production droughts would occur when increasing the solar power installed capacities. The results showed that increasing the current amount of installed wind power would have a small impact on the winter residual load events. This can be explained by the percentile-based definition of energy droughts, for which high residual load (above the 90th percentile) will still occur in winter, due to a higher demand (compared to summer events). Nevertheless, given that the demand patterns are expected to change under a warming climate, an extension of this analysis should include the climate change impact on energy droughts.

Moreover, it must be noted that the energy droughts were analysed separately for each country, and thus, one might expect that in a fully interconnected grid, the potential risks associated with energy droughts will be reduced. However, further analysis are required to provide a better assessment of the energy drought considering an interconnected power grid. Actual impacts on the transmission grid are the logical next step; but their analysis remains challenging at European scale because of the required detailed knowledge of the transmission grid and of the production infrastructure.

6. Conclusions

The main findings of this study can be summarised as follows:

Given the strong weather-dependence of renewable sources (wind and solar), but also the demand that is greatly driven by weather conditions, energy droughts exhibited a marked seasonal pattern, being generally more frequent and longer lasting in winter than in summer. Compared to winter, the number of summer energy droughts of residual load is generally smaller across almost entire Europe, due to a general reduced electricity demand, which leads to small demand energy droughts during the warmer months. However, exceptions are southern countries (e.g. Italy, Spain, Greece) that showed longer durations of residual load droughts in summer, which can most likely be explained by summer peak demand. Also in summer, longer episodes of high residual load were found in some northern countries (Denmark, Norway), as a result of episodes of low production of wind (which is the main contributor to the energy production here). Moreover, using a higher amount of wind installed capacities would reduce the severity of winter energy droughts, while increasing solar installed capacities would lead to less severe summer energy droughts, which highlights the relevance of temporal complementary between renewable sources.

The dependence between the energy drought duration and severity is clearly reflected by the copula results that showed a stronger dependence in winter, particularly in the case of the demand and residual load. We showed that moderate energy droughts are very frequent in winter, with short return periods (e.g. moderate energy droughts of production occur twice a season on average). The winter return periods of both production and residual load moderate droughts were similar across the countries, pointing out the strong relationship between the duration and the severity of droughts. Similar results were found for

severe and extreme winter energy droughts although the return periods increase with the severity of the energy droughts. Our results pointout smaller energy droughts in summer, especially from the load side, although we observed a large variability across European countries as a result of the different demand patterns across the regions.

In summary, the multivariate copula-analysis used here provides new insights into the dependence structure of the main characteristics of energy droughts, namely duration and severity, which is crucial to estimate the potential risks of such events. The estimated joint return periods pointed out that in winter European countries are exposed to frequent (particularly moderate and severe) energy droughts of both production and residual load. In summer, there is an increasing variability across Europe and only a few countries experience frequent energy droughts. The return periods as presented in this study can be used as a relevant measure of the risks associated with renewable production, but also with the demand side, which might be especially valuable for energy planners.

CRediT authorship contribution statement

Noelia Otero: Conceptualization, Methodology, Data Analysis, Writing – original draft, Writing – review & editing. **Olivia Martius:** Supervision, Writing – review & editing. **Sam Allen:** Methodology, Writing – review & editing. **Hannah Bloomfield:** Data curation, Writing – review & editing. **Bettina Schaefli:** Supervision, Writing – review & editing.

Declaration of competing interest

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.

Data and code availability

The time series of energy data used within this study are available from the Reading Research data repository:https://researchdata.reading.ac.uk/227. The code is available upon request to the corresponding author.

Acknowledgments

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.renene.2022.10.091.

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