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Standardised indices to monitor energy droughts

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Abstract

To mitigate the effects of climate change, energy systems are becoming increasingly reliant on renewable energy sources. Since these energy sources are typically dependent on the prevailing weather, renewable energy systems are susceptible to shortages during certain weather conditions. As renewable sources become larger contributors to the energy mix, the risks associated with these shortages, referred to as energy droughts, increase. Techniques to monitor energy droughts are therefore required to mitigate the associated societal impacts. In this paper, two standardised indices are introduced to monitor droughts in renewable energy systems. The indices incorporate energy demand and renewable energy production, and constitute analogues of the standardised precipitation index (SPI) and standardised precipitation evapotranspiration index (SPEI), two indices regularly employed operationally to monitor meteorological droughts. The indices are straightforward to construct, can be defined on any timescale, and can readily be compared for regions with different climates and installed capacities. We demonstrate how the standardised energy indices proposed herein can be used to define renewable energy droughts, for which there is not yet a recognised definition. To illustrate the practical utility of these indices, they are applied to reconstructed time series of electricity demand and wind and solar power generation across Europe.

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1. Introduction

To mitigate the effects of climate change, energy systems are becoming increasingly reliant on renewable energy sources (RES). Energy production from RES, such as wind and solar power, typically depends heavily on the prevailing weather. Although this means RES replenish naturally, balancing supply and demand in renewable energy systems becomes challenging, since certain weather conditions could result in simultaneously low renewable energy production and high energy demand, leading to shortages in the system (von Bremen, 2010; van der Wiel et al., 2019; Otero et al., 2022a).

Raynaud et al. (2018) termed these shortages "energy droughts", acknowledging the similarity between shortages in energy systems and the classical notion of a meteorological drought: both represent instances where the amount of a quantity needed to sustain an underlying process far exceeds the amount of this quantity that is produced. Previous studies have therefore suggested analysing energy droughts using methods commonly applied to meteorological droughts (see e.g. Ohlendorf and Schill, 2020; Jurasz et al., 2021; Otero et al., 2022b).

The impacts associated with meteorological droughts are well-documented, and several established procedures exist to help mitigate these impacts. These procedures could similarly be employed to minimise the risks of energy droughts. For example, most National Meteorological and Hydrological Services maintain drought monitoring systems, which identify when a drought is likely to occur, before relaying this information to the relevant authorities so that appropriate action can be taken (Hayes et al., 2011). As the share of energy supplied by RES increases, the impacts associated with energy droughts become more severe, making analogous systems to monitor energy droughts more appealing.

Meteorological droughts are typically defined in terms of two well-established standardised indices: the standardised precipitation index (SPI) of McKee et al. (1993), and the standardised precipitation-evapotranspiration index (SPEI) introduced more recently by Vicente-Serrano et al. (2010). The SPI is a standardised measure of the precipitation at a location, while the SPEI additionally incorporates evapotranspiration. These indices are commonly used for the operational monitoring of droughts, and the World Meteorological Organisation even encouraged all National Meteorological and Hydrological Services around the world to define meteorological droughts in terms of these standardised indices (Hayes et al., 2011).

Defining droughts in terms of standardised indices has several benefits. The indices are defined on a common scale, and are thus easy to interpret. This standardised scale also has an underlying probabilistic interpretation, making the indices ideal for risk management and decision-making. Moreover, since the standardisation can be performed separately for different seasons and locations, droughts can be defined in a relative sense, allowing the intensity of droughts in different climatic regions to readily be compared. As summarised by Zargar et al. (2011), standardised drought indices provide a "pragmatic way to assimilate large amounts of data into a quantitative information that can be used in applications such as drought forecasting, declaring drought levels, contingency planning and impact assessment."

In contrast to meteorological droughts, there is currently no universal definition of an energy drought. However, standardised energy indices can similarly be introduced for the purpose of monitoring and analysing energy droughts. The approach used to construct the SPI and SPEI can straightforwardly be applied to other variables, as has been done for example for temperature (Zscheischler et al., 2014), soil moisture (Hao and AghaKouchak, 2013), streamflow (Zaidman et al., 2002; Vicente-Serrano et al., 2012), and compound hot and dry conditions (Li et al., 2021). Hence, in this paper, we introduce a standardised renewable energy production index (SREPI) and a standardised residual load index (SRLI). The SREPI considers only the renewable energy production, and is therefore an energy-based analogue of the SPI, whereas the SRLI is defined in terms of the residual load, i.e. the difference between energy demand and renewable energy production. Since the SRLI accounts for both the supply and demand in the energy system, it constitutes an analogue of the SPEI for standard drought analysis. Just as meteorological droughts are defined in terms of the SPI and SPEI, we demonstrate how the standardised energy drought indices introduced herein can be used to define energy droughts.

To our knowledge, this is the first application of standardised drought indices in an energy context. The indices introduced here can be calculated using the `R` package available at `https://github.com/noeliaof/SEI`, which allows for the construction of arbitrary standardised indices, and is therefore applicable to both meteorological drought variables as well as the energy variables considered here. The standardised energy drought indices are introduced in the following section. Section 3 then describes how these indices can be used to define energy droughts. These indices are applied in a case study in Section 4, using reconstructed energy demand and wind and solar production data in several European countries, thereby demonstrating how these indices can be used in practice. Finally, Section 5 concludes.

2. Standardised energy indices

In this section, we introduce two standardised indices that can be used to monitor energy droughts. The indices are renewable energy-based analogues to the SPI and SPEI, and are constructed using the same methodology. As mentioned in the previous section, this approach has been used to define standardised indices corresponding to several hydro-meteorological processes. To construct the indices, we assume that there exists a time series of previous values of the renewable energy production, $P_1, \dots, P_n$, and the corresponding residual load, $L_1, \dots, L_n$. The observations could be on any timescale that is of interest. While the SPI and SPEI are most commonly defined on a monthly basis, we anticipate that shorter timescales (hourly or daily) will be most useful when constructing standardised indices for the planning and maintenance of energy systems.

The general approach to define standardised indices begins by estimating the cumulative distribution function (CDF) corresponding to these previously observed values, which we label F_P for the production and F_L for the residual load. The estimated CDF is then used to transform the observations onto a standardised scale, exploiting the *probability integral transform* to do so. In particular, if the renewable energy production observations arise according to the distribution F_P, then the probability integral transform (PIT) values $F_P(P_1), \dots, F_P(P_n)$ should constitute a sample from a uniform distribution between zero and one. The same is true for the residual load. While these PIT values could themselves be used as standardised indices, it is more common to further transform the PIT values using the quantile function of the standard normal distribution, Φ^{-1}, to obtain indices that resemble a sample from the standard normal distribution.

To estimate the CDFs F_P and F_L, we could assume that the renewable energy production and residual load observations have been drawn from a certain parametric family of statistical distributions: the SPI, for example, assumes precipitation follows a Gamma distribution (McKee et al., 1993), while the SPEI employs a log-logistic distribution (Vicente-Serrano et al., 2010). The parameters of the chosen distribution could then be estimated from the previous observations, using maximum likelihood estimation, for example. However, simple parametric families may not be flexible enough to model the distribution of the energy variables under consideration, which are governed by complex dynamical, physiological, and socioeconomic factors. As an alternative, if a sufficiently long time series of observations is available, then it is straightforward to estimate the CDF directly from the observations, rather than estimating the parameters of a parametric family of distributions. That is, F_P and F_L can be estimated using the empirical distribution function defined by the observations.

With this in mind, we define the standardised renewable energy production index (SREPI) corresponding to an observation of renewable energy production P_t as

$$\mathrm{SREPI}(P_t) = \Phi^{-1}\left(\frac{1}{n+2}\left[1 + \sum_{i=1}^{n} \mathbb{1}\{P_i \leq P_t\}\right]\right), \tag{1}$$

where $\mathbb{1}$ is the indicator function, equal to one if the argument inside the brackets is true, and zero otherwise.

Similarly, the standardised residual load index (SRLI) at time t is defined as

$$\mathrm{SRLI}(L_t) = \Phi^{-1}\left(\frac{1}{n+2}\left[1 + \sum_{i=1}^{n} \mathbb{1}\{L_i \leq L_t\}\right]\right). \tag{2}$$

Note that it need not be the case that $1 \leq t \leq n$, i.e. although the time series of past observations are required to calculate the indices, the SREPI and SRLI can also be obtained for observations that have not previously been observed.

For both indices, the term inside the round brackets is the empirical CDF defined by the observed sample of observations and P_t or L_t. The empirical CDF is constructed such that it is never equal to zero or one, in which case the standardised indices would not be well-defined. One benefit of using the empirical CDF is that the indices are based on ranks, giving them a clear interpretation in terms of historical observations: a high index corresponds to an observation that is large relative to the previously observed data, while a low index suggests the observation is small relative to the historical archive. Low values of the SREPI indicate lower-than-normal renewable energy production, whereas high values of the SRLI are synonymous with instances where the residual load is high, i.e. the demand considerably exceeds the renewable energy production. Both of these instances could result in energy shortages.

Additionally, in using the empirical distribution function, the indices do not make any distributional assumptions, which would need to be verified and checked at all locations and time periods at which the index is calculated - this is often overlooked when calculating the SPI and SPEI. One disadvantage of using the empirical CDF within Equations 1 and 2, rather than a parametric distribution, is that the index will assume only a finite number (n) of possible values. If n, the number of past observations from which the index is calculated, is large, then this will not be an issue in practice. Nonetheless, for completeness, potential parametric distributions that could be used to construct the SREPI and SRLI are analysed in the appendix.

Lastly, the SREPI can be interpreted as the relative position of the renewable energy production amongst previously observed values. Since renewable energy production is calculated by multiplying the installed capacity by a capacity factor, the index will not change if a different installed capacity is assumed when calculating the production. In particular, this means that the SREPI could be computed directly based on capacity factors rather than power production, without affecting the resulting index values.

3. Energy droughts

Just as the SPI and SPEI are used operationally to define meteorological droughts, the SREPI and SRLI allow for universal definitions of energy droughts. This can be achieved using thresholds of the indices. A shortage in the renewable energy system could occur due to low values of the renewable energy production, or high values of the residual load. Hence, energy droughts should correspond to low values of the SREPI or high values of the SRLI.

We therefore follow Raynaud et al. (2018) and introduce two separate types of energy drought. We say that an *energy production drought* occurs if the SREPI falls below -1, while an *energy supply drought* occurs if the SRLI exceeds 1. Following the definition of meteorological droughts given in McKee et al. (1993), and as recently presented in Otero et al. (2022b), the *intensity* of an energy drought at a given time can be further classified as moderate, severe, or extreme, with each category corresponding to an

Category	Production drought	Supply drought	Probability
Mild	-1 $<$ SREPI $<$ 0	0 $<$ SRLI $<$ 1	0.341
Moderate	-1.5 $<$ SREPI $\leq$ -1	1 $\leq$ SRLI $<$ 1.5	0.092
Severe	-2 $<$ SREPI $\leq$ -1.5	1.5 $\leq$ SRLI $<$ 2	0.044
Extreme	SREPI $\leq$ -2	2 $\leq$ SRLI	0.023

Table 1: Definitions of energy production droughts and energy supply droughts in terms of the SREPI and SRLI, respectively. The probability that each index will be in each interval at a randomly chosen time is also listed.

increasingly extreme threshold of the indices. These different categories of energy droughts are summarised in Table 1.

Since the indices are constructed so that they follow a standard normal distribution, we can immediately calculate the probability that each category of drought will occur. These probabilities are also listed in Table 1. Note that the thresholds 1, 1.5, and 2 are typically selected for practical convenience. Instead, it could be argued that it is more intuitive for the drought thresholds to correspond to quantiles of the standard normal distribution. For example, 1, 1.5, and 2 could be replaced by 1.28, 1.64 and 1.96, the 90^{th}, 95^{th}, and 97.5^{th} percentiles of the standard normal distribution, to give the drought definitions a more explicit probabilistic interpretation.

Energy droughts could last for just one unit of time, or for longer if the index satisfies the relevant criteria at successive time points. For the SPI and SPEI, the definition of a meteorological drought is often extended so that the drought does not end when the index no longer exceeds the relevant threshold, but instead continues until the index changes sign. In other words, the index must change sign before a new drought can begin. This accounts for instances where the index fluctuates around the threshold of interest, classing this as one persistent drought event rather than several small droughts. A similar convention could be adopted when defining energy droughts. When the index does not satisfy the criteria defining an energy drought, but has not yet changed sign from the previous drought, the energy drought is said to be “mild”. An illustration of this for an energy supply drought is presented in Figure 1.

The energy droughts have a fixed start and end time, which can easily be deduced from the time series of index values. The *duration* of a drought is then defined as the difference between these times. We can also assess a drought's *magnitude*, by considering the values of the index whilst the drought transpires. In particular, if a drought begins at time t and persists until time $t + D$, for some duration D, then the drought magnitude (DM) is defined as

$$\mathrm{DM} = \sum_{j=t}^{t+D-1} |I_j|, \tag{3}$$

where I is the standardised index under consideration, and $|I_j|$ is the absolute value of this index at time j (McKee et al., 1993). The drought magnitude must be larger than 1, but has no upper limit, i.e. $1 \leq \mathrm{DM} < \infty$. The larger the magnitude, the more severe the energy drought is.

These definitions of energy production and supply droughts can readily be applied at any location, regardless of their local climates and installed capacities. They can also be applied to time series on any timescale, introducing the concept of hourly, daily, and weekly drought events, for example. Note, however, that the magnitude of the drought will depend on the timescale of interest: shorter timescales should have a stronger temporal dependence,

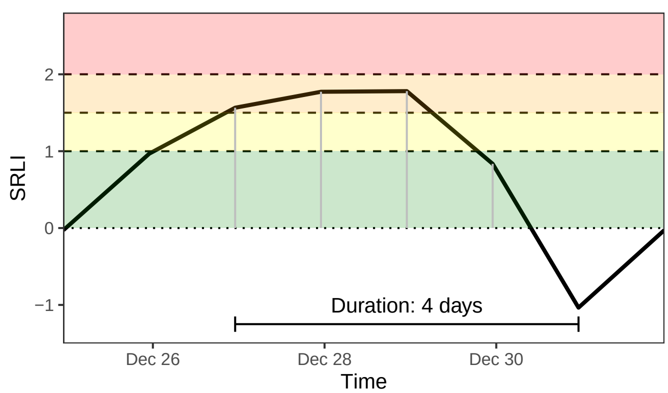

Figure 1: Example of an energy supply drought in Germany, December 2019. The drought begins when the SRLI first exceeds 1 (December 27th), and ends when the index changes sign (December 31st). The duration of the drought is therefore four days. The coloured regions represent the intensity of the drought at each time point: a mild drought event is green, a moderate event is yellow, a severe event is orange, an extreme event is red. The magnitude of the drought is 5.95, equal to the sum of the four vertical grey lines during the drought.

meaning more consecutive observations are defined as within a drought, leading to higher magnitudes. Nonetheless, if desired, the drought magnitude can itself be converted to a common scale by dividing DM by the timescale of the data.

4. Case study

4.1. Data

To demonstrate how these standardised indices can be implemented in practice, they are applied to time series of renewable energy production and residual load. The time series used here have been reconstructed from ERA5 reanalysis data (Hersbach et al., 2018) between 1979 and 2019, and are publicly accessible from the Reading Research and Data Repository (`https://researchdata.reading.ac.uk/273/`); see Bloomfield et al. (2020) for details on how the data has been reconstructed. Hourly data is available for 27 countries across Europe, and we assume here that resources are not shared between the different countries.

The time series of renewable energy production incorporates wind and solar power generation. It is assumed throughout that the installed wind and solar capacities are equal to those from 2017, since national installed capacities are readily available for this year. These installed capacities are available in the appendix. An increased installed capacity would impact the renewable energy production multiplicatively, and hence, as discussed in Section 2, this would not affect the SREPI values. The SRLI, on the other hand, depends on both the production and the demand, and the resulting SRLI values are not independent of the installed capacity. Although we use the installed capacities from 2017, the introduction of these standardised indices provides a convenient framework with which to study the sensitivity of these results to the installed capacity in the future.

The residual load is calculated by subtracting the wind and solar production from a time series of energy demand. The energy demand was estimated using a linear regression model, trained using data from 2016 and 2017, for which records of electricity demand are available from the ENTSO-E transparency platform (ENTSO-E, 2019). The linear regression model includes weather-dependent covariates, such as 2-metre temperature and the number of heating and cooling degree days, to estimate the energy demand. Further details of the data used herein, as well as the configuration of the regression model, are available in Bloomfield et al. (2020) and Otero et al. (2022b).

4.2. Results

4.2.1. Standardised energy indices

Examples of time series of the raw renewable energy production and residual load, as well as the corresponding SREPI and SRLI values are displayed in Figures 2 and 3 for the time period 2010 to 2020. Figure 2 contains the indices computed for Norway, while Figure 3 presents the time series for Spain. The index has been computed over hourly, daily, and weekly timescales, with the longer timescales clearly removing the short-term fluctuations in the time series of both the raw data and the standardised indices.

While the two countries have markedly different installed wind and solar capacities (see Figure B.9), leading to different scales of renewable energy production, the indices are able to account for the differing capacities in the two countries, providing a common scale to analyse. Nonetheless, the important information is still present from the time series of the indices. For example, it is clear to see that the SREPI and the SRLI are very seasonal for Norway, with high residual load indices in particular most likely to occur in winter, whereas the indices in Spain exhibit considerably less seasonal variation, owing to the amount of energy that is also required for cooling during summer. For concision, all further analysis considers only the daily SREPI and SRLI indices, though we note that all results could be similarly presented for indices defined on other timescales.

The common scale provided by the indices is evident also from Figure 4, which shows the histogram of the raw renewable energy production and residual load values for Norway, compared to a histogram of the corresponding daily SREPI and SRLI values. Figure 4 also displays the index assigned to a range of renewable energy production and residual load values. Clearly, the distribution of the raw values is rather irregular, and will change for all countries under consideration. The standardised indices, on the other hand, both closely resemble a standard normal distribution. This is the case for all countries, providing a common scale that allows for global definitions of energy droughts with a clear probabilistic interpretation. Additionally, the irregularity of the distributions in Figure 4 is not easily modeled using parametric families of statistical distributions (see appendix), highlighting the benefit provided by the more flexible empirical distribution function in data rich settings.

While energy droughts can be defined in terms of either the SREPI or the SRLI, the two indices provide complementary information. Nonetheless,

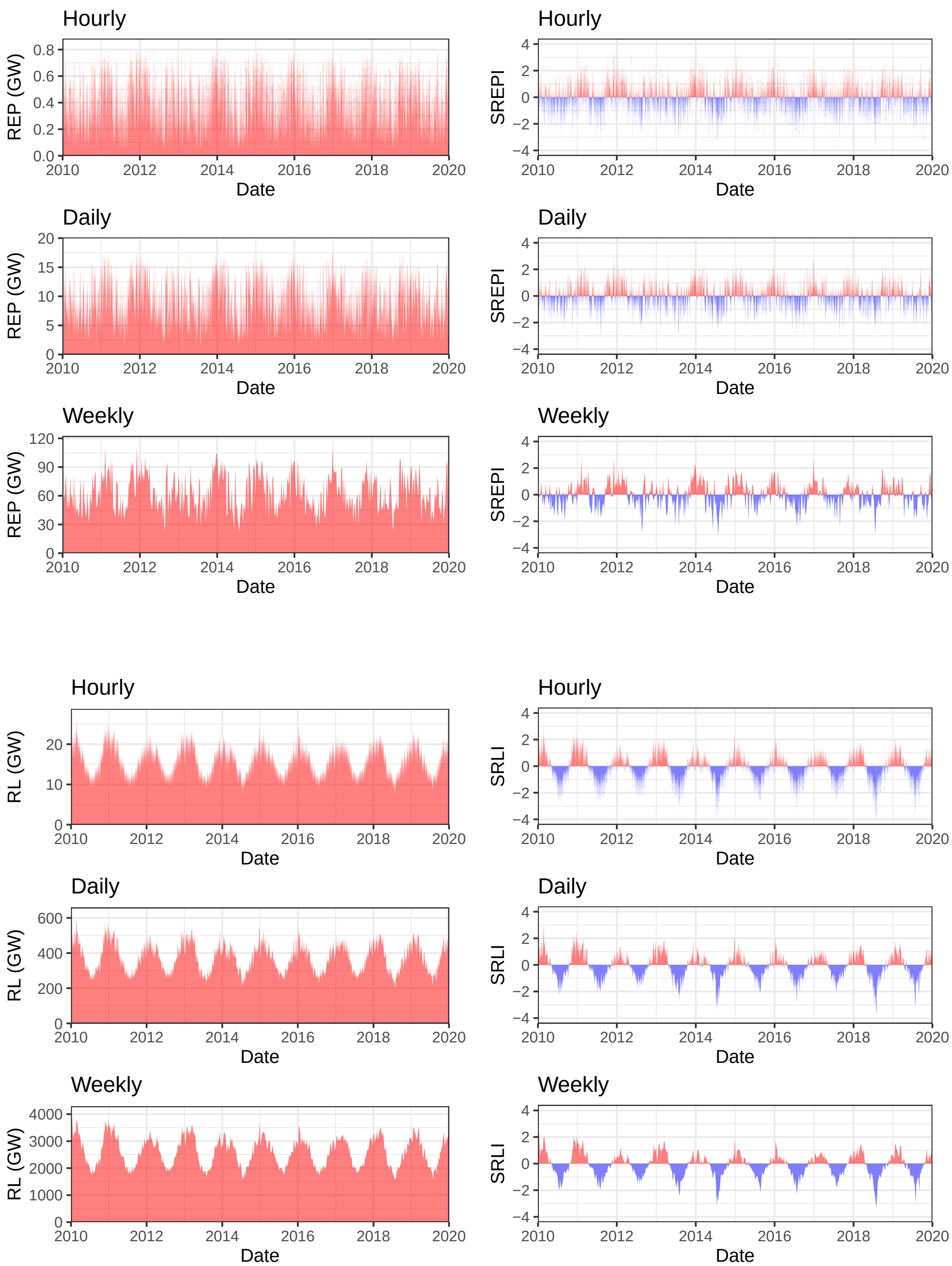

Figure 2: Time series of Norway's renewable energy production (REP) and residual load (RL), and the corresponding standardised indices, between 2010 and 2020. Time series are shown at hourly (1st row), daily (2nd), and weekly (3rd) timescales.

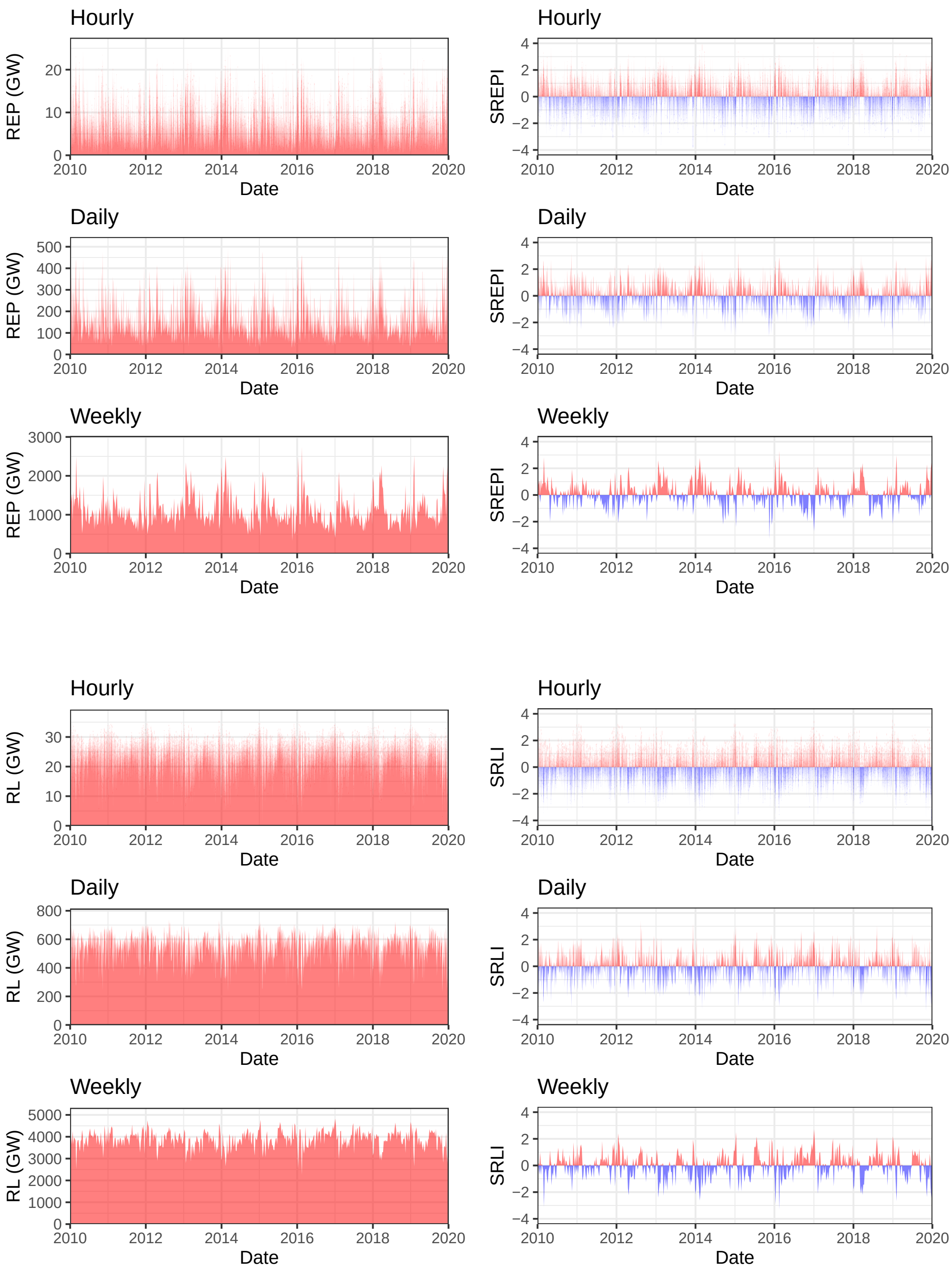

Figure 3: As in Figure 2 but for Spain.

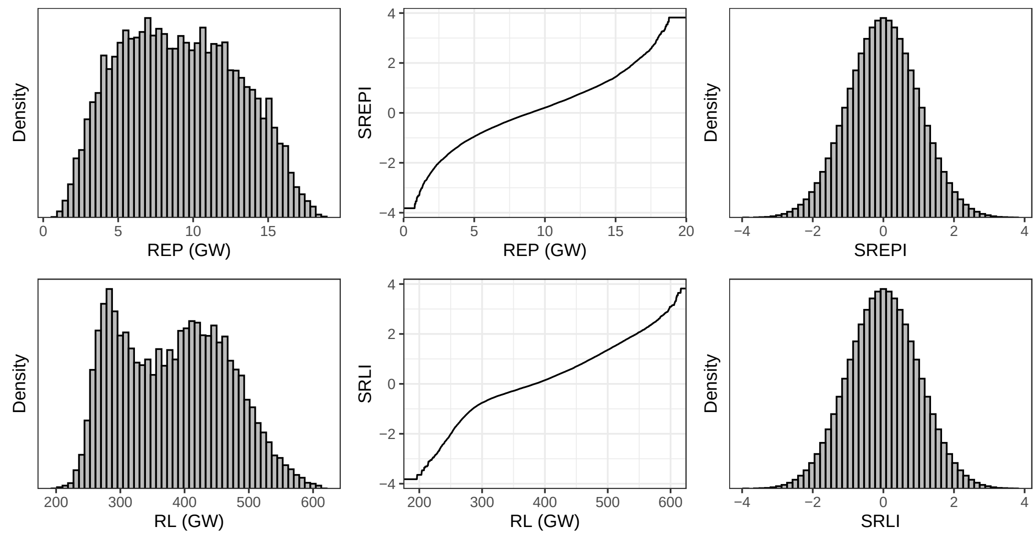

Figure 4: Histograms of Norway's daily renewable energy production (REP) and residual load (RL), as well as histograms of the corresponding standardised indices. The index assigned to each value of the production and residual load is also shown for this country.

in countries with a high installed capacity, the SREPI and SRLI should be strongly associated, since high residual loads will often be a result of low renewable energy production. On the other hand, if energy demand is exceptionally high relative to the renewable energy production, then the two indices could behave very differently. To illustrate the association between the droughts indices, Figure 5 displays the correlation between the SREPI and SRLI in each country. There is typically strong negative correlation between the two indices: as the SREPI decreases, the SRLI increases, as expected. This is particularly pertinent in countries with high installed capacities, such as Germany.

4.2.2. Energy droughts

Section 3 describes how the standardised energy indices can be used to define energy production and energy supply droughts. For the data considered here, Figure 6 displays the average number of droughts that occur each year in the 27 European countries for the extended summer months (AMJJAS) and extended winter months (ONDJFM). Figure 7 presents the corresponding average drought duration (in days). Energy production droughts tend to occur more frequently than energy supply droughts, but have a much lower expected duration. The reason for this is the weaker seasonal cycle in renewable energy production, other than in countries such as the Czech Republic (CR), Slovakia (Sva), Slovenia (Sve), and Switzerland (Swi), all of which have low wind capacities in comparison to their solar capacities. This supports the results in Otero et al. (2022b). Production droughts typically occur more frequently in summer since most countries have a higher installed wind capacity than solar capacity, with wind expected to dominate in winter and solar in summer. The opposite is therefore true for the countries listed above.

In these countries, energy supply droughts tend to be much longer lasting, comprising a large proportion of the extended winter season. Supply droughts, more generally, occur with a higher frequency in winter in almost all countries, reflecting that energy demands are typically considerably higher in winter than in summer. For countries with warmer climates, such as Italy, Portugal, and Spain, energy supply droughts are relatively more frequent in summer than other countries, due to an increase in summer energy demand.

As well as monitoring the frequency and duration of energy droughts using the standardised indices introduced herein, Equation 3 also demonstrates how they can be used to quantify the magnitude of each drought. The average magnitude of droughts is strongly correlated with the duration of the

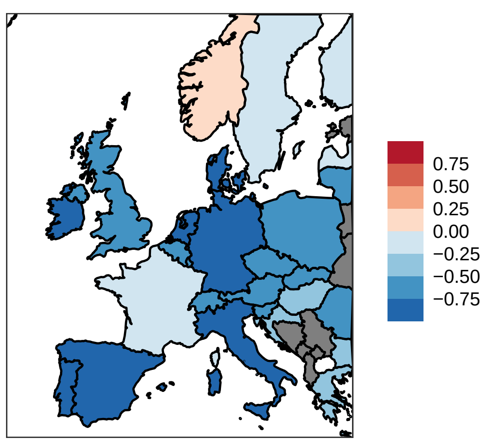

Figure 5: Pearson's correlation between the SREPI and SRLI in each country. Grey areas represent countries that were not considered in this study.

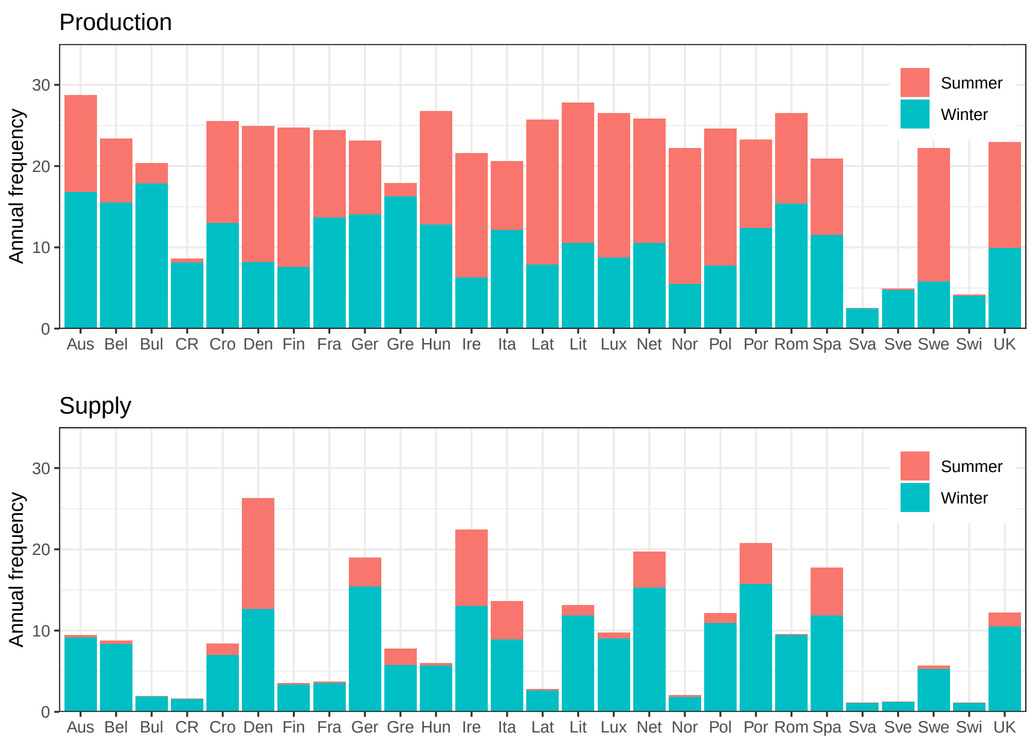

Figure 6: Average number of energy production and energy supply droughts per year in each country. The frequency is divided into the proportion expected to occur in extended winter and summer seasons.

droughts, and this is illustrated in Figure 8. Again, since Slovakia, Slovenia, and Switzerland have the longest-lasting droughts, they also have the droughts with the highest magnitude on average.

5. Discussion

This paper has introduced standardised indices that can be used to monitor and analyse energy droughts. Two indices are defined: the standardised renewable energy production index (SREPI), and the standardised residual load index (SRLI). The indices have been constructed analogously to the SPI and SPEI, two well-known standardised indices used to assess meteorological droughts. The SREPI is a standardised measure of the renewable energy production, and therefore constitutes an energy-based analogue of the SPI.

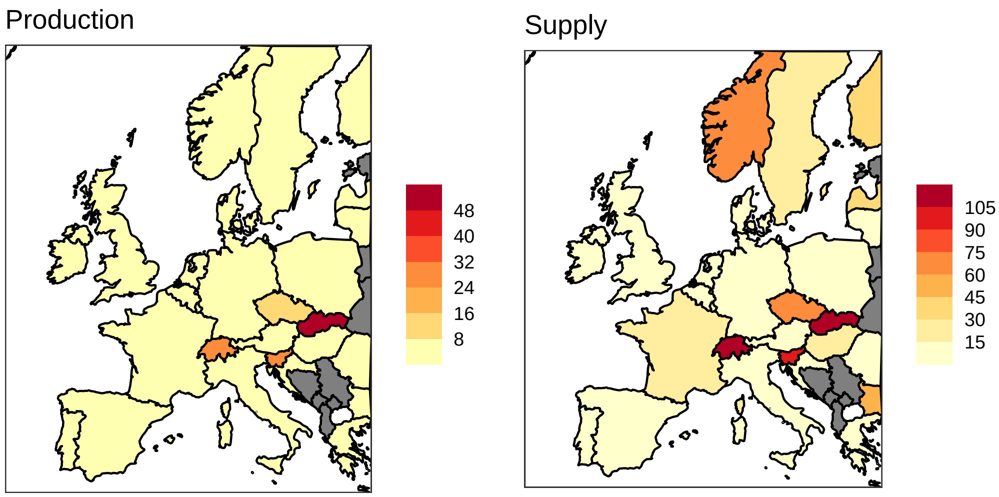

Figure 7: Average duration (in days) of the energy production and energy supply droughts in each country.

The SRLI, on the other hand, additionally accounts for the current energy demand, analogously to how the SPEI incorporates evapotranspiration.

Low values of the SREPI and high values of the SRLI are synonymous

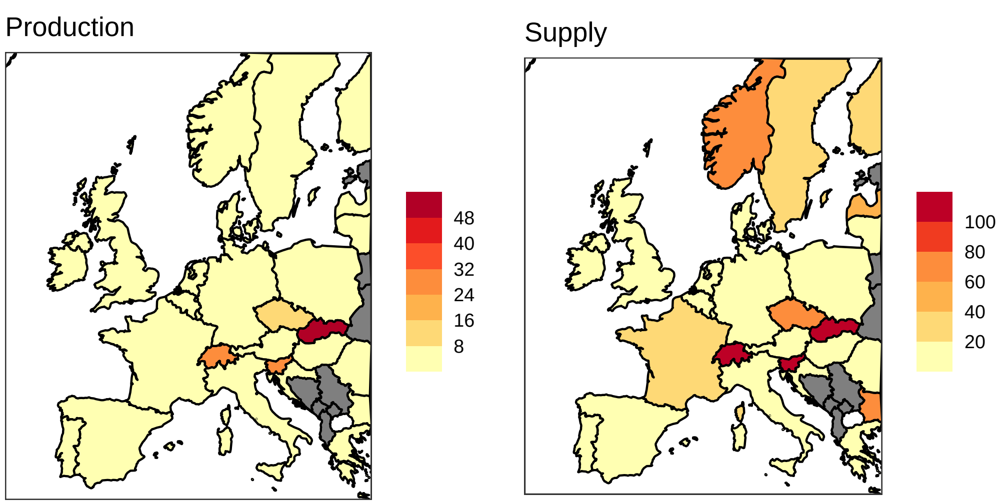

Figure 8: Average magnitude (defined as in Equation 3) of the energy production and energy supply droughts in each country.

with potential shortages in the renewable energy system. Raynaud et al. (2018) recently noted the similarity between meteorological droughts and energy shortages, leading them to introduce the concept of an energy drought. As renewable energy sources become responsible for a larger proportion of international energy production, the risks associated with such shortages increase, and more effort should therefore be devoted to the monitoring of energy droughts. The SPI and SPEI are commonly used within operational meteorological drought monitoring systems, and the SRLI and SREPI could similarly be implemented within energy drought monitoring systems.

In particular, the SPI and SPEI provide a recognised and accepted way of defining meteorological droughts. We demonstrate here how the SREPI and SRLI could similarly be used to define energy droughts. Since the indices are on a standardised scale, the corresponding droughts can be defined using relevant ranges of the index values, where the ranges have clear probabilistic interpretations. Moreover, these indices can be applied to energy variables separately at different locations, facilitating a straightforward comparison between the indices in different regions, regardless of their varying climates and installed capacities.

Section 4 illustrates how these standardised indices could be applied in practice. They are applied to reconstructed time series of electricity demand and renewable energy production for several European countries. While national data is used here, the indices could also be applied to data on a finer spatial resolution. Moreover, the data we consider here only utilises energy production from wind and solar. Although these are typically the two most influential sources of renewable energy, future studies could additionally consider other sources, such as hydropower, which is a major source of renewable energy in countries such as Switzerland. Note that the definition of the SREPI and SRLI would not change, though previous measurements of the renewable energy production and residual load should be calculated when incorporating these additional RES. Otherwise, including an influential source of renewable energy would inflate the index.

While we have focused on renewable energy production and the resulting residual load, which we argue are particularly important to monitor due to their dependence on the prevailing weather conditions, the approach used to construct these standardised indices could readily be applied to other variables. For example, a standardised energy demand index could analogously be defined by replacing the production or residual load time series in Equations 1 and 2 with a time series of previously observed energy demand values.

Separate indices could also be derived for different sources of renewable energy, such as solar and wind. This would allow a more targeted analysis when the production of wind or solar energy is low, rather than the overall production. Similarly, these indices could be used to define and study individual production droughts, such as wind droughts, solar droughts, or hydropower droughts.

In converting the distributions of energy production and demand to standardised scales, such indices could also be used to monitor instances where there is a surplus of renewable energy generated, caused by high production and reduced demand. For example, low pressure weather systems are typically associated with strong winds but milder temperatures, leading to a large wind power production relative to the energy demand. Although these surpluses are less impactful than energy droughts, they could additionally be useful when designing renewable energy storage systems. The amount of energy stored for future use could additionally be incorporated into the standardised indices introduced here, possibly within the residual load, in order to fully capture the renewable energy system as it evolves.

While the energy indices proposed herein have been used to monitor past time series of energy supply and demand, future studies could also investigate how these indices will change as a result of climate change. For example, as temperatures increases, the energy demand in summer will likely increase, resulting in smaller residual load indices. This would then allow us to assess the risks and impacts associated with energy droughts (defined in terms of today's climate) as the climate changes, which would help to understand what installed capacities are required to mitigate these impacts in the future.

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Data Availability

The reconstructed energy production and demand data used herein is publicly accessible from the Reading Research and Data Repository (`https:`

//researchdata.reading.ac.uk/273/). Code to reproduce the results presented in this paper is available at https://github.com/noeliaof/Energy_Index.

Appendix A. Parametric distributions

In Section 2, we introduce the SREPI and SRLI using the empirical distribution function based on a time series of past observations. This is in contrast to the SPI, SPEI, and most other standardised indices, which typically assume the variable of interest follows some parametric distribution. In particular, the index corresponding to some value x_t is

$$\Phi^{-1}(F(x_t)),$$

where F is the cumulative distribution function of the assumed parametric distribution, typically estimated from a time series of observations $x_1, \dots, x_n$. When defining the SREPI and SRLI, we replace F with an empirical estimate of the distribution function, defined by these observations:

$$\hat{F}(x) = \frac{1}{n+2}\left[1 + \sum_{i=1}^{n} \mathbb{1}\{x \leq x_i\}\right].$$

While we argue that the empirical distribution function is more appropriate if there are sufficiently many observations (which will often be the case if the timescale of the variable of interest is relatively small), this appendix compares possible parametric distributions that could be employed to construct the indices.

For each country, several parametric distributions are fit to the time series of renewable energy production and residual load values, separately for hourly, daily, and weekly timescales. The following distributions were compared: the normal, truncated normal, log-normal, logistic, truncated logistic, log-logistic, exponential, gamma, and Weibull distributions. The truncated normal and truncated logistic distributions were truncated below at zero, so that zero probability density was assigned to negative values. In each case, the distribution with the lowest Akaike Information Criterion (AIC) was selected, and the resulting choices are displayed in Table A.2.

Clearly, there is a lot of variation in the optimal distribution to use when modelling the data, and the results change not only depending on the distribution, but also on the timescale of interest. In each case, the

Kolmogorov-Smirnov test was then applied to the estimated distributions, to assess whether the data can reasonably be assumed to have been drawn from this distribution. Table A.2 illustrates that at hourly and daily timescales, when the sample of observations is very large, the null hypothesis of equality in distribution is almost always rejected, suggesting the parametric distributions are not appropriate. While the distributions are often adequate for weekly accumulated renewable energy production values, they are generally not capable of accurately modelling the weekly residual loads. The reason for this is that the residual load is, of course, heavily influenced by the energy demand, which generally exhibits strong seasonal behaviour. This results in often multi-modal distributions (as illustrated, for example, in Figure 4), which are difficult to capture using conventional parametric families of distributions.

Results may be different if seasons were to be considered separately, though this also highlights the deficiency in using parametric distributions - the choice of distribution will change depending on several factors, and this should be accounted for when computing the index in different scenarios. The empirical distribution, however, provided enough data is available, is flexible enough to account for these features, regardless of what data is used.

Appendix B. Installed capacities

Figure B.9 displays the installed wind and solar capacities for each European country considered in Section 4. As discussed, the capacities correspond to those from 2017.

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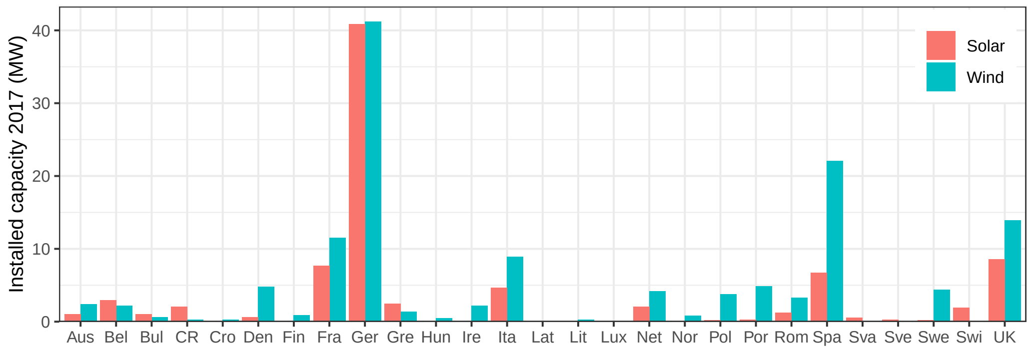

Figure B.9: Installed 2017 wind and solar capacities at each European country under consideration.

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	Renewable Energy Production			Residual Load		
Country	Hourly	Daily	Weekly	Hourly	Daily	Weekly
Aus	Weibull	Log-normal	**Gamma**	Normal	Log-normal	Log-normal
Bel	Tr. Normal	Weibull	**Gamma**	Gamma	Log-normal	Log-normal
Bul	Tr. Normal	Gamma	**Tr. Normal**	Log-normal	Log-normal	Log-normal
CR	Weibull	Weibull	Weibull	Log-normal	Log-normal	Log-normal
Cro	Log-normal	Log-normal	Gamma	Weibull	Log-normal	Log-normal
Den	Tr. Normal	Weibull	**Weibull**	Tr. Normal	Tr. Logistic	Tr. Logistic
Fin	Tr. Normal	Weibull	**Weibull**	Log-normal	Log-normal	Log-normal
Fra	Weibull	Log-normal	**Log-normal**	Log-normal	Log-normal	Log-normal
Ger	Weibull	Gamma	Gamma	Normal	Weibull	**Logistic**
Gre	Weibull	Weibull	**Weibull**	Log-normal	Log-normal	Log-normal
Hun	Tr. Normal	Log-normal	**Gamma**	Weibull	Log-normal	Log-normal
Ire	Tr. Normal	Weibull	**Weibull**	Tr. Normal	Weibull	Normal
Ita	Tr. Normal	Gamma	**Gamma**	Weibull	Log-logistic	Log-logistic
Lat	Gamma	Tr. Normal	**Weibull**	Weibull	Log-normal	Log-normal
Lit	Tr. Normal	Tr. Normal	**Gamma**	Weibull	Log-normal	Log-normal
Lux	Gamma	Weibull	Gamma	Weibull	Log-normal	Log-normal
Net	Tr. Normal	Weibull	**Gamma**	Weibull	Normal	**Log-normal**
Nor	Weibull	Weibull	Gamma	Gamma	Gamma	Gamma
Pol	Tr. Normal	Weibull	**Gamma**	Weibull	Log-normal	Log-logistic
Por	Gamma	Gamma	**Gamma**	Tr. Logistic	Weibull	Weibull
Rom	Gamma	Log-normal	**Log-normal**	Normal	Log-normal	Log-normal
Spa	Gamma	Log-normal	Log-normal	Weibull	Weibull	Weibull
Sva	Gamma	Weibull	**Weibull**	Gamma	Log-normal	Log-normal
Sve	Tr. Normal	Weibull	Weibull	Normal	Log-normal	Log-normal
Swe	Weibull	Weibull	**Gamma**	Gamma	Log-normal	Log-normal
Swi	Log-normal	Weibull	Weibull	Log-normal	Log-normal	Log-normal
UK	Weibull	Gamma	**Gamma**	Weibull	Log-normal	Log-normal

Table A.2: Parametric distributions that resulted in the lowest AIC when fit to hourly, daily, and weekly time series of the renewable energy production and residual load at each country. Bold values represent instances where the null hypothesis of the Kolgomorov-Smirnov test for equality in distribution was not rejected.