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Standardised indices to monitor energy droughts

Sam Allen[a,b,*], Noelia Otero[b,c,**]

[a] *Institute of Mathematical Statistics and Actuarial Science, University of Bern, Switzerland*
[b] *Oeschger Centre for Climate Change Research, University of Bern, Switzerland*
[c] *Institute of Geography, University of Bern, Switzerland*

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 are therefore required that can help policymakers to understand and mitigate the impacts associated with energy droughts. 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 to 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 facilitate comparisons between regions with different climates and installed capacities. We demonstrate how the standardised energy indices proposed herein can be used to define renewable energy droughts, and illustrate the practical utility of these indices in an application to reconstructed time series of electricity demand and wind and solar power generation across Europe.

Keywords: Energy drought, renewable energy production, residual load,

*Email: sam.allen@stat.unibe.ch
Address: Institute of Mathematical Statistics and Actuarial Science, Alpeneggstrasse 22, 3012 Bern, Switzerland
**Email: noelia.otero@giub.unibe.ch
Address: Institute of Geography, Hallerstrasse 12, 3012 Bern, Switzerland

1. Introduction

To mitigate the effects of climate change, energy systems are becoming increasingly reliant on renewable energy sources. While renewable sources provide a sustainable alternative to depleting fossil fuels, their introduction into energy mixes raises difficult questions for policymakers: What proportion of energy demand should be supplied by renewable sources? What is the optimal balance between different renewable sources, such as wind, solar and hydro power? Should we devote more resources to developing technology to store renewable energy? Does this outweigh the benefits of increasing our installed capacity? These questions are difficult to answer, especially because energy production from renewable sources typically depends heavily on the prevailing weather. Balancing supply and demand in renewable energy systems therefore 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).

Policymakers face the crucial task of designing energy systems that are simultaneously sustainable and resistant to shortages. As renewable sources become larger contributors to the energy mix, the risks associated with these shortages increase. Methodological tools are therefore required that permit a greater understanding of the risks associated with renewable energy shortages. Policymakers could use these tools to run experiments that analyse how different energy mix configurations affect the occurrence and severity of energy shortages. This would help to answer the above questions related to the diversification, storage, and sharing of renewable energy, thereby improving the effectiveness of renewable energy systems.

The availability of such tools is currently limited. Raynaud et al. (2018) term shortages in renewable energy systems "energy droughts", acknowledging the similarity between shortages in energy systems and the classical notion of a meteorological drought. 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 impacts associated with energy droughts become more severe, analogous systems to monitor energy droughts become more appealing.

Recent studies have 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). In this paper, we demonstrate how the standard definition of meteorological droughts can be leveraged when studying energy droughts in renewable energy systems, and we highlight the utility of this approach to policymakers when deciding how to design an effective, sustainable energy system.

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). We demonstrate that standardised indices can similarly be used to define and monitor droughts in renewable energy systems.

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. Since the standardisation can be performed separately for different seasons and locations, droughts can be defined in a relative sense, facilitating comparisons between droughts in regions with different climates and installed capacities. 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."

The approach used to construct the SPI and SPEI can readily be applied to other variables. 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, whereas the SRLI is defined in terms of the residual load, i.e. the difference between energy demand and renewable energy production. Just as meteorological droughts are defined in terms of the SPI and SPEI, we demonstrate how the standardised energy indices introduced herein can be used to define energy production and supply droughts.

To our knowledge, this is the first application of standardised drought indices in an energy context. The indices introduced herein can be calculated using the `SEI` package in `R`, which is available at `https://github.com/noeliaof/SEI`. The standardised energy indices are introduced in the following section, and Section 3 describes how these indices can be used to define energy droughts. We discuss the advantages of this approach, and compare it to alternative definitions of energy droughts that have been proposed in the literature. In Section 4, these indices are applied to reconstructed energy demand and wind and solar production data in several European countries, thereby demonstrating how these indices can be used in practice. We examine how the occurrence and severity of an energy drought is affected by the configuration of the energy system, including the mixing of different renewable sources, and our ability to store renewable energy. A conclusion is presented in Section 5.

2. Standardised energy indices

In this section, we introduce two standardised indices that can be used to monitor energy droughts. The indices can be thought of as renewable energy-based analogues to the SPI and SPEI, and are constructed using the same methodology. This approach has been used to define standardised indices corresponding to several hydro-meteorological processes, such as 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). 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. 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.

We define the standardised renewable energy production index (SREPI) corresponding to an observation of renewable energy production P_t as

$$\mathrm{SREPI}(P_t) = \Phi^{-1}\left(F_P(P_t)\right). \tag{1}$$

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

$$\mathrm{SRLI}(L_t) = \Phi^{-1}\left(F_L(L_t)\right). \tag{2}$$

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. 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. That is, F_P and F_L can be estimated using the empirical distribution function defined by the observations:

$$F_P(P_t) = \frac{1}{n+2}\left[1 + \sum_{i=1}^{n} \mathbb{1}\{P_i \le P_t\}\right];$$

$$F_L(L_t) = \frac{1}{n+2}\left[1 + \sum_{i=1}^{n} \mathbb{1}\{L_i \leq L_t\}\right],$$

where $\mathbb{1}$ is the indicator function, equal to one if the argument inside the curly brackets is true and zero otherwise. The terms inside the square brackets are simply the ranks of P_t among $P_1, \dots, P_n$, and L_t among $L_1, \dots, L_n$. The empirical CDFs are constructed such that they are never equal to zero or one, in which case the standardised indices would not be well-defined. 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.

One benefit of using the empirical distribution function within Equations 1 and 2 is that the indices do not make any distributional assumptions about the production and residual load, which would need to be verified at all locations and time periods for which the index is calculated. However, the resulting indices will only take on 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. We argue that at least $n = 100$ previous observations are required to define the standardised indices using the empirical distribution. For hourly data, this is just a few days; for daily data, a few months. This is decreased further if we aggregate data across several locations.

If fewer than 100 observations are available, then the CDFs F_P and F_L could be estimated using parametric distributions, or more flexible semi-parametric methods, such as kernel density estimation (e.g. Wilks, 2019). Potential parametric distributions that could be used to construct the SREPI and SRLI are analysed in the appendix.

3. Energy droughts

3.1. Defining droughts using standardised indices

Just as the SPI and SPEI are used operationally to define meteorological droughts, the SREPI and SRLI provide appealing definitions of energy droughts. 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.

Category	Production drought	Supply drought	Probability
Moderate	-1.64 $<$ SREPI $\leq$-1.28	1.28$\leq$ SRLI $<$ 1.64	0.050
Severe	-1.96 $<$SREPI $\leq$ -1.64	1.64 $\leq$ SRLI$<$ 1.96	0.025
Extreme	SREPI $\leq$-1.96	1.96$\leq$ SRLI	0.025

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.

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 -1.28, while an *energy supply drought* occurs if the SRLI exceeds 1.28. The threshold 1.28 corresponds to the 90th percentile of a standard normal distribution, meaning there is a 10% probability that the standardised indices will exceed this value at a randomly selected time. Higher thresholds could also be employed if we wanted energy droughts to occur with a higher baseline probability.

The value of the index provides a measure of the *intensity* of an energy drought. Following the definition of meteorological droughts given in McKee et al. (1993), the intensity at a given time can be classified into different categories, with each category corresponding to an increasingly extreme threshold of the indices (Otero et al., 2022b). Table 1 presents an example whereby energy droughts are classified into moderate, severe, and extreme droughts using the 90$^{\text{th}}$ (1.28), 95$^{\text{th}}$ (1.64), and 97.5$^{\text{th}}$ (1.96) percentiles of the standard normal distribution. Since the droughts are defined in terms of quantiles of the standard normal distribution, we can immediately calculate the probability that each category of drought will occur.

It is more common to employ the thresholds 1, 1.5, and 2 when classifying meteorological droughts, rather than 1.28, 1.64, and 1.96. These thresholds are typically selected for practical convenience. We argue that it is more intuitive for the drought thresholds to correspond to quantiles of the standard normal distribution since this gives 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. 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, though since energy droughts will typically be on shorter timescales than meteorological droughts, we anticipate that this will not be as useful.

We have outlined here the general framework that has been widely adopted to define meteorological droughts. However, practitioners need not need restrict themselves to this exact set up. While we define moderate, severe, and extreme droughts using the 90^{th}, 95^{th}, and 97.5^{th} percentiles of the standard normal distribution, they could also be defined using alternative quantiles: an extreme drought could be defined using the 99^{th} percentile (2.33) rather than the 97.5^{th} percentile, for example. Alternatively, a fourth category of energy droughts could be defined that is rarer than an extreme drought. The exact specifications of the droughts should depend on the problem at hand.

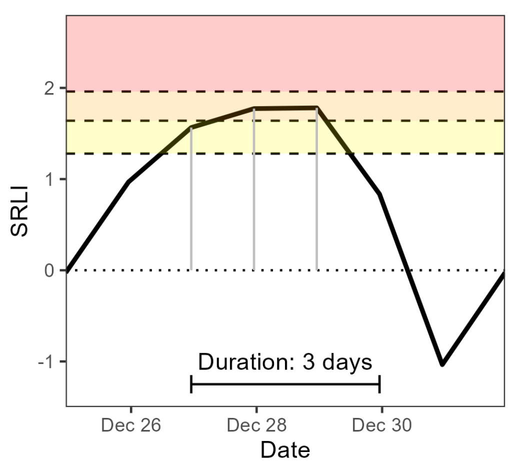


Figure 1: Example of an energy supply drought in Germany, December 2019. The drought begins when the SRLI first exceeds 1.28 (December 27th), and ends when the index falls below 1.28 (December 30th). The duration of the drought is therefore three days. The coloured regions represent the intensity of the drought at each time point: a moderate event is yellow, a severe event is orange, an extreme event is red. The magnitude of the drought is 5.12, equal to the sum of the three vertical grey lines during the drought (with values 1.57, 1.77, and 1.78).

3.2. Defining droughts using fixed thresholds

If the SREPI falls below the threshold -1.28, then the corresponding renewable energy production is less than the 10^{th} percentile of the previously observed production values. Likewise, if the SRLI exceeds the threshold 1.28, then the residual load is larger than the 90^{th} percentile of the previously observed load values. Hence, defining energy droughts in terms of standardised indices is equivalent to defining droughts in terms of quantiles of previously observed values. This is analogous to how energy droughts are defined in Otero et al. (2022b).

Raynaud et al. (2018) define an energy drought as the exceedance of a fixed, pre-specified threshold of the production or residual load, not necessarily equal to a quantile of the previously observed values. This more general definition is useful when policymakers have a specific target in mind for how much energy they want renewable sources to contribute. For example, if policymakers decide that renewable sources should supply at least 100GWh of energy to the national energy mix, then it makes sense to define energy production droughts as instances where renewable energy production falls below this threshold.

By using a fixed threshold, energy droughts will also be less likely to occur in regions with high installed capacities or favourable climates for generating renewable energy. This is in contrast to quantile-based definitions, which are constructed such that the probability of an energy drought is the same at all regions of interest, regardless of their climates and installed capacities. On the one hand, one could argue that droughts should occur less frequently at locations with higher installed capacities, making an absolute definition of an energy drought appealing; on the other hand, one could argue that energy droughts will be most impactful when the observed production or residual load differs from what we expect to occur, since policymakers tend to base their decisions on what they have previously observed. In this latter case, it is desirable to define droughts in a relative sense. Droughts defined in a relative sense also have meaningful probabilistic interpretations, making them particularly useful for decision making.

Both types of definition will be useful in different contexts. Importantly, both can be applied alongside standardised indices. For example, suppose an energy production drought is defined as when the renewable energy production P_t falls below a threshold t_P. We can convert this threshold to the standardised scale by applying the same transformation used to construct the indices, $\Phi^{-1}(\hat{F}_P(t_P))$. The same is true for residual load. We can then plot this transformed threshold on the standardised scale alongside the time series of standardised indices. The position of the threshold would change depending on the distribution of production or load values at each time and region of interest, providing an alternative perspective regarding how extreme the threshold is in relation to the previously observed production or residual load values at each time and region.

In this sense, the standardised indices transform the production and residual load to a common, probabilistically meaningful scale. While this allows droughts to be defined in terms of fixed thresholds on the standardised scale, as in Table 1, the indices can additionally be employed alongside alternative definitions of energy indices.

3.3. Drought characteristics

Using the criteria in Table 1, we define a drought as one or more consecutive days in a drought state. These 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 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. 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 the threshold used to define an energy drought, 1.28 for example, but has no upper limit. The larger the magnitude, the more severe the energy drought. While the intensity of a drought corresponds to how large the standardised index is at a given time, the drought magnitude additionally incorporates the drought's duration, recognising that longer droughts will typically be more impactful.

The drought magnitude can be computed for droughts defined in terms of a quantile-based threshold, as in Table 1, or a fixed threshold, as in Raynaud et al. (2018). The drought magnitude can then be compared for different locations, which is difficult to accomplish without standardisation.

The magnitude of the drought will depend on the timescale of interest: shorter timescales should have a stronger temporal dependence, meaning more consecutive observations are defined as within a drought, leading to higher magnitudes. To compare drought magnitudes on different timescales, we can divide DM by the timescale of the data; for example, to compare an hourly energy drought that lasts 24 hours to a daily energy drought that lasts one day, we can divide the hourly DM by 24. Alternatively, we could divide the magnitude by the duration of the drought, D, which would provide us with the average drought intensity per time unit. This provides a continuous alternative to the categories of drought intensity in Table 1. However, this would neglect the duration of the drought: an energy supply drought that lasts for ten days with average SRLI value 1.5, would be seen as less severe than a drought that lasts two days with average intensity 2, for example.

3.4. Influence of past data on the drought definition

Energy droughts defined using Table 1 correspond to production or residual load values that are extreme relative to previously observed values. These previously observed values are the time series $P_1, \dots, P_n$ and $L_1, \dots, L_n$ used to construct the standardised indices in Section 2. An important question is how to choose these time series; we do not need to use all available data, and the data we use will change the interpretation of the resulting droughts.

For example, by restricting attention to historical observations in summer, say, when calculating the indices, droughts can be interpreted as periods where the production or residual load is extreme compared to previous summers. If we use historical observations that span the whole year, then the definition of an energy drought would remain fixed over the year. Both definitions would be important for grid planning and operation in different contexts.

How should we select an appropriate subset of the historical data on which to calculate the indices? The answer depends on what policymakers want to achieve by analysing energy droughts. In regions where renewable energy production is very seasonal, if the standardised indices are built using data spanning the whole year, then droughts will cluster in the season where production is lowest. While this may be useful in some contexts, it may be more informative to use a seasonal or adaptive definition of an energy drought in this region. This could be achieved by stratifying the data into different seasons, or by using moving windows to construct the standardised indices.

Defining droughts using moving windows would also help to account for heterogeneity in the data due to a continually increasing number of renewable energy plants. The moving window would adjust itself over time to account for changes in renewable energy production and load. This heterogeneity could also be avoided by using long time series of data from a fixed production system, such as those derived from climate model simulations (e.g. Raynaud et al., 2018). This would additionally allow us to analyse energy droughts in different climate scenarios, since the standardised indices could be applied to the output from future climate projections. Doing so could provide valuable information regarding climate-driven changes in the energy sector.

The definition of an energy drought can be also be varied by stratifying the data from different locations: the standardised indices could be defined using observations at specific renewable energy plants, or by aggregating over several plants within a region. In the former case, the corresponding energy droughts will be defined on a local scale, whereas in the latter case, a drought will be an event that is extreme relative to the entire region.

Defining energy droughts using different data for different time periods and spatial regions is equivalent to employing a threshold of production or residual load that changes over time and space. By defining droughts in terms of standardised indices, the thresholds can be inferred directly from the data, rather than having to be specified manually. The interpretation of the resulting droughts will also be equivalent for all time periods and spatial regions, making the framework particularly convenient for comparative analyses of energy droughts.

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. Further work could additionally discuss the sensitivity of the droughts to sharing between neighbouring countries, as in Otero et al. (2022a).

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. 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

An example time series of the raw renewable energy production and residual load, as well as the corresponding SREPI and SRLI values, is displayed in Figure 2 for Spain during the time period 2010 to 2020. 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 different countries have markedly different installed wind and solar capacities (see Figure B.12), leading to different scales of renewable energy production, the indices are able to account for the differing capacities, 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 is very seasonal, with higher renewable energy production indices likely to occur in winter, whereas the SRLI indices exhibit considerably less seasonal variation. 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.

Figure 3 shows histograms of the raw renewable energy production and residual load values for Norway, compared to histograms of the corresponding

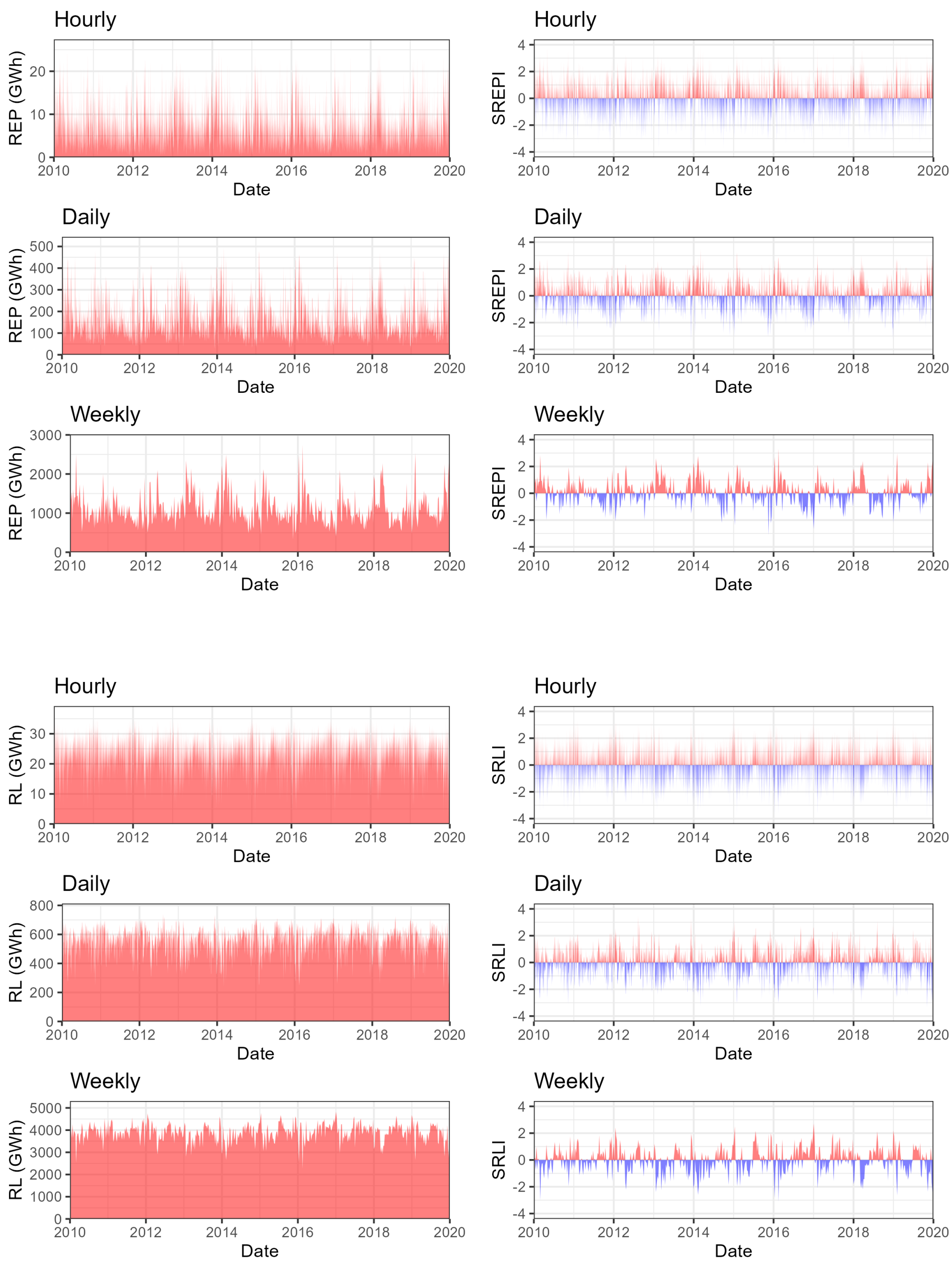


Figure 2: Time series of Spain's renewable energy production (REP) and residual load (RL), and the corresponding standardised indices, between 2010 and 2020. Time series are shown at hourly, daily, and weekly timescales.

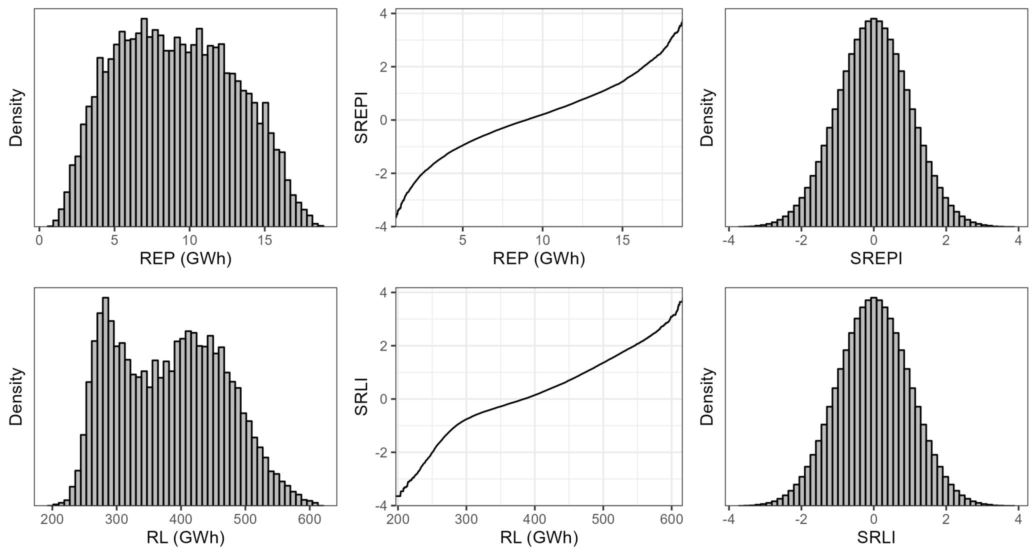


Figure 3: Histograms of Norway's daily renewable energy production (REP) and residual load (RL), as well as histograms of the corresponding standardised indices. The index assigned to each value of the production and residual load is also shown for this country.

daily SREPI and SRLI values. Figure 3 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 3 is not easily modelled 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, 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 4 displays the correlation between the SREPI and SRLI in each country. There is typically strong negative correlation between the two indices: as the SREPI decreasesat a given time decreases, the corresponding 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 5 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).

Production droughts typically occur more frequently in summer for countries that have a higher installed wind capacity than solar capacity, with wind expected to dominate in winter and solar in summer. The opposite is true for 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. Supply droughts occur with a higher frequency in winter in almost all countries, reflecting that energy demand is typically considerably higher in winter than in summer. For countries with warmer climates, such as Italy and Spain, energy supply droughts are relatively more frequent in summer than other countries, due to an increase in summer en-

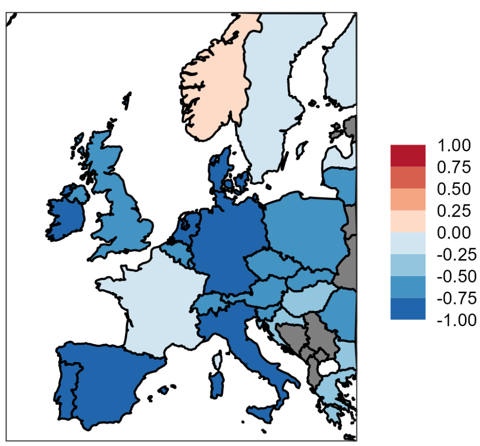


Figure 4: Pearson's correlation between the SREPI and SRLI in each country. Grey areas represent countries that were not considered in this study.

ergy demand for cooling.

Figure 6 presents the corresponding distribution of the drought duration (in days) for Germany, Norway, and Spain, three countries with varying climates and installed capacities. The annual demand, wind production, and solar production patterns are displayed for these three countries in Figure B.13. While energy production droughts tend to occur more frequently than energy supply droughts, they persist for less time. The reason for this is the weaker seasonal cycle in renewable energy production, which leads to the SRLI exhibiting a stronger temporal dependence than the SREPI. This is particularly the case in Norway, where the 2017 installed wind and solar capacity is very small compared to the energy demand. The residual load is therefore dominated by the strong seasonality of the energy demand. As discussed, in these cases, practitioners may find it more useful to define energy droughts seasonally rather than annually.

Figure 6 additionally contains the distribution of the drought magnitude for these three countries. The magnitude of a drought is strongly linked to its duration, and this is evident in Figure 6. Since Norway has longer-lasting supply drought, the magnitude of these droughts is also larger than in other countries. Since Germany has a much larger installed capacity, its production and supply droughts behave very similarly, and both have much lower magnitude than energy droughts in Norway. This is also the case for Spain.

More intense droughts are of particular interest to policymakers, and Figure 7 displays the duration and magnitude of droughts classed as severe and extreme in Table 1, i.e. when using a higher threshold of the standardised indices to define energy droughts. The criterion for a drought to occur is stronger, and the resulting droughts therefore occur less frequently and with less persistence. The magnitude of the energy supply droughts are also lower than when a moderate threshold is considered, though the lower duration of the severe energy production droughts appears to be counteracted by their increased intensity.

4.2.3. Mixing renewable energy sources

In this section, we investigate the effect of the energy mix configuration on the occurrence and magnitude of energy droughts. For example, policymakers may be interested in determining whether a renewable energy system could be made more robust by diversifying its sources of energy. Several studies have suggested that this is the case (e.g. Raynaud et al., 2018; Gan-

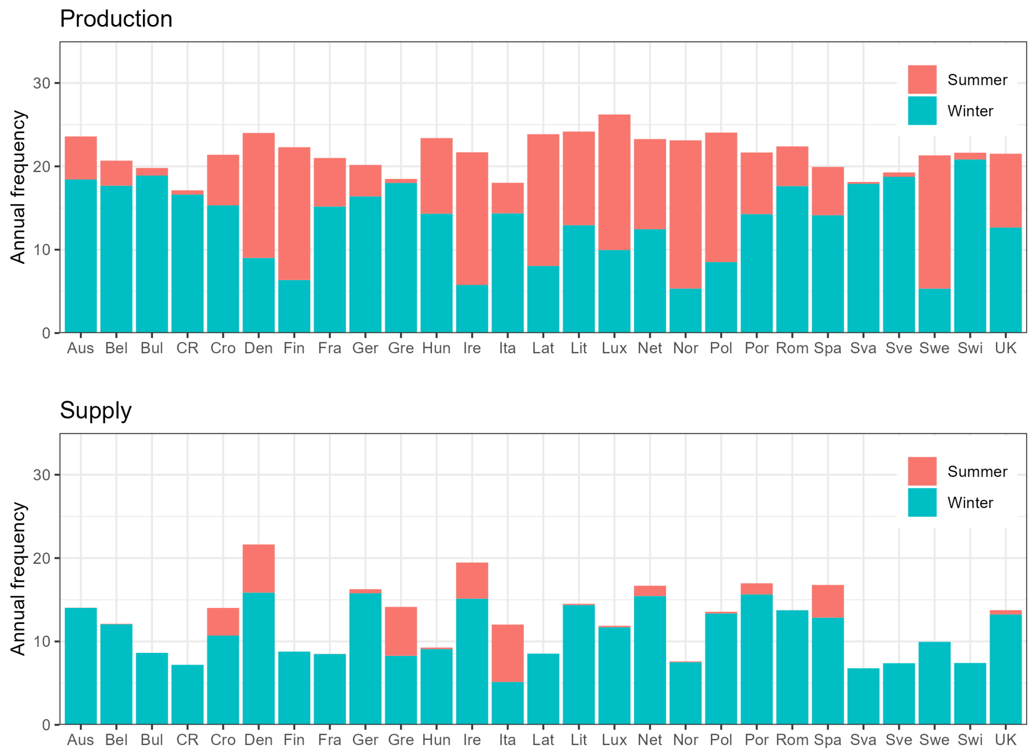
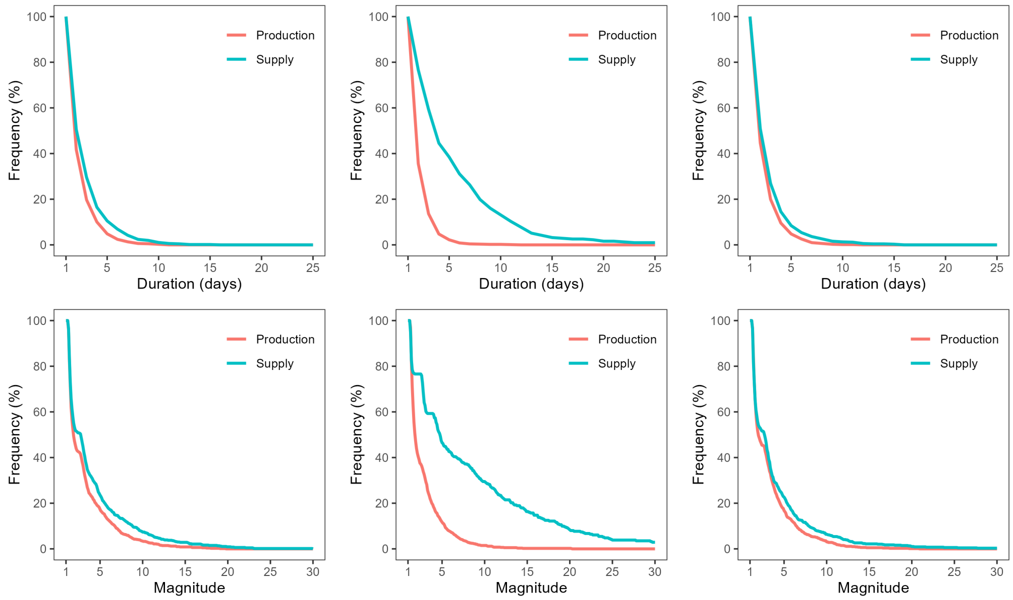


Figure 5: Average number of energy production and energy supply droughts per year in each country. The frequency is divided into the proportion of droughts expected to occur in extended winter and summer seasons. Country codes can be found in Table A.2.

gopadhyay et al., 2022).

In this study, it is assumed that wind and solar power are the only two renewable energy sources. We fix the total installed capacities in each country at their 2017 values, and vary the ratio of installed capacity supplied by wind and solar power. We assume a constant efficiency of the energy system, so that doubling the installed wind capacity will double the amount of wind power; this simplifies the interpretation of the results, but it would be straightforward to perform the analysis without this assumption.

Since the installed capacity is directly linked to the renewable energy production, we focus here on energy production droughts. Droughts are defined relative to the 2017 installed capacities. That is, the historical renewable energy production values used to define the SREPI are those calculated using the current (2017) installed capacities. We then compute the renewable



(a) Germany (b) Norway (c) Spain

Figure 6: Survival functions of the duration and magitude of energy production and supply droughts in Germany, Norway, and Spain. The frequency on the y-axis is the proportion of droughts that persist for longer than the number of days on the x-axis, respectively the proportion of droughts whose magnitude is larger than the magnitude on the x-axis.

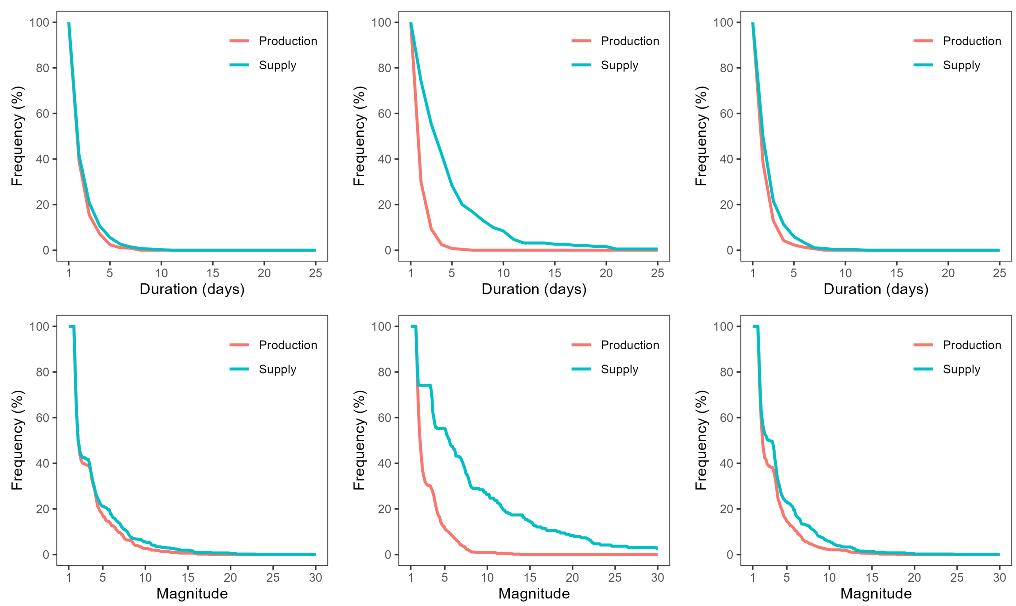
energy production that would be obtained for different configurations of the energy mix, and calculate the corresponding SREPI values. This allows us to analyse how the characteristics of droughts would change in relation to our current energy system, which we argue is most relevant for policy-makers. We consider 11 different cases, where wind capacity contributes $0\%, 10\%, 20\%, \dots, 100\%$ of the total installed capacity.

Figure 8 displays a daily time series of the SREPI in Portugal in 2019 for three of these 11 scenarios. The first assumes that all renewable energy is wind energy, which is relatively similar to the 2017 configuration in Portugal, the second scenario assumes that only solar power is available, while the third assumes that there is an even balance between wind and solar power. The SREPI is highly variable when only wind is used in the energy mix. If only solar is used, then the production follows a much more predictable pattern, with higher values in summer and lower values in winter. However, this regularity comes at the expense of production, with the SREPI failing to exceed 0.7 throughout the year.

The scenario with 50% wind capacity and 50% solar capacity provides a compromise between the two. The production is larger than when only solar power is available, but, compared to when only wind power is available, the variation in the production has been significantly reduced. Moreover, the risks of energy production droughts have significantly decreased: the SREPI is in a drought state on two days in 2019, compared with 32 days and 26 days when the energy system only uses wind or solar power, respectively. Similar results are seen for other years.

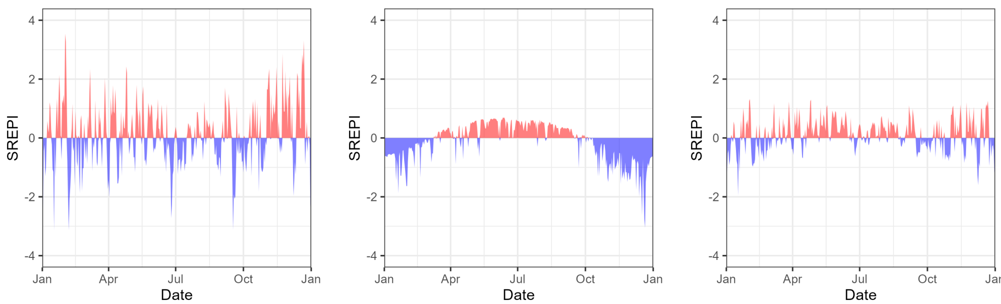
Figure 9 displays the proportion of days in an energy production drought over the 41 year period as the ratio of wind to solar installed capacities changes in each country. The crosses in Figure 9 represent the 2017 installed capacities, for which a drought should occur 10% of the time by definition. Energy production droughts tend to be most frequent when solar is the dominating source of renewable energy, though depending solely on wind power is also sub-optimal in most countries. Mixing wind and solar power generally reduces the occurrence of energy droughts.

While most countries have a much larger proportion of wind capacity than solar capacity, Figure 9 demonstrates that most countries could reduce the occurrence of energy droughts by switching to a configuration that has a more even balance between wind and solar power. In Austria, for example, roughly 70% of the wind and solar capacity is wind capacity, whereas Figure



(a) Germany (b) Norway (c) Spain

Figure 7: As in Figure 6 for energy droughts that are severe or extreme.



(a) Only wind

(b) Only solar

(c) 50/50 wind and solar

Figure 8: SREPI in Portugal in 2019 for energy systems with different proportions of wind and solar capacities. The total installed capacity is the same in all cases.

9 suggests that a more reliable energy system would be obtained if a larger proportion of renewable energy were supplied by solar power. There are some exceptions to this: Norway has a very high proportion of wind capacity, but this appears to be the optimal configuration for this country, perhaps since its climate increases the potential to generate wind power. Some countries, such as the Czech Republic, Slovakia, Slovenia, and Switzerland, have a very low installed wind capacity. Hence, for these countries, even a small increase in wind capacity can lead to major reduction in the number of droughts.

Figure 10 similarly shows the average magnitude of energy production droughts in these different energy mixes. There are some countries for which having only solar power makes droughts very seasonal. The resulting droughts can persist for weeks and therefore have a high magnitude. For visualisation, the magnitude has been truncated at 10 in Figure 10. This does not have influence on the majority of values, or the general conclusions drawn from the plot. The results are qualitatively similar to Figure 9. In particular, the magnitude of energy droughts can often be decreased by using a more balanced mix of renewable energy sources.

4.2.4. Storing renewable energy

Policymakers may also want to assess the benefits afforded by energy storage systems. We now examine the effect of storage on the standardised residual load index and the corresponding energy supply droughts. For the nationwide data we consider here, the renewable energy production from wind and solar is almost always lower than the energy load. This renders energy storage systems less effective, since there is rarely a surplus of renewable

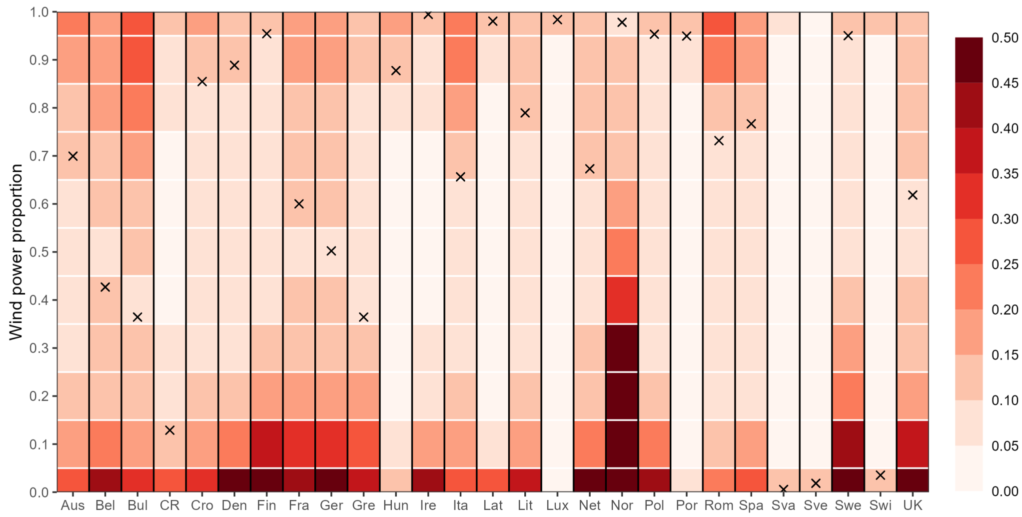


Figure 9: Proportion of days in an energy production drought for each country, as a function of the proportion of total installed capacity that is supplied by wind. A cross displays this proportion for the 2017 installed capacities.

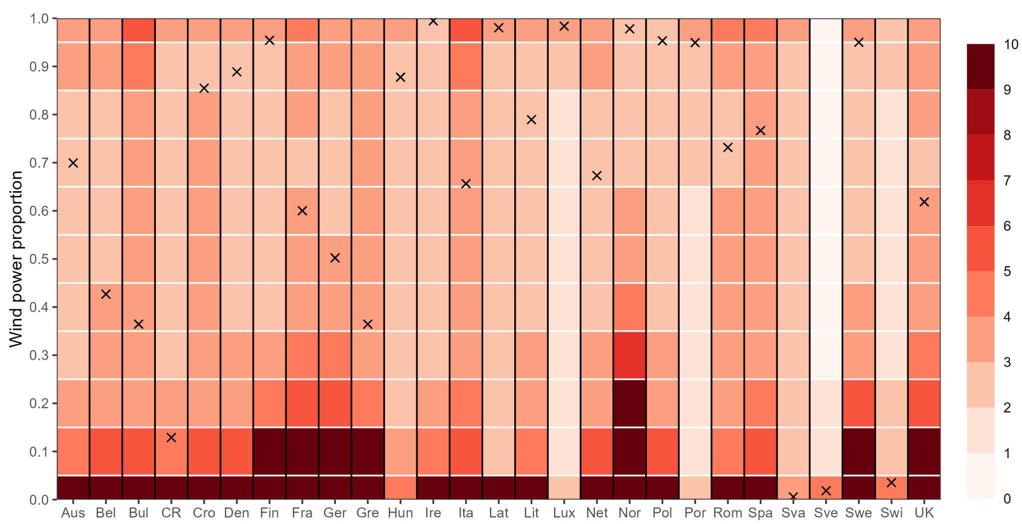
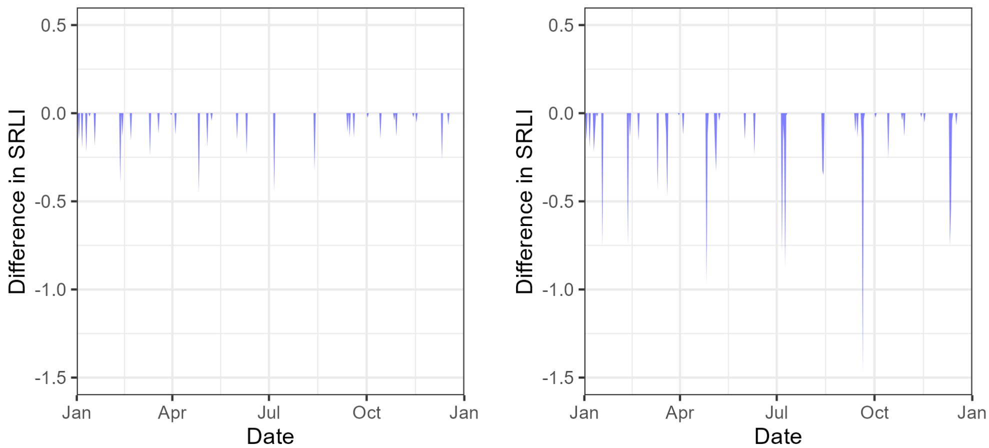


Figure 10: Average magnitude of energy production droughts for each country, as a function of the proportion of total installed capacity that is supplied by wind. A cross displays this proportion for the 2017 installed capacities. The colour bar has been truncated at 10 for visualisation.



(a) One day

(b) Seven days

Figure 11: Difference in SRLI when renewable energy can and cannot be stored. Results are shown for Denmark in 2019, when energy can be stored for (a) one day, and (b) seven days.

energy that can be stored. In this case, it is more beneficial to increase the installed capacity, rather than spending resources on energy storage systems.

However, to illustrate how the benefits of storage systems could be analysed using standardised energy indices, we restrict attention to Denmark, where there is a surplus of renewable energy on 16% of days. As in the previous section, we use the 2017 energy mix configuration to define the standardised indices. We then calculate the renewable energy production and residual load when different storage systems are available, and compute the corresponding SRLI. If the renewable energy production exceeds the energy demand, then this surplus is stored and used to reduce the residual load on the following day(s). We consider storage systems capable of storing energy for various lengths of time. We assume that both wind and solar energy can be stored with perfect efficiency, in the sense that no energy is lost, and that there is no upper bound to how much energy can be stored. This latter assumption is not unrealistic in our study, since the surpluses are relatively rare.

Figure 11 displays the difference in SRLI for Denmark in 2019, with and without storage capabilities. Results are shown for one-day and one-week storage systems. By storing renewable energy, the residual load never increases, meaning the SRLI either remains the same or decreases. With a one-day storage system, the reductions in SRLI are very small. These are much larger for a storage system with seven days of storage, though the number of energy droughts prevented from storage is still low. Nonetheless, even in this example where the renewable energy production is low compared to the energy demand, simple short-term storage systems do prevent energy droughts from occurring.

Similar results are obtained for longer storage systems, which can store energy for up to three months; since energy is stored relatively rarely, this stored energy is generally used up on intermediate days when the residual load is positive but not extreme. The amount stored is also typically small relative to the residual load itself. Increasing the length of the storage system therefore has little effect on the SRLI and the occurrence of energy droughts.

While this is in contrast to previous studies on storage systems in renewable energy systems, these studies consider more localised data, for which the renewable energy contribution is not low compared to the overall energy demand. In our study, storage systems are not particularly beneficial, since there is rarely left over energy to be stored. In this case, it is more beneficial to increased installed capacities. This could easily be verified using the standardised indices, but is not done so here for concision.

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. 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 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.

We demonstrate here how the SREPI and SRLI could 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 climates and installed capacities.

These indices provide an informative comparative tool that can assist policymakers on decisions related to the design of renewable energy systems, and the storage, sharing, and diversification of renewable energy. 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 (Otero et al., 2023).

We find that mixing renewable energy sources increases the robustness of an energy system to energy droughts, reinforcing the conclusions drawn in several previous studies (e.g. Raynaud et al., 2018; Jurasz et al., 2021; Gangopadhyay et al., 2022). However, this is not always the case: there are some countries for which the potential to generate large amounts of wind power outweighs the benefits afforded by having a more predictable energy supply. We additionally investigate the effects of storage on the occurrence of energy supply droughts. However, since it is rare that energy production exceeds energy demand, the effectiveness of these storage systems is limited for the case study presented herein. Nonetheless, the framework we implement using standardised indices could readily be adopted to study this in other data sets. The effects of oversizing renewable energy plants is also not considered here, but could be analysed analogously.

We have focused here 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. However, 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.

For countries that have small installed capacities, the residual load will generally be dominated by the energy demand, making energy supply droughts less relevant for policymaking. As an alternative, one could consider the ratio of renewable energy production to load, rather than the difference between them. This quantifies the proportion of energy demand that can be supplied by renewable sources, and should be more sensitive to production than the residual load. We do not consider this variable here, though standardised indices and energy droughts can readily be introduced for this variable using the framework discussed herein.

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, 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 increase, the energy demand in summer will likely also increase, resulting in larger 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. This, in turn, would help to understand what installed capacities, energy mixes, and more generally what policies, are required to mitigate these impacts in the future.

Acknowledgements

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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.

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 do not fit the data. 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 heavily influenced by the energy demand, which generally exhibits strong seasonal behaviour. This often results in multi-modal distributions (as illustrated in Figure 3, for example), 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.12 displays the installed wind and solar capacities for each European country considered in Section 4. As discussed, the capacities correspond to those from 2017. The sensitivity of the energy demand, wind production, and solar production is displayed in Figure B.13 for Germany, Norway, and Spain.

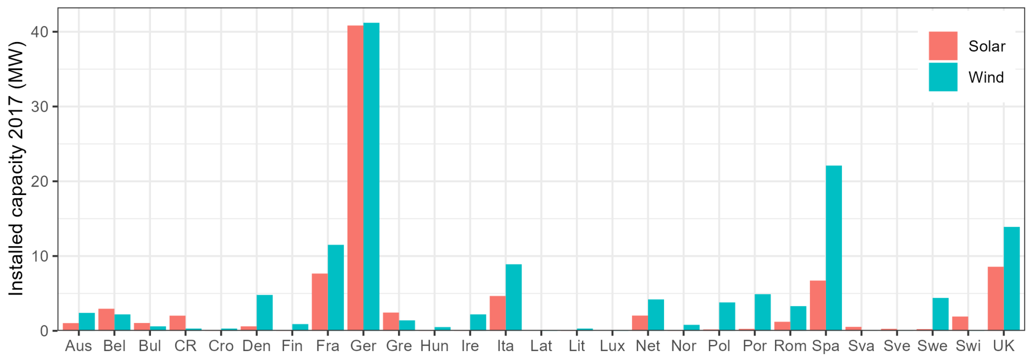
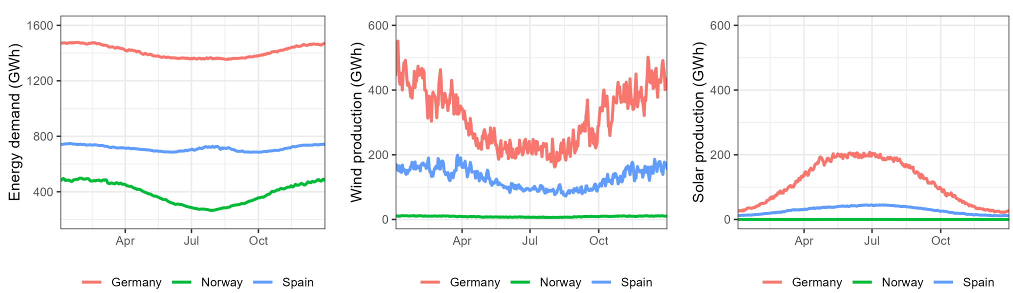


Figure B.12: Installed 2017 wind and solar capacities at each European country under consideration.



(a) Energy demand

(b) Wind production

(c) Solar production

Figure B.13: Annual mean demand, wind production, and solar production for Germany, Norway, and Spain. Note the different scale for demand and production.

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Country		Renewable Energy Production			Residual Load		
		Hourly	Daily	Weekly	Hourly	Daily	Weekly
Austria	Aus	Weibull	Log Norm	**Gamma**	Normal	Log Norm	Log Norm
Belgium	Bel	Tr. Norm	Weibull	**Gamma**	Gamma	Log Norm	Log Norm
Bulgaria	Bul	Tr. Norm	Gamma	**Tr. Norm**	Log Norm	Log Norm	Log Norm
Czechia	CR	Weibull	Weibull	Weibull	Log Norm	Log Norm	Log Norm
Croatia	Cro	Log Norm	Log Norm	Gamma	Weibull	Log Norm	Log Norm
Denmark	Den	Tr. Norm	Weibull	**Weibull**	Tr. Norm	Tr. Logit	Tr. Logit
Finland	Fin	Tr. Norm	Weibull	**Weibull**	Log Norm	Log Norm	Log Norm
France	Fra	Weibull	Log Norm	**Log Norm**	Log Norm	Log Norm	Log Norm
Germany	Ger	Weibull	Gamma	Gamma	Normal	Weibull	**Logistic**
Greece	Gre	Weibull	Weibull	**Weibull**	Log Norm	Log Norm	Log Norm
Hungary	Hun	Tr. Norm	Log Norm	**Gamma**	Weibull	Log Norm	Log Norm
Ireland	Ire	Tr. Norm	Weibull	**Weibull**	Tr. Norm	Weibull	Norm
Italy	Ita	Tr. Norm	Gamma	**Gamma**	Weibull	Log Logit	Log Logit
Latvia	Lat	Gamma	Tr. Norm	**Weibull**	Weibull	Log Norm	Log Norm
Lithuania	Lit	Tr. Norm	Tr. Norm	**Gamma**	Weibull	Log Norm	Log Norm
Luxembourg	Lux	Gamma	Weibull	Gamma	Weibull	Log Norm	Log Norm
Netherlands	Net	Tr. Norm	Weibull	**Gamma**	Weibull	Normal	**Log Norm**
Norway	Nor	Weibull	Weibull	Gamma	Gamma	Gamma	Gamma
Poland	Pol	Tr. Norm	Weibull	**Gamma**	Weibull	Log Norm	Log Logit
Portugal	Por	Gamma	Gamma	**Gamma**	Tr. Logit	Weibull	Weibull
Romania	Rom	Gamma	Log Norm	**Log Norm**	Normal	Log Norm	Log Norm
Spain	Spa	Gamma	Log Norm	Log Norm	Weibull	Weibull	Weibull
Slovakia	Sva	Gamma	Weibull	**Weibull**	Gamma	Log Norm	Log Norm
Slovenia	Sve	Tr. Norm	Weibull	Weibull	Normal	Log Norm	Log Norm
Sweden	Swe	Weibull	Weibull	**Gamma**	Gamma	Log Norm	Log Norm
Switzerland	Swi	Log Norm	Weibull	Weibull	Log Norm	Log Norm	Log Norm
United Kingdom	UK	Weibull	Gamma	**Gamma**	Weibull	Log Norm	Log Norm

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.