

Characterising Adverse Weather for the UK Electricity System, including addendum for surplus generation events

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1 Executive Summary

The first National Infrastructure Assessment, published by the National Infrastructure Commission (the Commission) in 2018, recommends targeting a transition of the UK electricity system to a highly renewable generation mix, incorporating increasing wind and solar power capacities. Transitioning to this highly renewable mix will increase the vulnerability of the UK's electricity system to adverse weather conditions such as sustained periods of low wind speeds leading to low wind generation, coupled with cold winter or high summer temperatures leading to peak electricity demand. Consequently, the Commission wants to improve understanding of the impact of adverse weather conditions on a highly renewable future system. This will support the recommendations it makes to government and provide beneficial inputs to those that model and design future electricity systems.

To improve this understanding, the Met Office have recommended developing a dataset of adverse weather scenarios, based on physically plausible weather conditions, representing a range of possible extreme events, and the affect of future climate change. This will allow for proposed future highly renewable electricity systems to be rigorously stress tested to ensure resilience to challenging weather and climate conditions.

This report presents the development and validation of an approach for characterising adverse weather events using meteorological data, focusing on long-duration wind-drought-peak-demand events. This characterisation will allow for these events to be identified within any meteorological data record, as required in future phases of this project. The method is applied to 40 years of historical meteorological data and the resulting adverse weather events within the historical report are presented.

Using insights from the electricity modelling literature, the developed method estimates daily weather dependent electricity demand from temperature, and wind generation from wind speed at turbine hub height. Estimated demand and generation are then used in combination to represent the demand that is not met by wind generation. A wind-drought-peak-demand adverse weather event is then identified as occurring when this quantity exceeds a high threshold. The robustness of the method is tested in a sensitivity study, in which a number of methodological input settings are varied and the identified adverse weather events are explored and compared. The observed consistency in periods of peak adverse weather across the sensitivity study settings gives good confidence that the developed method robustly identifies representative periods of adverse weather, relevant for testing the resilience of a range of potential future renewable electricity system configurations.

2 Introduction

The Met Office are developing a dataset of adverse weather events that can be used by energy system modellers to test the weather and climate resilience of potential future highly renewable electricity systems. Following on from the initial literature review ([Dawkins, 2019](#)) and project scoping report ([Butcher and Dawkins, 2020](#)), this phase of the project aims to develop an approach for characterising such adverse weather stress events for the electricity system, focusing on long-duration wind-drought-peak-demand events in winter (October-March) and summer (April-September). In doing so, this type of event can be identified within any meteorological data record, for example historical weather data or future climate change projections, allowing for them to be included within the final dataset of adverse weather events.

The method developed characterises long-duration wind-drought-peak-demand events using a stress event index, calculated from weather conditions in a region and their potential for producing electricity demand and generation. The approach draws on insights from the electricity modelling literature, such as [Bloomfield et al. \(2019\)](#), hydrological drought modelling literature, such as [Burke et al. \(2010\)](#), and the expertise of the project advisory and user groups, and is developed using a historical meteorological dataset.

Within this project, the aim is to keep the characterisation of adverse weather as independent of a particular future electricity system as possible. Hence, rather than use a planned future representation of demand or installed wind capacity, these configurations are left as general as possible, and a sensitivity study is conducted to explore the robustness of identified adverse weather events to changing these components of the electricity system. Specifically, the approach for estimating potential UK weather dependent demand from temperature is varied to explore the sensitivity to increased electrified heating in the UK, and the approach for estimating potential European wind generation from wind speed is varied to explore the sensitivity to whether a current-day or future highly-renewable scenario is considered. The results of the sensitivity study are used to identify whether the developed method is robust and able to represent periods of adverse weather, relevant for many different electricity system configurations.

This report first outlines the method developed for characterising long-duration wind-drought-peak-demand events, followed by the design of the sensitivity study. The results of this sensitivity study are then presented and discussed. Finally, tables of the long-duration wind-drought-peak-demand adverse weather events, identified within the historical period using the final stress event index, are provided.

3 Method

Wind-drought-peak-demand adverse weather events will occur within a region when wind speed, and hence wind renewable electricity generation is low, coupled with low/high winter/summer temperatures, leading to high electricity demand from heating/cooling. In particular, in a future highly renewable electricity system, these adverse weather events will occur and become long-duration events when electricity demand exceeds wind electricity generation for a prolonged period of time. As such, characterising this form of adverse weather events via a 'Wind-Drought-Peak-Demand Index' (WDI), will require the estimation of 'Demand-Net-of-Renewables', defined as the regional electricity demand minus the regional wind electricity generation. Here, these two components of Demand-Net-of-Renewables are calculated on a daily basis, using insights from [Bloomfield et al. \(2019\)](#), detailed in the following sections and summarised in the schematic shown in Figure 4. In this study, the historical 40-year (1979-2018) ERA5 meteorological reanalysis dataset ([Hersbach et al., 2018](#)) is used to represent the daily meteorological conditions in Europe. The same methods could, however, be applied to any meteorological dataset.

3.1 Estimating Weather Dependent Electricity Demand

Electricity demand varies with both societal factors, such as the day of the week, and meteorological conditions, such as temperature. Here, just the weather dependent variation in electricity demand is relevant for characterising adverse *weather* events within the WDI. This also means that the output events will represent meteorological conditions that could have occurred on any day of the week, leaving the energy modeller (user of the dataset) free to choose the societal factors they wish to explore. This weather dependent demand is estimated from meteorological conditions using the same method as developed by [Bloomfield et al. \(2019\)](#) (documented in their supplementary material).

Firstly, gridded near-surface (2 metres from surface) temperature data (here taken from ERA5) is used to calculate the daily average temperature over land (not sea) in the region of interest (e.g. the UK). Following this, the relationship between regional daily average temperature and regional weather dependent demand is assumed to be linear, with the nature of the relationship varying above and below certain temperature thresholds. This is demonstrated in Figure 1.

As shown in Figure 1, when regional daily average temperature is below a certain threshold (here 15.5°C) or above a different, higher threshold (22.0°C), the linear relationship between temperature and weather dependent demand has a different gradient. This changing relationship with temperature threshold represents the increasing heating demand on cooler days (less than 15.5°C) and increasing cooling demand on warmer days (greater than 22.0°C). If the temperature on a particular day is between these two thresholds, then it is assumed that the electricity demand is not weather-sensitive and is equal to a regional baseline electricity demand value. The two thresholds used in this study are consistent with those used by [Bloomfield et al. \(2019\)](#), who selected them based upon the European

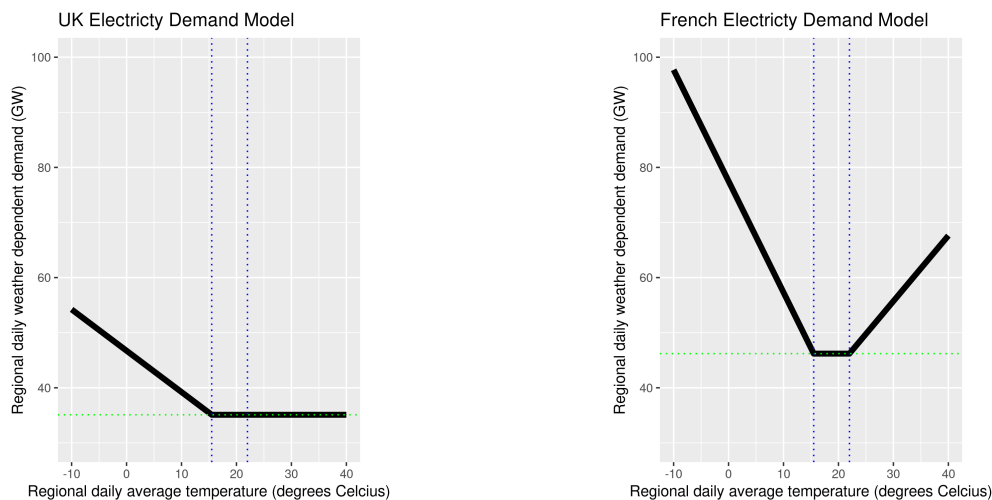


Figure 1: Diagrammatic representations of the UK (left) and French (right) weather dependent electricity demand models used within this study, taken from Bloomfield et al. (2019). These diagrams show how a given regional daily average temperature relates to regional daily weather dependent electricity demand in each of these countries. The blue dotted lines in each graph show the heating and cooling thresholds used by Bloomfield et al. (2019) and within this study (15.5 and 22.0°C respectively). The green dashed lines show the baseline electricity demand in each country.

Environment Agency and Intergovernmental Panel on Climate Change (IPCC) Working Group 3 (Edenhofer et al., 2014).

To implement this, two metrics of regional daily average temperature are calculated:

1. **Heating degree days (HDD):** When regional daily average temperature is below the chosen heating threshold (15.5°C), HDD is equal to the heating threshold minus the temperature on that day, and zero otherwise.
2. **Cooling degree days (CDD):** When regional daily average temperature is above the chosen cooling threshold (22.0°C), CDD is equal to the temperature on that day minus the cooling threshold, and zero otherwise.

Subsequently, the weather dependent demand (WDD) in a given region/country and on a given day (i.e. the y axis in Figure 1) can be calculated as:

$$\text{WDD} = a + b \times \text{HDD} + c \times \text{CDD}, \quad (1)$$

where HDD and CDD are values of the heating and cooling degree days metrics respectively for that given day and region, a is the regional baseline electricity demand value, b is the slope of the demand model below 15.5°C, and c is the slope of the demand model above 22.0°C (e.g. in Figure 1).

The values for a , b and c are different for each European country (see Table 10) and are taken from Bloomfield et al. (2019), who estimated these values using temperature and national energy demand data from 2016 and 2017¹. The supplementary material of Bloomfield et al. (2019) provides more information on the demand model development and model performance, i.e. how well equation 1 represents

¹<https://www.entsoe.eu/data/> (Accessed 29/09/2020)

true demand in each country.

In the UK (left panel of Figure 1) the baseline demand (green dashed line) $a = 35.1\text{GW}$; the heating slope $b = 0.75$, meaning that weather dependent demand increases by 0.75GW for every 1°C decrease in temperature below 15.5°C ; and the cooling slope $c = 0$, meaning that there is no significant weather sensitivity to cooling demand in the UK (currently no widespread use of air conditioning). In comparison, in France (right panel of Figure 1) the baseline demand (green dashed line) $a = 46.2\text{GW}$; the heating slope $b = 2.02$, meaning that weather dependent demand increases by 2.02GW for every 1°C decrease in temperature below 15.5°C ; and the cooling slope $c = 1.19$, meaning that weather dependent demand increases by 1.19GW for every 1°C increase in temperature above 22.0°C . The steeper heating slope in the French model represents how France use more electrified heating than in the UK, and the existence of a cooling slope represents how France uses electrified air conditioning for cooling.

In future phases of this project, the adverse weather metric developed in this study will be applied to future climate projections in order to identify and explore adverse weather in future climates. As described in [Butcher and Dawkins \(2020\)](#), the latest UK climate projections released by the Met Office in November 2018 ([Lowe et al., 2018](#)) show a clear increasing signal in UK temperatures. In particular, summer maximum temperatures are on average likely to rise by $2\text{-}3^\circ\text{C}$ in the south of the UK by 2100. Indeed, [Sanderson et al. \(2016\)](#) show how, by the mid 21st century, southern and central England and Wales are likely to have climates analogous to the current climate of northern and western France. This change in the future UK climate is likely to change cooling demand within the UK, with more people using air conditioning to improve their comfort during the hotter summers. For this reason, the UK demand model will be modified for this study to incorporate the cooling slope (c) of the French model (the analogous country for the UK's future climate).

The methods detailed in this section, and the resulting demand models for each European country (equivalent to the diagrams in Figure 1), provide an approach for estimating weather dependent demand in each country on a given day. This calculation process is further demonstrated graphically in the top panel of the schematic in Figure 4. These weather dependent demand estimates can then be combined with an estimate of regional daily wind electricity generation to quantify Demand-Net-of-Renewables, relevant for identifying periods of adverse weather for a renewable electricity system.

3.2 Estimating Wind Electricity Generation

The method developed to estimate regional daily wind electricity generation is, again, based on a number of insights from [Bloomfield et al. \(2019\)](#). Similar to [Bloomfield et al. \(2019\)](#) we base this calculation on gridded 100 metre wind speed data (i.e. wind speed 100 m above ground level), thought to be representative of the wind at turbine hub height. As in [Bloomfield et al. \(2019\)](#), and for the weather dependent demand calculation, here we initially apply this method to the gridded ERA5 meteorological reanalysis

dataset. In line with [Bloomfield et al. \(2019\)](#), who identified a substantial bias in the ERA5 100 m wind speeds when compared to leading wind-resource assessment datasets such as the Global Wind Atlas², these input wind speeds are first bias corrected. This is achieved in the same way as [Bloomfield et al. \(2019\)](#), by correcting the bias in the mean wind speed on a grid-point by grid-point basis (i.e. correcting each grid point separately), using the Global Wind Atlas wind speed data interpolated to each grid cell as the 'truth'.

On a given day, the wind power capacity factor, defined as the proportion of a turbine's maximum possible generation produced, is calculated by applying the turbine power curve (see Figure 2 a) to the bias corrected 100 m wind speed. For a given region/country, the capacity factor is calculated for each grid cell separately. Figure 2 (a) shows the three on-shore wind turbine power curves used by [Bloomfield et al. \(2019\)](#) to calculate the capacity factor in a given grid cell. These 3 turbines were chosen by [Bloomfield et al. \(2019\)](#) to be representative of type 1, 2 and 3 turbines from the International Electrotechnical Commission (IEC) wind speed classification respectively ([IEC, 2005](#)).

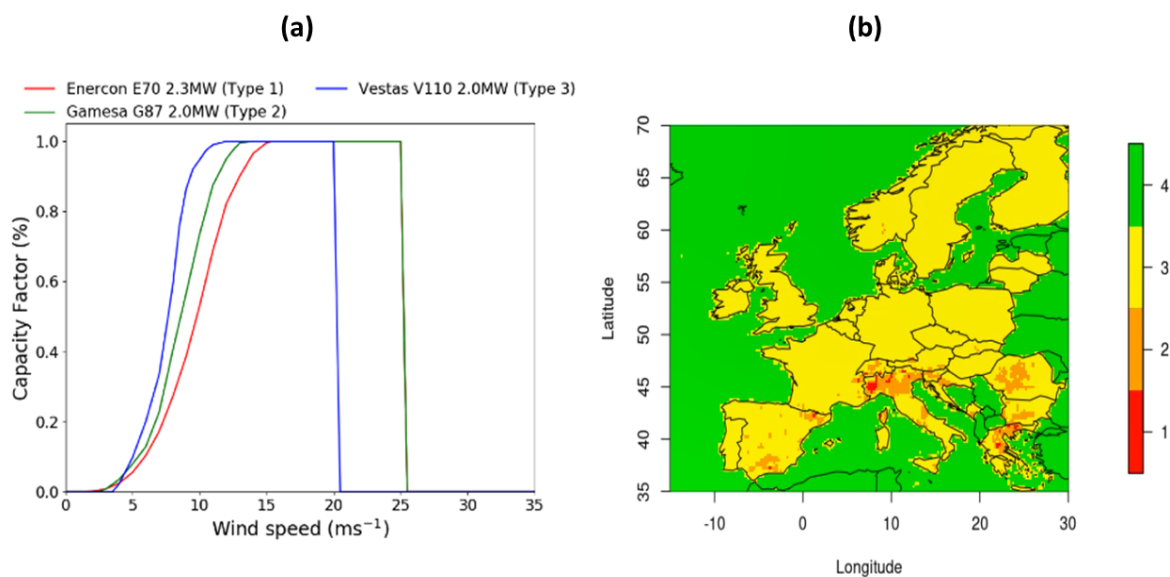


Figure 2: (a) Taken from the supplementary material of [Bloomfield et al. \(2019\)](#): representative on-shore wind power curves, (b) the turbine allocated to each grid cell in Europe, where 1, 2 and 3 relate to the on-shore turbine types 1, 2 and 3 in (a) respectively, and type 4 is the National Grid off-shore turbine type.

In each land grid cell, the most appropriate turbine (out of these three options) is chosen, based on the weather conditions there. Specifically, as in [Bloomfield et al. \(2019\)](#), it is assumed that all of the turbines within a grid cell are of the same type, and the selected turbine type is the one that maximises the capacity factor for the 40-year (1979-2018) mean of the bias corrected 100 m wind speed in that grid cell. Figure 2 (b) shows the resulting allocated turbine type in each ERA5 grid cell in Europe. Following

²<https://globalwindatlas.info> (Accessed 24/09/2020)

guidance from the project advisory group, the off-shore wind power capacity factor is specified as following the power curve used by National Grid when modelling off-shore turbines (described in Section 3.2 of [nationalgridESO 2019](#)).

Within each grid cell, the wind power capacity factor is then weighted by the installed wind capacity within that grid cell (as a fraction of the national total). In [Bloomfield et al. \(2019\)](#), this is achieved using the installed capacities of 2017, taken from the [thewindpower.net](#) database. Here, however, the aim is to keep the characterisation of adverse weather as independent of a particular future electricity system as possible. Hence, rather than use a current or planned future representation of installed capacities, each grid cell is weighted by the 'potential' for installed wind capacity.

In Great Britain, the potential for installed wind capacity is based on the analysis of [Price et al. \(2018\)](#), [Moore et al. \(2018\)](#) and [Price et al. \(2020\)](#). Within these studies, the potential locations of on- and off-shore wind turbines in Great Britain are derived based on in-depth explorations of technical, social and environmental restrictions. For example, on-shore restrictions include terrain steepness, distance from housing and the location of nature conservation areas, while off-shore restrictions include water depth, shipping routes and the UK government approval of off-shore regions for energy production. Elsewhere in Europe, less work has been done to define potential locations of wind turbines. As a result, a more simplistic approach is employed, which assumes that wind turbines cannot be built in "urban areas" as defined by Natural Earth³, but could be located anywhere else. In addition, no off-shore regions are specified for European countries other than the UK. This simplistic approach was necessitated by the timescale of the current study.

Figure 3 shows the resulting location of where wind turbines can and cannot be located in Europe within this study. In both Great Britain and the rest of Europe, this information is used to calculate the proportion of each ERA5 grid cell that has the potential to contain wind turbines. For example, if the blue region in Figure 3 intercepts half of a given grid cell, the installed capacity weighting in that grid cell is 0.5. The total daily wind power capacity factor in a region/country is then found by multiplying the wind power capacity factor, in each grid cell within that region, by the installed wind capacity weighting calculated for that grid cell (as a fraction of the total installed capacity weight in that region), and aggregating over the region.

Finally, for a given day, the regional total wind generation is calculated by multiplying the daily regional capacity factor by the national level of installed wind power. The current day national level of installed wind power in each country can be obtained from [thewindpower.net](#) website. These values are shown in the first column of Table 11. Since the aim of this project is to identify adverse weather events relevant for a highly renewable electricity system, here we represent the national level of installed wind power in

³<https://www.naturalearthdata.com/> (Accessed 24/09/2020)

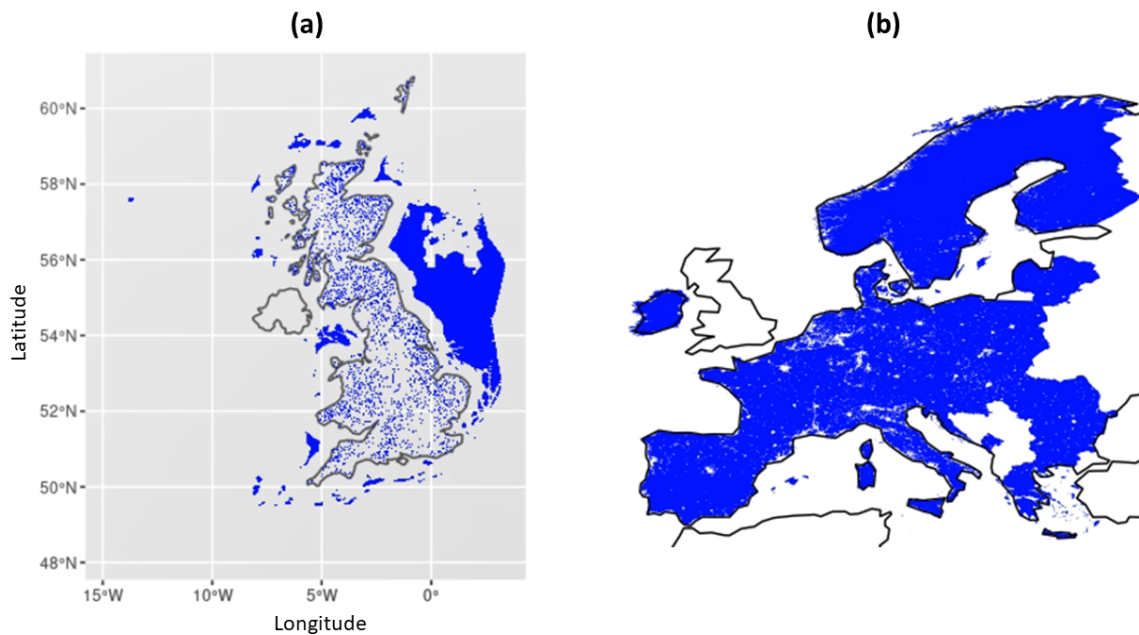


Figure 3: Maps showing the potential locations of wind turbines in Europe, used within this study, for (a) the UK, taken from Price et al. (2018), Moore et al. (2018) and Price et al. (2020), and (b) the rest of Europe, based on Natural Earth urban areas dataset (<https://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-urban-area/> accessed 24/09/2020). In both plots the blue shaded regions represent where wind turbines *can* be located, and the unshaded regions are where wind turbines *cannot* be located.

each country as an estimate of the possible level by 2050. Following guidance from the Committee on Climate Change and reports such as ‘Powering the Future: RenewableUKs Vision of the Transition’⁴, a national installed capacity of 120GW is employed for the UK. Further, Europe as a whole is represented as having installed wind capacity of 600GW, in line with Wind Europe’s past reports⁵. For countries other than the UK, the future highly-renewable national installed wind capacities are increased such that the proportion of total European installed capacity (600GW) in that country is equal to the current day proportion. These values are shown in the second column of Table 11.

This wind generation calculation process is demonstrated graphically in the middle panel of the schematic in Figure 4.

3.3 The Wind-Drought-Peak-Demand Index

The methods described in the previous two sections can be used to estimate daily weather dependent demand and daily wind generation from meteorological conditions in each European country listed in Tables 10 and 11. These two quantities can then be used together to calculate daily Demand-Net-of-Renewables, defined as daily weather dependent demand minus wind generation. This Demand-Net-of-Renewables metric therefore represents how much of the daily demand must be met by energy

⁴<http://vision.renewableuk.com/introduction> (Accessed 24/09/2020)

⁵http://www.ewea.org/fileadmin/files/library/publications/position-papers/EWEA_2050_50_wind_energy.pdf and <https://windeurope.org/wp-content/uploads/files/about-wind/reports/Wind-energy-in-Europe-Scenarios-for-2030.pdf> (Accessed 24/09/2020)

sources other than wind renewables. Hence, in a highly renewable electricity system, stressful meteorological days will be associated with positive values of this metric, and adverse weather events will be associated with days when this metric is particularly high.

Borrowing insights from hydrological drought modelling (Burke et al., 2010), rather than use daily Demand-Net-of-Renewables to identify adverse weather events, this metric is accumulated over a number of days to better represent the function of electricity storage during such events. This approach characterises how the electricity system may be able to cope with just one or two days of high demand and low wind generation, but how multiple days of above average Demand-Net-of-Renewables may lead to an issue for renewable electricity supply. Since long-duration (greater than 7 day) adverse weather events are of most interest here, the Demand-Net-of-Renewables metric is accumulated over every 7 day period, representing how 'bad' the previous week has been in terms of weather dependent Demand-Net-of-Renewables. As in hydrological drought modelling (Burke et al., 2010), this accumulated metric is then scaled by its long term average and standard deviation⁶ to give the final Wind-Drought-Peak-Demand Index (WDI). This calculation process is demonstrated graphically in the bottom panel of the schematic in Figure 4.

The WDI can then be used to identify periods of adverse weather. Again, this is done following insights from hydrological drought modelling, by defining an adverse weather day as any day on which the WDI exceeds its 90th percentile⁷. As Demand-Net-of-Renewables, and hence the WDI, is likely to be consistently higher in the winter compared to the summer (since temperatures are lower and hence demand is higher), a different threshold is used in winter (October - March) and summer (April - September). That is, the 90th percentile of summer-time WDI is used as the summer threshold, while the equivalent winter-time percentile is used in winter. This means that 10% of summer days and 10% of winter days within the period of interest will be classed as 'adverse', ensuring that an equal proportion of events occur in each season. When the WDI exceeds and then falls below this adverse weather threshold, this constitutes an 'event'. Again, similar to hydrological drought modelling, each event is then quantified in terms of its duration and severity. The duration is the number of days over which the WDI exceeds the adverse weather threshold, and the severity is the accumulated difference between the WDI and the threshold over the duration of the event. This is demonstrated in the third step in the bottom panel of Figure 4.

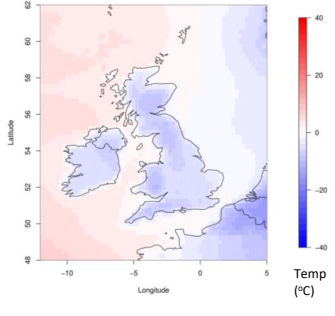
This method can therefore be used to identify periods of adverse weather for the electricity system, based on any suitable gridded meteorological data set. Using the calculated event durations and severities, particular events related to relevant return periods (e.g. 1 in 20 year event) in terms of duration and severity can then be identified and shared, as proposed in the project scoping report (Butcher and Dawkins, 2020).

⁶<https://www.mathsisfun.com/data/standard-deviation.html> (Accessed 30/09/2020)

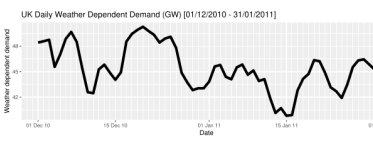
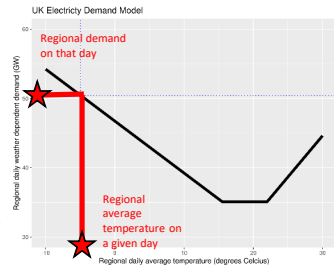
⁷<https://www.mathsisfun.com/data/percentiles.html> (Accessed 25/09/2020)

Regional Daily Weather Dependent Demand

1. For each day, calculate **average temperature over land in the region** (e.g. UK), using gridded temperature data (e.g. ERA5)



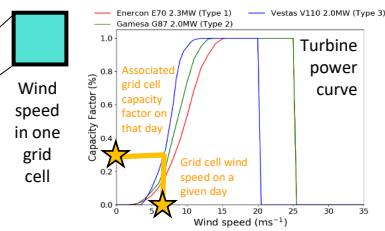
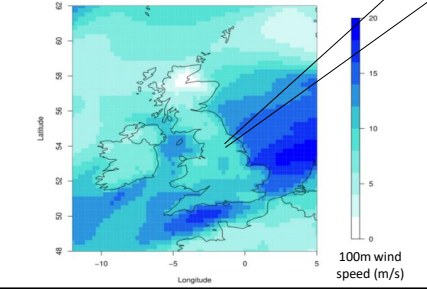
2. Use the national demand model to calculate **weather dependent demand** associated with that temperature (e.g. 50GW)



3. Repeat for **each day** (e.g. winter 2010/11)

Regional Daily Wind Generation

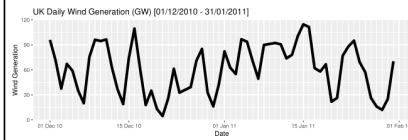
1. Bias correct **100m gridded wind speed data** (e.g. ERA5)



2. For each grid cell in the region (e.g. UK), and each day, calculate the **wind capacity factor** using the assign wind turbine power curve in that grid cell

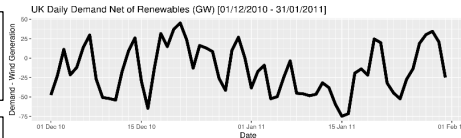
3. To calculate **regional daily wind generation**, multiply the wind capacity factor in each grid cell by the grid cell **installed wind capacity weighting**, aggregate over the whole region, and multiply by the **regional total installed wind capacity**

4. Repeat for **each day** (e.g. winter 2010/11)

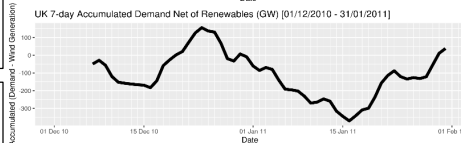


The Wind-Drought-Peak-Demand Index

1. For the region of interest (e.g. UK), calculate **Demand Net of Renewables** as demand minus wind generation on each day



2. Calculate the **7-day accumulated demand net of renewables** by aggregating over each 7 day period



3. Calculate the **Wind-Drought-Peak-Demand index** by scaling the 7-day accumulated demand net of renewables by its long-term average and standard deviation. **Identify events** as times when the index exceeds its 90th percentile, and calculate event durations and severities

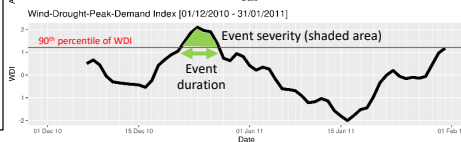


Figure 4: A schematic demonstrating the step-by-step methods used to (top panel) calculate regional daily weather dependent demand, (middle panel) calculate regional daily wind renewable electricity generation, and (bottom panel) calculate the wind-drought-peak-demand event index, identify adverse weather events, and calculate their duration and severity.

3.4 Sensitivity Study

The methods presented in the previous sections require a number of subjective choices. For example, the level of national installed wind capacity in each country, and the number of days Demand-Net-of-Renewables is accumulated over within the WDI calculation. It is therefore important to test the sensitivity of the method, and the adverse weather events that are ultimately identified, to variations in these subjective choices.

To achieve this, a sensitivity study is carried out, in which the method is repeatedly applied to the 40 years of ERA5 meteorological data, varying a selection of input settings. The output adverse weather events can then be explored and compared. These varied input settings are presented in Table 1. If the adverse weather events identified using the various sensitivity study settings are relatively consistent, this gives greater confidence that the WDI definition described in the previous sections is robust. That is, it will provide a method for identifying representative periods of adverse weather, relevant for testing the resilience of a *range* of electricity system configurations.

The first row of Table 1 varies the demand model, used to estimate UK daily weather dependent demand from daily average temperature (see Figures 1 and 4). Setting 1 uses the UK demand model heating slope (Figure 1 a), while setting 2 uses the French model heating slope (Figure 1 b). In both cases, the baseline demand is kept at the UK value (35.1GW). The French demand model has a steeper heating slope, meaning that decreasing temperatures lead to an increased level of demand for heating. This reflects how heating in France is more electrified than in the UK. Using this model to represent the UK in setting 2 therefore allows for the exploration of how electrifying heating in the UK may impact the characterisation of adverse weather. Since UK daily average temperature does not exceed the cooling threshold (22.0°C) at any point in the 40-year ERA5 record, the sensitivity study cannot explore any variation in the cooling slope.

The second row of Table 1 varies the national installed level of wind capacity in each European country. Setting 1 uses the estimated future installed capacities, as described in Section 3.2 and shown in the second column of Table 11. As an alternative, setting 2 uses the current day installed capacities (first column of Table 11), allowing for the exploration of how using a less highly-renewable European electricity system impacts the identification of adverse weather events.

The third row of Table 1 varies the UK on-shore wind power curve, which estimates grid cell daily wind capacity factor from 100 m wind speed in that grid cell. Following guidance from the project advisory group, the sensitivity of the method to using the power curve used by National Grid when modelling on-shore turbines (also described in Section 3.2 of [nationalgridESO 2019](#) rather than the three wind power curves used by [Bloomfield et al. \(2019\)](#), is explored. Setting 1 uses the previously introduced curves of [Bloomfield et al. \(2019\)](#), while setting 2 uses the National grid on-shore curve. In both settings, all other

European countries are represented by the [Bloomfield et al. \(2019\)](#) curves, and the UK off-shore region is modelled using the National grid off-shore curve.

The fourth row of Table 1 varies the number of days over which the WDI is accumulated. Setting 1 uses the previously defined 7-day accumulation definition, whereas setting 2 does not apply any accumulation within the WDI (see Section 3.3 for more information about the WDI). This is designed to test whether the subjective choice of accumulating over 7 days does indeed better characterise long-duration periods of adverse weather.

Finally, these settings are tested for both the UK and Europe. The primary focus of this project is to identify adverse weather for the UK electricity system. However, the meteorological conditions in the rest of Europe will have an impact on the UK, due to between-country electricity system interconnectivity. As such, it is relevant to characterise adverse weather for both the UK and for Europe as a whole. Exploring both regions here also allows for the identification of whether adverse weather events occur at the same or different times in the UK and Europe, and hence whether different datasets of adverse weather events should be created for each region.

Input	Setting 1	Setting 2
UK Demand Model	UK heating slope (D1)	French heating slope (D2)
Installed wind capacity	Future 2050 scenario (C1)	Current 2020 scenario (C2)
UK on-shore wind power curve	Bloomfield et al. (2019)	National Grid
Accumulation period	7 days	1 day
Region	UK	Europe

Table 1: Table of settings varied within the sensitivity study. The D1, D2, C1 and C2 labels relate to demand model settings 1 and 2 and installed wind capacity scenario settings 1 and 2 respectively, used as sensitivity study setting acronyms in Section 4.1. The proposed method detailed in Sections 3.1, 3.2 and 3.3 uses all options in the 'Setting 1' column.

The adverse weather events identified using these sensitivity study settings are also compared to those identified using the energy data of [Bloomfield et al. \(2019\)](#) (labelled as 'Uni of Reading' in the results plots). In this dataset, weather dependent demand is calculated using the same gridded temperature data as in this study, and the same UK demand model as in Setting 1 in Table 1. The wind generation is also calculated using the same bias corrected gridded wind speed data as in this study, however, the location and level of installed wind capacity throughout Europe is specified as that of 2017 (taken from thewindpower.net database). The UK on-shore wind power curves used are the same as in Setting 1 in Table 1.

Meteorological insight suggests that the conditions that lead to adverse weather (i.e. low wind speed and low/high temperatures in winter/summer) often persist for long durations and extend over large ar-

eas, hence it is expected that the most extreme adverse weather events will be largely consistent across the demand model and installed wind capacity settings in Table 1. For this reason it is also expected that the identified periods of adverse weather will align with those identified using the energy dataset developed and used by Bloomfield et al. (2019), even though the location of installed wind capacity is quite different.

The results of this sensitivity study are presented in Section 4.1.

4 Results

This section presents the results of the sensitivity study, described in detail in Section 3.4. The final set of adverse weather events identified within the ERA5 historical period using the WDI is then presented, characterising the 1 in 2, 5, 10, 20, 50 and 100 year return level events in terms of event duration and severity in summer and in winter, in the UK and in Europe.

4.1 Sensitivity Study

The methods presented in Sections 3.1, 3.2 and 3.3 are repeatedly applied to the 40 years of ERA5 meteorological data, varying the input settings as defined in Table 1 and described in detail in Section 3.4. This section presents the results of this sensitivity study, firstly for the UK, secondly considering Europe as a whole, and finally comparing the UK and Europe.

4.1.1 UK

Figures 5 and 6 show comparisons of the duration and severity of summer-time and winter-time adverse weather events when identified using (1) the two options for UK on-shore wind power curve and (2) the two options for WDI accumulation period (as shown in Table 1). In each case, the settings are compared based on density plots⁸ of the values of the adverse weather event durations and severities.

Figure 5 shows how the two options for UK on-shore wind power curve give almost identical results. Therefore, for simplicity and consistency with the rest of Europe, the Bloomfield et al. (2019) on-shore power curves will be used in the final WDI definition. Figure 6 shows how the durations and severities of adverse weather events are very different when the WDI uses non-accumulated Demand-Net-of-Renewables (1-day) and when a 7-day accumulation is used (see Section 3.3 for more detail about the WDI). In the 1-day setting, a majority of identified events have durations of less than 5 days, hence long-duration (greater than 7 day) events are not represented. Conversely, using the 7-day accumulation setting identifies events of much longer durations. This option therefore better characterises long-duration events, as is the aim of this part of the project, and will be used in the final WDI definition.

⁸<https://www.data-to-viz.com/graph/density.html> (Accessed 28/09/2020)

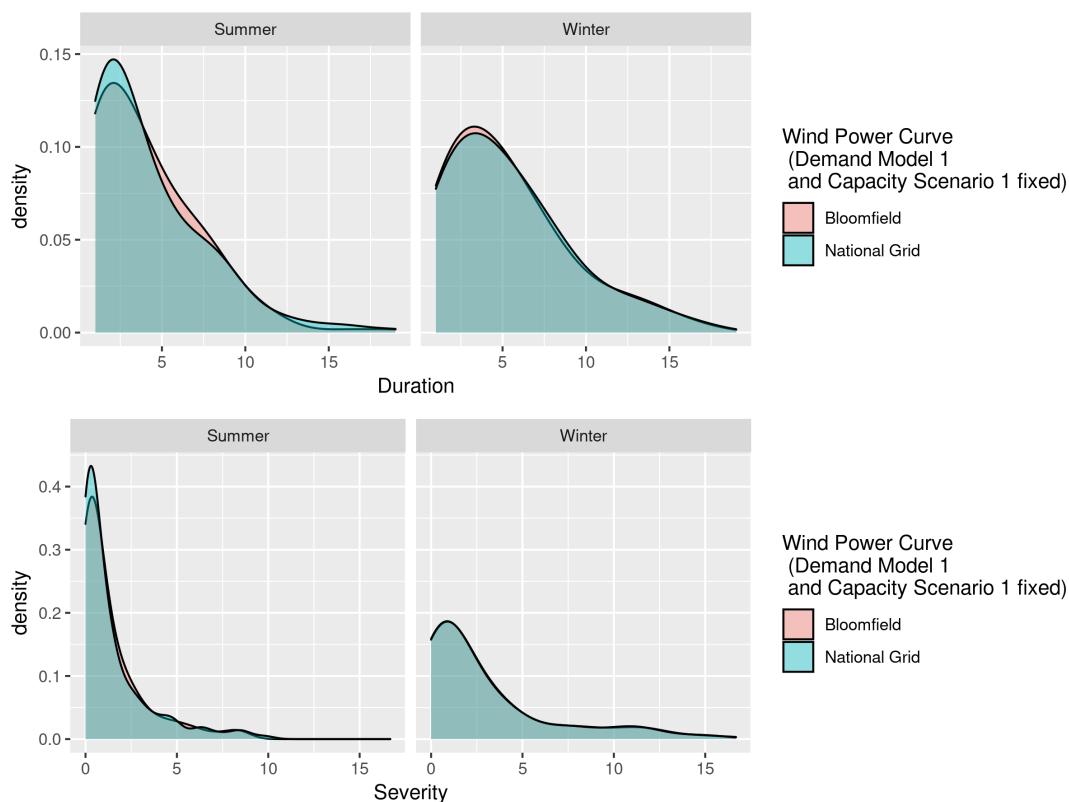


Figure 5: Density plots comparing the (top row) duration and (bottom row) severity of adverse weather events identified in (left column) summer and (right column) winter when using the two options for UK on-shore wind power curve specified in Table 1.

The density plots in Figure 7 show a comparison of the duration and severity of summer-time and winter-time adverse weather events when identified using each combination of UK demand model and installed wind capacity scenario as described in Table 1. These plots show how settings (D1,C1), (D1,C2) and (D2,C1) have very similar event durations and severities, while setting (D2,C2) gives slightly different, longer and more severe events. This difference between these two groups of settings is due to the relative dominance of the wind speed and temperature in the WDI calculation. For the first group of settings: (D1,C1), (D1,C2) and (D2,C1), the wind speed and hence wind generation part of the WDI is dominant because either the UK demand model is used, which is less sensitive to temperature (D1) and/or the installed wind capacity is set the future highly renewable scenario (C1). The WDI calculation in setting (D2,C2), on the other hand, is more dominated by temperature because it represents the French demand model (D2), which is more sensitive to temperature (steeper heating slope), and the current day level of installed wind capacity throughout Europe (C2). These results reflect a similar finding to those presented by Bloomfield et al. (2018), who show how the weather conditions that most strongly impact the British power system are different depending on the amount of installed wind power capacity, with cold temperature events having most impact in a low wind capacity scenario, and low wind speed events having most impact in a high wind capacity scenario.

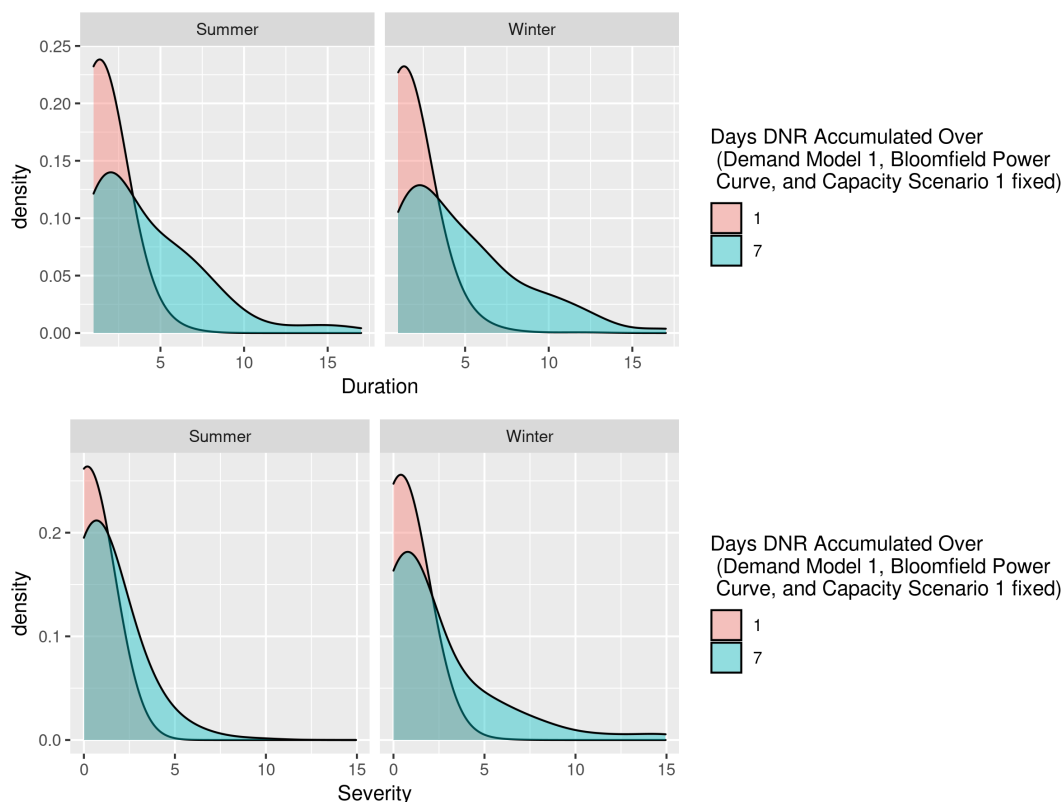


Figure 6: Density plots comparing the (top row) duration and (bottom row) severity of adverse weather events identified in (left column) summer and (right column) winter when Demand-Net-of-Renewables is accumulated over 7-days or not at all (i.e. 1 day), as specified in Table 1.

In this study, the aim is to develop an approach for characterising adverse weather events in a highly renewable electricity system. Hence, the (D1,C2) and (D2,C2) settings, characterising current day installed wind capacity (C2), are of less relevance. The consistency between the more relevant settings (D1,C1) and (D2,C1) in Figure 7, therefore, suggests good robustness in the WDI definition described in Section 3 (D1,C1) to the definition of the demand model (i.e. whether UK heating is electrified in the future or not). Following discussion with the project advisory group, two additional sensitivity tests were explored, and were found to further support this conclusion. Firstly, keeping the capacity scenario fixed as C1, the demand model heating slope was further increased to 3 GW/°C, characterising an even more sensitive demand-temperature relationship than D2 (the French heating slope). This could be thought of as a future in which the UK's heating system becomes even more dependent on electricity than the current French system. Adverse weather events identified by this alternative setting were also found to be consistent with (D1,C1) and (D2,C1). Secondly, the UK baseline demand level was varied by season to represent how demand for lighting changes throughout the year, such that instead of taking the value 35.1GW throughout the year, 45.1GW and 25.1GW were used in winter and summer respectively. This alternative setting was found to give almost identical adverse weather events to those identified using the (D1,C1) setting. This makes sense due to the relative scaling of the WDI, and hence the WDI threshold used to identify events (see Section 3.3).

The WDI robustness is further evidenced in Figures 8 and 9, which show a comparison of the WDI

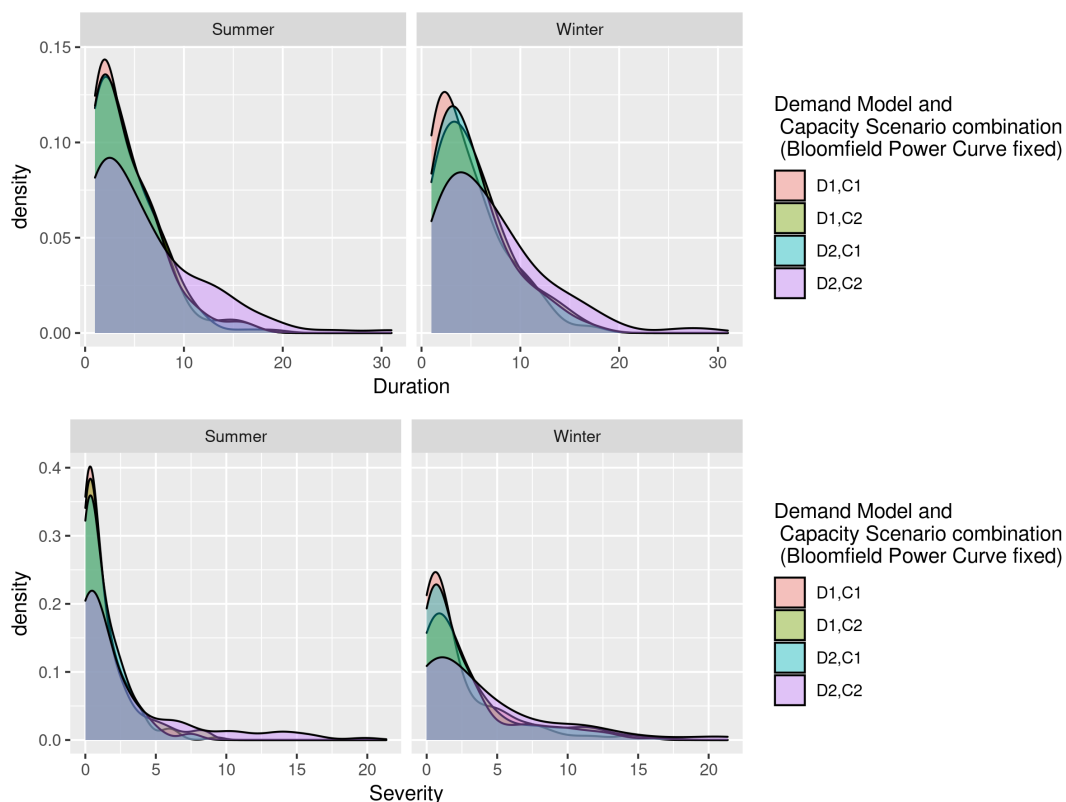


Figure 7: Density plots comparing the (top row) duration and (bottom row) severity of adverse weather events identified in (left column) summer and (right column) winter when using each combination of demand model and installed wind capacity scenario, as specified in Table 1. The labels D1, D2, C1 and C2 relate to the labels in Table 1.

during peak winter-time and summer-time adverse weather events in the UK, identified using each combination of UK demand model and European installed wind capacity scenario. These Figures show how the WDI looks very similar across settings, and again particularly for settings (D1,C1), (D1,C2) and (D2,C1). This is because, although the absolute Demand-Net-of-renewables will be different in each case (because a different combination of the demand model and installed wind capacity is used), when scaled by its long term average and standard deviation (separately for each setting) to calculate the WDI (see Section 3.3), a similar standardised metric is created across settings. This indicates that an adverse/stressful period of weather for the electricity system is likely to be adverse irrespective of the system set up (as was hypothesised in Section 3.4).

In the captions of Figures 8 and 9 the percentile (i.e. rank or extremity) of each of the events⁹ in each setting is given. These percentile values can be related to the event frequency, that is, on average how many events occur before seeing another event of a similar duration/severity:

- 1 in 2 events level: 50th percentile
- 1 in 5 events level: 80th percentile
- 1 in 10 events level: 90th percentile

⁹If there are 100 adverse weather events, the 90th percentile event in terms of the event duration/severity, is the one that has the 90th rank if all events are organised in ascending order according to their duration/severity.

- 1 in 20 events level: 95th percentile
- 1 in 50 events level: 98th percentile
- 1 in 100 events level: 99th percentile

These event frequencies can then be related to a 'return period'¹⁰, i.e. an estimate of the *time interval* between events of a similar duration/severity, by dividing the event frequency level by the average number of events per year. For example, if 120 events are identified within a 40 year period then there are on average 3 events per year, and hence the 99th percentile event has a return period of 100/3 years, and similarly the 98th percentile event has a return period of 50/3 years. Within the final datasets of adverse weather events, to be produced in future phases of this project, this characterisation of events (in terms of their return period in years) will be employed. This will allow for the identification of the 1 in 2, 5, 10, 20, 50 and 100 year return period events in terms of duration/severity, as proposed in [Butcher and Dawkins \(2020\)](#).

The percentiles presented in the captions of Figures 8 and 9 show how, as well as the timing and variability of the WDI being similar across sensitivity study settings (particularly (D1,C1), (D1,C2) and (D2,C1)), the event percentiles/ranks are also largely consistent. This means that, irrespective of the setting, similar events would be picked out of the meteorological record to represent the various return periods when creating the final adverse weather data set. This further indicates good robustness in the WDI definition.

Section 4.2 presents a series of tables showing the periods of UK adverse weather, picked out from the ERA5 dataset, to represent the six event frequency listed above. These are presented in terms of event duration and severity in winter and summer, and are identified using the WDI defined in Section 3 (D1, C1, [Bloomfield et al. \(2019\)](#) wind power curves, and 7-day accumulation period). These tables further show how a large number of the adverse weather events, identified using this definition of the WDI, are also identified by the other sensitivity study settings, particularly (D2,C1). These tables also show how there is most consistency across settings in the most extreme events (i.e. 90th percentile events and higher). These extreme events are most important for electricity system resilience testing. Hence, this consistency suggests that the most important events identified using the WDI, are representative of events that will have an impact on a range of future renewable electricity systems.

Figures 8 and 9 also present the equivalent WDI time series, calculated using the weather dependent demand and wind generation data of [Bloomfield et al. \(2019\)](#) (as explained in Section 3.4), for validation. These are labelled as 'Uni of Reading'. The UK weather dependent demand in [Bloomfield et al. \(2019\)](#) is equivalent to D1 setting. The wind generation in [Bloomfield et al. \(2019\)](#) uses the installed wind capacity and location of turbines as of 2017, rather than the 'potential' locations used here

¹⁰<https://niwa.co.nz/natural-hazards/faq/what-is-a-return-period> (Accessed 29/09/2020)

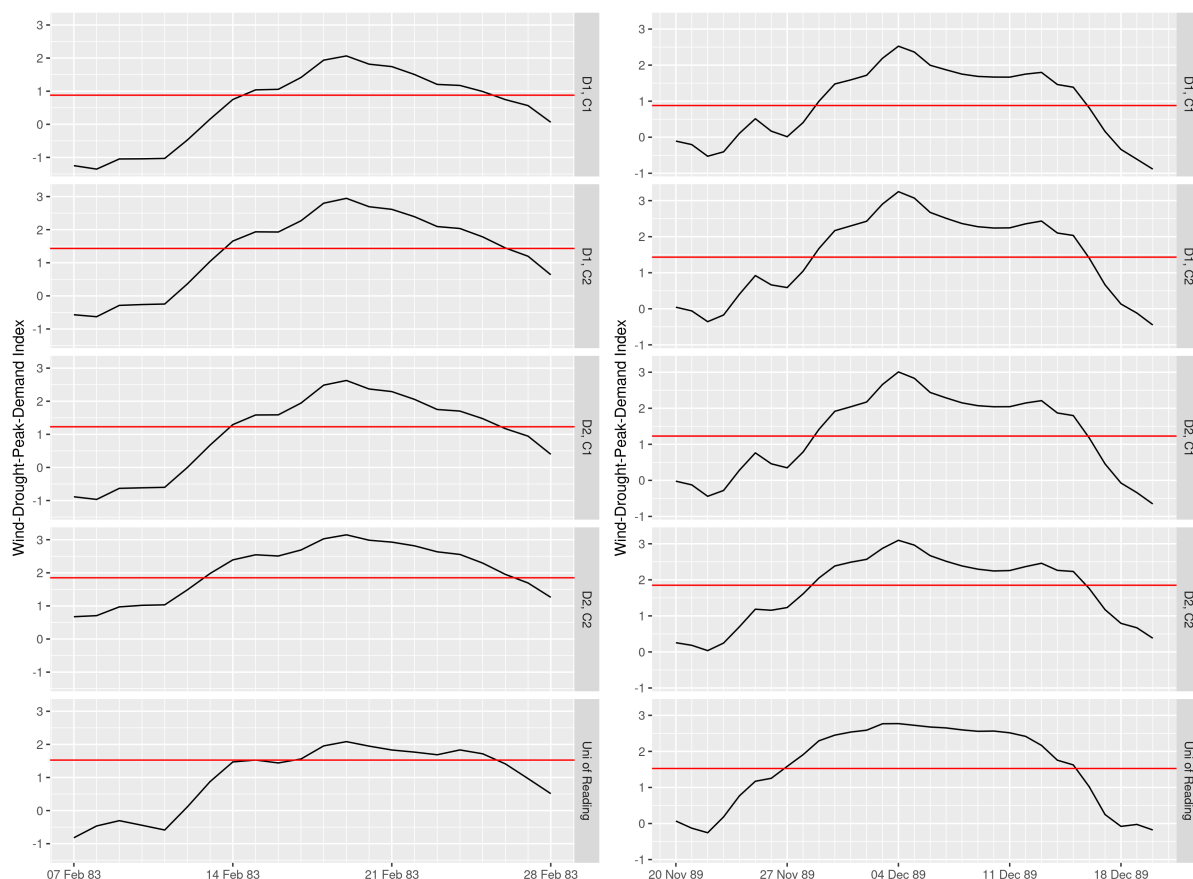


Figure 8: Time series plots of the wind-drought-peak-demand index during two peak UK winter adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the winter-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in February 1983, found to be the **89th, 92nd, 91st and 89th percentile event** in terms of severity in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. The right panel shows an event in November 1989, found to be the **99th, 100th, 99th and 96th percentile event** in terms of duration in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. In both cases, sensitivity study setting 1 is used for both the wind power curve and accumulation period, and equivalent time series of the index calculated using the University of Reading's energy dataset (Bloomfield et al., 2019) are presented for comparison.

(Figure 3). The University of Reading WDI time series in Figures 8 and 9 are therefore least consistent compared to the sensitivity study settings, however, in all cases an adverse weather event occurs. This is a very interesting result as it suggests that an extreme adverse weather event will impact the electricity system irrespective of exactly where the wind turbines are installed, supporting the hypothesis that such events are widespread enough to be picked out by a range of definitions of the WDI. This consistency between the WDI developed in this study (D1,C1) and that based on the data of Bloomfield et al. (2019) (University of Reading), also provides good confidence that the WDI is able to faithfully represent weather dependent demand and wind generation in the UK, and hence challenging periods when Demand-Net-of-Renewables is high. Further, Tables 2 - 5 show how the WDI picks out adverse weather events in the UK in the winters of 2009/10 and 2010/11, as well as the summer of 2018, periods that are known to have been challenging for the renewable electricity system.

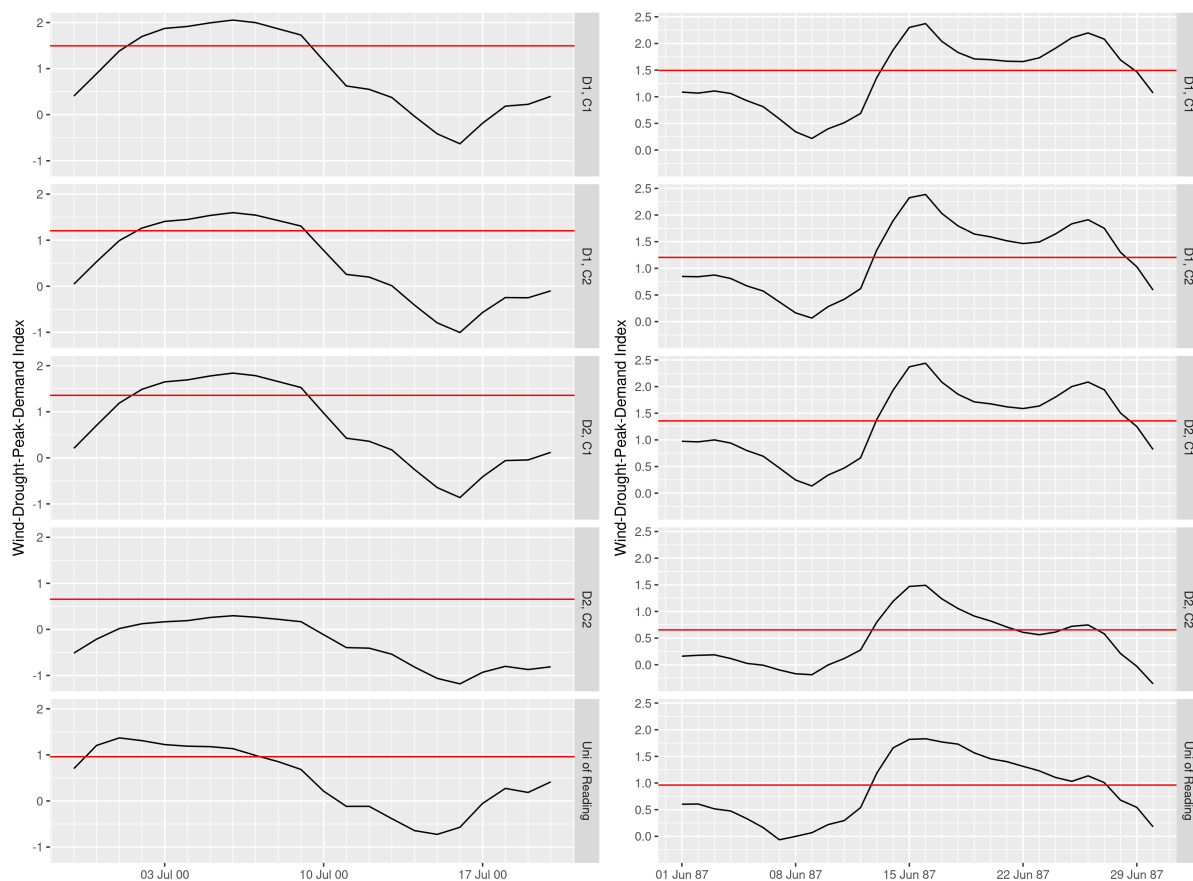


Figure 9: Time series plots of the wind-drought-peak-demand index during two peak UK summer adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the summer-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in July 2000, found to be the **89th, 90th and 90th percentile event** in terms of duration in the (D1,C1), (D1,C2) and (D2,C1) sensitivity study settings respectively (in this case no event is identified as occurring in the (D2,C2) setting). The right panel shows an event in June 1987, found to be the **99th, 100th, 100th and 76th percentile event** in terms of severity in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. In both cases, sensitivity study setting 1 is used for both the wind power curve and accumulation period, and equivalent time series of the index calculated using the University of Reading's energy dataset (Bloomfield et al., 2019) are presented for comparison.

4.1.2 Europe

A similar analysis to that presented for the UK in Section 4.1.1 is carried out for all of Europe. Equivalent results to those shown in Figures 5, 6 and 7 are found for Europe (not shown). This further supports the use of the Bloomfield et al. (2019) wind power curves and the 7-day accumulation period in the WDI definition. Varying the UK demand model (D1 or D2) has less impact on adverse weather events defined over all of Europe. This is to be expected since UK demand makes up only a fraction of the total demand picture over the whole of Europe. Most consistency is, instead, identified in settings with the same installed wind capacity (C1 or C2). The C1 option (highly-renewable) is most relevant here because the intention is characterise adverse weather for a highly-renewable electricity system. The consistency between C1 settings, i.e. (D1,C1) and (D2,C1), in Europe therefore further indicates good robustness in the WDI. That is, varying the demand model (i.e. whether UK heating is electrified in future or not) makes little difference to the adverse weather that is identified.

Figures 10 and 11 present equivalent comparisons of identified adverse weather events in Europe to those shown in Figures 8 and 9 for the UK. As in the UK, these plots show good consistency in the WDI in the different sensitivity study settings and in the University of Reading data (Bloomfield et al., 2019). Again, these events and their percentiles (ranks) are particularly consistent for (D1,C1) and (D2,C1), also evidenced in Tables 6 - 9.

Similar to the UK, this good agreement with the University of Reading data based metric suggest that the proposed WDI (calculated using D1 and C1) is able to represent weather dependent demand, wind generation, and hence challenging periods of weather in Europe. In addition, the consistency across sensitivity study settings also suggests that important Europe-wide events identified using the WDI are representative of events that will have an impact on a range of future renewable electricity systems.

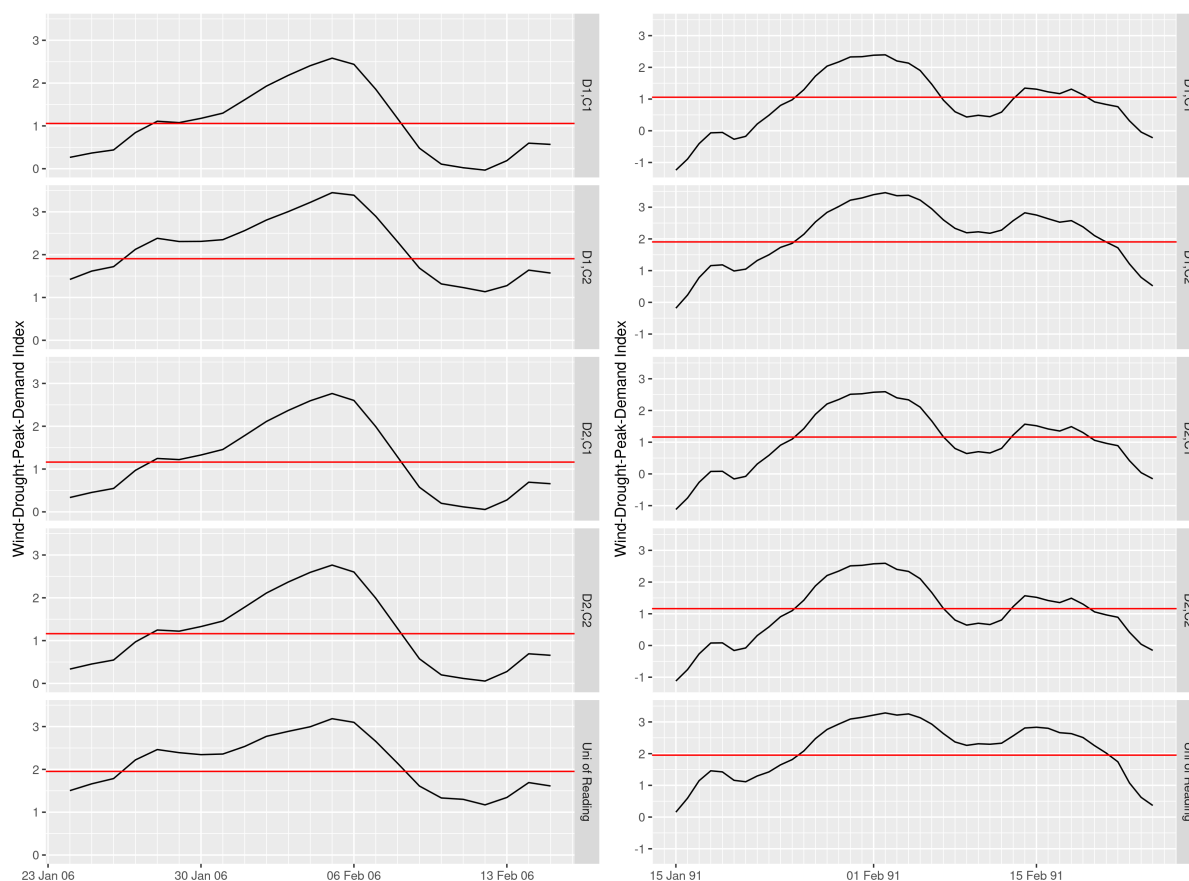


Figure 10: Time series plots of the wind-drought-peak-demand index during two peak European winter adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the winter-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in January/February 2006, found to be the **95th, 90th, 93rd and 88th percentile event** in terms of duration in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. The right panel shows an event in February 1991, found to be the **100th, 99th, 100th and 98th percentile event** in terms of severity in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. In both cases, sensitivity study setting 1 is used for both the wind power curve and accumulation period, and equivalent time series of the index calculated using the University of Reading's energy dataset (Bloomfield et al., 2019) are presented for comparison.

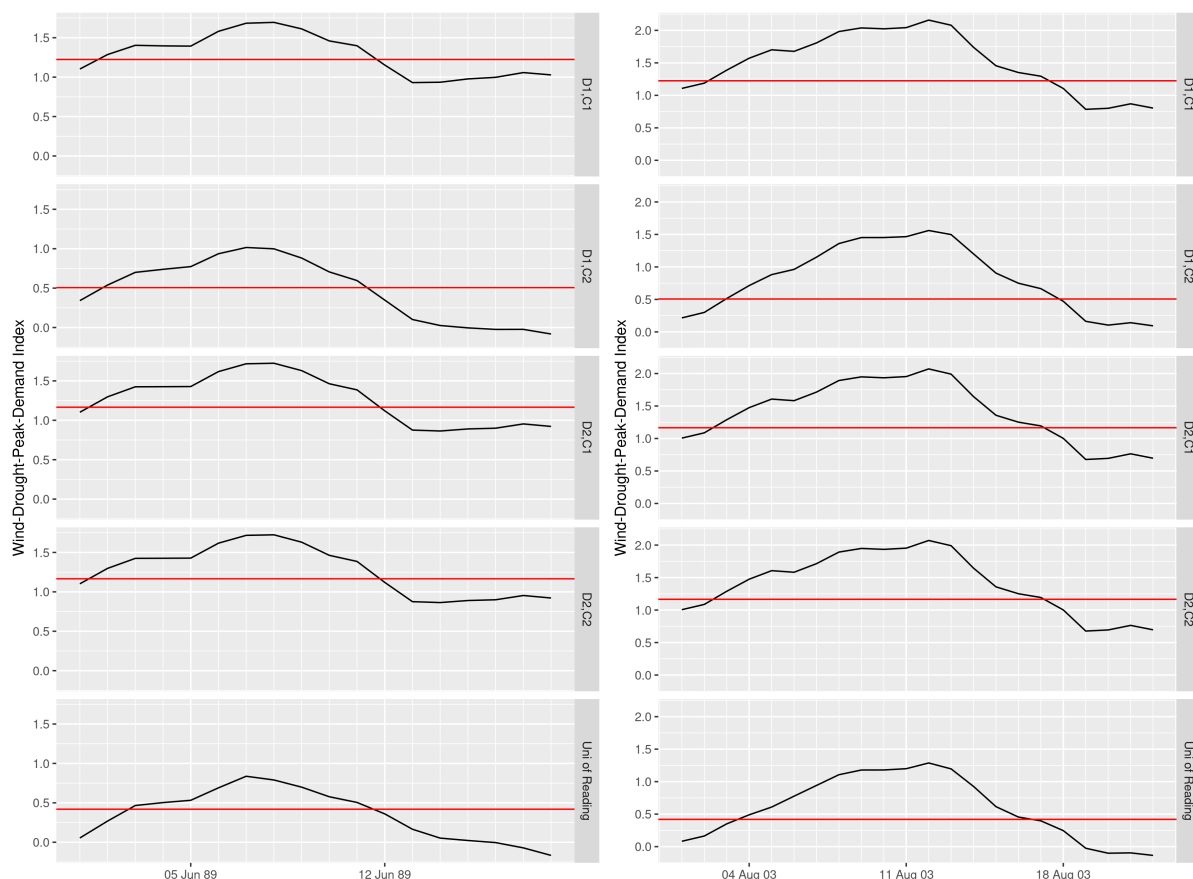


Figure 11: Time series plots of the wind-drought-peak-demand index during two peak European summer adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the summer-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in June 1989, found to be the **89th, 85th, 92nd and 71st percentile event** in terms of severity in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. The right panel shows an event in August 2003, found to be the **98th, 97th, 98th and 80th percentile event** in terms of duration in the (D1,C1), (D1,C2), (D2,C1) and (D2,C2) sensitivity study settings respectively. In both cases, sensitivity study setting 1 is used for both the wind power curve and accumulation period, and equivalent time series of the index calculated using the University of Reading's energy dataset (Bloomfield et al., 2019) are presented for comparison.

4.1.3 UK and Europe

Figure 12 presents the comparison of the WDI in the UK and Europe during two adverse weather events. These plots show how, for one of the most extreme events in each region, the WDI is quite different in the other region. Specifically, the 99th percentile winter-time event in Europe in terms of duration is the 28th percentile event in the UK, whereas the 99th percentile summer-time event in the UK in terms of severity is the 13th percentile event in Europe. These results suggest that, in general, adverse weather events are different in the two regions, supporting the need for producing separate datasets of adverse weather events for each region. Tables 2 - 9 do however, show that a number of adverse weather events are identified for both the UK and Europe, particularly in the winter (e.g. November 1987), suggesting some events are wide spread enough to significantly impact all of Europe and the UK.

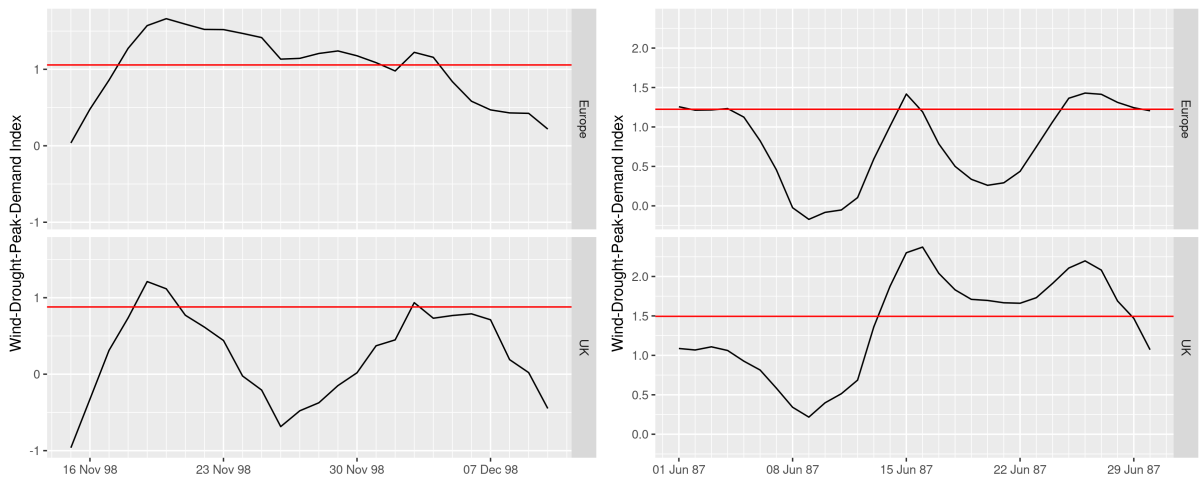


Figure 12: Time series plots of the wind-drought-peak-demand index during two peak adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in November 1998, found to be the European **99th percentile** winter-time event in terms of duration (**28th percentile event** in the UK). The right panel shows an event in June 1987, found to be the UK's **99th percentile** summer-time event in terms of severity (**13th percentile event** in Europe). In all cases, all other sensitivity study settings as set to option 1 (see Table 1).

4.2 Identified Adverse Weather Events

The sensitivity study results support the use of the WDI as defined in Section 3 to identify adverse weather events in the UK and Europe separately. As described in Section 3, this index calculates daily regional weather dependent demand from daily regional average temperature and the demand models of Bloomfield et al. (2019) using heating and cooling slopes as presented in Table 10. Regional daily wind generation is calculated for 100m wind speed in each grid cell in the region, by first calculating the grid cell wind capacity factor using the Bloomfield et al. (2019) wind turbine power curves on-shore, and the off-shore National Grid power curve off-shore, weighting this by the proportion of the grid cell in which wind turbines could potentially be installed, aggregating over the region and multiplying by the highly renewable estimates of future national installed wind capacities (second column of Table 11). The WDI is then calculated from daily Demand-Net-of-Renewables accumulated over a 7-day period, adverse weather events identified as times when this index exceeds its 90th percentile of the WDI in summer and winter, and events are characterised by their duration and severity. See Figure 4 for a schematic of this method.

Tables 2 - 9 present the adverse weather events identified using this final definition of the WDI, for UK and Europe, in summer and winter, and in terms of duration and severity separately. In each case, a selection of events associated with the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels are identified. For example, the 1 in 2 events level is the 50th percentile event, so events with percentiles between the 49th and 51st percentile are given. Following on from this work, it may be interesting to further validate these identified events by running them through detailed electricity system models, as described in Butcher and Dawkins (2020). Here, due to the limited historical data record (only 40 years) the events are characterised in terms of event frequency for simplicity. However, as previously noted, when this approach is used to identify adverse weather events for the final datasets based on longer data records (see Butcher and Dawkins 2020 for more detail), the events will be selected based on their return periods (in years).

4.2.1 UK

Tables of adverse weather events identified in the UK: 2, 3, 4, 5.

4.2.2 Europe

Tables of adverse weather events identified in the Europe: 6, 7, 8, 9.

Event No.	Duration Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	2015-01-22	3.00	0.25	No	No	No
2	49	2016-11-28	3.00	0.62	No	No	No
3	50	1987-12-01	4.00	0.70	No	No	No
4	51	1990-11-10	4.00	1.34	No	No	No
5	51	1992-01-15	4.00	0.41	No	Yes (48)	No
6	79	2011-03-25	7.00	4.70	No	No	No
7	79	2012-03-25	7.00	4.03	Yes (49)	No	No
8	80	2013-01-13	7.00	2.90	No	Yes (78)	No
9	81	2015-03-19	7.00	1.57	Yes (50)	No	No
10	81	2017-01-20*	7.00	4.63	Yes (78)	Yes (80)	No
11	89	1997-10-26	10.00	4.70	Yes (81)	Yes (81)	No
12	90	2006-01-29*	10.00	10.38	Yes (89)	Yes (90)	Yes (80)
13	90	2006-12-21*	10.00	8.81	No	No	No
14	91	2010-12-19	10.00	6.32	Yes (97)	Yes (96)	Yes (90)
15	94	1987-11-01*	12.00	14.70	Yes (91)	Yes (91)	No
16	95	1991-01-26*	12.00	11.48	Yes (91)	Yes (93)	Yes (99)
17	95	1993-10-28*	12.00	5.31	No	Yes (92)	No
18	96	1997-01-23*	12.00	8.06	Yes (93)	Yes (94)	No
19	97	2008-12-28*	12.00	7.89	Yes (96)	Yes (96)	Yes (88)
20	97	2010-02-15	12.00	7.53	Yes (99)	Yes (98)	Yes (93)
21	98	1987-02-14	13.00	9.14	Yes (95)	Yes (95)	No
22	99	1985-10-17	17.00	12.27	No	Yes (99)	No
23	99	2003-03-18*	14.00	14.54	Yes (96)	Yes (97)	No
24	100	1989-11-29*	17.00	14.95	Yes (100)	Yes (100)	Yes (96)

Table 2: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in winter in the UK in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of duration; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Tables 6-9), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1981-02-17*	5.00	0.88	No	No	No
2	49	2016-12-04	5.00	0.94	No	No	No
3	50	1991-10-26	3.00	0.96	No	No	No
4	51	2011-01-30*	3.00	0.97	Yes (52)	No	No
5	51	2012-03-16	4.00	1.02	No	No	No
6	79	1996-12-10*	8.00	3.75	No	Yes (82)	Yes (49)
7	79	2012-03-25	7.00	4.03	No	No	No
8	80	2011-03-04	6.00	4.23	Yes (79)	No	Yes (51)
9	81	1997-01-07	6.00	4.53	No	No	No
10	81	2017-01-20*	7.00	4.63	Yes (82)	No	Yes (51)
11	89	2015-10-01	10.00	6.02	No	No	No
12	90	1983-02-15	11.00	6.27	Yes (92)	Yes (91)	Yes (88)
13	90	2010-12-19	10.00	6.32	Yes (98)	Yes (96)	Yes (98)
14	91	2008-02-14	8.00	6.78	No	Yes (89)	No
15	94	1992-12-24*	10.00	7.97	Yes (94)	Yes (94)	Yes (88)
16	95	1997-01-23*	12.00	8.06	Yes (90)	Yes (92)	No
17	95	2006-12-21*	10.00	8.81	Yes (91)	Yes (93)	No
18	96	1987-02-14	13.00	9.14	Yes (97)	Yes (96)	Yes (90)
19	97	1991-01-26*	12.00	11.48	Yes (99)	Yes (99)	Yes (99)
20	97	2006-01-29*	10.00	10.38	Yes (98)	Yes (97)	No
21	98	1985-10-17	17.00	12.27	No	Yes (90)	No
22	99	1987-11-01*	12.00	14.70	Yes (94)	Yes (98)	No
23	99	2003-03-18*	14.00	14.54	Yes (93)	Yes (98)	Yes (50)
24	100	1989-11-29*	17.00	14.95	Yes (100)	Yes (100)	Yes (89)

Table 3: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in winter in the UK in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Tables 6-9), relevant for interconnectivity.

Event No.	Duration Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1995-06-04	3.00	0.87	No	Yes (48)	No
2	49	1996-09-06	3.00	0.80	No	No	No
3	50	1997-05-29	3.00	0.29	No	No	No
4	51	1997-08-18*	3.00	0.88	No	No	No
5	51	2001-08-05	3.00	0.54	No	No	No
6	79	2012-05-31	6.00	1.79	No	No	No
7	79	2013-06-06	6.00	2.44	No	Yes (78)	No
8	80	1981-08-29	7.00	3.43	No	Yes (80)	No
9	80	1982-05-17	7.00	1.54	Yes (79)	No	No
10	81	1983-07-22	7.00	1.91	No	No	No
11	81	1984-05-15	7.00	1.38	Yes (92)	Yes (88)	No
12	89	2000-07-02	8.00	3.16	Yes (90)	Yes (90)	No
13	89	2002-07-15	8.00	4.03	No	No	No
14	90	2002-08-07	8.00	2.95	No	No	No
15	90	2004-07-31*	8.00	2.51	Yes (48)	No	No
16	91	2014-07-25	8.00	1.77	No	No	No
17	94	2002-04-12	9.00	1.39	Yes (98)	Yes (93)	No
18	94	2016-06-08	9.00	3.89	Yes (91)	Yes (92)	No
19	95	1990-05-06	10.00	1.90	Yes (95)	Yes (95)	No
20	95	2018-07-17	10.00	4.12	No	Yes (94)	No
21	96	2018-06-03*	11.00	4.61	Yes (94)	Yes (97)	No
22	97	2006-07-19*	12.00	3.91	No	Yes (94)	No
23	97	2014-09-05*	13.00	3.33	Yes (78)	Yes (97)	No
24	98	1987-06-14	15.00	6.45	Yes (99)	Yes (99)	No
25	98	2000-07-23	14.00	6.09	Yes (93)	Yes (95)	No
26	99	1984-08-09	16.00	9.29	Yes (98)	Yes (98)	No
27	99	2010-05-15	15.00	6.02	Yes (100)	Yes (99)	Yes (93)
28	100	2013-07-11	17.00	5.87	Yes (50)	Yes (100)	No

Table 4: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in the UK in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of duration; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Tables 6-9), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1996-07-20	4.00	0.55	No	No	No
2	49	2014-06-04	3.00	0.55	No	No	No
3	50	1986-07-02	5.00	0.58	No	No	No
4	51	2010-07-26	5.00	0.63	No	No	No
5	51	2014-05-03	2.00	0.64	No	No	No
6	79	1983-04-06	6.00	1.90	Yes (98)	Yes (97)	Yes (99)
7	79	2005-07-13*	5.00	1.91	No	No	No
8	80	1980-05-30	6.00	2.06	Yes (88)	Yes (88)	No
9	80	1983-07-22	7.00	1.91	No	No	No
10	81	1983-08-23	8.00	2.19	No	No	No
11	81	2006-06-06	5.00	2.08	No	No	No
12	89	1997-07-08	9.00	3.14	No	No	No
13	89	2014-06-26*	7.00	3.02	No	No	No
14	90	1982-06-05*	8.00	3.27	No	Yes (80)	No
15	90	2000-07-02	8.00	3.16	No	No	No
16	91	2014-09-05*	13.00	3.33	Yes (54)	Yes (78)	No
17	94	2006-07-19*	12.00	3.91	Yes (49)	No	No
18	94	2016-06-08	9.00	3.89	No	No	No
19	95	1983-07-09	9.00	4.05	No	No	No
20	95	2002-07-15	8.00	4.03	Yes (82)	Yes (90)	No
21	96	2018-07-17	10.00	4.12	No	Yes (82)	No
22	97	1997-09-23*	9.00	5.37	Yes (93)	Yes (98)	Yes (50)
23	97	2018-06-03*	11.00	4.61	Yes (78)	Yes (91)	No
24	98	2010-05-15	15.00	6.02	Yes (99)	Yes (99)	No
25	98	2013-07-11	17.00	5.87	No	Yes (88)	No
26	99	1987-06-14	15.00	6.45	Yes (100)	Yes (100)	No
27	99	2000-07-23	14.00	6.09	No	Yes (96)	No
28	100	1984-08-09	16.00	9.29	Yes (94)	Yes (99)	No

Table 5: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in the UK in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Tables 6-9), relevant for interconnectivity.

Event No.	Duration Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1980-02-15	5.00	1.80	No	No	No
2	49	2018-02-21	4.00	1.59	No	No	No
3	50	1982-01-21	5.00	2.04	No	No	No
4	51	1984-02-16	5.00	2.99	No	No	No
5	79	2012-02-07	8.00	2.45	No	No	No
6	80	2017-01-21*	8.00	4.31	No	Yes (79)	No
7	81	1987-02-17	9.00	3.09	Yes (78)	No	No
8	81	1987-11-03*	9.00	4.01	No	Yes (80)	No
9	89	1991-12-02	11.00	4.34	Yes (79)	Yes (91)	No
10	89	1992-12-25*	11.00	7.17	No	Yes (88)	Yes (81)
11	90	1997-01-24*	11.00	4.84	No	Yes (89)	No
12	91	2003-02-11	11.00	6.37	No	Yes (90)	No
13	94	1991-01-26*	12.00	11.69	Yes (100)	Yes (95)	Yes (99)
14	95	1993-10-30*	12.00	3.59	No	Yes (92)	No
15	95	2006-01-28*	12.00	8.15	Yes (90)	Yes (93)	Yes (88)
16	96	2008-12-30*	12.00	5.87	Yes (93)	Yes (97)	Yes (92)
17	97	1981-02-15*	13.00	7.21	Yes (88)	Yes (93)	No
18	98	1985-01-08	13.00	9.06	No	Yes (98)	No
19	98	2003-03-19*	13.00	5.28	No	Yes (97)	No
20	99	1998-11-18	14.00	4.21	Yes (89)	Yes (96)	Yes (82)
21	100	1985-02-19	27.00	9.53	Yes (95)	Yes (100)	Yes (93)

Table 6: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in winter in Europe in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of duration; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in the UK (i.e. in Tables 2-5), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1994-02-22	4.00	1.17	Yes (49)	No	Yes (49)
2	49	2011-01-30*	4.00	1.35	No	No	No
3	50	1986-02-10	4.00	1.41	Yes (82)	No	Yes (81)
4	51	1991-03-15	4.00	1.42	No	No	No
5	79	1992-01-26	9.00	3.67	No	No	No
6	80	1996-12-10*	7.00	3.70	Yes (52)	Yes (79)	No
7	81	1989-12-01*	12.00	3.71	Yes (51)	Yes (80)	Yes (50)
8	81	2010-02-12	10.00	3.91	No	No	No
9	89	1997-01-24*	11.00	4.84	No	Yes (88)	No
10	89	2007-10-05	10.00	4.97	No	No	No
11	90	2006-12-23*	8.00	5.04	No	Yes (90)	No
12	91	2003-03-19*	13.00	5.28	No	No	No
13	94	1989-12-31	9.00	6.02	No	Yes (92)	Yes (80)
14	95	1993-02-10	8.00	6.18	No	Yes (91)	No
15	95	2003-02-11	11.00	6.37	Yes (89)	Yes (94)	No
16	96	1992-12-25*	11.00	7.17	Yes (90)	Yes (96)	Yes (88)
17	97	1981-02-15*	13.00	7.21	Yes (94)	Yes (97)	Yes (93)
18	98	1985-01-08	13.00	9.06	No	Yes (99)	No
19	98	2006-01-28*	12.00	8.15	Yes (91)	Yes (97)	Yes (89)
20	99	1985-02-19	27.00	9.53	Yes (96)	Yes (98)	Yes (94)
21	100	1991-01-26*	12.00	11.69	Yes (99)	Yes (100)	Yes (98)

Table 7: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in winter in Europe in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in the UK (i.e. in Tables 2-5), relevant for interconnectivity.

Event No.	Duration Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	2012-08-23	3.00	0.16	No	No	No
2	50	2013-07-17	3.00	0.40	No	Yes (92)	No
3	50	2014-08-06	3.00	0.35	No	No	No
4	51	2015-08-11	3.00	0.59	No	No	No
5	51	2017-09-22	3.00	0.56	No	No	No
6	79	1981-04-06	7.00	2.94	Yes (88)	No	Yes (79)
7	79	1982-06-05*	7.00	3.03	Yes (50)	Yes (79)	No
8	80	1982-07-23	7.00	0.52	No	No	No
9	81	1984-04-08	7.00	2.64	Yes (100)	Yes (80)	Yes (100)
10	81	1992-06-27	7.00	1.57	No	Yes (81)	No
11	89	1996-04-07	9.00	2.23	Yes (99)	Yes (93)	Yes (97)
12	89	1997-09-23*	9.00	2.03	No	No	No
13	90	2002-08-03	9.00	2.46	No	Yes (88)	No
14	91	2004-07-31*	9.00	3.91	No	Yes (89)	No
15	91	2010-06-26	9.00	1.89	No	Yes (90)	No
16	94	1984-08-14	11.00	3.95	Yes (51)	Yes (92)	No
17	94	1997-08-17*	11.00	3.32	No	Yes (94)	No
18	95	2016-07-23	11.00	3.11	No	Yes (95)	No
19	96	1981-08-04	13.00	3.26	No	Yes (96)	No
20	96	2018-06-02*	12.00	2.87	No	Yes (96)	No
21	97	2000-08-13	13.00	3.40	Yes (82)	Yes (97)	No
22	97	2006-07-20*	13.00	8.19	Yes (93)	Yes (98)	No
23	98	2003-08-03	15.00	7.95	Yes (97)	Yes (98)	Yes (88)
24	99	1990-05-09	16.00	4.80	Yes (82)	Yes (99)	No
25	99	2018-07-13	16.00	5.23	No	Yes (99)	No
26	100	1994-07-16	26.00	7.44	No	Yes (100)	No

Table 8: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in Europe in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of duration; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in the UK (i.e. in Tables 2-5), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration (Days)	Severity (GW)	In (D1,C2)? (Percentile)	In (D2,C1)? (Percentile)	In (D2,C2)? (Percentile)
1	49	1987-05-29	4.00	0.36	No	No	No
2	50	2006-06-18	3.00	0.37	No	No	No
3	50	2012-08-04	3.00	0.38	No	No	No
4	51	2005-07-14*	5.00	0.40	No	No	No
5	51	2013-07-17	3.00	0.40	No	Yes (90)	No
6	79	1990-06-16	6.00	1.70	No	Yes (81)	No
7	79	2014-09-06*	8.00	1.67	No	Yes (79)	No
8	80	2014-06-27*	6.00	1.74	No	Yes (80)	No
9	81	2007-06-09	7.00	1.88	No	Yes (80)	No
10	81	2008-05-16	8.00	1.83	No	No	No
11	89	1984-04-08	7.00	2.64	Yes (99)	Yes (95)	Yes (99)
12	89	1989-06-02	10.00	2.67	No	Yes (92)	No
13	90	2018-06-02*	12.00	2.87	No	Yes (88)	No
14	91	1981-04-06	7.00	2.94	Yes (93)	Yes (96)	Yes (92)
15	91	1982-06-05*	7.00	3.03	No	Yes (89)	No
16	94	1997-08-17*	11.00	3.32	No	Yes (90)	No
17	94	2013-07-21	10.00	3.27	No	Yes (90)	No
18	95	2000-08-13	13.00	3.40	No	Yes (92)	No
19	96	1984-08-14	11.00	3.95	No	Yes (94)	No
20	96	2004-07-31*	9.00	3.91	No	Yes (95)	No
21	97	1982-05-14	11.00	4.18	Yes (90)	Yes (97)	No
22	97	1990-05-09	16.00	4.80	No	Yes (98)	No
23	98	2018-07-13	16.00	5.23	No	Yes (98)	No
24	99	1994-07-16	26.00	7.44	No	Yes (99)	No
25	99	2003-08-03	15.00	7.95	Yes (97)	Yes (99)	No
26	100	2006-07-20*	13.00	8.19	Yes (94)	Yes (100)	No

Table 9: Table summarising the adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in Europe in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in the UK (i.e. in Tables 2-5), relevant for interconnectivity.

5 Summary and Conclusion

This report has presented a method for characterising long-duration wind-drought-peak-demand adverse weather events for renewable electricity system resilience testing, based on the meteorological conditions in a region. This approach represents daily regional weather dependent demand using daily regional average temperature and the demand models of [Bloomfield et al. \(2019\)](#); and daily regional wind generation using 100m wind speed, the wind turbine power curves of [Bloomfield et al. \(2019\)](#) and National Grid ([nationalgridESO, 2019](#)), a representation of the potential for installed wind capacity across Europe (using insights from [Price et al. \(2018\)](#) in Great Britain and Natural Earth urban areas in the rest of Europe), and estimates of highly renewable national installed wind capacities in European countries. Subsequently, an adverse weather index is developed using insights from hydrological drought modelling. This Wind-Drought-Peak-Demand Index is calculated from Demand-Net-of-Renewables, defined as daily regional weather dependent demand minus wind generation, accumulated over the preceding 7-day period and standardised by scaling by the long-term average and standard deviation. Adverse weather events are then identified as times when this index exceeds its 90th percentile in either summer and winter, and events are characterised by their duration and severity.

This approach aims to keep the characterisation of adverse weather as independent of a particular future electricity system as possible. This is achieved by using the 'potential' for installed wind capacity in each grid cell, rather than a current day or future representation of where wind turbines are actually located. To test the robustness of this characterisation, a sensitivity study is carried out in which subjectively-selected inputs of the method are modified, and the identified adverse weather events are explored and compared. In particular, the UK demand model and European installed wind capacities are varied. The results of this sensitivity study are also compared with those events identified using the energy data of [Bloomfield et al. \(2019\)](#), which represents the location and magnitude of installed wind capacities in Europe as of 2017.

For both the UK and Europe, the results of the sensitivity study showed good consistency in the adverse weather events identified using each combinations of demand model and installed wind capacity scenario. In particular, when the more relevant future highly-renewable installed wind capacity setting was used (C1), varying the UK demand model to represent either the existing relationship between temperature and demand (D1) or a more electrified heating scenario (D2) resulted in an almost identical WDI and subsequently identified adverse weather events. Exploring time series of adverse weather events in the different settings showed how the same events were identified in most cases, irrespective of the sensitivity study setting. This shows that adverse/stressful periods of weather for the electricity system are likely to be adverse irrespective of the system set up, as was previously hypothesised based on meteorological insights. In addition, it was found that the majority of adverse weather events identified using the proposed WDI definition (D1,C1), were also identified by the other sensitivity study

settings, particularly (D2,C1), and that they were, in general, of similar extremity (i.e. similar percentile levels). This consistency was observed primarily for the most extreme events (i.e. 90th percentile, or 1 in 10 year, events and higher), most important for resilience testing. This therefore showed that the most important events identified using the WDI, are likely to be representative of events that will have an impact on a range of future renewable electricity systems. This was further supported by the similarity of the WDI calculated using the energy data of [Bloomfield et al. \(2019\)](#), suggesting that extreme adverse weather event will impact the electricity system irrespective of exactly where the wind turbines are installed.

This consistency between the WDI developed in this study (D1,C1) and that based on the data of [Bloomfield et al. \(2019\)](#), also provided good confidence that the WDI was able to faithfully represent weather dependent demand and wind generation in the UK and Europe, and hence challenging periods adverse weather. This was further evidence by the identification of adverse weather events in the UK in the winters of 2009/10 and 2010/11, and the summer of 2018, periods known to have been challenging for the UK renewable electricity system.

The sensitivity study was also used to explore the method's sensitivity to the on-shore turbine power curve used, and the accumulation period within the WDI definition. The results of the study showed that the adverse weather events were approximately equal when comparing the two turbine options, and that the 7-day accumulation method better represented long-duration events, as was the aim of this study. In addition, the adverse weather events identified for the UK and Europe as a whole were compared. This showed that in some cases the extreme events in one region were not extreme in the other, supporting the need for two different adverse weather event datasets to characterise each region separately.

Finally, this report presented a series of tables summarising the adverse weather events identified using the final definition of the WDI, for UK and Europe, in summer and winter, and in terms of duration and severity separately. As a follow up to this work, it may be interesting to have energy modellers, such as those in the project user group, run these identified events through their energy system models, in order to further validate their characterisation of stressful weather.

This report has provided a validated method for characterising long-duration wind-drought-peak-demand adverse weather events for a highly renewable electricity system. This approach can now be used to identify such events within any meteorological data set, allowing for the development of the final adverse weather datasets in later phases of this project.

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7 Glossary

CDD = Cooling Degree Days

C1 = Wind capacity scenario setting 1 (see [Table 1](#))

C2 = Wind capacity scenario setting 2 (see [Table 1](#))

D1 = Demand model setting 1 (see [Table 1](#))

D2 = Demand model setting 2 (see [Table 1](#))

GW = Gigawatts

HDD = Heating Degree Days

IEC = International Electrotechnical Commission

IPCC = Intergovernmental Panel on Climate Change

WDD = Weather Dependent Demand

WDI = Wind Drought Index

8 Appendix

Country	Baseline demand in GW (<i>a</i>)	Heating slope (<i>b</i>)	Cooling slope (<i>c</i>)
Austria	6.8	0.09	0.85
Belgium	9.6	0.12	0.11
Bulgaria	3.8	0.1	0.13
Croatia	1.9	0.02	0.09
Czech Republic	7.1	0.1	0.11
Denmark	7.9	0.15	0
Finland	7.9	0.15	0
France	46.2	2.02	1.19
Germany	56.4	0.33	1.23
Greece	5.3	0.11	0.46
Hungary	4.8	0.03	0.09
Ireland	3	0.04	0
Italy	33.7	0.2	2.77
Latvia	0.8	0.01	0
Lithuania	0.8	0.01	0
Luxembourg	0.5	0	0
Montenegro	0.33	0	0.05
Netherlands	13	0.11	0.37
Norway	8.7	0.46	0
Poland	18.8	0.14	0.3
Portugal	5.6	0.1	0.1
Romania	6.4	0.07	0.2
Slovakia	3.2	0.03	0.06
Slovenia	1.5	0.01	0.04
Spain	28.5	0.25	0.93
Sweden	12	0.36	0
Switzerland	6.6	0.06	0
United Kingdom	35.1	0.75	1.19 (0 in Bloomfield et al. (2019))

Table 10: Table of demand model constants for each European country included within this study, taken from [Bloomfield et al. \(2019\)](#). The cooling slope in the UK is given the same value as in France, to capture future cooling demand under climate change (see Section 3.1). The constants *a*, *b*, and *c* relate to equation 1 and the diagrams shown in Figure 1.

Country	Current National Installed Wind Capacity (GW)	National Installed Wind Capacity Estimate for 2050 (GW)
Austria	2.8781	7.8996
Belgium	4.2301	11.6105
Bulgaria	0.6444	1.7687
Croatia	0.9114	2.5016
Czech Republic	0.3298	0.9052
Denmark	6.7167	18.4356
Finland	2.4399	6.6969
France	17.3442	47.6054
Germany	63.4961	174.2805
Greece	2.8575	7.8431
Hungary	0.3844	1.0551
Ireland	4.0267	11.0523
Italy	10.8624	29.8145
Latvia	0.0531	0.1457
Lithuania	0.5356	1.4701
Luxembourg	0.1535	0.4213
Montenegro	0.1175	0.3225
Netherlands	6.119	16.795
Norway	2.9549	8.1104
Poland	5.9153	16.2360
Portugal	5.4686	15.0099
Romania	2.9813	8.1829
Slovakia	0.0032	0.0088
Slovenia	0.0032	0.0088
Spain	24.1435	66.2677
Sweden	9.2226	25.31376
Switzerland	0.0868	0.2382
United Kingdom	30.105	120.00
Total	204.98	600.00

Table 11: Table of national installed wind capacity levels for European countries. The current vales (in the left column) are taken from thewind-power.net. The future 2050 values (right column) are estimated based on UK installed wind capacity increasing to 120GW and Europe as a whole increasing to 600GW. For countries other than the UK, the 2050 values are estimated such that the proportion of total European (excluding the UK) installed capacity in each country is equal to the current day proportion.

9 Addendum: Surplus Generation Events

This section has been added to the original report to present the complementary approach developed for characterising surplus generation adverse weather events. That is, periods of time during which a surplus of electricity is generated beyond that required. This is known to cause challenges for system operators in distributing the surplus power. These events do, however, provide opportunities for trading electricity to other European countries via interconnectivity. This type of event predominantly occurs in the summer, when demand is relatively low. This analysis therefore focuses on months April-September (inclusive).

This section firstly outlines the method developed for characterising long-duration surplus-generation events, followed by the design of an additional, similar sensitivity study to that described in Section 3.4. The results of this sensitivity study are then presented and discussed. Finally, tables of the long-duration surplus-generation adverse weather events are provided. These are identified within the historical period using the final stress event index.

9.1 Method

Surplus generation adverse weather events will occur within a region when wind speed and solar radiation are high, leading to high renewable electricity generation; and temperatures are moderate to high/low, leading to low heating/cooling demand in winter/summer. Since solar radiation is higher in the summer, due to the longer days, this form of adverse weather event is most likely to occur in the summer.

In particular, in a future highly renewable electricity system, these adverse weather events will occur and become long-duration events when renewable electricity generation exceeds electricity demand for a prolonged period of time. As such, characterising this form of adverse weather events via a 'Surplus-Generation Index' (SGI), will require the estimation of 'Renewables-Net-of-Demand', defined as the regional renewable electricity generation (from wind and solar) minus the regional electricity demand.

Two of the components of Renewables-Net-of-Demand have been calculated in the previous sections of this report: weather dependent demand, as described in Section 3.1; and wind generation, as described in Section 3.2. The third component, solar generation, is now calculated, again using insights from Bloomfield et al. (2019), as detailed in the following sections and summarised in the schematic shown in Figure 14. These three components are then combined to estimate daily Renewables-Net-of-Demand during summer months. The solar generation component was not included in the exploration of the wind-drought-peak-demand events, so as to focus specifically on wind drought conditions. This could, however be included within the index in later stages of the project if preferred by users. As in the previous part of this study, the historical 40-year (1979-2018) ERA5 meteorological reanalysis dataset is used to represent the daily meteorological conditions in Europe. The same methods could, however,

be applied to any suitable meteorological dataset.

9.1.1 Estimating Solar Generation

The method developed to estimate regional daily solar electricity generation is based on insights from [Bloomfield et al. \(2019\)](#), who follow a similar approach to [Bett and Thornton \(2016\)](#). Similar to [Bloomfield et al. \(2019\)](#), we base the calculation on gridded near surface air temperature and incoming surface solar radiation over land. As in the previous sections of this report, these gridded meteorological variables are taken from the ERA5 reanalysis dataset.

On a given day and within a given land grid cell, the solar power capacity factor, defined as the proportion of a solar panel's maximum possible generation produced, is calculated based on a linear function of the surface temperature and incoming surface solar radiation. This function first calculates the relative efficiency of the solar panel, η , as a function of surface temperature at that location and time, T :

$$\eta(T) = \eta_r(1 - \beta_r(T - T_r)), \quad (2)$$

where η_r is the photovoltaic panel efficiency evaluated at the reference temperature T_r , and β_r is the fractional decrease of cell efficiency per unit temperature increase. Following [Bloomfield et al. \(2019\)](#) and [Bett and Thornton \(2016\)](#), the constants in Equation 2 are defined as: $\eta_r=0.9$, $T_r=25^\circ\text{C}$ and $\beta_r=0.00042$. Here, the temperature at the location of the solar panel, T , is the grid cell near surface temperature value taken from the ERA5 dataset. The solar power capacity factor at the given time and location (grid cell) is then calculated as:

$$CF = \eta(T) \frac{G}{G_r}, \quad (3)$$

where G is the incoming surface solar radiation at that location and time, and G_r is the reference incoming surface solar radiation, set to 1000Wm^{-2} as in [Bloomfield et al. \(2019\)](#). As these are linear functions of temperature and solar radiation, solar generation varies linearly with these meteorological variables. This linear relationship is increasing with solar radiation and decreasing with temperature.

Similar to the wind generation calculation (Section 3.2), within each land grid cell the solar capacity factor (calculated as shown above) is then weighted by the installed solar capacity within that grid cell (as a fraction of the national total). In [Bloomfield et al. \(2019\)](#), this is achieved by assuming a uniform distribution of installed solar capacity over all land grid cells in each country. [Bloomfield et al. \(2019\)](#) note how, though crude, this spatial approximation is necessitated by the limited information available about where solar generation capacity is located throughout Europe. Within this study an equivalent uniform distribution of solar capacity is assumed for all European countries other than Great Britain.

In Great Britain, the potential for installed solar capacity in each land grid cell is informed by the analysis of [Price et al. \(2018\)](#), similar to the method used to weight the installed wind capacity in Section 3.2. As for installed wind capacity, [Price et al. \(2018\)](#) devise a region within Great Britain, within which solar capacity could be installed, based on a number of technical, social and environmental restrictions. These include ground steepness, land use type (e.g. areas of outstanding natural beauty), and policies to protect wildlife habitats.

Figure 13 shows the resulting location of where solar capacity can and cannot be installed within Great Britain, taken from [Price et al. \(2018\)](#). Equivalent maps for other European countries would be blue throughout (i.e. it is assumed that solar can be installed anywhere as in [Bloomfield et al. \(2019\)](#)). As in the wind generation calculation, the information in Figure 13, and the assumed uniform distribution in other countries, is used to calculate the proportion of each ERA5 grid cell that has the potential to contain solar panels. The total daily solar capacity factor in a region/country is then found by multiplying the solar capacity factor, in each grid cell within that region, by the installed solar capacity weighting calculated for that grid cell (as a fraction of the total installed capacity weight in that region), and aggregating over the region. Finally, for a given day, the regional total solar generation is calculated by multiplying the daily regional capacity factor by the national level of installed solar power.

The current day national level of installed solar power in each country can be obtained from the National Generation Capacity Data Platform¹¹. These values are shown in the first column of Table 12. Since the aim of this project is to identify adverse weather events relevant for a highly renewable electricity system, here we represent the national level of installed wind power in each country as an estimate of the possible level by 2050. Following guidance from the Committee on Climate Change and members of the project advisory group, a national installed capacity of 100 GW is employed for the UK. Further, Europe as a whole is represented as having installed wind capacity of 800 GW by 2050. Similar to the wind generation method (Section 3.2), for countries other than the UK, the future highly-renewable national installed solar capacities are increased such that the proportion of total European installed capacity (800 GW) in that country is equal to the current day proportion. These values are shown in the second column of Table 12.

This solar generation calculation process is demonstrated graphically in the top panel of the schematic in Figure 14.

¹¹https://data.open-power-system-data.org/national_generation_capacity/ (Accessed 13/01/2021)

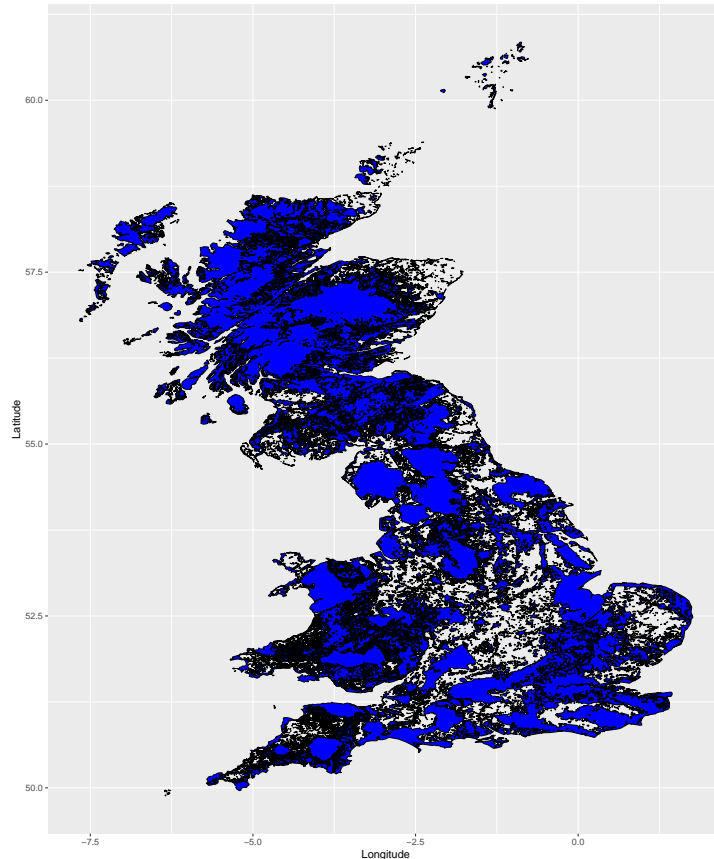


Figure 13: Map showing the potential location of installed solar capacity in Great Britain, as used within this study, taken from [Price et al. \(2018\)](#). The blue shaded regions (including the black outline of these regions) represent where solar panel *can* be located, and the unshaded regions (blank areas) are where solar panels *cannot* be located. Equivalent maps for other European countries would be blue throughout (i.e. it is assumed that solar panels can be installed anywhere, as in [Bloomfield et al. \(2019\)](#))

9.1.2 The Surplus-Generation Index

The methods described in previous sections (3.1, 3.2, 9.1.1) can be used to estimate daily weather dependent demand, daily wind generation, and daily solar generation from meteorological conditions in each European country listed in Table 12. These three quantities can then be used together to calculate daily 'Renewables-Net-of-Demand', defined as wind generation plus solar generation, minus weather dependent demand. This metric therefore represents how much renewable generation is left after demand for electricity is met, and hence how much unneeded electricity must be managed by the system operator. In a highly renewable future electricity system, adverse weather causing surplus generation events will be associated with days when this metric is particularly high.

As for the WDI (Section 3.3), Renewables-Net-of-Demand accumulated over a number of days is thought to be more relevant for capturing long-duration events and better representing the function of electricity storage. As for the WDI, the Surplus-Generation Index (SGI) is therefore based on Renewables-Net-of-Demand accumulated over every 7 day period, representing how bad the previous week has been in terms of accumulating surplus renewable generation net of weather dependent demand. Again, similar to the WDI, this accumulated metric is then scaled by its long term average and standard devi-

Country	Current National Installed Solar (GW)	National Installed Solar Capacity Estimate for 2050 (GW)
Austria	1.6190	10.8168
Belgium	3.3000	22.0477
Bulgaria	1.0590	7.0753
Croatia	0.0560	0.3741
Czech Republic	2.0680	13.8166
Denmark	1.0001	6.6818
Finland	0.1130	0.7550
France	9.4380	63.0566
Germany	40.7160	272.0291
Greece	2.6450	17.6716
Hungary	0.2200	1.4700
Ireland	0.0530	0.3541
Italy	20.2000	134.9590
Latvia	0.0030	0.02004
Lithuania	0.07	0.4677
Luxembourg	0.128	0.8552
Montenegro	0	0
Netherlands	3.9370	26.3036
Norway	0.045	0.3007
Poland	0.4301	2.8738
Portugal	0.5590	3.7348
Romania	1.3820	9.2333
Slovakia	0.5330	3.5610
Slovenia	0.2753	1.8396
Spain	12.3170	82.2916
Sweden	0.4350	2.9063
Switzerland	2.1710	14.5047
United Kingdom	13.3768	100.00
Total	118.1493	800.00

Table 12: Table of national installed solar capacity levels for European countries. The current vales (in the left column) are taken from the National generation capacity data platform¹¹. The future 2050 values (right column) are estimated based on UK installed solar capacity increasing to 100 GW and Europe as a whole increasing to 800 GW. For countries other than the UK, the 2050 values are estimated such that the proportion of total European (excluding the UK) installed capacity in each country is equal to the current day proportion.

ation to give the final SGI. This calculation process is demonstrated graphically in the bottom panel of the schematic is Figure 14.

In exactly the same way as the WDI, the SGI can be used to identify periods of adverse weather, by finding periods over which the SGI exceeds its 90th percentile. While summer-time (April-September) surplus generation events are the main focus of this analysis, the SGI is calculated for the whole year and (as in the WDI) a different summer and winter-time 90th percentile threshold is used to identify

adverse weather events in each season. This is done to allow for events that start in summer months but continue on into the winter to be fully captured (e.g. those that begin towards the end of September and carry on to October).

Each identified period of surplus generation adverse weather is then characterised in terms of its duration: the number of days over which the SGI exceeds the adverse weather threshold; and its severity: the accumulated difference between the SGI and the extreme threshold over the duration of the event. These metrics are demonstrated in the third step in the bottom panel of Figure 14.

As for the wind-drought-peak-demand adverse weather events, this method can be used to identify periods of adverse weather leading to surplus generation for the electricity system, based on any suitable gridded meteorological data set. Again, using the calculated event durations and severities, particular events related to relevant return periods (e.g. 1 in 20 year event) in terms of duration and severity can then be identified and shared, as proposed in the project scoping report ([Butcher and Dawkins, 2020](#)).

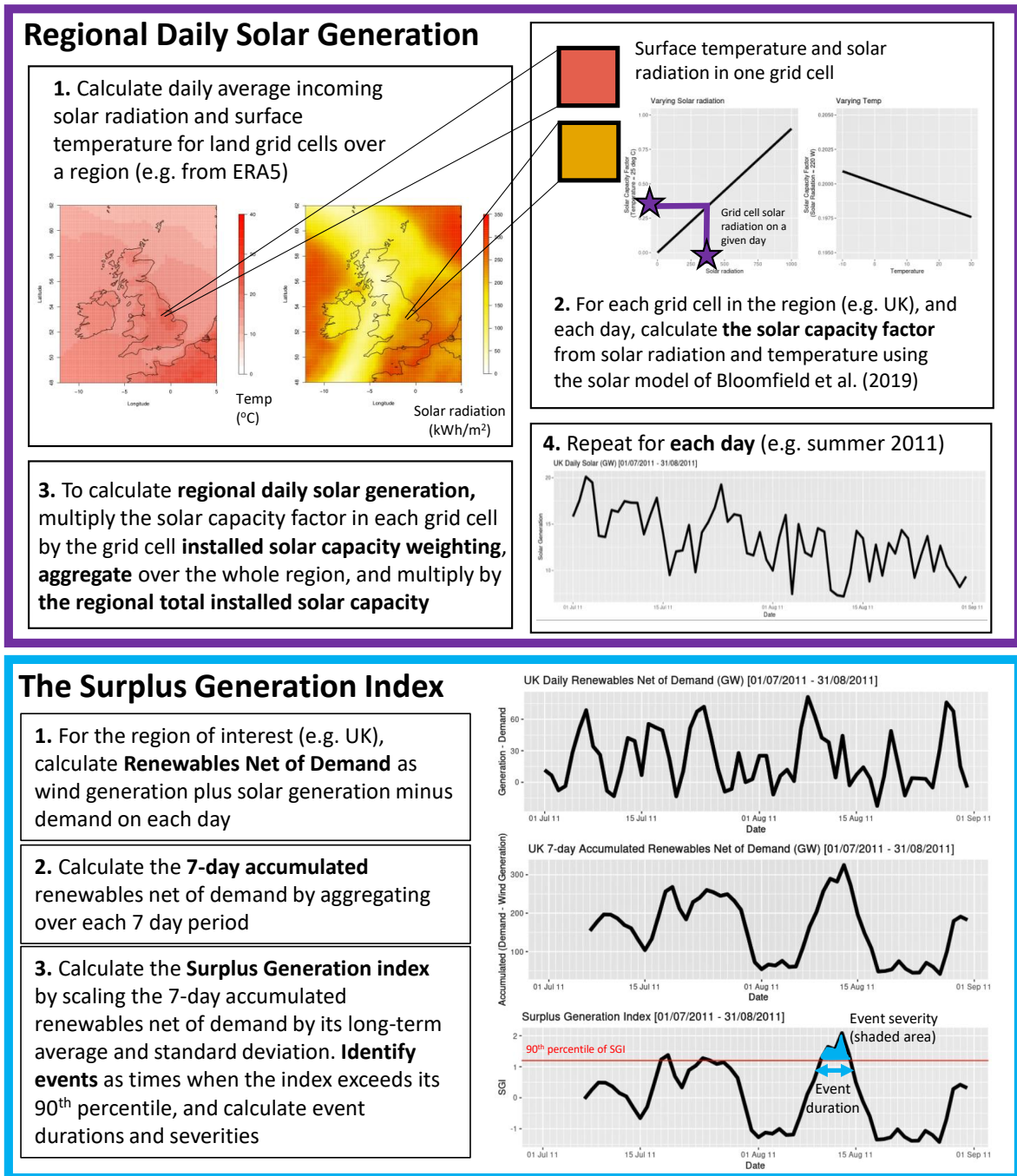


Figure 14: A schematic demonstrating the step-by-step methods used to (top panel) calculate regional daily solar renewable electricity generation, and (bottom panel) calculate the surplus generation event index, identify the associated adverse weather events, and calculate their durations and severities.

9.2 Sensitivity Study

Similar to the wind-drought-peak-demand events, a sensitivity study is carried out to explore how subjective modelling choices impact on the adverse weather events identified by the method. These varied input settings are presented in Table 13. Again, if the adverse weather events identified using the various sensitivity study settings are relatively consistent, this gives greater confidence that the SGI definition described in the previous section is robust. That is, it will provide a method for identifying representative periods of adverse weather, relevant for testing the resilience of a *range* of electricity system configurations.

For consistency with the WDI, the chosen UK demand model (D1) and the estimated 2050s national installed level of wind capacity in each European country (C1) are held constant. This sensitivity study therefore explores the sensitivity of the SGI to varying the national installed level of solar capacity in Europe. This is captured in the first row of Table 13. Setting 1 uses the current day installed capacities (first column of Table 12) while setting 2 represents the estimated future (2050) installed capacities, as described in Section 9.1.1 (second column of Table 12). In addition, here a third setting is used to represent a very highly renewable future 2050 scenario. In this setting all of the national installed solar capacities of 2050 in Table 12 are multiplied by 1.5. In addition, as for the WDI, these settings are tested for both the UK and Europe.

Input	Setting 1	Setting 2	Setting 3
Installed solar capacity	Current 2020 scenario (Sol C1)	Future 2050 scenario (Sol C2)	Very high future 2050 scenario (Sol C3)
Region	UK	Europe	-

Table 13: Table of settings varied within the SGI sensitivity study. The Sol C1, Sol C2 and Sol C3 labels relate to installed solar capacity scenario settings 1, 2 and 3 respectively, used as sensitivity study setting acronyms in Section 9.3.1. The proposed method detailed in Section 9.1.1 uses installed solar setting 2 (Sol C2).

As before, the adverse weather events identified using these sensitivity study settings are also compared to those identified using the energy data of Bloomfield et al. (2019) (labelled as ‘Uni of Reading’ in the results plots). As described in Section 3.4, Bloomfield et al. (2019) calculate weather dependent demand using the same gridded temperature data as in this study, and the same UK demand model as in Setting 1 in Table 13. The wind generation is also calculated using the same bias corrected gridded wind speed data as in this study, however, the location and level of installed wind capacity throughout Europe is specified as that of 2017 (taken from thewindpower.net database). The UK on-shore wind power curves used are the same as in Setting 1 in Table 1. The solar generation is calculated using the same solar radiation data as in this study, but the installed solar capacity in Great Britain is assumed to be distributed uniformly throughout, rather than being based on the criteria of Price et al. (2018) (Figure 13).

The results of this sensitivity study are presented in Section [9.3.1](#).

9.3 Results

This section presents the results of the surplus generation sensitivity study, described in detail in Section [9.2](#). The final set of surplus generation adverse weather events identified within the ERA5 historical period using the SGI is then presented, charactering the 1 in 2, 5, 10, 20, 50 and 100 return level events in terms of event duration and severity in summer, in the UK and in Europe.

9.3.1 Sensitivity Study

UK

Figure [15](#) shows a comparison of the duration and severity of summer-time surplus generation adverse weather events when identified using each national installed solar capacity scenario (Sol C1, Sol C2 or Sol C3), as defined in Table [13](#). This figure shows how the SGI, and hence the identified events, look very similar across all three settings. Further exploration of the output identified this to be due to the relative dominance of wind generation in the SGI calculation. In the UK, the daily solar capacity factor (calculated from daily average solar radiation) is found to always be less than approximately 0.3, while the daily wind capacity factor (calculated from daily average wind speed) reaches values of 0.98. Hence, even with 150GW of solar capacity installed in the UK (Sol C3), the generation from solar never exceeds 50GW, compared to up to 120GW of wind generation (the UK 2050s estimate of installed wind capacity used in this study). Similar to the conclusion of Section [4.1](#), this shows that, when a highly renewable wind generation future is considered (as is likely for the UK), the SGI is robust to the installed solar capacity scenario employed.

This SGI robustness is further evidenced in Figure [16](#) which shows a comparison of the SGI during two peak summer-time surplus generation adverse weather events in the UK, using the three different national installed solar capacities (using the UK demand model, D1, and the 2050s estimated installed national wind capacity, C1). This figure shows how the SGI looks very similar across settings. As for the WDI, this is because, although the absolute Renewables-Net-of-Demand will be different in each case (because a different installed solar capacity is used), when scaled by the long term average and standard deviation (separately for each setting) to calculate the SGI (see Section [9.1.2](#)), a similar standardised metric is created across the different settings. This indicates that an adverse/stressful period of weather for the electricity system is likely to be adverse irrespective of the system set up (as was found for wind-drought-peak-demand events). Indeed, the consistency in the percentiles/ranks of the events in Figure [16](#), and the events picked out from the historical period in Tables [14](#) and [15](#), further evidences the robustness of the SGI to the national installed solar generation scenario considered.

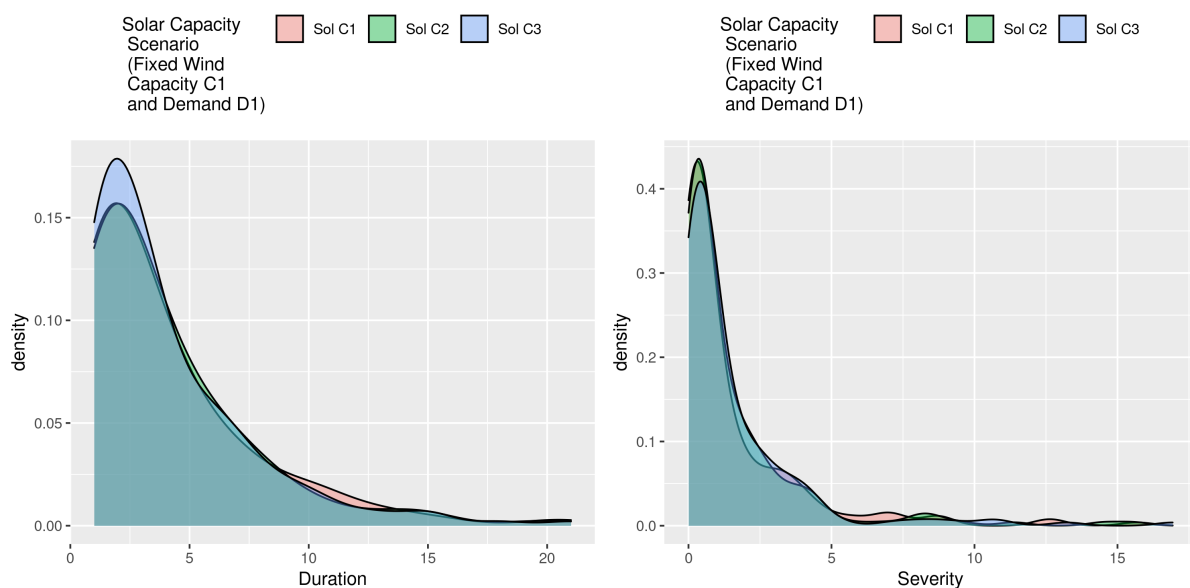


Figure 15: Density plots comparing the (left) duration and (right) severity of surplus generation adverse weather events identified in summer when using each installed solar capacity scenario (keeping the UK demand model, D1, and the installed wind capacity as that estimated for 2050, C1), as specified in Table 13. The labels Sol C1, Sol C2 and Sol C3 relate to the labels in Table 13.

This conclusion is also supported by the consistency with the University of Reading time series shown in Figure 16. This good agreement with the University of Reading data based metric suggests that the proposed SGI (calculated using demand D1, wind C1 and Sol C2) is able to represent weather dependent demand, wind generation, solar generation and hence challenging periods of weather in the UK leading to extreme surplus electricity generation. It has been concluded, therefore, that the final SGI definition be based on the UK demand model (D1), the 2050s estimate of future installed wind capacities (C1), as in the WDI, and the 2050s estimate of future installed solar capacities (Sol C2), as this definition characterises a highly renewable electricity system as is the focus of this study.

As discussed in the initial literature review (Dawkins, 2019), a potential approach for improving the UK electricity system resilience to weather and climate is to use the observed anti-correlation between wind and solar generation in the UK, as well as the dipole in meteorological conditions in the UK and southern Europe, to help balance the system. The final output of this project: a gridded meteorological dataset associated with adverse weather events, will allow energy system modellers to explore these ‘trade-offs’ and their potential for resilience during these stressful periods of weather. To facilitate in this, an additional metric has been devised for the surplus generation events. As these events are based on both wind and solar generation, the relative contribution of each form of generation to the overall accumulated surplus generation (i.e. the SGI) has been quantified. This metric will help users to identify events within the final dataset that are of particular interest e.g. those that are more associated with wind or solar generation. On each day, this relative contribution of each form of generation to the SGI is calculated as the accumulated 7 day wind/solar generation divided by the accumulated 7 day surplus generation and demand. The resulting two numbers for each day (one for the relative contribution of wind generation and one for the relative contribution of solar generation) sum to 1. For each surplus

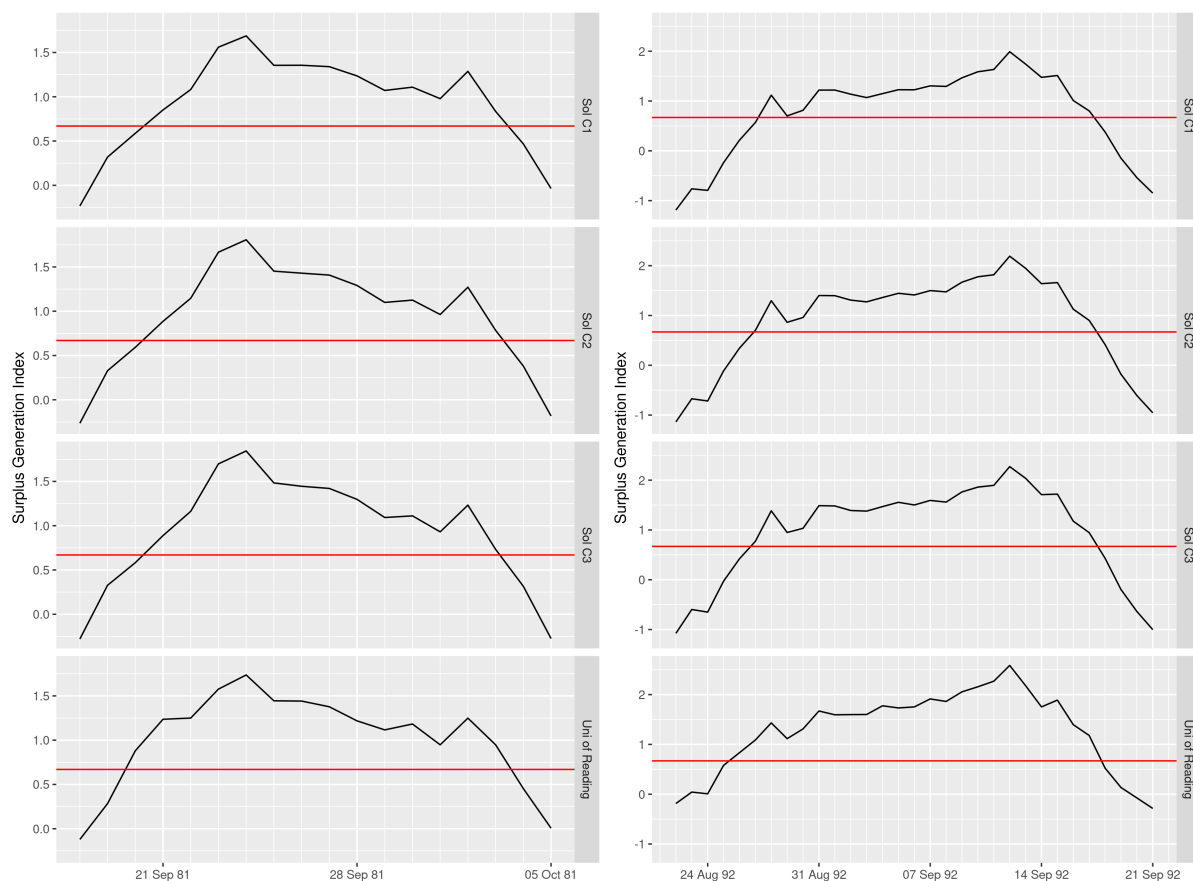


Figure 16: Time series plots of the surplus generation index (SGI) during two peak UK summer-time surplus generation adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the summer-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in September 1981, found to be the **91st percentile event** in terms of duration in all installed solar sensitivity study settings (Sol C1, Sol C2 and Sol C3). The right panel shows an event in August 1992, found to be the **99th, 99th and 98th percentile event** in terms of severity in installed solar sensitivity study settings Sol C1, Sol C2 and Sol C3 respectively. Equivalent time series of the SGI calculated using the University of Reading's energy dataset ([Bloomfield et al., 2019](#)) are presented for comparison.

generation adverse weather event identified in Tables 14 and 15, the average relative contribution of each form of generation over the duration of the event is given.

Figure 17 shows two examples of the daily relative contribution of wind and solar generation to the SGI (based on demand model D1, wind capacity scenario C1 and solar capacity scenario Sol C2) during two surplus generation adverse weather events. These show how, as previously noted, wind generation predominantly dominates the UK surplus generation events due to the relatively low daily solar capacity factor values calculated from daily average solar radiation. The August 1992 event, also presented in Figure 16, is shown in 17 (a) and (b). It can be seen that wind generation increasingly dominates this event, suggesting that in particular, high wind speeds are the reason for this surplus generation event. The June 2017 event (a 91st percentile event in terms of duration, as shown in Table 14) is presented in Figure 17 (c) and (d). These plots show how towards the end of the event, solar generation is increasingly dominant in causing the surplus generation.

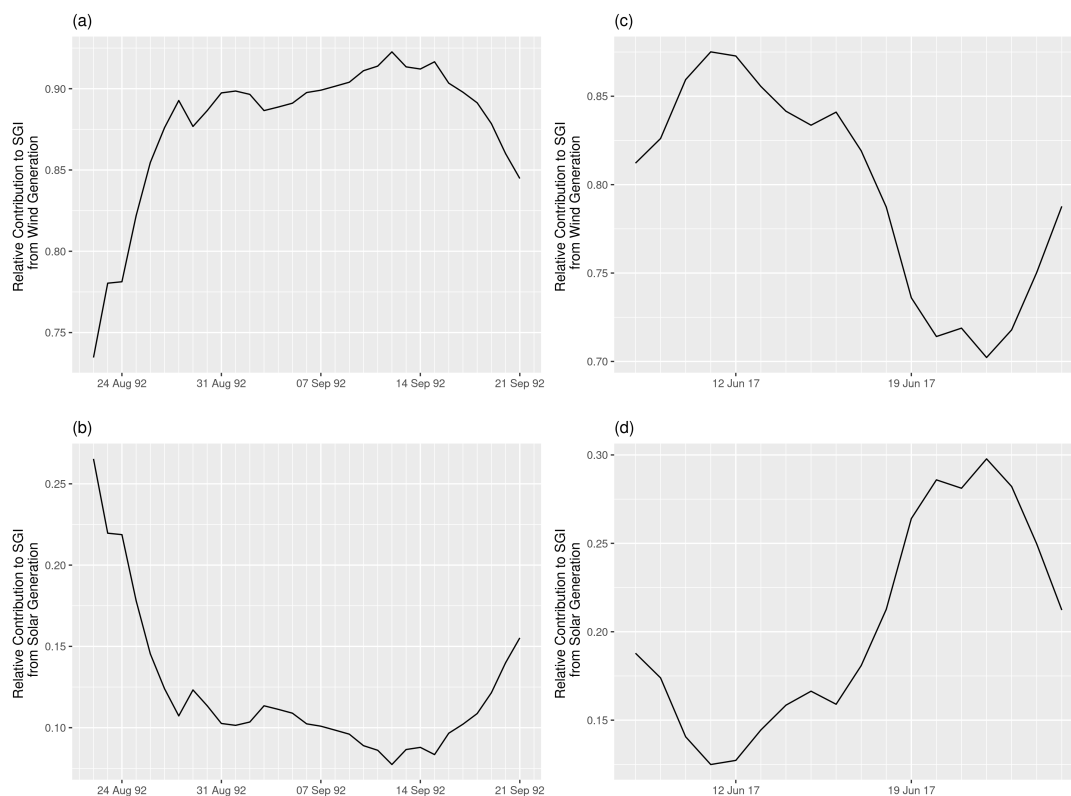


Figure 17: Time series plots of the daily relative contribution of wind generation (a) and (c) and solar generation (b) and (d) to the SGI during two surplus generation adverse weather events in the UK, left panel: August/September 1992 (99th percentile event in terms of severity), right panel: June 2017 (91st percentile event in terms of duration). Note that the y axes scales are different in each plot.

Europe

A similar analysis to that presented for the UK is carried out for all of Europe. Equivalent results to those shown in Figure 15 are found for Europe (not shown). This indicates that, similar to the UK, wind generation generally dominates periods of time with very high generation in Europe. Some small differences in the duration and severity of smaller events is however found, suggesting that in some European countries solar generation has a greater impact on events than in the UK.

Figure 18 presents an equivalent comparison of identified surplus generation adverse weather events in Europe to those shown in Figure 16 for the UK. As in the UK, these plots show good consistency in the SGI in the different sensitivity study settings and in the University of Reading data (Bloomfield et al., 2019). Again, these events and their percentiles (ranks) are largely consistent, also evidenced in Tables 16 and 17. Similar to the UK, this good agreement with the University of Reading data based metric suggests that the proposed SGI (calculated using demand D1, wind C1 and Sol C2) is able to represent weather dependent demand, wind generation, solar generation and hence challenging periods of weather in Europe leading to extreme surplus electricity generation. In addition, the consistency across sensitivity study settings suggests that important Europe-wide events identified using the SGI are representative of events that will have an impact on a range of future renewable electricity systems,

irrespective of the specific installed solar capacity scenario used.

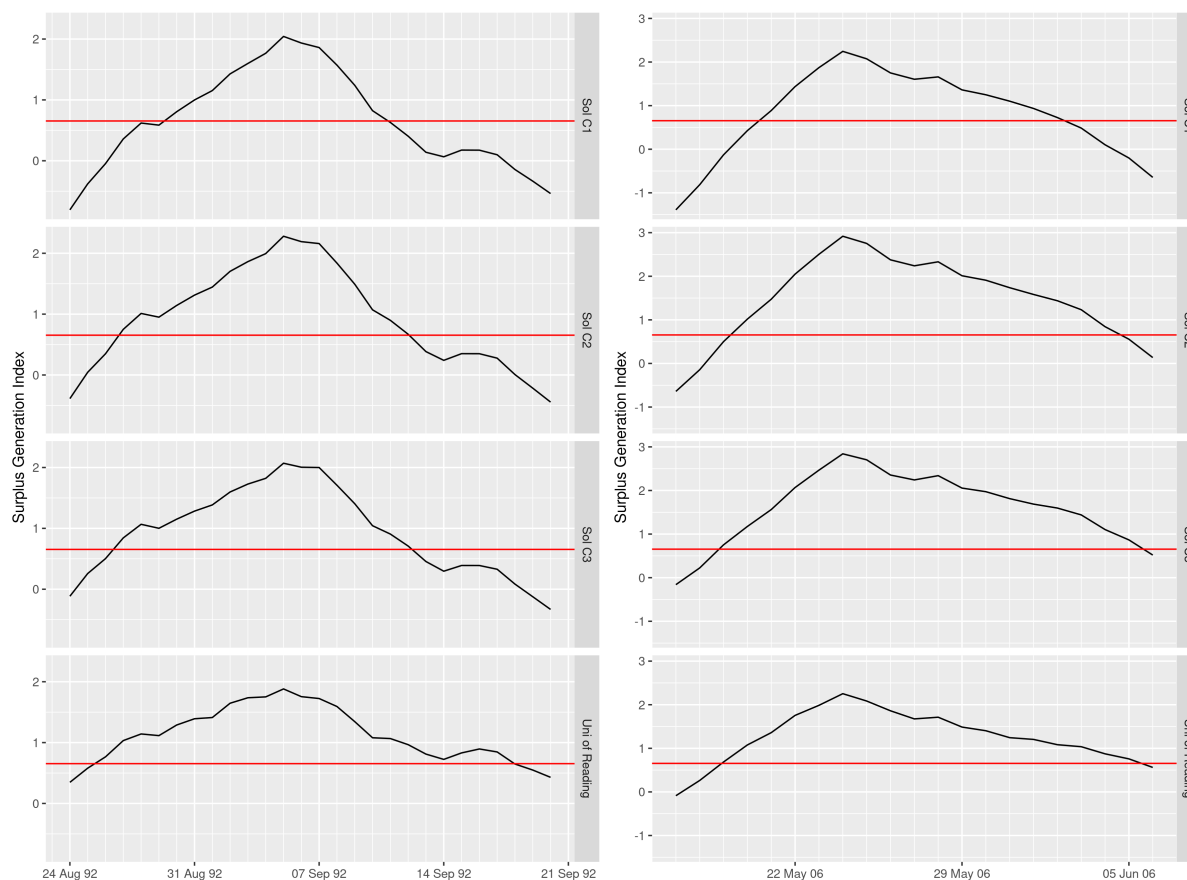


Figure 18: Time series plots of the surplus generation index (SGI) during two peak European summer-time surplus generation adverse weather events, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the summer-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in August/September 1992 (the same event as in the right panel of Figure 16), found to be the **97th, 97th and 91st percentile event** in terms of severity in sensitivity study settings Sol C1, Sol C2 and Sol C3 respectively. The right panel shows an event in May 2006, found to be the **99th, 98th and 99th percentile event** in terms of duration in installed solar sensitivity study settings Sol C1, Sol C2 and Sol C3 respectively. Equivalent time series of the SGI calculated using the University of Reading's energy dataset (Bloomfield et al., 2019) are presented for comparison.

Similar to UK events, the daily relative contribution of wind and solar generation to the SGI (based on demand model D1, wind capacity scenario C1 and solar capacity scenario Sol C2) has been calculated. This can be used to help identify which European surplus generation events are caused predominantly by high winds or solar radiation. For this purpose, for each surplus generation adverse weather event identified in Tables 16 and 17, the average relative contribution of each form of generation over the duration of the event is given. In addition, Figure 19 shows the daily relative contribution of wind and solar generation during two extreme surplus generation adverse weather events in Europe.

Figure 19 shows how, in Europe, solar generation makes more relative contribution to the SGI than seen in the UK. This is likely due to the sunnier conditions in more southern European countries. Specifically, Figure 19 shows how during the May 2006 event, the dominant source of renewable generation is wind, while in the June 1994 event solar generation is increasingly dominant, contributing more than 50% to

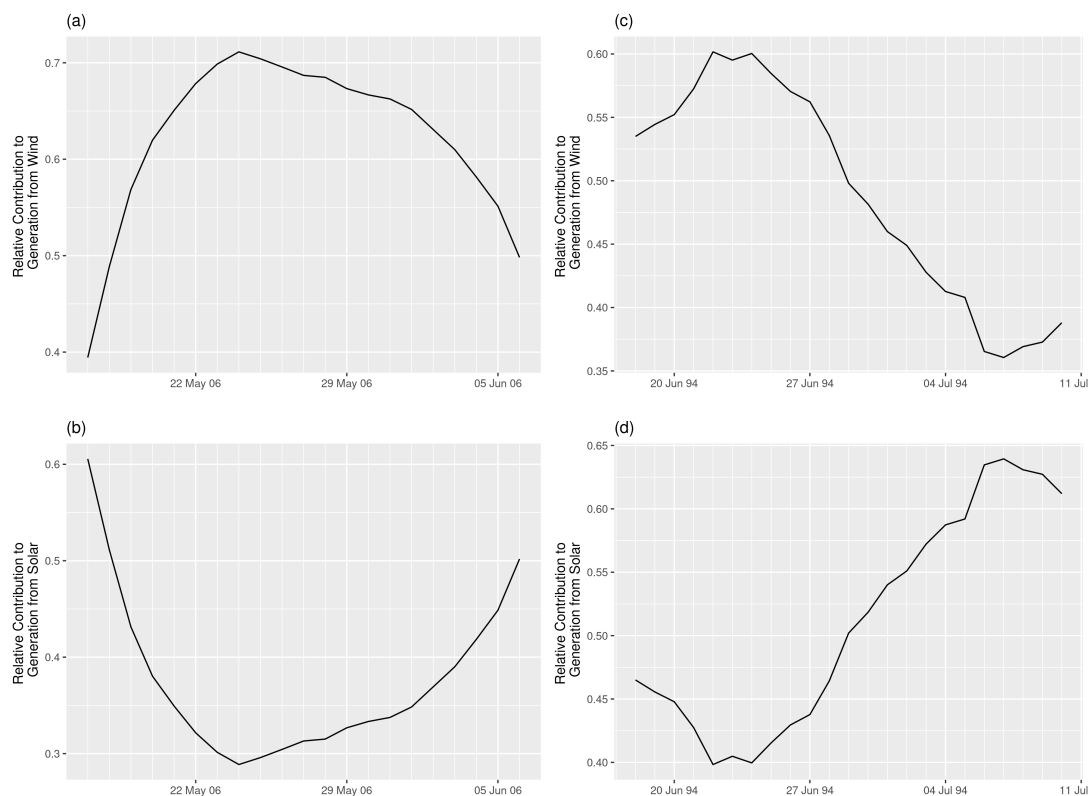


Figure 19: Time series plots of the daily relative contribution of wind generation (a) and (c) and solar generation (b) and (d) to the SGI during two surplus generation adverse weather events in Europe, left panel: May 2006 (99th percentile event in terms of duration), right panel: June 1994 (81st percentile event in terms of duration).

the SGI during the second half of the event.

UK and Europe

Figure 20 presents the comparison of the SGI in the UK and Europe during two surplus generation adverse weather events. These plots show how, for one of the most extreme events in each region, the SGI is quite different in the other region, similar to the WDI. Tables 14 - 17 highlight which of the UK and Europe events are also identified as occurring in the other region. While there are a few of these overlapping events, as found for the WDI, the difference in the events shown in Figure 20 suggests that a different data set of UK specific and Europe-wide events should be produced within the project.

9.3.2 Identified Surplus-Generation Adverse Weather events

The sensitivity study results support the use of the SGI as defined in Section 9.1.1 to identify adverse weather events in the UK and Europe separately.

Tables 14 - 17 present the adverse weather events identified using this final definition of the SGI, for UK and Europe, in summer only, and in terms of duration and severity separately. In each case, a selection of events associated with the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels are identified. For

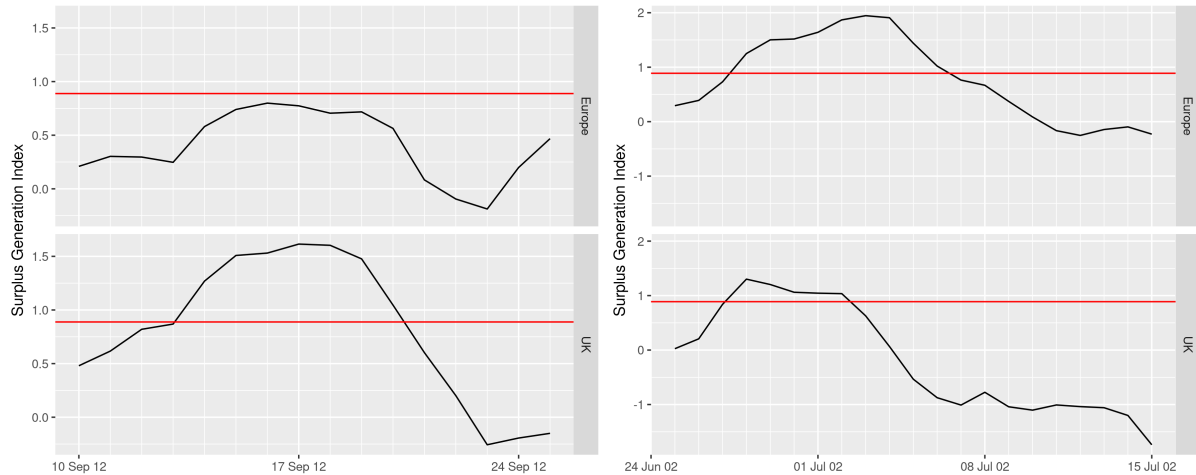


Figure 20: Time series plots comparing the surplus generation index during two peak summer-time surplus generation adverse weather events in the UK and in Europe, identified within the 40-year ERA5 meteorological record. In each plot the black line represents the index and the red line represents the summer-time adverse weather threshold. The event occurs when the index exceeds the threshold. The left panel shows an event in September 2012, found to be the **90th percentile event** in terms of severity in the UK (and not an event in Europe). The right panel shows an event in July 2002, found to be the **90th percentile event** in terms of duration in Europe (and the **75th percentile event** in the UK). In all cases this is based on the final SGI definition (demand D1, wind C1 and solar Sol C2).

example, the 1 in 2 events level is the 50th percentile event, so events with percentiles between the 49th and 51st percentile are given. Following on from this work, it may be interesting to further validate these identified events by running them through detailed electricity system models, as described in [Butcher and Dawkins \(2020\)](#). Here, due to the limited historical data record (only 40 years) the events are characterised in terms of event frequency for simplicity. However, as previously noted, when this approach is used to identify adverse weather events for the final datasets based on longer data records (see [Butcher and Dawkins 2020](#) for more detail), the events will be selected based on their return periods (in years).

Event No.	Duration Percentile	Start Date	Duration	Severity	Wind Contribution	Solar Contribution	In Sol C1? (Percentile)	In Sol C3? (Percentile)
1	49	1988-07-11	3.00	0.35	0.84	0.16	Yes (52)	Yes (48)
2	49	1990-04-15	3.00	0.69	0.88	0.12	No	Yes (48)
3	50	1991-05-04	3.00	0.68	0.87	0.13	No	Yes (49)
4	51	1992-04-30	3.00	0.68	0.87	0.13	No	Yes (51)
5	51	1992-05-06	3.00	0.84	0.87	0.13	No	Yes (51)
6	79	1992-05-28	6.00	3.11	0.80	0.20	No	Yes (78)
7	79	1997-09-12	6.00	1.40	0.89	0.11	Yes (96)	Yes (80)
8	80	1999-04-10	6.00	2.63	0.90	0.10	Yes (80)	Yes (81)
9	80	1999-05-23	6.00	2.18	0.84	0.16	No	No
10	81	2002-04-26	6.00	1.34	0.86	0.14	Yes (80)	Yes (81)
11	81	2005-09-27	6.00	1.29	0.92	0.08	No	No
12	89	1987-09-09	8.00	3.05	0.90	0.10	No	Yes (88)
13	89	2003-05-04	8.00	1.74	0.85	0.15	No	Yes (94)
14	90	2006-04-07	8.00	3.59	0.88	0.12	Yes (89)	Yes (89)
15	90	2009-05-06	8.00	3.33	0.86	0.14	No	Yes (92)
16	91	1981-09-22	9.00	4.43	0.93	0.07	Yes (91)	Yes (91)
17	91	2017-06-10*	8.00	2.31	0.85	0.15	Yes (49)	Yes (90)
18	94	1991-04-05	10.00	8.47	0.91	0.09	Yes (93)	Yes (94)
19	95	1986-08-29	11.00	4.20	0.89	0.11	Yes (95)	Yes (93)
20	95	2007-09-19	11.00	5.62	0.92	0.08	Yes (96)	Yes (95)
21	96	2001-09-08*	13.00	4.34	0.91	0.09	Yes (97)	Yes (96)
22	96	2014-08-13	11.00	3.61	0.86	0.14	Yes (94)	Yes (96)
23	97	2009-08-28	14.00	7.90	0.90	0.10	Yes (98)	Yes (97)
24	97	2011-05-18	13.00	8.54	0.86	0.14	Yes (97)	Yes (97)
25	98	2002-05-20	15.00	9.50	0.85	0.15	Yes (93)	Yes (98)
26	98	2004-09-14*	15.00	14.50	0.92	0.08	Yes (98)	Yes (98)
27	99	1992-08-30*	19.00	11.39	0.90	0.10	Yes (100)	Yes (99)
28	99	2018-09-13	15.00	6.77	0.92	0.08	Yes (99)	Yes (99)
29	100	1986-05-10	21.00	15.58	0.87	0.13	Yes (99)	Yes (100)

Table 14: Table summarising the surplus generation adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in the UK in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; the following two columns show the average relative contribution of wind generation and solar generation to the SGI over the duration of the event; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Table 16 or 17), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration	Severity	Wind Contribution	Solar Contribution	In Sol C1? (Percentile)	In Sol C3? (Percentile)
1	49	2009-08-01	2.00	0.57	0.86	0.14	Yes (48)	Yes (49)
2	49	2016-08-12	2.00	0.56	0.86	0.14	Yes (51)	No
3	50	2015-08-25*	5.00	0.57	0.88	0.12	No	No
4	51	1994-05-16	3.00	0.59	0.82	0.18	No	No
5	51	1994-06-09	2.00	0.59	0.84	0.16	No	No
6	79	1999-05-23	6.00	2.18	0.84	0.16	No	No
7	79	2013-05-13	5.00	2.19	0.86	0.14	No	Yes (81)
8	80	2004-04-05	4.00	2.25	0.89	0.11	Yes (78)	Yes (78)
9	80	2016-05-10*	6.00	2.20	0.82	0.18	No	No
10	81	1988-09-27*	4.00	2.30	0.94	0.06	No	No
11	81	2017-06-10*	8.00	2.31	0.85	0.15	No	No
12	89	2006-04-07	8.00	3.59	0.88	0.12	No	Yes (89)
13	89	2014-08-13	11.00	3.61	0.86	0.14	No	Yes (92)
14	90	1982-05-01*	6.00	3.91	0.87	0.13	No	Yes (93)
15	90	2012-09-14	7.00	3.83	0.91	0.09	Yes (92)	No
16	91	1982-08-18	9.00	3.95	0.88	0.12	Yes (90)	Yes (91)
17	91	1988-08-31	9.00	3.91	0.89	0.11	Yes (92)	Yes (89)
18	94	2005-04-07	7.00	4.48	0.89	0.11	Yes (91)	Yes (94)
19	95	1979-09-16	8.00	4.60	0.91	0.09	Yes (93)	Yes (92)
20	95	2007-09-19	11.00	5.62	0.92	0.08	Yes (96)	Yes (94)
21	96	2009-08-28	14.00	7.90	0.90	0.10	Yes (98)	Yes (96)
22	96	2018-09-13	15.00	6.77	0.92	0.08	Yes (97)	Yes (96)
23	97	1989-08-15	10.00	8.08	0.87	0.13	Yes (96)	Yes (97)
24	97	1991-04-05	10.00	8.47	0.91	0.09	Yes (98)	Yes (97)
25	98	2002-05-20	15.00	9.50	0.85	0.15	Yes (97)	Yes (99)
26	98	2011-05-18	13.00	8.54	0.86	0.14	Yes (95)	Yes (98)
27	99	1992-08-30*	19.00	11.39	0.90	0.10	Yes (99)	Yes (98)
28	99	2004-09-14*	15.00	14.50	0.92	0.08	Yes (100)	Yes (99)
29	100	1986-05-10	21.00	15.58	0.87	0.13	Yes (99)	Yes (100)

Table 15: Table summarising the surplus generation adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in the UK in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; the following two columns show the average relative contribution of wind generation and solar generation to the SGI over the duration of the event; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in Europe (i.e. in Table 16 or 17), relevant for interconnectivity.

Event No.	Duration Percentile	Start Date	Duration	Severity	Wind Contribution	Solar Contribution	In Sol C1? (Percentile)	In Sol C3? (Percentile)
1	49	1980-07-21	4.00	1.19	0.66	0.34	Yes (49)	No
2	49	1982-08-21	4.00	1.03	0.69	0.31	No	No
3	50	1985-04-30	4.00	0.96	0.71	0.29	No	No
4	51	1986-06-09	4.00	1.17	0.65	0.35	Yes (51)	Yes (50)
5	51	1988-09-27*	4.00	2.78	0.80	0.20	No	Yes (50)
6	79	1982-04-30*	7.00	4.06	0.71	0.29	No	No
7	79	1984-06-25	7.00	4.98	0.64	0.36	No	No
8	80	1993-07-07	7.00	3.37	0.61	0.39	No	Yes (79)
9	81	1994-06-22	7.00	3.21	0.58	0.42	No	Yes (95)
10	81	1998-09-13	7.00	2.90	0.78	0.22	Yes (97)	No
11	89	2001-09-09*	8.00	4.81	0.76	0.24	Yes (94)	No
12	90	2002-06-28	8.00	3.76	0.61	0.39	No	Yes (89)
13	90	2007-05-09	8.00	6.42	0.67	0.33	No	Yes (90)
14	91	2011-04-06	8.00	1.50	0.68	0.32	Yes (88)	No
15	94	1992-08-31*	10.00	6.64	0.73	0.27	Yes (98)	Yes (91)
16	95	2003-04-30	10.00	5.93	0.66	0.34	Yes (92)	Yes (95)
17	95	2009-09-01	10.00	4.77	0.70	0.30	Yes (95)	No
18	96	1990-07-05	11.00	8.07	0.64	0.36	Yes (91)	Yes (97)
19	97	1998-07-07	13.00	4.82	0.65	0.35	Yes (96)	Yes (98)
20	97	2011-05-24	12.00	4.79	0.59	0.41	No	Yes (99)
21	98	2006-05-21	14.00	12.26	0.67	0.33	Yes (99)	Yes (99)
22	99	2004-09-13*	16.00	8.67	0.76	0.24	Yes (99)	No
23	99	2007-06-28	15.00	7.60	0.62	0.38	No	Yes (100)
24	100	1983-09-05	18.00	8.65	0.75	0.25	Yes (100)	Yes (78)

Table 16: Table summarising the surplus generation adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in Europe in terms of duration**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; the following two columns show the average relative contribution of wind generation and solar generation to the SGI over the duration of the event; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a "*" are also identified as periods associated with an adverse weather event in the UK (i.e. in Table 14 or 15), relevant for interconnectivity.

Event No.	Severity Percentile	Start Date	Duration	Severity	Wind Contribution	Solar Contribution	In Sol C1? (Percentile)	In Sol C3? (Percentile)
1	49	1987-09-12	5.00	0.76	0.72	0.28	No	No
2	49	2018-06-22	3.00	0.77	0.59	0.41	No	No
3	50	2015-08-26*	4.00	0.78	0.65	0.35	Yes (50)	No
4	51	1997-06-25	4.00	0.78	0.63	0.37	No	Yes (52)
5	51	2013-04-18	4.00	0.85	0.66	0.34	No	Yes (50)
6	79	1993-07-26	6.00	2.67	0.64	0.36	No	Yes (81)
7	79	1998-08-23	6.00	2.69	0.70	0.30	No	No
8	80	1992-05-12	9.00	2.69	0.59	0.41	No	Yes (90)
9	81	2002-04-29	5.00	2.70	0.69	0.31	Yes (80)	Yes (78)
10	81	2017-06-09*	6.00	2.70	0.59	0.41	No	Yes (93)
11	89	1997-05-06	8.00	3.92	0.67	0.33	Yes (82)	Yes (89)
12	90	1982-04-30*	7.00	4.06	0.71	0.29	No	No
13	90	2016-05-08*	9.00	4.56	0.62	0.38	No	Yes (95)
14	91	2017-09-11	7.00	4.63	0.77	0.23	Yes (96)	Yes (79)
15	94	1984-06-25	7.00	4.98	0.64	0.36	No	Yes (95)
16	95	1994-06-04	8.00	5.27	0.63	0.37	Yes (82)	Yes (96)
17	95	2003-04-30	10.00	5.93	0.66	0.34	No	Yes (97)
18	96	2007-05-09	8.00	6.42	0.67	0.33	Yes (90)	Yes (97)
19	97	1992-08-31*	10.00	6.64	0.73	0.27	Yes (97)	Yes (91)
20	97	2007-06-28	15.00	7.60	0.62	0.38	No	Yes (99)
21	98	1990-07-05	11.00	8.07	0.64	0.36	Yes (93)	Yes (99)
22	99	1983-09-05	18.00	8.65	0.75	0.25	Yes (100)	Yes (88)
23	99	2004-09-13*	16.00	8.67	0.76	0.24	Yes (99)	No
24	100	2006-05-21	14.00	12.26	0.67	0.33	Yes (98)	Yes (100)

Table 17: Table summarising the surplus generation adverse weather events identified to represent the 1 in 2, 5, 10, 20, 50 and 100 event frequency levels **in summer in Europe in terms of severity**. The first column provides an event number; the second column identifies the percentile (rank) of the event in terms of severity; the following three columns give the start date, duration and severity of the events; the following two columns show the average relative contribution of wind generation and solar generation to the SGI over the duration of the event; and the final three columns identify whether the event would have been selected in an equivalent table for the other sensitivity settings, and if so what the percentile of the event is in that setting. Events labelled by a '*' are also identified as periods associated with an adverse weather event in the UK (i.e. in Table 14 or 15), relevant for interconnectivity.

9.4 Summary and Conclusion

This report addendum has presented a method for characterising long-duration surplus generation adverse weather events for renewable electricity system resilience testing, based on the meteorological conditions in a region. This approach represents daily regional weather dependent demand and daily regional wind generation in the same way as described for the wind-drought-peak-demand events. The additional calculation of solar generation is achieved using daily average temperature and solar radiation within the solar capacity factor model of [Bett and Thornton \(2016\)](#); a representation of the potential for installed solar capacity (uniform in Europe and using insights from [Price et al. \(2018\)](#) in Great Britain); and estimates of highly renewable national installed solar capacities across Europe, representative of the 2050s. Subsequently, an adverse weather index is developed. This Surplus-Generation-Index is calculated from Renewables-Net-of-Demand, defined as daily regional wind generation plus solar generation minus weather dependent demand, accumulated over the preceding 7-day period and standardised by scaling by the long-term average and standard deviation. Adverse weather events are then identified as times when this index exceeds its 90th percentile, with focus paid to those events that occur in summer, as this is when surplus generation is most often a problem. These summer-time events are then characterised by their duration and severity.

A study was carried out to explore the sensitivity of identified adverse weather events to the UK demand model used and the level of installed national solar capacities used. This showed that, particularly in the UK, the SGI and hence the adverse weather events identified were very consistent across the different sensitivity study settings. This was found to be due to the relative dominance of wind generation during these peak events. This therefore showed that the most important events identified using the SGI, are likely to be representative of events that will have an impact on a range of future renewable electricity systems with different installed solar capacities. This was further supported by the similarity of the SGI calculated using the energy data of [Bloomfield et al. \(2019\)](#).

Finally, this addendum presented a series of tables summarising the adverse weather events identified using the final definition of the SGI, for UK and Europe, in summer, and in terms of duration and severity separately. An additional metric was included within these tables, representing the relative contribution of wind and solar generation to the surplus generation event. This metric could help users of the final dataset to pick out the most relevant events for their analysis (e.g. if they are more interested in events with high winds or solar conditions). As a follow up to this work, it may be useful to have energy modellers, such as those in the project user group, run these identified events through their energy system models, in order to further validate their characterisation of stressful weather.

This addendum has provided a validated method for characterising long-duration surplus generation adverse weather events for a highly renewable electricity system. This approach can now be used to identify such events within any suitable meteorological data set, allowing for the development of the final

adverse weather datasets in later phases of this project.

9.5 Addendum Glossary

SGI = Solar Generation Index

Sol C1 = Solar capacity scenario setting 1 (see Table 13)

Sol C2 = Solar capacity scenario setting 2 (see Table 13)

Sol C3 = Solar capacity scenario setting 3 (see Table 13)

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