Adverse Weather Scenarios for Future Electricity Systems: Developing the dataset of long-duration events

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1 Executive Summary

The first National Infrastructure Assessment (National Infrastructure Commission, 2018), 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. This is consistent with a number of other recent reports such as the Climate Change Committee's Sixth Carbon Budget report (Climate Change Committee, 2020), and the International Energy Agency's Net Zero by 2050 Roadmap for the Global Energy Sector (International Energy Agency, 2021), all reflecting the need for a de-carbonised energy system to help tackle the climate crisis.

Whilst desirable, 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 want 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 been working with the National Infrastructure Commission and Climate Change Committee to develop a dataset of adverse weather scenarios, based on physically plausible weather conditions, representing a range of possible extreme events, and the effect of future climate change. This dataset will allow for proposed future highly renewable electricity systems to be stress tested to evaluate resilience to challenging weather and climate conditions. This insight comes at a relevant time - as reported in the Drax quarterly Energy Insights report (Staffell et al., 2021), the start of 2021 saw unusually cold weather coupled with plant outages, creating very tight supply margins, highlighting the need for intelligent future planning.

This report presents the development of this dataset of long-duration adverse weather scenarios. This dataset characterises winter-time and summer-time wind-drought-peak-demand events, and summer-time surplus generation events, in the UK and in Europe. It contains gridded daily average meteorological data (surface temperature, 100m wind speed and surface solar radiation) associated with a range of examples of such events, capturing various extreme levels (1 in 2, 5, 10, 20, 50 and 100 year return period events) and climate warming levels (current day, 1.5°C, 2°C, 3°C and 4°C above pre-industrial levels). The dataset is freely available to download from the Centre for Environmental Data Analysis archive[1], and a brief how-to guide for downloading the data is included at the end of this report.

Firstly, a summary of the methods developed for characterising and identifying long-duration adverse

[1] https://catalogue.ceda.ac.uk/uuid/7beeed0bc7fa41feb10be22ee9d10f00 (Accessed 01/06/2021)

weather events within any suitable gridded meteorological dataset, is given. These methods are based on insights from the energy modelling literature, and aim to be as energy system agnostic as possible. The approach taken for developing the final dataset is then presented. Adverse weather scenarios are identified in three data sources: historical observations; historical climate model hindcasts (providing more than 2000 alternative plausible weather years) and future climate projections (capturing how weather is likely to change in future climates). The methods developed for calibrating and imputing these climate model data sources are presented. These steps are necessary to ensure the data is fit for purpose.

Adverse weather scenarios identified across these three data sources are then used in combination to quantify the extremity (i.e. the return period) of events, and how these may change in future warmer climates. This information is subsequently used to select relevant events for the final dataset. The sensitivity of the highly-renewable UK electricity system to climate change (particularly rising global temperatures) is explored and discussed. This highlights how, in a UK system with high wind and solar renewable capacity, changing the generation or demand assumptions would not materially change the events identified as adverse, except where extreme levels of electric air conditioning for heating and cooling are tested.

This study therefore provides a consistent approach for identifying, characterising and quantifying adverse weather scenarios for highly-renewable electricity systems, while aiming to be as energy system agnostic as possible. The resulting 'Adverse Weather Scenarios for Future Electricity Systems' dataset of long-duration events is therefore relevant for stress testing a range of potential future electricity systems, ultimately helping to ensure security of supply in a future net-zero world.

2 Introduction

The Met Office has developed 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 for the initial literature review (Dawkins, 2019), project scoping report (Butcher and Dawkins, 2020), and the characterisation of long-duration adverse weather stress events (Dawkins and Rushby, 2021), this report presents the development of the 'Adverse Weather Scenarios for Future Electricity Systems' dataset of long-duration events.

As described in (Butcher and Dawkins, 2020), the final dataset is required to represent three forms of long-duration adverse weather scenario: winter-time wind-drought-peak-demand events, summer-time wind-drought-peak-demand events, and summer-time surplus generation events. These events are required to be contained within whole years of gridded meteorological data, for different regions (UK and Europe), at various extreme levels (1 in 2, 5, 10, 20, 50 and 100 year return period events), and for different climate warming levels (current day, 1.5°C, 2°C, 3°C and 4°C above pre-industrial levels).

Basing this adverse weather dataset on the historical observed record only, i.e. the ERA5 reanalysis data set (Hersbach et al., 2018), may only capture a narrow range of plausible weather conditions, and will not represent how such events may change in future climates. Therefore, methods previously developed for characterising and identifying long-duration adverse weather scenarios (Dawkins and Rushby, 2021), are applied to two additional data sources. Namely, the Met Office Decadal Prediction System (DePreSys)[2] hindcast (Dunstone et al., 2016), providing 40 alternative realisation of the historical period 1959-2016, and hence additional plausible weather conditions, and the UK Climate Projections (UKCP18) (Lowe et al., 2018), representing how weather is likely to change in the future as a result of climate change. The adverse weather scenarios identified in these three data sources are used in combination within a non-stationary statistical extreme value analysis (EVA) to quantify the likelihood (i.e. the return period) of events, and how these may change in future warmer climates. The results of this analysis are then used to pick relevant adverse weather scenarios from the DePreSys and UKCP18 datasets, to be used to represent the various required extreme levels and warming levels within the final dataset.

The DePreSys and UKCP18 data sources are both derived from climate models, hence methods are developed for validating, calibrating and imputing the data where necessary. This ensures, for example, that the climate model data is not too hot or too windy on average. Specifically, a univariate variance scaling approach is used to bias correct the model data, and data science generalised additive models are developed to estimate 100m (above ground) wind speed from 10m wind speed, and to estimate surface solar radiation coherently with other DePreSys weather variables. In addition, in both cases the

[2] A glossary of acronyms is presented in Section 8

climate model data is available on a 60 km $\times$ 60 km, daily spatial-temporal resolution, hence methods for downscaling in space and time are explored.

This report firstly summaries the approach developed for characterising long-duration adverse weather scenarios, as previously published in Dawkins and Rushby (2021). The method for creating the final dataset of long-duration adverse weather scenarios for future electricity systems is then presented. Initially, the two climate model datasets (DePreSys and UKCP18) are introduced, and the methods for calibrating and imputing them are described. The adverse weather scenarios identified in the three data sources are then compared and explored. Following this, the statistical EVA method used to quantify the likelihood of adverse weather scenarios in different climates is presented, and the approach used to select relevant periods of adverse weather for the final dataset, based on this analysis, is given. Finally, a full specification of the final 'Adverse Weather for Future Electricity Systems' dataset is provided, along with a brief how-to guide on how to download the dataset from the Centre for Environmental Data Analysis (CEDA) archive.

3 Summary of Phase 2 (a): Characterising long-duration adverse weather events

The Phase 2 (a) report (Dawkins and Rushby, 2021) presents the development and validation of an approach for characterising adverse weather events using meteorological data, focusing on long-duration wind-drought-peak-demand and surplus generation events. This method was applied to 40 years of historical (1979-2018) meteorological data taken from the ERA5 meteorological reanalysis dataset (Hersbach et al., 2018), and the resulting adverse weather events within the historical report were presented.

Since these adverse weather events occur when electricity generation and demand are high or low, methods for estimating electricity generation and demand from weather data were first developed. These representations of electricity generation and demand were then used to quantify unfavourable conditions through adverse weather metrics. In doing so, this 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.

The following section provides a brief summary of the Phase 2 (a) approach to give context for the application of these methods in Phase 2 (b), as presented in Sections 4 and 5. Please refer back to the Phase 2 (a) report for further detail (Dawkins and Rushby, 2021).

3.1 Estimating Weather Dependent Electricity Demand

Weather dependent demand (WDD)[3] is estimated from 2m above group (surface) air temperature data using the same method as developed by Bloomfield et al. (2019) (documented in their supplementary material). The relationship between temperature and weather dependent demand is modelled as being linear, with a different gradient below and above certain thresholds, representing the increase in heating or cooling demand with temperature. This is implemented using the following metrics:

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.

The WDD in a given country is then calculated as a function of the regional baseline electricity demand, HDD and CDD. These three parameters are different for each country, as presented in the supplementary material of Bloomfield et al. (2019) and in Table 10 of Dawkins and Rushby (2021).

[3] A glossary of acronyms is presented in Section 8

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 2-3°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, in this study, the UK demand model of Bloomfield et al. (2019) is modified to incorporate the cooling slope of the French model (taken to be an analogue for the UKs future climate). This is done to ensure that the increased demand for cooling in the UK, as a result of the rising summer-time temperatures, is captured when applying the method to future climate projections (See section 4.3).

3.2 Estimating Wind Electricity Generation

Regional daily wind renewable electricity generation is calculated using 100m wind speed data, to represent wind speed at turbine hub height. As in Bloomfield et al. (2019), the ERA5 100m wind speed data is bias corrected in each grid cell using the Global Wind Atlas[4]. For a given grid cell and day, the wind capacity factor, defined as the proportion of a turbines maximum possible generation, is calculated by applying a turbine power curve to the daily average wind speed in that grid cell. Here, the same 3 turbine power curves as presented in Bloomfield et al. (2019) are used. These represent the type 1, 2 and 3 turbines from the International Electrotechnical Commission (IEC) wind speed classification (IEC, 2005).

In each land grid cell, the most appropriate turbine (of these three options) is chosen. As in Bloomfield et al. (2019), the selected turbine type is the one that maximises the wind capacity factor for the 40-year (1979-2018) mean of the bias corrected 100m wind speed in that grid cell, and it is assumed that all of the turbines within a given grid cell are of the same type. The wind power capacity factor is then weighted by the installed wind capacity within the grid cell (as a fraction of the national total) and then aggregated over a region/country. The potential for installed wind capacity within each grid cell in Great Britain is based on technical, social and environmental restrictions explored by Price et al. (2018), Moore et al. (2018) and Price et al. (2020), with a more simplistic approach across the rest of Europe (turbines could be located anywhere onshore other than urban areas).

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 the thewindpower.net website. Since this study is concerned with capturing adverse weather events for a highly-renewable electricity system, the current

[4] `https://globalwindatlas.info` (Accessed 29/04/2021)

day national levels of installed wind power are scaled up to represent a plausible highly-renewable future as of 2050. Specifically, a national installed capacity of 120GW is employed for the UK and 600GW for Europe as a whole (with the proportion of European installed capacity in each country consistent with current day).

3.3 Estimating Solar Electricity Generation

Regional daily solar generation is calculated from surface air temperature and incoming surface solar radiation. Firstly, on a given day and within a given land grid cell, the solar power capacity factor, defined as the proportion of a solar panels maximum possible generation produced, is calculated based on a linear function of the surface temperature and incoming surface solar radiation, as in Bett and Thornton (2016). Similar to the wind generation calculation, the solar capacity factor is then weighted by the installed solar capacity within that grid cell (as a fraction of the national total). Within each grid cell, this installed solar capacity is based on the potential location of solar renewables, as defined by Price et al. (2018) for Great Britain, and using a simplistic approach of a uniform distribution for the rest of Europe (i.e. it is assumed that solar renewables can be installed anywhere, as in Bloomfield et al. (2019)).

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 renewables. The current day national level of installed solar in each country can be obtained from the National Generation Capacity Data Platform[5]. Similar to the wind generation calculation, a plausible highly-renewable future as of 2050 is represented here, by employing a national installed capacity of 100GW in the UK, and 800GW for Europe as a whole (again such that the proportion of European installed capacity in each country is consistent with current day).

3.4 The Wind-Drought-Peak-Demand Index (WDI)

The method for calculating the WDI is shown in the schematic in Figure 1.The estimates of daily weather dependent demand (Section 3.1) and daily wind generation (Section 3.2) are used to calculate daily Demand-Net-of-Renewables (DNR) for each county, defined as daily weather dependent demand minus wind generation. This DNR metric therefore represents how much of the daily demand must be met by energy 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 periods of time when this metric is particularly high.

Borrowing insights from hydrological drought modelling (Burke et al., 2010), in which drought is characterised by accumulating rainfall over several months, here the DNR metric is accumulated over every 7 day period, representing how ‘bad the previous week has been in terms of weather dependent DNR.

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

This is then scaled by its long-term average and standard deviation to give the final WDI.

The WDI is used to identify periods of adverse weather, based on when the WDI exceeds a high threshold. These ‘events can then be quantified in terms of duration and severity, and particular events related to relevant return periods (e.g. 1 in 20 year event) in terms of their duration and severity can be identified. 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.

A different threshold is used in winter (October - March) and summer (April - September). Specifically, the threshold is defined as the 90^{th} percentile of summer-time WDI in the summer (over the 40 historical years of data), and equivalently the 90^{th} percentile of winter-time WDI in the 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.

3.5 The Surplus-Generation-Index (SGI)

The method for calculating the SGI is shown in the schematic in Figure 2. Daily weather dependent demand (Section 3.1), daily wind generation (Section 3.2), and daily solar generation (Section 3.3) are used together to calculate daily Renewables-Net-of-Demand (RND), defined as wind generation plus solar generation, minus weather dependent demand. This allows the characterisation of surplus generation adverse weather events via the SGI. These events 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. This form of adverse weather event is explored in the summer time only (as specified in the scoping phase of this project Butcher and Dawkins 2020).

Similar to the WDI, the SGI is based on the difference between generation and demand (here RND) accumulated over every 7-day period (scaled by its long-term average and standard deviation), representing how bad the previous week has been in terms of accumulating surplus renewable generation net of weather dependent demand. Again, this metric is used to identify periods of adverse weather based on exceedance of its 90^{th} percentile. While summer-time (April-September) surplus generation events are the main focus of this analysis, the SGI is calculated for the whole year, using a different seasonal threshold (as in the WDI), so that events that start in summer months but continue on into the winter can be fully captured. These identified surplus generation events can then be quantified in terms of duration and severity and particular events related to relevant return periods (e.g. 1 in 20 year event) can be identified.

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) is also quantified. This metric

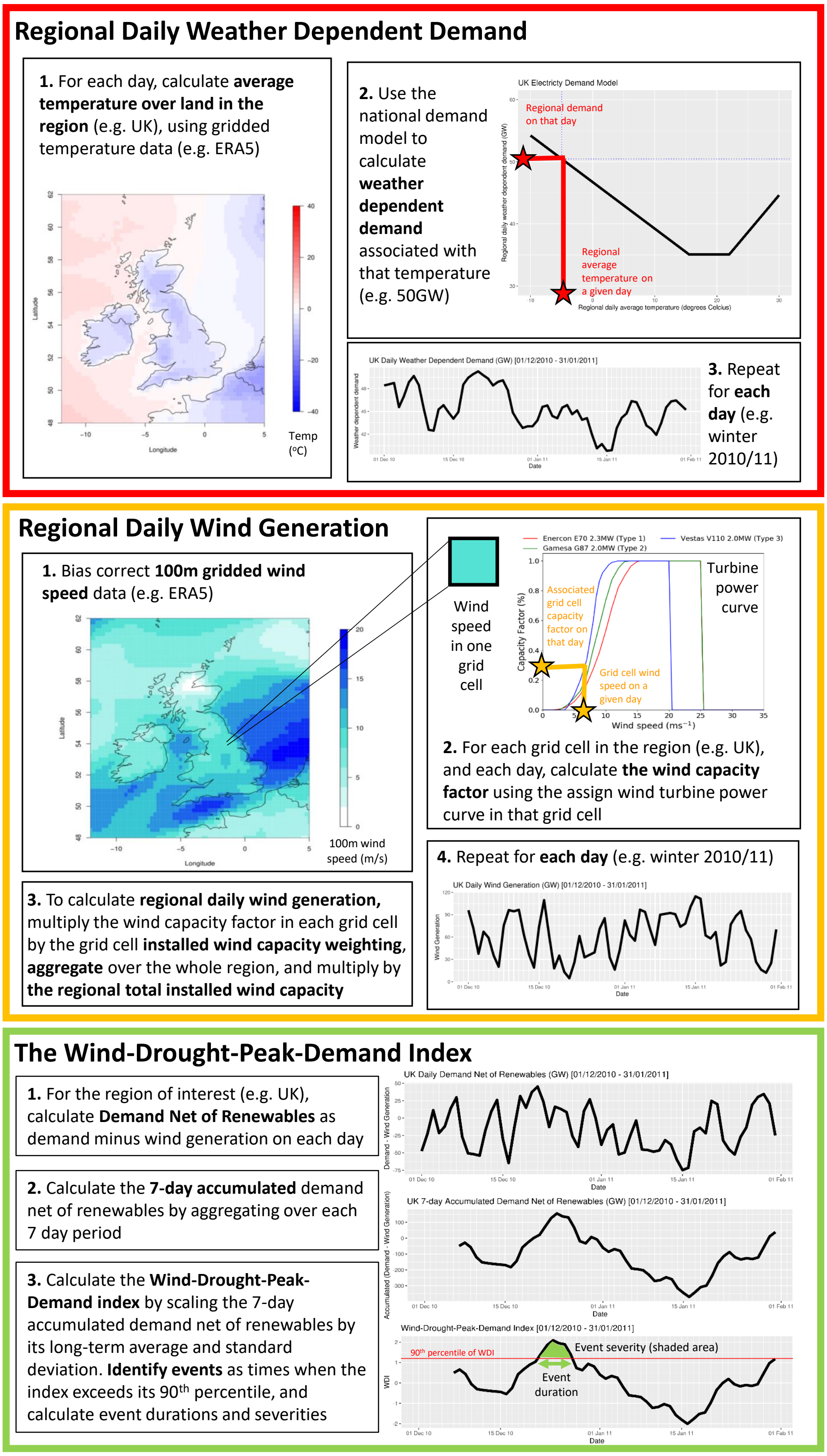

Figure 1: A schematic demonstrating the step-by-step methods used to (top panel) calculate regional daily weather dependent demand, (middle panel) calculate regional daily wind renewable electricity generation, and (bottom panel) calculate the wind-drought-peak-demand event index, identify adverse weather events, and calculate their duration and severity.

can be used to help identify events of interest within the final dataset e.g. those that are more associated with wind or solar generation.

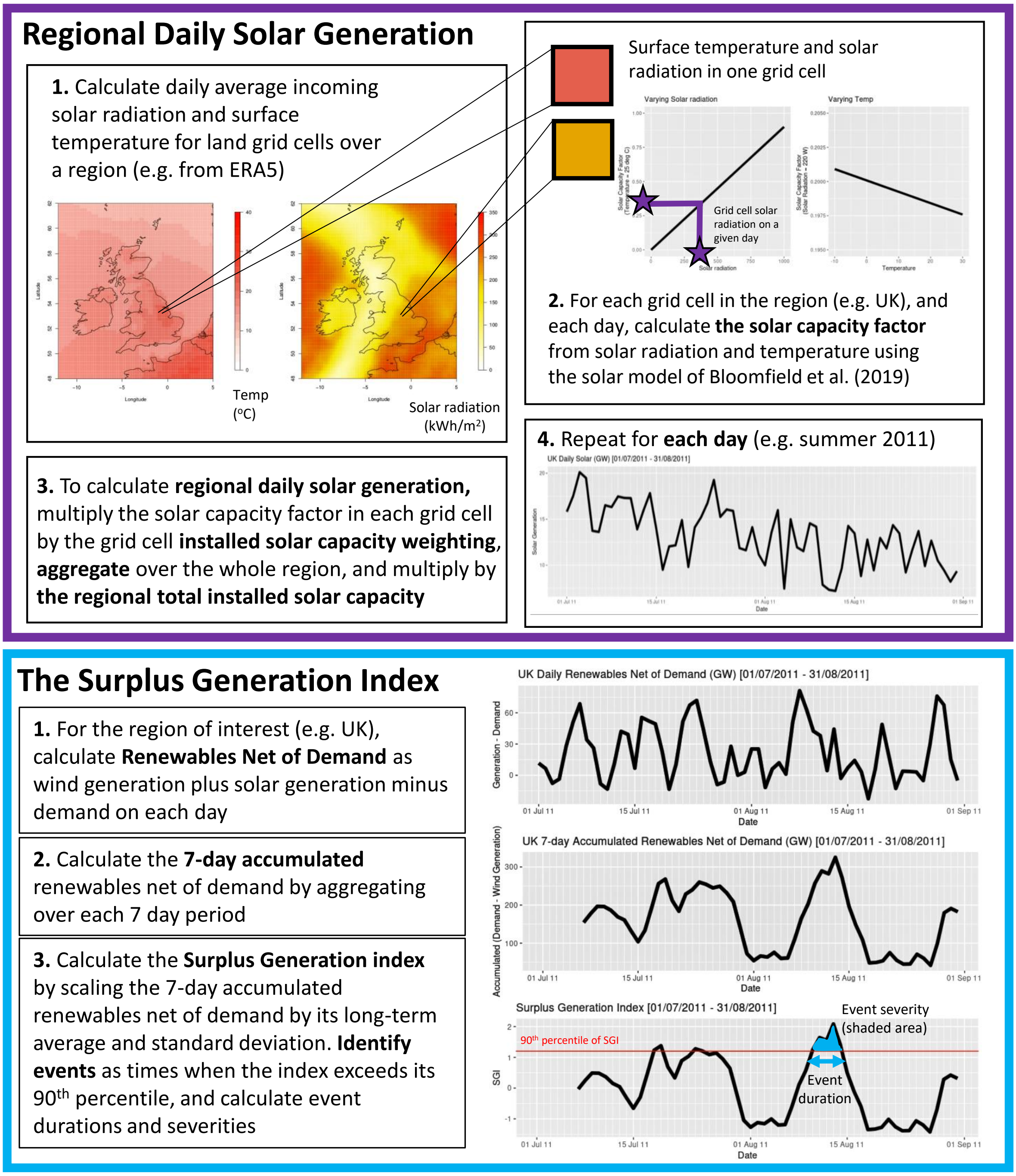

Figure 2: A schematic demonstrating the step-by-step methods used to (top panel) calculate regional daily solar renewable electricity generation, and (bottom panel) calculate the surplus generation event index, identify the associated adverse weather events, and calculate their durations and severities.

3.6 Sensitivity Study

The electricity system settings used within the methodology for characterising adverse weather were tested in a sensitivity study. The input settings were adjusted and the methods repeatedly applied to the 40 years of ERA5 meteorological data to explore the differences in the resulting identified events.

For wind-drought-peak-demand events, the national installed capacities, turbine power curve, WDI accumulation period and study region are varied. The sensitivity study showed that the adverse weather events identified using the various settings are largely consistent, particularly when highly-renewable national installed capacities are considered. This gives greater confidence that the WDI definition described in Section 3.4 is largely robust to these subjective choices. That is, the WDI metric provides a method for identifying representative periods of adverse weather, relevant for testing the resilience of a range of electricity system configurations.

The results also indicated that, in general, adverse weather events are different in the two regions (UK and Europe), supporting the need for producing separate datasets of adverse weather events for each region. However, some events were found to be widespread enough to significantly impact all of Europe and the UK.

A similar sensitivity study was undertaken for the SGI, however for consistency with the WDI, the chosen UK demand model and the estimated 2050s national installed level of wind capacity in each European country were held constant. This sensitivity study therefore explored the sensitivity of the SGI to varying the national installed level of solar capacity. The study found the SGI, and hence the identified events, were very similar across all settings. Further exploration of the output identified this to be due to the relative dominance of wind generation in the SGI calculation, particularly in the UK.
Further detail on the results of the sensitivity study for the different settings can be reviewed in Section 4.1 of the Phase 2 (a) report (Dawkins and Rushby, 2021).

4 Developing the dataset of long-duration adverse weather scenarios for future electricity systems

As highlighted in the 'Weather and Climate Related Sensitivities and Risks in a Highly Renewable UK Energy System' literature review (Dawkins, 2019), a limitation of many electricity system studies is the use of the relatively short historical observed record of meteorological data. In using this observed record only, natural climate variability and anthropogenic climate change are not adequately captured, which may lead to the under- or over-estimation of plausible extreme stress on the electricity system. That is, it may be physically plausible to observe a weather event more extreme than that experienced in the historical record, but that it just hasn't been observed within the limited record. Further, future global warming is likely to impact electricity system relevant meteorological variables, particularly temperature, which could lead to a change in the extremity of adverse weather scenarios.

To better capture alternative plausible weather conditions and anthropogenic climate change within the final dataset of long-duration adverse weather events, events are identified in two data sources, in addition to the ERA5 historical reanalysis (used in Phase 2(a) for event characterisation). Namely, historical climate model hindcasts (retrospective forecasts), which provide more than 2000 alternative plausible historical weather years; and future climate projections, capturing how weather is likely to change in future climates. These data sources are both derived from climate models, hence steps must be taken to validate, calibrate and impute the data where necessary to ensure the characteristics of the data (e.g. the average and variability) are consistent with the equivalent meteorological variables in the observed record. For example, to ensure that the climate model derived data is not biased to being too hot or too windy on average.

This section firstly introduces these two additional sources of data in more detail. The methods developed for validating, calibrating and imputing this data are then presented and discussed. Following this, adverse weather events identified within all data sources, characterising each event type (winter-time wind drought, summer-time wind drought and summer-time surplus generation), in both the UK and Europe as a whole, are explored and discussed. A statistical EVA[6] is then carried out to quantify the return period of events (e.g. 1 in 10 year event) at different future global warming levels, and an approach for using this quantification to select relevant events from the final dataset is presented.

[6] A glossary of acronyms is presented in Section 8

4.1 Data sources

4.1.1 DePreSys Hindcasts

The Met Office Decadal Prediction System (DePreSys)[7] has been used to produce a hindcast (retrospective forecast) dataset. This is made up of global ocean-atmosphere simulations, run freely for many 'model' months to produce new outcomes away from observations. Specifically, the model has been run 40 times for each year 1959 - 2015, initialised in November. This provides 2280 model years of plausible weather, more than 40 times the data available from the ERA5 reanalysis dataset, which is representative of the observed historical conditions only. The DePreSys dataset has been found to produce 'unseen' but plausible meteorologist conditions, more extreme than those seen in the historical record (Thompson et al., 2017). By applying the WDI and SGI to the DePreSys dataset, plausible adverse weather events, more extreme than those observed in the historical period, could be identified, providing additional relevant relevant for resilience testing (see Section 4.3). In addition, incorporating adverse weather events identified within these 2280 years greatly increases the size of the sample used in the statistical EVA, reducing the uncertainty in high return period estimated (see Section 4.4). It should be noted, however, that because the hindcasts are re-initialised each year based on observed conditions (e.g. the observed sea surface temperature), they are not a full expression of the possible natural variability in the ocean-atmosphere system. That is, they are not run freely for the full 57 year period, and hence may underestimate the true climate variability.

The DePreSys data set contains mean daily 60km gridded data for the following weather variables:

1. Surface air temperature;
2. Wind 'U' (east-west) and 'V' (north-south) components at 10m above the ground, which can be used to calculate 10m above ground wind speed[8];
3. Mean Sea Level Pressure.

As described in Section 3, for this study, weather dependent electricity demand is calculated from surface temperature, wind generation from 100m wind speed, and solar generation from solar radiation and surface temperature. These energy demand and generation values are then used to calculated the WDI and SGI, allowing for adverse weather events can be identified. Therefore, to allow for the the DePreSys dataset to be used within this study, 100m above ground wind speed and solar radiation must be estimated coherently with the available meteorological variables. The methods developed for this, and for calibrating the existing variables, are explained and validated in Section 4.2.

[7] https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/climate-models/depresys (Accessed 01/06/2021)
[8] http://colaweb.gmu.edu/dev/clim301/lectures/wind/wind-uv (Accessed 19/05/2021)

4.1.2 UK Climate Projections 2018 (UKCP18)

The United Kingdom Climate Projections (UKCP18) provide the most recent assessment of how the climate may change in the future (Lowe et al., 2018). They are based on the latest peer-reviewed climate science, inclusive of model data from both the Met Office Hadley Centre and other international climate-modelling centres. There are 28 global climate model (GCM) simulations providing worldwide coverage at a 60km horizontal resolution for the historical and future periods from 1900-2100. They are separated into two ensembles as they sample uncertainty in different ways:

1. The perturbed physics ensemble (PPE) is made up of 15 variants of the Met Office Hadley Centre model (hereafter referred to as PPE-15). The PPE-15 is created by perturbing a set of parameters within a single land/ocean model to sample a broad range of future outcomes in a systematic way.

2. The Coupled Model Intercomparison Project (CMIP) ensemble is made up of 13 models, produced by 13 separate institutions, from CMIP Phase 5 (hereafter referred to as CMIP-13). Since the models are created independently there is more scope to sample different sources of uncertainty.

The PPE-15 ensemble allows for a quantification of uncertainty owing to parameter uncertainties (how fast ice falls in clouds, for example), while the CMIP-13 ensemble allows for a quantification of uncertainties owing to structural model choices (the type of land and ocean models used, for example).

The availability of individual variables from CMIP-13 is dependent on whether the data was saved out by the institution. Unfortunately, daily and monthly solar radiation data is not available from any of the CMIP-13 models, wind speed is unavailable for four models and over an insufficient time period for a fifth. Due to these data availability issues, and in order to maintain consistency across the demand, wind and solar generation models in the uncertainty sampled, only the PPE-15 ensemble is used in this study.

Note that UKCP18 also has a suite of 12 regional climate model (RCM) simulations available at a 12km horizontal resolution; driven by 12 of the global PPE-15, which are dynamically downscaled. These have not been used in this study: whilst these simulations do provide additional value by better resolving physiographic features and simulating daily spatial detail of meteorological variables (Murphy, J. M. et al., 2018), the analysis at regional level looking at long duration events does not require such level of detail, and maintaining consistency in the resolution with other datasets of meteorological data is of a higher priority (the DePreSys dataset and ERA5 regridded data used for bias correction in the next section are both at a 60km resolution). Furthermore, there is a small reduction in the uncertainty sampled in the RCM suite (12 simulations rather than 15).

4.2 Data calibration

While these data sources provide a number of advantages in their representation of additional plausible weather years and the effect of climate change, they pose limitations in terms of climate model biases, the availability of meteorological variables, and spatial and temporal resolution. As a results, the DePreSys and UKCP18 data must undergo calibration to ensure they are fit for purpose.

Throughout, the data calibration uses the ERA5 reanalysis dataset as the observed 'truth'. The ERA5 data is on a 30km-hourly spatial-temporal resolution, and hence is regridded and temporally averaged to the same 60km-daily resolution as the DePreSys and UKCP18 datasets to allow for a direct comparison within this calibration. Bilinear interpolation[9] is used to regrid the ERA5 temperature, wind speed and mean sea level pressure data, while an area-weighted method[10] is used for solar radiation to ensure that the amount of radiative flux received over an area is preserved. In addition, the ERA5 100m wind speeds have been corrected using the Global Wind Atlas (as in Bloomfield et al. (2019) and descried in Dawkins and Rushby (2021)).

4.2.1 Bias correction of 10m wind speed, surface temperature and mean sea level pressure

Both the DePreSys and UKCP18 datasets are derived from climate models, which are imperfect representations of the physical climate system. As such, this data is likely to contain biases when compared to observations, for example conditions may be generally too hot or too windy.

DePreSys

When identifying adverse weather scenarios within the DePreSys hindcasts, surface temperature will be used to calculate energy demand; 10m wind speed data will be used to estimate 100m wind speed (see Section 4.2.2), which will be used to calculate wind renewable generation; and mean sea level pressure will be used to produce fields of solar radiation that are coherent with the other DePreSys variables (see Section 4.2.3), which will subsequently be used to calculate solar renewable generation. Therefore, within the DePreSys hindcast dataset, surface temperature, 10m wind speed and mean sea level pressure must be bias corrected.

Figure 3 shows the difference in the grid cell daily mean (average) and standard deviation (variability) of surface temperature, 10m wind speed and mean sea level pressure, when calculated based on the ERA5 data and the DePreSys hindcast data for all January days in the period 1979-2018. These plots show how, for example, the DePreSys data is biased to being too cold on average in some parts of Europe (particularly Norway), and not windy enough on average over much of the North Sea and Scandinavia.

A variance scaling method is used to bias correct the data (see section 3.1.6 of Luo et al. 2018). This form of univariate bias correction method adjusts the mean and standard deviation of the DePreSys data

[9] https://www.sciencedirect.com/topics/engineering/bilinear-interpolation (Accessed 29/04/2021)
[10] https://scitools.org.uk/iris/docs/v1.10.0/userguide/interpolation_and_regridding.html$#$area-weighted-regridding (Accessed 29/04/2021)

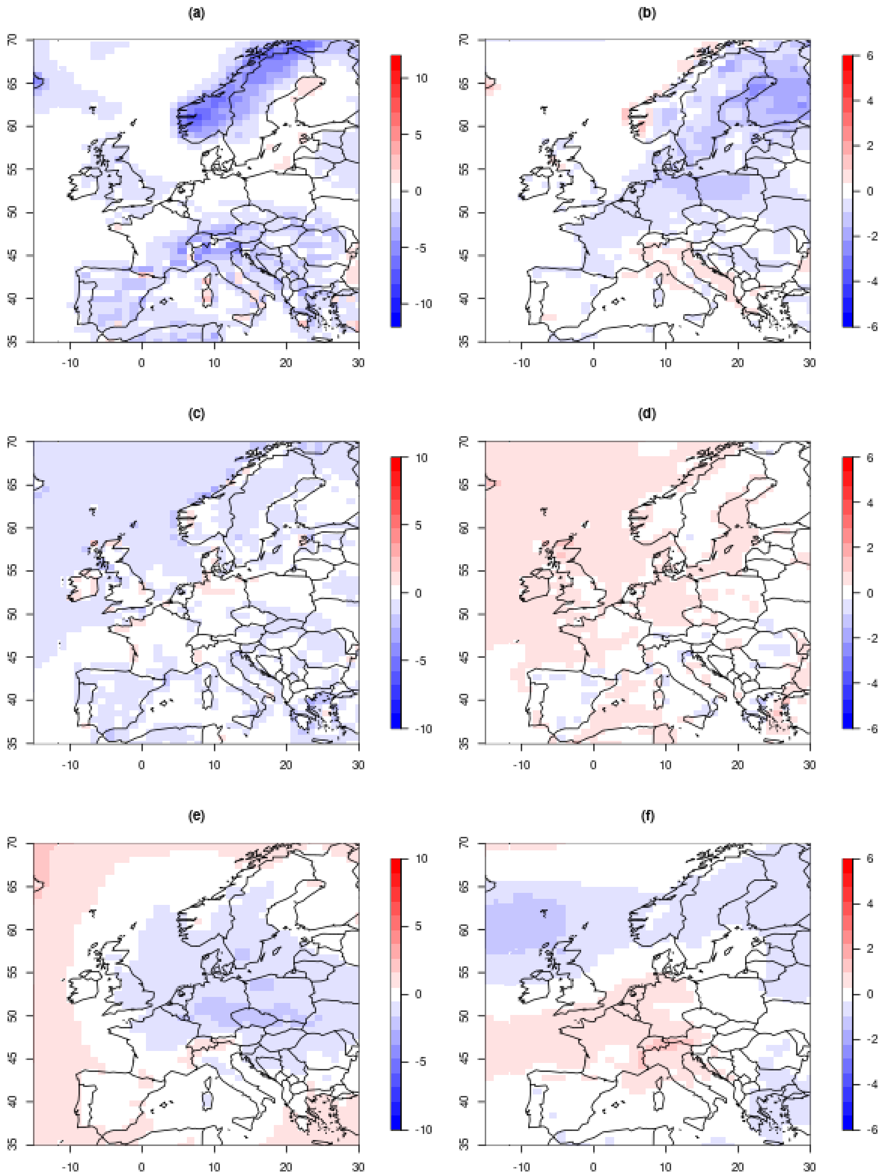

Figure 3: Spatial maps of the difference between the DePreSys and ERA5 grid cell mean (a,c,e) and standard deviation (b,d,e) for surface temperature (top row), 10m wind speed (middle row) and mean sea level pressure (bottom row), for all January days in the period 1979-2018. In each case the difference is calculated as DePreSys minus ERA5, meaning that a value above zero implies the DePreSys data is bias to being too high, and a value below zero implies the DePreSys data is bias to being too low.

in each grid cell and meteorological variable separately, such that it is equal to the mean and standard deviation of the equivalent grid cell and variable in the ERA5 data. The biases in the DePreSys data vary with the time of the year, hence this bias correction is applied to each month of the year separately (i.e. all January days in the period separately from all February days).

Figure 4 demonstrates this bias correction in each variable in January, for a single grid cell in the UK. These plots show how the distribution of the DePreSys data (orange) is adjusted by the variance scaling method to ensure the mean and standard deviation is consistent with the distribution of the equivalent ERA5 data (blue). For example, in Figure 4 (a) and (b), the DePreSys data is shifted slightly to the right to increase temperatures and wind speed, both identified as being biased too low on average compared

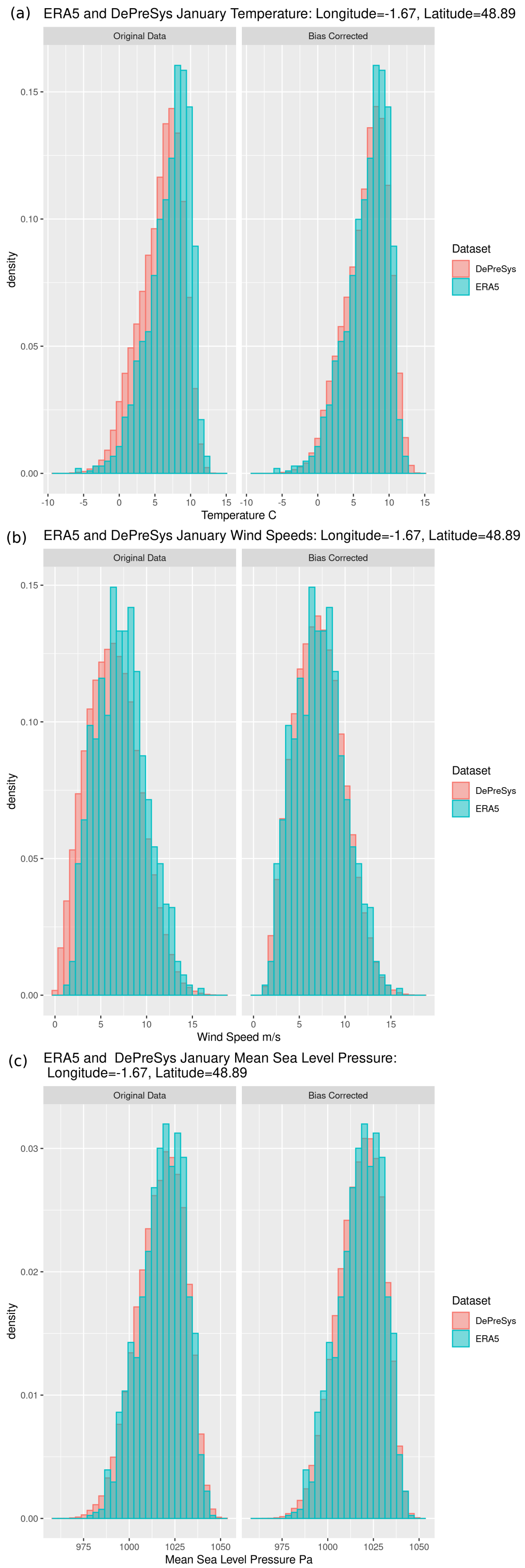

Figure 4: For (a) surface temperature (b) 100m wind speed and (c) mean sea level pressure, histograms comparing the distribution of ERA5 and DePreSys January data in a single UK grid cell, for the original (non-bias corrected) DePreSys daat (left), and for the bias corrected DePreSys data (right).

to ERA5 in Figure 3.

The bias correction method applied here is a univariate method, meaning that it is applied to each grid cell and variable separately. This makes the assumption that the temporal, spatial and inter-variable dependence in the DePreSys data is physically consistent and hence does not need to be corrected. This assumption is thought to be reasonable because the DePreSys data is derived from a physical climate model. Multivariate bias correction methods allow for multiple variables and locations to be biased corrected together, also allowing any biases in these dependences to be corrected. The application of such methods to large climate and weather datasets (such as these) is known to be computationally challenging and cause over-fitting (Cannon, 2018), and hence applying such methods was found to be beyond the scope of this study. The final DePreSys weather data, used to identify adverse weather scenarios, derived from the data bias corrected here are comprehensively validated in Section A.1, showing how the temporal, spatial and inter-variable dependences in the ERA5 data are captured well by the calibrated DePreSys data. These plots (Figures 31 - 42) show that applying a univariate bias correction does not cause any unusual dependence structures within the resulting data.

UKCP18

For the UKCP18 data, the bias correction is achieved using a 'built-in' approach within the statistical EVA applied to the adverse weather scenarios (explained further in Section 4.4 and based on the method of Brown et al. (2014)). This EVA bias correction method is applied to the duration/severity of adverse weather events themselves rather than the underlying meteorological variable. However, since wind generation is calculated from wind speed data using a non-linear wind power curve (Figure 1), any biases in the wind speed data will be greatly amplified by the power curve. For this reason, the UKCP18 10m wind speed data is bias correct prior to identifying the adverse weather events. The same variance scaling method is used to bias correct this 10m wind speed data from UKCP18, using ERA5 as the truth.

In addition, the variance scaling bias correction method assumes stationarity (i.e. that the variable being corrected is not systematically changing over time). This assumption is seen to be acceptable for UKCP18 wind speed data, which does not show a clear change in the future in the UKCP18 projections (Lowe et al., 2018), but would not be acceptable for UKCP18 surface temperature, which has been shown to increase in the future (Lowe et al., 2018; Murphy, J. M. et al., 2018). This therefore necessitates the bias correction of UKCP18 surface temperature using an alternative approach which allows for non-stationarity (changes over time) to be retained, such as the EVA approach described above and in Section 4.4.

Applying the variance scaling bias correction to UKCP18 10m wind speed data achieves equivalent consistencies with the mean and standard deviation of ERA5 as shown for DePreSys in Figure 4. This

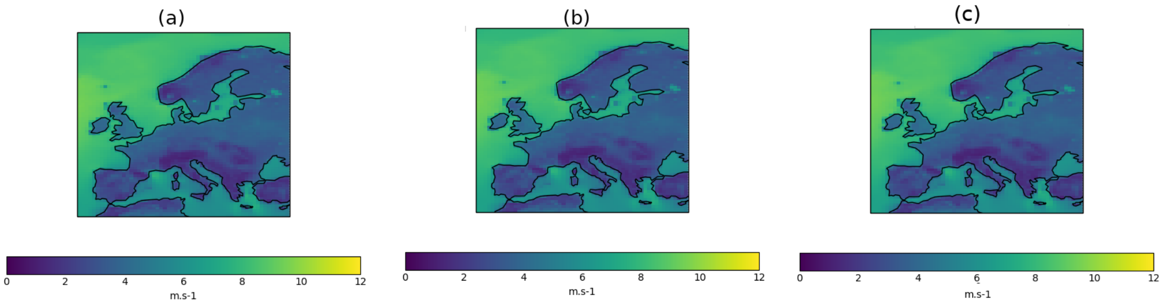

Figure 5: Spatial maps of the mean 10m wind speed in each 60 km grid cell, calculated for (a) ERA5, (b) bias corrected DePreSys and (c) bias corrected UKCP18, over the full period of each dataset.

is evidenced in the similarity between the ERA5 and UKCP18 mean 10m wind speed across Europe in Figure 5 (a) and (c), also consistent with the DePreSys 10m wind speed mean shown in Figure 5 (b).

4.2.2 Representing 100m wind speed

Wind generation calculations require turbine height wind speeds, generally around 100m above ground. The wind speed data available in DePreSys and UKCP18 is 10m above the ground, so a method must be developed to scale this wind speed data to the 100m above ground height. Existing methods such as the log law[11] and power law[12] can be used to scale wind speed from one height to another, however these make assumptions about the surface roughness or wind shear exponent. In addition, discussions with experts within the Met Office highlighted how these laws may not hold as well for low wind speeds, which are particularly important when investigating wind droughts in this study.

An alternative approach, commonly used to correct and adjust wind data (e.g. Dunstan et al. 2016), is to employ a data science modelling technique to represent the relationship between the two wind speed heights (here 10m and 100m) within a dataset that contains both levels (e.g. ERA5), and then use this relationship to scale the data within another dataset that just contains one level (here DePreSys and UKCP18). In this case, a data science method known as Generalised Additive Modelling (GAM)[13] is used. This type of model aims to represent a response/target variable (here 100m wind speed) using a combination of smooth functions of other variables (e.g. 10m wind speed).

Figure 6 shows the relationship between daily mean 10m and 100m above ground wind speed, taken from the ERA5 dataset, for a single 60 $\times$ 60 km grid cell. This figure shows how there is a strong linear relationship between 10m and 100m wind speed, that varies slightly by season. To capture these observed relationships, the GAM is structured such that the response/target variable (100m wind speed) is estimated based on 10m wind speed and ‘day of the year’. Additional explanatory variable are also included to help improve the predictability of the model (i.e. how well 100m wind speed is estimated from other variables). Since the aim it to apply the GAM to the DePreSys data to allow for 100m wind

[11] `http://www.met.reading.ac.uk/~marc/it/wind/interp/log_prof/` (Accessed 02/06/2021)
[12] `https://websites.pmc.ucsc.edu/~jnoble/wind/extrap/` (Accessed 02/06/2021)
[13] `https://datascienceplus.com/generalized-additive-models/` (Accessed 24/05/2021)

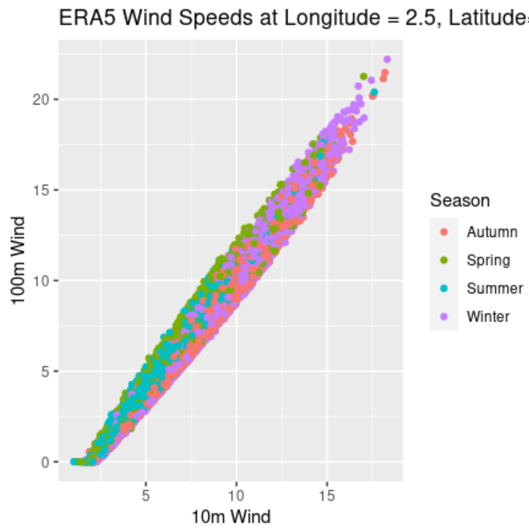

Figure 6: The relationship between daily average 10m and 100m (above ground) wind speed, taken from ERA5 (bias corrected and re-gridded as explained at the beginning of Section 4.2 and Section 4.2.1), for the period 01/01/1979 - 31/12/2018 in a single 60 $\times$ 60 km grid cell. Each data point is a day within the record, and each is coloured according to the season that day falls in: Autumn (Sept-Nov), Winter (Dec-Feb), Spring (Mar-May) and Summer (Jun-Aug).

speed to be estimated for this dataset, these additional variables must be available within the DePreSys hindcasts (see Section 4.1.1). Hence, the grid cell surface temperature and the year are included as additional explanatory variables. In addition, the relationship between 10m and 100m wind speed is found to vary with location (due to differences in surface orography). For this reason, a separate GAM model is trained for each grid cell in the European domain.

Figure 7 presents an example of the GAM, trained on the ERA5 data in a single grid cell. The four plots shows the smooth function fitted to each of the explanatory variables (10m wind speed, temperature, day of the year and year). These show how, as well as the strong relationship between 10m and 100m wind speed seen in Figure 6, there is a linear relationship between temperature and 100m wind speed (as temperature increases so does 100m wind speed), and a non-linear relationship with the day of the year (100m wind speed is generally lower in summer/autumn). Similar relationships are found in other grid cells. These four smooth functions can be used to predict 100m wind speed based on these four variables, by summing f(variable), where the value of the variable is representative of that given day (i.e. the 10m wind speed, temperature, day of year and year).

A cross-validation method is used to validate this model. The GAM is trained on a subset of the ERA5 data (80%), and then used to estimate 100m wind speed for the remaining 20% of the (un-modelled) test data. An example of the relationship between the predicted and true 100m wind speed in one grid cell is presented in Figure 8 (a). This shows how the model is able to very accurately estimate 100m wind speed from the four explanatory variables. Specifically, in this grid cell 98.8% of the variance in the 100m wind speed data is explained by the GAM model, with 100% equating to perfect predictability. A similarly high proportion of the variance is explained (high predictability is achieved) in GAMs trained

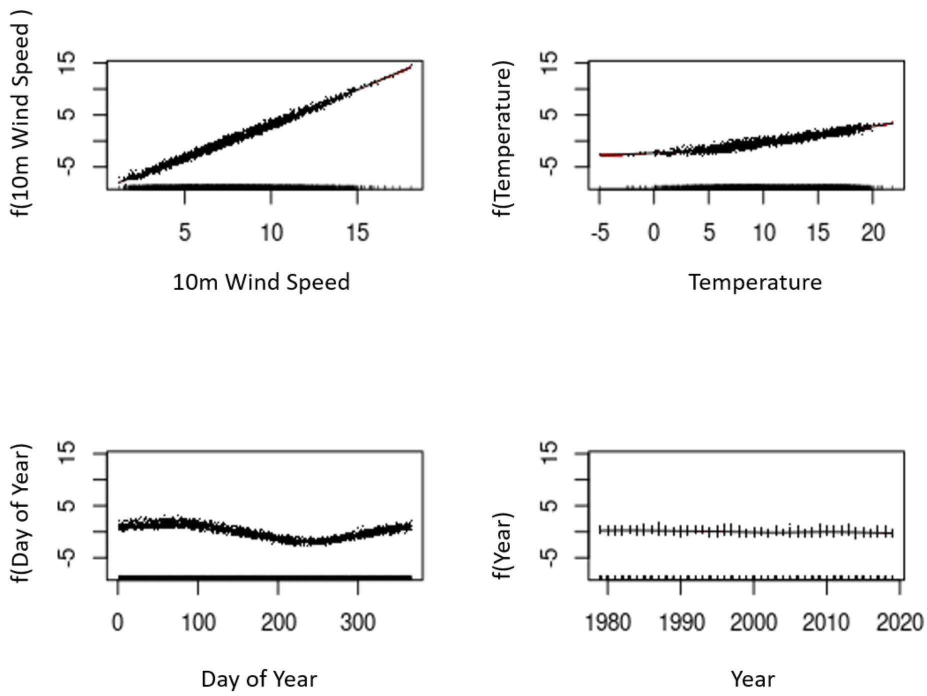

Figure 7: A graphical representation of the the Generalised Additive Model trained on ERA5 data in a single grid cell. Each of the four plots shows the smooth function fitted to each of the explanatory variables (10m wind speed, temperature, day of the year and year), which are used in combination (summed together) to estimate the response/target variable (100m wind speed). In each plot the ticks along the x axis show where the data lies along this dimension.

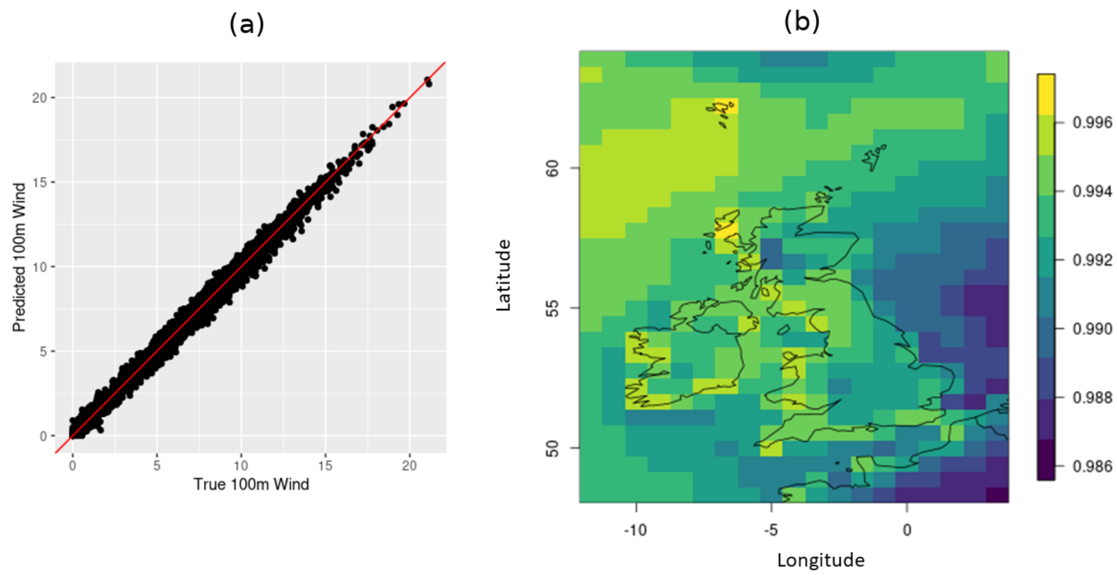

Figure 8: (a) Scatter plot of 'true' daily average 100m wind speed from ERA5, and the associated predicted daily average 100m wind speed from the GAM based on 10m wind speed, surface temperature, day of the year and the year, for the cross validation test data in grid cell: longitude 2.5 and latitude 51.7. (b) A map of the proportion of variance in 100m wind speed explained the GAM fitted to each variable in the UK region, where a value of 0.996 represents 99.6% of the variance being explained. This value is also know as the coefficient of determination or R-squared.

on each grid cell of the European region, a subset of which are shown in Figure 8 (b).

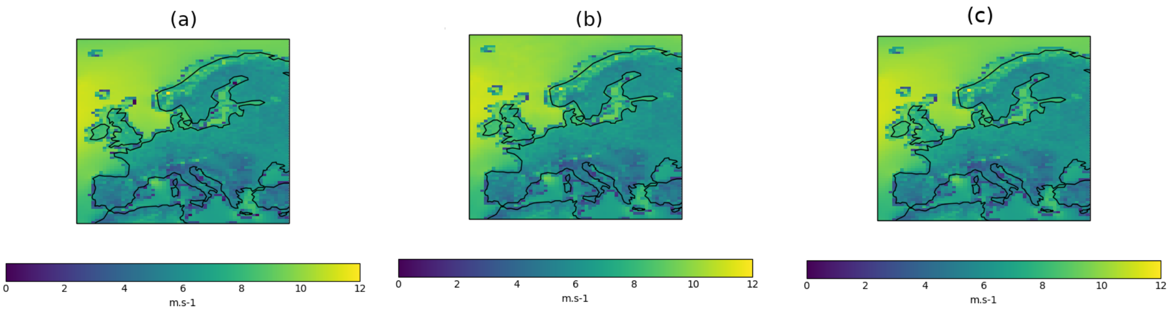

Figure 9: Spatial maps of the mean 100m wind speed in each 60 km grid cell, calculated for (a) ERA5, (b) predicted from GAM for DePreSys and (c) predicted from GAM for UKCP18, over the full period of each dataset.

These grid cell GAMs are subsequently applied to the 2280 model years of DePreSys historical hindcast data. The bias corrected daily mean surface temperature and 10m wind speed (see Section 4.2.1) are used with the temporal variables 'day of the year' and 'year', within the GAM smooth functions, to predict the associated daily mean 100m wind speed value. As shown in Figure 9 (a) and (b), this provides DePreSys 100m wind speed values that are consistent on average with ERA5 data, and hence can be used to estimate wind generation within this study. This estimated 100m wind speed data is further validated in Section A.1. Figures 31 - 42 show how the inter-variable, spatial and temporal variability of this estimated DePreSys 100m wind speed data is very similar to that seen in the ERA5 record.

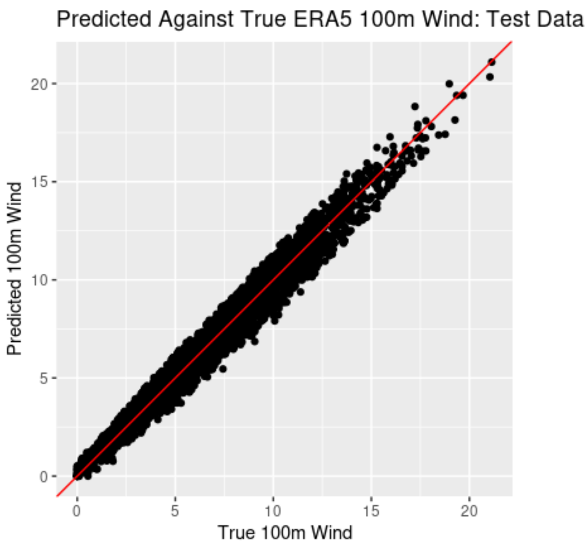

Figure 10: Scatter plot of 'true' daily average 100m wind speed from ERA5, and the associated predicted daily average 100m wind speed from the GAM based on 10m wind speed and moth of the year, for the cross validation test data in grid cell: longitude 2.5 and latitude 51.7.

In a similar way, the UKCP18 daily average 10m wind speed data is scaled to the 100m level. In this case, a slightly different GAM is trained on the ERA5 data. This must be done because the UKCP18 surface temperature data has not yet been bias corrected (as explained in Section 4.2.1), hence it cannot be used as an input in the GAM. In addition, the UKCP18 data is produced on a 360-day calendar, to the year 2098, meaning that the 'day of the year' is not consistent with ERA5, and the ERA5 'year' variable doesn't capture all of the UKCP18 years. Instead, the GAM is structured such that the response/target variable (100m wind speed) is estimated based on 10m wind speed (which has been bias corrected, see Section 4.2.1) and 'month of the year'. This modified GAM is found to still provide a high level of predictability, as shown in Figure 10, in which 97.1% of the variance in the ERA5 100m wind speed data is explained by the alternative GAM model. These UKCP18 grid cell GAMs are applied to the bias corrected 10m wind speed data from the 15 UKCP18 global projects over the period 1979-2098. Again, as shown in Figure 9 (a) and (c), this provides UKCP18 100m wind speed values that are consistent on average with ERA5 data, and hence can be used to estimate wind generation within this study.

4.2.3 Representing surface solar radiation

The DePreSys hindcast dataset does not contain surface solar radiation information (see Section 4.1.1), hence this meteorological variable must be estimated to allow for solar generation to be calculated and used within the adverse weather scenario SGI.

Within this study this is achieved by estimating surface solar radiation from other meteorological variables (e.g. temperature and wind speed) using a data science model. Specifically, as described in Section 5.2.4 of Butcher and Dawkins (2020), 'residual solar radiation', defined as the difference between the solar radiation available at the top of the atmosphere (TOA) and that experienced at the surface, is estimated and then transformed back to raw solar radiation. The TOA solar radiation, can be calculated for a given day of the year, time of the day, and longitude-latitude location based on simple astronomical principles related to the Earths rotation and movement around the sun (Meeus, 1998), and hence the residual solar is the part of the surface solar radiation that directly depends on the meteorological conditions (i.e. cloud cover).

Similar to the approach taken to model 100m wind speed (Section 4.2.2), a GAM is used to represent the relationship between residual solar radiation and other meteorological variables. As before, this GAM is trained on the ERA5 dataset (from which solar radiation information *is* available), and then applied to the DePreSys data, providing an estimate of the residual and hence surface solar radiation at any given time or location, coherently with other the other DePreSys meteorological variables.

The daily average residual solar radiation (surface minus TOA radiation) is therefore calculated for the ERA5 record and the relationship between this and a number of other variables is captured using a GAM. This is done for land locations only because solar generation currently occurs on-land only. As for 100m wind speed, since the aim is to apply the GAM to the DePreSys data to allow for solar radiation to be estimated for this dataset, the meteorological variables used within the GAM must be available within the DePreSys hindcasts (see Section 4.1.1). The GAM is therefore structured such that the response/target variable (residual solar radiation) is estimated based on:

- Surface temperature

- Wind speed (10m above ground)
- Mean sea level pressure
- North Atlantic Oscillation (NAO) - an index calculated as the difference between mean sea level pressure at Iceland and the Azores islands, known to have a strong influence on the weather in the UK, particularly in the winter[14]
- Day of the year
- Longitude
- Latitude

Terms that represent the interaction between these variables are also included in the GAM. In addition, since residual solar radiation is strictly negative (the surface radiation can never be greater than the TOA radiation), the residual solar radiation is log-transformed[15] to ensure the underlying assumptions of the GAM model are met.

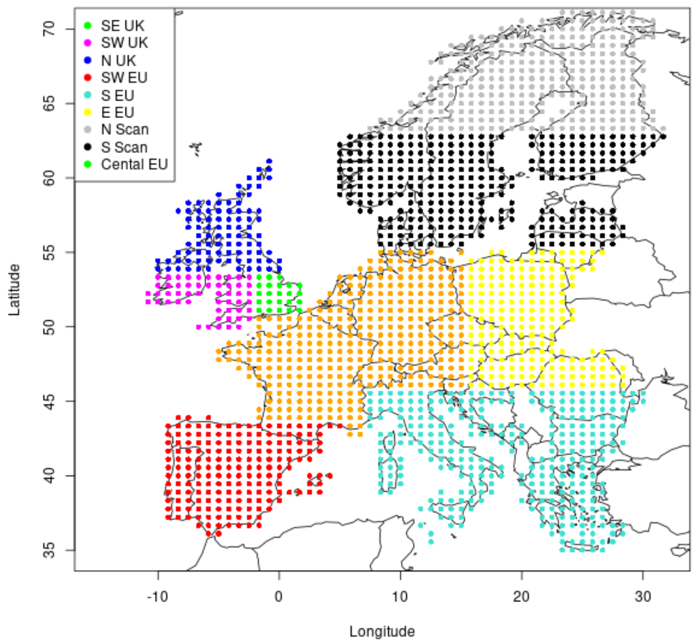

Figure 11: Map showing the land grid cells within the European domain included in each of the 9 regional solar radiation GAMs.

The relationship between residual solar radiation and these variables is likely to be different in different regions of Europe. For example, because the NAO has a different impact on the weather in the north and south of Europe (Jerez et al., 2015). For this reason, land locations associated with European

[14] `https://www.metoffice.gov.uk/weather/learn-about/weather/atmosphere/north-atlantic-oscillation` (Accessed 26/05/2021)

[15] $`https://www-users.york.ac.uk/~mb55/yh_stats/trans.htm`$, (Accessed 26/05/2021)

countries of interest (those included in the analysis of Bloomfield et al. 2019) are divided into 9 regions with one GAM trained on each region. These regions are shown in Figure 11.

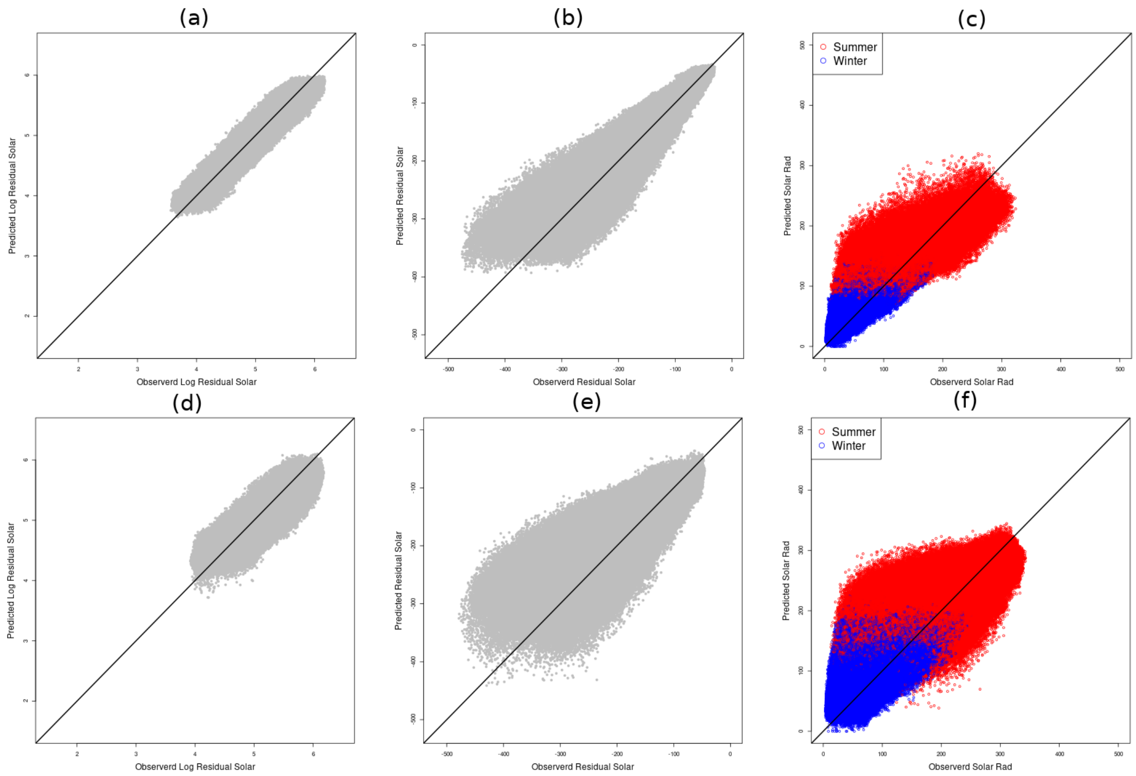

Figure 12: For South-East UK (top row) and South-West Europe (bottom row), (a)/(d) scatter plot of 'true' daily average log-transformed residual solar radiation from ERA5, and the associated predicted daily average log-transformed residual solar radiation from the GAM based on surface temperature, 10m wind speed, mean sea level pressure, NAO, day of year, longitude and latitude, for a 20% sample of cross validation test data, (b)/(e) scatter plot of 'true' and predicted daily average residual solar radiation (not log-transformed), and (c)/(f) scatter plot of 'true' and predicted daily average solar radiation (adding on TOA solar radiation), where days in summer and winter are differentiated between as red/blue respectively.

Figure 12 (a) and (d) show how the GAM predictions (based on the variables listed above) of log-transformed residual solar radiation align closely with the true log-transformed residual solar radiation in the South-East UK (SE UK) and South-West Europe (SW EU) regions. These two regions are presented as a demonstration of the models, and achieve a coefficient of determination (R-squared, or variance explained by the model) of 92% and 80% respectively. Similar predictability is achieved in the other 7 regions, as demonstrated in Table 1. Figure 12 (b) and (e) show the relationship between predicted and true residual solar radiation (i.e. removing the log-transform in a and d) and Figure 12 (c) and (f) show the resulting relationship between predicted and true surface solar radiation (i.e. adding on TOA solar radiation). These plots show how the predictions are particularly good for the higher solar radiation values in the summer, a desirable result as these are the solar conditions that are most relevant for generation and are associated with surplus generation in summer, hence such events will be represented well by the predictions.

To estimate daily surface solar radiation values consistent with the other meteorological conditions in the DePreSys dataset, the trained GAMs are applied to the same variables in the 2280 DePreSys hindcast

Region	R-squared
South-East UK	0.92
South-West UK	0.90
North UK	0.93
South-West Europe	0.80
South Europe	0.81
East Europe	0.91
North Scandinavia	0.97
South Scandinavia	0.95
Central Europe	0.89

Table 1: Table summarising the coefficient of determination (R-squared), or variance explained, by each of the regional residual solar radiation GAMs.

years. Namely, bias corrected daily mean surface temperature, 10m wind speed and mean sea level pressure (see Section 4.2.1), NAO calculated from bias corrected mean sea level pressure, day of the year, longitude and latitude. The predictions of log-transformed residual solar radiation from the solar GAMs are then transformed back to surface solar radiation, as in Figure 12.

The DePreSys solar radiation predictions from the GAMs represent the most likely (mean) solar radiation to occur at the same time as the other meteorological variables. As shown in Figure 13 (a), this means that the regional seasonal mean solar radiation in ERA5 is captured well by the DePreSys predictions, but that they do not capture the full variability seen in the ERA5 data. As a results, the most extreme high and low solar values are not represented, particularly in the summer. To correct for this, a univariate variance scaling bias correction, as described in Section 4.2.1, is applied to the predicted DePreSys solar radiation data. As in Section 4.2.1 this is done separately for each grid cell and each calendar month. Figure 13 (b) shows how this bias correction step helps to improve the variability in the DePreSys predicted solar radiation.

This approach has provided a representation of surface solar radiation that is coherent with the 2280 years of DePreSys wind speed and temperature hindcast data, with consistent characteristics (mean and variability) to those in the ERA5 solar radiation data record. This therefore provides data that can be used to estimate solar generation for the DePreSys model years within this study. This estimated DePreSys surface solar radiation data is also further validated in Section A.1. Figures 31 - 42 show how the inter-variable, spatial and temporal variability of this data is very similar to that seen in the ERA5 record.

[16] https://statistics.laerd.com/statistical-guides/understanding-histograms.php (Accessed 27/05/2021)

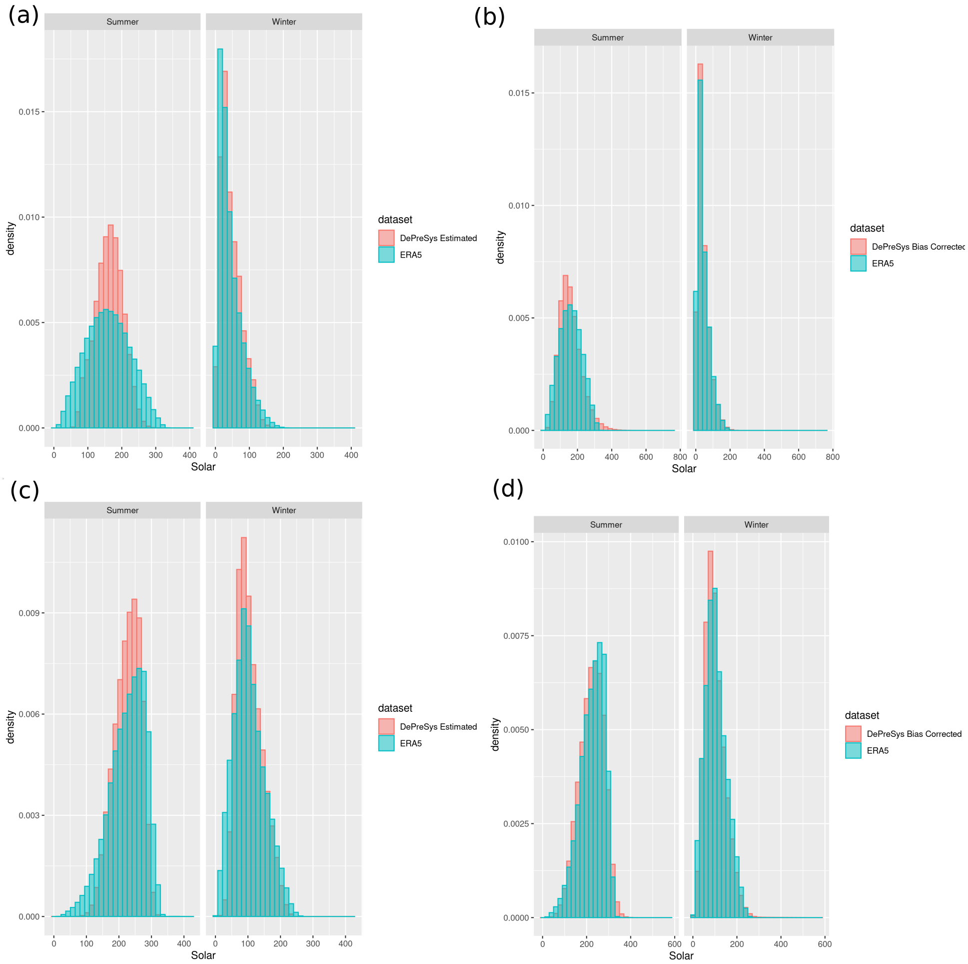

Figure 13: For South-East UK (top row) and South-West Europe (bottom row), (a)/(c) histograms[16] of ERA5 daily average solar radiation and predicted (from the solar GAM) DePreSys daily average solar radiation, over the full period of each data set and shown separately for summer and winter days, and (b)/(d) as in (a)/(c), but for bias corrected predicted DePreSys daily average solar radiation.

4.2.4 Spatio-temporal statistical downscaling

As described in Butcher and Dawkins (2020), many electricity system models ingest 30km spatial, and hourly temporal, resolution weather information, such as ERA5 reanalysis. The DePreSys hindcasts provide meteorological information at a 60km, daily resolution. Therefore, in order to align the data associated with the adverse weather scenarios selected from DePreSys for the final dataset (see Section 5) with the data currently used by energy modellers, a statistical downscaling approach is proposed to fill in the gaps in the low-resolution data (Butcher and Dawkins, 2020). This method was, however, found to require additional development, not achievable within the time-scales of this project, hence unfortunately spatio-temporal statistical downscaling was not ultimately applied within this study.

Similar to the previous sections, a GAM approach was explored. In this case, the aim is to estimate the high resolution (30km hourly) meteorological information from the low resolution (60km daily average) version of the same meteorological variable. It is, however, essential that the low resolution, daily and 60km grid cell average values are conserved, to ensure that the same underlying meteorological conditions are preserved in the downscaled data. For example, estimated hourly temperature values from the downscaling model must average to give the same daily mean as the value they were downscaled from. To ensure this, the GAM target/response variable is specified as the difference between the high and low resolution data. For example, in terms of time and temperature, the target/response variable is the difference between hourly temperature and the daily average temperature on the corresponding day. This target variable is then estimated based on the combination of smooth functions of the time of the day, longitude and latitude.

This GAM approach is applied separately for each European country, each calendar month and for each meteorological variable: surface temperature, 100m wind speed, and surface solar radiation. Temperature and solar radiation have a strong diurnal (within day) cycle, particularly in the summer months, peaking in the middle of the day and dropping to their lowest over night. For this reason, the GAMs for temperature and solar radiation are found to have good skill in predicting hourly (high resolution) behaviour. Wind speed, on the other hand, does not have such a strong or consistent diurnal cycle, and hence the method is found to have low skill when downscaling wind speed information in time. Alternative, more complex approaches must therefore be explored for downscaling wind speed in time, which could not be achieved in the time-scales of this study.

Further, the approach taken to ensure the low resolution, daily and 60km grid cell average information is conserved (i.e. modelling the different between high and low resolution data), is found to create an issue when modelling meteorological variables that must be greater than zero (i.e. wind speed and solar radiation). Specifically, a negative prediction of high resolution wind speed/solar radiation (which is not physically possible) occurs in some cases, when predictions of the difference between high and low resolution from the GAM are too low and hence remain negative when the low resolution variable is added back to the prediction.

The approach was successfully applied to the surface temperature data, however, to ensure consistency across the meteorological data included within the final adverse weather scenario dataset, the low resolution (60km daily average) calibrated DePreSys data is provided for all three variables: surface temperature, 100m wind speed, and surface solar radiation.

Downscaling of data for energy applications is an active research area, with several groups including at the Met Office and University of Reading currently working in this area. It is therefore possible that any alternative approaches that are developed in the future could be applied to the data contained within the final adverse weather scenario dataset, providing data at the desired higher resolution.

4.3 Exploring adverse weather scenarios in ERA5, DePreSys and UKCP18

The methods described in Section 3 for calculating the WDI[17] and SGI are applied to the three data sources: ERA5 reanalysis (Jan 1979 - Dec 2018, 1 realisation), calibrated DePreSys (Nov 1959 - Oct 2016, 40 realisations) and the UKCP18 Hadley centre global projections with calibrated wind speed (Jan 1979 - Dec 2098, 15 realisations). Adverse weather events are then identified within each of the data sources, using a the same fixed adverse weather event thresholds across all three, specified as the 90$^{\mathrm{th}}$ percentile of the WDI and SGI in the ERA5 record (i.e the same thresholds as use in Phase 2 a). As shown in Figures 1 and 2, in each data source, the time steps over which the indices exceed these extreme thresholds are classed as adverse weather and a single event is captured each time the index exceeds and then drop below the threshold. Each event is then characterised in terms of duration (the number of days over which the threshold is exceeded), and severity (the accumulated exceedance of the threshold over the duration of the event).

Event type	Number of ERA5 events	Number of DePreSys events	Number of UKCP18 events
UK winter wind drought	156	7044	4822
UK summer wind drought	178	9738	7296
UK summer surplus generation	184	6128	7158
Europe winter wind drought	135	6347	4514
Europe summer wind drought	161	9481	9349
Europe summer surplus generation	156	4139	9012

Table 2: Table summarising the number of adverse weather events identified in each data source for each adverse weather event type.

Table 2 summaries the number of adverse weather events identified in each data source, for each adverse weather event type. As would be expected, the DePreSys and UKCP18 data sources, which represent 2280 and 1800 model years of data respectively, provide many more adverse weather events than identified in the ERA5 historical observed record only. This much larger sample size of events provides much greater precision in the adverse weather scenario return period estimation, presented in Section 4.4.

For each event type, the adverse weather events identified in each data source can be compared and explored. Comparing the events in ERA5 and DePreSys provides an additional validation of the calibrated DePreSys data, which will be used to represent adverse weather scenarios in the final dataset (see Section 4.5), and observing changes in UKCP18 events over time gives an initial indication of the impact of climate change on the adverse weather scenarios. It should be noted that the aim of this study is not to assess the impact of climate change on electricity systems. The purpose is to identify a sys-

[17] A glossary of acronyms is presented in Section 8

tem agnostic approach (or as near as possible) for quantifying adverse weather scenarios, to ultimately provide a useful dataset for assessing the vulnerability of future system configurations.

In addition, the UKCP18 surface temperature and surface solar radiation data has not been bias corrected at this stage. As discussed in Section 4.2.1, this bias correction is carried out within the statistical EVA, to allow for the non-stationary in the data to be retained. This means that here, the UKCP18 adverse weather event durations and/or severities may be biased to being too low or high compared to ERA5 and DePreSys. These UKCP18 events should therefore not be directly compared to the other two data source in the following plots and instead only the events within the UKCP18 data itself can be compared with each other. Events within DePreSys and ERA5 can, however, be compared because all meteorological variables within the DePreSys record have been calibrated and validated (see Sections 4.2 and A.1).

Moreover, when observing the results in the following plots, it is important to remember that the underlying simplistic electricity system set up (as described in Section 3) remains fixed throughout the full time period (1959-2098). That is, in this study the electricity system does not evolve over time, as it will do in the real world, and hence the way in which each adverse weather event type changes over time is based solely on changes in the weather and climate, and not the electricity system. Here, the current day temperature-demand relationship in each country (taken from Bloomfield et al. 2019) is used throughout the period, when in reality this relationship is likely to change over time with, for example, the increased use of heat pumps. In addition, the installed level of wind and solar renewables is fixed at a highly renewable level throughout Europe for the full period, rather than being representative of actual historical capacity and gradually increasing future capacity. This approach is taken because it allows for the extremity of adverse weather events to be consistently compared across different global warming levels (see Section 4.4).

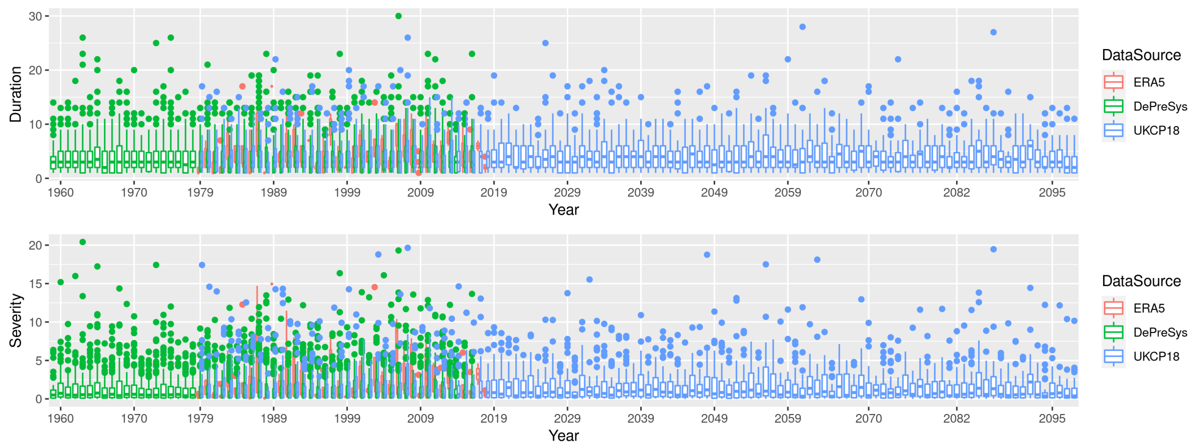

Figure 14: Box and whisper plots showing the distribution of **UK winter-time wind-drought-peak-demand** event durations (top) and severities (bottom) for events identified in each data source within each year.

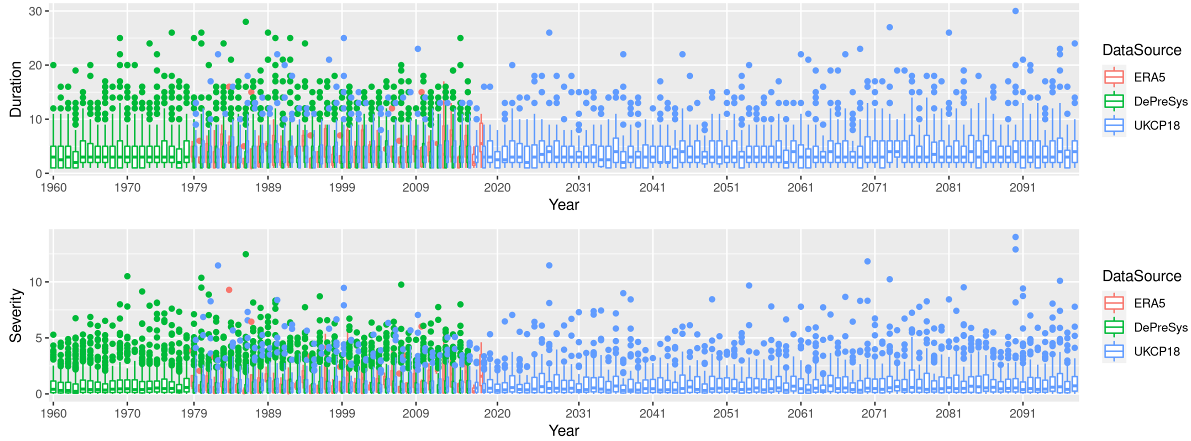

Figure 15: Box and whisper plots showing the distribution of **UK summer-time wind-drought-peak-demand** event durations (top) and severities (bottom) for events identified in each data source within each year.

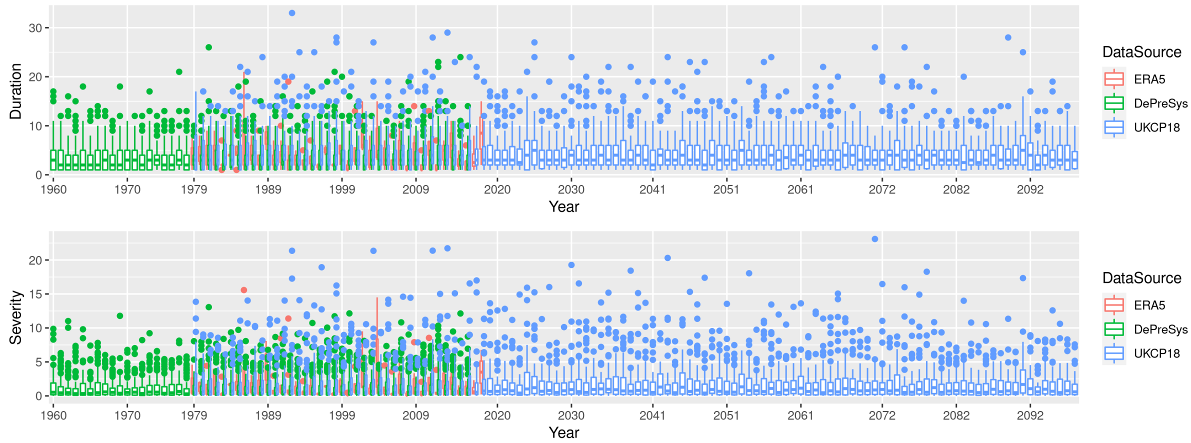

Figure 16: Box and whisper plots showing the distribution of **UK summer-time surplus generation** event durations (top) and severities (bottom) for events identified in each data source within each year.

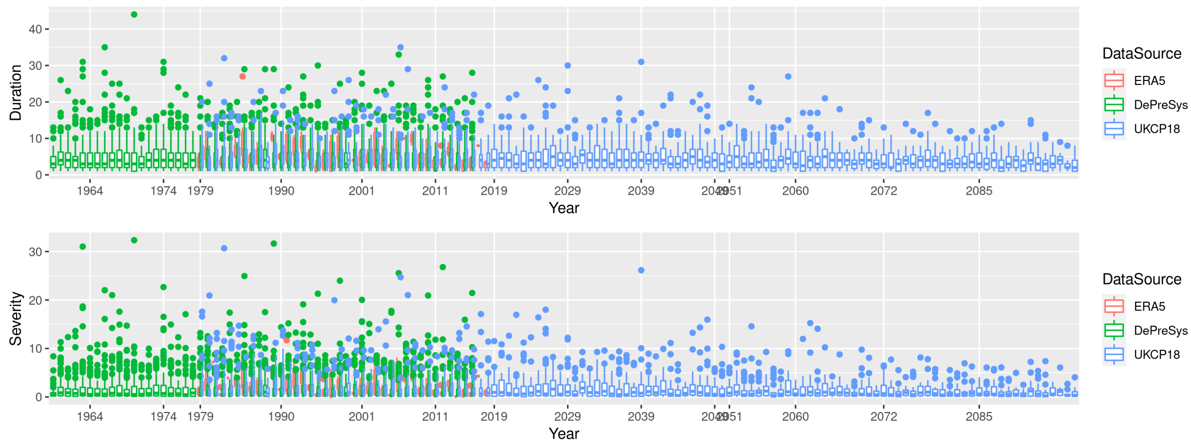

Figure 17: Box and whisper plots showing the distribution of **Europe wide winter-time wind-drought-peak-demand** event durations (top) and severities (bottom) for events identified in each data source within each year.

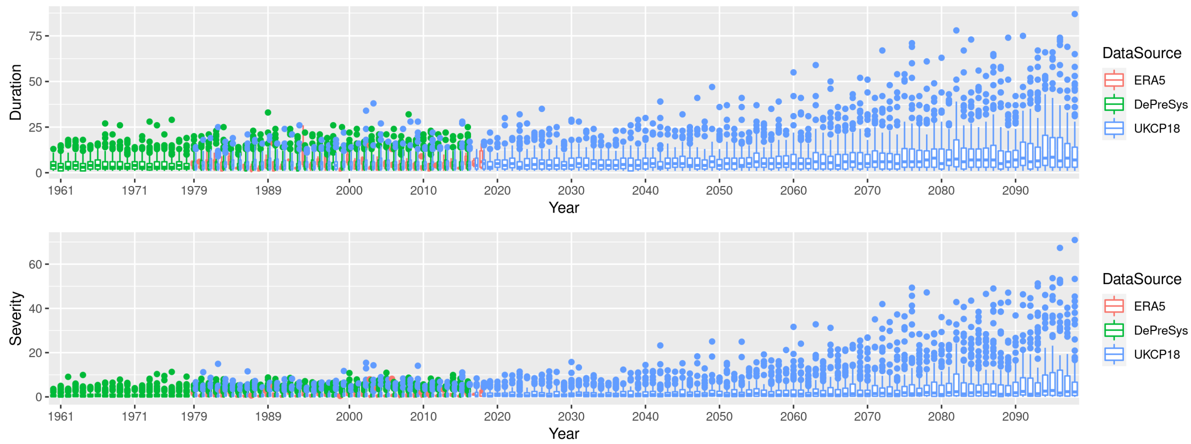

Figure 18: Box and whisper plots showing the distribution of **Europe wide summer-time wind-drought-peak-demand** event durations (top) and severities (bottom) for events identified in each data source within each year.

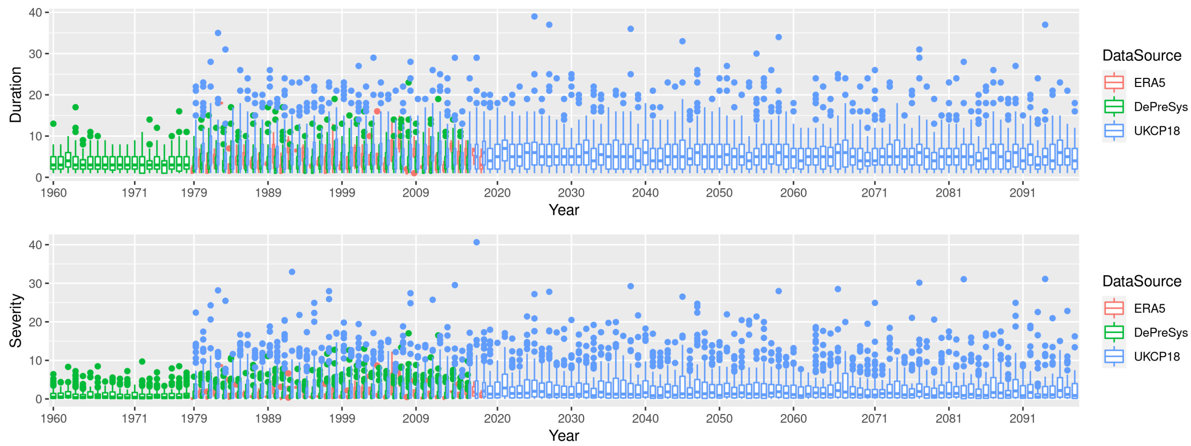

Figure 19: Box and whisper plots showing the distribution of **Europe wide summer-time surplus generation** event durations (top) and severities (bottom) for events identified in each data source within each year.

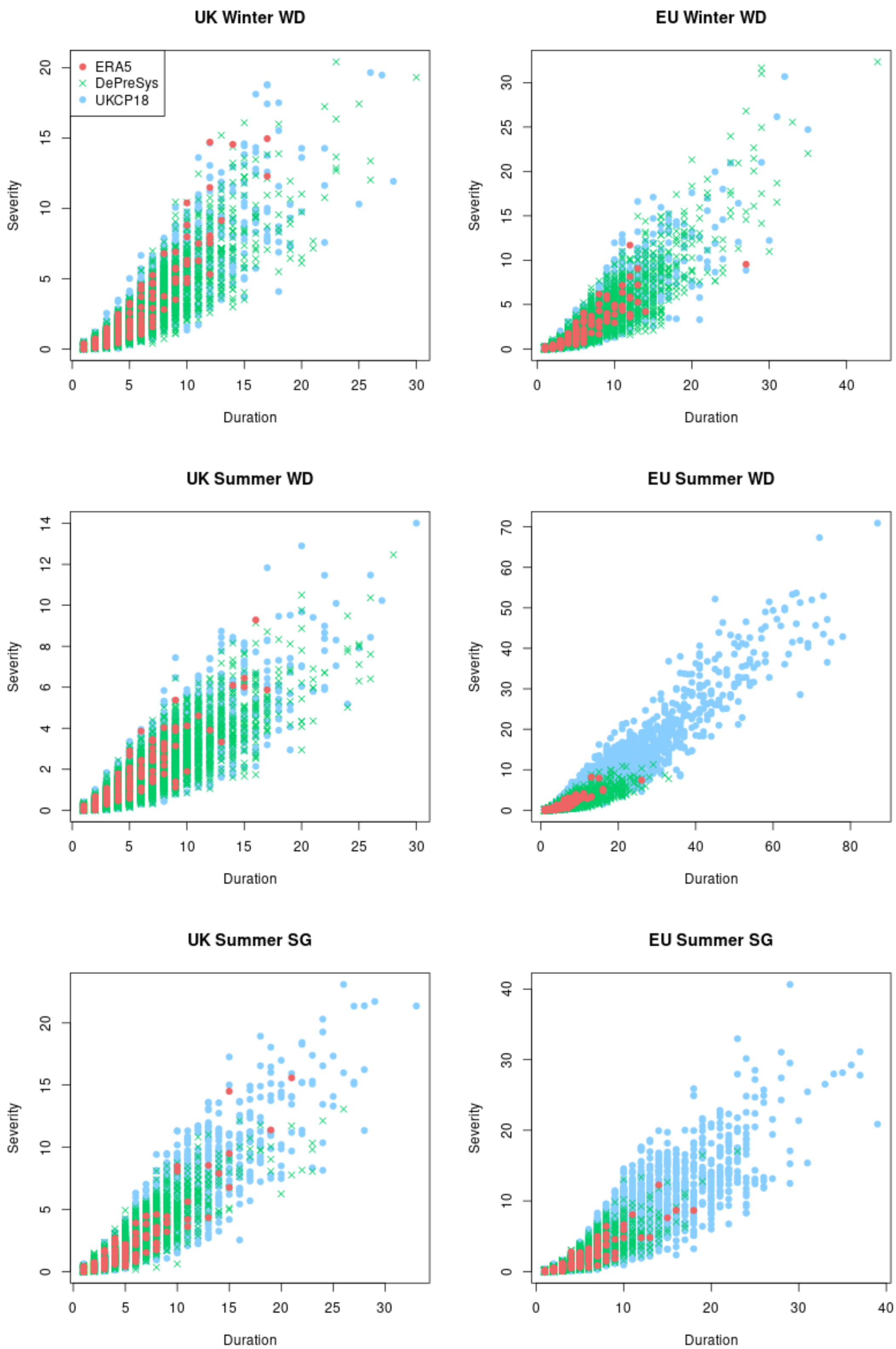

Figure 20: Scatter plots of adverse weather event durations and severities. Each panel represents a different event type as described in the panel heading (where WD=wind-drought-peak-demand and SG=surplus generation), and each point represents a different event, with events from each data source (ERA5/DePreSys/UKCP18) differentiated between.

Figures 14 - 20 present comparisons of the adverse weather event durations and severities for events identified in the three data sources. These figures show how, for all event types, the DePreSys hindcasts include events that are more extreme than those observed in the historical record (ERA5). Similar to other studies that have used the DePreSys hindcasts (Thompson et al., 2017), this means that including these additional 2280 model years of data within the analysis allows for the exploration of 'unseen', unprecedented meteorological events, as was the aim specified in the scoping phase of this project (Butcher and Dawkins, 2020).

While more extreme events are captured within the DePreSys hindcasts, the DePreSys event durations and severities are largely consistent (i.e. not much larger) with those in the ERA5 data, providing further validation of the underlying calibrated DePreSys meteorological data. In particular, the scatter plots in Figure 20 show how the ERA5 and DePreSys events have similar relationships between event duration and severity in each event type. Again, this indicates that the DePreSys events are behaving in a similar to the ERA5 events, and hence the calibrated DePreSys meteorological data is behaving sensibly. Further, some of the most extreme UK and European wind-drought-peak-demand events in the DePreSys record are observed in the years 1963 and 1979, consistent with key years identified by McCaskill and Hudson (2006) in their book 'Frozen in Time - The Years when Britain Shivered'.

Focusing on the UKCP18 events only in Figures 14 - 19, allows for an initial exploration of the effect of climate change on the adverse weather scenarios, remembering that any change over time is due to changes in the meteorological conditions only (as a fixed electricity system is used over the full period). As discussed in Dawkins (2019), UKCP18 projections show a clear increasing signal in UK temperatures (Lowe et al., 2018). Specifically, the UKCP18 results suggest that winter minimum temperatures are on average likely to rise by 1-2°C throughout the UK by 2100; and summer maximum temperatures are on average likely to rise by 2-3°C in the south of the UK by 2100 (dependent on the climate change Representative Concentration Pathway[18]). The effect of climate change on wind speeds and solar irradiance, on the other hand, is less well understood (Lowe et al., 2018), with various studies showing conflicting results (Dawkins, 2019). There has been some consideration within the UKCP18 analysis (Lowe et al., 2018), of how climate modes of variability, such as the North Atlantic Oscillation (NAO), will change in future climates. The UKCP18 climate projections indicate a possible decrease in the number of winter days in the negative phase of the NAO (associated with blocking, low wind speed and cold condition) and a corresponding increase in positive NAO (windy and mild) days. Lowe et al. (2018) note, however, that the cause of this is not currently understood.

When considering UKCP18 events in Europe as a whole (Figures 17 - 19), there is an indication that, due to changes in the climate, European-wide winter-time wind-drought-peak-demand events (as defined in this study) may *decrease* in duration and severity, while summer-time wind-drought-peak-

[18] `https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---representative-concentration-pathways.pdf` (Accessed 09/06/2021)

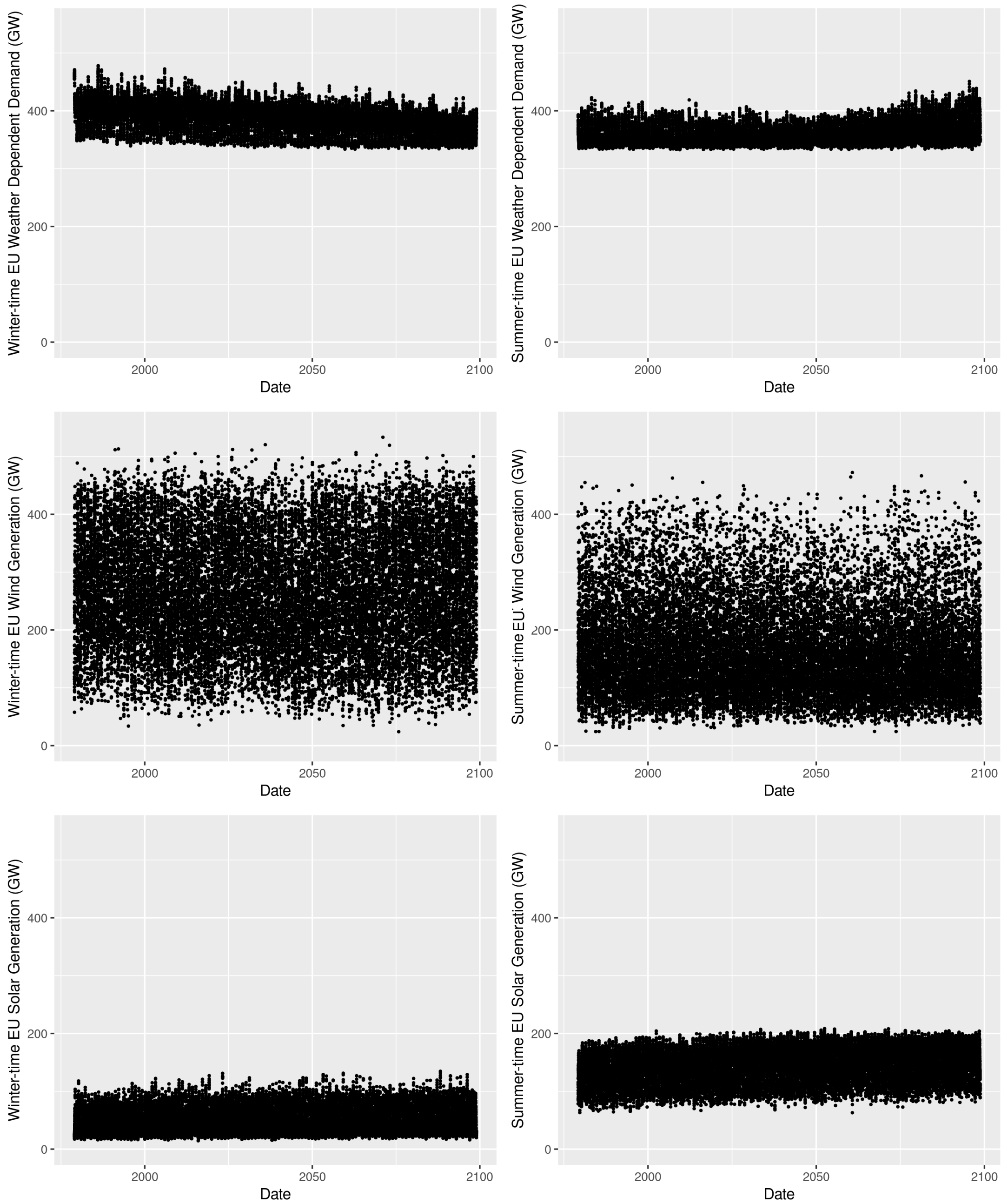

Figure 21: Scatter plots of European winter-time (left) and summer-time (right) daily weather dependent demand (top), wind generation (middle) and solar generation (bottom), for each day in the UKCP18 record, for the Hadley Centre PPE memeber 1. These electricity system metrics are calculated from the daily meteorological conditions using the methods described in Section 3.

demand events may *increase* in duration and severity. Exploration of the UKCP18 European wind generation and weather dependent demand (the two components that make up the WDI), shown in Figure 21, indicates that this change over time is predominantly due to changes in the weather dependent demand component of the WDI. The wind speed and resulting wind generation is relatively stationary throughout the period, consistent with insight from UKCP18 documentation (Lowe et al., 2018). Winter and summer temperatures are, however, increasing in the UKCP18 projections, as global warming increases, causing a reduced demand for heating in the winter and an increased demand for cooling in the summer. The higher rate of change in the events in summer compared to winter in the later half of the 21st century reflect how summer temperatures are expected to increase more than winter temperatures (see Figure 5.2 in the Met office UKCP18 Land Report[19]).

Interestingly, the same climate change sensitivity is not seen in the European summer-time surplus generation events (Figure 19), due to the inclusion of solar generation within the SGI. Figure 21 shows how summer-time solar generation is increasing slightly over the future period, which when combined with wind generation dominates over the change in demand in the SGI, hence reducing the impact of changing temperatures on the surplus generation events.

Considering the UKCP18 events in the UK only, Figures 14 - 16 indicate that, based on the fixed highly-renewable electricity system set up used in this study, there is no clear climate change effect on the duration or severity of UK adverse weather events. Figure 22 shows how, although there is some evidence of climate driven change in WDD in the UK, both the WDI and SGI are dominated by wind generation (which reaches much larger values, due to the high wind generation potential and level of wind renewables installed in the UK in this study). Since wind speed and hence wind generation does not change systematically over time with climate change (as seen in Europe), this then leads to consistent adverse weather events in the UK into the future.

Interestingly, it can also been seen in Figure 22 that UK summer-time WDD does not increase over time, as it does in Europe, in fact a very small negative trend can be seen. Even though the French CDD slope is used in the UK demand model (see Section 3.1), the daily average temperature in the UK in summer (April-September), used in the WDD calculation, is still often lower than the heating demand threshold (15.5°C) causing a small decrease in heating demand as temperatures increase over the period. In addition, the cooling demand threshold (22°C) is exceeded relatively infrequently throughout the period, and only after about 2050, which is not enough to create a positive demand trend. It may be expected, however, that the uptake in air conditioning in the UK is more related to overnight high temperatures associated with heatwaves (Nairn and Fawcett, 2015), not captured in the simplistic electricity system model used in this study. In addition, applying the demand model to potentially biased UKCP18 temperature data may mean that the cooling threshold is not exceeded as frequently as it should be. The impact of this on the results of the study are, however, expected to be small due to the dominance of wind generation in the wind drought events.

To determine the sensitivity of the selection of wind drought events to the assumed levels of electrified heating, Figure 23 shows how the magnitude and variability of UKCP18 future winter-time weather dependent demand and wind-drought-peak-demand event severities change when the UK HDD slope is varied in the implemented electricity system. This HDD slope represents how many additional GW of power are required for each degree Celsius colder it is in the winter (see Section 3.1), hence a higher

[19] `https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/UKCP18-Land-report.pdf` (Accessed 28/05/2021)

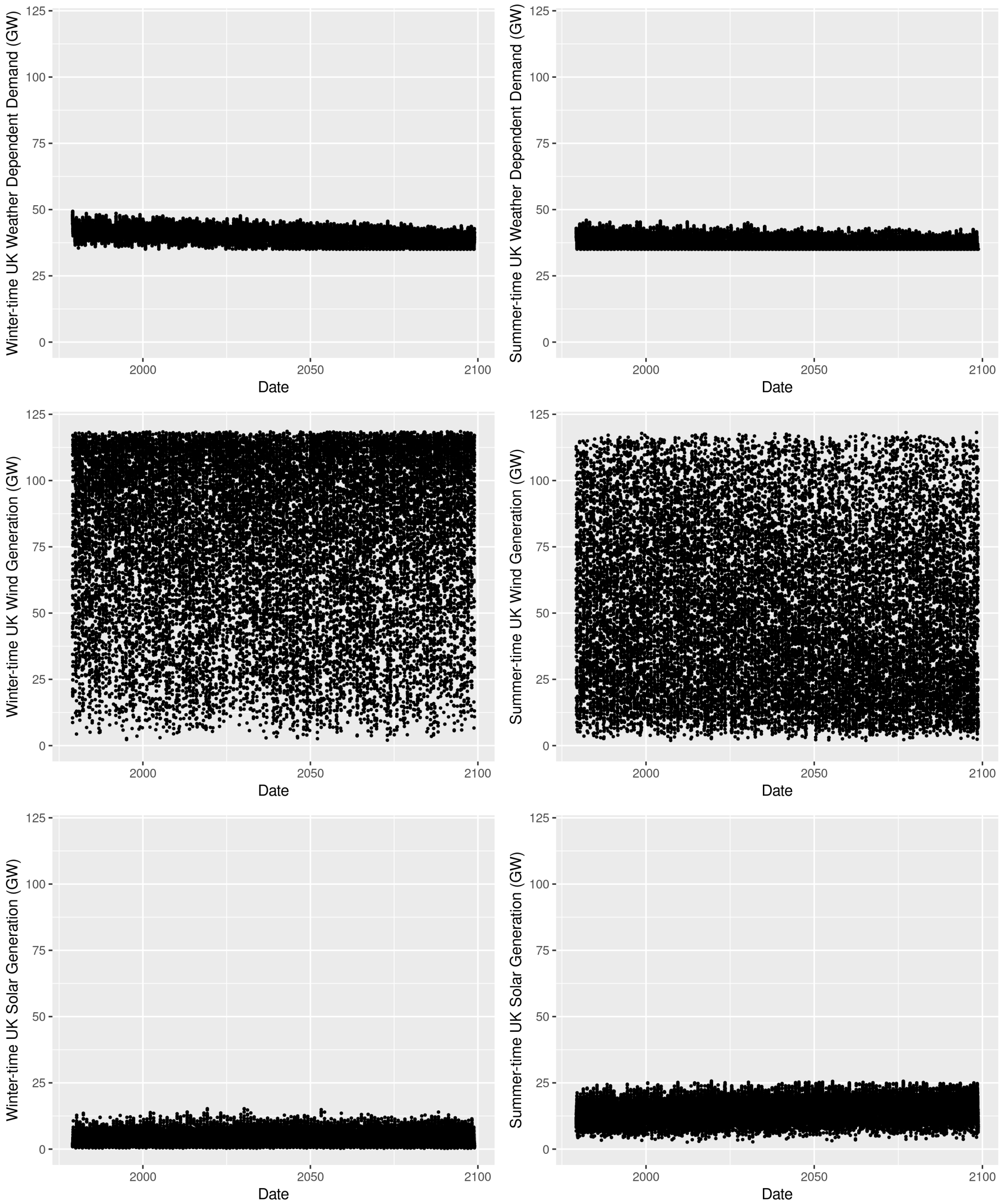

Figure 22: Scatter plots of UK winter-time (left) and summer-time (right) daily weather dependent demand (top), wind generation (middle) and solar generation (bottom), for each day in the UKCP18 record, for the Hadley Centre PPE memeber 1. These electricity system metrics are calculated from the daily meteorological conditions using the methods described in Section 3. It should be noted that in the UK, summer-time daily weather dependent demand (April-Sept) includes demand for heating, hence why this has also experiences a downward trend over time.

value represents a more sensitive temperature-demand relationship.

The top row of Figure 23 presents the winter-time WDD and wind-drought-peak-demand event severities when a HDD slope of zero is used. In this case, the temperature has no impact on the WDI (WDD remains constant), and hence the wind-drought-peak-demand events are based solely on wind generation. The severity of these events show no clear climate change signal, reflecting UKCP18 findings related to wind speed (Lowe et al., 2018).

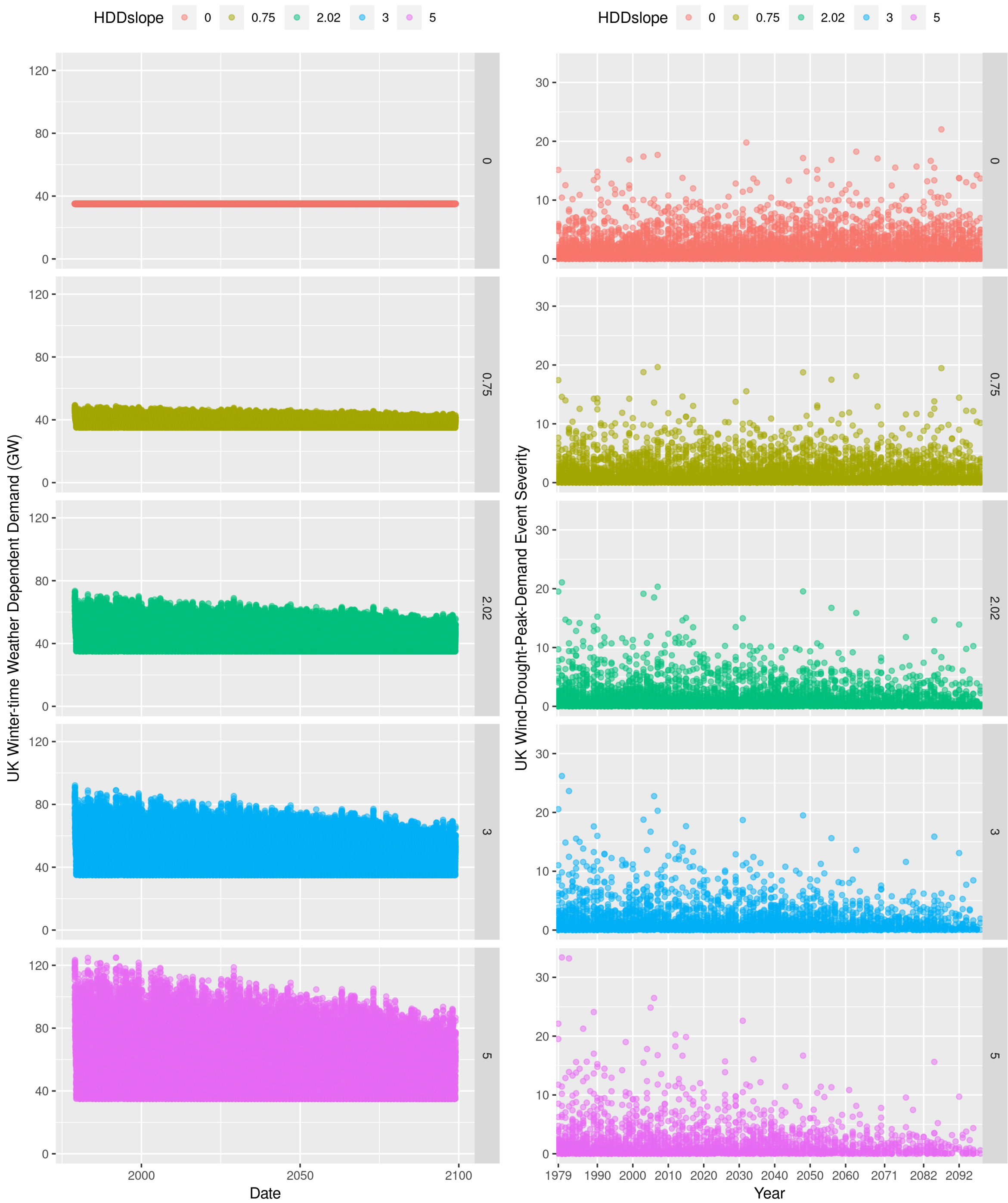

Figure 23: (Left) Scatter plots of UK winter-time weather dependent demand for each day in the UKCP18 record (for the Hadley Centre PPE memeber 1), varying the heating degree day slope (temperature-demand sensitivity) in winter, and (right) Scatter plots of the resulting UK winter-time wind-drought-peak-demand event severities from the UKCP18 record (for all 15 Hadley Centre PPE memeber), again varying the heating degree day slope. A heating degree day slope of 0 is included to show how the winter-time wind-drought-peak-demand events vary when based solely on wind generation; 0.75 is the current-day UK heating degree day slope; 2.02 is the French heating degree day slope, characterising an increased electrification of heating; and 3 and 5 represent increasingly electrified heating systems in the UK.

The other rows in Figure 23 represented HDD slopes of 0.75 (the current-day UK HDD slope), 2.02 (the French HDD slope, characterising an increased electrification of heating), and 3 and 5 represent increasingly electrified heating systems in the UK, deemed unlikely be the project advisory group.

Comparing the winter-time WDD (left column of Figure 23) to UK wind generation magnitudes in Figure 22 (middle panel), it can be seen that the UK WDD increases to levels close to that of wind generation (120GW) when the HDD slope increases to 5 GW per degree Celsius. As a result, in this case, the WDI is no longer dominated by the wind generation and is equally sensitive to changes in temperature. This results in a stronger climate change signal in the resulting wind-drought-peak-demand event severities (right column of Figure 23). The results highlight how, in a highly-renewable UK system (where a high level of wind renewables are installed), climate sensitivity is still small when the French HDD slope is employed, and even when this HDD relationship is increased to 3 GW per degree Celsius. This demonstrates how the energy system studied here appears insensitive to expected changes to future climate. Specifically, the level of installed renewables in the UK must be lower than that estimated for 2050, and/or the electrification of heating and cooling must be increased beyond the French models to identify a strong sensitivity to climate change.

As previously noted, the aim of this study is not to assess the impact of climate change on electricity systems. The purpose is to identify a system agnostic approach (or as near as possible) for quantifying adverse weather scenarios, to ultimately provide a useful dataset for assessing the vulnerability of future system configurations.

As such, the electricity system configuration used in this study (described in Section 3) is implemented to ensure a highly-renewable system is represented (high levels of wind and solar renewables installed), and to remain as electricity system agnostic as possible (not making assumptions about how demand may change or where renewables may be located in the future), following guidance from the project advisory group of energy experts. Hence, although the climate change sensitivity captured within the final dataset of adverse weather scenarios may be somewhat conditional on this chosen electricity system configuration (as shown in Figure 23), ultimately the dataset is relevant for a range of potential future electricity system. This dataset can now be widely used to explore how such relevant adverse weather scenarios will impact *other* electricity system configurations (e.g. those with highly electrified heating/cooling).

4.4 Statistical extreme value analysis to quantify adverse weather in different climates

The aim of this study is to produce a dataset of adverse weather scenarios, characteristic of various extreme levels (i.e. return periods), and climate change warming levels. Specifically, the 1 in 2, 5, 10, 20, 50 and 100 year return period events for warming levels representative of current day (1.2°C), and 1.5°C, 2°C, 3°C, and 4°C above pre-industrial, are to be shared (Butcher and Dawkins, 2020).

To achieve this, a non-stationary statistical EVA[20] is implemented (Coles, 2001), based on the dura-

[20] A glossary of acronyms is presented in Section 8

tions and severities of adverse weather scenarios identified in the three data sources (as presented in Section 4.3). This analysis provides a return level curve for each event type (wind-drought, surplus generation), event metric (duration, severity) and global warming level of interest (1.2, 1.5, 2, 3, 4°C above pre-industrial). This analysis can then be used to identify the extremity of an adverse weather scenario expected to occur on average once every N years (i.e. a 1 in N year event) for that given event type, event metric and global warming level.

As described in Section 5.3 and Figure 64 of Dawkins (2019), a statistical extreme value distribution, such as the Generalised Pareto Distribution (GPD)[21], can be fitted to the extremes of a variable (e.g. temperature above a high threshold), and used to parametrically estimate the probability of observing a value of a given magnitude (e.g. the probability of observing a temperature of 30°C). That is, the parameters that explain the shape of the fitted GPD (the scale and shape parameters[21]) can be used within the GPD probability density function[21] to calculate this event probability.

This probability can then be equated to a return period (or recurrence interval), representative of the number of years on average you would have to wait to see an event of the same magnitude. For example if the fitted GPD specifies a 0.01 (or 1%) probability of observing a temperature of 30°C in a year, then this event has been modelled as occurring on average once every 100 years, equivalent to having a return period of 100 years. Note that these values are purely for demonstration and are not based on real data.

Further, it may be expected that this probability will change over time, for example due to climate change. This means that the modelled variable (e.g. temperature) is expected to be non-stationary, and hence a non-stationary (changing over time) GPD should be fitted instead. In this case, the parameters of the GPD, and in some cases the GPD high threshold (Brown et al., 2014), are able to vary in time by conditioning on a relevant explanatory variable such as global mean surface temperature (GMST), known to be a good representation of the magnitude of climate change (Brown et al., 2014). In the non-stationary case, the parameters of the GPD depend on the relevant explanatory variable (e.g. GMST) and hence the GPD takes on a different shape for any given value of this variable. For example, this could mean that the fitted GPD specifies a 0.01 (or 1%) probability of observing a temperature of 30°C in any given year for the current day global warming level (1.2°C above pre-industrial), but a 0.05 (or 5%) probability of observing a temperature of 30°C in any given year for a warming level of 2°C above pre-industrial. This means that this is a 1 in 100 year event in the current day climate, but a 1 in 20 year event (occurring on average 5 times in 100 years) in the warmer climate. As above, these values are purely for demonstration and are not based on real data.

As discussed in Section 5.2.5 of Butcher and Dawkins (2020), this non-stationary EVA approach has

[21] `http://www.nematrian.com/GeneralisedParetoDistribution` (Accessed 28/05/2021)

previously been used by Brown et al. (2014) to produce time-dependent projections of future extreme rainfall and temperature in the UK. Similar to the above example, Brown et al. (2014) condition their EVA model parameters on GMST, allowing for extremes to be estimated for any given warming level of interest. In addition, the model is fitted to both climate projections, so future warming levels can be considered, as well as historical observations within an overlapping time period, to allow for the climate projections to be bias corrected. This bias correction is achieved by conditioning the EVA model parameters on a bias term (as well as global mean temperature) that is only applied to data from the climate projections. This term can then be 'turned off' to allow for non-biased estimates of future extremes (see Brown et al. (2014) for more detail).

In this study, a similar approach is used to quantify the extremes of the adverse weather event durations and severities. This allows for the return period of the event durations/severities to be quantified, and subsequently used to pick relevant events for the final dataset. For example, allowing for insights such as: a UK winter-time wind-drought-peak-demand-event expected to occur on average once every 20 years (1 in 20 year event) in the current day climate (warming level 1.2°C above pre-industrial) has a duration of 13-14 days.

Similar to Brown et al. (2014), here, a non-stationary EVA model is fit to event durations/severities taken from both climate projections and historical data, and the parameters of the EVA model (here a GPD) are conditioned on GMST and a climate model bias term. Brown et al. (2014) fit their EVA model to each climate model projection individually to allow for the climate model structural and parametric uncertainty to be fully captured. Here, however, since adverse weather events rather than raw meteorological data are being modelled, the relatively small sample size of events in an individual climate projection result in the fitted EVA model being very sensitive to outliers (extreme high or low values) in the UKCP18 data. Hence here the UKCP18 adverse weather events, for the whole PPE ensemble, are pooled together into one EVA model for each event type and metric. In addition, in this study, only the Hadley Centre PPE-15 are used, due to the lack of availability of solar radiation in the CMIP5 models (as described in Section 4.1.2). This means climate model structural uncertainty is not captured here. The Hadley Centre models are known to become warmer more rapidly than the CMIP5 models over the future period (Figure 5.2 of Murphy, J. M. et al. 2018). This is, however, not an issue within this analysis because the extremity of events is captured in terms of warming level, not time.

As well as including historical *observed* events (from ERA5), here, the DePreSys historical *hindcast* events are also included within each EVA model. These DePreSys events, taken from more then 2000 years of meteorological data, are treated as additional historical observations, thought to be acceptable based on the numerous validations presented in this report. This therefore greatly reduces the uncertainty in the high return period estimates. That is, since the DePreSys events represent well over 100 years of meteorological information, estimating the 1 in 100 year return period event can be done with much greater certainty than if only events from the 40 ERA5 years of data were used.

When implementing a GPD EVA analysis, a suitable high threshold of the modelled variable (e.g. event duration) must be selected, above which the GPD is fitted. This is done to satisfy the statistical assumptions of the GPD (Coles, 2001), and to ensure the GPD fits well to the extreme values in the data. Here, it is essential that the EVA model is able to represent the (relatively low) 1 in 2 year event level, to allow for this event to be captured within the final dataset, as specified in the scoping phase of the project (Butcher and Dawkins, 2020). For each adverse weather event type and metric combination to be modelled (i.e. UK winter wind drought durations, UK winter wind drought severities, UK summer wind drought durations, etc.), the percentile of the modelled variable equivalent to the 1 in 2 year event is calculated and used as the threshold above which to fit the GPD. If one adverse weather event occurs each year, this 1 in 2 year event level would be the 50$^{\mathrm{th}}$ percentile (equivalent to the median) of the modelled variable. However, multiple events occur in each year, hence the percentile of the modelled variable equivalent to the 1 in 2 year event is scaled by the number of events per year. The resulting percentile thresholds used in each GPD model are shown in Table 3. In all cases, these thresholds were found to be high enough to accurately model the observed 1 in 100 year extreme level (the highest level to be selected for the final data set).

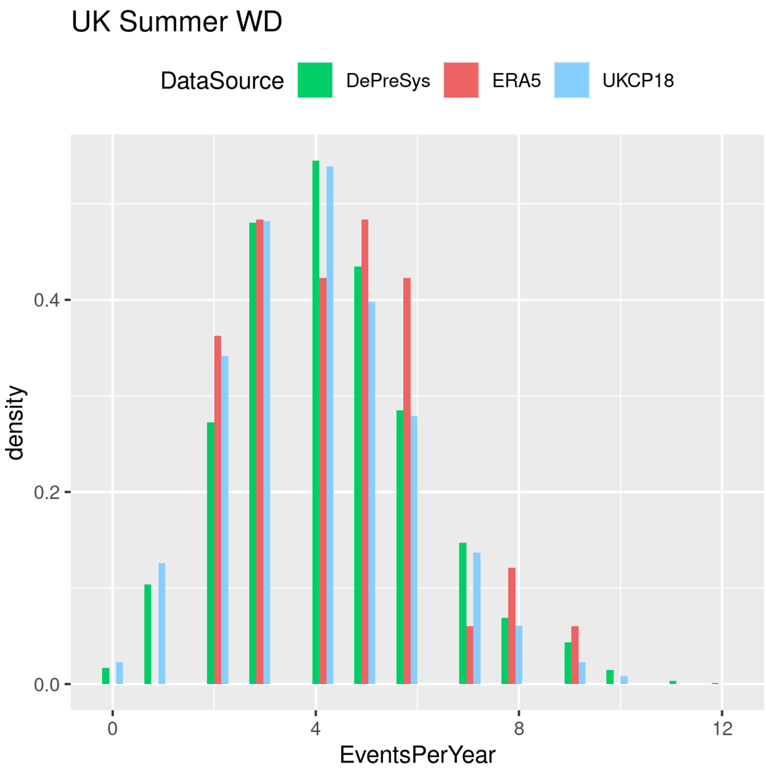

Figure 24: A histogram of the number of UK summer-time wind-drought-peak-demand events per year over all years in the data used within this study: ERA5 (Jan 1979 - Dec 2018, 1 realisation), DePreSys (Nov 1959 - Oct 2016, 40 realisations) and the UKCP18 Hadley Centre (Jan 1979 - Dec 2098, 15 realisations), shown separately for each data source.

The number of events per year is calculated by taking the median number of events per year in the historical ERA5 and DePreSys datasets. Figure 24 shows the number of summer-time wind-drought-peak-demand events per year in the three data sources. In this case the median number of events per year in the ERA5 and DePreSys datasets is 4 and the resulting threshold of the durations/severities is their 87.5$^{\text{th}}$ percentile. The number of events per year used in each GPD model is shown in Table 3.

Finally, a model selection process was carried out to explore the most appropriate EVA model structure. Non-stationary GPD models were fit to each adverse weather event type and metric combination (i.e. UK winter wind drought durations, UK winter wind drought severities, UK summer wind drought durations, etc.), to explore four model structures:

(1) Different climate model bias terms for each of the UKCP18 PPE-15 members, and the effect of GMST modelled in both the GPD scale parameter and GPD shape parameter;

(2) Different climate model bias terms for each of the UKCP18 PPE-15 members, and the effect of GMST modelled in the GPD scale parameter only;

(3) A single bias terms for all UKCP18 PPE-15 members, and the effect of GMST modelled in both the GPD scale parameter and GPD shape parameter;

(4) A single bias terms for all UKCP18 PPE-15 members, and the effect of GMST modelled in the GPD scale parameter only.

In each case, the model Akaike information criterion (AIC)[22], a mathematical method for evaluating model fit, was calculated and compared. Across all of the EVA models, model structure (4) was found to most often given the best fit, and was consistently either the best or second best model, in terms of the AIC.

The EVA model structure (4) is fitted to each adverse weather event type and metric combination. This is done using a Bayesian statistical modelling framework, using the `extRemes` package[23] in the R statistical computing environment, resulting in an estimated 'posterior' distribution[24] of values for each model parameter. These model fits are summarised in Table 3. Column 5 of this table (the posterior mean of the GPD scale bias term) shows how the models correctly identify the larger climate model bias seen in UKCP18 surplus generation events in Europe, in Figure 19. In addition, column 6 (the posterior mean of the GPD scale GMST change term) presents the correct direction of change with GMST in each case: winter wind droughts and summer surplus becoming less extreme (negative values), and summer wind droughts becoming more extreme (positive values), due to rising temperatures and hence reduced demand in winter and increased demand in summer. Further, as seen in Figures 14 - 19, this change is greatest in European-wide summer wind droughts (largest values in column 6), as also discussed in Section 4.3.

[22] https://www.scribbr.com/statistics/akaike-information-criterion/ (Accessed 29/05/2021)
[23] https://cran.r-project.org/web/packages/extRemes/extRemes.pdf (Accessed 11/06/2021)
[24] https://towardsdatascience.com/probability-concepts-explained-bayesian-inference-for-parameter-estimation-90e8930e5348 (Accessed 29/05/2021)

Event type and metric	Events per year	GPD threshold (percentile)	GPD scale intercept term	GPD scale bias term	GPD scale GMST change term	GPD shape
UK winter wind drought, Duration	3	83.3	1.260	0.054	-0.009	-0.072
UK winter wind drought, Severity	3	83.3	0.729	0.178	-0.045	0.082
UK summer wind drought, Duration	4	87.5	1.399	-0.098	0.034	-0.100
UK summer wind drought, Severity	4	87.5	0.268	-0.069	0.042	0.039
UK summer surplus generation: Duration	3	83.3	1.141	0.35	-0.032	-0.056
UK summer surplus generation: Severity	3	83.3	0.544	0.472	-0.024	0.058
Europe winter wind drought, Duration	3	83.3	1.546	-0.041	-0.048	-0.042
Europe winter wind drought, Severity	3	83.3	0.9	0.101	-0.099	0.148
Europe summer wind drought, Duration	4	87.5	1.441	-0.029	0.241	-0.056
Europe summer wind drought, Severity	4	87.5	0.164	0.163	0.322	0.131
Europe summer surplus generation: Duration	2	75.0	1.013	0.591	-0.019	-0.07
Europe summer surplus generation: Severity	2	75.0	0.504	0.841	-0.026	0.064

Table 3: Table summarising the non-stationary GPD fits to each adverse weather event type and metric combination. The number of events per year (column 2) is calculated as the median number of events per year in the historical ERA5 and DePreSys datasets combined. The GPD threshold (column 3) is the percentile of the modelled variable (duration/severity) above which the GPD is fitted, calculated as the percentile equivalent to a 1 in 2 year event. The GPD has two parameters: scale and shape. The scale parameter is modelled as varying over time (non-stationary) conditioned on GMST and a climate model bias term, hence the scale parameter is a combination of an intercept term (column 4), the climate model bias term (column 5) and the GMST change effect (column 6). The shape parameter is modelled as being stationary and unbiased in the climate model (column 7). For each model parameter, the Bayesian posterior distribution mean is given (i.e. the best estimate of this value from the model).

Figures 25 and 26 and Tables 4 - 15 present the final results of the statistical EVA. These plots shown in Figures 25 and 26 reflect the findings in Section 4.3. They further show how, based on the electricity system characterisation used in this study, the greatest difference between warming levels is found in the European wind-drought-peak-demand events, particularly in summer; and that only a small difference is found across the warming levels in the UK events. Tables 4 - 15 summarise the key return levels of interest within this study, and therefore highlight the extremity of events that should be used to represent each return period and warming level in the final 'Adverse Weather Scenarios for Future Electricity Systems' dataset. For example, it is shown in Table 4 that the 1 in 20 year return level UK winter-time wind-drought-peak-demand event, in terms of duration and in the current day climate (warming level 1.2°C above pre-industrial) is 13-14 days long. This means that UK winter-time wind-drought-peak-demand events in this range should be selected to represent this event type, return period and warming level in the final dataset.

Moreover, the results of this EVA can be used to more accurately quantify the extremity of the ERA5

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	6 (6,6)	9 (9,9)	11 (11,12)	13 (13,14)	16 (16,17)	18 (17,19)
1.50	6 (6,6)	9 (9,9)	11 (11,12)	13 (13,14)	16 (15,17)	18 (17,19)
2.00	6 (6,6)	9 (9,9)	11 (11,12)	13 (13,14)	16 (15,17)	18 (17,19)
3.00	6 (6,6)	9 (9,10)	11 (11,12)	13 (13,14)	16 (15,17)	18 (17,19)
4.00	6 (6,6)	9 (9,10)	11 (11,12)	13 (12,15)	16 (15,17)	18 (16,20)

Table 4: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK winter-time wind-drought-peak-demand event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the top left panel of Figure 25.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	2.8 (2.7,2.8)	4.7 (4.5,4.9)	6.3 (6,6.5)	7.9 (7.5,8.3)	10.2 (9.6,10.9)	12.1 (11.3,13)
1.50	2.8 (2.7,2.8)	4.7 (4.5,4.8)	6.2 (5.9,6.5)	7.8 (7.4,8.3)	10.1 (9.5,10.8)	12 (11.1,12.9)
2.00	2.8 (2.7,2.8)	4.6 (4.4,4.8)	6.1 (5.8,6.5)	7.7 (7.3,8.2)	10 (9.3,10.7)	11.8 (10.9,12.7)
3.00	2.7 (2.7,2.8)	4.5 (4.3,4.8)	6 (5.6,6.4)	7.5 (6.9,8.1)	9.6 (8.8,10.5)	11.4 (10.3,12.5)
4.00	2.7 (2.7,2.8)	4.4 (4.2,4.7)	5.8 (5.3,6.3)	7.3 (6.6,8)	9.3 (8.4,10.4)	11 (9.7,12.4)

Table 5: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK winter-time wind-drought-peak-demand event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the top right panel of Figure 25.

adverse weather scenarios identified and presented in the Phase 2 (a) report (Dawkins and Rushby, 2021), better putting these events into context. For example, the most extreme UK winter-time wind-drought-peak-demand event in the ERA5 record, which began on 29$^{\text{th}}$ November 1989 and lasted 17 days (See Table 2 in Dawkins and Rushby 2021), has a return period of 69 years in terms of duration, according to the best estimate from the associated EVA models (top panel of Figure 25). This event is also identified as impacting all of Europe beginning on 1$^{\text{st}}$ December 1989 and lasting 12 days (See Table 7 in Dawkins and Rushby 2021). Using the EVA models developed in this phase of the project it can be calculated that, in Europe, this event has a return period of 6 years in terms of duration. These EVA models, summarised in the curves presented in Figures 25 and 26, can be used in a similar way to estimate the return period of any of the ERA5 events presented in the Phase 2 (a) report (Dawkins and Rushby, 2021), in terms of both duration and severity.

It should be noted here that this study quantifies the likelihood of adverse weather events in terms of their duration and severity separately. An extension of this work could look to capture future severity-duration return level curves, i.e. the interaction between these characteristics, using a statistical model similar to the heatwave simulator of Brown (2020).

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	7 (7,7)	10 (10,11)	13 (13,13)	15 (15,16)	18 (18,19)	20 (19,21)
1.50	7 (7,7)	10 (10,11)	13 (13,13)	15 (15,16)	18 (18,19)	20 (20,21)
2.00	7 (7,7)	10 (10,11)	13 (13,14)	16 (15,16)	19 (18,19)	21 (20,22)
3.00	7 (7,7)	11 (10,11)	13 (13,14)	16 (15,17)	19 (18,20)	21 (20,23)
4.00	7 (7,7)	11 (10,11)	14 (13,14)	16 (15,17)	19 (18,21)	22 (20,24)

Table 6: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK summer-time wind-drought-peak-demand event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the middle left panel of Figure 25.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	2.1 (2.1,2.1)	3.3 (3.2,3.4)	4.3 (4.2,4.5)	5.3 (5.1,5.6)	6.7 (6.4,7.1)	7.8 (7.4,8.3)
1.50	2.1 (2.1,2.1)	3.3 (3.2,3.5)	4.3 (4.2,4.5)	5.4 (5.1,5.6)	6.8 (6.4,7.2)	7.9 (7.4,8.4)
2.00	2.1 (2.1,2.1)	3.4 (3.3,3.5)	4.4 (4.2,4.6)	5.4 (5.2,5.7)	6.9 (6.5,7.3)	8 (7.4,8.6)
3.00	2.1 (2.1,2.1)	3.4 (3.3,3.6)	4.5 (4.2,4.8)	5.6 (5.2,6)	7.1 (6.5,7.7)	8.2 (7.6,9)
4.00	2.1 (2.1,2.1)	3.5 (3.3,3.7)	4.6 (4.3,5)	5.8 (5.3,6.3)	7.3 (6.6,8.1)	8.5 (7.6,9.5)

Table 7: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK summer-time wind-drought-peak-demand event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the middle right panel of Figure 25.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	6 (6,6)	9 (8,9)	11 (10,11)	13 (12,13)	15 (14,16)	17 (16,18)
1.50	6 (6,6)	9 (8,9)	11 (10,11)	13 (12,13)	15 (14,16)	17 (16,18)
2.00	6 (6,6)	9 (8,9)	11 (10,11)	12 (12,13)	15 (14,16)	16 (16,17)
3.00	6 (6,6)	9 (8,9)	10 (10,11)	12 (12,13)	15 (14,15)	16 (15,17)
4.00	6 (6,6)	8 (8,9)	10 (10,11)	12 (11,13)	14 (13,15)	16 (15,17)

Table 8: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK summer-time surplus-generation event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the bottom left panel of Figure 25.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	2.6 (2.6,2.7)	4.2 (4.1,4.4)	5.5 (5.3,5.8)	6.9 (6.5,7.2)	8.7 (8.2,9.3)	10.2 (9.5,10.9)
1.50	2.6 (2.6,2.7)	4.2 (4.1,4.4)	5.5 (5.3,5.8)	6.8 (6.5,7.2)	8.7 (8.1,9.2)	10.1 (9.4,10.9)
2.00	2.6 (2.6,2.6)	4.2 (4,4.4)	5.5 (5.2,5.8)	6.8 (6.4,7.2)	8.6 (8,9.2)	10 (9.3,10.9)
3.00	2.6 (2.6,2.6)	4.2 (4,4.4)	5.4 (5.1,5.8)	6.7 (6.2,7.2)	8.4 (7.8,9.2)	9.9 (9,10.8)
4.00	2.6 (2.5,2.6)	4.1 (3.9,4.4)	5.3 (4.9,5.8)	6.6 (6,7.2)	8.3 (7.5,9.2)	9.7 (8.7,10.9)

Table 9: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **UK summer-time surplus-generation event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the bottom right panel of Figure 25.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	7 (7,7)	11 (11,11)	14 (13,15)	17 (16,18)	21 (20,22)	23 (22,25)
1.50	7 (7,7)	11 (11,11)	14 (13,14)	17 (16,18)	20 (19,22)	23 (22,25)
2.00	7 (7,7)	11 (10,11)	14 (13,14)	17 (16,18)	20 (19,22)	23 (21,24)
3.00	7 (7,7)	11 (10,11)	13 (13,14)	16 (15,17)	19 (18,21)	22 (20,24)
4.00	7 (7,7)	11 (10,11)	13 (12,14)	16 (14,17)	19 (17,21)	21 (19,24)

Table 10: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European winter-time wind-drought-peak-demand event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the top left panel of Figure 26.

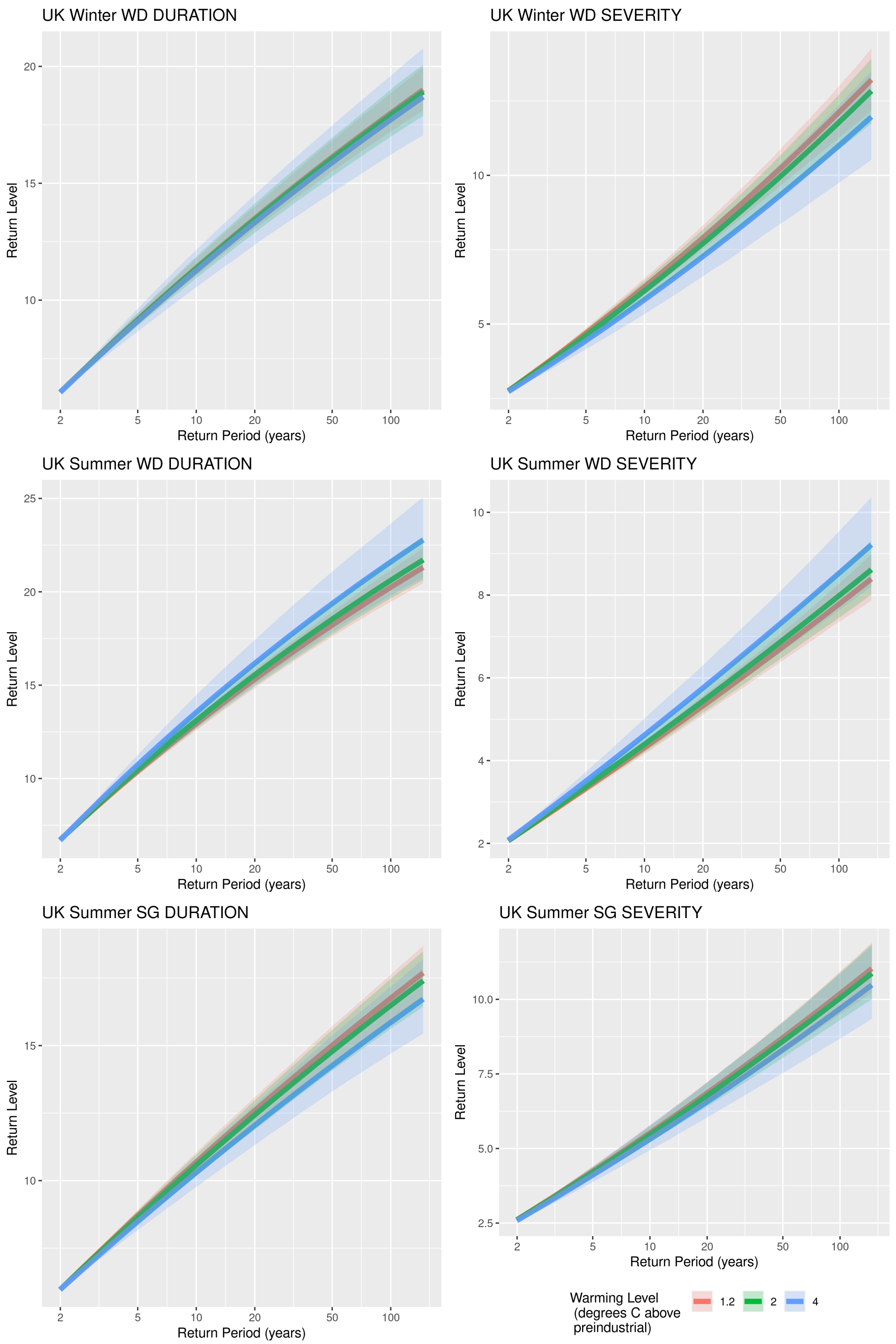

Figure 25: UK event return level plots, showing the level of the modelled variable, Duration/Severity, (on the y axis) associated with a given return period in years (on the x axis), plotted on a logarithmic scale, for three key warming level of interest (shown in different colours). The solid lines represent the return level curves based on the Bayesian posterior mean (i.e. the best estimate), and the shaded areas represent the 95% credible intervals around these best estimates. This means that the true return level has a 95% probability of being within the shaded area. Return level plots are presented for each adverse weather event type and metric combination in the UK, as described in the title of each panel, where WD=Wind Drought and SG=Surplus Generation.

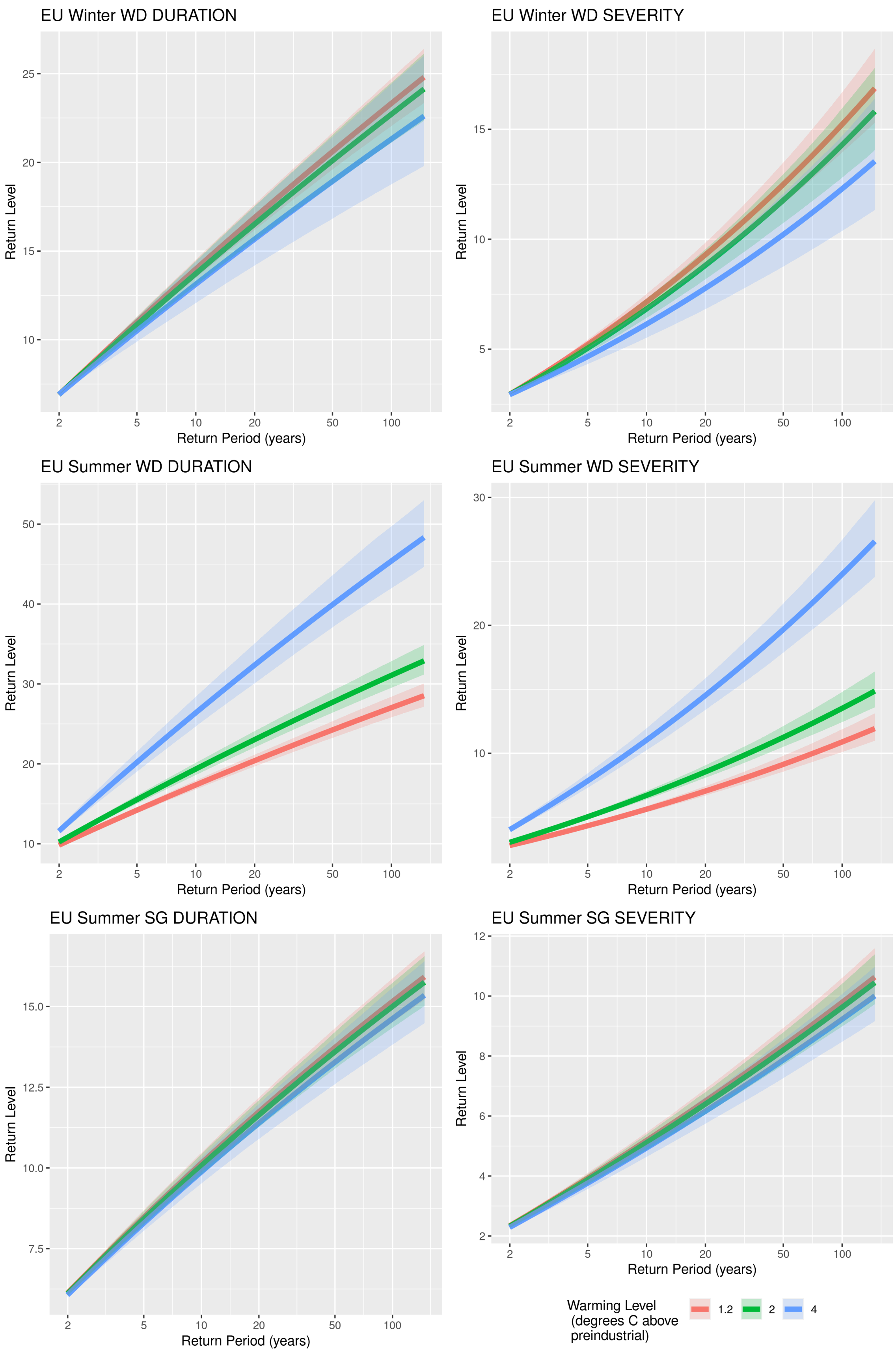

Figure 26: European event return level plots, showing the level of the modelled variable, Duration/Severity, (on the y axis) associated with a given return period in years (on the x axis), plotted on a logarithmic scale, , for three key warming level of interest (shown in different colours). The solid lines represent the return level curves based on the Bayesian posterior mean (i.e. the best estimate), and the shaded areas represent the 95% credible intervals around these best estimates. This means that the true return level has a 95% probability of being within the shaded area. Return level plots are presented for each adverse weather event type and metric combination in Europe, as described in the title of each panel, where WD=Wind Drought and SG=Surplus Generation.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	3 (2.9,3)	5.2 (5,5.4)	7.2 (6.8,7.5)	9.3 (8.8,9.8)	12.5 (11.6,13.5)	15.2 (13.9,16.7)
1.50	3 (2.9,3)	5.2 (5,5.4)	7 (6.7,7.4)	9.1 (8.6,9.7)	12.2 (11.3,13.2)	14.9 (13.5,16.4)
2.00	2.9 (2.9,3)	5 (4.8,5.3)	6.8 (6.4,7.3)	8.8 (8.2,9.5)	11.8 (10.7,13)	14.3 (12.8,16)
3.00	2.9 (2.9,3)	4.8 (4.6,5.2)	6.5 (6,7.1)	8.3 (7.5,9.2)	10.9 (9.7,12.5)	13.2 (11.5,15.3)
4.00	2.9 (2.9,2.9)	4.7 (4.3,5.1)	6.1 (5.5,6.9)	7.8 (6.8,9)	10.2 (8.8,12.1)	12.3 (10.4,14.7)

Table 11: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European winter-time wind-drought-peak-demand event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the top right panel of Figure 26.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	10 (10,10)	14 (14,15)	17 (17,18)	20 (20,21)	24 (23,25)	27 (26,28)
1.50	10 (10,10)	15 (14,15)	18 (17,19)	21 (21,22)	25 (24,27)	28 (27,30)
2.00	10 (10,10)	16 (15,16)	19 (19,20)	23 (22,24)	28 (26,29)	31 (30,33)
3.00	11 (11,11)	18 (17,18)	22 (21,24)	27 (26,29)	33 (31,35)	37 (35,40)
4.00	12 (11,12)	20 (19,22)	26 (25,28)	32 (30,35)	40 (37,44)	45 (42,50)

Table 12: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European summer-time wind-drought-peak-demand event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the middle left panel of Figure 26.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	2.8 (2.7,2.8)	4.3 (4.2,4.5)	5.6 (5.4,5.9)	7 (6.7,7.4)	9.1 (8.6,9.8)	10.9 (10.1,11.9)
1.50	2.9 (2.8,2.9)	4.6 (4.4,4.7)	6 (5.7,6.3)	7.6 (7.2,8)	9.9 (9.2,10.6)	11.8 (10.9,12.9)
2.00	3 (3,3.1)	5 (4.8,5.2)	6.7 (6.4,7)	8.5 (8.1,9.1)	11.2 (10.5,12.1)	13.5 (12.4,14.8)
3.00	3.5 (3.3,3.6)	6.2 (5.9,6.6)	8.5 (8,9.1)	11.1 (10.3,11.9)	14.8 (13.6,16.1)	17.9 (16.3,19.7)
4.00	4 (3.8,4.3)	7.8 (7.3,8.4)	11 (10.2,12)	14.5 (13.4,15.9)	19.7 (17.9,21.7)	24 (21.6,26.7)

Table 13: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European summer-time wind-drought-peak-demand event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the middle right panel of Figure 26.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	6 (6,6)	8 (8,9)	10 (10,10)	12 (11,12)	14 (13,14)	15 (15,16)
1.50	6 (6,6)	8 (8,9)	10 (10,10)	12 (11,12)	14 (13,14)	15 (14,16)
2.00	6 (6,6)	8 (8,9)	10 (10,10)	12 (11,12)	14 (13,14)	15 (14,16)
3.00	6 (6,6)	8 (8,9)	10 (10,10)	12 (11,12)	13 (13,14)	15 (14,16)
4.00	6 (6,6)	8 (8,9)	10 (10,10)	11 (11,12)	13 (13,14)	15 (14,16)

Table 14: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European summer-time surplus-generation event duration** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the bottom left panel of Figure 26.

WL (°C)	RL:2 years	RL:5 years	RL:10 years	RL:20 years	RL:50 years	RL:100 years
1.20	2.3 (2.3,2.4)	3.9 (3.8,4.1)	5.2 (5,5.5)	6.5 (6.2,6.9)	8.3 (7.9,8.9)	9.8 (9.2,10.6)
1.50	2.3 (2.3,2.4)	3.9 (3.7,4.1)	5.2 (4.9,5.4)	6.5 (6.1,6.9)	8.3 (7.8,8.9)	9.7 (9.1,10.5)
2.00	2.3 (2.3,2.4)	3.9 (3.7,4.1)	5.1 (4.9,5.4)	6.4 (6.1,6.8)	8.2 (7.7,8.8)	9.6 (9,10.4)
3.00	2.3 (2.2,2.4)	3.8 (3.6,4)	5 (4.8,5.3)	6.3 (5.9,6.7)	8 (7.5,8.7)	9.4 (8.7,10.2)
4.00	2.3 (2.2,2.4)	3.8 (3.6,4)	4.9 (4.6,5.3)	6.2 (5.7,6.6)	7.9 (7.3,8.6)	9.2 (8.5,10.1)

Table 15: Table summarising the 1 in 2, 5, 10, 20, 50, and 100 year return level (RL) of **European summer-time surplus-generation event severity** for each warming level (WL) of interest. In each case, the Bayesian posterior mean (best estimate) is given, with the 95% credible interval around this shown in brackets. These values summarise the curve shown in the bottom right panel of Figure 26.

4.5 Selecting adverse weather scenarios for the final dataset

This section describes the approach used to select relevant adverse weather scenarios for the final dataset. These scenarios are selected predominantly from the calibrated DePreSys[25] hindcast data. This data source is used rather than ERA5 or UKCP18 because the ERA5 reanalysis data is already available to download and use[26], so provision of data from this data set would provide less additional information compared to existing datasets and previous reports, and the underlying UKCP18 meteorological data has not been fully bias corrected (see Section 4.2.1).

Adverse weather scenarios are selected to represent:

1. Each adverse weather **event type**: winter-time wind-drought-peak-demand events, summer-time wind-drought-peak-demand events, and summer-time surplus-generation events;
2. In each **region**: the UK, and Europe as a whole;
3. For a number of **extreme levels**: 1 in 2, 5, 10, 20, 50 and 100 year return levels;
4. In terms of the two adverse weather **event metrics**: duration and severity;
5. For as many **warming levels** as are different/distinct for a given event type, region, return level and metric, from: current day (1.2°C), 1.5°C, 2°C, 3°C and 4°C above pre-industrial global mean temperature.

In each case, the DePreSys adverse weather scenarios are selected based on the EVA results shown in Tables 4 - 15. Specifically, this is based on the uncertainty range associated with that given combination of event characteristics (event type, region, return level, metric and warming level). For example, adverse weather scenarios selected for the final dataset to represent UK winter-time wind-drought-peak-demand events with a return period of 100 years in terms of duration in the current day climate, are selected from those identified as having durations in the range 17-19 days (see Table 4).

In addition, Tables 4 - 15 are used to identify how many distinct warming levels should be represented within the final dataset for each combination of event type, region, event metric and return level. This is done by observing, within each column of each table, which of the best estimates of the return levels shown in each row for each warming level (i.e. the number outside of the brackets), lie within the uncertainty range of the previous warming levels.

For example, in the case of UK winter-time wind-drought-peak-demand event durations (Table 4), for every return level (each column), the best estimate of the associated durations in each warming level (each row) is within the uncertainty range of the lowest warming level (1.2°C). This means that for this even type, region, and event metric, the events selected for the final dataset to represent each

[25] A glossary of acronyms is presented in Section 8

[26] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5 (Accessed 02/06/2021)

return level are representative of all warming levels (1.2-4°C). That is, there is no climate change effect observed in these events within this study, subject to the assumptions of the methodology. This is consistent with the exploration of these events within this study in Section 4.3 (Figure 14) and the associated EVA model presented in Section 4.4 (Figure 25 top left panel).

Conversely, in the case of European summer-time wind-drought-peak-demand event durations (Table 12), focusing on the 20 year return level (the fourth column), it can be seen that while the best estimate of the return level for the 1.5°C warming level is within the uncertainty range of the 1.2°C warming level, 21 is within (20,21), the best estimate of all of the other warming levels is outside of the uncertainty range of the previous warming level. That is, 23 is not within (21,22), 27 is not within (22,24) and 32 is not within (26,29). Hence, for this even type, region, and event metric events selected for the final dataset are chosen to represent warming levels 1.2-1.5°C, 2°C, 3°C and 4°C.

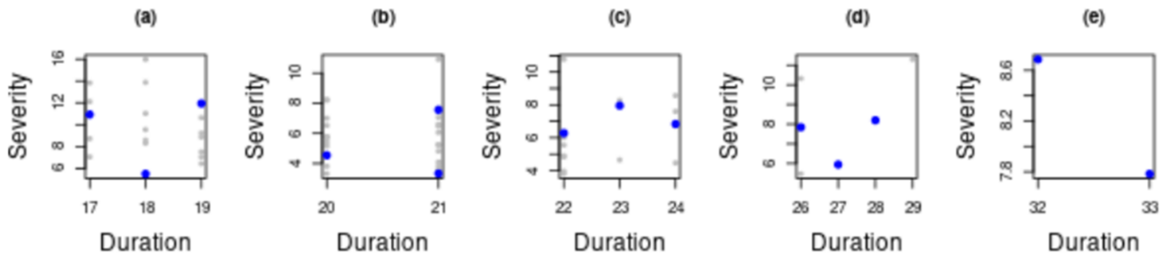

Figure 27: A graphical representation of the events selected from the DePreSys record to represent (a) UK winter-time wind-drought-peak-demand scenarios with a 1 in 100 year duration in warming levels 1.2-4°C (see Table 4), (b) European summer-time wind-drought-peak-demand scenarios with a 1 in 20 year duration in warming level 1.2-1.5°C (see Table 12), (c) as in b, but for warming level 2°C, (d) as in b, but for warming level 3°C, (e) as in b, but for warming level 4°C. Each point represents the duration/severity of DePreSys events within the relevant range of the event metric (in these cases duration). **All events within this range are shown in grey, and those selected for the final dataset in each case are shown in blue**.

For each distinct warming level, up to 3 events are selected from the DePreSys record. Where more than 3 DePreSys events have durations/severities within the specified event metric range, 3 events are selected that sample the range of both the duration and severity of representative events. This is demonstrated in Figure 27, for the event combination examples introduced above. Specifically, the first of the 3 events is selected (blue points) at random from those in the lower half of points in terms of both duration and severity, the second is selected at random from those in the upper half of points in terms of both duration and severity, and the third event is selected at random from those remaining. As can be seen in Figure 27, this gives a good spread of events in terms of their extremity within the range specified in the statistical EVA.

In some cases, such as can be seen in Figure 27 (e), only 2 DePreSys events have durations/severities within the specified event metric range. In this case only 2 events are included for that event combination within the final dataset. Further, for European summer-time wind-drought-peak-demand scenarios with return periods greater then 20 years and higher warming levels, there are occasions when no DePreSys events are as extreme as the specified return level range. Specifically, the most extreme

DePreSys event in terms of duration is 33 days long, hence no events exist within the 1 in 50 year 4°C warming level range, (37,44), or the 1 in 100 year 4°C and 3°C warming level ranges, (35,40) and (42,50) respectively (see Table 12), and similarly for severity (see Table 13). In these cases, a single event is selected from the UKCP18 record instead.

As well as including events representative of the six return periods of interest, the maximum three events in each combination of event type, region and event metric are also included within the final dataset. These events are include to allow for the value of the DePreys data to be fully realised through representing unprecedented 'unseen' conditions, more extreme than those seen in the observed ERA5 record. No return level has been assigned to these events, but due to the length of the DePreSys record (2280 years), the most extreme event in each case has a return period of approximately 2000 years (in the historical climate).

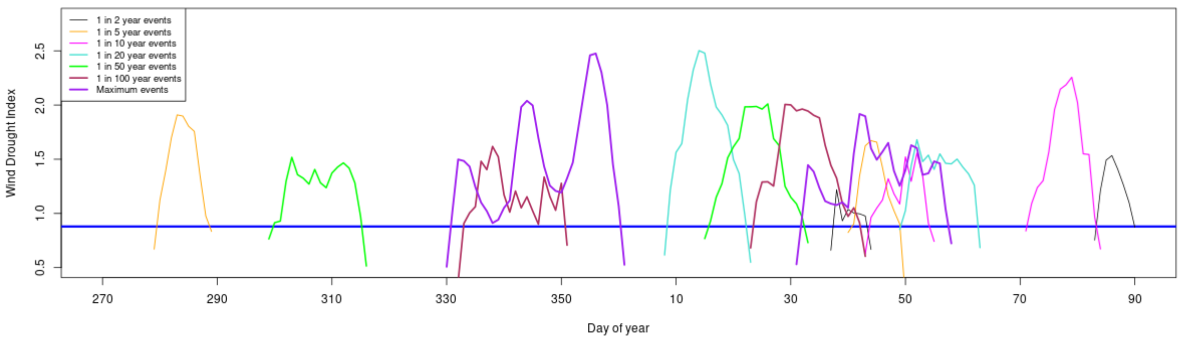

Figure 28: A comparison of the wind drought index (WDI) during a subset of the UK winter-time wind-drought-peak-demand events selected from the DePreSys record to represent different extreme levels in terms of duration for the final dataset. Each event is plotted as a function of the days of the year over which it occurred (x axis). The extremity of each event is represented by the colour of the WDI curve (as described in the legend), and the thick blue horizontal line represents the UK winter-time wind-drought-peak-demand event threshold, used to identify adverse weather events (as described in Section 3.4).

Figure 28 shows the WDI during a subset of the UK winter-time wind-drought-peak-demand events selected to represent different extreme levels in terms of duration for the final dataset. This figure provides a demonstration of how the events of the same extremity (return period) and of different extremities (including the maximum events) compare to one another and differ. This shows how including events across multiple extreme levels, that also sample the range of both event metrics (duration and severity), gives a diverse range of events, as is relevant for thorough electricity system resilience testing.

Based on this selection method, a total of 412 adverse weather scenarios are selected and included within the final dataset of 'Adverse Weather Scenarios for Future Electricity Systems'. Of these, 403 are taken from the DePreSys record and 9 from UKCP18. Tables 16 - 22 in the Appendix (Section A.2) summarise these all of these 412 events in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination).

For each selected event, the associated gridded surface temperature, 100m wind speed and surface solar radiation data is provided within the final dataset. For the 403 events selected from the DePreSys record, this data is taken from the calibrated variables (as described and validated in Sections 4.2 and A.1). This data has therefore been bias corrected. For the 9 events taken from the UKCP18 record, only the 100m wind speed data has been bias corrected (as described in Section 4.2.1). The surface temperature and solar radiation data have been taken directly from the UKCP18 global projections (cropped to the European region) and hence may still contain biases. These should therefore be used with caution.

It should also be noted that using this approach, in which primarily historical DePreSys adverse weather scenarios are used to represent events in future warming levels, means that the underlying meteorological data associated with the event is not taken from a period with the same global warming level. For example, DePreSys events in 1965, 1974 and 1987 are selected to represent the UK winter wind-drought-peak-demand scenario with a 100 year return period in terms of severity at the 4°C warming level, as shown in rows 4-6 from the bottom of Table 16. As previously described, this approach was taken because the DePreSys data has been fully bias corrected while the UKCP18 data has not. As such, while the characteristics of the adverse weather event itself (the duration or severity) will be representative of the future warming level (as is the aim of the study), it should be highlighted that the meteorological conditions that underpin the event may not be representative of that warming level. In particular, surface temperature values may be lower on average in the data taken from the historical period. Since (especially for the UK) wind dominates the WDI (as described in Section 4.3), this is not expected to impact results when testing the resilience of very renewable future electricity systems, except in the case where extremely high electrification of the heating and cooling is assumed to have taken place. In this case it may be appropriate for the user to apply an uplift factor to the temperatures, similar to the approach used by Hay et al. (2000).

5 The Adverse Weather Scenarios for Future Electricity Systems dataset

The final dataset of adverse weather scenarios for future electricity systems consists of daily time series of gridded surface temperature, 100m wind speed and net surface solar radiation, at a 60 x 60 km spatial resolution, covering a European domain. This data is representative of a selection of adverse weather scenarios, as summarised in Tables 16 - 22 in the Appendix (Section A.2).

Each adverse weather scenario is contained within a time slice of data. For summer-time events, one calendar year (January - December) of data is provided, with the summer-time event occurring in the summer of that year. For winter-time events, two calendar years of data are provided, with the winter-time event occurring in the winter (October-March) intersecting the two calendar years. The data has been made available in a NetCDF format, and in all cases, the start date, duration and severity of the adverse weather event, contained within the time slice of data, are given in the NetCDF global attributes (see Section A.3).

Three types of long-duration adverse weather scenarios are represented: winter-time wind-drought-peak-demand events, summer-time wind-drought-peak-demand events, and summer-time surplus generation events. These are provided at various extreme levels (1 in 2, 5, 10, 20 ,50 and 100-year events); and for a range of current and nominal future climate change warming levels (1.2 [current day as of 2021], 1.5, 2, 3, and 4 degrees Celsius above pre-industrial level), representative of events impacting either just the UK, or Europe as a whole.

As described in previous sections of this report, the data provided are derived from the Met Office DePreSys hindcast, according to the climate change impacts identified from UKCP18. These sections presented the methods developed for characterising and representing these adverse weather scenarios, and the approach used to compile the final dataset.

Use of this data is subject to the terms of the Open Government Licence [27], and the following acknowledgement must be given when using the data: '© Crown Copyright 2021, Met Office, funded by the National Infrastructure Commission'.

This dataset is freely available to download (see Section 5.1), and hence can be widely used to more rigorously stress test proposed future highly renewable electricity systems. This will help to better ensure electricity system resilience to challenging weather and climate conditions, and security of supply in a net-zero future.

[27] http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/ (Accessed 03/06/2021)

5.1 Downloading the data

The gridded meteorological data contained within the Adverse Weather Scenarios for Future Electricity Systems dataset can be freely downloaded from the CEDA archive:

- Project record: `https://catalogue.ceda.ac.uk/uuid/701276b1c63d48e784ba1f3673607628`;
- Dataset record: `https://catalogue.ceda.ac.uk/uuid/7beeed0bc7fa41feb10be22ee9d10f00`;
- Data repository: `https://data.ceda.ac.uk/badc/deposited2021/adverse_met_scenarios_electricity/data`

Downloading the data requires the user to register for a free CEDA account[28]. Once registered, the user can download the data from the data repository (accessed using the link provided above). A 'README.txt' file is include within the data repository, explaining the filing system, file naming convention used, and file meta data in detail. A copy of this file is also included in the Appendix of this report (Section A.3). The user should refer to this file and the screen-shots shown in Figures 29 and 30 when downloading data from the Adverse Weather Scenarios for Future Electricity Systems dataset.

Each panel within Figures 29 and 30 shows a step in the navigation of the CEDA filing system from the data repository, to reach the gridded meteorological data associated with 'event 1', selected to represent winter-time wind-drought-peak-demand scenarios in the UK, at a 1 in 100 year return level in terms of duration, for all global warming levels (1.2-4°C). Screen-shot (a) shows the full data repository; (b) the sub-directories contained within the 'winter_wind_drought' directory in (a) related to the event region; (c) the sub-directories contained within the 'uk' directory in (b) related to the extreme level (return period); (d) the sub-directories contained within the 'return_period_1_in_100_years' directory in (c) related to the event metric; (e) the sub-directories contained within the 'duration' directory in (d) related to the global warming level; (f) the sub-directories contained within the 'gwl12-4degC' directory in (e) related to the event number; and (g) the gridded meteorological data associated with surface solar radiation (ssr), surface temperature (tas) and wind speed (windspeed). The file path in each case is shown at the top of the panel, ending at '.../data/winter_wind_drought/uk/return_period_1_in_100_years/duration/gwl12-4degC/event1'. An equivalent route can be taken to the gridded data associated each adverse weather scenario contained within the dataset (i.e. each event in each row of Tables 16 - 22). For example, the gridded meteorological data associated with 'event 1', selected to represent summer-time wind-drought-peak-demand scenarios in Europe, at a 1 in 20 year return level in terms of severity, for global warming level 4°C would be reached via the file path '.../data/summer_wind_drought/europe/return_period_1_in_20_years/severity/gwl4degC/event1'.

Each gridded meteorological data file is provided in a NetCDF format, and in all cases, the start date, duration and severity of the adverse weather event, contained within the time slice of data, are given in

[28] `https://services.ceda.ac.uk/cedasite/register/info/` (Accessed 03/06/2021)

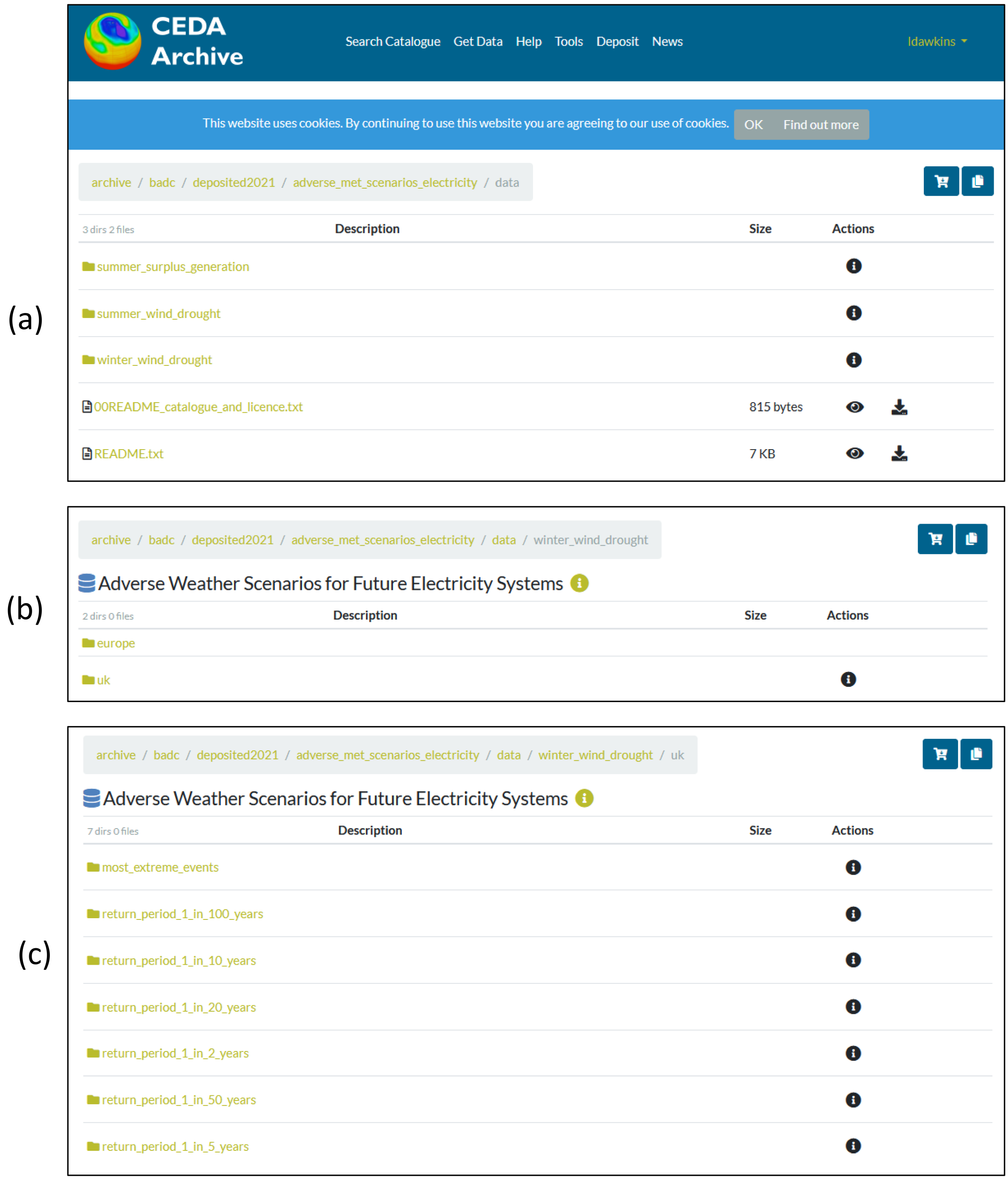

Figure 29: Screen-shots showing the navigation of the CEDA filing system from the data repository, to reach the gridded meteorological data associated with 'event 1', selected to represent winter-time wind-drought-peak-demand scenarios in the UK, at a 1 in 100 year return level in terms of duration, for all global warming levels (1.2-4°C): Part 1.

the NetCDF global attributes. These are described in more detail in the associated 'README.txt' file contained within the data repository and shown in Section A.3.

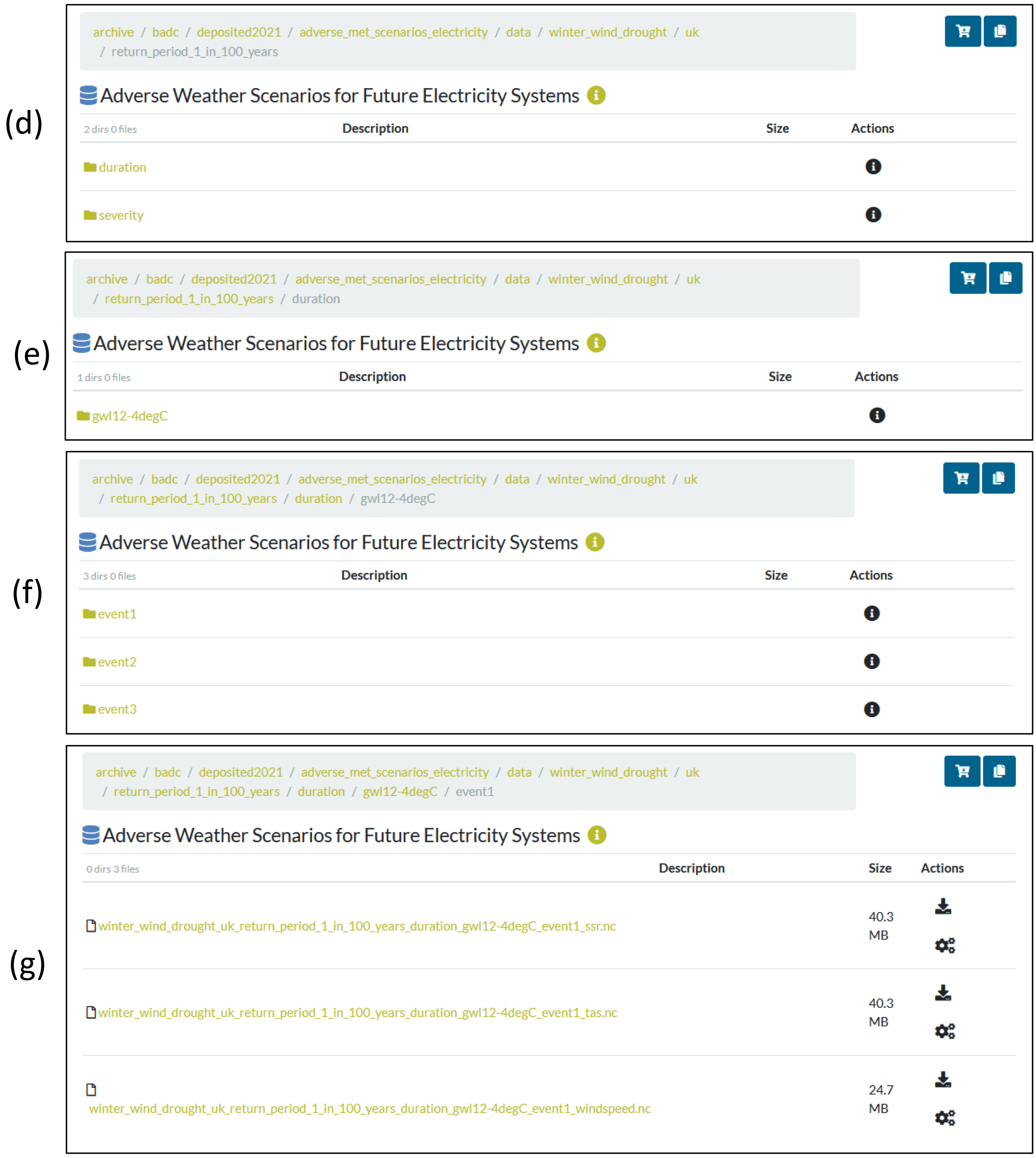

Figure 30: Screen-shots showing the navigation of the CEDA filing system from the data repository, to reach the gridded meteorological data associated with 'event 1', selected to represent winter-time wind-drought-peak-demand scenarios in the UK, at a 1 in 100 year return level in terms of duration, for all global warming levels (1.2-4°C): Part 2.

6 Summary and Conclusion

This report has presented the methods developed for creating the 'Adverse Weather Scenarios for Future Electricity Systems' dataset of long-duration events. This dataset characterises winter-time and summer-time wind-drought-peak-demand events, and summer-time surplus generation events, in the UK and in Europe. It contains gridded daily average meteorological data (surface temperature, 100m wind speed and surface solar radiation) associated with a range of examples of such events, capturing various extreme levels (1 in 2, 5, 10, 20, 50 and 100 year return period events) and climate warming levels (current day, 1.5°C, 2°C, 3°C and 4°C above pre-industrial levels). The dataset is freely available to download from the CEDA archive.

Firstly, a summary of the methods developed for characterising and identifying long-duration adverse weather events within any suitable gridded meteorological dataset, was presented. Following this, adverse weather scenarios were identified within three data sources: historical reanalysis (ERA5); historical climate model hindcasts (providing more than 2000 alternative plausible weather years), created using the Met Office decadal prediction system; and future climate projections (capturing how weather is likely to change in future climates), taken from UKCP18. These data sources are used to allow for alternative plausible (potentially more extreme) adverse weather scenarios than those seen in the historical record to be represented, and to allow for the effect of climate change to be explored and captured.

Before identifying the adverse weather scenarios in the climate model hindcasts and projections, the associated meteorological data underwent calibration and rigorous validation. This was done to ensure that the climate model data was not biased or missing any information, and hence was fit for purpose. Specifically, a univariate variance scaling approach was used to bias correct the model data, and data science generalised additive models are developed to estimate 100m (above ground) wind speed from 10m wind speed, and to estimate surface solar radiation coherently with other weather variables. These models are shown to produce calibrated hindcast data that has characteristics (such as inter-variable, spatial and temporal dependencies) consistent with historical reanalysis.

In addition, in both cases the climate model data was available on a 60 km $\times$ 60 km, daily spatial-temporal resolution, hence methods for downscaling in space and time were explored. A downscaling method was successfully applied to the surface temperature data, however, further method development was found to be required for the 100m wind speed and surface solar radiation variables. This necessitated the sharing of the lower resolution version of all variables, for consistency. Downscaling of data for energy applications is an active research area, with several groups currently working in this area. It is therefore possible that any alternative approaches that are developed in the future could be applied to the data contained within the final adverse weather scenario dataset, providing data at the desired higher resolution.

Adverse weather scenarios identified across the three data sources were then compared graphically, identifying that, as hoped, for all event types, the hindcasts included events that were more extreme than those observed in the historical record (ERA5). This means that including these additional 2000 model years of data within the analysis allows for the exploration of ‘unseen’, unprecedented meteorological events. In addition, the change in UKCP18 adverse weather scenarios over time was explored as an initial indication of the effect of climate change. This highlighted the climate sensitivity of European-wide wind-drought-peak-demand scenarios, particularly in the summer, due to rising temperatures and hence changes in demand for heating/cooling; and the relative lack of climate sensitivity in UK scenarios. This was shown to be due to the relative dominance of wind generation within the UK, due to the high level of installed UK wind renewables used in this study. A brief sensitivity study was included to explore how this climate sensitivity changed when an increasingly strong temperature-demand relationship was used (i.e. increasing the electrification of heating). This showed that moderate increases in this temperature-demand relationship, equivalent to the current day French system, gave consistent results. This means that in order for a climate change signal to be expected in the severity or duration of UK wind-drought-peak-demand events either: the installed renewables must be lower than currently anticipated for 2050; and/or the electrification of heating and cooling must increase beyond the current French levels.

The aim of this study is not to assess the impact of climate change on electricity systems, but to develop a system agnostic approach for quantifying adverse weather scenarios, to ultimately provide a useful dataset for assessing the vulnerability of future system configurations. As such, the sensitivity study showed that although the climate change sensitivity of events may be somewhat conditional on the chosen electricity system configuration, the adverse weather scenarios shared here are relevant for a range of potential future electricity systems. Hence, these can now be used by others to further explore how such adverse weather scenarios will impact *other* electricity system configurations (e.g. those with highly electrified heating/cooling).

A non-stationary statistical extreme value analysis was then applied to the adverse weather scenarios for the three data sources in combination, to quantify the extremity (i.e. the return period) of events, and how these may change in future warmer climates. This analysis provided a return level curve for each event type (winter wind-drought-peak-demand, summer wind-drought-peak-demand and summer surplus generation), event metric (duration, severity), region (UK and Europe), and global warming level of interest (1.2, 1.5, 2, 3, 4°C above pre-industrial global mean temperature). For each event combination, the extreme value analysis model was conditioned on global mean surface temperature, subsequently allowing for the extremity of the given event metric (duration/severity) associated with a return level of interest (e.g. 1 in 100 years) to be estimated for any given global mean surface temperature warming level. For example, allowing for insights such as: a UK winter-time wind-drought-peak-demand-event expected to occur on average once every 20 years (1 in 20 year event) in the current day climate (warming level 1.2°C above pre-industrial) has a duration of 13-14 days. A number of different extreme value analysis model structures were tested and validated, and the final models, based on the best fitting model structure, were found to produce results consistent with those in the initial exploration of the adverse weather scenarios.

The results of the statistical extreme value analysis were then used to select relevant adverse weather scenarios to represent each event combination. These results were first used to identify how many distinct warming levels should be represented in each event combination. For each distinct warming level, 3 adverse weather scenarios were then sampled from those within the DePreSys hindcast record characterising the associated return level range (e.g. 13-14 days). This was done such that a the 3 events captured a range of values of the event metrics. Where the return level range was too high to include any DePreSys events, one event from the UKCP18 record was included. The underlying gridded DePreSys hindcast has been fully bias corrected, however UKCP18 temperature and solar radiation data has not, hence these UKCP18 events should be used with caution.

Finally, the resulting 'Adverse Weather Scenarios for Future Electricity Systems' dataset of long-duration events was summarised and a brief how-to guide on downloading the data from the CEDA archive was included.

This study has provided a consistent approach for identifying, characterising and quantifying long-duration adverse weather scenarios for highly-renewable electricity systems, while aiming to be as energy system agnostic as possible. The resulting 'Adverse Weather Scenarios for Future Electricity Systems' dataset of long-duration events is therefore relevant for stress testing a range of potential future electricity systems. This will ultimately help energy system modellers to ensure security of supply in a future net-zero world.

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8 Glossary

AIC = Akaike information criterion

CEDA = Centre for Environmental Data Analysis

CDD = Cooling Degree Days

CMIP = Coupled Model Inter-comparison Project

DePreSys = Decadal Prediction System

DNR = Demand Net of Renewables

EVA = Extreme Value Analysis

GAM = Generalised Additive Model

GCM = Global Climate Model

GMST = Global Mean Surface Temperature

GPD = Generalised Pareto Distribution

GW = Gigawatt

HDD = Heating Degree Days

IEC = International Electrotechnical Commission

NAO = North Atlantic Oscillation

PPE = Perturbed Parameter Ensemble

RCM = Regional Climate Model

RL = Return Level

RND = Renewables Net of Demand

SE UK = South East UK

ssr = surface solar radiation

SW EU = South West Europe

SGI = Surplus Generation Index

tas = temperature at surface

TOA = Top Of Atmosphere

UKCP18 = United Kingdom Climate Projections 2018

WDD = Weather Dependent Demand

WDI = Wind Drought Index

windspeed = wind speed (at 100m)

WL = Warming Level

A Appendix

A.1 Validation of Calibrated DePreSys data

This section presents a thorough validation of the final calibrated DePreSys data, used to identify the DePreSys adverse weather events in Section 4.3, and make up the final 'Adverse Weather Scenarios for Future Electricity Systems' dataset in Section 5. These plots are referred to and discussed in Section 4.2.

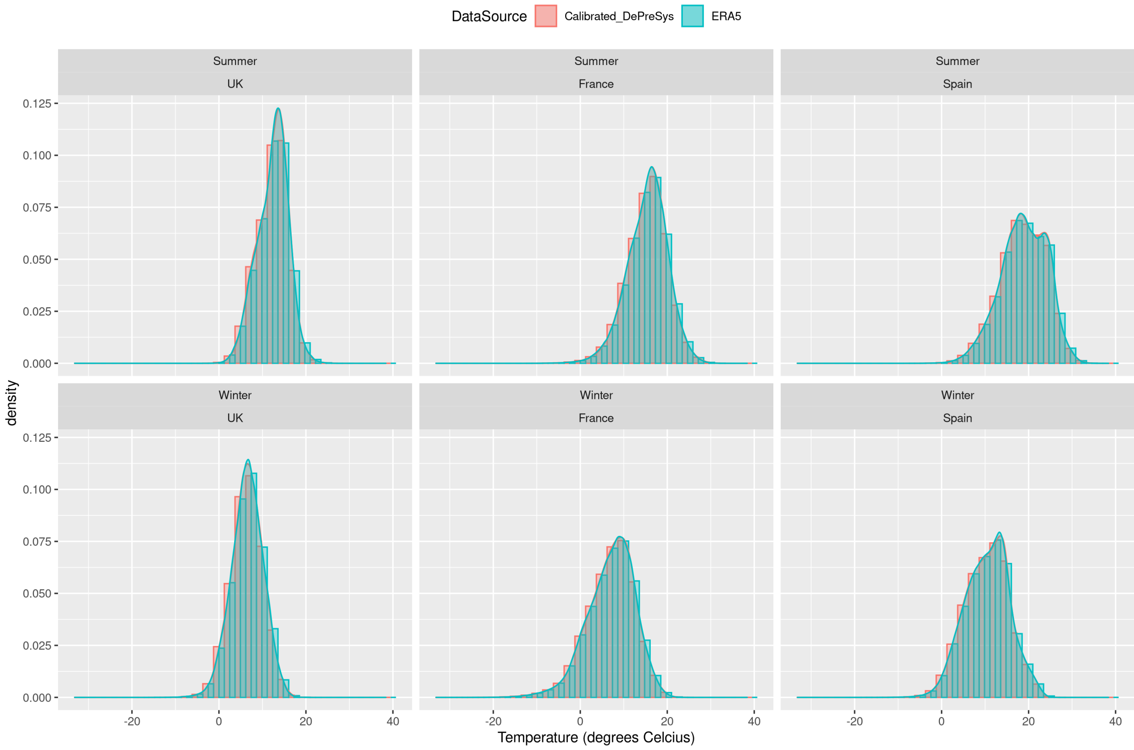

Figure 31: A comparison of the distribution of surface temperature data in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

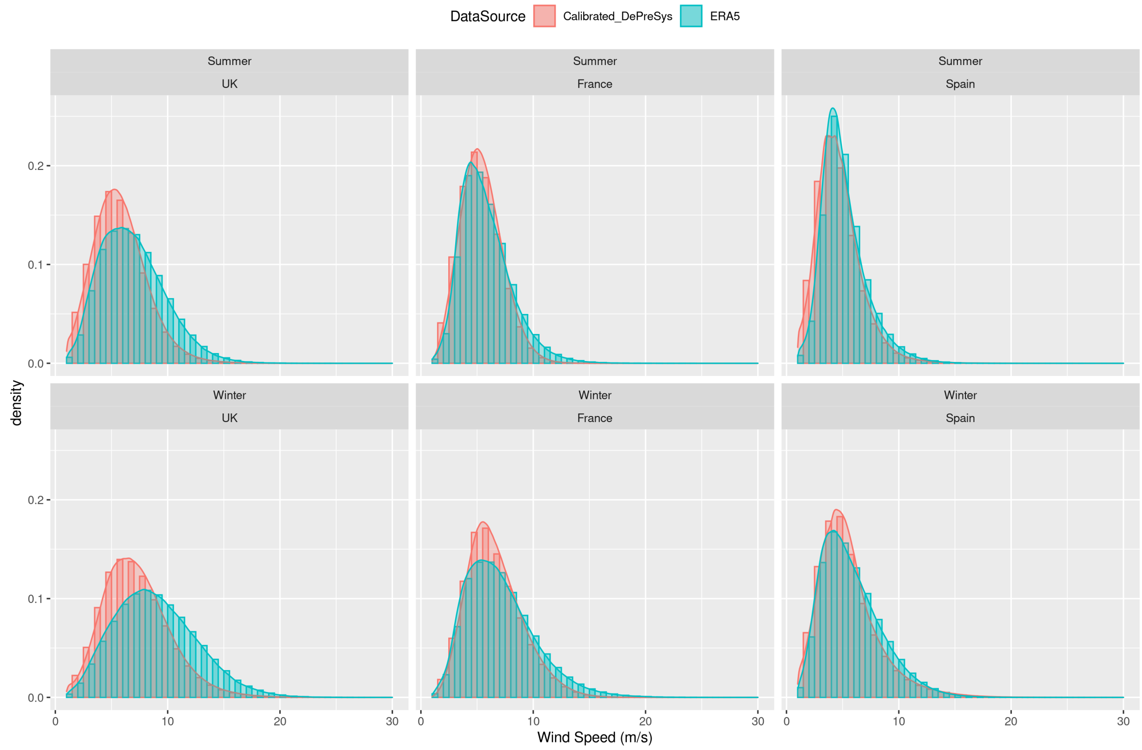

Figure 32: A comparison of the distribution of 100m wind speed data in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

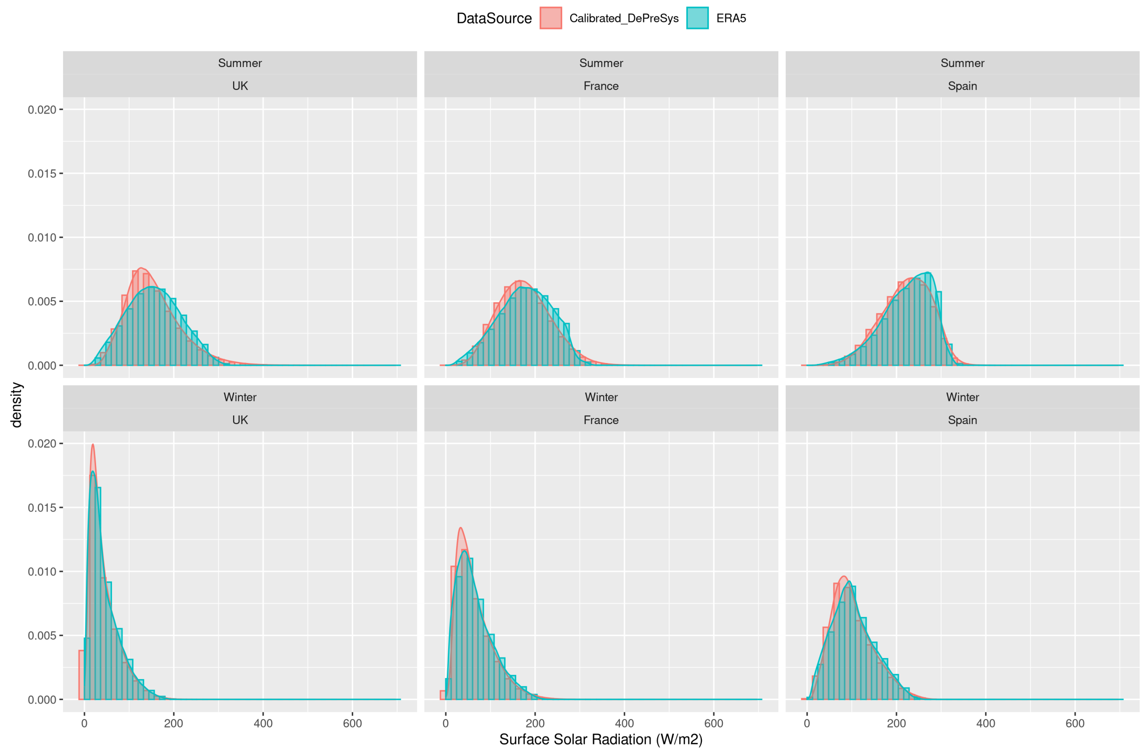

Figure 33: A comparison of the distribution of surface solar radiation data in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

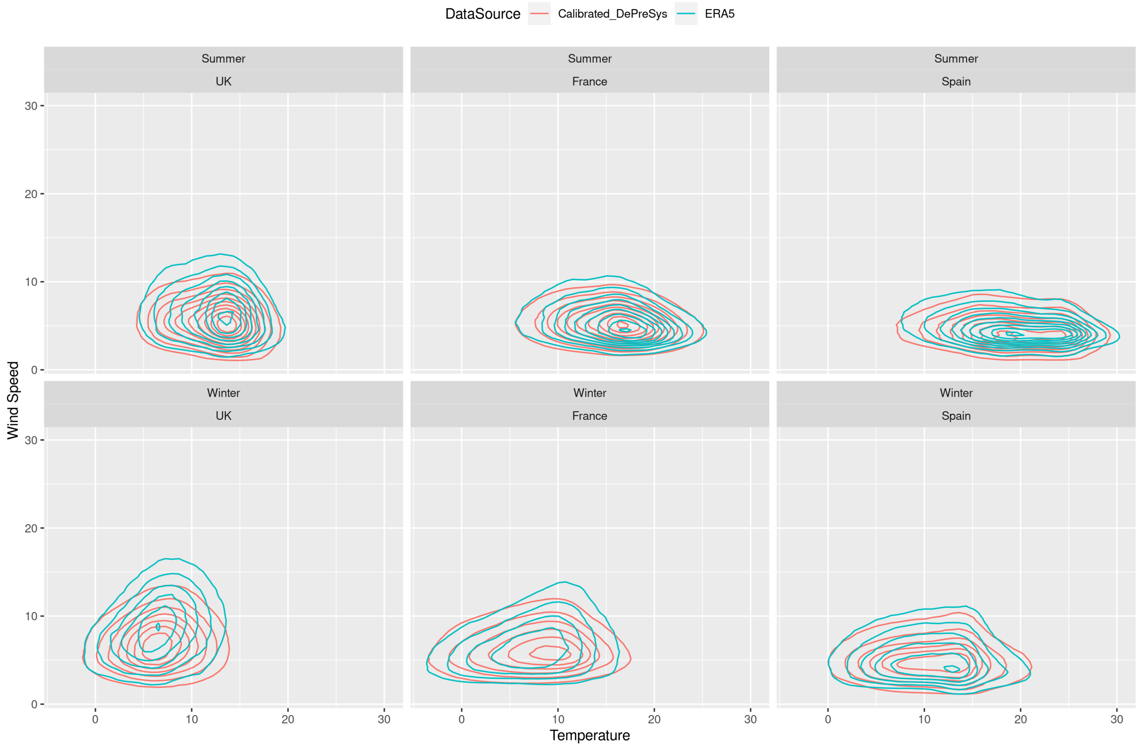

Figure 34: A comparison of the relationship between surface temperature and 100m wind speed in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

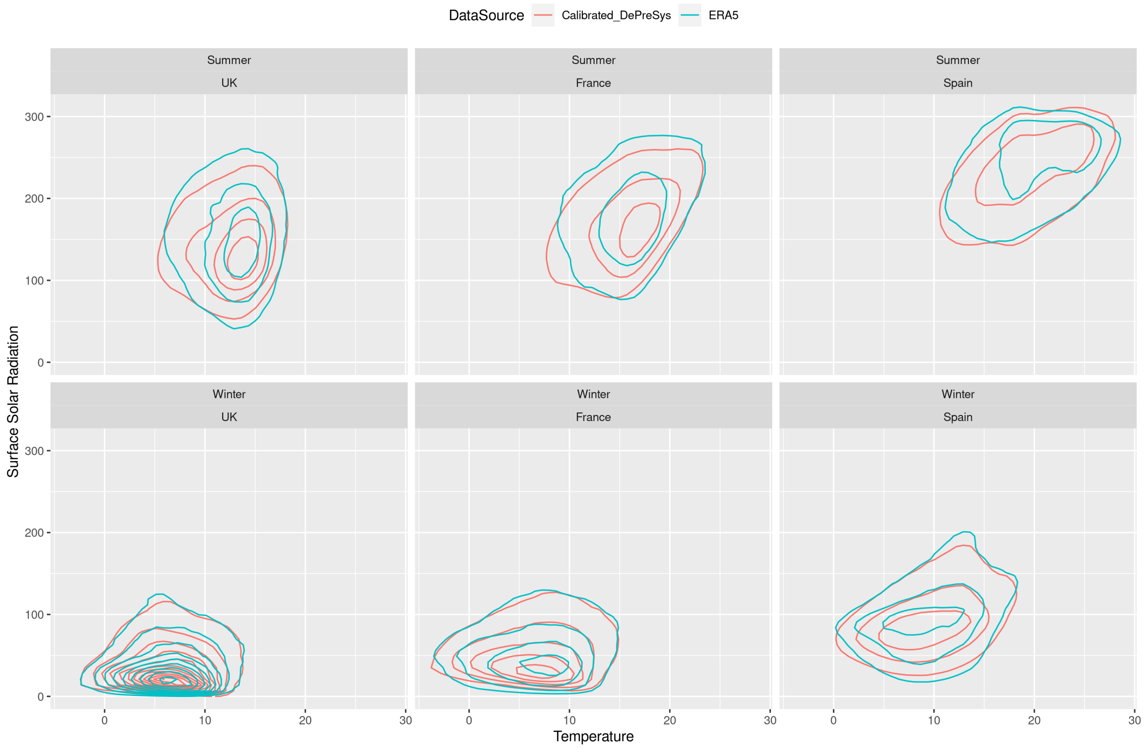

Figure 35: A comparison of the relationship between surface temperature and surface solar radiation in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

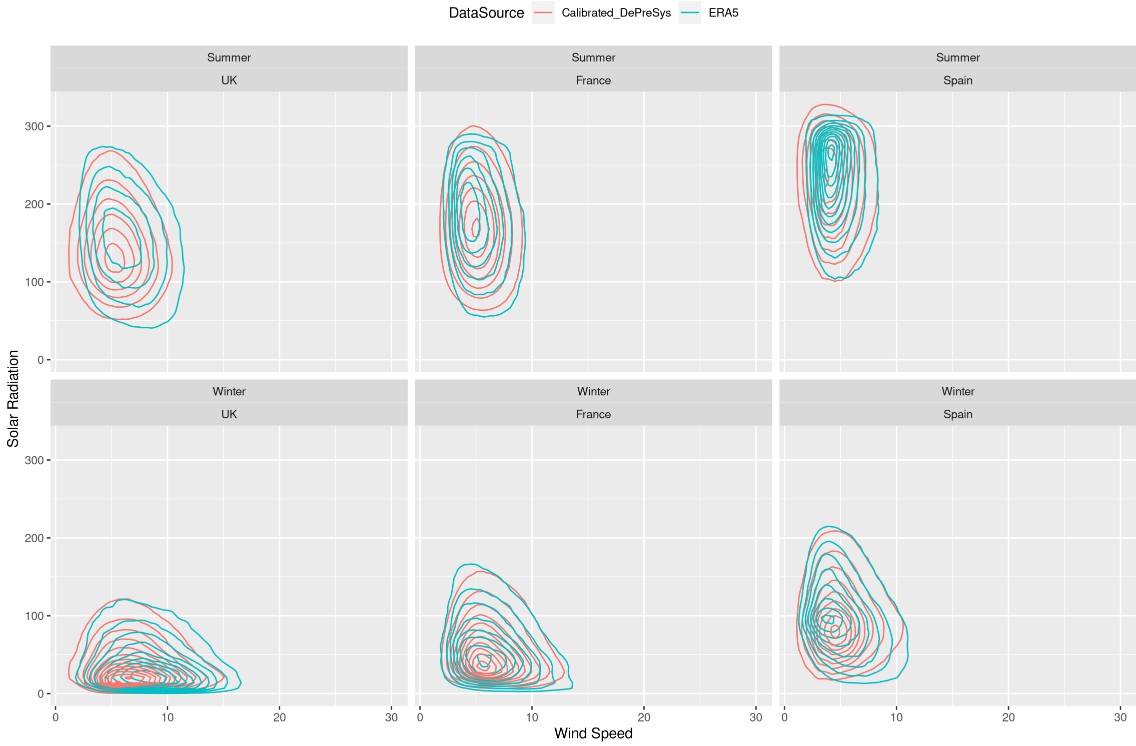

Figure 36: A comparison of the relationship between 100m wind speed and surface solar radiation in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

Figure 37: A comparison of the temporal variability of surface temperature (for the years 2000-2005) in the ERA5 and calibrated DePreSys datasets, for the UK (left), France (middle) and Spain (right).

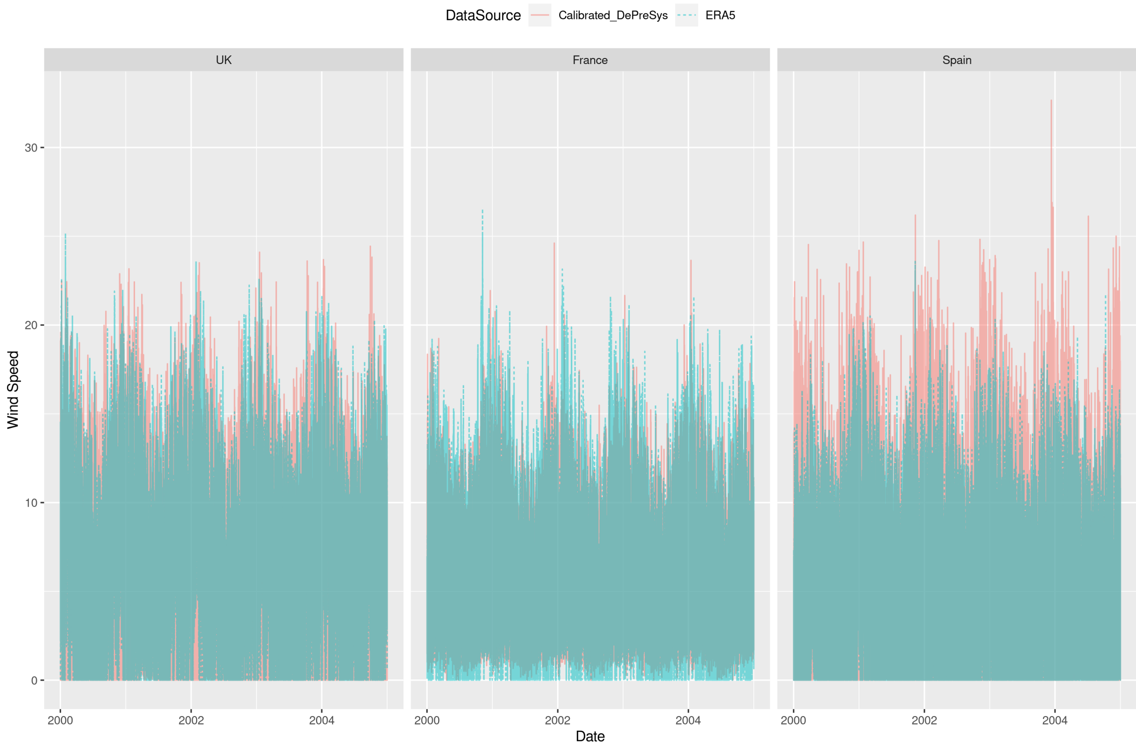

Figure 38: A comparison of the temporal variability of 100m wind speed (for the years 2000-2005) in the ERA5 and calibrated DePreSys datasets, for the UK (left), France (middle) and Spain (right).

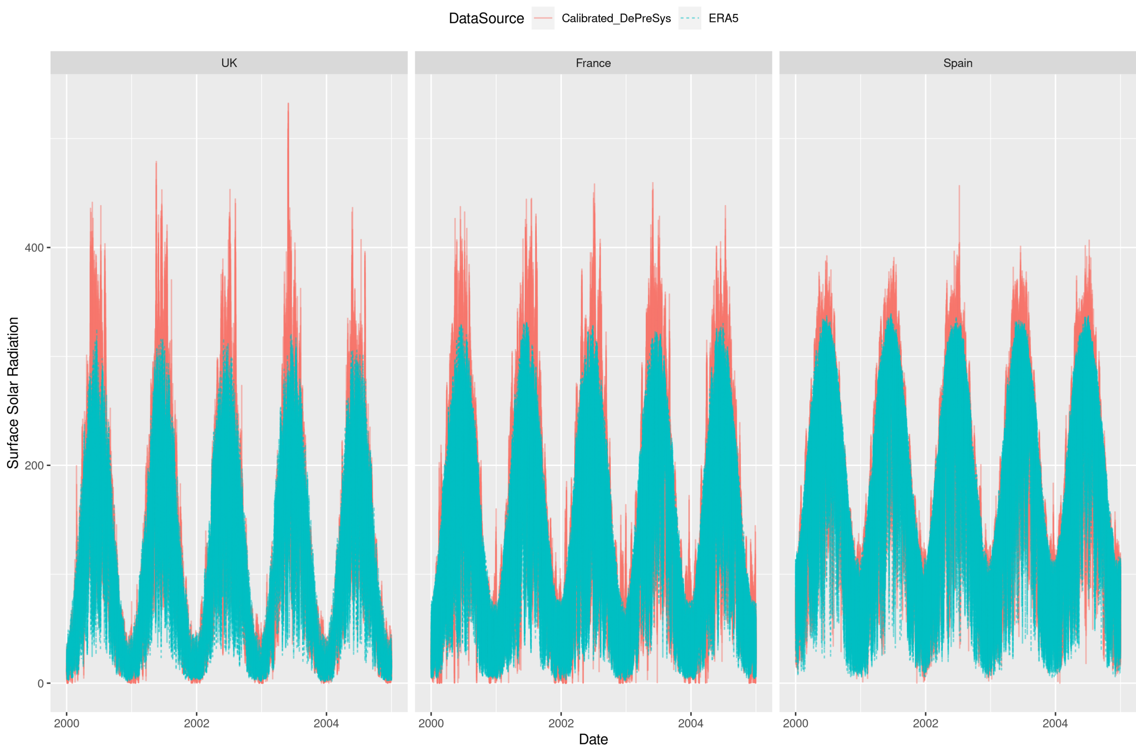

Figure 39: A comparison of the temporal variability of surface solar radiation (for the years 2000-2005) in the ERA5 and calibrated DePreSys datasets, for the UK (left), France (middle) and Spain (right).

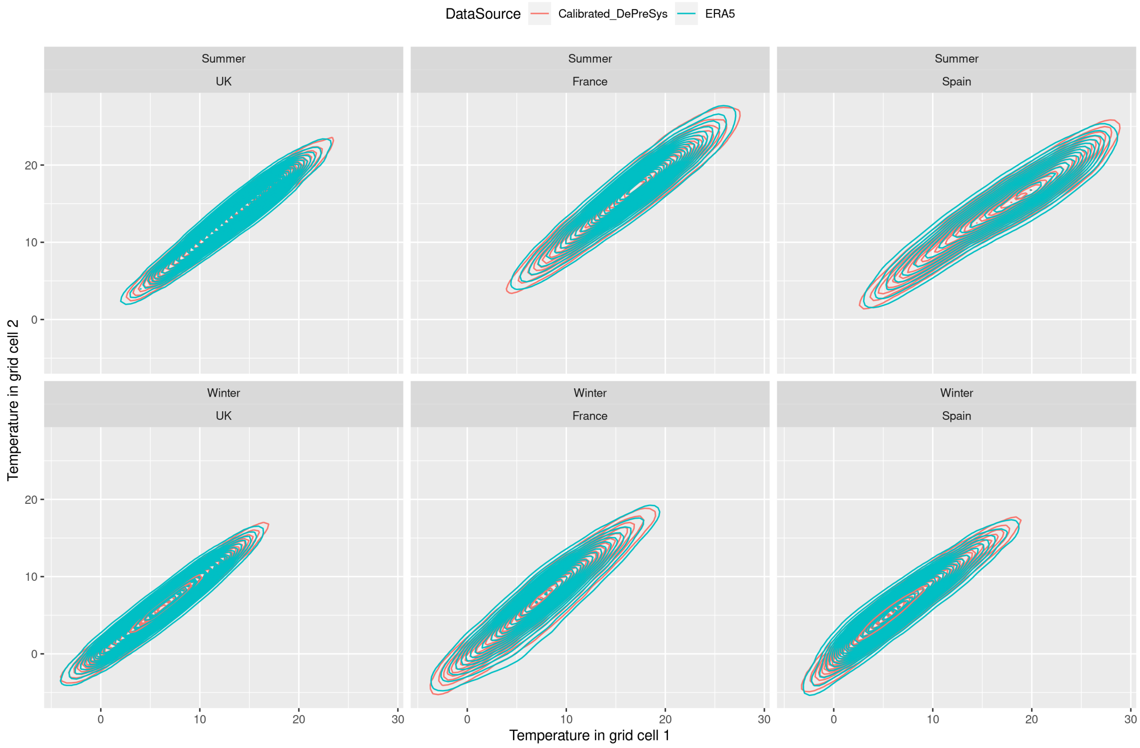

Figure 40: A comparison of the relationship between surface temperature in two grid cells located approximately 170km apart in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

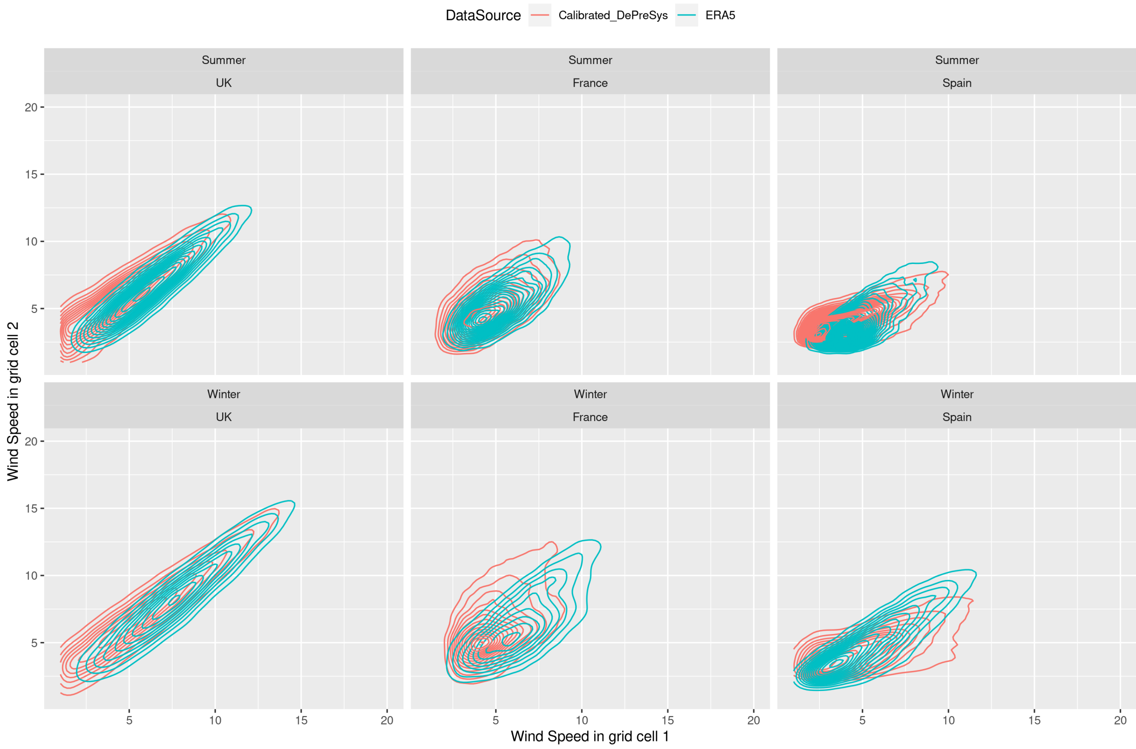

Figure 41: A comparison of the relationship between 100m wind speed in two grid cells located approximately 170km apart in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

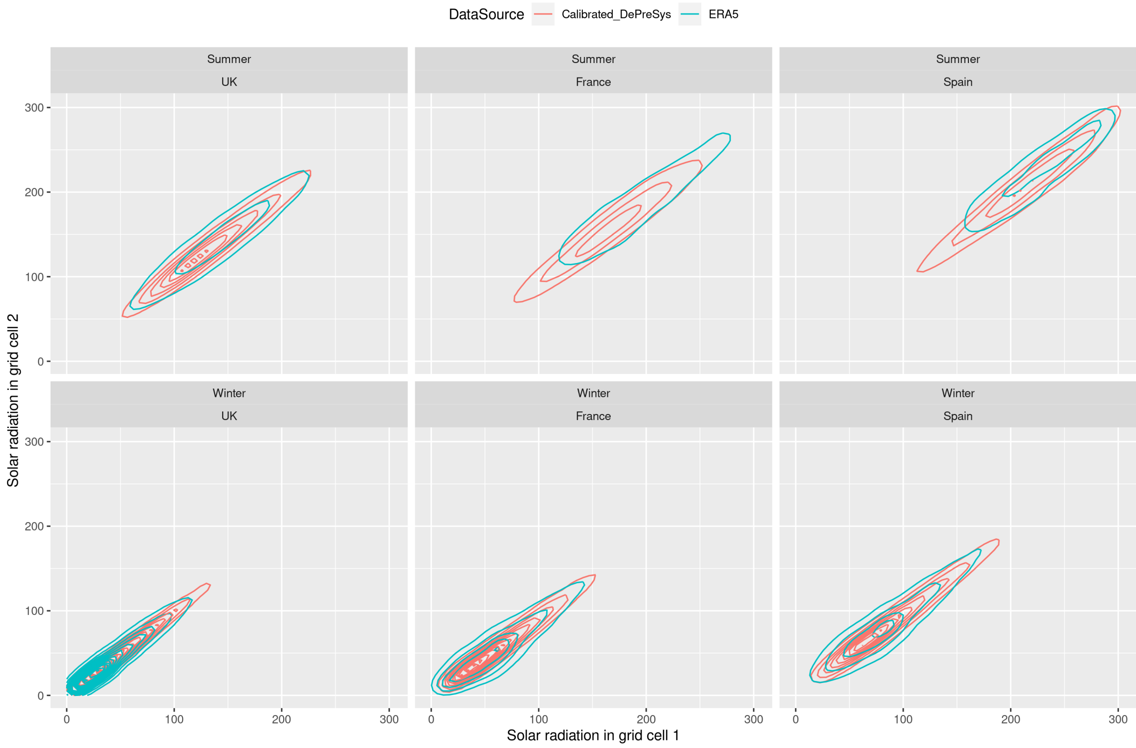

Figure 42: A comparison of the relationship between surface solar radiation in two grid cells located approximately 170km apart in the ERA5 and calibrated DePreSys datasets, in summer (top row) and winter (bottom row) for the UK (left), France (middle) and Spain (right).

A.2 Tables of selected events

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	6	0.89	1993-02-06	UK_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	1
DePreSys	6	2.29	1976-12-12	UK_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	2
DePreSys	6	2.75	1999-03-24	UK_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	3
DePreSys	9	3.81	1978-02-09	UK_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	1
DePreSys	9	6.02	2011-10-11	UK_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	2
DePreSys	9	5.35	1993-03-02	UK_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	3
DePreSys	11	3.69	1998-02-12	UK_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	1
DePreSys	12	9.29	1995-03-12	UK_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	2
DePreSys	11	5.54	2005-10-04	UK_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	3
DePreSys	13	7.17	2012-02-18	UK_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	1
DePreSys	14	13.21	2002-01-08	UK_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	2
DePreSys	14	3.59	1987-11-01	UK_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	3
DePreSys	16	6.41	1987-10-31	UK_Winter_WD_Duration_RTL=50years_warmlev=1.2-4degC	1
DePreSys	17	10.93	1974-01-15	UK_Winter_WD_Duration_RTL=50years_warmlev=1.2-4degC	2
DePreSys	16	12.35	1969-02-03	UK_Winter_WD_Duration_RTL=50years_warmlev=1.2-4degC	3
DePreSys	18	5.49	2012-12-02	UK_Winter_WD_Duration_RTL=100years_warmlev=1.2-4degC	1
DePreSys	19	11.94	1987-01-23	UK_Winter_WD_Duration_RTL=100years_warmlev=1.2-4degC	2
DePreSys	17	10.93	1974-01-15	UK_Winter_WD_Duration_RTL=100years_warmlev=1.2-4degC	3
DePreSys	30	19.31	2006-12-01	UK_Winter_WD_Duration_Maximum	1
DePreSys	26	13.36	1963-01-31	UK_Winter_WD_Duration_Maximum	2
DePreSys	26	12.01	1975-03-04	UK_Winter_WD_Duration_Maximum	3
DePreSys	5	2.74	1974-12-19	UK_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	1
DePreSys	8	2.79	2005-12-27	UK_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	2
DePreSys	7	2.75	1975-03-07	UK_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	3
DePreSys	6	4.52	1971-02-11	UK_Winter_WD_Severity_RTL=5years_warmlev=1.2-3degC	1
DePreSys	11	4.88	2008-12-16	UK_Winter_WD_Severity_RTL=5years_warmlev=1.2-3degC	2
DePreSys	12	4.55	1975-01-11	UK_Winter_WD_Severity_RTL=5years_warmlev=1.2-3degC	3
DePreSys	6	4.25	2005-12-02	UK_Winter_WD_Severity_RTL=5years_warmlev=4degC	1
DePreSys	14	4.52	1983-12-11	UK_Winter_WD_Severity_RTL=5years_warmlev=4degC	2
DePreSys	8	4.49	1970-02-08	UK_Winter_WD_Severity_RTL=5years_warmlev=4degC	3
DePreSys	9	6.10	1972-12-14	UK_Winter_WD_Severity_RTL=10years_warmlev=1.2-3degC	1
DePreSys	11	6.36	1970-02-16	UK_Winter_WD_Severity_RTL=10years_warmlev=1.2-3degC	2
DePreSys	7	6.23	1980-12-04	UK_Winter_WD_Severity_RTL=10years_warmlev=1.2-3degC	3
DePreSys	8	5.61	2008-02-28	UK_Winter_WD_Severity_RTL=10years_warmlev=4degC	1
DePreSys	10	5.95	1985-12-06	UK_Winter_WD_Severity_RTL=10years_warmlev=4degC	2
DePreSys	9	6.10	1972-12-14	UK_Winter_WD_Severity_RTL=10years_warmlev=4degC	3
DePreSys	8	7.59	1975-03-09	UK_Winter_WD_Severity_RTL=20years_warmlev=1.2-3degC	1
DePreSys	13	7.85	1989-01-06	UK_Winter_WD_Severity_RTL=20years_warmlev=1.2-3degC	2
DePreSys	12	7.94	2009-12-29	UK_Winter_WD_Severity_RTL=20years_warmlev=1.2-3degC	3
DePreSys	10	6.91	1969-02-22	UK_Winter_WD_Severity_RTL=20years_warmlev=4degC	1
DePreSys	12	7.56	2010-12-05	UK_Winter_WD_Severity_RTL=20years_warmlev=4degC	2
DePreSys	8	7.59	1975-03-09	UK_Winter_WD_Severity_RTL=20years_warmlev=4degC	3
DePreSys	13	9.82	1974-02-24	UK_Winter_WD_Severity_RTL=50years_warmlev=1.2-3degC	1
DePreSys	16	10.22	2001-12-18	UK_Winter_WD_Severity_RTL=50years_warmlev=1.2-3degC	2
DePreSys	22	10.76	2011-02-20	UK_Winter_WD_Severity_RTL=50years_warmlev=1.2-3degC	3
DePreSys	9	8.56	1970-02-15	UK_Winter_WD_Severity_RTL=50years_warmlev=4degC	1
DePreSys	18	9.54	1968-02-19	UK_Winter_WD_Severity_RTL=50years_warmlev=4degC	2
DePreSys	13	9.15	1979-11-24	UK_Winter_WD_Severity_RTL=50years_warmlev=4degC	3
DePreSys	15	12.25	2005-01-28	UK_Winter_WD_Severity_RTL=100years_warmlev=1.2-3degC	1
DePreSys	23	12.86	2010-12-18	UK_Winter_WD_Severity_RTL=100years_warmlev=1.2-3degC	2
DePreSys	14	11.84	1983-01-25	UK_Winter_WD_Severity_RTL=100years_warmlev=1.2-3degC	3
DePreSys	14	9.70	1965-12-07	UK_Winter_WD_Severity_RTL=100years_warmlev=4degC	1
DePreSys	17	10.93	1974-01-15	UK_Winter_WD_Severity_RTL=100years_warmlev=4degC	2
DePreSys	18	11.03	1987-10-30	UK_Winter_WD_Severity_RTL=100years_warmlev=4degC	3
DePreSys	23	20.41	1963-02-09	UK_Winter_WD_Severity_Maximum	1
DePreSys	30	19.31	2006-12-01	UK_Winter_WD_Severity_Maximum	2
DePreSys	25	17.42	1973-02-16	UK_Winter_WD_Severity_Maximum	3

Table 16: Table summarising the events selected to represent the UK winter-time wind-drought-peak-demand scenarios in terms of duration and severity, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here WD=wind-drought-peak-demand, and RTL=return level.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	7	1.18	1988-07-07	UK_Summer_WD_Duration_RTL=2years_warmlev=1.2-4degC	1
DePreSys	7	3.30	2008-07-22	UK_Summer_WD_Duration_RTL=2years_warmlev=1.2-4degC	2
DePreSys	7	3.87	1983-07-21	UK_Summer_WD_Duration_RTL=2years_warmlev=1.2-4degC	3
DePreSys	10	2.69	2005-07-12	UK_Summer_WD_Duration_RTL=5years_warmlev=1.2-4degC	1
DePreSys	11	3.85	2003-07-23	UK_Summer_WD_Duration_RTL=5years_warmlev=1.2-4degC	2
DePreSys	10	3.46	1999-08-04	UK_Summer_WD_Duration_RTL=5years_warmlev=1.2-4degC	3
DePreSys	13	3.83	1978-06-05	UK_Summer_WD_Duration_RTL=10years_warmlev=1.2-3degC	1
DePreSys	13	5.77	1973-07-30	UK_Summer_WD_Duration_RTL=10years_warmlev=1.2-3degC	2
DePreSys	13	3.80	2002-07-03	UK_Summer_WD_Duration_RTL=10years_warmlev=1.2-3degC	3
DePreSys	13	2.42	1982-07-14	UK_Summer_WD_Duration_RTL=10years_warmlev=4degC	1
DePreSys	14	7.33	1977-04-09	UK_Summer_WD_Duration_RTL=10years_warmlev=4degC	2
DePreSys	14	3.40	1980-04-05	UK_Summer_WD_Duration_RTL=10years_warmlev=4degC	3
DePreSys	15	3.25	1990-07-07	UK_Summer_WD_Duration_RTL=20years_warmlev=1.2-4degC	1
DePreSys	16	6.46	1982-07-21	UK_Summer_WD_Duration_RTL=20years_warmlev=1.2-4degC	2
DePreSys	15	4.07	1990-06-26	UK_Summer_WD_Duration_RTL=20years_warmlev=1.2-4degC	3
DePreSys	18	4.69	1992-07-25	UK_Summer_WD_Duration_RTL=50years_warmlev=1.2-4degC	1
DePreSys	19	8.12	1974-07-23	UK_Summer_WD_Duration_RTL=50years_warmlev=1.2-4degC	2
DePreSys	18	8.33	1990-08-16	UK_Summer_WD_Duration_RTL=50years_warmlev=1.2-4degC	3
DePreSys	19	5.31	2014-06-20	UK_Summer_WD_Duration_RTL=100years_warmlev=1.2-3degC	1
DePreSys	20	9.76	2007-09-29	UK_Summer_WD_Duration_RTL=100years_warmlev=1.2-3degC	2
DePreSys	21	4.35	1991-07-10	UK_Summer_WD_Duration_RTL=100years_warmlev=1.2-3degC	3
DePreSys	20	4.35	2015-08-16	UK_Summer_WD_Duration_RTL=100years_warmlev=4degC	1
DePreSys	24	9.49	1980-07-19	UK_Summer_WD_Duration_RTL=100years_warmlev=4degC	2
DePreSys	28	12.47	1986-07-17	UK_Summer_WD_Duration_Maximum	1
DePreSys	26	7.61	1976-08-05	UK_Summer_WD_Duration_Maximum	2
DePreSys	26	10.37	1980-07-11	UK_Summer_WD_Duration_Maximum	3
DePreSys	4	2.10	1984-08-09	UK_Summer_WD_Severity_RTL=2years_warmlev=1.2-4degC	1
DePreSys	12	2.10	1990-08-23	UK_Summer_WD_Severity_RTL=2years_warmlev=1.2-4degC	2
DePreSys	10	2.10	2004-08-27	UK_Summer_WD_Severity_RTL=2years_warmlev=1.2-4degC	3
DePreSys	8	3.24	1995-06-26	UK_Summer_WD_Severity_RTL=5years_warmlev=1.2-3degC	1
DePreSys	11	3.30	1996-07-27	UK_Summer_WD_Severity_RTL=5years_warmlev=1.2-3degC	2
DePreSys	12	3.25	1989-06-03	UK_Summer_WD_Severity_RTL=5years_warmlev=1.2-3degC	3
DePreSys	8	3.48	1994-04-11	UK_Summer_WD_Severity_RTL=5years_warmlev=4degC	1
DePreSys	16	3.66	1977-08-09	UK_Summer_WD_Severity_RTL=5years_warmlev=4degC	2
DePreSys	7	3.50	2003-08-13	UK_Summer_WD_Severity_RTL=5years_warmlev=4degC	3
DePreSys	9	4.29	2003-07-21	UK_Summer_WD_Severity_RTL=10years_warmlev=1.2-3degC	1
DePreSys	13	4.44	2005-08-06	UK_Summer_WD_Severity_RTL=10years_warmlev=1.2-3degC	2
DePreSys	9	4.35	1996-06-13	UK_Summer_WD_Severity_RTL=10years_warmlev=1.2-3degC	3
DePreSys	7	4.39	1973-08-05	UK_Summer_WD_Severity_RTL=10years_warmlev=4degC	1
DePreSys	14	4.61	1971-07-18	UK_Summer_WD_Severity_RTL=10years_warmlev=4degC	2
DePreSys	10	4.96	1978-04-15	UK_Summer_WD_Severity_RTL=10years_warmlev=4degC	3
DePreSys	11	5.13	1998-04-29	UK_Summer_WD_Severity_RTL=20years_warmlev=1.2-3degC	1
DePreSys	14	5.57	2011-07-29	UK_Summer_WD_Severity_RTL=20years_warmlev=1.2-3degC	2
DePreSys	10	5.35	1989-04-06	UK_Summer_WD_Severity_RTL=20years_warmlev=1.2-3degC	3
DePreSys	10	5.35	1989-04-06	UK_Summer_WD_Severity_RTL=20years_warmlev=4degC	1
DePreSys	21	5.97	1989-06-27	UK_Summer_WD_Severity_RTL=20years_warmlev=4degC	2
DePreSys	11	5.50	1994-08-10	UK_Summer_WD_Severity_RTL=20years_warmlev=4degC	3
DePreSys	16	6.46	1982-07-21	UK_Summer_WD_Severity_RTL=50years_warmlev=1.2-3degC	1
DePreSys	21	6.90	1989-07-04	UK_Summer_WD_Severity_RTL=50years_warmlev=1.2-3degC	2
DePreSys	15	6.42	1975-07-01	UK_Summer_WD_Severity_RTL=50years_warmlev=1.2-3degC	3
DePreSys	13	7.18	1975-09-25	UK_Summer_WD_Severity_RTL=50years_warmlev=4degC	1
DePreSys	25	7.99	2015-04-06	UK_Summer_WD_Severity_RTL=50years_warmlev=4degC	2
DePreSys	24	7.87	1973-07-08	UK_Summer_WD_Severity_RTL=50years_warmlev=4degC	3
DePreSys	15	7.60	1990-04-07	UK_Summer_WD_Severity_RTL=100years_warmlev=1.2-3degC	1
DePreSys	25	8.10	1990-07-16	UK_Summer_WD_Severity_RTL=100years_warmlev=1.2-3degC	2
DePreSys	26	7.61	1976-08-05	UK_Summer_WD_Severity_RTL=100years_warmlev=1.2-3degC	3
DePreSys	14	8.16	1987-08-07	UK_Summer_WD_Severity_RTL=100years_warmlev=4degC	1
DePreSys	20	8.87	1981-04-10	UK_Summer_WD_Severity_RTL=100years_warmlev=4degC	2
DePreSys	16	8.15	1974-07-28	UK_Summer_WD_Severity_RTL=100years_warmlev=4degC	3
DePreSys	28	12.47	1986-07-17	UK_Summer_WD_Severity_Maximum	1
DePreSys	20	10.50	1970-08-19	UK_Summer_WD_Severity_Maximum	2
DePreSys	26	10.37	1980-07-11	UK_Summer_WD_Severity_Maximum	3

Table 17: Table summarising the events selected to represent the UK summer-time wind-drought-peak-demand scenarios in terms of duration and severity, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here WD=wind-drought-peak-demand, and RTL=return level.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	6	0.73	2011-07-09	UK_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	1
DePreSys	6	2.45	1965-08-28	UK_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	2
DePreSys	6	3.03	2007-05-06	UK_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	3
DePreSys	8	1.50	1985-04-14	UK_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	1
DePreSys	9	5.07	2010-09-21	UK_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	2
DePreSys	8	4.61	2001-09-06	UK_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	3
DePreSys	10	3.52	1969-09-15	UK_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	1
DePreSys	11	5.49	2012-04-01	UK_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	2
DePreSys	10	7.87	1997-04-08	UK_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	3
DePreSys	12	4.62	2002-04-01	UK_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	1
DePreSys	13	6.95	2012-09-16	UK_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	2
DePreSys	12	6.32	2007-09-18	UK_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	3
DePreSys	14	4.88	1998-05-03	UK_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	1
DePreSys	15	8.90	2012-09-15	UK_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	2
DePreSys	14	8.29	2007-07-28	UK_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	3
DePreSys	16	7.63	1991-09-05	UK_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	1
DePreSys	18	11.78	1969-09-12	UK_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	2
DePreSys	17	9.22	1973-05-21	UK_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	3
DePreSys	26	13.06	1981-09-11	UK_Summer_SG_Duration_Maximum	1
DePreSys	24	12.13	2015-04-01	UK_Summer_SG_Duration_Maximum	2
DePreSys	23	10.33	2012-09-15	UK_Summer_SG_Duration_Maximum	3
DePreSys	6	2.62	1976-09-25	UK_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	1
DePreSys	10	2.68	2011-04-17	UK_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	2
DePreSys	7	2.63	2007-09-16	UK_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	3
DePreSys	8	4.20	1995-04-01	UK_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	1
DePreSys	10	4.34	1981-09-19	UK_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	2
DePreSys	12	4.19	1967-06-01	UK_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	3
DePreSys	8	5.36	2007-05-05	UK_Summer_SG_Severity_RTL=10years_warmlev=1.2-4degC	1
DePreSys	12	5.74	2000-04-01	UK_Summer_SG_Severity_RTL=10years_warmlev=1.2-4degC	2
DePreSys	8	5.72	1991-04-19	UK_Summer_SG_Severity_RTL=10years_warmlev=1.2-4degC	3
DePreSys	8	6.50	1991-09-07	UK_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	1
DePreSys	13	7.03	2012-09-11	UK_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	2
DePreSys	9	6.80	2011-09-16	UK_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	3
DePreSys	12	8.47	1994-09-16	UK_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	1
DePreSys	19	9.03	2008-04-16	UK_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	2
DePreSys	14	8.29	2007-07-28	UK_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	3
DePreSys	17	9.87	1960-04-19	UK_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	1
DePreSys	16	10.04	1962-04-24	UK_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	2
DePreSys	18	9.80	1964-09-11	UK_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	3
DePreSys	26	13.06	1981-09-11	UK_Summer_SG_Severity_Maximum	1
DePreSys	16	12.14	2000-09-15	UK_Summer_SG_Severity_Maximum	2
DePreSys	24	12.13	2015-04-01	UK_Summer_SG_Severity_Maximum	3

Table 18: Table summarising the events selected to represent the UK summer-time surplus-generation scenarios in terms of duration and severity, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here SG=surplus-generation, and RTL=return level.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	7	1.89	2010-11-20	EU_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	1
DePreSys	7	3.59	1989-01-14	EU_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	2
DePreSys	7	5.27	1990-02-05	EU_Winter_WD_Duration_RTL=2years_warmlev=1.2-4degC	3
DePreSys	11	1.71	1963-03-14	EU_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	1
DePreSys	11	6.28	1994-01-10	EU_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	2
DePreSys	11	5.04	2005-03-02	EU_Winter_WD_Duration_RTL=5years_warmlev=1.2-4degC	3
DePreSys	13	3.40	1967-02-02	EU_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	1
DePreSys	14	13.16	2002-01-08	EU_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	2
DePreSys	15	6.18	2009-02-09	EU_Winter_WD_Duration_RTL=10years_warmlev=1.2-4degC	3
DePreSys	16	6.54	1968-01-27	EU_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	1
DePreSys	18	17.40	1983-01-23	EU_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	2
DePreSys	17	8.10	1960-01-10	EU_Winter_WD_Duration_RTL=20years_warmlev=1.2-4degC	3
DePreSys	20	11.79	1987-01-20	EU_Winter_WD_Duration_RTL=50years_warmlev=1.2-2degC	1
DePreSys	21	14.71	1969-02-02	EU_Winter_WD_Duration_RTL=50years_warmlev=1.2-2degC	2
DePreSys	20	8.69	1984-01-06	EU_Winter_WD_Duration_RTL=50years_warmlev=1.2-2degC	3
DePreSys	18	10.40	1970-01-05	EU_Winter_WD_Duration_RTL=50years_warmlev=3-4degC	1
DePreSys	20	11.79	1987-01-20	EU_Winter_WD_Duration_RTL=50years_warmlev=3-4degC	2
DePreSys	19	15.06	2002-01-14	EU_Winter_WD_Duration_RTL=50years_warmlev=3-4degC	3
DePreSys	23	7.63	2004-12-31	EU_Winter_WD_Duration_RTL=100years_warmlev=1.2-3degC	1
DePreSys	25	17.76	2005-02-06	EU_Winter_WD_Duration_RTL=100years_warmlev=1.2-3degC	2
DePreSys	22	8.60	1966-11-20	EU_Winter_WD_Duration_RTL=100years_warmlev=1.2-3degC	3
DePreSys	20	8.69	1984-01-06	EU_Winter_WD_Duration_RTL=100years_warmlev=4degC	1
DePreSys	21	12.30	1979-01-28	EU_Winter_WD_Duration_RTL=100years_warmlev=4degC	2
DePreSys	23	7.63	2004-12-31	EU_Winter_WD_Duration_RTL=100years_warmlev=4degC	3
DePreSys	44	32.34	1970-01-19	EU_Winter_WD_Duration_Maximum	1
DePreSys	35	22.03	1966-12-28	EU_Winter_WD_Duration_Maximum	2
DePreSys	33	25.55	2006-11-29	EU_Winter_WD_Duration_Maximum	3
DePreSys	6	2.92	1993-03-25	EU_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	1
DePreSys	9	2.96	2010-02-13	EU_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	2
DePreSys	6	2.97	1964-01-23	EU_Winter_WD_Severity_RTL=2years_warmlev=1.2-4degC	3
DePreSys	7	5.17	1986-01-20	EU_Winter_WD_Severity_RTL=5years_warmlev=1.2-2degC	1
DePreSys	13	5.24	1998-01-17	EU_Winter_WD_Severity_RTL=5years_warmlev=1.2-2degC	2
DePreSys	14	5.06	1963-02-06	EU_Winter_WD_Severity_RTL=5years_warmlev=1.2-2degC	3
DePreSys	8	4.60	1978-02-20	EU_Winter_WD_Severity_RTL=5years_warmlev=3-4degC	1
DePreSys	12	5.08	1973-01-03	EU_Winter_WD_Severity_RTL=5years_warmlev=3-4degC	2
DePreSys	9	5.08	1998-12-30	EU_Winter_WD_Severity_RTL=5years_warmlev=3-4degC	3
DePreSys	7	6.86	1995-01-15	EU_Winter_WD_Severity_RTL=10years_warmlev=1.2-2degC	1
DePreSys	14	7.13	2001-12-05	EU_Winter_WD_Severity_RTL=10years_warmlev=1.2-2degC	2
DePreSys	10	6.97	1963-01-19	EU_Winter_WD_Severity_RTL=10years_warmlev=1.2-2degC	3
DePreSys	11	6.19	1971-11-28	EU_Winter_WD_Severity_RTL=10years_warmlev=3-4degC	1
DePreSys	16	6.57	1973-02-05	EU_Winter_WD_Severity_RTL=10years_warmlev=3-4degC	2
DePreSys	19	6.34	1993-02-19	EU_Winter_WD_Severity_RTL=10years_warmlev=3-4degC	3
DePreSys	13	9.18	1974-11-29	EU_Winter_WD_Severity_RTL=20years_warmlev=1.2-2degC	1
DePreSys	18	9.51	2008-02-23	EU_Winter_WD_Severity_RTL=20years_warmlev=1.2-2degC	2
DePreSys	16	8.84	1968-02-23	EU_Winter_WD_Severity_RTL=20years_warmlev=1.2-2degC	3
DePreSys	13	7.93	1968-12-06	EU_Winter_WD_Severity_RTL=20years_warmlev=3-4degC	1
DePreSys	15	9.09	1985-12-24	EU_Winter_WD_Severity_RTL=20years_warmlev=3-4degC	2
DePreSys	16	8.68	2009-02-18	EU_Winter_WD_Severity_RTL=20years_warmlev=3-4degC	3
DePreSys	18	11.81	2011-02-16	EU_Winter_WD_Severity_RTL=50years_warmlev=1.2-2degC	1
DePreSys	21	13.04	1993-01-01	EU_Winter_WD_Severity_RTL=50years_warmlev=1.2-2degC	2
DePreSys	14	12.93	1987-03-15	EU_Winter_WD_Severity_RTL=50years_warmlev=1.2-2degC	3
DePreSys	12	10.19	1970-02-14	EU_Winter_WD_Severity_RTL=50years_warmlev=3-4degC	1
DePreSys	17	10.99	2007-12-10	EU_Winter_WD_Severity_RTL=50years_warmlev=3-4degC	2
DePreSys	23	12.35	1961-02-21	EU_Winter_WD_Severity_RTL=50years_warmlev=3-4degC	3
DePreSys	14	14.39	1990-02-01	EU_Winter_WD_Severity_RTL=100years_warmlev=1.2-2degC	1
DePreSys	25	15.62	2001-02-13	EU_Winter_WD_Severity_RTL=100years_warmlev=1.2-2degC	2
DePreSys	16	14.24	1967-02-05	EU_Winter_WD_Severity_RTL=100years_warmlev=1.2-2degC	3
DePreSys	18	12.22	1988-02-03	EU_Winter_WD_Severity_RTL=100years_warmlev=3-4degC	1
DePreSys	25	14.93	1968-02-02	EU_Winter_WD_Severity_RTL=100years_warmlev=3-4degC	2
DePreSys	19	11.87	2012-01-17	EU_Winter_WD_Severity_RTL=100years_warmlev=3-4degC	3
DePreSys	44	32.34	1970-01-19	EU_Winter_WD_Severity_Maximum	1
DePreSys	29	31.65	1989-01-03	EU_Winter_WD_Severity_Maximum	2
DePreSys	29	31.02	1963-02-01	EU_Winter_WD_Severity_Maximum	3

Table 19: Table summarising the events selected to represent the European winter-time wind-drought-peak-demand scenarios in terms of duration and severity, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here WD=wind-drought-peak-demand, and RTL=return level.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	10	2.21	2010-08-18	EU_Summer_WD_Duration_RTL=2years_warmlev=1.2-2degC	1
DePreSys	10	3.02	2007-08-02	EU_Summer_WD_Duration_RTL=2years_warmlev=1.2-2degC	2
DePreSys	10	1.41	1976-07-18	EU_Summer_WD_Duration_RTL=2years_warmlev=1.2-2degC	3
DePreSys	11	1.99	2014-08-04	EU_Summer_WD_Duration_RTL=2years_warmlev=3degC	1
DePreSys	11	3.14	1999-08-03	EU_Summer_WD_Duration_RTL=2years_warmlev=3degC	2
DePreSys	11	1.97	1969-08-10	EU_Summer_WD_Duration_RTL=2years_warmlev=3degC	3
DePreSys	11	2.38	2006-07-01	EU_Summer_WD_Duration_RTL=2years_warmlev=4degC	1
DePreSys	12	2.86	2009-06-30	EU_Summer_WD_Duration_RTL=2years_warmlev=4degC	2
DePreSys	11	1.66	1967-05-02	EU_Summer_WD_Duration_RTL=2years_warmlev=4degC	3
DePreSys	14	3.51	2012-07-14	EU_Summer_WD_Duration_RTL=5years_warmlev=1.2-1.5degC	1
DePreSys	15	3.97	1980-07-30	EU_Summer_WD_Duration_RTL=5years_warmlev=1.2-1.5degC	2
DePreSys	14	3.84	1983-07-19	EU_Summer_WD_Duration_RTL=5years_warmlev=1.2-1.5degC	3
DePreSys	15	3.64	1962-08-13	EU_Summer_WD_Duration_RTL=5years_warmlev=2degC	1
DePreSys	16	4.94	2000-07-21	EU_Summer_WD_Duration_RTL=5years_warmlev=2degC	2
DePreSys	16	2.49	1997-07-15	EU_Summer_WD_Duration_RTL=5years_warmlev=2degC	3
DePreSys	17	2.98	1990-08-11	EU_Summer_WD_Duration_RTL=5years_warmlev=3degC	1
DePreSys	18	5.64	2010-08-16	EU_Summer_WD_Duration_RTL=5years_warmlev=3degC	2
DePreSys	17	2.86	2003-08-16	EU_Summer_WD_Duration_RTL=5years_warmlev=3degC	3
DePreSys	20	4.62	1972-07-02	EU_Summer_WD_Duration_RTL=5years_warmlev=4degC	1
DePreSys	21	7.65	2012-07-30	EU_Summer_WD_Duration_RTL=5years_warmlev=4degC	2
DePreSys	22	3.96	2013-07-14	EU_Summer_WD_Duration_RTL=5years_warmlev=4degC	3
DePreSys	17	2.98	1990-08-11	EU_Summer_WD_Duration_RTL=10years_warmlev=1.2-1.5degC	1
DePreSys	18	5.64	2010-08-16	EU_Summer_WD_Duration_RTL=10years_warmlev=1.2-1.5degC	2
DePreSys	17	2.86	2003-08-16	EU_Summer_WD_Duration_RTL=10years_warmlev=1.2-1.5degC	3
DePreSys	19	4.69	1987-08-01	EU_Summer_WD_Duration_RTL=10years_warmlev=2degC	1
DePreSys	20	6.52	1982-04-06	EU_Summer_WD_Duration_RTL=10years_warmlev=2degC	2
DePreSys	19	5.44	1997-08-03	EU_Summer_WD_Duration_RTL=10years_warmlev=2degC	3
DePreSys	21	6.06	1981-07-20	EU_Summer_WD_Duration_RTL=10years_warmlev=3degC	1
DePreSys	24	6.84	1990-07-31	EU_Summer_WD_Duration_RTL=10years_warmlev=3degC	2
DePreSys	21	3.33	1996-08-16	EU_Summer_WD_Duration_RTL=10years_warmlev=3degC	3
DePreSys	27	5.94	1967-08-02	EU_Summer_WD_Duration_RTL=10years_warmlev=4degC	1
DePreSys	26	7.84	1969-07-30	EU_Summer_WD_Duration_RTL=10years_warmlev=4degC	2
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Duration_RTL=10years_warmlev=4degC	3
DePreSys	20	4.54	1979-06-26	EU_Summer_WD_Duration_RTL=20years_warmlev=1.2-1.5degC	1
DePreSys	21	7.56	1975-08-05	EU_Summer_WD_Duration_RTL=20years_warmlev=1.2-1.5degC	2
DePreSys	21	3.33	1996-08-16	EU_Summer_WD_Duration_RTL=20years_warmlev=1.2-1.5degC	3
DePreSys	22	6.28	1992-08-12	EU_Summer_WD_Duration_RTL=20years_warmlev=2degC	1
DePreSys	24	6.84	1990-07-31	EU_Summer_WD_Duration_RTL=20years_warmlev=2degC	2
DePreSys	23	7.95	1982-07-25	EU_Summer_WD_Duration_RTL=20years_warmlev=2degC	3
DePreSys	27	5.94	1967-08-02	EU_Summer_WD_Duration_RTL=20years_warmlev=3degC	1
DePreSys	26	7.84	1969-07-30	EU_Summer_WD_Duration_RTL=20years_warmlev=3degC	2
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Duration_RTL=20years_warmlev=3degC	3
DePreSys	33	7.78	1989-07-14	EU_Summer_WD_Duration_RTL=20years_warmlev=4degC	1
DePreSys	32	8.69	2008-07-17	EU_Summer_WD_Duration_RTL=20years_warmlev=4degC	2
DePreSys	23	7.95	1982-07-25	EU_Summer_WD_Duration_RTL=50years_warmlev=1.2-1.5degC	1
DePreSys	25	7.97	1983-07-28	EU_Summer_WD_Duration_RTL=50years_warmlev=1.2-1.5degC	2
DePreSys	23	4.65	1987-08-07	EU_Summer_WD_Duration_RTL=50years_warmlev=1.2-1.5degC	3
DePreSys	27	5.94	1967-08-02	EU_Summer_WD_Duration_RTL=50years_warmlev=2degC	1
DePreSys	26	7.84	1969-07-30	EU_Summer_WD_Duration_RTL=50years_warmlev=2degC	2
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Duration_RTL=50years_warmlev=2degC	3
DePreSys	33	7.78	1989-07-14	EU_Summer_WD_Duration_RTL=50years_warmlev=3degC	1
DePreSys	32	8.69	2008-07-17	EU_Summer_WD_Duration_RTL=50years_warmlev=3degC	2
DePreSys	27	5.94	1967-08-02	EU_Summer_WD_Duration_RTL=100years_warmlev=1.2-1.5degC	1
DePreSys	26	7.84	1969-07-30	EU_Summer_WD_Duration_RTL=100years_warmlev=1.2-1.5degC	2
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Duration_RTL=100years_warmlev=1.2-1.5degC	3
DePreSys	33	7.78	1989-07-14	EU_Summer_WD_Duration_RTL=100years_warmlev=2degC	1
DePreSys	32	8.69	2008-07-17	EU_Summer_WD_Duration_RTL=100years_warmlev=2degC	2
DePreSys	33	7.78	1989-07-14	EU_Summer_WD_Duration_Maximum	1
DePreSys	32	8.69	2008-07-17	EU_Summer_WD_Duration_Maximum	2
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Duration_Maximum	3
UKCP18	40	23.84	2093-07-04	EU_Summer_WD_Duration_RTL=50years_warmlev=4degC	1
UKCP18	37	23.36	2077-07-05	EU_Summer_WD_Duration_RTL=100years_warmlev=3degC	1
UKCP18	45	37.36	2097-07-22	EU_Summer_WD_Duration_RTL=100years_warmlev=4degC	1

Table 20: Table summarising the events selected to represent the European summer-time wind-drought-peak-demand scenarios in terms of duration, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here WD=wind-drought-peak-demand, and RTL=return level.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	10	2.73	2013-08-02	EU_Summer_WD_Severity_RTL=2years_warmlev=1.2degC	1
DePreSys	14	2.76	1983-06-25	EU_Summer_WD_Severity_RTL=2years_warmlev=1.2degC	2
DePreSys	14	2.74	2000-08-03	EU_Summer_WD_Severity_RTL=2years_warmlev=1.2degC	3
DePreSys	9	2.83	2012-07-22	EU_Summer_WD_Severity_RTL=2years_warmlev=1.5degC	1
DePreSys	12	2.86	2011-07-14	EU_Summer_WD_Severity_RTL=2years_warmlev=1.5degC	2
DePreSys	7	2.81	1983-08-07	EU_Summer_WD_Severity_RTL=2years_warmlev=1.5degC	3
DePreSys	8	3.03	2001-08-03	EU_Summer_WD_Severity_RTL=2years_warmlev=2degC	1
DePreSys	13	3.05	1996-08-06	EU_Summer_WD_Severity_RTL=2years_warmlev=2degC	2
DePreSys	8	3.03	2001-08-03	EU_Summer_WD_Severity_RTL=2years_warmlev=2degC	3
DePreSys	9	3.35	2005-07-09	EU_Summer_WD_Severity_RTL=2years_warmlev=3degC	1
DePreSys	12	3.52	1974-04-29	EU_Summer_WD_Severity_RTL=2years_warmlev=3degC	2
DePreSys	13	3.56	1989-08-11	EU_Summer_WD_Severity_RTL=2years_warmlev=3degC	3
DePreSys	9	3.82	1994-04-13	EU_Summer_WD_Severity_RTL=2years_warmlev=4degC	1
DePreSys	15	4.05	2007-07-03	EU_Summer_WD_Severity_RTL=2years_warmlev=4degC	2
DePreSys	10	3.86	2005-08-02	EU_Summer_WD_Severity_RTL=2years_warmlev=4degC	3
DePreSys	11	4.29	1989-08-09	EU_Summer_WD_Severity_RTL=5years_warmlev=1.2degC	1
DePreSys	14	4.45	1996-08-05	EU_Summer_WD_Severity_RTL=5years_warmlev=1.2degC	2
DePreSys	14	4.38	2005-08-07	EU_Summer_WD_Severity_RTL=5years_warmlev=1.2degC	3
DePreSys	10	4.43	1988-04-03	EU_Summer_WD_Severity_RTL=5years_warmlev=1.5degC	1
DePreSys	19	4.69	1987-08-01	EU_Summer_WD_Severity_RTL=5years_warmlev=1.5degC	2
DePreSys	14	4.50	1966-04-23	EU_Summer_WD_Severity_RTL=5years_warmlev=1.5degC	3
DePreSys	12	4.92	1991-08-01	EU_Summer_WD_Severity_RTL=5years_warmlev=2degC	1
DePreSys	16	5.20	1992-08-10	EU_Summer_WD_Severity_RTL=5years_warmlev=2degC	2
DePreSys	15	5.02	1978-07-06	EU_Summer_WD_Severity_RTL=5years_warmlev=2degC	3
DePreSys	16	6.11	1995-07-13	EU_Summer_WD_Severity_RTL=5years_warmlev=3degC	1
DePreSys	20	6.52	1982-04-06	EU_Summer_WD_Severity_RTL=5years_warmlev=3degC	2
DePreSys	19	6.34	2004-08-01	EU_Summer_WD_Severity_RTL=5years_warmlev=3degC	3
DePreSys	13	7.71	1983-04-06	EU_Summer_WD_Severity_RTL=5years_warmlev=4degC	1
DePreSys	25	7.97	1983-07-28	EU_Summer_WD_Severity_RTL=5years_warmlev=4degC	2
DePreSys	18	7.59	2004-04-06	EU_Summer_WD_Severity_RTL=5years_warmlev=4degC	3
DePreSys	15	5.57	2011-08-07	EU_Summer_WD_Severity_RTL=10years_warmlev=1.2degC	1
DePreSys	20	5.78	2007-08-08	EU_Summer_WD_Severity_RTL=10years_warmlev=1.2degC	2
DePreSys	14	5.53	1987-08-06	EU_Summer_WD_Severity_RTL=10years_warmlev=1.2degC	3
DePreSys	17	5.91	2008-08-18	EU_Summer_WD_Severity_RTL=10years_warmlev=1.5degC	1
DePreSys	25	6.01	1999-08-05	EU_Summer_WD_Severity_RTL=10years_warmlev=1.5degC	2
DePreSys	17	5.83	1977-08-10	EU_Summer_WD_Severity_RTL=10years_warmlev=1.5degC	3
DePreSys	17	6.45	1983-07-01	EU_Summer_WD_Severity_RTL=10years_warmlev=2degC	1
DePreSys	24	6.73	2006-08-09	EU_Summer_WD_Severity_RTL=10years_warmlev=2degC	2
DePreSys	13	6.99	1994-07-03	EU_Summer_WD_Severity_RTL=10years_warmlev=2degC	3
DePreSys	18	9.07	1962-04-06	EU_Summer_WD_Severity_RTL=10years_warmlev=3degC	1
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Severity_RTL=10years_warmlev=3degC	2
DePreSys	20	8.20	1980-07-21	EU_Summer_WD_Severity_RTL=10years_warmlev=3degC	3
DePreSys	26	10.33	1974-07-19	EU_Summer_WD_Severity_RTL=10years_warmlev=4degC	1
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_RTL=10years_warmlev=4degC	2
DePreSys	22	10.77	2000-08-09	EU_Summer_WD_Severity_RTL=10years_warmlev=4degC	3
DePreSys	18	6.74	1987-04-02	EU_Summer_WD_Severity_RTL=20years_warmlev=1.2degC	1
DePreSys	24	6.84	1990-07-31	EU_Summer_WD_Severity_RTL=20years_warmlev=1.2degC	2
DePreSys	15	7.11	1994-04-09	EU_Summer_WD_Severity_RTL=20years_warmlev=1.2degC	3
DePreSys	18	7.59	2004-04-06	EU_Summer_WD_Severity_RTL=20years_warmlev=1.5degC	1
DePreSys	25	7.97	1983-07-28	EU_Summer_WD_Severity_RTL=20years_warmlev=1.5degC	2
DePreSys	33	7.78	1989-07-14	EU_Summer_WD_Severity_RTL=20years_warmlev=1.5degC	3
DePreSys	18	9.07	1962-04-06	EU_Summer_WD_Severity_RTL=20years_warmlev=2degC	1
DePreSys	28	8.20	1973-07-07	EU_Summer_WD_Severity_RTL=20years_warmlev=2degC	2
DePreSys	20	8.20	1980-07-21	EU_Summer_WD_Severity_RTL=20years_warmlev=2degC	3
DePreSys	26	10.33	1974-07-19	EU_Summer_WD_Severity_RTL=20years_warmlev=3degC	1
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_RTL=20years_warmlev=3degC	2
DePreSys	22	10.77	2000-08-09	EU_Summer_WD_Severity_RTL=20years_warmlev=3degC	3
DePreSys	18	9.07	1962-04-06	EU_Summer_WD_Severity_RTL=50years_warmlev=1.2degC	1
DePreSys	15	9.47	1975-04-15	EU_Summer_WD_Severity_RTL=50years_warmlev=1.2degC	2
DePreSys	19	9.16	1978-07-29	EU_Summer_WD_Severity_RTL=50years_warmlev=1.2degC	3
DePreSys	18	9.91	1964-04-02	EU_Summer_WD_Severity_RTL=50years_warmlev=1.5degC	1
DePreSys	26	10.33	1974-07-19	EU_Summer_WD_Severity_RTL=50years_warmlev=1.5degC	2
DePreSys	15	9.47	1975-04-15	EU_Summer_WD_Severity_RTL=50years_warmlev=1.5degC	3
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_RTL=50years_warmlev=2degC	1
DePreSys	22	10.77	2000-08-09	EU_Summer_WD_Severity_RTL=50years_warmlev=2degC	2
DePreSys	21	10.91	2005-08-02	EU_Summer_WD_Severity_RTL=50years_warmlev=2degC	3
DePreSys	26	10.33	1974-07-19	EU_Summer_WD_Severity_RTL=100years_warmlev=1.2degC	1
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_RTL=100years_warmlev=1.2degC	2
DePreSys	22	10.77	2000-08-09	EU_Summer_WD_Severity_RTL=100years_warmlev=1.2degC	3
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_RTL=100years_warmlev=1.5degC	1
DePreSys	21	10.91	2005-08-02	EU_Summer_WD_Severity_RTL=100years_warmlev=1.5degC	2
DePreSys	29	11.30	1976-08-05	EU_Summer_WD_Severity_Maximum	1
DePreSys	21	10.91	2005-08-02	EU_Summer_WD_Severity_Maximum	2
DePreSys	22	10.77	2000-08-09	EU_Summer_WD_Severity_Maximum	3
UKCP18	24	14.50	2068-08-10	EU_Summer_WD_Severity_RTL=20years_warmlev=4degC	1
UKCP18	31	14.81	2091-07-16	EU_Summer_WD_Severity_RTL=50years_warmlev=3degC	1
UKCP18	36	19.82	2088-07-15	EU_Summer_WD_Severity_RTL=50years_warmlev=4degC	1
UKCP18	24	13.50	2080-07-12	EU_Summer_WD_Severity_RTL=100years_warmlev=2degC	1
UKCP18	27	17.89	2089-08-02	EU_Summer_WD_Severity_RTL=100years_warmlev=3degC	1
UKCP18	37	24.18	2082-07-03	EU_Summer_WD_Severity_RTL=100years_warmlev=4degC	1

Table 21: As in Table 20, but for severity.

DataSource	Duration	Severity	StartDate	Label	EventNumber
DePreSys	6	1.90	2015-06-25	EU_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	1
DePreSys	6	4.29	2009-04-10	EU_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	2
DePreSys	6	3.96	1986-07-31	EU_Summer_SG_Duration_RTL=2years_warmlev=1.2-4degC	3
DePreSys	8	3.86	1981-05-20	EU_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	1
DePreSys	9	5.78	1981-04-01	EU_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	2
DePreSys	8	1.34	2005-06-01	EU_Summer_SG_Duration_RTL=5years_warmlev=1.2-4degC	3
DePreSys	10	2.74	1986-05-17	EU_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	1
DePreSys	10	13.03	2002-04-19	EU_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	2
DePreSys	10	5.16	2012-09-29	EU_Summer_SG_Duration_RTL=10years_warmlev=1.2-4degC	3
DePreSys	11	4.94	1992-07-08	EU_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	1
DePreSys	12	7.43	1983-04-27	EU_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	2
DePreSys	11	4.15	2012-09-12	EU_Summer_SG_Duration_RTL=20years_warmlev=1.2-4degC	3
DePreSys	13	2.70	1989-06-27	EU_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	1
DePreSys	14	7.76	1990-04-09	EU_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	2
DePreSys	13	3.49	2001-05-02	EU_Summer_SG_Duration_RTL=50years_warmlev=1.2-4degC	3
DePreSys	16	8.49	1977-04-06	EU_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	1
DePreSys	15	5.56	1981-06-04	EU_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	2
DePreSys	15	5.98	1987-04-11	EU_Summer_SG_Duration_RTL=100years_warmlev=1.2-4degC	3
DePreSys	23	17.02	2008-04-16	EU_Summer_SG_Duration_Maximum	1
DePreSys	19	12.75	1998-04-12	EU_Summer_SG_Duration_Maximum	2
DePreSys	19	16.49	2012-04-09	EU_Summer_SG_Duration_Maximum	3
DePreSys	5	2.33	1975-09-14	EU_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	1
DePreSys	6	2.38	1979-05-06	EU_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	2
DePreSys	5	2.30	2005-09-18	EU_Summer_SG_Severity_RTL=2years_warmlev=1.2-4degC	3
DePreSys	7	3.83	1983-05-25	EU_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	1
DePreSys	13	4.08	2003-09-27	EU_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	2
DePreSys	7	3.93	1960-04-27	EU_Summer_SG_Severity_RTL=5years_warmlev=1.2-4degC	3
DePreSys	7	5.18	1969-09-22	EU_Summer_SG_Severity_RTL=10years_warmlev=1.2-3degC	1
DePreSys	14	5.38	2014-05-15	EU_Summer_SG_Severity_RTL=10years_warmlev=1.2-3degC	2
DePreSys	8	5.22	1960-05-26	EU_Summer_SG_Severity_RTL=10years_warmlev=1.2-3degC	3
DePreSys	8	4.71	1972-05-26	EU_Summer_SG_Severity_RTL=10years_warmlev=4degC	1
DePreSys	9	5.29	1991-06-28	EU_Summer_SG_Severity_RTL=10years_warmlev=4degC	2
DePreSys	8	5.22	1960-05-26	EU_Summer_SG_Severity_RTL=10years_warmlev=4degC	3
DePreSys	8	6.34	1999-04-12	EU_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	1
DePreSys	14	6.51	1980-07-02	EU_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	2
DePreSys	13	6.42	1960-04-21	EU_Summer_SG_Severity_RTL=20years_warmlev=1.2-4degC	3
DePreSys	8	8.31	1962-04-25	EU_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	1
DePreSys	10	8.47	1966-05-13	EU_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	2
DePreSys	9	7.92	1976-04-01	EU_Summer_SG_Severity_RTL=50years_warmlev=1.2-4degC	3
DePreSys	11	9.71	1972-04-02	EU_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	1
DePreSys	13	10.31	1984-05-09	EU_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	2
DePreSys	12	9.23	1998-06-27	EU_Summer_SG_Severity_RTL=100years_warmlev=1.2-4degC	3
DePreSys	23	17.02	2008-04-16	EU_Summer_SG_Severity_Maximum	1
DePreSys	19	16.49	2012-04-09	EU_Summer_SG_Severity_Maximum	2
DePreSys	12	13.36	2007-04-20	EU_Summer_SG_Severity_Maximum	3

Table 22: Table summarising the events selected to represent the European summer-time surplus-generation scenarios in terms of duration and severity, for each extreme level and warming level(s) of interest. Each event is summarised in terms of the data source (DePreSys or UKCP18); event duration; event severity; the event start date within the data record; a label explaining the event type, region, metric and return level it represents; and the number of the event (up to 3 selected to represent each event combination). Here SG=surplus-generation, and RTL=return level.

A.3 Data download README file

```
#######################################################################################################
README file to explain naming convention and file structure in the 'The Adverse Weather Scenarios for
Future Electricity Systems' data set
#######################################################################################################

The dataset contains time slices of surface temperaure (tas), 100m wind speed (windspeed) and surface
solar radiation (ssr), containing adverse weather scenarios for future electricity systems.

The first set of directories represent the three forms of adverse weather scenario considered:
1. Winter-time wind-drought-peak-demand events (winter_wind_drought)
2. Summer-time wind-drought-peak-demand events (summer_wind_drought)
3. Summer-time surplus renewable generation events (summer_surplus_generation)

Next, the region over which the adverse weather scenario is defined is selected:
1. UK only (uk)
2. Europe as a whole (europe)
Note: UK only events are those that are identified as impacting the UK, but meteorological data for all
of Europe are still provided.

Following this, the return period of interest is selected (i.e. how often the adverse weather scenario
is expected to occur on average). Adverse weather scenarios are available for 6 different return
periods, as well as the three most extreme events in the historical DePreSys hindcast record for that
event type:
1. 1 in 2 year (return_period_1_in_2_years)
2. 1 in 5 year (return_period_1_in_5_years)
3. 1 in 10 year (return_period_1_in_10_years)
4. 1 in 20 year (return_period_1_in_20_years)
5. 1 in 50 year (return_period_1_in_50_years)
6. 1 in 100 year (return_period_1_in_100_years)
7. Most extreme events (most_extreme_events)

Next, the adverse weather scenario metric is selected, representing in what way the event is
characterised, i.e. in terms of:
1. Duration (duration)
2. Severity (severity)

Following this, the global warming level of interest is selected:
1. Global warming level 1.2 degrees Celcius above pre-industrial level (gwl12degC)
2. Global warming level 1.5 degrees Celcius above pre-industrial level (gwl15degC)
3. Global warming level 2 degrees Celcius above pre-industrial level (gwl2degC)
4. Global warming level 3 degrees Celcius above pre-industrial level (gwl3degC)
5. Global warming level 4 degrees Celcius above pre-industrial level (gwl4degC)

In each case, the number of global warming level directories depends how the event duration/severity
changes at different global warming level, according to the statistical extreme value analysis (see
accompanying reports for these results).
```

For example, for winter-time wind-drought-peak-demand events in the UK with a return period of 1 in 20 years in terms of duration, events are found to be consistent across all global warming levels. This directory is therefore expressed as 'gwl12-4degC'.

Conversely, for summer-time wind-drought-peak-demand events in Europe with a return period of 1 in 20 years in terms of duration, events are found to differ when the global warming level exceeds 1.5 degrees Celcius. These directories are therefore expressed as 'gwl12-15degC', 'gwl2degC', 'gwl3degC' and 'gwl4degC'.

Finally, the event number is chosen. In most cases three adverse weather scenarios/events are provided (selected from the DePreSys hindcast as described in the accompanying reports):
1. Event 1 (event1)
2. Event 2 (event2)
3. Event 3 (event3)

In some cases, where only two events exist within the DePreSys hindcast at the extreme level of interest, just these two events are provided. In the small number of cases where the DePreSys hindcast does not contain any events at the extreme level of interest, one event is provided from the UKCP18 global projections.
***NOTE: In the UKCP18 events the 100m wind speed data has been bias corrected but the surface temperature and surface solar radiation have not.

Each of the event directories then contains the gridded meteorological data associated with the adverse weather event. Each adverse weather scenario is contained within a time slice of data. For summer-time events, one calendar year (January - December) of data is provided, with the summer-time event occurring in the summer of that year. For winter-time events, two calendar years of data are provided, with the winter-time event occurring in the winter (October-March) intersecting the two calendar years. This data is privided for surface temperaure (tas), 100m wind speed (windspeed) and surface solar radiation (ssr).

The directory route to the first event representative of a winter-time wind-drought-peak-demand adverse weather scenario in the UK with a return period of 1 in 20 years in terms of duration and all global warming levels is therefore:

winter_wind_drought/uk/return_period_1_in_20_years/duration/gwl12-4degC/event1/

And contained within this directory are three NetCDF files, each containing meterological data for the same time slice but for each of the three meteorological variables:
1. winter_wind_drought_uk_return_period_1_in_20_years_duration_gwl12-4degC_event1_ssr.nc (surface solar radiation)
2. winter_wind_drought_uk_return_period_1_in_20_years_duration_gwl12-4degC_event1_tas.nc (surface temperature)
3. winter_wind_drought_uk_return_period_1_in_20_years_duration_gwl12-4degC_event1_windspeed.nc (wind speed at 100m hieght)

The metadata within each of these NetCDF files describes the data dimenations, details about the available variables, and global attributes describing the event specification (as described above), and the start date, duration and severity of the adverse weather scenario contained within the time slice of data.

For example, the metadata from the file 'winter_wind_drought/uk/return_period_1_in_20_years/duration/gwl12-4degC/event1/winter_wind_drought_uk_return_period_1_in_20_years_duration_gwl12-4degC_event1_tas.nc' looks like this:

```
netcdf classic {
dimensions:
longitude = 85 ;
latitude = 81 ;
time = 731 ;
variables:
NC_DOUBLE longitude(longitude) ;
NC_CHAR longitude:units = "degrees_east" ;
NC_CHAR longitude:long_name = "longitude" ;
NC_DOUBLE latitude(latitude) ;
NC_CHAR latitude:units = "degrees_north" ;
NC_CHAR latitude:long_name = "latitude" ;
NC_DOUBLE time(time) ;
NC_CHAR time:units = "hours since 1970-01-01 00:00:00" ;
NC_CHAR time:long_name = "time" ;
NC_DOUBLE t2m(longitude, latitude, time) ;
NC_CHAR t2m:units = "K" ;
NC_DOUBLE t2m:_FillValue = NaN ;

// global attributes:
NC_CHAR :Project = "Adverse weather scenarios for electricity systems  Met Office,
National Infrastructure Commition and Climate Change Committee" ;
NC_CHAR :Event specification = "winter_wind_drought_uk_return_period_1_in_20_years_duration_gwl12-4degC" ;
NC_CHAR :Event start date = "2012-02-18" ;
NC_CHAR :Event duration = "13 days" ;
NC_CHAR :Event severity = "7.17 (no units)" ;
NC_CHAR :Domain = "Europe" ;
NC_CHAR :Resolution = "60km" ;
NC_CHAR :Frequency = "daily" ;
NC_CHAR :Calendar = "gregorian" ;
NC_CHAR :Meteorological variable = "Surface air temperature" ;
NC_CHAR :Originating data source = "DePreSys" ;
}
```

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Devon
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