Adverse Weather Scenarios for Renewable Energy System Testing

Discovery Phase

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Met Office

Contents

1. Executive Summary

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

To improve this understanding, the Met Office have recommended developing a data set 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 will allow for proposed future highly renewable electricity systems to be rigorously stress tested to ensure resilience to challenging weather and climate conditions. This data set is not expected to be a replacement for the current approach of using many years of historical weather conditions to optimise the planned electricity system design, but being a set of extreme events that can be used as an additional stress test for a specific system design of interest.

This report summarises the findings of the Discovery phase of a project to develop these adverse weather scenarios for electricity system modelling. It has been completed by the Met Office in partnership with the Commission and the Committee on Climate Change (CCC). The aim of the Discovery phase has been to investigate the feasibility of producing a widely useable extreme weather data set for energy system modelling.

Stakeholder engagement: The project team solicited feedback from a broad cross-section of energy system modellers across government, industry and academia to develop understanding of the process of energy modelling, limitations associated with the existing use of weather data, and identify unmet needs. There was broad consensus amongst those who were interviewed or responded to the survey that there was value in developing new weather datasets that could be used to assist in designing and testing the resilience of future energy systems. In particular, it was identified that modelling teams have no consistent methodologies for incorporating how climate change may impact on future renewable energy generation and demand. It was also observed that current methodologies, using relatively short datasets, are unlikely to capture the extent of plausible extreme events that may have a high impact on a future electricity system.

Specification of requirements & project scope: The requirements for the adverse weather datasets are summarised, based upon the feedback from the stakeholder engagement. These include both long-duration electricity shortfall and surplus events, and short-duration electricity generation ramping events. A key challenge, highlighted through the stakeholder engagement, was how to define the adverse weather conditions. This is because the definition of what constitutes an adverse weather event potentially will change according to both future demand and generation capacity mix. In addition, this is a highly multidimensional problem, with the extreme event being defined in terms of magnitude, spatial extent and duration in time. It is therefore recommended that this key challenge be addressed first within the following project phases, with guidance and insights from the project advisory and user groups.

The datasets developed within this project will not be designed to replace the current weather data used for energy system optimisation, and will not provide typical weather years for future decades. Rather, they will provide periods of adverse weather conditions for the system, with an associated probability and climate-warming level, which can be incorporated within a particular system configuration to stress test resilience. For example, to answer questions such as: Does this future highly renewable system of interest (e.g. one that has been found to be some way optimal in terms of cost and carbon emissions, as identified in the Assessment) provide resilient electricity generation able to meet demand during a 1 in 20 year, long-duration weather stress event, characteristic of a 2 degree warmer world?

Method scoping and feasibility: The key questions to be addressed are: (1) How can adverse weather conditions be characterised? (2) Could something worse than that observed in the historical period have plausibly happened? (3) How might adverse weather change in future climates? A number of possible approaches for addressing these questions are explored, their relative strengths and weaknesses identified, and a recommendation on the most appropriate method to pursue is made. Each step of the recommended approach is then explored in more detail to provide a better understanding of how they would work and whether they are computationally feasible. This is achieved based on expert insights from relevant scientists and literature, and where relevant, through exploratory data analysis.

Recommendations: For both long- and short-duration stress events a methodology is recommended in which the definition of what constitutes an extreme event is initially developed. Following this, these definitions are used with relevant sources of meteorological data to create datasets of adverse weather scenarios, characterising extreme events of various extreme levels, for different regions of Europe, and a range of future climate warming levels, based on many years of plausible weather. The resulting datasets could be used by energy system modellers to ensure rigorous stress testing of future system designs to the effect of weather and climate.

These outputs will build upon the insights of the Met Office literature review (Dawkins, 2019) by characterising the five key types for adverse weather stress events, and by producing datasets that span the full European domain in a spatially and temporally coherent way. This will allow for the exploration of the identified potential opportunities in balancing the energy system. The adverse weather datasets created within the project will also help to fill the gaps identified by the literature review, by providing events that characterise extremes in the summer-time and in solar conditions, by using many more years of plausible weather data to better represent climate variability and extremes, and by quantifying the effect of climate change on adverse weather conditions.

The value in these datasets would be to increase confidence that future electricity system models, used to inform government policy advice and investment decision making, are resilient to a range of plausible adverse weather scenarios. The scenarios generated will take account of climate change and provide a consistent basis for modelling teams to test different aspects of the future electricity systems.

2. Introduction

2.1 Context

There is wide agreement that greenhouse gas emissions from the energy sector must be reduced if climate change is to be limited to safe levels (IPCC, 2014). Consequently, the National Infrastructure Assessment (the Assessment) written by the National Infrastructure Commission (the Commission) and published in 2018, included a “Low Cost, Low Carbon” chapter, for which an in-depth analysis of the optimal future electricity system was commissioned from Aurora Energy Research. This work has subsequently been updated to reflect the government’s updated ambition to meet a net zero emissions target by 2050[1]. The analysis indicated that whole system costs would be broadly similar for an energy mix of relatively low renewable generation (40% in 2050) compared to a very highly renewable mix (90% in 2050). As a result, in order to keep open the option of a highly renewable generation mix, the Commission recommended targeting 50% renewable electricity generation by 2030. Further, the Committee on Climate Change is currently working on the Sixth Carbon Budget[2], which will explore futures with a minimum of 60% renewables, and other scenarios with very high levels of renewables (70%-90%).

An electricity system with an increasing renewable mix will become increasingly sensitive to the weather. For example, an electricity system that is highly dependent on wind power during winter may encounter challenges during extended periods (multiple days) of very cold (high demand) and still (low wind power supply) meteorological conditions. The future highly renewable electricity system must therefore be designed with the renewable mix, flexible generation, storage, and smart energy technologies required to ensure demand can be met for a range of plausible meteorological scenarios. Accordingly, within the Assessment, the Commission acknowledge the importance of developing a better understanding of how a highly renewable electricity system will perform under adverse weather conditions, and hence commissioned the Met Office to complete a review of literature relevant to this topic (Dawkins, 2019).

This literature review highlighted how extreme meteorological stress on the electricity system can be broadly characterised in five ways: winter-time peak residual demand (demand net of renewable supply); summer-time wind drought, coincident with high cooling demand; wind power ramping (large fluctuations in power generation in a short time window); solar photovoltaic (PV) ramping; and summer-time surplus renewable generation, coincident with low demand. The reviewed studies indicated a number of electricity system resilience opportunities associated with utilising the spatial and temporal variability as well as the dependence between relevant meteorological conditions. For example, the dipole in meteorological conditions in North and South Europe, the anti-correlation between wind speed and solar irradiance in the UK, particularly in summer could all act to improve electricity system resilience. The literature review also highlighted the link between relevant meteorological conditions and large-scale modes of climate variability (such as the North Atlantic Oscillation). In addition, climate change studies were shown to indicate, with high confidence, that the UK climate will become increasingly warm under all representative concentration pathways, and that a long historical period of meteorological data is required to represent natural climate variability.

[1] https://www.nic.org.uk/wp-content/uploads/Net-Zero-6-March-2020.pdf (Accessed 17/04/2020)
[2] https://www.theccc.org.uk/2019/10/17/ccc-to-publish-sixth-carbon-budget-in-september-2020/ (Accessed 17/04/2020)

A number of gaps in current understanding were, however, also identified including the under representation of summer-time electricity system stress (which may become more severe in a warming climate due to an expected uptake in air conditioning), and the absence of solar irradiance and climate change in many electricity system resilience studies. Further, all reviewed resilience studies were shown to be based on a limited historical period of meteorological data which may not include all plausible extreme conditions.

Further research is therefore required to address these gaps in current understanding and comprehensively test the resilience of a future highly renewable electricity system to extreme meteorological conditions. Specifically, this resilience must be tested against a range of extreme meteorological stress events, at many plausible extreme levels (beyond those observed in the recent historical period), whilst also accounting for climate variability and climate change.

As recommended within the literature review, these gaps could be addressed by creating a set of electricity system relevant, extreme meteorological stress scenarios. These created scenarios could then be incorporated within energy system models, such as that developed by (Staffell & Pfenninger, 2018), and hence be used to identify the optimal future system in terms of cost and carbon emissions, that is also resilient to future extreme weather in a changing climate.

Following completion of the literature review, the Commission decided to pursue a project exploring the feasibility of developing these extreme weather scenarios for future electricity system testing. This report summarises this project – the Discovery phase.

2.2 Objective and outcomes of project

The overall objective of the project is: To provide a widely usable data set of adverse meteorological conditions, characteristic of a range of electricity system extreme stress scenarios, in current and future climates, at various relevant extreme levels. The scenarios included within this data set will be informed by the initial Discovery phase.

This report summarises the outputs of the Discovery phase of the project. The aim and outputs of this phase are as follows:

Aim: Investigate the feasibility of producing a widely useable extreme weather data set. This will involve exploring the current use of weather scenarios within existing energy models and assessing the feasibility of the proposed model methodology.

Outputs: This report summarising user surveys, exploratory data assessment and model methodology evaluation. The work will also produce a final scope for phases two and three of the project**.**

2.3 Discovery Methodology

The Discovery phase has been undertaken jointly between the Commission and the Met Office team, with additional input from the Committee on Climate Change. The purpose of the Discovery phase was to engage with stakeholders, refine the team's knowledge of the problem, and more fully define the outputs of the project. This phase builds directly upon the literature review that was completed in 2019.

Specific questions that the Discovery phase has focussed on include:

- Who will the proposed datasets be targeted at?
- How will the data be used to inform future electricity systems modelling?
- How will it create value as an authoritative dataset?
- How will the data be made available to people and managed on an ongoing basis, and in what format?
- How should stress events be characterised?
    - Spatial extent
    - Duration
    - Maximum/minimum temperature
    - Wind speed characteristics
- What will be the spatial and temporal resolution of the data?
- How extreme should the meteorological events be?

Stakeholder engagement

The Met Office worked with Commission and CCC project team members to design an initial qualitative questionnaire. This defined the questions to be answered through the Discovery phase in order to develop our understanding of the problem, clarify needs, and define the follow on project. Key stakeholders from across the energy modelling community were identified as targets for initial interviews.

The Met Office team then met face to face with a number of these stakeholders. Representatives from the following stakeholder organisations were interviewed:

- Department for Business, Energy and Industrial Strategy (BEIS) energy team
- Energy Systems Catapult
- Commercial energy modellers – Aurora and AFRY (formerly Poyry)
- Academic teams at Imperial College London and University College London

Based upon feedback from this initial phase, the questionnaire was revised and made available to the wider community of electricity system modellers across the UK. Additional responses were received following direct emails to known contacts within key organisations and by contacting the wider community of energy modellers through the Power Swarm web channel[3]. Following this second phase of engagement, the team received further feedback from the following organisations:

- National Grid
- University of Reading
- University of Strathclyde
- Imperial College London

[3] http://powerswarm.co.uk/ (Accessed 27/04/2020)

- EDF Energy
- Bristol Energy

Model feasibility assessment

A number of possible approaches and relevant data sets are available for addressing the needs of this project, as informed by the stakeholder engagement. This part of the Discovery phase firstly aimed to explore these possible approaches, identify their relative strengths and weaknesses, and make a recommendation on the most appropriate method to pursue. Following this, each step of the recommended approach was explored in more detail to provide a better understanding of how the methods would work and their computational feasibility. This was achieved based on expert insights from relevant scientists and literature, and where relevant, exploratory data analysis.

Discovery user group workshop, report and revised project proposal

A user group workshop was held on 20 March 2020. The findings from the Discovery phase were presented back to the broader user and stakeholder group. At this meeting the user group discussed the findings and priorities for the next phases of the project.

This Discovery report has been drafted following the user group session. Following acceptance of this report by the Commission and the project advisory group, the Met Office will draft a revised proposal for the delivery phases of the project.

Project advisory group

An advisory group has been established by the Commission to act as advisors for this project and to guide the work completed to make sure that it delivers to agreed outcomes.

The advisory group has membership from the following organisations:

- National Infrastructure Commission (Chair)
- Committee on Climate Change
- BEIS
- Energy Systems Catapult
- University College London
- Ofgem
- Met Office project team members

3. Stakeholder engagement

3.1 Energy system modelling

Why model the future electricity system?

The project team interviewed a cross-section of energy modellers who are focussed on different aspects of the electricity system. The main themes on the value of energy modelling are summarised in the table below. These themes are characteristic of the Energy Trilemma of sustainability, equity (keeping the system affording and prices down) and security (resilience).

Transition to a low carbon economy	To build understanding of how the UK electricity system can transition to net zero carbon by 2050 and identify the pathways in terms of generation mix, storage and flexibility on the system in order to get there.
Economic business case	To identify the business case for investment and understand profitability of generation, storage, transmission and flexibility infrastructure.
Financial sustainability	To evaluate future energy prices to try and optimise energy mix, storage and flexibility to ensure a sustainable market.
Resilience of electricity system	To ensure that the electricity system remains resilient to changing patterns of demand and increasing variability in generation capacity.

What is modelled?

The groups surveyed identified three broad stages of electricity system modelling that are undertaken. These are:

i. Demand modelling
ii. Capacity planning
iii. Generation modelling

Figure 1 broadly illustrates how these three stages of modelling fit together in a value chain. Note that some groups combine some of these stages in their work and Figure 1 is only intended as an indicative illustration of the approach.

Demand models are set up to predict future energy demand. For example, heat models predict the component of future energy demand that is associated with heating requirements. This combines projections of energy supply and emissions with temperature data. These models incorporate potential policy decisions, such as whether to support electric heat pumps and/or hydrogen to meet future domestic heating need, and take account of timescales for decarbonisation of the heating system, to help quantify impacts on overall energy demand.

The outputs of the demand models are used to inform the **Capacity Planning** stage. This stage also takes account of policy decisions relating to the future energy mix as well as the projected costs associated with generation, storage and system flexibility. The output of the capacity planning stage is an understanding of potential future energy generation capacity as well as an idea of its spatial distribution.

The future capacity mix is then an input into **generation dispatch** stage which determines the hour by hour (or half hour) generation mix, i.e. to determine which generation plant will dispatch each hour for a future scenario. High resolution weather data is a key input into this stage of the modelling process as it determines both the heating demand and also the variability of wind and solar generation.

By understanding the hourly generation mix, energy modellers are also able to derive energy prices, likely emissions, how much transmission is required across the system and how much margin there is (generation net demand). These factors can be used to understand more about the future resilience of the electricity system for a given capacity mix.

Some groups combine the last two stages in the value chain (capacity planning and generation dispatch) in optimisation models. This is an iterative process that allows parts of the capacity mix to be varied in order to optimise outputs for a given set of input data. These types of modelling frameworks help to factor in the intermittency associated with variable renewable energy generation for planning decision making.

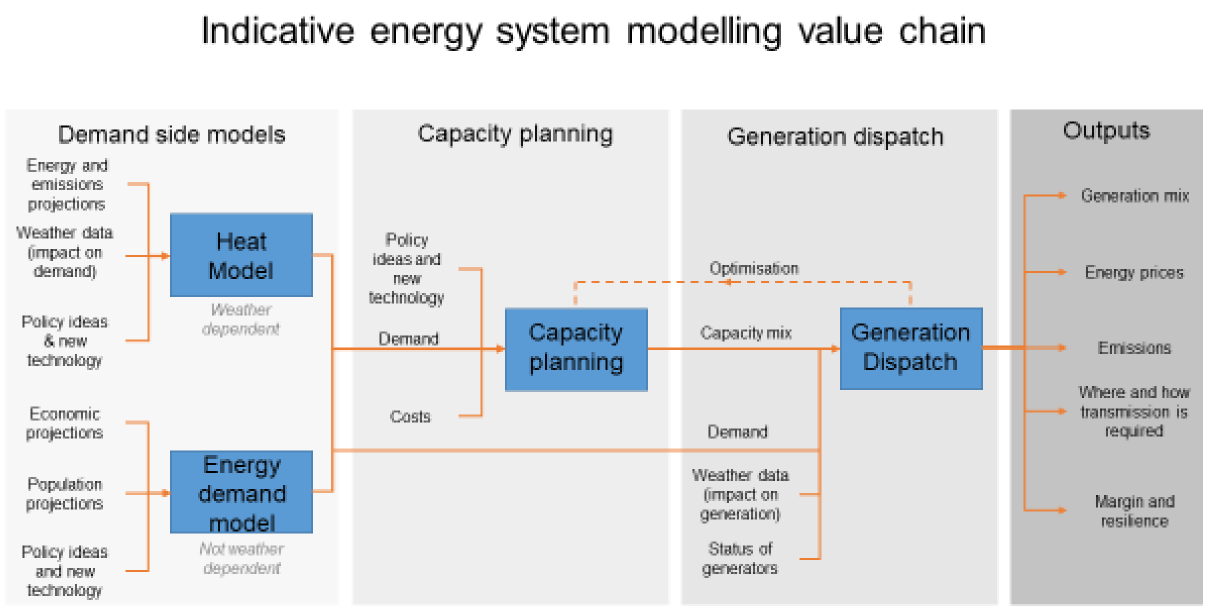

Figure 1 Indicative electricity system modelling value chain

Energy system models are configured in different ways depending on whether the focus of the work is on planning of a new capacity mix, or on testing a certain configuration of energy system under operational constraints. When using energy models for planning, the aim is to test the performance of various mixes of generation capacity. These models will typically not capture the level of technical detail, or temporal and spatial resolution, that might be tested through a more operationally focused model. In these the capacity mix and other planning assumptions are fixed which means that the models can be operated at higher resolutions and contain more technical details about the responses of the system to the changing input data.

One of the key differences between planning and operational model types is that planning models assume perfect foresight in terms of the weather that is going to be happening for the rest of the year; whereas as an operational type model will only see the weather a few days ahead.

3.2 How is weather information currently being used?

What types of weather data are used?

There is a lot of commonality in the ways and types of weather information that is currently being used by the energy modelling teams that were surveyed. Most of the teams used weather model reanalysis data as the primary input into their models. A reanalysis is when past observation data is assimilated into weather forecast models to produce a gridded dataset of past weather conditions. There are two main datasets that are used, the ERA5 dataset from the European Centre for Medium range Forecasting (ECMWF) and MERRA which is produced by NASA. The horizontal resolution of the ERA5 data is approximately 31km at mid-latitudes (0.25°), MERRA is slightly coarser. These datasets have an hourly temporal resolution.

Some modellers also use additional satellite based observations to provide solar radiation data as this is not well resolved in the data made available through ERA5.

One academic team has used climate model data to drive electricity system models. Some teams have also incorporated uplifts in degree-days due to climate change. Degree days are used to determine the number of days when heating of buildings would be required.

Which weather parameters are ingested into models?

The key weather parameters that electricity system modellers are using from these datasets include:

i. Wind at height (near surface)
ii. Temperature (at 2 metres)
iii. Solar irradiance (direct and diffuse)
iv. Humidity (generally of secondary importance)

Snow fall, lying snow, rainfall run off and stream flow were also identified as important when teams are looking at inputs from hydro-generation. A few groups are also interested in tidal and wave information. A much wider set of data is used by some of the academic groups who analyse variables such as large scale weather patterns, pressure fields and high level winds to improve the inference of weather conditions.

How is weather data selected?

How weather data is currently selected varies greatly according to the type of modelling that a group is undertaking. Many groups will use the past five, or ten, available weather years as the basis for their modelling. Others have the computing capacity to run their models with much larger datasets and use the full 30+ year ERA5 dataset[4] as the basis for their analysis. It has been noted, however, that in some cases energy modellers use just one year of weather data.

Usually groups use at least one year of data at a time to drive their models and use different past weather years to test future combinations of energy demand and generation mix. Some modelling groups use more sophisticated techniques such as creating hundreds of thousands of Monte Carlo simulations from the available datasets to help explore more extreme scenarios.

What are the most important weather stress events?

Most of the electricity system modellers that responded to the questionnaire identified winter-time peak residual demand events as the highest priority weather stress event that concerned them with respect to the resilience of the future electricity system. These occur when blocking high conditions lead to extended periods of low wind speeds across a spatial domain of the UK and north-west Europe coupled with cold weather conditions. These events can last several days.

A number of the teams were also concerned about the emerging importance of summer-time wind droughts. These occur when blocking high conditions give rise to low wind speeds coupled with very high temperatures. These are likely to become more important if increasing number of heatwave conditions across the UK give rise to much more widespread uptake of cooling. It is possible that the increasing amounts of solar generation could in part offset this need.

Other types of longer duration events that were also highlighted included: extended periods of surplus renewables generation; and periods of low water resources and associated impact on hydro generation.

The most important shorter duration events identified were wind and solar ramping events that cause sudden and widespread variations in electricity generation. For example during wind storms, turbines typically cut out when wind speeds exceed 25m/s and this can cause sudden fluctuations in generation. Other forms of short duration events on the system that were highlighted included lightning strikes causing temporary outages to parts of the system. Short duration events were considered to be less significant than longer duration events by those involved in this stakeholder engagement, as short-term storage and smart techniques to manage short duration fluctuations in supply are becoming increasingly available on energy systems.

Overall the most important phenomena were thought to be winter and summer wind droughts. Other events were thought to be less critical to system resilience.

A number of the respondents identified that they don't explicitly try to identify stress periods at all in their modelling. In a sense they are working the other way around, i.e. they are trialling future scenarios of energy capacity mix and demand and these combinations determine the sensitivities to weather conditions. This is a reflection of the multi-dimensional nature of the problem. For example, a winter peak residual demand event is defined both by the low wind speeds, which result in reduced generation, and low temperatures, which result

[4] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5 (Accessed 05/03/2020)

in increased demand. As you increase the amounts of wind generation on the system, what constitutes a peak event becomes more dominated by the low wind speeds and less by high demand. Conversely, if the amounts of electric heating on the system increases, then the low temperatures become more important to the definition of a peak event.

How changes to weather conditions resulting from climate change are incorporated into electricity system modelling?

The vast majority of respondents indicated that climate change has not been coherently incorporated into their modelling, although one of the academic groups is exploring how climate projections could be used to achieve this. The energy scenarios that are being tested are largely driven by the need to transition to a lower carbon economy, but the weather data being used to test these scenarios reflects past observed conditions. Some of the groups identified that mean uplifts in temperatures due to climate change were incorporated into calculations of degree-days which are used to calculate heating demand.

Almost all of the survey participants identified that being able to use data that was representative of future climate as something that they thought was important to do.

3.3 Limitations of current approach to using weather data

Whilst the current approaches used by the teams that were interviewed make the best use of the weather data that is currently available, the following limitations in the current approach were identified:

- There is no clear definition of what constitutes adverse weather conditions (either in terms of return period, or severity, spatial distribution or timescale)
- Data selected is assumed to represent the current and future variability and extremes adverse conditions
- None of the current methodologies fully represent changes to adverse weather conditions that may result from climate change
- There is no consistency in the methods used to select weather data which means that different modelling groups could get quite different answers to similar questions about future system resilience.

4. Specification of Requirements & Project Scope

4.1 Considerations for adverse weather dataset

Through the engagement with the energy modelling community there is widespread support for a project to develop some additional weather datasets to inform future electricity system modelling.

The key question that needs to be addressed is how to ensure that datasets produced are representative of adverse weather, relevant for future highly renewable electricity systems. This is because the definition of what constitutes an extreme event may change according to the amount, types and distribution of renewable generation and storage; as well as the expected demand profiles. There are a couple of ways that this could be addressed:

i. Provide datasets for thousands of years' worth of data and run energy models for all of them. For most groups we spoke to this would be impractical given the data volumes involved.
ii. Develop a method for identifying periods of adverse weather for the electricity system from meteorological data sets, relevant for a range of possible future system configurations. This could be achieved by developing a set of stress event indices (one for each type of adverse weather event) based on weather conditions in each location and their potential for creating electricity demand and generation, using relationships as in (Bett & Thornton, 2016) and the expertise and insights of the project advisory and user groups. This approach is similar to that used to develop other weather impact indices, such as the heat wave severity index derived by (Nairn & Fawcett, 2015), and the hydrological drought indices currently used by the Met Office to better understand UK water resource management.

It is suggested that the second option is the most pragmatic, particularly as the focus in this project is on resilience and stress testing future electricity system designs to understand whether they are resilient to adverse weather conditions.

Linked in with this problem, there are also questions around how extreme the adverse weather scenarios that are selected should be. 1 in 20 year events are generally agreed to be an industry standard that systems are designed towards. It is also suggested that this is supplemented with datasets representative of 1 in 5 year and 1 in 2 year extreme events to represent less extreme conditions. This would allow sensitivity testing of the electricity system to different extreme levels to be conducted.

4.2 Value in adverse weather datasets

The respondents to the questionnaire identified the value in the adverse weather datasets as follows:

- **Consistency:** A defined way of identifying adverse weather and a set of adverse weather scenarios would enable the robustness of different elements of the future electricity system to be tested in a more consistent and coherent way.

- **Representing extreme events:** Greater confidence that data used in modelling is representative of climate variability. Using historical data alone may not capture plausible extreme events that could be high impact in terms of the resilience of the future electricity system – especially in a changing climate.
- **Climate Change:** Ability to account for climate change in the design of future electricity system by creating weather data that is representative of expected conditions during the operation of the future electricity system.

4.3 Table of requirements

The table below is a summary of the specification of requirements for the adverse weather data to support future electricity system modelling.

Spatial domain	**Europe-wide** to enable the value of interconnectors across Europe on resilience of UK electricity system to be assessed.
Spatial Resolution	**~30km** in line with the ERA5 datasets currently used
Duration of datasets	At least **1-year** duration data sets to capture longer duration peak demand events such as wind and solar droughts. This makes sure that effectiveness of storage on system can be assessed. Datasets of a **few days or weeks** duration will be sufficient to capture the shorter duration events such as ramping.
Temporal resolution	**Hourly** (or half hourly) datasets required for longer duration events. Higher frequency data may be required to assess short duration ramping events.
Weather parameters	Most important parameters highlighted by all survey respondents i. **Wind at hub height** ii. **Temperature** iii. **Solar irradiance (Direct and diffuse)** Secondary parameters highlighted by some respondents: iv. Humidity v. Rainfall and run-off (important for hydro) vi. Tidal and wave data (might become more important in the future)
Stress scenarios that are most important	The following types of stress events were identified as priorities by those interviewed in the following order: i. **Long duration winter peak residual demand event**. This is a sustained period of low wind speeds over UK and NW Europe coupled with cold temperatures (high heating demand). ii. **Long duration summer wind drought.** This is a sustained period of low wind speeds over the UK and NW Europe coupled with high temperatures (high cooling demand).

	iii. **Surplus renewable generation (particularly solar).** Sustained periods where renewable generation from wind and/or solar outstrips demand. iv. **Ramping events.** Sudden and widespread fluctuations in renewable energy resource. This could occur during a wind storm when turbines cut out when wind speeds exceed 25m/s; or when the onset of cloudy conditions give rise to sudden reduction in solar generation.
Critical thresholds	There are no critical thresholds defined for the stress events identified. This is because the stress events are defined by the expected combinations of generation capacity mix as well as future demand profiles. It is suggested that the project team work with the qualitative guidance of the expert energy system modellers in the advisory and user groups to develop an approach for defining adverse stress events in terms of meteorological extremes, relevant to a range of future electricity systems. System operators are trying to maintain system resilience to 1 in 20 year events – this is a standard across the industry. It is also suggested that these are supplemented with 1 in 5 year and 1 in 2 year adverse events. This would allow users to conduct sensitivity testing to various extreme levels.
Climate change planning horizons	Datasets should be representative of today's climate (2020s) and of the 2050s. The significance of the 2050s timescale is that it aligns with policy targets for the UK achieving net zero. Some groups, including National Grid, are also forward planning towards the 2070s. The suggested way of specifying the requirement would be to generate the stress scenarios based upon different warming levels (e.g. 2°C and 4°C of global warming beyond preindustrial levels). These warming levels can then be associated with different decades along different radiative concentration pathways[5]. The advantage of taking this approach is that it disaggregates the datasets from uncertainty around future carbon emissions and climate sensitivity. Specifically 1.5, 2, 3 and 4°C warming levels are of primary interest.
Data formats and access	NetCDF is a standard data format that is widely used. Some groups import data as CSV files, so it may be useful to have some data accessible in this format. The datasets should be made accessible through some kind of web portal or API (there are several existing platforms that could be used).

[5] see Tables 2 and 3 in the UKCP18 Derived Projections of Future Climate over the UK report: https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/UKCP18-Derived-Projections-of-Future-Climate-over-the-UK.pdf (Accessed 16/04/2020)

4.5 Project Scope

The datasets developed within this project are intended to be a set of extreme adverse weather events, characteristic of physically plausibly meteorological conditions that can be used to as an additional stress test for future electricity system planning. They are not intended to replace the current energy modelling approach for electricity system optimisation, of using many years of reanalysis to identify the best solution in terms of cost and carbon emissions. Hence, this data set of adverse weather scenarios will primarily address the fourth key energy modelling themes in the table in Section 3.1 (resilience of electricity system), but will also help to stress test the energy model planning related to the other three themes (transition to a low carbon economy, economic business case and financial sustainability).

Specifically, these datasets will help to answer questions such as:

- Does this future highly renewable system of interest (e.g. one that has been found to be some way optimal in terms of cost and carbon emissions, as identified in the Assessment) provide resilient electricity generation able to meet demand during a 1 in 20 year long-duration weather stress event, characteristic of a 2 degree warmer world?
- To what extent could an additional European interconnector improve resilience to a 1 in 5 year summer wind drought extending across NW Europe, given reliance on wind generation in other parts of Europe?
- What is the impact of surplus summer solar generation on network resilience during a 1 in 20 year event in today's climate?

A typical weather year for future decades will not be provided as part of this project, however 1 in 2 and 1 in 5 year return level adverse weather events will be included within the dataset to represent the more typical types of events that may be experienced in future climates.

The proposed methodology for creating these adverse weather stress events, representative of future climates, uses future climate projections in combination with extended datasets of plausible historical weather years. The resulting events will therefore characterise both a comprehensive representation of climate variability and extremes (based on the many years of plausible historical weather), as well as the effect of climate change (based on the climate projections). This could not be achieved by using climate projections only.

5. Method Scoping & Feasibility Study

Within this section, a methodology for addressing the identified key questions and values of the project will be scoped and assessed for computational feasibility. The aim is to provide a widely usable data set of adverse meteorological conditions, contained within whole years of gridded temperature, wind speed and solar irradiance at the same spatial-temporal resolution as gridded reanalysis data, characteristic of a range of electricity system extreme stress scenarios, in current and future climates, at various relevant extreme levels.

Firstly, the definition of what constitutes an 'adverse weather event' must be explored and derived. Following this, periods of adverse weather during the historical period of meteorological records (1979-present) can be identified and contextualized. However, in using this limited historical period of observed weather information only, more extreme scenarios that *could* have plausibly occurred during the historical period, are not captured. Further, this forty year record is not long enough to comprehensively represent a 1 in 20 year return level. In addition, this historical period of weather is not representative of the possible future climate, for which electricity system is being planned for (e.g. 2050 onwards). The latest UK climate change projections (UKCP18) indicate that UK temperatures will continue to rise in the 21st century. This will likely have an impact on UK electricity demand in both winter and summer, and is not captured by the historical period of weather.

The scoped methodology must therefore address three key questions:

1. **How can adverse weather events be characterised using meteorological information?**

2. **Could something worse than that observed in the historical period have plausibly happened?**

3. **How might these adverse conditions change in future climates?**

Stakeholder engagement identified that long-duration (>7 days) wind/solar drought events, which characterise prolonged periods of low energy generation and could also coincide with high energy demand, are of key interest. As such, the first sections of this report focus on a method for representing this type of event. In Section 5.3 the initial scoping of a further project phase for representing short-duration ramping events is presented.

Method scoping has involved discussions with a number of relevant experts within the Met Office:

- Hazel Thornton and Philip Bett, Science Manager and Senior Scientist in the Met Office Climate Adaptation group, experts in the relationship between weather and energy demand/generation;
- Joana Mendes, Senior Scientific Consultant in the Met Office Industry Consultancy group, expert in using meteorological information to inform the solar energy industry;
- Simon Brown, Science Manager for the Met Office Climate Extremes group, expert in how meteorological extremes may change in future climates;
- Theo Economou, Senior Lecturer in Statistics at the University of Exeter and Met Office statistical advisor, expert in environmental statistical modelling;
- Nick Dunstone, Science Manager of the Met Office Climate Dynamics group, expert in inter-annual to decadal climate prediction and variability;

- Jason Lowe and Fai Fung, Head of Climate Knowledge Integration and Mitigation Advice, and Climate Services Manager at the Met Office, experts in climate modelling, climate change and UKCP18;
- Dan Bernie, Science Manager of the Met Office UK Climate Resilience team, expert in climate resilience, risk and mitigation;

Additionally, comments and advice from the project user group and advisory group have been incorporated. The depth and breadth of knowledge belonging to these experts has ensured a rigorously thought through methodology which, following the successful achievement of each stage, will meet the goals of the project.

5.1. Method Scoping: Long-duration Events

Within the following section, we describe a number of possible approaches and available relevant data sets, highlighting their strengths and weaknesses. We then make a recommendation of the method expected to provide the best results, and the required methodological steps.

5.1.1. Available data sets, their benefits and limitations

To achieve the goals of the project and produce a set of representative electricity system relevant adverse weather scenarios contained within whole years of gridded temperature, wind speed and solar irradiance, one or more relevant meteorological datasets must be identified.

There are a number of potential sources of meteorological data, each with its own strengths and weaknesses in relation to the desired output of this project. In particular, how appropriate each data set is for deriving the definition of an 'adverse weather event', how well they are able to capture plausible scenarios more extreme than those observed in the historical period, and the effect of climate change on the relevant meteorological variables and scenarios (i.e. the three key questions posed at the beginning of Section 5).

Reanalysis Data

Meteorological reanalysis[6] data sets, such as ERA5[7], are the gridded weather data commonly used by energy modellers. These datasets are available at spatial resolutions of up to approximately 30 x 30 km and temporal resolutions of up to one hour, for the period 1979 to present day (i.e. currently for the last 40 years).

This type of data set is a gridded representation of the weather that has been observed over the historical period. As such, the meteorological conditions at each location can be related directly to historical energy generation and demand information to inform the development of the definition of the adverse weather stress event indices. Hence, reanalysis data is relevant for addressing key question 1.

[6] https://www.ecmwf.int/en/research/climate-reanalysis (Accessed 02/03/2020)
[7] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5 (Accessed 05/03/2020)

Once an approach for identifying adverse weather events has been developed, such events could be identified within these reanalysis data sets already currently used by electricity system modellers. This would help to give context to challenging periods of weather for a renewable electricity system within the last 40 years, and would increase the range of weather information for those energy modellers who currently use only 5-10 years of data. This approach would, however, still limit the set of extreme weather scenarios to only represent those that occurred in the historical period, and would not characterise the effect of climate change. Hence, this approach would not address key questions 2 and 3. It therefore remains to identify possible meteorological data sets that could be used to address these two further key questions.

Weather Generator Simulations

Synthetic weather can be simulated using a statistical/data-science model, developed to represent the spatial-temporal behaviour of relevant weather variables. This method is often referred to as a weather generator[8]. This approach is common in the fields of hydrology and water resource management, and examples of such models include (Jones, et al., 2010), (Serinaldi & Kilsby, 2012) and (Stoner & Economou, 2020). This type of approach was initially proposed for this project as, once the data science model has been fitted (and validated), many thousands of years of synthetic weather can be generated relatively computationally quickly (compared to a complex physical weather/climate model such as the Met Office's HadGEM3[9]). In being able to generate so many years of synthetic weather, this approach would be able represent adverse weather scenarios not captured within the observed period. In addition, methods exist for incorporating the effect of climate change on the meteorological variable simulated from the model (Brown, et al., 2014). This approach could therefore be used address key questions 2 and 3.

Statistical weather generator models are, however, not constrained by the physical equations of the atmosphere (unlike physical climate/weather models) and may therefore simulate synthetic weather that is not physically plausible. In addition, fitting/training such models is extremely computationally expensive, particularly with the level of complexity required to capture multiple hourly weather variables accurately at a high spatial resolution, as required for this project. This was demonstrated in a recent project carried out by the Met Office within the water industry, for which a weather generator model was developed to simulate daily rainfall at three sites in the UK. This model took 2 months to develop and fit/train to these three sites. Scaling this weather generator up to model three meteorological variables (temperature, wind speed and solar irradiance) rather than just one, at an hourly temporal resolution rather than daily, and at a 30 km resolution over all of Europe (more than 300,000 grid cells) rather than at 3 locations, would therefore be computationally infeasible.

Hindcast (Retrospective Forecast) Data

An alternative approach for creating synthetic weather is to make use the large ensembles of coupled model runs used in seasonal and decadal climate prediction. These datasets represent plausible `alternative realities' to what was actually observed over the last decades. Such data sets are often referred to as hindcasts, and one such data set has been created using the Met Office Decadal Climate Prediction System, known as DePreSys (Dunstone, et al., 2016). This system uses a global ocean-atmosphere coupled climate

[8] https://www.ipcc-data.org/guidelines/pages/weather_generators.html (Accessed 13/03/2020)
[9] https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/climate-models/hadgem3 (Accessed 03/03/2020)

model, and has been run 40 times for each year during the period 1959-2015. The model is initialised each November with atmospheric, oceanic, and sea-ice observational data, as well as historical anthropogenic and natural climate forcings. Therefore, the DePreSys data set consists of 40 ensemble members (alternative realities) of the 57 year historical period, equivalent to 2280 model years of plausible weather, representative of historical climate conditions.

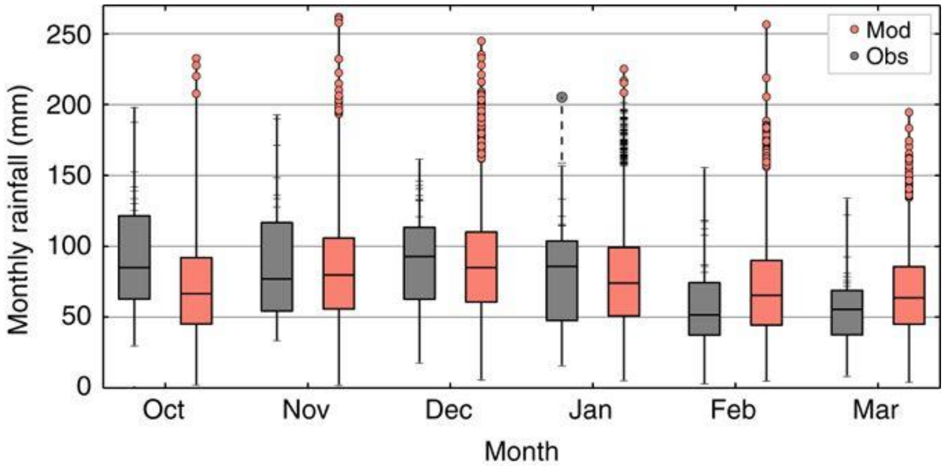

Figure 2: Taken from (Thompson, et al., 2018), Unprecedented monthly rainfall in all winter months. South east England monthly rainfall totals from observations (grey) and the model (red) for October to March. The box represents the interquartile range and the range of the whiskers represents the minimum and maximum monthly rainfall totals. Red dots indicate model months with greater total rainfall than has yet been observed and ticks on the upper observations line indicate values in the upper quartile of events. For January the ticks on the model line indicate months above the observed record prior to 2014 and the grey dot above the observations indicates the record observed monthly rainfall of January 2014

DePreSys has recently been used as a tool for exploring extreme, unprecedented meteorological events (Thompson, et al., 2018) following the UNprecedented Simulated Extremes using ENsembles (UNSEEN) method. This method uses the large ensemble of simulations from the DePreSys hindcasts to identify and characterise `black swan' events more extreme than those in the observational record, as demonstrated in Figure 2. A similar approach could be attempted to identify and extract extreme, unprecedented events relevant for renewable electricity system stress testing. This set of events would be representative of many more years of weather than the historical period alone, and would hence address key question 2 posed at the beginning of Section 5. In addition, climate models are constrained by the physical equations of the atmosphere, and hence simulations will retain physical plausibility.

The purpose of the DePreSys system is to forecast from several months ahead to several years. For this purpose it is designed to represent climate variability, which in turn is essential for capturing a range of plausible scenarios. Some aspects of the system that promote good representation of climate variability are: a resolved stratosphere[10] and high spatial resolution in the atmosphere and ocean. These aspects have been shown to lead to improvements in the representation of synoptic weather patterns, such as cyclonic storms and blocking highs, which are associated with wind droughts (Williams, 2015).

[10] https://www.metoffice.gov.uk/research/climate/earth-system-science/stratosphere (Accessed on 03/03/2020)

This higher spatial resolution is, however, nominally lower than the resolution of the latest generation of reanalysis data sets currently used by electricity system modellers (approximately 30 km). In addition, the DePreSys data set provides only temperature, wind speed, wind direction and mean sea level pressure (mslp) at a daily temporal resolution. This means that the hourly variability in each relevant meteorological variable, as is required for electricity system modelling, is not characterised, and no solar irradiance information is available. If used, this data set would therefore require a downscaling[11] step to achieve the desired spatial-temporal resolution, and a representation of solar irradiance. Finally, the DePreSys hindcasts are representative of the historical period only, and therefore do not characterise the effect of climate change. Using this data set would therefore require an additional exploration and quantification of the effect of climate change in order to address key question 3 in Section 5.

Climate Model Experiment Data

Following a similar method to that used to create a hindcast data set (as described above), a recent climate model experiment carried out by scientists in the Netherlands (Wiel, et al., 2019), used a global climate model to not only simulate multiple realisations of a historical period (in their case 2000 years characteristic of 2011-2015) but also for a future climate (2000 years characteristic of pre-industrial conditions + 2^{o}C warming). Using this data set to characterise extreme adverse weather events would, in a similar way to the hindcast data, address key question 2 in Section 5 due to the extended length of the period being represented (2000 years). In addition, the data set has some consideration of the effect of climate change, and hence also goes some way in addressing key question 3.

This climate model experiment was, however, carried out using a climate model with a relatively low spatial resolution of 100 x 100 km. This means that the higher resolution advantages described in the previous section in relation to the DePreSys climate model are not realised here, namely the representation of synoptic weather patterns important for more realistically characterising wind drought conditions. In addition, similar to the DePreSys hindcast data set, this low resolution climate model data would need to be downscaled to the higher spatial resolutions currently ingested by electricity system models. Moreover, the quantification of the effect of climate change within this data set is limited to one specific future warming level. Therefore, this data is not representative of a projected future with varying warming levels, limiting context and flexibility in the adverse weather event analysis.

UK Climate Projections: UKCP18

The Met Office released the latest UK climate projections in November 2018 (Lowe, 2018). These projections include:

- A new set of 28 global climate model projections to 2100, comprising simulations from both the latest Met Office Hadley Centre climate model and global climate models from around the world;
- A set of 12 regional climate model projections on a finer scale (12km) for the UK and Europe to 2080;
- A set of 12 projections produced with a model of horizontal/spatial scale 2.2km to 2080, better able to represent some small-scale processes seen in the atmosphere, such as those important for large convective storms in the summer;

[11] https://gisclimatechange.ucar.edu/question/63 (Accessed on 04/03/2020)

- An updated set of probabilistic projections, giving estimates of different future climate outcomes to 2100;

More information about UKCP18 can be found on the Met Office website[12], which links to a number of relevant reports.

Figure 3 summaries the climate model information available from UKCP18, detailing the horizontal/spatial resolution of each data set, the greenhouse gas emission scenarios considered, and the time-period and geographical domain covered.

Dataset	Emissions scenarios	Time period	Geographical domain
Probabilistic projections	RCP2.6, RCP4.5, RCP6.0 RCP8.5, SRESA1B	1961-2100	UK
Global (60km) projections	RCP8.5	1900-2100	UK, Global
Regional (12km) projections	RCP8.5	1981-2080	Europe, UK
Local (2.2km) projections*	RCP8.5	1981-2000, 2021-2040 2061-2080	UK

Figure 3: Taken from the UKCP18 Factsheet: UKCP Local (2.2km) Projections, Summary of UKCP18 climate models and scenarios for projections over land.

The UKCP18 probabilistic projections are not spatially coherent (i.e. the spatial dependence between locations is not realistic) because the uncertainty in each grid cell is considered separately[13]. These projections are therefore not relevant for use within this project. The local (2.2 km) projections are only available for the UK, hence, while they may be relevant for informing about the effect of climate change on small-scale processes in the UK, they cannot be used to create the European-wide spatial-temporal meteorological fields required for representing long-duration adverse weather scenarios in this project.

The global (60 km) projections have the greatest coverage in time (1900-2100) and space (global). As well as this, there are a larger number of these projections (28) which have been produced by a range of climate models (Met Office and other global modelling centres). This means that their use is recommended when an exploration of a wider range of future outcomes is more important than spatial detail. The regional (12 km) projections consist of fewer (12) projections over a shorter time-period (1981-2080), covering the required European domain. The increased resolution of these projections compared to the global projections means their use is recommended when improved representation of extremes or spatial detail is more important than exploring a wider range of future outcomes.

Since both a wide range of future scenarios and consideration of the extremes are relevant to this project it may be necessary to use the two datasets in tandem. Using UKCP18 climate change projections to directly represent future relevant decades (e.g. the 2050's), would provide a comprehensive characterisation of the effect of climate change on the relevant meteorological variable and scenarios, hence addressing key question 3 in Section 5. However, since there are only 28 or 12 projections available from the global/regional data sets respectively, the full variability and extremity of plausible meteorological scenarios (as

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[12] https://www.metoffice.gov.uk/research/approach/collaboration/ukcp/about (Accessed 13/03/2020)

[13] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---how-to-use-probabilistic-projections-maps.pdf (Accessed 17/04/2020)

would be captured by the 40 historical runs in the DePreSys hindcasts) would not be captured. This approach would therefore not address key question 2.

This climate variability could, in some way, be inferred by the historical period of UKCP18 global projections. These comprise 15 projections of the period 1900-2018 created using the Met Office global climate model. This climate model is very similar to that used to simulate the DePreSys hindcasts, however, for the UKCP18 application the historical period is initialised only once, pre 1900, for each of the 15 projections, rather than every November (as is done in the DePreSys hindcasts). This means that the UKCP18 projections are allowed to evolve freely for the entire historical period, and hence are not necessarily representative of observed historical climate variability (i.e. the observed phases of climate modes of variability such as the North Atlantic Oscillation[14]). This could be advantageous in creating alternative realities with very different, and hence more extreme, meteorological conditions than those in the observations. However, it also means that the data has less context when used to supplement the observed historical period.

In addition, the 15 Met Office global historical projections are each initialised with a slightly different set of climate model parameters in order to quantify climate model uncertainty. This means that the 15 'alternative realities' created using this approach capture both climate variability and climate model parameter uncertainty, and hence these two types of uncertainty cannot be disentangled and understood in isolation. This has the implication of creating too wide or too narrow a set of realisations. Similar to the DePreSys data set, if used within this project, this UKCP18 historical data set would need to be downscaled to the required higher spatial-temporal resolution, and an approach for combining this information with the future projections would need to be developed. The UKCP18 simulations do, however, provide some information about solar radiation (unlike DePreSys), although no focus has been paid to this output in UKCP18 documentation thus far, hence it's validity would need to be explored before use.

5.1.2. The Proposed Method

As evidenced by Section 5.1.1, no single data set is able to address every requirement of this part of the project: to develop an approach for identifying 'adverse weather events' and produce a set of long-duration electricity system relevant adverse weather scenarios, contained within whole years of hourly, 30 km gridded temperature, wind speed and solar radiation, representative of a large number of plausible weather years and the effect of climate change. Therefore, rather than using just one data set, a method is proposed that draws upon the advantages of various sources.

It is recommended that this project phase be carried out in two stages. These stages are summarised in Figure 4.

[14] https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/ens-mean/nao-description (Accessed 13/03/2020)

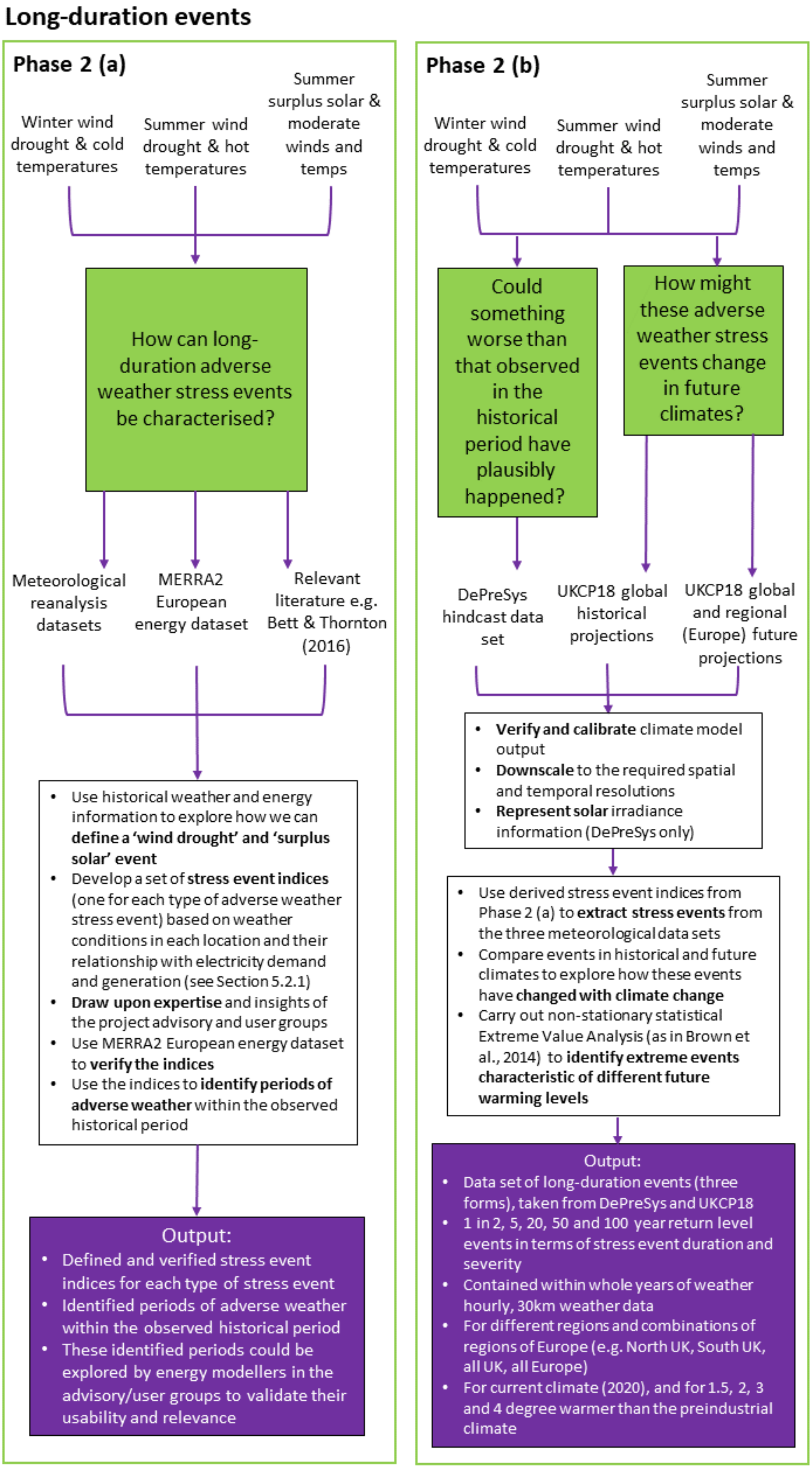

Figure 4: A diagram summarising the proposed method for completing Phase 2 of the project

Phase 2 (a): How can long-duration adverse weather stress events be characterised?

The first stage aims to address key question 1. This involves using meteorological reanalysis datasets, European energy data sets, literature insights, and the expertise of the project advisory and user groups to develop an approach for characterising long-duration adverse weather stress events using meteorological information.

This will be achieved by developing a set of stress event indices (one for each type of adverse weather type) based on weather conditions in each location and their potential for creating electricity demand and generation. In doing so, this will allow for the identification of periods of adverse weather stress events in any meteorological data set, which can ultimately be used to construct the final dataset of adverse weather events. An approach for doing so is explored in more detail in Section 5.2.1.

The output of Phase 2(a) will be a clear set of definitions of what constitute each type of long-duration adverse weather stress event of interest. This will allow for periods of adverse weather to be identified within the historical record, which could be subsequently explored by energy modellers in the advisory/user groups to validate their usability and relevance.

Phase 2 (b): Could something worse than that observed in the historical period have plausibly happened? And how might these adverse conditions change in future climates?

The second stage aims to address key questions 2 and 3. The final dataset of adverse weather events should characterise many more plausible weather years than those in the observational record, and the effect of climate change.

Following the discussions in Section 5.1.1, it is recommended that the DePreSys hindcast data set be used to represent adverse weather in the historical period, as it is known to most comprehensively quantify the variability of the observed historical period. Further, the future part of the UKCP18 global and regional climate projections should then be used to explore how adverse weather may change in future climates. Therefore, it is also recommended that the UKCP18 *historical* simulations be used alongside DePreSys to give context to the future climate projections.

Using the stress event indices developed in Phase 2 (a), periods of adverse weather could then be identified in both data sets and used to construct data sets of extreme events characteristics of many plausible weather year and climate change.

Following these recommendations, the methodological steps for using DePreSys hindcasts in combination with UKCP18 output to meet the needs of this stage of the project are as follows:

1. **Verify and calibrate climate model data**

   Climate models are mathematical representations of reality and are therefore known to have biases compared to observed weather. This first step in the methodology will assess and correct these biased in the DePreSys and UKCP18 historical simulations. Possible methods for doing so, and their feasibility, are discussed further in Section 5.2.2.

2. **Downscale climate model data to higher spatial-temporal resolution**

The DePreSys hindcast data and UKCP18 global historical simulation and future projections are available on a 60 km resolution in space and a daily resolution in time. A method must therefore be developed for downscaling this data to be consistent with the spatial-temporal resolution of the popular reanalysis data currently used by many electricity system modellers: 30 km in space and hourly in time. Possible methods for doing so, and their feasibility, are discussed further in Section 5.2.3.

3. **Represent solar radiation**

   The DePreSys hindcast data set does not contain solar irradiance information. A method must therefore be developed for representing solar irradiance based on geographical information and other weather variables (e.g. temperature and wind speed). Possible methods for doing so, and their feasibility, are discussed further in Section 5.2.4.

4. **Incorporate climate change**

   The effect of climate change on relevant meteorological variables and the adverse weather scenarios must be quantified by exploring the various future outputs of UKCP18. The characterisation of adverse weather scenarios must then be adjusted to follow this insight. This is discussed further in Section 5.2.5.

This type of approach, whereby firstly a comprehensive historical characterisation of ‘extreme risk’ is achieved, followed by an exploration of how this may change in future climates, is common scientific practise in the field of environmental risk quantification.

The output of this stage of the project would be a data set of long-duration events (three forms), taken from DePreSys and UKCP18, contained within whole years of weather hourly, 30km weather data. The dataset would characterise 1 in 2, 5, 20, 50 and 100 year return level events in terms of stress event duration and severity, representative of different regions and combinations of regions of Europe, and climates characteristic of 1.5, 2, 3 and 4 degree warmer than the preindustrial climate.

5.2. Method Feasibility: Long-duration Events

This section explores the feasibility of each stage of the method proposed in Section 5.2.1 in order to better understand how the method will work. This is achieved both in terms of expert insights from relevant scientists and literature, and, where appropriate, based on exploratory data analysis.

5.2.1. Define adverse weather indices (Phase 2 a)

As previously noted, a key question arising from the stakeholder engagement was: how can adverse weather stress events be defined and hence identified within meteorological data sets?

The focus of this part of the project is on creating a set of long-duration adverse weather events, characteristic of multiple consecutive days of low renewable energy generation (wind/solar) and high energy demand. As discussed in the literature review (Dawkins, 2019), such events will be important to characterise in both the winter, when demand is currently highest in the UK, and summer, when the demand for cooling could be increasingly high due to climate change. These types of adverse weather events fall into three categories (as in the Table in Section 4.3):

- Winter-time wind drought coincident with below average temperatures
- Summer-time wind drought coincident with above average temperatures
- Summer-time surplus solar coincident with average wind speeds and temperatures

The challenging in creating a definition for such events is in their multi-dimensionality. The 'extremity' of such an event could depend on its magnitude (how adverse the weather becomes), spatial extent (how much of the electricity system is experiencing adverse weather), as well as its duration (how long the adverse weather persists for).

When developing the definition of a 'wind drought' or a 'solar surplus' we could learn from methods in the field of rainfall drought modelling, e.g. (Burke, et al., 2010). Often rainfall drought is quantified using a 'drought index', representing the accumulated rainfall over a period of interest (e.g. the preceding 6 months), calculated over a number of time steps (e.g. a number months over many years). The time steps over which the drought index falls below some extreme threshold are then considered to be periods of drought. The duration (number of time steps below the threshold) and severity (accumulated drought deficit below the threshold) of these drought events can then be quantified, as shown in Figure 5. These drought characteristics are then often used to identify particularly bad periods and understand how drought events vary over time.

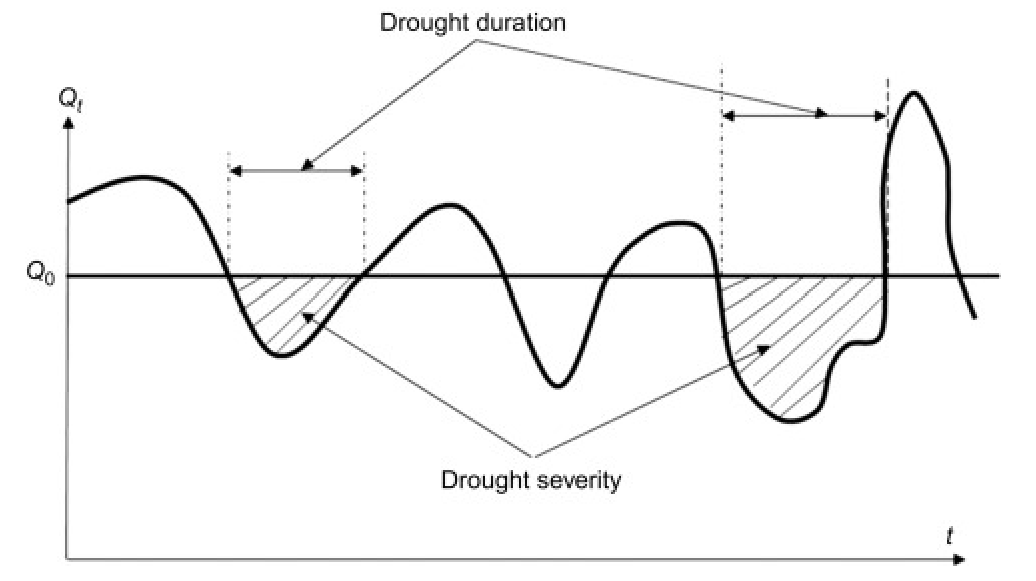

Figure 5: A schematic taken from https://www.sciencedirect.com/topics/earth-and-planetary-sciences/drought, demonstrating how drought duration and severity are often characterised in the rainfall drought literature: as the length of time (t) and accumulated deficit in the drought index (Q_t) below a threshold (Q_o), respectively.

(Nairn & Fawcett, 2015) use a similar approach to develop a heat wave intensity index. This index, named the excess heat factor, is derived as the function of various measures of

temperature including the three-day-averaged daily mean temperature, found to capture heatwave intensity as it applies to human health outcomes well.

In the context of long-duration, electricity system relevant wind droughts and surplus solar events, such indices could be calculated from wind speed, solar irradiance and temperature data. As in the rainfall drought and heatwave examples described above, the best way in which to use the weather variables to characterise the adverse event would be explored and an optimal stress event index identified.

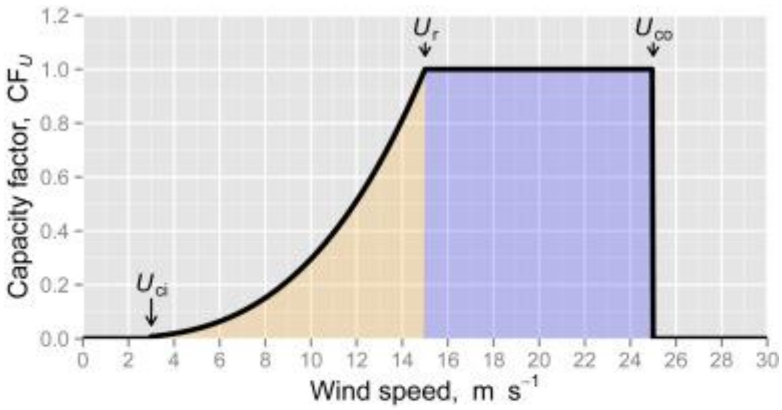

Figure 6: Taken from (Bett & Thornton 2016), Power curve of the wind shown in terms in the capacity factor.

For wind droughts, for example, such an index could be calculated from wind speeds and temperatures that fall below or exceed specified thresholds know to relate to renewable generation and demand for electricity. This could incorporate insights from relevant literature, such as the wind power curve presented in (Bett & Thornton, 2016), shown in Figure 6, and the electricity demand model of (Bloomfield, et al., 2018). It may also be relevant to accumulate the weather variables over a number of hours or days to reflect the function of electricity storage during such long-duration events. The weather thresholds and functions that will be explored in this stage of the project will be informed by relevant literature, as well as the expert insights of the energy modellers in the project advisory and user groups.

As well as severity and duration, the spatial extent of such drought events is relevant. To accommodate this additional dimension, these stress event indices could be calculated by accumulating grid cell indices over a number of specific regions of the UK and Europe, identified based on their variability/co-variability in meteorological conditions. As discussed in the literature review (Dawkins, 2019): Sections 3.2 and 5.3, with the focus of the UK electricity system the European domain could be characterised in this way by 7 regions: South and East UK, South and West UK, North UK, the North Sea, Northern Europe, Central Europe and Southern Europe.

This would provide coincident (in time) drought indices for these different regions, which could be used in a similar way to a single drought index, to calculate combined drought durations and severities for different combinations of regions, and hence different spatial extents. These combined drought indices could then be used to identify the top N events or specific return period events in terms of duration, severity and spatial extent. In addition, extreme weather scenarios could be identified for different, relevant combinations of spatial regions. For example, scenarios with extreme winter-time wind drought severity could be identified for the northern UK region only, as well as scenarios with extreme severity when all European regions are considered. This would allow different users of the data set to select events of most relevance to their particular application/region, e.g. someone exploring the potential for wind energy in northern UK could primarily use the set of adverse weather scenarios selected as relevant for the northern UK region.

As previously highlighted, the definition of what constitutes an 'extreme' event for a specific electricity system may change according to the amount, types and distribution of renewable generation and storage installed; as well as the expected demand profiles considered. As the aim of this project is to produce a widely useable dataset of extreme stress events, that can be used to stress test the resilience of a range of possible futures, this stage of the project will focus on developing stress event indices that make no assumption about specific future systems. It is hypothesised that this can be achieved by quantifying the 'potential' for renewable generation and electricity demand in any given grid cell, rather than weighting certain locations by installed capacity or population. This will provide indices that identify stress events characteristic of extreme *weather*, independent of the electricity system configuration, but where the weather is used in a way that relates well to electricity generation and demand. This approach is supported by the insight that meteorological conditions (such as low wind speeds) that persist for long durations (a week or more) are often also found to extend over large areas (all of the UK and possibly Europe). Hence, considering all locations as relevant for the event indices (not just those in which future renewables will be installed), the index is likely to still relate well with periods of challenging weather for a future electricity system, as all locations will be affected by the adverse conditions.

These indices could be refined by comparing event metrics (i.e. wind drought severity) applied to historical reanalysis data, with historical energy generation and demand data. For this, for example, the data set recently produced by the University of Reading could be used: the MERRA2[15] derived time series of European country-aggregate electricity demand, wind power generation and solar power generation (based on the electricity system of 2017)[16]. Exploring this relationship would help us to ensure that our drought index is able to capture the trade-off between energy demand and generation, based on meteorological variables. In addition, particular historical periods that were known to challenge the electricity system (e.g. January 2010 and July 2018) could be used as case studies to verify how the stress event indices perform.

Once the stress event indices have been derived, they can be used to identify periods of adverse weather within the historical reanalysis data sets. The energy modellers in the advisory/user groups could then be given the opportunity to explore the impact of these identified periods within their electricity system models to validate their usability and relevance.

The aim is to then use a finalised set of stress event indices to identify extreme adverse weather events in the DePreSys and UKCP18 data sets (Phase 2 b). Extreme stress events could then be identified as the top N% of events in terms of their duration and/or severity. As well as this, statistical extreme value analysis (EVA) methods could be used to model extreme drought/surplus event durations and severities, and hence identify which weather

[15] https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/ (Accessed 11/03/2020)

[16] https://researchdata.reading.ac.uk/239/ (Accessed 11/03/2020)

events are characteristic of specific extreme levels, such as a 1 in 20 year event (equivalent to an event with a 5% probability of occurring in any given year). For example, suppose a 1 in 20 year wind drought duration is found to be 1 week, we could then go back to the DePreSys data set and pick out events with that duration to represent this return level. Further, we could use this drought index approach to explore and quantify the time between drought events.

5.2.2 Verify and calibrate climate model data (Phase 2 b)

Both the DePreSys hindcast data set and UKCP18 global historical projections are climate model representations of historical periods. While the exact day-to-day meteorological conditions will not be the same as those actually experienced, it is expected that each model simulation/projection of the historical period will have a similar 'climatology' (long-term distribution of weather) compared to the observations. That is, for example, at a given location, the climate models should have the same average temperature, wind speed etc., as have been observed. If this is not the case it may be that the climate model is biased (i.e. tends to be too hot or too cold at that location) and this must be corrected for before the climate model data can be used to represent the historical period.

DePreSys

In previous work carried out within the Met Office, the biases in DePreSys have been quantified by comparing the distribution of the weather variable of interest (e.g. temperature) from the DePreSys data set, with the equivalent distribution from a gridded observational or reanalysis data set in the same historical period. This is done on a grid cell by grid cell basis, focusing on comparing the mean, standard deviation (variability), skewness and kurtosis[17] of the distributions.

As an initial exploration of the DePreSys data set we have extracted and compared the distribution of mean sea level pressure (mslp) from DePreSys with that in the ERA5[7] reanalysis data set. The mslp is used here as regional patterns in pressure can be used to characterise temperature, wind speed and solar irradiance (Dawkins, 2019).

This initial exploration was carried out for approximately 300 DePreSys 60 km grid cells covering the UK, and for the period 1979-2015. Here ERA5 is used as a representation of the observations as this is the data set currently used by electricity system modellers to represent observed meteorological conditions. The 30 km resolution ERA5 data is regridded to the same 60 km grid as DePreSys to allow for a direct comparison. Figure 7 shows this comparison for two of the 60 km grid cells.

Figure 8 shows the same comparison of the mslp distributions between DePreSys and ERA5 across all of the 300 grid cells, in terms of the distribution mean, standard deviation, skewness and kurtosis. Where the ERA5 distribution metric (e.g. mean) is greater than or less than the range of the metric calculated from each of the 40 DePreSys hindcast ensemble members, the grid cell is specified as being biased in that metric. According to the results shown in Figure 8, at the location on the top row of Figure 7 (Ireland), DePreSys has a distribution that is biased in terms of the mean, skewness and kurtosis; while at the

[17] https://www.usna.edu/Users/oceano/pguth/md_help/html/moment_stats_2.htm (Accessed on 05/03/2020)

location on the bottom row of Figure 7 (London) DePreSys is unbiased in all distribution metrics.

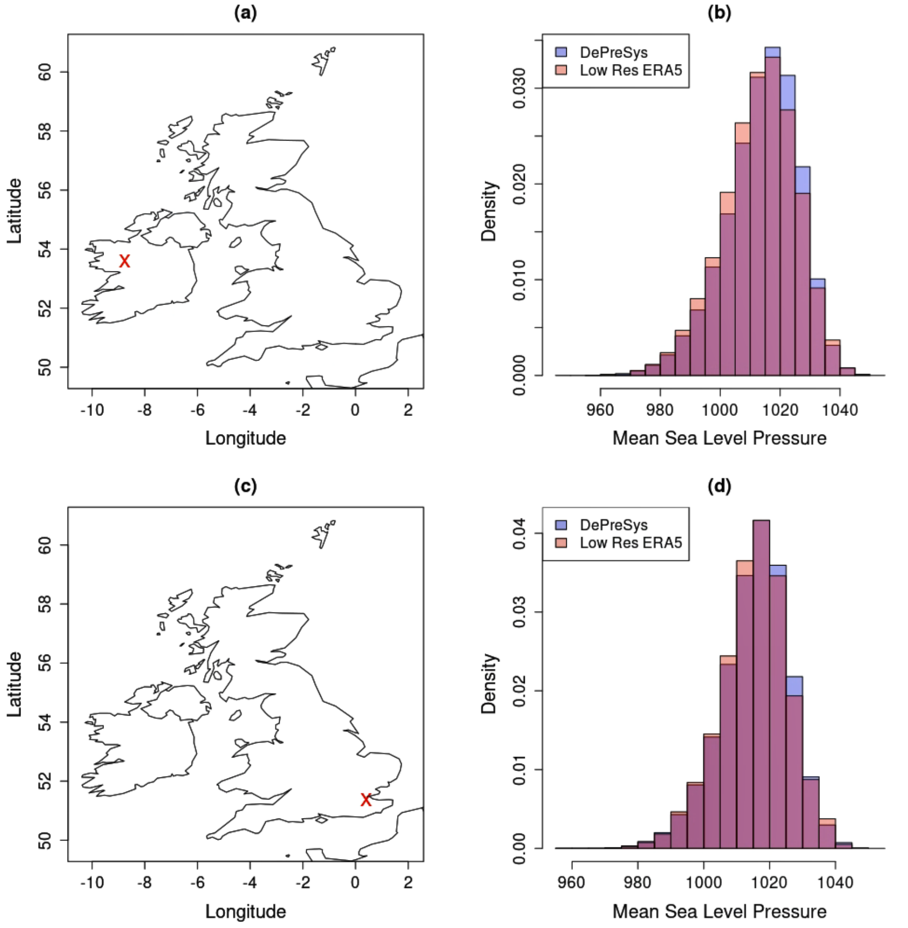

Figure 7: A comparison of the distribution of daily mean sea level pressure (mslp) in the period 1979-2015, from the DePreSys hindcast data set and from the ERA5 reanalysis data set (regridded to the same low spatial-temporal resolution as DePreSys), in two DePreSys grid cells within the UK (in each row). The locations of the grid cells are shown on the UK maps in the left panels (a and c), comparisons of the two distributions in the form of histograms[18] are shown in the right panels (b and d).

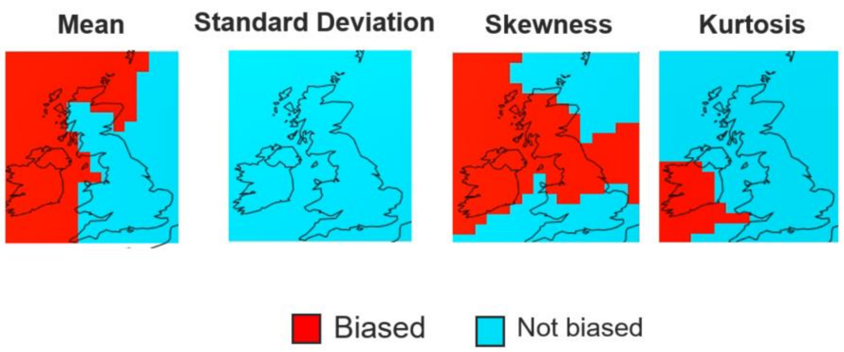

Figure 8: Maps showing where the DePreSys hindcast data is biased compared to ERA5, in terms of the mean, standard deviation, skewness and kurtosis of the distributions of mslp in the period 1979-2015.(e.g. the distributions shown in Figure 7).

[18] https://www.mathsisfun.com/data/histograms.html (Accessed on 05/03/2020)

There are well-established statistical methods for transforming distributions to be representative of other distributions. Such approaches could be used to transform the DePreSys weather variable to look more like ERA5. One such method is known as quantile mapping/matching. This approach maps the ranked data of one distribution to the value of the associated rank in another distribution. After applying this method, the two distributions match exactly, as demonstrated in Figure 9 (b).

This approach could be used to bias correct DePreSys mslp (and other weather variables) within each grid cell, and the resulting bias maps equivalent to those shown in Figure 8 would be fully blue for all of the four distribution metrics. However, in doing so some of the additional information contained within DePreSys would be lost. Most importantly, the maximum value of the weather variable in the DePreSys data would be mapped to the maximum value in the ERA5 data. Hence, while the duration and spatial extent of extreme highs and lows would be retained, the magnitude of these extremes will be limited to not exceed those within the observation record.

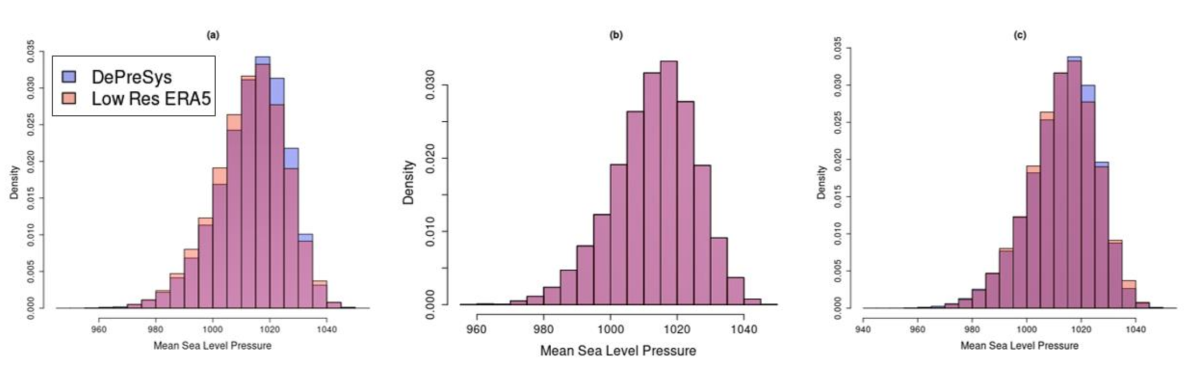

Figure 9: Demonstration of the change in the DePreSys mslp distribution at the Ireland location (top row of Figure 7) from the original distribution (a), following bias correction using (b) quantile mapping and (c) mean and standard deviation rescaling.

Since the aim of using the DePreSys hindcast data set it to more comprehensively represent all plausible extreme scenarios, the extremes must not be restricted in this way. Hence an alternative, less strict bias correction approach could be followed. Specifically, the mean and standard deviation of the DePreSys distribution could be rescaled to match that of the ERA5 distribution, leaving the skewness and kurtosis unaltered.

The result of applying this adjustment to the Ireland location is shown in Figure 9 (c). Now, rather than the two distributions matching up exactly, the mean and spread of the DePreSys distribution align more closely with the ERA5 data, and the extremes of the DePreSys data are allowed to be greater in magnitude compared to ERA5. The resulting bias maps equivalent to those shown in Figure 8 would be fully blue for the mean and standard deviation distribution metrics.

Applying such bias correction methods to each meteorological variable on a grid-cell-by-grid-cell basis will, however, lead to a general distortion of the relationships between the meteorological variables (e.g. the relationship between wind speed and temperature) and there correlations across space. This could lead to unrealistic meteorological fields. Hence, as recommended by (Cannon, 2016), in cases where retaining this between variable and spatial coherence is important (as it is here), applying a multivariate bias correction approach is necessary. Specifically, (Cannon, 2016) and (Bürger, et al., 2011) describe a multivariate generalisation of the mean and standard deviation rescaling approach described above, which replaces the standard deviation with the multivariate covariance matrix[19].

This multivariate bias correction approach is simple to apply, with many examples of its application in the literature. It will therefore be feasible for use to bias correct the DePreSys hindcast data across the European domain, in multiple meteorological variables (i.e wind speed and temperature), as required for this project.

UKCP18 global historical projections

When developing the UKCP18 data sets the Met Office Hadley Centre carried out extensive evaluation of the historical period.

Figure 10, taken from the UKCP18 land projections science overview (Murphy, 2018), shows the mean bias in temperature taken from the UKCP18 global historical projection when compared to reanalysis, separately for December-January-February and June-July-August. These results indicate a significant cold bias over most of the northern hemisphere continental land mass in winter.

The same multivariate mean and covariance scaling method detailed above could be used to adjust any biases identified within the UKCP18 global historical projections. Again, since this is simple to apply, this is a feasible approach for adjusting this large data set across Europe.

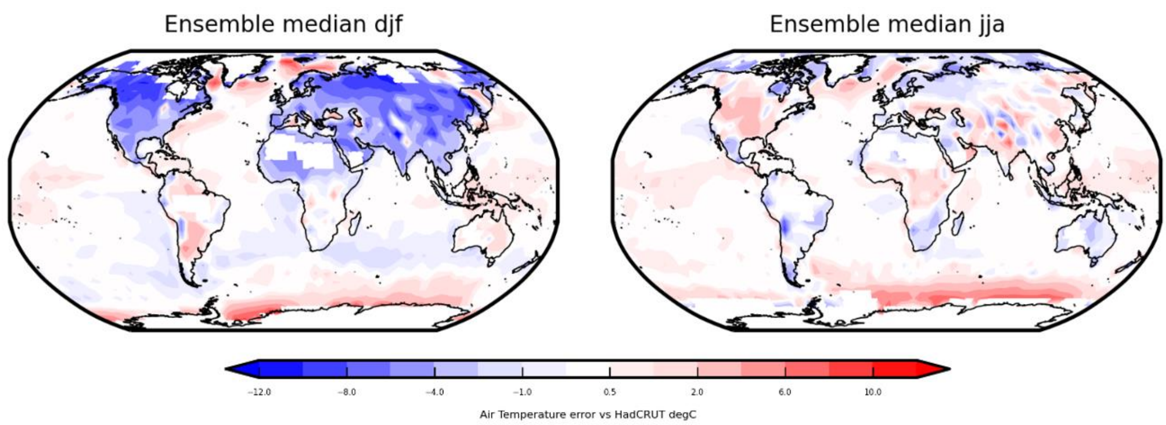

Figure 10: Taken from (Murphy, 2018): Twenty-year mean biases in surface air temperature (°C) simulated by the 15 members of the Met Office global PPE. Errors for December-January-February (DJF) and June-July-August (JJA) are calculated relative to ERA-Interim reanalyses of observations[20], for 1981-2000.

Further validation of these two data sets could be carried out using the weather patterns introduced in Section 4.2 of (Dawkins, 2019). As described in (Dawkins, 2019), (Neal, et al., 2016) have developed an approach for summarising North Atlantic mslp patterns into 30 general weather patterns. These patterns are characteristic of various temperature-wind-solar conditions, a number of which are highlighted in (Dawkins, 2019) as being potentially representative of adverse weather condition relevant for the electricity system, such as high

[19] https://datascienceplus.com/understanding-the-covariance-matrix/ (Accessed 24/03/2020
[20] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim (Accessed 09/03/2020)

pressure blocking conditions which lead to wind droughts. This further validation of the DePreSys and UKCP18 climate data sets could therefore involve exploring whether the frequency and persistence of these weather regimes is consistent with observations, the results of which will give further context to the data sets used within this study.

5.2.3. Downscale climate model data to higher spatial-temporal resolution (Phase 2 b)

Currently, electricity system models ingest 30 km spatial, and hourly temporal, resolution weather information. The DePreSys hindcast data and UKCP18 global historical projections provide mslp, wind speed, wind direction, temperature, and solar irradiance (in the case of UKCP18), at a 60 km, daily resolution. In order to align with the data currently used by energy modellers, these climate model data sets must be downscaled to a higher spatial-temporal resolution, or in other words, we need to 'fill in the gaps' in the low-resolution data.

This can be achieved using a statistical data science modelling approach. Specifically, the ERA5 reanalysis data can be used at both its original resolution (High resolution ERA5) and re-gridded to the lower 60 km daily DePreSys resolution (Low resolution ERA5) by averaging in space and time, to understand the statistical relationship between low and high resolution representations of the meteorological variables. This downscaling relationship is characterised using a data science model, which can then be used to transform the low resolution DePreSys data, representing adverse weather scenarios not captured by ERA5, to the higher resolution required by electricity system modellers. This downscaling process is demonstrated in Figure 11.

Figure 11: Diagram demonstrating the statistical data science downscaling modelling framework: trained on low resolution and high resolution ERA5 and then used to downscale low resolution DePreSys to the high ERA5 resolution.

There are many data science modelling approaches that can be used to capture this downscaling relationship. One such approach is to fit a Generalised Additive Model (GAM)[21]. This type of model is particularly relevant when the relationship being represented is non-linear. This is important here as the downscaling relationship is likely to vary non-linearly in space and time, with longitude, latitude, time of the day and time of year. This GAM approach has been commonly used in the literature to downscale climate model data, e.g. (Korhonen, et al., 2013).

[21] http://environmentalcomputing.net/intro-to-gams/ (Accessed on 06/03/2020)

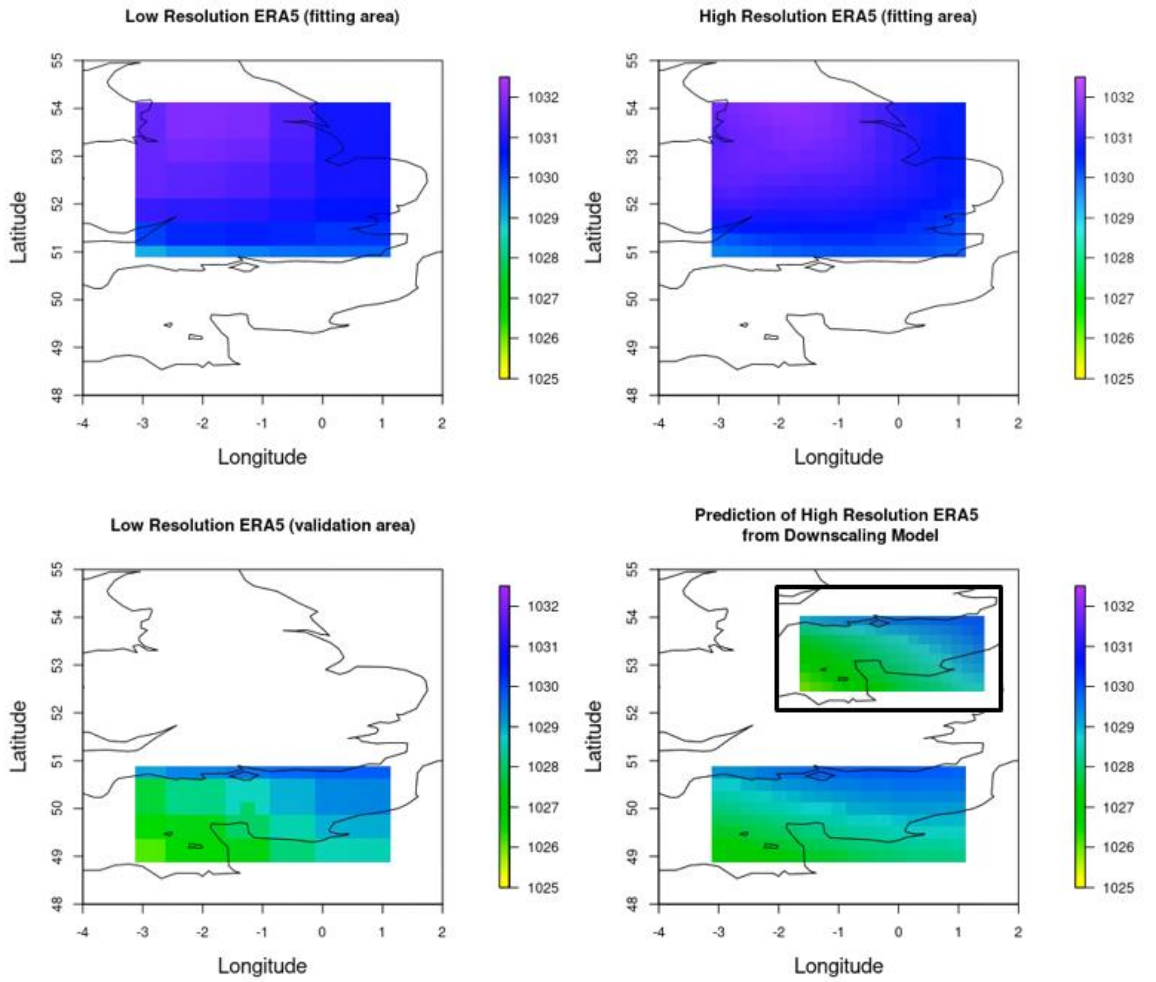

Figure 12: A demonstration of the data science spatial downscaling approach, trained to transform daily low resolution (60 km) mslp to daily high resolution (30 km) mslp. The plot on the top right shows the original high resolution ERA5 mlsp on 1st January 2009 in the fitting region, top left shows the equivalent data re-gridded to the 60 km resolution of DePreSys by averaging in space and time. The downscaling model is trained on these two data fields, to transform from low resolution to high resolution. The plot on the bottom left shows the low resolution ERA5 data in the validation region. This data is fed into the downscaling model and used to predict mslp at a high spatial resolution, as shown in the bottom right plot. The true high resolution ERA5 mslp in this validation region is shown in the top corner of this plot for comparison. The same data science modelling approach is then extended to downscale in both space and time. The GAM modelling framework is now trained to capture the relationship between daily 60 km ERA5 mslp (low resolution ERA5) and hourly 30 km ERA5 mslp (high resolution ERA5), where this relationship is allowed to vary non-linearly with longitude, latitude, time of the day and time of the year.

To demonstrate this downscaling approach and test its feasibility, ERA5 mslp data covering a small UK region for a single year (here 2009, chosen at random) has been extracted, and used to train a data science model in the form of a GAM. Initially this downscaling is explored in space (rather than space and time). The GAM is therefore trained to capture the relationship between daily 60 km ERA5 mslp (low resolution ERA5) and daily 30 km ERA5 mslp (high resolution ERA5), where this relationship is allowed to vary non-linearly with longitude and latitude. A demonstration of this spatial downscaling is shown in Figure 12. The spatial downscaling model is trained on a ‘fitting area’ of the UK region, shown in the top row of Figure 12, and then used to downscale low resolution mslp to high resolution mslp in a ‘validation area’, shown in the bottom row of Figure 12. Here, ERA5 is used in both stages of the modelling demonstration to allow for the downscaled output to be compared to the ‘true’ high resolution ERA5 in the validation region. This comparison is made in the bottom right plot in Figure 12, showing good agreement between the model output and the true mslp. This therefore indicates good promise in using this method for downscaling.

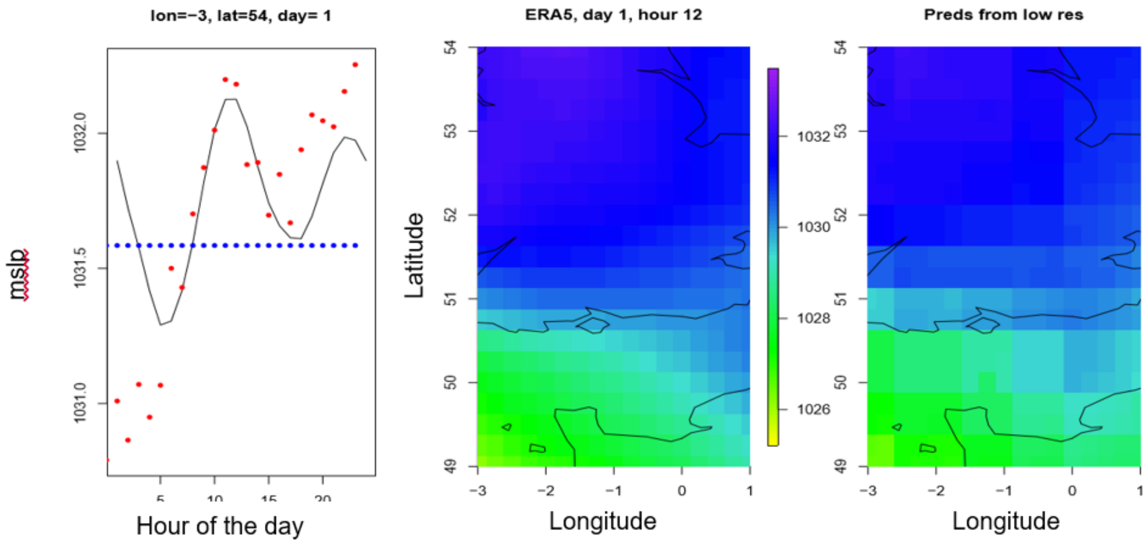

Figure 13: A demonstration of the data science spatial-temporal downscaling approach, rained to transform daily low resolution (60 km) mslp to hourly high resolution (30 km) mslp. This model is fitted to all data in 2009 and used to downscale low resolution ERA5 mslp to high resolution on 1st January 2009. The plot on the left shows the true ERA5 hourly mslp (red dots), daily mean ERA5 mslp (blue dashed line) and the downscaling model representation of hourly mslp (black line) for 1st January 2009 in one grid cell (longitude:-3, latitude:54), the middle plot shows the true high resolution ERA5 mslp at 12pm across the study region, and the plot on the right shows the high resolution prediction of mslp from the spatial-temporal downscaling model.

The same data science modelling approach is then extended to downscale in both space and time. The GAM modelling framework is now trained to capture the relationship between daily 60 km ERA5 mslp (low resolution ERA5) and hourly 30 km ERA5 mslp (high resolution ERA5), where this relationship is allowed to vary non-linearly with longitude, latitude, time of the day and time of the year.

A demonstration of this spatial-temporal downscaling is shown in Figure 13. The model is now trained on all days in 2009 and then used to downscale low resolution (daily) mslp to high resolution (hourly) mslp on 1st January 2009. The results in Figure 13 show that the downscaling model is able to capture the daily variability in mslp reasonably, and the resulting downscaled spatial field of mslp at 12pm shows generally good agreement with the true ERA5 mslp.

While it is expected that the results in Figure 13 could be improved with further model development, this data-science modelling approach for downscaling low resolution climate model data (DePreSys and UKCP18) is showing good promise. In addition, it is known that there is a more distict within-day cycle in temperature, wind speed and solar irradiance (Dawkins, 2019) compared to mslp, hence temporal downscaling will be more sucessful in these weather variables. In addition, in order to characterise long-duration, multi-day events, it is not essential to recreate the exact hourly variability, rather a plausible realisation is necessary.

The downscaling model presented here can be trained/fitted in minutes and is therefore well suited for application to whole years of climate model output, as would be required for this project, confirming its feasibility. An additional advantage of using a data science approach for downscling is that each downscaled field will have an associated quantification of uncertainty. This means that, rather than just using the downscaled mean (as shown in Figures 12 and 13) a range of plausible downscaled high resolution fields can be provided, giving a number of alternative plausible adverse weather scenarios.

When completing this phase of the project it will be important to rigorously validate the data science modelling framework that is developed. This could be achieved using an approach similar to that shown in Figure 9, comparing downscaled ERA5 in a region not included within the model fitting/training, with the true high resolution ERA5 in that region (i.e. cross-validation). In addition, the resulting downscaled gridded data must be comprehensively verified to ensure it is realistically representing the relevent meteological variables. Specifically, the spatial and temporal correlations in the meteorological variables must be explored to ensure they are consistant with those in the reanalysis data. Further, the correlations between different meteorological variables in the downscaled data must also be explored to ensure they reflect the relationships seen in the reanalysis.

It must be noted that when aiming to represent long-duration adverse weather events such as wind droughts, very accurately characterising the hourly small-scale variability in each weather variable is less relevant. Rather, it will be more important to correctly represent the average underlying weather (ensured through the data calibration step), and that the downscaling models simply produces plausible high resoltuion variability in the weather variables. Furthermore, the most important variables in these events (wind and temperature) vary relatively slowly in space and time at the resolution of interest.

5.2.4. Represent solar radiation (Phase 2 b)

The DePreSys hindcast data set contains temperature, wind speed, wind direction and mslp at a daily resolution. Further weather variables are available at a monthly temporal resolution, however, none of these relate to solar irradiance. As a result, if the DePreSys data set is used in this project to more comprehensively represent the variability and extremity of historical weather scenarios, an approach must be developed for representing solar radiation on the same space-time grid as the other relevant weather variables.

The solar radiation available at the top of atmosphere (TOA), i.e. above the clouds, 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 Earth's rotation and movement around the sun (Meeus, 1998). Figure 14 shows a representation of how TOA solar radiation, calculated based on these principles, varies with time and across the UK domain.

In capturing this available TAO solar radiation, most of the variability in solar radiation explained by spatial and temporal information (e.g. longitude-latitude, time of day) is represented. It therefore remains to develop a model for adjusting this TOA radiation to represent surface solar irradiance, according to the meteorological conditions that are available from the DePreSys data set. Again, this can be achieved using a data science modelling framework, similar to that used for downscaling, as presented in Section 5.2.3.

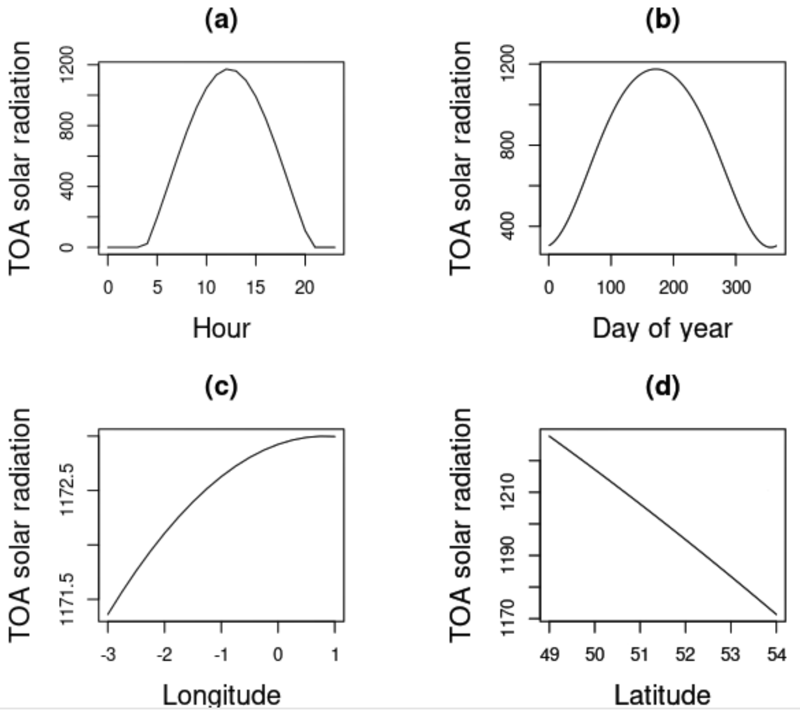

Figure 14: The variability in TOA solar radiation with (a) hour of the day [on 30th June 2009, for longitude:-3, latitude:54], (b) day of the year [at 12 noon, for longitude:-3, latitude:54], (c) Longitude [on 30th June 2009, at 12 noon, for latitude:54], and (d) Latitude [on 30th June 2009, at 12 noon, for longitude:-3].

To test the feasibility of such an approach, we develop a GAM model for predicting hourly ‘residual’ solar irradiance (surface solar irradiance minus TOA solar) in one high-resolution grid cell, from daily low-resolution mslp, temperature, wind speed, wind direction and NAO, a large-scale climatic mode of variability, known to influence UK weather. Again, this GAM is developed using ERA5 gridded output only to allow for validation of the predicted output compared to true high resolution ERA5 solar irradiance.

Figure 15 shows the relationship between ERA5 hourly residual solar radiation and other weather variables on a daily resolution, during summer, in one grid cell (longidue:-3, latitude:54). These plots indicate various non-linear relationship between these weather variables, which could be captured by the GAM model and used to predict hourly residual solar irradiance. For example, there is an indication that windier, cooler days in summer have generally lower residual solar radiation. This aligns with expectations, as windier and cooler conditions often coincide with cloudy skies in summer. In addition, Figure 15 correctly identifies how higher mslp leads to clear skies conditions and hence higher residual solar irradiance.

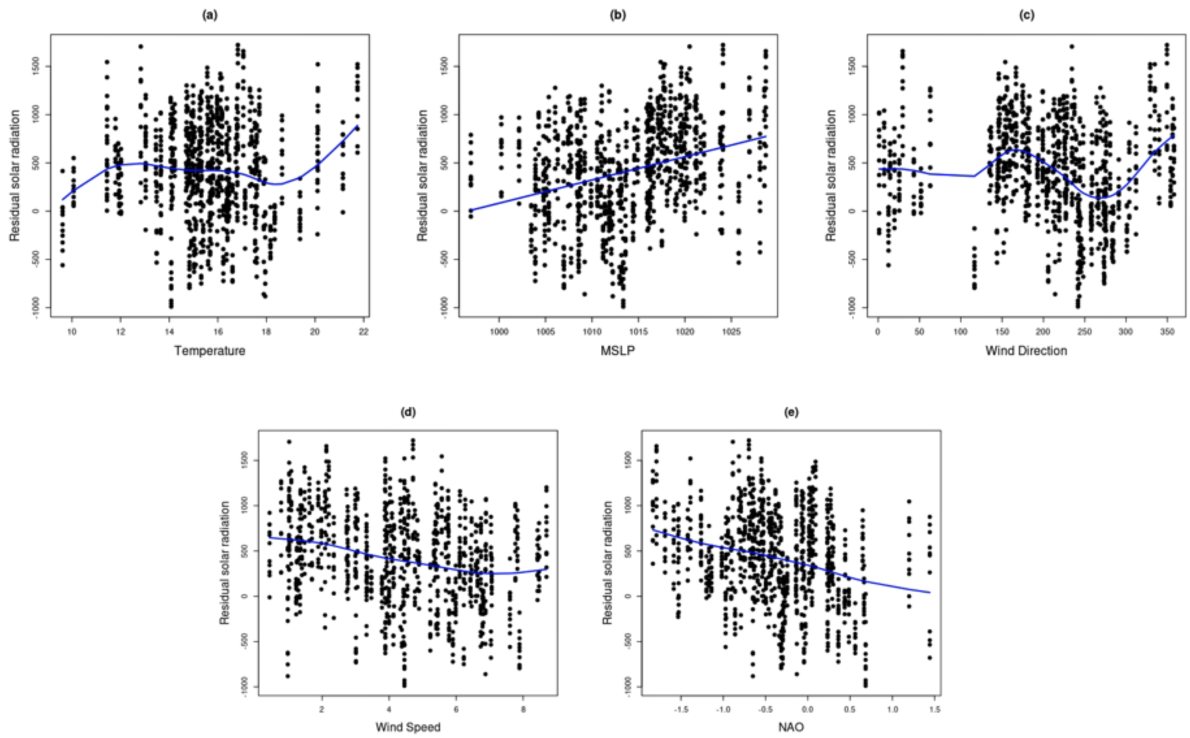

Figure 15: The relationship between ERA5 hourly residual solar irradiance (surface solar irradiance minus TOA solar radiation) and ERA5 daily (a) temperature, (b) mslp, (c) wind direction, (d) wind speed, and (e) NAO, for summer months (June, July, August), 8am-6pm, for high-resolution grid cell longidue:-3, latitude:54. In each plot a cubic smoothing spline[22] is included (blue line), showing the general non-linear relationship between the two variables in the plot.

The relationship between these weather variables and residual solar irradiance is likely to vary with time of year. For example, anomalously cold conditions are associated with clear skies and hence high solar radiation in winter, while hotter than average temperatures are associated with the same conditions in summer. This can be accounted for within the GAM model by allowing the relationships between weather variables to vary with time of year. In addition, we can use insights from the known meteorology of the UK to improve the success of the prediction model. Specifically, it is known that, when wind is blowing from the south-west and temperatures are lower/higher than average in summer/winter, it is likely to be cloudy and hence solar irradiance will be low, while when wind is blowing from the north-east and temperatures are higher/lower than average in summer/winter, there are likely to be clear skies in the UK and hence solar radiation will be high. The GAM modelling framework allows us to represent this by including the effect of the interaction between wind direction, temperature and time of year, on the residual solar irradiance.

Figure 16 presents the validation of this GAM modelling framework, developed to represent hourly residual solar irradiance in 2009 in a single high-resolution grid cell (longidue:-3, latitude:54). This model can be used to represent surface solar radiation by adding back on TOA solar radiation.

[22] https://www.centerspace.net/smoothing-cubic-splines (Accessed 09/03/2020)

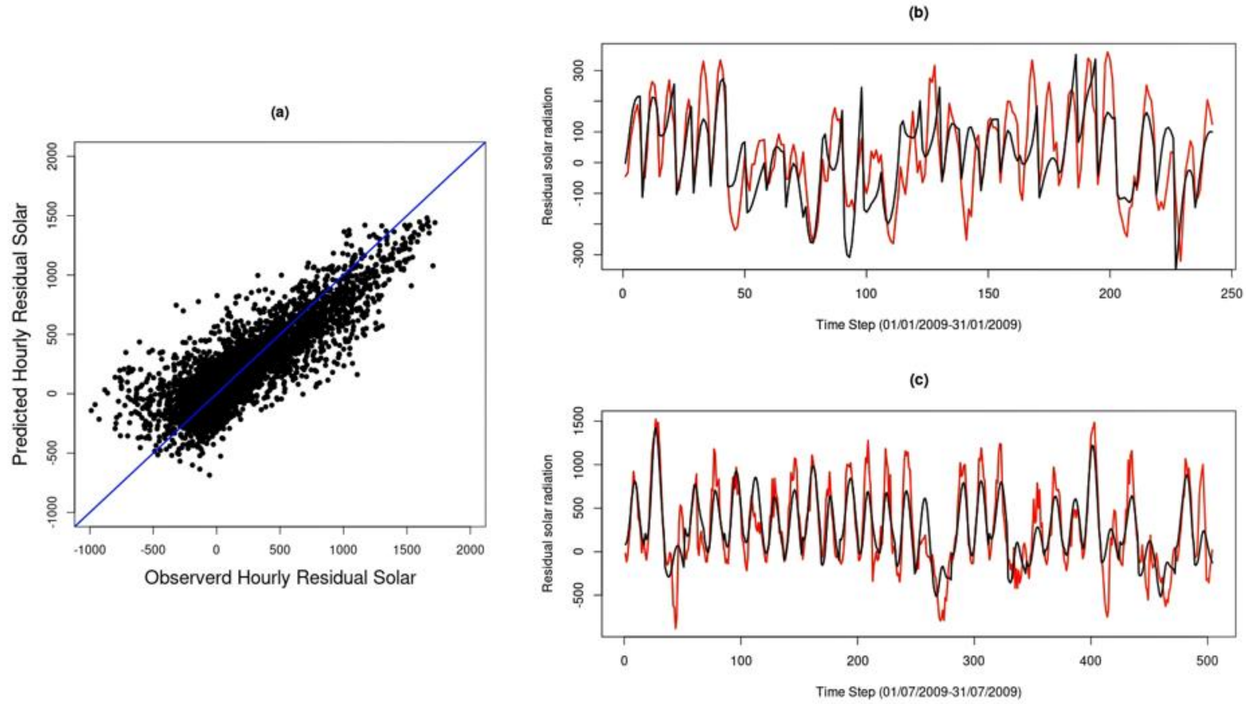

Figure 16: A demonstration of the GAM model developed to predict hourly high-resolution residual solar irradiance from daily low-resolution mlsp, wind speed, wind direction, temperature and NAO. This model is trained/fitted using ERA5 data from all hours in 2009 with TOA solar radiation greater than zero, for one high-resolution (30 km) grid cell in the UK domain (longidue:-3, latitude:54). Plot (a) shows a scatter plot of the relationship between ERA5 true 'observed' hourly residual solar irradiance, and hourly residual solar irradiance predicted from the GAM model for all modelled hours in 2009. The blue line indicates where y=x, i.e. where the true and predicted values are the same. Plots (b) and (c) show the same comparison but as a time series for modelled hours in (a) January 2009 and (b) July 2009, where the red line is the ERA5 true 'observed' hourly residual solar irradiance and the black line is predicted hourly residual solar irradiance from the GAM model.

The results in Figure 16 show how the flexible GAM modelling framework is able to capture the variability in the observed hourly residual solar irradiance. This is evidenced by the points in plot (a) lying close to the line y=x (i.e. truth and predicted values are similar), and reflected in the alignment of the true (red) and predicted (black) times series in plots (b) and (c). It is clear from Figure 16 (b) and (c) that the model is better at predicting residual solar irradiance from other weather variables in summer months. The GAM model is even able to capture some of the very extreme residual solar irradiance values in the observed time series (e.g. the second peak in Figure 16 c). This is advantageous, as quantifying solar irradiance in summer will be of most importance when considering adverse weather scenarios for the electricity system. A number of the observed summer peaks are, however, not captured by the model, reflected in how the scatter points in Figure 16 (a) lie below the lie y=x for high levels of residual solar. Further work is required to tune the GAM model to better represent all peaks in solar, as these will be important for accurately representing surplus solar stress events. Consistent results to those shown in Figure 16 are found when the model is trained to predict residual solar radiation in alternative grid cells in the UK domain.

This approach for representing solar radiation is therefore showing good promise. Similar to the GAM models developed in the previous section, this model takes minutes to fit to a single year and grid cell, indicating its feasibility to be extended to model across more years and grid cells.

5.2.5. Incorporate climate change (Phase 2 b)

As discussed in the related literature review (Dawkins, 2019), the latest UK climate projections released by the Met Office in November 2018 (Lowe, 2018), show a clear increasing signal in UK temperatures. The magnitude of this increase depends on the level of climate change mitigation employed globally and the ultimate sensitivity of the climate system to greenhouse gas emissions, characterised by the Representative Concentration Pathways (RCPs) described in Section 7.4 of (Dawkins, 2019). Specifically, the UKCP18 results suggest that winter minimum temperatures are on average most likely to rise by 1 – 2°C throughout the UK by 2100; and summer maximum temperatures are on average most likely to rise by 2 - 3 °C in the south of the UK by 2100. Further, the UKCP18 headline findings report[23] notes how, in the recent past (1981-2000), the chance of seeing a summer as hot as 2018 was low (<10%), while currently (2018/19) the chance is between 10-20%, and due to further warming will increase to approximately 50% by 2050. As discussed in on page 62 of (Dawkins, 2019), this projected warming in the UK is likely to affect energy demand in the UK, both in terms of potentially reducing winter-time heating demand and increasing summer-time cooling demand.

The effect of climate change on wind speeds and solar irradiance, on the other hand, is less well understood (Dawkins, 2019), with various studies showing conflicting results. It is important to note, however, that often these studies focus on the mean of the meteorological variable, and hence there may be a plausible change affecting the extreme adverse weather scenarios, which must be captured.

There has been some consideration within the UKCP18 analysis (Lowe, 2018), of how climate modes of variability, such as the 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, 2018) note, however, that it is unclear if this change in NAO is due to natural variability or is part of a human driven trend. Recent work within the Met Office has also aimed to explore how the occurrence and persistence of the previously introduced weather regimes (Neal, et al., 2016) may change in the future. Very preliminary results indicate a possible increase in the occurrence and persistence of blocking weather patterns (which lead to low wind speeds) in the summer and an increase in the occurrence of stormy weather patterns in the winter. These insights highlight the importance of capturing the effect of climate change on the meteorological conditions associated with the adverse weather scenarios produced by this project.

Initially, an exploration could be carried out to understand how adverse weather scenarios, identified using the derived adverse weather event metric (e.g. wind drought index), change in future climates. This could be achieved by identifying adverse weather events using future years from both the UKCP18 *global* projections (to better capture the range of possible futures) and *regional* projections (to better capture small scale atmospheric processes), and observing how the events change in terms of duration and severity, with time, under different RCPs, and across different regions. This exploration would allow a more explicit understanding of how climate change will impact electricity system resilience, answering questions such as: do long-duration adverse weather scenarios related to peak energy

[23] https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-headline-findings-2.pdf (Accessed 13/03/2020)

shortfall get longer, more severe, more frequent? And how does this change vary across different regions of Europe?

Following this, it will be important to characterise any identified change in adverse weather, within the data set of scenarios produced within this project. There are a number of relevant projects ongoing at the Met Office from which a method for doing so could be derived from. In a similar way, these projects aim to characterise environmental risk in the historical period and then quantify and represent this risk in future climates. One such project, funded through the Met Office is aiming to combine methods for estimating flood risk in the UK with future climate projections, to create a future flood risk assessment tool. This project began in early 2020, hence the approaches for doing so are still evolving. Possible methods for adjusting their flood risk to account for climate change currently involve either using UKCP18 projections directly and quantifying the risk in future decades, or using the projections to define climate uplift/change factors, which can be used to adjust the historical risk maps to represent future increases/decreases in risk.

Another relevant on-going project is the development of the Bank of England's 2021 biennial exploratory scenarios on the financial risks from climate change[24]. This project aims to develop a number of plausible future climate narratives, and produce the corresponding climate projections, to allow for the exploration of the financial risks posed by climate change. Again, this project is in its infancy, hence the method for producing the necessary climate projections for relevant weather variables is still to be developed. However, it is expected that this will involve adjusting current conditions to represent the required change in climate, hence again using an uplift/change factor approach.

In these types of project, employing an uplift/change factor approach has advantages over directly using the UKCP18 projections, as it allows for the often-richer quantification of the variability in historical risk to be combined with the possible change in future conditions. As such, this approach has been widely used in the past to adapt historical weather to be representative of the future. For example, within the UKCP09 weather generator (Jones, et al., 2011), and many climate change impact assessment studies, as discussed by (Anandhi, et al., 2011). In most cases, however, this approach is used to characterise changes in the mean/average meteorology (e.g. a mean shift in temperature), and is less frequently applied to extreme meteorological phenomena. In addition, it is not clear how such an approach could be extended to adjust adverse weather scenarios to represent future changes in the duration of events.

An alternative method, first developed by (Brown, et al., 2014), has been recently used within a project to quantify the change in meteorological extremes in the UKCP18 projections. This approach is similar to the statistical EVA modelling approach discussed in Section 5.2.1. Here, however, rather than fitting the EVA model to historical events only (i.e. wind drought event severity from the DePreSys hindcasts), events for the UKCP18 future projections are also used, and the EVA model is allowed to vary in time with global mean temperature. Hence, the resulting EVA model characterises the meteorological stress event index as a function of global mean temperature (which is a representation of the magnitude of climate change). This approach would therefore allow for the identification of adverse weather scenarios, characteristic of a required return period (e.g. a 1 in 20 year event) and of the global mean temperature for a year of interest (e.g. 2050) or a warming level of interest (e.g. 2ºC above preindustrial levels). Once this EVA model has been fitted, exploring

[24] https://www.bankofengland.co.uk/paper/2019/biennial-exploratory-scenario-climate-change-discussion-paper (Accessed 12/03/2020)

different warming levels (e.g. 1.5, 2, 3 and 4ºC) is easily achieved by simply adjusting the 'global mean temperature' variable in the model. This method therefore has the potential to be used to extract adverse weather scenarios of various extreme levels (return periods) for various decades and climate change futures. This method has also recently been used by Met Office colleagues to quantify a high return level extreme temperature event in Wales, characteristic of future climate change to 2080, relevant for informing a nuclear infrastructure safety case.

All of these potential methods are based on peer-reviewed literature, have been applied on numerous occasions to similar problems, and hence will be feasible to use within this project. The preferred method for this application will evolve through ongoing engagement with relevant experts involved in the aforementioned projects.

5.3 Method Scoping: Short-duration Events

As well as long-duration wind and solar drought events, short-duration extreme fluctuations in wind and solar conditions challenge the resilience of a highly renewable electricity system. For example (Cannon, et al., 2015) found that in the period 1980-2012, wind capacity factor changes of up to 80% have been experienced within 3 hour time windows. In addition, these events are likely to become more extreme and frequent in future electricity systems with higher installed wind and solar capacities and higher demand due to electrification of the heating systems. It is therefore important that they are also captured within the final data set of adverse weather scenarios.

5.3.1 Relevant data sets

This type of short-duration meteorological event is often characterised by a large change in wind/solar energy generation in a short period of time (i.e. a matter of hours), leading to what is known as a 'ramp' in energy generation. As such, the hour-to-hour variability in the data used to characterise such events is very important and must be accurately represented. For this reason, using the downscaled climate model data (DePreSys and UKCP18 historical projections) described in relation to the long-duration methodology in previous sections, would not be optimal here. Rather, a data set of hourly or sub-hourly meteorological variables should be used. In addition, for understanding the resilience of the UK electricity system to this type of event, meteorological information across only the UK is required (i.e. interconnectivity with Europe is not as relevant on these short time scales).

Currently, reanalysis data sets are often used to explore this type of event, for example the work of (Cannon, et al., 2015). These data sets are advantageous in being available for up to a 1-hourly temporal resolution, however, they are known to underestimate extreme weather compared to raw observations (Cannon, et al., 2015). Being able to accurately represent extremes is particularly relevant for this application, hence reanalysis data may not be optimal.

As an alternative, the Met Office UK land observation system[25] data set could be used. This consists of temperature, wind speed, pressure and cloud cover information recorded at an hourly resolution across a dense system of sensors in the UK. In addition, this information could be supplemented by satellite observations, such as from SARAH[26], which provides half-hourly solar irradiance information in the period 1983-2013.

In using just the observational period, however, we are not addressing key question 2 posed at the beginning of Section 5: *Could something worse than that observed in the historical period have plausibly happened?* Since these short-duration events are, by their very nature, shorter than the long-duration events, there will likely be many more of them within the observation record. In addition, since these are more local phenomena, there are likely to be more examples of them within the observational record. As a result, their variability will be better represented by the historical record. These observations could, however, be supplemented with short-range (out to 12 hours) high resolution (hourly, 1.5 -2.2km) weather forecasts from the Met Office UK forecasting system[27]. Historical forecasts from this model have been archived since 2010, and are available in both deterministic and ensemble forecast[28] formats from MOGREPS-UK (Met Office Global and Regional Ensemble Prediction System - UK). Including these forecasts would therefore provide a number of alternative 12 hour periods to those that have been observed since 2010, and hence may characterise short-duration ramping events more extreme than those experienced in the observational record. Similar to the DePreSys and UKCP18 model data, these weather model generated forecasts would require validation and calibration to ensure their accuracy in representing observed meteorological variables.

5.3.2. Define and identify adverse weather scenarios

Short-duration adverse weather scenarios are characterised by a large change in energy generation in a small time window. Since this definition is related to energy generation, and not the meteorological variable itself, again, the available weather data must be related to energy generation in order to identify extreme adverse weather events.

Similar to the long-duration event, this could be achieved by developing stress event indices to characterise these short-duration ramping events in terms of the related meteorological conditions. These could quantify the change in winds/solar conditions, the time window over which the change occurred, and the spatial extent of the rapid change. In addition, the most relevant form of the meteorological variables must be explored, for example, it may be more relevant to study wind-gusts[29] rather than wind speeds when aiming to represent wind ramping events.

Again, these indices could be verified using historical energy data, as well as the insights of expert energy modellers in the project advisory and user groups.

[25] https://www.metoffice.gov.uk/weather/guides/observations/uk-observations-system (Accessed 13/03/2020)
[26] https://climatedataguide.ucar.edu/climate-data/surface-solar-radiation-data-set-heliosat-sarah-edition-1 (Accessed 13/03/2020)
[27] https://www.metoffice.gov.uk/research/approach/modelling-systems/unified-model/weather-forecasting (Accessed 13/03/2020)
[28] https://www.metoffice.gov.uk/research/weather/ensemble-forecasting/what-is-an-ensemble-forecast (Accessed 13/03/2020)
[29] https://www.thoughtco.com/why-wind-gusts-3444339 (Accessed 24/03/2020)

Once these stress event indices have been developed, the most extreme events, or events associated with specific return periods, could be selected using empirical or statistical EVA methods.

5.3.3. Explore the effect of climate change

Wind speed and solar irradiance are most important for characterising these short-duration adverse weather scenarios. As previously described in Section 5.2.5, the effect of climate change on these two variables is less well understood compared to, for example, temperature. Further, changes in short-duration fluctuations of these variable within climate change projections have not yet been explored, since until very recently the spatial-temporal resolution of climate models has not allowed this level of detail.

The new UKCP18 high-resolution (2.2km) future projections are run at a high enough resolution to resolve the types of meteorological conditions that may lead to rapid changes in generation. These projections contain 3-hourly wind speeds and wind-gusts for the UK to 2080. This data could therefore be used to explore how climate change may affect fluctuations in wind speed over 3 hour time windows. This insight could then be used to understand and characterise wind ramping events in future climates. These UKCP18 projections do not provide sub-daily solar information and hence cannot be used to explore future changes in solar ramping events.

5.3.4. The Proposed Method

A similar two stage approach is proposed for the short-duration event phase of the project. In the first stage, the definition of what constitutes wind and solar ramping events is explored using historical weather and energy information, addressing key question 1 at the beginning of Section 5. The second stage then aims to address key questions 2 and 3, by using these stress event definitions to identify adverse weather in the MOGREPS-UK ensemble forecasts and high resolution UKCP18 future projections. This two stage approach is summarised in Figure 17.

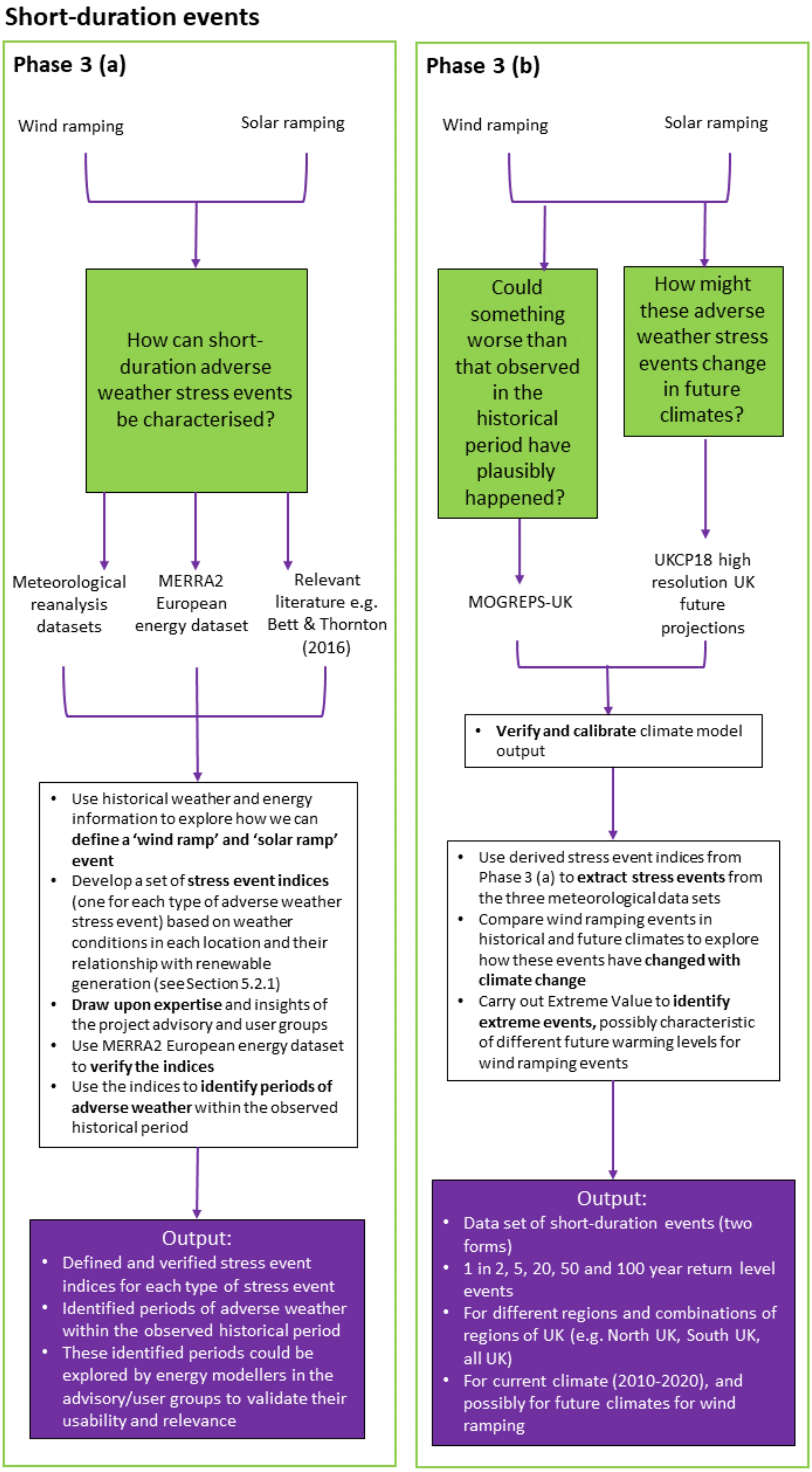

Figure 17: A diagram summarising the proposed method for completing Phase 3 of the project

6. Summary of recommendations

Through the stakeholder engagement, the Discovery phase has identified the need for a set of electricity system relevant adverse weather scenarios, characteristic of many years of plausible weather, and the effect of climate change. These weather scenarios must be contained within whole years of gridded temperature, wind speed and solar irradiance information, at the same spatial-temporal resolution as gridded reanalysis data. They must characterise extreme adverse weather events of various extreme levels, for different regions of Europe, and a range of future climate change scenarios, and be relevant for a range of possible electricity system configurations.

These adverse weather scenarios should be used in combination with, rather than instead of, existing weather data sets which are currently used to optimise electricity system design. These scenarios should be used as an additional ‘weather stress test’ of a designed electricity system, to ensure its resilience to plausible extreme weather, representative of future climates. In doing so, energy modellers will have increased confidence that future electricity system models, used to inform government policy advice and investment decision making, are resilient to a range of plausible adverse weather scenarios.

Long-duration, energy shortfall and surplus events were identified as being the most important to study, followed by short-duration renewable generation ramping events.

In developing these datasets of adverse weather stress events, three key questions will need to be addressed:

1. **How can adverse weather events be characterised using meteorological information?**
2. **Could something worse than that observed in the historical period have plausibly happened?**
3. **How might these adverse conditions change in future climates?**

For both long-duration (Phase 2) and short-duration (Phase 3) stress events, it is recommended that these three key questions be addressed in two stages. The first stage answering key question 1 and the second stage answering key questions 2 and 3. The proposed data sets and steps involved in completing these project phases are summarised in Figures 4 and 17.

For long-duration stress events, Phase 2 (a) aims to draw upon insights from hydrological drought modelling and heatwave characterisation to develop a set of stress event indices characteristic of winter-time wind drought with below average temperatures, summer-time wind drought with above average temperatures, and summer-time surplus solar. These indices will be developed and verified using historical meteorological and energy data, as well as the insights of energy modellers in the project advisory and user groups. Phase 2 (b) will then use these derived stress event indices to explore adverse weather in the DePreSys and UKCP18 historical and future projections. As these are climate model data sets they must first be verified and calibrated, and downscaled to the required spatial-temporal resolution. In addition, solar information must be modelled for the DePreSys output. The final output of this phase of the project will be:

- Defined indices that can be used to identify long-duration stress events in climate data sets.
- Data set of long-duration events (three forms), taken from DePreSys and UKCP18
- 1 in 2, 5, 20, 50 and 100 year return level events in terms of stress event duration and severity
- Contained within whole years of weather hourly, 30km weather data
- For different regions and combinations of regions of Europe (e.g. North UK, South UK, all UK, all Europe)
- For current climate (2020), and for 1.5, 2, 3 and 4^{o}C warmer than the preindustrial climate

For short-duration stress events, Phase 3 (a) will also develop a set of stress event indices, however in this phase characteristic of renewable generation ramping events (wind and solar). Similar to the long-duration events, these indices will be developed and verified using historical meteorological and energy data, as well as the insights of energy modellers in the project advisory and user groups. Phase 3 (b) will then use these derived stress event indices to explore adverse weather in the Met Office ensemble weather forecasts (MOGREPS-UK) and UKCP18 high resolution future projections of wind speeds and wind gusts. Again, this weather and climate model data will require verification and calibration. The final output of this phase of the project will be:

- Defined indices that can be used to identify short-duration stress events in meteorological datasets.
- Data set of short-duration events (two forms)
- 1 in 2, 5, 20, 50 and 100 year return level events
- For different regions and combinations of regions of UK (e.g. North UK, South UK, all UK)
- For current climate (2010-2020), and possibly for future climates for wind ramping

Energy modeller role

During these project phases there will be opportunities for the energy modelling experts in the project advisory and user groups to help inform and verify the project outputs.

Specifically, expertise will be drawn upon in a qualitative way when developing the stress event indices. For example, to help inform how the meteorological variables influence electricity generation and demand. Following this, the energy modellers will be given the opportunity to validate the derived stress event indices, by ingesting identified periods of historical reanalysis adverse weather within their existing energy models. This will help to discern whether these periods identified as stress events by the derived indices are indeed challenging for a range of energy models, and for the future systems that are of relevance to the potential users of the final adverse weather dataset.

Throughout the project, the energy modelling experts in the project advisory and user groups will also be able to test and explore the various output data sets as they become available. The feedback from these experts will then help to inform further stages and phases of the project.

Filling in the gaps

The literature review, completed by the Met Office in 2019, highlighted insights, and remaining gaps, in understanding the weather and climate related risks to the UK electricity system. This review identified the key types for adverse weather stress events for the electricity system, possible opportunities in resilience associated with utilising the spatial and temporal variability as well as the dependence between relevant meteorological conditions, and a number of existing gaps in understanding. These included the under representation of summer-time electricity system stress (which may become more severe in a warming climate due to an expected uptake in air conditioning), the absence of solar irradiance and climate change in many electricity system resilience studies, and the current use of limited historical periods of meteorological data which may not include all plausible extreme conditions.

The outputs of the next phases of this project will build upon the insights of the literature review by characterising the five key types for adverse weather stress events, and by producing datasets that span the full European domain in a spatially and temporally coherent way. This will allow energy modellers to explore the identified potential opportunities in balancing the energy system using, for example, the dipole in meteorological conditions in North and South Europe, and the summer-time anti-correlation between wind speed and solar irradiance in the UK.

The adverse weather datasets created within the project will also help to fill the gaps identified by the literature review, by providing events that characterise extremes in the summer-time, and in solar conditions (as well as winter-time and adverse wind and temperature events). The extreme events will also be characteristic of many more years of plausible weather data than is currently used, helping to better represent climate variability and extremes. Finally, the project will address the important gap in understanding the effect of climate change on electricity system resilience.

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8. Glossary

DePreSys = Decadal Climate Prediction System

ECMWF = European Centre for Medium-range Weather Forecasting

ERA5 = ECMWF fifth generation reanalysis data set

EVA = Extreme Value Analysis

GAM = Generalised Additive Model

HadGEM3 = Hadley Centre Global Environment Model version

MERRA2 = Modern-Era Retrospective analysis for Research and Applications, Version 2

MOGREPS-UK = Met Office Global and Regional Ensemble Prediction System - UK

mslp = mean sea level pressure

NAO = North Atlantic Oscillation

RCP = Representative Concentration Pathway

SARAH = Surface solar radiation data set - Heliosat

TOA = Top Of Atmosphere

UKCP18 = UK Climate Projections 2018

UNSEEN = UNprecedented Simulated Extremes using Ensembles

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