Enabling Resilient UK Energy Infrastructure: Natural Hazard Characterisation Technical Volumes and Case Studies

Volume 2:

Extreme High and Low Air Temperature

LC 0064_18V2

EDF Energy · energy technologies institute · IChemE Advancing Chemical Engineering Worldwide · Institution of Mechanical Engineers · Met Office · Mott MacDonald

Legal Statement

Authors: Kate Brown, Erika Palin, Kate Salmon (Met Office); Tony Hull (Mott MacDonald)
Chief Technical Officer: Hugo Winter (EDF Energy)

Version	Date	Details
0.1	26/01/18	Submitted for IPR
0.2	22/02/18	IPR comments addressed and submitted to CTO
1.0	21/03/18	CTO comments addressed and submitted to ETI
2.0	02/05/18	ETI and NHP3 Steering Committee comments addressed

This document forms part of the Energy Technologies Institute (ETI) project 'Low Carbon Electricity Generation Technologies: Review of Natural Hazards', funded by the ETI and led in delivery by the EDF Energy R&D UK Centre. The aim of the project has been to develop a consistent methodology for the characterisation of natural hazards, and to produce a high-quality peer-reviewed set of documents suitable for use across the energy industry to better understand the impact that natural hazards may have on new and existing infrastructure. This work is seen as vital given the drive to build new energy infrastructure and extend the life of current assets against the backdrop of increased exposure to a variety of natural hazards and the potential impact that climate change may have on the magnitude and frequency of these hazards.

The first edition of *Enabling Resilient UK Energy Infrastructure: Natural Hazard Characterisation Technical Volumes and Case Studies* has been funded by the ETI and authored by EDF Energy R&D UK Centre, with the Met Office and Mott MacDonald Limited. The ETI was active from 2007 to 2019, but to make the project outputs available to industry, organisations and individuals, the ETI has provided a licence to the Institution of Mechanical Engineers and Institution of Chemical Engineers to exploit the intellectual property. This enables these organisations to make these documents available and also update them as deemed appropriate.

The technical volumes outline the latest science in the field of natural hazard characterisation and are supported by case studies that illustrate how these approaches can be used to better understand the risks posed to UK infrastructure projects. The documents presented are split into a set of eleven technical volumes and five case studies.

Each technical volume aims to provide an overview of the latest science available to characterise the natural hazard under consideration within the specific volume. This includes a description of the phenomena related to a natural hazard, the data and methodologies that can be used to characterise the hazard, the regulatory context and emerging trends. These documents are aimed at the technical end-user with some prior knowledge of natural hazards and their potential impacts on infrastructure, who wishes to know more about the natural hazards and the methods that lie behind the values that are often quoted in guideline and standards documents. The volumes are not intended to be exhaustive and it is acknowledged that other approaches may be available to characterise a hazard. It has also not been the intention of the project to produce a set of standard engineering 'guidelines' (i.e. a step-by-step 'how to' guide for each hazard) since the specific hazards and levels of interest will vary widely depending on the infrastructure being built and where it is being built. For any energy-related projects affected by natural hazards, it is recommended that additional site- and infrastructure-specific analyses be undertaken by professionals. However, the approaches outlined aim to provide a summary of methods available for each hazard across the energy industry. General advice on regulation and emerging trends are provided for each hazard as context, but again it is advised that end-users investigate in further detail for the latest developments relating to the hazard, technology, project and site of interest.

The case studies aim to illustrate how the approaches outlined in the technical volumes could be applied at a site to characterise a specific set of natural hazards. These documents are aimed at the less technical end-user who wants an illustration of the factors that need to be accounted for when characterising natural hazards at a site where there is new or existing infrastructure. The case studies have been chosen to illustrate several different locations around the UK with different types of site (e.g. offshore, onshore coastal site, onshore river site, etc.). Each of the natural hazards developed in the volumes has been illustrated for at least one of the case study locations. For the sake of expediency, only a small subset of all hazards has been illustrated at each site. However, it is noted that each case study site would require additional analysis for other natural hazards. Each case study should be seen as illustrative of the methods outlined in the technical volumes and the values derived at any site should not be directly used to provide site-specific values for any type of safety analysis. It is a project recommendation that detailed site-specific analysis should be undertaken by professionals when analysing the safety and operational performance of new or existing infrastructure. The case studies seek only to provide engineers and end-users with a better understanding of this type of analysis.

Whilst the requirements of specific legislation for a sub-sector of energy industry (e.g. nuclear, offshore) will take precedence, as outlined above, a more rounded understanding of hazard characterisation can be achieved by looking at the information provided in the technical volumes and case studies together. For the less technical end-user this may involve starting with a case study and then moving to the technical volume for additional detail, whereas the more technical end-user may jump straight to the volume and then cross-reference with the case study for an illustration of how to apply these methodologies at a specific site. The documents have been designed to fit together in either way and the choice is up to the end-user.

The documents should be referenced in the following way (examples given for a technical volume and case study):

ETI. 2018. *Enabling Resilient UK Energy Infrastructure: Natural Hazard Characterisation Technical Volumes and Case Studies,* Volume 1 – Introduction to the Technical Volumes and Case Studies. IMechE, IChemE.

ETI. 2018. *Enabling Resilient UK Energy Infrastructure: Natural Hazard Characterisation Technical Volumes and Case Studies,* Case Study 1 – Trawsfynydd. IMechE, IChemE.

Contents

This report aims to guide and aid the reader in the study and interpretation of techniques that can be used within the energy industry to assess the risks posed by extreme temperature. As a result, the report is intended for those with an interest in assessing the impacts of extreme temperature events, such as how they would affect physical infrastructure or operational planning.

The focus of this report is on extremes of daily maximum and minimum air temperature. However, a brief description and discussion of the following hazards is also provided: extreme water temperature (sea-surface temperature, river and lake temperatures), frazil, rapid changes in air temperature, and wildfires.

1.1 Context: UK temperature climatology and extremes

Temperature is defined as the degree or intensity of heat present in a substance or object, especially as expressed according to a comparative scale and shown by a thermometer or perceived by touch. There is no all-encompassing definition of what constitutes an extreme temperature within the UK, either in the energy sector or meteorological community. Instead, the definition of an extreme event depends upon the particular part of the energy sector being considered, as well as the physical location of the site of interest. For example, it would be expected that the robustness of the nuclear power sector to withstand extremes of temperature is far greater than that of the solar energy sector or energy transmission sector, due to the greater potential impact of any adverse event affecting the nuclear power sector.

To help put extreme temperature events — both future and historical — into context, a brief description is provided for the following parameters of interest for the UK:

- mean daily maximum (minimum) summer (winter) temperatures for the period 1981 to 2010;
- mean hottest (coldest) day in summer (winter) for the period 1981 to 2010; and
- the most extreme temperatures recorded.

The mean daily maximum temperature is computed by taking the mean of all the daily maximum temperatures from each summer period (June to August) for 1981 to 2010, giving thirty values (one per summer), which are then averaged. Thirty years is a standard period used when calculating climate statistics, starting with a year that ends with the digit '1' and ending with a year that ends with the digit '0' (*World Meteorological Organization, 2011*). Similarly, the mean hottest daily maximum is computed by taking the maximum of the daily maximum temperatures instead of the mean. A similar logic applies to minimum and coldest temperatures, with the temperatures being taken from the winter period (December to February).

The mean daily maximum temperature, 1981 to 2010, ranges from less than 14 °C in the Highlands of Scotland to over 21 °C in the south-east of England. In general, the mean daily maximum temperatures are cooler to the west and north of the UK compared to temperatures in the south and east of the UK.

In winter, the south-west has the warmest average minimum temperatures, above 3 °C, and the Central Highlands of Scotland have the coolest average minimum temperatures, less than –4 °C. Generally, coastal areas have warmer averages than inland areas, due to the warming influence of the sea in winter.

On average, hottest daily maxima in summer for the period 1981 to 2010 can reach 31 °C in parts of south-east England. Conversely, on average, coldest daily minima in winter for the period 1981 to 2010 can be –10 °C or colder in the Scottish Highlands.

The absolute highest and lowest temperatures on record for each country within the UK are shown in *Table 1* and *Table 2*. For the UK as a whole, Faversham in Kent has the maximum temperature recorded, 38.5 °C, and Braemar in Aberdeenshire and Altnaharra in the Highlands the lowest value, –27.2 °C. Braemar (OS grid reference NO150913), at 339 m above sea level, is one of the higher villages in the UK; as a result, its temperatures will typically be cooler than those at other sites, as air typically cools between 0.5 °C and 1 °C per 100 m in the troposphere (the part of the atmosphere nearest the surface). In addition, Braemar is flanked by four mountains, the lowest of which has an elevation of 538 m. These mountains can significantly affect the minimum temperature recorded at Braemar (*Graham, 1982*), especially during clear winter nights with little wind. As the air over the mountain cools, it begins to flow downhill leading to very low temperatures in the valley beneath. The record low temperature at Braemar on 10th January 1982 is thought to be the result of this downward flow of cold air off mountains, known as *katabatic wind** (*Holden, 2008*); a similar meteorological process is also believed to account for the equal record minimum temperature recorded at Altnaharra, on 30th December 1995.

*All technical terms marked in blue can be found in the Glossary section.

Table 1. Highest temperatures on record in countries of the UK. (Source: Met Office, 2018a; © Crown copyright Met Office 2018).

Country	Temperature (°C)	Date	Location
England	38.5	10th August 2003	Faversham (Kent)
Wales	35.2	2nd August 1990	Hawarden Bridge (Flintshire)
Scotland	32.9	9th August 2003	Greycrook (Scottish Borders)
Northern Ireland	30.8	12th July 1983	Shaw's Bridge, Belfast (County Antrim)
		30th June 1976	Knockarevan (County Fermanagh)

Table 2. Lowest temperatures on record in countries of the UK. (Source: Met Office, 2018a; © Crown copyright Met Office 2018)

Country	Temperature (°C)	Date	Location
Scotland	–27.2	10th January 1982	Braemar (Aberdeenshire)
		11th February 1895	Braemar (Aberdeenshire)
		30th December 1995	Altnaharra (Highland)
England	–26.1	10th January 1982	Newport (Shropshire)
Wales	–23.3	21st January 1940	Rhayader (Powys)
Northern Ireland	–18.7	24th December 2010	Castlederg (County Tyrone)

1.2 Impacts of extreme temperatures on the energy sector

Extremes of temperature can affect not only the generation of energy, but also energy transmission, distribution, demand and price, and can have health and safety implications for energy-related businesses. Described below are some brief examples of how extreme temperatures have affected the energy industry both within the UK and in Europe.

In France, many nuclear reactors use river water as a coolant. Water used in cooling will itself become warmer in the process; it is returned to the rivers once it has cooled in order to reduce the impact on the environment. In 2003, France experienced a significant ***heatwave*** resulting in some river water levels dropping so low that using the river water as a coolant became impossible. As a result, the reactors affected had to be shut down. In other reactors, and for a number of conventional power stations, the temperature of the water after the cooling process exceeded the environmental safety levels for discharging back to the rivers (*UNEP, 2004*). As energy demand soared within France, exports of energy to other European countries, including Britain, halved during peak periods in order to serve domestic demand. More recently, a heatwave in the UK in September 2016 caused a surge in the price of electricity, as people looked to cool their homes and businesses. The wholesale market price surpassed prices usually seen in the mid-winter months, the typical annual peak demand period (*Ambrose, 2016*).

In addition, not only can extremes of temperature cause an increase in the demand for energy, as businesses and homes look to provide comfortable environments, but they can also have a significant impact on the production and transmission of energy. Examples of impacts of high temperatures include a decrease in the efficiency of thermal conversion, a decrease in the capability of transmission lines to convey the energy, and sagging of transmission lines beyond their design parameters.

2.1 Key influences on UK weather and climate

The UK lies at latitudes of approximately 50°N to 60°N, which means that it can be influenced by air masses originating from a variety of locations (*Figure 1*). The weather experienced by the UK essentially depends on the dominant air mass at a particular time.

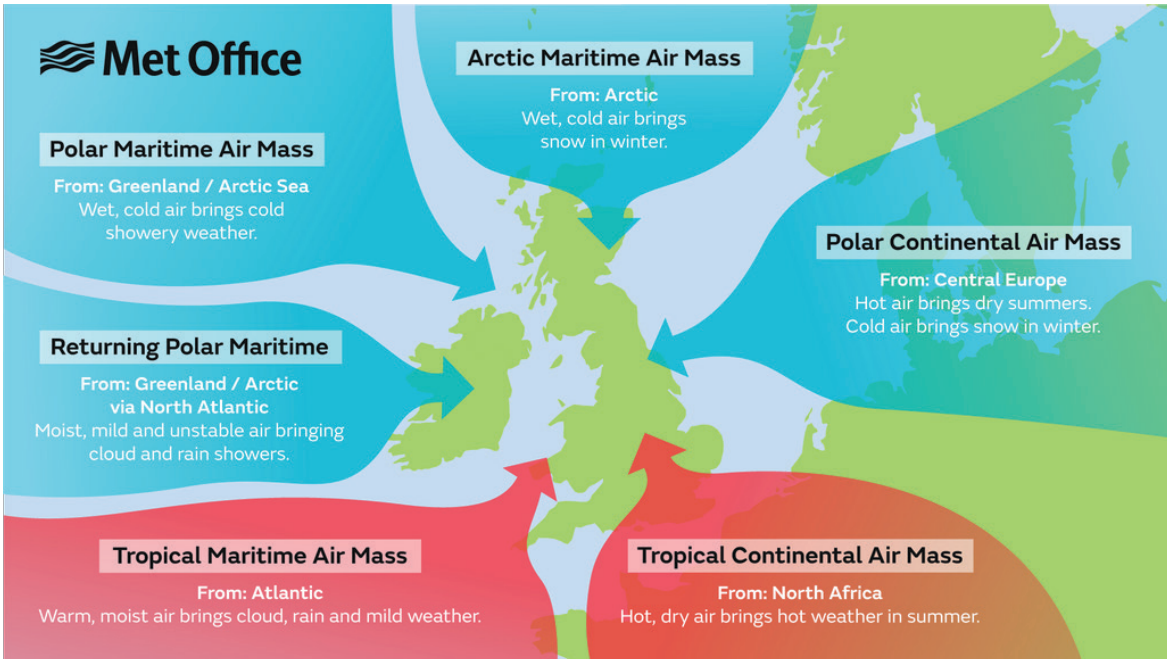

Figure 1. Air masses affecting the UK and their likely impacts in particular seasons. (© Crown Copyright Met Office 2018)

As an island nation, the influence of the sea on the UK climate is another significant factor to consider. In particular, the warm ocean current known as the Gulf Stream, and its northern extension, the *North Atlantic Drift*, have a warming effect, giving the UK much milder winters compared to other countries at a similar latitude.

More generally, the natural variability of the global climate is influenced by large-scale climatic factors called *modes of variability*. The interaction of these modes of variability with one another causes many complex feedbacks, leading to cycles of natural variation in our climate that operate over many timescales, extending even to multiple decades. Two of these naturally-occurring, low-frequency quasi-oscillations are the El Niño Southern Oscillation (ENSO), a coupled ocean-atmosphere variation in the Pacific Ocean region, and the North Atlantic Oscillation (NAO), a pattern of pressure variability over the North Atlantic, usually described as a pressure difference between the usually low pressure over Iceland and the usually high pressure over the Azores. The NAO, in particular, influences the winter climate of the UK. It moves between positive and negative phases (*Figure 2*). In the positive phase, the Iceland/Azores pressure difference is larger, and this is usually associated with stormier, milder winters due to an intensified jet stream bringing westerly flow across the UK. In the negative phase, the pressure difference is smaller, and this is usually associated with calmer, colder winters, due to a weaker and more disrupted jet stream which may allow flow from other directions to dominate.

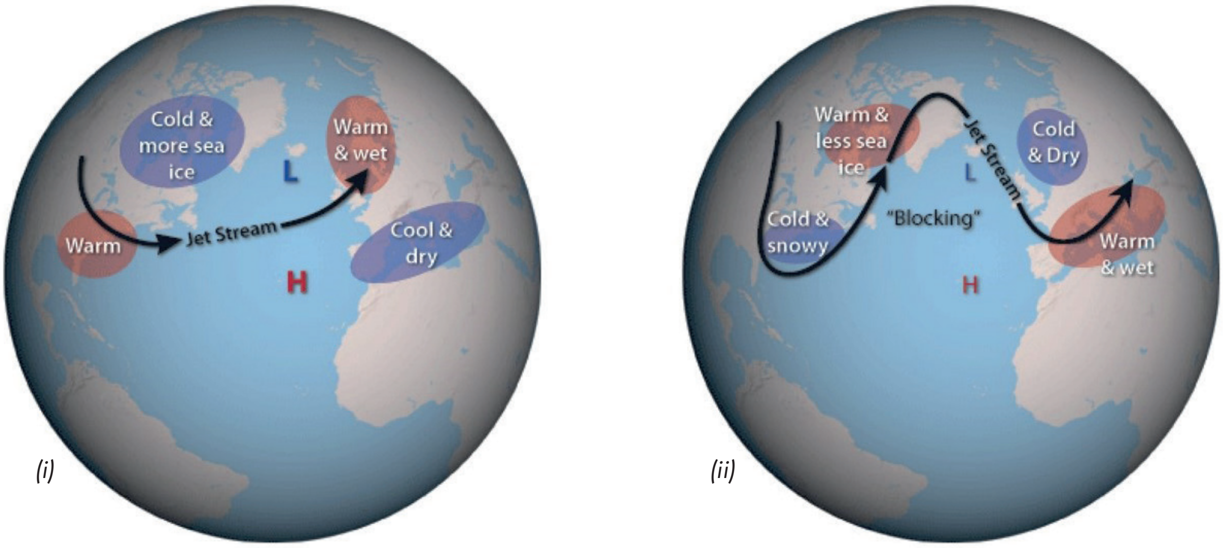

Figure 2. The NAO in its positive (left) and negative (right) phases, showing the influence on the winter climate of the North Atlantic region. Met Office 2018b. (© Crown Copyright Met Office 2018)

2.2 Maximum temperatures

In the UK, the average summer (June to August) maximum temperatures are typically cooler nearer the coast compared to inland temperatures; see *Figure 3*. This is because land and water have different heat capacities, with land warming (and cooling) more quickly than water — so the sea has a moderating influence on the temperatures experienced at the coast. The warmest area is the south-east of England and this reflects the influence of air masses of continental origin. Average summer maximum temperatures for the south-east of England in excess of 21 °C are typical. The west and north of the UK see generally cooler average summer maximum temperatures.

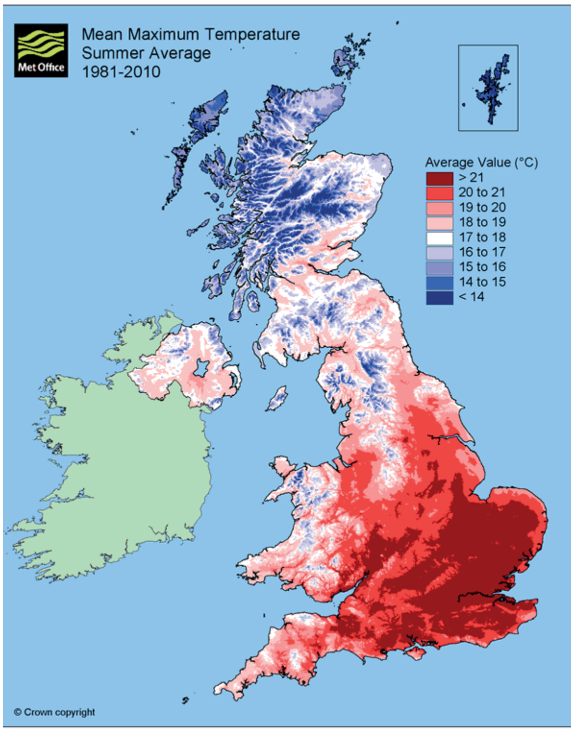

Figure 3. Map of average daily summer (June to August) temperature for the period 1981 to 2010, from the National Climate Information Centre. (© Crown Copyright Met Office 2018)

Burt (2004) described 'very hot' weather in the UK as 'loosely, maxima of 33–34 °C or above' and described the general conditions necessary for this to occur:

- An established high soil moisture deficit — dry soils absorb less solar radiation in evaporating moisture, leaving more energy available as ***sensible heat*** to warm the air.
- A high solar angle — typically, a time lag after the equinox is required to allow the atmosphere to warm up, so the highest air temperatures are most likely to occur mid-July to mid-August.
- A warm anticyclone (high pressure system) — the air flows clockwise around an anticyclone and so the position of the high pressure system centred over continental Europe produces a 'conveyor belt' of warm air to the UK, that originated in North Africa and the Sahara. In the UK, the highest temperatures usually occur under the influence of this tropical continental air mass, resulting in temperatures over 30 °C by day and around 15 °C to 20 °C at night.
- Anticyclonic subsidence — this caps vertical mixing of strongly heated surface air, essentially preventing any clouds from forming and so ensuring that optimal levels of incoming solar radiation are received at the ground.

On very hot days, the difference between temperatures experienced at a coastal site and a nearby inland site could be of the order of 5 °C. The hottest day on record in the UK was 5th

August 2003 when an instantaneous temperature of 38.5 °C was recorded at Faversham in Kent, an inland site; the heat was mainly confined to the south-east of England, as a frontal system introduced cloudier conditions to western areas. Although coastal sites are generally cooler than inland sites in summer, it is worth noting that on the same day the temperatures recorded for parts of coastal east Kent were also very high, between 34 °C and 36 °C.

In the context of the high temperatures recorded on 10th August 2003 for eastern and south-eastern England, *Burt (2004)* attributes the most important factors as:

- proximity to the very warm air being advected from the continent;
- the absence of cloud cover;
- the distribution of surface wind flow, which was to the west and north-west of London, and as a result the already warm air was warmed further as it moved inland and flowed across London; and
- the presence of very dry subsiding air.

Depending on the particular energy asset under consideration, different variables relating to extreme temperatures may be required to enable appropriate design or review. Examples include:

- maximum/minimum instantaneous temperature in a day;
- most extreme 24-hour mean temperature;
- most extreme 12-hour mean temperature.

2.2.1 Heatwaves

A heatwave is defined as a prolonged period of abnormally hot weather. Historically, in the UK, the most impactful heatwaves have occurred in July and August (e.g. the August 2003 and July 2006 events), but heatwaves outside these months are also possible, and heatwaves lasting multiple months may also occur, e.g. the summer 1976 heatwave which lasted from mid-June until the end of August (*Met Office, 2018e*).

Currently, there is no universal definition of a heatwave (*Sanderson and Ford, 2016*). The Met Office's definition of a heatwave (*Met Office, 2018d*) is based upon the World Meteorological Organization definition, which is when the daily maximum temperature for more than five consecutive days exceeds the average maximum temperature by 5 °C, with the average maximum temperature being calculated for the period 1961 to 1990.

A further system, the Heat-Health Watch system, operating in England only, considers heatwaves from a human-health perspective. Alerts under this system are region-specific and are issued when the daily maximum temperature on two or more consecutive days is forecasted to be higher than a region-specific threshold and at least one intervening daily minimum temperature is forecasted to be higher than a region-specific threshold (*Sanderson and Ford, 2016*). As this system is focused on resilience of the human population, it may be less appropriate for use in evaluating heatwave impacts on the energy system, unless human-health impacts are of particular interest (e.g. for the management of new infrastructure builds where personnel are working outside).

2.3 Minimum temperatures

The lowest temperatures across the UK are usually associated with air masses from the north and east. An example, from the extremely cold month of December 2010, is shown in *Figure 4*. An anticyclone (high pressure) sits to the west of the UK, bringing air from a northerly direction (blue arrow).

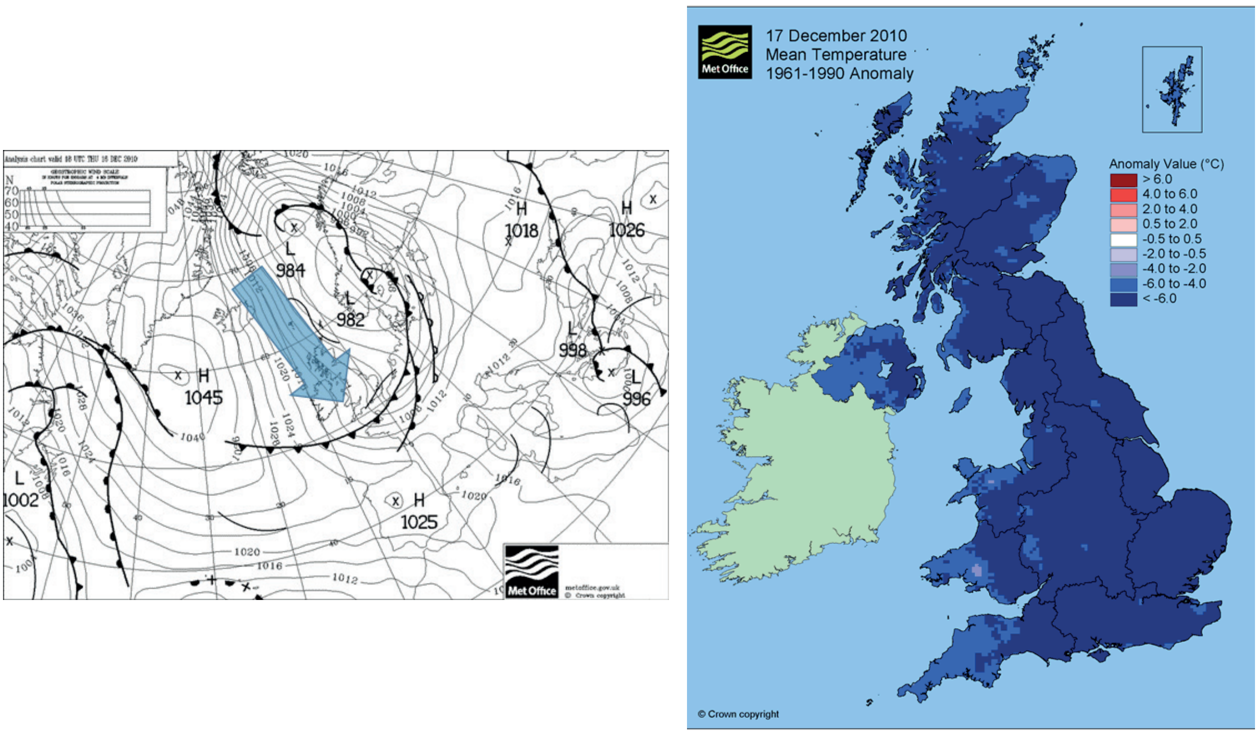

Figure 4. Surface pressure chart for 18:00 GMT on 16th December 2010 (left), showing an air mass of Arctic origin moving southwards across the UK (blue arrow). This resulted in extremely low temperatures the following day (right) which subsequently persisted for several days. (Left panel © Crown Copyright Met Office 2018. Right panel source: National Climate Information Centre, © Crown Copyright Met Office 2018)

The very coldest conditions will typically occur on clear, calm nights, especially if the ground is snow-covered:

- The ground constantly (day and night) emits infrared radiation, while the sun's radiation warms the ground during daylight hours only. Clouds are able to trap more of the infrared radiation emitted by the ground, stopping it from escaping to space. However, cloudless skies at night mean that there is nothing to stop the infrared radiation from escaping back to space, thereby allowing the ground (and the near-surface air) to cool more than it would on a cloudy day.
- Snow acts as an insulator, meaning that the warmth of the soil cannot permeate through the snow to raise the temperature of the near-surface air. Snow-covered ground also has a high *albedo* (reflectivity) compared to ground that is free from snow. This means that, during the day, more incident radiation from the sun is reflected from snow-covered ground (rather than being absorbed), so the ground (and the near-surface air) cannot warm up as much when it is snow-covered.

One such night was 10th January 1982 when the lowest temperatures on record in the UK were recorded: –27.2 °C at Braemar (also repeated at Braemar in 1882 and 1995) and –26.1 °C at Newport (Shropshire) (see *Table 2*). Coastal areas, with the exception of Cornwall, generally experienced minima between –3 °C and –7 °C in England and Wales on that day.

The daily minimum temperature at a particular locality in the UK also depends on the location in question, its distance from the sea, and its altitude. Generally, the western parts of the country have a milder climate, due to the influence of the North Atlantic Drift. However, most of the significant areas of higher ground are also on the western side of the country; the higher altitude of these areas means that they experience lower temperatures.

Figure 5 shows a map of the average daily minimum temperatures for the UK (1981 to 2000) for the winter period (December to February). These average maps are generated using observational data that have been interpolated onto a 5 km gridded dataset, taking into account the effect of altitude, urban areas and proximity to the coast. The figure shows that west-facing coastlines and islands experience average daily winter minimum temperatures of approximately 3 °C or more. These areas are warmer than inland temperatures by at least 1 to 2 °C, on average; on the coldest of nights, this discrepancy could be larger, especially for calm nights with snow lying on the ground (particularly so if the inland site was snow-covered and the coastal site was not). The east coast of the UK does not exhibit such a marked difference in night-time temperatures compared with sites further inland, due to the proximity of the relatively cold North Sea. The effect of altitude can also be observed, with the Scottish Highlands, the Pennines, the mountains of Wales and the moors of south-west England, all visible as colder areas of the UK. There is also some evidence of the urban heat island effect, with London and Manchester standing out as areas with higher winter minima due to the heat generated by the cities themselves. The effect is the same in any urban area (and not just for winter but throughout the year); it is the chosen map colour scale that highlights it for these two cities only.

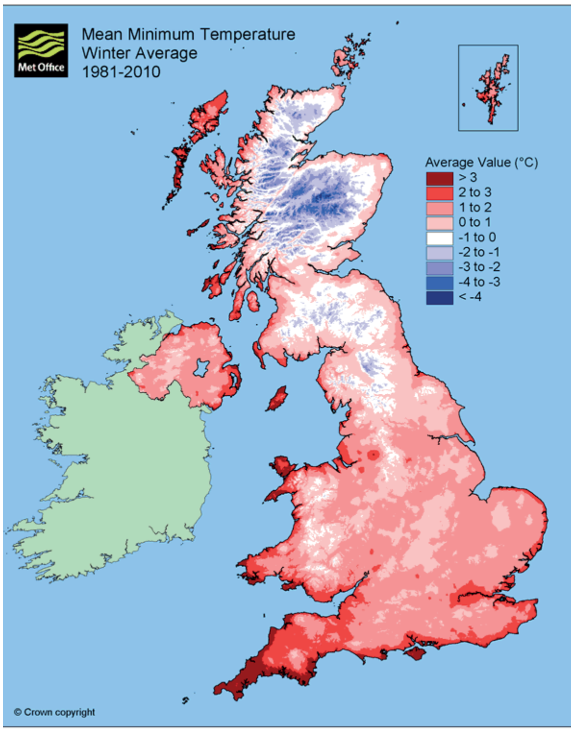

Figure 5. Map of average daily minimum winter (December to February) temperature for the period 1981 to 2010, from the National Climate Information Centre (© Crown Copyright Met Office 2018)

3.1 Types of data available for hazard characterisation

A non-exhaustive list of sea-surface temperature and air temperature datasets (both commercially and publicly available) is provided in *Table 3*. The main types of data available that may be useful for the characterisation of extreme temperatures by the methods described in *Sections 4* and *5.1* are:

- Observations – *Section 3.2* describes how air temperature is measured at Met Office meteorological observing stations and *Section 3.3* describes sources of water temperature data. These data may be:
  - point observations, i.e. values observed at a particular location;
  - gridded observations, i.e. derived from point observations by interpolating them onto a grid; or
  - obtained by combining observations from different sources, e.g. point observations and satellites for the Scottish sea water temperature data (*Section 3.3*).
- Modelled data, including:
  - reanalysis data, derived via a technique that combines observations with numerical weather model runs to provide estimates for all locations within the UK (*Section 3.3.1*); and
  - projections of future climate, created using climate models (*Sections 3.3.2* and *7.4*).

3.1.1 The Central England Temperature record

A dataset worthy of particular mention in this volume is the Central England Temperature (CET). The CET is the longest instrumental record of temperature in the world, with monthly averages available since 1659 and daily averages since 1772. The unusual length of this data series makes it an appealing potential source for data to support analysis of extreme air temperature. However, it is an areal statistic for inland England only, taken from at least three sites, roughly corresponding to the Lancashire plains, London area and Hereford. As a result, care should be taken when using the CET to represent localised extremes. Over the course of the CET record, different stations have been included. Whilst corrections have been made to ensure that the mean of the CET is homogenised when different stations are used, it is unclear as to the effect that these different stations may have on the statistical characteristics of the extreme events.

An alternative approach for obtaining daily series for any location would be to use the daily National Climate Information Centre (NCIC) gridded UK dataset for 1960 to present. The interpolation accounts for terrain, coastal and urban influences and uses all available station data rather than just the three CET sites, however the downside is that the record length available is shorter. This interpolation will again reduce extreme values for individual sites, but will provide better local information than the CET. This daily dataset is included in the list of available data sources in *Table 4*.

*Table 3. Non-exhaustive list of temperature datasets. (*Note: SST = sea-surface temperature).*
[1]www.metoffice.gov.uk/hadobs [2]cci.esa.int

		Dataset	Type	Domain		Time		Parameters	
				Region	Resolution	Period	Time step	Air temperature	SST*
Historical	Observations	Marine observations	Site	Global	Best cover around Europe	From 1854, waves. Good confidence from 1990s	Up to half hourly	x	x
Historical	Observations	UK observations	Site	UK	~200 to 300 sites for most parameters	From 1850, good coverage from 1960s	Up to 1 minute, good coverage at 1 hourly	x	
Historical	Observations	CET	Areal average	UK	Inland England	From 1772 to present – mean, from 1878 to present – max and min	Daily	x	
Historical	Observations	NCIC	Gridded	UK	5 km	From 1910, good coverage from 1960s	Temperature daily, sea-surface temperature monthly.	x	
Historical	Observations	hadobs[1]	Gridded	Global		1850 to 2014	Annual	x	x
Historical	Observations	HadISST[1]	Gridded	Global		1870 to present	Daily, monthly, annual		x
Historical	Observations	HadSST3[1]	Gridded	Global		1850 to present	Daily, monthly, annual		x
Historical	Observations	EN4[1]	Gridded	Global		1900s to present	Monthly		x
Historical	Observations	HadGOA[1]	Gridded	Global		1956 to 2004	Monthly		x
Historical	Observations	HadAT[1]	Gridded	Global, regional		1958 to present	Monthly, seasonal	x	
Historical	Observations	ESA CCI[2]	Gridded	Global, regional		1985 to present	Daily, monthly, annual		x
Historical	Reanalysis	ERA-i	Gridded	Global	~80 km	1979 to near present (3 months in arrears)	3 hours	x	
Historical	Reanalysis	MERRA	Gridded	Global	~40 km	1979 to near present (1 month in arrears)	1 hour	x	
Historical	Reanalysis	AMM	Gridded	Europe	7 km	1985 to 2015	1 hour		x
Future	Projections	Met Office Hadley Centre + other IPCC models	Gridded	Global	~100 to 200 km	Preindustrial to 2099	Various	x	x
Future	Projections	UKCP09 (POLCOMS)	Gridded	UK	12 km, 25 km	2010 to 2099	Daily		x
Future	Projections	UKCP09 (Probabilistic projections)	Gridded	UK	25 km	1961 to 2099	Annual averages	x	

3.2 Observing air temperature

Observations of temperature from Met Office observing sites are made using a Stevenson screen. This is an enclosure designed to hold meteorological instruments, placed at a height of 1.25 m above the ground; see *Figure 6*. One of the instruments inside a Stevenson screen is the thermometer, which measures the *dry bulb temperature*. The louvred design of the Stevenson screen allows exactly these conditions to be experienced by the thermometer.

Figure 6. AA Stevenson screen and its surroundings. Met Office 2018c. (© Crown Copyright Met Office 2018)

The sites for weather stations are selected to ensure that the observations are representative of the wider area around the station and not unduly influenced by local effects. Ideally, weather stations should be sited:

- on level ground, covered by short-cropped grass;
- away from trees, as they can have sheltering or shading effects on the measurement of wind and sunshine;
- away from buildings, as they can have a warming effect on the measurement of temperature;
- not on the top of hills or on the side of a steep escarpment where winds will be unrepresentative of the wider area.

In addition, it is better to avoid sites that are in frost hollows, where overnight temperatures on still clear, nights may be far lower than the surrounding area.

By convention, all meteorological observing stations that record daily maximum and minimum air temperature record it over the period 09:00 to 09:00 GMT. As a result, the 'minimum temperature' for a given date is the lowest temperature recorded between 09:00 the previous day and 09:00 on the day in question, whilst the 'maximum temperature' for a given date is the highest temperature recorded between 09:00 on the day in question and 09:00 on the following day.

Met Office observing sites are not fixed. New stations are opened, existing stations may close, and some stations may move within their sites, e.g. at airports. There is reasonable coverage across the UK of Met Office observing stations that report maximum/minimum and hourly temperatures, as shown in *Figure 7*. Temperature records are also available from stations that have ceased reporting temperatures in the present day, and these records can be especially useful in extending the record length, provided that the current and closed sites are climatologically similar.

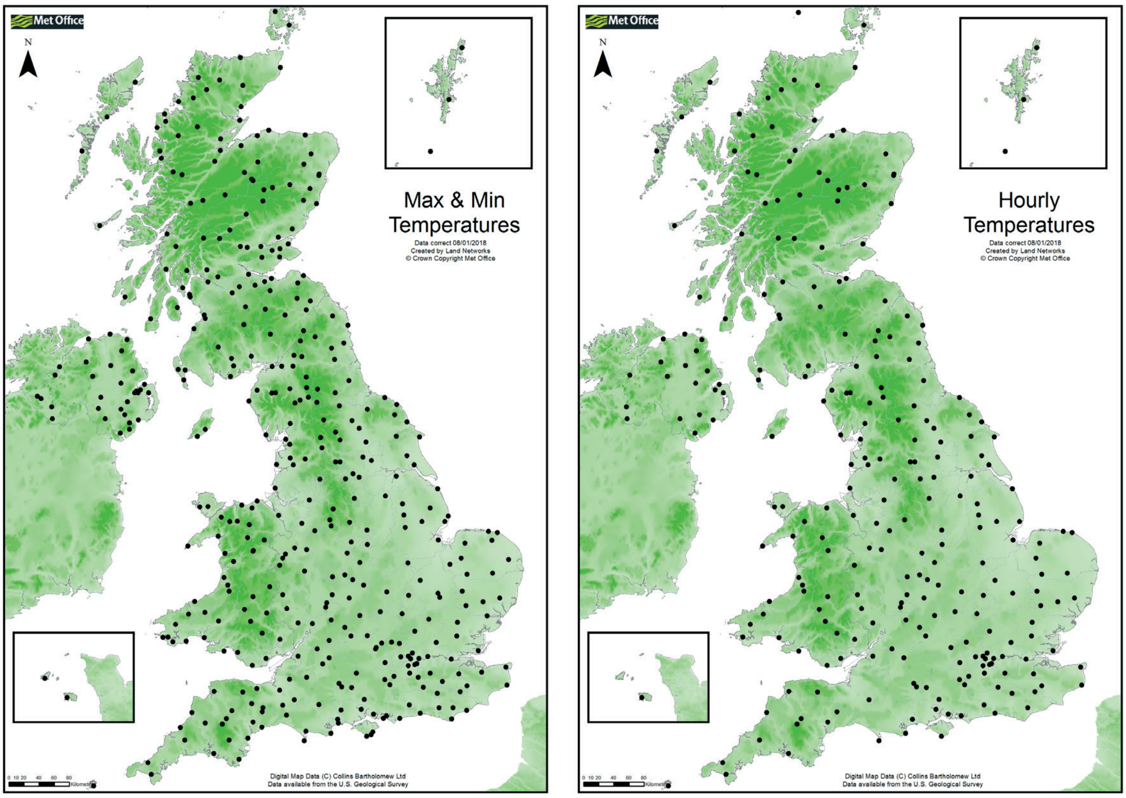

Figure 7. Met Office observing station network, showing stations (dots) that report daily maximum and minimum temperatures (left) and hourly temperatures (right). Data correct as of 8th January 2018.
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3.3 Observing coastal sea-surface temperature and surface water temperature

The Centre for Environment, Fisheries and Aquaculture Science (Cefas) has a coastal area network which records coastal sea-surface temperatures at sites around England and Wales. Access is available to 40 stations, of which 24 are still reporting, with most of the records beginning in 1960. These temperature records are a mixture of monthly and daily temperatures. Further information about these sea-surface temperature records can be obtained from *Cefas (2018)*.

Monthly sea-surface temperatures are available for Scotland from 1997 to 2013 for 13 sea areas around Scotland. More information can be obtained from *Marine Scotland (2018)*.

The Environment Agency has an archive of surface water temperature data from more than 30,000 sites across England and Wales, with data up to 2007 and with most records beginning in the 1980s. Typically, the water temperature data are as either spot samples from routine monitoring (e.g. monthly) or high resolution samples (sub-hourly). Further information about the data can be obtained from *Natural Resources Wales (2018)*.

3.3.1 Reanalysis

Reanalysis essentially involves using historical observations, retrospectively, to drive a numerical weather prediction (NWP) model, i.e. a model that is normally used for forecasting the weather in real time. Rather than being allowed to evolve freely, the model is systematically constrained at reasonable intervals (say, 12 hours) by the assimilation of further historical observations at each such interval. The advantage of this process is that it produces a gridded dataset of potentially many variables, and potentially spanning several decades and large geographical areas (even global). There are some limitations; mainly these relate to the limitations of the chosen NWP model (i.e. how well it performs in terms of modelling key weather parameters) and to any deficiencies in the quality of the observations ingested into the process.

3.3.2 Climate modelling

Future projections of UK climate can be obtained from climate modelling studies. Climate models often have similar configurations to NWP models, but because climate projections span decades rather than hours to days ahead, they are run slightly differently (e.g. with longer time steps). Projecting future climate involves a number of assumptions and uncertainties; see *Section 7.4* for a further discussion of some of these.

The current main source of UK climate projections, for both land and marine regions of the UK, is the UK Climate Projections 2009 (UKCP09) Project. For example, the land projections provide data at up to 25 km resolution for the whole UK, for a range of parameters relevant to energy (including temperature), spanning time periods out to the 2080s. These climate projects are scheduled to be updated later in 2018 (*UKCP Project, 2018*), and are briefly discussed in *Section 7.4.4*. There are also coordinated global climate modelling activities under the Coupled Model Intercomparison Project (CMIP) programme. This involves collaborative working between multiple climate modelling centres around the world, to build and develop climate models, evaluate their performance, and produce global future projections. The most recent of these activities is CMIP5 (*Taylor et al., 2012*), under which projections from 24 global climate models have been produced; most of these are available for commercial use. These projections were used to inform the most recent Intergovernmental Panel on Climate Change Assessment Report (*IPCC, 2013*). While global projections are necessarily made at lower resolution than regional projections like UKCP09, their global context makes them useful in, for example, evaluating external (non-UK) risks to the UK energy sector.

This section outlines a range of methodologies that can be used to characterise extreme temperatures in the UK. Simple analyses of the historical record are discussed in *Sections 4.1* and *4.2*, before a more complex and powerful analytical technique, extreme value analysis (EVA), is introduced and discussed in *Section 4.3*. *Section 4.4* discusses additional aspects that may be pertinent to undertaking an EVA.

4.1 Maximum/minimum temperatures based on historical data

A preliminary way to characterise extreme temperatures is to obtain an initial order-of-magnitude estimate by examining observed extreme values (events) in the historical record.

Individual station records typically have comparatively short record lengths, especially when compared to the timescales on which the climate varies naturally. Examples of modes of variability are briefly discussed in *Section 2.1*; other modes of variability exist which vary over multiple decades (e.g. the Atlantic Multidecadal Oscillation, AMO – *Schlesinger and Ramankutty, 1994*). Records that are comparatively short compared to the natural climate variability are unlikely to contain the most extreme event possible. Consequently, using the most extreme event recorded in a station record as a limit, for possible future extreme temperature events, is very likely to result in underestimating the magnitude of the extreme temperature, especially when there are no practicable, physical bounds associated with temperature extremes.

4.2 Frequency analysis of historical observations

In frequency analysis, the emphasis is on using the observed data, such as daily maximum and minimum temperatures, to construct cumulative frequency distributions. Extreme events are then defined, for example as any event where the observed value falls in the top 5% of the record. However, without making any assumption about how the data are distributed, it is impossible to estimate the probability of an extreme event of greater magnitude than the maximum value in the data series from a cumulative frequency distribution. Furthermore, the threshold used to identify an extreme event is also arbitrary. Consequently, the number and frequency of extreme events obtained from a cumulative frequency distribution are likely to be strongly dependent on the threshold choice.

Other problems may arise due to the length of the time series of observations, as described in *Section 4.1*. In addition, if there are any gaps in the observational record this could lead to the omission of some extreme events making the time series even less representative.

4.3 EVA: stationary and non-stationary approaches

EVA is less constrained by the limitations discussed in *Section 4.2*, and is a methodology that is commonly used within the energy industry and beyond. It is a statistical method that can be used to estimate the probability and severity of events that are more extreme than any that exist in a given data series. EVA is discussed in the following sections, but the reader should also consult Volume 1 — Introduction to the Technical Volumes and Case Studies for a broader discussion of the technique.

Essentially, EVA involves modelling the most extreme part of a statistical distribution of values with a mathematical function known as the extreme value distribution (EVD). Commonly-used EVDs within the meteorological and climate science community are the generalised extreme value distribution (GEV, *Section 4.3.1*), the generalised Pareto distribution (GPD, *Section 4.3.3*) and the Poisson-generalised Pareto distribution (Poisson-GPD, also *Section 4.3.3*).

EVA can be used on datasets which may only contain a limited set of extreme events. For example, a 20-year observation record could be used to estimate the annual probability of exceeding a predefined threshold value, which may be larger than any value within the observed record length. Similarly, if the annual probability of exceeding a predefined threshold is required (Volume 1 — Introduction to the Technical Volumes and Case Studies defines the term annual exceedance probability, or AEP, as the annual probability of exceeding a specific level), EVA could be used to estimate the magnitude of this event associated with that probability.

However, it is important to remember that the uncertainty in the projected extreme events will increase as the inverse of the AEP (which equates to a period of time that is measured in years, e.g. T-years, the return period) approaches the length of the data series. The uncertainty increases still further as the inverse of the AEP exceeds the length of the data series.

4.3.1 The generalised extreme value (GEV) distribution

The GEV distribution is usually fitted to a set of extreme events, where the extreme events are defined as the most extreme event that occurred within a fixed time period such as seasons or years, e.g. annual maximum temperature or seasonal minimum temperatures. The process of selecting the most extreme observation in a fixed time period is also called a block maxima approach. A GEV distribution is described by three parameters: location, scale and shape.

The location parameter is analogous to the mean of a normal distribution in that an increase in the location parameter results in the entire distribution shifting to higher values while the form of the distribution remains unchanged.

The scale and the shape parameters together determine the rate at which the magnitudes of the extremes (the return level) alter with lengthening return period. This is illustrated in *Figure 8*, which shows the effect of the scale and shape parameters on the return-level curves. The shape parameter increases from left to right, from –0.2 through zero to 0.4, whilst the scale parameter increases from 1 at the top, 4 in the centre to 8 at the bottom.

The scale parameter is always positive as it measures the amount of spread in the data: the larger the scale parameter, the greater the spread. In the return-level plots, as the scale parameter increases so does the range of return levels.

The shape parameter controls whether the return-level curve is bounded, reaches a limit, or not. The left-most column in *Figure 8* shows return-level curves for a shape parameter of –0.2 with different scale parameters; a close inspection shows that the curve is levelling off as the return period increases. In other words, the return-level curves are approaching an asymptotic limit — a boundary that cannot be exceeded.

Plots in the central column have a shape parameter of zero; the return-level points would appear broadly to lie on a straight line which increases linearly as the return period increases on the log scale. Plots in the right-most column have a shape parameter of 0.4; here the return-level curves are increasing exponentially as the return period increases.

Considering all plots in *Figure 8* together, the return-level curves show that, for a specified return period and for increasing values of the shape and scale parameters, the associated return-level value increases.

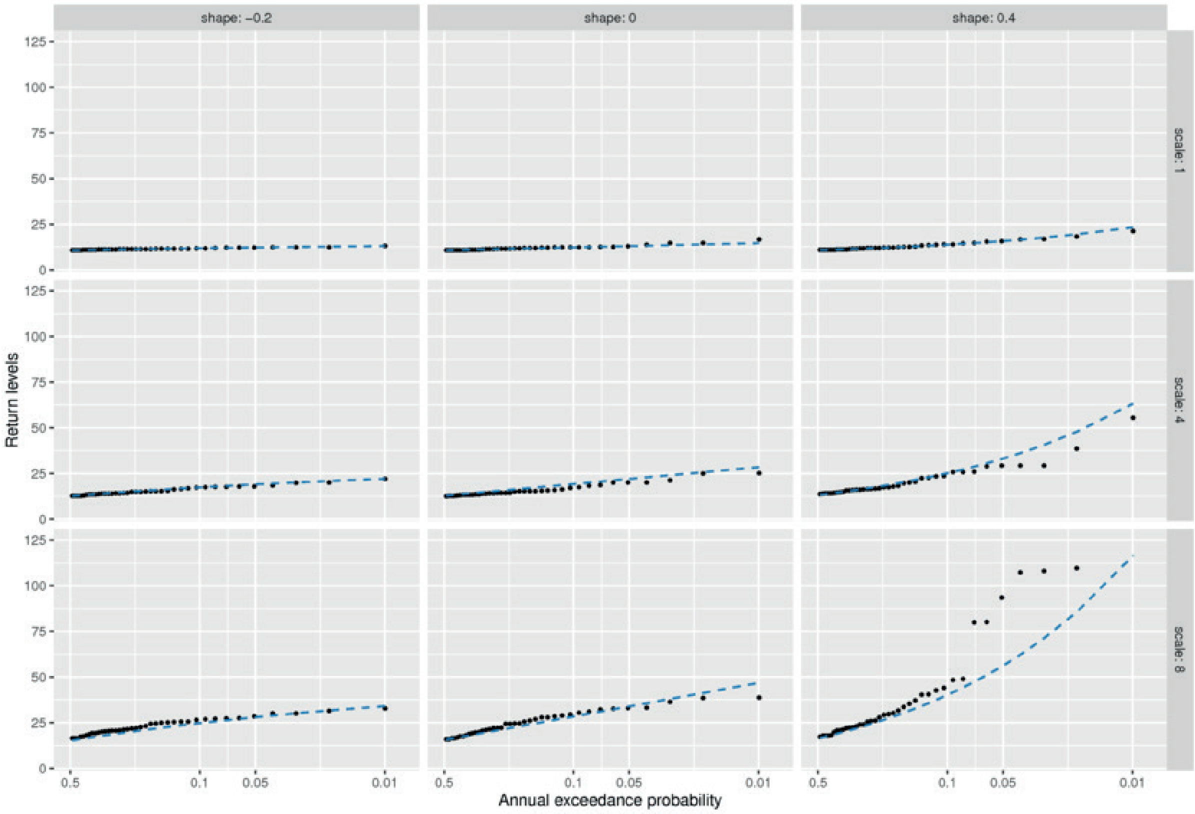

Figure 8. An illustration of how the scale and shape parameters in a GEV model affect the associated return-level curves. Columns, left to right: shape parameter values of −0.2, 0 and 0.4. Rows, top to bottom: scale parameter values of 1, 4 and 8. The location parameter is the same in all panels and all panels are plotted on the same scale for ease of comparison. Observations are represented by black dots and fitted GEV model is represented by blue dashed lines. Note the logarithmic scale on the x-axis.

Note that the 'generalised' part of the GEV distribution refers to the fact that it is a generalised form of three slightly different distributions: the Gumbel, Fréchet and negative Weibull distributions. These are associated with particular values and ranges of the shape parameter, *Table 4*. However, when using the GEV distribution no decision is required before the analysis as to whether the shape parameter is less than zero, zero or greater than zero.

Table 4. Characteristics of specific forms of the GEV distribution.

Distribution	Shape parameter can take values…	Asymptotically, this distribution is…
Negative Weibull	Less than zero	Bounded
Gumbel	Zero	Unbounded
Fréchet	Greater than zero	Unbounded

As mentioned previously, when using a GEV model, extremes are selected using the block maxima approach. One criticism of fitting an EVD using a block maxima approach is that it limits the number of extreme events used during the statistical model fit. This can be a problem especially if the time series of observations has a comparatively short length, compared to the inverse of the desired AEP. Smaller samples of extreme events will generally result in the parameters of the EVD having larger uncertainties and in an increase in the variability associated with any return levels generated from the fitted GEV distribution. Another disadvantage of the block maxima approach is that it discards multiple extreme events that fall within the same block (e.g. year), even if some of those events are amongst the largest extreme events in the record. These issues have, in the past, motivated research into approaches that use more of the extreme events within the observation record.

4.3.2 Threshold exceedance approaches

Some authors have argued (*Coles, 2001*; *Katz et al., 2005*; *Brown et al., 2008*) that if an entire time series of daily observations is available, then it is better to avoid the block maxima approach. An alternative approach is to define a threshold and then define values that exceed this threshold as extreme events. This is called the threshold exceedance approach. The choice of threshold is analogous to choosing the block size in a GEV analysis (e.g. blocks of a year, season, month, etc.), in that the choice of threshold (or block size for a GEV analysis) can have significant consequences on the subsequent EVA.

Too low a threshold (or block sizes which contain only a few observations) can violate the assumption that the selected values come from an EVD. This can ultimately lead to biases in the estimation of the parameters of the EVD and return values, which may lead to underestimates or overestimates.

On the other hand, too high a threshold (or choosing a block size which contains a large number of observations for a GEV analysis) can lead to parameter estimates with high variance. Whilst this may have little effect on the estimate of return levels themselves (provided there are sufficient blocks or observations to ensure an appropriate fit), the associated confidence intervals may become large, possibly to the extent that they may be of no practical use for the application under consideration.

Good practice endeavours to choose a threshold that is as low as possible, so that the uncertainty associated with the extreme value parameters can be better quantified, yet still satisfies the assumption that the data come from an EVD.

4.3.3 The generalised Pareto distribution (GPD) and Poisson-GPD

The GPD and the Poisson-GPD are typically fitted to data that have been defined as extreme using a threshold exceedance approach. A GPD is used to model the intensity of an extreme event, i.e. by how much is the defined threshold exceeded. A GPD, like the GEV, is defined by location, scale and shape parameters.

The Poisson-GPD model is one example of the Marked Point Process (MPP) model and as its name implies, has two components: a Poisson process which models how many times an extreme threshold is exceeded, and a generalised Pareto distribution which models by how much the threshold set for the Poisson distribution is exceeded. A Poisson-GPD model is also defined by location, scale and shape parameters.

There are many similarities between the parameters of the GEV and the parameters of the Poisson-GPD. Indeed, given a suitably large threshold, the shape parameters of the Poisson-GPD tend towards the GEV parameters (*Coles, 2001*).

4.4 Factors to be considered in conducting an EVA

Aside from considering the choice of method (block maxima vs threshold exceedance approach) and the ensuing choice of EVD, there are other considerations to bear in mind in conducting an EVA, such as those described in *Sections 4.4.1* to *4.4.5*.

4.4.1 Independence of extreme events

Extreme value theory assumes that the data are independent and identically distributed; i.e. the extreme events are not clustered together in time and they are all sampled from a single parent distribution, arising from the same physical process. An example would be the warmest temperature experienced at a specific UK site associated with a slow-moving anticyclone.

One approach to ensuring that the data are temporally independent is to decluster; i.e. to define clusters of extreme events that are contiguous in time and separated from other clusters by a contiguous series of non-extreme events of fixed minimum length. From each of the extreme clusters, the most extreme event is extracted and analysed (*Coles, 2001*). However, research suggests that using all data to estimate the parameters for a threshold approach to EVA will give better parameter estimates, compared to taking a subset of the data to ensure independent observations (*Fawcett and Walshaw, 2012*). If all the data are used it is necessary to modify the estimates of uncertainty associated with the EVD parameters, as they will be too small.

4.4.2 Covariates

So far in this discussion, it has been assumed that the data being used to conduct the EVA are stationary; i.e. the statistical properties of the distribution (the EVD parameters) do not change in a systematic way with time. As discussed in *Section 4.1*, it is known that the climate, and in particular the temperatures of the UK, are heavily influenced by the season and large-scale atmospheric circulation patterns like the NAO, a source of large-scale variability in mid-latitude temperatures. As a result, the ability to include and assess possible covariates into the EVA is desirable. This is easy to achieve if the statistical models are fitted using the ***method of maximum likelihood*** (*Coles, 2001*). Examples in the literature where the parameters of the EVD (the location, scale and shape) depend on the covariates include *Katz et al. (2002)*, *Hanel et al. (2009)*, *Brown et al. (2014)* and *Brown (2018)*.

Any covariates included in an EVD should be assessed for statistical significance (i.e. does the inclusion of the covariate improve the fit of the EVD to the data, does it explain more of the '***noise***'?) using likelihood ratio tests (*Coles, 2001*) or Akaike information criterion type statistics:

- A likelihood ratio test compares the likelihood of a model with stationary parameters (one without covariates) to that of an EVD where the parameters are allowed to depend on covariates. The ratio of likelihoods follows the chi-square distribution, and as a result, stationarity can be assessed using statistical tests based on the chi-square distribution.
- The Akaike information criterion (AIC) statistic adds a penalty term on to the likelihood, resulting in the likelihood increasing as the number of covariates included in the model increases. Generally, a model with a smaller AIC statistic is preferred to one with a larger AIC statistic.

4.4.3 Pooling station data

As mentioned in *Section 4.3.1*, one difficulty with an EVA for a specific site is that often there is only a limited number of extreme data points available.

One possible approach to increase the number of observations of extreme events is to pool information from nearby observing stations, assuming that they have similar climatologies. This could lead to an increase in the accuracy of the parameter estimates and reduce the uncertainty associated with the estimates for EVD parameters that were common to all the observing stations; see *Section 7.6*. In meteorological and climatological studies, the shape parameter is typically assumed to be constant for observing stations that are in close proximity and that have similar topography. However, for other parameters such as the location parameter, small differences between stations can be included by specifying a set of index variables as covariates. These indexing variables specify whether observations come from a particular station or not, similar to the approach that Brown et al. (2014) used to distinguish between actual observations and numerical model output. Should it also be desirable to include larger scale covariates, such as NAO, in the analysis, then these are assumed to affect all stations in a similar manner, and typically no adjustment is made to the EVD parameter estimates to include the individual stations' response to the covariate.

The condition that stations have similar climatologies is important. Stations that are geographically close may still experience different effects, e.g. a station at the coast and a station at high altitude may be close together yet show very different meteorological behaviour.

4.4.4 Confidence intervals

Confidence intervals help quantify the uncertainty associated with deriving the desired statistic, such as a return level, from a sample of data. An *X*% confidence interval gives an estimated range of values which has a probability *X*/100 that it contains the unknown population parameter (the true return level or population return level). Confidence intervals can be either one-sided or two-sided. If the interval is two-sided, then the bounds of the confidence intervals are normally referred as the upper or lower *X*% confidence limits around the estimated parameter, i.e. the most likely value of the return value. Standard confidence intervals used within statistical analysis are 90%, 95% and 99%. Higher confidence values, e.g. 99%, will have a greater range of return levels compared to smaller confidence values. Within the nuclear industry, an upper confidence limit equivalent to the 84th percentile of the return level distribution is often required.

There are different ways of calculating confidence intervals on return levels. Two commonly used approaches include the delta method, the profile-likelihood approach and the parametric bootstrap. The delta method relies on the approximate normal of the estimates of the EVD to obtain confidence intervals. However, Coles (2001) suggests using profile likelihood to produce confidence intervals as generally they prove to be more accurate. The width of the confidence intervals are approximately the same, but the profile likelihood intervals tend to be shifted towards the more extreme events compared to the delta intervals, so the intervals for the profile-likelihood are skewed around the return-level curve, as illustrated in Figure 9. Encouragingly, this skewed confidence interval now contains the most extreme observation which fell outside of the confidence interval generated using the delta approach.

An alternative approach to the profile likelihood confidence interval is the parametric bootstrap confidence interval. Briefly, a parametric bootstrap generates many samples of data from a known or assumed EVD — the parent distribution. To each generated sample of data an EVD is fitted and the appropriate return level for the desired annual exceedance probability derived, so each sample provides one return level value. As many different samples of data from the parent EVD are generated and to each of these an EVD distribution is fitted, it is possible to derive a distribution of the desired return level. Appropriate confidence intervals can then be extracted from this distribution of return levels. An alternative form of bootstrap is the non-parametric bootstrap, where samples of data are generated by resampling with replacement from the original dataset and fitting an EVD to the samples, rather than sampling from a parent distribution as for the parametric bootstrap. *Kyselý (2008)* found that for small and moderate sized samples (where the number of extreme events is less than 60) the confidence intervals generated by the non-parametric approach were too narrow and underestimated the real uncertainty.

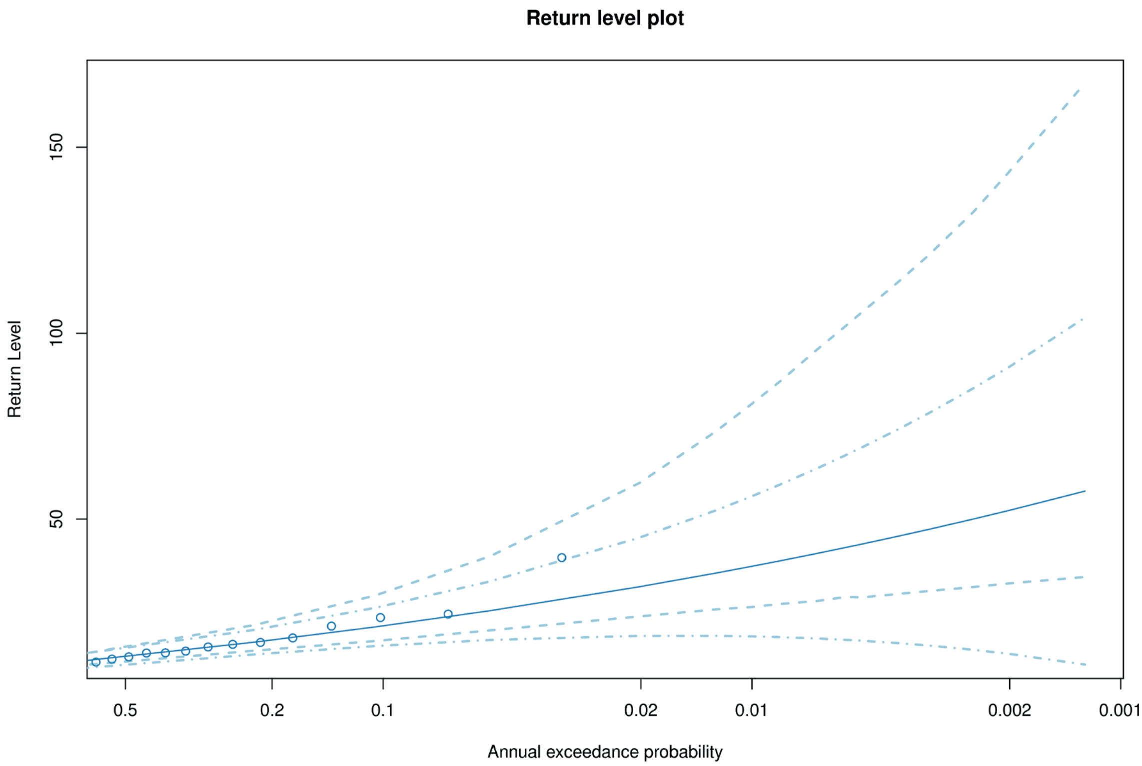

Figure 9. An illustration of a return level plot (solid line) from fitting a GEV model to data simulated from a GEV distribution with a location parameter of 10, scale of 4 and shape of 0.2. A 95% confidence interval is derived for which the upper and lower confidence bounds are shown, as calculated by the delta (dot-dashed lines) and the profile-likelihood (dashed lines) approaches.

4.4.5 Fit diagnostics

Once the parameters of an EVD have been estimated, the quality of the fit of the distribution to the data should be assessed using either goodness-of-fit tests or diagnostic plots. Examples of goodness-of-fit tests include the Kolmogorov-Smirnov, Anderson-Darling and Cramer-von Mises tests. These tests assume that the data are from the desired EVD and then assess the probability that this is true. For standard statistical tests, such as the t-test, this is often done by comparing the t-statistic to a critical value. However, using the derived parameters from the EVD in goodness-of-fit tests affects the critical values. To overcome this issue, *Brown et al. (2008)* used bootstrap samples created from randomly sampling the fitted distribution to create new datasets to which the same EVD is re-fitted and for which goodness-of-fit statistics are calculated.

Diagnostic plots are also available and aid in the interpretation of the fit of the EVD and in the selection of the suitable thresholds for distributions fitted to threshold exceedance datasets. *Figure 10* illustrates a selection of diagnostic plots for a GEV distribution fitted to 30 observations sampled from a GEV distribution with a location of 10, scale of 4 and shape of 0.2. These plots compare the data to the fitted GEV model and unsurprisingly, as the data were generated from a GEV distribution, the fit of the GEV to the data is good.

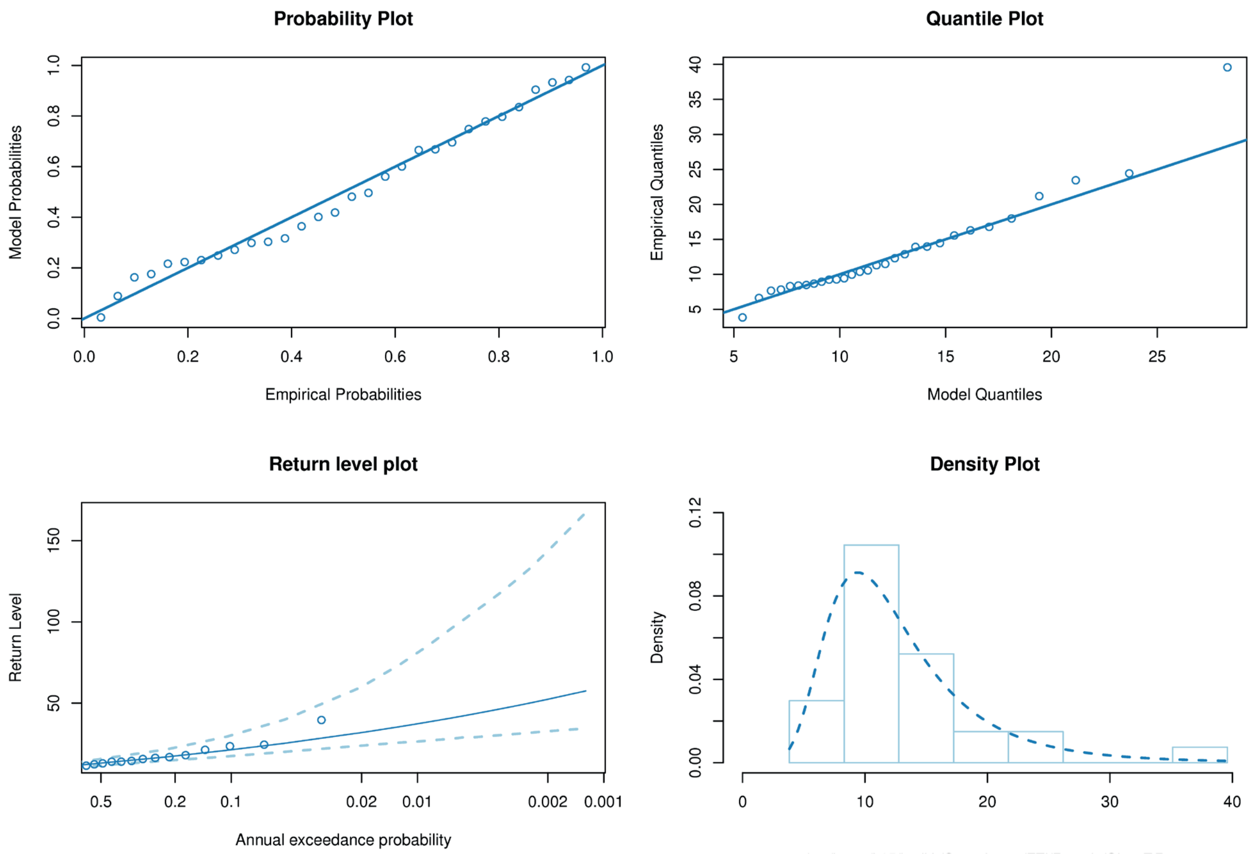

Figure 10. Diagnostic plots for GEV fitted to 30 observations of simulated data from a GEV distribution with a location parameter of 10, scale of 4 and shape of 0.2.

The first plot, at top-left, is a probability plot. Probability plots compare the probabilities derived from both the fitted EVD and the empirical distribution for a range of given quantiles (return levels). A statistical model that fits the data well will have points (circles) which lie closer to the 1-1 correspondence line (solid line) compared to poorer fitting statistical models. Unsurprisingly, as the data were sampled from a GEV distribution, the probability plot shown in *Figure 10* suggests that the GEV distribution fits the data well.

A quantile plot is the converse of a probability plot, as quantiles (return levels) are derived from probabilities, instead of deriving probabilities from return levels. Again, a statistical model that fits the data well will have points (circles) that are close to the 1-1 correspondence line (solid line). It is not unusual to see deviations from the 1-1 correspondence line for one or two of the larger quantiles, due to sample size limitations. However, systematic deviations from the 1-1 correspondence line or a large number of deviations would give cause for concern. The points in the quantile plot at top-right in *Figure 10* lie close to the 1-1 correspondence line with the exception of the largest quantile, suggesting that there is no evidence to doubt the fit of the GEV distribution.

The bottom-left plot shows the return levels plotted against the return periods on a logarithmic scale. The circles represent the data, the solid line is the fitted statistical model, and the dashed lines are the upper and lower confidence bounds of the fitted return levels from the fitted statistical model, using 95% profile-likelihood confidence intervals. Again, there is no evidence to suggest that the data deviate significantly from the fitted statistical model, with all the points, bar the most extreme data point, lying within the enclosed confidence limits. Due to the positive shape parameter, the curve of the return-level plot suggests that there is no statistical limit to the return levels as they increase (i.e. as the AEP decreases).

The final plot, at bottom-right, is a probability density plot derived from the fitted model compared to a histogram of the data. The two plots are similar to each other, again suggesting that the GEV distribution is a reasonable fit to the data. Overall, all four diagnostic plots suggest that the GEV is, unsurprisingly, a good model to use with these data.

4.4.6 Bivariate distributions

For some meteorological phenomena, rather than there being a single variable that is of interest (such as the intensity of the temperature), the focus of interest may be on two (or more) variables. For example, when analysing heatwaves, not only is the intensity of the event of interest, but also its duration. In such cases how the variables behave when either variable (or both variables) are extreme can have an important impact on the fitting of an extreme value model. *Coles (2001)* provides an introduction to multivariate extremes, and *Winter et al. (2016a, 2016b)* discuss examples of the analysis of heatwaves.

5.1 Extreme high and low water temperature

5.1.1 Water heat capacity

Water has a large heat capacity, so daily and sub-daily observations of maximum and minimum water temperatures are highly likely to be dependent, as water temperatures vary more slowly than air temperatures. This may affect the surface temperature of rivers, lakes, oceans and seas. In addition, the temperature of deeper water will vary even more slowly.

One approach to overcome such dependency is to partition the data into periods of similar length (e.g. years) and extract the maximum and minimum surface temperatures within each period, i.e. take a block maxima approach. If such an approach is employed, then careful consideration of the start and end dates is necessary to avoid having two neighbouring, extreme observations falling into separate periods and causing possible dependency issues within the data. For example, if the period is the calendar year, an extreme multi-day cold period of surface water temperature could, hypothetically, result in one year having the coldest temperature on 31st December and the next year having its coldest temperature on 1st January.

5.1.2 Oceans and seas

Seas and oceans have a lower freezing point, −1.8 °C, compared to fresh water, due to the salinity of the water. In addition, as water nears its freezing point, the density of the water increases and this colder, denser water tends to sink. As a result, a large part of the column of water below the surface must approach −1.8 °C for sea ice to form, and sea ice consequently forms slowly compared to freshwater ice.

When fitting an EVD it is also assumed that there are no changes of state in the physical system, such as water turning into ice. If the original data sampled contained minimum water temperature events that were above the freezing point of salt water, then the validity of any return levels which approached the freezing point would be questionable.

In general, UK sea temperatures are colder in the north compared to the south. However, the lowest temperatures are found in the North Sea as this area does not benefit from the warm waters of the Gulf Stream, which affect the more westerly sea areas.

Over the available record, the average monthly sea-surface temperature around the UK ranges from approximately 1 °C in the winter to over 24 °C in the summer depending on region and annual variation. *Joyce (2006)* also found that for England and Wales, all coastal sea areas have shown an overall increase in temperature during the period 1985 to 2004, of 0.5 °C to 0.75 °C.

5.2 Frazil ice formation

Frazil ice occurs on turbulent water surfaces which are supercooled to temperatures below the freezing point. Any ice crystals that start to form on the surface of the water are quickly broken down, due to the turbulence, into smaller ice pieces that form a suspension of crystals which can have a slush-like appearance. Although ice typically floats on water, if the water is turbulent and the ice crystals are small relative to the current speeds, then the ice crystals can descend to the bottom and continue to grow in the supercooled surroundings. Frazil ice can constitute a blocking hazard for the cooling water intakes for thermal and nuclear power stations.

5.3 Very rapid change in air temperatures

In general, whilst there are very few datasets available of diurnal temperature ranges, in practice diurnal temperature ranges are easy to calculate from observing sites that report maximum and minimum daily temperatures. If sub-daily rapid temperature changes are required, again these are easy to derive from stations that report hourly data. Note that stations reporting hourly data record an instantaneous value (on the hour) which will not necessarily be the maximum temperature observed in the past hour.

One of the largest diurnal temperature ranges observed for the UK was on 14th January 1979 when Lagganlia (near Aviemore in Scotland) recorded a minimum of –23.5 °C and a maximum of 6.6 °C, a change of 30.1 °C in one day. Research internal to the Met Office suggests that, as a rule of thumb, a diurnal temperature range in the UK exceeding 20 °C is not uncommon, above 25 °C is unusual and above 30 °C is exceptional. However, the diurnal temperature range is location-specific, with the largest values across parts of Scotland and around frost hollows (low-lying areas, such as valley bottoms or smaller hollows). The frosts usually occur on dry, clear and cold nights, when cold air descends down neighbouring slopes and falls into the hollows from which it is slow (or unable) to escape, resulting in frost occurring more frequently, in the hollows, than in the surrounding area.

In theory, using the daily maximum and minimum temperatures to define the diurnal temperature range could result in a time interval of up to 48 hours between the two values. As the observing period is between 09:00 and 09:00 (see *Section 3.2*), one cold night can provide the minimum temperature for two consecutive observing periods (i.e. if the temperatures that morning around 09:00 prove to be the lowest temperatures for both the preceding and subsequent 24-hour windows).

In cases where rapid changes in temperature are of interest, and temperature data are therefore required at sub-daily timescales (e.g. six-hourly, hourly, etc), additional factors become relevant. One of these is the availability and appropriateness of sub-daily data from particular sources. Although algorithms exist that can be used to derive hourly data from daily values, these techniques may not capture the largest range of hourly temperature values, as they are effectively fitting smoothed curves to daily temperature values such as daily mean, maximum and minimum temperatures (*Chow and Levermore, 2007*). In addition, if only hourly instantaneous records of temperature are available (or derived), i.e. values that are observed (or valid) on the hour, then it is very unlikely that the largest range of hourly temperatures will be captured, as this largest range is highly likely to occur at times which are not synchronous to the actual hourly observing (or validity) time.

5.4 Wildfires

A wildfire is 'any uncontrolled vegetation fire which requires a decision, or action, regarding suppression' (*Forestry Commission, 2014*). In the UK, wildfires occur during the spring and summer, on moorlands, heaths, grassland, forest/woodland and agricultural land. They are primarily started by people, whether accidentally or deliberately (*Knowledge for Wildfire Forum, 2018*), and are listed in the National Risk Register of Civil Emergencies (*Cabinet Office, 2017*).

The UK Fire and Rescue Services attend around 70,000 wildfires each year (*University of Manchester, 2013*). The majority of wildfires tend nevertheless to be small incidents; *Gazzard et al. (2016)* reported that 99% of wildfires in Great Britain affect an area of less than one hectare. However, some evolve into major incidents in dry and windy conditions when there has been a build-up of dry or dead vegetation. Forest and woodland fires constitute a relatively small fraction of all wildfire incidents, but their impacts can be large and costly (*Forestry Commission, 2014*). The 2011 Swinley Forest fire in Berkshire for example affected 300 hectares, threatened critical infrastructure and had an associated estimated cost of at least £1 million.

Wildfire damage is caused through fire, heat and smoke. Example impacts (*Natural Hazards Partnership, 2016*) are:

- damage to, or loss of, property and infrastructure (e.g. power lines);
- closure of the transport network jeopardising access to energy infrastructure, because of poor visibility and pollutant exposure;
- health problems, such as breathing problems, due to the smoke composition, with

- pollutant concentrations highest near the wildfire but potentially still posing a significant risk long distances away (dense smoke plumes can travel significant distances);
- pollution of water when ash and other burn residues penetrate the soil;
- loss of life.

Most wildfires occur during the spring and summer. In the spring, a large amount of ground vegetation is dry or dead, and acts as fuel. Both seasons also exhibit spells of dry and windy weather which favours the spread of wildfires, even if these spells tend to be relatively short-lived (*Forestry Commission, 2014; Cabinet Office, 2017*).

While weather conditions for severe wildfires are already present under the current climate, climate change is expected to increase the risk. As reported in the *UK Climate Change Risk Assessment 2017* (*Brown et al., 2016*), "projections of drier summers with increased soil moisture deficits would suggest an increase in the number of fires and the area affected (Medium confidence). This may be further exacerbated by possible changes in the frequency and intensity of droughts, although this is currently highly uncertain. It is also likely that weather conditions that promote wildfires will increase if there is an increased frequency of warmer and drier springs (Low confidence)."

5.5 Enthalpy

Enthalpy is essentially a measure of the energy content of a substance, its latent and sensible heat, and it is closely related to the temperature of that substance. Latent heat is the heat taken in or given out by a substance as it changes from one physical state to another, e.g. from a gas to a liquid, without a change in temperature. In the energy sector, enthalpy is an important topic of interest in terms of the efficiency of heating, ventilation and air conditioning (HVAC).

The enthalpy of air varies depending on its moisture content. Unlike temperature, enthalpy is not directly observed, but can be derived from meteorological variables such as temperature, pressure and humidity, plus known constants (latent heat of evaporation, specific heat capacity and density of the air). Enthalpy is measured in J/kg.

Once values of enthalpy have been derived at the desired temporal resolution, it is possible to analyse the most extreme values using a similar approach to that taken for maximum temperature, as described in *Section 4*, and subject to similar caveats i.e. independence of observations, assessment of stationarity within the time series of enthalpy values, etc. However, when investigating the efficiency of HVAC, not only is the extreme value of enthalpy of interest but also the concurrent air temperature. In these circumstances, using a more complex EVA approach, such as a conditional extremes model (*Heffernan and Tawn, 2004*), may be a more appropriate approach. A conditional extremes model investigates the behaviour of one variable as the other becomes extreme — so the behaviour of air temperature could be investigated for extreme values of enthalpy, or the behaviour of enthalpy for extreme values of air temperature.

Enthalpy, like temperature, is expected to increase through the 21st century, as enthalpy is related to humidity, and warmer air can hold more water vapour. As a result, it is expected that the return levels associated with annual exceedance probabilities will also increase through the 21st century.

In this section, specific guidance on regulatory instruments, codes and standards applicable to extreme temperature hazards are considered. For more information on general regulatory considerations, please see Volume 1 — Introduction to the Technical Volumes and Case Studies.

The general approach of the nuclear industry to natural hazards is also described in Volume 1. Under the Office for Nuclear Regulation (ONR) Safety Assessment Principles (SAPs) (*ONR, 2014*), simple compliance with codes and standards may not necessarily comprise a robust safety substantiation for nuclear plants. Industry practice is for operators to apply codes and standards as a minimum and to consider events that are beyond the 1 in 10,000-year design basis. The SAPs represent relevant good practice for nuclear safety; however, it is also recognised that nuclear safety standards may not need to be applied to all energy infrastructure installations.

Although health and safety legislation exists for prevention of exposure of people to hazardous temperatures at work, and building regulations exist for safety and sustainability of all buildings, there is no specific legislation relating directly to extreme ambient temperatures. Health and safety legislation is discussed generally in Volume 1 — Introduction to the Technical Volumes and Case Studies. Building regulations control how buildings are to be designed or modified on the public grounds of safety and sustainability. The latest and current version are *The Building Regulations (2010)*, though the accompanying Approved Documents have been revised separately on occasions since then. A complete revision of the regulations has already been through a consultation stage and is expected in 2018.

Knowing that extreme temperatures cannot be prevented or avoided, the options for risk reduction are directed to protection and mitigation, as the consequences of extreme temperatures can often be minimised by using appropriate design principles or features.

For such considerations, various standards exist that are aimed at providing protection for systems, structures and components (SSCs), examples of which are:

Structures

Concrete structures specified and constructed according to Eurocode standards are generally resistant to thermal stresses in the range that could be encountered during extreme ambient temperature events (in the UK). Steel and other structures could have a more marked reaction that must be considered during design, operation and through-life maintenance. This is addressed in different Eurocodes. Eurocodes are published as EN 1990 through to EN 1999 and replaced various British Standards when they were adopted.

Electrical systems/electronic components

These can be very sensitive to changes in temperature as some components are designed to operate close to their breakdown temperature (upper limit) and many will not function or will show impaired performance at lower temperatures. In addition, some electronic components/systems can fail when there is a rapid change in temperature. For example, in the railway sector a link has been established between changes in temperature (15 °C to 20 °C in a day) and particular types of signalling equipment. Such components are often protected against environmental variations by enclosures and HVAC systems, as well as alarm/trip systems to protect against instability or damage. The core standard for electrical installations is BS 7671 (the IET Wiring Regulations) and the accompanying Design Guides. Moisture protection of components/systems, including that resulting from temperature variations, is covered by the Ingress Protection (IP) rating in accordance with IEC standard 60529.

Solar Photovoltaic (PV)

Performance and efficiency of solar PV installations can be affected significantly by temperature variations and extremes. The reader is directed to BS EN 61215-1:2016 for an overview of standards that may be applicable, depending on usage.

HVAC systems

These are commonly used to regulate temperature and humidity within structures, including for plant, equipment and people. HVAC system design for protection of plant and equipment performance and reliability is driven entirely by the requirements of the equipment concerned and is usually derived from the equipment manufacturers' instructions rather than standards or rules. Protection of people is a separate issue discussed below.

People

The Workplace (Health, Safety and Welfare) Regulations 1992 lay down particular requirements for most aspects of the working environment, including that "the temperature in all workplaces inside buildings shall be reasonable". Approved Codes of Practice offer some guidance as to what might be considered reasonable, though it will be dependent on application. Extremes of temperature are relevant to both personnel safety and continuity of business; however, protection of people is effectively assured by operating and emergency response procedures.

Energy production/transmission/distribution may be consequently affected by personnel responses.

This list is not intended to be exhaustive in respect of the SSCs that could be vulnerable to temperature extremes. There are numerous other types of SSC that may be important to the overall operability and protection of installations. These include fuel systems (e.g. diesel), water-based services (e.g. cooling to standby equipment) and mechanical systems (e.g. those requiring effective lubrication). Although standards exist for the composition and testing of fuels, lubricants, etc, these relate mainly to suppliers rather than users.

Again, using the nuclear industry as a leading example with respect to the extreme temperature hazard, Annex 5 of the latest version of the technical assessment guide for external hazards (*ONR, 2017*) states:

"The extreme ambient temperature hazard is ameliorated by the slow development of extreme conditions and the relatively long timescales for the plant to respond. It can be assumed that there will be at least several hours' notice of extreme conditions developing, and often several days. High temperatures are a potential challenge to electrical equipment which may have essential safety functions. Low temperatures may through brittle fracture of safety related structures and/or the freezing of liquid filled systems pose a threat to safety functions. Low temperatures may also threaten cooling water supplies through freezing. High ambient temperatures may also be accompanied by solar gain. Methods for assessment of this can be found in BS 5400. The inspector should establish that the potential threats and consequences are recognised by the operators and appropriate prearranged responses are embodied in operating instructions.

"It is possible that there is a need for operating rules/instructions which limit activities, for example crane usage during periods of particularly low temperature.

"If extended periods of sub-zero temperatures occur, there is a possibility of the development of sea ice (or frazil). This is a slow developing process, and one which the plant operators should have contingency for recognising."

ONR (2017) expects that design basis events should take account of reasonable combinations of extreme conditions that may be expected to occur, and of consequential hazards from adjacent facilities arising from the extreme conditions. Combinations or consequential hazards could mean that SSCs are exposed to conditions or substances that they were not designed to withstand.

For extreme temperatures, arrangements that give forewarning of developing conditions that could realistically give rise to a challenge to the effective functioning of safety-related SSCs should be provided. Given the slow-developing nature of the extreme events, reacting to developing extremes is unlikely to be a challenge for designers or operators. Plant outages, however, may be unavoidable.

Operators may consider producing a hazard severity/frequency curve to define a design basis for natural hazards, where possible. Such a curve could incorporate geographical data (e.g. as described in *Section 4*). However, it is also noted in *Section 4* that some difficulties exist in generating extreme temperature return periods with confidence.

7.1 Climate change

Within the scientific literature, there are a number of studies that have investigated changes in the nature of extreme events in recent decades, leading to the *IPCC (2013)* concluding that it was virtually certain that the global mean temperature has increased since the late 19th century. *IPCC (2013)* also concluded that, for extreme temperature events, it was very likely that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased globally since about 1950 and it is likely that these changes have occurred across most of Europe. As a result, it is important that any methodology used to study extreme temperatures (for both main and minor phenomena described in this volume) and using past observations should consider the effect that climate change could have on the results, and the suitability of these results to the nature of the application and any future period under consideration.

7.2 The effect of climate change on extreme air temperatures

Temperature extremes are projected to continue warming during the 21st century. Confidence in the output from climate models (on which this projection is based) is generally good, as they are able to reproduce observed temperature changes during the 20th century with confidence (*Clark et al., 2006*; *Tebaldi et al., 2006*; *Kharin et al., 2007* and *2013*).

In addition, *Kharin et al. (2007, 2013)* investigated how the 1 in 20-year extreme temperatures could change. They concluded that the simulated, present-day, 1 in 20-year extreme temperatures compared well to extreme temperatures calculated from global reanalysis datasets, and that the 1 in 20-year extreme warm temperature events followed changes in summer mean temperatures through the 21st century.

The *IPCC (2013)* concluded that climate models project near-term changes in the intensity and spatial extent of heatwaves and warm spells, and that — for Europe — high-percentile summer temperatures are projected to warm faster than mean temperatures. As a result, it is anticipated that climate change could cause warmer UK extreme temperatures and that extreme temperature events could warm more than mean events throughout this century.

7.3 Physical limits on extreme air temperatures

To date, within the scientific literature, no existing methodologies exist that could be used to determine limits to extreme air temperatures. Expert opinion within the Met Office is that a physical limit for pre-2100 temperature at any non-specific location on Earth can in principle be determined from an equilibrium energy balance calculation, i.e. by finding the temperature that would be reached at the point when the incoming radiation from the sun is balanced by outgoing radiation. However, for a non-specific point on Earth, this value would be expected to be very high, and as such would not provide any practical limits to the upper bounds of any extreme return values. It would be very difficult, if not impossible, to construct a hard upper limit for any UK site, as there are many factors influencing behaviour at individual sites — such as coastal effects, advection (the horizontal movement of air masses, influenced by the global dynamics, which in turn affects local climate as discussed in *Section 2.1*), and topographical effects that are not well constrained. It may be possible to use meteorological models in experimental mode to understand better the limits of temperature at any UK site. However, this is not a recommended course of action due to the uncertainties that would necessarily be introduced with regard to the plausibility of any scenario.

Currently, the highest acknowledged temperature in the world is 56.7 °C, recorded in Death Valley, California in 1913; other locations have recorded values in excess of 50 °C, such as Tunisia, Australia and Israel. More recently, temperatures of 54.0 °C were measured on 22nd July 2016 in Mitribah, Kuwait and of 53.9 °C at Basra, Iraq. All of these sites would be described as arid desert regions, which reflects their mid-latitude locations (within 30 degrees of the Equator). As a result, these temperatures are not representative of UK sites, and do not provide realistic upper limits for extreme UK temperatures.

The very lowest temperatures that have been recorded are over permanent snow or ice fields in high-latitude sites. The lowest temperature recorded is –89.2 °C at Vostok in Antarctica on 21st July 1983. Again, it is extremely unlikely that a temperature this low would occur at any UK site (compare this value with the lowest recorded UK temperature of –27.2 °C).

7.4 Summary of climate models and associated uncertainty

Climate models represent the climate system using mathematical equations, representing the processes in the system, discretised onto a grid. Within the climatological community, climate models are used to investigate the possible effects that anthropogenic greenhouse gas emissions may have on the future climate system. However, the climate system is very complex, and no climate model can capture perfectly all of the processes within it. For example, some processes may occur at a finer spatial resolution than that of the model grid and hence may not be captured. Additionally, scientific understanding of the processes may also be limited, which in turn limits capability to capture these processes in a model.

As a result, climate modelling will always be prone to some inevitable degree of uncertainty, and it is important to characterise these uncertainties — especially when considering possible future climate. Sources of uncertainty associated with future climate include structural uncertainty, emissions uncertainty, internal model uncertainty, and climate model resolution. These are outlined briefly in the following subsections.

7.4.1 Structural uncertainty

There are many climate modelling centres around the world, developing different climate model versions which, although based on the same physics and with similar representations of the fundamental processes, will vary to some extent in their structure (hence the term structural uncertainty). Climate modelling groups endeavour to represent the climate in the best possible way, but because of these uncertainties different modelling groups can and do use different, but still plausible, representations of the climate processes.

The mathematical processes involved within a climate model represent the climate system based on current knowledge of the atmosphere, land surface, cryosphere and ocean processes. These processes are allowed to interact with each other, producing feedback which can either reinforce the effects of climate change or reduce them. However, representation of these processes in a model is based on a mixture of observation, theory and simulations, many of which cannot be explicitly incorporated into models. This can add to the uncertainty associated with a particular climate model.

7.4.2 Emissions uncertainty

Running a climate model requires the provision of various inputs. For modelling the future climate, one of these inputs is an estimate of future greenhouse gas emissions. However, since the evolution of future greenhouse gas emissions cannot be known with certainty, these have to be approximated under a series of future emissions scenarios (hence the term emissions uncertainty). These are plausible future pathways along which our future greenhouse gas emissions could evolve, making certain assumptions about population, societal behaviour, etc. Climate models can be driven with different emissions scenarios to explore the possible impact of different pathways of human development on the projected future climate. The most commonly used set of emissions scenarios are given in the *Special Report on Emissions Scenarios* (SRES) (*IPCC, 2000*).

More recently, climate modelling has begun to use representative concentration pathways, or RCPs (*van Vuuren et al., 2011*), which instead characterise the atmospheric concentrations of greenhouse gases, rather than the level of emissions.

7.4.3 Resolution of climate models and internal model uncertainty

Climate models can be run at a number of different spatial scales, depending on whether the goal is to understand how climate change could affect the Earth as a whole, or how it could affect specific regions. Regional climate models (RCMs) are run at a much finer spatial resolution compared to global climate models (GCMs), though RCMs take their boundary conditions from GCMs, so may inherit any biases in the driving GCM. Even within regional climate models, many important physical processes cannot be resolved at the resolution of the model (e.g. cloud formation). As a result, these subgrid-scale processes need to be parameterised. Different parameterisation schemes can, and do, provide plausible yet different projections of climate model variables, such as daily temperature. So every single model projection has a level of uncertainty associated with it (internal model uncertainty).

Ideally, this uncertainty should be quantified too. One approach is to run the same climate model but to use several different, but still plausible, parameterisation schemes. This can create an ensemble of climate model projections, and the perturbed set of models from which the projections arise is known as a perturbed physics ensemble (PPE). For the UK, *Murphy et al. (2009)* developed a small RCM PPE that looked at how the atmosphere responded to changes in the greenhouse gas emissions through the 21st century.

7.4.4 Summary considerations and forward look

Bearing in mind the above uncertainties, it is advised that any projection of future extreme events should ideally also quantify sources of future uncertainty; examples include the uncertainty associated with anthropogenic and natural greenhouse gas emissions and with population growth, and also the structural and internal model uncertainty.

An approach that considered all three sources of uncertainty in the creation of climate model projections especially for the UK was that employed by UKCP09 (*Murphy et al., 2009*). These official projections for the UK have been in use for almost a decade; the next release of official UK climate projections, the UK Climate Projections 2018 (UKCP18) Project (*UKCP Project, 2018*), is scheduled for 2018. These projections will provide an update to UKCP09 and a range of different tools and data for use in assessing climate impacts on the UK. Some initial guidance has been issued by the project, including a Q&A (*UKCP Project, 2016*), a discussion of whether UKCP09 is still an appropriate tool for adaptation planning, covering projections for both land and marine environments (*UKCP Project, 2017a*), and a UKCP18 project overview (*UKCP Project, 2017b*). Other outputs will become available in due course.

7.5 Future site-specific projections of return levels for extreme air temperatures

For many long-lived infrastructure projects, it is desirable to obtain site-specific projections of return levels for future periods. In addition to the climate model structural and internal uncertainties, described above, there are two further issues that need to be considered:

- non-stationarity within climate projections of temperature; and
- using climate model output that is appropriate to a particular spatial area to produce site-specific return levels.

7.5.1 Non-stationarity

EVA assumes that the observations are independent of one another. Under climate change, observations of temperature are projected to warm over the 21st century and this is what is observed in the climate model output of temperature time series. As a result, temperature output from climate models cannot be considered as a stationary time series. Consequently, to satisfy the assumption of stationarity for an EVA and to derive return levels appropriate to specific periods in the future, the non-stationarity present within the data needs to be explicitly considered.

In the scientific literature, different methodologies that account for the non-stationarity in the data have been described. Examples include *Brown et al. (2008, 2014)*, *Nogaj et al. (2006)* and *Parey et al. (2007)*, who allow the parameters of the EVD to vary in time. An alternative approach is to fit stationary EVD to short periods of climate model data (*Frei et al., 2006*; *Beniston et al., 2007*).

7.5.2 Spatial considerations

All climate model output represents an areal average, at the resolution at which the climate model is run. If future site-specific values are required, then it becomes necessary to downscale, i.e. to make assumptions about how the behaviour of the climate model relates to the site of interest. One commonly used approach assumes that the difference between the anomalies between future return levels and present-day return levels calculated from climate model output can be directly applied to the site return levels. These site return levels are obtained from an EVA using present-day and past observed historical records for the site of interest.

7.6 Alternative approaches

Research continues to explore approaches that will help to quantify the uncertainty associated with an EVA, via both statistical and climatological techniques. A brief description of some of these techniques is provided below.

7.6.1 Emerging statistical techniques

Within the extreme value community, statisticians are investigating techniques that look to incorporate more information about the spatial nature of physical phenomena. One established approach is that of regional frequency analysis (RFA) *(Hosking and Wallis, 1997)*. Briefly, an RFA approach is a multistep approach that aims to pool homogeneous spatial data and fit a regional probability distribution to this pooled data. *L-moments* are used to derive the parameter estimates and choose a probability distribution. One difficulty with using L-moments is that covariates in the parameters cannot be incorporated. Both *Cooley et al. (2007)* and *Davison et al. (2012)* have investigated different approaches, based on *latent variables*, to include spatial information about extreme events and so reduce the uncertainty associated with an EVA.

Another area of active research is to incorporate information about the physical processes, possibly using Bayesian techniques, into the analysis. Examples of information that could be used include results from previous analyses, physical constraints, or plausible ranges for parameters gathered from observations, simulations or expert elicitation.

The methodology presented in this technical volume for the analysis of extreme air temperatures touches on the degree of statistical complexity that can be required when fitting statistical models to extreme data, assessing the models, and interpreting the results.

Current research is starting to focus on more advanced statistical models which can make better use of multiple sources of data to reduce statistical uncertainty (see Volume 1 — Introduction to the Technical Volumes and Case Studies). These approaches may in the future become standard techniques that can be easily applied. As a result, the reader may wish to consult the latest literature or consider the possibility of engaging experts in order to benefit from the latest techniques and to ensure the robustness and appropriateness of any statistical analysis to answer their particular questions.

7.6.2 UNSEEN method (UNprecedented Simulated Extremes using ENsembles)

Following on from the above discussion around reducing uncertainty using multiple data sources, one way to do this is with climate models. It is generally assumed that an observed sample of meteorological data is representative of the local climate. However, given the rarity of extreme events and the nature of natural variability, this assumption is difficult to verify without a long time series of observations of the order of several hundred years. Since such long time series are not generally available (the CET being a notable exception), climate models can be used to provide a much larger sample of events than those which have currently been observed, but which are still meteorologically realistic (*van den Brink et al., 2004, 2005*).

One example of this approach is the so-called UNSEEN method (*Thompson et al., 2017*). This was first used as part of the National Flood Resilience Review (*HM Government, 2016*). A simulated 1400-year model archive of many possible realisations of the current UK climate was produced; these simulated years were created using data from a particular type of climate model (the Met Office's decadal prediction system; *Dunstone et al., 2016*), combined with actual observations for each year. The climate model was driven with observed levels of greenhouse gases, atmospheric aerosols and solar radiation. A large number of simulated years were created by taking advantage of the sensitivity of weather to small perturbations (also known as the 'butterfly effect') to create many different realisations of the atmospheric state. In these many realisations of current UK climate, there may be extreme values produced which are outside the realms of those in the observational record, but still consistent with the current climate. This can therefore potentially provide a more realistic estimate of the risk of extremes. This dataset may not fully sample the range of all possible near-future atmospheric conditions; however, it will sample a broader range of atmospheric states than have been observed within the recent period.

7.6.3 H++ climate scenarios

As part of the second *UK Climate Change Risk Assessment* (*HM Government, 2017*), a set of plausible high-end climate change scenarios were developed. These scenarios, known as H++, are intended to provide a high-impact, low-likelihood set of events which can be compared to other outcomes from climate models, thereby allowing decision-makers to stress-test the resilience of their assets and procedures to unlikely but plausible (and potentially impactful) climate outcomes (*CCC, 2015*). The H++ scenarios are available for a range of parameters including heatwaves and cold snaps.

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Albedo
The fraction of solar radiation reflected by a surface or object, often expressed as a percentage. Fresh snow has a high albedo, reflecting about 80% of the incoming solar radiation, compared to the lower albedo of grass (about 25%) and forest (about 5 to 10%).

Dry bulb temperature
The temperature of air as measured by a thermometer freely exposed to the air but shielded from moisture and radiation, typically by a Stevenson screen.

Heatwave
A prolonged period of abnormally hot weather.

Katabatic wind
A particular type of wind formed on nights with clear skies and where there is little of no wind. A cold layer of air forms near to the ground. For sloping ground, the air close to the ground is colder than air at the same level but at some horizontal distance. Gravity causes this cold and more dense air to flow beneath the warmer and lighter air producing a katabatic wind.

L-moment
A method to estimate the parameters of a distribution using the order of magnitude of the observations. It is analogous to the method of maximum likelihood.

Latent variable
A variable that cannot be directly observed but can be inferred, via a mathematical model, from other observable variables.

Method of maximum likelihood
A way of deriving the parameters of a statistical model, given observations. The parameter values are found such that they maximise the likelihood (the probability) that the process described by the model produced the data that were actually observed.

Modes of variability
A climate pattern that has a set pattern of spatial and temporal behaviour, typically affecting specific regions and over seasonal or longer timescales. This behaviour occurs on a quasi-regular basis. Examples of modes of variability include the North Atlantic Oscillation, El Niño Southern Oscillation and the Atlantic Multi-decadal Oscillation .

Noise (statistical)

The unexplained variability present within a sample of data.

North Atlantic Drift

An ocean current that flows eastwards of 45°W and northwards of 40°N. It is a part of what is commonly known as the 'Gulf Stream'. The other parts are the Florida Current which originates in the Gulf of Mexico and flows through the Straits of Florida to about 40°N, and the Gulf Stream which, more precisely, flows eastward to 45°W.

Sensible heat

A thermodynamic term for thermal energy whose transfer to or from an object results in a change in its temperature; as the term suggests, it is heat that can be felt.

AEP	Annual exceedance probability
AIC	Akaike information criterion
AMM	Atlantic Meridional Mode
AMO	Atlantic Multidecadal Oscillation
BS	British Standard
Cefas	Centre for Environment, Fisheries and Aquaculture Science
CET	Central England Temperature
CMIP(5)	(Fifth) Coupled Model Intercomparison Project
ECMWF	European Centre for Medium-range Weather Forecasts
ENSO	El Niño Southern Oscillation
ERA-i	ECMWF Interim Re-Analysis
EVA	Extreme value analysis
EVD	Extreme value distribution
GCM	Global climate model
GEV	Generalised extreme value (distribution)
GMT	Greenwich Mean Time
GPD	Generalised Pareto distribution
HVAC	Heating, ventilation and air conditioning
IPCC	Intergovernmental Panel on Climate Change
MERRA	Modern Era Retrospective-analysis for Research and Applications
MPP	Marked Point Process
ONR	Office for Nuclear Regulation
NAO	North Atlantic Oscillation
NCIC	The Met Office National Climate Information Centre
NWP	Numerical weather prediction
PPE	Perturbed physics ensemble
PV	Photovoltaic
RCM	Regional climate model
RCP	Representative concentration pathway
RFA	Regional frequency analysis
SAPs	Safety Assessment Principles
SSCs	Systems, structures and components
SRES	[IPCC's] *Special Report on Emissions Scenarios*
UKCP09	United Kingdom Climate Projections 2009
UKCP18	United Kingdom Climate Projections 2018
UNSEEN	UNprecedented Simulated Extremes using ENsembles

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