Regional statistical modelling of hourly extreme precipitation in the United Kingdom

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For Dad and Mum

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Abstract

In the UK, various studies have investigated daily extreme precipitation; however, increases in recent flash flood events indicate the need for improved understanding and methods associated with sub-daily extremes. This thesis attempts to fill this gap by examining quality-controlled hourly precipitation data from 1992-2014 at 197 gauges across the UK, and using climatological predictors to develop a regional statistical model which quantifies the frequency and intensity of hourly extreme precipitation.

Regional annual exceedance probabilities for sub-daily extreme precipitation were first estimated using the daily UK extreme regions. Results suggested these regions did not adequately reflect the spatial variation of sub-daily extreme precipitation. The sub-daily extremes showed clear seasonality with short-duration extremes (1h and 3h) predominantly in summer, and longer duration extremes (12h and 24h) distributed throughout late autumn and winter. Moreover, the diurnal cycle of short-duration extremes centres on the afternoon, with a peak typically between 1400 and 1700, especially in southern and eastern regions.

Hourly gauges were clustered using a statistical approach, employing the annual maxima, peak over threshold indices and weather types to develop five new regions, which reflect the impacts of orography, seasonality, and atmospheric. Regional frequency analysis with L-Moments was then used to estimate growth curves for the new homogeneous hourly extreme precipitation regions.

Time-dependent Poisson-GP regional statistical models were developed to simulate hourly extreme precipitation, using atmospheric circulation, temperature, and moisture content as predictive covariates. The model indicated a noticeable peak in the occurrence of hourly extremes in summer, especially in southern regions. A simple pseudo global warming scenario of 2°C was used to demonstrate the model potential. It projected an increase in the frequency and intensity of hourly extremes of up to 17%, which is higher than suggested by Clausius-Clapeyron, highlighting a need to review design guidelines for future extreme precipitation in the UK.

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List of publications

The following journal article is product of this thesis and referenced at the beginning of the relevant chapters. I took the lead role in the article and was responsible for code development, figure drawing and writing. The co-authors contributed to research ideas and manuscript editing:

Darwish, M., Fowler, H.J., Blenkinsop, S. and Tye, M.R. (2018) 'A regional frequency analysis of UK sub-daily extreme precipitation and assessment of their seasonality', International Journal of Climatology, 38(13), pp. 4758–4776. doi.org/10.1002/joc.5694

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Abbreviations

AEP: Annual exceedance probability
AIC: Akaike Information Criterion
AMAX: Annual maximum
AMO: Atlantic Meridional Oscillation
AMOC: Atlantic Meridional Overturning Circulation
CA: Cluster analysis
CAPE: Convective available potential energy
CC: Clausius–Clapeyron
CDF: Cumulative distribution function
CPM: Convective permitting models
DDF: Depth-Duration-Frequency
DEFRA: Department for Environment, Food & Rural Affairs
DEM: Digital elevation model
DPT: Dew point temperature
EA: East Anglia
Elev: Elevation
ENSO: El Nino Southern Oscillation
ES: East Scotland
EVT: Extreme value theory
FEH: Flood estimation handbook
FOR: Forth
FSR: Flood studies report
GCM: General circulation models
GEV: General extreme value
GLM: Generalized linear modelling
GP: General Pareto
GPD: General Pareto distribution
HadUKP: Hadley Centre UK Precipitation
HUM: Humber
i.i.d: independent and identically distributed

INTENSE: INTElligent use of climate models for adaptatioN to non-Stationary hydrological Extremes
IPCC: Intergovernmental panel on climate change
Lat: Latitude
Lon: Longitude
ME: Mid East
MIDAS: Met office integrated data archive system
MSLP: Mean sea level pressure
MSW: Mid South West
MW: Mid Wales
NAO: North Atlantic oscillation
NE: North East
NHI: North Highlands and Islands
NI: North Ireland
N-SQ99: Number of summer (April-September) events exceeding SQ99
NW: North West
N-WQ99: Number of winter (October-March) events exceeding WQ99
PC: Principal component
PCA: Principal component analysis
PGW: Pseudo global warming
POT: Peaks over threshold
Q99: Precipitation 0.99 quantile
RCM: Regional climate models
RFA: Regional frequency analysis
RMed: Median of annual maximum precipitation
SE: South East
SEPA: Scottish Environmental Protection Agency
SLP: Sea level pressure
SOL: Solway
SQ99: Summer (April-September) precipitation 0.99 quantile
SS: South Scotland
SST: Sea surface temperature

SW: South West
TCWV: total column water vapour
Tmax: Median of maximum temperature on Q99 days
Tmin: Median of minimum temperature on Q99 days
UKCP: UK climate projections
WQ99: Winter (October-March) precipitation 0.99 quantile
WT: Weather types

Chapter 1. Introduction

Daily and sub-daily extreme precipitation events are major cause of flooding, soil erosion, pollution and landslides, which have potentially high impacts on urbanised areas, transportation, human society, and infrastructure (IPCC, 2012). Various studies of daily observations have indicated an increase in the frequency and intensity of extreme precipitation across the globe in the last few decades (Alexander *et al.*, 2006; Westra *et al.*, 2013; Donat *et al.*, 2017). The changing behaviour of the extremes has attracted researchers from different fields to characterise their patterns, estimate associated risks, and evaluate their relationship to climate change and related, potentially driving, climatic variables (e.g. temperature, moisture content).

In the last few decades, significant flood events arising as a consequence of extreme precipitation have occurred in the UK. Examples include the Boscastle 2004 flood which was caused by intense convective precipitation (50mm/hr) (Golding et al., 2005) and the UK 2007 floods which were caused by frontal precipitation associated with slow moving depressions across the British Isles (Blackburn *et al.*, 2008). The latter resulted in high insurance claims and a significant hit for infrastructure and critical services (Chatterton et al., 2010). In 2012, Newcastle experienced a flood caused by intense precipitation where ~50mm precipitation occurred in 2 hours and affected more than 1200 properties (Archer and Fowler, 2018). Stern (2006) reported that floods are among the most costly extreme events in the UK, while the UK environment agency warned that flood related damages could increase up to 60% more by 2035, unless prompt actions and adaptation policies are implemented (Chatterton et al., 2010).

However, the response of extremes to ongoing climate change is considered a challenge for scientists and decision makers due to the numerous, complex physical and thermodynamic contributions governing extreme events (Herring et al., 2014). Climate change studies which have investigated daily extremes frequency and return estimates using physical theory (e.g. O'Gorman and Schneider, 2009), observations (e.g. Fischer and Knutti, 2016), and model simulations (e.g. Kharin et al., 2007) have agreed that extremes have intensified and predicted to continue to increase in response to warming climate especially in wet regions, however, the response to future climate change is noticeably uncertain with high sensitivity, especially for convective conditions. Extreme precipitation are generated from various processes, and might be associated with a range of conditions depending on location and seasonality such as the large atmospheric circulation, multitude and tropical cyclones, atmospheric rivers, and local convective complexes, which makes understanding and predicting changes difficult (Schumacher and Johnson, 2005; Gosling et al., 2011). Furthermore, the IPCC (2012) reported strong spatial and temporal variation in extreme precipitation, which adds more challenges to extremes simulating.

Recently, Donat et al. (2017) reported that existing storm management infrastructure is inadequate to control the increasing precipitation extremes and totals in different regions. Policy makers and designers have highlighted the need for adaptation planning strategies and reliable risk estimates (Stocker et al., 2013). Arnbjerg-Nielsen et al. (2013), who reviewed current methods for assessing future precipitation changes and their impacts on urban drainage systems, reported that in spite of the improved understanding and characterisation of precipitation under climate change, the estimation of risks remains challenging due to the needed high spatio-temporal resolution, besides the difficulty in monitoring and quantifying the extremes. Therefore, investigating the temporal and spatial characteristics of precipitation extremes, in addition to their related climatological variables is crucial to quantify extremes intensity and frequency, evaluate the potential risks, and implement adaptation plans.

Theoretically, the physical processes generating precipitation are well established, especially for mean (climatological) precipitation, however, simulating and describing the exact interaction between the various processes is not practically possible due to its complexity and associated uncertainties (Demirdjian et al., 2018). Furthermore, the relationship between mean and extreme precipitation is not straightforward, particularly for increasingly extreme precipitation events (Zhou and Lau, 2017), which adds more ambiguity in understanding extremes, while using general circulation models (GCMs) and regional climate models (RCMs) to simulate extremes frequency and intensity at small spatial scales is computationally expensive (Chan et al., 2013). Extremes are rare by nature, and quantifying their occurrence frequency and intensity is challenging. Consequently, statistical analysis and modelling have been adopted due to its potential in characterising extremes patterns without prior knowledge of all complex atmospheric processes (Rohrbeck et al., 2018).

1.1. UK daily Precipitation

Similar to the trend of globally increasing extremes, various studies have reported increasing daily and multi-daily precipitation intensity and frequency in the UK (Osborn *et al.*, 2000; Fowler and Kilsby, 2003a; Fowler and Kilsby, 2003b; Simpson and Jones, 2014). These increasing trends have been reported for different periods, and durations, which indicates the consistency of the reported increasing trends.

Daily mean and extreme precipitation have been investigated thoroughly in the UK taking the advantage of a rich data archive and dense gauge network. The UK precipitation record goes back to 1766, where the daily, monthly, seasonal, and annual precipitation data is produced by the Hadley Centre for climate prediction and research (HadUKP). Originally, the monthly data series was constructed by Wigley et al. (1984), and was updated by Wigley and Jones (1987), Gregory et al. (1991), Jones and Conway (1997), and Alexander and Jones (2000). The data series are updated in real time for all regions and used in various hydrological applications (e.g. calculating regional totals, estimated return levels). However, Simpson and Jones (2012) indicated that uncertainties and potential inhomogeneities associated with the HadUKP datasets, are higher for regions with sparse gauges than dense gauged regions.

Therefore, Wigley *et al.* (1984) identified 5 regions in England and Wales using mean daily precipitation, which were subsequently extended to 9 regions for the UK and Northern Ireland by Gregory *et al.* (1991). Identifying precipitation regions provides the ability to pool data from different locations across each region, which provides data for ungauged locations, and reduce the uncertainties in sparsely gauged regions (Hosking and Wallis, 2005). The regions have been used to estimate return levels and evaluate the changes in trends and patterns of mean precipitation (e.g. Jones and Conway, 1997; Simpson and Jones, 2014), extreme precipitation (e.g. Fowler and Kilsby, 2003b; Jones et al., 2013), and future projections of extremes (e.g. Fowler and Wilby, 2010). However, Jones et al. (2014) reported that the HadUKP regions do not represent the variability of the frequency, magnitude, and seasonality of daily extremes within each region efficiently.

Thus, a new 14 region classification has been developed using daily extremes between 1961-2009 to provide reliable estimates of return levels, and describing spatial and temporal characteristics of extremes (Jones et al., 2014). The regions were developed using regional frequency analysis (RFA) and extreme value theory (EVT) suggested by Hosking and Wallis (2005), with a focus on different extremes characteristics such as seasonal timing and magnitude of extremes. The 14 regions showed an improved performance in estimating return levels compared to the HadUKP regions, especially for daily extremes, and indicated clearer upward trends in annual maxima for the investigated period between 1961-2009 (Jones et al., 2014).

On the other hand, hydrological designs in the UK adopted the Flood Estimation Handbook (FEH) (Faulkner, 1999) approach as standard practice to estimate return levels and produce growth curves for anticipated locations. The FEH approach propose having data that equals to five times the desired event return frequency. For example, 20-years event requires having data for 100 years. The FEH provides UK-wide growth curves for hourly and daily durations (1h up to 8days), therefore, different bodies have adopted this approach primarily for flood mapping studies, flood risk assessments, and the design of flood mitigation (Kjeldsen *et al.*, 2008). However, using the method to estimate sub-daily events is challenged by the limited and scarce data availability. Furthermore, the FEH approach recommends using similar catchments to assess ungauged locations (Faulkner, 1999), which might provide misleading results for the estimated precipitation levels, especially convective and extreme precipitation, due to noticeable spatial variation in extreme precipitation (Brunsdon et al., 2001; Arnbjerg-Nielsen et al., 2013).

Nevertheless, neither the regional estimation approaches (e.g. HadUKP regions), nor the point of interest estimation approaches (e.g. FEH) consider the climatological variable in the UK when estimating return levels, even though significant relationships have been reported between climatological variables (e.g. temperature, atmospheric rivers, atmospheric pressure) and precipitation in the UK (e.g. Wilby et al., 1997; Kilsby et al., 1998; Frei et al., 2006; Lavers et al., 2013; Blenkinsop et al., 2015). Furthermore, the HadUKP regions (Gregory et al., 1991) were defined using precipitation data only and without incorporating the other related climatological variables.

1.2. UK Sub-daily extreme precipitation

In contrast with longer timescales, few studies have investigated sub-daily extreme precipitation in the UK due to the scarcity of quality-controlled, long, and homogeneous observations (Westra et al., 2014; Blenkinsop et al., 2017), despite their relation to pluvial floods and impact on urbanised areas (Dale et al., 2017; Archer and Fowler, 2018). Recently, Blenkinsop et al. (2017) investigated the UK observed climatology of sub-daily extreme precipitation and reported noticeable seasonality. Furthermore, investigating the scaling relationship between observed sub-daily extremes and temperature in the UK indicated a potential increase in precipitation intensities events under warmer climate (Blenkinsop et al., 2015). Climatological studies, using climate models, projected an increase in sub-daily precipitation, especially in summer (Chan et al., 2014a; Kendon et al., 2018), while a significant relation with large scale atmospheric circulation (e.g. mean sea level pressure (MSLP), convective available potential energy (CAPE)) has been reported (Chan et al., 2017). Moreover, Kendon *et al.* (2018) reported a noticeable difference between hourly and daily extremes predictions in the UK, where the model indicates that hourly extremes would intensify 5-10 years and decades earlier than daily extremes in winter and summer seasons respectively. Lately, Lewis et al. (2018) produced 1 km resolution gridded hourly precipitation dataset for the UK, developed using more than 1900 quality controlled gauges.

Despite the importance of having a regional assessment of sub-daily extremes in the UK and their potential impacts, none of the studies to date have performed regional frequency analysis using observational data. Studies which have evaluated extreme precipitation events in terms of their impacts and potential adaptations have reported that the lack of thorough choice of statistical distributions and models for extreme events increases the uncertainty, especially when used for generating design guidelines (Hailegeorgis et al., 2013; Simpson and Jones, 2014). Existing studies of sub-daily extremes have focused on individual sites, which is usually challenged by the limited data record, gauging network density, instrumental and human errors (Paixao et al., 2011). Regional assessment would benefit stakeholders to evaluate any location (gauged or ungauged) without limitations related to administrative and regulatory boundaries, and reduce the impact of data scarcity (Durrans and Kirby, 2004; Dittrich et al., 2016). Therefore, this research attempts to quantify hourly and multi-hourly extreme precipitation regionally, assess the usage of existing precipitation regions, define the statistical relationship between hourly extremes and related (potentially driving) climatological variables.

1.3. Statistical downscaling

Typically, GCMs and RCMs are used to simulate atmospheric circulation and predict future events. However, the spatial resolution of these is too coarse, and they are usually used to simulate large scale atmospheric circulation. Moreover, Prudhomme *et al.* (2002) reported that GCM/RCM simulations and predictions for short time scale events (i.e. less than monthly) has a lower confidence compared to longer durations.

Various studies (e.g. Xu, 1999; Maraun *et al.*, 2010b) have reported that using GCMs/RCMs for hydrological assessment might not be suitable due to:

1- The decreasing accuracy of GCMs/RCMs when applied to hydrological applications of interest, which have fine spatial and temporal scales.
2- The decreasing accuracy of simulated hydrological variables of interest (e.g. precipitation, potential evapotranspiration) compared to other climatic variables (e.g. temperature, sea level pressure).

Therefore, convective permitting models (CPMs) are usually used to simulate atmospheric circulation and climatological events (e.g. precipitation) for small scale and short duration hydrological applications (i.e. high spatial and temporal resolution). However, using CPMs is challenged by the need for high computational resources and long run times (Prein *et al.*, 2015).

Consequently, statistical downscaling approaches have been applied to GCM/RCM outputs, especially over urbanised areas, where dynamical simulations are computationally expensive (Maraun *et al.*, 2010b). Statistical downscaling employs the empirical relation between observed weather variables (e.g. precipitation, temperature), and the related climatological variables (e.g. sea level pressure (SLP), surface temperature, dew point temperature (DPT), geopotential height, sea surface temperature (SST), and North Atlantic oscillation (NAO)) to simulate future precipitation patterns at a finer resolution (Benestad, 2010; Arnbjerg-Nielsen et al., 2013). Large scale predictors are better represented in models than the variables being predicted (Maraun *et al.*, 2010b), thus statistical downscaling provides the flexibility of modelling extremes and ability to determine regression relations using well established frameworks such as generalized linear modelling (GLM) (e.g. Hertig et al., 2014) and artificial neural network modelling (e.g. Paulin et al., 2005). However, it should be noted that statistical downscaling results and performance depends on the reliability of the defined relationship between the precipitation and climatological predictor variables, which indicates the importance of having accurate climate model outputs (Maraun *et al.*, 2010b).

Therefore, this research attempts to quantify the statistical relationship between hourly extremes and related (potentially driving) climatological variables, and to use this relationship to develop a reliable statistical model and simulate extreme hourly precipitation in the UK. This statistical model would provide an alternative to the computationally expensive RCMs and/or CPMs, employing the statistical downscaling approach to estimate extreme precipitation frequency and intensity, and quantify the characteristics of extremes (i.e. frequency and intensity) under various climatic scenarios.

1.4. Research aims and objectives

The overall aim of this research is to develop a statistical model employing recently available quality controlled hourly precipitation data and related climatological variables to simulate hourly extreme precipitation intensity and frequency. The outcome of this research would be a methodology to estimate regional return estimates, quantify extremes frequency and intensity, and evaluate potential behaviour under future climate change

Therefore, this research will address the following research objectives:

1- To perform an exploratory analysis of hourly and multi-hourly extremes precipitation, seasonality, diurnal cycle, and return estimates using annual maximum (AMAX) precipitation data.
2- To assess the efficacy of using existing extreme precipitation regions in the UK to characterise the sub-daily extremes.
3- To define potentially new UK extreme precipitation regions based on hourly data and other climatological variables.
4- To estimate hourly precipitation regional return levels by fitting regional statistical distributions using extreme value theory (EVT).
5- To investigate the statistical relationships between hourly extremes and potential climatological drivers such as the North Atlantic Oscillation (NAO), sea surface temperature (SST), and air temperature.
6- To build a statistical model to simulate extreme hourly precipitation in the UK using the climatological variables identified in Objective 5.
7- To apply the statistical model developed to meet Objective 6 to evaluate the frequency and intensity of hourly extreme precipitation under potential climate changes.

1.5. Thesis structure

Chapter 2 reviews literature relating to daily and sub-daily extreme precipitation in the UK. The chapter examines trends in the historical mean and extreme daily precipitation in the UK, and the commonly used methods to analyse precipitation. Furthermore, the chapter outlines the advancement in UK sub-daily extreme precipitation analysis, including a quality controlled hourly precipitation dataset that is used throughout the thesis. Moreover, the chapter highlights future projections of sub-daily precipitation for the UK and associated challenges.

Chapter 3 provides an exploratory analysis of hourly and multi-hourly extreme precipitation in the UK. The diurnal cycle, seasonality, and frequency of extremes across the UK are investigated regionally. Furthermore, regional estimation of the return estimates across the UK, and the efficacy of using the existing daily extreme precipitation regions are introduced in this chapter. The work presented in this chapter has been published in Darwish *et al.* (2018), and indicates the need for sub-daily extreme precipitation regions.

Chapter 4 presents the development of new UK hourly extreme precipitation regions, which were defined using the quality controlled precipitation dataset, additional climatological variables, and the novel use of European weather patterns. Furthermore, the assessment of the new regions' homogeneity, and their efficacy to analyse hourly extreme precipitation in the UK and estimate return levels, indicates an improved performance compared to the existing UK daily extreme precipitation regions.

Chapter 5 employed the new defined regions to develop a statistical model that is simple and efficient to quantify hourly extreme precipitation intensity and frequency in the UK. The model was developed using the extreme value theory and the generalized linear modelling approach. Furthermore, the model included various climatological variables to account for the varying nature of extreme precipitation in the UK.

Finally, the main conclusions, summary of results, and the potential future work to enhance and extend this research are presented in Chapter 6.

Chapter 2. Literature Review

This chapter begins with a review of the literature on precipitation trends with a broad, global context and then a focus on the United Kingdom. It is divided into four main sections: firstly, it presents an overview of precipitation formation processes, reviewing global and regional studies (Section 2.1). Second, studies of the climatology and trends in European sub-daily extreme precipitation are reviewed (Section 2.2). Next, trends in UK daily and sub-daily precipitation are reviewed (Section 2.3), then, variables which have an effect on UK precipitation such as atmospheric circulation, oceanic circulation and temperature, are discussed (Section 2.4). Finally, a summary and identified gaps in the existing literature are presented (Section 2.5).

2.1. Precipitation overview

Precipitation usually occurs when moist air rises to higher altitudes where it cools and condenses due to the lower temperature in high atmospheric layers. The rise of the moist air forms clouds full of water drops, which in turn grow larger either due to additional condensation or due to further collision with other droplets. As they grow larger, the droplets' own weight eventually overcome the uplifting air forces and fall due to gravity as precipitation.

The geographical location of the UK is responsible for its rapidly changing and unstable weather conditions. To illustrate, seven major air masses from both warm (tropical) regions and cold (polar) regions, each of which has distinctive temperature and humidity characteristics, may affect the United Kingdom causing different precipitation and extreme events to occur (Mayes and Wheeler, 2013). Consequently, precipitation amounts vary significantly across the United Kingdom. The UK Met Office average annual precipitation maps between 1981-2010, show that generally the further west and the higher the altitude, the greater the annual precipitation (Met-Office, 2016). Moreover, the maps show that the mountains of Wales, Scotland, Northern England and South West England are the wettest parts of the country, compared to the south and the southeast geographical. This may be attributed to the different precipitation generating mechanisms in the UK, the varied configuration of the coastline, and the rain shadow effect, where mountainous parts of the South West and Wales force the ascent of air to higher altitudes, leading to precipitation occurrence before moving further towards the southern and southeast regions (Mayes, 2013).

Each precipitation type is generated in different temporal and spatial circumstances as follows:

1- Relief precipitation occurs when warm, moist air is forced to rise over high areas, cools, and condensation occurs to form precipitation.
2- Frontal precipitation, which is common in the UK (Holt et al., 2001), forms as a result of warm and cold air masses meeting. As the air masses have different characteristics, they will not mix and a front will be formed. The warmer air mass, which is less dense than the cold air mass, is forced to rise and accordingly cool with condensation leading to precipitation occurrence.
3- Convective precipitation, which is very common in the southern part of the UK during summer (Holt *et al.*, 2001; Holley *et al.*, 2014; Blenkinsop *et al.*, 2015), is a result of heating of an air mass over a warm land surface. This process will cause the air to become warmer and lighter, and be lifted higher, with cooling and subsequently condensation causing precipitation.

In the UK, relief and frontal precipitation events are due to synoptic scale systems while convective precipitation is due to local scale events (Mayes, 2000).

In recent decades, daily precipitation has shown increasing frequency/intensity trends across different areas around the globe (Westra et al., 2013). Extreme precipitation and climate change with its consequences of increasing, floods, and other environmental, economic and societal impacts have particularly attracted researchers from different fields and disciplines to study and understand their occurrence, frequency, and magnitudes. IPCC (2012) claimed that the impacts of the increasing frequency and intensity of daily extreme precipitation over vast areas of the globe have increased, indicating that it is therefore essential to analyse and predict such events.

Recent studies have confirmed that precipitation intensity has increased considerably over recent decades, for both daily (Westra et al., 2013; Alexander, 2016) and sub-daily precipitation (Westra et al., 2014), while 65% of the studied areas around the world experienced increasing annual maximum daily intensity and/or frequency (Min et al., 2011) , which indicates increasing potential for flooding. Lenderink and Van Meijgaard (2008) reported that sub-daily extremes are more sensitive to climate change and potential temperature increase, leading to a greater intensification compared to daily extremes. In the UK, investigating the scaling relationship between the observed hourly extremes and temperature, suggested that precipitation will intensify with temperature according to the Clausius–Clapeyron (CC) relationship

(Blenkinsop et al., 2015; Blenkinsop et al., 2018). The CC relationship explains the increased capacity of warmer air to hold moisture under constant relative humidity; a ~6–7% increase in precipitation per 1ºC increase in temperature. A general agreement between the studies is that increasing atmospheric temperature could increase precipitation intensities for daily and sub-daily precipitation events.

The assessment of a range of data in relation to the impacts of climate change indicates that floods arising as a result of intense precipitation are among the most costly and critical hazards arising as a consequence of climate change (Stern, 2006). These may lead to casualties, infrastructure damage, disruption of transportation links as well as damages to natural ecosystems (Stern, 2006; Gosling *et al.*, 2011; IPCC, 2012; Hallegatte *et al.*, 2013). The UK has one of the most vulnerable economies to damages from flooding (Ramsbottom et al., 2012). DEFRA (2012) highlights that insurance claims would increase dramatically in the next decades, which indicates the importance of characterising and understanding intense precipitation. Moreover, Chatterton et al. (2010) predict an increase in the UK flooding costs and damages unless strategic actions and solutions are planted, which makes predicting and simulating extreme events crucial elements in national and international plans in this respect. However, sub-daily extremes have not been studied extensively due to the shortage of the robust data and records that cover long period of time.

2.2. Sub-daily extremes in Europe

Investigating various studies of changes in sub-daily precipitation regionally suggested that most focused on individual sites, while fewer considered regional scale assessment (Westra *et al.*, 2014; Blenkinsop *et al.*, 2018). In Europe, Leahy and Kiely (2011), studied short extreme precipitation in Ireland using thirteen hourly precipitation stations extending from 1957 to 2008. They used the general Pareto distribution (GPD) to fit peaks over threshold (POT) observations for each station, reporting that significant changes were observed in short duration extreme precipitation, where a 30 year return period storm shifted to be a 10 year return period, though noticeable spatial variability was observed in the results. The variability and the local variation, which might occur due to the differences in exposure or orography of the stations (Leahy and Kiely, 2011), shows the complexity of the short duration extreme precipitation events and the need for more investigation rather than using traditional statistical methods.

Furthermore, Arnone et al. (2013) studied hourly and sub-daily annual maxima for extreme precipitation events (1-, 3-, 6-, 12- and 24 hours) in Sicily using 60 rain gauges for the period 1956 to 2005. They quantified changes in extreme precipitation, observing an increasing trend in sub-daily extremes intensity and a significant increase in their occurrence especially at 1-hour duration, while longer durations (i.e. 12-, and 24 hour) extreme precipitation events showed a negative trend. Moreover, an increasing trend in the relative contribution and occurrence of heavy precipitation events occurred, however the total annual precipitation showed a decrease.

Hanel et al. (2016) analysed sub-daily heavy summer precipitation events for the Czech Republic, using 17 gauges between 1961–2011. They reported that most of the investigated gauges showed significantly positive intensity trends, and more frequent occurrence of extreme events. Furthermore, more than 50% of the gauges experienced an increasing contribution from extreme precipitation to the total summer precipitation.

Recently, Forestieri et al. (2018) used regional frequency analysis approach to analyse the hourly and multi-hourly extremes in Sicily, which helped to identify extremes homogeneous regions, derive regional growth curves, and provide updated return estimates. The results showed that, for low return periods, different distribution performed similarly and accurately, yet for long duration results varied spatially (Forestieri et al., 2018). This indicates the need of having longer hourly extremes record, to assure more accurate results.

In concise terms, quantifying sub-daily precipitation is necessary for the management of urban drainage (Arnbjerg-Nielsen et al., 2013) especially under a changing climate, while the lack of long hourly precipitation records and spatial variation of extreme precipitation, makes adaptation to the risk of flash flooding problematic. In particular, this high spatial variability suggests using regional approaches and other related climate variables to understand the sub-daily extremes (Leahy and Kiely, 2011; Arnone et al., 2013; Westra et al., 2014).

2.3. Historical and future precipitation in the UK

In recent decades the UK has experienced significant extreme precipitation derived floods such as the 2004 Boscastle floods (Burt, 2005; Golding et al., 2005) and 2007 UK summer floods (Blackburn et al., 2008). UK flood magnitudes and frequency have increased significantly in recent decades (Pattison and Lane, 2012), and are expected to increase in the future (IPCC, 2012), which shed light on the importance of understanding extreme precipitation patterns in the UK, especially that adapting to extreme is a national priority as advised by the UK climate change risk assessment (CCRA, 2017) .

UK daily precipitation has been studied using the rich archive of data to analyse and describe trends in extremes and their drivers. These have used both instrumental observations (Alexander and Jones, 2000; Fowler and Kilsby, 2003b; Maraun et al., 2008; Jones et al., 2014; Simpson and Jones, 2014), and climate models (Dale, 2005; Fowler and Wilby, 2010) across different spatial and temporal scales. These studies could be used in risk assessment and management to produce the required recommendations and design guidelines to achieve both adaptation and mitigation of extreme events impacts (Dale *et al.*, 2017). The evidence showed that it is profoundly complicated to simulate and understand the behaviour of extreme precipitation events due to the complex and disproportionate relation between climatological events and their potential drivers (Dale, 2005; IPCC, 2012; Hulme, 2014).

Relatively few of studies have investigated sub-daily precipitation events either globally or in in the UK (Westra et al., 2014; Blenkinsop et al., 2018; Darwish et al., 2018), due to sparse observations (Blenkinsop et al., 2017). Besides, the difficulty and the computationally demanding simulation of these events using climate models induce additional challenges to the analysis process (Chan et al., 2014b). Overall, these studies agreed that UK sub-daily extreme precipitation events show a noticeable seasonal behaviour, and further investigation is required to quantify sub-daily extremes frequency, intensity, and future projections (Chan et al., 2014a; Blenkinsop et al., 2015; Tye et al., 2016; Blenkinsop et al., 2017).

Hence, this chapter will 1) review major studies that have analysed mean and extreme precipitation including: sub-daily, daily, and multi-daily precipitation, patterns and behaviour of events during different seasons in the UK; 2) review climate model future projections; 3) review the relationship between extreme precipitation and related climatic variables.

2.3.1. UK Mean precipitation

A great deal of literature has investigated precipitation events and their patterns in the mid-latitude and northern hemisphere regions. These indicate a significant increase in the intensity and frequency of precipitation events during the last century (Osborn et al., 2000; Meehl et al., 2007; Pattison and Lane, 2012; Burt et al., 2014).

One of the benefits of having a long precipitation data archive in the UK is that it has enabled the study of UK precipitation trends using different methods and techniques for different periods. These studies showed no significant trend in annual UK precipitation (Perry, 2006; de Leeuw *et al.*, 2016). Nevertheless, significant long-term trends and noticeable spatial variations were observed in seasonal precipitation in particular, during winter and summer (Alexander and Jones, 2000; Osborn *et al.*, 2000; Mills, 2005; Leeuw *et al.*, 2015). Trends in UK daily precipitation for each season will be reviewed in this section.

- ***Winter (Dec-Jan-Feb)***

Jones and Conway (1997), who updated the study of Wigley and Jones (1987), studied UK precipitation using nine spatially coherent precipitation regions, where an unweighted regional average approach was adopted for each region during the period between 1767 and 1995. The study found a significant long-term precipitation trend increase of 67 mm and 139 mm over the whole period in England and Wales, and Scotland respectively.

Further, Osborn *et al.* (2000) studied trends in the daily intensity of UK precipitation using 110 reasonably evenly distributed gauges recording daily observations for the period between 1961 and 1995. The study categorized total precipitation into ten categories based on their seasonal contributions. The results showed an upward trend in mean winter precipitation, where an increasing number and greater intensity of wet days (day with at least 0.3 mm of precipitation) confirmed this rise. This increase was linked to an upward trend of the North Atlantic Oscillation (NAO) index during the same period. Additionally, Alexander and Jones (2000) used the 9 HadUKP spatially coherent precipitation regions, and average monthly precipitation data for the period 1961 to 2000 to find a significant increase in monthly precipitation over the UK with a noticeable increase in the western part of Scotland were in line with previous studies. Extending this study, Mills (2005) tried to model precipitation in the UK using different trends modelling techniques between the year 1766 and 2002 based on monthly series. The results showed that the winter precipitation trend increased 12% between 1766 and 2002. Simpson and Jones (2014) also reported an increase in the trend of the 50th, 90th, 95th, and 99th percentile precipitation between 1931 and 2011, although this was not significant in all regions; most of the significant precipitation intensity increase occurred in northern regions and Scotland. Extending the analysis back up to 1766 showed significant mean increasing trends over the longer term, especially in England and Wales.

Recently, Leeuw et al. (2015) studied the variability and trends of mean precipitation in the UK. The study used the daily average of the spatially distributed rain gauges in the 9 UK precipitation regions which were used by Alexander and Jones (2000) for the period 1931 to 2014. The results agreed with previous research, detecting a positive winter precipitation trend. Moreover, a decrease in the contribution of lighter precipitation events and an increase in the contribution of extreme precipitation events to the total seasonal precipitation are observed.

- ***Spring (Mar-April-May)***

Generally speaking, spring has shown no significant long term trends (Alexander and Jones, 2000; Osborn *et al.*, 2000; Mills, 2005; Jones *et al.*, 2013; Leeuw *et al.*, 2015; de Leeuw *et al.*, 2016). Osborn *et al.* (2000) reported a weak increase in mean precipitation in Northern Ireland and Scotland due to an increasing number of wet days, while England has experienced a decline in the number of wet days resulting in a slight decrease in mean precipitation.

Using spatially averaged monthly series, Alexander and Jones (2000) found that an increasing trend is observed in March while a decreasing trend was observed in April for the period between 1766 and 2000 over England and Wales. On the other hand, Mills (2005) supported the results of (Osborn *et al.*, 2000), and showed that spring experienced a fluctuating trend for the period from 1766 to 2002, with a weak increasing trend. The study showed that a postitve trend was observed in March and April, while May showed a negative trend. More recently, de Leeuw *et al.* (2016) who studied the spring precipitation trend for the period 1931 to 2014 and three sub periods 1961-2006, 1961-2014, and 1979-2014,reported that large interannual variability were observed in spring, and no significant trend can be determined.

- ***Summer (June-July-August)***

A great deal of literature has reported that long term mean summer precipitation has shown a negative trend (Wigley and Jones, 1987; Jones and Conway, 1997; Alexander and Jones, 2000; Osborn *et al.*, 2000; Mills, 2005; Simpson and Jones, 2014); nevertheless, some recent research has shown that recent decades experienced a positive trend in summer precipitation in the UK (Simpson and Jones, 2014; de Leeuw et al., 2016). Osborn et al. (2000), using daily observations between 1961 and 1995 from 110 gauges, reported a weak decline in seasonal summer precipitation totals at most UK gauges, with a reduction in the contribution of heavy precipitation categories. Addtionally, the study found that the number of wet days decreased in 90% of the gauges during the same period, which in turn results in a decline in mean seasonal precipitation levels. These results were confirmed by Alexander and Jones (2000) who reported a significant decrease in the total precipitation amount in every region during July and August between 1873 and 2000 across England and Wales. Alexander and Jones (2000) explained that the precipitation decrease could be due to an increase in anticyclonic conditions which might be the reason for the negative trend . Mills (2005) used monthly data extended back to 1766, reporting consistent results with the previous research and confirmed a negative trend in summer precipitation, specifically, during June and July.

Later, Simpson and Jones (2014) reported a similar pattern for daily precipitation over the period 1931 to 2011 with mostly negative intensity trends in the 9 regions except in North East England, though the researchers argued that this negative trend is within the range of natural variability. Most recently, de Leeuw *et al.* (2016) analysed daily precipitaton over a similar period and reported that the seasonal precipitation trend showed a decrease up to the end of the last century, changing to become postive between 2007 and 2012. The study attributed this change to the fact that these years had greater total precipitation than the long term average (1931 to 2014), and both 2007 and 2012 were the wettest summer season in the record.

- ***Autumn (Sep-Oct-Nov)***

Mean autumn precipitation in the UK has generally shown no significant long-term trend. Osborn *et al.* (2000) reported a weak decrease in the number of wet days (days with at least 0.3 mm of precipitation) in England, although the mean wet days precipitation total increased in 91 out of 110 gauges. This increased the seasonal mean precipitation especially in North Scotland and Southwest England, though no significant trend was observed. Nevertheless, Alexander and Jones (2000) found an increase in the precipitation amount in Scotland and North Ireland during October and November between 1931 and 2000, though not enough evidence for a significant long-term trend in autumn mean precipitation.

Mills (2005) supported the preceding argument and pointed out that observing a significant and a clear trend for autumn precipitation in the UK is relatively difficult to identify due to annual and seasonal variability. Mills (2005) reported that different trends were found throughout the record (1766-2002), and no significant trend can be determined. This result was validated by Simpson and Jones (2014), who extended the precipitation data record period to 2011, reporting that the monthly mean record revealed a significant increasing trend only in Scotland, and a decreasing trend in England and Wales, though both are within the bounds of natural variability.

2.3.2. UK daily extreme precipitation

Different studies have attempted to identify, describe and characterise extreme precipitation events in the UK using various methods and techniques (e.g. Fowler and Kilsby, 2003b; Maraun *et al.*, 2008; Fowler and Wilby, 2010; Burt and Ferranti, 2012; Simpson and Jones, 2014). The studies agree on significant seasonal behaviour in the trends of extreme precipitation events in recent decades, with a noticeable spatial variation (Fowler and Kilsby, 2003a; Jones *et al.*, 2014; Simpson and Jones, 2014). The UKCP18 reported an increase about 17% in the total precipitation from extremely wet days in the last decade compared to the 1961-1990 period, especially in northern regions (i.e. Scotland), while a non-significant increase occurred in southern regions (Lowe *et al.*, 2018). The increases in extremes is likely to result in increased flooding (Fowler and Wilby, 2010; Westra *et al.*, 2014). Trends in UK daily extreme precipitation in each season will be discussed and presented in this section.

- ***Winter (Dec-Jan-Feb)***

Generally speaking, the analysis of winter daily extremes has used different indices to characterise trends in precipitation such as the annual maxima precipitation accumulation, multi-daily precipitation extremes, 90^{th}-, 95^{th}-, and 99^{th}- percentile, indicated a significant increase in winter precipitation intensity trends.

Simpson and Jones (2014), extracted daily precipitation data from the Met Office Hadley Centre 5km gridded dataset extending from 1931 to 2011. Using the HadUKP regions (Alexander and Jones, 2000), they adopted different indices for each season such as, the 50^{th}, 90^{th}, 99^{th} percentiles, maximum 5-day precipitation total and the consecutive dry day index (longest number of consecutive days with less than 1 mm precipitation) to evaluate extreme precipitations trends. The results showed an increase in trends in daily extremes in all UK regions and for all indices, especially, in the Scottish and northern regions.

Similarly, Jones *et al.* (2013), who extended the Fowler and Kilsby (2003b) extreme precipitation analysis, and used 223 gauges covering the UK, reported a significant increase in the intensity of the 1-day extremes in all regions with an inter-decadal behaviour. Furthermore, long duration events (5- and 10 days) showed an increasing trend in northern parts of the UK. In addition, Fowler and Kilsby (2003b) who studied 204 rain gauges using the regionalization method and HadUKP regions, reported that most regions showed a significant increase in the daily and multi-daily (2-, 5-, 10 day) extreme precipitation intensity, especially in Scotland, though some regions in England only showed a slight increase.

Burt and Ferranti (2012), who used precipitation data between 1961 and 2006, adopted the analysis method used by Osborn *et al.* (2000) and Maraun *et al.* (2008), studying percentiles of extreme precipitation events across regions using different indices, and focusing on the top category of each gauge, contributing 10% of the total precipitation. They also analysed the daily total that is equalled or exceeded on 0.25% of all days (1 in 400 years), the results agreeing with the earlier results of Osborn *et al.* (2000) and Maraun *et al.* (2008), indicating extreme precipitation intensity has increased significantly, especially in northern and western parts of the UK.

Finally, Brown *et al.* (2008) analysing daily precipitation data for 1958 to 2004 reported that return level estimates for 1-day extremes show wetter winters with higher intensity, yet less frequent extreme events, especially in the west of the UK.

- ***Spring (March-April-May)***

Extreme spring precipitation has shown fluctuating results. Simpson and Jones (2014), used a range of indices to identify upward trends, especially in Scotland, though few of these were statistically significant. Jones *et al.* (2013) reported similar results, with the regional median seasonal maxima for the spring between 1961 and 2009 showing an increase across most UK regions, though the results are significant in northern regions only. They attributed the increasing trend in these regions to the exceptionally heavy long duration events which dominanted the 1991-2000 decade. Furthermore, eastern regions in the UK had a “marginal increase” in the 1-day precipitation 10 year return period totals, while varying trends were observed at longer return periods (25 and 50 years). In addition, the most significant return estimate increases were observed for long duration accumulations (5- and 10-days).

Maraun *et al.* (2008) reported positive trends and a higher contribution from extreme precipitation events to the total precipitation in Scotland, North Ireland, and Southwest England, while, other regions displayed either little or marginal negative trends. These results agree with Osborn *et al.* (2000), who observed high spatial variability in the results with an increasing contribution of heavy precipitation events to total spring precipitation in Scotland and central and eastern England, while the opposite was observed in Wales, North and Southwest England.

Finally, Fowler and Kilsby (2003a) found that the greatest changes and the most regionally varying trends in HadUKP regions (Alexander and Jones, 2000) occurred in spring and autumn, in agreement with Osborn *et al.* (2000), who reported an increasing contribution of heavy precipitation to total precipitation in Scotland and central and eastern England, while the opposite occurred in Wales, North and Southwestern England.

- ***Summer (June-July-August)***

Studies that considered summer precipitation trends have consistently identified decreasing trends in most UK regions, especially the southern part of the UK. Simpson and Jones (2014) observed that extreme summer precipitation intensity trends declined (not statistically significant) across most UK regions for daily extremes, except in eastern England.

The findings of Jones *et al.* (2013), using precipitation data between 1961 and 2009, were in line with those of Fowler and Kilsby (2003b) and reported significant decrease in estimated summer extreme precipitation return levels and median seasonal maximum event , especially for 1-day events in southern regions. In addition, Jones *et al.* (2013) and Burt and Ferranti (2012) agreed that the percentage contribution of the heaviest precipitation to total summer amount has decreased.

Maraun *et al.* (2008) and Osborn *et al.* (2000) reported that UK summer precipitation intensity time series shows an inter-annual behaviour, which was evidenced by a distinct maximum in the late 1960s followed by a downward and varying behaviour.

- ***Autumn (September-October-November)***

Spatially and temporally varying trends have been identified in autumn extreme precipitation. Recently, Tye et al. (2016) simulated the spatial and temporal patterns of extreme daily precipitation occurrence using a generalized additive model, and reported that autumn extreme daily precipitation has a higher likelihood across the UK than in the previous century. Moreover, autumn extreme daily precipitation events are mostly associated with a higher probability of occurrence during either early autumn in the north and west, or later in the season in the south and east(Tye *et al.*, 2016).

Simpson and Jones (2014) observed that trends in autumn 1-day extreme precipitation over the past century were weak and showed mixed signals. On the other hand, the authors agreed with previous results in which a positive trend was observed in the intensity during autumn multi-day (5- and 10-days) extreme precipitation in several regions, especially Scotland (Fowler and Kilsby, 2003a; Maraun et al., 2008; Jones et al., 2013; Jones et al., 2014). These trends were though statistically insignificant in most regions, with no clear evidence to discern the trends from naturally short-term variability.

Furthermore, Maraun et al. (2008) confirmed earlier results by Osborn et al. (2000), and reported spatially varying results, where a significant rise in the contribution of autumn heavy precipitation events to total precipitation across the UK was identified, with the exception of Northern Ireland and Northwest England, which showed insignificant decreasing contribution trends.

Allan et al. (2009) also found that autumn trends were within the limits of natural and decadal variability and thus, in the absence of definitive evidence contrary to that reviewed from the literature, it may be assumed that no long-term trend can be identified during autumn.

2.3.3. UK sub-daily precipitation

As discussed earlier, long-term sub-daily data observations are scarce in both: globally and in the UK. Therefore, climatological analysis of sub-daily (including hourly) UK extremes are limited in the literature (Westra et al., 2014; Blenkinsop et al., 2018; Kendon et al., 2018). Extreme short precipitation is the major source for pluvial flooding, which is expected to increase under different climate change scenarios, and add more challenges to adaptation plans (Murray and Ebi, 2012). Hand et al. (2004) analysing 50 UK precipitation events identified as extreme by the Flood Studies Report

(NERC, 1975) showed that among the investigated events, all those of less than 5 hr duration were convective, which indicates the importance of characterising short intense precipitation.

The Flood Estimation Handbook (FEH) provides UK-wide estimates of annual maximum median (RMed) precipitation for hourly and daily durations (1h up to 8 days), and is used to produce design precipitation estimates (Faulkner, 1999). However, the AMAX gauges data average record length is less than 23 years (22.7 years), while some gauges have a record length of 2 years only, and further data is needed to assure reliable estimates (Kjeldsen *et al.*, 2008). Furthermore, Dale *et al.* (2017), using a climate analogue approach and a very high-resolution (1.5 km) climate model, reported that new hourly precipitation projections are higher than existing UK climate change allowances for intense precipitation, while flood volume and pollution events are expected to increase in the future. Therefore, characterising hourly extremes in the UK is essential to update the precipitation estimates, design guidelines, and to implement adaptation plans.

Blenkinsop *et al.* (2017) reported that when investigating hourly precipitation totals in the UK, 1-, 3-, and 6 hour totals show a similar spatial intensity behaviour, where precipitation is more intense to the west of the UK. Moreover, these short duration totals are mainly a function of local scale events, while events of periods longer than 12 hours are usually mediated by synoptic scale features. Blenkinsop and Fowler (2013) also drew attention to the importance of assessing hourly precipitation events using different approaches such as seasonal maxima and POT seasonal data to ensure having reliable results.

Thus, Blenkinsop *et al.* (2017) produced precipitation dataset, which were collated from precipitation gauges spanning across the UK between 1949 and 2011, and subjected to a series of strict quality-control (QC) procedures to identify potentially suspect values, and assure having a reliable dataset. Moreover, Lewis *et al.* (2018) extended the work up to 2014 and developed a sub-daily gridded dataset.

Blenkinsop *et al.* (2017) investigated hourly precipitation extremes in the UK using the annual maxima, and reported that during summer, southern parts experience the greatest intensity and frequency of hourly precipitation, while the diurnal cycle peaks in late afternoon to early evening. This is indicative of the generating mechanism of extremes during summer, where sub-daily events are generated with a significant contribution of convection occurring due to the relatively high temperatures, in contrast with extremes occurring at other times of the year through other mechanisms (e.g. frontal or orographic precipitation).

Recently, Xiao et al. (2018), who analysed mean hourly precipitation intensities collected from 90 stations in the UK for the period 1998 to 2015 to characterise UK hourly precipitation, reported that UK precipitation frequency and intensity peaks in the early morning and the late afternoon respectively. A noticeable relationship between the peak time and both the location and the duration of the precipitation event was observed, with most of the long duration events (i.e. lasting > 6h) occurring in the early morning and along the western coast, and short precipitation events (i.e. lasting < 6 hr) occurring in the late afternoon. They also reported noticeable spatial variation in frequency especially during summer and spring, which is consistent with Blenkinsop et al. (2017) who used hourly extremes, though a larger dataset was used.

2.3.4. Future Projections

Climate model projections show an increase in precipitation frequency and intensity over the northern regions of the hemisphere and northern Europe, which highlights the potential related hazards such as increasing flooding and the need of reliable future estimates (Hartmann et al., 2013).

In the UK, daily and multi-daily extremes have been studied and simulated using climate models, where projections have shown that the frequency of extreme precipitation events are projected to increase during winter, whereas, in summer less intense extreme precipitation is likely to occur (Fowler and Ekström, 2009; Murphy et al., 2009; Fowler and Wilby, 2010). The recently released UKCP18 (Lowe *et al.*, 2018) projections indicate reductions in summer precipitation intensity trends, especially over England and Wales, while a gradual increase is projected in winter. Climate model projections show broad agreement with observational studies (Osborn *et al.*, 2000; Burt and Ferranti, 2012; Simpson and Jones, 2014), though daily and multi-daily extremes are well simulated by regional climate models in all seasons except in summer (Lean et al., 2008; Hanel et al., 2009; Chan et al., 2013).

However, to date few studies have examined projections of changes in sub-daily precipitation extremes because of the inability of coarse-resolution dynamical models to reliably simulate sub-daily precipitation and in particular extremes (Chan *et al.*, 2018b; Kendon *et al.*, 2018).

Kendon *et al.* (2014) investigated hourly extreme precipitation with climate change in the UK using a high resolution model, and reported that the model simulations indicate an increase in hourly extremes intensity in winter, while a significantly intensification and increasing number of extreme events in summer leading to flash floodings. Recently, Kendon *et al.* (2018), using the 1.5 km climate model to assess southern UK region, confirmed the projected intensification, and projected hourly extremes would intensify 5-10 years and decades earlier than daily extremes in winter and summer seasons respectively. Therefore, reliable observational and statistical studies are required to improve future simulations and enhance our return estimates and hydrological design guidelines.

2.4. Extreme precipitation related climatic variables

Hydrological and climatological studies have constantly indicated a strong relation between the extreme precipitation and various climatic variables. The studies emphasised on the climate variability and extreme precipitation caused by the oceanic-atmospheric across the UK. Thus, this section will present the associated climatic circulation with extreme precipitation in the UK.

2.4.1. Atmospheric Circulation

European climate is highly variable and affected by wide range of large-scale circulations, which are produced by atmospheric and oceanic conditions. The impact of these large circulations is obvious in Europe due to its location in mid and high-latitudes, bounded by the North Atlantic and Arctic Oceans (Jones and Conway, 1997; Hurrell and Deser, 2010; Woollings, 2010). These large-scale circulations affect winds, precipitation and temperature in Europe.

The uneven solar heating of the planet causes differences of atmospheric pressure which controls the movement of airflow (Woollings, 2010). In Europe, the irregular fluctuation of atmospheric pressure over the North Atlantic Ocean has a strong effect on the atmospheric circulation pattern especially over Western Europe and it is considered as the dominant mode of northern hemisphere atmospheric variability (Scaife et al., 2008; Hurrell and Deser, 2010; Woollings, 2010). This fluctuation of atmospheric pressure called the North Atlantic Oscillation (NAO), is characterised by the pressure difference between high pressure centred over the Azores islands and low pressure centred over Iceland (Hurrell and Deser, 2010). The NAO has two phases representing the pressure gradient between the Azores and Iceland, where the positive phase denotes strong and higher than usual pressure difference, and the negative phase denotes weak and lower than usual pressure difference (Osborn et al., 1999).

This atmospheric pressure gradient between the two locations (i.e. Azores islands and Iceland) controls the westerly winds, which flow from North America towards Europe, particularly, during winter (Jones and Conway, 1997; Trenberth et al., 2007). The westerly winds control the transport of heat and moisture, which in turn have impacts on both temperature and precipitation over western Europe (Uvo, 2003).

During the positive NAO mode, the westerly winds become stronger and convey more moist air over northern Europe. This contributes to a rise in temperature and precipitation over northern parts of Europe and the opposite over southern parts (Guerreiro et al., 2014). Conversely, the negative NAO mode creates weaker westerly winds, consequently, the temperature decreases along with precipitation over northern Europe; with the opposite over southern Europe.

In the UK, precipitation tends to be inversely correlated with atmospheric pressure, and highly influenced by the NAO phase, therefore the NAO index has been used to study UK weather (Murphy and Washington, 2001). Osborn et al. (2000) reported that during UK winter, the positive NAO phase generates strong westerly winds, leading to more intense and frequent precipitation events, especially in west and north parts of the UK. Furthermore, observed increases in the total amount of precipitation and the number of wet days are associated with a positive NAO (Osborn et al., 2000).

In the previous century, the NAO showed significant variability. During the first four decades (1900-1940), the NAO showed a strong positive and increasing trend, which was followed by a downward trend for the period between 1940 and 1970, and an increasing trend from 1970 until the end of the century. This increasing trend in recent decades might explain the observed increasing precipitation and intensity in northern and western parts of the UK (Gillett, 2005; Simpson and Jones, 2014). This variability in the NAO has been attributed to different variables and processes. Osborn (2004) claimed that this upward trend is associated with a stratospheric cooling and deeper polar vortex. However, the IPCC (2007) suggested that NAO decadal variability might be due to extratropical ocean influences, land surface forcing and other external factors. Yet, no solid scientific agreement or explanation for NAO variability during the last century has been established (Woollings, 2010).

Recently, Brown (2018) reported that positive NAO would reduce the extreme precipitation during spring and autumn, however, increasing the likelihood during winter. Positive NAO phase during winter would increase both: intensity and frequency of extremes, which is similar to the NAO driven changes in extra-tropical cyclones

Alternatively, other studies have found that in the UK, airflow strength, direction and vorticity may be used as covariates to represent atmospheric circulation (Jenkinson and Collison, 1977; Jones et al., 1993; Maraun et al., 2010a). Airflow strength represents the air mass speed over a specific area and it is highly likely to be related to the NAO, while airflow direction signifies its source (Marshall et al., 2001). Moreover, the airflow vorticity indicates whether a cyclonic or an anticyclonic airflow is dominant. Maraun et al. (2010a) reported that for the western coast of the UK, especially in Scotland, using the airflow strength only as a covariate would provide a better prediction for the 90% quantile precipitation compared to the base model. These results are consistent with the previous results (Osborn et al., 2000) in which a significant relation between the NAO phase and precipitation in the western part of the UK was found.

Maraun et al. (2010a) reported that airflow direction is a crucial covariate in predicting precipitation in the UK except in Scotland and the western coast, while airflow vorticity is a better predictor in Scotland and the northern parts of the UK. Conway et al. (1996), using the airflow indices (i.e. strength, direction and vorticity) in GCMs, found that vorticity has a strong influence on the probability of precipitation and the mean wet day amount in all regions of the UK, especially in winter. On the other hand, the influence of flow strength and the direction indices is weaker than the vorticity, and is regionally dependent. These results were confirmed by Osborn et al. (1999) who found that vorticity has a higher correlation with the precipitation amount compared to other indices. However, the studies agreed that airflow indices predict the wet day probability more precisely than the mean wet day amount (Conway et al., 1996; Osborn et al., 1999).

2.4.2. Oceanic circulation

Oceanic circulation has a significant Impact on our climate and weather globally. It has a key role in transferring heat, water mass movement, cycling and storage of chemical species, and nutrient content of the oceans (Kuhlbrodt et al., 2007). The oceanic circulation is a result of the combined oceanic current that moves the seawater in the oceans, forming a global conveyer belt which moves due to winds, heat and density difference (Trenberth and Caron, 2001). In the mid to high-latitude, the Atlantic Meridional Overturning Circulation (AMOC) is the dominant current which affects the Atlantic Ocean and the climate of the northern and western countries in Europe.

The Atlantic Meridional Overturning Circulation (AMOC) conveys the salty and warm water in its upper layer toward the northern parts of the Atlantic ocean while colder water is transferred to the southern parts of the Atlantic by deep water layers (U.S. Geological Survey, 2012). This movement of warm water toward the northern parts of the Atlantic Ocean brings heat (up to 10^5W) from the tropics and southern hemisphere toward the North Atlantic, which maintains the mild climate in northwestern Europe (Trenberth and Caron, 2001; Kuhlbrodt et al., 2007).

In recent decades, there has been a concern about the AMOC response to climate change and its impacts. This concern is raised due to the melting of the Greenland ice sheet and the increasing precipitation events at high-latitudes which cause a weakening of the AMOC (Allen and Ingram, 2002). A reduction of the AMOC could affect the El Nino Southern Oscillation (ENSO), the position of the intertropical convergence zone, Atlantic Ocean fauna and flora, Atlantic ocean sea surface temperature, and sea level, resulting in more severe winters in north and western Europe (Trenberth and Caron, 2001; Vellinga and Wood, 2002; Levermann *et al.*, 2005; Schmittner, 2005; Timmermann *et al.*, 2005). In contrast, other researchers reported that a weakening of the AMOC could counterbalance the effect of the globally increasing temperature (Meehl et al., 2007).

However, studies agree that despite uncertainties in the AMOC behaviour, it is unlikely for the AMOC to have unforeseen significant weakening or a complete shutdown, and an abrupt change or shutdown of the AMOC would need a long duration to take place, while the expected maximum reduction is 30% (Meehl *et al.*, 2007; Clark *et al.*, 2008). The occurrence of such an event would have a significantly severe effect on north western Europe winter, temperature levels and precipitation events, and it is highly unlikely to happen in the 21st century (Meehl *et al.*, 2007; Clark *et al.*, 2008).

2.4.3. Temperature

The global mean temperature has increased significantly in the last century mostly due to anthropogenic activities which increased the concentration of greenhouse gases in the atmosphere (IPCC, 2013). Based on different climate models, using different emission scenarios, this increase is projected to escalate during the current century to between 2ºC to 4ºC (IPCC, 2012). The increase in mean global temperature would be accompanied by changes in atmospheric and oceanic circulation, which in turn would impact on precipitation globally, while substantial changes in the mid and high-latitude precipitation will be observed (Collins et al., 2013; IPCC, 2013).

The Clausius-Clapeyron (C-C) equation describes the thermodynamic response of the atmosphere to a change in temperature, indicating that under constant relative humidity an increase of the moisture holding capacity of the atmosphere at a rate of 6-7% per 1°C increase in temperature would occur, leading to a corresponding increase in precipitation (Trenberth et al., 2003). However, increases in precipitation in different places globally might not follow the C-C equation due to two main reasons: the nonlinearity in the C-C equation, and the dependency of precipitation on other factors such as the relative humidity, the atmospheric circulation, and the ability of the troposphere to radiate away latent heat released by precipitation (Allen and Ingram, 2002).

Furthermore, different models have suggested that a latitudinal dependence is expected in the increasing precipitation, with a higher increase expected closer to the higher-latitudes (Trenberth, 2011; Utsumi *et al.*, 2011; O'Gorman, 2015). Further, the mid-latitudes precipitation increases would be the most consistent with the C-C equation, while low-latitudes and high-latitudes are suggested to have an increase of 3-4%/°C and 7%/°C consecutively (Allen and Ingram, 2002; Huntington, 2006; Pall *et al.*, 2007). Recently, Westra et al. (2014) have shown that an increase at a rate between 5.9%-7.7%/°C in the median intensity of the annual global maximum has been observed.

Observational studies, which have investigated daily precipitation events, indicated an increase following the C-C relation. Liu and Allan (2012) using global satellite observations reported a precipitation increase of 6%/ºC. Haerter *et al.* (2010), investigated daily extreme precipitation in Germany and its relation to other variables using the C-C equation, and reported that there is an increasing trend, though less than expected according to the C-C relation.

On the other hand, sub-daily extreme precipitation events have shown markedly varying results. Berg and Haerter (2013) reported that hourly precipitation intensity in Germany has increased at a rate higher than the C-C relation for convective precipitation events only, which emphasize the impact of seasonal dependence as convective precipitation primarily occurs in summer. In the Netherlands, western Europe and Hong Kong, the precipitation relationship with temperature was double the C-C rate for the temperature range between 12ºC to 20ºC (Lenderink and Van Meijgaard, 2008; Lenderink *et al.*, 2011). Hardwick Jones *et al.* (2010) found that the rise on the hourly precipitation intensity rate exceeds the C-C relation in Australia for the for temperatures between 20ºC to 26ºC. Contrary, hourly extreme precipitation intensity in the UK, showed an increase following the C-C scaling rate, with marginal seasonal differences (Blenkinsop *et al.*, 2015; Chan *et al.*, 2016).

2.4.4. Atmospheric moisture

Atmospheric moisture availability, which has a significant relation with temperature and evapotranspiration levels, plays a crucial role in determining precipitation occurrence and intensity (Barry and Chorley, 2009). The moisture cycle begins with oceans, in which the water vapour enters the atmosphere by evaporation from the oceans and returns to the surface as a precipitation through the condensation process (Barry and Chorley, 2009). This moisture is responsible for 60% of global terrestrial precipitation (Trenberth *et al.*, 2007; Gimeno *et al.*, 2012). Recent decades showed an increase in the oceanic evaporation due to climate change, which lead to the occurrence of extreme events including, heavy precipitation, floods, and droughts (Galarneau *et al.*, 2010; Knippertz and Wernli, 2010; Chang *et al.*, 2012; Xu *et al.*, 2015).

The literature suggests that the change in the atmospheric moisture capacity might affect the nature of precipitation events, causing increased occurrence of heavy precipitation, with no change or even a decrease in mean precipitation (Allen and Ingram, 2002; Trenberth *et al.*, 2003; Frei *et al.*, 2006). In recent decades, over the northern hemisphere regions, human anthropogenic activities were the main reason for the increasing atmospheric moisture capacity (Gabriele *et al.*, 2015), where an increase at a rate consistent with the C-C relation has been observed (Santer *et al.*, 2007; Durre *et al.*, 2009; Trenberth, 2011). This is consistent with observations of change over the ocean (e.g. Trenberth and Shea, 2005; Chung *et al.*, 2014), land (e.g. Willett *et al.*, 2010), and future projections (e.g. Allen and Ingram, 2002). Furthermore, studies have linked the change in the atmospheric moisture capacity over oceans to the C-C relationship, while the increases are somewhat less over land, especially where water availability is limited (Allen and Ingram, 2002; Trenberth et al., 2003).

Trenberth *et al.* (2007) reported that an increase in cloud cover and atmospheric moisture over oceanic areas since 1970 has been observed, which lead to an increasing frequency of intense precipitation events. These results are consistent with (Labat et al., 2004), who used reanalyses of the world continental runoff from major rivers between 1920 and 1995, where it was found that a more intense hydrological cycle of evapotranspiration and intense precipitation globally has occurred. This increase in the moisture capacity could affect both the greenhouse effect and the hydrological cycle by providing positive feedback to the climate change and more atmospheric moisture which would be condensed and turned into heavy precipitation (Huntington, 2006; Trenberth, 2011; Gabriele *et al.*, 2015).

2.5. Summary

Intense precipitation has increased noticeably in the last few decades both globally and in the UK, leading to economic, infrastructure, urbanisation, and health challenges. Different plans and design guidelines are required to adapt to extreme precipitation, yet, further analysis is required to characterise and simulate these extremes. In the UK, studies have analysed extremes on different time scales (i.e. multi-daily, daily, and sub-daily) using both observational and modelling analyses.

Daily and multi-daily extreme precipitation have been studied thoroughly in the UK using the advantage of having a rich archive of rain gauge data. Observational studies, using different metrics and indices, have agreed that precipitation trends show wetter winters and drier summers. These are accompanied by trends indicating a higher contribution of extremes to the total seasonal precipitation, which indicates the importance of characterising extremes in the UK (Jones and Conway, 1997; Alexander and Jones, 2000; Fowler and Kilsby, 2003b; Maraun et al., 2008; Jones et al., 2013). Furthermore, autumn and spring showed a spatial and temporal varying trend through the last few decades, though no significant trends were observed in these seasons (Alexander and Jones, 2000; Simpson and Jones, 2014). These results are consistent with projected future changes, and indicate that general circulation models (GCM) and regional climate models (RCM) can simulate daily and multi-daily precipitation reliably (Fowler and Wilby, 2010; Maraun *et al.*, 2010b).

Relatively few studies have characterised sub-daily extremes in the UK due to the limited data availability, though they have a strong association with flash flooding, especially in urbanised areas and fast responding catchments (Dale *et al.*, 2017; Prein *et al.*, 2017). Observations of UK hourly extremes show spatial and seasonal variation, with a higher frequency in summer, especially in southern regions (Blenkinsop et al., 2017). On the other hand, modelling studies agreed that using RCMs to simulate hourly extremes is computationally expensive, while return estimates don't agree with observational studies, especially in summer (Chan et al., 2018a; Kendon et al., 2018). Thus, convective permitting models (CPMs) are used to simulate sub-daily extremes with high resolution, due to its potential of providing dynamical representation of convective conditions. Studies indicated that CPM simulates the sub-daily extremes better than standard climate models, and might be used to provide improved precipitation projections (Prein *et al.*, 2017; Blenkinsop *et al.*, 2018; Chan *et al.*, 2018a; Kendon *et al.*, 2018). Therefore, further observational studies are of importance to validate and calibrate modelling performance (Blenkinsop *et al.*, 2018).

Observational and modelling studies in the UK agree that hourly extremes are mostly generated by convective mechanisms, while daily extremes might be caused by different precipitation generating mechanisms (Blenkinsop *et al.*, 2017; Chan *et al.*, 2017). However, a noticeable relation with large-scale circulation systems such as atmospheric and oceanic circulations including the NAO, and with temperature, have been observed for both hourly and daily extremes (Jones et al., 1997; Blenkinsop et al., 2015; Hofstätter et al., 2018), therefore, quantifying their relationship would enhance our future projections and simulation.

Currently, the flood estimation handbook (FEH) (Faulkner, 1999), provides design growth curves to estimate hourly precipitation, yet, the data used has short record length. Therefore, statistical regional analysis for hourly extremes, where extreme regions are delineated based on climatological characteristics is required to enhance estimations of sub-daily precipitation, especially for ungauged locations. Regional analysis pools climatologically similar data, increases data availability, and produces statistically homogeneous and reliable estimates. Furthermore, most existing studies, which investigated return estimates, growth curves, and precipitation changes for extremes have used on-site analysis rather than regional analysis approach.

Chapter 3. regional frequency analysis of UK hourly and multi-hourly extreme precipitation

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Floods related to extreme precipitation events, especially intense, short duration precipitation, may cause significant damage in urbanised areas, including transport infrastructure, electricity networks, and property. These events are expected to increase in frequency with climate change but their characteristics, at either hourly or multi-hourly timescales, have been little studied compared with daily timescales due to short and poor quality data records. A central objective of this research is to quantify hourly and multi-hourly extreme precipitation, its seasonality, and diurnal cycle using annual maximum (AMAX) precipitation data.

In this chapter, AMAX hourly and multi-hourly (3-, 6-, 12-, and 24h) precipitation accumulations in the UK are investigated using a recently available, quality controlled hourly precipitation dataset for the period 1992-2014. This includes the seasonality and diurnal cycle, and the use of the regional frequency analysis (RFA) approach with L-moments to produce at-site return level estimates. Existing extreme precipitation regions are used to provide regional-scale return levels. The chapter concludes with a new, subjectively defined regionalisation for hourly extremes based on the results presented.

Moreover, the research also shows that the existing UK extreme precipitation regions may not appropriately reflect regional differences in sub-daily extreme precipitation behaviour

3.1. Introduction

An increased understanding of extreme weather events is essential given that climate change will likely lead to an increase in the occurrence and magnitude of some types of events. The IPCC Special Report on Extremes IPCC (2012) stated that the frequency and intensity of extreme weather events have increased over large parts of the globe and extreme precipitation events on daily timescales are observed to have increased in frequency and intensity in some parts of the world (Alexander *et al.*, 2006; Alexander, 2016; Donat *et al.*, 2017). This is consistent with research by Min *et al.* (2011) who reported increasing trends in the annual maxima of daily precipitation for 65% of the data-covered land area over the period 1951-1999. Moreover, Arnell and Gosling (2016) reported that the frequency of floods with a 1% annual exceedance probability (100 year return period) will be doubled across 40% of the globe by 2050. According to Tye (2015) and Arnell and Gosling (2016), such increases will affect man-made infrastructure mostly through increases in surface water runoff, leading to flooding and other destructive events.

In the UK, several studies have reported significant increasing trends in daily and multi-day extreme precipitation events (Osborn *et al.*, 2000; Fowler and Kilsby, 2003a; Maraun *et al.*, 2008; Simpson and Jones, 2014). Osborn *et al.* (2000) reported an increased contribution of heavy precipitation events to total precipitation, especially in winter. Moreover, Fowler and Kilsby (2003b) reported increasing intensity of heavy multi-day (5 and 10 day) precipitation events in northern and western parts of the UK, particularly in autumn and winter. Maraun *et al.* (2008) confirmed an increasing contribution of daily heavy precipitation events in the UK and identified an increasing trend in the intensity of winter daily events in northern and western parts of the UK, and a negative trend in summer intensities in most UK regions. Recently, Jones *et al.* (2013) confirmed an increasing frequency of extreme daily precipitation events in the UK during spring, autumn, and winter, contrary to a recognised a decrease in summer. Moreover, Tye (2015) reported a statistically significant increase in the probability of multi-day extreme precipitation events during the late summer and autumn, when most UK daily precipitation extremes occur. Simpson and Jones (2014) analysed extreme precipitation events and found a similar, statistically significant, pattern of wetter winters, and drier summers in the UK, though they reported a recent succession of wet summers and dry winters.

Although daily and multi-day extreme precipitation events have been studied extensively, relatively little research has analysed sub-daily precipitation due to the scarcity of quality-controlled, long, and homogeneous observations (Westra *et al.*, 2014; Blenkinsop *et al.*, 2017). However, such events are important because they produce pluvial floods which especially affect urban areas and small steep catchments, and can be very flashy in nature (Archer *et al.*, 2017; Archer and Fowler, 2018). The

Stern Review (Stern, 2006) suggested that, globally and in the UK, intense precipitation derived floods are among the costliest and most critical of climate change impacts, leading to the loss of human life, infrastructure damage, water resource and transportation disruption, as well as considerable damage to ecosystems.

The relationship between intense precipitation and pluvial floods suggests that both the intensity and frequency of pluvial floods in urbanised areas will be significantly affected by any change in extreme sub-daily precipitation events (Westra *et al.*, 2014). Their significance was demonstrated by the UK summer floods of 2007, where two-thirds of affected properties were inundated by pluvial flooding (Pitt, 2008), and it is currently estimated that ~3 million properties are at risk from surface water flooding in England (Environment Agency, 2014). There is therefore a clear need for a better understanding of likely future changes in extreme sub-daily precipitation event intensities to enhance adaptation potential capabilities (Westra *et al.*, 2014).

Relatively few studies have investigated changes in observed sub-daily extreme precipitation events around the world, but those undertaken to date have generally indicated increasing intensities (Westra *et al.*, 2014) albeit generally at local to regional scales. Madsen *et al.* (2009) reported an intensification in Denmark extreme sub-daily precipitation events, consistent with results from Sicily (Arnone *et al.*, 2013), Canada and the United States (Burn *et al.*, 2011; Kunkel *et al.*, 2013; Muschinski and Katz, 2013; Barbero *et al.*, 2017) and South Africa (Roy and Rouault, 2013). Kendon *et al.* (2018) provide evidence of an increase in the intensity of UK summer hourly extremes over the last 30 years but suggest that this (and recent variability in winter trends) may be strongly influenced by large-scale modes of variability such as the Atlantic Meridional Oscillation (AMO) and North Atlantic Oscillation (NAO). The most extensive analyses of sub-daily precipitation have focussed on the relationship between extreme precipitation intensity and temperature (Lenderink and Van Meijgaard, 2008; Hardwick Jones *et al.*, 2010; Utsumi *et al.*, 2011; Berg and Haerter, 2013), including for the UK (Blenkinsop *et al.*, 2015), known as Clausius-Clapeyron (CC) scaling. The CC relationship explains the increased capacity of warmer air to hold moisture under constant relative humidity; a ~6-7% increase in precipitation per 1°C increase in temperature. A general agreement between the studies is that increasing atmospheric temperature could increase precipitation intensities for daily and sub-daily precipitation events, with enhanced scaling (super-CC) for the latter (Westra *et al.*, 2014) though this is not the case in UK observations (Blenkinsop *et al.*, 2015).

Recently, Blenkinsop *et al.* (2017) summarised the climatology of UK hourly extremes, noting that the highest frequency and intensity of hourly extreme precipitation events occur in summer, with most events (excluding winter) during late afternoon as might be expected from convective precipitation. Hand *et al.* (2004) analysed 50 UK precipitation events identified as extreme by the Flood Studies Report (NERC, 1975) and reported that among the investigated events, all extreme events of less than 5 hours duration were convective; while events of up to 12 hours had at least a convective component. In addition, Hand *et al.* (2004) reported that extreme precipitation events are unlikely to occur in February, March and April, while convective events are most likely in June, July, and August. A key point to note however is that short duration, intense precipitation is poorly simulated by regional climate models, typically at resolutions of 12-25km (Chan *et al.*, 2014b; Westra *et al.*, 2014) due to the use of convection parameterisation schemes. Very high-resolution, convection-permitting models offer improved simulation of these events (Chan *et al.*, 2014b; Kendon *et al.*, 2014; Prein *et al.*, 2015), but are computationally demanding and have so far been run for only limited regions (Kendon *et al.*, 2017). This emphasises the importance of observational-based research to enhance understanding of sub-daily precipitation event characteristics, drivers and processes, in addition to providing the means for climate model validation.

Most studies of sub-daily extreme precipitation so far have focused on individual sites (Westra *et al.*, 2014). However, in this research, we investigate the spatial and temporal distribution of UK hourly and multi-hourly (3-, 6-, 12-, and 24h) extreme precipitation using regions identified for daily extreme precipitation by Jones *et al.* (2014). Annual maxima (AMAX) are used to examine the seasonal and diurnal cycles of sub-daily extremes and to estimate the at-site and regional intensities of low probability events using a regional frequency analysis (RFA) approach with L-Moments estimation. RFA has been applied in hydrological and climatological studies in different countries across the world (Fowler and Kilsby, 2003b; Lee and Maeng, 2003; Trefry *et al.*, 2005; Norbiato *et al.*, 2007; Wallis *et al.*, 2007) and provides advantages over at-site estimation, including the assessment of ungauged areas, reduced impact of instrumental or human error, and therefore enhanced capacity for planning, designing, and managing infrastructure in a changing climate (Paixao *et al.*, 2011).

This research is the first to examine both hourly and multi-hourly AMAX precipitation events and assess the appropriateness of the existing UK extreme precipitation regions (Jones *et al.*, 2014) for sub-daily extremes. We also describe the first application of RFA to the UK hourly precipitation dataset. The chapter is presented as follows. In Section 3.2 we describe the datasets used in the research, then, in Section 3.3, we present the methods and statistical tools used to explore and analyse the data. Next, the spatial and temporal distribution of UK hourly and multi-hourly AMAX are described and return level estimates of AMAX are presented in Section 3.4. Subsequently, the results and their implications for urban drainage design are discussed in Section 3.5. Finally, we present our conclusions and recommendations in Section 3.6.

3.2. Data

This research uses an hourly precipitation dataset for the UK derived from rain gauges spanning different periods between 1949 and 2014 (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018). The dataset (up to 2011) was collected by Blenkinsop *et al.* (2017) from three sources: the UK Met Office Integrated Data Archive System (MIDAS), the Scottish Environmental Protection Agency (SEPA), and the UK Environment Agency (EA). Blenkinsop *et al.* (2017) performed a series of site-specific quality control (QC) procedures on the data to detect accumulated totals, malfunctioning gauges and unfeasible extreme precipitation totals including a comparison with a gridded daily precipitation dataset. This was subsequently extended to 2014 and subjected to additional quality control checks against neighbouring gauges (Lewis *et al.*, 2018).

Blenkinsop *et al.* (2017) reported that the rain gauges' coverage increase noticeably from the mid- 1980s, while most of the gauges started functioning in the early- to mid-1990s. Furthermore, implementing the QC procedure on the gauges reduces data availability and capacity for a meaningful analysis (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018). Previous analyses considered a gauge to be suitable for climatological analysis and have a "complete" record if no more than 15% of hourly data are missing in a given year/ season, and selected the data between 1992-2014 for the analysis as a trade-off between having a long records and data availability (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018).

Hence, to facilitate the comparison with other researchers, and to ensure the use of a reliable dataset that reflect the climatology of extremes well, the same gauge selection criteria were adopted in this research. Consequently, gauges which have more than 85% of their record complete (i.e. non-missing and data not flagged by the QC process) for each year in the period 1992-2014 are used in this research. In total, 197 gauges fulfilled these criteria (Figure 1) and have been selected for further analysis.

Finally, the 14 UK daily extreme precipitation regions (Figure 1), created by Jones *et al.* (2014), are used to assess the temporal and spatial characteristics of extreme hourly and multi-hourly precipitation. Although these regions are defined from extreme daily precipitation for the period 1961-2009, it is the only UK regional precipitation classification based on extremes and is a reasonable first basis by which to assess sub-daily extremes. However, we modify this slightly as the “Mid Wales” region contained only two gauges, merging this with the “South West” to create a modified “Mid Wales and South West” region (MSW). Both regions are located on the west coast of the UK and are highly influenced by north-westerly frontal systems (Lapworth and McGregor, 2008). Figure 1 shows the regions pre- and post-modification, with subsequent analyses presented using the 13 ‘post-modification’ UK extreme precipitation regions.

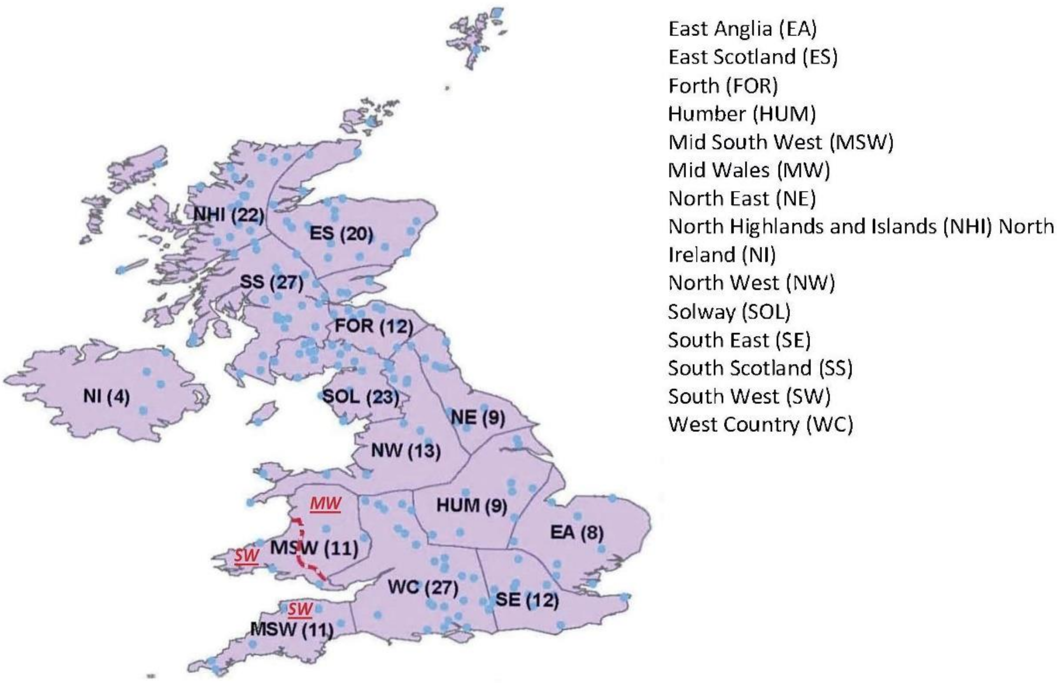

Figure 1: Distribution of 197 hourly rain gauges (blue dots) and UK extreme precipitation regions as defined by Jones et al (2014). Boundary and text in red denote merged regions (MW and SW were merged to form MSW due to limited gauge data in MW). Numbers in brackets denote the total number of gauges in each region.

3.3. Methodology

3.3.1. Exploratory data analysis

Multi-hour accumulations for 3-, 6-, 12-, and 24h periods were calculated for each gauge meeting the record completeness criterion presented in the data section. The 3-, 6-, and 12h accumulations were calculated using a rolling window, while the 24h accumulation was calculated using both a 24h rolling window and a fixed window starting at 09:00 to be comparable with existing analyses using daily records (e.g. Maraun *et al.*, 2008; Jones *et al.*, 2014; Simpson and Jones, 2014) Analysis showed similar results for accumulations derived using both approaches (Figure A1, Appendix A) and so only a 24h fixed window is presented here to facilitate the comparison with other studies. An individual 3-, 6-, 12-, and 24h accumulation was treated as missing if at least 1, 2, 3, or 4 values respectively were absent in each accumulation window. For multi-hourly precipitation, the n hour accumulation is obtained as the sum of the accumulation at a given hour and the preceding n-1 hours, for example, a 3h accumulation at 15:00 is derived from the 1h accumulated total at 13:00, 14:00, and 15:00. Annual maxima (AMAX) were then extracted for each gauge. Subsequently, the AMAX for all gauges in each region were pooled, and regional frequency density plots (for 1h and 3h AMAX) were constructed to show the diurnal cycle of extreme occurrence. The 3h AMAX diurnal cycle was constructed by counting each 3h AMAX at the end of the measuring window hour n, and fitting a smoothed diurnal profile using a kernel density estimation. The resulting diurnal profile of AMAX in each region was assessed for 1h and 3h accumulations only as most of the convective and intense precipitation events in the UK have a short duration (Hand *et al.*, 2004), notwithstanding the trivial value of deriving the diurnal cycle for 6h and 12h accumulations.

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In contrast, the seasonality was examined for all accumulation periods, for both the frequency and magnitude of AMAX. The AMAX seasonality for each accumulation period was investigated using circular statistics (Reed and Robson, 1999). Circular statistics convert the angular position of the calendar day at noon, θ, (also called Julian day in this research, which is the number of elapsed days since the beginning of a particular calendar year) in radians, to a vector based quantity of mean direction, $\bar{r}$, and centroid of action, $\bar{\theta}$. Thus, for *n* events at *i* stations, the mean day of the year for events, $\bar{\theta}$, and the concentration of the seasonal distribution, $\bar{r}$. are calculated with event dates represented by the angle θ on a circle of unit radius, and are calculated from the number of days since the start of the calendar year:

$$\theta = (\text{day no.})\frac{2\pi}{no.\ of\ days\ in\ year} \quad (1)$$

Then the centroid of the events is determined by the coordinates:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} cos\,(\theta_i) \text{ and } \bar{y} = \frac{1}{n}\sum_{i=1}^{n} sin\,(\theta_i) \quad (2)$$

while the values of the mean day of the year for event occurrence, $\overline{\theta}$, and the overall dispersion of events ($\bar{r}$) around the mean day are calculated by:

$$\bar{\theta} = \begin{cases} \tan^{-1}\frac{\bar{y}}{\bar{x}}, & when\ \bar{x} \geq 0, \bar{y} \geq 0 \\ \tan^{-1}\frac{\bar{y}}{\bar{x}} + \pi, & when\ \bar{x} < 0 \\ \tan^{-1}\frac{\bar{y}}{\bar{x}} + 2\pi, & when\ \bar{x} \geq 0, \bar{y} \leq 0 \end{cases} \quad (3)$$

$$\bar{r} = \sqrt{\bar{x}^2 + \bar{y}^2} \quad (4)$$

Values of $\bar{r}$ closer to 1 indicate a higher concentration of occurrence around $\bar{\theta}$, and therefore a stronger seasonal signal. Conversely, values of $\bar{r}$ closer to 0 indicate large dispersion and a less clear seasonal signal.

3.3.2. Extreme value theory (EVT)

The extreme value theory (EVT) statistical approach has been adopted widely in hydrological applications to analyse and model extremes where precipitation data are assumed to represent a random draw from an underlying probability distribution, and characterising extreme values corresponds to defining the upper tail of the distribution (Coles et al., 2001; Katz et al., 2002). The EVT approach fits a probability distribution to the data, estimates the distribution parameters, and estimates the hydrological event return levels (Davison and Huser, 2015). EVT, unlike the standard statistical approaches which are concerned with mean data behaviour, are designed to reflect the behaviour of rare extreme events (Coles *et al.*, 2001).

EVT results thus provide the recurrence average of each event, which may be expressed as annual exceedance probability (AEP), and are used in practical applications such as drainage system design. For instance, an event with a specific magnitude that occurs on average once every 25 years, has an annual exceedance probability (probability of annual recurrence for a similar or greater event magnitude) of 4% (i.e. 1/25), while the corresponding intensity of the event is referred to as the 25-year return level. However, it should be noted that the AEP is the probability of a similar event occurrence in each year, while the occurrence of an event in any year does not affect the occurrence probability in any subsequent year. Therefore, for the aforementioned example (i.e. an event of magnitude X and AEP of 4%) the probability of having an event of magnitude X or greater in each year is 4%, regardless of the occurrence of such an event in any other year.

To determine the behaviour of extremes using EVT, general extreme value (GEV) and general Pareto (GP) distributions have been used often for hydrological and climatological data. The GEV distribution usually employs the high (or low) values of a dataset, where the datasets are defined as block maxima, while the GP distribution employs the data over a predefined threshold (Coles et al., 2001). Generally speaking, GEV is commonly used for large datasets, whereas, GP is used when data availability is limited (Katz et al., 2002). For instance, You et al. (2011) employed EVT to evaluate changes in precipitation and temperature extremes across China and their relation to large scale circulation, while Fowler and Kilsby (2003a) investigated the implications of changes in seasonal and annual extreme precipitation in the UK. Furthermore, Durrans and Kirby (2004) employed EVT to analyse extreme frequencies either on-site or regionally, while Jones et al. (2014) adopted the EVT approach to define new daily extreme precipitation regions in the UK. Schindler et al. (2012) also used it to validate RCM simulations over the UK.

The cumulative distribution function (CDF) for the GEV distribution F, is expressed as follows:

$$F\ (x;\theta) = \exp\left\{-\ \left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{5}$$

where x is the event maxima value of interest and θ is the parameter set (μ, σ, ξ) used to specify the distribution, while the centre is given by the location (μ), the spread by the scale (σ) and the behaviour of the upper tail by the shape (ξ). Based on the shape parameter, the GEV can take one of three forms: Gumbel, or light tailed, when ξ is zero; Fréchet, or heavy tailed, if ξ is positive; and Weibull, or bounded, when ξ is negative.

On the other hand, the cumulative distribution function (CDF) for the GP distribution F, is expressed as follows:

$$F\ (x;\theta) = 1-\left[1+\xi\left(\frac{x}{\sigma}\right)\right]^{-1/\xi} \tag{6}$$

where x is the event maxima value of interest and θ is the parameter set (σ, ξ) used to specify the distribution, while the spread is given by the scale (σ) and the behaviour of the upper tail by the shape (ξ). The two distributions are directly related through the shape parameter (Coles *et al.*, 2001; Katz, 2010)

In this chapter, the traditional stationary extreme precipitation frequency analysis approach, where the observations are assumed to be independent and identically distributed (i.i.d.), is adopted. Recently, Serinaldi and Kilsby (2015) reported that the common used length of AMAX data is usually insufficient to provide reliable return estimates for both stationarity and nonstationary cases, while using a nonstationary model would add unavoidable uncertainties due to the unknown evolution of the process dynamics. Serinaldi and Kilsby (2015) suggested that additional information will be needed to reduce the nonstationary model uncertainties including hydroclimatic, socio-economic, and historical data. Moreover, they concluded that due to the multiple interacting factors in hydrometerological data sets, inferring non-stationarity of data might not be easy, and stationarity should remain the default assumption. It has been suggested that using non-stationarity should be accompanied by socio-economic, technical, and legislation considerations (Serinaldi and Kilsby, 2015). Therefore, model parameters (μ, σ, ξ) derived from the observed precipitation record in this chapter are assumed to remain constant across the period of record and into the future.

3.3.3. Regional Frequency Analysis (RFA)

A regional frequency analysis (RFA) using L-Moments estimation (Hosking and Wallis, 2005) was adopted to represent and characterise hourly extreme precipitation. According to Sarhadi and Heydarizadeh (2014), the main benefits of RFA compared to at-site estimation are improved estimates of the distribution tails, and the ability to estimate events in ungauged locations. Furthermore, L-moments parameter estimation is more robust to outliers compared with conventional moments or Maximum Likelihood Estimation (Hosking and Wallis, 2005). Following Hosking and Wallis (2005), we applied RFA using L-Moments by first assessing region homogeneity using the heterogeneity measure (H), screening each region's data using the discordancy measure (D), then fitting a regional distribution and constructing growth curves, enabling the estimation of regional and at-site return levels.

Hosking and Wallis (2005) derived D and H by calculating different L-moment ratios relations and combinations. The value D assesses the similarity between each station's L-moment ratios and the average L-moment ratios of the other stations in the region. Accordingly, D is calculated as:

$$Di = \frac{1}{3}\left[(u_i - \underline{u})^T \ (u_i - \underline{u})S^{-1}\right] \quad (7)$$

where u_i is a vector containing three L-moment ratios (i.e., L-variation, L-skewness and L-kurtosis) for site i, u is the vector containing the simple average L-moment ratios, S is the sample covariance matrix of L-moments of all sites, and T denotes transposition of a vector or matrix. The site is considered non discordant if the D_i value does not exceed the $D_{critical}$ value. Hosking and Wallis (2005) have provided guidelines to determine $D_{critical}$ value in each region based on the number of gauges used.

The heterogeneity measure (H), compares the between-site variability of L-moments with what would be expected for a homogeneous region. The between site-variability is compared with repeated Monte-Carlo simulations of a homogeneous region with the same site's record length. Accordingly, H is calculated as:

$$H = \frac{(V - \mu_v)}{\sigma_v} \quad (8)$$

where μ_v and σ_v are the mean and standard deviation of *Nsim* values of V (*Nsim* is the number of simulation data). V is calculated from the regional data as follows:

$$V = \left\{\frac{\sum_{i=1}^{N} n_i\left[t^i - t^R\right]^2}{\sum_{i=1}^{N} n_i}\right\}^{\frac{1}{2}} \quad (9)$$

Where n *stands for* record length of site *i*, t^i is L-moment ratios (i.e., L-variation, L-skewness and L-kurtosis) for site *i*, and t^R is the regional average of L-moment ratios*;* Hosking and Wallis (2005) consider the region as "acceptably homogeneous" if H < 1, “possibly heterogeneous" if 1 ≤ H < 2, and “definitely heterogeneous” if H ≥ 2.

To minimise the impact of localised extreme precipitation events and variations between gauge locations, we take the standard RFA approach and first standardise AMAX data for each gauge by dividing by the gauge's median AMAX (RMed). Then, a regional mean RMed weighted by each gauge record length was calculated for each region. This regional RMed was used to estimate regional return levels, while individual gauge RMed were used to estimate the return levels at each location. Regional return level estimates were derived from generalized extreme value (GEV) distributions fitted to the regionally pooled AMAX. Further details on this approach can be found in Jones *et al.* (2013). The fitted distributions were used to estimate the individual gauge and regional precipitation intensities corresponding to defined annual exceedance probabilities (20%, 10%, 4%, 2%) or return periods (5-, 10-, 25-, and 50 years) by multiplying the standardised return level estimates by the gauge RMed or weighted regional RMed for the gauge and regional estimates respectively.

Finally, independence and stationarity are important underlying assumptions for regional frequency analysis. In this research, using AMAX at each gauge assures the use of independent events, with only one event selected per calendar year. On the other hand, it has been noted that the typically used length of AMAX data is insufficient to detect trends, and therefore using a nonstationary model would add unavoidable uncertainties (Serinaldi and Kilsby, 2015). Moreover, Madsen *et al.* (2013) reviewed European design guidelines and reported that all existing design guidelines are based on stationary data analysis and it has been suggested that stationarity should remain the default assumption in the absence of longer observation records (Madsen *et al.*, 2013; Serinaldi and Kilsby, 2015), which is presumed in this research.

3.4. Results

3.4.1. Diurnal cycle and seasonality of AMAX events

The diurnal profiles in Figure 2 show that most 1h AMAX occur during the afternoon between 12:00 and 18:00, with a peak typically between 14:00 and 17:00, especially in south-eastern and eastern regions such as the North East, Humber, East Anglia, and South East. However, the profile in northern regions (e.g. South Scotland) is relatively flat, indicating a weaker diurnal cycle. Blenkinsop et al. (2017) also describe the diurnal cycle for summer mean wet hour intensities with over half of the regions possessing a clear diurnal cycle, also peaking in the mid- to late afternoon though with lower amplitude cycles in the west. This spatial variation is likely associated with different mechanisms generating extreme 1h precipitation, as convective processes become less dominant to the north and west of the UK where AMAX are also more likely to occur outside summer. The diurnal profile for 3h AMAX shows that in most UK regions the frequency density also peaks during the afternoon but over a longer period compared to the 1h AMAX and with a smaller amplitude. It is possible that this difference could arise as the 3h AMAX accumulation reduces the influence of very short, heavy events by including other more moderate events occurring across three successive hours, but is also likely to arise partially as an artefact of the rolling window approach to calculate 3h accumulations.

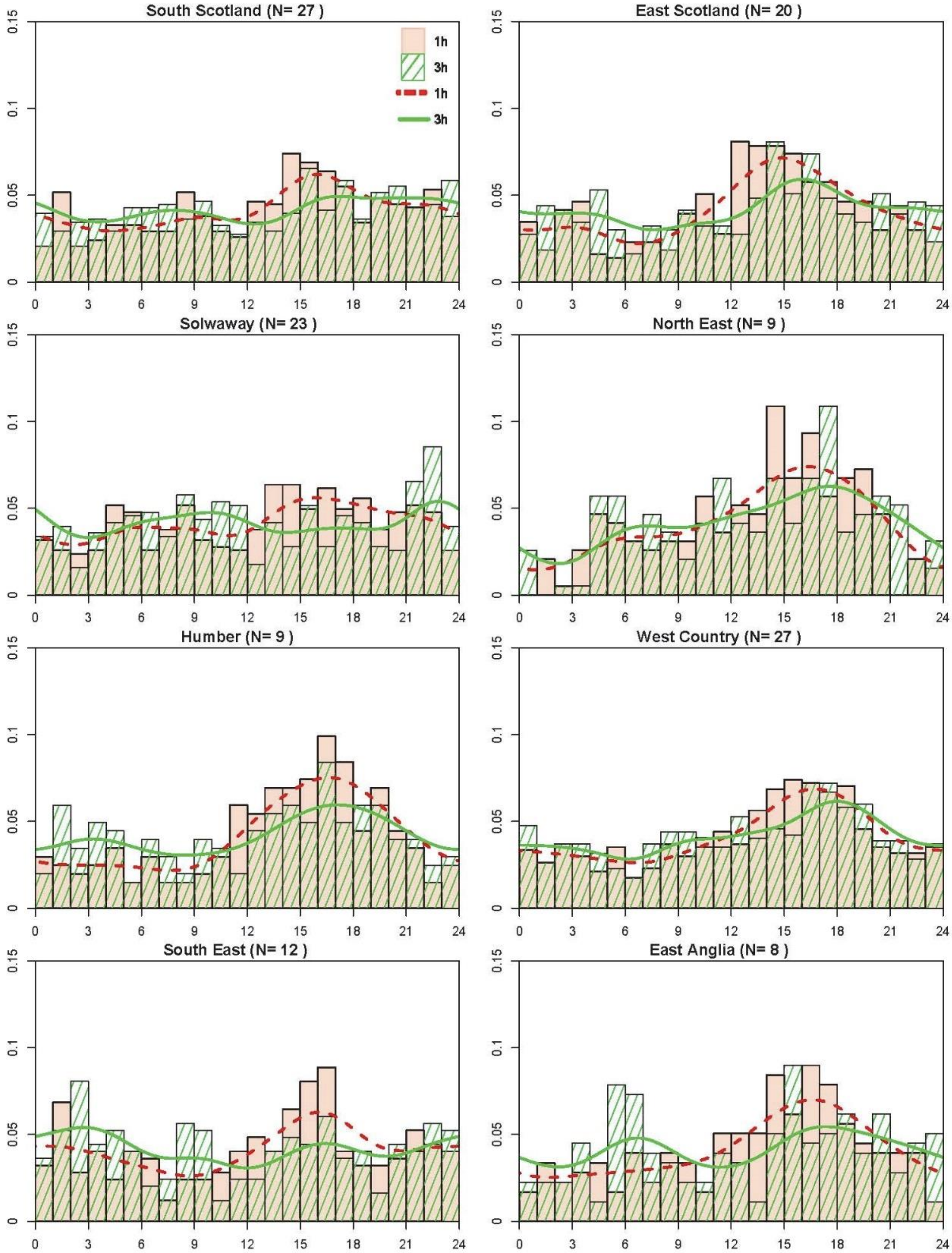

Figure 2: Regional hourly frequency density plots and diurnal profiles of 1h and 3h AMAX for selected regions. The smoothed diurnal profiles were fitted using kernel density estimations. The 3h AMAX is calculated as the accumulation of the hourly record for hour n, n-1, and n-2, and plotted at hour n. For example, an accumulation at 15:00 is the total of precipitation at 13:00, 14:00, and 15:00. N denotes the number of gauges in each region. Frequency density of event (y-axis), and hours of the day (x-axis).

The annual distribution of AMAX for all durations is summarised in Figure 3 for eight regions (NHI, SS, SOL, NW, NE, HUM, SE, and EA). All demonstrate distinct seasonality in hourly and multi-hourly AMAX – notably 1h AMAX occurrence is highly concentrated in summer (JJA) in most regions. In the most northerly regions (NHI, SS, SOL) 1h AMAX are concentrated mostly from late summer (July, August) through to mid-autumn (and for NHI, to winter) whilst in other regions these occur most frequently during the period from June to September, with a strong August peak. Comparing the distributions of multi-hourly AMAX indicates for northerly regions (NHI, SS, SOL, NW) a gradual shift in the peak frequency from the summer months to later in the year as the accumulation period increases (Figure 3). However, in southern and eastern regions (NE, HUM, EA, SE) there is less difference between accumulation periods which may suggest that in these areas AMAX are predominantly produced by the same mechanism regardless of accumulation period. In these regions the timing of 1h and 3h AMAX (short duration) peak frequencies are similar whilst the timing of 12h and 24h AMAX (longer duration) are very similar across all regions. For 6h AMAX, the timing is similar to longer durations in some regions but in others the monthly distributions are intermediate between those of short and longer durations. Finally, we note that the seasonality of 24h AMAX derived using a rolling window accumulation is similar to that derived using a fixed window at 09:00 (Figure A1, Appendix A), thus we focus on results using the latter to allow comparison with previous studies of daily precipitation.

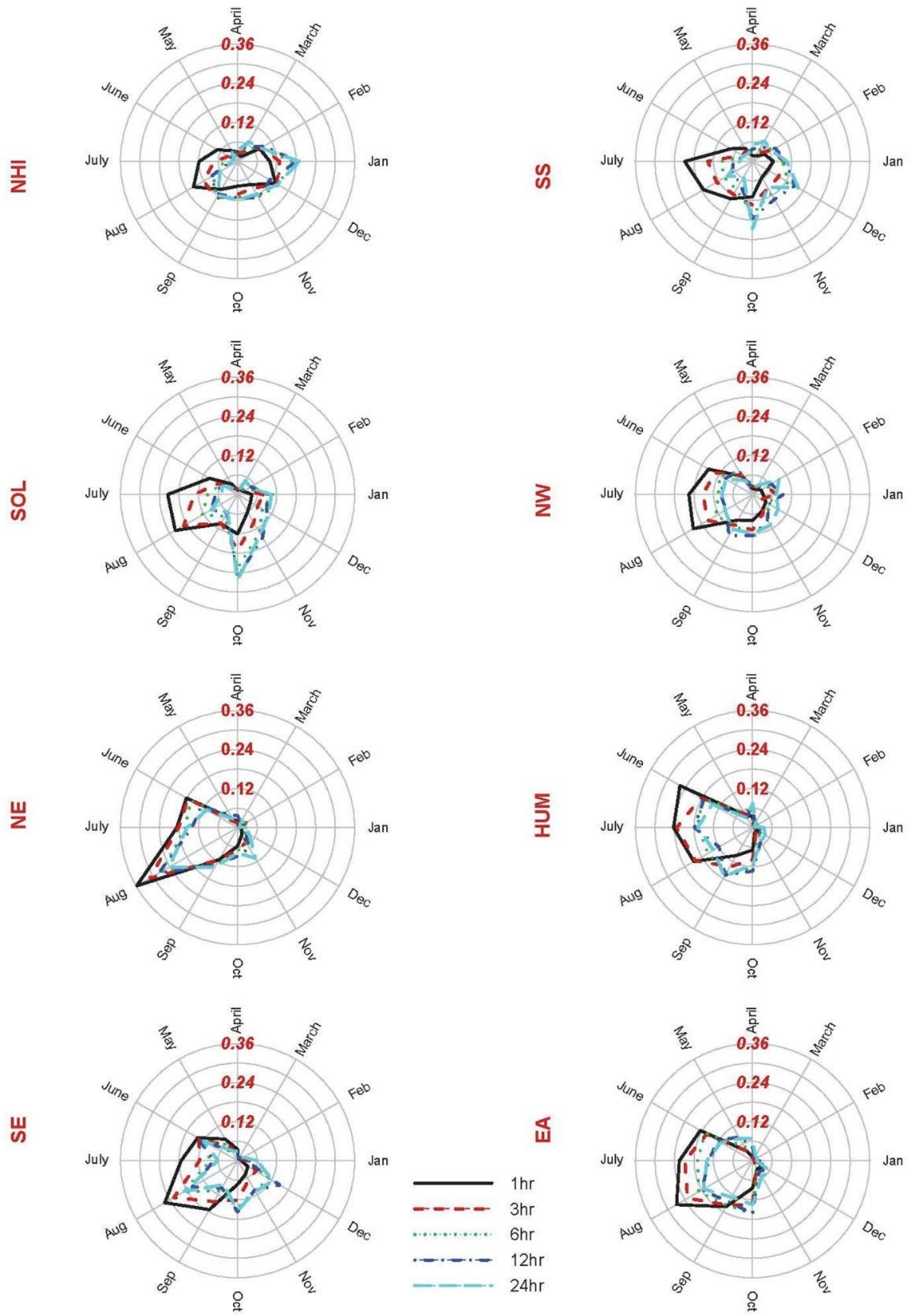

Figure 3: Regional monthly frequency densities of 1-, 3-, 6-, 12- and 24h AMAX in the UK. Red (italicised) values denote the frequency density scale.

The seasonality of hourly/multi-hourly AMAX was further quantified using circular statistics (Reed and Robson, 1999). Blenkinsop *et al.* (2017) assessed the n-largest 1h accumulations in the UK during 1992-2011, but hourly and multi-hourly AMAX have not yet been assessed. Figure 4 (quantified in Table B1, Appendix B) shows that the mean occurrence of 1h AMAX is in summer (Julian day 200 to 244) for most regions, with a mean occurrence day (θ) in August for 11 of the 13 regions, and in July and October for HUM and NHI respectively. Moreover, r values are higher in eastern and southern regions compared to western and northern regions, increasing from 0.24 (NHI) to 0.74 (EA). High r values indicate that AMAX occurrence is more strongly clustered around θ, confirming a summer dominance for 1h AMAX in the southern and eastern UK. The weaker seasonality in northern regions could be attributable to either within gauge or between gauge variability in the occurrence of AMAX and indicates that gauges across individual regions could be characterised by significantly variable seasonality. Figure 4 also indicates increasing θ values (i.e. mean occurrence later in the year) and decreasing r values (i.e. greater dispersion) for multi-hourly AMAX compared to hourly. For example, for SE, θ shifts from early-August (1h) to late-September (24h) whilst the dispersion increases, as r decreases from 0.64 to 0.35. This is consistent with Figure 3, which shows that longer duration AMAX (12h and 24h) occur later in the year and display weaker seasonality compared with 1h AMAX. These results are also consistent with those obtained by Blenkinsop *et al.* (2017) using the same dataset but using an n-largest approach, finding greater 1h dispersion in northern regions (i.e. NHI, ES, SS) compared to southern and eastern regions (i.e. NE, HUM, EA, SE). They also showed that the seasonality of the largest events broadly reflects that of mean wet hour intensities and that spatial patterns in seasonal 99th quantile intensities were consistent with those for mean intensities across the UK. Similarly, Jones *et al.* (2013) showed a summer seasonality for 1d (24h) AMAX in eastern regions, especially late summer, while other regions tended to experience 24h AMAX in late autumn. Figure 4 therefore suggests a stronger seasonality at all accumulation periods in eastern regions (NE, HUM and EA) compared with other parts of the country though this becomes much weaker as the period increases.

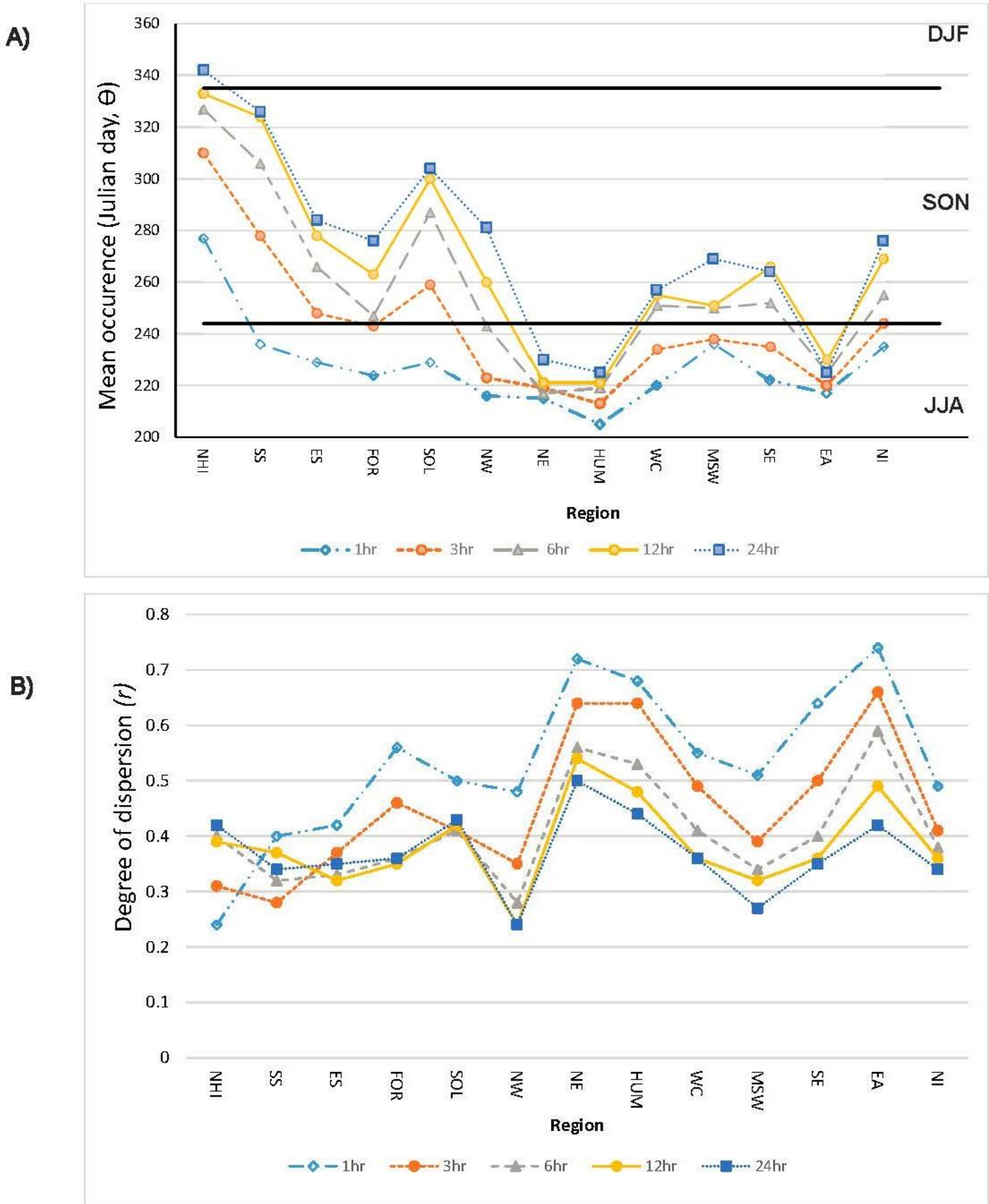

Figure 4: Regional circular statistics representing seasonality of occurrence of hourly and multi-hourly AMAX. Figure (A), mean AMAX occurrence day (Julian day, θ); Figure (B), degree of dispersion (r) indicating the degree to which AMAX are seasonally concentrated, ranging from 0 to 1, with higher values indicating greater concentration around θ. Refer to Figure 1 for region abbreviations.

Figure 5 shows the frequency density of 1h AMAX per month (black), and the magnitude of the standardised AMAX (red). This reveals that in Scotland (e.g. NHI, ES, and SS), the peak magnitude of maxima does not necessarily coincide with the peak frequency. Many of the most intense 1h AMAX occur in winter through to early spring (Dec - Mar). In contrast, the most intense 1h AMAX in southern or eastern regions (e.g. NE and EA) generally occur during summer, consistent with the period of peak frequency. The coincidence of peak AMAX occurrence and frequency in these regions may be attributable to the dominance of one precipitation mechanism producing most of the AMAX. As these occur mostly in summer, precipitation in southern and eastern regions are likely to be generated primarily by convection. In contrast, in regions where peak AMAX frequency and intensity do not coincide, different mechanisms are likely to be responsible for AMAX occurring at different times of the year. Results for 3h and 12h AMAX are presented in Figures A2 and A3 respectively for comparison given their representativeness of other durations noted above.

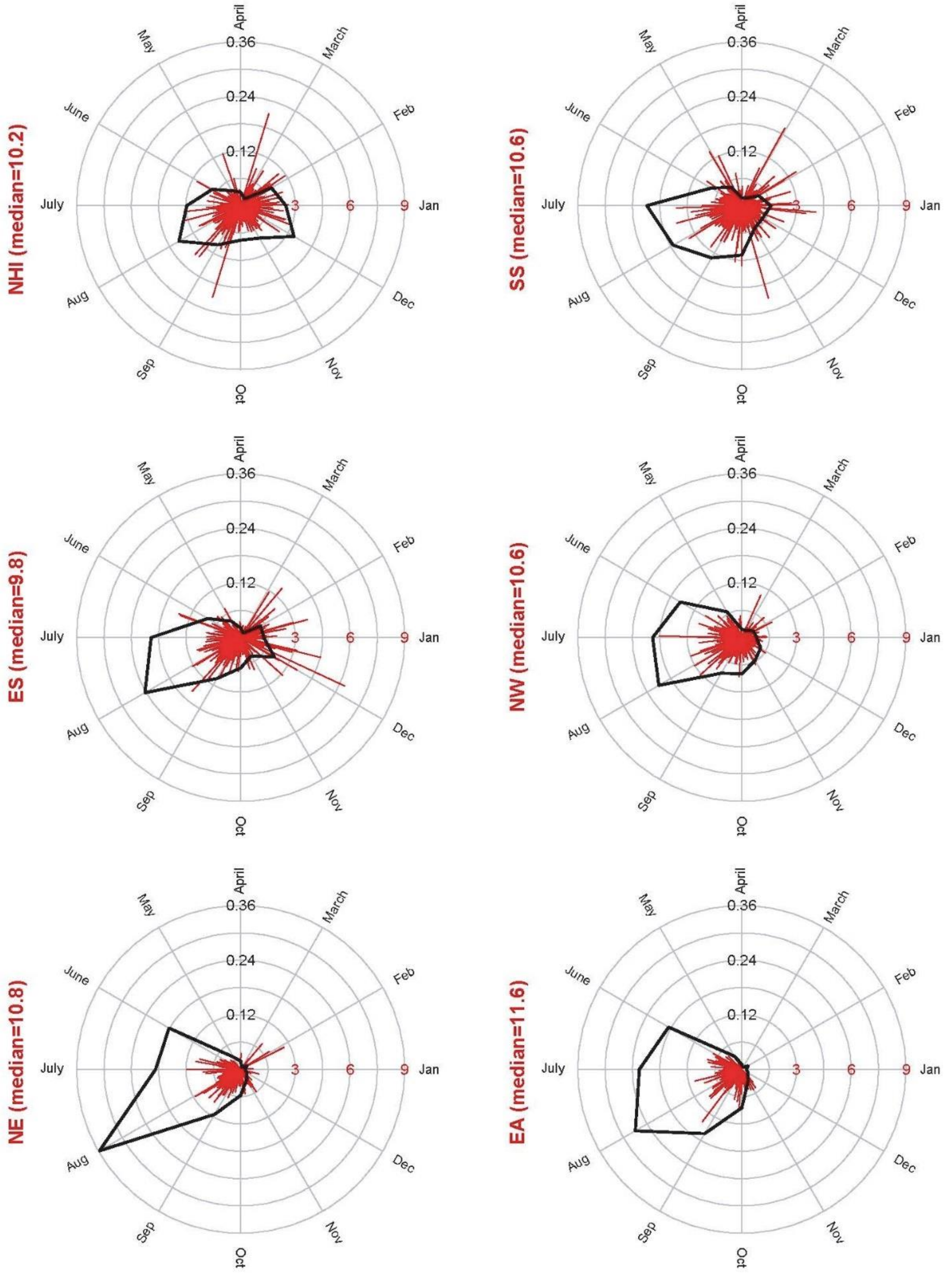

Figure 5: Monthly 1h AMAX regional frequency density (black), and hourly AMAX standardised by the regional median (red) for selected regions. The regional median (mm) is stated for each region, and radial lines denote 1st day of each month.

3.4.2. Regional frequency analysis

Regional frequency analysis (Hosking and Wallis, 2005) was used to estimate return levels for different durations. The homogeneity assessment (Table 1) shows that most of the existing extreme precipitation regions are homogeneous (H < 1) whilst the West Country marginally exceeds the homogeneity test (H=1.01), North West (NW) is classified as possibly heterogeneous (H=1.62), and Solway (SOL) is definitely heterogeneous (H=2.71). The discordancy measure, D, for the gauges in each region showed that none of the gauges is discordant. A region is homogenous if H < 1, including negative H values, possibly heterogeneous if 1≤H<2, and definitely heterogeneous if H ≥ 2, and the gauges are not discordant if the maximum gauge discordancy value is less than $D_{critical}$ ($D_{max} < D_{critical}$). Hosking and Wallis (2005) provide guidelines to determine $D_{critical}$ based on the number of gauges used.

Region name	Homogeneity (H)	No. of gauges	Max. gauge discordancy value/ max. allowed value ($D_{critical}$)
East Anglia	0.02	8	1.78 / (2.14)
East Scotland	0.99	20	2.21 / (3.00)
Forth	0.27	12	2.24 / (2.63)
Humber	-0.40	9	1.77 / (2.33)
Mid South West	0.13	11	1.68 / (2.63)
North East	0.82	9	1.89 / (2.33)
North Highland and Islands	0.39	22	2.97 / (3.00)
North Ireland	0.94	4	1.00 / (1.00)
North West	1.62	13	2.31 / (2.87)
Solway	2.71	23	2.56 / (3.00)
South East	0.73	12	1.76 / (2.76)
South Scotland	-0.63	27	2.70 / (3.00)
West Country	1.01	27	2.25 / (3.00)

Table 1: Extreme precipitation regional homogeneity assessment for 1h AMAX and the gauge discordancy assessment (Hosking and Wallis, 2005). Region is homogenous if H < 1, possibly heterogeneous if 1≤H<2, and definitely heterogeneous if H ≥ 2, and the gauges are not discordant if the maximum gauge discordancy test value < $D_{critical}$.

The two non-homogeneous regions (NW and SOL) were also reported as such for daily extreme precipitation by Jones *et al.* (2014). Further investigation of AMAX data for these regions showed that in NW just two gauges provide four of the five highest recorded AMAX, with both located on the region borders. However, since these gauges were non-discordant they were retained within the NW region analysis. For SOL, one gauge recorded a 1h AMAX of 82mm h^{-1} which is 20mm greater than the next ranked AMAX and more than double the 3rd ranked value in the region. This gauge has the highest D value, but is not discordant. This gauge is also located on the region borders and is one of only two gauges located at an elevation exceeding 350m (all other 21 gauges in the region are located at elevations < 250m). Since the AMAX have been verified against neighbouring gauges, this gauge was retained for analysis within the SOL region. We therefore retained the 13 extreme precipitation regions to estimate regional hourly and multi-hour return levels. This also facilitates comparison with the 1d AMAX return levels estimated by Jones *et al.* (2014) using daily gauge data.

The regional return level estimates for 1h, 24h, and daily AMAX (Jones *et al.*, 2014) are presented in Figure 6. We also compared the results for 24h AMAX using the fixed 09:00 accumulation period with those using rolling 24h windows to test for underestimation of AMAX due to aggregation at constant time intervals (e.g. Morbidelli *et al.*, 2017) but this produced comparable results (see Figure A4 Appendix A). The 1h AMAX (Figure 6, red line) return levels have a similar distributional shape across the UK, with heavy tails since the shape parameter, ξ, is greater than 0 (ξ>0). A Q-Q plot (Figure 7) assesses the method and assumptions, showing that the fitted model and the observed data are a good match, and the assumptions of independence and stationarity do not affect the quality the fitted distributions. On the other hand, the 24h AMAX (Figure 6, black line) and daily AMAX return level estimates by Jones *et al.* (2014) (green line), are generally slightly flatter indicating that ξ is closer to 0. The results for 24h and daily AMAX are similar for all regions except NI, FOR and NW. The differences in North Ireland (NI) are likely due to differences in the number of gauges used in both studies: daily gauges (25) and sub-daily gauges (4). In Forth (FOR) the difference is due to the occurrence of 24h AMAX exceeding 150mm and 200mm in May 2006 and August 2007 respectively, while daily AMAX in Jones *et al.* (2014) did not exceed 85mm. This is because the hourly data used here is derived from a different set of rain gauges to those of Jones *et al.* (2014) which only provided precipitation accumulations at 09:00 and at different locations over a different period (1961-2009). For the North West (NW), it is uncertain what is causing the difference, but is again likely due to the different gauges and periods used. For most regions the fitted distributions for both 24h AMAX accumulations and daily AMAX are similar despite these differences. Figure 6 (and growth curves in Figure A5) show that the fitted GEV of the daily precipitation return level estimates by Jones *et al.* (2014) and the 24h accumulation used in this research are similar in most regions, especially for return periods of up to 100 years (i.e. annual exceedance probability ≥1%), providing confidence in the data used in this study. We note though that as the daily precipitation records used in Jones *et al.* (2014) have a longer duration (1960-2009) and a larger sample size compared to the 24h accumulation record length used in this research (1992-2014), the confidence intervals for the daily return estimates are narrower than those for the 24h accumulations. Moreover, the results in Figure 6 show that the 1hr AMAX return levels and confidence intervals show some similarity across regions with no significant difference, which suggests the need for new and potentially fewer representative regions to reflect the spatial differences between gauges. This similarity across regions is confirmed by the fitted growth curves in Figure A6.

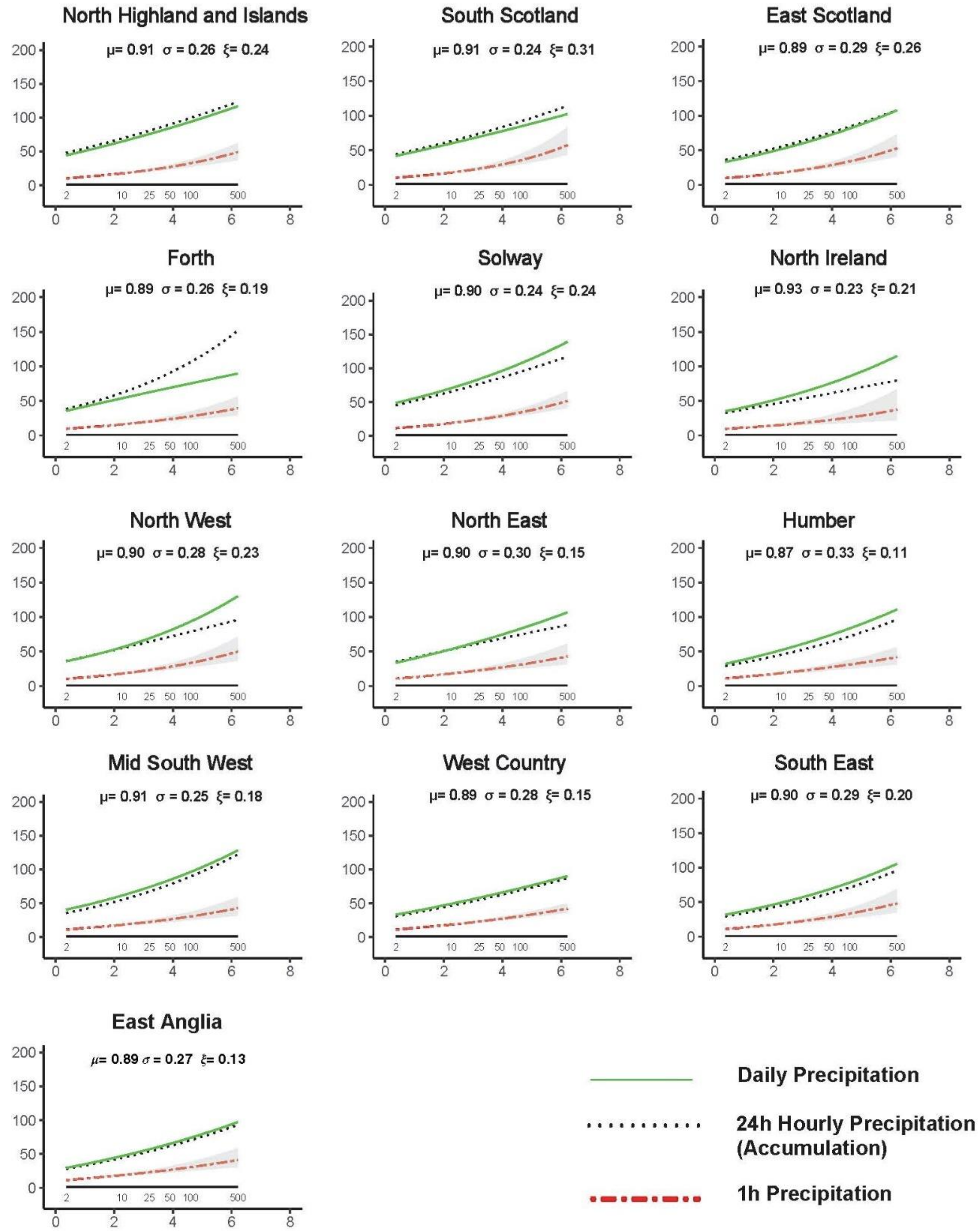

Figure 6: Return level plots of fitted regional GEV distributions for 1h AMAX (red) and 95% confidence interval (grey shaded), 24h AMAX (black), and daily AMAX (from Jones et al. 2014) (green). Return level estimates in mm (y-axis), return periods in years (upper x-axis) and Gumbel reduced variate (lower x-axis). The 1h AMAX GEV distribution parameters μ, σ and ξ are also shown.

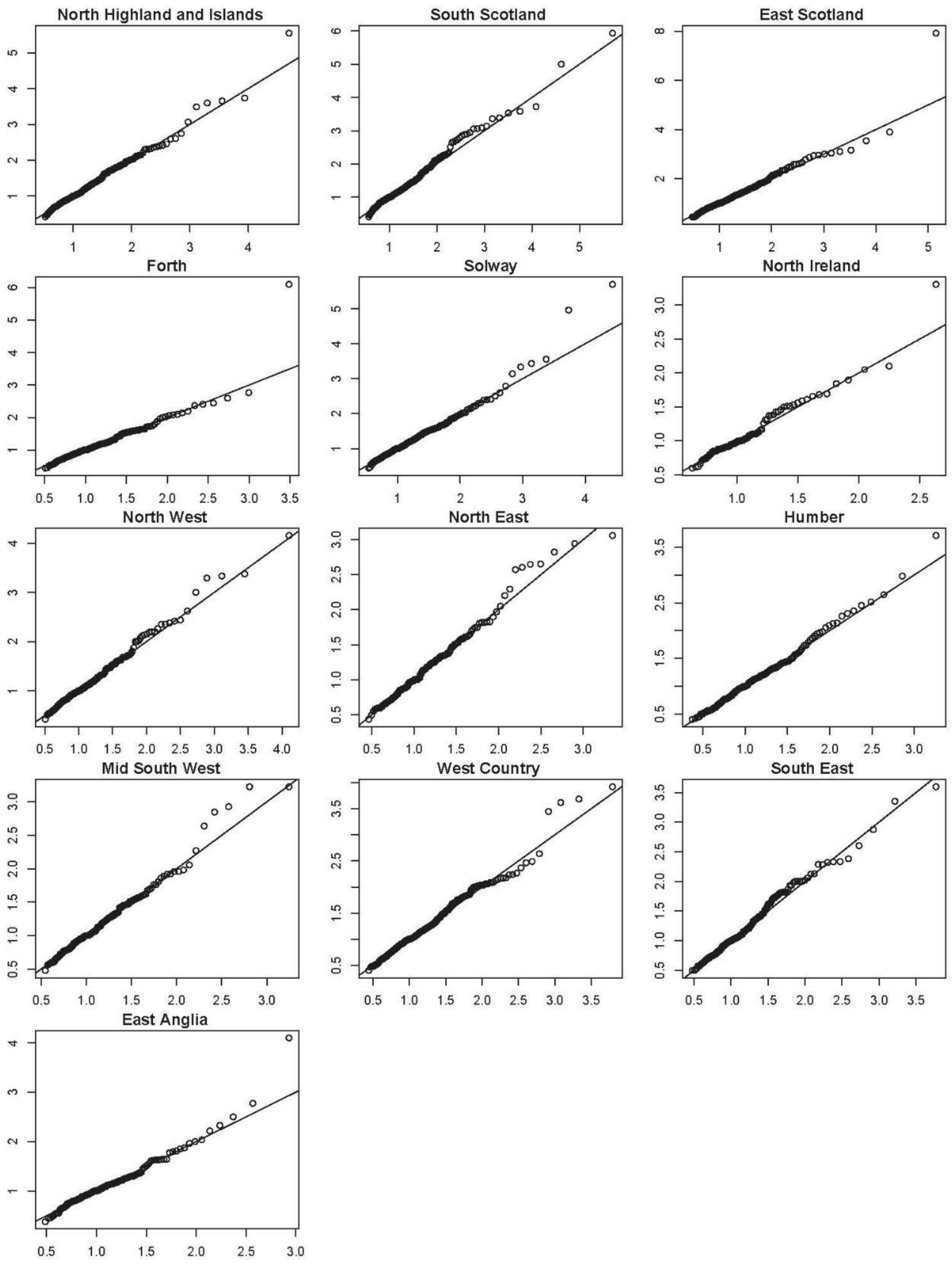

Figure 7: Q-Q plots for the AMAX fitted GEV distributions. Sample (observed) growth curve quantiles (y-axis) and theoretical growth curve quantiles (x-axis). The growth curve represents the multiple increase of a given return level over an index value, in this case the 2-year return level.

The hourly return level estimates for each gauge in Figure 8 are derived from the regional fitted GEV distributions multiplied by the site-scaling factor (the gauge RMed). The return level estimates indicate higher values for central and southern UK regions compared to northern regions for all return periods (5-, 10-, 25-, and 50-years) but especially for shorter return periods. For example, the 5- and 25-year return level estimates are less than 13mm and 19mm respectively for many gauges in northern regions, while for the same return periods, only one gauge in central and southern UK has a similar return estimate, with all other gauges exceeding these values. This is consistent with results from Figure 5, and confirms that 1h AMAX typically tend to be lowest in the most northern regions although the largest absolute magnitudes do not follow this pattern. Further results for multi-hourly (3h and 12h) return level estimates are presented in Figures A7 and A8 in Appendix A.

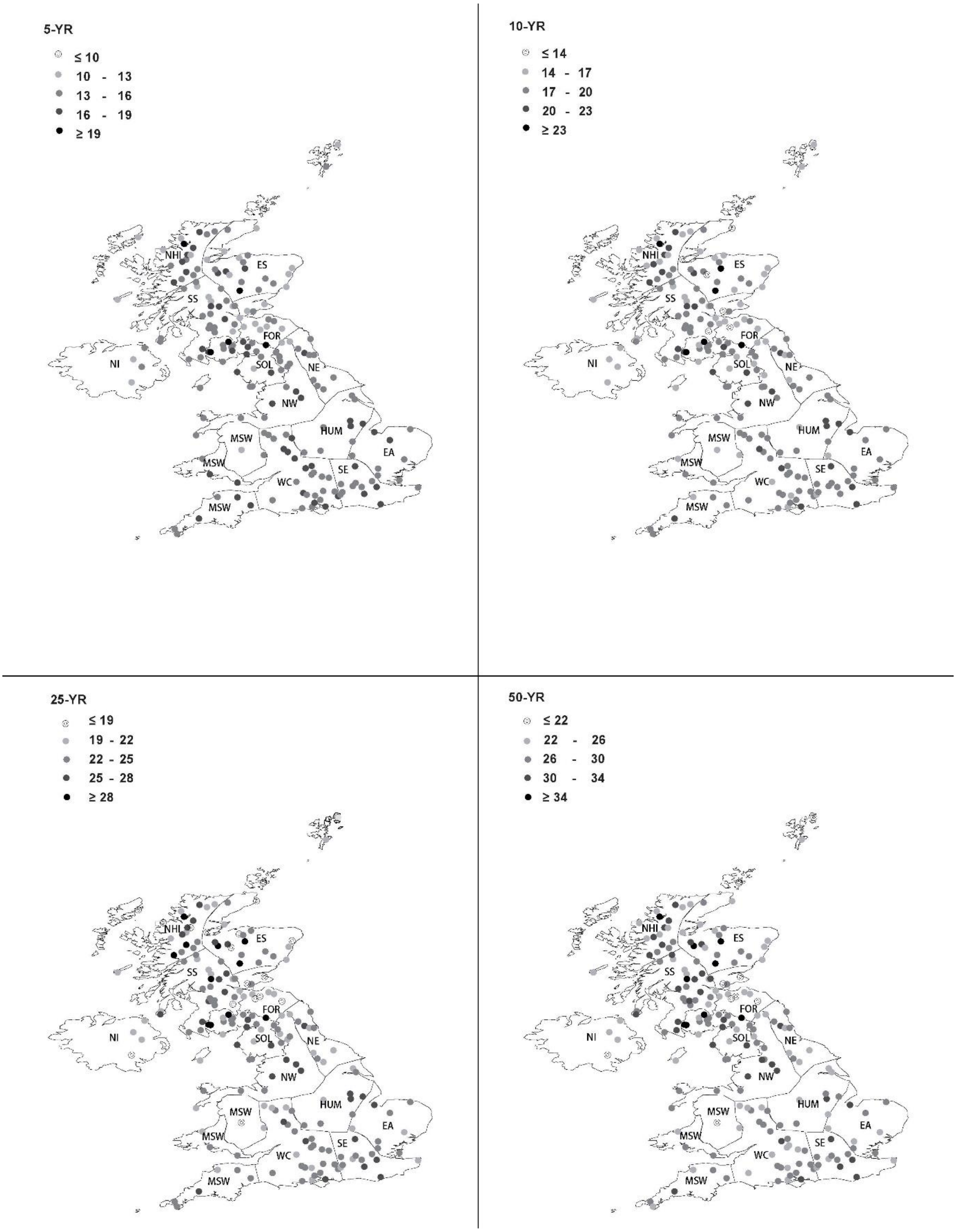

Figure 8: Return level estimates (mm h-1) for UK 1h AMAX precipitation at each gauge for return periods of 5-, 10-, 25- and 50 years (20%, 10%, 4%, 2% annual exceedance probabilities (AEPs)). Estimates for each gauge are calculated from the fitted regional GEV growth curve multiplied by the site scaling factor (gauge RMed).

3.5. Discussion

Growing evidence of intensifying extreme precipitation and its associated impacts has created a need to better characterise sub-daily precipitation events. Such events are associated with flash flooding and adversely affect urban areas and fast responding catchments. In this research, we have examined the temporal and spatial patterns of hourly and multi-hourly extreme precipitation events in the UK.

Our results in Figures 3-5 show that 1h AMAX are most likely to occur in summer compared to other, longer durations, typically extending from early summer through to early autumn (June-September) with a peak in August for most regions, extending later in the year in northern and western regions. We observe that 1h and 3h AMAX have similar seasonality in southern and eastern regions in terms of mean and most frequent occurrence although 3h AMAX are slightly more widely distributed throughout the year. We also show that 12h and 24h AMAX are less likely to occur in summer than other seasons, apart from in southeast and eastern regions of England (e.g. NE, HUM, SE, EA). 6h AMAX were found to have a seasonal occurrence and intensity pattern broadly transitional between short and longer accumulation periods. These differences in the characteristics and seasonality of precipitation at different accumulations demonstrate that using a scaling factor or regression relationship to estimate 1h extremes from those on daily timescales will likely produce misleading results, as they occur at different times of the year in some regions and are therefore likely to be caused by different processes. Consequently, many of our current tools for climate adaptation, such as uplifts used for drainage system design or sustainable drainage systems (National Suds Working Group, 2004; Dale *et al.*, 2017) may need to be revised using new 1h AMAX information.

Seasonal patterns in 24h and 1h AMAX occurrence are similar to previously published results for daily and hourly extreme precipitation (Jones *et al.*, 2013; Blenkinsop *et al.*, 2017). Jones *et al.* (2013) found that UK 1d to 10d AMAX in HadUKP northern regions (e.g. South Scotland, North Scotland, East Scotland, which are analogous but not identical to NHI, ES, SS, and parts of FOR and SOL in this research) mostly occur in late autumn and winter, which is similar to results presented here for 24h AMAX in northern regions (e.g. NHI, SS, SOL, and NW). In contrast, results showing that for most regions (e.g. SS, NW, SE, HUM, EA, NE) 1h AMAX mainly occur between summer and early autumn are consistent with the seasonal distributions of n-largest events identified by Blenkinsop *et al.* (2017). Results presented here also demonstrate that the mean occurrence day, calculated from circular statistics, tends towards autumn and winter as event duration increases from 1h to 24h (most noticeably in northern regions) which is consistent with the seasonality presented by Jones *et al.* (2013) for daily precipitation accumulations.

These results also indicate some similarity between the 1h and 3h (short duration) AMAX, and between the 12h and 24h (longer duration) AMAX. For short duration AMAX, mean occurrence day (θ) mostly occurs in summer (Figure 4A) between mid-July and September (Julian day 200 to 273). In contrast, for longer duration AMAX θ is generally between September and December (Julian day 244 to 365). In particular, 12h and 24h AMAX behave similarly to each other in terms of their mean day of occurrence and dispersion throughout the year regardless of region. For 1h and 3h AMAX though the similarity is confined to mean (summer) occurrence in southern and eastern regions whilst for northern and western regions there are greater differences between these two accumulation periods. For example, the difference in 1h and 3h θ is less than 2 weeks for central and southern regions, reaching up to 6 weeks for northern regions (e.g. NHI), whilst for longer durations the difference in θ between 12h and 24h AMAX is less than 3 weeks across all regions. The consistency at longer durations might be expected as both 12h and 24h extremes are less sensitive to short, very intense events and are both likely to be more strongly influenced by large-scale weather systems that affect large areas of the UK and produce less intense but more persistent precipitation throughout the year and particularly in autumn and winter which may also contribute to the greater dispersion (lower r) observed as duration increases. This is particularly the case in northern and western regions, which are less influenced by convective precipitation and where larger differences between 1h and 3h AMAX occurrence could be due to the reduced influence of short, heavy events in 3h AMAX and the greater contribution of moderate precipitation sustained over 3 hours with orographic enhancement of precipitation from weather systems across upland areas. The similarity of the mean occurrence of 1h and 3h AMAX in central and southern regions meanwhile could conversely be in part related to the dominance of convectively driven short, intense events which will produce a 1h AMAX and contribute significantly to the 3h accumulation, leading to a 3h AMAX in the same day. The future availability of a sub-hourly dataset for the UK could enable the role of short, convective events to be explored in more detail.

Collectively therefore the circular statistics and seasonality plots reflect the principal precipitation generation mechanisms throughout the year. That is, short duration extremes, shown to mainly occur from summer through to early autumn, predominantly arise from convective processes (Hand *et al.*, 2004), particularly in the south and east of the UK (e.g. van Delden, 2001) where there is least variability in the timing of AMAX (generally higher r values). This is consistent with the high convective available potential energy (CAPE) in this region (Holley *et al.*, 2014) and with thunderstorm climatologies for the UK (Holt *et al.*, 2001). The relationship between UK hourly and daily extremes and temperature has also been shown to be stronger in summer (approximate CC scaling) compared with winter (Blenkinsop *et al.*, 2015; Chan *et al.*, 2016) which also points to local thermodynamics as a significant driver of these extremes. In contrast, longer duration AMAX are more likely to occur either in autumn or winter in some regions and with a noticeably lower frequency in summer compared to short duration extremes in all regions. This suggests that longer duration extremes are less strongly influenced by convective processes and, as discussed above, are more likely caused by mid-latitude cyclonic systems which dominate throughout autumn and winter. Synoptic scale circulation systems have been shown to play a strong role in daily precipitation intensity across the UK with strong, cyclonic flow producing higher intensities throughout the year and westerly flow producing higher intensities in the north west of the UK (Osborn *et al.*, 1999; Tye *et al.*, 2016). This is partly associated with the North Atlantic Oscillation which has particularly strong correlations with precipitation over this region in winter (Murphy and Washington, 2001). Recent research suggests that atmospheric rivers also have a role in the development of winter floods over the UK but have little influence over summer extreme precipitation (Lavers *et al.*, 2011; Champion *et al.*, 2015). Local factors may also modify large-scale behaviour; Svensson and Jakob (2002) identified the importance of orographic enhancement and land-sea contrasts in producing a morning peak in the occurrence of heavy precipitation at a site in southern Scotland. A greater understanding however is needed of the various drivers of sub-daily precipitation and the interactions between them. The investigation of drivers of sub-daily extremes is part of ongoing work in the INTENSE (INTElligent use of climate models for adaptatioN to non-Stationary hydrological Extremes) project (Blenkinsop *et al.*, 2018).

Applying the homogeneity assessment approach by Hosking and Wallis (2005), we demonstrated that most of the existing extreme daily precipitation regions (Jones *et* *al.*, 2014) are homogeneous for 1h AMAX. Fitted GEV distributions for the 24h AMAX between 1992-2014 show close results to the fitted distributions for daily AMAX precipitation between 1961-2009 by Jones *et al.* (2014). The similarity of these results indicates that the data used in this research has an adequate record length, when pooled regionally, to analyse UK precipitation extremes. Moreover, this provides evidence that the quality control approach adopted by Blenkinsop *et al.* (2017) and Lewis *et al.* (2018), has produced a reliable precipitation dataset. The 1h AMAX return level estimates derived here showed a similar pattern and magnitude in neighbouring regions which indicates the potential for reshaping or merging the existing regions into fewer regions for future 1h extreme precipitation analysis.

In an attempt to rationalise these regions into fewer, more representative regions for hourly precipitation, an initial examination is presented here as a precursor to a more extensive new regionalisation for hourly precipitation. Combining the existing regions into new regions is a simple approach that offers the potential to enhance statistical estimates through providing more gauges per region, thus improving results for ungauged areas. To illustrate the potential for redefining regions for sub-daily precipitation, the whole UK as a single region was examined and the heterogeneity test results showed a high value (H= 2.61), indicating a definitely heterogeneous region. Since some of the return level plots in Figure 6 (and growth curves in Figure A6) were so similar, the existing regions were then subjectively merged into 3 regions (Figure 9), defined as North, West, and East. These were created using the simple approach of subjectively grouping the existing regions based on the return levels of the individual gauges for the 1h AMAX return periods shown in Figure 8 (5-, 10-, 25-, and 50 years). Different combinations of regions were examined using the same approach, yet this grouping resulted in the best homogeneity results. Indeed, the homogeneity measure (H) (Hosking and Wallis, 2005) for each region suggests that the proposed regions are homogeneous. Further improvements may be achieved by using statistical analyses of hourly precipitation variables and associated metrics in a more formal methodology such as that of Jones *et al.* (2014). This will be undertaken in the subsequent chapter.

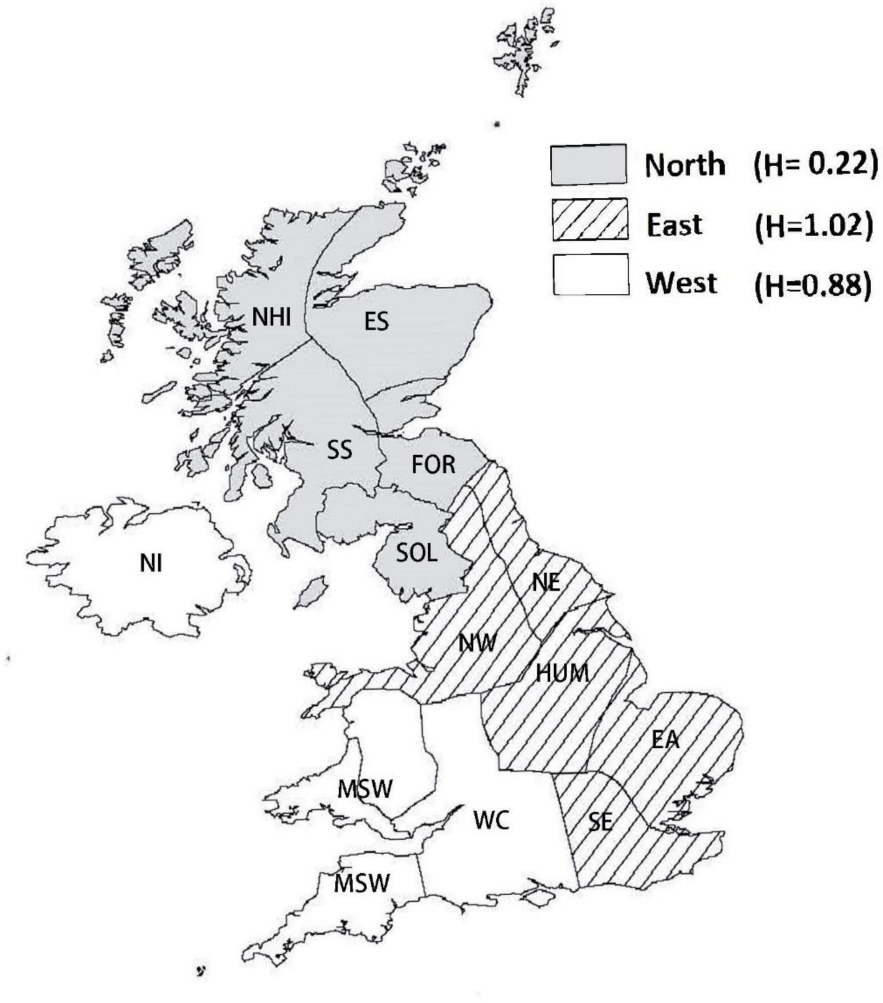

Figure 9: Potential rationalisation of precipitation regions based on subjective assessment of the 1h AMAX fitted GEV distributions. H denotes the heterogeneity measure for each region using Hosking and Wallis (1998).

3.6. Conclusion

The results presented in this paper have implications for a number of aspects of research into sub-daily extreme precipitation. Significantly, they demonstrate the reliability of the hourly data used in this research, which could be used to provide better guidance for practitioners in the UK water sector by updating and improving the Flood Estimation Handbook (FEH) (Faulkner, 1999) design precipitation depths generated by the Depth-Duration-Frequency (DDF) model. The FEH approach uses historical data, hence, having updated, robust, and quality controlled hourly datasets up to 2014 (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018) would enhance the FEH estimations.

The analysis of hourly and multi-hourly AMAX has demonstrated that 1h AMAX in the UK show a different seasonality to that of daily AMAX and that the relationship between the two durations varies spatially. This suggests that using existing approaches to design and assess drainage systems which use a weather generator (e.g. UKCP09) to simulate hourly resolution data might produce misleading results. The climate model output, precipitation estimates, and other variables in the UKCP09 weather generator are primarily estimated at the daily level, with simple disaggregation methods to generate hourly resolution data (Jones *et al.*, 2009; Kellagher *et al.*, 2009; CIWEM, 2016). Our research suggests that disaggregation methodologies that use this spatially extensive dataset and better reflect the differences between daily and sub-daily extremes (and their spatial variability) could be used to produce more reliable estimates of sub-daily extremes.

Our research also shows that the existing UK extreme precipitation regions may not appropriately reflect regional differences in sub-daily extreme precipitation behaviour, as return level estimates show similarity across neighbouring regions. The development of new regions is recommended, based on the characteristics of hourly extreme precipitation events and allowing for the limited availability of data. It is likely, however, that the number of regions needed to describe variability in sub-daily extreme precipitation across the UK is significantly smaller than that needed for daily extremes.

One of the major challenges in implementing plans and guidelines to manage pluvial flooding in the UK is the ability to predict potential changes in short, intense precipitation events. These challenges have impacts on urban drainage design guidelines, precipitation event risk assessments, and infrastructure management. However, as regional climate models (RCMs) use convection parameterisation schemes, they are generally unable to reproduce the small-scale convective systems that produce short duration events (Fowler and Ekström, 2009) such as the 1h and 3h AMAX examined here and which dominate summer UK extremes. Although, very high resolution convection-permitting models are able to better simulate convective precipitation events (e.g. Chan *et al.*, 2014b; Chan *et al.*, 2018a; Kendon *et al.*, 2018) they are computationally intensive and have, so far, only been run over small domains (see Prein *et al.* (2015) and Kendon *et al.* (2017) for review). Recent advances have been made in connecting hourly extreme precipitation simulated by convection-permitting models to synoptic-scale predictors in coarser resolution RCMs, and producing simple downscaling relationships (Chan *et al.*, 2018b). Further, statistical analysis of observed sub-daily extreme precipitation and its relation with climatological variables (e.g. temperature, sea level pressure, vertical velocity, humidity) will allow us to build observation-based statistical models for hourly and multi-hourly precipitation events. Such models could improve our understanding of short duration precipitation extremes and their potential future behaviour by validating the outputs of climate models and potentially providing a statistical downscaling short-cut (e.g. Fowler and Kilsby, 2007; Chan *et al.*, 2018b) to convection-permitting modelling. This research also has further implications for how such analyses of model projections are undertaken. Although the most frequent occurrence of short duration precipitation extremes is during summer, many hourly and multi-hourly AMAX occur between May and October depending on the region. The traditional seasonal division (summer: JJA) may therefore not be appropriate for the analysis of changes in such events if warming extends the 'convective season'.

Finally, the difference in seasonality between sub-daily and daily extreme precipitation in the UK highlights the challenges in simulating and understanding extreme events using current statistical scaling and modelling approaches, particularly across durations. Better understanding of the characteristics of extreme precipitation and its drivers (Pfahl *et al.*, 2017), including at sub-daily timescales would help in exploiting and delivering the synergies between observational and modelling studies to reduce the uncertainties in our future predictions, guidelines and adaptation plans.

Chapter 4. New hourly extreme precipitation regions and regional annual probability estimates for the UK

Existing UK extreme precipitation regions and urban drainage design guidelines are based on daily datasets, while various studies predict noticeable differences in the response of daily and sub-daily extremes in the UK to potential climate change. Recent flooding related to extreme precipitation in the UK has highlighted the importance of characterising these events, therefore, defining new hourly extreme precipitation regions would enhance our understanding of extremes, and provide a more appropriate tool to analyse sub-daily extremes.

In this chapter, the quality controlled hourly precipitation dataset from 1992-2014, geographical and topographical characteristics (e.g. latitude, elevation), and other climatological variables (e.g. temperature) are used to characterise the hourly extreme precipitation climatology in the UK, and to define five new, homogeneous hourly extreme regions. Furthermore, this chapter demonstrates the novel use of a European weather patterns classification to reflect the role of the large scale circulation, and provide a dynamical basis for the hourly extreme regions.

In meeting a central objective of this research by defining UK extreme precipitation regions based on hourly data and related climatological variables, this chapter concludes by employing these regions to quantify return estimates of hourly extreme precipitation across the UK.

4.1. Introduction

Recent decades have seen increases in the frequency and intensity of extreme precipitation in different regions which lead to increases in pluvial and fluvial flooding (Alexander *et al.*, 2006; Min *et al.*, 2011; IPCC, 2012; Westra *et al.*, 2014). Such increases impose challenges for wastewater and flood risk management, including the planning and designing of hydraulic structures, storm water drainage systems, and flood control structures, where accurate and reliable precipitation estimates are paramount (Durrans and Kirby, 2004; Madsen *et al.*, 2009). Furthermore, potential hazards of intense precipitation and associated flash floods in the UK can have significant effects on infrastructure, transportation, society and urbanized areas (Stern, 2006). However, most observational based studies to date have examined historic changes in precipitation only at daily and multi-day timescales due, in part, to the limited availability of high-resolution precipitation observations and the statistical challenges of accurately determining sub-daily precipitation probability. These challenges are due to the lack of high quality long hourly precipitation records and to sparsely distributed gauge networks (Westra *et al.*, 2014). The latter is particularly important due to the highly variable nature of hourly extreme precipitation reflecting the localised nature of intense storms and their relationship to location and climatological factors (e.g. latitude, temperature gradient) (Alexander and Arblaster, 2009; Mishra *et al.*, 2012; Westra *et al.*, 2014; Forestieri *et al.*, 2018).

Globally, most analyses of sub-daily precipitation extremes have reported increasing intensities (Westra *et al.*, 2014). In Europe, Madsen *et al.* (2009) reported an intensification in Denmark, lending support to results from the Netherlands (Lenderink *et al.*, 2011), Italy (Arnone *et al.*, 2013; Vallebona *et al.*, 2015), and the Czech Republic (Hanel *et al.*, 2016). Researchers on the other side of the Atlantic have reported similar increasing intensities in Canada and the USA (Burn *et al.*, 2011; Kunkel *et al.*, 2013; Muschinski and Katz, 2013; Barbero *et al.*, 2017). Recently, similar increases have also been reported in Australia (Zheng *et al.*, 2015; Hajani *et al.*, 2017; Guerreiro *et al.*, 2018). Such increases in intensity have been linked to the enhanced moisture holding capacity of the atmosphere as described by the Clausius-Clapeyron relationship. Whether the increases are more closely related to air temperature or dew point temperature has been the subject of debate (e.g. Lenderink and Van Meijgaard, 2010; Ali and Mishra, 2017), with more recent research favouring the latter as less dependent on a constant relative humidity assumption (Ali et al., 2018). The relationship between temperature and sub-daily extremes has been investigated in numerous observational analyses (Hardwick Jones *et al.*, 2010; Lenderink *et al.*, 2011; Mishra *et al.*, 2012; Blenkinsop *et al.*, 2015; Barbero *et al.*, 2017).

While historical precipitation events are often used to estimate structural design capacity (Smithers and Schulze, 2001), extreme precipitation analysis based on observational data is strongly influenced by data quality, record length, and the spatial and temporal distribution of data (Westra *et al.*, 2014). Thus, regional frequency analysis (RFA), or region of influence approaches (ROI), are often used to supplement and improve extreme hydrological analyses where there is limited temporal or spatial data availability (Hosking and Wallis, 2005; Sarhadi and Heydarizadeh, 2014). The RFA methodology has also been used successfully in different locations to estimate the annual exceedance probability (AEP) of extremes (Fowler and Kilsby, 2003a;

Fowler and Kilsby, 2003b; Lee and Maeng, 2003; Trefry *et al.*, 2005; Norbiato *et al.*, 2007; Jones *et al.*, 2014). AEPs are more commonly referred to as "return periods" or "recurrence intervals". In keeping with recent research on the communication of risks (e.g. Grounds *et al.*, 2018) and for clarity, we use the term AEP throughout this chapter.

A requirement of the RFA approach, employed widely to examine UK precipitation data, is the pooling of data within homogeneous regions. Previously, Wigley *et al.* (1984) identified 5 regions in England and Wales using mean daily precipitation, which were subsequently extended to 9 regions for the UK and Northern Ireland by Gregory *et al.* (1991). Alexander and Jones (2000) used these regions to develop the Hadley UK precipitation (HadUKP) regional daily observation series which is updated in near real-time. These regions have been widely used, including for the analysis of UK precipitation trends (Osborn *et al.*, 2000; Simpson and Jones, 2014) and to perform RFA (Fowler and Kilsby, 2003a; Fowler and Kilsby, 2003b; Jones *et al.*, 2013; Jones *et al.*, 2014).

Jones *et al.* (2014) reported that the HadUKP regions do not reflect regional variations in the frequency, magnitude and seasonality of UK daily extreme precipitation and therefore derived 14 regions that are more appropriate to analyse daily extremes. However, Darwish *et al.* (2018) presented a similar argument that neither the HadUKP regions nor those of Jones *et al.* (2014) are suitable for analysing sub-daily precipitation extremes, motivating the current research.

In this chapter, we use an objective clustering of rain gauges and a regional frequency analysis of extreme precipitation as in Jones *et al.* (2014) to identify new, statistically homogeneous regions for UK hourly precipitation extremes, which reflect spatial variation and improve AEP estimates for hourly precipitation extremes. These new regions are identified from different climatological and site characteristics, including extreme precipitation intensity and frequency, seasonality measures, and prevailing weather types.

The chapter is organised into four further sections; Section 4.2 describes the datasets used in the research whilst Section 4.3 presents the methods and statistical tools used to explore and analyse the data and to identify the new homogeneous regions. Section 4.4 presents the new UK hourly extreme precipitation regions and the estimated annual exceedance probabilities derived from the RFA. Section 4.5 discusses the practical implications of the new regions as well as the research conclusions.

4.2. Data

This chapter uses a range of variables describing at-site characteristics (precipitation, temperature), site characteristics (location, elevation), as well as large-scale conditions (atmospheric circulation patterns) across the UK to identify homogeneous regions and characterise hourly extreme precipitation.

The primary at-site characteristics were derived from the UK hourly precipitation dataset, comprising rain gauges from three sources: the UK Met Office Integrated Data Archive System (MIDAS), the Scottish Environmental Protection Agency (SEPA), and the UK Environment Agency (EA). The dataset (up to 2011) was collected by Blenkinsop *et al.* (2017) who performed a series of site-specific quality control (QC) procedures on the data, with additional QC checks against neighbouring gauges undertaken by Lewis *et al.* (2018) while extending the dataset to 2014. To ensure a reliable dataset of sufficient record length, and to facilitate comparison with other research, only gauges with more than 85% of their record complete (i.e. non-missing and data not flagged by the QC process) for each year is used here. These criteria were selected as a trade-off between having long records and data completeness. Further details on the adoption of these criteria can be found in Section 3.2.

Moreover, site characteristics including the longitude and latitude of each rain gauge were derived from rain gauge metadata. However, not all gauges were accompanied by elevation data; absent data were derived from a global digital elevation model (DEM) with a horizontal grid spacing of approximately 250 metres (Jarvis *et al.*, 2008).

For each rain gauge, corresponding series of daily maximum, minimum and mean temperature between 1992 and 2014 were obtained from the UKCP09 gridded dataset at a resolution of 5x5 km, and based on surface observations from 1960 to 2014 covering the whole of the UK (Hollis and McCarthy, 2017). Consequently, a total of 197 rain gauges distributed across the UK covering the period 1992-2014 were used in this study alongside the gridded daily temperature series.

Atmospheric circulation over the North Atlantic ocean has a strong effect on Western European weather, affecting air flow, moisture content, and other characteristics which in turn control precipitation patterns (Scaife *et al.*, 2008; Hurrell and Deser, 2010; Woollings, 2010). WTs developed from climatic variables (i.e. mean sea level pressure (MSLP), wind speed, and wind direction) have long been used both in Europe (e.g. Lamb, 1991; Bissolli and Dittmann, 2001) for different purposes including: assessing

UK precipitation and global meteorological relationships (Knight *et al.*, 2017), investigating future European precipitation (Fereday *et al.*, 2018), forecasting coastal floods around the UK (Neal *et al.*, 2018), and in the construction of a precipitation and drought climatology for the UK (Richardson *et al.*, 2018). Thus, the final dataset used here is that of Neal *et al.* (2016) who classified large-scale atmospheric circulation conditions over Europe into 30 Weather Types (WTs), deriving a smaller set of 8 WTs (Table 2), using K-means clustering, for the purposes of evaluating forecasts.

Here, the subset of 8 WTs between 1992-2014 are used to provide additional understanding of the physical processes of UK hourly extreme precipitation, underpinning the new precipitation regions and associated AEP estimates. The final investigated hourly extremes dataset is relatively limited, therefore, using the 8 WTs provides a balance to reflect the relationship between WTs and hourly extremes, providing a reasonable sample of events across the types. Using the classification of 30 WTs would split the extremes across too large a number of WTs which is impractical for further analysis, and makes the relationship indistinguishable. Thus, the 8 WTs were selected for the analysis in this research.

Weather type (WT)	Description
1. NAO-	All sub-types going into this type in general have positive MSLP anomalies to the north of the UK and negative MSLP anomalies to the south of the UK, resulting in a negative NAO pattern.
2. NAO+	All sub-types going into this type in general have negative MSLP anomalies to the north of the UK and positive MSLP anomalies to the south of the UK, resulting in a zonal (positive NAO) type.
3. Northwesterly	All sub-types going into this type in general have negative MSLP anomalies to the northeast of the UK and positive MSLP anomalies to the southwest of the UK, resulting in a north-westerly flow. Sub-patterns going into this type vary between being cyclonic and anticyclonic, but the direction of flow is the same.
4. Southwesterly	All sub-types going into this type in general have negative MSLP anomalies to the northwest of the UK and positive MSLP anomalies to the southeast of the UK, resulting in a southwesterly flow. Sub-types going into this type vary between being cyclonic and anticyclonic but the direction of flow is the same.
5. Scandinavian high	All sub-patterns going into this type in general have negative MSLP anomalies to the west of the UK and positive MSLP anomalies to the east of the UK, resulting in a south to southeasterly flow. Most sub-patterns in this type are anticyclonic.
6. High pressure center over UK	Both sub-types going into this type have positive MSLP anomalies over the UK and to the south of the UK, with weak negative MSLP anomalies to the north of the UK. This results in an anticyclonic westerly or southwesterly flow.
7. Low close to UK	Both sub-types going into this type extend a trough over the UK. Negative MSLP anomalies are centred just to the west of the UK resulting in a cyclonic southwesterly flow.

8. Azores high	Only one of the 30 types goes into this type which shows an anticyclonic westerly flow over the UK, with an Azores high extension.

Table 2: *Descriptions of the eight weather patterns from the European and North Atlantic Daily to Multi-decadal Climate Variability (EMULATE) MSLP (EMSLP) data (1850–2003) as derived in Neal et al, 2016. Weather type names and descriptions are relevant to the UK. MSLP and NAO denote mean sea level pressure and North Atlantic Oscillation respectively.*

4.3. Methodology

We apply a statistical approach to cluster gauges with similar characteristics together and create homogeneous regions for assessing the spatial pattern of hydrological processes. This method has been used widely in the literature (Wigley *et al.*, 1984; Dales and Reed, 1989; Jones *et al.*, 2014; Sarhadi and Heydarizadeh, 2014; Forestieri *et al.*, 2018). In addition, the frequency of occurrence of UK weather types is incorporated into the analysis, and used to delineate the new regions, to ensure that the new regions reflect both the statistical and physical behaviour of hourly extreme precipitation.

The following sections describe the process of selecting appropriate variables (Section 4.3.1), identification of new homogeneous regions (Section 4.3.2), an estimation of regional AEP for UK hourly extreme precipitation (Section 4.3.3), data independence (Section 4.3.4), and goodness of fit (Section 4.3.5).

4.3.1. Variable Selection

The UK is located downstream of the Atlantic storm track, which produces a strong temporal variation in precipitation (de Leeuw *et al.*, 2016). Furthermore, extreme hourly UK precipitation displays geographical and seasonal variability, with most hourly extremes occurring in summer, especially in the southern and eastern UK (Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018). This seasonality is associated with different daily and sub-daily extreme precipitation generating mechanisms. North-western areas are more strongly influenced by extreme precipitation arising from large scale circulation and frontal systems occurring in autumn and winter than in the south and southeastern parts of the UK where extremes tend to be dominated by short duration, convective precipitation occurring in summer (Jones *et al.*, 2014; Darwish *et al.*, 2018). Previous studies at daily timescales have selected variables which reflect these topographical and climatological variations (Wigley *et al.*, 1984; Dales and Reed, 1989; Reed and Robson, 1999; Maraun *et al.*, 2008; Jones *et al.*, 2014).

In this research, statistics for different climatological variables are investigated and the extent to which they reflect variability in hourly extreme precipitation frequency and intensity patterns in the UK were assessed before selecting the most relevant variables for further analysis. Data availability, possible correlation between variables, the relevance to hourly precipitation extremes and their generating processes were considered prior to further analysis.

Firstly, the geographical and topographical characteristics, latitude (Lat), longitude (Lon) and elevation (Elev), were allocated for each gauge as detailed in Section 4.2 (see also Table 3). Previous examination of UK hourly and daily extremes used annual maxima (AMAX), the 0.99 wet day/hour quantiles (Q99) (Alexander and Jones, 2000; Jones *et al.*, 2014; Simpson and Jones, 2014; Darwish *et al.*, 2018), or N maximum events per year to define extremes (Blenkinsop et al., 2017). Here, the median AMAX (RMed) and the 0.99 wet hour quantile for annual (Q99), summer half year (April-September) (SQ99), and winter half year (October-March) (WQ99) hourly precipitation were calculated for each gauge to capture the variability in regional annual and seasonal precipitation intensity. As an approximation to the regional and seasonal differences in extreme frequency, the number of hours exceeding SQ99 in summer and WQ99 in winter were derived (denoted as N-SQ99, and N-WQ99 respectively). In reality, this value will be skewed by the number of complete record years as well as the wet hour frequency; however, this offers a characterisation of the spatial differences in the number of wet hours. We calculated these statistics using hourly declustered precipitation (the highest hourly value per day) for each gauge to ensure independent precipitation values.

Precipitation seasonality was then quantified using circular statistics (Reed and Robson, 1999) to represent the mean occurrence day of hourly precipitation extremes ($\bar{\theta}$), and the overall dispersion ($\bar{r}$) of the events around $\bar{\theta}$. The circular statistics were calculated for each gauge using hourly precipitation greater than Q99, using the method stated in Section 3.3.1. Values of r closer to 1 (0) indicate a higher (lower) concentration of events around θ, and therefore a stronger (weaker) seasonal signal.

Furthermore, the median of maximum and minimum recorded temperature values (Tmax, Tmin) on the Q99 precipitation days was extracted for each gauge. The relation between UK extreme hourly precipitation and temperature has been investigated by Blenkinsop *et al.* (2015) who showed that UK hourly extremes scale with temperature according to the thermodynamic Clausius-Clapeyron (CC) relation, which states a 6-7% increase in atmospheric moisture holding capacity per 1°C increase in temperature, under constant relative humidity. Table 3 provides a summary of the selected variables and their description.

Variable	Description
Lat	Latitude of rain gauge
Lon	Longitude of rain gauge
Elev	Elevation of rain gauge
Q99	Precipitation 0.99 quantile (wet hours)
SQ99	Summer (April-September) precipitation 0.99 quantile (wet hours)
WQ99	Winter (October-March) precipitation 0.99 quantile (wet hours)
RMed	Median of AMAX precipitation 1992-2014
$\bar{\boldsymbol{\theta}}$	Average day of occurrence of events exceeding Q99 (rotated seasonal statistics)
$\bar{\boldsymbol{r}}$	Dispersion of events exceeding Q99 around $\bar{\boldsymbol{\theta}}$ (rotated seasonal statistics)
N-SQ99	Number of summer (April-September) events exceeding SQ99
N-WQ99	Number of winter (October-March) events exceeding WQ99
Tmax	Median of maximum temperature on Q99 days
Tmin	Median of minimum temperature on Q99 days

Table 3: Variables used to identify homogeneous regions for hourly extreme precipitation using principal components analysis. Each variable's contribution to the PCA results were assessed, and the most representative variables (shaded) were retained.

To reduce the number of variables used for each gauge, and to identify the most meaningful variables from those chosen for the analysis, principal component analysis (PCA) was performed. PCA reduces large multivariate statistical datasets to smaller and equally descriptive datasets that capture their similarities by creating linear combinations of the original data (Wilks, 2011). Each combination describes a proportion of the original data, called a principal component (PC). Hosking and Wallis (2005) reported the sensitivity of clustering algorithms to the Euclidean distance or scale of the variables used, and suggested rescaling the input variables before performing the clustering, to avoid the dominance of variables with large absolute values (e.g. altitude). Hence, all the variables in Table 3 were rescaled by dividing each variable value by its corresponding median before analysing the PCs.

Finally, different combinations of the variables in Table 3 were investigated using the variable loadings and variance, to determine the most representative combination of variables. The loadings, shown in Table 4, indicate the association between the original variables and the new linear combinations, while the proportion of variance explained by each PC indicates the importance of the PC. Combinations which achieved the highest explained variance, and variables showing high loadings were chosen for further analysis.

4.3.2. Clustering Analysis

To identify homogeneous regions for UK hourly extreme precipitation, a cluster analysis was undertaken on the final PC scores for each gauge. Cluster analysis (CA) using PC scores has been widely adopted in the literature (e.g. Gottschalk, 1985; Jones *et al.*, 2014; Sarhadi and Heydarizadeh, 2014; Forestieri *et al.*, 2018). Sarhadi and Heydarizadeh (2014) reported that CA is the most practical method to assess and pool similar hydrological and climatological data in homogeneous regions using their geographical, physical and statistical characteristics. It is assumed that all stations within the homogeneous regions identified by the CA will have similar distributions and characteristics, facilitating reliable probability estimates at data scarce or ungauged sites (Hosking and Wallis, 2005).

Generally, cluster analysis (CA) methods for hydrological studies adopt either a hierarchical clustering approach such as average and complete linkage (Jackson and Weinand, 1995; Ramos, 2001), and Wards method (Jackson and Weinand, 1995; Ramos, 2001; Sarhadi and Heydarizadeh, 2014), or a non- hierarchical clustering approach such as K-means method (Jones *et al.*, 2014).

The hierarchical approach clusters the two most similar objects together and continue to combine until all objects are in the same cluster. This approach has the advantage of visualising the clusters using a tree structure (i.e. dendrogram), and providing different groups based on the level of resolution being examined, without the need of determining the targeted number of clusters as an input (Tan, 2018). On the other hand, the non-hierarchical approach (e.g. K-means) clusters the data in independent groups, where the objects within each group are similar to each other and dissimilar to other groups (Tan, 2018). Furthermore, the K-means approach is sensitive to erroneous values, and requires the identification of the targeted number of clusters as an input, which requires a priori knowledge to avoid clustering the objects inaccurately (Ferro and Segers, 2003).

Therefore, Wards method was used in this study, which employs dendrograms to assess and visualise the correlation between input and output dissimilarities between different clusters. In addition, Wards method achieved the highest “Cophenetic correlation” coefficient values compared to both: K-mean and average and complete linkage, which measure how faithfully a dendrogram preserves the pairwise distances between the original unmodelled data points (Rao and Srinivas, 2006; Isik and Singh, 2008). The spatial and topographical contiguity of the regions were also reviewed to ensure coherency and relevancy to UK geographical and climatological conditions.

Rather than rely solely on a statistical estimation of hourly extreme precipitation regions, a dynamical approach was also employed by using the 8 European weather types (WTs) defined by Neal *et al.* (2016). The WTs indicate the prevalent circulation patterns over Europe and the UK each day. By assigning the appropriate WT to each gauge record of Q99, WQ99 or SQ99, it was possible to analyse the proportion of time each WT generated an extreme hourly precipitation. Mapping these proportions for each station, hence, provided insight into the atmospheric circulation patterns and physical processes associated with short-duration extreme precipitation and enabled dynamical confirmation of the statistically-derived regional clusters.

4.3.3. Regional Frequency Analysis (RFA)

The new regions’ homogeneity and the gauges’ discordancy within each region were assessed with respect to RFA guidelines as in Section 3.3.3 (see also Darwish *et al.* (2018)). Furthermore, the precipitation data in each gauge were standardised by dividing on the corresponding median to reduce the impact of potential spatial variation caused by imprecise recorded values. Then regional Generalised Extreme Value (GEV) and Generalised Pareto (GP) distributions were fitted to standardised annual maxima (AMAX) and wet hours exceeding the 0.99 quantile (Q99), respectively, to estimate AEPs for different durations as in Section 3.3.3 (see also Darwish *et al.* (2018)).

4.3.4. Data independence

Independence and stationarity are important underlying assumptions for regional frequency analysis. Therefore, the AMAX at each gauge was used to ensure having independent extremes for the fitted GEV distribution. Additionally, further steps were performed to ensure independent data for the GP distribution, where multiple observations might occur at the same time within each region.

Initially, the 0.99 quantile (Q99) for each gauge was calculated, then observations above Q99 were declustered and retained for further analysis. Subsequently, the Q99 observation from all the gauges within each region were grouped, and only the highest hourly precipitation value per day in each region was selected.

In this chapter, the ‘‘runs declustering’’ approach by Leadbetter *et al.* (1989), has been adopted to ensure Q99 data independence. The approach considers exceedances to belong to the same cluster if they are separated by less than a fixed number of occurrences r called “run length” (Tc). However, choosing the “run length” is arbitrary, and depends on investigated datasets (Acero *et al.*, 2011). Therefore, the improved and automated “run length” technique by Ferro and Segers (2003) was employed in the analysis which uses an extremal index variable (EΘ) to measure the degree of clustering of extremes instead of the arbitrary choice of the “run length”. This technique allows the assessment of the independence of each gauge data, using a different ‘‘run length’’, that is determined automatically as a function of the degree of clustering of extremes instead of using the same “run length” across the whole region.

Therefore, to find the suitable (Tc) for each gauge, an automated approach is used that only depends on the extremal index (Eθ), which is calculated from the N exceedances of the threshold considering the interexceedance times Ti expressed as following (Ferro and Segers, 2003):

$$E\theta(u) = \frac{2\left[\sum_{i=1}^{N-1}(T_i - 1)\right]^2}{(N-1)\sum_{i=1}^{N-1}(T_i - 1)\,(T_i - 2)} \qquad (10)$$

where N is the exceedances of the threshold (*u*) considering the interexceedance times *T*.

The extremal index (*EΘ*) takes a value in the interval [0, 1], where independent data, *EΘ* = 1, while *EΘ* =0 indicates full data dependence (clustering). The analysed gauges in this research have values higher than 0.7, indicating generally independent values.

4.3.5. Goodness of fit measure (Zdist)

Hosking and Wallis (2005) suggested using the Z_{dist} measure to assess the goodness of fit for a potential fitted distribution. Z_{dist} assesses the goodness-of-fit by comparing the difference between the L− kurtosis of the potential distribution and the regional average L- kurtosis of the region of interest, weighted proportionally to the sites' record lengths. The L− kurtosis of the potential distribution is estimated by simulating a large number of regions having the potential distribution, with L-moments ratios (i.e. L-variation, L-skewness, and L- Kurtosis) equal to the average regional L-moments ratios of the region of interest, besides having the same number of sites and record lengths. Therefore, Hosking and Wallis (2005) suggested that for each distribution, the goodness-of-fit measure is calculated as:

$$\text{Zdist} = (\tau_4^{DIST} - \tau_4^{R} + B^4) / \sigma^4 \quad (11)$$

Where τ_4^{DIST} is the L-kurtosis of the fitted distribution, and DIST can be any distribution (e.g. GEV, GPD), $\tau_4^{R}$is the regional average L-kurtosis , B^4 is the bias of τ_4^{R}, and σ^4 is the standard deviation of L- Kurtosis values from simulation. The bias (B^4) is calculated as:

$$B^4 = \frac{1}{N_{sim}} \sum_{m=1}^{N_{sim}} \overline{\tau_4^{m}} - \overline{\tau_4^{R}} \quad (12)$$

while the standard deviation of L- Kurtosis values from simulation (σ^4) is calculated as:

$$\sigma^4 = \sqrt[2]{\left\{\left(\frac{1}{N_{sim}}\right)\left[\sum_{i=1}^{N_{sim}}\left(\overline{\tau_4^{m}} - \overline{\tau_4^{R}}\right)^2 - (N_{sim}B_4)^2\right]\ \right\}} \quad (13)$$

where N_{sim} is a large simulation of data sets for a region with N sites, each having the potential distribution as its frequency distribution, and τ_4^{m} is the *m*th simulated region average L-kurtosis value.

Hosking and Wallis (2005) declare the fit to be adequate if Zdist is sufficiently close to zero, while a reasonable criterion is having | Zdist | ≤ 1.64, at an approximate confidence level of 90%.

4.4. Results

4.4.1. Principal Components Analysis

The variables presented in Table 3 were selected to capture the hydro-climatological characteristics of the UK hourly extremes, specifically spatial and temporal differences in frequency and intensity as reported in the literature (Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018). PCA was carried out for different combinations of the rescaled variables to confirm their efficacy in describing and explaining the data patterns, and to identify repetitive variables that could be dropped. For instance, the PCA results (i.e. PC loadings and total explained variance) showed that including seasonal quantiles (SQ99 and WQ99) might repeat information from the annual quantiles and did not increase the explained variance. Therefore, only the explanatory variables shaded in grey in Table 3 were retained for use.

PCA results for the selected variables (Table 4) show the variation explained by each principal component and the loading of each variable. PC1 explains 49% of the total variance and is related to temperature, emphasising temperature's strong association with hourly extreme precipitation. PC2 explains 19% of the variance and is related to hourly extreme precipitation intensity, with the highest loadings associated with RMed and Q99. The absolute loadings of extreme precipitation intensity variables in PC2 are noticeably higher than for other variables. PC3 explains 11% of the variance and is related to the spatial seasonality and frequency of extreme hourly precipitation, in addition to orography. Finally, PC4 (not shown) explains less than 5% of the variance, with the highest loading variables similar to those of PC3 (elevation, N-SQ99, and $\bar{\theta}$).

Variable	PC1	PC2	PC3
LAT	0.318	0.329	0.133
LON	-0.317		-0.276
Elevation	0.229	-0.248	-0.459
Q99		**-0.636**	0.256
RMed		**-0.619**	
$\bar{\boldsymbol{r}}$	0.366	-0.151	
$\bar{\boldsymbol{\theta}}$	-0.255		**0.541**
N-SQ99	0.259		**0.544**
N-WQ99	0.383		0.138
Tmax	**-0.406**		
Tmin	**-0.404**		
Proportional contribution (explained variance)	*49%*	*19%*	*11%*

Table 4: Loadings of each variable in the first three principal components and proportional contribution to the explained variance. Values in bold are the 2 most significant contributing variables for each principal component. Loadings smaller than ±0.1 are not reported for clarity.

Selecting the adequate number of components to reflect the data characteristics is subjective, and may be based on various factors such as the scree plot, which measures the variance (i.e. eigenvalues) associated with each component, the total explained variance, and the component eigenvalue. Jolliffe (2002) suggested using the number of components on the scree plot where the slope of the curve shows a levelling off (elbow). Other researchers have suggested using standard approaches such as selecting components with eigenvalues > 1 (Eder, 1989), or using components that explain most of the variability (i.e. greater than 70%) (Jolliffe, 1990).

The scree plot (Figure 10) indicates that the variance curve (red line) decreases slightly after the 3rd principal component, while the total explained variance (blue line) indicates that the first three components capture 79% of the data variance. Moreover, the 4th principal component (Comp.4) explains less than 5%. Additionally, only the eigenvalues of the first three components are greater than 1 and therefore only these (1-3) were retained for subsequent use in the clustering analysis.

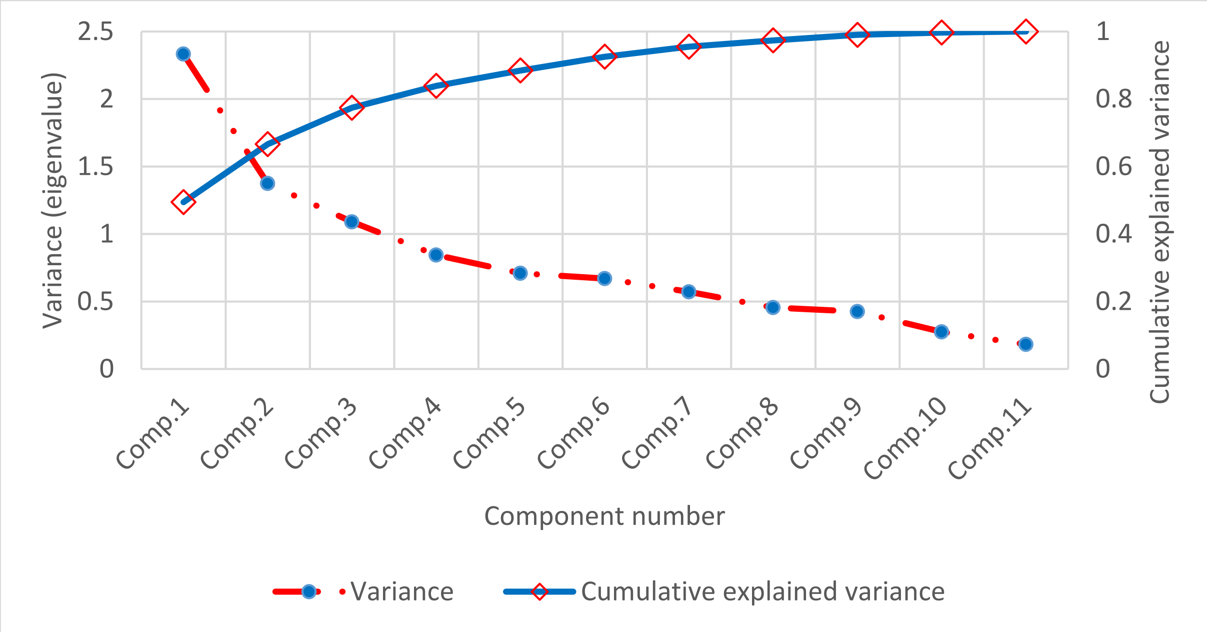

Figure 10: Scree plot of the principle component analysis (PCA) for the various climatological variables in Table 4. Eigenvalue of each component (left Y-axis) (Blue line), cumulative explained variance (right Y-axis) (Red line), and component number (X-axis).

4.4.2. Regional Clustering Analysis

As outlined in Section 4.3.2, three different clustering approaches were assessed (Wards, K-means, and average and complete linkage), with Wards method achieving the highest “Cophenetic correlation” value (0.78) and most successfully delineating spatially-contiguous homogeneous regions. Wards method has been used in other hydro-climatic research (Jackson and Weinand, 1995; Ramos, 2001), and is recommended as a robust method for variable classification (Modarres and Sarhadi, 2011).

PC scores for the three components were calculated for each gauge. These scores were then spatially clustered individually (i.e. PC1, PC2, and PC3) and jointly (i.e. PC 1-3) using Wards method for a range of 3 to 9 target clusters. Comparison of the clusters from the individual component scores were assessed for their conformity to the physical interpretations described above; while the cumulative scores helped to visualise the best regional configuration. Figure 11 illustrates that clustering the gauges into 4, 5, or 6 regions best captures the seasonal and locational differences in hourly precipitation extremes. Using only three regions did not delineate orographic behaviour sufficiently, while using greater than six regions subdivided the southernmost regions with little physical justification. The results indicated that four regions (Figure 11a, PC1-3 and PC2) were able to capture the east-west precipitation difference caused by orographic effects in the north and central UK, though it was not able to capture the variation in the south and south-eastern regions. On the other hand, 6 regions (Figure 11c, PC1-3, PC1, and PC3) begin to subdivide parts of the south and south west UK, and clustered climatologically different regions together such as Northern Ireland and north-east England (Figure 11c, PC1-3, PC1, and PC2). Using 5 clusters (Figure 11b), best captured the east-west and north-south patterns, and reflected the orographic effects and seasonal drivers.

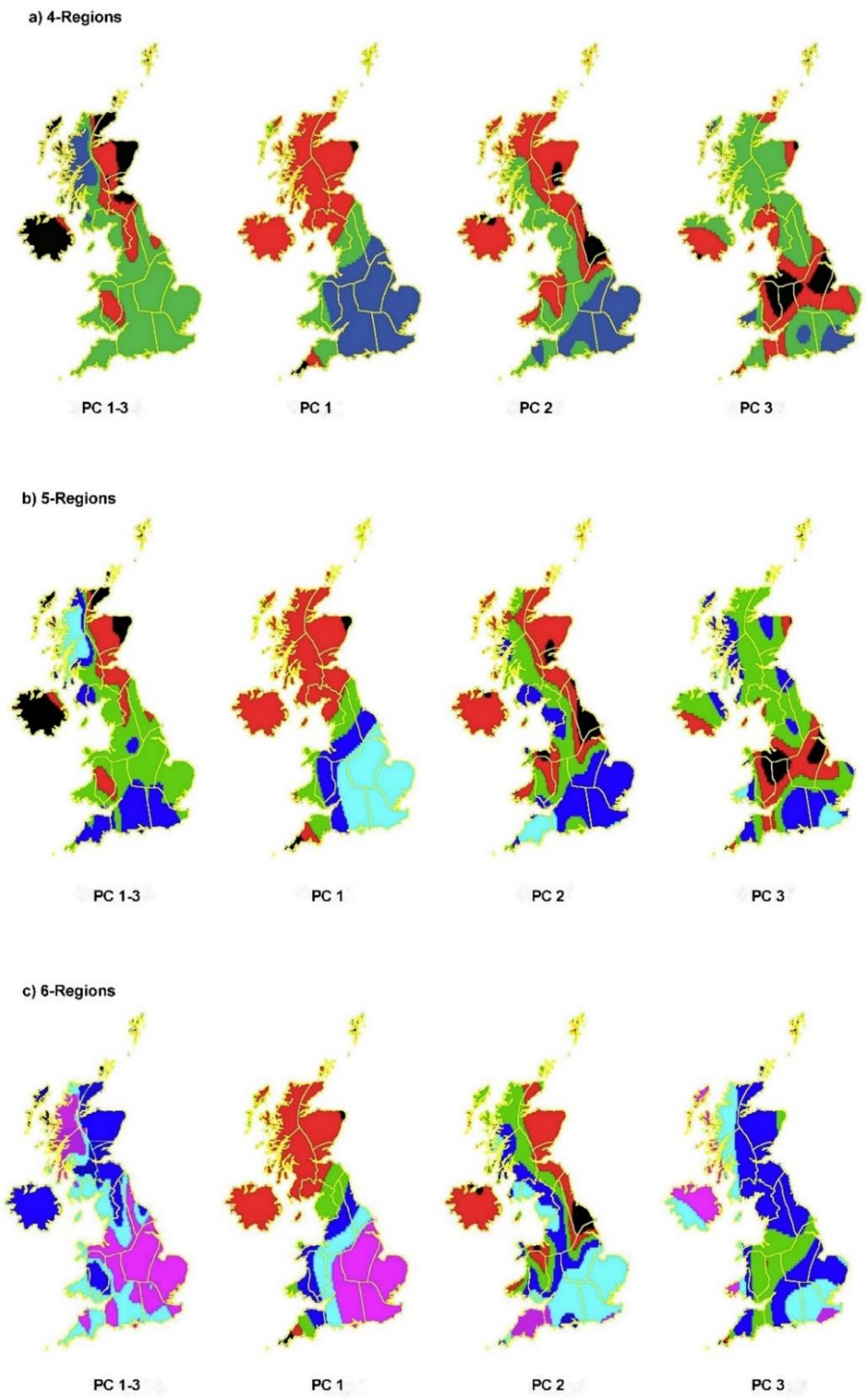

Figure 11: PCA clustering results for UK hourly precipitation using Wards clustering approach for (a) 4 regions; (b) 5 regions; and (c) 6 regions. Kernel-smoothed PCA scores for all components PC1 to 3 (left column) and individually (i.e. PC1, PC2, and PC3) (right three columns) are illustrated. Yellow line are the existing daily extreme regions by Jones et al, (2014), and presented here for reference only.

As the choice of five regions rather than four or six is relatively subjective, a physical reasoning approach was also adopted to assess whether the statistically derived regions adequately encompass known weather patterns. Physical reasoning for the clusters was assessed by comparing the proportion of events exceeding Q99 at each gauge corresponding with each of the 8 daily WTs (Neal *et al.*, 2016) for the period 1992-2014 (Figure 12). This was repeated for the winter half-year (N-WQ99) and summer half-year (N-SQ99) (Figures A9 and A10 respectively). The main WTs associated with extreme precipitation are WT2 (i.e. NAO+ pattern) and WT4 (i.e. Southwesterly pattern), which are associated with 51% (WT2: 32%, WT4: 19%) of precipitation exceeding Q99 (Figure 12). Both weather types are characterised by southwesterly flow, bringing warm, moist air, and more frequent stormy weather, especially in winter (Figure A9). WT2 contributes a similar proportion of events exceeding Q99 precipitation to most gauges, and affects the whole country, noticeably in winter where the UK is affected by westerly storms (Figure A9). However, in summer (Figure A10), the total contribution of WT2 (22%), is reduced compared to annual (32%) or winter (40%), and occurs mostly in the north-western UK. In contrast, WT4 shows a high occurrence only in the north-western UK annually (Figure 12), and seasonally (Figures A9 and A10), which agrees with the direction and track of the dominant south-westerly flow characterising this WT.

Conversely, WTs 6 and 8 (i.e. high pressure centred over UK and Azores high, respectively in Neal *et al.* (2016) are associated with only 5% of events exceeding Q99 annually across the UK. Both WTs 6 and 8 are characterised by anticyclonic high pressure areas over the UK, leading to dry conditions and warm weather in summer, and clear skies and cold nights in winter, consistent with low precipitation frequency.

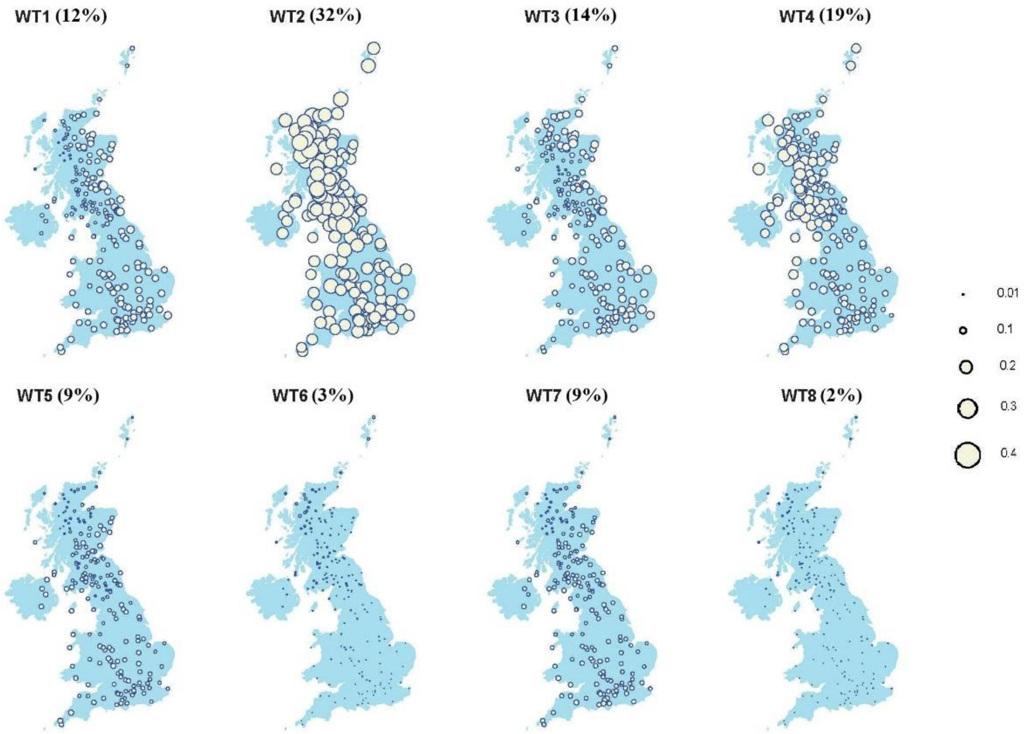

Figure 12: Proportion of days exceeding Q99 hourly precipitation for each gauge across the 8 weather types identified by Neal et al. (2016) over the period 1992-2014. Numbers in brackets represent the percentage of all days on which each weather type occurs. Circle diameter indicates the proportion of Q99 events within each weather type for each gauge.

Figures 12, A9 and A10 all show a clear east-west pattern in WTs 1, 3, and 4 caused by the northeasterly, northwesterly, and southwesterly flow respectively, with a weaker north-south precipitation pattern (e.g. WTs 3, and 4). While a formal cluster analysis of the WT occurrence patterns was not carried out, visual comparison of Figures 13a and 13b indicates that the main regions of influence for each WT are broadly similar to those derived from a statistical analysis. The WT results (Figure 12 and 13b) also confirm that either 4 or 5 regions best accommodate the spatial characteristics of extreme hourly precipitation. Based on the occurrence patterns and events exceeding the annual and seasonal Q99 extremes in each gauge associated with WTs 1-4 (Figures 12, A9, and A10), the clustered PCA (Figure 11b), and the comparison between WTs and PCA clusters in Figure 13, five regions were finally selected to represent hourly precipitation extremes in the UK.

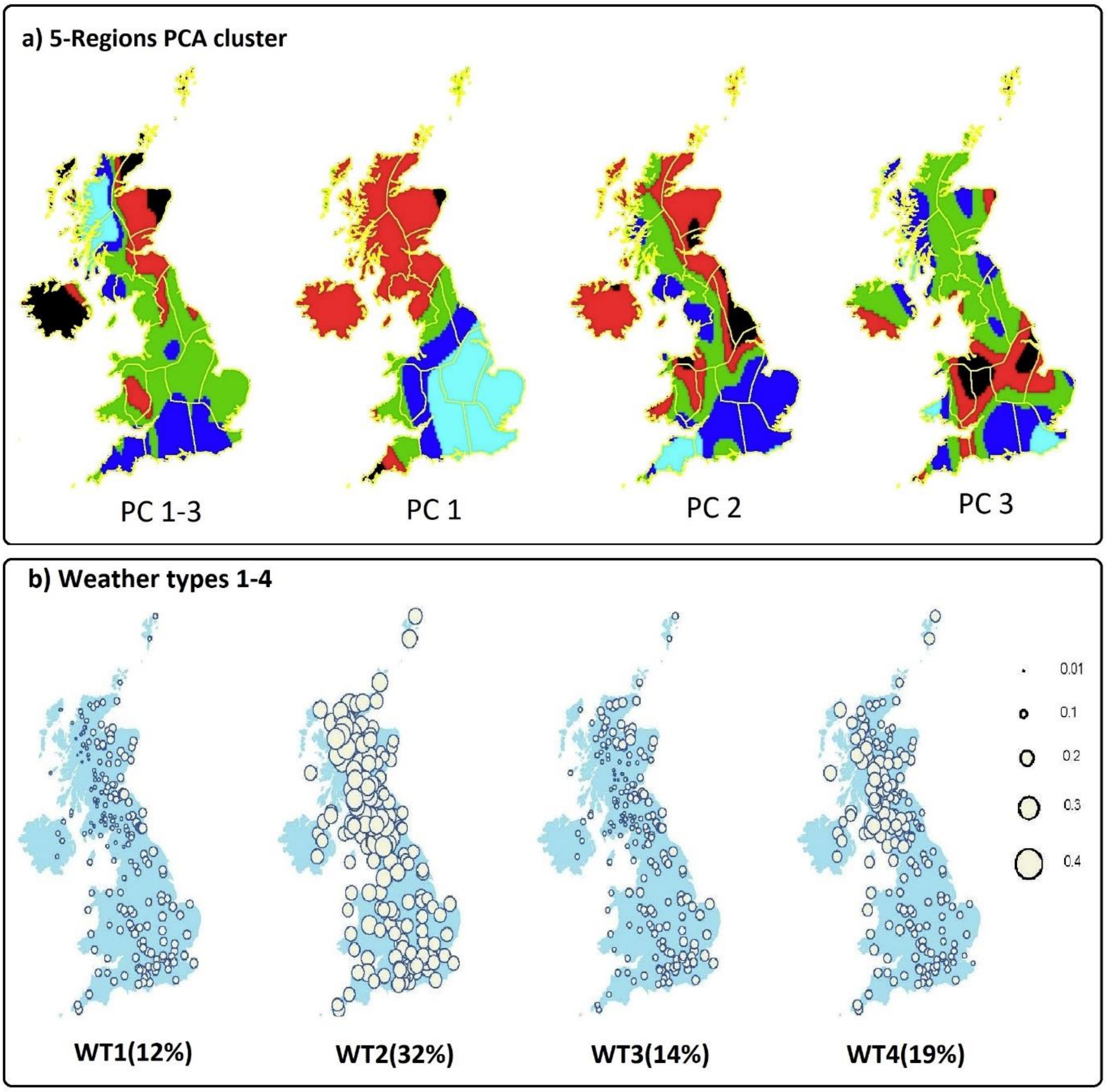

Figure 13: Comparison between (a) the PCA clustering results for UK hourly precipitation using Wards clustering approach for 5 regions; and (b) the proportion of days exceeding Q99 hourly precipitation for each gauge across weather types 1 to 4 identified by Neal et al. (2016) over the period 1992-2014. Yellow line (Figure 13a) are the existing daily extreme regions by Jones et al, (2014), and presented here for reference only. Numbers in brackets represent the percentage of all days on which each weather type occurs. Circle diameter indicates the proportion of Q99 events within each weather type for each gauge.

The final selection of 5-regions and the defined boundaries are set to reflect the hourly extremes spatial variation across the UK based on the PCs and WTs (Figures 13a and 13b). For instance, Figure 13a indicates that PC1 reflects the southeast and southwest boundaries, while PC2 indicates northern regions east-west divide, which highlights the orography and the role of the highlands. Furthermore, the east-west divide in PC2

(Figure 13a) is in line with the existing daily regions (e.g. Alexander and Jones, 2000; Jones *et al.*, 2014), and the WT 4 (Figure 13b) occurrence patterns. In addition, both: PC 1 and PC 3 (Figure 13a) indicates the existence of a transitional region and separation between northern and southern regions, which is apparent in WT2 (Figure 13b) frequency pattern, as it decreases from north to south. The final boundaries were selected based on visual inspection, the PCs results, and basic clustering of the WTs occurrence frequency pattern.

4.4.3. Regional homogeneity

Following the approximate delineation of five regions from the clustering analysis and subsequent visual confirmation that these are physically representative (Figure 13), formal regional boundaries draw on the extreme daily precipitation regions (Jones *et al.*, 2014) with refinements from statistical analyses, below, and geographical knowledge. Each region was tested for homogeneity, using regional discordancy and homogeneity tests (Hosking and Wallis, 2005). Where gauges appeared to be inconsistent with the remaining region, we tested whether to place the gauge in an alternative region, remove it, or whether there was a justification for the discordancy. This resulted in no modifications or changes as described in further details below, since the investigations showed no physical reason or relocation possibility. The final five new regions are shown in Figure 14: North West (NW), North East (NE), South East (SE), Mid East (ME), and South West (SW). These contain 70, 51, 49, 7, and 20 hourly gauges respectively and satisfy the minimum station density and homogeneity criteria for RFA (Hosking and Wallis, 2005).

The results illustrate that the new regions reflect the impact of UK orography, proximity to the sea, and large-scale atmospheric drivers, capturing the west-east precipitation gradient (demonstrated by NE-NW and SW-SE regions), as well as the north-south precipitation extremes variation along the eastern side of the country (regions SE-ME-NE).

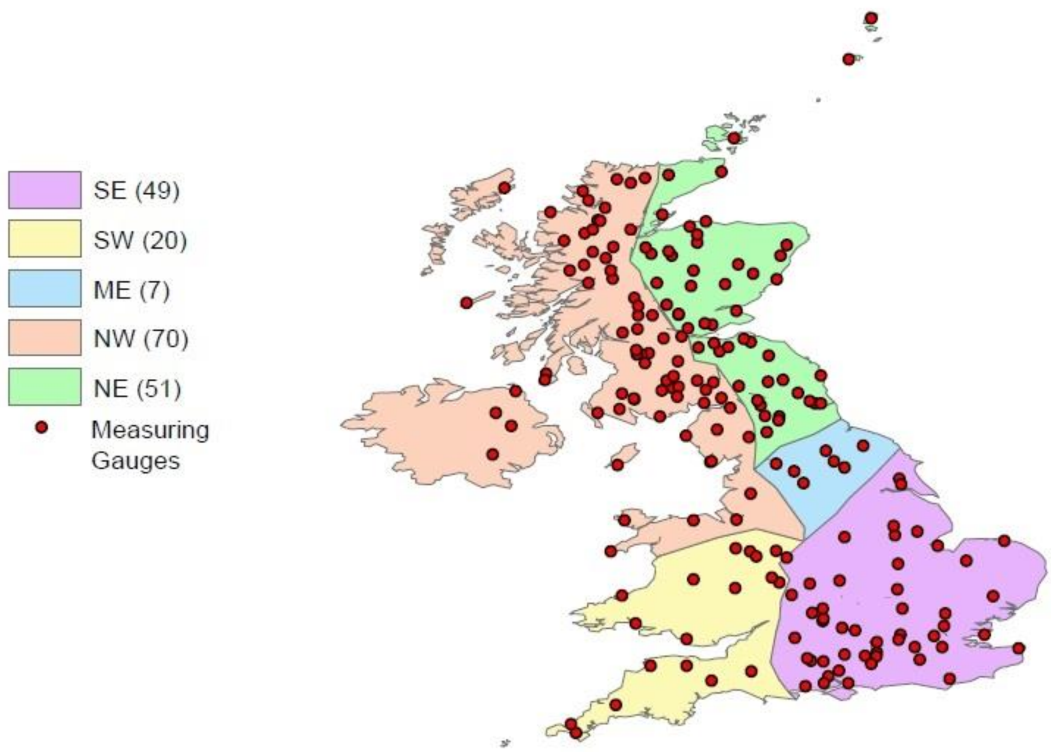

Figure 14: Final delineation of UK extreme hourly precipitation regions. Regions are: South East (SE), South West, Mid-East (ME), North West (NW), and North West (NW). The value in parentheses denotes the number of hourly gauges in each region.

Table 5 contains homogeneity measures (H_1, H_2, and H_3) and maximum gauge discordancy measures (D) (Hosking and Wallis, 2005) for each region. The results confirm that gauges in the regions SE, SW, NE and ME are not discordant ($D_{max} < D_{crit}$), and that the SE, SW, and NW regions are “homogeneous” with (H_1) values of 0.83, 0.94, and 0.56 respectively. The results for ME show that the region is possibly heterogeneous, with a H_1 value of 1.13, but no alterations were made as the gauges are not discordant and the limited number of gauges (7) increases uncertainty associated with this analysis (Jones *et al.*, 2010).

Region	**Homogeneity measures (H)**			Goodness of fit measure (**Z_{dist}**) **GEV/GP**	No. of gauges	Max discordant gauge (D_{max})	D_{crit}
	H_1	***H_2***	***H_3***				
SE	**0.83**	0.32	0.04	**-0.22/0.31**	49	**2.63**	3.00
SW	**0.94**	0.96	0.89	**-0.17/-0.43**	20	**1.84**	3.00
ME	**1.13**	0.75	0.72	**0.18/0.36**	7	**1.45**	1.92
NW	**0.56**	-0.57	-0.06	**-1.57/0.62**	70	**3.7**	3.00
NE	**2.71**	0.87	0.23	**1.18/-0.23**	51	**4.49**	3.00

Table 5: Gauge discordancy (D), region homogeneity (H) and goodness of fit (Z) assessment for the UK hourly extreme precipitation regions (SE, SW, ME, NW, and NE) shown in Figure 14. The table shows the number of gauges in each region and the maximum recommended gauge discordant value (D_{crit}) for each region.

For NW, only one gauge is discordant (D= 3.7 > $Dcrit$= 3), though the region is homogeneous, and removing it from the region only improves the homogeneity value slightly. Relocating the gauge to another region is not possible due to its location, but as the gauge observations match neighbouring gauges on the same day, we decided to retain the gauge within this region. For the NE region, one discordant gauge (D= 4.49 > D_{crit}= 3) also makes the region heterogeneous (H= 2.71). The gauge has a very high 1h AMAX value in August 2007 (51.2mm, the highest of any gauge in that year), but there is no evidence that this is erroneous or the result of a malfunctioning gauge and it is in keeping with the observed weather during that period (Met Office, 2007). Relocating the gauge to other regions affected the homogeneity of the neighbouring regions, while subdividing the NE region also did not improve the results. While removing the gauge improved the homogeneity of the region noticeably (H=1.2), Hosking and Wallis (2005) recommend retaining discordant sites unless a physical reason justifies removing it. Thus, we decided to retain the gauge in the NE region. The other homogeneity measures (i.e. H_2 and H_3), though having less power to discriminate between homogeneous and heterogeneous regions, indicate that all regions are definitely homogeneous ($H_{2,3}$ <=1), including NW, which confirms the suitability of 5 regions for further analysis.

Due to the nature of extremes and the limited availability of 1h precipitation observations, having definitively homogeneous regions for the RFA is challenging in practice, even after performing subjective modification, relocation, and elimination of discordant gauges to improve clustering results (Hosking and Wallis, 2005; Yang *et* *al.*, 2010; Sarhadi and Heydarizadeh, 2014). Thus, we believe that our results reflect the highest practical extent, considering the limited data availability and the spatially varying nature of hourly extremes in the UK.

4.4.4. Regional Frequency Analysis and AEP Estimates

The goodness of fit measure (Z_{dist}) for the GEV and GP distributions were assessed for AMAX and Q99 hourly precipitation, respectively, for each region. The results in Table 5 show that both distributions' Z_{dist} values are within the recommended guideline ($|Z_{dist}|<1.64$) (Hosking and Wallis, 2005) and therefore should be able to reflect the spatial patterns in the AMAX and Q99 hourly precipitation in the UK.

The fitted growth curves for each region in Figure 15 show that both distributions have similar shapes and growth factors with overlapping confidence intervals, although the GEV growth curves are marginally steeper, in all regions. GEV confidence intervals are wider than those for the GP distribution due to the hourly Q99 having 2 to 3 times as many observations as those for hourly AMAX for the same period (1992- 2014), and less variance in the series. Growth curves are steeper for both distributions in northern regions (i.e. NE and NW), where the highest hourly extremes were recorded and precipitation generated by large-scale circulation dominates, than for southern regions (i.e. SE and SW), where convective precipitation mostly dominates extremes, reflecting the role of large synoptic circulation in producing high hourly extremes. Confidence intervals for the fitted distributions in ME are wide due to limited gauges (only 7) in the region, which increases the sensitivity to extreme values (Hosking and Wallis, 2005; Jones *et al.*, 2010).

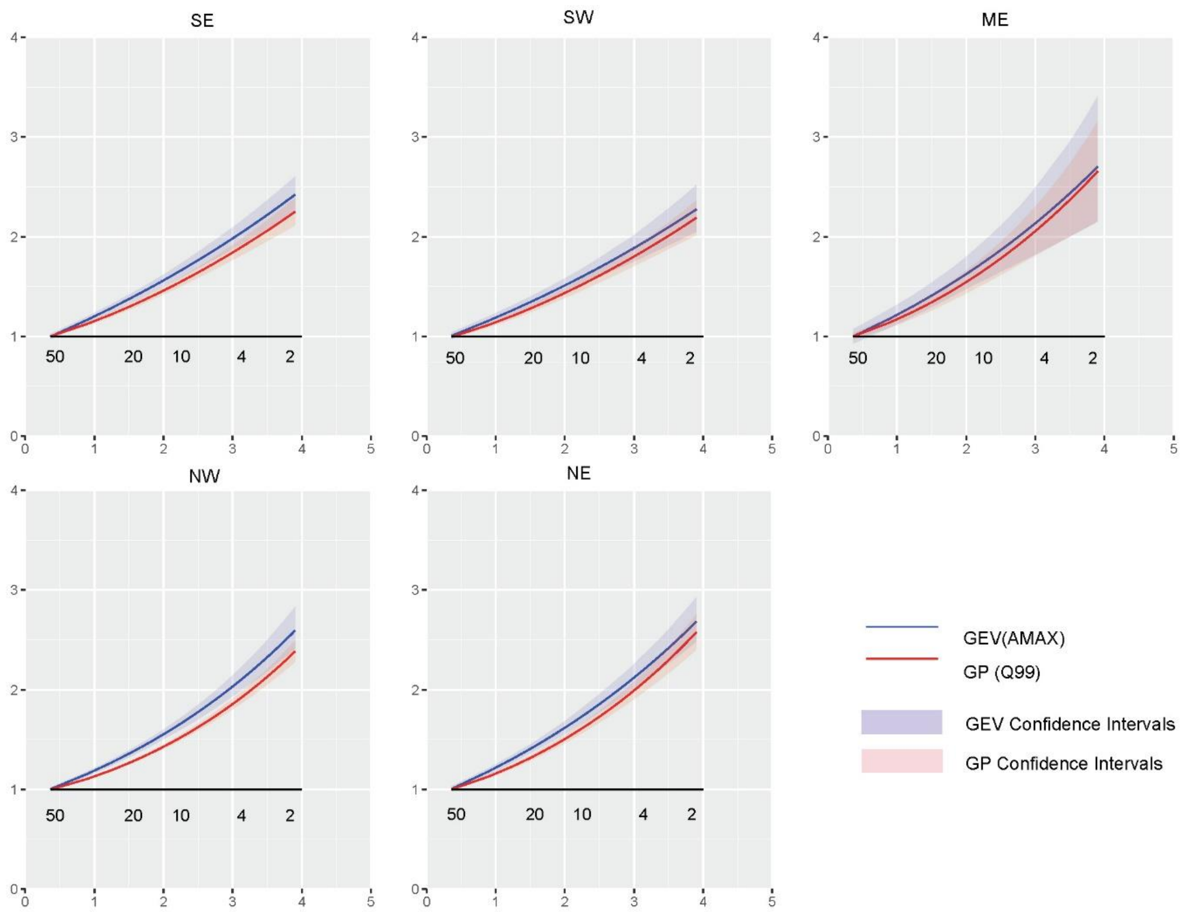

Figure 15: Fitted regional GEV and GP growth curves for 1h standardized AMAX (blue) and Q99 (red) respectively, and confidence intervals for the fitted GEV distribution (blue shading) and GP distribution (red shading). Growth factor (y-axis), Annual Exceedance Probability (AEP) in % (upper x-axis), and Gumbel reduced variate (lower x-axis). The growth curve represents the multiple increase of a given AEP over an index value, here the 50% AEP.

Probability estimates were calculated for both regional distributions for 20%, 4%, and 2% AEPs across the UK by multiplying the regional GEV or GP growth factor by the gauge specific RMed or median Q99, respectively. We produce a spatial estimate of the AEPs through a kernel estimation smoothing on the gauge estimates. Figures 16a and 16b highlight the increasing gradient of intensity from the northwest to southeast UK for both the GEV and GP distributions for all AEP estimates. However, it should be noted that differences between the RMed and median Q99 estimates can lead to marginal differences in the AEP estimates even though the growth curves appear similar in Figure 15. The GP estimates suggest smoother and more continuous patterns, with a slightly lower precipitation intensity, compared to the GEV estimates.

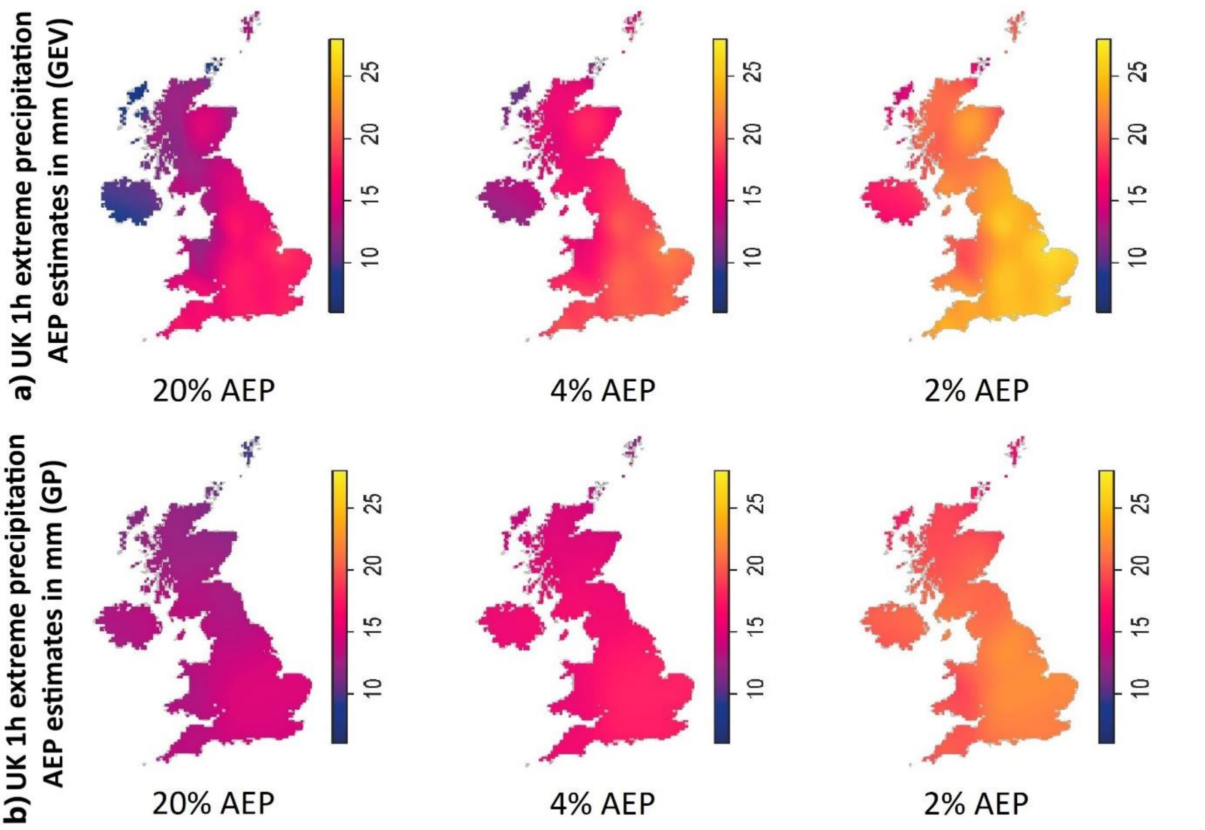

Figure 16: Estimates for the UK 1h extreme precipitation in mm for 20%, 4%, 2% annual exceedance probabilities (AEPs)) using the GEV distribution (a) and GP distribution (b). Estimates for each gauge are calculated from the fitted regional growth curve multiplied by the site scaling factor (gauge RMed).

Assessing the frequencies of each WT (Table 6) shows that for WTs 1 to 4, which are associated with more than 75% of hourly extremes exceeding Q99, WT2 (i.e. NAO+ pattern) and WT4 (i.e. south-westerly flow pattern) are associated with most of the annual extremes (i.e. 51%) in the UK. Moreover, WT2 alone is associated with 40% of extremes in winter, which is approximately double its summer frequency (22%). In contrast, WT1 (i.e. NAO- pattern) and WT3 (i.e. north-westerly pattern) frequency in summer increase noticeably compared to winter. Furthermore, the results indicate that summer extreme precipitation is associated with a wider range of WTs (i.e. WTs 1 to 4), with comparable frequencies, while winter extremes are dominated by WT2.

The WTs frequencies in Figures 13, A9, A10, and Table 6 indicate that WTs 1 and 3 are mostly associated with heavy showers over eastern England especially during summer (Figure A10), suggesting the role of convective conditions in generating precipitation. In contrast, WTs 2 and 4 are associated with more frequent stormy weather, especially in winter (Figure A9), indicating the role of large-scale precipitation.

		Weather Type							
		WT1	**WT2**	**WT 3**	**WT 4**	**WT 5**	**WT 6**	**WT 7**	**WT 8**
Proportion of each WT in all regions	**Annual** (Figure 12)	12%	32%	14%	19%	9%	3%	9%	2%
	Winter (Figure A9)	9%	40%	11%	21%	7%	2%	8%	2%
	Summer (Figure A10)	17%	22%	16%	18%	11%	4%	10%	2%

Table 6: Proportion of Weather types (WT) 1 to 8 (Neal et al, 2016) across all the proposed UK 5 regions annually, in winter, and in summer (underlined).

We also assessed the median of Q99 hourly precipitation for each weather pattern in each region, where the median of each region and weather type relative to the region mean was calculated, to evaluate the regional relation between the hourly extremes' magnitudes and the weather types. The results in Figure 17 show that the Q99 hourly precipitation median of WTs 3 and 2 are lower than for most of the other weather types, whilst the highest median values occur for WTs 5 and 1. This contrasts with the results for hourly extreme event frequencies presented in Figure 12 where those for WTs 3 and 2 were noticeably higher than for WT5. This indicates that the highest hourly precipitation extremes might not be associated with the weather types that produce the most frequent Q99 hourly extremes.

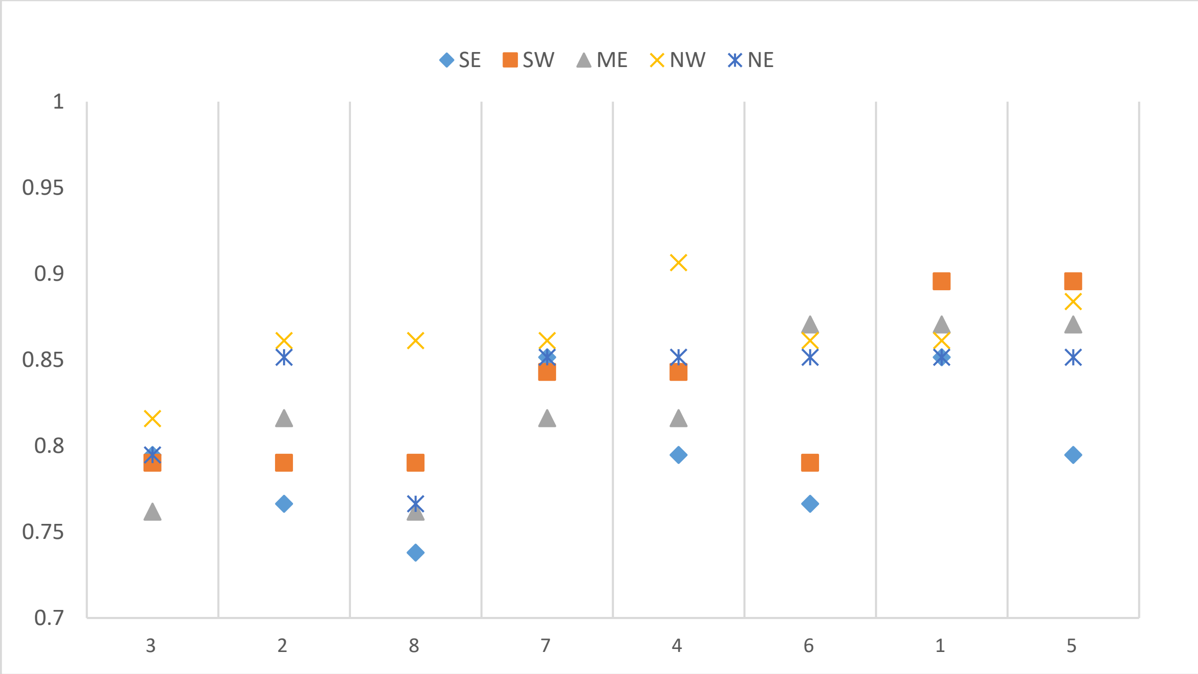

Figure 17: Median of hourly Q99 precipitation 1992–2014 for each region (SE, SE, ME, NW, and NE) and for each of the 8 weather patterns (Neal et al., 2016) (X-Axis), expressed as the median of each region and weather type relative to the region mean (Y-axis). The weather types are ordered left to right from the lowest UK relative median precipitation to the highest. Y-axis (after Richardson et al., 2018 Figure 5).

4.5. Discussion and conclusions

This study aimed to provide a reliable regional characterisation of hourly extremes which could lead to improved estimates for various applications in different engineering and climatological areas. Using the regional approach would reduce the impact of hourly precipitation data scarcity and erroneous recorded data, while the existing daily precipitation regions were not able to capture the spatial variation of hourly extremes across the UK

A principal component analysis and clustering approach was adopted to identify five new, homogeneous extreme precipitation regions to reflect hourly extreme precipitation variations across the UK. These were then adopted in a regional frequency analysis to estimate precipitation annual exceedance probabilities for each region. The study used a new, quality controlled hourly precipitation dataset (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018) together with associated site characteristics (e.g. elevation) and different at-site hydro-climatological characteristics (i.e. temperature, precipitation seasonality) to identify the regions. Further, using weather types as an auxiliary variable ensured characterising large-scale atmospheric circulation systems, and representing important precipitation-generating processes, which provided physical plausibility for the regional definition. Previous work in the UK identified precipitation regions using either daily mean (Wigley *et al.*, 1984; Gregory *et al.*, 1991), or extreme daily precipitation (Jones *et al.*, 2014). This research presents physically plausible regions to improve the characterisation and estimation of short-duration precipitation extremes.

Orographic characteristics and large-scale atmospheric circulation patterns showed a noticeable role in delineating the extreme precipitation regions, which is consistent with daily extreme precipitation studies in the UK and elsewhere (e.g. Jones *et al.*, 2014; Johnson *et al.*, 2016). The impact of the Pennines and Southern Uplands and the Cambrian mountains is reflected in the east-west delineation, coupled with the most frequent weather types (i.e. WTs 2, 3, and 4) characterised by NAO+, south westerly, and north westerly circulation flows. This corroborates the northwest-southeast precipitation patterns reported in previous studies of daily (Jones *et al.*, 2014) and hourly precipitation extremes (Blenkinsop *et al.*, 2017).

The new regions were assessed for homogeneity (Hosking and Wallis, 2005). The results showed that the most robust homogeneity measure, is either homogeneous or marginally exceeds the limit in all regions except NW. The heterogeneity in NW is caused by a single gauge which recorded a verified hourly observation of 51.2 mm in August 2007, and so was retained. The validity of subjective relocation or removal of gauges was confirmed with additional homogeneity measures and no further changes made.

Growth curve estimates for regional GEV and GP distributions show similar results, with steeper curves for the GEV and overlapping confidence intervals. Wider confidence intervals in ME compared to other regions, arising from data scarcity, highlights the importance of having dense gauging networks. The growth curves estimates show a noticeable difference between northern and southern regions, with a steeper GEV curves in northern regions, contrasting with estimates made by Darwish *et al.* (2018) using the existing daily UK extreme regions (Jones *et al.*, 2014), where the growth curves indicated similar results across northern and southern regions. This indicates that the new proposed regions could capture the spatial variation and the hourly extremes patterns across the UK more precisely.

The annual exceedance probability (AEP) maps for probabilities of 20%, 4%, and 2% concur with previous findings of an increasing pattern of hourly and daily extremes from the northwest to the southeast (Jones *et al.*, 2014; Blenkinsop *et al.*, 2017). While

GP distribution probability estimates are marginally smoother and less sensitive to outliers compared with the GEV, estimates for both distributions are comparable across the UK.

Finally, the relationship between hourly extremes and weather types showed that WTs 5 and 1 have the highest relative median Q99 precipitation intensity, while WT2 has the highest frequency of Q99 precipitation events but a lower corresponding relative median intensity. These WTs are characterised by southeasterly and northeasterly flows that travel across southeast England. Although WT5 is not associated with a high frequency of hourly extremes, its dominance as a summer weather type influences the higher intensity of those precipitation events which do occur. Recent analysis of daily mean precipitation by Richardson *et al.* (2018) found a stronger relationship for the lower intensity results with WTs 2 and 7. While this may seem counterintuitive, it is corroborated by recent research indicating that changes in mean precipitation are not necessarily matched by those in the extremes (Swain *et al.*, 2018), and that the most intense precipitation occurs in fewer events (Westra *et al.*, 2014; Prein *et al.*, 2017; Pendergrass, 2018). The results also indicate a difference between weather types associated with mean daily and hourly extreme precipitation within the UK, and their different generating mechanisms. This confirms the inadequacy of the existing daily mean precipitation regions (Alexander and Jones, 2000) and daily extreme precipitation regions (Jones *et al.*, 2014) to assess hourly extreme precipitation in the UK, which was reported in Darwish *et al.* (2018).

In conclusion, this chapter has analysed hourly extreme precipitation and associated climatological variables to identify new, homogeneous regions which facilitate the analysis and estimation of hourly extreme precipitation in the UK. The developed regions capture the hourly extremes spatial variation across the UK, and could be used to perform further regional investigation and statistical modelling of extreme precipitation.

Chapter 5. Statistical modelling of UK extreme hourly precipitation and future climate change responses

Quantifying extreme precipitation has always been a major challenge for both scientists and decision makers. Extreme precipitation is among the most destructive climatological events, is highly associated with flash floods, and poses a multidimensional threat to urbanised areas. Moreover, simulating extreme precipitation using climate models is highly associated with uncertainties, due to scarce data, high variability, coarse resolution, and interaction with different climatological variables. Typically, statistical analysis assuming stationary processes is used to assess extreme precipitation and implement urban drainage design guidelines, however, it is increasingly being observed that extreme precipitation is a non-stationary process due to both natural and anthropogenically induced climate variability.

In this chapter the hourly precipitation dataset from 1992-2014, and other climatological variables (e.g. temperature, atmospheric pressure) acting as covariates, are employed to develop a statistical model that can simulate extreme precipitation frequency and intensity, and account for the non-stationary behaviour of extremes. This would provide an alternative to the computationally expensive climate models, and facilitate the assessment of hourly extremes across the UK.

Among the objectives of this research is the quantification of the intensity and frequency of extreme hourly precipitation under potential climate change using the developed statistical model. Therefore, in this chapter extreme value theory and the newly developed regions for hourly extremes (Chapter 4) are used to simulate the response of future extreme precipitation to potential climate change.

The chapter concludes with a skilful statistical model that simulates hourly extremes intensity and frequency in the UK. Furthermore, the statistical model indicated noticeable increase in the UK hourly extreme precipitation intensity and frequency during summer, as a response to potential climate change.

5.1. Introduction

Providing reliable precipitation simulations is of importance for many different applications, as they are used as basic input into precipitation-runoff, groundwater, agricultural and water-usage models (Yunus *et al.*, 2017). This is of particular importance as many studies have reported global increases in the frequency and intensity of extreme precipitation (Trenberth *et al.*, 2003; Alexander *et al.*, 2006; Fowler and Ekström, 2009; Maraun *et al.*, 2010b; Jones *et al.*, 2013; Simpson and Jones, 2014) while the second UK Climate Change Risk Assessment (Defra, 2017) suggests that climate change will increase fluvial and surface flooding in the UK and related risks (e.g. coastal erosion, marine and fresh water ecosystems pollution). However, sub-daily extremes have so far received limited attention, mainly due to the limited availability of high-resolution precipitation observations, the statistical challenges of accurately determining sub-daily precipitation probabilities and the challenge of simulating the intensity and frequency of precipitation events in physically-based models (Westra *et al.*, 2014; Blenkinsop *et al.*, 2017).

Convection-permitting models (CPMs) are now commonly used as powerful tools to simulate hourly extreme precipitation (Westra *et al.*, 2014; Chan *et al.*, 2016). However, achieving accurate and reliable simulations from CPMs is computationally-expensive and time-demanding (Chan *et al.*, 2014a). Therefore, statistical downscaling of climate model output is commonly used to provide a reliable, computationally inexpensive, and flexible approach to simulate and estimate extreme precipitation from coarse-resolution climate model outputs (Fowler *et al.*, 2007). Statistical downscaling has been employed to project changes in future precipitation (Dobler *et al.*, 2013; Shashikanth *et al.*, 2016), to derive extreme projections under climate change (Hertig *et al.*, 2014; Ning *et al.*, 2015), and to improve the statistical distribution of daily precipitation amounts (Benestad, 2010). Maraun *et al.* (2010b), who reviewed the use of precipitation downscaling methods for climate change projections, reported that the statistical downscaling of precipitation enhances the outputs from coarse-resolution climate models, adds considerable value to their projections, and facilitates end users' assessment of climate change and its hydrological impacts. Furthermore, Vrac and Naveau (2007) suggest that statistical downscaling approaches can incorporate different flexible statistical modelling such as generalized linear modelling (GLM) and extreme value theory (EVT), which are computationally efficient and practical, to improve estimation of extremes.

The GLM has been used widely to simulate and characterise the frequency of intense precipitation in different locations (Chandler and Wheater, 2002; Benestad, 2010; Hertig *et al.*, 2014). Yang *et al.* (2005) and Benestad (2007) used the GLM to model station-based daily precipitation data in southern England and extreme precipitation over northern Europe respectively. Recently, Hertig *et al.* (2014) adopted a GLM approach to perform statistical modelling of extreme precipitation indices for the Mediterranean area under future climate conditions.

Extreme value theory (EVT) has also been used widely to characterise extreme precipitation in different locations and for different durations. Vrac and Naveau (2007) used EVT to improve the representation of local daily extreme precipitation in Illinois, USA, while Wi *et al.* (2016) adopted EVT to perform frequency analysis of extreme precipitation in South Korea for sub-daily durations (1-, 6-, 12-, and 24-hours). In the UK, Jones *et al.* (2013) employed EVT to assess changes in seasonal and annual daily extreme precipitation. Jones *et al.* (2014) further extended this approach to characterise daily extremes and identify extreme precipitation regions for the UK, before developing a Generalised Additive Model for UK daily precipitation extreme frequency (Tye *et al.*, 2016).

UK extreme precipitation is influenced by both large scale atmospheric circulation patterns such as synoptic weather systems and atmospheric rivers, besides local weather such as convective instability (Cyril *et al.*, 2007; Champion *et al.*, 2015). Therefore, it is important to consider both as potential drivers of changes in sub-daily extreme precipitation. Recently, various studies investigated subdaily precipitation in the UK (e.g. Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018; Lewis *et al.*, 2018; Xiao *et al.*, 2018) Blenkinsop *et al.* (2017) developed a new quality controlled dataset for UK hourly precipitation, and examined its seasonal and diurnal climatology; Lewis *et al.* (2018) used this to produce a new 1 km resolution gridded hourly precipitation dataset for the UK. Additional analysis of average hourly precipitation over the UK by Xiao *et al.* (2018) reported noticeable peaks in early morning and afternoon, with apparent regional variation in spring and summer. Subsequently, as detailed in Chapter 3 of this thesis, Darwish *et al.* (2018) assessed sub-daily extreme precipitation patterns, their diurnal cycle, and produced annual probability estimates using regional frequency analysis (RFA) for the daily extreme precipitation regions developed by (Jones *et al.*, 2014). This showed the need for new regions to capture spatial and temporal characteristics of hourly extremes, performed in Chapter 4. As detailed in Chapter 4 of this thesis, EVT, climatological clustering, and regional frequency analysis (RFA) approach are used to identify hourly extreme precipitation regions in the UK.

Here, our goal is to develop a simple and reliable statistical model that can simulate hourly extreme precipitation patterns in the UK, using relevant climatological predictors reflecting large-scale and local conditions. This should provide a practical alternative to high-resolution climate modelling to simulate realistic frequencies and intensities of hourly precipitation extremes, as well as to assess the potential impact of climate change scenarios. We use a GLM embedded in EVT distributions to model hourly precipitation extremes across the UK, at 197 UK gauges using the hourly extreme precipitations regions established in Chapter 4. Although existing regulations and design guidelines for flood infrastructure assume stationary conditions (Madsen *et al.*, 2013), this assumption in EVT is questionable, due to non-stationary caused by anthropogenic warming as well as natural climatic variability (Salas and Obeysekera, 2013). Therefore, several studies recommend the adoption of non-stationary analyses (Renard *et al.*, 2006; Katz, 2010; Rootzén and Katz, 2013).

In recent decades, various studies have adopted non-stationarity in the analysis of trends in observed hydrological events (e.g.Franks, 2002; Vogel et al., 2011), estimation of frequency distribution (e.g. Katz et al., 2002; Raff et al., 2009), and determination of risk and design guidelines for hydrological structures within a non-stationary framework (e.g. Mailhot and Duchesne, 2009; Rootzén and Katz, 2013; Salas and Obeysekera, 2013).

In this chapter, GLM and EVT non-stationary distributions coupled with downscaled climate variables and observed NAO datasets are adopted to quantify the UK hourly extreme precipitation (i.e. frequency and intensity). This is the first study to investigate hourly extreme precipitation in the UK, build a statistical model that employ various climatic variables to quantify hourly extreme precipitation characteristics (i.e. frequency and intensity) while considering for the non-stationary nature of the hydrological events, and evaluate potential changes under climate change scenario.

The Chapter is structured as follows. Following a description of hourly precipitation data, and the potential climatological predictors in Section 2, the methodology, probability distributions, statistical model selection and validation process outlined in Section 3. The results of correlations between hourly extremes and related climatological variables (e.g. Temperature, Sea level pressure), selection of covariates, statistical model performance, and a pseudo-global warming approach to analyse future behaviour are presented in Section 4. Finally, Section 5 discusses the results, the potential implications from the statistical modelling, and future research.

5.2. Data

5.2.1. Precipitation data

This research uses an hourly precipitation dataset for the UK derived from precipitation gauges covering the years from 1992 - 2014 (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018). The dataset (up to 2011) was collected by Blenkinsop *et al.* (2017) from three sources: the UK Met Office Integrated Data Archive System (MIDAS), the Scottish Environmental Protection Agency (SEPA), and the UK Environment Agency (EA). Blenkinsop *et al.* (2017) performed a series of site-specific quality control (QC) procedures on the data to detect accumulated totals, malfunctioning gauges and unfeasible extreme precipitation totals. This was subsequently extended to 2014 and subjected to additional QC checks against neighbouring gauges (Lewis *et al.*, 2018). Here we apply the additional criteria of having at least 85% of the gauge record complete (i.e., non-missing and data not flagged by the QC process) for each year in the period 1992–2014. In total, 197 gauges distributed across the UK (shown in Figure 1) fulfilled the criteria. These criteria were selected as a trade-off between having long records and data completeness. Further details on the adoption of these criteria can be found in Section 3.2.

Moreover, the UK hourly extreme precipitation regions (Figure 14) developed in Chapter 4, which were identified from a principal components analysis of extreme precipitation statistics, climatological variables (e.g. temperature), location characteristics, and the spatial analysis of predominant weather types (Neal *et al.*, 2016), are used to analyse the hourly extremes, as well as to build and validate the statistical model.

5.2.2. Predictors

In the UK, hourly extreme precipitation is related to both large-scale circulation patterns (Cyril *et al.*, 2007; Champion *et al.*, 2015) as well as to local, convective-scale processes (Blenkinsop *et al.*, 2015; Chan *et al.*, 2018b). There is a lack of understanding of conditions driving extreme hourly precipitation in the UK (Holley *et al.*, 2014; Blenkinsop *et al.*, 2015). Therefore, a range of traditional and novel climatic variables associated with hourly precipitation extremes in the UK were investigated as potential predictors to build the statistical model (see Table 7 and further detailed below). These variables were selected to reflect both local conditions and large-scale circulation associated with extremes. They represent the convective potential, temperature, atmospheric pressure, and moisture content conditions.

A simple sinusoidal formula premised on the Julian day (number of elapsed days since the beginning of a particular year) of occurrence, and often adopted to simulate regular annual fluctuations (Rust *et al.*, 2009), was also used as a predictor to reflect the seasonality of the hourly extremes with all potential predictors. However, using the sinusoidal formula alone does not represent hydrological extreme (i.e. precipitation and floods) seasonality in the UK adequately, due to the fluctuations caused by atmospheric oscillations (Huntingford *et al.*, 2014; Tye *et al.*, 2016)

All potential predictors and climatic variables except the NAO are based on 0.75° × 0.75° gridded daily averaged output (Figure 18) for the period 1992–2015 from the European Center for Medium-Range Weather Forecasts (ECMWF) Interim reanalysis dataset (Dee *et al.*, 2011). For each variable, a daily area average of each grid cell was calculated, thereafter, the value was assigned to the gauges within the grid cell. The NAO index, which is defined as the normalized pressure difference between Azores and Iceland, was derived from a monthly pressure observational dataset between 1992-2015 (Jones *et al*., 1997).

Variable	**Measured phenomenon**	**Acronym**
Seasonality		
$Sine\left(\frac{2\pi * Julian\ day}{365.25}\right)$	Seasonality	*Sin (Ө)*
$Cosine\left(\frac{2\pi * Julian\ day}{365.25}\right)$	Seasonality	*Cos (Ө)*
Convective variables		
Convective available potential energy	Availability of convective conditions	CAPE
Convective inhibition	Energy needed to initiate convective precipitation	CIN
Temperature variables		
Temperature at 2m level	Temperature near the surface ~2m above the ground	T-2m
Dew point temperature	Temperature to which air must be cooled to become saturated with water vapour	DPT
Sea surface temperature	Water temperature close to the ocean surface	SST
Atmospheric variables		
North Atlantic Oscillation	Normalized sea-level pressure difference between predefined locations	NAO
Sea level pressure	Atmospheric pressure at sea level	SLP
Atmospheric pressure 850-, 700-, 500hPa height	Actual height of a pressure surface above mean sea-level	Z850,Z700,and Z500
Moisture variables		
Total column water vapour	Total gaseous water contained in a vertical column of atmosphere	TCWV

Table 7: Potential predictors used to develop a statistical model of the frequency and intensity of hourly precipitation extremes.

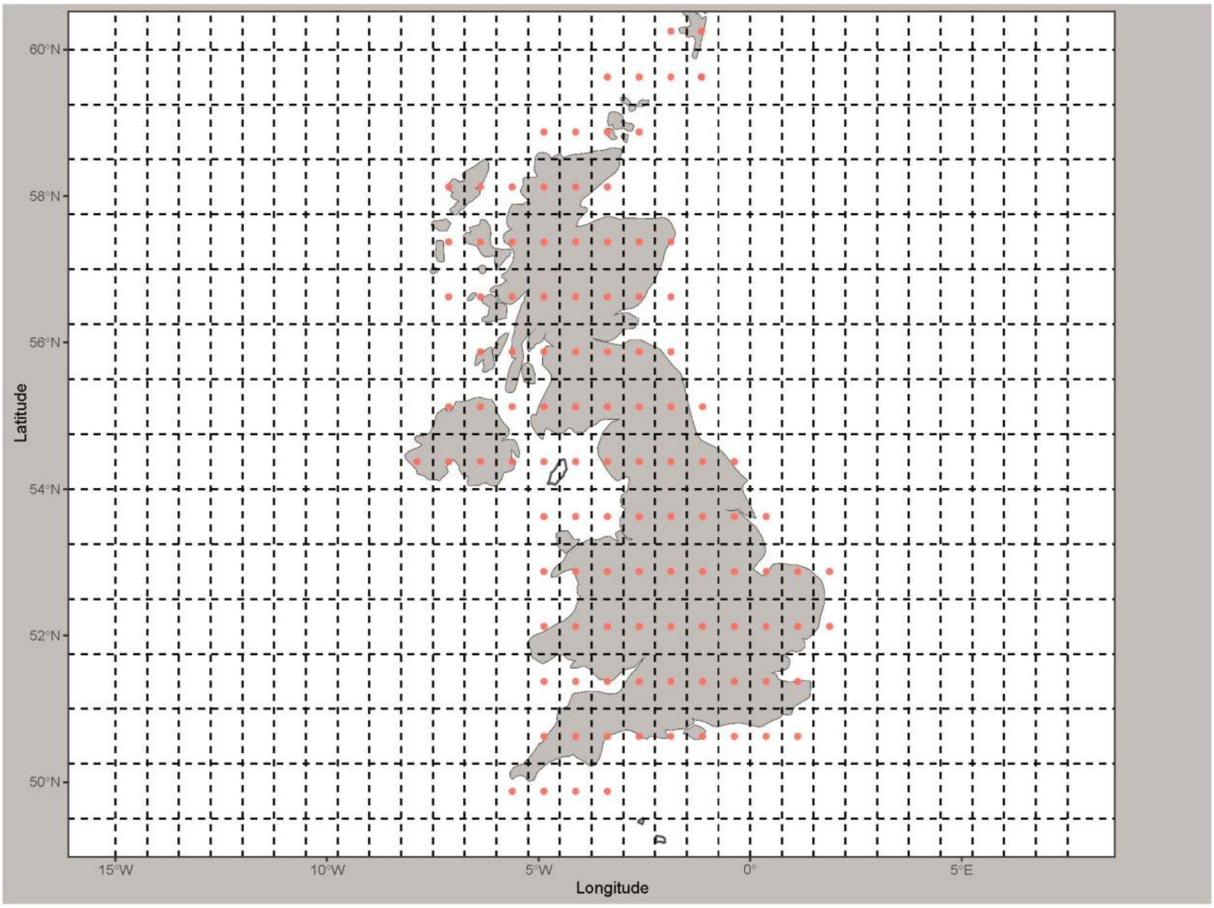

Figure 18: The 0.75° × 0.75° grid, where the daily average of all potential climatic variables (except the NAO) over the UK are extracted from European Center for Medium-Range Weather Forecasts (ECMWF) Interim reanalysis dataset between 1990-2015 (Dee et al., 2011). For each variable, a daily area average of each grid cell was calculated (red dots), thereafter, the value was assigned to the gauges within the grid cell

- ***North Atlantic Oscillation (NAO)***

The NAO is defined as the normalized sea-level pressure (SLP) difference between the subtropical high (i.e. Azores) and polar low (i.e. Iceland), and is the dominant mode of climate variability around the North Atlantic (Hurrell, 1995; Hall and Hanna, 2018). The NAO has positive and negative phases. In winter, a positive NAO phase is associated with increasing storm activity over the UK and northern Europe, while in summer, a negative NAO phase is associated with higher precipitation intensity (Hall and Hanna, 2018). Recent improvements in seasonal NAO predictability have the potential to improve precipitation predictability in the UK (Hanna and Cropper, 2017; Hall and Hanna, 2018).

Several studies have reported on the importance of the NAO in modulating precipitation over Europe (e.g. Hurrell, 1995; Jones *et al.*, 1997; Cropper *et al.*, 2015).

Hanna and Cropper (2017) reported a significant relation between the NAO and climate variability over the North Atlantic. In addition, Sutton and Dong (2012), analysing European climate using mean temperature, pressure, and precipitation, showed that during the 1990s, a substantial shift in the European climate coincided with a significant warming of the North Atlantic Ocean. This climate shift was characterised by anomalously wet summers in northern Europe, and hot, dry, summers in southern Europe, emphasising the important role of the North Atlantic Ocean for European weather. In the UK, the NAO index can be used as a proxy for north Atlantic jet streams and storm track variability and, hence, UK precipitation (Vallis and Gerber, 2008; Hanna and Cropper, 2017). Therefore, the NAO index (Jones et al., 1997) is examined for use as a covariate in the statistical modelling to characterise the frequency and intensity of extremes.

- ***Convection parameters (CAPE and CIN)***

In the UK, different studies have reported that extreme precipitation events in the UK, especially in summer, mostly occur due to convective conditions (Bennett *et al.*, 2006; Kendon *et al.*, 2014; Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018). A significant proportion of UK precipitation is produced by convective clouds associated with both frontal activity and air-mass cumulonimbus clouds (Bennett *et al.*, 2006). The coastline, the topography, and the wind direction across the UK all have a significant influence on the initiation of convection (Hand, 2005; Bennett *et al.*, 2006); The UK is also often subject to convection that has initiated on the European continent (Flack et al., 2016). Moreover, convective conditions are highly variable in the UK, both spatially and temporally, with maximum activity during summer (Holley *et al.*, 2014).

The initiation of convective precipitation conditions requires three components: atmospheric instability, moisture availability, and lifting forces (Johns and Doswell, 1992). Two related parameters are used here that represent these components - convective available potential energy (CAPE) and convective inhibition (CIN).

CAPE denotes the potential available energy to form cumulus convection which leads to convective precipitation. It is characterised by a positive virtual temperature difference between an idealised rising air parcel and its environment, vertically integrated with respect to the natural logarithm of pressure (p) between the level of free convection (LFC) and equilibrium level (EL) (Riemann-Campe et al., 2011). Parcel theory defines CAPE as a thermodynamic parameter reflecting atmospheric instability and moisture, which measures the potential buoyancy of a theoretical rising air parcel and its environment. CIN denotes the energy needed by the parcel to overcome the boundary layer to reach the CAPE (Moncrieff and Miller, 1976). For convection to occur, a rising air parcel must overcome any available convective inhibition (CIN).

CAPE can be calculated as:

$$CAPE = \int_{LFC}^{EL} R_d \left(T_{vp} - T_{ve}\right) d\ln(p) \tag{14}$$

while CIN is calculated as:

$$CIN = \int_{SFC}^{LFC} R_d \left(T_{ve} - T_{vp}\right) d\ln(p) \tag{15}$$

Where *LFC* is the pressure of the level of free convection, *SFC* is level of the surface or beginning of parcel path, *EL* is pressure of the equilibrium level, R_d is the gas constant, p is the atmospheric pressure, T_{vp} and T_{ve} are parcel and environmental virtual temperatures respectively.

Accordingly, the higher the value of CAPE, the greater the potential for severe convection. However, the ascent of air should also overcome any stable boundary layer (i.e. where the boundary layer has a high CIN value) to generate severe convection (Holley et al., 2014). Thus CAPE and CIN are explored for inclusion as covariates.

- ***Temperature (T-2m and DPT)***

Temperature has a significant physical and climatological relation with precipitation, and is considered as one of the defining controls on precipitation intensity. It should be noted that the relationship with precipitation occurrence is far more complicated and can vary both by season and location (e.g. Cong and Brady, 2012; Tencer *et al.*, 2014). The relation between temperature and extreme precipitation are governed by the Clausius–Clapeyron (C-C) relation, which explains the increased capacity of warmer air to hold moisture under constant relative humidity. Trenberth *et al.* (2003) hypothesised that under the C-C relation a 6–7% increase in the intensity of extreme precipitation is expected per 1°C increase in temperature if relative humidity remains constant. This rate has been confirmed for daily precipitation intensities by a number of studies including Fischer and Knutti (2016) and Westra *et al.* (2013). However, the intensity relation with temperature is also complicated by other factors such as changes in large-scale circulation (Trenberth and Shea, 2005; Trenberth, 2011), event type (Wasko and Sharma, 2014), and moisture content (Lenderink and Van Meijgaard, 2008).

Climate models suggest that increasing temperature would increase the capacity of warm air to hold more moisture, leading to an increase in daily and hourly extreme precipitation (Allan and Soden, 2008; Arnbjerg-Nielsen *et al.*, 2013; Kendon *et al.*, 2014). Observational studies support this result, and report increasingly intense precipitation extremes due to increasing temperature (Alexander *et al.*, 2006; Trenberth, 2011; Alexander, 2016).

Recent studies of sub-daily extreme precipitation have confirmed the C-C relation and indicated an increase in intense precipitation on short observational timescales with temperature increase (Lenderink and Van Meijgaard, 2008; Hardwick Jones *et al.*, 2010; Lenderink *et al.*, 2011; Barbero *et al.*, 2017; Blenkinsop *et al.*, 2018; Kendon *et al.*, 2018). In the UK, Blenkinsop et al. (2015) confirmed that hourly extremes follow approximately the C-C relation, and the increase is centred around 6.9% $°C^{-1}$, although the relation varies seasonally. Other studies have shown super C-C scaling for hourly precipitation intensities (e.g. Lenderink and Van Meijgaard, 2008).

Lenderink and Van Meijgaard (2008) reported that highest sub-daily precipitation intensities are associated with convective showers, which are highly related to surface temperature and moisture availability. Therefore, 2m surface air temperature and dew point temperature (DPT) are investigated as potential covariates for the statistical modelling. Dew point temperature (DPT) reflects the temperature to which air must be cooled to become saturated with water vapour, which will be condensed into the liquid state, forming precipitation once air temperature cools further (Wallace and Hobbs, 2006).

Both of these variables have been used in previous research, and can be used to scale the relation between extreme precipitation and temperature, though using the dew point temperature is preferable as it has less spatial and temporal variation, and it quantifies explicit information on both temperature and near-surface humidity (Kürbis *et al.*, 2009; Lochbihler *et al.*, 2017; Ali *et al.*, 2018).

- ***Sea surface temperature (SST)***

The North Atlantic plays a major role in determining the climatology of Europe and the UK. Gastineau and Frankignoul (2015) reported that summer atmospheric circulation and sea level pressure over the Atlantic are highly affected by the preceding spring

Atlantic sea surface temperature (SST), and this affects European summer weather. The hydrological cycle, moisture content, and atmospheric circulation over the UK are largely affected by North Atlantic climatology (Colman, 1997; Sutton and Hodson, 2005). Wang and Dong (2010) indicated that increased North Atlantic SSTs would increase oceanic evaporation, generating positive moisture anomalies moving over the UK. Moreover, Sutton and Dong (2012), analysing European climate change patterns in the 1990s, reported that North Atlantic Ocean warming is a key driver in determining European summer climate and precipitation patterns.

Recently, Ossó et al. (2018) confirmed the SST relation with south east Atlantic summer precipitation, especially in the UK, and reported that summer precipitation patterns can be predicted using the preceding spring Atlantic SST index. In addition, SST patterns control the position of the jet stream over the North Atlantic, which affects UK precipitation in all seasons (Ossó et al., 2018). Similarly, Wilby et al. (2004) and Neal and Phillips (2009) reported robust relationships between summer precipitation in the UK south and southeast regions and preceding North Atlantic SSTs. Furthermore, Lavers et al. (2013), reported that transferred moisture from the North Atlantic, which has a directly proportional relationship with SSTs, contributes noticeably to winter extreme precipitation in the UK.

Here, coincident and lagged SST values are considered as potential predictors. We examine the relation between hourly extremes in the UK and both SSTs and an SST index (Ossó et al., 2018). The SST mean over the domains located in the north west (42°N–52°N, 52°W–40°W) (Domain 1) and south east (35°N–42°N, 35° W–20°W) (Domain 2) of the North Atlantic on the day of the extreme (SST-Avg), and 4 months earlier (SST-Avg-lag) are investigated (Figure 19). The SST index, which is the difference in average SST between the two domains, is investigated over the same time frames (SST-Index and SST-Index-4lag).

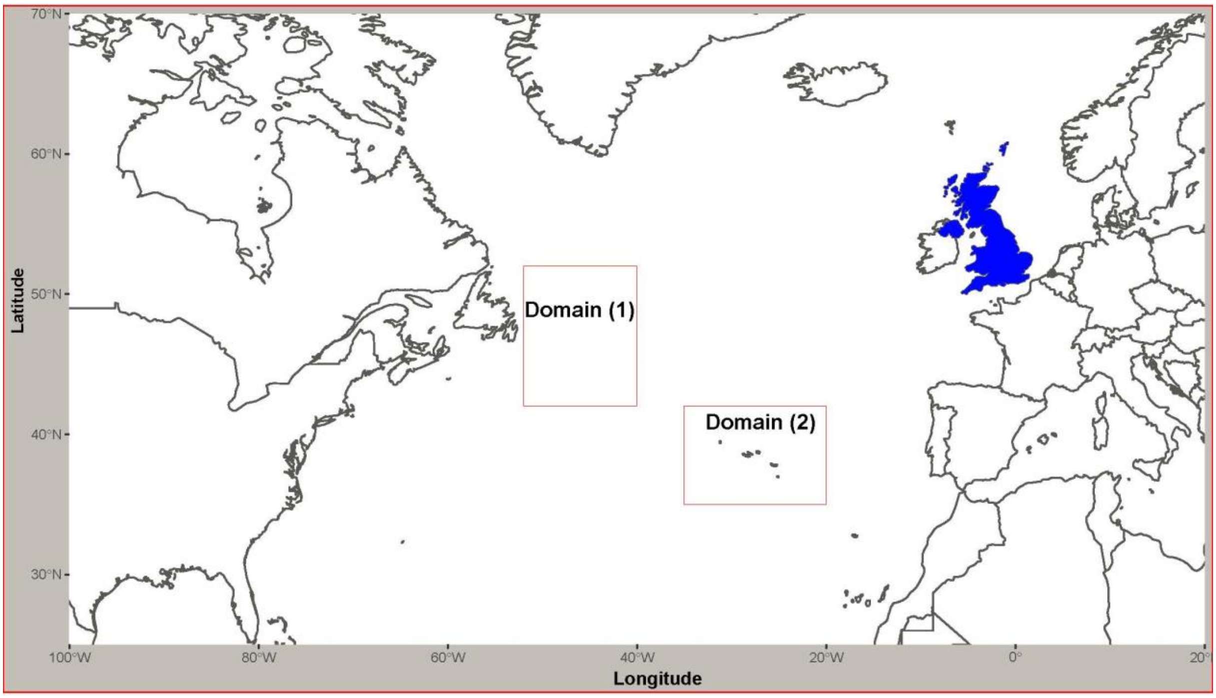

Figure 19: The domains located in the north west (42°N–52°N, 52°W–40°W) (Domain 1) and south east (35°N–42°N, 35°W–20°W) (Domain 2) of the North Atlantic, where the sea surface temperature (SST) between 1990-2015 was extracted, to investigate its relation with hourly extremes in the UK. Longitude (x-axis) and latitude (y-axis)

- ***Atmospheric pressure***

Atmospheric pressure, and its derived indices, play a significant role in the climatology of the UK. High and low pressure systems have a significant role in determining airflow directions and consequently influence heavy precipitation (Barry and Chorley, 2009).

Hofstätter et al. (2018), who analysed large-scale, heavy precipitation over Europe and the role of atmospheric cyclones, reported significant relations with the geopotential height at different levels such as: 850-hPa (Z-850), 700-hPa (Z-700), and 500-hPa (Z-500). Esteban et al. (2006) analysed the daily atmospheric circulation over western Europe using reanalysis data and found that using Z-500 characterizes well enough the complex circulation variability. Moreover, Kilsby et al. (1998) confirmed the benefit of using mean sea level pressure (MSLP) to predict precipitation statistics in the UK, suggesting that using other circulation data, such as upper air circulation (e.g. Z-750 or Z-500) would improve the physical basis of regression models.

Tye et al. (2016) reported a strong significant seasonal relationship between daily precipitation extremes and MSLP, especially in the north and west of the UK. This supported prior research by Lavers et al. (2013) on the role of atmospheric rivers over the UK in transferring moisture from the Atlantic, and their dependence on MSLP. Recently, Chan *et al.* (2018b) used MSLP and Z-850 relative vorticity as predictors, among other large-scale variables, to assess convection-permitting climate simulations in the southern UK, demonstrating that their inclusion in a statistical model well enhance the simulation of hourly extreme precipitation.

Therefore, the correlation of MSLP and geopotential height at different levels (i.e. Z-850, Z-700, and Z-500) with hourly extreme precipitation is also investigated for use as predictors in the statistical model.

- ***Total column of water vapour (TCWV)***

Total column water vapour (TCWV) is a measure of the total gaseous water contained in a vertical column of the atmosphere. It represents over 99% of the atmospheric moisture, and comprises the major source of atmospheric energy governing the process of cloud formation, energy exchange within a system, and the development of weather systems on short time scales (Wypych et al., 2018).

Trenberth (2011) indicated that the strong correlation between TCWV and SSTs, could lead to more extremes in the future under different climate change scenarios. Wypych et al. (2018) confirmed the importance of TCWV over Europe and the North Atlantic, besides the significance of atmospheric circulation in forming the moisture content, especially in winter. Furthermore, Beckmann and Adri Buishand (2002) used TCWV to statistically downscale and simulate precipitation occurrence and frequency in Europe (i.e. Germany and the Netherlands) from a GLM, and reported that TCWV is among the most powerful predictors of wet-day precipitation amounts. Blackburn et al. (2008) reported that during the UK 2007 floods, a similar weather system could not have produced the same floods without the available TCWV over the UK, which was much higher than the average. Therefore, the TCWV over the UK is also considered as a predictor for hourly extreme precipitation.

5.3. Methodology

Hourly precipitation across the UK is investigated and modelled using GLM and EVT to simulate both the occurrence and intensity at extreme levels. Extreme events are rare and infrequent by definition, which incorporates a noticeable uncertainty in estimating the underlying distribution parameters (Naveau et al., 2005). Here we use peak over threshold (POT) data to identify the parameters of a Poisson process.

5.3.1. Generalized linear model (GLM)

Adopting a stochastic weather generator approach (e.g. Furrer and Katz, 2008) we assume that the processes governing extreme precipitation occurrence and the extremity of the intensity are similar but not necessarily the same. Thus, we adopted the Poisson distribution to simulate the arrival rate, or occurrence, of an extreme event. Given that an event has occurred, its intensity is then described by the GPD.

GLMs are a flexible generalization of ordinary linear regression that allow for response variables that have error distribution models other than a normal distribution (Olsson, 2002). The GLM uses a link function to relate the linear model to the response variable and generalizes the linear regression, which allows the magnitude of the variance of each measurement to be a function of its predicted value.

The Y outcome of the dependent variables is assumed to be generated from a particular distribution in the exponential family, such as normal, binomial, Poisson or gamma distributions (Madsen and Thyregod, 2010). The mean, μ, of the distribution depends on the independent variables, $\boldsymbol{X}$, through:

$$\mathrm{E}(\mathbf{Y}) = \mu = g^{-1}(\mathbf{X}\boldsymbol{\beta}) \tag{16}$$

where E(Y) is the expected value of Y; $X\beta$ is the linear predictor, a linear combination of unknown parameters β; and g is the link function.

- ***Poisson distribution***

The Poisson distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time or space at a known constant rate (λ); each event is assumed independent of the previous (Madsen and Thyregod, 2010). For an average number of events in time interval (t), the Poisson probability density function (pdf) is:

$$\mathbb{p}(\mathrm{Y} = \mathrm{y}) = \frac{e^{-\lambda}\lambda^{y}}{y!}, y = 0,1,2,3, \dots \tag{17}$$

Where λ is the average number of events occurring in time t, and y any positive number of events.

Rearranging the proper functional form to solve for λ provides a construct for the log likelihood function and the parameter estimation. The resultant statistical model, referred to as the Poisson regression model, can then be used to predict the probability occurrence of extreme precipitation.

The Poisson distribution assumes equality in the variance (V_i) and mean (E_i) of the data, both of which equal the event rate (λ_i), also referred to as equidispersion. Variance greater than mean of the data implies overdispersion, and a negative binomial distribution would be more appropriate. Contrary, estimated variance smaller than the mean of the data, underdispersion, indicates that events arrive at a rate which is more regular or uniform than expected from a Poisson process.

- ***Link function g(μ)***

The link function $g(\mu)$ is used to establish a relationship between the count response Y and the linear predictors $X_1,\ldots,X_n$ in a GLM. It is chosen based upon the type of data in the model. The general form of the link function is

$$g(\mu) = \boldsymbol{X}\beta \tag{18}$$

In this research, the precipitation occurrence data is discrete count data; therefore, for Poisson distributed data, the link function is

$$g(\mu) = \log(\lambda) \tag{19}$$

5.3.2. Extreme Value Theory (EVT)

Extreme value theory describes a family of distributions which characterise the tail of the distribution of a series of maximum values without a priori knowledge of the underlying behaviour (Coles et al., 2001). When considering the maxima within a certain period, the two main approaches used are either block maxima (BM) where data are grouped into blocks of the same duration, or peaks over threshold (POT), where the values exceeding a specified threshold are selected for the analysis.

Hourly precipitation data are limited and scarce, therefore, the POT approach is adopted here to maximise the available data. The POT approach utilizes additional information about the extreme upper tail, which provides more accurate parameter and quantile estimates (e.g. Katz et al., 2002). It has been widely used to estimate climatic extreme variables such as extreme precipitation (e.g. Francisco Javier et al., 2011; Thiombiano et al., 2017), temperature (e.g. Cheng et al., 2014), and wind velocity (e.g. Pandey et al., 2003).

An adequate asymptotic distribution to describe the behaviour of events over a threshold is the Generalized Pareto Distribution (GPD) defined by Coles et al. (2001) with the following cumulative distribution function (CDF):

$$\mathrm{H(y)} = 1 - \left(1 + \frac{\xi \mathrm{y}}{\tilde{\sigma}}\right)^{-1/\xi} \tag{20}$$

where ξ and $\tilde{\sigma}$ are the shape and scale parameters respectively, while y are the excesses over a selected threshold u. At a sufficiently high threshold, the Generalized Extreme Value (GEV) distribution (describing BM) and the GPD become mathematically equivalent, sharing a common shape parameter and with easily interpretable definitions of the GEV's location, and GP's threshold and scale parameters (Coles et al., 2001).

Specifying the threshold in the POT approach is essential to achieve the balance between bias and the variance of the distributions (Coles et al., 2001; May, 2004). Generally speaking, defining the threshold will control the sample size and distribution behaviour. Having a low threshold would violate the GPD asymptotic and data independence assumptions. While having too high a threshold would eliminate some of the extreme values, and retain few values for the analysis (Coles et al., 2001). Previous examination of daily precipitation over Europe examined different thresholds such as the 0.95 and 0.99 quantiles, reporting better results for the 0.99 quantile (Anagnostopoulou and Tolika, 2012; Jones et al., 2014). Moreover, Anagnostopoulou and Tolika (2012) reported that this threshold is the most appropriate for extreme precipitation over Europe, and provides more coherent results compared to other thresholds and facilitates better comparison with a GEV analysis. In this research, the 0.99 threshold was used since it achieves a balance between having a high threshold and sufficient sample size.

The *GPD density functions assume stationarity, therefore, it can capture the temporal behaviour of extremes within the analysis period given that the extreme mechanisms are stationary. However, assuming a stationary climate might not be valid due to both naturally occurring climate oscillations or anthropogenic activities. Therefore, a non-stationary approach is adopted in this chapter to account for climate variation, where time-dependent variables are incorporated in parameter (i.e.* shape and scale parameters) *estimation.*

Accordingly, different climatological predictors (Table 7) were employed to estimate the GPD parameters (i.e. shape and scale) in this chapter*, with the most suitable predictors retained to account for the parameter estimation. This would allow the parameters* to vary with time based on the combination of climatological variables such as temperature and atmospheric pressure. *However, the shape parameter (ξ), which is the most complex to be estimated, was considered constant due to its noisy pattern, and to keep in line with previous similar studies (e.g. Haagenson et al., 2013; Jones et al., 2014; Condon et al., 2015; Wi et al., 2016). Therefore, the GPD parameters are introduced to the GPD distribution as following:*

$$log[\sigma(x)] = \beta_{0,\sigma} + \beta_{1,\sigma}x_1 + \cdots\cdots\cdots\cdots\cdots\cdots + \beta_{n,\sigma}x_n \qquad (21)$$

$$\xi(\mathrm{t}x) = \xi \qquad (22)$$

where (σ) is the scale parameter, (ξ) is the shape parameter, variables x_1, x_2, …, x_n are the covariates (which can include time as a covariate to consider a temporal trend), and β_0, β_1, …, β_n are the coefficients, at time t.

Meanwhile, most of the existing metrics and design guidelines in Europe are based on stationary data analysis (Madsen *et al.*, 2013). The existing design guidelines account for hydrological risks (e.g. pluvial and fluvial floods, extreme precipitation) using the “return period” variable, where the designed structures (e.g. dams, sewers) are able to cope with hydrological events of a specified return period (e.g., the 100-year flood), and the event frequency distribution remains stationary through time (e.g. from 20 up to 100 years).

However, while using the non-stationary approach it should be noted that the distribution frequency reflects the probability of a given event (e.g. flood, extreme precipitation) magnitude occurring over a specified time period (e.g. 20 year). A similar concept was introduced for hydrological analysis purposes by various researchers, using “design life level” instead of “return period” to reflect the risk associated with a specific magnitude event (e.g. Rootzén and Katz, 2013; Salas and Obeysekera, 2013; Condon *et al.*, 2015).

In this research, the non-stationary GPD distribution along with the NAO observational dataset (Jones *et al.*, 1997) and downscaled climatic variables from the European

Center for Medium-Range Weather Forecasts (ECMWF) Interim reanalysis dataset (Dee *et al.*, 2011) were adopted to characterise hourly extreme precipitation intensity in the UK.

5.3.3. Poisson-GPD Distribution relation

The GPD is used to assess the magnitude of hourly precipitation events exceeding the predefined threshold, while the Poisson distribution is used to model the occurrence of extreme precipitation exceeding the threshold *u* in any given year. Therefore, the combined Poisson-GPD relationship can be defined using the following probability distribution function (PDF) (Wi et al., 2016):

$$H(y) = exp\left\{-\lambda(1+\frac{\xi y}{\tilde{\sigma}})^{-1/\xi}\right\} \quad (23)$$

where λ is the arrival rate of excesses over the threshold.

5.3.4. Data independence

The Poisson distribution and EVT assume observations above the defined threshold to be statistically independent (Coles *et al.*, 2001), which is hard to achieve in real climatological applications. Furthermore, since the data has a short time-scale (i.e. hourly), dependence may occur frequently, even if only values above a very high threshold are selected. Hourly extreme precipitation in UK northern regions are often generated by large-scale mechanisms (Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018), which can lead to a temporal dependence.

Therefore, the 0.99 quantile (Q99) for each gauge was calculated, and observations above Q99 were declustered and retained for further analysis. Subsequently, the Q99 observations from all the gauges within each region was grouped, and only the highest hourly precipitation value per day in each region was selected. The “run decluster” approach detailed in section 4.3.4 was adopted to perform the declustering, with the independence of each gauge data assessed using the extremal index (*EΘ*). This measures the degree of local dependence in the extremes of a stationary process (Northrop, 2015). For independent data, *EΘ* = 1, while *EΘ* =0 indicates full data dependence (clustering). The results showed that most of the gauges have values higher than 0.7, indicating generally independent values.

5.3.5. Regional Data Pooling

Here, we aim to characterise hourly extreme precipitation regionally, using the new homogeneous extreme precipitation regions developed from the Q99 precipitation extremes in Chapter 4. Therefore, a predefined location for each region, at which the model will be built and validated, is required, and for which the geometric centres of the hourly extreme regions shown in Figure 14 are used.

Finally, to overcome any residual regional dependence, as extremes will likely be observed at more than one station in a region (Khaliq *et al.*, 2006; Sugahara *et al.*, 2009; AghaKouchak and Nasrollahi, 2010), the retained data in the previous step (Section 5.3.4) (i.e. the highest Q99 hourly precipitation value per day in each region) will be used to develop the model.

5.3.6. Parameter Estimation

To facilitate the inclusion of time-dependent parameters that account for seasonality, ,the maximum likelihood estimation (MLE) method (Coles et al., 2001), is used in this research to estimate the GPD parameters. MLE is asymptotically normally distributed and the variance is asymptotically minimal, which facilitates the derivation of confidence intervals for the distribution quantiles. Millar (2011) described the MLE as following:

Let x1, x2, x3, . . . , xn be n observations of a random sequence with probability density function $f(x|\theta)$, where θ is the vector of parameters of this function. If one considers that the observations xi is statistically independent, the joint probability density function for this sample is the product of the individual densities, called the likelihood function:

$$L\ (\theta|x) = \prod_{i}^{n} f\ (x_i|\theta) \tag{24}$$

In general, this function is written as:

$$Log\ L\ (x|\theta) = \sum_{i=1}^{n} Log\ f\ (x_i|\theta) \tag{25}$$

In the process of the inference of θ, the MLE aims that all the relevant information in the observed data is contained in the likelihood function, to determine the best probability density functions that produce the given sample.

Katz et al. (2002) indicated that MLE outperform other approaches in having consistency parameters estimates, and flexibility of incorporating non-stationary features into the distribution parameters as covariates. Moreover, MLE performance has been reported to be better than other approaches (e.g. L-Moments) in the presence of time-varying climatic variables and for adequate sample sizes (Zhang et al., 2005; White et al., 2008; Jones et al., 2014; Wi et al., 2016)

5.3.7. Model selection

Model assessment is essential to validate the proposed statistical model, thus the predictive ability, model consistency, and model structure are evaluated using statistical and graphical approaches. The literature on extreme precipitation modelling using either GLM or EVT suggests different methods to assess model efficacy such as parameter significance, quantile plots, the Akaike Information Criterion (AIC), distribution plotting, or likelihood ratio tests (Coles et al., 2001; Chatterton et al., 2010; Davison and Huser, 2015).

The AIC, which estimates the relative quality and predictive power of statistical models for a given set of data (Akaike, 1981), is used to select the best model and predictive variables. The AIC estimates the likelihood of a model to predict the future values, and the number of used variables in each model, where a trade-off between the model goodness of fit and complexity is evaluated (Burnham and Anderson, 2003). The AIC model selection criteria recommends choosing the model with the lowest AIC value; however, further investigation should be performed before choosing the model with the lowest AIC value, especially when the difference between models is small (Akaike, 1992) as the method penalises more complex models. AIC is a relative measure of goodness of fit, and does not assess the absolute model quality or the null model, hence, it should be used in combination with other statistical tests (Akaike, 1992).

An alternative statistical measure, the likelihood-ratio test (LRT) is also used to compare the goodness of fit between models. LRT compares a relatively more complex model to a simpler model, and reports the significance of adding more parameters to the model (Nogaj et al., 2006). Therefore, the method is valid when analysing nested models, where the complex model has one or more additional variables.

Visual comparison of the fitted models' performance is achieved with quantile-quantile (Q-Q) plots, which assess the similarity between observed and predicted quantiles. If the model fits the data perfectly, the plotted points will approximately lie on the line y=x, while a large deviation is evidence of the opposite. Confidence estimates of the model fit are developed from 500 bootstrapped samples.

5.3.8. Model predictions

Finally, the statistical model is used to assess the potential impact of climate change and temperature increase in the UK. Significant increases in temperature and precipitation in recent decades have been reported and confirmed globally (Rahmstorf and Coumou, 2011; Donat et al., 2013), while climate models project a further increase either in temperature or in precipitation frequency and intensity across northern Europe (Fischer and Knutti, 2015). Using the statistical model to identify the nature of future changes is a robust alternative to support future adaptation plans and design guidelines where complex dynamical models are not affordable or achievable.

In this research, the pseudo global warming (PGW) method (Kimura and Kitoh, 2007) for a scenario that restricts global warming to 2 degrees Celsius or lower, as suggested by the Paris climate agreement (Paris agreement, 2015), is adopted to assess future extreme precipitation patterns. The gridded daily averaged data between 1990-2015 from the European Center for Medium-Range Weather Forecast Interim reanalysis (ECMWF) dataset (Dee et al., 2011), will be used to establish a control climate (CTL), and the 2ºC degrees increase will be relative to this period. Dynamical models premised on PGW use the sum of observations (reanalysis data) as the initial and boundary conditions for regional model integrations, with the global warming increment is estimated from simulations with global coupled climate models (Kimura and Kitoh, 2007). The statistical equivalent adopts predictive parameters that are broadly dictated by their physical response to an increase in global mean temperature of 2° C.

5.4. Results

As discussed in previous sections, pooled hourly Q99 were declustered to ensure higher probability of independence. Extremal index EΘ values of 0.79, 0.74, 0.77, 0.73, and 0.71 for the regions SE, SW, ME, NE, and NW, respectively, indicate that the remaining data in each region can be considered to be independent. All subsequent analyses presented below use the declustered data.

5.4.1. Climatic predictor initial selection

Before developing the statistical model to simulate UK hourly extreme precipitation, an exploratory analysis of the correlation between hourly extreme intensity and the proposed variables (Table 7) was performed. Some of these variables are physically related (e.g. temperature, CAPE), therefore, collinearity should be considered when choosing the best statistical predictors. The correlation analyses shown in Figures 20 and 21 are derived from simple linear models of precipitation intensity against the relevant time-dependent variable. Regressions for precipitation occurrence are not shown as the results are broadly similar.

The results in Figures 20 and 21 show that a majority of the potential variables are significantly correlated with hourly extreme precipitation intensity across the UK, while most of the non-significantly correlated gauges are in the north west region (NW). For instance, CAPE and CIN are known to drive short duration convective events, which are more common in the warmer southern regions. In contrast, air flow (represented by geopotential height), NAO and SLP are more frequently associated with large-scale frontal systems over the north and west of the UK; such events may have embedded convective cells, making these variables more significant in NW rather than the south. Thus, all variables in Table 7 are explored further in deriving the statistical models for hourly extreme precipitation occurrence and intensity.

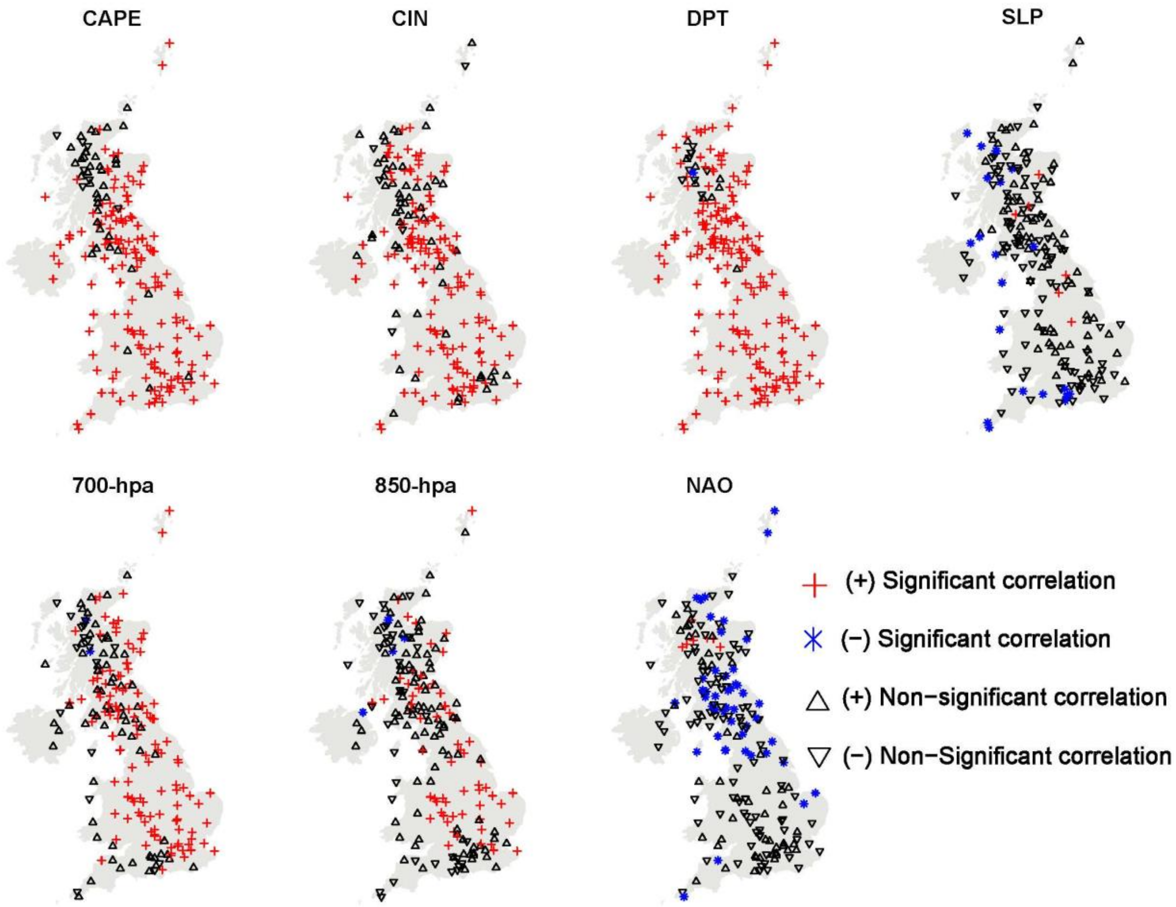

Figure 20: The Spearman correlation between hourly extreme intensities above the Q99 and potential climatological predictors. The assessed predictors are: convective available potential energy (CAPE), convective inhibition (CIN), dew point temperature (DPT), sea level pressure (SLP), pressure level height 700-, 850hPa (Z700-, Z850), and North Atlantic oscillation (NAO). The positive and negative significantly correlated gauges are indicated by red and blue colour respectively. Moreover, positive and negative non-significantly correlated gauges are indicated by black upward and downward arrows respectively.

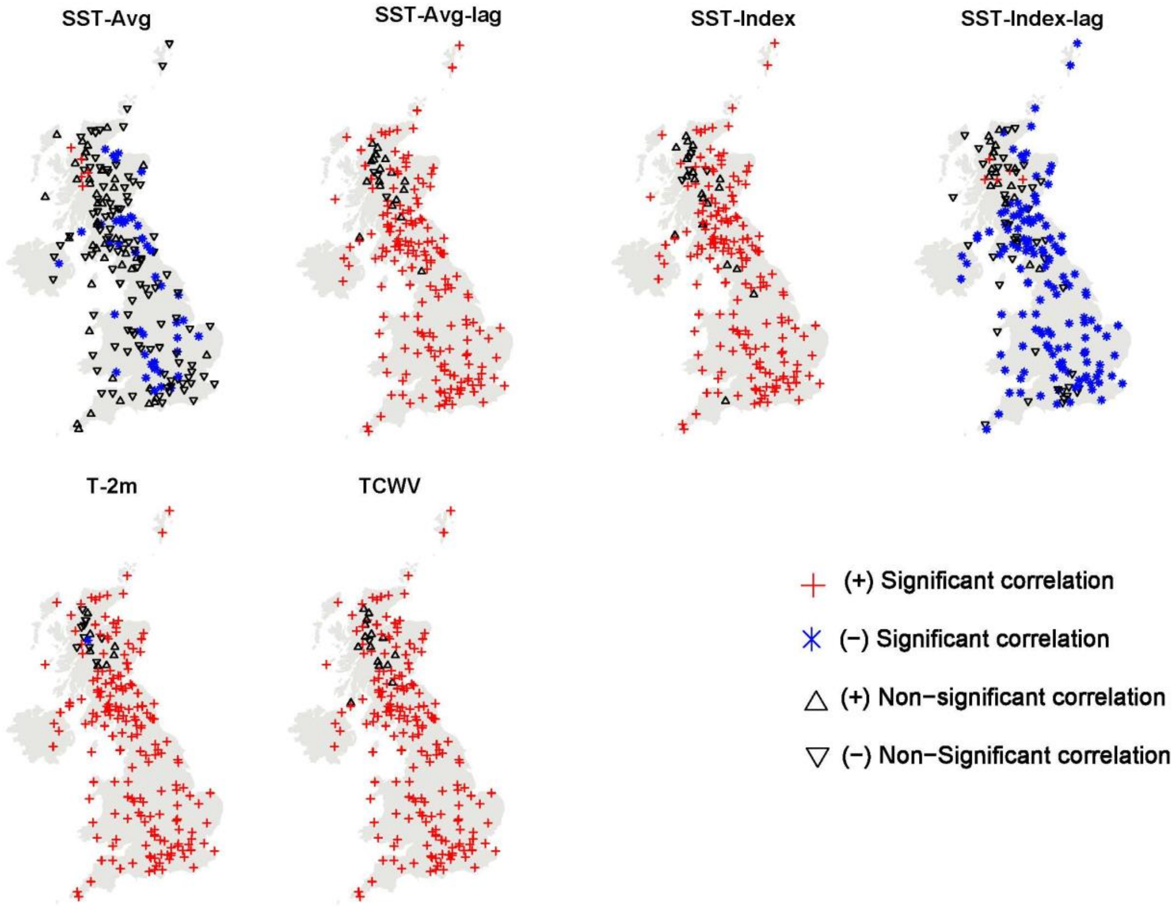

Figure 21: As for Figure 20 but assessed predictors are: sea surface temperature average over NW (42°N–52°N, 52°W–40°W), and SE (35°N–42°N, 35° W–20°W) domains of the North Atlantic on Q99 days (SST-Avg), 4-month lagged sea surface temperature average (SST-Avg-lag), sea surface temperature difference between NW and SE domains on Q99 days (SST index), 4-month lagged sea surface temperature difference between NW and SE domains (SST-index-lag), near-surface air temperature (T-2m), and total column water vapour (TCWV). The positive and negative significantly correlated gauges are indicated by red and blue colour respectively. Moreover, positive and negative non-significantly correlated gauges are indicated by black upward and downward arrows respectively.

5.4.2. Poisson model

The statistical models use climatic variable measurements between 1992 and 2014 in each regions' geometric centroid. The period 1992-2011 was used for parameter estimation and model fitting, while the period 2012-2014 was used for model validation.

Potential climatic variables were used as predictors in the GLM, and a backward model selection approach was adopted to determine the most significant predictors. The initial GLM (for each of the estimated parameter sets of the Poisson and the GPD) included all the candidate variables. Then the variables' significance was assessed, to remove the least significant variable. The process was then repeated until only significant variables remained and deleting further variables would reduce the models' adequacy. Furthermore, model fit criterion (AIC), histograms, Q-Q plots, and Likelihood-ratio test (LRT) of the model before and after removing each variable was checked after each iteration, to ensure statistical improvement at each stage. Additionally, variables with potential interaction such as: convective variables (i.e. CAPE and CIN), atmospheric pressure (i.e. Z-850 and Z-700), and temperature (i.e. T-2m and DPT) were assessed separately and simultaneously.

- ***Poisson***

The Poisson model utilises the GLM to predict a time-varying arrival rate (λ) for hourly extreme precipitation occurrences. The final selection of covariates includes the North Atlantic Oscillation (NAO), dew point temperature (DPT), atmospheric pressure at 700-hPa (Z-700), and the sinusoidal values of the Julian day of occurrence (Sin (Θ), Cos (Θ)) in the form:

$$\mathrm{Log}\lambda(x)= \beta_0+\beta_1(\mathrm{Sin}(\Theta_t))+\beta_2\,(Cos(\Theta_t))+\beta_3(NAO_t)+\beta_4(\mathrm{DPT}_t)+ \beta_5(\mathrm{Z\text{-}700}_t) \qquad (26)$$

Figure 22 shows the Q-Q plots for each region, and indicate a similar agreement between the observed and statistically simulated data for hourly extremes between 1992-2011.

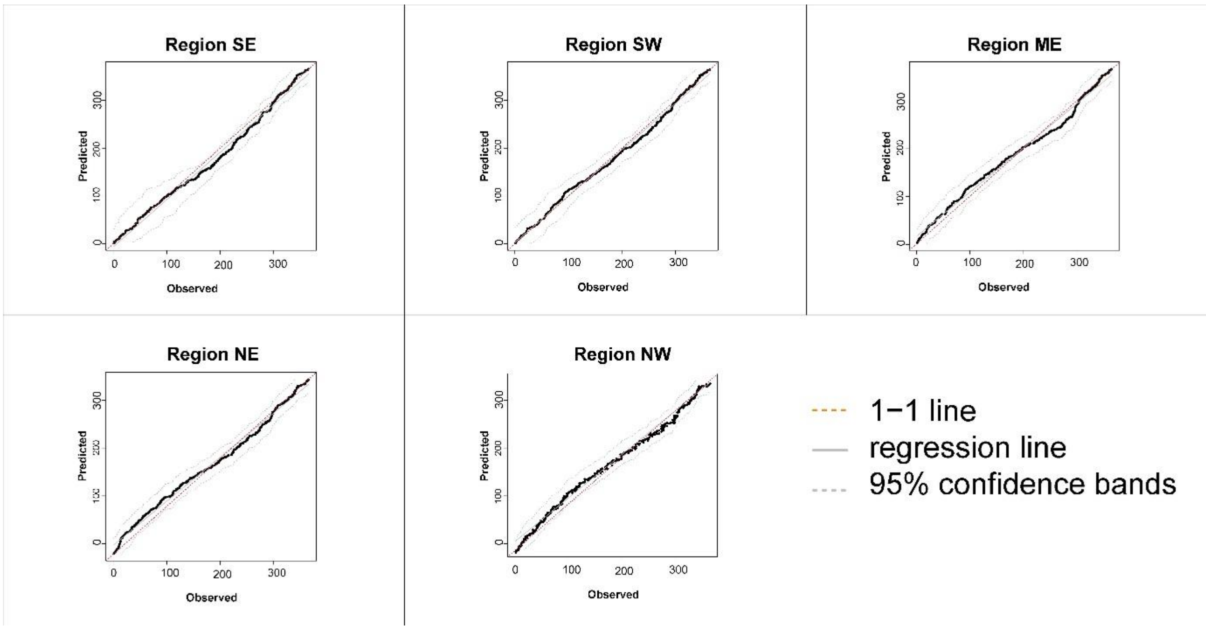

Figure 22: Q-Q plots for Q99 hourly extreme frequency predicted by the Poisson GLM for the years 1992-2011 in each region. Q99 hourly extreme occurrence by Julian day for observed quantiles (x-axis), and Poisson predicted quantiles using NAO, Z-700, DPT, and sine/cosine Julian day as predictors (y-axis). Confidence bands are developed from 500 bootstrapped samples. The continuous solid line is the prediction regression line, while the dotted line is the 1-1 reference line.

Figure 23 shows the model validation results for each region, using the observed and statistically simulated Q-Q plots for years 2012-2014. The results again show concordance between the regression line and 1-1 line, indicating reliable simulation.

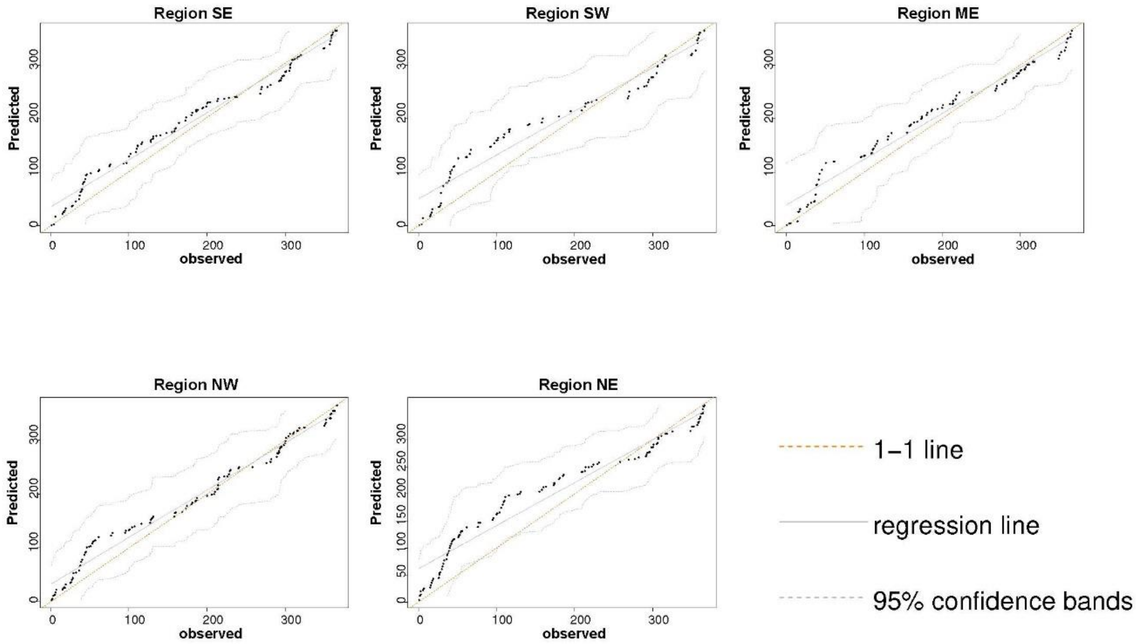

Figure 23: Validation Q-Q plots for the Q99 hourly extremes frequency predicted by the Poisson model for years 2012-2014 in each region. Q99 hourly extremes occurrence by Julian day for observed quantiles (x-axis), and Poisson predicted quantiles (y-axis). Details as for Figure 22.

- ***Generalized Pareto distribution (GPD)***

The statistical model development utilises the observed precipitation intensity and the corresponding time-dependent covariates – as for the Poisson model. Initial GPD parameter estimates are obtained from a stationary model fit to the observed pooled precipitation data. Climatic variables are then only incorporated in the GPD scale parameter to account for non-stationarity; the shape parameter and threshold are both assumed to remain constant (e.g. Katz *et al.*, 2002; Cheng *et al.*, 2014).

The final model includes the sine and cosine terms for Julian day (Sin (Θ), Cos (Θ)), combined with CAPE. The statistical model takes the relationship:

$$\log \tilde{\sigma} = \beta_0 + \beta_1(\mathrm{Sin}(\Theta_t)) + \beta_2\,(Cos\Theta_t) + \beta_3(CAPE_t) \qquad (27)$$

$$\log(\xi + \tfrac{1}{2}) = \beta_0 \qquad (28)$$

This produced the most predictive model, with the lowest AIC value. Assessing the likelihood ratio test between the base model and the final model shows a very significant improvement in the time-dependent model at a 5% level.

The Q-Q plots in Figure 24 show the statistically predicted vs observed hourly extreme quantiles for each region between 1992-2011. Subsequently, the proposed GPD model was validated using data between 2012-2014 (Figure 25). For a meaningful comparison and interpretation of the two statistical models, precipitation intensities are estimated utilising covariates for the days of occurrence predicted by the Poisson model. As with the Poisson model, the results show concordance between the y=x and regression lines, indicating reliable performance for the statistical model.

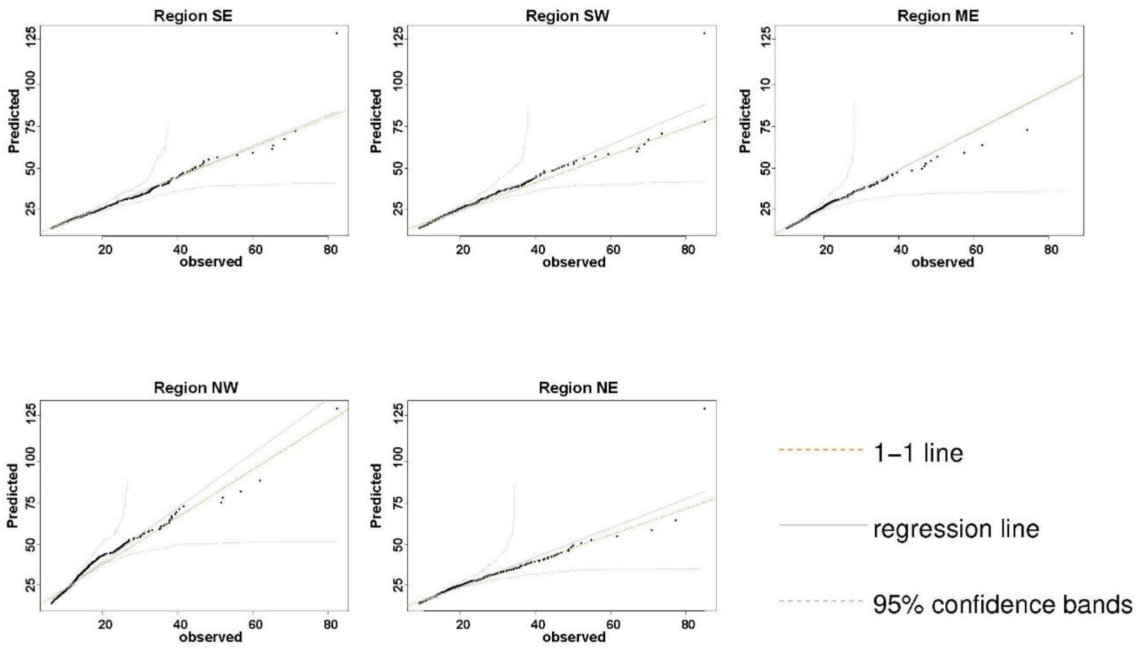

Figure 24: Q-Q plots for Q99 hourly extremes predicted intensity by the GPD for the years 1992-2011 in each region. Q99 hourly extreme intensity for observed quantiles in mm/hr (x-axis), and GPD predicted extreme intensity quantiles in mm/hr (y-axis). The continuous solid line is the prediction regression line, while the dotted line is the 1-1 reference line.

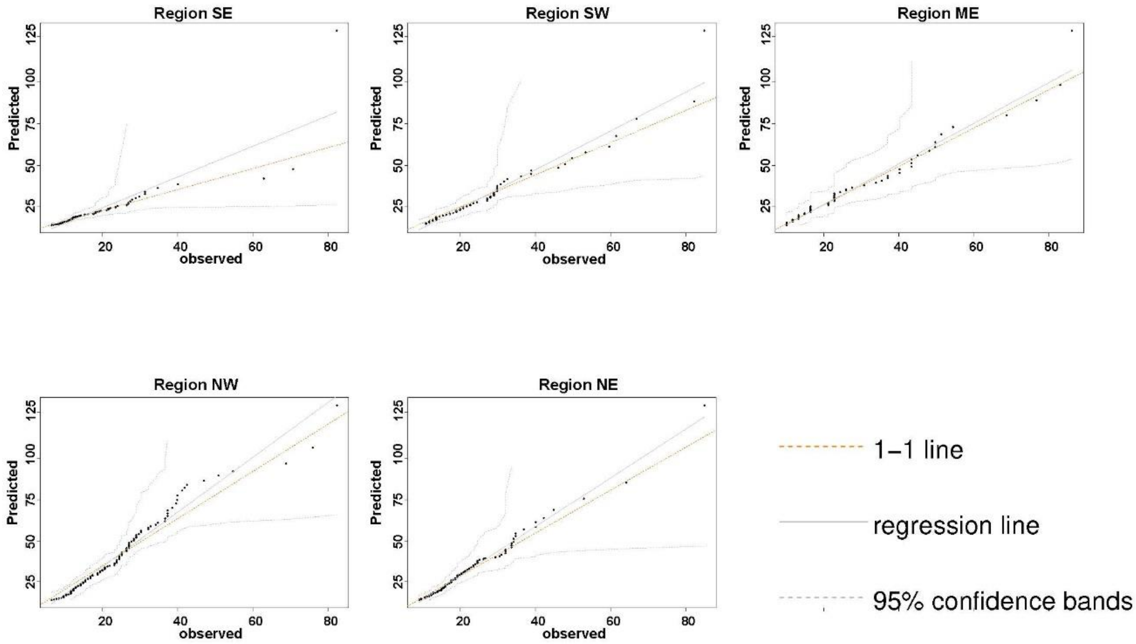

Figure 25: Validation Q-Q plots for the Q99 hourly predicted intensities by the GPD for the years 2011-2014 in each region. Q99 hourly extreme intensity for observed quantiles in mm/hr (x-axis), and GPD predicted extreme intensity quantiles in mm/hr (y-axis). The continuous solid line is the prediction regression line, while the dotted line is the 1-1 reference line.

5.4.3. Pseudo Global Warming Method

Finally, the statistical model is used to assess the potential impact of a simple scenario of 2^{o}C warming in the UK using a PGW approach. DPT (in the Poisson model) was increased by a corresponding 2^{o}C. The relation between the T-2m and DPT is controlled by the relative humidity equation, which reflects the ratio between available moisture in the air (i.e. vapour pressure, E) and the air moisture capacity (i.e. saturation humidity, Es). The RH equation formula is:

$$RH = 100\% \times (E/Es) \quad (29)$$

as stated in Stull (2018) for which, according to an approximation of the Clausius-Clapeyron equation:

$$E = E_0 \times \exp[(L/Rv) \times ((1/T_0) - (1/DPT))] \quad (30)$$

and

$$Es = E_0 \times \exp[(L/Rv) \times ((1/T_0) - (1/T))] \quad (31)$$

where E_0 = 0.611 kPa, L is a latent-heat parameter and Rv is water-vapor gas constant where (L/Rv) = 5423 K (in Kelvin, over a flat surface of water), T_0 = 273 K (Kelvin), T is temperature (in Kelvin), and DPT is dew point temperature (also in Kelvin).

Accordingly, for T-2m (T in Equation 31) between 5 -25^oC, and under constant relative humidity, the DPT ranges between 1.8^oC and 21.4^oC respectively. The difference between T-2m and DPT is relatively constant and varies slightly between 3.2 ^oC-3.6^oC. Thus, in this research the difference between T-2m and DPT is assumed constant, and DPT was increased by 2^oC, to match the adopted climate warming scenario (i.e. 2^oC increase according to Paris agreement).

On the other hand, large-scale atmospheric variables (i.e. Z-700 and NAO), were retained without modification. Gastineau and Frankignoul (2015) reported that Z-700 and NAO are related to large-scale atmospheric circulation rather than atmospheric temperature. Moreover, though SST has a noticeable relation with the NAO and might increase due to global warming, no significant causal effect of SST anomalies on the NAO has been identified (Weile *et al.*, 2004). Furthermore, Rind, D. et al. (2005) suggested that no sufficient information and research are available to evaluate impact of potential climate change on the NAO, while available research and model simulations reported an inconsistent prediction. Finally, SST is not used as a predictor neither in the statistical model nor in the PGW. Thus Z-700 and NAO were used without adjustment.

Thereafter, CAPE (in the GPD model) was increased using the relationship between temperature and precipitation quantiles identified by North and Erukhimova (2009):

$$\ln I_p = C + 0.068\ DPT + 0.5 \ln CAPE \quad (32)$$

where C is a constant value of 0.2, equals to slope coefficients of simple $\ln I_p$ and ln CAPE regression as suggested by Lepore *et al.* (2015).

The probability of extreme precipitation, and associated intensity, on each calendar day for the base climatology (derived from control years 1990-2015) and with the effects of 2^oC PGW were assessed for each region. As with the model development and validation, the Poisson model simulates the most likely days of extreme precipitation occurrence, and the GPD simulates the range of probable precipitation intensities on those days. As the Poisson model can only simulate the probability of an event, given that climatological rather than observed variables are used, we consider the extreme precipitation days to be days with the highest 1% probability of occurrence, defined by region. The Poisson model uses unchanged climatologically averaged values for NAO, and climatologically averaged DPT uplifted by 2°C. While the GPD uses climatologically averaged CAPE as modified by the relationship in Equation 32.

The results in Figure 26 (a and b) show the probability of extreme precipitation for each calendar day in the NW and SE regions. A similar pattern is apparent across all UK regions, where the highest probability of Q99 occurring is in summer. The PGW results show that the probability of occurrence of hourly extreme precipitation would increase up to 60% due to the temperature increase in all seasons, while the highest increase would occur in summer. Results for the regions NE, ME, and SW are very similar and not presented.

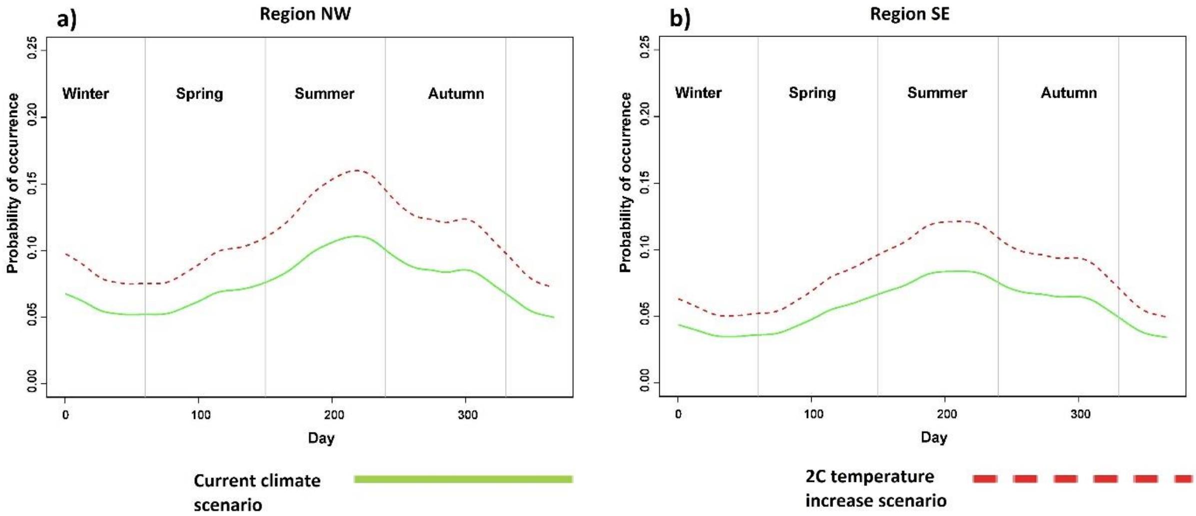

Figure 26: Comparison of daily probability of Q99 occurrence under current climate (solid line) and predicted global temperature increase of 2C (dotted line) in a) NW and b) SE. Julian days of occurrence (X-axis), and the probability of occurrence (Y-axis).

The GPD model results in Figure 27 show estimated precipitation intensity with an annual exceedance probability (AEP) of 5% (20-year return level equivalent) for each calendar day under current and PGW climate conditions. However, it should be noted that these results should be interpreted in conjunction with the Poisson model where approximately 30 days would actually occur. The result is similar for all seasons, with slight variations in northern regions (e.g. NW), while the annual probability estimates in southern regions (e.g. SE) noticeably peak in summer. Furthermore, the response to the 2^{o}C warming shows a predicted intensity increase of between 13% and 17%, at or just above C-C scaling. The highest increase occurs in SE during summer. The results indicate clearly that the intensity of hourly precipitation extremes in southern regions (e.g. SE) are more sensitive to convective conditions, which are reflected by the CAPE variable.

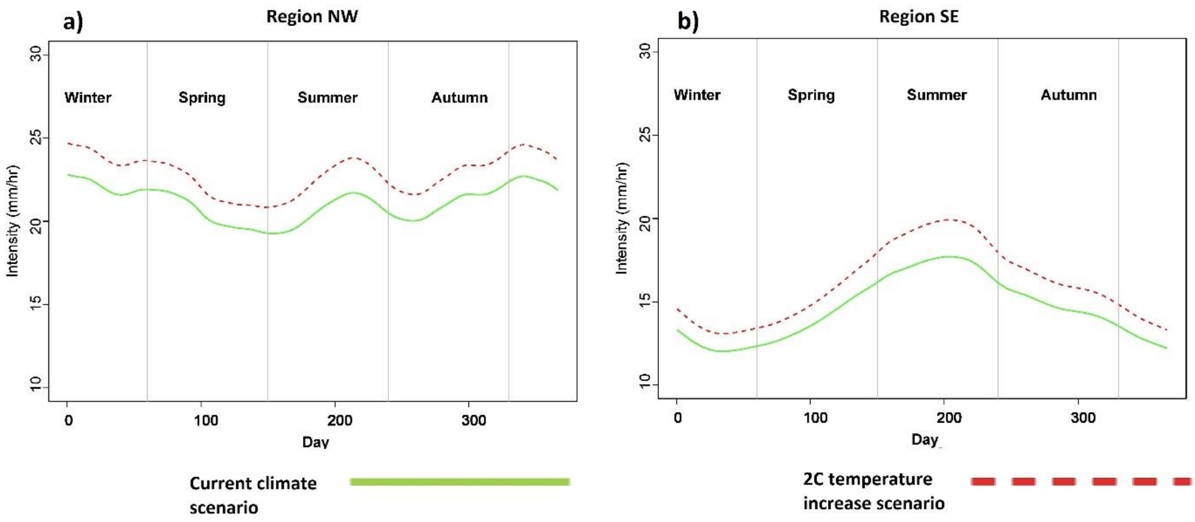

Figure 27: Comparison of extreme precipitation intensity under current climate (solid line) and predicted global temperature increase of 2C (dotted line) according to Paris agreement in a) NW and b) SE. Julian days of occurrence (X-axis), and the intensity in mm/hr (Y-axis).

5.5. Discussion and Conclusion

This research presents non-stationary Poisson-GPD models to simulate the frequency and intensity of hourly precipitation extremes in the UK. Large-scale atmospheric variables, local conditions, and seasonality including NAO, CAPE, Dew point temperature and sine/cosine Julian day, were incorporated in GLMs to estimate the statistical model parameters. Each climatic variable was selected on the basis of its physical plausibility and knowledge of atmospheric processes, then examined for statistical significance before being confirmed as a predictor. However, the statistical model results also highlighted that a longer hourly precipitation record is necessary to generate more robust results and reduce uncertainty.

Resultant Poisson and GPD statistical models generally performed well across the UK. However, greater uncertainty surrounds the predictions for northern regions (e.g. NW), where there was less significance in the correlations between hourly precipitation extremes and the selected covariates. As expected, the Poisson model across southern regions (i.e. SW and SE) identifies a noticeable peak in summer precipitation probability and intensity compared to other seasons. Seasonal extreme precipitation occurrence is similar in other regions, but there is less seasonal variability in extreme precipitation intensity. The differences between northern and southern regions are likely attributable to the different precipitation generating mechanisms in across the UK, as summarised by previous research (Blenkinsop *et al.*, 2017; Darwish *et al.*, 2018). Northern regions are mostly dominated by large-scale forcing, while central and southern regions are dominated by convective precipitation. Initial examination of other large-scale predictors (i.e. NAO, SLP, SST) indicated that there is a more important role for local conditions compared to large-scale climatic variables in the prediction of hourly extreme precipitation across the UK.

The Poisson model, which simulates the occurrence of hourly precipitation extremes, highlights that extreme hourly events have a strong dependence on both large-scale circulation (i.e. NAO and Z-700), and local-scale thermodynamic conditions reflected by the dew point temperature (DPT). This agrees with Chan *et al.* (2018b) who reported that large-scale predictors from regional climate models demonstrate skill in predicting the occurrence of extreme hourly events in convective permitting models (CPMs) for the southern UK. Furthermore, Ali *et al.* (2018) indicated a strong linkage between hourly precipitation extremes intensity and DPT, and the suitability of using DPT as an indicator of thermodynamically-driven future changes.

Simulating the intensity of hourly extremes using the GPD distribution indicates that local conditions play a major role in determining the intensity of extremes, more so than large-scale atmospheric processes. The statistical model shows that convective available potential energy (CAPE), is the best potential predictor in combination with seasonality for the intensity of UK precipitation extremes. This is consistent with the identified important role of CAPE in generating extreme precipitation over the UK (Holley *et al.*, 2014; Blenkinsop *et al.*, 2015). While convective inhibition (CIN) could also be used, CAPE and CIN are related, which would lead to collinearity within a statistical model. Using a non-stationary GPD with CAPE as a covariate to characterise extreme precipitation intensity, is a flexible and appropriate method to incorporate the complex relationship between precipitation and temperature (Lenderink and Van Meijgaard, 2008; Blenkinsop *et al.*, 2015).

The utility of the statistical model is demonstrated by examining changes in the probability and intensity of hourly extreme precipitation, at the geometric centre of each region, under a pseudo-global warming scenario of 2^{o}C utilising ECMWF reanalysis data (Dee *et al.*, 2011) from 1990-2015, to simulate hourly extreme precipitation. The

PGW approach indicates increasing probability of hourly extreme occurrence in summer up to 60%, especially in southern regions (e.g. SE). Associated annual probability estimates of hourly extreme intensity also increase; the increases are noticeably higher in the summer across southern regions. The transition from the dominance of large-scale frontal systems to localized convective rain with higher temperatures across the UK in summer and spring (Blenkinsop *et al.*, 2015), means that the seasonal peak in intensity is not as important in other regions. However, all regions indicated an increase in intensity of between 13% and 17% in response to a potential 2°C climate change scenario in the UK. This increase is consistent with the C-C scaling of observed hourly extremes across the UK, with a slight super C-C scaling during summer, especially in the south of the UK (Champion *et al.*, 2015)

Running the statistical models presented here is considerably less computer intensive than developing and running convection permitting models (CPMs). Thus, for applications where knowledge of the full dynamical processes is not essential, or where time and resources do not permit, these models could be used to downscale and simulate hourly extremes in the UK. Changes to sub-daily extremes have previously been assessed either by disaggregating daily precipitation from coarse resolution regional climate models (RCMs) or directly from regional climate models (RCMs). However, both methods are computationally expensive, and the former can introduce additional high uncertainty in disaggregating the data. A further benefit of the statistical models developed in this research is that they confirm hypotheses that were previously only tested dynamically, providing decision-makers with a general direction of future changes.

Madsen *et al.* (2013) reported that most of the existing guidelines in Europe on design floods and design precipitation are based on frequency analyses assuming stationary conditions in a certain time window. Using GLMs within the Poisson and GP distributions allows for flexible incorporation of temporally and spatially varying external predictors to account for non-stationarity in hourly extreme precipitation.

The statistical model can be used for different hydrological applications, such as estimating the future intensity or frequency of hourly extremes at a regional or site specific scale. For instance, other reanalysis datasets or PGW scenarios, or indeed model predicted values of CAPE, NAO, and DPT from coarse resolution model results, could be used to estimate future precipitation in specific regions. Alternatively, these same data and statistical relationships could be used in conjunction with regional and site specific growth curve relationships to estimate future at-site precipitation conditions, and hence likely flood impacts.

This chapter demonstrates that large-scale dynamics as well as local thermodynamic processes exert an influence over UK hourly extremes, but further understanding of these and their spatial variability is required. The results confirm the importance of seasonality, where the models suggested including the Julian day sine and cosine to simulate extremes, while the model predictions showed peaks in summer intensity and frequency compared to other seasons. Design assumptions are often made based on pre-determined seasons; decision-makers would welcome planning information where there is strong evidence for changes that might affect water resource operations (e.g. Morss *et al.*, 2018). The main challenges in this research would be having a longer quality controlled hourly data record, better characterising hourly extremes in terms of their spatial and temporal variance across the UK, and determining the best approach to modify the statistical model to account for each site specific characteristics. In particular, the spatial coverage within some regions, e.g. MW, is weak and would benefit from additional observational records. Ongoing research in Newcastle University is investigating these issues with the INTENSE project (Blenkinsop *et al.*, 2018), and will be addressed in future research.

Design guidance and adaptation plans in the UK adopt the estimates and approaches provided by Defra (Defra, 2017) and the Environment Agency (Environment Agency, 2014), where an increase in precipitation intensity (referred to in practice as an uplift) of around 10% for the period 2025-2055 is estimated relative to the 1961-90 baseline. However, these estimates are based on daily precipitation data. The results in our research show that for a 20 year return period (5% AEP), an increase of up to ~17% could occur due to 2°C global warming, suggesting that the existing guidance may not be valid for sub-daily extremes. Using output from a convection permitting climate model, Kendon *et al.* (2018) also reported that changes in hourly precipitation extremes in the UK would occur before changes in daily precipitation.

Similarly, Dale *et al.* (2017) suggest the importance of having updated and dedicated allowance estimates to account for sub-daily extreme precipitation changes, especially to reduce the risk for vulnerable locations to flash flooding and short intense precipitation such as urbanised areas. Moreover, Madsen *et al.* (2013) reported that the existing regulations and design guidelines for flood infrastructure assume stationary conditions, which is questionable in the EVT. Therefore, developing a statistical model while adopting non-stationary analyses would enhance the simulation of precipitation events and designing guidelines.

Chapter 6. Conclusion

6.1 Summary of results

This thesis has investigated sub-daily extreme precipitation in the UK to develop a statistical model which simulates the frequency and intensity patterns of hourly extreme precipitation. The thesis used a recently collated and quality controlled hourly precipitation dataset collected from 1900 gauges covering the period 1949 - 2014, distributed across the UK (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018). This is the first observed hourly precipitation dataset in the UK to have gone through an extensive series of site-specific, quality control procedures and a comparison with a gridded daily precipitation dataset to identify malfunctioning gauges and erroneously recorded readings, in particular to exclude suspect extreme precipitation totals. Furthermore, an additional criterion of having less than 15% missing or excluded data per year was implemented, as detailed in section 3.2, to ensure use of reliable and representative data. In total, the data from 197 gauges, which fulfilled the quality control procedure (Blenkinsop *et al.*, 2017; Lewis *et al.*, 2018) and the additional record completion criteria (i.e. having less than 15% missing or excluded data per year) between 1992 – 2014, have been employed in this research.

The thesis motivations, aims, and objectives were discussed in Chapter 1, and indicated a substantial need to quantify the frequency and intensity of sub-daily extreme precipitation in the UK. This was justified by the recent short, intense precipitation generated floods and the contrasting characteristics of sub-daily and daily precipitation extremes (e.g. in terms of frequency, seasonality, processes). Furthermore, the existing urban drainage design guidelines are based on daily and multi-day precipitation extremes, and using these guidelines to assess the short intense events might provide imprecise results. Moreover, climate models expect sub-daily precipitation extremes to increase at a rate exceeding that for daily extremes. This could lead to increased flooding, especially in urbanised areas.

However, and despite the importance of investigating sub-daily extreme events, relatively few studies have investigated observed sub-daily extremes compared to daily extremes due to data scarcity, while using climate models to derive projections of sub-daily extremes is computationally expensive. Thus, statistical downscaling and modelling of hourly precipitation extremes in the UK are suggested as alternatives to characterise sub-daily extremes and estimate return levels, providing the information necessary to update infrastructure design guidelines, and implement adaptation plans.

In Chapter 2, a comprehensive review of the existing literature and the latest studies related to daily and sub-daily extreme precipitation were reported. The chapter reviewed a wide range of studies which employed various approaches to investigate mean and extreme precipitation characteristics on daily timescales, and related climatic drivers in the UK. Daily mean precipitation has shown seasonally varying trends, with an increasing trend in winter, decreasing in summer, and mixed non-significant trends in autumn and spring (Gregory *et al.*, 1991; Alexander and Jones, 2000; Osborn *et al.*, 2000; Jones *et al.*, 2013). Furthermore, studies on daily timescales have indicated increases in the intensity of winter precipitation extremes, while increasing frequencies of summer extreme precipitation have been observed (Fowler and Kilsby, 2003b; Jones *et al.*, 2013; Simpson and Jones, 2014). In addition, analysing daily precipitation in the UK indicated a noticeable seasonality, especially for extremes.

Daily extremes have been investigated using point of interest and regional approaches. In the UK, the Flood Studies Report (FSR) (NERC, 1975) followed by the Flood Estimation Handbook (FEH) (Faulkner, 1999) have been used to estimate precipitation and flood frequency on-site, while the HadUKP regions (Alexander and Jones, 2000) have been used for regional analysis. On-site approaches provide a reliable estimate for mean precipitation, whereas, the regional frequency approach provides a more accurate estimate for extremes, with the benefit of using regionally pooled data, reducing the impact of missing and erroneous values, and facilitating the evaluation of ungauged locations (Alexander and Jones, 2000). Nevertheless, a recent investigation of the efficacy of the HadUKP regions by Jones *et al.* (2014), indicated that these regions are not appropriate for use with extremes even, on daily timescales. Thus, new regions were developed to assess daily extreme precipitation in the UK (Jones et al., 2014). In contrast, relatively few studies have investigated sub-daily precipitation extremes in the UK, due to short and poor quality data records (Westra *et al.*, 2013; Blenkinsop *et al.*, 2018), although there is a strong association with flash floods (Dale *et al.*, 2017).

Thus, an exploratory analysis of annual maxima (AMAX) of hourly and multi-hourly (i.e. 3-, 6-, 12-, and 24-hr) extreme precipitation accumulations in the UK was carried out in Chapter 3. Using the regional frequency analysis approach, the seasonality and diurnal cycle were investigated. The findings indicated a noticeable peak in the frequency of short-duration extremes (i.e. 1- and 3-hr) between 1400 and 1700, especially in the southern UK, which is in line with results from (Xiao et al., 2018). This peak indicates a strong relation with convection-generating mechanisms, especially in southern UK regions. Furthermore, the results showed a difference in the seasonality of short-duration (i.e. 1- and 3-hr) and long-duration precipitation extremes (i.e. 12- and 24-hr). Short-duration extremes occur mostly in summer, while long-duration extremes occur throughout late autumn and winter. This study is the first to quantify and compare the seasonality of hourly, multi-hourly, and daily (i.e. 3-, 6-, 12-, and 24-hr) extreme precipitation accumulations in the UK, and to extend the limited analysis of subdaily extremes by Blenkinsop *et al.* (2017) (Objective 1). Further, regional hourly return level estimates across the UK were calculated by fitting both the Generalized Extreme Value (GEV) and Generalized Pareto (GP) distributions, using the existing daily extreme regions of Jones *et al.* (2014). The results showed higher return level estimates for southern regions compared with other parts of the UK. In addition, the return estimates for the 24-hr extremes and daily extremes from (Jones *et al.*, 2013) showed similar results, which indicates the accuracy and reliability of the hourly used data. However, the hourly return level estimates indicated some similarity across regions with no significant differences. Moreover, hourly and daily precipitation extremes in the UK demonstrate a noticeable spatial variation in occurrence patterns and frequency. Combined, these suggest that new and potentially fewer representative regions would adequately reflect the spatial variation of UK short-duration precipitation extremes. This study is the first to introduce a formal assessment of hourly UK extreme precipitation using extreme value theory (EVT) and the existing daily extreme regions (Objectives 2 and 4).

Accordingly, new hourly UK extreme precipitation regions were defined in Chapter 4. The new regions were developed using the quality controlled hourly dataset and various extreme precipitation indices (e.g. annual 0.99 quantile, median of AMAX precipitation), geographical and topographical characteristics (i.e. latitude, longitude, elevation), rotated seasonal statistics, temperature, and weather types reflecting atmospheric and large circulations.

The five new hourly extreme precipitation regions fulfil the regional homogeneity requirements (Hosking and Wallis, 2005), while the regional delineation indicates a strong relation with the large-scale atmospheric circulation and local conditions. In addition to that, the developed regions show a clear east-west delineation in the UK, which is in line with the daily extreme precipitation regions reported by Jones *et al.* (2014) and indicate the important role of orography and the prevailing westerly winds in also characterising hourly precipitation extremes. The new regions are the first to be developed based on hourly extreme precipitation in the UK, and to reflect their spatial variation. In addition, they can serve hydrologists, climatologists, and policy makers either for formal or indicative assessment of extreme precipitation return estimates and design guidelines (Objective 3). Thereafter, the new extreme regions were employed to quantify regional hourly precipitation extremes by estimating return levels across the UK regions using the GEV and GP distributions (i.e. EVT distributions). The return level maps indicated an increasing pattern from northwest towards southeast, which supports the reported UK hourly extreme precipitation climatology published in Blenkinsop *et al.* (2017).

Moreover, the new hourly extreme precipitation regions were better able to capture variations in hourly extreme precipitation across the UK compared to the existing regions. For example, the fitted GEV and GP growth curves for the new regions indicated steeper curves in northern regions compared to southern regions. This is in contrast to growth curves for hourly precipitation extremes developed using the daily UK extreme regions (Jones *et al.*, 2014), which showed similar estimates of return level for all regions. Moreover, the results indicate the efficacy and potential capabilities of using the new regions for investigating extremes in the UK.

Accordingly, the new hourly extreme precipitation regions were used in Chapter 5 to develop a statistical model simulating the frequency and intensity of UK hourly precipitation extremes. To start with, the statistical correlation between different climatological variables and hourly extremes were explored, where the results showed that local condition variables (e.g. Convective Available Potential Energy (CAPE), dew point temperature (DPT)) have a higher correlation compared to large-scale variables (e.g. North Atlantic oscillation (NAO), sea surface temperature (SST)) across the UK. Moreover, the results confirmed the role of local climatic variables, especially the hypothesised strong relation between hourly precipitation extremes and convection-generating mechanisms (Blenkinsop et al., 2017; Darwish et al., 2018). Furthermore, the correlation between hourly extremes and climatic variables in southern regions is higher than in northern regions, especially for temperature, convection (e.g. CAPE), and water vapour content (e.g. total column water vapour (TCWV)) variables, which indicates the strong relation between hourly extremes and local scale processes in southern parts of the UK.

Thereafter, a statistical model was developed using the Poisson-GPD distribution approach, employing different potential driving climatological variables representing both the large-scale climatic circulation and local conditions. Investigating the correlation of hourly rainfall extremes with various climatological variables and employing them in the development of the model was an essential part of quantifying the behaviour of UK hourly extremes (Objectives 5 and 6).

Using various model selection and evaluation techniques (e.g. Q-Q plots, AIC) to determine the best predictors, the results showed that employing the Julian day sine and cosine, the NAO, atmospheric pressure at 700hPa height (Z-700), and DPT in the Poisson model would best simulate hourly extreme precipitation frequency. In contrast, the GPD approach employing the Julian day sine and cosine, and the convective available potential energy (CAPE) best simulates hourly extreme precipitation intensity. This indicates that the occurrence of extremes has a strong relation to both large-scale circulation (i.e. NAO and Z-700) and local conditions (i.e. DPT), while intensity is controlled by local conditions of instability (i.e. CAPE). However, including the seasonality as a predictor is essential to simulate both the frequency and intensity, which is in line with the observed seasonality in UK hourly precipitation extremes. The resultant model is the first to simulate hourly extreme frequency and intensity reliably, and could serve as an indicative alternative to dynamical climate models, with noticeably lower computational demand (Objectives 4 and 6).

Thereafter, the Poisson-GP statistical model was used to simulate hourly precipitation extremes in the UK under a simple scenario of potential climate change. The pseudo global warming (PGW) method (Kimura and Kitoh, 2007), and a scenario of 2°C increase in mean temperature as agreed in the Paris Agreement (Paris agreement, 2015) was adopted to evaluate change to the 20-yr return level estimate. The results indicated that this scenario would lead to an increase in both the frequency and the intensity of hourly precipitation extremes across the UK (e.g. NW and SE regions). Moreover, the change in the frequency of hourly extremes showed that the increase in summer is higher than other seasons across the UK.

However, intensity changes showed that the highest increase would occur in summer across the southern regions only, while the increase in northern regions would be comparable in all seasons. The future scenario indicated an increase between 13%-17% in the 20-yr return level estimates under a 2ºC warming across the UK regions (e.g. NW and SE regions), which is slightly higher than the C-C scaling rate. On the other hand, existing urban drainage guidelines in the UK (e.g. DEFRA, 2012), which are based on daily precipitation data, suggest a climate uplift of 10% for 2025-2055. Thus, the results in this research suggest that existing guidelines for hourly precipitation extremes should be reviewed. This is in line with recent research by Kendon et al. (2018), where CPMs were used to project changes to future hourly precipitation extremes. The results suggested that hourly precipitation extremes will intensify at a rate higher than both the rate of increase of daily precipitation extremes and the suggested rates for existing guidelines in the UK.

The results indicate that the developed model can capture the seasonality and spatial variation across the UK, and indicates comparable results to CPM projections, without the need for high computational requirements, through the demonstration of a very simple scenario approach. This model can be used to provide drainage authorities with a scenario or probabilistic decision making approach to address the potential changes in future precipitation.

This research 3stationary EVT methods coupled with regional frequency analysis (RFA) and downscaled climatic variables to simulate hourly extreme precipitation frequency and intensity in the UK. In addition, a demonstration of its potential application to project potential changes under a climate warming scenario is presented (Objective 4 and 7).

6.2 Results in the context of the existing literature

Statistical modelling and downscaling have been adopted widely to simulate extreme precipitation characteristics. In this research, we aimed to quantify hourly extreme precipitation intensity and frequency in the UK to enhance the existing literature, and develop a model that is predictive but simple.

The results in Chapter 3 presented the noticeable difference between hourly and daily precipitation extremes in terms of frequency and intensity patterns. These results indicate that existing approaches of using the scaling relation or simple disaggregation to simulate sub-daily extremes from daily extremes (e.g. UKCP09) might be misleading, while updated hourly extreme precipitation return estimates and urban drainage design guidelines should be developed for sub-daily precipitation. Similarly, Kendon et al. (2018) indicated that changes in sub-daily precipitation extremes would emerge sooner than daily extremes, while sub-daily precipitation rates (i.e. intensity) rather than daily accumulations should be evaluated to determine the impacts of extremes. Moreover, Dale et al. (2017) reported similar results, and indicated that existing guidelines are not designed to be applied to sub-daily precipitation. The results presented in Chapter 3 support the fact that quantifying the nature of hourly and multi-hourly extremes in the UK enhances our understanding of current extreme patterns, diurnal cycle, and seasonality in the UK. All these are within the scope of the INTENSE project (Blenkinsop et al., 2018) that is currently investigating sub-daily extremes to quantify observed historical changes and characterise sub-daily extremes on a broader, global scale.

Importantly, the newly defined hourly extreme regions in Chapter 4 are the first to employ the weather patterns of (Neal *et al.*, 2016), besides extreme precipitation indices, to delineate precipitation regions in the UK. The new regions outperform the existing daily mean (Alexander and Jones, 2000) and extreme (Jones *et al.*, 2014) regions in evaluating the return estimates and growth curves for hourly extremes. Additionally, they can be employed to estimate growth curves either using the single largest event per year (AMAX) or using precipitation over a selected threshold (POT). Moreover, existing urban drainage design guidelines focus on the single largest event per year, which might not be adequate for planning in regions under multiple consecutive intense events, particularly with climate change. Thus using the new regions provides the capability of using and comparing both approaches: AMAX and POT. It is paramount that policy makers should consider embedding both approaches in practice. Additionally, employing weather patterns in the prediction of hydrological events is well established in the literature (Vuillaume and Herath, 2017), and in this research we showed the potential of using these to reflect the relationship between large-scale atmospheric variables and hourly extreme precipitation in the UK.

Thereafter, the statistical model developed in Chapter 5, which simulates the frequency and intensity of hourly extreme precipitation in the UK could enhance ongoing research by helping to evaluate the performance of convection-permitting models (CPMs). The statistical model indicated the potential of simulating the frequency of extremes using large-scale variables (e.g. NAO, Z-700), which would allow effective targeting of CPM downscaling simulations. Recently, Chan *et al.* (2018b) employed large-scale and other variables to quantify the regression relationship between the occurrence of extreme hourly precipitation events and vertical stability and circulation predictors in the southern UK 1.5km resolution CPM, finding similar predictors were of importance in model simulations.

However, the results presented in this thesis are based on a limited precipitation record (i.e. 23 years). Providing robust quantitative estimates of the future frequency of such extremes are essential to implement adaptation planning. Thus, the statistical model developed in this study can be employed alongside the improvements in CPM simulations to, for example, create an ensemble of observational and modelling based predictions. Additionally, it could be employed to improve existing UK climate projections (e.g. as part of UKCP18), as part of improving sub-daily modelling capabilities (e.g. in projects such as INTENSE), or more widely as part of coordinated regional climate multi-model downscaling projects (e.g. CORDEX-FPS).

Moreover, the statistical model showed a strong relation between convective conditions and hourly precipitation extremes with CAPE employed to simulate extreme precipitation intensities. These results can be incorporated into ongoing research into the roles of local thermodynamics and large-scale atmospheric circulation as drivers of changes in intense precipitation through linking observational analyses with those based on CPMs. The statistical model, using CAPE among other predictors, estimated an intensity increase of between 13%-17% under a simple 2°C warming scenario, which slightly exceeds the C-C relationship and agrees with the approximate C-C scaling found by Blenkinsop *et al.* (2015) for UK hourly observations and the scaling rate obtained from a CPM by Chan *et al.* (2016) for the southern UK.

In meeting each of the objectives outlined in Chapter 1 of this thesis, the results presented here add to our knowledge of extreme precipitation in the UK. The observed hourly extreme precipitation climatology, regional growth curves, and statistical model indicate a noticeable seasonality and an increase in summer extremes with thermodynamic warming, which are consistent with future projections from dynamical climate models. Importantly, the statistical model did not assume stationarity when estimating the model parameters which is a common assumption with methods used to create the current hydrological and drainage guidelines in Europe. Thus, the statistical model could be used together with estimates of change in the model predictors from climate models to help provide robust quantitative estimates and enhance the existing literature to implement and develop the required adaptation and design guidelines under a warming climate.

6.3 Future work

Considering the nature of extreme precipitation, and the wide range of uncertainties associated with their patterns and behaviour, this research could be enhanced in several ways, to achieve a better understanding of sub-daily precipitation extremes and to employ the results further to improve the existing literature and hydrological application in practice.

6.3.1 Data collection

In this research, hourly extreme precipitation was investigated using 197 gauges across the UK representing extremes between 1992 and 2014 (i.e. only 23 years). The limited data range was necessary to ensure having a complete and representative record of hourly extremes. However, this short record was reflected in the relatively wide confidence intervals in the estimated regional growth curves, especially in regions with limited rain gauges. Furthermore, most of the hourly precipitation data in the UK is accumulated from tipping bucket data, thus, future work could include improvements in data collection and exploring the use of different datasets (e.g. gauges, radar, and satellite data). The analysis should then be expanded to include the newly collected data, which would add further value to the hourly extreme precipitation analysis. Recent research has achieved a notable advance in sub-daily precipitation data collection and quality control across the UK (e.g. Blenkinsop et al., 2017; Lewis et al., 2018), and future plans would suggest the use of the gridded dataset (Lewis *et al.*, 2018) and historical UK precipitation archive (Rodda et al., 2009) , which would facilitate the assessment of ungauged locations.

6.3.2 Seasonal assessment

This study found noticeable seasonality in hourly extreme precipitation, which is in line with the existing literature that has studied extremes, either using observations or climate models. The results illustrated a visible peak in occurrence for hourly extremes in summer, in particular for the southern UK. Investigating extreme precipitation in each season using the same dataset used in this research would limit the data availability per season. Thus, future research should take the advantage of the advancement in data collection to investigate hourly precipitation extremes seasonally using both AMAX and POT approaches, which may reflect the characteristics of extremes more closely.

6.3.3 Statistical model transferability

The statistical model in this research (Chapter 5) was developed at the centroid of the defined homogeneous regions (Chapter 4), to facilitate the consideration of different climatological variables (e.g. NAO, DPT, CAPE), which were used as predictors. The regions homogeneity was tested and indicated similar hourly extreme precipitation patterns across each region, with marginal spatial variation. The model used regionally pooled hourly precipitation data, which increases the reliability of the model and reduces the impact of spatial variation but does not necessarily allow robust local estimates. Therefore, further investigation could include determining the scaling relation between hourly precipitation extremes and the predictor variables at individual locations, to implement and transfer the model in various locations across each region.

6.3.4 Comparison with existing approaches

In this research, developing new hourly extreme precipitation regions was motivated by the inadequacy of the existing daily extreme precipitation regions to capture the spatial and temporal variation in hourly extremes across the UK. The new regions employed different extremes and indices in their construction than their daily counterparts, with the novel use of European weather patterns to delineate the new regions and provided more reliable estimates compared to existing regional assessment approaches in the UK (e.g. Alexander and Jones, 2000; Jones *et al.*, 2014). However, future work could include a comparison with existing on-site, station-centred return level estimate approaches (e.g. FEH) to augment our understanding about the impact of data scarcity in the regionalisation approach, and to provide a tool to improve and validate the current hourly extreme precipitation regions.

6.3.5 Urbanised area adaptation plans

The defined extreme regions reflect hourly extreme precipitation on a regional scale and can be used to estimate growth curves at different locations by using the scaling relation between the hourly extreme precipitation regional median (RMed) and the gauge median as described in Chapter 4. However, in urbanised areas, where short, intense precipitation is associated with flash flooding which poses a significant threat to lives and infrastructure, further investigation should be conducted to feed this information into effective adaptation plans. Future research could build on this study to assess the impact of climate change on return level estimates for different durations and return periods using the outputs of current state-of-the-art climate models to provide the predictors. Moreover, this research might be used in conjunction with the UK future projections (e.g. UKCP18) to provide decision makers an insight of potential impact across the urbanised areas.

References

Acero, F.J., García, J.A. and Gallego, M.C. (2011) 'Peaks-over-threshold study of trends in extreme rainfall over the Iberian Peninsula', *Journal of Climate*, 24(4), pp. 1089-1105.

AghaKouchak, A. and Nasrollahi, N. (2010) 'Semi-parametric and parametric inference of extreme value models for rainfall data', *Water resources management*, 24(6), pp. 1229-1249.

Akaike, H. (1981) 'Likelihood of a model and information criteria', *Journal of econometrics*, 16(1), pp. 3-14.

Akaike, H. (1992) 'Information theory and an extension of the maximum likelihood principle', in *Breakthroughs in statistics*. Springer, pp. 610-624.

Alexander, L.V. (2016) 'Global observed long-term changes in temperature and precipitation extremes: A review of progress and limitations in IPCC assessments and beyond', *Weather and Climate Extremes*, 11(Supplement C), pp. 4-16.

Alexander, L.V. and Arblaster, J.M. (2009) 'Assessing trends in observed and modelled climate extremes over Australia in relation to future projections', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 29(3), pp. 417-435.

Alexander, L.V. and Jones, P.D. (2000) 'Updated precipitation series for the UK and discussion of recent extremes', *Atmospheric science letters*, 1(2), pp. 142-150.

Alexander, L.V., Zhang, X., Peterson, T.C., Caesar, J., Gleason, B., Klein Tank, A.M.G., Haylock, M., Collins, D., Trewin, B., Rahimzadeh, F., Tagipour, A., Rupa Kumar, K., Revadekar, J., Griffiths, G., Vincent, L., Stephenson, D.B., Burn, J., Aguilar, E., Brunet, M., Taylor, M., New, M., Zhai, P., Rusticucci, M. and Vazquez-Aguirre, J.L. (2006) 'Global observed changes in daily climate extremes of temperature and precipitation', *Journal of Geophysical Research: Atmospheres*, 111(D05109).

Ali, H., Fowler, H.J. and Mishra, V. (2018) 'Global Observational Evidence of Strong Linkage Between Dew Point Temperature and Precipitation Extremes', *Geophysical Research Letters*, 45(22), pp. 12,320-12,330.

Ali, H. and Mishra, V. (2017) 'Contrasting response of rainfall extremes to increase in surface air and dewpoint temperatures at urban locations in India', *Scientific reports*, 7(1), p. 1228.

Allan, R., Tett, S. and Alexander, L. (2009) 'Fluctuations in autumn–winter severe storms over the British Isles: 1920 to present', *International Journal of Climatology*, 29(3), pp. 357-371.

Allan, R.P. and Soden, B.J. (2008) 'Atmospheric Warming and the Amplification of Precipitation Extremes', *Science*, 321(5895), pp. 1481-1484.

Allen, M.R. and Ingram, W.J. (2002) 'Constraints on future changes in climate and the hydrologic cycle', *Nature*, 419(6903), pp. 224-232.

Anagnostopoulou, C. and Tolika, K. (2012) 'Extreme precipitation in Europe: statistical threshold selection based on climatological criteria', *Theoretical and applied climatology*, 107(3-4), pp. 479-489.

Archer, D.R. and Fowler, H.J. (2018) 'Characterising flash flood response to intense rainfall and impacts using historical information and gauged data in Britain', *Journal of Flood Risk Management*, 11, pp. S121-S133.

Archer, D.R., Parkin, G. and Fowler, H.J. (2017) 'Assessing long term flash flooding frequency using historical information', *Hydrology Research*, 48(1), pp. 1-16.

Arnbjerg-Nielsen, K., Willems, P., Olsson, J., Beecham, S., Pathirana, A., Gregersen, I.B., Madsen, H. and Nguyen, V.T.V. (2013) 'Impacts of climate change on rainfall extremes and urban drainage systems: a review', *Water Science and Technology*, 68(1), pp. 16-28.

Arnell, N.W. and Gosling, S.N. (2016) 'The impacts of climate change on river flood risk at the global scale', *Climatic Change*, 134(3), pp. 387-401.

Arnone, E., Pumo, D., Viola, F., Noto, L.V. and La Loggia, G. (2013) 'Rainfall statistics changes in Sicily', *Hydrology and Earth System Sciences*, 17(7), pp. 2449-2458.

Barbero, R., Fowler, H.J., Lenderink, G. and Blenkinsop, S. (2017) 'Is the intensification of precipitation extremes with global warming better detected at hourly than daily resolutions?', *Geophysical Research Letters*, 44(2), pp. 974-983.

Barry, R.G. and Chorley, R.J. (2009) *Atmosphere, weather and climate*. Routledge.

Beckmann, B.R. and Adri Buishand, T. (2002) 'Statistical downscaling relationships for precipitation in the Netherlands and North Germany', *International Journal of Climatology*, 22(1), pp. 15-32.

Benestad, R.E. (2007) 'Novel methods for inferring future changes in extreme rainfall over Northern Europe', *Climate Research*, 34(3), pp. 195-210.

Benestad, R.E. (2010) 'Downscaling precipitation extremes', *Theoretical and Applied Climatology*, 100(1-2), pp. 1-21.

Bennett, L.J., Browning, K.A., Blyth, A.M., Parker, D.J. and Clark, P.A. (2006) 'A review of the initiation of precipitating convection in the United Kingdom', *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography*, 132(617), pp. 1001-1020.

Berg, P. and Haerter, J.O. (2013) 'Unexpected increase in precipitation intensity with temperature—A result of mixing of precipitation types?', *Atmospheric Research*, 119, pp. 56-61.

Bissolli, P. and Dittmann, E. (2001) *The objective weather type classification of the German Weather Service and its possibilities of application to environmental and meteorological investigations*.

Blackburn, M., Methven, J. and Roberts, N. (2008) 'Large-scale context for the UK floods in summer 2007', *Weather*, 63(9), pp. 280-288.

Blenkinsop, S., Chan, S.C., Kendon, E.J., Roberts, N.M. and Fowler, H.J. (2015) 'Temperature influences on intense UK hourly precipitation and dependency on large-scale circulation', *Environmental Research Letters*, 10(5), p. 054021.

Blenkinsop, S. and Fowler, H. (2013) *Vulnerability, Uncertainty, and Risk@ sQuantification, Mitigation, and Management*. ASCE.

Blenkinsop, S., Fowler, H.J., Barbero, R., Chan, S.C., Guerreiro, S.B., Kendon, E., Lenderink, G., Lewis, E., Li, X.-F. and Westra, S. (2018) 'The INTENSE project: using observations and models to understand the past, present and future of sub-daily rainfall extremes', *Advances in Science and Research*, 15, pp. 117-126.

Blenkinsop, S., Lewis, E., Chan, S.C. and Fowler, H.J. (2017) 'Quality-control of an hourly rainfall dataset and climatology of extremes for the UK', *International Journal of Climatology*, 37(2), pp. 722-740.

Brown, S., Boorman, P., Buonomo, E., Burke, E., Caesa, J., Clark, R., McDonald, R. and Perry, M. (2008) *Extremes atlas: A climatology of extremes for the UK. A baseline for UKCP09*. The Met Office, H.C. [Online]. Available at: http://ukclimateprojections.metoffice.gov.uk/media.jsp?mediaid=87920&filetype=pdf.

Brown, S.J. (2018) 'The drivers of variability in UK extreme rainfall', *International Journal of Climatology*, 38(S1), pp. e119-e130.

Brunsdon, C., McClatchey, J. and Unwin, D.J. (2001) 'Spatial variations in the average rainfall–altitude relationship in Great Britain: an approach using geographically weighted regression', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 21(4), pp. 455-466.

Burn, D.H., Mansour, R., Zhang, K. and Whitfield, P.H. (2011) 'Trends and variability in extreme rainfall events in British Columbia', *Canadian Water Resources Journal*, 36(1), pp. 67-82.

Burnham, K.P. and Anderson, D.R. (2003) *Model selection and multimodel inference: a practical information-theoretic approach*. Springer Science & Business Media.

Burt, S. (2005) 'Cloudburst upon Hendraburnick down: the Boscastle storm of 16 August 2004', *Weather*, 60(8), pp. 219-227.

Burt, T.P. and Ferranti, E.J.S. (2012) 'Changing patterns of heavy rainfall in upland areas: a case study from northern England', *International Journal of Climatology*, 32(4), pp. 518-532.

Burt, T.P., Jones, P.D. and Howden, N.J.K. (2014) 'An analysis of rainfall across the British Isles in the 1870s', *International Journal of Climatology*.

CCRA (2017) *UK Climate Change Risk Assessment 2017*. London, UK. [Online]. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/584281/uk-climate-change-risk-assess-2017.pdf (Accessed: 02/02/2019).

Champion, A.J., Allan, R.P. and Lavers, D.A. (2015) 'Atmospheric rivers do not explain UK summer extreme rainfall', *Journal of Geophysical Research: Atmospheres*, 120(14), pp. 6731-6741.

Chan, S.C., Kahana, R., Kendon, E.J. and Fowler, H.J. (2018a) 'Projected changes in extreme precipitation over Scotland and Northern England using a high-resolution regional climate model', *Climate Dynamics*, pp. 1-19.

Chan, S.C., Kendon, E.J., Fowler, H.J., Blenkinsop, S., Ferro, C.A.T. and Stephenson, D.B. (2013) 'Does increasing the spatial resolution of a regional climate model improve the simulated daily precipitation?', *Climate dynamics*, 41(5-6), pp. 1475-1495.

Chan, S.C., Kendon, E.J., Fowler, H.J., Blenkinsop, S. and Roberts, N.M. (2014a) 'Projected increases in summer and winter UK sub-daily precipitation extremes from high-resolution regional climate models', *Environmental Research Letters*, 9(8), p. 084019.

Chan, S.C., Kendon, E.J., Fowler, H.J., Blenkinsop, S., Roberts, N.M. and Ferro, C.A. (2014b) 'The value of high-resolution Met Office regional climate models in the simulation of multihourly precipitation extremes', *Journal of Climate*, 27(16), pp. 6155-6174.

Chan, S.C., Kendon, E.J., Roberts, N., Blenkinsop, S. and Fowler, H.J. (2018b) 'Large-scale predictors for extreme hourly precipitation events in convection-permitting climate simulations', *Journal of Climate*, 31(6), pp. 2115-2131.

Chan, S.C., Kendon, E.J., Roberts, N.M., Blenkinsop, S. and H.J., F. (2017) 'Synoptic predictors for extreme hourly precipitation events in convection-permitting climate simulations', *Journal of Climate*.

Chan, S.C., Kendon, E.J., Roberts, N.M., Fowler, H.J. and Blenkinsop, S. (2016) 'The characteristics of summer sub-hourly rainfall over the southern UK in a high-resolution convective permitting model', *Environmental Research Letters*, 11(9), p. 094024.

Chandler, R.E. and Wheater, H.S. (2002) 'Analysis of rainfall variability using generalized linear models: a case study from the west of Ireland', *Water Resources Research*, 38(10), pp. 10-1-10-11.

Chang, C.-P., Lei, Y., Sui, C.-H., Lin, X. and Ren, F. (2012) 'Tropical cyclone and extreme rainfall trends in East Asian summer monsoon since mid-20th century', *Geophysical Research Letters*, 39(18), pp. n/a-n/a.

Chatterton, J., Viavattene, C., Morris, J., Penning-Rowsell, E.C. and Tapsell, S.M. (2010) 'The costs of the summer 2007 floods in England'.

Cheng, L., AghaKouchak, A., Gilleland, E. and Katz, R.W. (2014) 'Non-stationary extreme value analysis in a changing climate', *Climatic change*, 127(2), pp. 353-369.

Chung, E.-S., Soden, B., Sohn, B.J. and Shi, L. (2014) 'Upper-tropospheric moistening in response to anthropogenic warming', *Proceedings of the National Academy of Sciences*, 111(32), pp. 11636-11641.

CIWEM (2016) *Rainfall Modelling Guide*. London: Urban Drainage Group- Chartered Institute of Water and Environmental Management, Urban Drainage Group-Chartered Institute of Water and Environmental Management. [Online]. Available at: http://www.ciwem.org/wp-content/uploads/2016/03/CIWEM-UDG-Rainfall-Guide-2016.pdf (Accessed: 22 July 2017).

Clark, P.U., Weaver, A.J., Brook, E., Cook, E.R., Delworth, T.L. and Steffen, K. (2008) 'Abrupt Climate Change. A report by the US Climate Change Science Program and the Subcommittee on Global Change Research', *US Geological Survey, Reston, VA*.

Coles, S., Bawa, J., Trenner, L. and Dorazio, P. (2001) *An introduction to statistical modeling of extreme values*. Springer.

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W.J., Johns, T. and Krinner, G. (2013) 'Long-term climate change: projections, commitments and irreversibility'.

Colman, A. (1997) 'Prediction of summer central England temperature from preceding North Atlantic winter sea surface temperature', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 17(12), pp. 1285-1300.

Condon, L.E., Gangopadhyay, S. and Pruitt, T. (2015) 'Climate change and non-stationary flood risk for the upper Truckee River basin', *Hydrology and Earth System Sciences*, 19(1), pp. 159-175.

Cong, R.-G. and Brady, M. (2012) 'The interdependence between rainfall and temperature: copula analyses', *The Scientific World Journal*, 2012.

Conway, D., Wilby, R.L. and Jones, P.D. (1996) 'Precipitation and air flow indices over the British Isle', *Climate Research*, 7(2), pp. 169-183.

Cropper, T., Hanna, E., Valente, M.A. and Jónsson, T. (2015) 'A daily Azores–Iceland North Atlantic Oscillation index back to 1850', *Geoscience Data Journal*, 2(1), pp. 12-24.

Cyril, M., Humphrey, L., Keith, B., John, N., Nigel, R., Peter, C., Andrew, R. and Alan, B. (2007) 'Combination of Mesoscale and Synoptic Mechanisms for Triggering an Isolated Thunderstorm: Observational Case Study of CSIP IOP 1', *Monthly Weather Review*, 135(11), pp. 3728-3749.

Dale, M. (2005) 'Impact of climate change on UK flooding and future predictions', *Proceedings of the ICE-Water Management*, 158(4), pp. 135-140.

Dale, M., Luck, B., Fowler, H.J., Blenkinsop, S., Gill, E., Bennett, J., Kendon, E. and Chan, S. (2017) 'New climate change rainfall estimates for sustainable drainage', *Proceedings of the Institution of Civil Engineers - Engineering Sustainability*, 170(4), pp. 214-224.

Dales, M.Y. and Reed, D.W. (1989) *Regional flood and storm hazard assessment*. Institute of Hydrology.

Darwish, M., Fowler, H.J., Blenkinsop, S. and Tye, M.R. (2018) 'A regional frequency analysis of UK sub-daily extreme precipitation and assessment of their seasonality', *International Journal of Climatology*, 38(13), pp. 4758–4776.

Davison, A.C. and Huser, R. (2015) 'Statistics of extremes', *Annual Review of Statistics and its Application*, 2, pp. 203-235.

de Leeuw, J., Methven, J. and Blackburn, M. (2016) 'Variability and trends in England and Wales precipitation', *International Journal of Climatology*, 36(8), pp. 2823-2836.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G. and Bauer, d.P. (2011) 'The ERA-Interim reanalysis: Configuration and performance of the data assimilation system', *Quarterly Journal of the royal meteorological society*, 137(656), pp. 553-597.

DEFRA (2012) *The UK climate change risk assessment 2012 evidence report*.

Defra, U.K. (2017) *UK Climate Change Risk Assessment 2017*. London, UK: Department for Environment, Food & Rural Affairs,

. [Online]. Available at: www.gov.uk/government/publications.

Demirdjian, L., Zhou, Y. and Huffman, G.J. (2018) 'Statistical Modeling of Extreme Precipitation with TRMM Data', *Journal of Applied Meteorology and Climatology*, 57(1), pp. 15-30.

Dittrich, R., Wreford, A. and Moran, D. (2016) 'A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward?', *Ecological Economics*, 122, pp. 79-89.

Dobler, C., Bürger, G. and Stötter, J. (2013) 'Simulating future precipitation extremes in a complex Alpine catchment', *Natural Hazards and Earth System Sciences*, 13(2), pp. 263-277.

Donat, M.G., Alexander, L.V., Yang, H., Durre, I., Vose, R., Dunn, R.J.H., Willett, K.M., Aguilar, E., Brunet, M. and Caesar, J. (2013) 'Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: The HadEX2 dataset', *Journal of Geophysical Research: Atmospheres*, 118(5), pp. 2098-2118.

Donat, M.G., Lowry, A.L., Alexander, L.V., O'Gorman, P.A. and Maher, N. (2017) 'Addendum: More extreme precipitation in the world's dry and wet regions', *Nature Climate Change*, 7(2), pp. 154-158.

Durrans, S.R. and Kirby, J.T. (2004) 'Regionalization of extreme precipitation estimates for the Alabama rainfall atlas', *Journal of Hydrology*, 295(1-4), pp. 101-107.

Durre, I., Williams, C.N., Yin, X. and Vose, R.S. (2009) 'Radiosonde-based trends in precipitable water over the Northern Hemisphere: An update', *Journal of Geophysical Research: Atmospheres (1984–2012)*, 114(D5).

Eder, B.K. (1989) 'A principal component analysis of SO2− 4 precipitation concentrations over the eastern United States', *Atmospheric Environment (1967)*, 23(12), pp. 2739-2750.

Environment Agency (2014) *Flood and coastal erosion risk management. Long-term investment scenarios (LTIS) 2014*. Environment Agency, Bristol, UK.

Esteban, P., Martin-Vide, J. and Mases, M. (2006) 'Daily atmospheric circulation catalogue for Western Europe using multivariate techniques', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 26(11), pp. 1501-1515.

Faulkner, D. (1999) *Flood estimation handbook, volume 2: Rainfall frequency estimation*. United Kingdom: Institute of Hydrology Wallingford.

Fereday, D., Chadwick, R., Knight, J. and Scaife, A.A. (2018) 'Atmospheric Dynamics is the Largest Source of Uncertainty in Future Winter European Rainfall', *Journal of Climate*, 31(3), pp. 963-977.

Ferro, C.A.T. and Segers, J. (2003) 'Inference for clusters of extreme values', *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 65(2), pp. 545-556.

Fischer, E.M. and Knutti, R. (2015) 'Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes', *Nature Climate Change*, 5, p. 560.

Fischer, E.M. and Knutti, R. (2016) 'Observed heavy precipitation increase confirms theory and early models', *Nature Climate Change*, 6, p. 986.

Flack, D.L.A., Plant, R.S., Gray, S.L., Lean, H.W., Keil, C. and Craig, G.C. (2016) 'Characterisation of convective regimes over the British Isles', *Quarterly Journal of the Royal Meteorological Society*, 142(696), pp. 1541-1553.

Forestieri, A., Lo Conti, F., Blenkinsop, S., Cannarozzo, M., Fowler, H.J. and Noto, L.V. (2018) 'Regional frequency analysis of extreme rainfall in Sicily (Italy)', *International Journal of Climatology*.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007) 'Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling', *International Journal of Climatology*, 27(12), pp. 1547-1578.

Fowler, H.J. and Ekström, M. (2009) 'Multi-model ensemble estimates of climate change impacts on UK seasonal precipitation extremes', *International Journal of Climatology*, 29(3), pp. 385-416.

Fowler, H.J. and Kilsby, C.G. (2003a) 'Implications of changes in seasonal and annual extreme rainfall', *Geophysical Research Letters*, 30(13).

Fowler, H.J. and Kilsby, C.G. (2003b) 'A regional frequency analysis of United Kingdom extreme rainfall from 1961 to 2000', *International Journal of Climatology*, 23(11), pp. 1313-1334.

Fowler, H.J. and Kilsby, C.G. (2007) 'Using regional climate model data to simulate historical and future river flows in northwest England', *Climatic Change*, 80(3-4), pp. 337-367.

Fowler, H.J. and Wilby, R.L. (2010) 'Detecting changes in seasonal precipitation extremes using regional climate model projections: Implications for managing fluvial flood risk', *Water Resources Research*, 46(3).

Francisco Javier, A., José Agustín, G. and María Cruz, G. (2011) 'Peaks-over-Threshold Study of Trends in Extreme Rainfall over the Iberian Peninsula', *Journal of Climate*, 24(4), pp. 1089-1105.

Franks, S.W. (2002) 'Identification of a change in climate state using regional flood data', *Hydrology and Earth System Sciences*, 6(1), pp. 11-16.

Frei, C., Schöll, R., Fukutome, S., Schmidli, J. and Vidale, P.L. (2006) 'Future change of precipitation extremes in Europe: Intercomparison of scenarios from regional climate models', *Journal of Geophysical Research: Atmospheres*, 111(D6), pp. n/a-n/a.

Furrer, E.M. and Katz, R.W. (2008) 'Improving the simulation of extreme precipitation events by stochastic weather generators', *Water Resources Research*, 44(12).

Gabriele, C.H., Emily, B., Richard, P.A., William, J.I., Debbie, P., Kevin, E.T., Robin, S.C., Phillip, A.A., Beena Balan, S., Andreas, B., Aiguo, D., Paul, J.D., David, E., Hayley, J.F., Elizabeth, J.K., George, J.H., Chunlei, L., Robert, M., Mark, N., Timothy, J.O., Nikolaos, S., Peter, A.S., Pier-Luigi, V., Susan, E.W., Laura, J.W., Kate, M.W. and Xuebin, Z. (2015) 'Challenges in Quantifying Changes in the Global Water Cycle', *Bulletin of the American Meteorological Society*, 96(7), pp. 1097-1115.

Galarneau, T.J., Bosart, L.F. and Schumacher, R.S. (2010) 'Predecessor Rain Events ahead of Tropical Cyclones', *Monthly Weather Review*, 138(8), pp. 3272-3297.

Gastineau, G. and Frankignoul, C. (2015) 'Influence of the North Atlantic SST variability on the atmospheric circulation during the twentieth century', *Journal of Climate*, 28(4), pp. 1396-1416.

Gillett, N.P. (2005) 'Climate modelling: northern hemisphere circulation', *Nature*, 437(7058), pp. 496-496.

Gimeno, L., Stohl, A., Trigo, R.M., Dominguez, F., Yoshimura, K., Yu, L., Drumond, A., Durán-Quesada, A.M. and Nieto, R. (2012) 'Oceanic and terrestrial sources of continental precipitation', *Reviews of Geophysics*, 50(4).

Golding, B., Clark, P. and May, B. (2005) 'The Boscastle flood: Meteorological analysis of the conditions leading to flooding on 16 August 2004', *Weather*, 60(8), pp. 230-235.

Gosling, S.N., Dunn, R., Carrol, F., Christidis, N., Fullwood, J., Gusmao, D.d., Golding, N., Good, L., Hall, T. and Kendon, L. (2011) 'Climate: Observations, projections and impacts', *Climate: Observations, projections and impacts*.

Gottschalk, L. (1985) 'Hydrological regionalization of Sweden', *Hydrological Sciences Journal*, 30(1), pp. 65-83.

Gregory, J.M., Jones, P.D. and Wigley, T.M.L. (1991) 'Precipitation in Britain: An analysis of area-average data updated to 1989', *International Journal of Climatology*, 11(3), pp. 331-345.

Grounds, M.A., LeClerc, J.E. and Joslyn, S. (2018) 'Expressing flood likelihood: return period versus probability', *Weather, climate, and society*, 10(1), pp. 5-17.

Guerreiro, S.B., Fowler, H.J., Barbero, R., Westra, S., Lenderink, G., Blenkinsop, S., Lewis, E. and Li, X.-F. (2018) 'Detection of continental-scale intensification of hourly rainfall extremes', *Nature Climate Change*, 8(9), pp. 803-807.

Guerreiro, S.B., Kilsby, C.G. and Serinaldi, F. (2014) 'Analysis of time variation of rainfall in transnational basins in Iberia: abrupt changes or trends?', *International Journal of Climatology*, 34(1), pp. 114-133.

Haagenson, E., Rajagopalan, B., Summers, R.S. and Roberson, J.A. (2013) 'Projecting demand extremes under climate change using extreme value analysis', *Journal-American Water Works Association*, 105(2), pp. E40-E50.

Haerter, J.O., Berg, P. and Hagemann, S. (2010) 'Heavy rain intensity distributions on varying time scales and at different temperatures', *Journal of Geophysical Research: Atmospheres (1984–2012)*, 115(D17).

Hailegeorgis, T.T., Thorolfsson, S.T. and Alfredsen, K. (2013) 'Regional frequency analysis of extreme precipitation with consideration of uncertainties to update IDF curves for the city of Trondheim', *Journal of Hydrology*, 498(0), pp. 305-318.

Hajani, E., Rahman, A. and Ishak, E. (2017) 'Trends in extreme rainfall in the state of New South Wales, Australia', *Hydrological Sciences Journal*, 62(13), pp. 2160-2174.

Hall, R.J. and Hanna, E. (2018) 'North Atlantic circulation indices: links with summer and winter UK temperature and precipitation and implications for seasonal forecasting', *International Journal of Climatology*, 38, pp. e660-e677.

Hallegatte, S., Green, C., Nicholls, R.J. and Corfee-Morlot, J. (2013) 'Future flood losses in major coastal cities', *Nature climate change*, 3(9), pp. 802-806.

Hand, W.H. (2005) 'Climatology of shower frequency in the British Isles at 5 km resolution', *Weather*, 60(6), pp. 153-158.

Hand, W.H., Fox, N.I. and Collier, C.G. (2004) 'A study of twentieth-century extreme rainfall events in the United Kingdom with implications for forecasting', *Meteorological Applications*, 11(1), pp. 15-31.

Hanel, M., Buishand, T.A. and Ferro, C.A.T. (2009) 'A nonstationary index flood model for precipitation extremes in transient regional climate model simulations', *Journal of Geophysical Research: Atmospheres*, 114(D15).

Hanel, M., Pavlásková, A. and Kyselý, J. (2016) 'Trends in characteristics of sub-daily heavy precipitation and rainfall erosivity in the Czech Republic', *International Journal of Climatology*, 36(4), pp. 1833-1845.

Hanna, E. and Cropper, T.E. (2017) 'North Atlantic oscillation', *Oxford Research Encyclopedia of Climate Science*.

Hardwick Jones, R., Westra, S. and Sharma, A. (2010) 'Observed relationships between extreme sub-daily precipitation, surface temperature, and relative humidity', *Geophysical Research Letters*, 37(22).

Hartmann, D.L., Klein Tank, A.M.G., Rusicucci, M., Alexander, L.V., Broenniman, B., Charabi, Y., Dentener, F.J., Dlugokencky, E.J., Easterling, D.R. and Kaplan, A. (2013) 'Observations: atmosphere and surface'.

Herring, S.C., Hoerling, M.P., Peterson, T.C. and Stott, P.A. (2014) 'Explaining extreme events of 2013 from a climate perspective', *Bulletin of the American Meteorological Society*, 95(9), pp. S1-S104.

Hertig, E., Seubert, S., Paxian, A., Vogt, G., Paeth, H. and Jacobeit, J. (2014) 'Statistical modelling of extreme precipitation indices for the Mediterranean area under future climate change', *International Journal of Climatology*, 34(4), pp. 1132-1156.

Hofstätter, M., Lexer, A., Homann, M. and Blöschl, G. (2018) 'Large-scale heavy precipitation over central Europe and the role of atmospheric cyclone track types', *International journal of climatology : a journal of the Royal Meteorological Society*, 38(Suppl Suppl 1), pp. e497-e517.

Holley, D.M., Dorling, S.R., Steele, C.J. and Earl, N. (2014) 'A climatology of convective available potential energy in Great Britain', *International Journal of Climatology*, 34(14), pp. 3811-3824.

Hollis, D. and McCarthy, M. (2017) 'UKCP09: Met Office gridded and regional land surface climate observation datasets' Met Office; Centre for Environmental Data Analysis. UK. Available at: http://catalogue.ceda.ac.uk/uuid/87f43af9d02e42f483351d79b3d6162a (Accessed: 29-11-2018).

Holt, M.A., Hardaker, P.J. and McLelland, G.P. (2001) 'A lightning climatology for Europe and the UK, 1990–99', *Weather*, 56(9), pp. 290-296.

Hosking, J.R.M. and Wallis, J.R. (2005) *Regional frequency analysis: an approach based on L-moments*. New York: Cambridge University Press.

Hulme, M. (2014) 'Attributing weather extremes to 'climate change' A review', *Progress in Physical Geography*, 38(4), pp. 499-511.

Huntingford, C., Marsh, T., Scaife, A.A., Kendon, E.J., Hannaford, J., Kay, A.L., Lockwood, M., Prudhomme, C., Reynard, N.S., Parry, S., Lowe, J.A., Screen, J.A., Ward, H.C., Roberts, M., Stott, P.A., Bell, V.A., Bailey, M., Jenkins, A., Legg, T., Otto, F.E.L., Massey, N., Schaller, N., Slingo, J. and Allen, M.R. (2014) 'Potential influences on the United Kingdom's floods of winter 2013/14', *Nature Climate Change*, 4, p. 769.

Huntington, T.G. (2006) 'Evidence for intensification of the global water cycle: review and synthesis', *Journal of Hydrology*, 319(1), pp. 83-95.

Hurrell, J.W. (1995) 'Decadal trends in the North Atlantic Oscillation: regional temperatures and precipitation', *Science*, 269(5224), pp. 676-679.

Hurrell, J.W. and Deser, C. (2010) 'North Atlantic climate variability: the role of the North Atlantic Oscillation', *Journal of Marine Systems*, 79(3), pp. 231-244.

IPCC (2007) 'Impacts, Adaptation and Vulnerability. Contribution of Working Group Ⅱ to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change', *UK and NEW YORK, USA: Cambridge University Press*.

IPCC (2012) *Managing the risks of extreme events and disasters to advance climate change adaptation : Special report of the Intergovernmental Panel on Climate Change*. Cambridge, England & New York, NY, USA: Cambridge University Press.

IPCC (2013) 'Climate change 2013 the physical science basis, working group I contribution to the fifth assessment report of the intergovernmental panel on climate change'. Cambridge University Press Cambridge, UK.

Isik, S. and Singh, V.P. (2008) 'Hydrologic regionalization of watersheds in Turkey', *Journal of Hydrologic Engineering*, 13(9), pp. 824-834.

Jackson, I.J. and Weinand, H. (1995) 'Classification of tropical rainfall stations: a comparison of clustering techniques', *International Journal of Climatology*, 15(9), pp. 985-994.

Jarvis, A., Reuter, H., Nelson, A. and Guevara, E. (2008) *Hole-filled seamless SRTM data V4. Tech. rep., International Centre for Tropical Agriculture (CIAT)*.

Jenkinson, A.F. and Collison, F.P. (1977) 'An initial climatology of gales over the North Sea', *Synoptic climatology branch memorandum*, 62, p. 18.

Johns, R.H. and Doswell, A.D. (1992) 'Severe Local Storms Forecasting', *Weather and Forecasting*, 7(4), pp. 588-612.

Johnson, F., Hutchinson, M.F., Beesley, C. and Green, J. (2016) 'Topographic relationships for design rainfalls over Australia', *Journal of Hydrology*, 533, pp. 439-451.

Jolliffe, I.T. (1990) 'Principal component analysis: a beginner's guide—I. Introduction and application', *Weather*, 45(10), pp. 375-382.

Jolliffe, I.T. (2002) 'Choosing a subset of principal components or variables', *Principal component analysis*, pp. 111-149.

Jones, M., Fowler, H.J., Kilsby, C.G. and Blenkinsop, S. (2010) 'An updated regional frequency analysis of United Kingdom extreme rainfall 1961–2009', *Proceedings of BHS 2010: Role of Hydrology in Managing Consequences of a Changing Global Environment*, pp. 110-118.

Jones, M.R., Blenkinsop, S., Fowler, H.J. and Kilsby, C.G. (2014) 'Objective classification of extreme rainfall regions for the UK and updated estimates of trends in regional extreme rainfall', *International Journal of Climatology*, 34(3), pp. 751-765.

Jones, M.R., Fowler, H.J., Kilsby, C.G. and Blenkinsop, S. (2013) 'An assessment of changes in seasonal and annual extreme rainfall in the UK between 1961 and 2009', *International Journal of Climatology*, 33(5), pp. 1178-1194.

Jones, P.D. and Conway, D. (1997) 'PRECIPITATION IN THE BRITISH ISLES: AN ANALYSIS OF AREA-AVERAGE DATA UPDATED TO 1995', *International Journal of Climatology*, 17(4), pp. 427-438.

Jones, P.D., Hulme, M. and Briffa, K.R. (1993) 'A comparison of Lamb circulation types with an objective classification scheme', *International Journal of Climatology*, 13(6), pp. 655-663.

Jones, P.D., Jonsson, T. and Wheeler, D. (1997) 'Extension to the North Atlantic oscillation using early instrumental pressure observations from Gibraltar and south-west Iceland', *International Journal of Climatology*, 17(13), pp. 1433-1450.

Jones, P.D., Kilsby, C.G., Harpham, C., Glenis, V. and Burton, A. (2009) 'UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator'.

Katz, R.W. (2010) 'Statistics of extremes in climate change', *Climatic Change*, 100(1), pp. 71-76.

Katz, R.W., Parlange, M.B. and Naveau, P. (2002) 'Statistics of extremes in hydrology', *Advances in Water Resources*, 25(8), pp. 1287-1304.

Kellagher, R.B.B., Cesses, Y., Di Mauro, M. and Gouldby, B.P. (2009) 'An urban drainage flood risk procedure-a comprehensive approach', *The WaPUG Annual Conference*. HR Wallingford, Blackpool.

Kendon, E.J., Ban, N., Roberts, N.M., Fowler, H.J., Roberts, M.J., Chan, S.C., Evans, J.P., Fosser, G. and Wilkinson, J.M. (2017) 'Do convection-permitting regional climate models improve projections of future precipitation change?', *Bulletin of the American Meteorological Society*, 98(1), pp. 79-93.

Kendon, E.J., Blenkinsop, S. and Fowler, H.J. (2018) 'When will we detect changes in short-duration precipitation extremes?', *Journal of Climate*, 31(7), pp. 2945-2964.

Kendon, E.J., Roberts, N.M., Fowler, H.J., Roberts, M.J., Chan, S.C. and Senior, C.A. (2014) 'Heavier summer downpours with climate change revealed by weather forecast resolution model', *Nature Climate Change*, 4(7), pp. 570-576.

Khaliq, M.N., Ouarda, T., Ondo, J.C., Gachon, P. and Bobée, B. (2006) 'Frequency analysis of a sequence of dependent and/or non-stationary hydro-meteorological observations: A review', *Journal of hydrology*, 329(3-4), pp. 534-552.

Kharin, V.V., Zwiers, F.W., Zhang, X. and Hegerl, G.C. (2007) 'Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations', *Journal of Climate*, 20(8), pp. 1419-1444.

Kilsby, C.G., Cowpertwait, P.S.P., O'Connell, P.E. and Jones, P.D. (1998) 'Predicting rainfall statistics in England and Wales using atmospheric circulation variables', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 18(5), pp. 523-539.

Kimura, F. and Kitoh, A. (2007) 'Downscaling by pseudo global warming method', *The Final Report of ICCAP*, 4346.

Kjeldsen, T.R., Jones, D.A. and Bayliss, A.C. (2008) *Improving the FEH statistical procedures for flood frequency estimation* (SC050050). Bristol,UK: Environment Agency Agency, E. [Online]. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/291096/scho0608boff-e-e.pdf (Accessed: 20/02/2019).

Knight, J.R., Maidens, A., Watson, P.A.G., Andrews, M., Belcher, S., Brunet, G., Fereday, D., Folland, C.K., Scaife, A.A. and Slingo, J. (2017) 'Global meteorological influences on the record UK rainfall of winter 2013–14', *Environmental Research Letters*, 12(7), p. 074001.

Knippertz, P. and Wernli, H. (2010) 'A Lagrangian Climatology of Tropical Moisture Exports to the Northern Hemispheric Extratropics', *Journal of Climate*, 23(4), pp. 987-1003.

Kuhlbrodt, T., Griesel, A., Montoya, M., Levermann, A., Hofmann, M. and Rahmstorf, S. (2007) 'On the driving processes of the Atlantic meridional overturning circulation', *Reviews of Geophysics*, 45(2).

Kunkel, K.E., Karl, T.R., Brooks, H., Kossin, J., Lawrimore, J.H., Arndt, D., Bosart, L., Changnon, D., Cutter, S.L., Doesken, N., Emanuel, K., Groisman, P.Y., Katz, R.W., Knutson, T., apos, Brien, J., Paciorek, C.J., Peterson, T.C., Redmond, K., Robinson, D., Trapp, J., Vose, R., Weaver, S., Wehner, M., Wolter, K. and Wuebbles, D. (2013) 'Monitoring and understanding trends in extreme storms: state of knowledge', *Bulletin of the American Meteorological Society*, 94(4), 2013/04//, p. 461+.

Kürbis, K., Mudelsee, M., Tetzlaff, G. and Brázdil, R. (2009) 'Trends in extremes of temperature, dew point, and precipitation from long instrumental series from central Europe', *Theoretical and Applied Climatology*, 98(1-2), pp. 187-195.

Labat, D., Goddéris, Y., Probst, J.L. and Guyot, J.L. (2004) 'Evidence for global runoff increase related to climate warming', *Advances in Water Resources*, 27(6), pp. 631-642.

Lamb, H.H. (1991) 'British Isles daily wind and weather patterns 1588, 1781–86, 1972–91, and shorter earlier sequences', *Climate Monitor*, 20, pp. 47-70.

Lapworth, A. and McGregor, J. (2008) 'Seasonal variation of the prevailing wind direction in Britain', *Weather*, 63(12), pp. 365-368.

Lavers, D.A., Allan, R.P., Villarini, G., Lloyd-Hughes, B., Brayshaw, D.J. and Wade, A.J. (2013) 'Future changes in atmospheric rivers and their implications for winter flooding in Britain', *Environmental Research Letters*, 8(3), p. 034010.

Lavers, D.A., Allan, R.P., Wood, E.F., Villarini, G., Brayshaw, D.J. and Wade, A.J. (2011) 'Winter floods in Britain are connected to atmospheric rivers', *Geophysical Research Letters*, 38(23).

Leadbetter, M.R., Weissman, I., De Haan, L. and Rootzén, H. (1989) 'On clustering of high values in statistically stationary series', *Proc. 4th Int. Meet. Statistical Climatology*, 16, pp. 217-222.

Leahy, P. and Kiely, G. (2011) 'Short Duration Rainfall Extremes in Ireland: Influence of Climatic Variability', *Water Resources Management*, 25(3), pp. 987-1003.

Lean, H.W., Clark, P.A., Dixon, M., Roberts, N.M., Fitch, A., Forbes, R. and Halliwell, C. (2008) 'Characteristics of high-resolution versions of the Met Office Unified Model for forecasting convection over the United Kingdom', *Monthly Weather Review*, 136(9), pp. 3408-3424.

Lee, S.H. and Maeng, S.J. (2003) ' Frequency analysis of extreme rainfall using L-moment. Irrigation Drain', *Irrigation Drain*, 52(3), pp. 219-230.

Leeuw, J., Methven, J. and Blackburn, M. (2015) 'Variability and trends in England and Wales precipitation', *International Journal of Climatology*.

Lenderink, G., Mok, H.Y., Lee, T.C. and Van Oldenborgh, G.J. (2011) 'Scaling and trends of hourly precipitation extremes in two different climate zones–Hong Kong and the Netherlands', *Hydrology and Earth System Sciences*, 15(9), pp. 3033-3041.

Lenderink, G. and Van Meijgaard, E. (2008) 'Increase in hourly precipitation extremes beyond expectations from temperature changes', *Nature Geoscience*, 1(8), pp. 511-514.

Lenderink, G. and Van Meijgaard, E. (2010) 'Linking increases in hourly precipitation extremes to atmospheric temperature and moisture changes', *Environmental Research Letters*, 5(2), p. 025208.

Lepore, C., Veneziano, D. and Molini, A. (2015) 'Temperature and CAPE dependence of rainfall extremes in the eastern United States', *Geophysical Research Letters*, 42(1), pp. 74-83.

Levermann, A., Griesel, A., Hofmann, M., Montoya, M. and Rahmstorf, S. (2005) 'Dynamic sea level changes following changes in the thermohaline circulation', *Climate Dynamics*, 24(4), pp. 347-354.

Lewis, E., Quinn, N., Blenkinsop, S., Fowler, H.J., Freer, J., Tanguy, M., Hitt, O., Coxon, G., Bates, P. and Woods, R. (2018) 'A rule based quality control method for hourly rainfall data and a 1 km resolution gridded hourly rainfall dataset for Great Britain: CEH-GEAR1hr', *Journal of hydrology*, 564, pp. 930-943.

Liu, C. and Allan, R.P. (2012) 'Multisatellite observed responses of precipitation and its extremes to interannual climate variability', *Journal of Geophysical Research: Atmospheres (1984–2012)*, 117(D3).

Lochbihler, K., Lenderink, G. and Siebesma, A.P. (2017) 'The spatial extent of rainfall events and its relation to precipitation scaling', *Geophysical Research Letters*, 44(16), pp. 8629-8636.

Lowe, J.A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard, T., Kaye, N., Kendon, E., Krijnen, J., Maisey, P., McDonald, R., McInnes, R., McSweeney, C., Mitchell, J.F.B., Murphy, J., Palmer, M., Roberts, C., Rostron, J., Sexton, D., Thornton, H., Tinker, J., Tucker, S., Yamazaki, K. and Belcher, S. (2018) *UKCP18 Science Overview report*. Exeter, UK: Met Office, H.C. [Online]. Available at: https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/UKCP18-Overview-report.pdf (Accessed: 03/02/2019).

Madsen, H., Arnbjerg-Nielsen, K. and Mikkelsen, P.S. (2009) 'Update of regional intensity–duration–frequency curves in Denmark: tendency towards increased storm intensities', *Atmospheric Research*, 92(3), pp. 343-349.

Madsen, H., Lawrence, D., Lang, M., Martinkova, M. and Kjeldsen, T.R. (2013) *A review of applied methods in Europe for flood-frequency analysis in a changing environment: Floodfreq COST action ES0901 European procedures for flood frequency estimation* (1906698368). Wallingford, U. K.: Centre for Ecology & Hydrology on behalf of COST

Madsen, H. and Thyregod, P. (2010) *Introduction to general and generalized linear models*. CRC Press.

Mailhot, A. and Duchesne, S. (2009) 'Design criteria of urban drainage infrastructures under climate change', *Journal of Water Resources Planning and Management*, 136(2), pp. 201-208.

Maraun, D., Osborn, T.J. and Gillett, N.P. (2008) 'United Kingdom daily precipitation intensity: improved early data, error estimates and an update from 2000 to 2006', *International Journal of Climatology*, 28(6), pp. 833-842.

Maraun, D., Rust, H.W. and Osborn, T.J. (2010a) 'Synoptic airflow and UK daily precipitation extremes', *Extremes*, 13(2), pp. 133-153.

Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, T., Themeßl, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M. and Thiele-Eich, I. (2010b) 'Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user', *Reviews of Geophysics*, 48(3), pp. n/a-n/a.

Marshall, J., Kushnir, Y., Battisti, D., Chang, P., Czaja, A., Dickson, R., Hurrell, J., McCartney, M., Saravanan, R. and Visbeck, M. (2001) 'North Atlantic climate variability: phenomena, impacts and mechanisms', *International Journal of Climatology*, 21(15), pp. 1863-1898.

May, W. (2004) 'Variability and extremes of daily rainfall during the Indian summer monsoon in the period 1901–1989', *Global and Planetary Change*, 44(1-4), pp. 83-105.

Mayes, J. (2000) 'Changing regional climatic gradients in the United Kingdom', *Geographical Journal*, 166(2), pp. 125-138.

Mayes, J. (2013) 'Regional weather and climates of the British Isles – Part 2: South East England and East Anglia', *Weather*, 68(3), pp. 59-65.

Mayes, J. and Wheeler, D. (2013) 'Regional weather and climates of the British Isles - Part 1: Introduction', *Weather*, 68(1), pp. 3-8.

Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P., Gaye, A.T., Gregory, J.M., Kitoh, A., Knutti, R., Murphy, J.M. and Noda, A. (2007) 'Global climate projections', *Climate change*, 283.

Met-Office (2016) *UK climate*. Available at: http://www.metoffice.gov.uk/public/weather/climate (Accessed: 26/01/2016).

Met Office (2007) *August 2007 UK overview*. Available at: https://www.metoffice.gov.uk/climate/uk/summaries/2007/august (Accessed: 08/02/2019).

Millar, R.B. (2011) *Maximum likelihood estimation and inference: with examples in R, SAS and ADMB*. John Wiley & Sons.

Mills, T.C. (2005) 'Modelling precipitation trends in England and Wales', *Meteorological applications*, 12(02), pp. 169-176.

Min, S.-K., Zhang, X., Zwiers, F.W. and Hegerl, G.C. (2011) 'Human contribution to more-intense precipitation extremes', *Nature*, 470(7334), pp. 378-381.

Mishra, V., Wallace, J.M. and Lettenmaier, D.P. (2012) 'Relationship between hourly extreme precipitation and local air temperature in the United States', *Geophysical Research Letters*, 39(16).

Modarres, R. and Sarhadi, A. (2011) 'Statistically-based regionalization of rainfall climates of Iran', *Global and Planetary Change*, 75(1-2), pp. 67-75.

Moncrieff, M.W. and Miller, M.J. (1976) 'The dynamics and simulation of tropical cumulonimbus and squall lines', *Quarterly Journal of the Royal Meteorological Society*, 102(432), pp. 373-394.

Morbidelli, R., Saltalippi, C., Flammini, A., Cifrodelli, M., Picciafuoco, T., Corradini, C., Casas-Castillo, M.C., Fowler, H.J. and Wilkinson, S.M. (2017) 'Effect of temporal aggregation on the estimate of annual maximum rainfall depths for the design of hydraulic infrastructure systems', *Journal of Hydrology*, 554, pp. 710-720.

Morss, R.E., Cuite, C.L., Demuth, J.L., Hallman, W.K. and Shwom, R.L. (2018) 'Is storm surge scary? The influence of hazard, impact, and fear-based messages and individual differences on responses to hurricane risks in the USA', *International journal of disaster risk reduction*, 30, pp. 44-58.

Murphy, J.M., Sexton, D.M., Jenkins, G.J., Booth, B.B., Brown, C.C., Clark, R.T., Collins, M., Harris, G.R., Kendon, E.J. and Betts, R.A. (2009) 'UK climate projections science report: climate change projections'.

Murphy, S.J. and Washington, R. (2001) 'United Kingdom and Ireland precipitation variability and the North Atlantic sea-level pressure field', *International Journal of Climatology*, 21(8), pp. 939-959.

Murray, V. and Ebi, K.L. (2012) 'IPCC special report on managing the risks of extreme events and disasters to advance climate change adaptation (SREX)', *Journal of epidemiology and community health*, 66(9), pp. 759-760.

Muschinski, T. and Katz, J.I. (2013) 'Trends in hourly rainfall statistics in the United States under a warming climate', *Nature Climate Change*, 3(6), pp. 577-580.

National Suds Working Group (2004) 'Interim code of practice for sustainable drainage systems', *Londres: National SUDS Working Group*.

Naveau, P., Nogaj, M., Ammann, C., Yiou, P., Cooley, D. and Jomelli, V. (2005) 'Statistical methods for the analysis of climate extremes', *Comptes Rendus Geoscience*, 337(10-11), pp. 1013-1022.

Neal, R., Dankers, R., Saulter, A., Lane, A., Millard, J., Robbins, G. and Price, D. (2018) 'Use of probabilistic medium-to long-range weather-pattern forecasts for identifying periods with an increased likelihood of coastal flooding around the UK', *Meteorological Applications*, 25(4), pp. 534-547.

Neal, R., Fereday, D., Crocker, R. and Comer Ruth, E. (2016) 'A flexible approach to defining weather patterns and their application in weather forecasting over Europe', *Meteorological Applications*, 23(3), pp. 389-400.

Neal, R.A. and Phillips, I.D. (2009) 'Summer daily precipitation variability over the East Anglian region of Great Britain', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 29(11), pp. 1661-1679.

NERC (1975) *Flood Studies Report,Natural Environment Research Council,*. London, UK.

Ning, L., Riddle, E.E. and Bradley, R.S. (2015) 'Projected changes in climate extremes over the northeastern United States', *Journal of Climate*, 28(8), pp. 3289-3310.

Nogaj, M., Yiou, P., Parey, S., Malek, F. and Naveau, P. (2006) 'Amplitude and frequency of temperature extremes over the North Atlantic region', *Geophysical Research Letters*, 33(10).

Norbiato, D., Borga, M., Sangati, M. and Zanon, F. (2007) 'Regional frequency analysis of extreme precipitation in the eastern Italian Alps and the August 29, 2003 flash flood', *Journal of Hydrology*, 345(3–4), pp. 149-166.

North, G.R. and Erukhimova, T.L. (2009) *Atmospheric thermodynamics: elementary physics and chemistry*. Cambridge University Press.

Northrop, P.J. (2015) 'An efficient semiparametric maxima estimator of the extremal index', *Extremes*, 18(4), pp. 585-603.

O'Gorman, P.A. and Schneider, T. (2009) 'The physical basis for increases in precipitation extremes in simulations of 21st-century climate change', *Proceedings of the National Academy of Sciences*, 106(35), pp. 14773-14777.

O’Gorman, P.A. (2015) 'Precipitation Extremes Under Climate Change', *Current Climate Change Reports*, 1(2), pp. 49-59.

Olsson, U. (2002) 'Generalized linear models', *An applied approach. Studentlitteratur, Lund*, 18.

Osborn, T.J. (2004) 'Simulating the winter North Atlantic Oscillation: the roles of internal variability and greenhouse gas forcing', *Climate Dynamics*, 22(6-7), pp. 605-623.

Osborn, T.J., Conway, D., Hulme, M., Gregory, J.M. and Jones, P.D. (1999) 'Air flow influences on local climate: observed and simulated mean relationships for the United Kingdom', *Climate Research*, 13(3), pp. 173-191.

Osborn, T.J., Hulme, M., Jones, P.D. and Basnett, T.A. (2000) 'Observed trends in the daily intensity of United Kingdom precipitation', *International Journal of Climatology*, 20(4), pp. 347-364.

Ossó, A., Sutton, R., Shaffrey, L. and Dong, B. (2018) 'Observational evidence of European summer weather patterns predictable from spring', *Proceedings of the National Academy of Sciences*, 115(1), pp. 59-63.

Paixao, E., Auld, H., Mirza, M.M.Q., Klaassen, J. and Shephard, M.W. (2011) 'Regionalization of heavy rainfall to improve climatic design values for infrastructure: case study in Southern Ontario, Canada', *Hydrological Sciences Journal*, 56(7), pp. 1067-1089.

Pall, P., Allen, M.R. and Stone, D.A. (2007) 'Testing the Clausius–Clapeyron constraint on changes in extreme precipitation under CO2 warming', *Climate Dynamics*, 28(4), pp. 351-363.

Pandey, M.D., Van Gelder, P.H.A.J.M. and Vrijling, J.K. (2003) 'Bootstrap simulations for evaluating the uncertainty associated with peaks-over-threshold estimates of extreme wind velocity', *Environmetrics*, 14(1), pp. 27-43.

Paris agreement (2015) *PARIS AGREEMENT* Paris, France. [Online]. Available at: https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

Pattison, I. and Lane, S.N. (2012) 'The relationship between Lamb weather types and long-term changes in flood frequency, River Eden, UK', *International Journal of Climatology*, 32(13), pp. 1971-1989.

Paulin, C., Yonas, B.D. and François, A. (2005) 'Downscaling Precipitation and Temperature with Temporal Neural Networks', *Journal of Hydrometeorology*, 6(4), pp. 483-496.

Pendergrass, A.G. (2018) 'What precipitation is extreme?', *Science*, 360(6393), pp. 1072-1073.

Perry, M. (2006) 'A spatial analysis of trends in the UK climate since 1914 using gridded datasets', *Climate memorandum*.

Pfahl, S., O'Gorman, P.A. and Fischer, E.M. (2017) 'Understanding the regional pattern of projected future changes in extreme precipitation', *Nature Climate Change*, 7(6), p. 423.

Pitt, M. (2008) 'The Pitt review: learning lessons from the 2007 floods', *London: Cabinet Office*.

Prein, A.F., Langhans, W., Fosser, G., Ferrone, A., Ban, N., Goergen, K., Keller, M., Tölle, M., Gutjahr, O. and Feser, F. (2015) 'A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges', *Reviews of geophysics*, 53(2), pp. 323-361.

Prein, A.F., Rasmussen, R.M., Ikeda, K., Liu, C., Clark, M.P. and Holland, G.J. (2017) 'The future intensification of hourly precipitation extremes', *Nature Climate Change*, 7(1), p. 48.

Prudhomme, C., Reynard, N. and Crooks, S. (2002) 'Downscaling of global climate models for flood frequency analysis: where are we now?', *Hydrological processes*, 16(6), pp. 1137-1150.

Raff, D.A., Pruitt, T. and Brekke, L.D. (2009) 'A framework for assessing flood frequency based on climate projection information', *Hydrology and Earth System Sciences*, 13(11), pp. 2119-2136.

Rahmstorf, S. and Coumou, D. (2011) 'Increase of extreme events in a warming world', *Proceedings of the National Academy of Sciences*, 108(44), pp. 17905-17909.

Ramos, M.C. (2001) 'Divisive and hierarchical clustering techniques to analyse variability of rainfall distribution patterns in a Mediterranean region', *Atmospheric Research*, 57(2), pp. 123-138.

Ramsbottom, D., Sayers, P. and Panzeri, M. 2012. Climate change risk assessment for the floods and coastal erosion sector. UK Climate Change Risk Assessment. Defra, London. , D, Sayers, P. and Panzeri, M. (2012) 'Climate change risk assessment for the floods and coastal erosion sector', *Defra Project Code GA0204. Report to Defra, London, UK*.

Rao, A.R. and Srinivas, V.V. (2006) 'Regionalization of watersheds by hybrid-cluster analysis', *Journal of Hydrology*, 318(1-4), pp. 37-56.

Reed, D. and Robson, A. (1999) *Procedures for flood freequency estimation, Volume 3: Statistical procedures for flood freequency estimation*. Wallingford: Institute of Hydrology.

Renard, B., Lang, M. and Bois, P. (2006) 'Statistical analysis of extreme events in a non-stationary context via a Bayesian framework: case study with peak-over-threshold data', *Stochastic environmental research and risk assessment*, 21(2), pp. 97-112.

Richardson, D., Fowler, H.J., Kilsby, C.G. and Neal, R. (2018) 'A new precipitation and drought climatology based on weather patterns', *International Journal of Climatology*, 38(2), pp. 630-648.

Riemann-Campe, K., Blender, R. and Fraedrich, K. (2011) 'Global memory analysis in observed and simulated CAPE and CIN', *International Journal of Climatology*, 31(8), pp. 1099-1107.

Rodda, H.J.E., Little, M.A., Wood, R.G., MacDougall, N. and McSharry, P.E. (2009) 'A digital archive of extreme rainfalls in the British Isles from 1866 to 1968 based on British Rainfall', *weather*, 64(3), pp. 71-75.

Rohrbeck, C., Eastoe, E.F., Frigessi, A. and Tawn, J.A. (2018) 'Extreme value modelling of water-related insurance claims', *The Annals of Applied Statistics*, 12(1), pp. 246-282.

Rootzén, H. and Katz, R.W. (2013) 'Design life level: quantifying risk in a changing climate', *Water Resources Research*, 49(9), pp. 5964-5972.

Roy, S.S. and Rouault, M. (2013) 'Spatial patterns of seasonal scale trends in extreme hourly precipitation in South Africa', *Applied Geography*, 39, pp. 151-157.

Rust, H.W., Maraun, D. and Osborn, T.J. (2009) 'Modelling seasonality in extreme precipitation', *The European Physical Journal Special Topics*, 174(1), pp. 99-111.

Salas, J.D. and Obeysekera, J. (2013) 'Revisiting the concepts of return period and risk for nonstationary hydrologic extreme events', *Journal of Hydrologic Engineering*, 19(3), pp. 554-568.

Santer, B.D., Mears, C., Wentz, F.J., Taylor, K.E., Gleckler, P.J., Wigley, T.M.L., Barnett, T.P., Boyle, J.S., Brüggemann, W. and Gillett, N.P. (2007) 'Identification of human-induced changes in atmospheric moisture content', *Proceedings of the National Academy of Sciences*, 104(39), pp. 15248-15253.

Sarhadi, A. and Heydarizadeh, M. (2014) 'Regional frequency analysis and spatial pattern characterization of Dry Spells in Iran', *International Journal of Climatology*, 34(3), pp. 835-848.

Scaife, A.A., Folland, C.K., Alexander, L.V., Moberg, A. and Knight, J.R. (2008) 'European climate extremes and the North Atlantic Oscillation', *Journal of Climate*, 21(1), pp. 72-83.

Schindler, A., Maraun, D. and Luterbacher, J. (2012) 'Validation of the present day annual cycle in heavy precipitation over the British Islands simulated by 14 RCMs', *Journal of Geophysical Research: Atmospheres*, 117(D18).

Schmittner, A. (2005) 'Decline of the marine ecosystem caused by a reduction in the Atlantic overturning circulation', *Nature*, 434(7033), pp. 628-633.

Schumacher, R.S. and Johnson, R.H. (2005) 'Organization and environmental properties of extreme-rain-producing mesoscale convective systems', *Monthly weather review*, 133(4), pp. 961-976.

Serinaldi, F. and Kilsby, C.G. (2015) 'Stationarity is undead: Uncertainty dominates the distribution of extremes', *Advances in Water Resources*, 77, pp. 17-36.

Shashikanth, K., Ghosh, S., Vittal, H. and Karmakar, S. (2016) 'Future projections of Indian summer monsoon rainfall extremes over India with statistical downscaling and its consistency with observed characteristics', *Climate Dynamics*, pp. 1-15.

Simpson, I.R. and Jones, P.D. (2012) 'Updated precipitation series for the UK derived from Met Office gridded data', *International Journal of Climatology*, 32(15), pp. 2271-2282.

Simpson, I.R. and Jones, P.D. (2014) 'Analysis of UK precipitation extremes derived from Met Office gridded data', *International Journal of Climatology*, 34(7), pp. 2438-2449.

Smithers, J.C. and Schulze, R.E. (2001) 'A methodology for the estimation of short duration design storms in South Africa using a regional approach based on L-moments', *Journal of Hydrology*, 241(1-2), pp. 42-52.

Stern (2006) *The economics of climate change, the Stern review.* . Cambridge, UK: Cambridge University Press.

Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K. and Boschung, J. (2013) *IPCC, 2013: summary for policymakers in climate change 2013: the physical science basis, contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, New York, USA.

Stull, R.B. (2018) 'Practical meteorology: an algebra-based survey of atmospheric science'.

Sugahara, S., Da Rocha, R.P. and Silveira, R. (2009) 'Non-stationary frequency analysis of extreme daily rainfall in Sao Paulo, Brazil', *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 29(9), pp. 1339-1349.

Sutton, R.T. and Dong, B. (2012) 'Atlantic Ocean influence on a shift in European climate in the 1990s', *Nature Geoscience*, 5, p. 788.

Sutton, R.T. and Hodson, D.L.R. (2005) 'Atlantic Ocean forcing of North American and European summer climate', *science*, 309(5731), pp. 115-118.

Svensson, C. and Jakob, D. (2002) 'Diurnal and seasonal characteristics of precipitation at an upland site in Scotland', *International journal of climatology*, 22(5), pp. 587-598.

Swain, D., Langenbrunner, B., David Neelin, J. and Hall, A. (2018) *Increasing precipitation volatility in twenty-first-century California*.

Tan, P.-N. (2018) *Introduction to data mining*. Pearson Education India.

Tencer, B., Weaver, A. and Zwiers, F. (2014) 'Joint occurrence of daily temperature and precipitation extreme events over Canada', *Journal of Applied Meteorology and Climatology*, 53(9), pp. 2148-2162.

Thiombiano, A.N., El Adlouni, S., St-Hilaire, A., Ouarda, T.B.M.J. and El-Jabi, N. (2017) 'Nonstationary frequency analysis of extreme daily precipitation amounts in Southeastern Canada using a peaks-over-threshold approach', *Theoretical and Applied Climatology*, 129(1), pp. 413-426.

Timmermann, A., An, S.I., Krebs, U. and Goosse, H. (2005) 'ENSO Suppression due to Weakening of the North Atlantic Thermohaline Circulation*', *Journal of Climate*, 18(16), pp. 3122-3139.

Trefry, C.M., Watkins Jr, D.W. and Johnson, D. (2005) 'Regional rainfall frequency analysis for the state of Michigan', *Journal of Hydrologic Engineering*, 10(6), pp. 437-449.

Trenberth, K.E. (2011) 'Changes in precipitation with climate change', *Climate Research*, 47(1), p. 123.

Trenberth, K.E. and Caron, J.M. (2001) 'Estimates of meridional atmosphere and ocean heat transports', *Journal of Climate*, 14(16), pp. 3433-3443.

Trenberth, K.E., Dai, A., Rasmussen, R.M. and Parsons, D.B. (2003) 'The Changing Character of Precipitation', *Bulletin of the American Meteorological Society*, 84(9), pp. 1205-1217.

Trenberth, K.E. and Shea, D.J. (2005) 'Relationships between precipitation and surface temperature', *Geophysical Research Letters*, 32(14).

Trenberth, K.E., Smith, L., Qian, T., Dai, A. and Fasullo, J. (2007) 'Estimates of the Global Water Budget and Its Annual Cycle Using Observational and Model Data', *Journal of Hydrometeorology*, 8(4), pp. 758-769.

Tye, M.R. (2015) 'Understanding the risks from extreme rainfall', *Proceedings of the Institution of Civil Engineers - Forensic Engineering*, 168(2), pp. 71-80.

Tye, M.R., Blenkinsop, S., Fowler, H.J., Stephenson, D.B. and Kilsby, C.G. (2016) 'Simulating multimodal seasonality in extreme daily precipitation occurrence', *Journal of hydrology*, 537, pp. 117-129.

U.S. Geological Survey (2012) *Atlantic meridional overturning circulation*. Available at: www.eoearth.org/view/article/150290/ (Accessed: January 19).

Utsumi, N., Seto, S., Kanae, S., Maeda, E.E. and Oki, T. (2011) 'Does higher surface temperature intensify extreme precipitation?', *Geophysical Research Letters*, 38(16).

Uvo, C.B. (2003) 'Analysis and regionalization of northern European winter precipitation based on its relationship with the North Atlantic oscillation', *International Journal of Climatology*, 23(10), pp. 1185-1194.

Vallebona, C., Pellegrino, E., Frumento, P. and Bonari, E. (2015) 'Temporal trends in extreme rainfall intensity and erosivity in the Mediterranean region: a case study in southern Tuscany, Italy', *Climatic Change*, 128(1-2), pp. 139-151.

Vallis, G.K. and Gerber, E.P. (2008) 'Local and hemispheric dynamics of the North Atlantic Oscillation, annular patterns and the zonal index', *Dynamics of atmospheres and oceans*, 44(3-4), pp. 184-212.

van Delden, A. (2001) 'The synoptic setting of thunderstorms in western Europe', *Atmospheric research*, 56(1-4), pp. 89-110.

Vellinga, M. and Wood, R.A. (2002) 'Global Climatic Impacts of a Collapse of the Atlantic Thermohaline Circulation', *Climatic Change*, 54(3), pp. 251-267.

Vogel, R.M., Yaindl, C. and Walter, M. (2011) 'Nonstationarity: flood magnification and recurrence reduction factors in the United States 1', *JAWRA Journal of the American Water Resources Association*, 47(3), pp. 464-474.

Vrac, M. and Naveau, P. (2007) 'Stochastic downscaling of precipitation: From dry events to heavy rainfalls', *Water resources research*, 43(7).

Vuillaume, J.-F. and Herath, S. (2017) 'Improving global rainfall forecasting with a weather type approach in Japan', *Hydrological sciences journal*, 62(2), pp. 167-181.

Wallace, J.M. and Hobbs, P.V. (2006) *Atmospheric science: an introductory survey*. Elsevier.

Wallis, J.R., Schaefer, M.G., Barker, B.L., Taylor, G.H. and Hydrol. Earth Syst. Sci. (HESS) 11 (1) (2007) 'Regional precipitation-frequency analysis and spatial mapping for 24-hour and 2-hour durations for Washington State', *Hydrology and Earth System Sciences*, 11(1), pp. 415-442.

Wang, C. and Dong, S. (2010) 'Is the basin-wide warming in the North Atlantic Ocean related to atmospheric carbon dioxide and global warming?', *Geophysical Research Letters*, 37(8).

Wasko, C. and Sharma, A. (2014) 'Quantile regression for investigating scaling of extreme precipitation with temperature', *Water Resources Research*, 50(4), pp. 3608-3614.

Weile, W., Bruce, T.A., Robert, K.K. and Ranga, B.M. (2004) 'The Relation between the North Atlantic Oscillation and SSTs in the North Atlantic Basin', *Journal of Climate*, 17(24), pp. 4752-4759.

Westra, S., Alexander, L.V. and Zwiers, F.W. (2013) 'Global increasing trends in annual maximum daily precipitation', *Journal of Climate*, 26(11), pp. 3904-3918.

Westra, S., Fowler, H.J., Evans, J.P., Alexander, L.V., Berg, P., Johnson, F., Kendon, E.J., Lenderink, G. and Roberts, N.M. (2014) 'Future changes to the intensity and frequency of short-duration extreme rainfall', *Reviews of Geophysics*, 52(3), pp. 522-555.

White, E.P., Enquist, B.J. and Green, J.L. (2008) 'On estimating the exponent of power-law frequency distributions', *Ecology*, 89(4), pp. 905-912.

Wi, S., Valdés, J.B., Steinschneider, S. and Kim, T.-W. (2016) 'Non-stationary frequency analysis of extreme precipitation in South Korea using peaks-over-threshold and annual maxima', *Stochastic environmental research and risk assessment*, 30(2), pp. 583-606.

Wigley, T.M.L. and Jones, P.D. (1987) 'England and Wales precipitation: a discussion of recent changes in variability and an update to 1985', *Journal of Climatology*, 7(2), pp. 1-246.

Wigley, T.M.L., Lough, J.M. and Jones, P.D. (1984) 'Spatial patterns of precipitation in England and Wales and a revised, homogeneous England and Wales precipitation series', *Journal of Climatology*, 4(1), pp. 1-25.

Wilby, R.L., O'Hare, G. and Barnsley, N. (1997) 'The North Atlantic Oscillation and British Isles climate variability, 1865–1996', *Weather*, 52(9), pp. 266-276.

Wilby, R.L., Wedgbrow, C.S. and Fox, H.R. (2004) 'Seasonal predictability of the summer hydrometeorology of the River Thames, UK', *Journal of Hydrology*, 295(1-4), pp. 1-16.

Wilks, D.S. (2011) *Statistical methods in the atmospheric sciences*. Academic press.

Willett, K.M., Jones, P.D., Thorne, P.W. and Gillett, N.P. (2010) 'A comparison of large scale changes in surface humidity over land in observations and CMIP3 general circulation models', *Environmental Research Letters*, 5(2), p. 025210.

Woollings, T. (2010) 'Dynamical influences on European climate: an uncertain future', *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 368(1924), pp. 3733-3756.

Wypych, A., Bochenek, B. and Różycki, M. (2018) 'Atmospheric Moisture Content over Europe and the Northern Atlantic', *Atmosphere*, 9(1), p. 18.

Xiao, C., Yuan, W. and Yu, R. (2018) 'Diurnal cycle of rainfall in amount, frequency, intensity, duration, and the seasonality over the UK', *International Journal of Climatology*, 38(13), pp. 4967-4978.

Xu, C.-y. (1999) 'Climate change and hydrologic models: A review of existing gaps and recent research developments', *Water Resources Management*, 13(5), pp. 369-382.

Xu, G., Osborn, T., Matthews, A. and Joshi, M. (2015) 'Different atmospheric moisture divergence responses to extreme and moderate El Niños', *Climate Dynamics*, pp. 1-18.

Yang, C., Chandler, R.E., Isham, V.S. and Wheater, H.S. (2005) 'Spatial-temporal rainfall simulation using generalized linear models', *Water Resources Research*, 41(11).

Yang, T., Shao, Q., Hao, Z.-C., Chen, X., Zhang, Z., Xu, C.-Y. and Sun, L. (2010) 'Regional frequency analysis and spatio-temporal pattern characterization of rainfall extremes in the Pearl River Basin, China', *Journal of Hydrology*, 380(3-4), pp. 386-405.

You, Q., Kang, S., Aguilar, E., Pepin, N., Flügel, W.-A., Yan, Y., Xu, Y., Zhang, Y. and Huang, J. (2011) 'Changes in daily climate extremes in China and their connection to the large scale atmospheric circulation during 1961–2003', *Climate Dynamics*, 36(11), pp. 2399-2417.

Yunus, R.M., Hasan, M.M., Razak, N.A., Zubairi, Y.Z. and Dunn, P.K. (2017) 'Modelling daily rainfall with climatological predictors: Poisson-gamma generalized linear modelling approach', *International Journal of Climatology*, 37(3), pp. 1391-1399.

Zhang, X., Hegerl, G., Zwiers, F.W. and Kenyon, J. (2005) 'Avoiding inhomogeneity in percentile-based indices of temperature extremes', *Journal of Climate*, 18(11), pp. 1641-1651.

Zheng, F., Westra, S. and Leonard, M. (2015) 'Opposing local precipitation extremes', *Nature Climate Change*, 5(5), p. 389.

Zhou, Y. and Lau, W.K.M. (2017) 'The relationships between the trends of mean and extreme precipitation', *International Journal of Climatology*, 37(10), pp. 3883-3894.

Appendices

Appendix A: Supporting figures

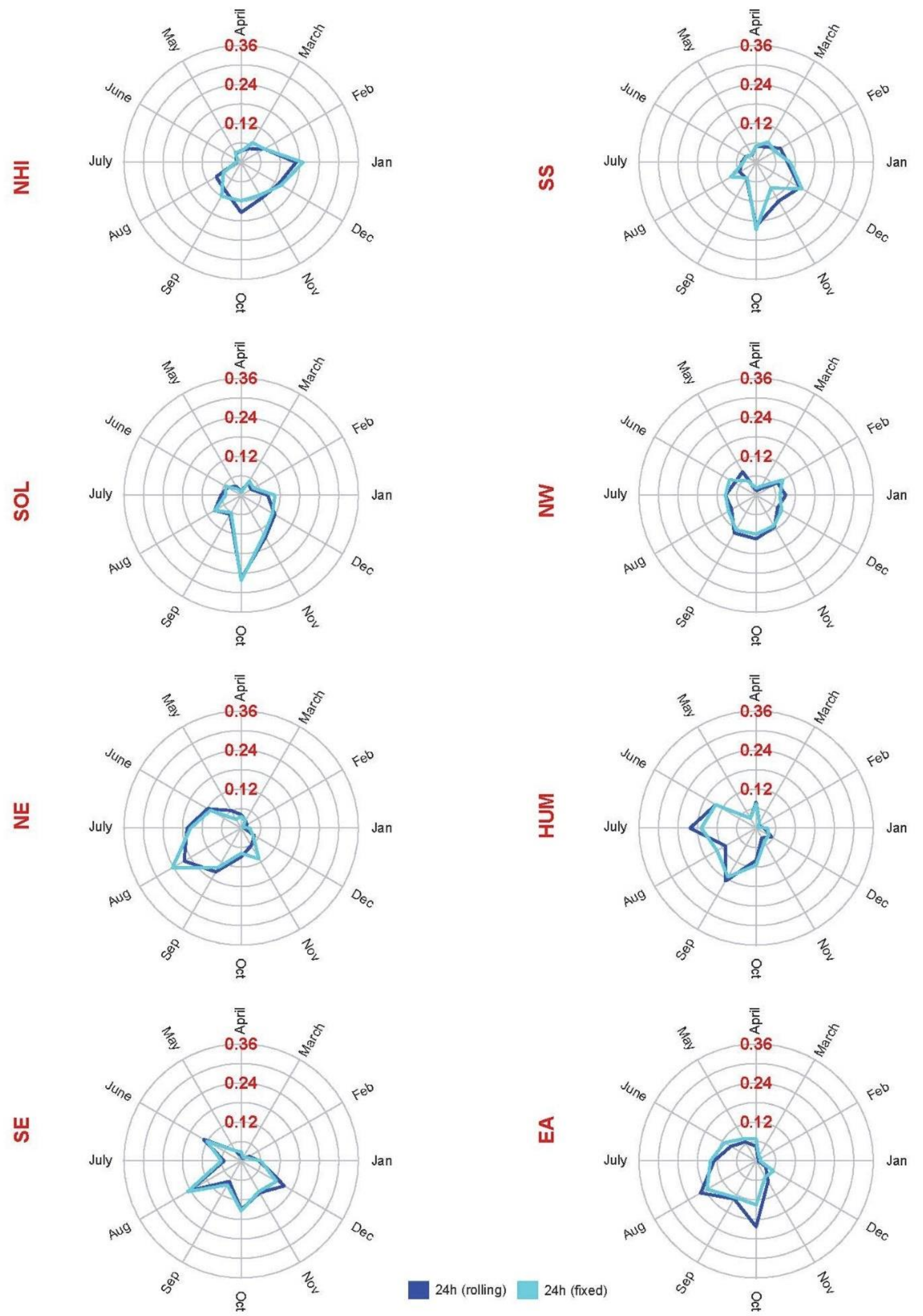

Figure A 1: Regional monthly frequency densities of 24h AMAX rolling window accumulation (dark blue) and 24h AMAX fixed window accumulation at 09:00 (cyan) in the UK. Values in red denote the frequency density scale.

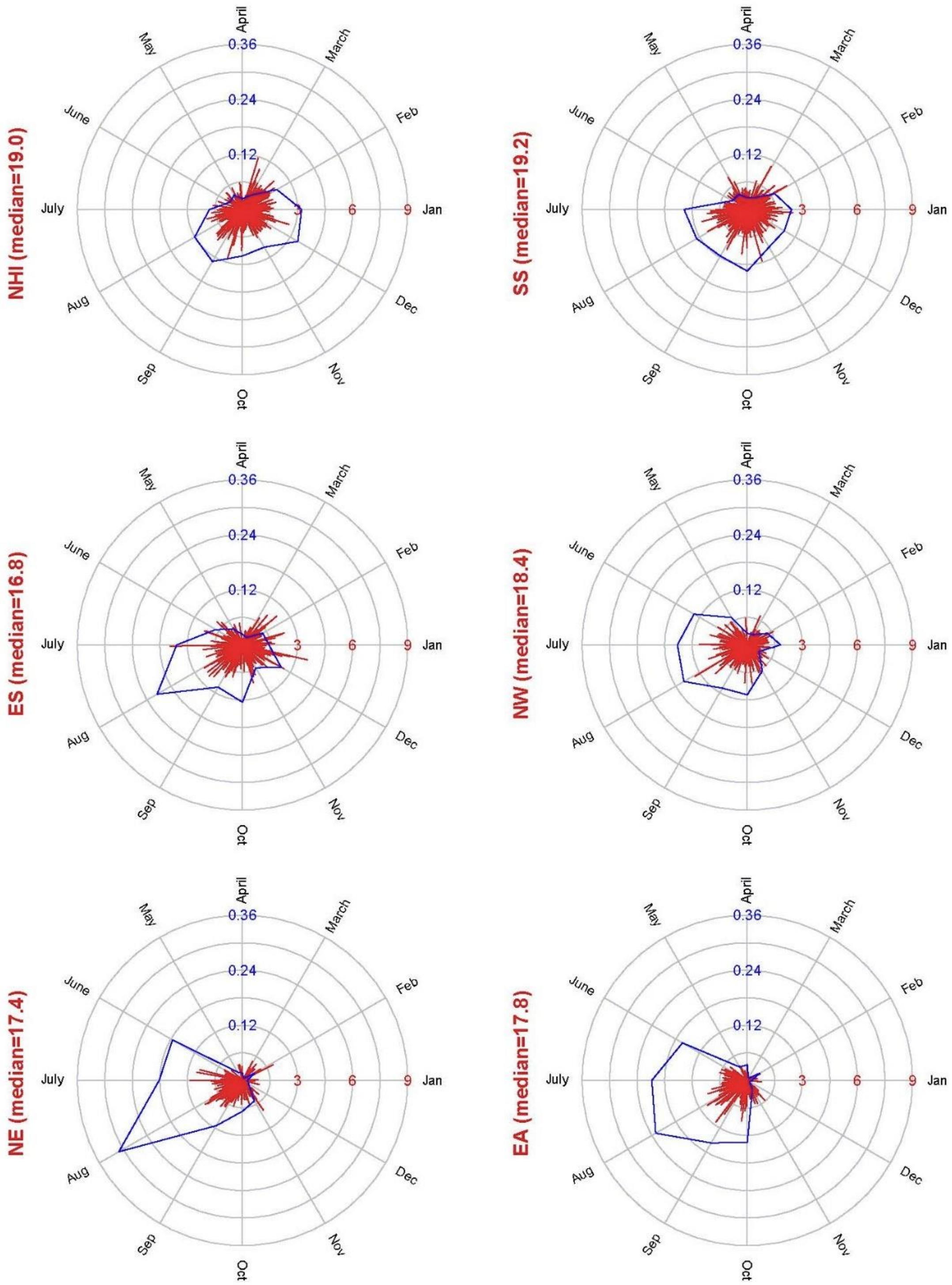

Figure A 2: Monthly 3h AMAX frequency density (blue), and 3h AMAX standardised by the regional median (red). The regional median (mm) is stated for each region, and radial lines denote 1st day of each month. Selected regions shown as in main paper.

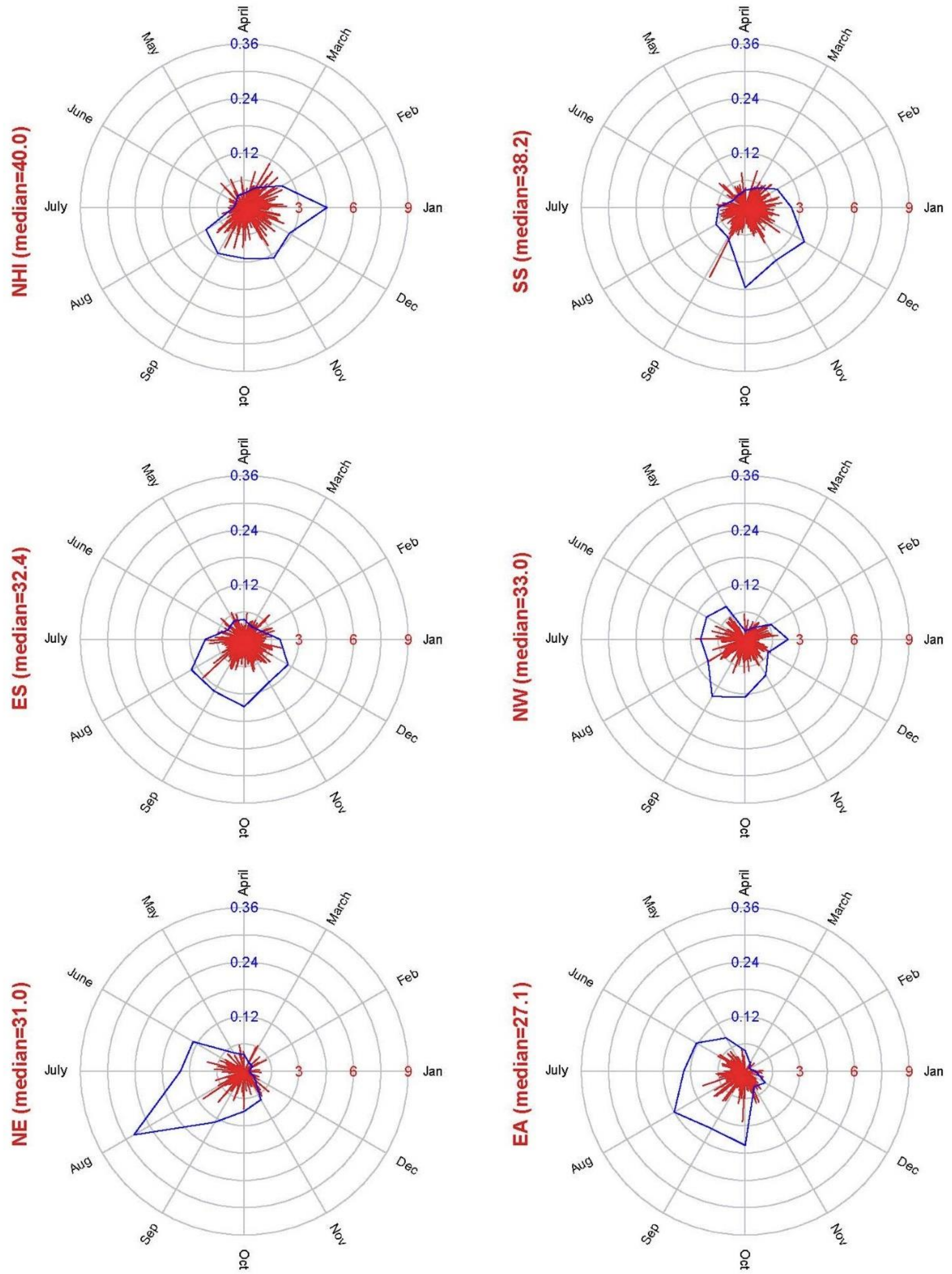

Figure A 3: Monthly 12h AMAX frequency density (blue), and 12h AMAX standardised by the regional median (red). The regional median (mm) is stated for each region, and radial lines denote 1st day of each month. Selected regions shown as in main paper.

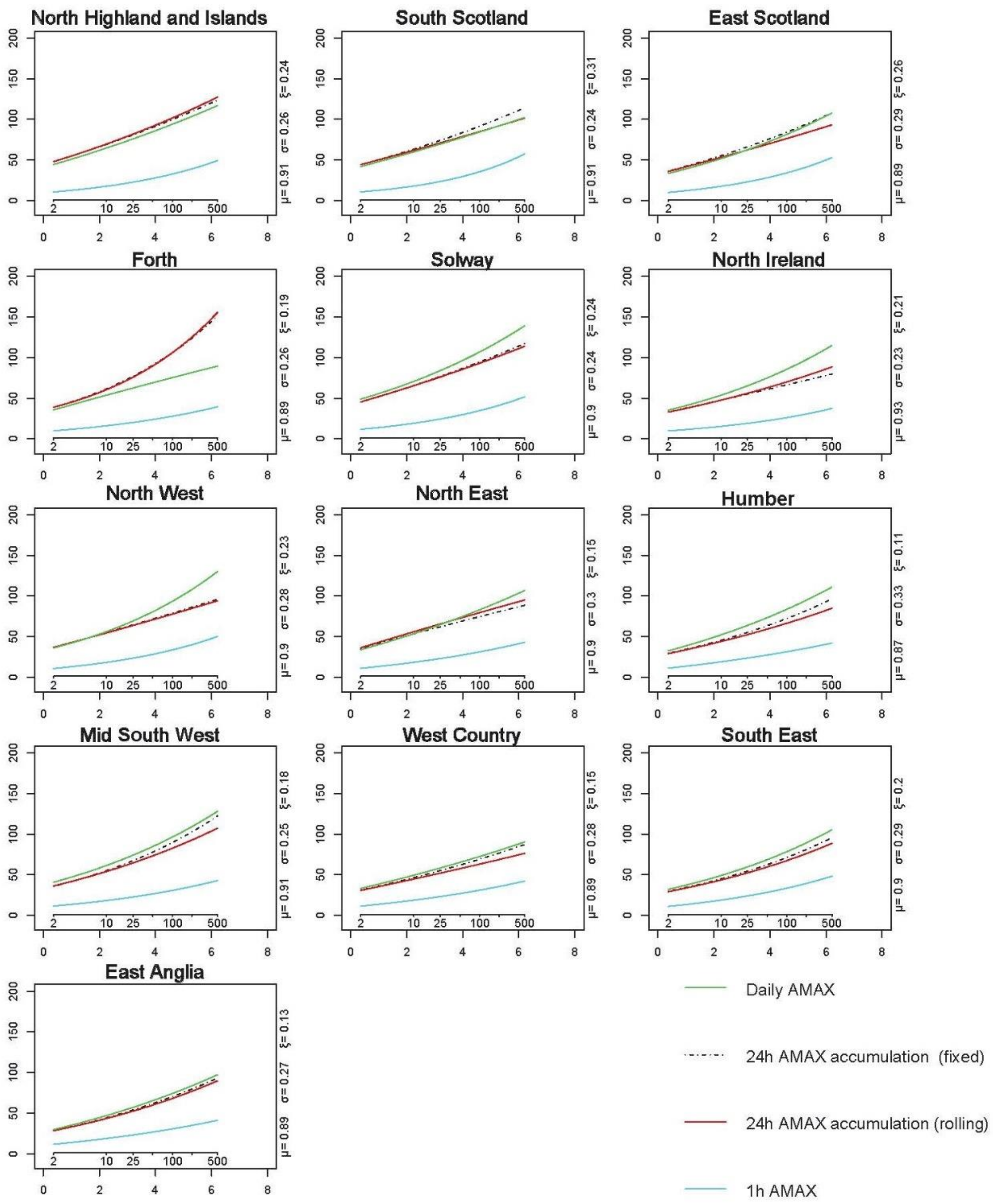

Figure A 4: Return level plots of fitted regional GEV distributions for daily AMAX (from Jones et al. 2014) (green), 24h AMAX fixed window accumulation at 09:00 (dashed black), 24h AMAX rolling window accumulation (red), and 1h AMAX (cyan). Return level estimates in mm (left y-axis), return periods in years (upper x-axis) and Gumbel reduced variate (lower x-axis). The 1h AMAX GEV distribution parameters μ, σ, and ξ are also shown.

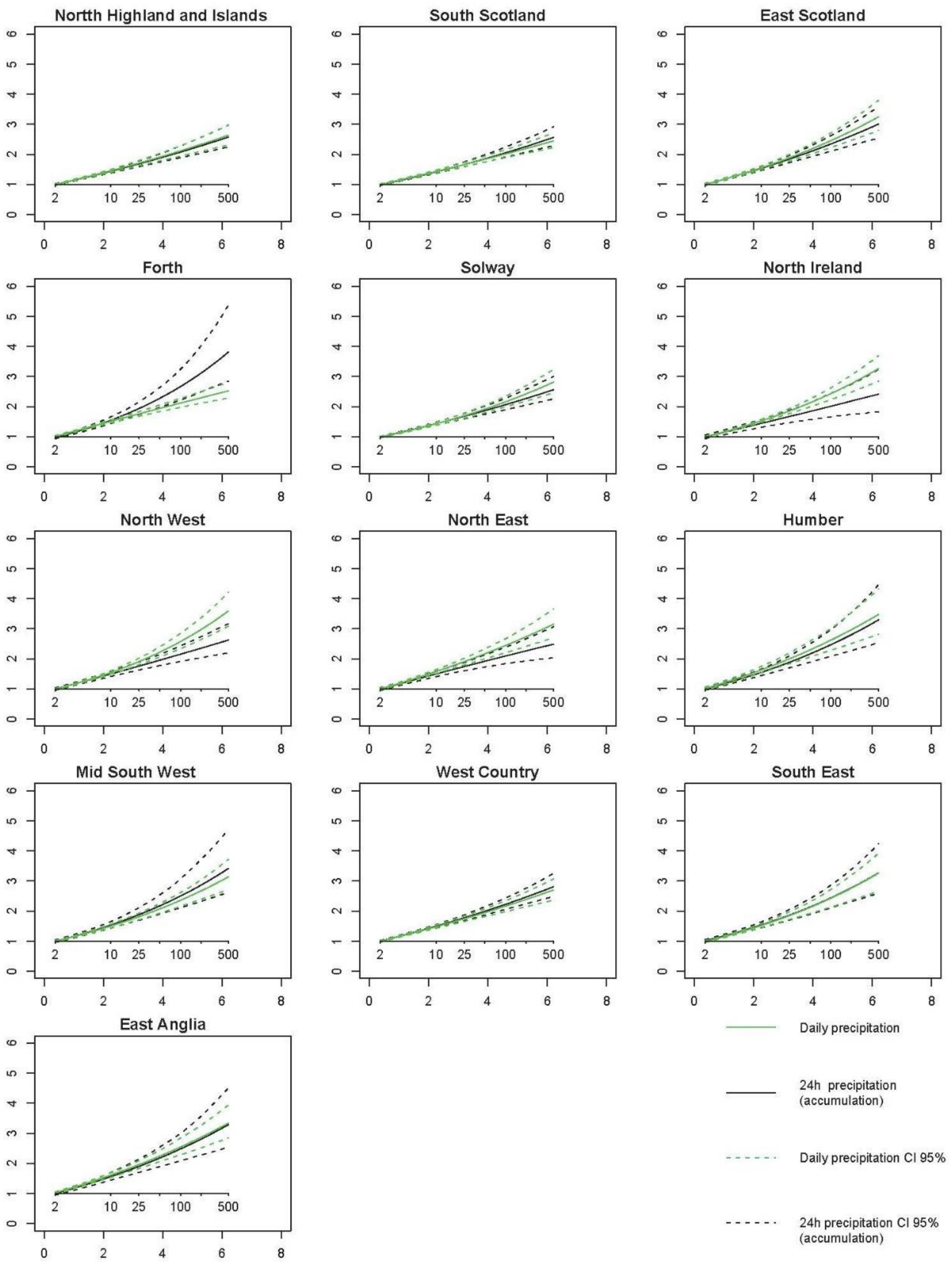

Figure A 5: Fitted growth curves for 24h standardized AMAX accumulation (black), and daily AMAX (from Jones et al. 2014) (green), and confidence interval for each distribution (dashed lines). Growth factor (y-axis), return periods in years (upper x-axis) and Gumbel reduced variate (lower x-axis). The growth curve represents the multiple increase of a given return level over an index value, here the 2-year return level.

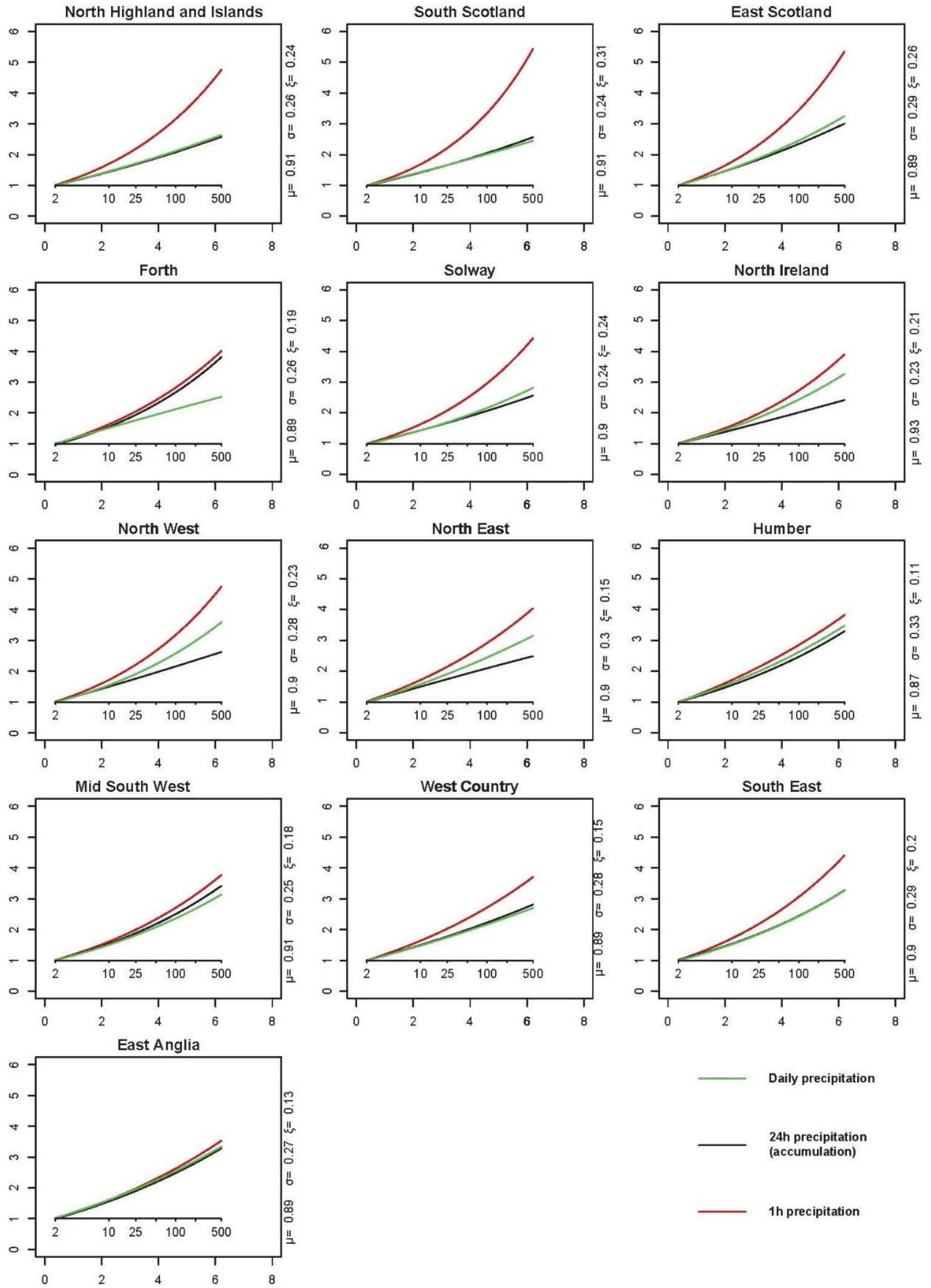

Figure A 6: Fitted growth curves for standardized 1h AMAX (red), 24h AMAX (black), and daily AMAX (from Jones et al. 2014) (green). Growth factor (left y-axis), return periods in years (upper x-axis) and Gumbel reduced variate (lower x-axis). The 1h AMAX GEV distribution parameters μ, σ, and ξ are also shown. The growth curve represents the multiple increase of a given return level over an index value, here the 2-year return level.

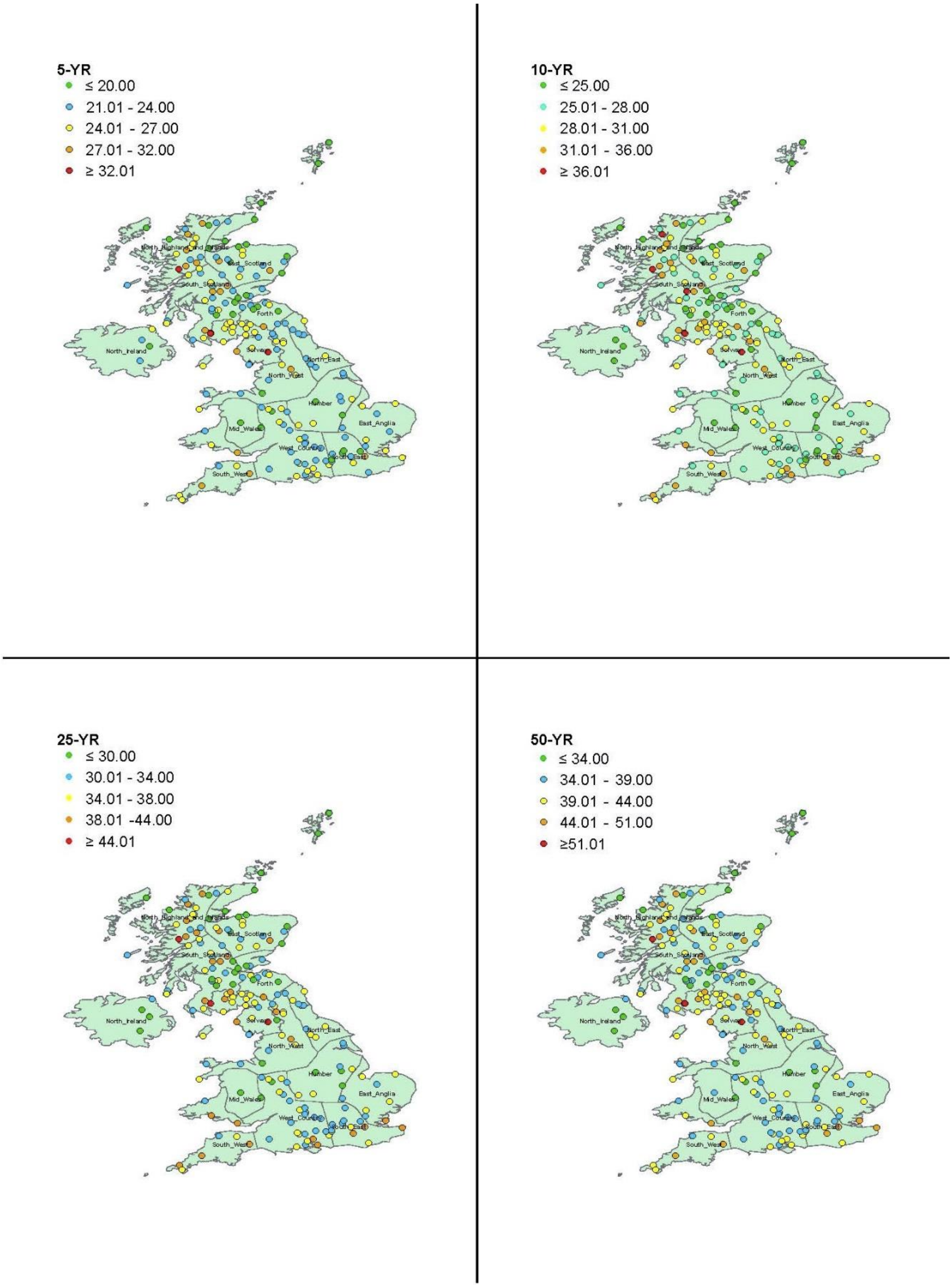

Figure A 7: Return level estimates (mm h-1) for UK 3h AMAX precipitation at each gauge for return periods of 5-, 10-, 25- and 50 years (20%, 10%, 4%, 2% annual exceedance probabilities (AEPs)). Estimates for each gauge are calculated from the fitted regional GEV growth curve multiplied by the site scaling factor (gauge RMed).

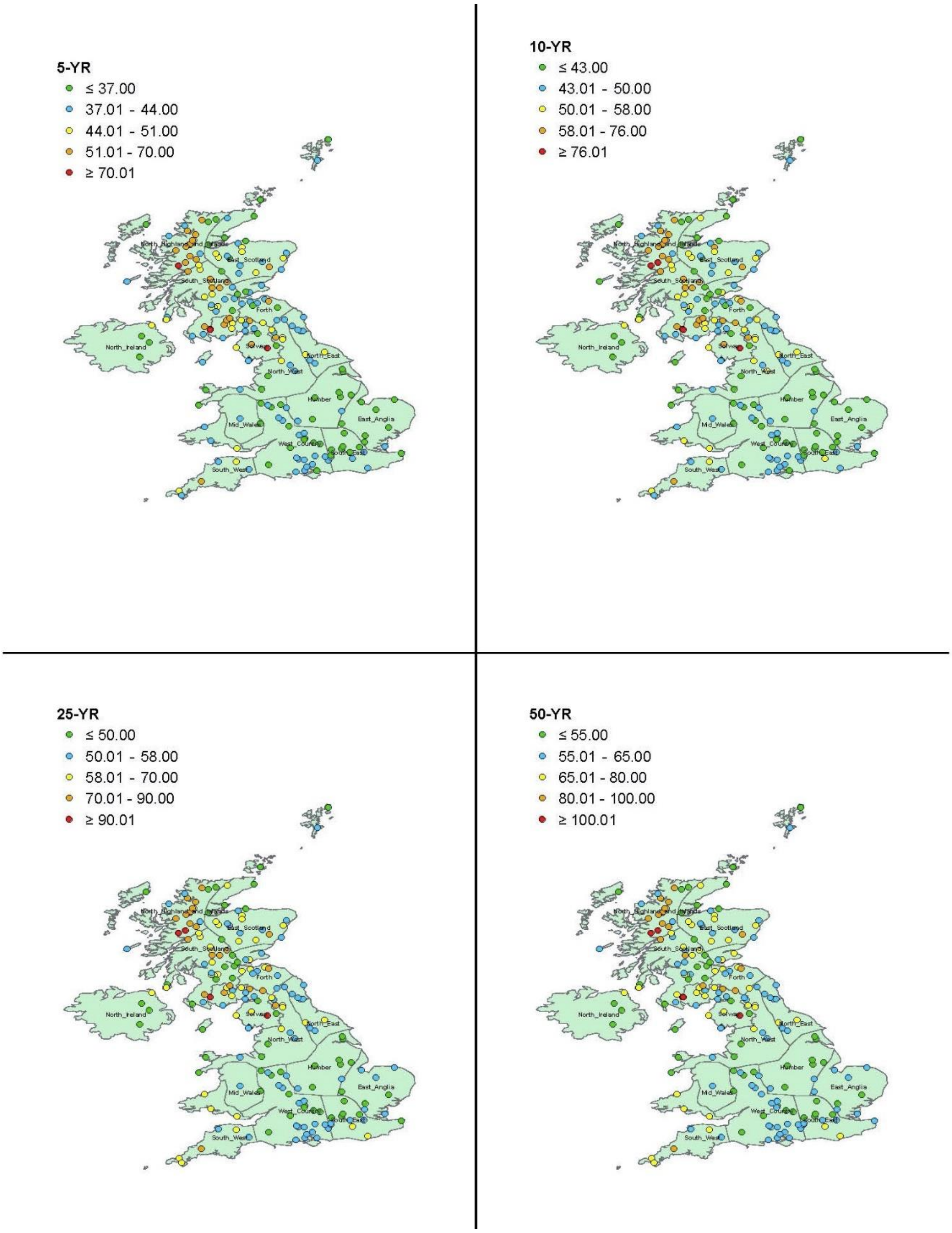

Figure A 8: Return level estimates (mm h-1) for UK 12h AMAX precipitation at each gauge for return periods of 5-, 10-, 25- and 50 years (20%, 10%, 4%, 2% annual exceedance probabilities (AEPs)). Estimates for each gauge are calculated from the fitted regional GEV growth curve multiplied by the site scaling factor (gauge RMed).

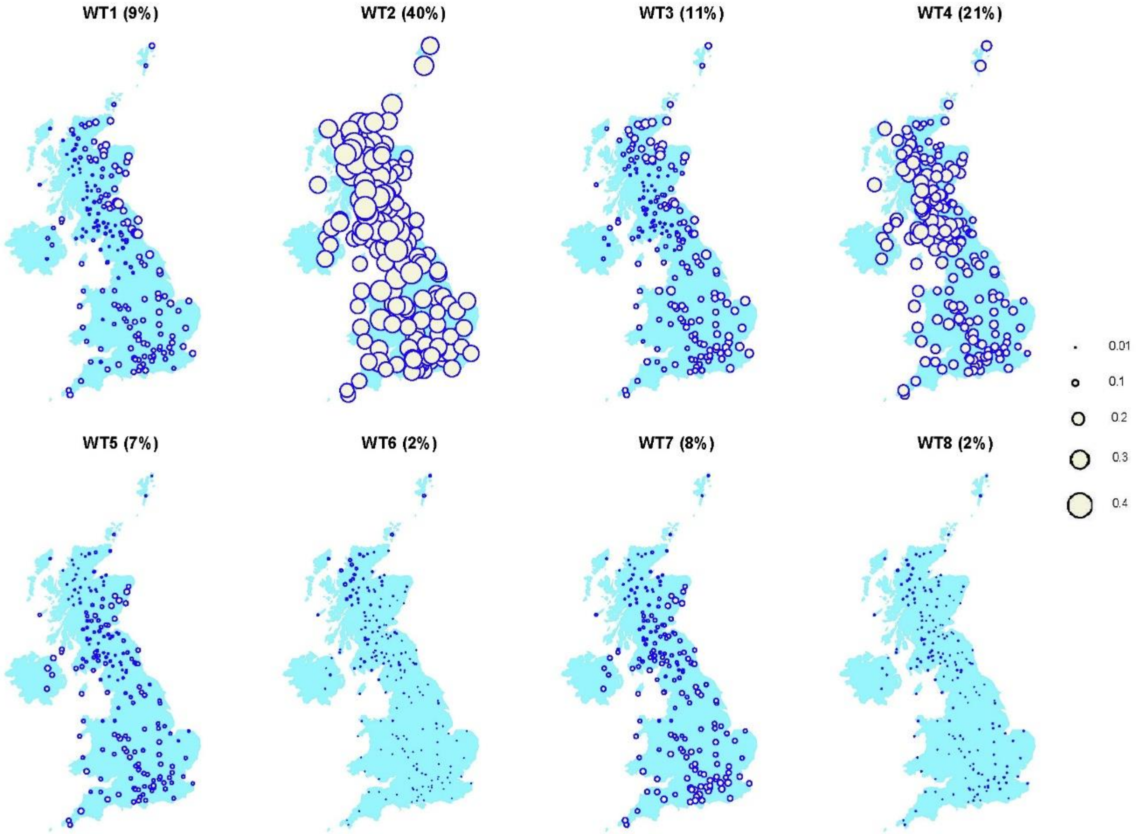

Figure A 9: Occurrence proportion of days exceeding the Q99 hourly precipitation for each gauge across the 8 weather types identified by Neal et al. (2016) in the winter half year (Oct-March, N-WQ99) over the period 1992-2014. Circle diameter indicates the proportion of events within each weather type for each gauge.

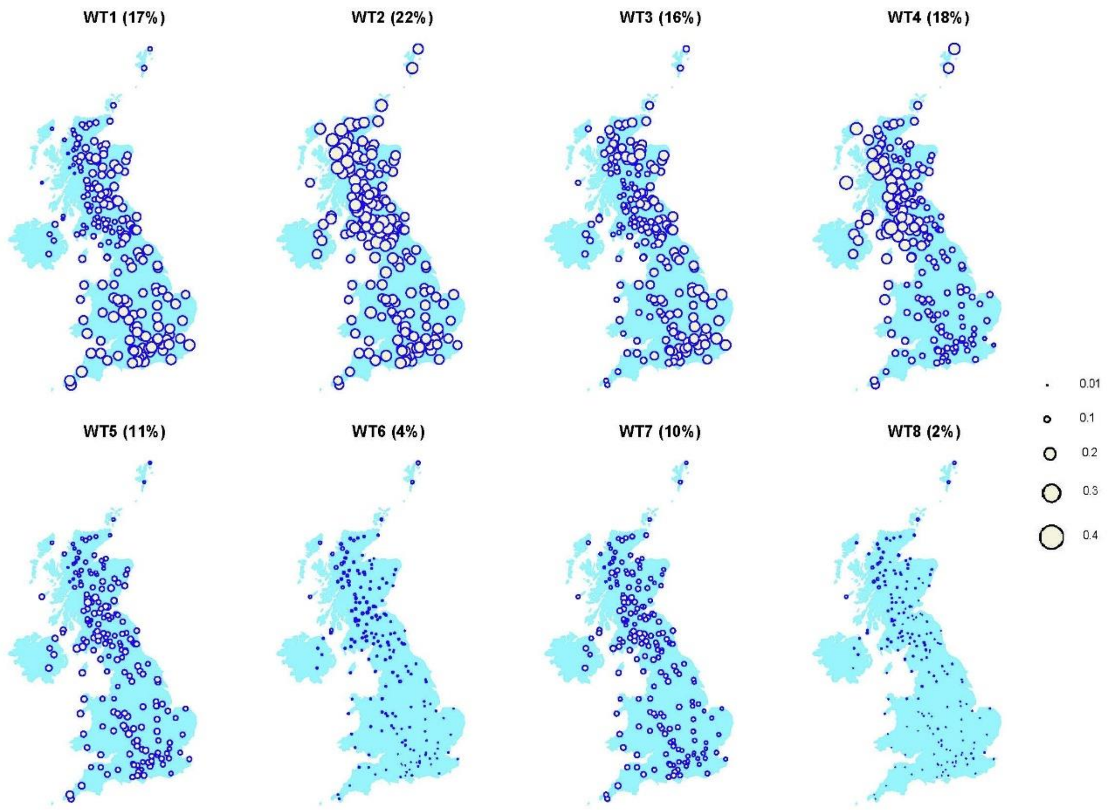

Figure A 10: Occurrence proportion of days exceeding the Q99 hourly precipitation for each gauge across the 8 weather types identified by Neal et al. (2016) in the summer half year (Apr-Sept, N-SQ99) over the period 1992-2014. Circle diameter indicates the proportion of events within each weather type for each gauge.

Appendix B: Supporting tables

	(θ)					r				
Region	**1h**	**3h**	**6h**	**12h**	**24h**	**1h**	**3h**	**6h**	**12h**	**24h**
North Highland and Islands	277	310	327	333	342	0.24	0.31	0.4	0.39	0.42
South Scotland	236	278	306	324	326	0.4	0.28	0.32	0.37	0.34
East Scotland	229	248	266	278	284	0.42	0.37	0.33	0.32	0.35
Forth	224	243	247	263	276	0.56	0.46	0.36	0.35	0.36
Solway	229	259	287	300	304	0.5	0.41	0.41	0.42	0.43
North West	216	223	243	260	281	0.48	0.35	0.28	0.24	0.24
North East	215	219	217	221	230	0.72	0.64	0.56	0.54	0.5
Humber	205	213	219	221	225	0.68	0.64	0.53	0.48	0.44
West Country	220	234	251	255	257	0.55	0.49	0.41	0.36	0.36
Mid South West	236	238	250	251	269	0.51	0.39	0.34	0.32	0.27
South East	222	235	252	266	264	0.64	0.5	0.4	0.36	0.35
East Anglia	217	220	225	230	225	0.74	0.66	0.59	0.49	0.42
North Ireland	235	244	255	269	276	0.49	0.41	0.38	0.36	0.34

Table B 1: Regional circular statistics representing seasonality of occurrence of hourly and multi-hourly AMAX events. Statistic θ denotes mean occurrence day (Julian day); r indicates the degree to which events are seasonally concentrated, ranging from 0 to 1, with higher values indicating greater concentration around θ.