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

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Short title

New UK hourly extreme precipitation regions

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Abstract

Recent flooding related to extreme precipitation in the UK has highlighted the importance of better understanding these events. Many studies have quantified annual exceedance probabilities (or return periods) for UK extreme daily precipitation using fixed regions (e.g. HadUKP) and region of interest (ROI) (e.g. Flood Estimation Handbook) approaches, although fewer have evaluated short-duration events, which are important for flash flooding. Existing UK extreme precipitation regions are based on daily datasets which have different characteristics compared to sub-daily extremes, and their application to quantify short-duration extremes may therefore be inappropriate.

We use a recently available, quality-controlled hourly precipitation dataset for the UK from 1992-2014 to derive various extreme precipitation indices (e.g. annual maxima, 0.99 quantile) which are combined with additional climatological variables (e.g. temperature), geographical characteristics (e.g. latitude), and weather patterns (WPs) to characterise the UK hourly extreme precipitation climatology and to define five new hourly extreme regions. These regions fulfil regional homogeneity and discordancy statistical measures, and reflect the dynamical processes associated with the weather pattern categorisation defined over the UK and surrounding European area. Thereafter, we use regional frequency analysis (RFA) to fit Generalised Extreme Value (GEV) and Generalised Pareto (GP) distributions to 1h annual maxima (AMAX) and 0.99 quantile (Q99) precipitation, respectively, to calculate regional annual probability estimates (AEP) for 20%, 10% and 2% (i.e. 5-, 10-, and 50-year return periods).

The new regions capture the spatial variation of hourly precipitation across the UK. Furthermore, the AEP estimates using both distributions are similar for each region. Finally, the WPs associated with the frequency and intensity of the most extreme hourly precipitation accumulations are not identical to results reported by others for daily precipitation.
Recent decades have seen increases in the frequency and intensity of extreme precipitation in different regions which have led to increases in flooding (Alexander et al., 2006; Min et al., 2011; IPCC, 2012; Westra et al., 2014). Such increases impose challenges including, wastewater and flood risk management, planning and design of hydraulic structures, drainage systems, and flood control structures, making accurate precipitation estimates paramount (Durrans and Kirby, 2004; Madsen et al., 2009).

Most observational studies examining historic changes in precipitation have done so at daily and multi-day timescales due, in part, to the limited availability of high-resolution precipitation observations and to sparsely distributed gauge networks (Westra et al., 2014).

Globally, most analyses of sub-daily precipitation extremes have reported increasing intensities (Westra et al., 2014; Tye et al., 2018). For example, in Europe, Madsen et al. (2009) reported an intensification in Denmark, consistent with 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 have reported similar increasing intensities in North America (Burn et al., 2011; Kunkel et al., 2013; Muschinski and Katz, 2013; Barbero et al., 2017), and in Australia (Hajani et al., 2017; Guerreiro et al., 2018). This intensification may be associated with the enhanced moisture holding capacity of a warmer atmosphere as described by the Clausius-Clapeyron (CC) relationship. Consequently, the scaling relationship between temperature and sub-daily extremes has been extensively investigated in observational analyses (Hardwick Jones et al., 2010; Lenderink et al., 2011; Mishra et al., 2012; Blenkinsop et al., 2015; Barbero et al., 2017). Describing these by air temperature or dew point temperature (DPT) is controversial (e.g. Lenderink and Van Meijgaard, 2010; Ali and Mishra, 2017). Recently; DPT is favoured as it is less dependent on the assumption of constant humidity (Ali et al., 2018).

The frequency analysis of historical precipitation events is crucial in planning and designing infrastructure (Smithers and Schulze, 2001). However, extreme precipitation analysis based on observational data is strongly influenced by data quality, record length, and data spatial and temporal distribution (Westra et al., 2014; O’Gorman, 2015). Overcoming limitations imposed by short or non-existent records
of precipitation, regional frequency analysis (RFA) is often used in preference to at-site frequency analyses (Hosking and Wallis, 2005; Sarhadi and Heydarizadeh, 2014). With RFA, extreme precipitation data from gauges within a region are pooled, typically standardised by an index precipitation (e.g. median). A single frequency distribution is then fitted to the pooled data, assuming the standardised precipitation data form a homogeneous region. Spatial variation of precipitation depths within the region is accounted for by variation in the index across the region. RFA may be undertaken using geographically fixed or flexible regions. With the former approach, the standardised precipitation frequency curve (known as the precipitation growth curve) is uniform across the region, whereas with the latter, referred to as the region-of-influence (ROI) approach, regions are defined individually for the point where the precipitation frequency estimate is needed. Consistent with recent research on the communication of risks (e.g. Grounds et al., 2018), we use the term annual exceedance probability (AEP) throughout this paper in preference to return period or recurrence interval to describe the RFA results.

Various researchers have used the fixed-region RFA methodology successfully to estimate the AEP of extremes (e.g. Fowler and Kilsby, 2003; Lee and Maeng, 2003; Trefry et al., 2005; Norbiato et al., 2007; Jones et al., 2014). This approach involves data pooling within pre-defined 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, 2003; 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, therefore; derived a new 14 regions to analyse daily extremes. Similarly, Darwish et al. (2018) presented a similar argument that Jones et al. (2014) regions are not suitable for analysing sub-daily precipitation extremes, motivating this research. Furthermore, recent floods from intense storms (e.g. Newcastle City Council, 2013), and the contrasting characteristics (e.g. frequency, seasonality, and processes) of
sub-daily and daily precipitation extremes (e.g. Blenkinsop et al., 2017; Darwish et al., 2018), indicate the need for new sub-daily extreme regions to derive more accurate AEP estimates than those obtained from regions based on daily precipitation. Moreover, climate models project sub-daily precipitation extremes to increase at a rate exceeding that for daily extremes (Kendon et al., 2018), which could lead to increased flooding, especially in urbanised areas. Thus, defining new sub-daily extreme regions would facilitate a timely provision of more accurate estimates.

This paper uses an objective clustering of precipitation gauges and undertake a RFA of extreme precipitation, as in Jones et al. (2014), to identify new, statistically homogeneous regions for UK hourly precipitation extremes, which reflect the spatial variation of hourly extremes and estimates of AEPs. These regions are identified from different climatological and site characteristics, including extreme precipitation intensity and frequency, seasonality measures, and prevailing weather patterns (WPs) to reflect the spatial and temporal characteristics of hourly precipitation. This should provide a better regional estimates of extreme hourly precipitation.

2- Data

This study uses variables describing at-site climatological characteristics (e.g. precipitation, temperature), site characteristics (e.g. location, elevation), and large-scale conditions (e.g. 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 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. Consequently, a total of 197 rain gauges distributed across the UK covering the period 1992-2014 were investigated.
Site characteristics including the longitude and latitude of each rain gauge were derived from gauges’ metadata. However, not all gauges were accompanied by elevation data, therefore 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 precipitation gauge, corresponding series of UK 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 (Hollis and McCarthy, 2017).

Atmospheric circulation over the North Atlantic Ocean has a strong effect on weather over Western Europe, affecting air flow and moisture content, which in turn control precipitation patterns (Scaife et al., 2008; Hurrell and Deser, 2010; Woollings, 2010). Weather patterns developed from climatic variables (i.e. mean sea level pressure (MSLP), wind speed, and wind direction) have long been used (e.g. Lamb, 1972; Lamb, 1991; Bissolli and Dittmann, 2001) for different purposes including: assessing UK precipitation and global meteorological relationships (Jones et al., 1993; Kelly et al., 1997; Barrow and Hulme, 2014; Knight et al., 2017), investigating future European precipitation (Fereday et al., 2018), forecasting UK coastal floods (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 the UK and surrounding European area into 30 WPs, deriving a smaller set of 8 WPs, using K-means clustering, for the purposes of evaluating forecasts. The MSLPs associated with each WP have only subtle differences in some cases, making the smaller set of generalised weather conditions more appropriate for analyses of the type presented in this paper. Using the classification of 30 WPs resulted in small sample sizes whereas using 8 provided a reasonable sample of events across the patterns, which assess the relationship between WPs and hourly extremes reliably. Therefore, the subset of 8 WPs summarising the prevalent circulation conditions over the UK each day 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.

3- Methodology

As noted in Section 1, RFA may be undertaken either using fixed, homogeneous regions, or be defined flexibly, using the ROI approach. Both methods have been used in the analysis of UK precipitation extremes. The Flood Studies Report (FSR) (NERC, 1975) analysis of precipitation frequency was based on a subtle regionalisation scheme, in which two geographically fixed regions were supplemented by the pooling of precipitation data according to the value of the index precipitation (estimated 5-year return period precipitation depth). The FSR was subsequently replaced with the Flood Estimation Handbook (FEH) (Faulkner, 1999), which adopted a ROI approach to both precipitation and flood frequency analysis.

Recently, the FEH was updated with FEH13 based on the outputs of the project “Reservoir safety: long return period rainfall” (Stewart et al., 2013) to overcome the issues encountered when estimating rare events by the original FEH model (Stewart et al., 2008; Prosdocimi et al., 2017). The FEH13 methods are the current industry standard for precipitation frequency estimation in the UK, widely used by practitioners.

Both the FEH and FEH13 precipitation frequency procedures adopt the focused rainfall growth extension (FORGEX) method (Reed et al., 1999). This pools data from expanding circular regions centred on the point of interest to generate estimates for long return periods (Svensson and Jones, 2010). The size of a region is a trade-off between keeping a region small, and therefore relevant, and avoiding excessive extrapolation beyond the information available in the region to obtain accurate results (Reed et al., 1999). While less convenient to apply, the ROI approach avoids discontinuities at regional boundaries, and focuses the analysis on the site of interest (Stewart et al., 1999). However, having enough data in the circular regions is challenging, especially for short-duration precipitation and coastal regions (Svensson and Jones, 2010; Hailegeorgis et al., 2013). It also does not necessarily produce statistically homogeneous regions as it does not account for the spatial variability of precipitation arising, for example, as a result of topographical or climatological variations (Kyselý et al., 2011; Cristiano et al., 2017).
Noting these limitations, we apply a statistical approach to cluster gauges with similar characteristics together and create fixed homogeneous regions as has been widely used 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 to the standard methodology, here, the frequency of occurrence of UK WPs is used to delineate the new regions to ensure the reflection of hourly extreme precipitation statistical and physical behaviour.

The following sections describe the process of selecting appropriate variables (Section 3.1), identification of new homogeneous regions (Section 3.2), and the estimation of regional AEP for UK hourly extreme precipitation (Section 3.3).

### 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). Therefore, researchers investigating daily extremes have employed related climatic variables to capture the behaviour of extremes (Wigley et al., 1984; Dales and Reed, 1989; Reed and Robson, 1999; Maraun et al., 2008; Jones et al., 2014). Similarly, extreme hourly UK precipitation displays noticeable geographical and seasonal variability, with most hourly extremes occurring in summer, especially in southern and eastern regions (Blenkinsop et al., 2017; Darwish et al., 2018). This seasonality is associated with various 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 south and south-eastern areas where extremes tend to be more strongly dominated by short-duration, convective precipitation occurring in summer (Jones et al., 2014; Darwish et al., 2018).

In this research, statistics for different climatological variables are investigated, while 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 were considered prior to further analysis.
Firstly, the geographical and topographical characteristics, latitude (Lat), longitude (Lon) and elevation (Elev), were determined for each gauge as detailed in Section 2 (see also Table 1). Previous examination of UK hourly and daily extremes used annual maxima (AMAX), the 0.99 wet day/hour quantiles (Q99) (e.g. 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 (e.g. Blenkinsop et al., 2017). Here, the median AMAX (RMed) and the 0.99 wet hour (i.e. total hourly precipitation ≥ 1mm) 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 declustered hourly precipitation maxima (retaining 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 (θ), and the overall dispersion (r) of the events around θ. Circular statistics were calculated for each gauge using hourly precipitation greater than annual Q99. Values of r closer to 1 (0) indicate a higher (lower) concentration of events around θ, and therefore a stronger (weaker) seasonal signal.

The median of maximum and minimum recorded temperature values (Tmax, Tmin) on the Q99 precipitation days was also 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 CC relationship, which states a 6-7% increase in atmospheric moisture holding capacity per 1°C increase in temperature, under constant relative humidity. Table 1 provides a summary and description of the selected variables.
To reduce the number of investigated variables, 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 1 were rescaled by dividing each variable value by its corresponding median before analysing the PCs.

Thereafter, different combinations of the variables in Table 1 were investigated, using the variable loadings to determine the most representative combination, and avoid using any redundant variables. The combinations assessed the efficacy of using similar variables (e.g. Q99 and SQ99, Tmax and Tmin) in the PCA, by assessing the total explained variance. For instance, the PCA results (i.e. PC loadings and total explained variance; not shown), indicate 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 1 were retained for use. The loadings, shown in Table 2, indicate the association between the original variables and the new linear combinations along with the proportion of variance explained by each PC. Combinations which achieved the highest explained variance (i.e. shaded variables in Table 1), were chosen for further analysis.

3.2. Clustering Analysis

To identify homogeneous regions for UK hourly extremes, a cluster analysis was undertaken on the final PC scores for each gauge. Cluster analysis (CA) using PC scores has been widely adopted (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, 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 probability estimates at data scarce or ungauged sites (Hosking and Wallis, 2005).

Hydrological studies have employed various clustering methods such as: average and complete linkage (Jackson and Weinand, 1995; Ramos, 2001), Wards method (Ramos, 2001; Sarhadi and Heydarizadeh, 2014), and the K-means method (Jones et al., 2014). Wards method is recommended as a robust approach for variable classification (Modarres and Sarhadi, 2011) and employs dendrograms to assess the correlation between input and output dissimilarities for different clusters. It was used in this study after comparison with the other methods and achieving the highest resultant maximum “Cophenetic correlation” coefficient value (0.78) (e.g. Rao and Srinivas, 2006; Isik and Singh, 2008). It was also able to produce the most successfully spatially-contiguous homogeneous regions which indicates that it is the most suitable method to assign the gauges into distinctive groups.

Rather than rely solely on a statistical estimation of hourly extreme precipitation regions, a dynamical approach was also employed by using the WPs defined by Neal et al. (2016) and described in Section 2. By assigning the appropriate WP to the occurrence of Q99, WQ99 or SQ99 precipitation at each gauge, it was possible to analyse the proportion of hourly extreme precipitation attributable to each WP. Mapping these proportions for each station provided insight into the atmospheric circulation patterns and, therefore, physical processes associated with short-duration extreme precipitation and enabled dynamical justification of the statistically-derived regional clusters.

### 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 outlined in Darwish et al. (2018). The extreme precipitation data (i.e. AMAX and Q99) of each gauge were then standardised by dividing by the corresponding gauge median to reduce the impact of erroneous or imprecise recorded values. Regional Generalised Extreme Value (GEV) and Generalised Pareto (GP) distributions were fitted to standardised annual maxima (AMAX) and hours exceeding the 0.99 quantile (Q99), respectively, to produce growth curves and estimate AEPs for hourly extreme precipitation as in Darwish et al. (2018). It should be noted that growth curves reflect the return estimates for the standardised
extreme precipitation (i.e. AMAX and Q99), and values should be multiplied by the region or gauge median to estimate the absolute AEP for the region and site respectively.

4- Results

4.1. Principal Components Analysis

The variables listed in Table 1 were selected to capture the spatial and temporal hydro-climatological characteristics of the UK hourly extremes, 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, besides identifying repetitive variables. Consequently, the combination which provided the highest total explained variance was selected, indicating that using the seasonal quantiles (SQ99 and WQ99) does not increase the total explained variance, retaining only the explanatory variables, shaded in grey in Table 1.

PCA results for the selected variables (Table 2) show the variation explained by the first 3 principal component and the loading of each variable. PC1 explains 49% of the total variance and with the highest absolute loadings for Tmax and Tmin reflects temperature variability and its 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 pattern of seasonality and frequency of extreme hourly precipitation, in addition to orography. PC4 (not shown) explains less than 5% of the variance, with the highest loaded variables similar to those of PC3 (elevation, N-SQ99, and $\bar{\theta}$). Moreover, the scree plot (Figure 1) indicates that the variance curve (red dashed line) is slightly decreasing after the 3rd component, while the total explained variance (blue continuous line) of the first 3 components capture 79% of data variance. Hence, only the first 3 components were retained for subsequent use in the clustering analysis as suggested by PCA guidelines (Jolliffe, 1990; Jackson, 1993).
PC scores for the three components were calculated for each gauge and were then spatially clustered individually (i.e. separately for PC1, PC2, and PC3) and jointly (i.e. PCs 1-3) using Wards method for a range of 3 to 9 target clusters. Comparison of the clusters from the individual gauge component scores were assessed for their conformity to the physical interpretations described above; while the cumulative scores helped to visualise the best regional configuration. Clustering the gauges into 4, 5, or 6 regions best captures the seasonal and locational differences in hourly precipitation extremes (Figure 2). Using only three regions did not delineate orographic behaviour sufficiently, while using more than six regions subdivided the southernmost regions with little physical justification. The results indicated that four regions (Figure 2a, PC1-3 and PC2) captured 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 2c, PC1-3, PC1, and PC3) begin to subdivide parts of the south and southwest UK, and clustered climatologically different regions together such as Northern Ireland and northeast England (Figure 2c, PC1-3, PC1, and PC2). Using 5 clusters (Figure 2b), best captured the east-west and north-south patterns, reflecting the orographic effects and seasonal drivers associated with hourly precipitation extremes.

A physical reasoning approach was also adopted to assess whether the statistically derived regions adequately reflect known WPs and processes. 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 WPs (see Neal et al. (2016) for detailed description of WPs) for the period 1992-2014 (Figure 3). This was repeated for the winter half-year (N-WQ99) and summer half-year (N-SQ99) (Supplementary Figures S1 and S2 respectively). The main WPs associated with extreme precipitation are WP2 (i.e. NAO+ pattern) and WP4 (i.e. south-westerly pattern), which are associated with 51% (WP2: 32%, WP4: 19%) of precipitation exceeding Q99 (Figure 3). Both WPs are characterised by south-westerly flow, bringing warm, moist air, and more frequent stormy weather, especially in winter (Supplementary Figure S1). WP2 contributes a similar proportion of events exceeding Q99 precipitation to most gauges, and affects the whole country, noticeably in winter when the UK is more affected by westerly storms (Supplementary Figure S1). However, a noticeable reduction in the
contribution of WP2 is observed in summer (Supplementary Figure S2), with a total contribution of 22%, mostly in the north-west UK. Moreover, the contributions of WP1 (NAO- pattern) and WP3 (north-westerly pattern), which are associated with the most common air mass affecting the British Isles, the polar maritime (Met Office, 2018), increase noticeably in summer, indicating the higher association with hourly convective extremes. Both WPs (i.e. WP 1 and 3) are characterised by north-easterly and north-westerly flow respectively, bringing cold air and are associated with showery weather. In contrast, WP4 shows a high occurrence only in the north-western UK annually (Figure 3), and seasonally (Supplementary Figures S1 and S2), compared to other regions, which is consistent with the direction and track of the dominant south-westerly flow characterising this WP.

Conversely, WPs 6 and 8 (i.e. high pressure centred over UK and the Azores high, respectively in Neal et al. 2016) are associated with only 5% of events exceeding Q99 annually across the UK. Both of these WPs 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. However, it should also be noted that WPs do not occur with equal frequency, which has a small effect on the relative frequency of Q99 days with respect to each WP and does not fully reflect the propensity of each WP to generate extreme precipitation. However, this effect is considered to be very small with regard to the drier WPs such as WP 6 and 8. Refer to Richardson et al. (2018) for an assessment of the relative frequency of each WP between 1850-2015.

Figure 3, and Supplementary Figures S1 and S2 show a clear east-west pattern in WPs 1, 3, and 4 caused by north-easterly, north-westerly, and south-westerly flows respectively, with a weaker north-south precipitation pattern (e.g. WPs 3 and 4). While a formal cluster analysis of the WP occurrence patterns was not carried out, visual investigation of Figures 3, S1, and S2 indicates that the main regions of influence for each WP are broadly similar to those derived from the PCA clustering. The WP results (Figure 3) also suggest that either 4 or 5 regions best accommodate the spatial characteristics of extreme hourly precipitation. Based on the combination of the clustered PCA (Figure 2b) and the patterns of events exceeding the annual and seasonal Q99 extremes in each gauge associated with WPs 1-4 (Figure 3, Supplementary Figures S1, S2, and represented by the direct comparison between
PCA clusters and influence of WPs in Figure 4), five regions were finally selected to represent hourly precipitation extremes (Figure 5).

Figure 4a indicates that PC1 reflects the southeast and southwest boundaries, while PC2 indicates an east-west divide in northern regions, highlighting the role of orography. This is also consistent with the occurrence patterns associated with WPs 1, 3, and 4 (Figure 4b). In addition, both PC1 and PC3 (Figure 4a) indicate the existence of a transitional region and separation between northern and southern regions which is also apparent in WPs 1, 3, and 4 (Figure 4b). The final boundaries (Figure 5) were therefore selected based on visual inspection, the PCA results, and qualitative assessment of the WP frequency patterns.

Assessing the relative occurrence of extremes with each WP (Table 3) shows that WPs 1 to 4 are associated with more than 75% of hourly extremes exceeding Q99, WP2 (i.e. NAO+ pattern) and WP4 (i.e. south-westerly flow pattern) are associated with most of the annual extremes (i.e. 51%) in the UK. Moreover, WP2 solely is associated with 40% of extremes in winter, which is approximately double its summer frequency (22%). In contrast, WP1 (i.e. NAO- pattern) and WP3 (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 WPs (i.e. WPs 1 to 4), with comparable frequencies, while winter extremes are dominated by WP2. Regional variations in the relative occurrence of Q99 rainfall with each WP are summarised in Supplementary Table S2 and are considered further in the discussion section.

The WP proportions suggest that patterns 1 and 3 are mostly associated with heavy showers over eastern England especially during summer (Supplementary Figure S2), suggesting the role of convective conditions in generating precipitation. In contrast, WPs 2 and 4 are associated with more frequent stormy weather, especially in winter, indicating the role of large-scale precipitation.

### 4.3. Regional homogeneity

Following the initial delineation of five regions from the clustering analysis and subsequent visual confirmation that these are physically representative (Figure 4), in addition to previous geographical knowledge of UK orographic characteristics, formal
regional boundaries were defined (Figure 5). Each region was tested for homogeneity, using regional discordancy and homogeneity tests (Hosking and Wallis, 2005). Where gauges appeared to be inconsistent with the rest of the region, we tested whether to place the gauge in adjacent regions, remove it, or whether there was a justification for the discordancy. This resulted in no modifications or changes as described in detail below, since these investigations showed no physical reason or justifiable relocation. The final five new regions are referred to as North West (NW), North East (NE), South East (SE), Mid East (ME), and South West (SW), containing 70, 51, 47, 9, and 20 gauges respectively, satisfying the RFA station’s density and homogeneity criteria (Hosking and Wallis, 2005).

The new regions reflect the impact of UK orography, proximity to the sea, potential thermodynamic and large-scale atmospheric drivers. Moreover, they capture the west-east precipitation gradient (demonstrated by NE-NW and SW-SE regions), and the north-south variation in precipitation extremes along the eastern side of the country (regions SE-ME-NE).

Table 4 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, and ME are not discordant ($D_{\text{max}} < D_{\text{crit}}$), and that the SE, SW, and NW regions are “homogeneous” with ($H_1$) values of 0.89, 0.94, and 0.56 respectively. The results for ME show that the region is possibly heterogeneous, with a $H_1$ value of 1.15, but no alterations were made as the gauges are not discordant and the limited number of gauges (9) increases uncertainty associated with this analysis (Jones et al., 2010).

For NW, only one gauge is discordant ($D= 3.7 > D_{\text{crit}}= 3$), 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 are consistent with neighbouring gauges across the period of observations, we retained the gauge within this region. For the NE region, one discordant gauge ($D= 4.49 > D_{\text{crit}}= 3$) 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 consistent 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. However, removing the gauge improved the homogeneity of the region noticeably ($H=1.2$), yet Hosking and Wallis (2005) recommend retaining discordant sites unless a physical reason justifies removing it. Thus, we retained 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 ($H_{2,3} \leq 1$), including NW, which confirms the suitability of 5 regions for further analysis.

Due to the nature of extremes and the scarcity of 1h precipitation observations, having definitively homogeneous regions for the application of RFA is challenging in practice, even after performing subjective modification, relocation, and elimination of discordant gauges (Hosking and Wallis, 2005; Yang et al., 2010; Sarhadi and Heydarizadeh, 2014). Thus, these results represent a pragmatic solution considering the limited data availability and the spatially varying hourly extremes in the UK.

4.4. Regional Frequency Analysis and AEP Estimates

Before performing the RFA, 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. Table 4 shows that the $Z_{dist}$ values for both distributions are within the recommended guidelines ($|Z_{dist}| \leq 1.64$) (Hosking and Wallis, 2005) and are appropriate to estimate AEPs, describe the spatial patterns in AMAX, and Q99 hourly precipitation in the UK.

The fitted growth curves for each region in Figure 6 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 also 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 exhibiting less variance in the series. Growth curves are steeper for both distributions in northern regions (i.e. NE and NW), where the highest few individual hourly extremes relative to each gauge median were recorded. In southern regions (i.e. SE and SW), where convective precipitation mostly dominates, precipitation extremes are high and show relatively low variability throughout the record, which
results in relatively close values to each gauge median, and flatter growth curves. As the growth curves are fitted using standardised values rather than absolute values, the rare extreme events which occurred in northern regions lead to steeper curves in these areas. However, absolute values of hourly precipitation extremes in southern regions are generally higher due to their convective nature. It is also noted that confidence intervals for the fitted distributions in ME are wider due to limited gauge numbers (9) in the region, which increases the sensitivity to extreme values (Hosking and Wallis, 2005; Jones et al., 2010).

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. A spatial estimate of the AEPs was then produced through kernel estimation smoothing of the gauge estimates. Figure 7a and 7b highlight the increasing gradient of intensity from the northwest to southeast UK for both distributions (GEV and GP) 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, though the growth curves appear similar in Figure 6. These features are also confirmed by the AEP values derived for four illustrative cities (Supplementary Table S1) demonstrating the importance of reliable local information to inform infrastructure planning and improve resilience to flash floods in urban areas. Overall, the GP estimates suggest smoother and more continuous patterns, with a slightly lower precipitation intensity, compared to the GEV.

For each region we also assessed the median of Q99 hourly precipitation for each WP, where the median of each region and WP relative to the region Q99 mean was calculated, to evaluate the regional relation between the magnitudes of hourly extremes and the WPs. Figure 8 shows that the relative median of the Q99 hourly precipitation for WPs 3 and 2 are lower than for most of the other WPs, whilst the highest relative median values occur for WPs 5 and 1. Additionally, WP 7 shows the highest relative median in SE, albeit it has low frequency, especially in winter. This contrasts with the results for hourly extreme event frequencies presented in Figure 3 where those for WPs 3 and 2 were noticeably higher than for WP5, and indicates that the highest hourly precipitation extremes might not be associated with the WPs that produce the most frequent Q99 hourly extremes. Moreover, it indicates that the highest extreme precipitation might not be solely due to the large-scale conditions, which are
reflected by the WPs, alternatively they might be related to local conditions in summer where land temperatures are higher than sea temperatures, leading the heaviest showers to occur over eastern England (Met Office, 2018).

5- Discussion and conclusions

This study aimed to provide a reliable regional characterisation of hourly extremes, and to define a set of regions explicitly describing hourly extreme precipitation behaviour. This could improve AEP estimates for various engineering and climatological applications. Using a fixed regions approach reduces the impact of hourly precipitation data scarcity by pooling observations within a region of similar behaviour, which enhance the AEP estimates in gauged and ungauged sites.

Previous work in the UK identified precipitation regions using either daily mean (Wigley et al., 1984; Gregory et al., 1991), or daily extreme precipitation (Jones et al., 2014). This research therefore presents physically plausible regions to improve the characterisation and estimation of short-duration precipitation extremes. The existing daily precipitation regions, which also use the fixed region approach, do not capture the spatial variation of hourly extremes across the UK due to the differences between daily and sub-daily extreme precipitation. Further, the ROI approach (e.g. FEH) lacks the physical basis in the pooling of gauges that is provided by specifically accounting for the spatial variability of precipitation extremes and its driving variables. Various studies have reported that using a fixed regions approach to estimate extreme precipitation return levels provides more precise results with smaller errors compared to using ROI, and efficiently reduce random and climatologically irrelevant variations in estimating model parameters and high quantiles (Kyselý et al., 2011; Carreau et al., 2012; Das, 2019). Furthermore, Kyselý et al. (2011) reported that using the at-site estimation approach to estimate extreme precipitation may be significantly affected by the inclusion of a single (outlying) observation, where the estimates would be uncertain.

This study used a quality controlled hourly precipitation dataset (Blenkinsop et al., 2017; Lewis et al., 2018) with associated site characteristics (e.g. elevation) and different at-site hydro-climatological characteristics (e.g. temperature) to identify the new regions. PCA and clustering approach was adopted to identify five homogeneous extreme precipitation regions to reflect hourly extreme precipitation variations across
the UK. Further, using WPs 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. These regions were then adopted in RFA to estimate precipitation AEPs.

Orographic characteristics and large-scale atmospheric circulation patterns played 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 Welsh Cambrian mountains is reflected in the east-west delineation, coupled with the most frequent WPs (i.e. WPs 2, 3, and 4) characterised by NAO+, north-westerly, and south-westerly flows respectively. This corroborates the northwest-southeast precipitation patterns reported in previous studies of hourly precipitation extremes by Blenkinsop et al. (2017).

The homogeneity assessment (Hosking and Wallis, 2005) for the new regions indicated that they are all either homogeneous or marginally exceed the homogeneity limit in all regions except for NE. The heterogeneity in NE is caused by a single gauge which recorded a verified hourly observation of 51.2 mm in August 2007, thus was retained. The validity of subjective relocation or removal of gauges was confirmed with additional homogeneity measures and no further changes were 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, highlight the importance of having dense gauging networks. The growth curves show steeper GEV curves in northern regions in comparison to southern regions, unlike estimates made by Darwish et al. (2018) using the existing daily UK extreme regions of Jones et al. (2014), where the growth curves indicated similar results across all regions. This suggests that the new proposed regions could capture the spatial variation of hourly extremes across the UK more precisely.

The AEP maps for probabilities of 20%, 4%, and 2% concur with previous findings of a pattern of increasing hourly extremes from the northwest to the southeast (Blenkinsop et al., 2017). Moreover, GP distribution probability estimates are
marginally smoother and less sensitive to outliers compared with the GEV distribution, while estimates for both distributions are comparable across the UK.

Analysing the relationship between hourly extremes and WPs showed that WPs 5 and 1, which are characterised by south-easterly and north-easterly flows respectively, produce the highest relative median Q99 precipitation intensity, while WP2, which is characterised by zonal flows (NAO+ in Neal et al., 2016), has the highest frequency of Q99 precipitation events but a lower corresponding relative median intensity.

Regionally, in SE, WP7 has the highest relative median (Figure 8) but is associated with only 9% of Q99 events annually (Figure 3; Table 3). Thus, although both WP5 and WP7 are not associated with high frequencies of hourly extremes, their association with rare, high intensity precipitation events that occur in summer, especially in southern regions (Met Office, 2018) leads to a higher relative median indicating that the atmospheric circulation patterns do not have comparable relationships with the frequency and intensity of hourly extremes.

As alluded to above, the influence of specific WPs may also vary regionally. For example, WP5 and WP7 are characterised by southerly flow and are jointly associated with more than 20% of UK summer Q99 extremes (Table 3; Supplementary Figure S2). However, they have a higher association with annual Q99 occurrence in the southern half of the UK (ME, SE and SW, Supplementary Table S2) compared to those in the north (NW and NE) and have a greater association with extremes in southern regions during summer compared to annual or winter extremes (Supplementary Figures S1 and S2) which might indicate a local condition leading to convective events in these regions. WP5 in particular is characterised by southerly flow which may bring warm air from the Spanish plateau, that, in the presence of other climatological conditions (e.g. strong summer sunshine), leads to downpours of precipitation during the summer in southern regions (i.e. “Spanish plumes”) (Lewis and Gray, 2010). Very specific, local weather conditions that are associated with southern flow over southern UK regions may lead to extreme summer precipitation events (Burton, 2011). Previous research has indicated that in northern regions extremes are caused by a few large-scale weather conditions and have a significant correlation with the NAO (Lavers et al., 2010), while in southern regions, local and synoptic weather conditions might interact, leading to extreme precipitation events of different timescales, especially in summer (Hand et al., 2004; Burton, 2011). Here, WPs 2 and 4, which are associated
with lower pressure to the north of the UK, result in slightly higher association with Q99 occurrence in NW than other regions (Supplementary Table S2) as zonal westerly or south-westerly flow is affected by orography. Such regional variations confirm that the intensity or frequency of hourly precipitation events may be influenced by interaction with local conditions, rather than just those at the larger scale reflected by the WPs.

Recent analysis of daily mean precipitation by Richardson et al. (2018) found that WPs 2 and 7 are associated with the highest relative median precipitation. This is corroborated by recent research indicating that changes in mean precipitation are not necessarily matched by those in the extremes (Swain et al., 2018). In addition, the difference of the WPs’ relative median in each region between mean and extreme precipitation highlights corresponding differences in the 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, as initially identified in Darwish et al. (2018).

In conclusion, this research has analysed hourly extreme precipitation and associated climatological variables to identify new, homogeneous regions which facilitate the estimation of hourly extreme precipitation in the UK. The developed regions better capture the spatial variation of hourly extremes across the UK compared to the existing daily extreme regions. They provide an alternative to the ROI approach (e.g. as employed in the FEH), in which data is not openly accessible, and condone important characteristics and drivers of precipitation variability. These new regions could be used to perform improved regional investigations which reflect the spatial variation of hourly extremes. This would provide better estimates of AEPs that can be used to estimate various event storms for flood studies. However, the data used in this research have limited record length (1992-2014), thus, including longer hourly precipitation series (e.g. FEH and FEH13) would enhance the analysis of precipitation frequency, and should be considered in future research. The new regions could be employed for the application of statistical downscaling of extreme precipitation in the UK, which provides an alternative to computationally demanding convection-permitting regional climate models, to simulate changes in extremes in the UK and manage potential climate change impacts.
Acknowledgements

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Figure 1: Scree plot of the principle component analysis (PCA) for the various climatological variables in Table 2. Eigenvalue of each component (left Y-axis) (Red dashed line), cumulative explained variance (right Y-axis) (Blue continuous line), and component number (X-axis)
Figure 2: 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 - 3 (left column) and individually (i.e. PC1, PC2, and PC3) (right three columns) are illustrated. The black dashed lines indicate the preliminary identified borders of each cluster.
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Figure 4: 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 patterns (WP) 1 to 4 over the period 1992-2014. Numbers in brackets represent the percentage of the Q99 days on which each weather pattern occurs. Circle diameter indicates the proportion of Q99 events under each WP for each gauge. Black dashed line (4a) and black lines (4b) reflect the preliminary identified clusters using the PCA and WP occurrence frequency patterns respectively.
Figure 5: Final delineation of UK extreme hourly precipitation regions. Regions are: South East (SE), South West, Mid-East (ME), North West (NW), and North East (NE). The values in parentheses denote the number of hourly gauges in each region.
Figure 6: 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.
Figure 7: Estimates for 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 gauge scaling factor (gauge RMed). Approximate values of 1h extreme precipitation for the cities of Aberdeen, Glasgow, Manchester, and London are presented in Supplemental Table S1.
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### Tables

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

Table 1: Variables used to identify homogeneous regions for hourly extreme precipitation using a principal components analysis. The contribution of various variable combinations to the analysis results (Section 4.1) were assessed, and the most explanatory variables (shaded in grey) were retained.
<table>
<thead>
<tr>
<th>Variable</th>
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<td>Tmin</td>
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</table>

Proportional contribution (explained variance) 49% 19% 11%

Table 2: Loadings of each variable in the first three principal components (PCs) and proportional contribution to the explained variance. Values in bold are the two most significant contributing variables for each principal component.
Table 3: Percentage of annual and seasonal hourly extremes exceeding Q99 over the period 1992-2014 by each WP across the UK as shown in Figures 3, S1, and S2 for annual winter and summer cases respectively.

<table>
<thead>
<tr>
<th>Weather Pattern</th>
<th>WP1</th>
<th>WP2</th>
<th>WP3</th>
<th>WP4</th>
<th>WP5</th>
<th>WP6</th>
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<td>21</td>
<td>7</td>
<td>2</td>
<td>8</td>
<td>2</td>
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<tr>
<td>Summer</td>
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<td>22</td>
<td>16</td>
<td>18</td>
<td>11</td>
<td>4</td>
<td>10</td>
<td>2</td>
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Table 4: Gauge discordancy (D), regional homogeneity (H) and goodness of fit (Z) assessment for the UK hourly extreme precipitation regions (SE, SW, ME, NW, and NE) shown in Figure 5. The table shows the number of gauges in each region, the number of discordant gauges in each region, and the maximum recommended gauge discordant value (D_{crit}) for each region.
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Figure S1: Proportion of days exceeding Q99 hourly precipitation for each gauge occurring across the 8 weather patterns identified by Neal et al. (2016) in the winter half year (Oct-Mar, N-WQ99) over the period 1992-2014. Numbers in brackets represent the percentage of the winter Q99 days on which each weather pattern occurs. Circle diameter indicates the proportion of winter Q99 events within each weather pattern for each gauge.

Figure S2: Proportion of days exceeding Q99 hourly precipitation for each gauge occurring across the 8 weather patterns identified by Neal et al. (2016) in the summer half year (Apr-Sep, N-SQ99) over the period 1992-2014. Numbers in brackets represent the percentage of the summer Q99 days on which each weather pattern occurs. Circle diameter indicates the proportion of summer Q99 events within each weather pattern for each gauge.

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Table S1: 1h extreme precipitation estimates in Aberdeen, Glasgow, Manchester, and London in mm using GEV and GP distributions for annual exceedance probability (AEP) of 20%, 4%, and 2%.

Table S2: Percentage of annual extremes exceeding Q99 in each of the UK hourly extremes regions over the period 1992-2014 by each weather pattern.