ABSTRACT: The effect of large-scale modes of climate variability on extreme UK daily rainfall, together with potential trends is investigated with non-stationary extreme value analysis. Extreme rainfall is identified from 25 km gridded observations spanning 1958–2012 and to which generalized extreme value (GEV) distributions are fitted. The GEV location and scale parameters are assessed for their dependence on indices of the El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO) and Atlantic Multi-decadal Oscillation (AMO), together with any evidence of trend. The influence of indices and trend are assessed individually and in combination, for individual months and 3-month rolling seasons. To improve signal-to-noise ratio all data below 200 m elevation is pooled. The NAO is found to have the greatest impact with positive NAO reducing the likelihood of extreme rainfall from spring to autumn, but increasing it in winter. London’s 50-year return level for JJA (DJF) ranges from 34(26) mm day$^{-1}$ at maximum NAO to 51(24) mm day$^{-1}$ minimum NAO over the observed period. A weak ENSO influence is only found for early winter (NDJ) and no influence detected for PDO or AMO. Trends towards more extreme rainfall were found for OND and DJF; however, the inclusion of NAO resulted in reduced magnitude and significance for DJF trends. Robust trends were found for the winter half year irrespective of NAO influence, with London’s 50-year return level increasing by 5%. Extreme rainfall changes associated with NAO are consistent with NAO driven changes in extra-tropical cyclones. Positive NAO non-winter months have fewer less intense storms crossing the UK in contrast to winter where they are more frequent and intense. The speed of storms is also higher during positive NAO winters which can mitigate increases in the rarest events.

KEY WORDS extreme rainfall; extreme value theory; climate; variability; North Atlantic Oscillation; NAO; extra-tropical cyclones

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1. Introduction

1.1. Observed changes in extreme rainfall

Severe flooding, whatever the national context, causes significant societal damage. The Pakistan floods of 2010 lead to more than 1700 deaths and nearly 2 million homes being destroyed (Oxfam, 2010). The UK summer flooding in 2007 is estimated to have cost £3 billion (ABI, 2007). It has been postulated for many years that extreme rainfall will occur more frequently in a warmer climate (Trenberth, 1999; Allen and Ingram, 2002) which obviously is of great concern given its impacts. The modelling of future climate with increased levels of greenhouse gasses has provided strong support for this view (Zwiers and Kharin, 1998; Kharin et al., 2007, 2013) at least for areas of the globe which are now not arid and dominated by large-scale atmospheric subsidence (Fischer et al., 2014). A historical overview of the evolution of our understanding of extreme rainfall changes is given by Fischer and Knutti (2016). Identifying extreme rainfall changes in the observed record, as the concentration of greenhouse gasses increases and the world warms, has been more difficult due to the degree of internal variability in the climate system on a wide range of time and space scales. There have been a number of studies that identify changes when considering the global (Alexander et al., 2006; Westra et al., 2013; Fischer and Knutti, 2014) and continental scales (van den Besselaar et al., 2013; Westra et al., 2013; Fischer and Knutti, 2016). At smaller scales trends in extreme precipitation have been identified, e.g. Jones et al. (2014, 2013) find trends for sub-UK regions, but this is a challenging task as substantial trends over smaller regions can arise purely from natural variability (Maraun et al., 2011; Fischer and Knutti, 2014) and thus are also sensitive to time period analysed (de Leeuw et al., 2016).

1.2. Detecting anthropogenic influence

There has also been considerable effort to discern and quantify the impact anthropogenic activities, particularly the emission of greenhouse gasses, has had on observed extreme rainfall. Again to minimize the impact of internal natural variability this has in general been at the larger global and continental scales (Min et al., 2011; Zhang
et al., 2013; Fischer and Knutti, 2015, 2016), although this is hampered by limited observational coverage. More recently, focus has turned to quantifying how the increased concentration of greenhouse gasses has altered the statistical properties of extreme rainfall typically by repeated simulation with climate models of periods when extreme rainfall has occurred, where the influence of greenhouse gasses and their wider effects are both included and excluded. The challenge facing such studies is that both the anthropogenic influence on thermodynamics and the atmospheric dynamics that lead to the extreme rainfall need to be accurately captured. For UK extreme wet events, anthropogenic impacts have been identified (Pall et al., 2011; Schaller et al., 2016) although some results can be difficult to interpret physically such as a discernible impact being found for July UK rainfall but not for June or August (Otto et al., 2015).

1.3. Large-scale drivers of extreme rainfall

The variability in extreme rainfall can arise from many sources both local and remote. The El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO) and the North Atlantic Oscillation (NAO) have all been found to have far reaching impacts on rainfall extremes, particularly for North America (Kenyon and Hegerl, 2010; Zhang et al., 2010; Whan and Zwiers, 2017). European climate variability is dominated by the NAO (Hurrell and Van Loon, 1997) with its effects on extreme rainfall seen in winter (Scaife et al., 2008) and summer Bladé et al. (2012). This influence is principally mediated through the varying of the preferred path of extra-tropical storms across the Eastern Atlantic and Europe with positive NAO characterizing increased UK and Northern European winter storminess (Feser et al., 2015) but reducing summer storminess (Folland et al., 2009; Dong et al., 2013). Longer timescale variability within Atlantic sea surface temperatures, represented by the Atlantic multi-decadal oscillation (AMO), has also been identified as potentially affecting UK and European rainfall (Dong et al., 2013).

1.4. Statistics of extreme events

Extreme value analysis has been used for many years to characterize the likelihood and magnitude of rare events. Much of this work has been performed within a stationary framework, i.e. an assumption is made that all variability within the data is stochastic and can be modelled with extreme distributions that do not vary with time. With the increasing concern that the climate is changing and thus changing our exposure to extreme meteorological risks such a framework is no longer suitable and a non-stationary one is required. Initially future changes were characterized by looking at ‘time-slices’ from climate simulations of 20–30 years duration, assuming stationarity within these time-slices and fitting stationary extreme distributions to compare future return levels with present day values (Kharin et al., 2007 used 2046–2065, 2081–2100 vs 1981–2000; Nikulin et al. (2011) used 2071–2100 vs 1961–1990); however, with longer simulations covering the whole 21st century (and longer) this approach excludes valuable data. More recently it has become common to either allow extreme value (EV) parameters to change linearly with time (García et al., 2007; Brown et al., 2008; Kharin et al., 2013) or with global temperature (Hanel et al., 2009; Brown et al., 2014). Non-stationarity arising from internal modes of climate variability, such as ENSO, PDO and the NAO have also been included (Zhang et al., 2010; Whan and Zwiers, 2017).

In this paper the effect on extreme daily UK rainfall of large-scale modes of climate variability, represented by observed indices of ENSO (as expressed by the NINO34 index), PDO, NAO and AMO, together with any residual trend are quantified. Sources for the indices are given in the acknowledgements. The indices and trend are used as covariates in non-stationary EV distributions fitted to individual or selected contiguous months to resolve the annual cycle of their effects. The following section details the methodology used, followed by results for individual covariates, multiple covariates and finally the combined influence on observed rainfall of the identified drivers of extreme UK rainfall. Possible physical mechanisms by which these influences are mediated are then discussed followed by conclusions.

2. Methodology

2.1. Characterization of the influence of large-scale modes of variability

Here, a methodology is developed that combines aspects of Hanel et al. (2009) and Zhang et al. (2010) using UK observed gridded daily rainfall data for 1958–2012 developed by the Met Office in support of the UK Climate Projections (Jenkins et al., 2008). The extreme heavy rainfall is characterized by fitting the generalized extreme value (GEV) distribution to monthly daily maximum rainfall (i.e. 12 values per year per grid box). For a given grid box the GEV distribution function is:

$$G(z; \mu, \sigma, \xi) = \exp \left\{ - \left[ 1 + \xi \left( \frac{z - \mu}{\sigma} \right) \right]^{1/\xi} \right\}$$

(1)

where, $\mu$, $\sigma$ and $\xi$ are the location, scale and shape parameters, respectively. A more intuitive representation of the GEV is through the corresponding quantile relationship where the $m$-year return level or quantile is given by

$$z_m = \begin{cases} \mu - \frac{\xi}{\xi - 1} \ln \left( 1 - \frac{1}{m} \right), & \xi \neq 1 \\ \mu - \frac{\sigma}{\ln \left( 1 - \frac{1}{m} \right)}, & \xi = 0 \end{cases}$$

(2)

from which it can be seen that the location parameter can be interpreted as the intercept of a quantile vs return period curve, scale the gradient and shape the curvature. Here, negative shape parameters correspond to bounded distributions.

Hanel et al. (2009) transform data from different grid points onto the same scale by dividing the selected data for
each grid point \( s \) by estimates of its corresponding location parameter \( \mu_0(s) \) resulting in a quantile equation of the form

\[
\begin{cases}
1 - \frac{\gamma(s)}{\xi(s)} & \frac{1}{1 - \ln \left( 1 - \frac{1}{m} \right)} \xi \neq 0 \\
1 - \gamma(s) \ln \left[ 1 - \ln \left( 1 - \frac{1}{m} \right) \right] & \xi = 0
\end{cases}
\]

where, the new scale parameter \( \gamma(s) = \sigma(s)/\mu_0(s) \). Note that \( \gamma = 1 \) when \( m = 1/(1 - 1/e) = 1.58 \) years, the return period corresponding to the location parameter. From this, one can see that for grid points where \( \gamma(s) \) and \( \xi(s) \) are the same their marginal characteristics are also the same and hence can be pooled together for further analysis. The shape parameter \( \xi \), even with long data sets, is very poorly constrained and it is exceptionally rare to be able to formally discern two different grid boxes to have differing shape values. We therefore assume the shape to be constant over all grid points. Visual inspection of \( \gamma \) indicates some variation over the UK particularly with orographic height.

We therefore partition the data into two subsets, selecting for analysis grid points below 200 m (Figure 1) resulting in 319 grid points. As a sensitivity test an alternative domain has no material effect on the results or conclusions drawn later using the larger domain.

To discern the influence of modes of climate variability on extreme rainfall, the location and scale parameters are allowed to depend on covariates (Zhang et al., 2010), comprising of indices, derived from observations, for each of the modes of interest (NAO, ENSO, PDO, AMO) and one to represent a linear trend (TRND). Each covariate was resolved at monthly timescales to avoid spurious associations with synoptic timescales and are standardized.

The covariates are introduced into the location and scale parameters for grid points \( s \) through time \( t \) for the original unscaled data in the following way

\[
\begin{align*}
\mu(s, t) &= \mu_0(s) \exp \left( \sum_{i=1}^{n} a_i I_i(t) \right) \\
\sigma(s, t) &= \sigma_0(s) \exp \left( \sum_{i=1}^{n} \beta_i I_i(t) \right)
\end{align*}
\]

where, \( I(t) \) is a vector of the \( n = 5 \) covariates listed above and \( a_i \) and \( \beta_i \) are their corresponding location and scale parameters. The shape parameter is kept constant as discussed above. When all data is scaled by the stationary location parameter \( \mu_0(s) \), to allow pooling, these parameters become

\[
\begin{align*}
\mu(t) &= \exp \left( \sum_{i=1}^{n} a_i I_i(t) \right) \\
\gamma(s, t) &= \gamma_0(s) \exp \left( \sum_{i=1}^{n} \beta_i I_i(t) \right)
\end{align*}
\]

Data is pooled for regions for which \( \gamma_0(s) \) and \( \xi \) are constant. Fitting such a GEV distribution assumes that the impact of each covariate scales with the value of the location parameter at each grid point. This is a reasonable first order assumption, with the change in extreme rainfall being proportional to the current intensity of extreme rainfall for a region. The advantage of this approach, however, is that all points within the pooled region are providing information on the effect the covariates have on extremes, greatly increasing the sample size and thus the precision of the estimates of their effect. A disadvantage of this approach is that it introduced dependence into the data as neighbouring grid points will tend to experience extremes at the same time. Fawcett and Walshaw (2007) assess the impact of including such data in the analysis of extremes and conclude that better estimates of extreme distribution parameters are made with their inclusion over data that has been declustered to improve independence, but that adjustments need to be made when calculating standard errors of parameters.

It cannot be assumed that the impact of the covariates will be constant throughout the year, however, partitioning the data, say by month, reduces the sample size. GEV models that resolve all months for all covariates could be applied but the large number of parameters (156) proved computationally challenging, particularly with the bootstrapping procedure used for significance testing (see later). Instead GEVs were fitted to either single months or selected contiguous months using the corresponding value of covariates for the month in which each datum resides.

There is also the potential issue of dependence between the covariates which are implicitly assumed to be independent in Equations (4) and (5). In practice this is not an issue with this study as after each covariate’s effect is determined in isolation very few situations are found where multiple covariates are required.
Parameters are estimated using maximum likelihood methods. However, due to temporal dependence between data from neighbouring grid boxes standard significance tests using the likelihood ratio are not possible. Approaches to correct the likelihood for dependence are available but due to the complexity of the fitted model bootstrapping approaches are adopted. The significance of an individual covariate can be tested through repeatedly randomizing the covariate of interest and refitting to produce a range of parameter estimates that arise from fitting to noise. Here, we use 10,000 randomizations to estimate limits outside of which parameters are considered significant at the 5% level. When more than one covariate is used only one covariate is randomized in turn to assess significance.

With the five potential covariates and the different months that could be included there are a large number of permutations for potential GEV models that could be fitted and for which parameters would need testing for significance. To make this task more tractable the impact of each covariate on the location parameter is initially assessed in isolation for single and rolling 3 month seasons. Those covariates found significant in isolation are then assessed in combination with other covariates that are found to be significant, again for location only. Once the dependence of the location parameter on covariates is determined the process is repeated for the scale parameter. No dependence of the shape parameter is attempted. For ease of reference different GEV models will be referred to via the first letter of the covariates that are included for the location and scale, e.g. LTE.SN identifies the GEV model with the location depending on TRND and ENSO and the scale depending on NAO.

With such a large number of models to be tested for significance there is a danger of type I errors, that of incorrectly rejecting the null hypothesis and wrongly concluding a covariate has an effect on UK rainfall. The probability of obtaining at least one false positive $R$ when all null hypotheses are true for $n$ independent tests, each conducted at significance level $\alpha$, is

\[ R = 1 - (1 - \alpha)^n \] (8)

Thus, a set of 12 monthly tests at the 5% level for a single covariate will have a greater than 50% chance of producing one or more type I error. To mitigate this issue it is assumed that the influence of any covariate will exhibit some coherence from month to month. Thus, a significant result is assessed with regard to neighbouring months to see if the sign of any covariate impact is consistent irrespective of calculated $p$-values.

The goodness of fit for the fitted GEV models is assessed using the Anderson-Darling statistic (Stephens, 1977). The null hypothesis is that the data are drawn from a GEV distribution with unknown parameters and is rejected when the test statistic is larger than critical values that are estimated through bootstrapping. Following the approach of Hanel et al. (2009), to preserve the spatial dependence between grid points, the data for a certain year are resampled with replacement simultaneously rather than for individual grid points independently. In contrast to Hanel et al. (2009) non-stationarity here is relatively small and thus the goodness of fit tests are performed under the assumption of stationary data and fitting stationary GEV distributions to individual months and rolling 3 month seasons. Ten thousand replications are performed to which are fitted GEV distributions and Anderson-Darling statistics calculated and critical values estimated. In all cases the fitted GEV model are found to be good fits at the 5% level and it is inferred that subsequently fitted non-stationary GEV will also be good fits as increasing degrees of freedom will improve fit.

Although not the focus of this study, the derived shape parameter values are given for reference. An annual cycle is detected in the shape from the analysis of pooled data for points below 200m, showing a minimum in January ($-0.02$) and a maximum in July (0.10). When GEV distributions are fitted to individual gridpoints separately the January shape has a mean and standard deviation of $-0.02$ and 0.04 and a 95% range of $-0.09$ to 0.05 whereas corresponding July values are 0.04, 0.06, $-0.03$ and 0.11. Intervening months tend to have a slightly smaller range. With regard to the spatial distribution there is a tendency for the shape to be lower in the south relative to the north and lower to the west relative to the east. Papalexiou and Koutsouyiannis (2013), in their global assessment of the GEV shape parameter, suggest a value of 0.11–0.13 which is at the higher end of the values found here. Potential causes of the difference could be the use of annual maxima and the smaller number of stations representing the UK used in their study (7 vs >650, Jenkins et al., 2008).

3. Results

3.1. Single covariate

Single covariate GEV location parameters are presented in Tables 1 and 2 for single month and rolling 3-month data. The NAO is found to be the most pervasive with 9 of 12 3-month rolling seasons showing significant impact on the location parameter. Single month results show fewer significant results which is to be expected with the smaller data sample, though all single months show the same sign of NAO influence between March and November. For these months and the 3 month seasons of MAM to OND positive NAO reduces extreme rainfall, whereas for DJF it increases extreme rainfall.

For TRND, positive values are found for all months between September and March but only two (February, October) show significance. For the 3-month data only DJF and OND show significance. Including other months in the winter half year also produces significant trends (see Table 3) with the largest trend found for ONDJFM of 0.13 and $p$-value of 0.00.

For the remaining covariates (ENSO, PDO and AMO) their impact on UK extreme rainfall is less clear with parameter values being smaller and showing greater
variability in sign from month to month suggesting there is no underlying influence.

For ENSO there is a potential positive effect on winter rainfall with November and NDJ showing significance, however, extending the data sample to include more months (OND, ONDJFM) does not improve significance. AMJ is also identified as significant, increasing late spring rainfall, though from the single month results this appears to be driven by April and June. Extending to MAMJ leads to a non-significant result.

No significant impact form PDO is found for single months and only JAS shows significance for the 3-month data where positive PDO appears to be reducing extreme rainfall in the UK. Extending the selected data to JASO leads to non-significance. Pooling November and December yields a parameter value of 0.04 with a p-value of 0.02 suggesting PDO increases extreme rainfall for these months, though this should be viewed with caution. Two months in isolation is a short period for such a remote climate mode of variability to have an impact on the UK and the adjacent months have PDO parameters indicating an opposite effect suggesting this significance may be spurious.

AMO is somewhat similar with only one single month (October) indicating significance though with adjacent months suggesting an AMO impact of the opposite sign (albeit non-significant). This large October value is also seen affecting the 3-month results with OND also indicating significance.

In summary, when each covariate is assessed in isolation NAO is found to have an impact on UK extreme rainfall for most of the year, ENSO potentially impacts late spring (AMJ) and winter (NJD), PDO and AMO are not found to have a significant role and any trend appears to be restricted to the winter half year.

### 3.2. Multiple covariates

From the single covariate results months and combination of months were identified which potentially are influenced by multiple covariates. The combined impact of NAO and TRND for 3-month data is considered first. For all 3-month combinations only OND returned significant parameters for both of 0.15 (0.01) and −0.04 (0.04), TRND and NAO, respectively, p-values in parentheses. The impact of including NAO for DJF reduces the magnitude of the TRND parameter to 0.08 (from 0.12) and it being deemed non-significant, in contrast to when TRND is fitted in isolation. This suggests that the changes in NAO over the period of observations contains characteristics similar to a trend, illustrated by a 0.29 correlation between these covariates for this season (corresponding correlation for OND is 0.04). This is a known feature of the NAO record where particularly between the 1960s and 1990s the NAO is found to have an impact on UK extreme rainfall.

#### Table 1. Covariate dependent location parameters from GEVs fitted to individual months.

| Trend | p-Value | NAO | p-Value | ENSO | p-Value | PDO | p-Value | AMO | p-Value |
|-------|---------|-----|---------|------|---------|-----|---------|-----|---------|
| January | 0.02 | 0.84 | 0.06 | 0.11 | 0.04 | 0.36 | −0.01 | 0.90 | 0.00 | 0.90 |
| February | **0.25** | **0.02** | 0.08 | 0.11 | −0.03 | 0.54 | 0.00 | 0.96 | 0.02 | 0.64 |
| March | 0.08 | 0.39 | −0.05 | 0.16 | 0.01 | 0.79 | 0.06 | 0.11 | 0.00 | 0.90 |
| April | −0.10 | 0.39 | −0.06 | 0.16 | 0.07 | 0.12 | −0.02 | 0.65 | −0.00 | 0.97 |
| May | 0.07 | 0.43 | −0.02 | 0.56 | −0.00 | 0.99 | 0.02 | 0.44 | 0.02 | 0.63 |
| June | 0.07 | 0.47 | −0.14 | 0.00 | 0.07 | 0.06 | 0.01 | 0.78 | 0.04 | 0.33 |
| July | −0.02 | 0.82 | −0.05 | 0.08 | −0.01 | 0.84 | −0.05 | 0.11 | 0.02 | 0.46 |
| August | −0.04 | 0.80 | −0.10 | 0.01 | 0.00 | 0.93 | −0.05 | 0.29 | −0.02 | 0.63 |
| September | 0.02 | 0.87 | −0.10 | 0.02 | −0.03 | 0.45 | −0.06 | 0.21 | −0.02 | 0.73 |
| October | **0.33** | **0.00** | −0.14 | 0.00 | 0.02 | 0.75 | −0.01 | 0.89 | **0.12** | **0.01** |
| November | 0.03 | 0.57 | −0.04 | 0.06 | **0.05** | **0.04** | 0.03 | 0.15 | −0.02 | 0.28 |
| December | 0.10 | 0.26 | 0.06 | 0.05 | 0.03 | 0.37 | 0.06 | 0.09 | 0.01 | 0.70 |

Each covariate’s effect is assessed in isolation and for the location parameter only. Bold indicates significance at 5% level.

#### Table 2. As for Table 1 but GEVs fitted to 3-month rolling seasons.

| Trend | p-Value | NAO | p-Value | ENSO | p-Value | PDO | p-Value | AMO | p-Value |
|-------|---------|-----|---------|------|---------|-----|---------|-----|---------|
| DJF | **0.12** | **0.04** | 0.07 | **0.01** | 0.01 | 0.61 | 0.02 | 0.47 | 0.01 | 0.56 |
| JFM | 0.11 | 0.08 | 0.03 | 0.24 | 0.00 | 0.85 | 0.02 | 0.51 | 0.01 | 0.59 |
| FMA | 0.07 | 0.28 | −0.02 | 0.42 | 0.01 | 0.64 | 0.01 | 0.69 | 0.01 | 0.70 |
| MAM | 0.01 | 0.84 | −0.05 | 0.04 | 0.02 | 0.26 | 0.02 | 0.40 | 0.01 | 0.77 |
| AMJ | 0.01 | 0.94 | −0.07 | 0.00 | **0.04** | **0.04** | 0.01 | 0.81 | 0.02 | 0.43 |
| MJJ | 0.04 | 0.38 | −0.06 | 0.00 | 0.02 | 0.33 | −0.00 | 0.91 | 0.02 | 0.19 |
| JJA | 0.01 | 0.84 | −0.09 | 0.00 | 0.02 | 0.34 | −0.02 | 0.27 | 0.01 | 0.53 |
| JAS | −0.01 | 0.90 | −0.09 | 0.00 | −0.01 | 0.51 | −0.05 | **0.03** | −0.00 | 0.86 |
| ASO | 0.10 | 0.15 | −0.12 | 0.00 | −0.01 | 0.81 | −0.04 | 0.15 | 0.03 | 0.22 |
| SON | 0.11 | 0.06 | −0.10 | 0.00 | 0.01 | 0.83 | −0.01 | 0.71 | 0.03 | 0.19 |
| OND | **0.15** | **0.00** | −0.04 | 0.04 | 0.03 | 0.17 | 0.03 | 0.19 | **0.04** | **0.05** |
| NDJ | 0.05 | 0.34 | 0.03 | 0.17 | **0.04** | **0.05** | 0.03 | 0.15 | −0.00 | 0.87 |

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Table 3. Summary of parameters for covariates that are found to have significant impact on UK rainfall.

| Months included | GEV model | Location dependence | Scale dependence |
|-----------------|-----------|---------------------|------------------|
|                 |           | TRND                | NAO              | ENSO             | NAO              |
| DJF             | LTN       | (0.08)              | 0.06             |                  |                  |
| MAM             | LN        |                     | −0.05            |                  |                  |
| AMJ             | LNE       | −0.07               | (0.04)           | −0.06            |                  |
| MJJ             | LN, SN    | −0.08               |                  | −0.07            |                  |
| JJA             | LN, SN    | −0.11               |                  |                  |                  |
| JAS             | LN        | −0.09               |                  |                  |                  |
| ASO             | LN        | −0.12               |                  |                  |                  |
| SON             | LN        | −0.10               |                  |                  |                  |
| OND             | LTN       | 0.15                | −0.04            | 0.04             |                  |
| NDJ             | LE        |                     |                  |                  |                  |
| SOND            | LTN       | 0.11                | −0.05            |                  |                  |
| SONDJ           | LT        | 0.09                |                  |                  |                  |
| SONDJF          | LT        | 0.12                |                  |                  |                  |
| ONDJFM          | LT        | 0.13                |                  |                  |                  |
| SONDJFM         | LT        | 0.11                |                  |                  |                  |
| JJASON          | LN6SN     |                     |                  |                  | −0.05            |

Where more than one covariate is significant values are from GEV models fitted to all significant covariates simultaneously. The significance of those in parentheses is debatable – see text. Definitions of the GEV models can be found in the text.

to high values (Osborn, 2006). Whether the changes in observed extreme rainfall for this season is due to an underlying secular change or is the result of this low frequency natural variability in the NAO is difficult to discern. The inclusion of TRND has minimal impact on the NAO coefficients nor on their significance suggesting NAO is the dominant effect. However, when the selected data is extended to the winter half year (ONDJFM). The TRND is found to be significant and NAO not. This could be due to a single covariate for NAO over these months not adequately capturing the NAO influence. To address this an additional model was constructed where a single trend parameter was fitted to all the winter half year months and individual monthly parameters for NAO. This returns the parameters, 0.10 (0.01) TRND and the monthly NAO values −0.12 (0.00), −0.05 (0.03), 0.05 (0.10), 0.05 (0.26), 0.08 (0.09), −0.06 (0.07) ONDJFM, respectively, p-values in parentheses. Here, the TRND parameter is found to be significant in spite of any NAO effects being accounted for, which suggests that a trend is present when considering all data from the winter half year though this presumably is in part due to the significant trend in NAO (OND). Whether there is a trend in DJF alone cannot, however, be robustly identified.

3.3. Scale dependence

The effects of the covariates on the GEV scale parameter are now estimated. As for the location parameter each covariate is assessed in isolation but with both the location and scale parameters being allowed to be dependent. Significance is again assessed through bootstrapping with both location and scale being fitted against the bootstrapped covariate simultaneously. No significant impact of ENSO, PDO, AMO or TRND on the scale parameter was found for either the single or the 3-month data. NAO was found to have a significant effect on the scale for the 3-month seasons of MJJ and JJA (−0.06 (0.01) and −0.07 (0.00), respectively, p-value in parentheses) with positive NAO acting to reduce extreme UK rainfall. For all but January and April, the NAO parameters are negative suggesting more months could potentially be included. The combined months of JJAS, JJASO and JJASON with separate NAO dependent location parameters for each month but a common NAO dependant scale parameter all give significant results with JJASON (identifying the GEV model as LN6SN) returning −0.15 (0.00), −0.07 (0.01), −0.12 (0.00), −0.11 (0.00), −0.15 (0.00) and −0.04 (0.02) for the six location parameters and −0.05 (0.00) for the single scale dependent parameter.

In contrast, both the PDO impact in JAS and the AMO impact in OND are deemed non-significant as their parameters are substantially altered when other covariates (NAO, TRND + NAO, respectively, see Table 2) are introduced. Hence, it is concluded that PDO and AMO have no discernible impact on UK extreme rainfall when other more dominant drivers of variability are taken into account.
3.3.1. Summary of location and scale dependence

Table 3 collates the covariate dependent parameters that have been shown to be significant. Parameters are from GEV models where all significant covariates are fitted jointly but with significance established through bootstrapping covariates separately. As discussed earlier the magnitude and significance of TRND for DJF depends on the model fitted. The ENSO parameter for AMJ does not change in magnitude with the introduction of NAO but is reduced to marginally outside the 5% level.

The variation through the year of the location dependence on TRND and NAO, and the scale dependence on NAO for the GEV model LTN.SN is plotted in Figure 2. From this it can be seen that there are two distinct periods where there is no trend (MAM to JAS) and where there is (ASO to FMA) albeit both non-significant. However, the consistency in sign of the winter half year indicates that potentially there is an underlying signal which is born out when more of these months are aggregated (see Table 3). For NAO there is more of an annual cycle on its impact on the location parameter with most of the year being negative (i.e. positive NAO reducing extreme rainfall) but positive in the winter months. With the scale parameter the sign of the NAO impact is negative for all 12 3-month seasons suggesting the possibility of an underlying impact even though only two seasons (MJJ and JJA) are individually identified as significant. Possible causes for this observed behaviour are discussed later.

3.4. Changes in extreme rainfall due to covariates

The effects of the covariates on actual return levels can be calculated with Equation (3) and the appropriate $\mu_0(s)$ for the grid point of interest. Figure 3 presents changes in the 50 year daily rainfall return level due to the covariates that are identified as significant (Table 3) in each season for the grid box containing London. The baseline values are calculated for all covariates set to zero apart from the TRND covariate which is set at the median value which corresponds to the year 1986. The bars for NAO and ENSO represent the change in the 50 year return level due to $\pm 1$ standard deviation of the covariates, for TRND the bars represent the change over the observing period 1958–2012. For OND the 2.3 mm day$^{-1}$ change due to TRND represents an increase over the period of approximately 7%. The ENSO driven change for DJF represents an increase of approximately 3% between positive and negative ENSO conditions. JJA experiences the largest changes due to NAO with positive NAO reducing extreme rainfall by 6 mm day$^{-1}$ (16%) with respect to negative NAO conditions. In contrast positive NAO increases the DJF 50 year return level rainfall by 4%.

The joint impact of the NAO on the location and scale parameter can be seen in the return level curves for JJA in Figure 4. Positive NAO reduces the location parameter which translates the return level curve uniformly downwards. The impact of positive NAO on the scale is to reduce the mean gradient of the curve, as can be seen by the distance between the $+\text{NAO}$ and $-\text{NAO}$ curve increasing as return period increases. Thus, the location effect changes
all return levels by the same amount whereas the scale effect has a greater impact on longer return periods, e.g. the reduction due to the NAO changing from −1 SD to +1 SD for the 3 year return level of ≈3 mm day\(^{-1}\) is almost entirely due to the change in the location parameter. At the 200 year return level this reduction has increased to 8 mm day\(^{-1}\) with the additional 5 mm day\(^{-1}\) due to the reduction in the scale parameter.

The consequence of such non-stationary in daily rainfall is that the probability of a specific value of rainfall changes from year to year. This is shown in Figure 5 where the year-to-year variability of the return value for a specific probability is plotted together with the year-to-year variability of the probability (or return period) for a specific rainfall value. As can be inferred from the magnitude of the covariate parameters, NAO driven variability is greatest for JJA with the return value associated with the probability of 0.02 (or 50 year return period) ranging from 34 to 51 mm day\(^{-1}\) over the observed record. The impact of year-to-year NAO variability is smaller in DJF but there is a small gradual rise from 24 to 25 mm due to the TRND covariate. This is more readily seen when translated into yearly values of return period for the average 50 year return value (calculated by setting all covariates to their median value), producing changes from >60 year return periods in the earlier part of the record falling to approximately 45 year periods by the end. In contrast, NAO JJA variability has caused the return period for the average 50 year return level to vary between <20 and >90 years.

4. Physical causes

There are many potential drivers of change in extreme rainfall. The increased moisture carrying capacity of the atmosphere as it warms, through the Clausius–Clapeyron relation, will be a key driver of future changes (Allen and Ingram, 2002). Year-to-year variability in extreme rainfall is more likely to be due to variability in atmospheric dynamics (Kenyon and Hegerl, 2010). For the UK and European region much of the extreme rainfall arises from extra-tropical cyclones (XTCs, Pfahl and Wernli, 2012) so variations in XTCs and mechanisms that cause year-to-year variability in XTCs are obvious candidates through which variability in extreme rainfall might occur. To assess this, North Atlantic and Eurasian XTC track statistics (Hodges, 1994, 1995, 1996; Hodges et al., 2011) were calculated by season for years where the NAO index was either in the upper tercile or the lower tercile of the observed values. Differences in XTCs between these high and low NAO years are plotted in Figure 6. The top row of Figure 6 plot shows the changes in track density for standard seasons from which it can be seen that positive NAO causes the storm track, that is the preferred path of XTCs across the Atlantic and Europe, to move northwards relative to the XTC track climatology. The track climatology migrates northwards in the summer and back south in the winter which results in the NAO driven variability reducing the number of XTCs crossing the UK during summer and increasing their number during winter during the positive NAO phase. This is consistent with the seasonal cycle of the NAO impact on the location parameter of the fitted GEV (Figure 2). In addition changes in the intensity of XTCs with NAO (middle row Figure 6) could also contribute to the severity of extreme rainfall, being lower in JJA and higher in DJF.

It is somewhat surprising that the GEV scale parameter does not particularly follow this pattern of decrease in summer and increase in winter for positive NAO conditions, but rather for all seasons in the year we find NAO reduces the scale parameter (i.e. the rate at which extreme rainfall increases with rarity reduces, Figure 2). Only 2 of the 12 3-month rolling seasons are found to be significant (MJJ and JJA); however, the probability for all 12 to be negative is small, somewhat less than 0.5\(^4\) (assuming worst case for dependence yielding only 4 independent samples). A potential mechanism by which the winter location increases but the scale does not could be via the speed of XTCs (bottom row Figure 6). During winter the average speed of XTCs increases across the UK with positive NAO which is not the case for summer. Thus, whilst positive NAO conditions in winter lead to more XTCs crossing the UK resulting in increased frequency of moderate extremes and a larger location parameter, the higher speeds could restrict the opportunity for larger accumulations. The XTCs pass through quicker and the more extreme accumulations increase less than the more moderate extremes which are reflected in the reduced scale parameter. The evidence presented here is only suggestive of the NAO impact on extreme UK rainfall being mediated through XTCs in this way. Further study is required to establish this mechanism more robustly, perhaps through identifying the rainfall from individual XTCs during high and low NAO years.
5. Conclusions and future work

The effect of large-scale modes of climate variability on extreme daily UK rainfall has been assessed together with identifying potential trends for all months and rolling 3-month seasons. The modes assessed were ENSO, PDO, NAO and AMO. The impact on extreme rainfall of a mode or whether a trend is present was determined by fitting non-stationary GEV distributions with GEV parameters depending on indices of each mode and/or have a linear trend term. Combined influences of modes and trend were also assessed. To improve signal-to-noise ratio all data for UK grid points below 200 m were pooled in the analysis after transforming the data from each grid point onto common margins so that they are identically distributed over time.

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The NAO is found to have the largest effect on UK extreme daily rainfall with positive NAO reducing the likelihood of extreme rainfall from spring to autumn, but increasing its likelihood in winter. For example, the JJA (DJF) 50 year return level for London has ranged from 34 (26) mm day$^{-1}$ at the maximum observed NAO to 51 (24) mm day$^{-1}$ for the minimum observed NAO between 1958 and 2012. In terms of probabilities, fixing the rainfall magnitude at the average 50 year return level, JJA (DJF) return periods have varied from 96 (38) years for the maximum NAO to 15 (74) years for minimum NAO. ENSO is only found to have a significant effect in early winter (months NDJ) marginally increasing extreme rainfall and no significant effect of PDO or AMO was found for any month or combination of months. Trends towards more extreme rainfall were found for OND and DJF; however, the inclusion of NAO resulted in a much reduced magnitude and significance for the DJF trend suggesting that some previously reported trends in winter extreme rainfall (Marau et al., 2008) may be due, at least in part, to natural variability. Expanding the trend analysis to include all winter half year months, however, yielded robust trends irrespective of any NAO influence, with London’s 50 year return level increasing by 6% over the period 1958–2012 which corresponds to return periods changing from 1 in 59 years to 1 in 42 years with respect to the average 50 year return level. However, extreme rainfall trends that are detected over relatively short climatological periods can be found to be not significant when longer records are analysed (de Leeuw et al., 2016).

XTCs are the primary meteorological phenomena by which extreme rainfall is produced in the UK (Pfahl and Wernli, 2012). Analysis of storms over the east Atlantic and Europe shows the NAO modulates extreme rainfall through altering the number of storms crossing the UK and their characteristics. High NAO reduces the number of storms crossing the UK in non-winter months as well as reducing their intensity. In winter, however, whilst high NAO increases the number and intensity of storms crossing the UK they are also moving faster which may reduce increases in the rarer events, as indicated by the GEV scale parameter not increasing with NAO in winter.

Recent work identifies an increased risk of extreme rainfall in the UK arising from the anthropogenic emissions of greenhouse gases and the resultant global warming. Pall et al. (2011) find it is very likely (90% level) that the risk of the observed autumn (SON) 2000 extreme daily river run-off had been increased by more than 20% due to anthropogenic activity. Their river run-off being derived from England and Wales total daily rainfall. Schaller et al. (2016) find human influence increased the number of days with zonal flow and subsequent high monthly rainfall that occurred in southern England in January 2014. The different metrics used in these studies to those used here make comparison of results difficult; however, trends are identified here for OND, DJF and the winter half year as a whole, with trends in SON marginally outside the significance threshold, thus showing some agreement with these studies. Otto et al. (2015), however, using England and Wales total 5 day rainfall, find July extreme precipitation has more than doubled due to anthropogenic climate change, which is not supported by results presented here. In contrast, Otto et al. (2015) also find no such anthropogenic influence in June or August, consistent with results here. The July discrepancy may be due to differences in metric, 5 day total rainfall for a large area vs 1 day pooled gridded rainfall, though differences in spatial and temporal scale did not prevent agreement with the two previously highlighted studies. Given the considerable influence of NAO on extreme JJA rainfall found here, the largest in the year, one could speculate that choices of Otto et al. (2015) in model design and method, such as the derivation of necessary boundary forcings, might inadvertently favour one particular phase of the NAO which could result in significantly different rainfall climatologies that could be mistakenly identified as anthropogenic forced changes. Analysis of rainfall arising from XTCs explicitly, and any influence of anthropogenic activities, could help resolve this further and is the subject of future work.

With regard to future changes in extreme rainfall, results presented here emphasize the necessity for accurate simulation of the large-scale drivers of storm variability and any change that they might undergo in a warmer world. Whilst Pall et al. (2011) found no evidence for changes in dynamics arising from human climate influence on the autumn 2000 event, Schaller et al. (2016) find that a third of the attributed anthropogenic influence in the increased risk of the 2014 UK floods was due to changes in dynamics. The relative roles into future of dynamics and thermodynamics for extreme rainfall are still not completely understood, particularly for complex meteorological systems such as the Asian monsoon (Fischer and Knutti, 2016).

Rainfall accumulations over 24 h, as used here, will tend to measure the rainfall characteristics of XTCs and their frequency, particularly in non-summer months. The timescales that are relevant for fluvial flooding tend to be somewhat longer and therefore integrate in time some of the mechanisms and variability found here. The net result of more or less storms that are more or less intense and travelling faster or slower is difficult to anticipate but is required for well-informed flood risk management. Thus, a useful extension of this work would be to assess the drivers of multi-day rainfall. In addition, the tailoring of regions from which to pool data to better reflect the spatial influence of modes of climate variability would be advantageous and is the subject of future research.

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