LETTER

Estimating unprecedented extremes in UK summer daily rainfall

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Abstract
The UNSEEN (unprecedented simulated extremes using ensemble) method involves using a large ensemble of climate model simulations to increase the sample size of rare events. Here we extend UNSEEN to focus on intense summertime daily rainfall, estimating plausible rainfall extremes in the current climate. To address modelling limitations simulations from two climate models were used; an initialised 25 km global model that uses parameterised convection, and a dynamically downscaled 2.2 km model that uses explicit convection. In terms of the statistical characteristics that govern very rare return periods, the models are not significantly different from the observations across much of the UK. Our analysis provides more precise estimates of 1000 year return levels for extreme daily rainfall, reducing sampling uncertainty by 70%–90% compared to using observations alone. This framework enables observed daily storm profiles to be adjusted to more statistically robust estimates of extreme rainfall. For a damaging storm in July 2007 which led to surface water flooding, we estimate physically plausible increases in the total daily rainfall of 50%–100%. For much of the UK the annual chance of record-breaking daily summertime rainfall is estimated to be around 1% per year in the present-day climate. Analysis of the dynamical states in our UNSEEN events indicates that heavy daily rainfall is associated with a southward displaced and meandering North Atlantic jet stream, increasing the advection of warm moist air from across Southern Europe and the Mediterranean, and intensifying extratropical storms. This work represents an advancement in the use of climate modelling for estimating present-day climate hazards and outlines a framework for applying UNSEEN at higher spatial and temporal resolutions.

1. Introduction

Extreme rainfall is a primary driver of flooding and can lead to significant societal impacts and risk to life. However, what happens during an event is but one realisation of the weather in our climate system. Other realisations may include more damaging or severe extremes, which could easily happen in the current climate but have not (yet) been realised. Quantifying the likelihood of such extremes is non-trivial and using only observations will lead to an incomplete understanding of the true climate exposure.

The overall flood risk for an area, and the specific impact caused by individual events, depends upon many climate and non-climate factors. Nevertheless, most notable inland flooding events across the UK are associated with extreme rainfall events. For example during 2007 (Mayes 2008), heavy rainfall (e.g. figure 1(a)) from several slowing moving low pressure systems associated with a southward shift of the North Atlantic jet stream and enhanced moisture advection from the south, caused widespread disruption and £4 billion in damages (Chatterton et al 2010). Reflecting the considerable risk posed to livelihoods, flooding is a topic of high priority in the UK (Pitt 2008, HM Government 2016, Cabinet Office 2017), and local-scale flood risk maps have been developed (Environment Agency 2019).

However, quantifying the magnitude and associated uncertainty of such extreme return levels is inherently difficult, primarily due to the limited set of observations available. Firstly, the observational
Figure 1. Observed extreme summertime daily rainfall characteristics from the HadUK-grid dataset (1961–2016). (a) A severe rainfall event on 20 July 2007, (b) the absolute maximum value, in mm. Data has been re-gridded to ∼25 km spatial scale.

The network is not constant and exhibits periods of very sparse coverage, such as during the first half of the 20th century (Kendon et al. 2020a). Secondly, the climate system is non-stationary, with multidecadal variability (Jones et al. 2013) and anthropogenic climate change (Pall et al. 2011) reducing the relevance of historical events for the present-day climate. Finally, many extreme daily rainfall events occur within large-scale frontal systems (Hand et al. 2004) simultaneously affecting multiple regions (figure 1(a)), reducing the number of independent events. The impact of this limited sampling of extreme events can be seen within the observed daily maximum rainfall field (figure 1(b)). These maxima exhibit considerable small-scale spatial variations with very high values adjacent to much lower totals. This is very unlikely to reflect a physical difference in exposure, except perhaps in very localised and specific conditions (Golding et al. 2005).

To address some of these issues a range of methods have been developed and applied (Svensson and Jones 2010) often employing extreme value analysis (EVA) combined with regional-pooling techniques (Reed et al. 1999, Fowler and Kilsby 2003, Hanel et al. 2009, Stewart et al. 2011, Brown 2018). However, careful consideration is needed as pooling across small regions may not increase the sample size of independent events due to the inherent spatial scales of events (e.g. figure 1(a)). Similarly, too large an area may include processes and characteristics which are not representative of the specific region of interest. Nevertheless, even with regional-pooling, uncertainty bounds remain large when based solely on the observational record (Fowler and Kilsby 2003, Jones et al. 2014). In view of this uncertainty two separate methods were officially recommended in the UK for assessing exposure at the very rare return levels, the flood studies report and flood estimation handbook (FEH, Stewart et al. 2011). Hence, current methods are limited in their ability to provide extreme rainfall estimates, such as those up to 1000 year return level.

Recently state-of-the-art climate models have been utilised to address such knowledge gaps. Known as UNSEEN (unprecedented simulated extremes using ensemble, Thompson et al. 2017), this involves using a large ensemble of initialised climate model simulations to increase the sample size of rare events. The method was developed to assess the likelihood of unprecedented UK rainfall in winter months (Thompson et al. 2017) and has been further applied to heatwaves (Thompson et al. 2019, Kay et al. 2020), rainfall trends (Kelder et al. 2020), the Indian summer monsoon (Jain et al. 2020), sudden stratospheric warming events (Wang et al. 2020) and agricultural impacts (Kent et al. 2017, 2019). Due to the very large ensemble sizes, the uncertainty from internal variability—a primary driver of exposure over the coming decades (Hawkins and Sutton 2009)—can be calculated. Thus, model simulations can provide a highly relevant set of alternative ‘observations’ from which to assess present-day exposure.

Summertime flooding can be caused by localized extreme sub-daily rainfall (Archer and Fowler 2018), or daily rainfall extremes associated with larger scale weather systems, such as those seen in the summer of 2007 (Mayes 2008). Here we investigate the latter, by performing the first UNSEEN analysis for daily rainfall focusing on heavy summertime events. We extend the UNSEEN methodology with EVA and make use of large ensembles of simulations from two climate models; an initialised 25 km global model that uses parameterised convection, and a dynamically downscaled 2.2 km model with explicit convection (Kendon et al. 2014, 2017) which overcomes some of the limitations of coarse models associated with the representation of orography (Smith et al. 2015).
and convection (Molinari and Dudek 1992, Chan et al 2014).

In section 2 the data sources are detailed. In section 3 we describe the regional pooling approach and in section 4 we assess climate model fidelity. The UNSEEN 1000 year return level, including a case study event, are shown in section 5.

2. Datasets

Observations of summer (June-July-August, JJA) precipitation across the UK were extracted from HadUK-grid dataset (Hollis et al 2019, 1 km native resolution) for the period 1961–2018. Prior to 1961 the observational network is very sparse, with the number of stations increasing by a factor of 5–6 within the second half of the 21st century (Kendon et al 2020a). Additional meteorological quantities (sea-level pressure, humidity and wind) were extracted from ERA5 (Hersbach et al 2020, 0.5° resolution, 1950 onwards). Hourly precipitation from the 20 July 2007 were extracted from CEH-GEAR 1 h to provide sub-daily storm profile (Lewis et al. 2019).

The UNSEEN analysis uses two climate model ensembles:

(a) GloSea5 is a global seasonal forecasting system with 24 members initialised each year from 1993 to 2016, providing 576 simulated years of the current climate. We use an experimental high-resolution version of the system, running on an N512 grid (~25 km, Scaife et al. 2019). It is based on the second global coupled configuration of the third Hadley Centre Global Environmental Model (HadGEM3, Williams et al 2015). Eight hindcast members from 24 April, 1 May and 7 May initialisation dates are pooled to provide a total of 24 simulated summers each year (MacLachlan et al. 2015).

(b) UKCP-local (UK Climate Projections) is an un-initialised 12 member convective permitting climate model ensemble covering the UK, for 1981–2020, providing 480 simulated years (2.2 km native scale, Kendon et al 2019). The ensemble was driven by a 12 member 12 km resolution European ensemble, which in turn was driven by 12 global model climate simulations (~60 km native resolution) from a perturbed physics ensemble (Murphy et al 2018). The 2.2 km members have identical model set up, but different boundary conditions. Additional meteorological variables (sea-level pressure, humidity and wind) were extracted from the 12 matching global climate simulations on a ~0.5° horizontal resolution. The UKCP-local projections were rerun due to an issue in the representation of graupel (Kendon et al 2020b), and new projections were released in July 2021 (Kendon et al 2021). The analysis here uses the original dataset released in September 2019, however, the impact of the rerun on summertime daily rainfall extremes is relatively small.

All precipitation data was re-gridded to the GloSea5 N512 (~25 km) grid.

3. Regional frequency analysis

The focus of this study is very rare events and the 1000 year return period, and thus we examine model fidelity with EVA techniques. Given the relatively short observational record, here we make use of regional pooling to enhance the signal and reduce grid cell noise (figure 1(b)). We apply the index-flood regional frequency approach (Hanel et al 2009) for summertime block maxima daily rainfall. This utilises the generalised extreme value (GEV) distribution, defined as:

\[ G(x; \mu, \sigma, \xi) = \begin{cases} \exp\left(-\left(1 + \frac{x - \mu}{\sigma} \right)^{-1/\xi}\right), & \xi \neq 0 \\ \exp\left(-\exp\left(-\frac{x - \mu}{\sigma}\right)\right), & \xi = 0 \end{cases} \]

where \( \mu, \sigma \) and \( \xi \) are the location, scale, and shape parameters respectively. The block maxima series for all grid cells within a specified region are standardised and pooled into a single series. Standardisation is achieved by division with the estimated location parameter. A GEV distribution is then fit, using maximum-likelihood estimation, and forms the regional growth curve, which is used to re-estimate the location parameters and standardised precipitation series. The entire process is repeated until convergence, which was generally achieved in less than ten iterations. The regionally homogenous growth curve has a location equal to 1, a standardised scale parameter known as the dispersion coefficient (\( \gamma \), often referred to as the coefficient of variation), and shape parameter \( \xi \). The GEV for each grid cell \( s \) is then defined as the regional growth curve multiplied by the locally varying location parameter:

\[ G_s(\mu, \sigma, \xi) = \mu_s G(1, \gamma, \xi). \]

The shape parameter, the most uncertain of the three, and the dispersion coefficient, are constant within each region. Thus, the standardised growth rate within each region is constant. Regional definitions are taken from Jones et al (2014) and discordancy checks (Hosking and Wallis 1997) applied to ensure their appropriateness for the datasets used here. Grid cells classified as less than 50% land are masked.

4. Climate model fidelity

Initial assessment of summertime daily rainfall characteristics indicates that both models correctly capture the frequency of wet days, although GloSea5
Figure 2. Climate model fidelity results for GloSea5 (middle) and UKCP-local (bottom) compared against observations (HadUK-grid, top), covering 1993–2016 for JJA seasonal maxima of daily rainfall. Colours show the central value based on all data; stippling indicates where the model exhibits a significant bias (95%) compared to HadUK-grid for the 1993–2016 period. The overall fidelity result (j) and (o) is based only on the scale, shape and 100 year fields. Units are mm (a), (b), (d), (f), (g), (i), (k), (l), (n) and dimensionless (c), (h), (j), (m), (o). Note that the regional-scale location bias has been removed in (f) and (k).

exhibits an over-occurrence of light rain and drizzle (not shown).

To assess fidelity we first subsample the larger climate model ensembles into samples of equal size to the observations (here defined as the 1993–2016 period covered by GloSea5 initialisations). For each subsample the regional frequency analysis is performed and the GEV parameters estimated. For GloSea5 we randomly selecting one member for each of the 24 years from. For UKCP-local we randomly select from the entire pool of members and years to generate a sample of size 24. The process is repeated 1000 times and 95% confidence intervals estimated; the corresponding observational values are then compared to these confidence intervals to determine significant differences.

Fidelity is assessed for the GEV scale and shape parameters, as well as the 100 year return level. For GloSea5 the location bias is approximately 3–5 mm depending on region, and for UKCP-local individual members exhibit different location parameters (95% significance), stemming from the different driving global models. However, location bias has little impact on the 1000 year return level and is removed from the regional average of each member of UKCP-local, and all members for GloSea5, before pooling. Additional checks were performed using visual inspection and an Anderson–Darling goodness-of-fit test (Brown 2018). To preserve spatial dependence, each random subsample is chosen based on its year and ensemble member, retaining the original spatial field (Hanel et al 2009, Brown 2018).

The fidelity results (figures 2(j) and (o)) indicate that both GloSea5 and UKCP-local are generally not significantly different (95% level) from the observations in terms of their shape and scale parameters. There are some discrepancies near coastlines and over high ground for GloSea5, but the general picture across most urban areas is good. As the region-wide location bias is removed prior to regional-pooling, the resulting grid cell specific location parameters for both models show little bias (figures 2(f) and (k)). For GloSea5 this occurs within regions exhibiting considerable elevation changes. The scale parameter is generally smaller in GloSea5 than UKCP-local and shows less association with elevation. Bias in the GloSea5 scale parameter is largely found in high elevation regions in northern England and Scotland. This likely stems from GloSea5's much lower native resolution and representation of orography.

The climate model shape parameters are generally more positive than the HadUK-grid estimates. However, in all regions the shape parameter for both models exhibits no significant bias, although we note that formally discerning statistical differences for this parameter is notoriously difficult (Brown 2018).
5. Results

The UNSEEN 1000 year return level for daily summertime rainfall is shown in figure 3. The regional pooling methodology defined above is applied 1000 times using random samples from of length equal to the model ensembles (n = 576 and n = 480 for GloSea5 and UKCP-local respectively). Fidelity results (figures 2(j) and (o)) are used to mask model data. The UNSEEN 1000 year return level estimate is then calculated as the 2.5–97.5 percentile range across the available samples at each grid cell. Using both GloSea5 and UKCP-local in all grid cells does not substantially affect these results (not shown), however, we strictly mask based on the fidelity tests to provide the most robust estimates.

Across much of the UK the 1000 year return level daily rainfall is estimated to be between 90 and 120 mm (figures 3(a) and (b), note the use of a 25 km spatial scale). Unlike shorter return periods (e.g. figures 2(d), (i) and (n)), it is the scale and shape parameters which primarily drive the spatial pattern and so it is not dominated by orography which mainly influences the location parameter. Instead, higher return levels, and a greater uncertainty range, are generally in southern and central regions. This is due to a larger and more variable estimate of the shape parameter within the UNSEEN bootstraps. It is seen in both GloSea5 and UKCP-local and thus does not appear related to specific modelling limitations.

One major advantage of the UNSEEN method is the more precise determination of rare extremes and when combined, the very large climate model ensembles used here greatly reduce the sampling uncertainty associated with estimating the magnitude of rare events (figure 3(c)). In almost all regions the uncertainty range is reduced by 70%–90% (calculated as the percentage reduction between the HadUK-grid and UNSEEN 1000 year 95% confidence intervals).
This reduction is greater than 50% for most areas even with comparison to a stationary GEV estimated using the longer 1961–2016 observational period.

Combining the observed maximum rainfall (figure 1(b)) with the UNSEEN analysis, the annual chance of unprecedented daily rainfall can be estimated (figures 3(d) and (e)). For 32%–54% of all UK grid cells the annual chance is less than 1% (i.e. rarer than 1-in-100 years), but the upper bound rises to almost 15% (approximately 1-in-6 years) in south east England. The spatial pattern seen here largely reflects the absence of extreme historical rainfall events in the south east. This contrasts with south west England in which observed events close to the UNSEEN 1000 year return period have already occurred, such as ex-hurricane Charley in 1986 (Shawyer 1987) and torrential rain in 1997 (Sibley 2017).

For historical storm events that align with the spatial and temporal scales assessed here, the storm’s profile can be scaled up to the UNSEEN 1000 year return level, to provide a plausible 1000 year daily rainfall event. We assume no systematic difference in the shape or duration of moderate and extreme events, thus it is appropriate to simply multiply the entire observed profile by a single scaling factor. This is in-line with current flood-modelling (Stewart et al. 2011, Dale 2021), although may not be suitable for climate change assessments (Lenderink et al. 2017, Fowler et al. 2021). Comparison of moderate and extreme storm profiles within the UKCP-local dataset indicates this is reasonable in the current climate. The uplifted profiles can be used with local-scale modelling as ‘what if’ scenarios, supporting flood management and resilience.

As an example, we demonstrate this for a surface water flooding event in Solihull, UK, during 20 and 21 July 2007 (Solihull Metropolitan Borough Council 2011, figure 1). The exposure profile for Solihull (figure 4(a)) indicates that this event of 66 mm in 24 h relates to a return period of approximately 50 years. The UNSEEN analysis (green cone) sits well within the observational uncertainty (grey cone), and correspondence with the industry standard FEH13 method (Stewart et al. 2011), with a simple areal reduction factor (Kjeldsen 2007), is good. The older FEH99 (Reed et al. 1999) method and the central estimate from HadUK-grid (1993–2016 period) fall slightly outside the UNSEEN analysis. Using 1961–2016 improves the agreement and reflects sensitivity of the 1000 year return level to the GEV fit (Papalexiou and Koutsoyiannis 2013).

The UNSEEN estimated 1000 year return level for Solihull is 95–130 mm. Using hourly rainfall from CEH-GEAR-1 h (Lewis et al. 2019) the observed storm profile can be uplifted to plausible extreme 1000 year return level estimates through a simple scaling of approximately 45% and 100% (figure 4). These are calculated as the UNSEEN lower and upper 1000 year return level estimates (95 and 130 mm) divided by the total 24 h observed rainfall amount (66 mm).

Finally, we make use of our dynamical models to assess the large-scale atmospheric conditions associated with extreme daily rainfall events. We identify the top 1% of daily rainfall maxima within a given region, with a separation time of at least 2 d. This equates to 85 and 100 events for UKCP-local and GloSea5 respectively. We then calculate composite anomalies, taking the 11 d rolling mean centred on each rainfall event, with the daily climatology removed. A two-tail Student-T test is used to calculate where the composites are significantly different from zero (95% level). For both models we find the identified events to be approximately randomly distributed across years, and a weak association with the regional-average seasonal rainfall totals.

Analysis of composites for the West Country region (see Jones et al. 2014) highlights a significant link between extreme daily rainfall and wider conditions across the North Atlantic (figure 5). A
significant low-pressure anomaly at the surface is located south west of the UK. There is a corresponding signal in the upper-troposphere, representing a deep trough associated with a southward shift and meandering of the North Atlantic jet stream. This represents a large-scale deviation of the jet and is seen across both models and ERA5. A region of northward wind anomalies throughout the troposphere (i.e. barotropic in structure) is located over the UK and Europe, indicating the presence of warm moist air which can help intensify extratropical storm rainfall. This is particularly clear within the northward vapour transport anomalies (qv850, figure 5). These patterns are remarkably similar to those seen during extreme events in 1952 and 2007 (McGinnigle 2002, Blackburn et al 2008) and provide further confidence in the models’ abilities to simulate conditions that drive extreme daily rainfall. The anomaly composites are relatively consistent for regions across southern and central UK, whilst over the northern UK a more zonal structure of the North Atlantic jet stream is seen. However due to the significant orographic features care must be taken on the interpretation in these regions.

6. Discussion and conclusions

In this study we present the first application of the UNSEEN methodology to daily summertime rainfall and estimate plausible extreme return levels across the UK. Our results show a spatial pattern of exposure with some of the highest 1000 year return daily rainfall extremes found across central and southern UK. Using over 1000 simulated summers the uncertainty due to internal variability is considerably reduced. For the magnitude of very rare events (i.e. 1000 year return period) it is reduced by 70%–90% compared to estimates based solely on observations. These new estimates allow historical storm profiles to be uplifted to plausible extreme return periods. Such profiles can
then drive local-scale flooding models and ultimately
better inform flood management and resilience. Fur-
thermore, these large ensembles can estimate the like-
lihood of unprecedented events. For much of the UK
the chance of record daily rainfall is estimated to be
less than 1% per year but this rises to 5%–10% per
year across the south east, primarily due to a relative
absence of extreme observed events in recent decades.
Intense hourly rainfall events are not addressed here,
and so the results cannot be used to infer information
on plausible flash flooding from such events.

To address potential modelling uncertainty, we
made use of two very different climate model
ensembles. Whilst specific rainfall events will be dif-
ferrnt between the two models (Kendon et al 2014),
relatively small differences are found in the 1000 year
return levels for the current climate. This is perhaps
surprising given the large differences in model struc-
ture and resolution and suggests that for simulating
daily rainfall extremes convection parameterisa-
tion performs well, and that initialisation of observed
conditions is not critical for estimating GEV char-
acteristics. In general, the parameterised convection
underestimates heavy rainfall events, whilst the explic-
it representation within the convection permitting
model compares well with observations across the
UK, including regions of significant elevation. Grid
point storms can affect models such as GloSea5 (Chan
et al 2014) but these have only a minor effect on the
daily rainfall fields (the hourly rainfall is not available
in this case). Both models indicate that large-scale
driving dynamics are the dominant processes for daily
extremes across the UK and comparison with ERA5
provides further confidence in the model simulations.
However, it is important to note that the models are
not perfect representations of the real world and other
sources of uncertainty remain, including modelling
uncertainty. A useful extension of this work would be
to utilise additional ensembles from more models to
better understand this aspect. Such ensembles could
provide useful information on meso-scale character-
istics or weather regimes associated with extremes,
which could support near-term forecasting efforts.

When estimating the 1000 year return level much
of the uncertainty stems from the GEV shape para-
eter. We apply a regional-pooling approach which
allows the shape to vary between each region. This
aligns with current operational approaches (Reed et al
1999, Svensson and Jones 2010, Stewart et al 2011) as
well as other studies (Brown et al 2014, Jones et al
2014, Murphy et al 2020). However, this raises an
important question regarding which physical mech-
anism could drive spatial patterns in the shape para-
eter across the UK? This is beyond the scope of
this study and a question for future research. Inter-
estingly, both models exhibit more positive shape
parameters in southern UK compared to the obser-
vations, although this is not significant. However, a
more positive shape parameter is seen if extending the
observational time series back to 1900 (not shown),
indicating that this region may just have been for-
tunate not to have experienced such extreme rainfall
events in recent years. Longer term trends and decadal
variability may also be playing a role (Jones et al 2013,
Simpson and Jones 2014).

One limitation of the regional-pooling approach
is that it introduces discontinuities at regional bor-
ders. Furthermore, the exact regional definitions are
often subjective, and could alter with temporal and
spatial resolutions of interest (Dawish et al 2021). As
an alternative, generalised additive models in which
the GEV parameters are estimated as smoothly vary-
ing quantities are a recent development (Youngman
2019). Whilst there remain complexities in how to
apply these for comparing climate models to observ-
ational datasets, this could be an important future
research development. We note that the methodology
developed here can easily be applied to other seasons,
regions, countries, or time scales, including sub-daily
rainfall extremes which drive flash-flooding events.

The focus of this study is the current climate, rep-
resenting the near-term risk in the next few years.
However, we note that for much of the UK the esti-
imated upper bound on the 1000 year return level is
20%–30% greater than the lower bound. This is
important as the uplift currently utilised for climate
change assessments (Dale et al 2017), is similar to the
plausible range due to internal variability calculated
here. How this affects assessment of future periods in
which both natural variability and anthropogenic cli-
mate change (Fowler et al 2021) will drive extremes
is unclear. Given our findings, very large ensembles
of climate projections (e.g. Eyring et al 2016) could
be utilised to explore this further. For sub-daily
rainfall extremes, large convective-permitting model
ensembles are likely to be needed (Kendon et al 2014).

Data availability statement
The data that support the findings of this study are
available upon reasonable request from the authors.

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