Record-breaking daily rainfall in the United Kingdom and the role of anthropogenic forcings

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Abstract
The breaking of the United Kingdom's daily rainfall record in October 2020 made a striking addition to the list of recent heavy precipitation events in the country. Mounting evidence from attribution research suggests that such extremes become more frequent and intense in a warming climate. Although most studies consider extreme events in specific months or seasons, here we investigate for the first time how extremes of the wettest day of the year may be influenced by anthropogenic forcings. Data from large multimodel ensembles indicate that the moderate historical trend towards wetter conditions will emerge more strongly in coming decades, while a notable anthropogenic influence on the variability of the wettest day may be identified as early as the 1900s. Experiments with different forcings are employed to estimate the changing probability of extremes due to anthropogenic climate change in a risk-based attribution framework. We introduce a new methodology of estimating probabilities of extremes in the present and future that calibrates data from long simulations of the preindustrial climate to the mean state and variability of the reference climatic period. The new approach utilises larger samples of rainfall data than alternative methods, which is a major advantage when analysing extremely rare events. The record rainfall of the wettest day in year 2020 is estimated to have become about 2.5 times more likely because of human influence, while its return time, currently about 100 years, will decrease to only about 30 years by 2100. Compared to a hypothetical natural climate, we estimate a 10-fold increase in the chances of such extreme rainfall events in the United Kingdom by the end of this century, which underlines the need for effective adaptation planning.

1 | INTRODUCTION

On October 3, 2020, the United Kingdom received a provisionally estimated average 31.7 mm of rainfall, setting a new record for the country's wettest day according to observations since 1891. To appreciate the enormity of this extreme rainfall amount, it was pointed out that the water which fell on that single day was enough to fill Loch Ness, the United Kingdom's largest lake by volume (Met Office Press Office, 2020). The event developed following the passage of storm Alex, which brought strong winds and prolonged heavy rainfall across the United Kingdom,

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Kingdom with 4-day accumulations reaching 150 mm in some regions (Kendon and McCarthy, 2020). Thankfully, the impacts from the rainfall were not severe, though wet extremes with more catastrophic impacts have recently hit the United Kingdom and are still fresh in public memory. Only a year before the 2020 record, extreme flooding wreaked havoc in Yorkshire, leading to loss of life and livelihood (Kendon, 2019). Although the prevalent atmospheric conditions are invariably major drivers of such events, understanding the underpinning role of anthropogenic climate change and how it might alter their frequency is crucial, in order to help communities effectively plan their adaptation and reduce their vulnerability.

In a warming climate, the atmosphere can hold more water vapour in line with the Clausius–Clapeyron relation, and wet extremes would therefore be expected to become more intense (Allan et al., 2014). Indeed, attribution studies provide evidence that the hydrological cycle has been strengthened in recent decades under the influence of anthropogenic forcings (Wu et al., 2013; Padrón et al., 2020), leading to a detectable intensification of extreme rainfall on global and continental scales (Dong et al., 2020). Regional changes are often too complex to be explained by the simple Clausius–Clapeyron relation (Kumar et al., 2015), stressing the need for in-depth studies with a regional focus. For example, Christidis and Stott (2021) report opposite trends in European summer rainfall extremes, with increases in the north and decreases in the south of the continent. Shifting the focus to the United Kingdom and changes in autumn events, Cotterill et al. (2021) estimate a 60% increase in the frequency of extreme daily precipitation since 1900 with a further 85% increase by the end of this century under a high emissions scenario.

In addition to attribution of climatic trends, attribution research also examines how specific extreme weather and climate events may be influenced by anthropogenic forcings and estimates how certain event characteristics, like the frequency or intensity, may be altered by human influence (Stott et al., 2016). Attribution assessments of high-impact events around the world for different types of extremes are published on an annual basis in a popular special report by the Bulletin of the American Meteorological Society (BAMS; e.g., Herring et al., 2020). There is a pressing demand for information on the changing likelihood of extremes, which can aid, for example, a more effective design of flood defences, buildings, or transport infrastructure, making them most suitable for the future climate (Betts, 2021). Therefore, the importance of integrating event attribution into the framework of developing climate services has long been recognised (Hewitt et al., 2012). Studies of flooding and extreme rainfall events with dire socioeconomic impacts in the United Kingdom corroborate that their likelihood has been on the rise under the influence of anthropogenic warming (Pall et al., 2011; Christidis and Stott, 2015; Schaller et al., 2016; Otto et al., 2018; Davies et al., 2021).

In this article, we (a) show how anthropogenic influence may have led to notable temporal changes in both the mean state and the variability of the wettest day, (b) investigate the anthropogenic influence on the likelihood of breaking the wettest day record in 2020 and on the risk of having days with rainfall higher than that in 2020, and (c) estimate how the likelihood of such events may further change during the course of the century. Unlike previous studies that consider seasonal and monthly events, or shorter events linked to specific seasons, here we use the wettest day of the year as our event definition, which would generally occur at different times each year and develop under different synoptic conditions. This definition may implicate higher variability that could potentially make the anthropogenic effect more difficult to detect. Finally, we introduce a new method of constructing the present-day and future distributions of the wettest day from which the probabilities of extremes are derived. The method provides larger samples, which are valuable for the likelihood estimation of extremely rare events.

The remainder of this article is structured as follows: the observational and model data used in the attribution analysis and the methodology are discussed in Section 2. Section 3 presents results, including changes in the return times of extreme events due to human influence, as well as risk ratio estimates. The main findings and concluding remarks are discussed in Section 4.

## 2 DATA AND METHODS

### 2.1 Observations

We compute annual values of the wettest day in the United Kingdom, henceforth referred to as Rx01, from mean daily rainfall observations and simulated data averaged over UK land. The observational data come from HadUK-Grid (v1.0.2.1; Hollis et al., 2019), a dataset derived from meteorological stations across the United Kingdom and interpolated onto a uniform grid, which offers full land coverage. The full data acquisition and quality control of raingauge observations take around 6 months. The 2020 values reported in this manuscript are therefore provisional based on the real-time observing networks available in October 2020, and as such are subject to further minor revision upon completion of the
quality control. Timeseries of Rx01 anomalies constructed with HadUK-Grid data since year 1891 are illustrated in Figure 1a and indicate a moderate increase in Rx01 of 0.025 mm/year. The 2020 Rx01 record, as well as the previous UK record (August 25, 1986), is marked in the figure. Time series from ECMWF’s reanalysis of the 20th century (ERA-20C; Poli et al., 2016) reassuringly indicates a variability pattern akin to HadUK-Grid (supporting information, Figure S1). In most years, Rx01 falls in autumn and winter months with the highest percentage corresponding to October (Figure 1b). A similar distribution among the months is also seen in the models used in this study. Figure 1c,d depicts the atmospheric circulation on the 2 days with the highest Rx01 values in the United Kingdom, as represented by the mean 500 hPa geopotential height (Z500) anomaly. The anomalies were constructed with data from the ERA5 reanalysis (Hersbach et al., 2020). During the 2020 event, a negative Z500 anomaly (marking the centre of storm Alex) was prominent south of the United Kingdom with associated weather fronts bringing heavy rainfall across the United Kingdom. The 1986 event, on the other hand, was linked to the passage of former hurricane Charley, identified by the negative Z500 anomalies west of the United Kingdom.

2.2 | CMIP6 models

We also compute model-based estimates of Rx01 using daily rainfall data from simulations with nine coupled climate models that took part in the World Climate Research Programme’s Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring et al., 2016). We select models that provide ensembles of simulations with all historical climatic forcings (ALL) starting in 1850 and extended to the end of the century with the medium emissions scenario SSP2-4.5 (Riahi et al., 2017) and simulations with natural forcings only (NAT) to year 2020. Each model also provides long control simulations of the preindustrial climate (CTL) with no external forcings, which are used in our attribution methodology. In summary, we utilise ensembles of 32 ALL simulations, 41 NAT simulations, and 5,752 CTL years in total. Details of the CMIP6 data are given in the supporting information, Table S1. The model data were re-gridded onto a common grid (N216). Using different versions on HadUK-Grid with horizontal resolution from 1 to 60 km, we confirm that data re-gridding does not introduce a major uncertainty on estimated Rx01 trends and variability.

2.3 | Modelled changes in the mean state and variability

Timeseries of Rx01 anomalies from the ALL and NAT simulations are shown in Figure 2a. We compute anomalies relative to the 19th-century period 1850–1899, which is closer to the preindustrial climate and can therefore account for most of the anthropogenic influence when comparing the ALL with the NAT climate. The observed 2020 and 1986 values of Rx01 provide thresholds for the definition of extreme events in our attribution analysis. Their equivalent values in the model climate are approximated by the anomalies in the ALL ensemble that lie the same amount of SDs above the 1961–1990 mean as in
HadUK-Grid (Christidis et al., 2019). The two thresholds are marked on Figure 2a. The thresholds could also be estimated by matching percentiles of the generalised extreme value (GEV) distribution applied to observed and modelled data. This alternative approach is found to yield very similar threshold values. The yellow line on the figure represents the smoothed ALL ensemble mean and illustrates the temporal change of Rx01 under the influence of external forcings. The models show no clear change in the mean Rx01 until about the end of the 20th century, but a steady increase thereafter.

Interestingly, we find that human influence not only changes the mean state of Rx01 but also its variability. Using 30-year rolling windows, we construct timeseries of the SD from the ALL and NAT simulations and plot the means of the two ensembles in Figure 2b. The ALL simulations suggest a rapid increase in variability after the mid-20th century. Christidis and Stott (2021) reported similar increases in European summer rainfall variability in CMIP6 simulations. Although one might expect that human influence would be less prominent in the earlier part of the timeseries, we note a clear separation between ALL and NAT since the end of the 19th century, with lower variability under the effect of human influence. This could indicate an early manifestation of the aerosol forcing effect in the United Kingdom that could be driven by the modification of cloud properties by aerosol particles. As the greenhouse gas forcing intensifies during the course of the 20th century, the anthropogenic warming dominates over the aerosol effect leading to an increase in the Rx01 variability. Even in the more stationary NAT climate, the Rx01 variability appears to have a characteristic pattern that might be linked, for example, to volcanic effects. The SD from equal segments of CTL simulations with the nine models lies, as expected, within the range of the NAT experiment. Although these preliminary findings are very revealing, a more detailed follow-up study needs to be undertaken to better understand the contribution of different external drivers to changes in rainfall variability.

2.4 | Model evaluation

We next carry out simple standard model evaluation tests (Christidis et al., 2013) to ensure the CMIP6 models provide a realistic representation of Rx01 and are therefore fit for purpose. Historical trends in Rx01 are small and sensitive to the end-points of the period used. Figure 3a shows trends to the present day from different starting points from the observations and the ALL simulations. The observed trends are higher when the earlier decades are included in the trend estimation but become consistent with the model range and are close to the ensemble mean by 1920. As an increase in Rx01 emerges more clearly towards the end of the 20th century, the consistency in more recent decades is reassuring. The discrepancy when early years are included does not necessarily indicate a limitation of the models but could arise from the poorer observational coverage in the early years. Indeed, the number of stations contributing to the HadUK-Grid data set increases from approximately 100 in 1891 to a peak of approximately 5,000 in the mid-1970s, and declining to 2,400 presently. Rx01 timeseries from ERA-20C (supporting information, Figure S1a) also indicate higher anomalies than HadUK-Grid in earlier
years and yield smaller trends that agree better with the models. Historical distributions of Rx01 constructed from detrended HadUK-Grid and ALL data over the common observational period (1891–2020) are in good agreement (Figure 3b), and a Kolmogorov–Smirnov test indicates they are indistinguishable when tested at the 10% significance level. Finally, power spectra suggest that the simulated variability over different timescales is consistent with the observed variability (Figure 3c). Although the evaluation tests are more indicative rather than conclusive due to the relatively small observational sample, they do not raise concerns about the ability of the models to represent the UK mean Rx01, but in fact indicate that they provide sufficiently good data for our attribution study.

2.5 | Methodology

The majority of event attribution studies follow a risk-based framework that we also adopt here (Stott et al., 2016). This approach utilises large ensembles of simulations with and without anthropogenic forcings (ALL vs. NAT) to construct probability distributions of the relevant variable (in this case Rx01) in a hypothetical natural world and the present (or also future) climate. Estimates of the probability of exceeding a threshold that defines extreme events are then obtained from the different distributions and, by comparing the ALL and NAT probabilities, the anthropogenic influence on the likelihood of extreme events is assessed. We derive changes in the likelihood of setting a new UK record in year 2020 by defining extreme events as exceedances of the 1986 Rx01 value. For the likelihood of events more extreme than in year 2020, we consider exceedances of the 2020 Rx01. The same two thresholds are used to estimate the likelihood of extreme events at the end of the century.

We construct the NAT distribution of Rx01 using data from all the simulated years (1850–2020) of the NAT experiment. This yields a sample size of 7,011 (171 years × 41 simulations), which is large enough to estimate the likelihood of extremely rare events. As the ALL climate is non-stationary, we cannot utilise all the simulated data of the ALL experiment, but we can select a subset of the data in a time-window around the year of interest (Christidis and Stott, 2015). For example, we can construct present and future distributions of Rx01 using data from the ALL simulations in the 30-year periods 2005–2034 and 2071–2100. This generates samples with a size of 960 (30 years × 32 simulations). Although this approach yields smaller, although still good-sized, ALL samples, a large amount of simulated data remain unused. A way round would be to assume time-varying distribution parameters (Maraun et al. 2009; van Oldenborgh et al., 2016), which in our case would be challenging, as we find a distinct change not only in the mean state of Rx01 but also in its variability. Here, we propose a new approach that increases the sample size and realistically represents the mean state and variability of Rx01.

The new method employs the long CTL simulations of the pre-industrial climate and adjusts them to the mean state and variance of the desired climatic period. Although scaling-based techniques have been previously used in bias-correction methodologies, here we extend the application to event attribution research. For the present-day climate, we adjust (by simple scaling) the CTL SD of the models to the one that best represents year 2020 (Figure 2b) and then shift the adjusted CTL data to the 2020 mean state (yellow line Figure 2a). Similarly, for the end of the century, we adjust the SD to an estimated value of 3.2 mm and shift to the mean state of 2,100. Using this approach, we calibrate the large sample of CTL data to the specific climatic parameters of the
desired period obtained from the ALL experiment. Hence, we estimate the ALL probabilities from a much larger sample of 5,752 Rx01 values. Probabilities of threshold exceedance are computed with simple ranking statistics, while, as in previous work, the uncertainty range is estimated with a Monte Carlo bootstrap procedure (Christidis et al., 2013) by resampling the modelled Rx01 data 1,000 times. The adjustment of the CTL data could also be implemented based on parameters of the GEV distribution derived from ALL data within a time-window of the reference climate. Such an approach would be sensitive to the representation of noise in the chosen window, and we find (not shown here) that it yields consistent probabilities with our methodology.

3 | ATTRIBUTION

The change in the Rx01 distribution under anthropogenic influence is shown in Figure 4a. We note a temporal shift in the overall distribution towards higher rainfall amounts relative to the NAT climate, as well as an increase in its spread. Exceeding high thresholds becomes much more common by 2,100. Return times of extreme events and changes in their likelihood (risk ratios) are reported in Table 1 and illustrated in Figure 4b,c. Human influence is estimated to have made it 2.5 times more likely to set a new record in year 2020. The models suggest that Rx01 at least as high as the 2020 record would occur once in about 300 years in the natural world, but the return time has now decreased to about a century and will further decrease to only about 30 years by 2,100. Extremes like in 1986 and 2020 become relatively common by the end of the century with approximately a 10-fold increase of their chance of occurrence relative to the NAT climate. Such events are estimated to be 2–3 times more common in the present-day climate.

We test the new methodology by also computing the present and future probabilities of extreme events from 30-year time slices of the ALL simulations as described in Section 2.5. The probability estimates from the ALL time-slices are very similar to those obtained from CTL but have a larger uncertainty range due to the smaller samples (Figure 4b). A second test (not shown) that applies the new methodology to CTL data to infer NAT probabilities also confirms similar results to the ones reported for NAT in Table 1. Finally, we test the sensitivity of the probabilities derived with the CTL data to the specified
levels of variance used for the data calibration. Figure 2b indicates that there is indeed some uncertainty in the SD of Rx01. For the present-day climate, we shift the 2020 SD level marked on Figure 2b by ±0.1 mm and recalculate the probabilities. This only moderately increases the uncertainty range of the return time to 82–192 years for the 2020 threshold and 46–85 years for the 1986 threshold. A smaller effect is found for the future uncertainties. We thus conclude that our approach offers a reliable alternative way to investigate past, present, and future risks of extreme events.

4 DISCUSSION

Our analysis adds to the evidence of human influence leading to more extreme rainfall in the United Kingdom. This is the first event attribution study to examine changes in the wettest day of the year and establish that despite the large variability, a signal of more frequent extremes has emerged and will continue to intensify in coming decades. Human influence is shown to have had a clearer effect on the Rx01 variability than on its historical trend. Nevertheless, a prominent and steady rise in the mean Rx01 is projected during the course of this century under SSP2-4.5, giving rise to higher trends going forward. Changes in the mean state and spread of the Rx01 distribution made it about 2.5 times more likely to hit a new record in 2020, while by 2100 such an event is estimated to occur every few decades. There are of course limitations to our analysis stemming, for example, from the effect of variability that partly obscures the climate change signal, methodological uncertainties like the variance levels used for the scaling of CTL data, model limitations, or uncertainties in future emission pathways. Although several of these limitations have been explored and are reflected in reported uncertainty estimates, future research should aim to further reduce their impact.

The event attribution methodology introduced in our study enables a better utilisation of model data, obtaining information from experiments with historical forcings to adjust long simulations of the pre-industrial climate. Comparison with the common alternative approach of estimating probabilities from short time-windows of the historical simulations shows not only consistency but also a reduction in the uncertainty range. The latter is a major advantage of the new approach, which would be better demonstrated in studies of rarer extremes and/or smaller ALL samples. In this article, we attempt to provide a best estimate of the change in the likelihood of extremely wet days from an ensemble of state-of-the-art coupled climate models. A comparison with analyses from attribution systems with a quasi-operational set up, like the one pioneered by the Hadley Centre (Christidis et al., 2013; Ciavarella et al., 2018), would be a useful future extension of this work once the necessary simulations become available. It is important to note, however, that differences in the framing may be reflected in the results (Christidis et al., 2018); the Hadley system is built on an atmospheric model and therefore provides probabilities conditioned on the observed oceanic state. Despite framing differences, all event attribution studies help form a solid scientific basis for decision-making that can aid United Kingdom’s adaptation to the most adverse impacts of climate change.

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CONFLICT OF INTEREST
The authors declare that they have no conflict of interest.

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SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section at the end of this article.

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