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Climate variability conceals emerging hydrological trends across Great Britain

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ABSTRACT

Detecting a climate change signal from observed trends in river flows and hydrological extremes is challenging given the limited length of observations and the effects of internal climate variability. There has been an increasing call to better integrate historical observations with model projections, particularly given apparent inconsistencies between observed and projected hydroclimate trends. Here we use the UK as a case study of a region with apparent incongruity between past trends and future projections, such as observed summer wetting but broad agreement between climate models of reduced summer rainfall and river flows. Applying dynamical adjustment shows empirically that internal atmospheric circulation variability was a dominant factor in the observed positive summer rainfall trends over 1981–2010. Characterising the impacts of internal climate variability is crucial to fully appraising the range of possible hydrological extremes in current and future climate. Hence, we use a single model initial condition large ensemble (SMILE), with RCP8.5 forcing, to drive hydrological models at 190 catchments to explore the wide range of past and future river flow and hydrological drought trends that could arise due to internal variability. The results place the observed trends in context, showing that large ensembles are needed to fully capture the range of variability. This includes robust drying and wetting trends that could have occurred, thus in part reconciling the fact that observed trends may at first seem inconsistent with projections. Our results further show that the timing of a robust climate change signal above historical variability (i.e., a Time of Emergence) in river flows may remain obscured for decades due to the range of hydrological variability. There are however clear hotspots, such as decreasing low flows in southwest England, with an imminent ToE. However, a late ToE does not negate the potential for increased risk and adaptation measures should be formulated before a statistically significant climate signal emerges.

1. Introduction

Hydrological droughts impact water resources and cause significant environmental and agricultural impacts, as highlighted by the recent 2018–19 and 2022 UK droughts (Barker et al., 2024; Turner et al., 2021). Successive generations of UK climate projections generally suggest an increase (decrease) in winter (summer) rainfall over the 21st century (Lowe et al., 2018). Hydrological simulations from multiple generations of climate change projections broadly agree on a reduction in summer flows and an increase in the frequency and severity of UK hydrological droughts (see reviews in Chan et al., 2022a; Lane and Kay, 2023; and the latest UK climate projections 2018 (UKCP18) projections: Parry et al., 2024).

Inevitably, there are substantial uncertainties in future projections, and there is an important role for analysing historical river flow trends, to provide an observational baseline and constrain future projections. In the UK, studies have found statistically significant positive trends in observed winter flows in northern and western regions, consistent with increased winter rainfall (Hannaford et al., 2021; Harrigan et al., 2018) associated with recent variability in atmospheric circulation (i.e. winter North Atlantic Oscillation) (Hall and Hanna, 2018). In contrast, observed trends for other seasons are often weak for both rainfall (e.g., Murphy et al., 2023; Ossó et al., 2022) and river flows (Hannaford et al., 2023a). An example of apparent incongruity between observed trends and climate change projections is summer UK rainfall. Positive observed summer rainfall trends for the UK were found over the 1951–2016

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period (e.g., Ossó et al., 2022) and few catchments exhibit statistically significant summer river flow trends (Barker et al., 2024; Hannaford et al., 2023a). The England and Wales Precipitation (EWP) series stretching back to the 1766 does show a long-term trend towards drier summers. However, a reconstruction of the record by Murphy et al. (2020) with independent predictors showed no significant trend, suggesting that poor network density and uncertain data quality in the early parts of the record are further confounding factors. This is despite hydrological projections from multiple generations of UK climate projections suggesting a clear reduction in summer flows by the 2020s and continued reduction in the future (e.g., Arnell, 2003; Guillod et al., 2018; Kay et al., 2021; Rudd et al., 2019). The UK therefore provides an interesting case study of a region with apparent discrepancy between past trends and model projections at the regional scale, which provides water managers and policymakers with a conundrum in long-term water resources planning – but one which is shared in many parts of the world and for other hydro-meteorological variables (e.g., Piniewski et al., 2022; Shaw et al., 2024; Simpson et al., 2025).

There are a number of challenges complicating the detection of climate change driven trends in hydrological variables. First, studies have shown that trends can be highly sensitive to the period over which the trend is computed. For example, the presence of particularly wet or dry periods at the start of the record (e.g., clustering of droughts in the 1960s–70s, when many UK river flow records began) means that the calculated trend may differ from the trend computed from longer records (e.g., Hannaford and Buys, 2012; Slater et al., 2021). Second, internal variability, the inherent randomness within the physical climate system, causes large daily to decadal variability (Lehner and Deser, 2023). Internal variability can lead to record-breaking events even in the absence of a climate change driven trend (e.g., droughts: Chan et al., 2023; "record-shattering" heatwaves: Fischer et al., 2021 and floods: Goulart et al., 2024; Thompson et al., 2017). For example, the chance alignment of consecutive dry seasons/years could lead to unprecedented multi-year events (e.g., Chan et al., 2022a; van der Wiel et al., 2022). Additionally, the observed trend is just one realisation out of many equally plausible, alternative realisations that could have happened given the combination of both a forced climate change trend and internal variability (Simpson et al., 2025). The effects of internal variability on circulation-related variables, such as rainfall are not well sampled (i.e. stochastic, or aleatoric uncertainty is high), and complicate the detection of a thermodynamic climate change signal. The response of atmospheric circulation to climate change also remains uncertain (Shepherd, 2014). Third, human influences on catchments (e.g., land use change and urbanisation) and river flows (e.g., abstraction and impoundments) are further confounding factors in trend detection as flow variability may not fully reflect rainfall variability (Burn et al., 2012; Hannaford et al., 2023a; Wilby et al., 2017).

Given these challenges, trends calculated from short observed records may not be representative of the long-term climate change signal (Wilby, 2006; Wilby et al., 2008). This represents a challenge for decision-makers, who are faced with a broad range of potential future outcomes from climate models but, at times, either a lack of robust trends in the observations or apparent inconsistencies between observed and modelled trends (e.g., Shaw et al., 2024). Several approaches have been proposed to discern a climate change forced trend from the observations and to better characterise the effect of internal variability. First, the "dynamical adjustment" technique aims to estimate the effects of atmospheric circulation-related variability in observed trends and does not require climate model information (Deser et al., 2016; Guo et al., 2019). Lehner et al. (2018) applied the dynamical adjustment technique to analyse recent rainfall trends in southwest US and found that the observed strongly negative rainfall trend could largely be attributed to internal variability. Second, initialised climate predictions have also emerged as an approach to sample for climate extremes as they isolate internal variability (Kelder et al., 2022; van der Wiel et al., 2019; Chan et al., 2023). This includes ensemble reforecasts (e.g., Brunner and Slater, 2022; Chan et al., 2024; Kelder et al., 2020), decadal predictions (e.g., Thompson et al., 2017) and single-model-initial-condition large ensembles (SMILEs) (e.g., Deser et al., 2020). As shown by Deser and Phillips (2023) and Jain et al. (2023), SMILEs show the diversity of temperature and regional rainfall trends that could have occurred in the past 50 years, including both wetting and drying trends when looking across all ensemble members, bringing into question the common practice of using a small number of ensemble members in multi-model ensembles to assess models' ability to reproduce observed trends. SMILEs also provide an opportunity to estimate the signal-to-noise (SN) ratio and the Time of Emergence (ToE). The SN ratio refers to the projected change in a certain climate variable (i.e. signal) relative to the full range of possible variability over a baseline period (i.e. noise) and the Time of Emergence (ToE) is the time period when future changes exceeds historical variability (Hawkins et al., 2020; Hawkins and Sutton, 2012). This concept has the potential to inform decision-makers about the timing of changes over a typical planning horizon. Studies have used various methods to estimate ToE for rainfall and temperature using observations (e.g., Ossó et al., 2022). Similar techniques have been applied for hydrological variables such as river flows (e.g., John et al., 2023; Muelchi et al., 2021; Müller et al., 2024) and groundwater levels (e.g., Ascott et al., 2022) using multi-model climate ensembles. There have been a number of calls to better integrate these approaches (e.g., Hannaford et al., 2023b; Shaw et al., 2024), leveraging the respective benefits of observations (events or changes that unfolded in reality which water managers have experience of, or which systems have been designed against) and climate model information (that can better characterise the effect of internal variability).

While there are national hydrological projections, such as the eFLaG projections for the UK by Hannaford et al. (2023b), studies often consider a relatively small number of ensemble members and national climate projections like the perturbed parameter ensemble (PPE) in UKCP18 do not systematically explore the full range of internal climate variability. Given the above arguments for improved reconciliation of observation- and model-based projections, our overall objective here is to use SMILEs to contextualise past trends and appraise trend detectability. There has been limited, but growing, use of SMILEs for hydrological applications, especially with the availability of dynamically downscaled datasets (e.g., Hydro-SMILE – Brunner et al., 2021). We apply this to Great Britain (GB), motivated by the noted discordancy between recent observations and projections – and given the evolution of long-term planning which has increasingly mandated the need to test water supply systems to droughts beyond the historical envelope (e.g., Counsell and Durant, 2023). However, this is a generic methodology that could be applied elsewhere using increasingly available SMILE datasets and open-access hydrological models. The specific aims of this study are to:

- Apply dynamical adjustment to estimate the contribution of atmospheric circulation variability to observed seasonal rainfall trend;
- Investigate the effects of internal variability in past and future rainfall trends over Great Britain (GB) using the 50-member, CRCM5-LE SMILE;
- Use SMILE output to drive hydrological simulations at catchments across GB to explore past and future trends and variability in river flows and hydrological drought characteristics;
- Characterise the range of internal variability and estimate the time of emergence (ToE) for future changes in rainfall and river flow variables.

2. Methods

Fig. 1 shows a schematic of the methodological steps involved in this study. The methods for dynamical adjustment and hydrological modelling are further described below.

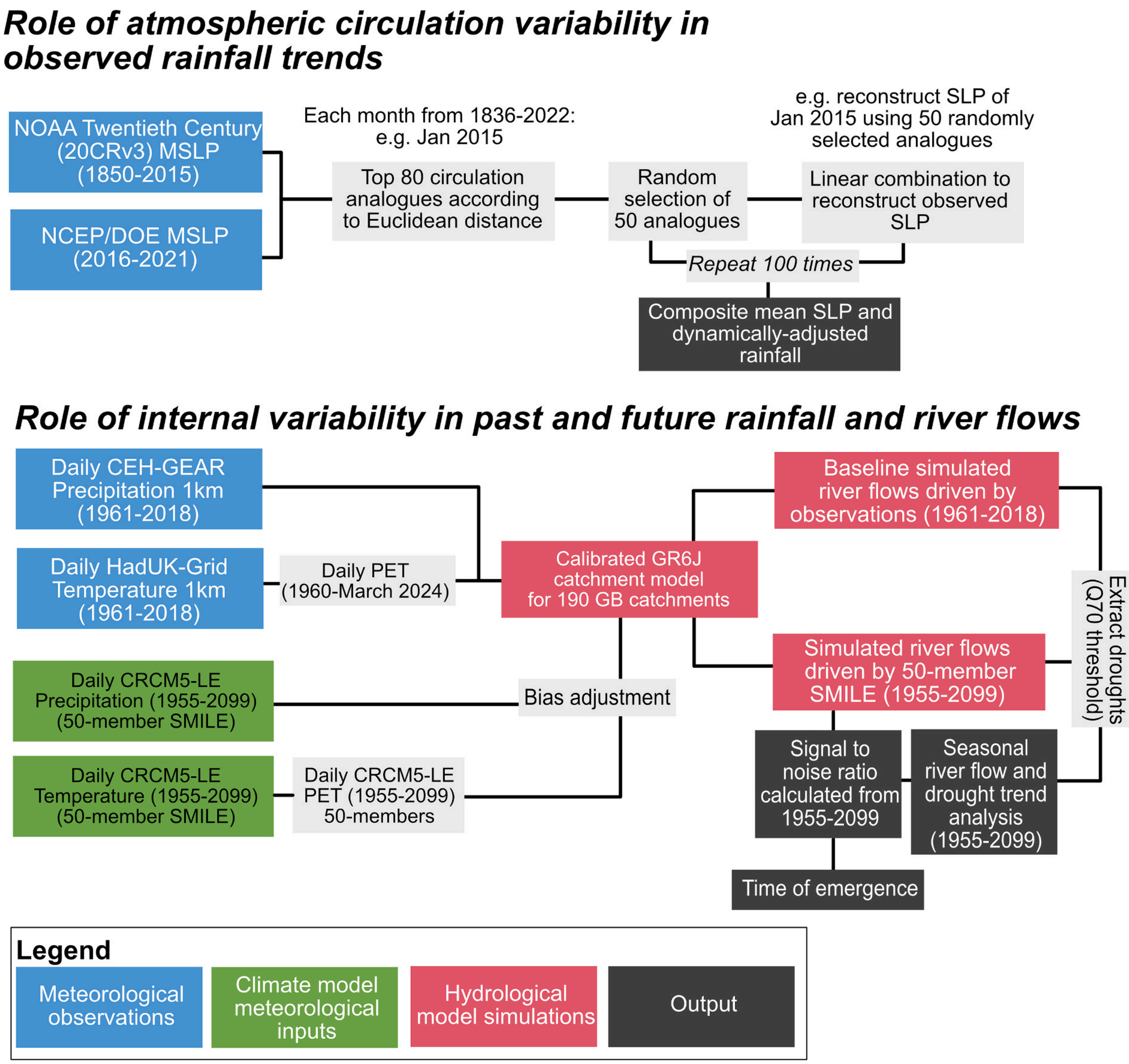

Fig. 1. Schematic of the data sources and methodological steps involved in this study.

2.1. ClimEx CRCM5-LE

This study uses the CRCM5-LE (Canadian Regional Climate Model 5 – Large Ensemble) SMILE, dynamically downscaled from the CanESM2 (Canadian Earth System Model) global climate model (GCM) large ensemble using the CRCM5 regional climate model (RCM) (Fyfe et al., 2017; Leduc et al., 2019). CRCM5-LE was chosen as it is the only publicly available dynamically downscaled SMILE covering the UK. CRCM5-LE consists of 50 ensemble members at 0.11° spatial resolution (12 km) across the European domain for the period 1955–2099. The SMILE was created by random atmospheric perturbations to the model's initial conditions and forced with observed climate forcings across the historical period until 2005 and the RCP8.5 emissions scenario until 2099. Model members gradually diverge due to internal climate variability and all 50 members are considered independent after the initial five years, as detailed in Fyfe et al. (2017) and Leduc et al. (2019). CRCM5-LE has previously been used to evaluate circulation variability (e.g., Mahmoudi et al., 2021; von Trentini et al., 2020; von Trentini et al., 2019), drive hydrological models to understand floods and droughts (e.g., Brunner et al., 2021; Faghih and Brissette, 2023; Poschlod et al., 2020) and to assess wildfire danger (e.g., Miller et al., 2024).

Prior to hydrological modelling, bias adjustment was performed by pooling modelled rainfall and temperature, to preserve the range of internal variability of the ensemble, and comparing them with observations from 1961 to 2018. Using the power transformation approach from Leander and Buishand (2007) for rainfall, adjustments were made to match the observed coefficient of variation and monthly means and a simple scaling factor for temperature to match the monthly means. Fig. S1 shows projected change in bias corrected seasonal rainfall and temperature between 2050–2079 and 1981–2010 from the CRCM5-LE compared with other climate projections, including the selected models within CMIP5, the Euro-CORDEX experiment and the UKCP18 12 km ensemble.

2.2. Hydrological modelling

The same 190 catchments within GB used within recent UK national hydrological projections (Hannaford et al., 2023b) were selected for this study. The catchments selected provide good geographic coverage and represent a wide range of physical catchment characteristics (selected catchments shown in Fig. S2). The set include 80 catchments within the near-natural UK Benchmark Network (UKBN) (Harrigan et al., 2018) but also include artificially influenced sites with good data quality and long data length. The extent of artificial influences for all sites are described in the “Factors Affecting Runoff” codes on the NRFA website. Further details of catchment selection are detailed in Hannaford et al. (2023b). GR6J, a conceptual, daily catchment hydrological model with six parameters available for calibration, was used to simulate river flows. GR6J was developed from the four-parameter variant (GR4J) to improve simulation of low flows (Pushpalatha et al., 2011) and is increasingly used to assess the hydrological impacts of climate change in the UK (e.g., Chan et al., 2023; Hannaford et al., 2023b; Parry et al., 2024; Tanguy et al., 2023) and for both operational forecasting and water resources planning by UK water companies (e.g., Anglian Water, 2022). While human influences (e.g. abstraction and discharges) are not explicitly included in the hydrological model simulations, their net effects are implicitly accounted for as they are calibrated using observed river flows. Abstractions or discharges will also change in the future, but this is not accounted for in the current framework. As noted by Hannaford et al. (2023a), given the large uncertainty associated with future socio-economic changes, assuming that current human influences remain unchanged in the future is reasonable for most practical applications.

Daily observed rainfall was obtained from the 1 km CEH-GEAR dataset (Tanguy et al., 2021). Daily maximum and minimum temperature were obtained from the 1 km HadUK-Grid dataset (Hollis et al., 2019). Daily potential evapotranspiration (PET) was calculated using the temperature-based McGuinness-Bordne equation previously calibrated for the UK by Tanguy et al. (2018). Catchment average rainfall and PET were used as input to the hydrological model and calibrated against observed river flows from the UK National River Flow Archive (NRFA) for the period 1961–2018. The multi-objective calibration strategy from Smith et al. (2019) was used to select the top performing parameter set according to six performance metrics for different aspects of the hydrograph (Table S1). Details of the calibration strategy are provided in the Supplementary Materials (Section S1.1). The top performing parameter set was used to simulate river flows for the observed period (1961–2018) and for each ensemble member of the CRCM5-LE (1955–2099) driven by bias-adjusted temperature and rainfall. Model performance for each of the evaluation metrics using the top parameter set is shown in Fig. S3.

2.3. Drought event extraction

Hydrological drought events were extracted using a variable threshold method (Van Loon, 2015), which is widely used within the UK (e.g, Parry et al., 2024; Tanguy et al., 2023). The 70th percentile of the flow duration curve (Q70) calculated from simulated river flows over the baseline period for each month was chosen as the threshold. A drought event is defined as any time period when river flows are below the monthly varying Q70. Total deficit was calculated for each drought event, defined as the sum of flow deficit (deviation from the Q70 threshold). The Q70 indicator was chosen as it is commonly used for hydrological drought extraction in the UK. This follows the methodology set out in the latest national hydrological projections by Parry et al. (2024), which noted a Q70 threshold ensures that multi-year droughts are adequately pooled instead of being split into multiple events given a wet interlude. Sensitivity of the results to the drought threshold is examined by extracting droughts using the 90th percentile of the flow duration curve (Q90).

2.4. Trend detection

First, the dynamical adjustment technique is used to estimate the contribution of atmospheric circulation variability to observed rainfall trends, based on the methods outlined in Deser et al. (2016) and O'Reilly et al. (2017). In brief, monthly mean sea level pressure (MSLP) over the European domain (70°W-30°E, 20°-80°N) for the period 1836–2022 were extracted from the NCEP 20th Century Reanalysis version 3 (1836–2015) and the NCEP/NCAR reanalysis (2016–2022). The two reanalysis datasets are regridded to a common 2.5° and combined following a simple linear scaling method as outlined in Faranda et al. (2023). The combined MSLP is then detrended for each month and each grid cell. For each month of each year (e.g., January 2015), the top 80 closest analogues of the same calendar month according to their Euclidean distance is selected (e.g., top 80 Januaries between 1836 and 2022, excluding 2015, closest to January 2015). A sub-sample of 50 analogues is then randomly selected and linearly combined using multiple linear regression to reconstruct the target SLP field. Detrended rainfall anomalies associated with the 50 analogue months are extracted from the HadUK-Grid observations and the same coefficients estimated from multiple linear regression of the MSLP fields are used to linearly combine rainfall anomalies and obtain the dynamically reconstructed rainfall for the target month. The random subsampling is repeated 100 times and the resulting 100 SLP and rainfall maps are averaged. The linear trend of the observed and dynamically reconstructed rainfall is calculated separately, with the difference between the two indicative of the role of circulation variability in the observed trend.

Second, trends for rainfall and simulated river flows are calculated for each ensemble member of the ClimEx large ensemble and following the resampling procedure outlined in Jain et al. (2023) which was developed from the UNprecedented Simulated Extremes using ENsembles. (UNSEEN) technique (Thompson et al., 2017). The UNSEEN approach aims to sample within initialised climate model simulations for rare and unprecedented extremes beyond the historical observed record. Resampling was applied to examine the effect of internal variability on trends in rainfall and river flows over the historical period. Modelled rainfall and river flows were spatially averaged over England, Scotland and Wales and detrended by removing the ensemble mean trend over the historical period. Subsequently, ensemble members and years were randomly selected to form 10,000 sub-samples of 30-year length. Years were selected in consecutive three-year blocks to retain any interannual temporal autocorrelation that may exist for rainfall. The linear trend, expressed in total rainfall and mean river flows over 30 years, were calculated for each sub-sample. The Mann-Kendall test for monotonic trends was applied to estimate the direction and statistical significance in river flow and hydrological drought trends over both the historical and future periods, using the *Kendall* R package (McLeod and McLeod, 2015). This follows well established methods for flow trend detection in the UK (e.g., Hannaford et al., 2023a; Hannaford and Buys, 2012; Wilby, 2006). In brief, a positive MK statistic (MKZs) indicates an increasing trend. A two-tailed MK test was employed with statistical significance assessed at the 5 % significance level (i.e. $|MKZs| > 1.96$). Serial correlation is checked for each catchment and when significant autocorrelation is detected, a block bootstrapping approach was used to calculate MKZs with block resampled series, with block length of 4 and 10,000 resamples. This was applied separately for river flows over the observed period (1961–2018) and for simulated flows driven by the CRCM5-LE for all 50 ensemble members (1955–2099). Sensitivity of trends to different time windows were tested by calculating the MKZs for 15-year moving windows with all possible start and end years between 1955 and 2099, following Hannaford et al. (2013).

2.5. Time of emergence (ToE)

We estimate ToE for each catchment following the approach in Faghih and Brissette (2023). The approach is based on calculating the signal-to-noise (SN) ratio by estimating the climate change signal and the range of internal variability over a 30-year historical period (Hawkins et al., 2020; Mahmoudi et al., 2021). The ToE was estimated for mean seasonal rainfall, low flows (Q95), high flows (Q5) and mean seasonal flows. For each variable, the mean over the baseline period (1981–2010) was calculated for each ensemble member. The internal variability component is defined as the standard deviation of the 50 mean values over the baseline period. The mean of each variable was then calculated for each overlapping 30-year periods (e.g., 1981–2010, 1982–2011 … 2068–2099) and for each ensemble member. The difference between the means of each overlapping 30-year period and that of the baseline period was calculated and the climate change signal is the ensemble mean of the differences. The SN ratio is determined as the climate change signal over a 30-year future period divided by internal variability. The ToE is the middle year of the 30-year period where the climate change signal exceeds ± 1 standard deviation of the internal variability component (i.e. $|\mathrm{SN\,ratio}| > 1$). This indicates the emergence of a climate change signal relative to internal variability).

3. Results

3.1. Past trends

Fig. 2 shows an estimation of the contribution of atmospheric circulation variability to the observed seasonal rainfall trend via dynamical adjustment. A large proportion of the observed rainfall variability can be reconstructed from only considering atmospheric circulation variability, showing that the observed rainfall trend over 1981–2010 can largely be attributed to atmospheric circulation variability. It is notable that the dynamically reconstructed rainfall trend for autumn shows a greater drying than the observed trend, indicating a substantial influence of dynamical atmospheric circulation variability on autumn rainfall over this period.

The observed trend for 1961–1990 and 1981–2010 averaged across England fall within 95 % of the distribution of trends from 10,000 subsamples of 30-year periods from the CRCM5-LE SMILE for both seasonal rainfall (Fig. 3a) and simulated river flows (Fig. 2b) (Fig. S5 for Scotland and Wales). There are also considerable differences in the spatial pattern of rainfall trends across the 50 ensemble members (Fig. S4). The resampling procedure explores a wider range of plausible trends, including 30-year trends that are the reversal in sign of the observed trend. Taking the example of summer rainfall, the observed wetting trend over 1981–2010 is wetter than the trend simulated by all ensemble members over the same period. However, when considering all plausible 30-year trends from the resampling procedure, the observed trend lies within the larger range of plausible trends. The modelled distribution suggests that there is around a 4 % chance of a 30-year summer rainfall trend that is wetter than the observed 1981–2010 trend. Additionally, much of the observed summer wetting across 1981–2010 for England is much reduced after dynamical adjustment (i.e. observed minus dynamically reconstructed trend) and are in closer agreement with the ensemble members over the same period (i.e. green dotted lines in Fig. 3a).

The simulated observed river flow trend (i.e. simulated river flows over the observational period) for both 1981–2010 and 1961–1990 lie within 95 % of the modelled distribution for all seasons. The observed positive summer rainfall trend between 1981–2010 is reflected in the positive summer river flow trend. Resampling shows that there is a 10 % chance of a 30-year period wetter than the observed trend. The only exception is the positive winter river flow trend over 1961–1990 for catchments in Scotland, which lies above the 97.5th percentile (Fig. S5b). The observed trend in spring rainfall over 1981–2010 was slightly negative but not as substantial as the decreasing trend found for observed spring river flows over 1981–2010. This suggests the role of antecedent winter rainfall, the groundwater recharge period for most of England, which was less positive in 1981–2010 relative to 1961–1990. The resampled distribution estimates a 7 % chance of a 30-year spring river flow trend drier than the 1981–2010 trend in England.

The sensitivity of trends to varying start and end years is evident for summer river flows (Fig. 4a) and annual total drought deficit (Figs. 4b

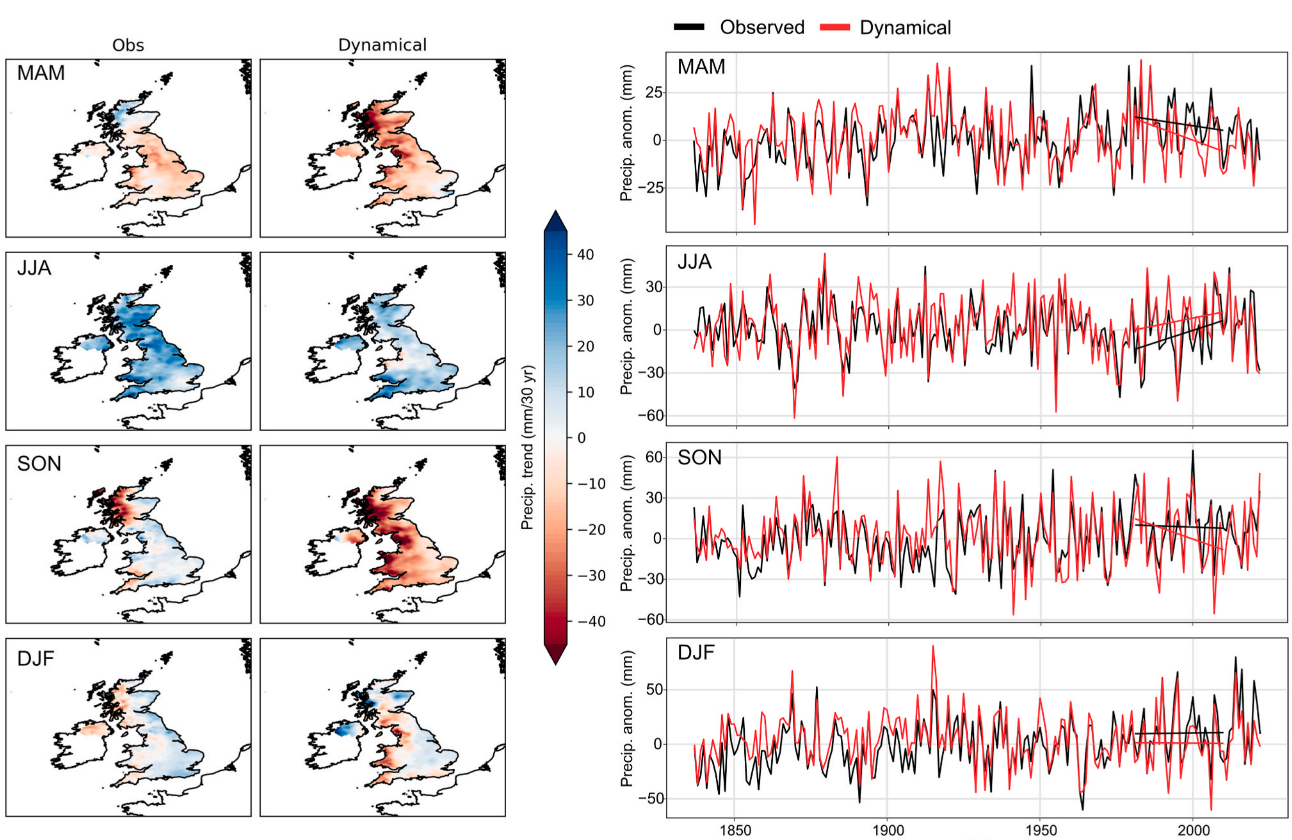

Fig. 2. Observed and dynamically reconstructed rainfall trend (mm/30-yr) over the 1981–2010 period (left) and UK-averaged anomalies (mm) over the entire 1836–2022 period (right) for each season for both the observed (black) and dynamically reconstructed (red) rainfall. The linear trend over 1981–2010 for observed (black) and dynamically reconstructed (red) rainfall is shown for each season. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

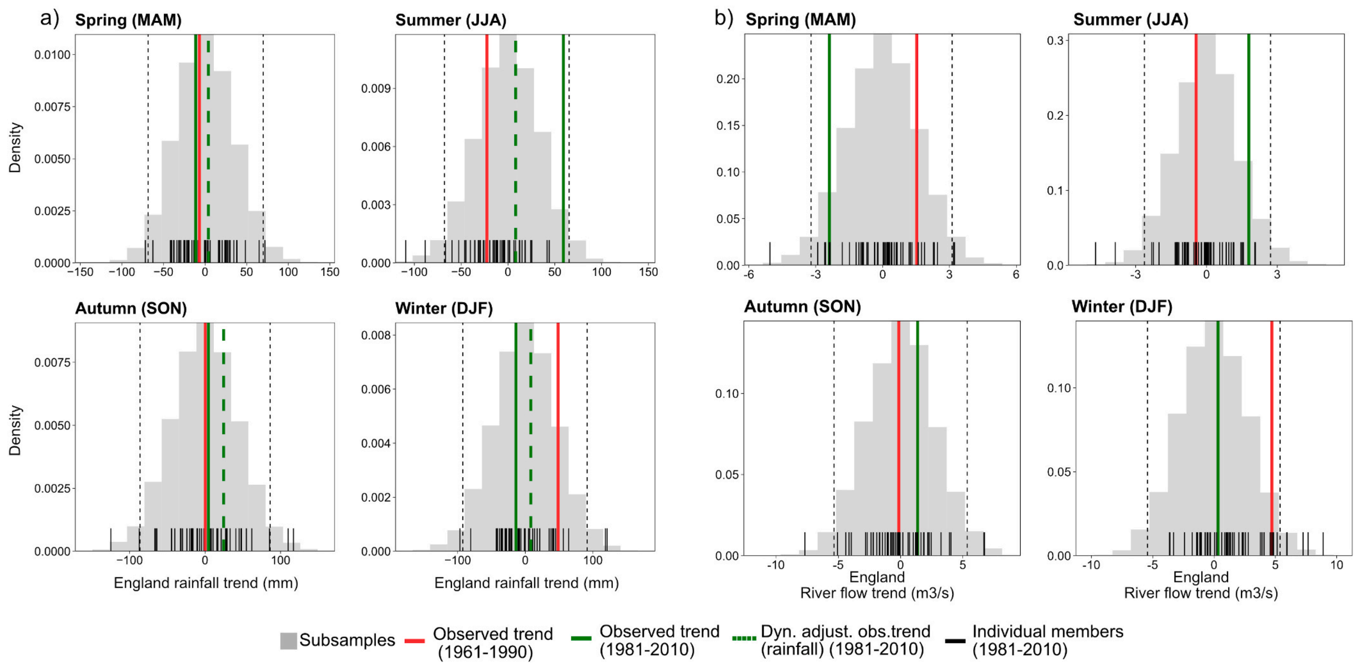

Fig. 3. Linear trend in a) mean seasonal rainfall and b) seasonal river flows over 30-year periods averaged for catchments in England. The grey shaded distribution represents the probability distribution of 10,000 sub-samples of 30-year length and the short solid black lines represent the linear trend of each ensemble member over the 1981–2010 period. The short solid black lines do not relate to values on the y-axis. The solid red and green lines represent the observed trend in rainfall and "simulated observed" trend for river flows over the 1961–1990 and 1981–2010 period respectively. The dashed green line represents the dynamically adjusted observed rainfall trend (observed minus dynamically reconstruction trend) for the 1981–2010 period. The dashed black lines represents the 2.5–97.5th percentiles, covering 95% of the model distribution. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and S6 for different seasons). The observed 1981–2018 summer river flow trend lies within the range of the large ensemble, which includes ensemble members with plausible wetting and drying trends. Varying the start year means the observed trend for summer flows occasionally lie at the edge of the ensemble range, especially the large positive trend when calculated from the 1970s, which contained several arid summers (e.g., summer 1976). The large variability in the computed trend with varying start years shows the influence of inter-decadal variability, such as the increasingly positive trend for observed summer river flows when calculated from the 1960s to the 1980s and an increasingly negative trend in observed autumn river flows when calculated from the 1990s and early 2000s. The observed trend in annual total drought deficit is positive for all six selected regions when calculating from 1961, suggesting less severe droughts over time. As with summer river flows, the observed trend lies within the range of the large ensemble which includes members with statistically significant worsening of droughts. Trends in more extreme droughts extracted using a Q90 threshold exhibit a similar pattern and similarly suggest less severe droughts since 1961 with a tendency for worsening droughts when calculating from the 2000s (Fig. S7). Additionally, hydrological drought events extracted over the historical period show that there is considerable scope for unprecedented events to occur with greater deficit and higher severity than the worst observed event (Fig. S8).

3.2. Future trends

Fig. 5a shows multi-temporal trend analysis for summer river flows by varying both start and end years in 15-year blocks for 1955–2099. The results show relative agreement and a clear climate change signal of decreasing summer river flows in the long term as shown by the ensemble mean but there are large differences between ensemble members in the direction of change over the near term and some differences in the magnitude of change, even for the long term. The long-term ensemble mean trend points towards a statistically significant increase in winter and spring river flows but greater disagreement over ensemble members for autumn flows (negative but statistically insignificant ensemble mean trend) (Fig. S9). Individual members show that the computed trend is sensitive to inter-decadal variability, and it is possible for individual members to exhibit trends that are opposite to the ensemble mean trend, even in the far future. For example, ensemble member 15 is one of two members projecting slight increases in long-term summer river flow, but the trend is influenced by a large wetting trend around the 2000s and becomes negative when calculated from the 2000s. The long-term trend for total drought deficit is less clear than summer river flows, indicating the larger role of internal variability in both historical and future drought trends. The ensemble mean shows a weak long-term trend, but some indication of a negative trend (worsening drought) when calculated from the 2000s into the mid-21st century (Fig. 5b). Disagreement in the long-term trend is shown by the two contrasting ensemble members, suggesting the uncertainty in the year-to-year variability in drought deficit may be greater than the trend and remains dominated by internal variability in the long term.

3.3. Time of Emergence (ToE)

Fig. 6 shows the difference in low (Q95) and high flows (Q5) calculated over consecutive 30-year periods compared to the baseline period (1981–2010) over the 21st century for six example catchments. There is considerable spread between the ensemble members, but the direction of change is clear and broadly linear for most catchments. This is especially prevalent for Q95, as shown by the fact that the climate change signal exceeds the range of internal variability in the historical period in all six examples. In contrast, changes in Q5 suggests possible non-linear behaviour, such as for the Lambourn (39019) and Ayr (83006) which shows considerable spread in the direction of change and the possibility of accelerated change by the end of the 21st century although the long-term climate change signal remains obscured by the range of natural variability.

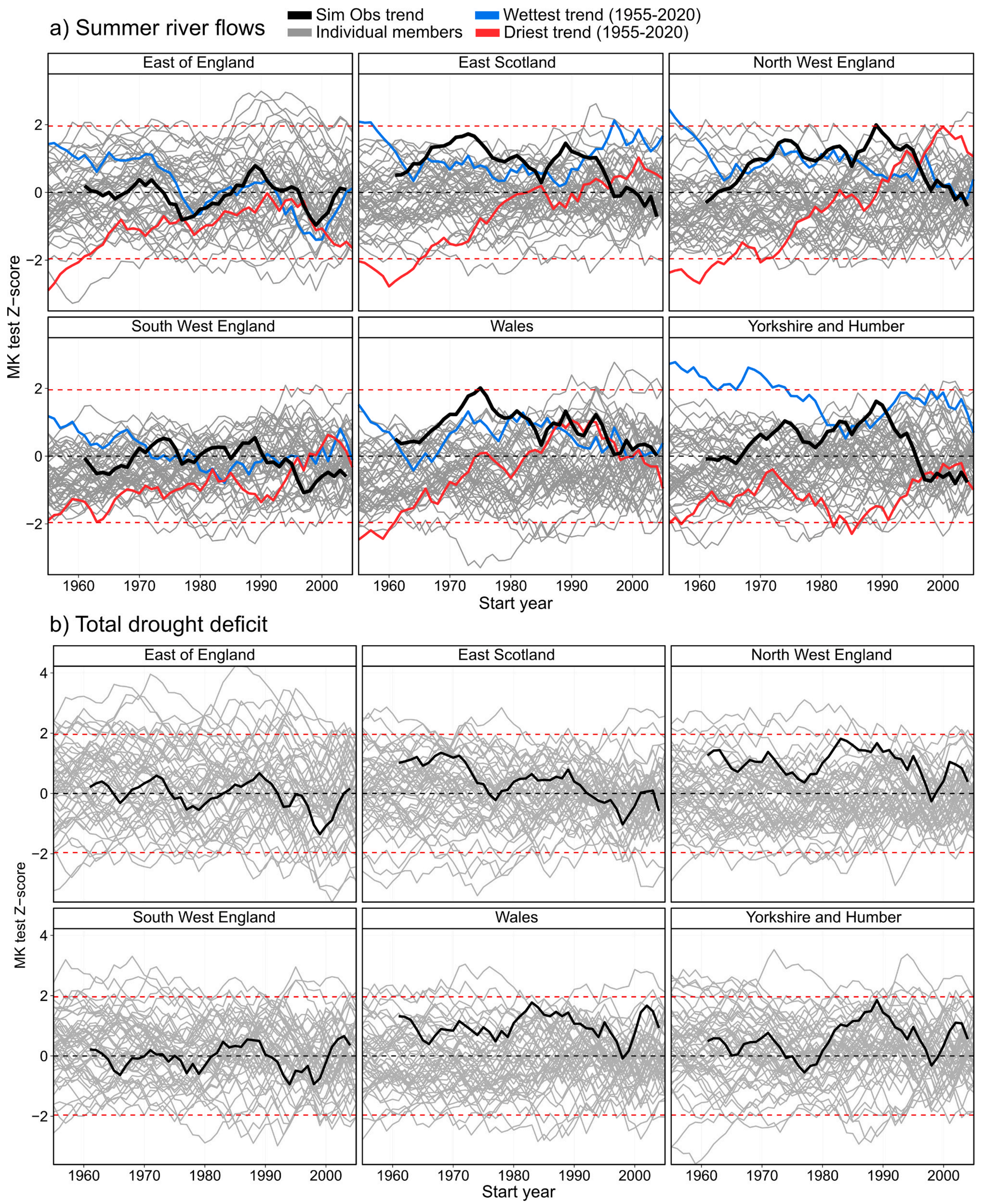

Fig. 4. MK Z-statistic in a) summer river flows and b) annual total drought deficit calculated using a Q70 threshold averaged across catchments in six different administrative regions computed from varying the start year with a fixed end year. Positive (negative) Z statistic indicate a positive (negative) trend. The trend over the observational period is calculated from 1961 with 2018 as the end year and the trend for each ensemble member of the large ensemble is calculated from 1955 with 2020 as the end year. The location of the six administrative regions is presented in Fig. S2. Serial correlation was found for 4.2% and 8.6% of the time series analysed across all catchments and time periods for summer river flows and total drought deficit, respectively.

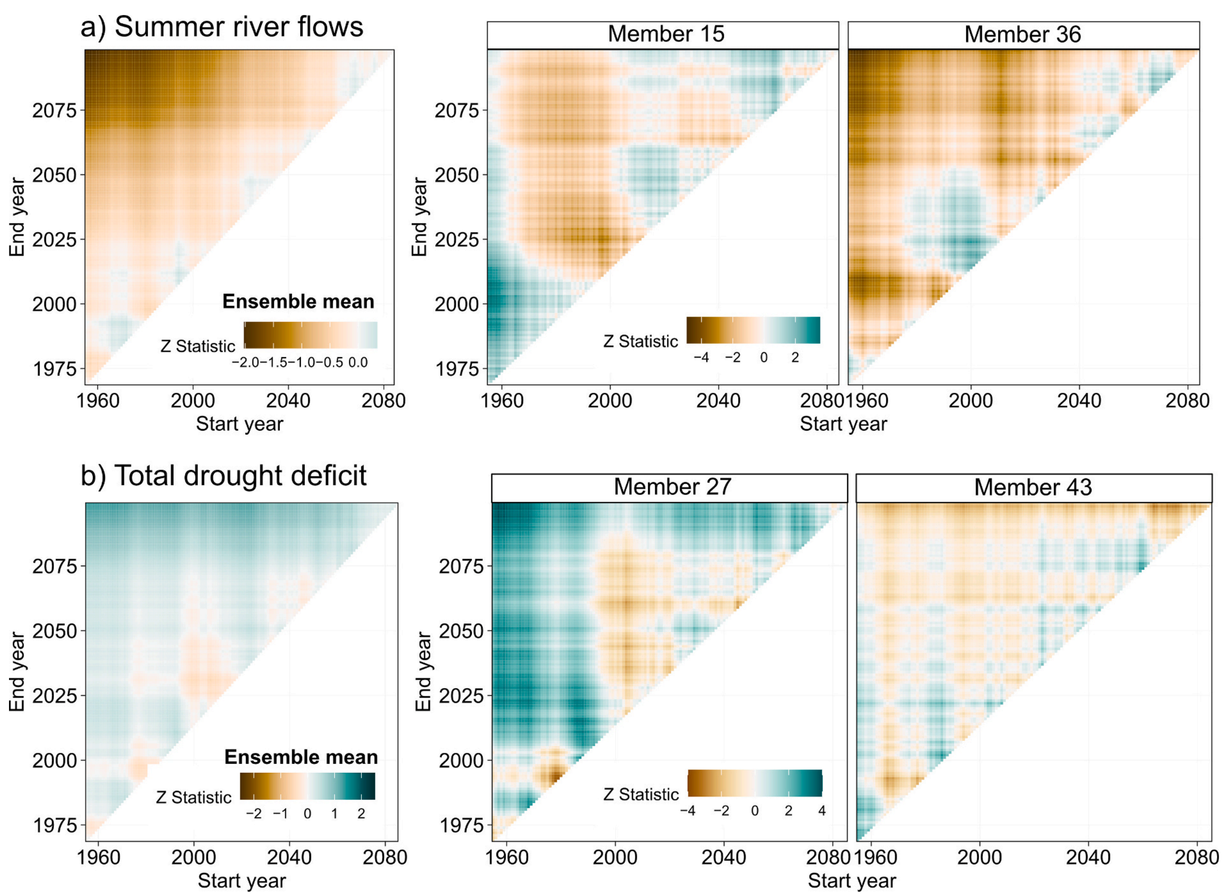

Fig. 5. Ensemble mean multi-temporal trend analysis represented via the Mann-Kendell Z statistic (colors) for a) summer river flows and b) total drought deficit calculated using a Q70 threshold averaged over all catchments in England (ensemble mean) and the equivalent for two contrasting ensemble members with the maximum and minimum long-term (1955–2099) trend. Trend is calculated for every 15-year block between 1955 and 2099 with varying start (horizontal axis) and end years (vertical axis).

Fig. 7a shows the SN ratio for the far future period (2068–2098) for different flow variables at each catchment, indicating the climate change signal in the flow trend that is clear beyond the internal variability. The SN ratio shows a signal of decreasing Q95 and summer flows along with increasing Q5 and winter flows that is spatially coherent across most catchments. There is a spatial contrast in the SN ratio for spring and autumn flows, with a positive (negative) signal across eastern (western) Britain in spring and a positive (negative) signal across northern (southern) England in autumn. Fig. 6b shows the estimated ToE for each river flow variable at each catchment. The ToE for Q95 is broadly earlier than for mean summer flows, including catchments in the East of England where change in Q95 emerges beyond internal variability by the 2070s–80s but does not emerge for mean summer flows within the 21st century. In contrast, the ToE for mean winter flows is similar to Q5, which are earlier compared to other seasons across most catchments. As would be expected, the direction of the climate change signal is broadly similar between rainfall and river flows but the climate change signal for rainfall is estimated to emerge earlier than that for river flows across all seasons (Fig. S10). The spatial pattern of ToE for winter rainfall is broadly similar between Q5 and mean winter flows with earlier emergence across western Britain. The signal for summer rainfall reduction is stronger than that for summer river flows and strongest across southern Britain, including for catchments in the southeast that have low SN ratios for summer river flows. The spatial pattern of ToE in rainfall for the different seasons is also broadly similar to that of seasonal river flows with the notable exception in autumn where the signal for rainfall is estimated to be positive across GB but the signal for river flows is estimated to be negative for groundwater-driven, slow-responding catchments in southern England.

4. Discussion

4.1. *Drivers of climate and hydrological trends*

Here we demonstrate that the inconsistency between trends in the recent past and both near and long-term future projections for UK rainfall and river flows may be attributed to sampling bias (i.e. the limited range of variability observed in the single realisation of the past). Dynamical adjustment show that atmospheric circulation variability was a dominant factor in the observed positive summer rainfall trends over 1981–2010. The large ensemble simulated rainfall further showed that robust trends that are substantially drier (or wetter) than the observed trend could have occurred in the historical period, associated with a wide range of plausible river flow outcomes, including droughts worse than the most severe observed event. Individual members with a clear summer drying trend over the historical period could have unfolded, and would be regarded as more consistent with climate projections (e.g., early UKCIP98 projections suggest a reduction in summer flows by the 2020s: Arnell, 2003). This highlights the need to compare observations with individual realisations across ensemble members of large ensemble model simulations to robustly evaluate whether observed trends are captured by climate model simulations (Simpson et al., 2025). Given future warming is certain, the large variability in rainfall highlights the importance of future rainfall trends in determining both meteorological and hydrological drought variability (Bevacqua et al., 2022).

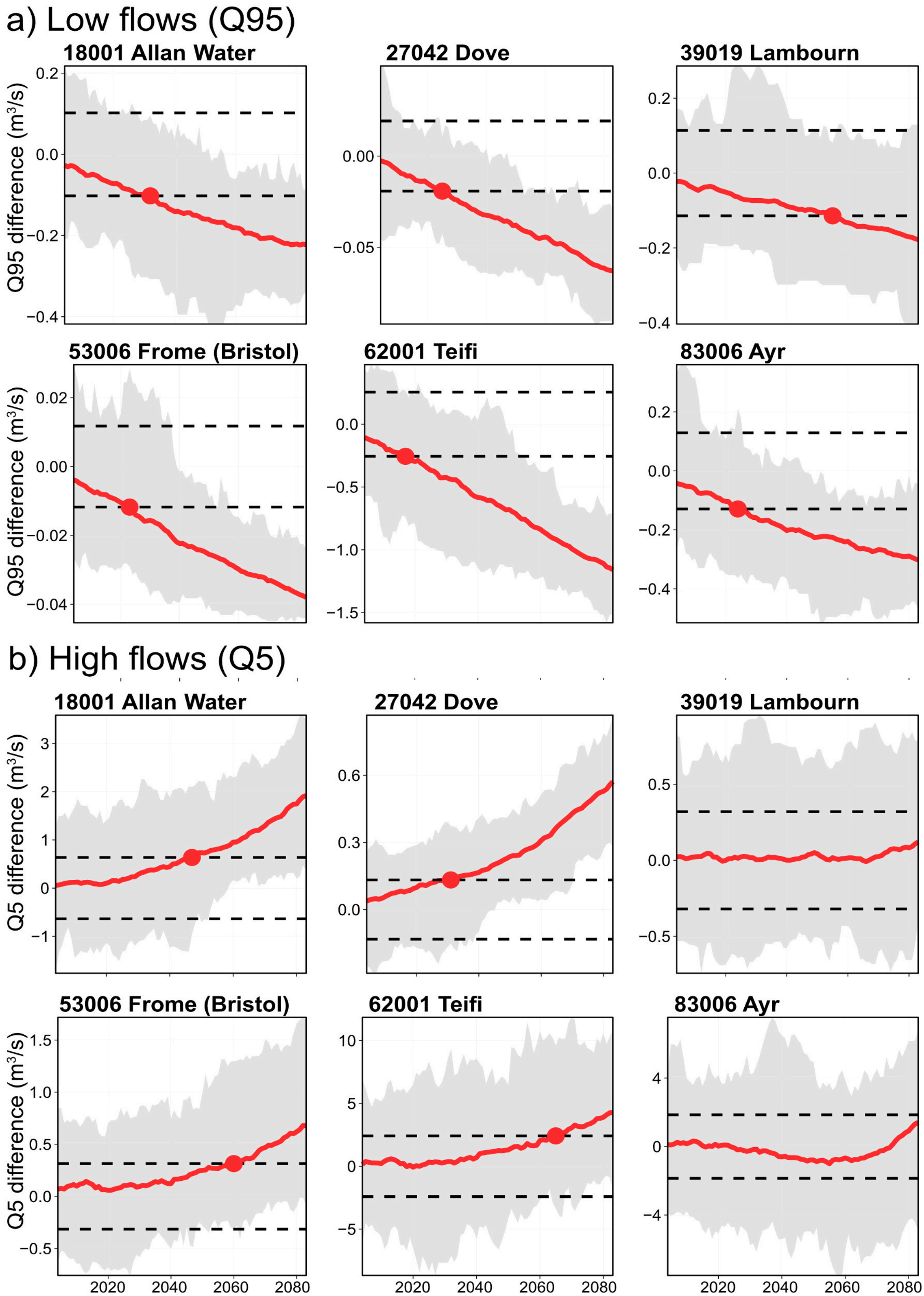

Fig. 6. Relative change (m^3/s) in a) low flows (Q95) and b) high flows (Q5) over consecutive 30-year time slices and the baseline reference period (1981–2010) for six selected catchments. The year on the horizontal axis represents the middle year of each 30-year time block and the shading the spread across the ensemble members. In each panel, the solid red line represents the ensemble mean and dashed horizontal black lines represent the range of internal variability (i.e., ± 1 standard deviation over the reference period). The red circle denotes the Time of Emergence (ToE) when the ensemble mean difference exceeds range of historical variability. The location of the six selected catchments is presented in Fig. S2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

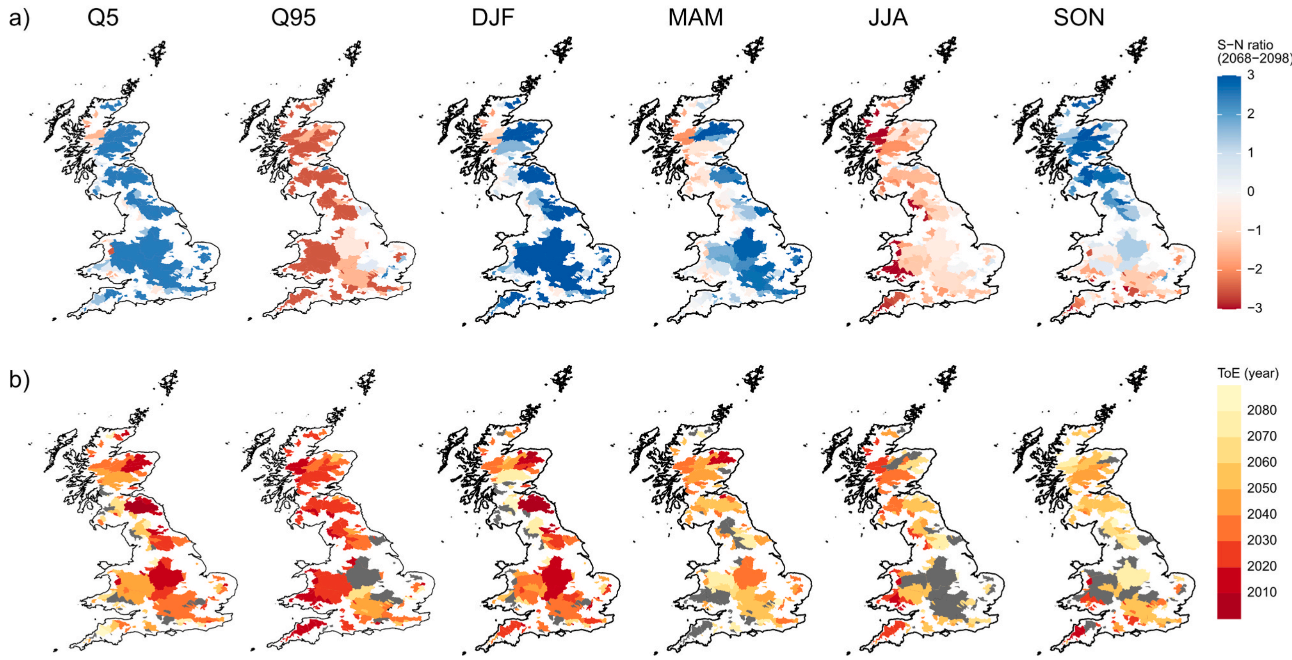

Fig. 7. a) Signal-to-noise (S-N) ratio (2068–2098) and b) the estimated Time of Emergence (ToE) (middle year of 30-year period) for high flows (Q5), low flows (Q95) and mean seasonal river flows. The catchments coloured in grey are ones where the ToE is not reached by the end of the 21st century.

An observed trend towards less severe droughts since the 1960s is in line with analysis in the UK (Hannaford et al., 2024) and across Europe (Peña-Angulo et al., 2022; Vicente Serrano et al., 2021). However, the results adds to findings that trends are sensitive to interannual and interdecadal variability (e.g., Hannaford et al., 2023b; Hannaford and Buys, 2012; Wilby, 2006) that calls into question how 'representative' observed trends are of longer-term underlying trends. For example, the positive trend in winter NAO was associated with high winter rainfall in the 1990s (Simpson and Jones, 2014), and the warm phase of the Atlantic Multi-decadal Variability contributed to the string of wet summers between 1981–2010 (Sutton and Dong, 2012; Sutton and Hodson, 2005). Dong and Sutton (2021) further found that summer atmospheric circulation during this period was characterized by an equatorwards shift in the North Atlantic jet stream associated with more rain-bearing cyclonic systems tracking across the UK.

While the use of SMILEs yields valuable insights by enabling us to disentangle internal variability and the climate change signal, their potential also relies on their ability to adequately approximate internal variability (Simpson et al., 2025). As shown by von Trentini et al. (2020), the ClimEx ensemble used in this study provides an adequate estimation of variability for seasonal mean rainfall and temperature and represents the observed variability well at the European scale, which supports its use in this study. However, this may not be true for other variables. For example, Vautard et al. (2023) showed that even large ensembles fail to reproduce the observed large positive trend in summer daily maximum temperature across parts of western Europe. This can arise due to model biases like under-estimation of atmospheric circulation variability within model simulations, such as that found for the winter NAO for the GloSea5 system, where simulations show weaker variability compared to observations (e.g., Stringer et al., 2020). Additionally, climate models tend to underestimate the persistence of atmospheric blocking leading to dry weather over the UK compared to historical observations and this bias remains despite increased atmospheric resolution in CMIP6 (Schiemann et al., 2020; Woollings et al., 2018). This has implications for multi-year droughts and confidence in their future changes remain weak as a result. The Multi-Model Large Ensemble Archive contains multiple SMILEs to fully assess inter-model uncertainty as well as internal variability, but the archived models are GCMs with coarse resolution (~100 km), which would require considerable post-processing prior to any catchment hydrological modelling and thus cannot be used as direct inter-comparison here. The use of simple rainfall-based statistical downscaling, such as Kay et al. (2023), has not been tested for SMILEs but is subject to future work.

4.2. Implications for hydrological droughts and water management

The estimated ToE highlights hotspots where changes have already exceeded natural variability or may do so imminently. Conceptually speaking, where there is an imminent ToE (e.g., increasing high flows for northern Britain and decreasing summer low flows for southwest England), adaptation measures should be in place well in advance of emergence – although in practice this depends on the regulatory regime and the risk appetite of individual decision-makers from different sectors. Nevertheless, the approach could provide useful insights to decision-makers for focusing adaptation efforts – although of course this would be in terms of high-level screening that would need extending using higher-resolution, local scale information or alternative suites of large ensemble climate model simulations to improve robustness. River flows are shown to exhibit larger variability compared to rainfall and the estimated ToE for river flows lags that for rainfall. The earlier ToE for Q95 relative to mean summer river flows also suggest stronger sensitivity of Q95 to changes in summer temperature (as shown by Charlton and Arnell, 2014). The RCP8.5 emissions scenario used in this study also represents the higher end of those considered by the IPCC, and more optimistic scenarios may delay the ToE. Future changes in low flows are more sensitive to emission scenarios compared to high flows (Arnell et al., 2021; Meresa et al., 2022), suggesting stronger influence of enhanced evapotranspiration in more pessimistic emission scenarios.

The SN ratio and ToE varies across catchments in Great Britain. The results show that it may take decades for some catchments before a statistically detectable climate signal emerge. This is due to a combination of both climatic factors (e.g., higher rainfall across western GB versus southeast England), and physical catchment characteristics (e.g., catchment size and hydrogeology) which governs the responsiveness of catchments to rainfall variability. For example, river flows are strongly linked to rainfall variability for fast-responding catchments in western

Britain, hence relatively stronger SN ratios and earlier ToE whereas for slow-responding catchments in southeast England, river flow variability are less reflective of rainfall variability and the influence of antecedent conditions are more important, leading to generally lower SN ratios and later ToE. It should be noted that the CanESM5 GCM is considered warm and wet with the ensemble mean CanESM5-LE projecting increasing rainfall over the summer half-year when averaged across Europe, an outlier compared to other selected SMILEs (Suarez-Gutierrez et al., 2023). Although projected changes for the UK lies within the wider inter-model spread (Fig. S3), the estimated ToE in this study may therefore be conservative estimates.

Trends can be small compared to large year-to-year variability. The estimation of ToE in this study relies on a clear ensemble mean trend. Disagreement between ensemble members leads to a late ToE or catchments not reaching ToE within the 21st century (e.g., for slow-responding, groundwater-driven catchments in southeast England). Given the important role of antecedent conditions in these catchments, the chance alignment of wet/dry seasons due to internally generated differences in the phasing of multiple modes of climate variability results in large year-to-year variability in rainfall and a thus a large range of possible river flow responses. However, a late ToE does not negate the potential for increased risk. The long-term ensemble mean trend may be a minor contributor to increased risk relative to the large variability in future droughts and there may be significant change in risk even without a clear ensemble mean trend (Shepherd, 2014; Sutton, 2019). Suarez-Gutierrez et al. (2023) recently showed that severity of European meteorological droughts expected for the end of the 21st century could unfold much sooner given large climate variability but the implications of this for hydrological droughts have not yet been investigated. Hence, in additional to coping with the observed historical variability, adaptation measures should also be tested with a diversity of events that could have occurred due to internal climate variability (Durant et al., 2024; Mankin et al., 2020) (such as through developing counterfactual event storylines of past drought that could have unfolded differently and lead to greater impacts – e.g., Chan et al., 2022b). Additionally, a "bottom-up" scenario-neutral approach to evaluate system sensitivity against a wide range of possible climatic changes can be used to construct stress tests and evaluate physical plausibility of simulated droughts from climate models (Prudhomme et al., 2010; Wilby and Dessai, 2010). Lengthening the observed record through meteorological data rescue and historical river flow reconstructions (e.g., Barker et al., 2019) are among additional methods that can be applied to evaluate the potential of unprecedented events that could arise from large climate and hydrological variability (Kelder et al., 2025).

Studies have long suggested that a "predict-then-act" paradigm in water resources planning, where adaptation decisions are made only when clear trends consistent with climate projections emerge from the observations, may be inappropriate (Dessai and Darch, 2014; Murphy et al., 2011; Wilby and Dessai, 2010). The ideal approach to communicate the effects of internal climate variability remains an open question. A potential way to incorporate information on internal variability could be through a discrete set of storylines describing multiple plausible hypotheses, conditioned on specific trajectories of atmospheric circulation changes (Shepherd et al., 2018; Shaw et al., 2024). For example, storylines of internal variability similar to that in Harvey et al. (2023) can similarly be created by partitioning ensemble members within a SMILE to describe the range of plausible changes in rainfall, river flows and drought events given specific alternative, equally plausible states of the North Atlantic jet stream.

5. Conclusion

In this study, we investigated the effect of internal variability on rainfall and river flows across Great Britain using a single-model-initial-condition large ensemble. We find that observed trends in rainfall and river flows are within the spread of the large ensemble, which includes a wide range of wetting and drying trends that could have occurred in the past purely due to internal climate variability. This enables greater understanding of the likelihood of the observed trend, which may at first seem inconsistent with future projections. Trends in river flows and hydrological drought are subject to larger variability compared to rainfall, are highly sensitive to multi-annual and multi-decadal variability and are associated with the occurrence of droughts worse than the most severe observed event. The Time of Emergence estimates show relatively early emergence of a climate signal beyond natural variability for winter river flows across northern GB, with implications for flood risk, and for low flows across southwest GB, with implications for water resources. Nevertheless, it may take decades before a climate change signal can be detected, necessitating the need to adopt adaptation measures before hydrological variables exceed natural variability. There was large disagreement among ensemble members over the climate change signal for summer river flows at some slow-responding catchments in southeast England, leading to the estimation of a late ToE and highlights the combined influence of internal variability on rainfall and antecedent conditions in determining future river flow variability at these catchments.

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CRediT authorship contribution statement

Wilson Chan: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maliko Tanguy:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Amulya Chevuturi:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Jamie Hannaford:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2025.133414.

Data availability

Simulated river flow for all selected GB catchments driven by the CRCM5-LE is available at (DOI: https://doi.org/10.5281/zenodo.13990611). UK rainfall and temperature data is available from the HadUK-Grid dataset (Hollis et al., 2019) and accessible via CEDA (https://catalogue.ceda.ac.uk/uuid/5a248096468640a6bfb0dfda8b018ac5/). Rainfall and temperature data for the CRCM5-LE is publicly available on the ClimEx website (https://www.climex-project.org/data-access/). Sample code for the trend detection methodology used in this study can be found at https://github.com/NERC-CEH/ROBIN_pipeline.

References

Anglian Water, 2022. Drought Plan 2022 [WWW Document]. URL https://www.anglianwater.co.uk/about-us/our-strategies-and-plans/drought-plan/ (accessed 3.6.23).

Arnell, N.W., 2003. Relative effects of multi-decadal climatic variability and changes in the mean and variability of climate due to global warming: future streamflows in Britain. J. Hydrol. 270, 195–213. https://doi.org/10.1016/S0022-1694(02)00288-3.

Arnell, N.W., Kay, A.L., Freeman, A., Rudd, A.C., Lowe, J.A., 2021. Changing climate risk in the UK: A multi-sectoral analysis using policy-relevant indicators. Clim. Risk Manag. 31, 100265. https://doi.org/10.1016/j.crm.2020.100265.

Ascott, M.J., Macdonald, D.M.J., Sandwidi, W.J.P., Black, E., Verhoef, A., Zongo, G., Tirogo, J., Cook, P., 2022. Time of emergence of impacts of climate change on groundwater levels in sub-Saharan Africa. J. Hydrol. 612, 128107. https://doi.org/10.1016/j.jhydrol.2022.128107.

Barker, L.J., Hannaford, J., Magee, E., Turner, S., Sefton, C., Parry, S., Evans, J., Szczykulska, M., Haxton, T., 2024. An appraisal of the severity of the 2022 drought and its impacts. Weather wea.4531. doi: 10.1002/wea.4531.

Barker, L.J., Hannaford, J., Parry, S., Smith, K.A., Tanguy, M., Prudhomme, C., 2019. Historic hydrological droughts 1891–2015: systematic characterisation for a diverse set of catchments across the UK. Hydrol. Earth Syst. Sci. 23, 4583–4602. https://doi.org/10.5194/hess-23-4583-2019.

Bevacqua, E., Zappa, G., Lehner, F., Zscheischler, J., 2022. Precipitation trends determine future occurrences of compound hot–dry events. Nat. Clim. Chang. 12, 350–355. https://doi.org/10.1038/s41558-022-01309-5.

Brunner, M.I., Slater, L.J., 2022. Extreme floods in Europe: going beyond observations using reforecast ensemble pooling. Hydrol. Earth Syst. Sci. 26, 469–482. https://doi.org/10.5194/hess-26-469-2022.

Brunner, M.I., Swain, D.L., Wood, R.R., Willkofer, F., Done, J.M., Gilleland, E., Ludwig, R., 2021. An extremeness threshold determines the regional response of floods to changes in rainfall extremes. Commun Earth Environ 2, 1–11. https://doi.org/10.1038/s43247-021-00248-x.

Burn, D.H., Hannaford, J., Hodgkins, G.A., Whitfield, P.H., Thorne, R., Marsh, T., 2012. Reference hydrologic networks II. Using reference hydrologic networks to assess climate-driven changes in streamflow. Hydrol. Sci. J. 57, 1580–1593. https://doi.org/10.1080/02626667.2012.728705.

Chan, W.C., Shepherd, T.G., Facer-Childs, K., Darch, G., Arnell, N.W., 2022a. Tracking the methodological evolution of climate change projections for UK river flows. Prog. Phys. Geogr.: Earth Environ., 030913332210792 https://doi.org/10.1177/03091333221079201.

Chan, W.C.H., Arnell, N.W., Darch, G., Facer-Childs, K., Shepherd, T.G., Tanguy, M., van der Wiel, K., 2023. Current and future risk of unprecedented hydrological droughts in Great Britain. J. Hydrol. 130074. https://doi.org/10.1016/j.jhydrol.2023.130074.

Chan, W.C.H., Shepherd, T.G., Facer-Childs, K., Darch, G., Arnell, N.W., 2024. Added value of seasonal hindcasts to create UK hydrological drought storylines. Nat. Hazards Earth Syst. Sci. https://doi.org/10.5194/nhess-24-1065-2024.

Chan, W.C.H., Shepherd, T.G., Facer-Childs, K., Darch, G., Arnell, N.W., 2022b. Storylines of UK drought based on the 2010–2012 event. Hydrol. Earth Syst. Sci. 26, 1755–1777. https://doi.org/10.5194/hess-26-1755-2022.

Charlton, M.B., Arnell, N.W., 2014. Assessing the impacts of climate change on river flows in England using the UKCP09 climate change projections. J. Hydrol. 519, 1723–1738. https://doi.org/10.1016/j.jhydrol.2014.09.008.

Counsell, C., Durant, M., 2023. Annex L: Water Supply: Observed and Projected - Review of the state of research on drought. Review of the Research and Scientific Understanding of Drought. Environment Agency.

Deser, C., Lehner, F., Rodgers, K.B., Ault, T., Delworth, T.L., DiNezio, P.N., Fiore, A., Frankignoul, C., Fyfe, J.C., Horton, D.E., Kay, J.E., Knutti, R., Lovenduski, N.S., Marotzke, J., McKinnon, K.A., Minobe, S., Randerson, J., Screen, J.A., Simpson, I.R., Ting, M., 2020. Insights from Earth system model initial-condition large ensembles and future prospects. Nat. Clim. Chang. 10, 277–286. https://doi.org/10.1038/s41558-020-0731-2.

Deser, C., Phillips, A.S., 2023. A range of outcomes: the combined effects of internal variability and anthropogenic forcing on regional climate trends over Europe. Nonlinear Processes Geophys. 30, 63–84. https://doi.org/10.5194/npg-30-63-2023.

Deser, C., Terray, L., Phillips, A.S., 2016. Forced and Internal Components of Winter Air Temperature Trends over North America during the past 50 Years: Mechanisms and Implications. J. Clim. 29, 2237–2258. https://doi.org/10.1175/JCLI-D-15-0304.1.

Dessai, S., Darch, G., 2014. Robust decision-making? Managing uncertainties in adapting water resource systems to a changing climate in England and Wales. In: Prutsch, A., Grothmann, T., McCallum, S., Schauser, I., Swart, R. (Eds.), Climate Change Adaptation Manual: Lessons Learned from European and Other Industrialised Countries. Routledge, Abingdon, pp. 208–212.

Dong, B., Sutton, R.T., 2021. Recent Trends in Summer Atmospheric Circulation in the North Atlantic/European Region: Is There a Role for Anthropogenic Aerosols? J. Clim. 34, 6777–6795. https://doi.org/10.1175/JCLI-D-20-0665.1.

Durant, M., Hall, E., Morris, A., Walburn, G., Wilcox, A., Counsell, C., 2024. The future is transient: Barriers and opportunities for improved UK water resource climate change assessments using the enhanced Future Flows and Groundwater (eFLaG) climate service products. Climate Resilience 3, e69.

Faghih, M., Brissette, F., 2023. The role of internal climate variability on future streamflow projections. J. Hydrol. 625, 130101. https://doi.org/10.1016/j.jhydrol.2023.130101.

Faranda, D., Pascale, S., Bulut, B., 2023. Persistent anticyclonic conditions and climate change exacerbated the exceptional 2022 European-Mediterranean drought. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/acbc37.

Fischer, E.M., Sippel, S., Knutti, R., 2021. Increasing probability of record-shattering climate extremes. Nat. Clim. Chang. 11, 689–695. https://doi.org/10.1038/s41558-021-01092-9.

Fyfe, J.C., Derksen, C., Mudryk, L., Flato, G.M., Santer, B.D., Swart, N.C., Molotch, N.P., Zhang, X., Wan, H., Arora, V.K., Scinocca, J., Jiao, Y., 2017. Large near-term projected snowpack loss over the western United States. Nat Commun 8, 14996. https://doi.org/10.1038/ncomms14996.

Goulart, H.M.D., Benito Lazaro, I., van Garderen, L., van der Wiel, K., Le Bars, D., Koks, E., van den Hurk, B., 2024. Compound flood impacts from Hurricane Sandy on New York City in climate-driven storylines. Nat. Hazards Earth Syst. Sci. 24, 29–45. https://doi.org/10.5194/nhess-24-29-2024.

Guillod, B.P., Jones, R.G., Dadson, S.J., Coxon, G., Bussi, G., Freer, J., Kay, A.L., Massey, N.R., Sparrow, S.N., Wallom, D.C.H., Allen, M.R., Hall, J.W., 2018. A large set of potential past, present and future hydro-meteorological time series for the UK. Hydrol. Earth Syst. Sci. 22, 611–634. https://doi.org/10.5194/hess-22-611-2018.

Guo, R., Deser, C., Terray, L., Lehner, F., 2019. Human Influence on Winter Precipitation Trends (1921–2015) over North America and Eurasia Revealed by Dynamical Adjustment. Geophys. Res. Lett. 46, 3426–3434. https://doi.org/10.1029/2018GL081316.

Hall, R.J., Hanna, E., 2018. North Atlantic circulation indices: links with summer and winter UK temperature and precipitation and implications for seasonal forecasting. Int. J. Climatol 38, e660–e677. https://doi.org/10.1002/joc.5398.

Hannaford, J., Barker, L., Turner, S., Parry, S., Tanguy, M., Chevuturi, A., 2023a. Annex B: Past variability in observed hydrological (river flow) drought. Review of the Research and Scientific Understanding of Drought, Environment Agency.

Hannaford, J., Buys, G., 2012. Trends in seasonal river flow regimes in the UK. J. Hydrol. 475, 158–174. https://doi.org/10.1016/j.jhydrol.2012.09.044.

Hannaford, J., Buys, G., Stahl, K., Tallaksen, L.M., 2013. The influence of decadal-scale variability on trends in long European streamflow records. Hydrol. Earth Syst. Sci. 17, 2717–2733. https://doi.org/10.5194/hess-17-2717-2013.

Hannaford, J., Mackay, J.D., Ascott, M., Bell, V.A., Chitson, T., Cole, S., Counsell, C., Durant, M., Jackson, C.R., Kay, A.L., Lane, R.A., Mansour, M., Moore, R., Parry, S., Rudd, A.C., Simpson, M., Facer-Childs, K., Turner, S., Wallbank, J.R., Wells, S., Wilcox, A., 2023b. The enhanced future Flows and Groundwater dataset: development and evaluation of nationally consistent hydrological projections based on UKCP18. Earth Syst. Sci. Data 15, 2391–2415. https://doi.org/10.5194/essd-15-2391-2023.

Hannaford, J., Mastrantonas, N., Vesuviano, G., Turner, S., 2021. An updated national-scale assessment of trends in UK peak river flow data: how robust are observed increases in flooding? Hydrol. Res. 52, 699–718. https://doi.org/10.2166/nh.2021.156.

Hannaford, J., Turner, S., Chevuturi, A., Chan, W., Barker, L.J., Tanguy, M., Parry, S., Allen, S., 2024. Have river flow droughts become more severe? A review of the evidence from the UK – a data-rich temperate environment. doi: 10.5194/hess-2024-293.

Harrigan, S., Hannaford, J., Muchan, K., Marsh, T.J., 2018. Designation and trend analysis of the updated UK Benchmark Network of river flow stations: the UKBN2 dataset. Hydrol. Res. 49, 552–567. https://doi.org/10.2166/nh.2017.058.

Harvey, B., Hawkins, E., Sutton, R., 2023. Storylines for future changes of the North Atlantic jet and associated impacts on the UK. Int. J. Climatol. joc.8095. https://doi.org/10.1002/joc.8095.

Hawkins, E., Frame, D., Harrington, L., Joshi, M., King, A., Rojas, M., Sutton, R., 2020. Observed Emergence of the Climate Change Signal: From the Familiar to the Unknown. Geophys. Res. Lett. 47, e2019GL086259. https://doi.org/10.1029/2019GL086259.

Hawkins, E., Sutton, R., 2012. Time of emergence of climate signals. Geophys. Res. Lett. 39, 2011GL050087. https://doi.org/10.1029/2011GL050087.

Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I., 2019. HadUK-Grid—A new UK dataset of gridded climate observations. Geosci Data J 6, 151–159. https://doi.org/10.1002/gdj3.78.

Jain, S., Scaife, A.A., Shepherd, T.G., Deser, C., Dunstone, N., Schmidt, G.A., Trenberth, K.E., Turkington, T., 2023. Importance of internal variability for climate model assessment. Npj Clim Atmos Sci 6, 68. https://doi.org/10.1038/s41612-023-00389-0.

John, A., Nathan, R., Horne, A., Fowler, K., Stewardson, M., Peel, M., Angus Webb, J., 2023. The time of emergence of climate-induced hydrologic change in Australian rivers. J. Hydrol. 619, 129371. https://doi.org/10.1016/j.jhydrol.2023.129371.

Kay, A.L., Griffin, A., Rudd, A.C., Chapman, R.M., Bell, V.A., Arnell, N.W., 2021. Climate change effects on indicators of high and low river flow across Great Britain. Adv. Water Resour. 151, 103909. https://doi.org/10.1016/j.advwatres.2021.103909.

Kay, A.L., Rudd, A.C., Coulson, J., 2023. Spatial downscaling of precipitation for hydrological modelling: assessing a simple method and its application under climate change in Britain. Hydrol. Processes 37 (2), e14823.

Kelder, T., Heinrich, D., Klok, L., Thompson, V., Goulart, H.M.D., Hawkins, E., Slater, L.J., Suarez-Gutierrez, L., Wilby, R.L., Coughlan De Perez, E., Stephens, E.M., Burt, S., Van Den Hurk, B., De Vries, H., Van Der Wiel, K., Schipper, E.L.F., Carmona Baéz, A., Van Bueren, E., Fischer, E.M., 2025. How to stop being surprised by unprecedented weather. Nat Commun 16, 2382. https://doi.org/10.1038/s41467-025-57450-0.

Kelder, T., Marjoribanks, T.I., Slater, L.J., Prudhomme, C., Wilby, R.L., Wagemann, J., Dunstone, N., 2022. An open workflow to gain insights about low-likelihood high-impact weather events from initialized predictions. Meteorol. Appl. 29. https://doi.org/10.1002/met.2065.

Kelder, T., Müller, M., Slater, L.J., Marjoribanks, T.I., Wilby, R.L., Prudhomme, C., Bohlinger, P., Ferranti, L., Nipen, T., 2020. Using UNSEEN trends to detect decadal changes in 100-year precipitation extremes. npj Clim. Atmos. Sci. 3, 1–13. https://doi.org/10.1038/s41612-020-00149-4.

Lane, R., Kay, A., 2023. Annex C: Modelling climate change impacts on UK hydrological drought: A review. Review of the Research and Scientific Understanding of Drought, Environment Agency.
Leander, R., Buishand, T.A., 2007. Resampling of regional climate model output for the simulation of extreme river flows. J. Hydrol. 332, 487–496. https://doi.org/10.1016/j.jhydrol.2006.08.006.
Leduc, M., Mailhot, A., Frigon, A., Martel, J.-L., Ludwig, R., Brietzke, G.B., Giguère, M., Brissette, F., Turcotte, R., Braun, M., Scinocca, J., 2019. The ClimEx Project: A 50-Member Ensemble of Climate Change Projections at 12-km Resolution over Europe and Northeastern North America with the Canadian Regional Climate Model (CRCM5). J. Appl. Meteorol. Climatol. 58, 663–693. https://doi.org/10.1175/JAMC-D-18-0021.1.
Lehner, F., Deser, C., 2023. Origin, importance, and predictive limits of internal climate variability. Environ. Res.: Climate 2, 023001. https://doi.org/10.1088/2752-5295/accf30.
Lehner, F., Deser, C., Simpson, I.R., Terray, L., 2018. Attributing the U.S. Southwest's Recent Shift Into Drier Conditions. Geophys. Res. Lett. 45, 6251–6261. https://doi.org/10.1029/2018GL078312.
Lowe, J.A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard, T., Kaye, N., Kendon, E., Krijnen, J., Maisey, P., McDonald, R., McInnes, R., McSweeney, C., Mitchell, J.F., Murphy, J., Palmer, M., Roberts, C., Rostron, J., Sexton, D., Thornton, H., Tinker, J., Tucker, S., Yamazaki, K., Belcher, S., 2018. UKCP18 Science Overview report, https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/UKCP18-Overview-report.pdf (last access: 3 May 2025).
Mahmoudi, M.H., Najafi, M.R., Singh, H., Schnorbus, M., 2021. Spatial and temporal changes in climate extremes over northwestern North America: the influence of internal climate variability and external forcing. Clim. Change 165, 14. https://doi.org/10.1007/s10584-021-03037-9.
Mankin, J.S., Lehner, F., Coats, S., McKinnon, K.A., 2020. The Value of Initial Condition Large Ensembles to Robust Adaptation Decision-Making. Earth's. Future 8, e2012EF001610. https://doi.org/10.1029/2020EF001610.
McLeod, A.I., McLeod, M.A., 2015. Package 'Kendall. R Software, London, UK.
Meresa, H., Donegan, S., Golian, S., Murphy, C., 2022. Simulated Changes in Seasonal and Low Flows with Climate Change for Irish Catchments. Water 14, 1556. https://doi.org/10.3390/w14101556.
Miller, J., Böhnisch, A., Ludwig, R., Brunner, M.I., 2024. Climate change impacts on regional fire weather in heterogeneous landscapes of central Europe. Nat. Hazards Earth Syst. Sci. 24 (2), 411–428.
Muelchi, R., Rössler, O., Schwanbeck, J., Weingartner, R., Martius, O., 2021. River runoff in Switzerland in a changing climate – runoff regime changes and their time of emergence. Hydrol. Earth Syst. Sci. 25, 3071–3086. https://doi.org/10.5194/hess-25-3071-2021.
Müller, O.V., McGuire, P.C., Vidale, P.L., Hawkins, E., 2024. River flow in the near future: a global perspective in the context of a high-emission climate change scenario. Hydrol. Earth Syst. Sci. 28, 2179–2201. https://doi.org/10.5194/hess-28-2179-2024.
Murphy, C., Bastola, S., Hall, J., Harrigan, S., Murphy, N., Holman, C., 2011. Against a 'wait and see' approach in adapting to climate change. Ir. Geogr. 44, 81–95. https://doi.org/10.1080/00750778.2011.615707.
Murphy, C., Coen, A., Clancy, I., Decristoforo, V., Cathal, S., Healion, K., Horvath, C., Jessop, C., Kennedy, S., Lavery, R., Leonard, K., McLoughlin, C., Moore, R., O'Hare-Doherty, D., Paisley, R., Prakash, B., Vatu, J., Thorne, P., Mateus, C., Ryan, C., Noone, S., 2023. The emergence of a climate change signal in long-term Irish meteorological observations. Weather Clim. Extremes 42, 100608. https://doi.org/10.1016/j.wace.2023.100608.
Murphy, C., Wilby, R.L., Matthews, T.K.R., Thorne, P., Broderick, C., Fealy, R., Hall, J., Harrigan, S., Jones, P., McCarthy, G., MacDonald, N., Noone, S., Ryan, C., 2020. Multi-century trends to wetter winters and drier summers in the England and Wales precipitation series explained by observational and sampling bias in early records. Int J Climatol 40, 610–619. https://doi.org/10.1002/joc.6208.
O'Reilly, C.H., Woollings, T., Zanna, L., 2017. The Dynamical Influence of the Atlantic Multidecadal Oscillation on Continental Climate. J. Clim. 30, 7213–7230. https://doi.org/10.1175/JCLI-D-16-0345.1.
Ossó, A., Allan, R.P., Hawkins, E., Shaffrey, L., Maraun, D., 2022. Emerging new climate extremes over Europe. Clim Dyn 58, 487–501. https://doi.org/10.1007/s00382-021-05917-3.
Parry, S., Mackay, J.D., Chitson, T., Hannaford, J., Magee, E., Tanguy, M., Bell, V.A., Facer-Childs, K., Kay, A., Lane, R., Moore, R.J., Turner, S., Wallbank, J., 2024. Divergent future drought projections in UK river flows and groundwater levels. Hydrol. Earth Syst. Sci. 28, 417–440. https://doi.org/10.5194/hess-28-417-2024.
Peña-Angulo, D., Vicente-Serrano, S.M., Domínguez-Castro, F., Lorenzo-Lacruz, J., Murphy, C., Hannaford, J., Allan, R.P., Tramblay, Y., Reig-Gracia, F., El Kenawy, A., 2022. The complex and spatially diverse patterns of hydrological droughts across Europe. Water Resour. Res. 58 (4), e2022WR031976.
Piniewski, M., Eini, M.R., Chattopadhyay, S., Okruszko, T., Kundzewicz, Z.W., 2022. Is there a coherence in observed and projected changes in riverine low flow indices across Central Europe? Earth Sci. Rev. 233, 104187. https://doi.org/10.1016/j.earscirev.2022.104187.
Poschlod, B., Willkofer, F., Ludwig, R., 2020. Impact of Climate Change on the Hydrological Regimes in Bavaria. Water 12, 1599. https://doi.org/10.3390/w12061599.
Prudhomme, C., Wilby, R.L., Crooks, S., Kay, A.L., Reynard, N.S., 2010. Scenario-neutral approach to climate change impact studies: Application to flood risk. J. Hydrol. 390, 198–209. https://doi.org/10.1016/j.jhydrol.2010.06.043.
Pushpalatha, R., Perrin, C., Le Moine, N., Mathevet, T., Andréassian, V., 2011. A downward structural sensitivity analysis of hydrological models to improve low-flow simulation. J. Hydrol. 411, 66–76. https://doi.org/10.1016/j.jhydrol.2011.09.034.
Rudd, A.C., Kay, A.L., Bell, V.A., 2019. National-scale analysis of future river flow and soil moisture droughts: potential changes in drought characteristics. Clim. Change 156, 323–340. https://doi.org/10.1007/s10584-019-02528-0.
Schiemann, R., Athanasiadis, P., Barriopedro, D., Doblas-Reyes, F., Lohmann, K., Roberts, M.J., Sein, D.V., Roberts, C.D., Terray, L., Vidale, P.L., 2020. Northern Hemisphere blocking simulation in current climate models: evaluating progress from the Climate Model Intercomparison Project Phase 5 to 6 and sensitivity to resolution. Weather Clim. Dyn. 1, 277–292. https://doi.org/10.5194/wcd-1-277-2020.
Shaw, T.A., Arias, P.A., Collins, M., Coumou, D., Diedhiou, A., Garfinkel, C.I., Jain, S., Roxy, M.K., Kretschmer, M., Leung, L.R., Narsey, S., Martius, O., Seager, R., Shepherd, T.G., Sörensson, A.A., Stephenson, T., Taylor, M., Wang, L., 2024. Regional climate change: consensus, discrepancies, and ways forward. Front. Clim. 6. https://doi.org/10.3389/fclim.2024.1391634.
Shepherd, T.G., 2014. Atmospheric circulation as a source of uncertainty in climate change projections. Nat. Geosci. 7, 703–708. https://doi.org/10.1038/ngeo2253.
Shepherd, T.G., Boyd, E., Calel, R.A., Chapman, S.C., Dessai, S., Dima-West, I.M., Fowler, H.J., James, R., Maraun, D., Martius, O., Senior, C.A., Sobel, A.H., Stainforth, D.A., Tett, S.F.B., Trenberth, K.E., van den Hurk, B.J.J.M., Watkins, N.W., Wilby, R.L., Zenghelis, D.A., 2018. Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. Clim. Change 151, 555–571. https://doi.org/10.1007/s10584-018-2317-9.
Simpson, I.R., Jones, P.D., 2014. Analysis of UK precipitation extremes derived from Met Office gridded data: Analysis of UK precipitation extremes. Int. J. Climatol. 34, 2438–2449. https://doi.org/10.1002/joc.3850.
Simpson, I.R., Shaw, T.A., Ceppi, P., Clement, A.C., Fischer, E., Grise, K.M., Pendergrass, A.G., Screen, J.A., Wills, R.C.J., Woollings, T., Blackport, R., Kang, J. M., Po-Chedley, S., 2025. Confronting Earth System Model trends with observations. Sci. Adv. 11, eadt8035. https://doi.org/10.1126/sciadv.adt8035.
Slater, L.J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., Kelder, T., Kowal, K., Lees, T., Matthews, T., Murphy, C., Wilby, R.L., 2021. Nonstationary weather and water extremes: a review of methods for their detection, attribution, and management. Hydrol. Earth Syst. Sci. 25, 3897–3935. https://doi.org/10.5194/hess-25-3897-2021.
Smith, K.A., Barker, L.J., Tanguy, M., Parry, S., Harrigan, S., Legg, T.P., Prudhomme, C., Hannaford, J., 2019. A multi-objective ensemble approach to hydrological modelling in the UK: an application to historic drought reconstruction. Hydrol. Earth Syst. Sci. 23, 3247–3268. https://doi.org/10.5194/hess-23-3247-2019.
Stringer, N., Knight, J., Thornton, H., 2020. Improving Meteorological Seasonal Forecasts for Hydrological Modeling in European Winter. J. Appl. Meteorol. Climatol. 59, 317–332. https://doi.org/10.1175/JAMC-D-19-0094.1.
Suarez-Gutierrez, L., Müller, W.A., Marotzke, J., 2023. Extreme heat and drought typical of an end-of-century climate could occur over Europe soon and repeatedly. Commun Earth Environ 4, 1–11. https://doi.org/10.1038/s43247-023-01075-y.
Sutton, R.T., 2019. Climate Science Needs to Take Risk Assessment Much More Seriously. Bull. Amer. Meteor. Soc. 100, 1637–1642. https://doi.org/10.1175/BAMS-D-18-0280.1.
Sutton, R.T., Dong, B., 2012. Atlantic Ocean influence on a shift in European climate in the 1990s. Nature Geosci 5, 788–792. https://doi.org/10.1038/ngeo1595.
Sutton, R.T., Hodson, D.L.R., 2005. Atlantic Ocean Forcing of North American and European Summer Climate. Science 309, 115–118. https://doi.org/10.1126/science.1109496.
Tanguy, M., Chevuturi, A., Marchant, B.P., Mackay, J.D., Parry, S., Hannaford, J., 2023. How will climate change affect the spatial coherence of streamflow and groundwater droughts in Great Britain? Environ. Res. Lett. 18, 064048. https://doi.org/10.1088/1748-9326/acd655.
Tanguy, M., Dixon, H., Prosdocimi, I., Morris, D.G., Keller, V.D.J., 2021. Gridded estimates of daily and monthly areal rainfall for the United Kingdom (1890-2019) [CEH-GEAR]. doi: 10.5285/DBF13DD5-90CD-457A-A986-F2F9DD97E93C.
Tanguy, M., Prudhomme, C., Smith, K., Hannaford, J., 2018. Historical gridded reconstruction of potential evapotranspiration for the UK. Earth Syst. Sci. Data 10, 951–968. https://doi.org/10.5194/essd-10-951-2018.
Thompson, V., Dunstone, N.J., Scaife, A.A., Smith, D.M., Slingo, J.M., Brown, S., Belcher, S.E., 2017. High risk of unprecedented UK rainfall in the current climate. Nat. Commun. 8, 107. https://doi.org/10.1038/s41467-017-00275-3.
Turner, S., Barker, L.J., Hannaford, J., Muchan, K., Parry, S., Sefton, C., 2021. The 2018/2019 drought in the UK: a hydrological appraisal. Weather 76, 248–253. https://doi.org/10.1002/wea.4003.
van der Wiel, K., Batelaan, T.J., Wanders, N., 2022. Large increases of multi-year droughts in north-western Europe in a warmer climate. Clim Dyn. https://doi.org/10.1007/s00382-022-06373-3.
van der Wiel, K., Wanders, N., Selten, F.M., Bierkens, M.F.P., 2019. Added value of large ensemble simulations for assessing extreme river discharge in a 2 C warmer world. Geophys. Res. Lett. 46 (4), 2093–2102.
Van Loon, A.F., 2015. Hydrological drought explained. WIREs Water 2, 359–392. https://doi.org/10.1002/wat2.1085.
Vautard, R., Cattiaux, J., Happé, T., Singh, J., Bonnet, R., Cassou, C., Coumou, D., D'Andrea, F., Faranda, D., Fischer, E., Ribes, A., Sippel, S., Yiou, P., 2023. Heat extremes in Western Europe increasing faster than simulated due to atmospheric circulation trends. Nat Commun 14, 6803. https://doi.org/10.1038/s41467-023-42143-3.
Vicente Serrano, S., Domínguez-Castro, F., Murphy, C., Hannaford, J., Reig, F., Peña-Angulo, D., Tramblay, Y., Trigo, R., MacDonald, N., Infante, D.L., Luna, Y., 2020.

Long-term variability and trends in meteorological droughts in Western Europe (1851–2018). Int. J. Climatol. 41 (S1), E690–E717.
von Trentini, F., Aalbers, E.E., Fischer, E.M., Ludwig, R., 2020. Comparing interannual variability in three regional single-model initial-condition large ensembles (SMILEs) over Europe. Earth Syst. Dyn. 11, 1013–1031. https://doi.org/10.5194/esd-11-1013-2020.
von Trentini, F., Leduc, M., Ludwig, R., 2019. Assessing natural variability in RCM signals: comparison of a multi model EURO-CORDEX ensemble with a 50-member single model large ensemble. Clim Dyn 53, 1963–1979. https://doi.org/10.1007/s00382-019-04755-8.
Wilby, R.L., 2006. When and where might climate change be detectable in UK river flows? Geophys. Res. Lett. 33, L19407. https://doi.org/10.1029/2006GL027552.
Wilby, R.L., Beven, K.J., Reynard, N.S., 2008. Climate change and fluvial flood risk in the UK: more of the same? Hydrol. Process. 22, 2511–2523. https://doi.org/10.1002/hyp.6847.
Wilby, R.L., Clifford, N.J., De Luca, P., Harrigan, S., Hillier, J.K., Hodgkins, R., Johnson, M.F., Matthews, T.K.R., Murphy, C., Noone, S.J., Parry, S., Prudhomme, C., Rice, S.P., Slater, L.J., Smith, K.A., Wood, P.J., 2017. The 'dirty dozen' of freshwater science: detecting then reconciling hydrological data biases and errors. WIREs Water 4, e1209. https://doi.org/10.1002/wat2.1209.
Wilby, R.L., Dessai, S., 2010. Robust adaptation to climate change. Weather 65, 180–185. https://doi.org/10.1002/wea.543.
Woollings, T., Barriopedro, D., Methven, J., Son, S.-W., Martius, O., Harvey, B., Sillmann, J., Lupo, A.R., Seneviratne, S., 2018. Blocking and its Response to Climate Change. Curr Clim Change Rep 4, 287–300. https://doi.org/10.1007/s40641-018-0108-z.