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Research papers

Current and future risk of unprecedented hydrological droughts in Great Britain

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ABSTRACT

The UK has experienced recurring hydrological droughts in the past and their frequency and severity are predicted to increase with climate change. However, quantifying the risks of extreme droughts is challenging given the short observational record, the multivariate nature of droughts and large internal variability of the climate system. We use EC-Earth time-slice large ensembles, which consist of 2000 years of data each for present-day, 2°C and 3°C conditions relative to pre-industrial, to drive hydrological models of river catchments in Great Britain (GB) to obtain a large set of plausible droughts. Since future warming is certain, the uncertainty in drought is mainly associated with uncertainty in precipitation. Estimates of unprecedented extremes show that the chance of a summer month in a given year drier than the observed driest summer (1995) is projected to increase with future warming (from 9% in the present-day (PD) to 18% in a 3°C warmer world (3C) for southeast England). For winter, the chance of a dry winter month drier than the observed driest winter (1991–92) slightly decreases (from 10% - PD to 8% − 3C for southeast England) but the chance of the driest winter does not change significantly with future warming. We add value to these probabilistic estimates by sampling for physical climate storylines of drought sequences characterised by dry spring-summers, autumn-winters and consecutive dry winters. Dry spring-summers are estimated to become drier with future warming primarily driven by reduced precipitation in summer. Dry autumn-winters may become wetter mainly driven by the general trend of more precipitation in winter although drought conditions triggered by moderate autumn–winter precipitation deficits may worsen given the higher likelihood of being followed by a dry summer. Similarly, drought impacts of consecutive dry winters, a particular risk for slow-responding catchments in the English Lowlands, may worsen with future warming as the intervening summer is projected to become hotter and drier. These storylines can be used to stress-test hydrological systems and inform decision-making.

1. Introduction

Hydrological droughts threaten public water supply and incur significant socio-economic and environmental consequences. The United Kingdom (UK) has experienced recurring periods of severe hydrological drought in the past (Marsh et al. 2007) and more recent events such as the 2010-12 (Kendon et al. 2013), 2018-19 (Turner et al. 2021) and 2022 droughts (Parry, 2022) showed that the UK remains vulnerable to the impacts of droughts. The latest UK climate projections (UKCP18) indicate wetter winters and drier summers with global temperature rise (Lowe et al. 2018). Some studies have found that this can translate into more intense and frequent drought events across the UK with southeast England more vulnerable to long duration multi-year droughts (Brunner and Tallaksen 2019; Arnell et al. 2021). The application of successive generations of UK climate change projections has shown that there is relative certainty over a reduction in summer flows, with river flow responses in other seasons dependent on catchment characteristics such as hydrogeology (e.g. Arnell 1992; Arnell 2003; Charlton and Arnell 2014; Kay et al. 2021). Uncertainty in the variability of future droughts is determined by changes in precipitation trends as droughts will always

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coincide with hot extremes relative to the present day as the climate continues to warm (Diffenbaugh et al. 2015; Bevacqua et al. 2022). The timing and sequence of precipitation deficits (e.g. consecutive dry winters) have been highlighted as particular sources of uncertainty (Folland et al. 2015; Chan et al. 2022a).

Water companies in the UK are required to publish quinquennial drought and water resources management plans outlining the management measures taken during droughts and strategies to increase resilience to severe droughts (1 in 200 years). Recent guidance has suggested for water resources management plans to outline actions needed to improve resilience to extreme droughts with a return period of 1 in 500 years (Ofwat, 2022). Understanding the nature of extreme droughts is challenging given the short observational record. This is further complicated by the multivariate nature of droughts, climate non-stationarity and internal climate variability. To expand the sample size, stochastic weather generators are regularly used in a risk-based approach where synthetic weather sequences are generated and a likelihood is assigned to the exceedance of certain critical thresholds (e.g. duration of water shortage) (Hall et al. 2020). Synthetic droughts can also be perturbed with climate model information on future changes in rainfall and temperature (Borgomeo et al. 2015). Another strategy is to reconstruct past river flows using hydrological models. Rainfall and river flow reconstructions have improved understanding of pre-1961 droughts and identified key drought periods that were previously not considered significant (Spraggs et al. 2015; Barker et al. 2019). These historic droughts can update existing reference droughts used by water companies to test supply systems and provide benchmarks for stochastically generated synthetic droughts (Barker et al. 2019).

An alternative approach to stochastic methods is the use of large ensemble model simulations. Lopez et al. (2009) and Fung et al. (2013) were among the first in the UK to use transient large ensemble climate model simulations in hydrological modelling with perturbed parameter ensembles (PPE) created by systematic variation of parameters within a single climate model. Applied at two river catchments, the studies highlighted the added value of large ensemble simulations for decision-making in water resources management and demonstrated a risk-based approach using physically based dynamical models. The UK's national climate change projections 2009 (UKCP09) and 2018 (UKCP18) also provide transient PPE regional climate model simulations which have been applied to assess high and low flows in the UK (e.g. Prudhomme et al. 2012; Kay 2021; Lane et al. 2022). The UKCP18 probabilistic projections strand extends the PPE simulations through statistical emulators to provide 10,000 samples of probabilistic monthly changes in climate variables but they are not spatially coherent which limits their use in spatial drought analyses. The main drawback of PPE simulations is that they combine both epistemic (due to lack of knowledge about climate processes) and aleatoric (due to randomness arising from internal climate variability) uncertainties, which restricts the robustness of risk estimates of regional climate extremes (Shepherd 2019). Compared to statistical and stochastic methods, large ensembles may be considered more physically based where rare outcomes are spatially and internally consistent which allows for an investigation of drivers of extreme events (van der Wiel et al. 2019; Maher et al. 2021; Mankin et al. 2020). Later studies expanded this providing a larger sample of PPE simulations enabled by volunteer computing from the weather@home project (Guillod et al. 2018). Applying the simulations for the Thames basin, Borgomeo et al. (2018) showed how large ensemble simulations can help assess the robustness of different water management options. The weather@home large ensemble applied on a national scale further highlighted the management challenges of spatially extensive droughts and concurrent severe drought conditions across different water resource zones (Rudd et al. 2019; Dobson et al. 2020; Murgatroyd et al. 2022).

Studies have also employed initialized large ensemble simulations to assess the chance of a range of unprecedented climate extremes. These ensembles are based on simulations from a single climate or weather forecast model. Different realisations of weather sequence are generated by perturbations made to the initial conditions for each ensemble member (known as single model initial condition large ensembles – SMILEs). Compared to existing transient PPE large ensembles, SMILEs represent stationary climate conditions at different global warming levels, with the uncertainty entirely aleatoric. Thus, SMILEs represent an opportunity to more robustly sample extreme events from an expanded range of possible outcomes (Suarez-Gutierrez et al., 2018; van der Wiel et al. 2019; Deser et al., 2020). This approach tackles the limitations of short observational records and explicitly isolates the effects of internal climate variability. One example of this is the UNprecedented Simulation of Extremes using ENsembles (UNSEEN) method presented by Thompson et al. (2017), using hindcasts generated from initialized climate model simulations to estimate the risk of high winter UK rainfall in the present day climate. Previous studies have also used seasonal hindcasts from an operational weather forecasting system to improve estimates of extreme storm surges (e.g. van den Brink et al., 2004). More recent studies have used initialized ensembles to explore climate extremes such as high rainfall (Thompson et al. 2017; Kelder et al. 2020; Kent et al. 2022), crop failures (Coughlan de Perez et al. 2023), heatwaves (Kay et al. 2020), meteorological droughts (Kent et al. 2019) and wildfires (Squire et al. 2021). In hydrology, initialised large ensembles have also been used in conjunction with hydrological models to understand hydrological extremes (e.g. van der Wiel et al. 2019; van Kempen et al. 2021; Kelder et al. 2022a; Brunner et al. 2021a; Brunner and Slater 2022). Similar approaches such as reinitialised simulations from a dynamical climate or weather forecast model based on observed atmospheric initial conditions have recently been used to generate additional plausible events that are even more extreme than observed extreme events (e.g. Gessner et al. 2022; Leach et al. 2022).

Alongside the development of a probabilistic risk-based approach, studies looking at the hydrological impacts of climate change have also employed more "bottom-up" sensitivity-focused approaches (see Chan et al. 2022b for a review on the uptake of various approaches over time in the UK). Stress-tests and storyline approaches have emerged to complement traditional climate change impact assessments that are typically top-down and constrained by selected GCMs (Stoelzle et al. (2018)). Storylines represent plausible pathways of how extreme events unfold based on discrete changes to event drivers and characteristics and can include outcomes beyond climate model simulations based on process understanding and other sources of evidence (Shepherd et al. 2018; Shepherd 2019). They need not have probabilities attached to them and add value to existing risk-based estimates by increasing process understanding of low-likelihood, high-impact events and decision-relevant outcomes. Rather than aggregating climate extremes, the storyline approach can also be used to better understand specific unfoldings of compound climate extremes (Zscheischler et al. 2020). The larger sample size of a SMILE provides an opportunity to bridge probabilistic estimates of climate extremes and more bottom-up storylines conditioned on specific compound conditions that are known to lead to high impact events (van der Wiel et al. 2020; Bevacqua et al. 2021).

In this study, we employ large ensemble climate model output to estimate the chance of unprecedented events and construct storylines of hydrological droughts in present and future climate. The specific objectives of this research are to:

- Employ SMILE data to estimate current and future chance of unprecedented low rainfall, high temperatures and hydrological droughts
- Understand the characteristics of unprecedented hydrological droughts and compare unprecedented droughts with past severe droughts
- Sample for storylines resembling specific conditions in present and future climate, including: 1) dry summer succeeding dry spring, 2) dry winter succeeding dry autumn and 3) consecutive dry winters, and construct stress tests for contrasting catchments.

2. Methods

2.1. Data

2.1.1. Observations and study catchments

In this study, river catchments from the Low Flow Benchmark Network (LFBN) designated by the National River Flow Archive (NRFA) that are within Great Britain (England, Scotland and Wales) are selected (Harrigan et al. 2018) (Figure. S1). An additional ten catchments were selected to consider key abstraction catchments for public water supply in the East Anglia region. The LFBN consists of catchments deemed suitable for low flow analyses and the same set of catchments has previously been used to analyse both past and future droughts in GB (Smith et al. 2019; Barker et al. 2019; Chan et al. 2022a). Daily precipitation and potential evapotranspiration (PET) from 1965 to 2015 are used to drive hydrological models of the selected catchments. Daily mean observed precipitation over a baseline period (1965–2015) is extracted from the CEH-GEAR dataset (Tanguy et al. 2018), observed temperature from CEH-CHESS (Robinson et al., 2020) and observed daily river flow from the National River Flow Archive (NRFA) via the *rnrfa* R package (Vitolo et al. 2016). PET is calculated using the temperature-based McGuiness-Bordne equation specifically calibrated for the UK based on Tanguy et al. (2018). This method has previously been shown to achieve good performance for the UK when compared to the Penman-Monteith equation (Tanguy et al. 2018). The equation has been used to derive historic PET since 1891 to reconstruct past drought events at a similar set of catchments as in Barker et al. (2019). The use of this equation for this study ensures that the drought characteristics calculated can be comparable. The precipitation and temperature datasets are chosen as they have previously been used successfully as inputs to hydrological models of a wide range of UK catchments (e.g. Coxon et al. 2019; Lane et al. 2022). As CEH-GEAR and CHESS do not provide data after 2017, mean seasonal temperature from the HadUK-Grid dataset (Hollis et al. 2019) from 2017 to 2021 is used to consider post-2015 extremes in Section 2.4 when estimating the chance of unprecedented extremes. The HadUK-Grid dataset is not used in subsequent hydrological modelling.

2.1.2. Climate model data

The SMILE data used is the EC-Earth time-slice large ensemble (van der Wiel et al. 2019). The large ensemble is based on the EC-Earth GCM v2.3 and is run for present day (equivalent to present day climate with observed global mean surface temperature for the period 2011–2015) and pre-industrial plus 2 °C and 3 °C global warming conditions. The spatial resolution of the EC-Earth v2.3 climate model is 1.1° x 1.1°. In accordance with previous regional studies which employed this large ensemble (e.g. van der Wiel et al. 2019; van der Wiel et al. 2020; Goulart et al. 2021), the data was re-gridded to 0.5° x 0.5° via bilinear interpolation. The large ensemble is based on transient projections following the RCP8.5 emissions pathway with 16 ensemble members. For each ensemble member, 25 new realizations are created through stochastic parameterizations of the initial conditions and run for 5 years. In total, they make up 2000 years of weather and climate data for each global warming level (i.e. 16 ensemble members × 25 realizations × 5 years = 2000 years). Further discussion of the configuration of the large ensemble can be found in van der Wiel et al. (2019). The same large ensemble has been widely used for climate impact modelling using hydrological models (van der Wiel et al. 2019; van Kempen et al. 2021; Kelder et al. 2022a) and crop yield models (van der Wiel et al. 2020; Vogel et al. 2021; Goulart et al. 2021). In this study, all ensemble members are pooled to form a continuous 2000-year time series of temperature and precipitation as has been done in previous studies using the same large ensemble (van Kempen et al. 2021; Kelder et al. 2022a). Note that this introduces 399 (out of 1999) spurious December to January transitions; the implications of this choice will be discussed when relevant.

2.2. Climate change scenarios

In this study, two methods are used to apply climate change scenarios in hydrological models: 1) the delta change method and 2) the direct use of bias-adjusted large ensemble simulations.

2.2.1. Delta change method

The delta change method scales or shifts the observed time series by change factors representative of projected climate change. Monthly change factors are calculated for each catchment by comparing the present-day and future monthly mean observed precipitation and temperature in the climate model. Change factors are applied multiplicatively (precipitation) or additively (temperature) to the observations. The basic delta method retains the temporal variability of the observations and a single set of change factors aggregated across the large ensemble may not reflect the full range of plausible changes arising from climate variability, e.g. changes in persistence. Hence, a modified delta change method based on the resampling methodology in Ledbetter et al. (2012) is used to give an indication of the possible range of change. For each original ensemble member, a resampling procedure randomly selects with replacement a block of monthly precipitation in the future period to form a new 30-year time series. This is repeated 30 times to create 30 change factor sets for each ensemble member for each catchment (30 change factor sets × 16 ensemble members = 480 change factor sets per catchment). Given that temperature values exhibit higher dependence between months, only one change factor set for temperature is created for each ensemble member. This method of resampling is appropriate given that UK precipitation exhibits low month to month autocorrelation and can be considered independent for each month (as shown in Ledbetter et al., 2012).

2.2.2. Bias adjustment method

The second method to apply climate projections in hydrological models to simulate river flows is by bias adjusting and downscaling climate model simulations so they can be directly used as input to hydrological models. It is common for climate model data to be bias-adjusted against observations before application in hydrological modelling. In this study, bias adjustment is performed for each catchment. Modelled precipitation is adjusted to match monthly observed means using multiplicative correction factors and temperature is adjusted additively. Initial tests found that the modelled GB-averaged mean monthly precipitation has a lower standard deviation compared to the observations. A power transformation is thus applied at each catchment to adjust the precipitation data to first match the monthly observed coefficient of variation and subsequently match monthly mean precipitation following the method set out in Leander and Buishand (2007). The data is corrected for excessive "drizzle", a well-known problem for GCMs, by setting precipitation below a threshold to zero. The threshold was determined for each catchment by matching the number of monthly precipitation days in the modelled data and observations. The threshold is then applied to the 2 °C and 3 °C simulations. An assumption is made that the biases targeted for correction and the bias correction technique maintain their validity for future time periods.

2.3. Hydrological modelling

The GR6J hydrological model is used to simulate river flows. GR6J is a bucket-type catchment hydrological model with six parameters available for calibration (Pushpalatha et al., 2011). The additional two parameters in GR6J compared to its sister model GR4J relate to an additional routing store and flow component designed to capture river flow recession (e.g. drainage from aquifers). This means that GR6J could be more appropriate in simulating flows in slower responding catchments underlain by permeable aquifers. GR4J has previously been used for drought analyses in GB (Smith et al. 2019; Barker et al. 2019; Chan et al. 2022a) and GR6J is used by individual water companies (e.g.

Anglian, 2022). Both models are most recently used within the eFLaG ensemble to assess UK droughts using the latest UKCP18 climate projections, showing that GR6J consistently outperforms GR4J for most catchments (Hannaford et al. 2023).

Calibration and validation of GR6J follows the Latin Hypercube Sampling (LHS) calibration strategy in Smith et al. (2019) which used LHS to identify suitable parameter sets for GR4J based on a number of model performance metrics for high, mean and low flows (Table S1). As shown in Smith et al. (2019), high flows, timing of flows and the overall water balance are all important components to consider for flow response during dry years. In Smith et al. (2019), the top 500 parameter sets were shown to be able to simulate past drought episodes in the UK well. 10,000 parameter sets for the six model parameters of GR6J were generated using LHS within the parameter limits outlined in Table S2 and used to simulate river flows for each catchment over a baseline period (1965–2015). The 10,000 parameter sets were ranked for each of the evaluation metrics from best to worst and a total score based on the sum of the ranks for each metric was assigned for each parameter set. For each catchment, the parameter set with the lowest total score (i.e. top performing) is then used to simulate river flows forced by daily precipitation and temperature (for PET) from the EC-Earth large ensemble. Figure S2 shows the performance of the top parameter set for each catchment for the six evaluation metrics.

2.3.1. Drought extraction and catchment clusters

Drought events are extracted using the variable threshold method (Van Loon 2015). This method is widely used and has been used to extract droughts at GB catchments from simulated river flows driven by the UKCP09 climate projections (e.g. Rudd et al. 2019). In this study, the 70th percentile of the flow duration curve (Q70) for each month is used as the threshold and any period below the monthly varying Q70 is defined as a drought. The variable threshold method is capable of extracting periods of low river flows in all seasons and can identify multi-year droughts which are particularly prevalent in southern England (due to the major role played by groundwater storage). For each event, maximum intensity (max. % deviation from threshold), mean deficit (mean % deviation from threshold divided by drought duration) and total duration are calculated. Short events separated by one month are pooled and droughts shorter than one month are removed.

River catchment clusters with similar drought dynamics are created following the same approach as in previous studies (Fleig et al. 2011; Hannaford et al. 2011; Kingston et al., 2013). For each catchment, a binary series of drought occurrence is created based on the drought events extracted. Agglomerative hierarchical clustering, implemented using the *TSclust* R package (Montero and Vilar 2014), is used to group catchments into clusters using the Ward's minimum variance method (Ward, 1963) based on the binary drought occurrence series. Fig. 1 shows the four clusters defined for the selected catchments. Clusters separate east and west Scotland and distinguish catchments in SE England. The clusters are able to separate the catchments based on a number of physical catchment characteristics as explained in Table S3. For example, the slower responding groundwater-dominated catchments in southern England (i.e. GB3 and some in GB4) with a higher baseflow index are particularly prone to multi-year droughts. The regional drought index (RDI) is calculated for each cluster by dividing the number of catchments in drought at any time by the total number of catchments in the cluster. The index thus varies between 0 (i.e. none of the catchments in the cluster are in drought) and 1 (i.e. all catchments in the cluster are in drought) for each time step. Spatially extensive drought events are defined as events affecting over 70% of the catchments in each cluster at the same time (i.e. RDI $\geq$ 0.7). For each of the spatially extensive events identified using RDI_{Q70}, the max. intensity and mean deficit of the event is taken as the mean of the characteristics in the affected catchments.

2.4. Chance of unprecedented extremes

The modelled precipitation from the EC-Earth large ensemble should be deemed credible compared to the observations before it can be used to estimate the chance of unprecedented extremes. The fidelity test for large ensemble data set out in Thompson et al. (2017) is applied individually for each catchment using bias adjusted precipitation. The test checks whether the model data can be considered as alternative realizations of the real world by comparing the statistical moments of the model data and the observations. 10,000 subsamples of monthly precipitation the same length as the observations are created through bootstrapping and the mean, standard deviation, skewness and kurtosis of each subsample are calculated. The resulting distribution of statistical moments from all subsamples is compared to the observed statistical moments. The model data is deemed to be statistically indistinguishable from the observations if the observed statistic falls within 95% (i.e. 2.5–97.5th percentiles) of the model distribution. Only the catchments where the fidelity test is passed are considered appropriate for use and included for hydrological modelling. As the bias adjustment procedure corrects for mean and standard deviation, the fidelity test is applied to skewness and kurtosis. Fig. 2 shows the model fidelity test at an example

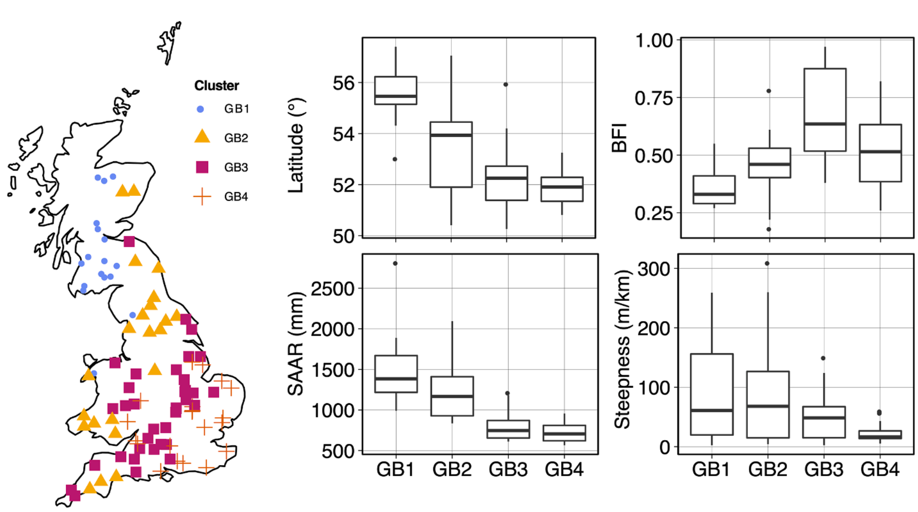

Fig. 1. a) Catchment clusters defined from spatially extensive droughts using the regional drought index (RDI_{Q70}) over the baseline period (1965–2015). b) Distribution of four selected catchment characteristics. The physical catchment characteristics include Latitude (°), SAAR – Standardised annual average rainfall (mm), BFI – Baseflow index, and catchment steepness (m/km) for catchments in each cluster.

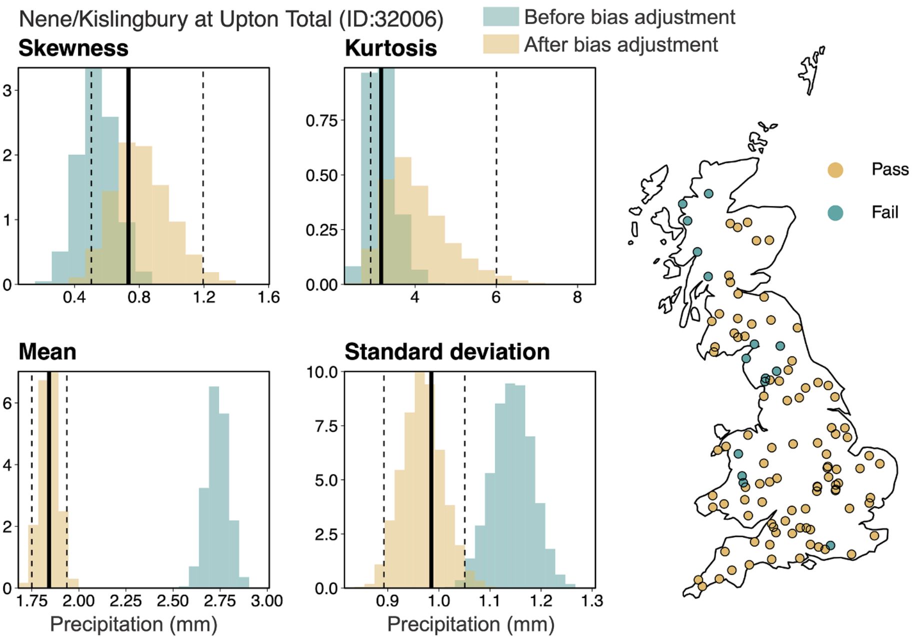

Fig. 2. Left) the distribution of mean, standard deviation, skewness and kurtosis of monthly mean precipitation (mm) from bootstrapped samples of model simulations at an example catchment in se england before (green) and after (yellow) bias adjustment compared to the observed value (1965–2015) (black line). The dotted lines indicate the 5th and 95th percentiles of the modelled distribution. Right) Fidelity result for all selected catchments across GB. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

catchment in SE England and the 95 catchments that have passed the fidelity test and retained for subsequent analysis. Catchments that did not pass the fidelity test include ones in central Wales, northwest England and northwest Scotland. These catchments fail as kurtosis and skewness remains outside the 95% of model distribution after bias adjustment. Failed catchments are mostly characterized by comparatively more complex orography at higher elevations which is less well represented in the relatively low-resolution climate models.

Estimates of the chance of unprecedented low precipitation, high temperature and hydrological droughts are quantified by comparing simulated events in the present-day, 2 °C and 3 °C large ensemble with the observations. For precipitation, simulated mean precipitation totals for summer (JJA) and winter (DJF) are ranked and the chance of any given month with total precipitation lower than the lowest observed mean summer or winter precipitation in any given year is calculated. The uncertainty of the estimates is calculated by creating subsamples of the model months 10,000 times and taking the 2.5% and 97.5% percentiles. The same procedure is repeated for temperature to calculate the chance of exceeding the highest observed mean summer and winter temperatures (1965–2015 CEH-CHESS and 2015–2021 HadUK-Grid). Unprecedented hydrological droughts represent the possibility of a drought with greater intensity or deficit than the worst observed drought in the baseline period.

2.5. *Storylines of specific conditions*

Storylines are constructed by following guidelines outlined in Bevacqua et al. (2021) and van der Wiel et al. (2021) to sample within large ensemble simulations to identify combinations of multiple drivers that can lead to extreme impacts. Given uncertainties associated with the atmospheric circulation response to climate change and the representation of drought persistence in climate models (Shepherd 2014; Moon et al. 2018), narrowing the focus by imposing specific conditions can provide a basis to understand worst cases, which can arise from the combination of the various storylines considered. In this study, we consider the following storylines: 1) dry springs (MAM) followed by dry summers (JJA), 2) dry autumns followed by dry winters (DJF) and 3) consecutive dry winters. These storylines are selected as they resemble conditions in past severe droughts. For example, the 1975–76 drought was characterized by a dry spring-summer period following a dry winter (Rodda and Marsh 2011) while the 1920–21 drought was mainly characterized by a dry autumn followed by a dry winter (van der Schrier et al. 2021). Storylines are selected by searching for consecutive negative mean precipitation anomalies relative to a 1965–2015 climatology for the respective seasons. Hydrological droughts arising from these conditions are preconditioned compound events where impacts may be amplified from a combination of successive climate-driven conditions (Zscheischler et al. 2020; van der Wiel et al. 2022).

Storylines can be used to stress test hydrological systems by testing their sensitivity to different combinations of event drivers (e.g. Stoelzle et al., 2020; Chan et al. 2022a; Wilby 2022). Synthetic drought sequences are created following the UKWIR drought vulnerability response surface framework (Counsell et al. 2017) by sampling within the large ensemble for months matching specific precipitation deficit levels to create progressively drier drought sequences (e.g. progressively drier spring-summers and autumn-winters). A 5-year warm-up period is created by selecting months within the large ensemble that are closest to mean conditions in terms of precipitation anomalies. A new meteorological sequence is then created comprising 1) a 5-year warm-up period, 2) a drought year where individual months are selected based on specific precipitation deficit levels, and 3) a repetition of the warm-up period. Temperature (and PET) is not varied, and average daily temperature is used. The entire sequence represents 10 years with one precipitation drought year characterized by the storyline conditions (e.g. dry spring-summer or dry autumn–winter). The sequence is fed through GR6J to obtain simulated river flows for each catchment.

3. Results

3.1. *Precipitation and river flow changes*

Projected changes in precipitation over the selected catchments in the EC-Earth large ensemble show drier summers and wetter winters with increasing temperature rise. Figure S3 compares the different estimates of projected changes in precipitation obtained from the delta method and directly from the bias-adjusted precipitation across the 16 ensemble members. The impact of the bias adjustment on temperature and precipitation is shown in Figure S4. The expanded set of change factors in the modified delta method incorporates climate variability and therefore shows a greater range of changes compared to a single set of change factors per ensemble member. Variation in the estimated rainfall changes for the latter two estimates mainly correspond to spread across the selected catchments.

River flows are projected to reduce in summer and early autumn across all catchment clusters but at different magnitudes. There is a greater reduction in river flows during these months in relatively slower responding catchments in GB3 (including groundwater dominated catchments with high BFI) compared to fast responding catchments in GB1. Catchments in GB3 are also more likely to experience a decrease in river flows in both the late spring and autumn months. The application of additional change factors from resampled precipitation also results in a greater range of projected changes in river flows compared to a single set of change factors per catchment and to using the bias-adjusted precipitation directly (Fig. 3). Monthly average river flows simulated with the bias-adjusted precipitation show a greater increase over spring and winter months compared to the delta method.

3.2. Simulated droughts

Using simulated river flows driven by the bias-adjusted precipitation and temperature enables the extraction of a much larger sample of drought events than is possible using observational datasets. Drought characteristics are generally projected to worsen with climate change, with differences in the magnitude of change between different catchments as shown by the selected examples in Fig. 4. For all three drought characteristics, projected change is similar in both magnitude and direction between the delta method and the bias-adjusted climate model data. The variability of drought characteristics extracted from droughts simulated using the bias-adjusted data is larger compared to using the delta method which retains observed drought periods. Although the sensitivity of droughts to climate change is broadly similar in the two estimates, the delta method may underestimate risk of extreme droughts especially if the worst historical record is a weak record that may be easily broken with a larger sample size and the effect of internal climate variability. Consequently, the simulated drought events are much better sampled using the bias-adjusted large ensemble data.

The physical credibility of the simulated events in a large ensemble can be assessed by investigating their atmospheric drivers and spatio-temporal variability (Kelder et al. 2022a,b). Comparison of the simulated droughts in the present-day large ensemble with observed droughts gives confidence that the simulated events are plausible (Fig. 5 for four example catchments). Simulated droughts span the entire range of drought characteristics in observed events. Unprecedented events, namely those with higher maximum intensity or greater deficit than the worst observed event, can also be identified (red dots in Fig. 5). A comparison of the atmospheric circulation patterns during the driest years shows that both dry summers and winters in the observations and the present-day large ensemble are characterized by blocking conditions and high pressure across the British Isles and continental Europe (Figure S5). While we do not expect the circulation patterns to be exactly the same between the model and the observations because of the effects of internal variability, the high pressure associated with the top five driest years in the model is of a similar magnitude to that of the top five driest years in the observations. The individual circulation patterns are associated with processes that would be expected to bring dry conditions to GB and show alternative patterns that could have been realised during droughts in the observed record.

Accumulation of precipitation (Table S4) and river flows (Table 1) across a 12- and 24-month period over lowland England (i.e. all catchments in GB3 and GB4) shows years with similar or greater accumulated deficits compared to the driest events in the observations. Folland et al. (2015) previously found, for lowland England, the driest 12-month

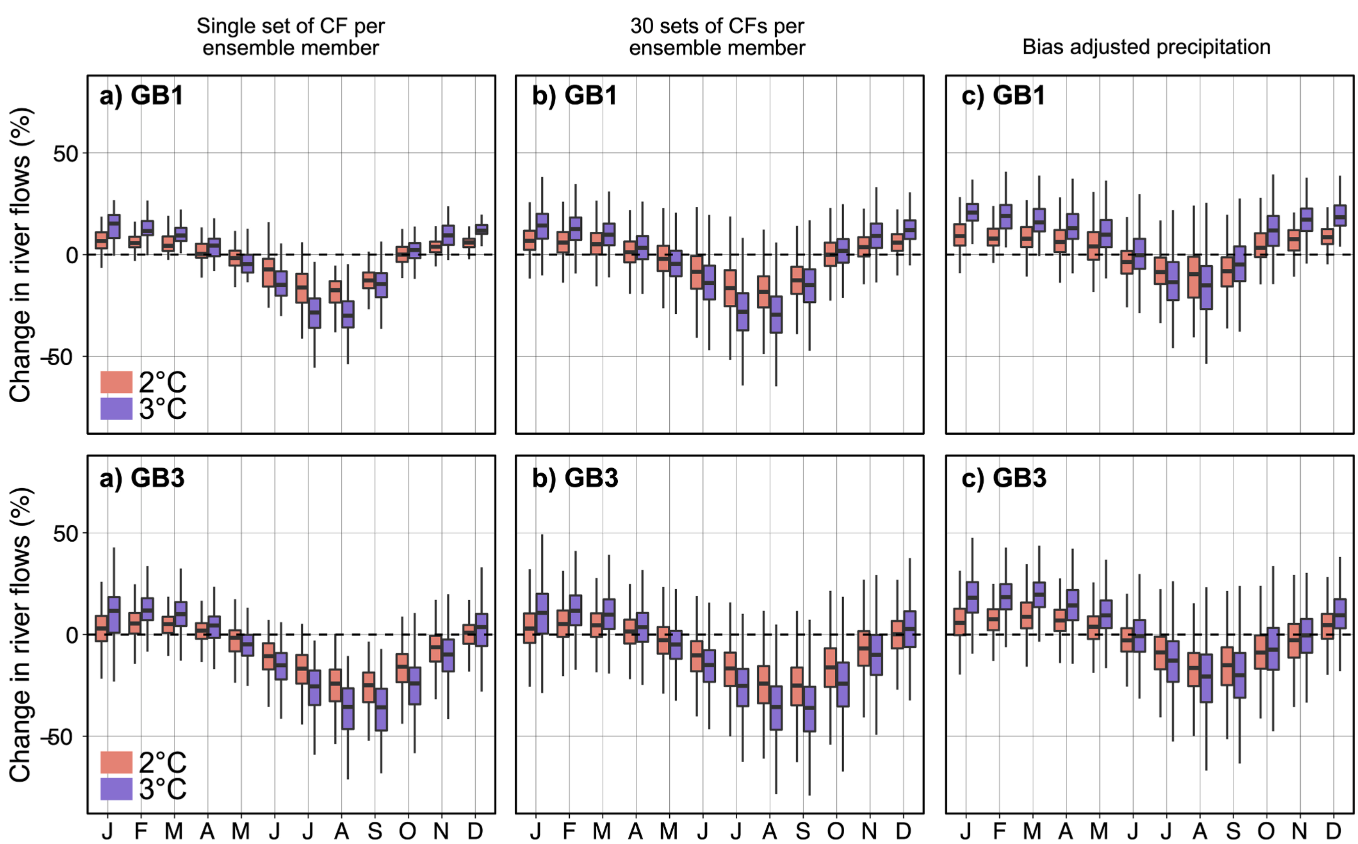

Fig. 3. Projected change in monthly river flows across catchments in GB1 (top) and GB3 (bottom) for 2 °C warming (orange) and 3 °C warming (blue) using a single set of change factors per catchment (a and d), 30 sets of change factors from resampled precipitation per catchment (b and e) and bias-adjusted precipitation and temperature per catchment (c and f). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

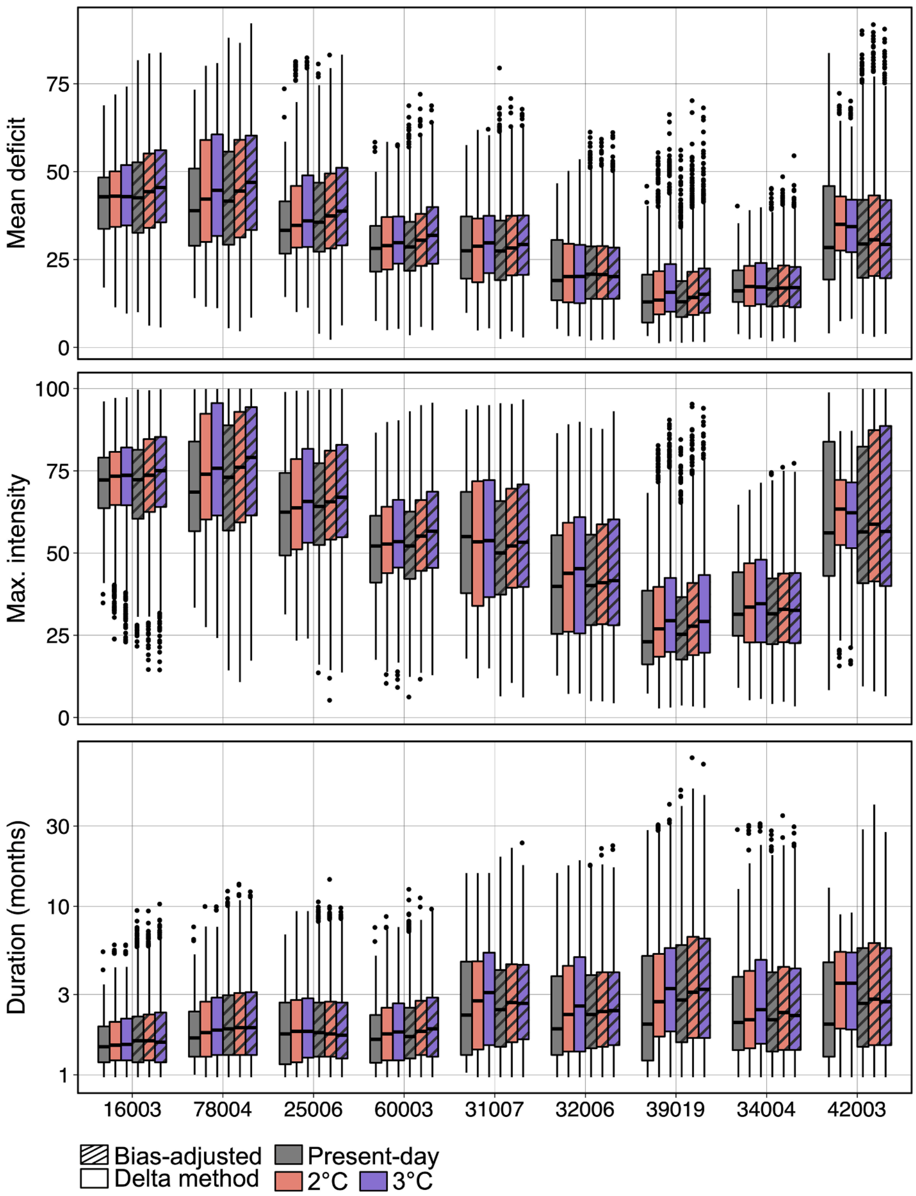

Fig. 4. Projected mean drought deficit (top), max. drought intensity (middle), and drought duration (bottom) for present day (grey), 2 °C (orange) and 3 °C (blue) extracted from simulated river flow using the delta method (solid colours) and the direct use of bias-adjusted temperature and precipitation (hatched). The boxplots show the median and span the 25th and 75th percentile with dots representing outliers higher than the 75th percentile. The numbers indicate selected catchment examples. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

period between 1910 and 2012 was 1975–76 which had 60% of average precipitation, and the driest 24-month period was 1990–92 with 73% of average precipitation. The driest 12-month period in terms of accumulated river flows in the observations was September 1975–76 with 34% of the 1965–2015 average, while the driest 24-month period was April 2010 to 2012 with 56% of the 1965–2015 average. The temporal evolution of daily river flows during the driest years in the present-day large ensemble also seems consistent with the hydrological behavior in the driest year in the observations with similar flow timing, adding to the physical credibility of the simulated events (Figure S6 for selected catchment examples). Relatively fast-responding catchments (e.g. 16003, 78004 and 25006) are characterized by a rapid decline in river flows over a short period of time, whereas slower responding catchments (e.g. 39019, 34004, 41027) see a gradual decline in river flows lasting over the entirety of the 12-month period and beyond. Accumulated precipitation and flow deficit over a longer period (>12 months) may be more appropriate for slower responding systems (such as a critical period of deficit accumulated over 18-months including two winters for several reservoir systems within East Anglia – Anglian, 2022).

3.3. *Chance of unprecedented extremes*

3.3.1. *Low precipitation and high temperature*

Fig. 6 and Table 2 shows the estimates for the chance of extremely low precipitation and high temperature in any summer and winter month in a given year for present-day, 2 °C and 3 °C warming averaged across two contrasting regions - GB1 (western Scotland) and GB4 (southeast England) (Figure S7 for catchments in GB2 and GB3). The warmest summer in the baseline period is 1995 for GB1 and 1976 for GB4 while the warmest winter is 1988–89 for GB1 and 2015–16 for GB4. There is little separating the warmest summers in the observations. For example, averaged across GB1, summer 1995 is tied with 1976 and 2021 at 13.9 °C. There is also only a 0.1 °C difference between summer 1976 and 2018 averaged over GB4. In the present-day, the estimates show that the chance of exceeding the observed maximum is higher in the summer compared to the winter. There is a clear increase in the chance of unprecedented high temperatures with warming. The warmest summer in the 3 °C large ensemble is estimated to be nearly 5 °C warmer than the observed maximum, whereas in winter this is > 2.5%. Average temperature for summer 2022 has exceeded records over southeast England (primarily including catchments in GB4). The mean

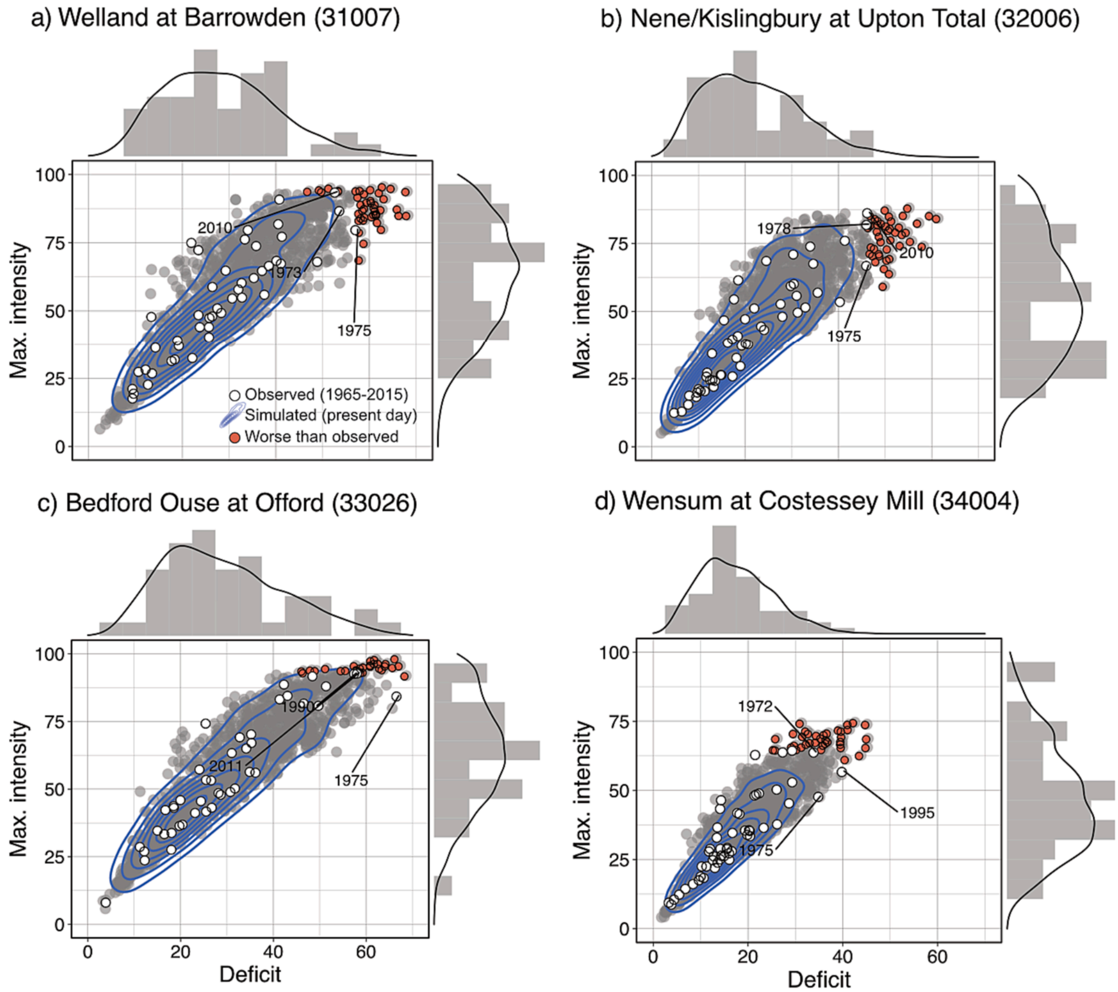

Fig. 5. Max. intensity and deficit of droughts extracted from the present-day large ensemble and in the baseline observed period (1965–2015) at four example catchments in SE England. Notable severe droughts in the observations are labelled. Red dots represent unprecedented events with either greater deficit or higher max. intensity than the worst observed event. The grey histogram represents the density of droughts in the observed period and the black line is the density in the large ensemble. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

temperature over southeast England for summer 2022 in the HadUK-Grid dataset is 18.02 °C (i.e. 0.2 °C higher than 1976) (NCIC, 2022). This is shown by the dashed line for GB4, indicating a 4% chance of exceedance in the present day, which increases to 24.4% and 53.5% with 2 °C and 3 °C warming.

The current and future chance of unprecedented dry summers and winters are more complex compared to temperature extremes. Summer 1976 and winter 1984–85 were the driest for GB1, and summer 1995 and winter 1991–92 for GB4. In the present day, catchments in GB1 are more likely to encounter an exceptionally dry summer month compared to GB4 while both clusters have a similar chance of an unprecedented dry winter. Like summer temperatures, the chance of an unprecedented dry summer is also estimated to increase with warming. Dry summers are estimated to be progressively drier with warming where events with a 1% probability of occurrence are estimated to have months with monthly precipitation that is 60% lower than the lowest observed mean summer precipitation for both regions.

The chance of any given winter month being drier than the observed driest winter is estimated to decline with future warming. This is consistent with projections of wetter winters in general. Despite this, both the chance and magnitude of the lowest probability events (<1% chance) are estimated to be similar across the present-day, 2 °C and 3 °C large ensemble. Events with a 1% chance of occurrence include winter months with less than half the lowest observed mean monthly seasonal precipitation totals for both regions. This implies that the chance of moderately dry winters may decrease but the chance of the driest winters with the highest return period may not decrease in likelihood compared to the present day.

3.3.2. Hydrological droughts

The chance of any given drought exceeding the mean drought deficit of six past selected severe droughts is estimated to increase with future warming (Fig. 7). The impacts of past drought events in GB vary spatially as reflected by the fact that certain past events are notably hard records to break for catchments in different clusters. The estimates indicate that past observed, and reconstructed droughts could be regarded as benchmark worst cases for certain catchments in the present-day but the chance of exceeding them is estimated to increase with future warming. For example, the 1975–76 drought is notably severe in terms of mean deficit for catchments in southern England, mostly coinciding with catchments in GB3 and GB4. The chance of exceeding it in these catchments for the present day is estimated to be particularly low with little change for GB4 even with future warming, confirming the extremeness of the river flow response during this drought. The 1975–76 drought was preceded by wetter than average conditions and flow response for slow responding catchments with higher BFI (included in GB3) was less impactful than otherwise, hence the fact that the chance of exceedance is higher for catchments in GB3 compared to GB4. River

Table 1
Top 10 a) 12- and b) 24-month periods with lowest accumulated river flows (expressed in mm) for catchments in southern England (GB3 and GB4) in the present-day large ensemble and the baseline period (the latter indicated with a specific year in bold).

Rank	Total river flows (mm)	% of 1965-2015 average	Deficit (mm)	Start month
a) 12-months				
1	84.5	31.4	-184.7	12
2	87.0	32.3	-182.4	11
3	87.0	32.3	-182.6	10
4	88.6	32.8	-181.3	9
5	90.8	33.7	-178.6	11
6	90.9	33.6	-179.5	1
7	91.5	33.9	-178.3	9
8 - 1975	**92.3**	**34.2**	**-177.3**	**10**
9	92.8	34.4	-177.2	2
10	93.7	34.7	-176.2	8
b) 24-months				
1	226.4	42.1	-310.8	9
2	227.6	42.4	-309.8	8
3	227.6	42.4	-309.2	10
4	235.2	43.8	-302.4	7
5	239.4	44.6	-297.0	11
6	239.7	44.6	-297.7	6
7	242.5	45.1	-295.2	4
8	242.9	45.2	-294.4	5
9	252.2	47.0	-284.2	12
10	252.8	47.1	-283.6	11
2010	**302.2**	**56.2**	**-235.4**	**4**

flow constructions from Smith et al. (2019) and Barker et al. (2019) showed that the mean deficit of the 1891–1910 "long drought" was most severe for catchments in GB1 and this is reflected by the relatively low chance of its exceedance for GB1 compared to the other clusters. In the present day, the chance of any given drought exceeding all four post-1965 droughts is < 10% across all catchments, except for GB1 and GB2 for the 2010–2012 drought which mostly affected southern catchments in GB3 and GB4 (Kendon et al. 2013). The change in chance of an unprecedented drought is least clear for the slow responding catchments in GB4.

3.4. Storylines of specific conditions

3.4.1. Dry spring-summers and autumn-winters

The unfolding of plausible droughts can be investigated using storylines characterized by different combinations of seasonal precipitation deficits. Fig. 8 shows, for relatively slow responding catchments in southern England (i.e. GB3), standardized temperature and precipitation anomalies for 1) dry springs followed by dry summers and 2) dry autumns followed by dry winters (see Figure S8 for equivalent figure for faster responding catchments in GB1). Drought years with dry spring-summers are more likely to have above average temperature anomalies, particularly in the summer months. Conversely, drought years with dry autumn-winters show no temperature signal in autumn and slightly below average temperatures in winter. Temperature anomalies across spring-summers and autumn-winters are projected to increase in all

Table 2
Chance (%) of any given summer or winter month in a single year with unprecedented (compared to 1965–2022 observations) a) high mean summer (JJA) and winter (DJF) temperatures and b) low mean summer (JJA) and winter (DJF) precipitation across all catchment clusters for the present-day (PD), 2C and 3C large ensemble. Values are rounded up to the nearest whole number.

	GB1	GB2	GB3	GB4
a) **High temperature**				
Summer				
PD (present-day)	9	8	6	6
2 °C warming	36	35	31	30
3 °C warming	66	64	60	58
Winter				
PD (present-day)	1	2	3	2
2 °C warming	6	12	14	9
3 °C warming	26	37	37	31
b) **Low rainfall**				
Summer				
PD (present-day)	14	8	7	9
2 °C warming	18	12	12	14
3 °C warming	20	15	15	18
Winter				
PD (present-day)	14	11	12	10
2 °C warming	11	9	10	9
3 °C warming	9	12	8	8

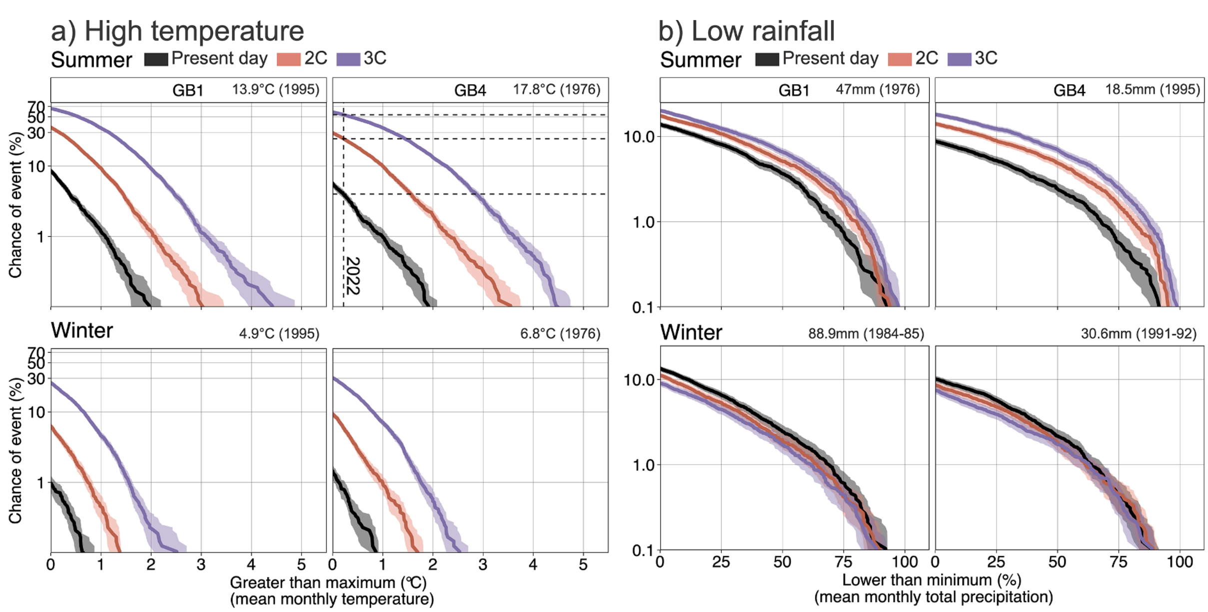

Fig. 6. Estimate of the chance of any given summer or winter month with unprecedented a) high mean summer (JJA) and winter (DJF) temperature and b) low mean summer (JJA) and winter (DJF) precipitation, for a single year, in GB1 and GB4 for the present-day (grey), 2 °C (orange) and 3 °C (blue) large ensemble. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

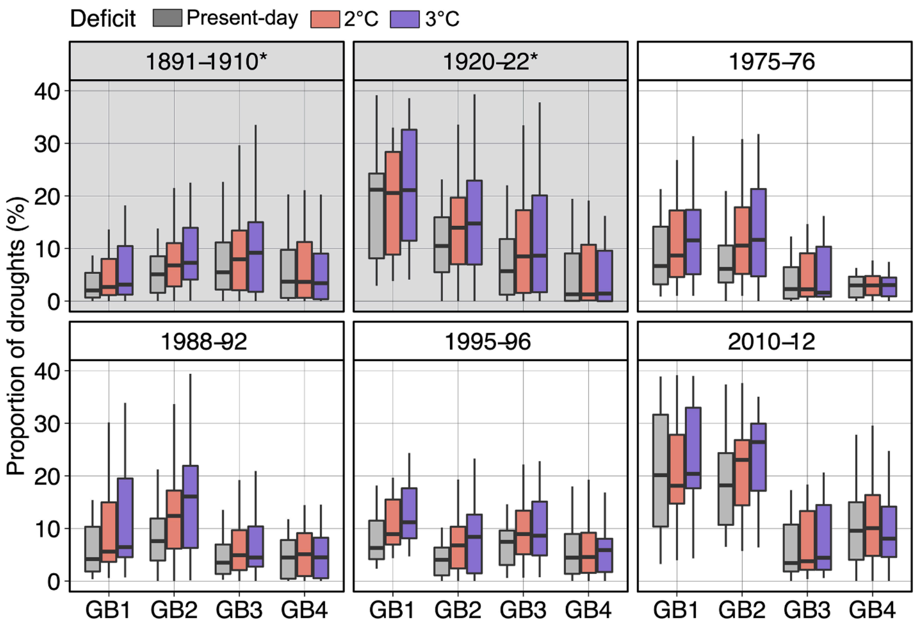

Fig. 7. Estimate of the chance of a given drought exceeding mean drought deficit of past drought events for catchments across the catchment clusters for the present-day (grey), 2 °C (orange) and 3 °C (blue) large ensemble. *Data for the 1891–1910 and 1920–22 droughts are based on river flow reconstructions from Smith et al. (2019) using the GR4J model applied for the LFBN catchments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

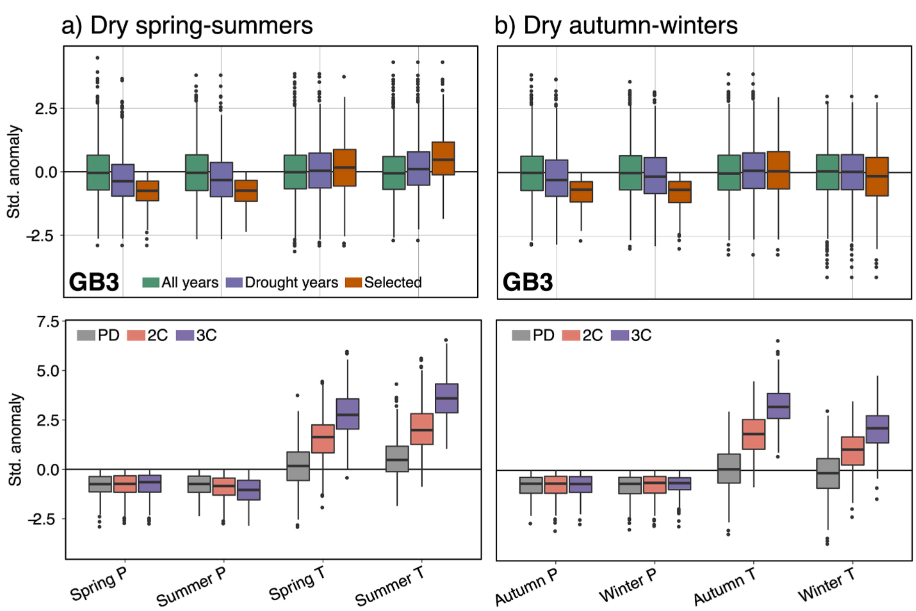

Fig. 8. Standardised precipitation and temperature anomalies from dry spring-summers (left) and dry autumn-winters (right) averaged across catchments in GB3. The top panel compares temperature and precipitation in all 2000 years of the large ensemble (green), in years with hydrological droughts (purple) and in selected storyline years in the present-day large ensemble (orange). The bottom panels show the equivalent anomalies for the two storylines in the present-day (grey), 2 °C (orange) and 3 °C (blue) large ensemble (standardised based on PD statistics). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

cases under future warming, with summer temperatures estimated to increase by the greatest magnitude. Except for drier summers with future warming in dry spring-summer sequences, there is a lack of change in the precipitation anomalies associated with dry springs and dry autumn-winters with future warming.

The time series of cumulative precipitation, PET and P-PET anomalies of the top 20 driest dry spring-summers and autumn-winters show how future events with the same conditions could develop (Fig. 9). The magnitude of change is greater for cumulative P-PET anomalies compared to cumulative precipitation anomalies, indicating that the projected increase in PET due to future summer warming is a significant contributor to future spring-summer drying. This is also shown by lower latent heat flux anomalies and greater cumulative P-AET anomalies for future dry spring-summers compared to the present-day, which is more prominent for GB3 (Figure S9). The projected increase in precipitation for both autumn and winter is more apparent in GB1 with wetter conditions in both seasons in future dry autumn-winters. Given the relatively faster responding catchments in GB1 and GB2, dry spring-summers or dry autumn-winters often coincide with short seasonal droughts in the winter or summer half years. The mean deficit of future droughts associated with the two storylines are estimated to worsen with future warming (Figure S10). Conversely, for GB3 and GB4, droughts coinciding with dry autumn-winters are more likely to have greater deficit compared to other droughts, reflecting the slow-responding nature of these catchments and their dependence on winter recharge (Figure S10).

Composite mean Z500 anomalies in present day and 3 °C warming show how high pressure circulation anomalies across the UK contribute to dry conditions during dry spring-summers and autumn-winters (Fig. 10). For present-day droughts in GB3 catchments, the centre of the high pressure is situated further southwards compared to droughts in GB1 catchments. In the future, dry conditions during years with dry spring-summers are characterized by a deepening of the high pressure over the UK in spring with larger changes for events impacting GB1.

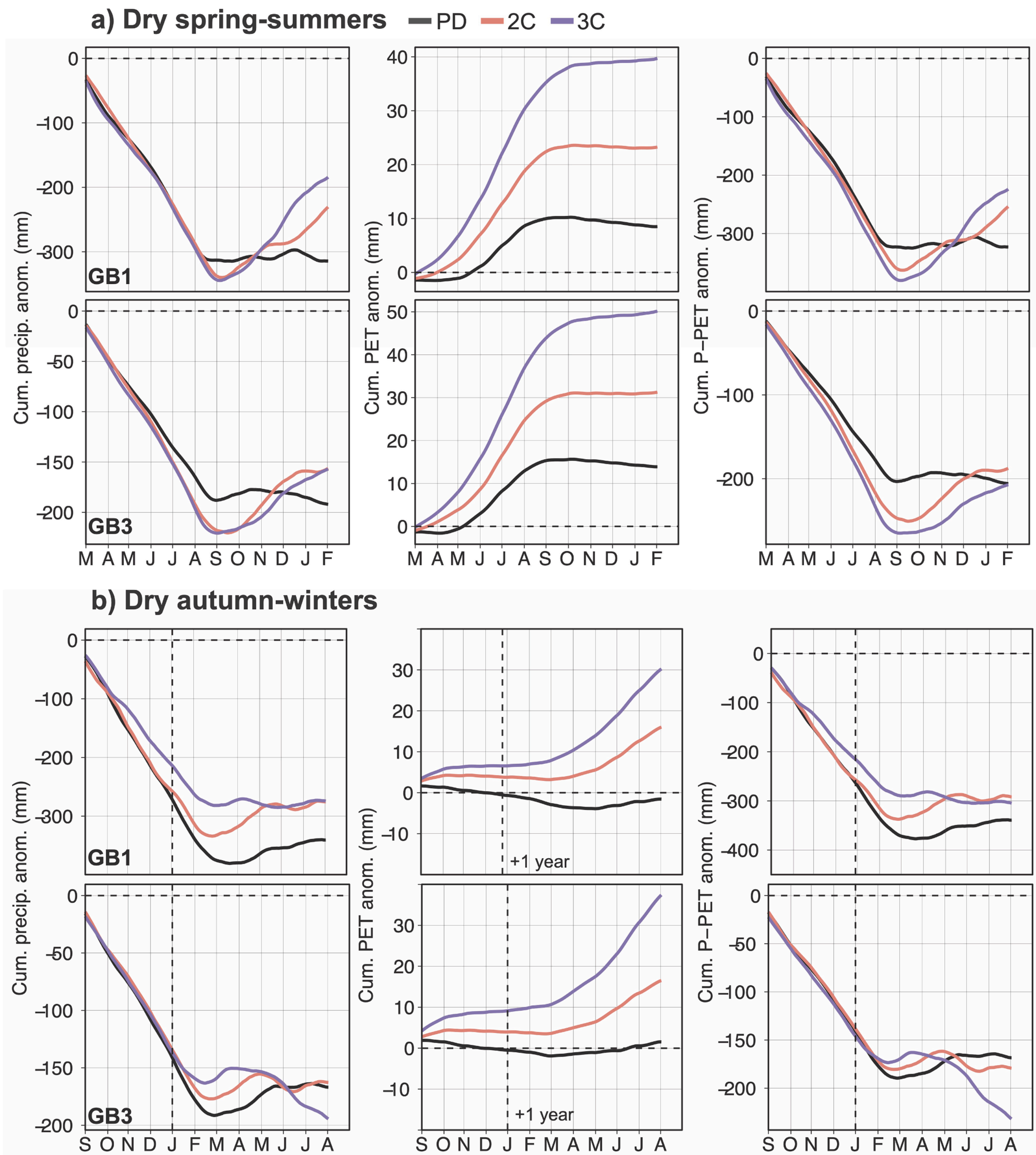

Fig. 9. Time series of mean cumulative precipitation, PET and P-PET anomalies during the top 20 (i.e. ~ 1 in 100 year events) driest a) dry spring-summers and b) dry autumn-winters for catchments in GB1 and GB3 in the present-day (black), 2 °C (orange) and 3 °C (blue) large ensembles. A 30-day running mean is applied for all variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

However, drier conditions in the summer months are characterized by weaker high-pressure conditions in the future for both GB1 and GB3 with a greater weakening of the high pressure for droughts in GB3 catchments. For future dry autumn-winters, the high pressure is estimated to deepen and shift eastwards in autumn for GB1 but weaken in the winter, consistent with general wetter winter conditions especially prevalent in Scotland and the English uplands. This is contrasted by the deepening of the high pressure during dry autumn-winters for GB3. It should be noted that circulation patterns were not bias-adjusted and future changes in circulation also include possible model bias.

3.4.2. *Consecutive dry winters*

Consecutive dry winters is a key driver of severe hydrological droughts for slow responding catchments in southern England (including catchments in GB3 and some catchments in GB4). The temporal dynamics of consecutive dry winters is worth exploring as the intervening seasons between dry winters do not necessarily need to be dry for significant impacts on river flows to develop. For example, the 2010–12 drought was characterized by two consecutive dry winters but both summers 2010 and 2011 had average precipitation over southern England (near 100% long term average) (Marsh et al., 2013). Fig. 11a

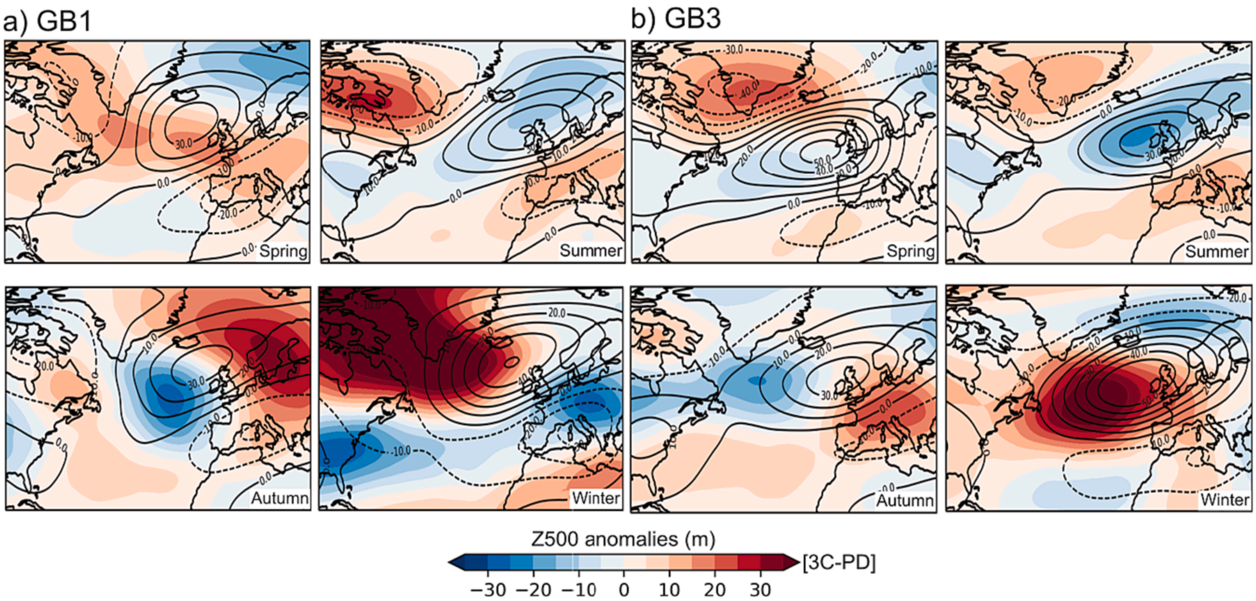

Fig. 10. Composite mean Z500 anomalies relative to 1965–2015 (ERA5) during dry spring-summers (top row) and dry autumn-winters (bottom row) for GB1 (left) and GB3 (right). Contours are Z500 anomalies in the present-day and the colours represent the change in anomalies between events in the 3 °C large ensemble minus the events in the present-day large ensemble.

and b shows precipitation and temperature anomalies associated with consecutive dry winters in the observations averaged across catchments in GB3, including years with severe droughts in the observations. Due to the set-up of the large ensemble, spurious Dec-Jan transitions are removed. Sampling for consecutive dry winters within the large ensemble shows that there are consecutive winters in the present-day

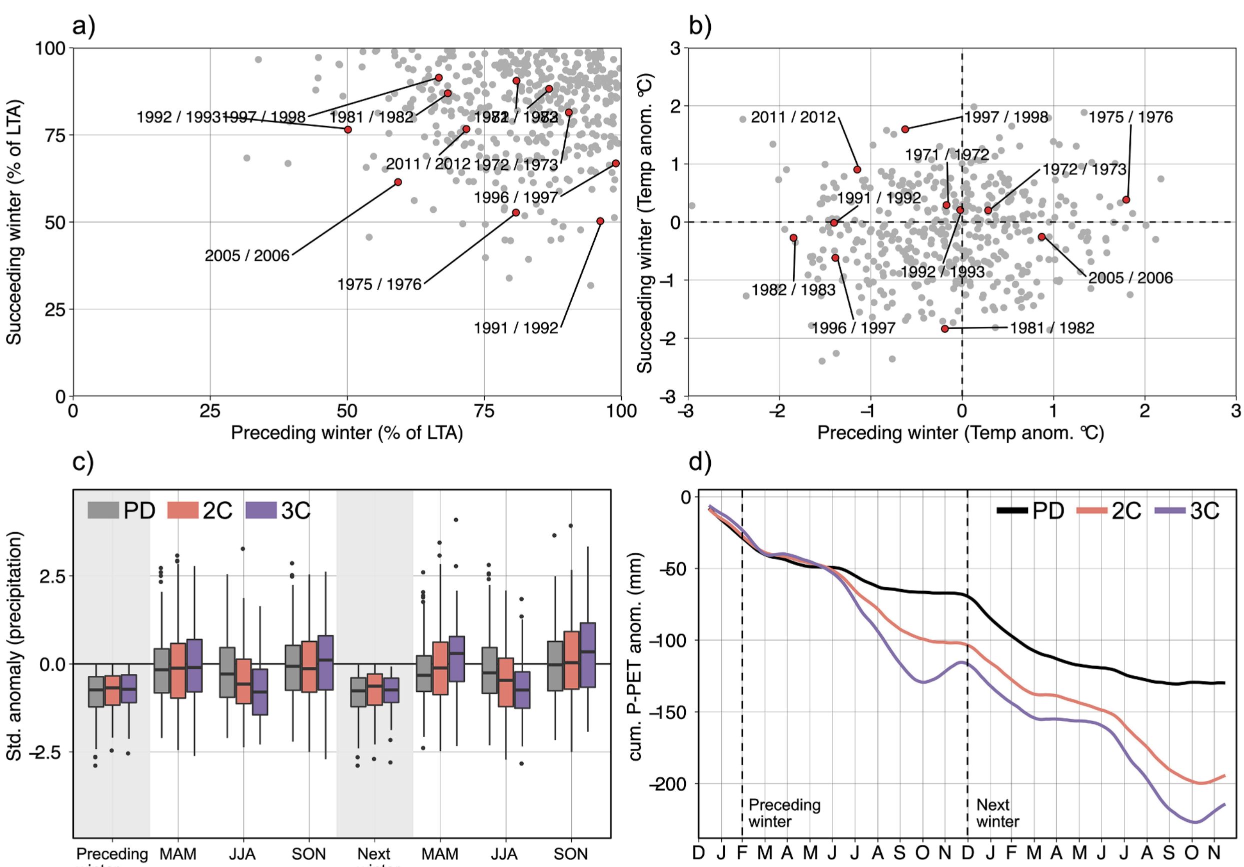

Fig. 11. A) precipitation (% of long term average 1975–2015) and b) temperature anomalies (°C) associated with all occurrences of consecutive dry winters in the present-day large ensemble (grey) and observation (red dots) averaged for catchments in GB3. The bottom row compares c) seasonal precipitation anomalies and d) cumulative P-PET anomalies during all drought years with consecutive dry winters in the present-day (grey), 2 °C (orange) and 3 °C (blue) large ensemble. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

large ensemble with greater precipitation deficit for both the preceding and succeeding winter than the driest observed consecutive dry winter sequence. Fig. 11c shows precipitation anomalies during future consecutive dry winters and the intervening seasons. Winter precipitation anomalies are not estimated to change significantly, likely reflecting the fact that the chance of the driest winter remains relatively unchanged with future warming (see Fig. 6). Drought years with consecutive dry winters show a large variation in the precipitation anomalies for intervening seasons. There is large variation in precipitation anomalies during spring and autumn (the median shows slightly wetter conditions) but a clear change in the intervening summer which is estimated to become drier with future warming in line with the general projections of drier summers. Composite mean P-PET anomalies across drought years with consecutive dry winters also show that drier summers and higher evaporative demand will generate greater cumulative deficit in future multi-year events with dry winter conditions (Fig. 12d). The equivalent figure for latent heat flux anomalies and cumulative P-AET anomalies also reflect this (Figure S11). The intervening summer between two consecutive dry winters is projected to experience enhanced evaporative demand which results in greater overall P-AET deficit compared to the present-day even though the intervening spring and autumn months are projected to be wetter, with more positive latent heat flux.

3.4.3. *Storylines for stress testing*

Storylines can be used to stress test hydrological systems by conditioning on different specified combinations of event drivers (Stoelzle et al., 2020; Chan et al. 2022a; Wilby 2022). Fig. 12 shows the impacts on 18-month (April start) river flow totals from dry spring-summer and autumn–winter sequences at various precipitation deficit levels for two contrasting catchments. Varying autumn–winter precipitation has a greater effect on 18-month river flow totals compared with spring-summer precipitation. The two catchments show a contrasting hydrological response with the impacts over 18-months being larger at Bedford Ouse (Cluster 4) compared to the Greta (Cluster 2), reflecting the persisting influence of precipitation deficits for slow-responding catchments. Certain outcomes may be implausible (e.g. 90% deficit for both spring and summer months in a year) and land–atmosphere feedbacks may be underestimated (due to temperature and PET not being varied). However, dry spring-summers and autumn-winters in the large ensemble (the crosses in Figure 14) clearly cover a large proportion of the response surface with seasonal combinations of precipitation deficits that are beyond what has been observed (the yellow dots in Fig. 12). Counterfactual event storylines can also be created by varying the intervening spring-summer periods between dry winters by different deficit levels to visualize the impacts on accumulated river flows over a critical period.

4. Discussion

4.1. *Risk of extreme droughts*

Compared to existing approaches such as the traditional climate model output or stochastic weather generators, initialized large ensemble climate model simulations can explore a fuller range of plausible outcomes and better consider plausible worst cases (Mankin et al. 2020). An additional advantage is that the physical credibility of simulated events can be verified more easily compared to stochastic

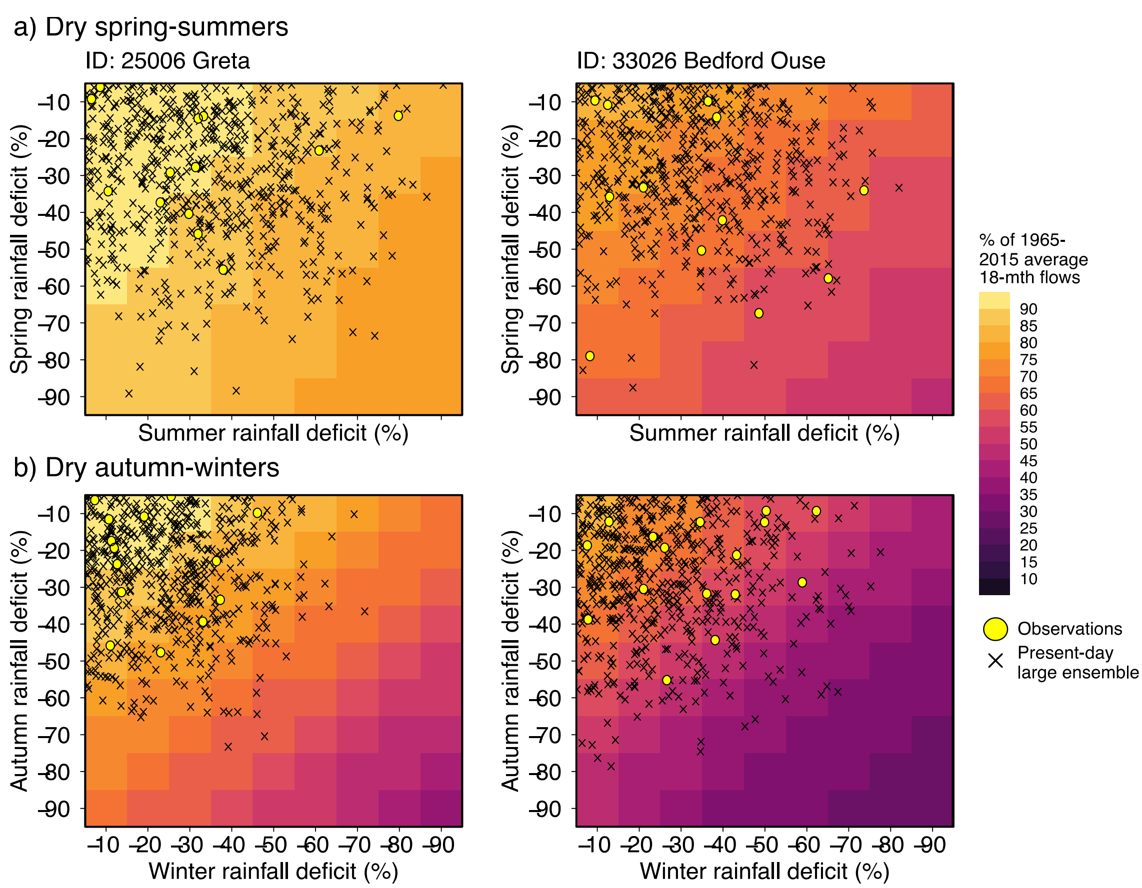

Fig. 12. Stress tests of two contrasting catchments based on sequences of dry spring-summers (top) and dry autumn-winters (bottom) at varying precipitation deficit levels. The colour shading shows the resulting 18-month river flow deficit as a percentage of the 1965–2015 average (April start). Yellow dots show observed events, crosses the events from the present-day large ensemble. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

weather generators. This is because analyses are based on a dynamical model that is physically self-consistent and the metrics describing the meteorological drivers of extreme events are more readily computable (e.g. Kay et al. 2020). It should be noted that depending on the set up of the large ensemble, their usefulness in assessing long-duration multi-year droughts may decline if simulations are reinitialised 12 months apart (e.g. the DePreSys3 dataset) or on seasonal timescales.

Results show an increasing chance of unprecedented hot and dry summers with future warming. This is consistent with multiple generations of climate projections estimating an increased severity of summer droughts across the UK driven by summer warming and increased PET, particularly for fast responding catchments (e.g. Blenkinsop and Fowler, 2007; Rudd et al. 2019). The results also show that although winters are projected to become wetter in general, the chance and magnitude of the driest winter occurring in any given year remains similar across the present-day, 2 °C and 3 °C large ensemble, indicating a continued risk of the most extreme dry winter months. The present-day chance of a given drought exceeding the characteristics of severe post-1891 droughts is consistent with the spatial patterns of worst-case historic droughts found in Barker et al. (2019). Although the chance of exceedance varies between catchments, our results show that the set of post-1891 droughts are relatively hard records to break although it becomes more likely that a given drought in a 2 °C and 3 °C warmer world will be more severe. Unprecedented droughts in the future are more likely to include precipitation deficits in the summer and river flow responses may be exacerbated due to the impacts of elevated evaporative demand from increased summer temperatures (as shown in Reyniers et al. 2023 with UKCP18). For example, Brunner et al. (2021b) has found that recent temperature increase has contributed to an increase in the spatial extent of US droughts from higher evaporative demand and more severe soil moisture deficits.

Compared to the EC-Earth large ensemble, the UKCP18 projections project a smaller increase in winter precipitation and a greater decrease in summer precipitation with greater warming. The UKCP18 projections also project drier autumns and springs over southeast England (Arnell et al. 2021), which leads to a delay in the soil wetting date (Kay et al. 2022) and shortens the groundwater recharge season. This may explain the differences in hydrological drought characteristics in the eFLaG ensemble compared to this study with the occurrence of longer and more severe hydrological droughts where low, median and high flows are all projected to decline for catchments southern and eastern England (Hannaford et al. 2023; Parry et al. 2023).

4.2. Bridging risk estimates and storylines

Storylines are complementary to the risk-based probabilistic estimates in Section 3.3. Although no probabilities are attached to each storyline, sampling for specific conditions within the large ensemble enable a fuller investigation of plausible worst cases and the unfolding of future events with the same drivers (van der Wiel et al. 2021, van der Wiel et al. 2022). The dry spring-summer and dry autumn–winter storylines resemble conditions observed in past severe droughts used as benchmark worst-case droughts (e.g. 1975–76 and 1921). The formulation of storylines which resemble known conditions in past events contributes to the growing use of event-based case studies to guide adaptation planning (Sillmann et al. 2021). For example, Baker et al. (2021) found that the likelihood of an extreme hot summer succeeding an extreme dry winter-spring period and the probability of an extreme hot-dry summer have increased since the 1970 s. The storylines in this study complement this result by showing that future dry spring-summers are estimated to generate greater deficit. van Garderen et al. (2021) demonstrated how storylines and a probabilistic approach can be complementary in climate attribution of extreme events. Similarly, Table 3 shows the insights gained in this study from the probabilistic estimates of unprecedented extremes and the different storylines of drought conditions.

Table 3
Example of how probabilistic estimates and the storyline approach can complement each other to provide additional insights to the nature of extreme droughts in present and future climate.

Probabilistic estimate of unprecedented extremes (Section 3.3)	High temperature - Averaged over catchments in southeast England, the chance of a given year with unprecedented high temperatures increases from 5.7% and 1.5% in the present day to 58.3% and 30.5% in a 3 °C warmer world for summer and winter respectively. Low precipitation - Averaged over catchments in southeast England, there is an 8.8% and 10.1% chance of an unprecedented dry summer or winter month, respectively, in any given year. This increases to 18.1% for summer and slightly decreases to 7.5% for winter in a 3 °C warmer world. The chance of the driest winter month in the large ensemble does not change significantly between present and future climate.
Storylines of drought conditions (Section 3.4)	Dry spring-summers are estimated to become drier with dry springs associated with deepening of high pressure and dry summers associated with enhanced evaporative demand. Dry autumn-winters may become wetter, due to wetter winters, but dry conditions may be prolonged even with moderate autumn–winter precipitation deficit if followed by a dry summer which is projected to become drier with warming. Multi-year droughts characterised by consecutive dry winters may worsen especially for slow-responding catchments (i.e. GB3) if the intervening summers are hotter and drier. Despite an expectation of future winter wetting, there is no clear change in the precipitation anomalies associated with future consecutive dry winters because of the need to make up for the lack of rainfall and higher evaporative losses in the intervening summer.

Circulation patterns for dry years in the present day large ensemble resemble both the dipole (high pressure centered over eastern Atlantic with positive anomalies to the north and negative anomalies to the south) and Azores high (high pressure centered over western Europe) circulation patterns responsible for European droughts identified in Kingston et al. (2015). The weakening of the high pressure with future warming during the summer months during dry spring-summer sequences is consistent with van der Wiel et al. (2021) which extracted summer drought analogues from the same large ensemble for the Rhine basin and showed weaker summer high pressure anomalies with future warming. This result could reflect a stronger influence of atmospheric circulation with warming as weaker anomalies lead to similar or higher levels of precipitation deficits. An increased influence of weather patterns associated with drier, settled conditions was found in both summer and autumn in the future in the UKCP18 projections (Cotterill et al. 2022; Pope et al. 2022). Although the EC-Earth large ensemble project in general wetter autumns, De Luca et al. (2019) found that CMIP5 models projecting a decrease in cyclonic type circulation patterns in autumn may lead to lower soil moisture and groundwater recharge at the beginning of winter. Given the continued risk of dry winters, this may increase the likelihood of winter droughts due to a shortened recharge season.

4.3. Limitations and further work

The main limitation of this study is that the EC-Earth large ensemble has a relatively coarse spatial resolution. This represents a drawback for impact modelling as bias adjustment and statistical downscaling procedures are required. Although requiring bias adjustment, large ensembles can provide valuable insights into plausible worst case droughts if simulated events are physically credible as demonstrated in this study. The bias correction factors applied to catchments in GB1 and GB2 were larger than for other catchments. This could be due to the spatial resolution of the large ensemble where complex orography in upland catchments is less well represented. A large bias adjustment could lead to events that are physically implausible (Kelder et al. 2022b), meaning the estimated chance of unprecedented extremes at these catchments may be over- or under-estimated. Although the meteorological drivers and the temporal dynamics of the driest events seem physically credible, future work could make use of SMILEs generated from regional climate models (e.g. Böhnisch et al. 2021). As the large ensemble is based on a single climate model, comparing results from different SMILEs could also increase the robustness of our results.

The estimate of unprecedented extremes only considers the chance of exceedance in the baseline period and is not sequentially updated as records are broken over time (the present-day estimates reflect the chance of exceedance based on 2011–2015 conditions). Future work could update this by tracking how the chance has changed over time. For example, Barker et al. (2019) showed that the risk of the 1975–76 drought has already increased since the 1970 s due to recent climate change. Similarly, Kay et al. (2020) showed that the chance of exceeding the 2018 heatwave temperatures has increased since 1960. The changing risk of compound hot and dry extremes is also not explicitly considered in this study as drought storylines are selected using precipitation anomalies. Given the focus of this study, this is justified as precipitation trends are the key driver of variability in future droughts. The storylines therefore already include the hottest and driest events as heat extremes are more likely in a 2 °C and 3 °C warmer world. However, more research is needed to consider the role of temperature as a driver of drought magnitude and intensity. For example, the role of land–atmosphere feedbacks during droughts in the UK requires further investigation, such as the soil moisture deficit exacerbating hot extremes and reinforcing low precipitation during anticyclonic conditions (Schumacher et al., 2019).

The choice of PET estimation method can affect simulated river flows. Although studies have suggested that PET-related uncertainty is generally less than GCM-related uncertainty due to the wide range of projected change in precipitation across climate models (e.g. Kay and Davies, 2008), future work could test the sensitivity of the results to alternative PET estimation methods. Furthermore, future work should also test the validity of simple temperature-based PET equations under non-stationary conditions. Additionally, given the set-up of the large ensemble (i.e. stitched together 5-year runs), the occurrence of consecutive dry winters (and thus multi-year droughts) is not well sampled, and the probability of their occurrence cannot be robustly estimated. Hence, it was not possible to specifically sample for three or more consecutive dry winters in the large ensemble, which is a well-known concern for the UK water industry. Future work could investigate the persistence of consecutive dry seasons (e.g. Wilby et al., 2015) and sample for multi-year events in different large ensemble datasets (e.g. van der Wiel et al. 2022). Possible changes in hydrological variability (e.g. drought to flood events) with climate change could also be sampled from large ensemble simulations to investigate changes in drought termination characteristics (e.g. Parry et al. 2016). The occurrence of dry winters arising from ENSO or other teleconnection patterns (e.g. Svensson and Hannaford 2019) also merits further investigation.

5. Conclusions

This study uses the EC-Earth time-slice large ensemble to estimate the current and future chance of unprecedented low rainfall, high temperature and hydrological droughts. Estimates suggest an increased risk of extremely dry summer months but a slight decrease in the chance of dry winter months with warming. Simulated river flows of GB catchments show a worsening of drought characteristics for most catchments with temperature rise. Comparing the much larger sample of plausible hydrological droughts with a selected number of severe post-1891 droughts highlights the spatial signature of past drought episodes and identifies droughts that are especially hard records to break for different parts of Great Britain.

The probabilistic risk estimates can be complemented by the storyline approach. Storylines of dry springs followed by dry summers, dry autumns followed by dry winters and consecutive dry winters are considered to understand the atmospheric circulation patterns associated with dry sequences and the unfolding of future events driven by the same conditions. Dry spring-summers are estimated to become drier with spring conditions associated with a deepening of the associated high-pressure system and summer conditions associated with increased evaporative demand. Winter conditions in dry autumn-winters are estimated to be wetter in the future compared to the present day, which implies a higher likelihood of seasonal summer droughts broken up by wet winters for fast-responding catchments. However, for slow-responding catchments and in southeast England, future severe multi-year droughts can unfold if multiple dry winters occur which are more likely to be associated with an intervening dry summer. Stress tests conditioned on different seasonal precipitation deficits of the various storylines can be designed to understand the effects of different seasonal combinations of precipitation deficits on accumulated river flows over critical periods and provide a basis for the construction of plausible worst case unrealised droughts.

CRediT authorship contribution statement

Wilson C.H. Chan: Conceptualization, Formal analysis, Data curation, Visualization, Writing – original draft. **Nigel W. Arnell:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Geoff Darch:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Katie Facer-Childs:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Theodore G. Shepherd:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Maliko Tanguy:** Conceptualization, Supervision, Writing – review & editing. **Karin van der Wiel:** Data curation, Writing – review & editing.

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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.

Data availability

Precipitation data (CEH-GEAR) are freely available on the Environmental Information Data Centre (https://doi.org/10.5285/ee9ab43d-a4fe-4e73-afd5-cd4fc4c82556, Tanguy et al., 2019). Daily mean temperature data (CEH-CHESS) are freely available on the Environmental Information Data Centre (https://doi.org/10.5285/2ab15bf0-ad08-415c-ba64-831168be7293, Robinson et al., 2020). Daily observed river flow data are available from the National River Flow Archive (https://nrfa.ceh.ac.uk/). The EC-Earth large ensemble input (2000 years of precipitation and PET) and output (2000 years of simulated river flows) for each catchment are available from the Environmental Information Data Centre (https://doi.org/10.5285/d966ae7f-a29b-4c57-835d-f4efd0d65c88). The full EC-Earth data are available with Karin van der Wiel (wiel@knmi.nl) on reasonable request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2023.130074.

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