A new approach to navigate uncertainty in climate-related hydrological drought risk

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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ABSTRACT

Hydrological droughts threaten public water supply and significantly impact the natural environment and other sectors. Quantifying the plausible worst case drought in the present day climate and understanding the impacts of climate change on future droughts help decision-makers formulate plans to enhance resilience. However, existing studies are often dominated by a top-down approach characterised by a cascade of uncertainty which particularly suffers from an insufficient exploration of low-likelihood, high-impact outcomes. This thesis aims to navigate uncertainty in the hydrological impacts of climate change by introducing a physical climate storyline approach. Drought storylines created from process understanding, pooling of ensemble reforecasts and sampling from large ensemble climate model simulations enhances risk awareness and aids robust decision-making for water resources planning.

Retrospective storylines of past droughts created by perturbations made to observed events embraces downward counterfactual thinking through identification of different ways in which events could have turned out worse. A more severe precipitation deficit in autumn 1975 for east England or an even drier winter 1975/76, both of which could have arisen from natural climate variability, could have led to a reduction in accumulated river flows by up to >50% at slow-responding catchments in East Anglia. Storylines of the 1976 drought could have surpassed the maximum intensity of the 1921-22 drought by up to >30% to become the most severe post-1891 drought for the region. Similarly, drier preconditions of the 2010-12 drought and a plausible third consecutive dry winter could have led to significantly more severe conditions across the UK. A third dry winter, in particular, could have led to conditions matching the benchmark multi-year drought for east England (1989-1993), highlighting the fact that the drought could be seen as a near miss. Placing the observed drought in a 2°C warmer climate is estimated to exceed mean deficit of the benchmark 1989-93 drought by >60% at some of the worst affected catchments.

Initialized large ensemble model simulations is an emerging way to create high-impact, low-likelihood storylines. Storylines of the 2022 drought in East Anglia created by combining observations with pooled ensemble reforecasts enable decision-makers to explore the likelihood of worst-case river flow trajectories, identify high impact combination of physical climate drivers to increase risk awareness during an on-going event. Further, application of the UNprecedented Simulated Extremes using ENsembles (UNSEEN) technique estimates that the chance of unprecedented high (low) summer temperature (rainfall) increases from 5.7% (8.8%) in the present day to 58.3% (18.1%) in a 3°C warmer world. The larger sample simulations are ideal for searching for high impact drought sequences where the physical credibility of simulated events may be verified more easily compared to statistical methods. The utility of the current generation of large ensemble simulations to sample for multi-year drought storylines is further discussed with drawbacks due to spatial resolution, the need for bias adjustment and the under-estimation of weather system persistence (such as atmospheric blocking).

The various methods presented in this thesis provide evidence of the magnitude of present and future extreme droughts. Outstanding research gaps to ensure the physical credibility of drought storylines include the need to improve quantification of observational data uncertainty and better characterisation of hydrological model realism during extreme droughts. The demonstrated value of the storyline approach contributes to the diversification of approaches used in water resources planning and could form a core part of planning to assist in stress-testing water resources systems and enhancing resilience to future droughts.

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AUTHORSHIP OF PAPERS

This thesis comprises four lead author papers. Data and methods for each chapter has been merged in Chapter 3: Data and methods. Chapters 2, 5 and 6 are published in full. Sections of Chapter 4 has been published. Estimated contribution for each paper is outlined below.

Chan, W. C.H., Shepherd, T. G., Facer-Childs, K., Darch, G., and Arnell, N. W.: Tracking the methodological evolution of climate change projections for UK river flows, Progress in Physical Geography: Earth and Environment, 030913332210792, https://doi.org/10.1177/03091333221079201, 2022a.

Estimated contribution: 85%. WCH conducted the literature search and wrote the manuscript with supervision and input from all co-authors at all stages, including the selection of papers included in the review and reference to non-academic papers and practitioners' guidance.

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

Estimated contribution: 85%. WCH conducted the formal analysis and wrote the manuscript. All co-authors provided input and contributed to the interpretation of the results.

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Estimated contribution: 85%. WCH conducted the formal analysis and wrote the manuscript. KvdW provided the large ensemble dataset. All co-authors provided input and contributed to the interpretation of the results.

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Estimated contribution: 85%. WCH conducted the formal analysis and wrote the manuscript. All co-authors provided input and contributed to the interpretation of the results. GD initiated the 3-months placement at Anglian Water from which this publication evolved.

LIST OF ACRONYMS

Acronym	Description
AET	Actual Evapotranspiration
AMV	Atlantic Multi-decadal Variability
ANG	Anglian
BFI	Baseflow Index
CMIP	Coupled Model Intercomparison Project
DTD	Drought termination duration
DTR	Drought termination rate
EA	East Atlantic pattern
ECMWF	European Centre for Medium-Range Weather Forecasts
eFLaG	enhanced Future FLows and Groundwater
ENSO	El Niño Southern Oscillation
GB	Great Britain
GCM	Global Climate Model
LFBN	Low Flow Benchmark Network
LTA	Long term average
MSLP	Mean Sea Level Pressure
NAO	North Atlantic Oscillation
NRFA	National River Flow Archive
PET	Potential Evapotranspiration
PPE	Perturbed Parameter Ensembles
RCM	Regional Climate Model
RCM	Regional climate model
SAAR	Standardised Annual Average Rainfall
SEAS5	Seasonal Forecasting System 5
SMILE	Single-Model-Initial-Condition-Large-Ensemble
SSI	Standardised streamflow index
SST	Sea Surface Temperature
UK	United Kingdom
UKCEH	UK Centre for Ecology and Hydrology
UKCP09	UK Climate Projections 2009
UKCP18	UK Climate Projections 2018
UNSEEN	UNprecedented Simulation of Extremes using ENsembles
Z500	Geopotential Height at 500hPa

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1 INTRODUCTION

1.1 Motivation

Droughts threaten public water supply and incur significant impacts on the natural environment and across multiple sectors (Wilhite et al., 2007). The direct impacts of droughts include, but are not limited to, reduced water supplies, agricultural crop failures (e.g. Beillouin et al., 2020), suspension of energy generation (e.g. van Vliet et al., 2016) and habitat fragmentation (e.g. Oliver et al., 2015). Additionally, droughts may indirectly lead to a range of health and socio-economic impacts such as water scarcity, displacement and income loss (UNCCD 2017). The impacts of droughts can also have cascading effects where an event in one region leads to cross-border socio-economic or political impacts in another region (e.g. Sternberg, 2011; van den Hurk et al., 2023). The occurrence of droughts is not limited to dry regions in semi-arid or arid environments (Mishra and Singh, 2010; Van Loon, 2015). Droughts are often slow-developing and long-lasting and the spatial and temporal aspects of the onset, development and recovery process can be very different between events. According to the European Commission, droughts cause annual economic losses of around €9 billion per year for the European Union (including the UK) (Rossi et al., 2023). Additionally, some of the most severe consequences of future climate change will be experienced through changes in the global water cycle and the frequency and severity of hydrological extremes.

Public perception of the UK being a "wet and rainy" [1] country with no risk of severe droughts is not consistent with past meteorological and river flow observations showing periodic periods of severe droughts (Marsh et al., 2007; Barker et al., 2019) and future projections suggesting a reduction in low flows and increase in drought severity with climate change (e.g. Arnell et al., 1990; Arnell, 1992a; Charlton and Arnell, 2014; Kay et al., 2021; Parry et al., 2023). However, the understanding of present-day drought risk is incomplete as it is limited by short observational records and hampered by the impacts of internal climate variability and the multivariate nature of individual drought events. Hydroclimate time series are often highly variable and relatively short observational records do not adequately sample plausible events and are not long enough to provide robust estimates of probability occurrence (Slater et al., 2021). A greater understanding of plausible worst cases, including descriptions of the unfolding of extreme events beyond historically observed events, is therefore highly relevant for risk awareness and preparedness.

Researchers have also highlighted several knowledge gaps in the understanding of climate impacts on UK droughts. The latest IPCC report indicated low confidence in projected changes in the frequency of hydrological droughts for Northern and Western Europe from mid-century (2050s) onwards (Douville et al., 2021). The magnitude of change in future droughts remains uncertain and studies diverge on changes to the frequency of severe multi-year droughts, with some suggesting increases in seasonal, shorter-duration droughts (Blenkinsop and Fowler, 2007; Chun et al., 2013) and others highlighting hotspots for future multi-year droughts (e.g. Prudhomme et al., 2014; Brunner and Tallaksen, 2019). Uncertainty in future changes in meteorological droughts is largely driven by substantial differences in projected precipitation change between different climate models. The use of different impact models (such as hydrological models) driven by projected precipitation from climate models and different drought indicators further accrue uncertainty along the modelling chain (Dessai and Hulme 2010). Additionally, traditional multi-model climate model ensembles do not represent the full range of possible outcomes and studies generally do not consider outcomes beyond the range of the multi-model ensemble, thus under-sampling low-likelihood, high-impact outcomes (Katzav et al., 2021; Sutton, 2019). There is thus an outstanding research gap to better understand the processes and magnitude of future events in a way that combines various sources of information to support operational decisions and long-term strategies to safeguard water supplies and the natural environment.

[1] "The Great British Rain Paradox" survey of 2000 adults showed that over 75% associate the UK with "wet and rainy" weather with little risk of drought and water shortages. [Great British Rain Paradox.pdf (hwmglobal.com)]

1.2 Typology of droughts

The definition of droughts varies for different sectors. No single universal definition of drought is likely to be sufficient to adequately consider the context of different sectors (Lloyd-Hughes, 2014). The most common classification separates events into meteorological, soil moisture, hydrological and socio-economic droughts (Van Loon 2015). Meteorological droughts refer to deficits in precipitation over a defined period caused by large-scale atmospheric circulation patterns. Soil moisture droughts (or agricultural droughts) are caused by low soil moisture due to below-average precipitation and can be exacerbated by high temperatures. Hydrological droughts refer to below average river flows, groundwater levels or reservoir stocks for a defined period which can be triggered by precipitation deficits and enhanced by high evaporative demand from high temperatures (Van Loon and Van Lanen, 2012).

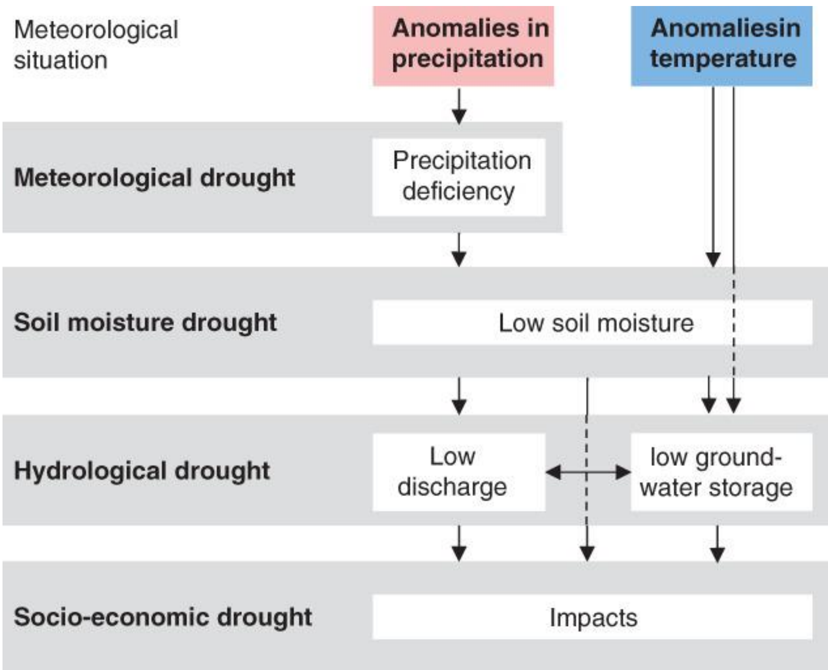

Figure 1.1 Schematic showing the classification of different types of droughts and their relationship with meteorological drivers and hydrological processes. [Figure from Van Loon, 2015]

As shown in Figure 1.1, meteorological droughts cascade and propagate through the water cycle and translate into hydrological droughts. There is often a time lag for meteorological droughts to propagate and result in hydrological droughts and drought duration tends to increase as prolonged hydrological droughts can be caused by a pooling of multiple shorter meteorological droughts (Van Loon and Van Lanen, 2012; Van Loon, 2015; Barker et al., 2016). Hence, the propagation of meteorological to hydrological drought is non-linear and heavily depends on a combination of factors such as human influences on the catchments (e.g. surface water abstractions) (Van Loon et al., 2016) and physical catchment characteristics (e.g. hydrogeology and catchment storage) (Van Loon, 2015; Barker et al., 2016). Socio-economic drought relates to the impacts of drought on human activities and the supply of economic commodities (e.g. water supplies, hydroelectricity and agricultural products) that may be dependent on levels of river flows, groundwater or reservoir levels (Wilhite et al., 2014).

1.3 UK droughts

The UK has experienced periodic periods of meteorological and hydrological droughts in the past and risks future water shortages and other drought impacts as a result of climate change and increasing water demand. The seminal publication by Marsh et al. (2007) used past instrumental observations and historical documentary evidence to compile a comprehensive chronology of major hydrological droughts for the period 1800-2006. Table 1.1 presents a series of major droughts in the UK since the mid-late 19th century and a brief description of each event, including the region that was most affected during each event. The list of drought events is based on the hydrological drought events identified by Marsh et al (2007) as well as river flow reconstructions in Barker et al. (2019), the more recent 2018-19 drought (Turner et al., 2021), and the 2022-23 drought (Parry, 2022).

1.3.1 Public water supply

The water industry in England is made up of private companies separated across different administrative regions (11 provide water supply and sewerage services and an additional 13 provide water-only services as of July 2023). Welsh Water (Dŵr Cymru), Scottish Water and Northern Ireland Water provide services for the remaining constituent parts of the UK. Cook (2017) and Parliamentary Office of Science and Technology (2021) provided comprehensive overviews of the responsibilities of private water companies and the respective legislation underpinning water supply and related environmental standards (e.g. EU Water Framework Directive to safeguard and

Table 1.1 Selected historic UK drought events since the 1890s and a brief description of the causes and regions that were most impacted.

Drought event	Description
1890-1910 "Long drought"	Long drought over a 20-year period characterized by multiple sequences of dry winters (particularly 1898, 1902, 1905 and 1909) punctuated by wet interludes. Spatially extensive over southern England and Wales and impacts were not experienced across all regions simultaneously.
1921-22	Major drought impacting England and Wales with a dry autumn-winter sequence followed by a dry spring-summer that was exacerbated by hot and dry summer. Benchmark worst historic drought for some reservoirs and hydrological systems in East Anglia (Anglian Water Drought Plan 2022).
1933-34	Severe drought beginning in winter 1932-33 in northern UK with severe impacts on river flows across the UK over 1934 before termination in 1934 for most catchments
1940s	Notable drought phases in a decade with multiple periods of moderate droughts, including 1944 and 1948 drought episodes impacting large parts of England and Wales.
1975-76	Dry winter 1975-76 followed by dry spring-summer and abrupt termination in autumn 1976. Major impacts on both river flows and groundwater levels and remains the benchmark event for many reservoirs and hydrological systems across England and Wales. Notable for the 1976 summer heatwave which remains one of the hottest summers on record but has since been joined by more recent summers (e.g. 2003, 2018 and 2022).
1988-93	Drier than average winters of 1988-89 and 1991-92 with initial impacts for catchments in northern UK before severe impacts developing over southern England from prolonged dry conditions exacerbated by the 1990 summer heatwave. The drought was particularly severe for groundwater dominated catchments.
2003	Characterised by the hot and dry summer during the 2003 European summer heatwave which was preceded by a dry winter and extended to autumn 2003.
2004-06	Drought inception during dry winter 2004-05 before a second consecutive dry winter 2005-06. Impacts on river flows exacerbated by dry summer 2006 before drought termination in autumn 2006. Impacts on river flows and groundwater levels were most severe across southern England.
2010-12	Multi-year event with two consecutive dry winters (2010-11 and 2011-12) and abrupt drought termination in late spring 2012. Record precipitation in spring 2012 and continued wet conditions across winter 2012-13 led to rapid drought termination. Hydrological impacts began in northwest UK and severe impacts on river flows developed across England and Wales by early spring 2012.
2018-19	Notable precipitation deficits over winter 2016-17 and autumn 2017 for southern England delayed groundwater recharge despite wetter conditions over winter 2017-18. Summer 2018 was amongst the warmest summer on record which saw significant declines in river flows but was generally not as severe as observed in summer 1976. Drought recovery during wet conditions in late summer 2019 and widespread termination from wet autumn-winter 2019-20.
2022-23	Driest spring-summer sequence since 1976 preceded by drier than average precipitation over winter 2021-22 (notably dry for southwest England). Severe impacts on river flows across England and Wales with flows exceeding the 2018 drought and approaching record low flows during 1976. Notable for the 2022 summer heatwave with 40°C recorded for the first time in July and amongst the warmest summers on record.

improve water quality). The regulatory framework for water resources planning is provided by the Department for Environment, Food and Rural Affairs (DEFRA), which publishes policy papers and proposes legislation pertaining to water resources and the natural environment. The Environment Agency is the environmental regulator responsible for long-term planning, issues abstraction licences for surface and groundwater sources and oversees management measures enacted by water companies during drought. The Water Services Regulation Authority (Ofwat) is the economic regulator for water companies and aims to ensure that water companies maintain a minimum standard of service a customer can expect and conduct periodic price reviews related to consumer bills. In addition to these main actors, several other public organisations such as Natural England and the Drinking Water Inspectorate advise the government on related issues such as the natural environment and drinking water quality.

Each water company has a statutory requirement to publish Water Resources Management Plans (WRMPs) every 5 years as part of the formal Asset Management Planning (AMP) cycle. WRMPs establish "levels of service", representing the maximum frequency by which customers experience supply restrictions and outline actions each water company takes to manage and secure water resources, looking ahead at least 25 years. Water companies are also required to produce business plans, submitted to Ofwat, outlining long-term business and efficiency objectives consistent with strategies outlined in their WRMPs. Based on the business plans, Ofwat conducts a Price Review which limits the price each water company is allowed to charge their customers, aiming to balance customer interests and long-term investment needs to further resilience of water supplies. Following the Water Act 2003, companies were also required to publish drought plans alongside the WRMPs in each AMP cycle which outline the various demand and supply management options to be taken before, during and after a drought to reduce water demand or increase water supply (Defra and Environment Agency, 2021). The Environment Agency also recommends testing the drought plan through worked examples. This can be demonstrated using past droughts or synthetic droughts of varying severity and length and normally includes the timing when drought trigger thresholds are crossed and when different management actions are enacted during different stages of the drought (Environment Agency, 2019). Following the publication of the National Framework for Water Resources (Environment Agency 2020), five regional groups covering England have been initiated to encourage cooperation between water companies and formulate integrated regional plans related to infrastructure development, transfers of water between water companies and cooperation with other water users (such as agriculture, industry and the natural environment).

1.3.2 Drought management options

Water companies must outline demand and supply management actions in their drought plans and prepare for the application of drought permits and drought orders during an event (Defra 2021). Table 1.2 shows the four levels of drought action in levels of increasing severity and examples of both demand- and supply-side management options. During a drought, demand management measures may include temporary use bans (TUBs) and non-essential use bans (NEUBs). Should a drought worsen, and river flows remain low, supply-side management options may be available. For example, water companies must demonstrate a serious deficiency of supplies due to an exceptional shortage of rainfall to apply for drought permits and drought orders to enable abstraction beyond the usual abstraction limits as detailed in water company drought plans (e.g. Anglian Water Drought Plan 2022). Drought triggers are defined for each level representing the threshold a drought must reach prior to initiating new drought management options at the next level. Drought triggers can be thresholds based on standardised indicators of precipitation, river flows, groundwater levels or reservoir stocks, beyond which new management options are available to safeguard public water supplies. Management options to be taken for each level of drought may differ between water companies and for each source (i.e. different reservoirs or rivers).

Table 1.2 Drought management options for four levels of drought severity based on information from Defra and Environment Agency (2021) and Cook (2017).

Level	Demand-side measures	Supply-side measures
L1	Increase communication with customers to improve water efficiency and reduce consumption.	Drought permits to abstract additional water in winter. Additional monitoring of sources (e.g. boreholes). Fast-track repairs and maintenance.
L2	Temporary Use Bans (TUBs) to impose restriction on water use (i.e. hosepipe bans). Drought permits to abstract additional water in the summer (low-risk abstraction balancing ecological demand and other water users)	Pause compensation releases from reservoirs. Reduce outage and leakages. Engineering options to maximise supply such as increasing drill depth of boreholes. Enhance conjunctive use of different sources (e.g. increase groundwater abstractions to maintain storage if surface sources are limited).
L3	Non-Essential Use Bans (NEUBs) should drought continues to worsen to restrict water use of commercial operations or	Regional water transfers between water companies. Re-instate reservoirs or boreholes that are unused.

	businesses in addition to the TUBs. Drought permits to enable additional abstraction that has a high risk to other water users and demands	
L4	Extreme measures such as standpipes as a last resort. Their implementation is likely to have major impacts on customers and require an emergency drought order issued by the Secretary of State.	Desalinization or more expensive infrastructure solutions

1.4 Drivers of UK precipitation

Hydrological extremes occur from a combination of dynamic (e.g. precipitation driven by weather patterns and remote teleconnections) and thermodynamic (e.g. evaporation driven by surface warming) drivers along with the influence of physical catchment characteristics. The drivers of UK precipitation are briefly reviewed here. Specific focus is given to the drivers of winter precipitation as the winter half-year is the primary period when aquifer and reservoir levels (particularly in southern and eastern England) are recharged, due to the lower evapotranspiration rates and thus a higher proportion of rainfall translated into river flows or recharged as groundwater (Folland et al., 2015). Precipitation deficits over the UK are often associated with atmospheric blocking conditions associated with a meandering and slow-moving jet stream that can be stalled in one position for a prolonged period. This results in high-pressure and settled conditions that can cause either prolonged high precipitation or precipitation deficits. There is a higher likelihood of heatwaves within the blocking region in the summer depending on the configuration and position of the blocking system (Kautz et al., 2022). Atmospheric blocking commonly occurs over Europe due to the influence of the jet stream and interacts with large-scale atmospheric circulation patterns such as the North Atlantic Oscillation (NAO) (Hurrell, 1995; Fereday et al., 2018). Variability in sea surface. Temperature (SST) anomalies in the North Atlantic interacts with atmospheric circulation patterns such as the NAO and different connections between the drivers are associated with summer droughts in different UK regions (Kingston et al., 2013). Precipitation anomalies can also be influenced by SST impacts arising from remote teleconnections, such as the El Niño Southern Oscillation (ENSO) (Fereday and Knight, 2022). For example, Svensson and Hannaford (2019) found that different combinations of winter North Pacific and North Atlantic SSTs lead to markedly different spring-to-autumn precipitation and streamflow responses.

Winter precipitation in the UK is particularly influenced by the state of the NAO (Wilby et al., 1997; Simpson and Jones, 2014). Variability in the NAO exhibits marked differences between northern and western regions and southern and eastern regions of the UK, reflecting the NW/SE climatological precipitation gradient. There is a positive association between NAO and precipitation for north/west Great Britain (Fowler and Kilsby, 2002; Svensson et al., 2015; West et al., 2019) and high river flows, possibly exacerbated by orographic enhancement of precipitation (West et al., 2022; Burt and Howden, 2013). Studies have highlighted that the variability of winter precipitation and temperature in other parts of Europe (including southern and eastern UK) are not solely explained by the NAO but from the combined influence of the NAO with other teleconnection patterns, particularly the East Atlantic (EA) pattern (Shorthouse and Arnell, 1999; Moore and Renfrew, 2012; Ionita, 2014; Kingston et al., 2015; Haslinger et al., 2019; West et al., 2021). A positive phase of the EA is characterised by anomalously high sea level pressure anomalies over Europe where the pressure centre is shifted towards the southeast compared to the NAO (Wallace and Gutzler, 1981). The combination of NAO and EA phases explains interannual variability in the jet speed and latitude of the North Atlantic jet stream (Woollings et al., 2010, 2014). The authors showed that the jet stream exhibits three preferred latitudinal positions that are explained by interactions between NAO and EA phases where NAO+/EA- conditions are associated with a more northerly jet stream and NAO-/EA+ with a more southerly latitude. As the EA pattern alters both the location and intensity of the NAO's pressure centres of action, such a displacement can either enhance or dampen the surface temperature and precipitation response in the UK (Comas-Bru and McDermott, 2014; Mellado-Cano et al., 2019; Hall and Hanna, 2018; West et al., 2021).

Additionally, SST anomalies in the North Atlantic exert an influence on atmospheric circulation (such as the NAO phase). The tripole pattern of SST anomalies in the North Atlantic prior to winter, illustrated by the differences in anomalies between the south of Greenland and southeast United States coast, may play a role in influencing the NAO (Rodwell et al., 1999). A positive SST tripole, indicated by warm anomalies south of Greenland and cold anomalies off the southeastern US coast, favours NAO+ conditions and wetter conditions in western UK whereas a negative tripole pattern is associated with drier than average precipitation (Rodwell et al., 1999; Fan and Schneider, 2012; Folland et al., 2015). Although the direct influence of ENSO on UK hydrological variability is small, studies have suggested a role for remote teleconnections in influencing UK winter precipitation and modulating the effects of NAO. For example, Wilby (1993) and Fraedrich (1994) showed that there is a tendency for more anticyclonic (cyclonic) weather types to occur given a winter with La Niña (El Niño) conditions in the historical observations. Composite sea level pressure patterns show strong negative anomalies over Scandinavia and positive anomalies over central Europe during La Niña winters but it remains difficult to separate the effect of ENSO from the NAO (Fraedrich, 1994; Shorthouse and Arnell, 1999). More recently, Folland et al. (2015) updated the evidence for ENSO influence on precipitation deficit in the winter half-year over southern England and confirmed the findings in earlier studies that La Niña winters generally favour NAO+ conditions with a higher likelihood of settled, dry weather over southern England.

On longer timescales, studies have shown that multi-decadal variability in the North Atlantic ocean (also known as AMV - Atlantic Multi-decadal Variability) influences European and UK climate. AMV could arise from the combination of natural internal decadal variability, external forcing (e.g. volcanic eruptions) and anthropogenically forced changes in North Atlantic sea surface temperatures and ocean circulation (such as the Atlantic Meridional Overturning Circulation) (Knight et al. 2005; Sutton and Dong 2012; Mann et al. 2021). The observed AMV fluctuates between warm and cold phases on a 50-70-year time scales, having been in an anomalously warm phase in the 1930s-1960s, a cold phase from the 1960s to late 1990s and a warm phase since (Sutton and Dong 2012; Zhang et al. 2019). The AMV influences European and UK climate by modulating ENSO and the NAO (Zhang et al. 2019). In the summer, the summer NAO (SNAO) is associated with changes in position of the North Atlantic storm tracks across northwest Europe (Folland et al. 2009). It has been shown from past observations that the warm (cold) phases of the AMV corresponds to negative (positive) phase of the SNAO and higher (lower) summer rainfall over the UK and northwestern Europe (Folland et al. 2009; Sutton and Dong 2012). The observed warm phase of the AMV between 1930s-1960s and since the 1990s likely contributed to the string of wet summers across northwestern Europe (dry summers in southern Europe) during both periods (Sutton and Dong 2012; Dong et al. 2013). Across the winter half-year, a negative AMV phase appears to encourage a positive NAO which dampens the rainfall response across western UK but relationships are weak (Folland et al. 2015). The multi-decadal variability of the AMV could thus play an important role in temporal clustering of hydrological extremes, giving rise to drought/flood-rich and drought/flood-poor periods (e.g. Blöschl et al. 2020).

1.5 Climate change and droughts

Anthropogenic climate change is projected to significantly alter the global water cycle through changes to both the timing and spatial patterns of precipitation and enhanced evaporative demand with warming (Douville et al. 2021). This is expected to lead to substantial changes in river flow patterns and seasonality, as well as the frequency and severity of hydrological extremes (Arnell and Gosling, 2013; Prudhomme et al., 2014). Changes in the global water cycle are expected as greenhouse gas emissions influence the global energy balance. At the global scale, the Clausius-Clapeyron relationship dominates the thermodynamic response where atmospheric water vapour increases with temperature rise (~7% increase per °C averaged globally) which results in changes to global evaporation and precipitation, such as the intensification of the hydrological cycle, specifically for extreme, short-duration, rainfall (Held and Soden, 2006; Allan et al., 2020). The thermodynamic response due to climate change results in the intensification of the global water cycle and global increases in mean evaporation and precipitation with temperature rise (Douville et al. 2021). Additionally, studies have found that plants might reduce transpiration because of the effect of elevated levels of carbon dioxide on the opening of plant stomata, thus increasing water availability globally (Betts et al., 2007).

At the regional scale, changes in future water availability are largely determined by variability and potential changes in circulation patterns, such as the position of the jet stream, leading to changes in the spatial and temporal characteristics of European and UK precipitation (Trenberth et al., 2014; Fereday et al., 2018; Zaitchik et al., 2023). Future variability in precipitation (and in turn river flows) is thus determined by a combination of an externally forced trend from increasing greenhouse gas emissions and internal climate variability arising from both "fast" and "slow" components of the climate system (Lehner and Deser, 2023). The latest national climate change projections (UK Climate Projections 2018) suggest hotter and drier summers and warmer and wetter winters (Lowe et al. 2018). National-scale assessment for the impacts of climate change on UK river flows point to a general reduction in annual river flow, except for western Scotland, with higher certainty over a decrease in summer but lower agreement over changes in winter (Arnell, 2011b; Prudhomme et al., 2012; Christierson et al., 2012). The latest evidence to inform the Third UK Climate Change Risk Assessment using the UK Climate Projections 2018 (UKCP18) suggests broadly that for the UK, the risks of both floods and droughts could increase under climate change, although not necessarily in the same locations. The UKCP18 probabilistic projections indicate a high likelihood of an increase in the intensity and frequency of hydrological droughts, and water resources shortages under high emission scenarios are projected to impact the entire UK, not just the drier regions in southeast England (HR Wallingford, 2020; Arnell et al., 2021).

1.5.1 UK water resources planning and climate change

The impacts of climate change have been considered in the water resources planning process by some water companies since the 1999 planning cycle. Arnell (2011) summarised the methodologies and approaches water companies have taken to incorporate climate change over the various planning cycles since 1999. Climate change did not feature strongly in initial water resources management plans and assessment of impacts was based on simple perturbations of monthly or annual factors to observed river flows to calculate a minimum buffer to ensure there was available water supply to satisfy demand (Arnell and Delaney, 2006; Arnell, 2011a). Subsequent planning cycles included both "wet" and "dry" climate change scenarios in their calculations with the use of hydrological models rather than flow factors. Water companies have been required by Ofwat to consider climate change in their plans since 2008 with emerging approaches such as probabilistic projections and the use of stochastic weather generators (Charlton and Arnell, 2011; Environment Agency, 2013). Following the UK Water Act 2014, water companies are required to consider water supply reliability under plausible worst-case droughts (Environment Agency, 2015). The latest regulator guidance also indicates a requirement for UK water companies to plan for a higher level of drought resilience (i.e. 1 in 500 years extreme drought). Table 1.3 shows water companies or water resources zones within individual companies that are designated as "seriously water-stressed" by the Environment Agency. The National Infrastructure Commission's Preparing for a drier future report identified parts of the UK that would require additional water capacity to prepare for severe and extreme droughts. The report recommended a twin-tracked approach to tackle the impacts of climate change on public water supplies to enhance supply through infrastructure investment and reduce demand through improving water use efficiency and reducing per capita water use consumption (National Infrastructure Commission, 2018).

Table 1.2 List of water companies and their regions designated as 'seriously water stressed' by the Environment Agency [Adapted from Parliamentary Office of Science and Technology (2021) according to information from Environment Agency (2021)]

Designated seriously water-stressed areas prior to 2021	**Additional areas assigned 'serious water stressed' designation in 2021** (Environment Agency, 2021)
Affinity Water	Cambridge Water
Anglian Water	Portsmouth Water
South East Water	South Staffordshire Water
Southern Water	Severn Trent Water – excluding Chester
Sutton and East Surrey Water	Veolia Water
Thames Water	Wessex Water
	South West Water – Bournemouth
	South West Water – Isles of Scilly

1.5.2 Sources of uncertainty and knowledge gaps

Researchers highlight several sources of uncertainties associated with understanding potential future changes. Sources of uncertainties can broadly be categorized into scenario uncertainty (from uncertainty in emissions scenario), epistemic (from a lack of knowledge of climate processes) and aleatoric (from the randomness due to internal climate variability) (Shepherd, 2019). Internal climate variability arises due to non-linearity in the natural climate system which introduces an element of randomness (or "noise") even in the absence of any external forcing (Deser, 2020; Lehner and Deser, 2023). Different climate system components and processes occur at various spatial scales and different rates (including faster mesoscale processes and slower processes related to sea surface temperatures or soil moisture) (Zappa et al., 2020; Lehner and Deser, 2023). This results in a wide range of day-to-day variability occurring around a long-term mean. Internal variability is not fully characterised for circulation-related aspects, as opposed to temperature which has a large climate change signal as future warming is certain. Observations of both atmospheric circulation indices and meteorological/hydrological drought trends also show high variability (Environment Agency 2023). Decision-makers may therefore risk under-estimating present and future risk of hydrological extremes such as consecutive sequences of dry seasons persisting over multiple years (e.g. consecutive summer meteorological droughts across multiple years – van der Wiel et al. 2023) or clustering of high rainfall events (Kendon et al., 2023) which could happen by chance and could exceed the worst historical event. Additionally, the most extreme events might not be found within a single realisation of climate model simulations due to internal variability even though an overall drying trend is projected (Ault et al., 2014). This has specific implications for estimating the impacts of a 1 in 500-year extreme drought as there is no standardised estimation method of such a drought and it remains unclear how to determine the plausibility of these events.

Projected change for regional precipitation is dominated by internal climate variability in the near-term and systematic differences in how different models represent climate processes at the longer timescale (Hawkins and Sutton, 2011; Shepherd, 2014). Past studies have shown that multiple generations of climate models tended to underestimate monthly and annual dry spell length and thus the risk of prolonged droughts (Ault et al., 2014; Moon et al., 2018). Additionally, there are significant biases in the representation of atmospheric blocking in climate models (Woollings et al., 2018; Kautz et al., 2022). Past studies have found that models underestimate atmospheric blocking frequencies over Europe in both winter and summer which is related to the representation of variability in the jet stream (Woollings et al., 2018). In general, climate models project a poleward shift in the jet stream with future warming but there is uncertainty over the magnitude of change which can lead to significant differences in temperature and precipitation patterns over the UK (Harvey et al., 2023).

The uncertainty in how atmospheric circulation responds to climate change and systematic errors in climate models presents a major challenge for providing regional climate change information (Shepherd, 2014, 2016). Studies often follow a risk-based probabilistic approach where the effect of climate change is obtained by comparing an event's probability occurrence in a factual world (e.g. present day) compared to a counterfactual world (e.g. without climate change) using multi-model ensembles (Stott et al., 2016). As shown by Clarke et al. (2023) for temperature-related extremes such as heatwaves in the UK, strong attribution statements for an ongoing event could even be made rapidly based on past attribution studies because different models and event definitions agree on a clear direction of change for events driven primarily by thermodynamic factors. However, if an event is driven by atmospheric circulation anomalies, it becomes more challenging to make definitive statements about the influence of climate change due to uncertainties in the response of atmospheric circulation to climate change (Shepherd, 2016). An example discussed by Rodrigues and Shepherd (2022) is the attribution of the 2013/14 South America drought. Assessing model consensus, in this case, is challenging as there is wide uncertainty over the projected change in precipitation for the region due to differences in the response of atmospheric circulation to climate change between models. Consequently, there is insufficient evidence to achieve statistical significance and attribute the event to climate change.

As highlighted by Zappa et al. (2021), numerous regions worldwide exhibit large projected changes in variables influenced by atmospheric circulation, with opposing signs across different climate models. The authors thus argue that a washed-out signal from a multi-model ensemble mean (i.e. lack of evidence from a traditional attribution framework) does not dismiss the potential for significant changes in risk, which remain pertinent for decision-making and climate adaptation. Despite this, studies have identified that a "predict-then-act" approach has been dominant in water resources planning, characterized by a tendency to wait until a robust climate change signal emerges from the observations or until clear trends emerge from climate models before any significant decisions are made (Murphy et al., 2011; Hall and Murphy, 2012; Dessai and Darch, 2014). However, given the large inter-model spread in projected change in circulation-related variables (such as precipitation) and the cascade of uncertainty, it has been argued that a shift away from a "predict-then-act" approach would be advantageous to ensure robust adaptation to climate change (Murphy et al., 2011).

1.6 The storyline approach

Recent proposals suggested creating "tales" or "physical climate storylines" to complement existing approaches and address existing knowledge gaps (Hazeleger et al., 2015; Shepherd et al., 2018). Physical climate storylines are defined as plausible, physically self-consistent descriptions of past or future events/pathways. Storylines are constructed by conditioning on a discrete set of changes (e.g. atmospheric circulation, management measures and event characteristics) which could lead to high impacts (Shepherd et al., 2018). This approach is particularly motivated by uncertainties in projected changes in circulation-related variables (such as precipitation) between different climate models arising from the lack of knowledge of how atmospheric circulation might respond to climate change (Shepherd, 2014). It is useful to distinguish between physical climate storylines and scenario storylines. Scenario storylines or narratives of climate change are regularly used in climate change assessments (e.g. emission scenarios - RCPs or shared socioeconomic pathways - SSPs). In this thesis, storylines are used to refer to physical climate storylines rather than scenario storylines and the use of specific emission scenarios is clearly noted.

The storyline approach is designed to navigate the cascade of uncertainty and provide decision-relevant information for climate change adaptation. Central to the storyline approach is the ability for users to decide which source(s) of uncertainty to focus on and analyze at what level of detail to navigate the uncertainty cascade in a way which best supports their decision-making. Storylines enable consideration of multiple plausible futures to avoid type II errors (i.e. missed warnings) and strengthen risk awareness (Shepherd et al, 2018). For example, storylines can represent "what-if" questions to understand high-impact outcomes by quantifying plausible conditions that could lead to adverse outcomes beyond critical thresholds without necessarily assigning probabilities to their occurrence (Shepherd, 2019; Sutton, 2019). Shepherd (2021) argues that this is particularly valuable from an adaptation context as it seeks to connect physical reasoning with existing statistical practices. Zappa and Shepherd (2017) presented a framework to delineate different physical climate storylines to describe the impacts arising from changes in remote atmospheric circulation drivers between different climate models. The authors presented four separate storylines that captured the overall spread of change in mean precipitation over the Mediterranean region from CMIP5 models. The storylines described the precipitation response from different degrees of change in tropical amplification and varying strength of the polar vortex per degree of global warming (Figure 1.2). The same framework has been applied in different regions and with different remote climate drivers. This includes storylines developed to represent the range of Southern Hemisphere precipitation response based on the strength of the stratospheric vortex and the degree of tropical warming (Mindlin et al., 2020) and storylines developed to represent precipitation changes in the Maritime Continent based on the strength of Pacific basin-wide SST warming and the zonal difference in SSTs between the eastern and western equatorial Pacific (Ghosh and Shepherd, 2023).

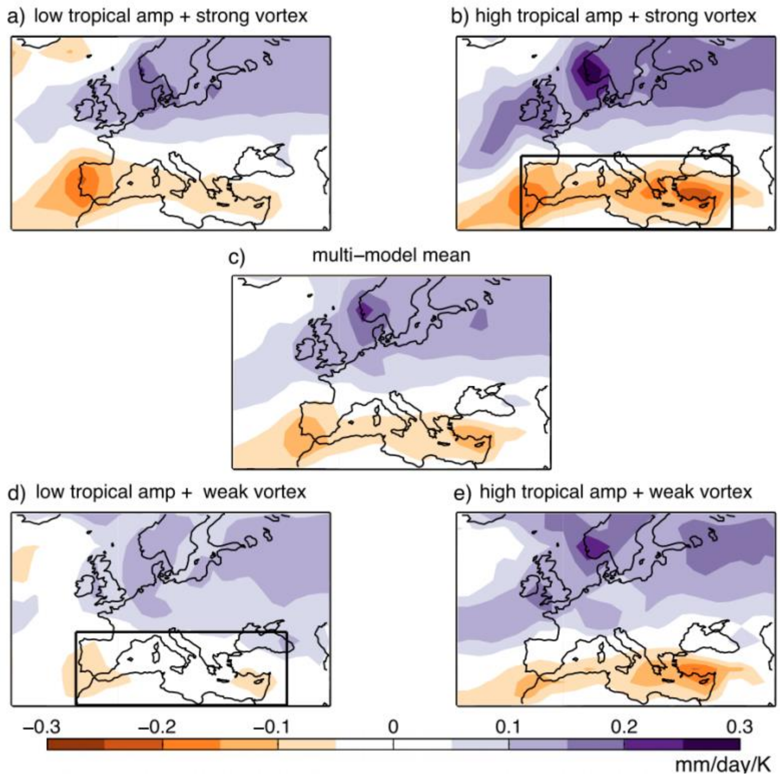

Figure 1.2 Storylines for change in cold season precipitation per degree warming in the Mediterranean region from Zappa and Shepherd (2017) conditioned on changes in remote climate drivers. Each panel represents different storylines representative of different degrees of change in tropical amplification and vortex strength based on the spread of CMIP5 model responses.

1.6.1 Drought storylines

Sillmann et al. (2021) recently advocated for the creation of event-based storylines. Event storylines aim to create decision-relevant climate information with a greater focus on the physical mechanisms leading to individual events. This can be represented through a causal network as seen in Figure 1.3 where each node refers to drivers of an event and can be conditioned upon and varied to create multiple plausible storylines (Doblas-Reyes et al. 2021) to describe "what-if" situations. The variation of values for each node can also be assigned conditional probabilities informed by expert knowledge such as the risk appetite of decision-makers/users (Young et al., 2021; Kunimitsu et al., 2023). An event-based storyline approach is well suited to understanding hydrological droughts. Analysing the spatial coherence of European hydrological droughts since the 1960s, Hannaford et al. (2011) noted that every event had distinctive drought signatures. In a case study of six significant droughts in the East Anglia region, Lister et al. (2018) also remarked on the need to consider droughts at various time scales, such as short seasonal droughts from extended dry and hot summers versus longer droughts from more prolonged precipitation deficits. While the river flow responses may be less dramatic in the latter, these longer droughts can have larger impacts on water resources over an extended period. There is therefore merit in looking at individual drought events following an event storyline approach as opposed to aggregating over many dissimilar droughts as is often the case in traditional climate change impact assessments. Storylines may be particularly useful to satisfy requirements in water resources planning such as assessing resilience to 1 in 500-year droughts for which there are no historical observations. In a retrospective comparison of the 2003 and 2015 European droughts, Laaha et al. (2017) demonstrated the merit of event-based studies with a detailed analysis of the temporal and spatial characteristics of the two droughts and their preconditions. The authors showed that new insights for drought management and early warning prediction can be gained by understanding the unique hydrological and drought-generating characteristics of both events.

Event storylines can also be used to explore the consequences if a historical event occurred in a future warmer climate or to understand counterfactuals to an observed event through changes to the events' causal aspects (Sillmann et al, 2021; Lloyd and Shepherd, 2020). Each event storyline is deterministic and need not be assigned a probability of occurrence. Context can be provided for individual event storylines, such as by calculating their conditional probability of occurrence obtained from sampling for similar events in large ensemble climate model simulations (Sillmann et al., 2019). Event storylines gain realism as they are created based on an observed event and can add value to existing approaches due to their high degree of conditionality. Table 1.4 summarises several past studies which have constructed heatwave and drought storylines using various approaches and data sources. Studies have applied techniques such as systematic perturbations to past events (e.g. Stoelze et al. 2014), spectral nudging of regional climate models (e.g. van Garderen et al, 2021), searching for analogue events with similar atmospheric circulation patterns (e.g. Faranda et al, 2023) and sampling for extreme events with similar impacts to observed events in large ensemble climate model simulations (e.g. van der Wiel et al, 2021). The studies have shown that drought storylines can be used to enhance our understanding of system vulnerability in both current and future climate. Advances in large ensemble climate model simulations, which provides multi-thousand years of plausible weather sequences in present and future climate, in particular, has further enabled the sampling of event storylines to inform the chance of extreme events and the magnitude of plausible worst cases (Bevacqua et al, 2023).

Table 1.3 Summary of the approach taken, and the individual storylines considered in past studies which have created heatwave and drought storylines.

Study	Period	Storyline(s)
Perturbations to past event		
Rangecroft et al. (2018)	Current and future	Narratives of South Africa droughts in warmer climate and with anthropogenic influences (e.g. dams and irrigation schemes)
Staudinger et al. (2015)	Current	Sensitivity test of drier initial conditions prior to the summer 2003 drought at Swiss catchments
Stoelzle et al. (2014) and Hellwig et al. (2021)	Current and future	Stress tests of past groundwater droughts from seasonal shift in recharge and changes in antecedent recharge across Germany
van den Hurk et al. (2023)	Current and future	Compound and cascading hydro-climatological events arising from remote climate drivers with socioeconomic impacts in Europe
Van Tiel et al. (2023)	Future	Repetition of three past severe European droughts (1976, 2003 and 2018) given initial conditions of near future and far future
Watts et al. (2012)	Current	Synthetic multi-year droughts ("long" droughts) created from stacking severe droughts in the 19th century
Woo (2021)	Current	What if northerly jet stream had persisted longer than observed in summer 1976
Sample from initialized large ensemble simulations		
Bevacqua et al. (2021)	Current	Impacts on crop yield from preconditioned compound event of hot and dry summer preceded by a dry spring
Bevacqua et al. (2022)	Future	Diverging precipitation trends associated with compound hot-dry events in Europe, USA and South America in future climate
Coughlan de Perez et al. (2023)	Current	Unprecedented hot-dry events associated with crop yield failures in USA and China sampled from SEAS5 hindcasts
Gessner et al. (2022)	Current	Worst-case European and US droughts generated from re-initialising large ensemble simulations and retaining events with low precipitation
Goulart et al. (2021)	Current and future	Hot-dry events similar in impact to the 2012 midwestern US drought in time-slice large ensembles for present-day, 2C and 3C warming
Leach et al. (2022)	Future	Future winters (including hottest and wettest) that are even more extreme than selected extreme winters in the UKCP18 projections
van der Wiel et al. (2021)	Current and future	Droughts with similar precipitation deficits to the 2018 drought for the Rhine basin in time-slice large ensembles for present-day, 2C and 3C warming
van der Wiel et al. (2022)	Current and future	Consecutive summer meteorological droughts for the Rhine basin in time-slice large ensembles for present-day, 2C and 3C warming
Sample from climate model simulations		
Aalbers et al. (2023)	Future	Unfolding of the 2018 European heatwave-drought in warmer climate given the same circulation patterns
Faranda et al. (2023)	Current	Sample for events with similar circulation patterns as 2022 summer in period with no climate change (pre 1910s) and period with climate change (post-1940s)
Fung et al., (2022)	Future	UK droughts driven by a set of eight weather patterns describing atmospheric circulation
van Garderen et al (2021)	Current	Unfolding of the 2010 Russian and 2003 European heatwaves in counterfactual without climate change but conditioned on atmospheric circulation of the observed event
Van Garderen and Mindlin (2022)	Current and future	Development of the 2011/12 Southeastern and South America drought in pre-industrial and 2C warmer climate conditioned on atmospheric circulation of the observed event

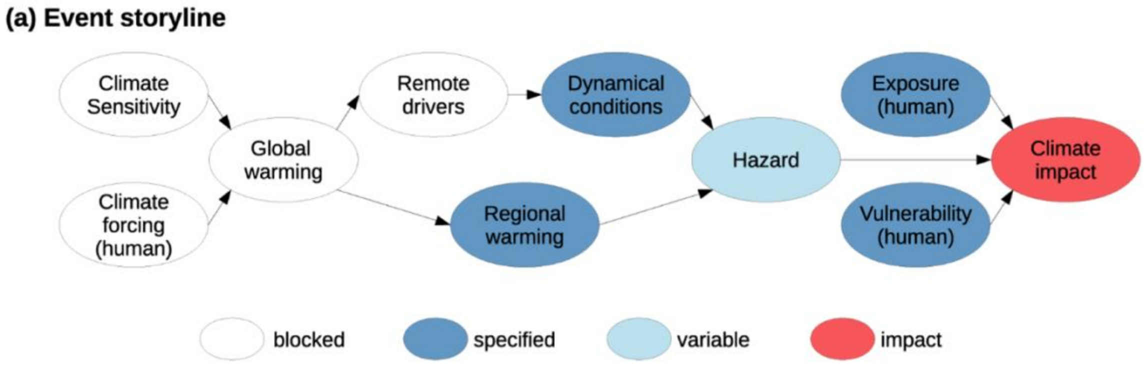

Figure 1.3 Event storyline expressed in a casual network for a particular hazard (Source: Doblas-Reyes et al. 2021). Each of the dark blue nodes is aspects that can be varied or conditioned upon to create multiple plausible storylines of the hazard that can result in different climate impacts.

1.7 Research questions

The previous sections introduced the motivation of this thesis and summarised key research gaps in understanding present and future risk of hydrological droughts in the UK. Section 1.6 outlined the rationale for a storyline approach to understand hydro-climatological extremes and reviewed recent studies which had applied this emerging approach to different climate extremes. To address the research gaps outlined in the previous sections and to understand the potential of applying a storyline approach to advance understanding of UK droughts, this thesis aims to address the following three general research questions:

1. **How have approaches to understanding the hydrological impacts of climate change in the UK developed over time?**

Much research has been carried out on the possible impacts of climate change for UK river flows and hydrological extremes, but past studies have used different approaches and techniques. The first research question aims to track the development of modelling approaches over time and identify the respective strengths and weaknesses of existing approaches in tackling some of the outstanding research gaps. This review also aims to identify emerging methods which can complement existing approaches to advance understanding of the impacts of climate change on UK hydrological extremes (Chapter 2).

2. **How can the storyline approach be applied to construct plausible worst cases and understand extreme UK droughts in current and future climate?**

The second research question aims to demonstrate the application of the storyline approach in various ways to create plausible worst-case droughts in both current and future climate. This research question makes use of multiple sources of evidence (such as observations, river flow reconstructions, seasonal hindcasts and climate model projections). Chapter 4 uses observations and the UK's national climate change projections (UKCP18) to construct downward counterfactuals of past drought events. Chapter 5 pools together seasonal hindcasts to assess the implications of continued dry conditions for the 2022 UK drought. Chapter 6 uses river flow reconstructions and novel large ensemble climate model simulations to estimate the chance and understand the processes of unprecedented droughts.

3. **What is the added value of a storyline approach to understand hydrological droughts in current and future climate and complement probabilistic estimates of drought hazard risk?**

The third research question aims to evaluate the utility of a storyline approach to understand hydrological droughts and demonstrate the advantage of bridging storylines with existing approaches (such as a probabilistic risk-based approach) to provide climate change information relevant for water resources planning and to assist in the stress-testing of hydrological systems under present and future climate (Chapter 6).

1.8 Structure of thesis

The structure of the thesis is broadly separated by the research questions outlined in the previous section. Chapter 2 presents a detailed review of the approaches taken in the published literature to understand the impacts of climate change on UK river flows over the past several decades. The observational and model-based data sources and approaches to hydrological modelling are presented in the Data and Methods chapter (Chapter 3). Chapter 4 presents an event-based analysis of the 1975-76 and 2010-12 droughts and demonstrates ways to create downward counterfactuals of the events. Building on retrospective analysis of past events, Chapter 5 demonstrates the application of an event storyline approach to an on-going event (i.e. the ongoing 2022 drought at the time of writing) to evaluate plausible worst cases in near real time. The last results chapter (Chapter 6) presents the use of large ensemble climate model simulations to obtain probabilistic estimates of drought hazard risk and demonstrates how a storyline approach can provide complementary information to understand the impacts of climate change and stress test hydrological systems. Chapter 7 summarises and discusses the overall findings and provides recommendations for future research to advance understanding of the present-day drought risk and impacts of future climate change on UK hydrological droughts.

2 METHODOLOGICAL EVOLUTION OF CLIMATE CHANGE PROJECTIONS FOR UK RIVER FLOWS

A version of this chapter has been published as a review paper in the journal *Progress in Physical Geography – Earth and Environment,* with the following reference:

Chan, W.C., Shepherd, T.G., Facer-Childs, K., Darch, G., Arnell, N.W., 2022. Tracking the methodological evolution of climate change projections for UK river flows. Progress in Physical Geography: Earth and Environment 030913332210792. https://doi.org/10.1177/03091333221079201

2.1 Introduction

A substantial amount of research has taken place over the last three decades on the impacts of climate change for river flows and hydrological extremes in the UK. Studies have used different modelling techniques and approaches to assess the hydrological impacts of climate change. The breadth of this research has been enabled by the dense network of hydrological and hydrometric monitoring of UK river catchments, which is characterized by its data quality and length (Hannaford, 2015). Previous review of the evidence base on projections using multiple generations of UK climate change scenarios show that there is broad agreement over a reduction in summer flows and a possible increase in winter flows, although this differs across different UK regions and the magnitude of change remains uncertain across different studies, regions and catchments (Arnell et al., 2015; Garner et al., 2017; Environment Agency, 2023)

Despite a large body of literature, uncertainty remains over the magnitude of projected change in different hydrological variables for different parts of the UK by studies using a variety of climate model output and modelling approaches. Existing approaches can broadly be separated into broad categories of "top-down" or "bottom-up" that are briefly described in the following two sub-sections. Details of methodologies within each broad approach is identified in the systematic literature search (Section 2.2).

2.1.1 "Top-down" approaches

The first approach is scenario-led and can be described as "top-down" and "science-first" according to guidelines developed by the Intergovernmental Panel on Climate Change (IPCC) (Jones et al. 2014). This approach is scenario-led as climate change scenarios describing different socio-economic pathways associated with different climate forcings are used as input to GCMs or Earth System Models to generate climate change projections. In its most basic form, output from a single climate model is taken and changes in various climate variables are used to drive impact models with embedded uncertainties associated with each step of the analysis is not explicitly quantified (Viner, 2002). Choices made along the impact modelling chain making up different sources of uncertainties include the choice of emission scenarios, GCMs (and climate sensitivity), hydrological models (and parameters), spatial downscaling approaches and risk indicators (Smith et al., 2018). Different sources of uncertainties are then accrued and increase at every step to make up the "cascade of uncertainty", meaning that uncertainty in the impact of concern, such as projected change in river flows, is often more uncertain than the uncertainty in projected change in precipitation itself (Viner, 2002; Wilby and Dessai, 2010) (Figure 2.1). Depending on the approach taken in specific impact studies, some of the uncertainties along the impact modelling chain can be explicitly represented while others may be omitted and it is often practically difficult to fully consider all sources of uncertainties (Smith et al., 2018).

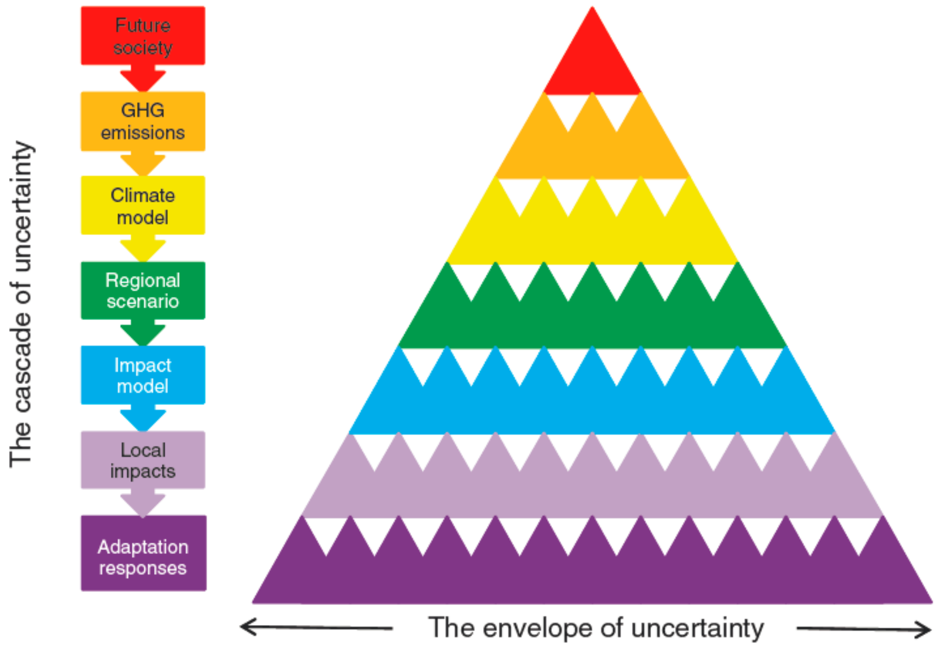

Figure 2.1 The cascade of uncertainty along a typical "top-down" impact modelling chain (Wilby and Dessai, 2010)

2.1.2 "Bottom-up" approaches

"Top-down" studies can be contrasted with "bottom-up" approaches which are not scenario-led and may be conducted independently from climate change scenarios often with greater involvement from stakeholders (Dessai et al., 2005). Conway et al., (2019) noted several advantages of "bottom-up" approaches, including the ability to retain regional to local granularity, a focus on process understanding, consider system sensitivity and a wider exploration of plausible outcomes for adaptation. Given that "top-down" approaches are more exposed to a cascade of uncertainty, "bottom-up" approaches often pay greater attention to system sensitivity ("sensitivity-led") and others are motivated by assessing robustness of different strategic plans and adaptation options over time for different stakeholders ("policy-first") (Viner, 2002; Falloon et al., 2014). For example, this can be incremental scenarios of change in different climate variables (such as incremental increase in temperature) used to populate response surfaces visualizing critical thresholds of system response to a changing climate (Mearns et al. 2001).

2.1.3 Aims and objectives

Stemming from evolving data availability and motivated by different ways to navigate the cascade of uncertainty, different "top-down" and "bottom-up" approaches have been used over the years. There is therefore merit in looking back at past studies to identify the approaches they took, their main contributions and the advantages and disadvantages behind each approach. In this chapter, modelling approaches of studies that investigate the impacts of climate change to UK river flows either at the catchment or national scale are identified and compared. There have been reviews of the potential impacts of climate change on hydrological variables for different regions of the UK (Arnell et al., 2015; Garner et al., 2017; Hannaford, 2015; Watts et al., 2015). There have also been a number of reviews of the different downscaling and bias correction techniques available for hydrological modelling (Fowler et al., 2007; Teutschbein and Seibert, 2013). This chapter places emphasis on the temporal development and main sources of evidence from different approaches. Although the review only focuses on studies investigating changes in UK river flows, the methodological approaches identified are also used elsewhere and the development of these approaches over time is likely to be similar in other contexts.

The specific aims of this chapter are to:

1 Track the development of approaches over time and identify how the different approaches have dealt with the different sources of uncertainty
2 Identify the uptake, advantages and disadvantages of the approaches, including factors that may present possible barriers to decision-making
3 Identify emerging approaches that could be used to complement existing approaches for the provision of regional climate change information

2.2 Systematic literature search

Relevant peer-reviewed publications from 1990 to May 2021 which investigated changes in river flows and hydrological extremes (i.e. floods and droughts) over UK catchments are identified. The search terms listed in Table 2.1 are used to search for relevant papers on the Scopus, Web of Science and Google Scholar databases. Other search terms related to individual hydrological sub-disciplines, variables or impact indices (e.g. water quality, hydro-ecology) are also relevant to assess the evidence base and could identify additional studies. However, the search terms employed are already able to retrieve a large number of studies with a focus on assessing changes in UK river flows. Only empirical studies that focus on understanding the changes to hydrological variables using hydrological models are included. Review papers, opinion articles and other non-empirical publications are excluded. Assessments of hydrological extremes and water resources availability have also been completed by private water companies, government agencies and research institutes which are published in research reports and conference proceedings. These have not been included as part of the reviewed papers due to their patchy nature of publication and the lack of detailed methods in certain publications. The earliest studies of climate change and UK river flows were reports prepared for the then Department of the Environment by the Institute of Hydrology (Arnell et al., 1990; Beran and Arnell, 1989). These, and subsequent, research reports informed the development of methods used by the water industry in the UK to estimate the effects of climate change on resources (Arnell, 2011a). In practice, the approaches developed in these reports have been presented in the peer-reviewed papers reviewed here.

Table 2.1 Search criteria and search terms employed to retrieve relevant papers

Search criteria	Search terms	Type
Title, keywords, abstract text	Hydrology, river flow(s), floods, droughts, runoff	Hydrological
	Climate change, climate impacts, impacts of climate change	Climate change
	United Kingdom (UK), England, Scotland Wales and Northern Ireland	Region

A total of 122 publications across 35 scientific journals are identified from 1990 to 2021. Figure 2.2 shows the number of publications per year and their regional coverage based on the UK's administrative region boundaries. Across the selected studies, 24 papers (20%) had a specific focus on droughts and 40 papers (33%) on floods. There is an uneven spatial coverage of the catchments considered in the identified publications. Catchments in southeast England were included most frequently, followed by catchments in Wales. In comparison, catchments in Northern Ireland were included least frequently. Additionally, studies have used a wide variety of hydrological models. The largest number of studies employed the PDM hydrological model followed by similar uptake across the CLASSIC, CATCHMOD and Grid-2-Grid models (inset Figure 2.2). Other hydrological models such as TOPMODEL have been widely used at UK catchments but have been used less often in climate change impact assessments. Out of the 122 publications, 63 (52%) made use of the downscaled UK regional climate change projections from the UK Climate Impacts Programme and Met Office with the remainder using either global or downscaled projections from different ensembles of climate models or an approach independent from climate model output.

Figure 2.2 Number of identified peer reviewed publications per year since 1990 (n=122) and the top five most employed hydrological model across all publications (inset) (left). Percentage of total publications which included catchments in each administrative region of the UK (right)

2.3 Development of modelling approaches

Four approaches to the development of climate scenarios are identified from the reviewed publications. Approaches to study the hydrological impacts of climate change have developed over the past three decades from an initial very simple approach. These developments have occurred in terms of (i) the type and number of scenarios that are used, and (ii) the way the scenarios have been applied (Table 2.2). Different approaches have shared some of the same methods in applying climate change scenarios and the various methods have been developed to suit individual aims of the different approaches. Figure 2.3 tracks the development of each approach over time and highlights seminal papers indicative of each approach. The following sections review the aims of each approach and the evidence and main contributions from selected studies. The following sub-sections provide details for each of the identified modelling approaches, examples of their use in the identified literature and high-level summaries of results from exemplar studies.

Table 2.2 Approaches identified in the reviewed papers and methods used to apply climate change scenarios.

	Approach			
Application method	Stylised	GCM/RCM-driven	Probabilistic	Scenario-neutral
Delta method	✓	✓	✓	✓
Bias adjustment		✓		
Stochastic (e.g. weather generator)		✓	✓	✓
Statistical (e.g. weather types)		✓		

2.3.1 Stylised approach

Early studies in the 1990s employed a stylised approach using the delta (or change factor) method where ad-hoc relative changes in monthly means are applied to observed climate variables (e.g. precipitation, temperature, potential evapotranspiration) to create model input time series. The delta method has since been used consistently across all the other approaches identified. The stylised approach stems from the limited number of GCMs and the coarse resolution of their output at the time. Stylised scenarios are separately defined for precipitation and temperature describing changes in monthly precipitation and potential evapotranspiration (PET) of various magnitudes at coarse spatial resolution. Relatively simple to apply with limited data requirements, stylised scenarios are particularly useful to understand and quantify plausible sensitivity ranges of individual catchments. The main contribution of the stylised approach is the understanding of hydrological system sensitivities across different UK regions and catchments.

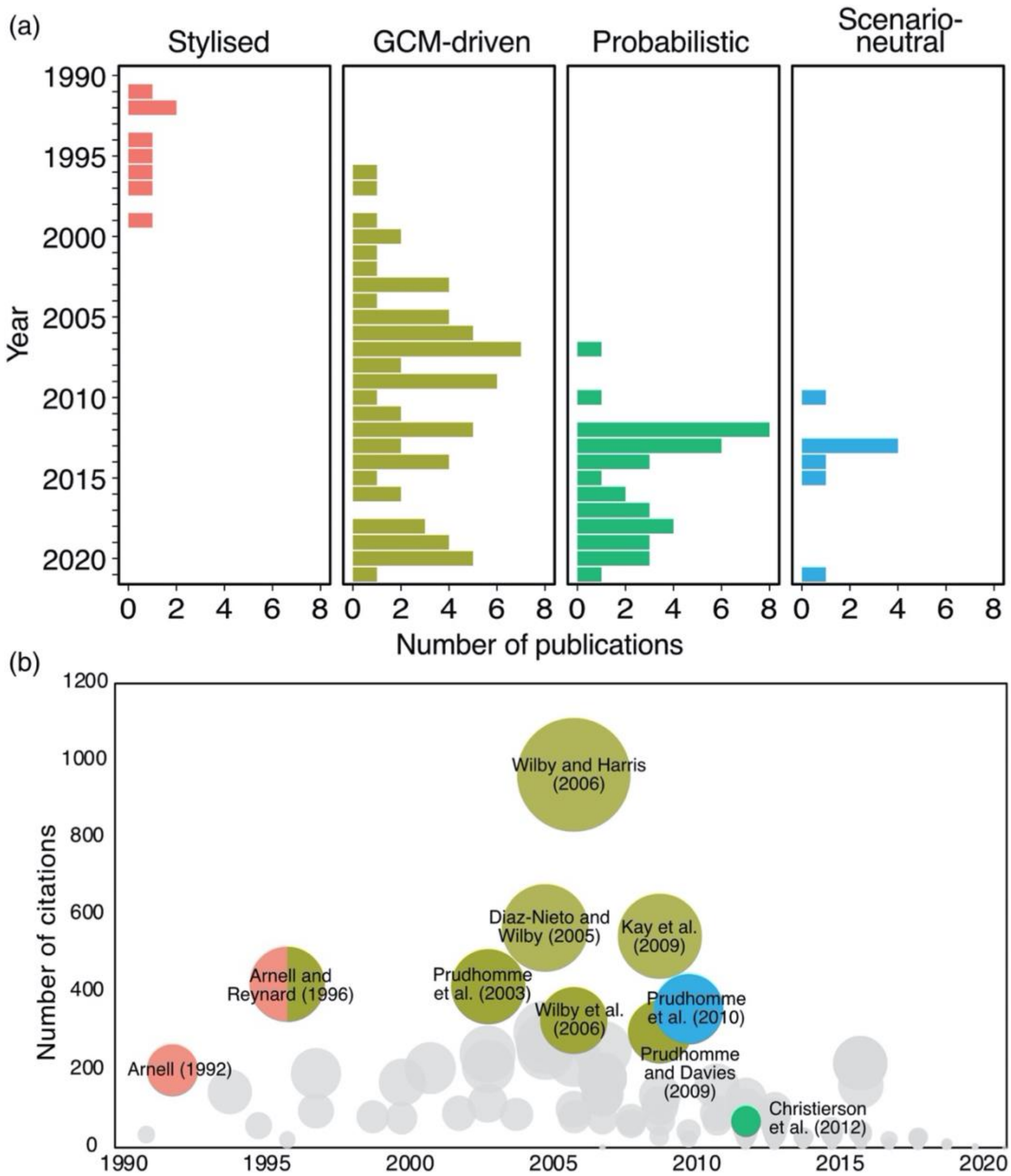

Figure 2.3 a) Modelling approach for each identified peer reviewed publication and b) Number of citations received for every publication. Representative publications for each modelling approach category and those which received over 300 citations are highlighted and coloured based on their modelling approach.

2.3.1.1 Summary of evidence

Following the release of the first IPCC assessment report in 1990, (Arnell, 1992a, b; Cole et al., 1991) were among the first published papers to investigate the impacts of climate change on UK river flows based on understanding at the time which suggested wetter winters and the possibility of drier summers. Cole et al. (1991) assessed changes to annual runoff and reservoir yield in contrasting regions of the UK (NW and SE. England) by perturbing precipitation and evaporation with seasonal mean changes to calculate annual runoff. They showed an overall 8% (4%) reduction in annual runoff for SE (NW) England with larger decreases in reservoir yields driven by an increase in evaporation. Similarly, Arnell (1992a, b) created seven stylised precipitation scenarios representing monthly and annual changes in precipitation made up by additional combinations of seasonal changes (e.g. 20% increase in all months or 15% decrease in summer). Applying different combinations of the stylised scenarios via a simple monthly water balance model, Arnell (1992a, b) showed that hydrological response to climatic change varies across different catchments. The results suggest particularly high sensitivity of annual and monthly river flow to how changes in precipitation are distributed across the year. For example, in fast responding northern catchments, reduction in summer precipitation has a significant (−35%) impact on summer river flows. In contrast, river flow response for lowland groundwater-dominated catchments during drier summers are determined by both catchment characteristics and the extent of increase in winter precipitation.

Later publications extended this approach to additional catchments with stylised scenarios constructed based on expert knowledge and process understanding gained from early climate models. An example are the precipitation scenarios in (Arnell and Reynard, 1996) which was created based on expert knowledge from the UK Climate Change Impacts Review Group representing “Wettest” (precipitation increase in all months by a large magnitude), “Driest” (precipitation reduction in all months with a larger reduction in summer) and “Best” (precipitation increase in all months except summer, where there is no change). This approach was subsequently used to quantified the relative contribution from different sources of uncertainty through different stylised scenarios based on high-level national estimates of the UKHI and CCC climate models (Boorman and Sefton, 1997). They confirmed that changes in river flows varied between catchments with different physical characteristics but also between different hydrological models following the same stylised scenario. The largest magnitude of change in mean and low flows was projected for the groundwater-dominated catchment considered.

2.3.2 GCM-driven studies

Growth in computational resources and availability of GCM model output enabled the dominance of GCM-driven studies since the mid-1990s (81 papers, 65%). These studies use climate model output directly, most commonly projections developed and led by the UK Climate Impact Programme (UKCIP98, UKCIP02) and the Met Office (UKCP09, UKCP18). Figure 2.4

shows the use of the delta method, statistical and dynamical downscaling in the GCM-driven studies identified.

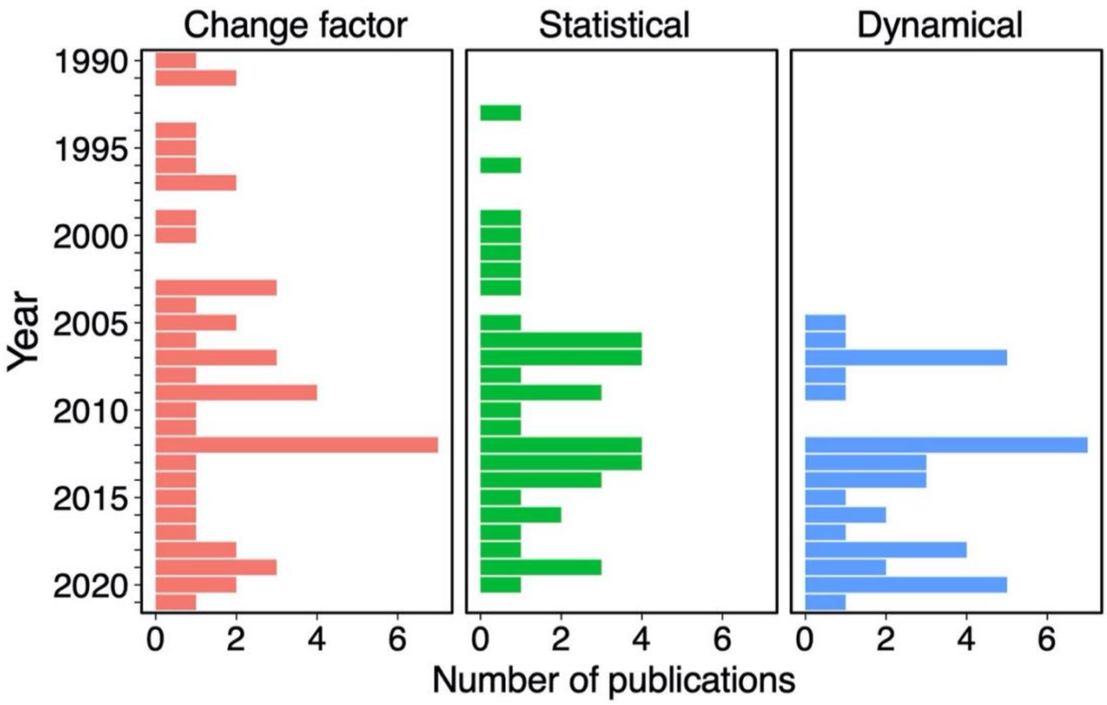

Figure 2.4 Development of approaches to generate climate change scenarios in GCM-driven studies for use in hydrological models.

First, the delta method, developed from the stylised approach, has been used consistently over the years. Most recently, the delta method has been used to apply dynamically downscaled regional climate models (RCMs) in the UKCP18 set of projections (Kay et al., 2021). This method preserves the temporal variability of the observed time series, which has been shown to be useful as it increases realism and familiarity to stakeholders (Watts et al., 2015; Arnell et al., 2021). Several GCM-driven studies have refined the delta method to include consideration of monthly variance for relative changes in wet and dry days and precipitation intensity (Reynard et al., 2001; Arnell, 2003, 2011b). The majority of studies following this approach have created scenarios representing specific time periods to be compared with the present, but a few have applied changes incrementally to create time series of evolving change (Arnell and Reynard, 1996; Arnell et al., 2021; Kay et al., 2021).

Second, bias correction and statistical downscaling techniques have also been used consistently alongside the delta method. Bias correction methods range from interpolation and area weighting of coarse GCM output to simple adjustments to the statistical moments of raw climate model output (Pilling and Jones, 1999). More complex regression-based methods have been used based on atmospheric circulation or weather types (Wilby, 2005; Wilby and Harris, 2006; Prudhomme and Davies, 2009). Stochastic weather generators have also been used and was a major part of the UKCP09 projections (Kay and Jones, 2012; Harris et al., 2013; Afzal and Ragab, 2020). Different statistical techniques correct for different kind of biases. In practice, it is often difficult to compare and validate the appropriateness of different techniques at multiple locations. Multiple statistical downscaling methods of varying complexities are therefore often used together before application in hydrological models (see Wilby et al., 2009 and Maraun et al., 2017 for details of the different possible methods).

Third, the use of RCM output was motivated by the ability to incorporate finer region-specific attributes. In practice, RCM model outputs are often subjected to the same types of statistical bias adjustments as discussed above to correct for different biases (Cloke et al., 2010; Lafon et al., 2013; Kay et al., 2015; Pasten-Zapata et al., 2020). Studies have made use of the RCM outputs from multiple generations of the UK climate change projections (Bell et al., 2007; Kay et al., 2015; Rudd et al., 2020) and large ensemble experiments (weather@home - Guillod et al., 2018; Kay et al., 2018) to drive regional-scale hydrological models. Both statistical and dynamical downscaling enable continuous simulation of hydrological variables over time with greater consideration of natural variability and changes in wet/dry sequences.

2.3.2.1 Summary of evidence

Figure 2.5 presents a high-level summary of the direction of projected change in river flows across different regions of the UK based on GCM-driven studies. GCM-driven studies often take the form of multi-model and multi-method experiments to navigate the uncertainty cascade which has become the standard for climate change impact assessments. Outputs from different climate models from multi-model intercomparison projections (MIPs) (e.g. CMIP3 and CMIP5) are often used to consider climate model uncertainty. Different emission scenarios, downscaling methods, and hydrological models are also considered with an aim to comprehensively analyse as large a number of uncertainty sources as possible. Successive studies comparing different sources of uncertainty along the impact modelling chain at different UK catchments show that GCM-related uncertainty is generally the largest source of uncertainty with differences in both sign and magnitude of projected change although there is greater agreement among the selected GCMs over a reduction in summer flows, particularly for catchments in southern England (Prudhomme et al., 2003; Wilby and Harris, 2006; Prudhomme and Davies, 2009; Kay et al., 2009; Arnell, 2011b). The relative significance of different sources of uncertainty also varies with the time horizon considered. Uncertainty in the near-term (2020s) is associated with natural climate variability while climate model and emission scenario uncertainty dominate in the mid- (2050s) and long-term (2080s) (Hawkins and Sutton, 2011). An additional source of GCM-related uncertainty is natural climate variability which is often overlooked in hydrological climate change impact assessments but can have a large impact on the magnitude of projected change in river flows as demonstrated by using a statistical resampling procedure applied to GCM model output (Ledbetter et al., 2012).

Additional sources of uncertainty form the cascade of uncertainty in GCM-driven studies. This includes uncertainty from different hydrological model structures particularly when considering intensity, frequency, and duration of hydrological extremes (Kay et al., 2009; Visser-Quinn et al., 2019; Parry et al., 2023) and the choice of hydrological indices for evaluating impacts (Ekström et al., 2018). Parameter uncertainty was also found to be particularly important for periods of low flows (Wilby and Harris, 2006; Arnell, 2011b). Comparing different statistical downscaling techniques, Diaz-Nieto and Wilby (2005) concluded that although different techniques agree on a reduction in the magnitude of low flows for the River Thames, the change factor method projects a larger reduction in all months compared to more conservative changes projected using statistically downscaled data. The use of downscaled data at different spatial resolutions adds to the GCM-related uncertainty and increases overall uncertainty (Orr et al., 2021). Kay et al. (2015) and Rudd et al. (2020) both found that the magnitude of change in increased peak flows can vary between the 1.5 km and 12 km RCM data in different regions of the UK (e.g. East England) with largest uncertainty for projected changes in winter and spring.

Region	Refs	Winter	Summer	Annual	Floods	Droughts
1	4,7,12,15,22,31,35,37,40	▲	▼	▬	▲	▬
2	9, 36, 39	▲	▬	▬	▲	No evidence
3	1,2,4,5,15,17,26,27,29, 30,31,34,36	▲	▼	▬	▲	▲
4	7,12,16,18,20,28,29,32, 36,39	▬	▼	▼	▲	▲
5	2,3,9,10,11,13,16,19,22, 23,24,25,27,29,31,33,34, 35,36,37,38,39,40,41,42	▬	▼	▼	▬	▲

▲ Increase ▬ Uncertain - could increase or decrease ▼ Decrease No evidence

Figure 2.5 High level summary of the hydrological impacts of climate change from studies employing a GCM-driven approach. Refer to Supplemental Table S1 for the corresponding citation to each reference index.

2.3.3 Probabilistic approach

UKCP09 was the first generation of UK climate change projections to provide probabilistic information (Murphy et al. 2009). Prior to UKCP09, climateprediction.net (CPDN) was the first to produce probabilistic projections and has been used in several studies to assess potential changes in UK river flows (New et al., 2007; Lopez et al., 2009; Fung et al., 2013). The authors used transient climate model simulations to create perturbed parameter ensembles (PPEs) through systematic variation of parameters within a single climate model. Applied at two river catchments, the studies highlighted the added value of PPEs to generate a probabilistic distribution following a risk-based approach using physically based dynamical models. The probabilistic strands of UKCP09 and later UKCP18 consist of, respectively 10,000 and 3000 equally plausible climate scenarios constructed using a statistical emulator tuned to GCMs representing both uncertainty in climate model (structural uncertainty) and parameterization parameter uncertainty. 25 of the reviewed papers have used the UKCP09 or UKCP18 probabilistic projections. The probabilistic projections are presented as monthly changes in weather variables, so have been applied using the delta method. The UKCP09 probabilistic projections can also be explored using the stochastic weather generator provided. Note that both UKCP09 and UKCP18 include projections based on individual GCMs and RCMs and studies employing data from these projections are considered GCM-driven studies, as covered in GCM-driven studies.

2.3.3.1 Summary of evidence

Figure 2.6 provides a high-level summary of projected change in river flows from studies employing probabilistic projections. The first use of the UKCP09 probabilistic projections was Kay and Jones (2012) which compared results using the different UKCP09 strands (probabilistic change factors, weather generator and RCM) at nine UK catchments. Using all 10,000 sets of probabilistic change factors and 100 sets of weather generator data, the study showed that most of the change factors point towards an increase in flood peaks with a 20-years return period except for selected catchments in Southern England which exhibited greater uncertainty in the sign of change. Although mean projected change is similar across the UKCP09 strands, the authors cautioned against the use of a single strand as the uncertainty range of the probabilistic change factors did not always incorporate the uncertainty range of the other strands. Christierson et al. (2012) was the first to present national scale projections of flow changes at 70 catchments for different probability percentiles. For the 50th percentile, the study found a reduction in summer flows across the UK, particularly southern England. There was greater uncertainty over changes in winter with enhanced flow seasonality and increased winter flows more prevalent in northern catchments (also found in Thompson, 2012 for Scotland). Changes for spring and autumn are smaller with catchments in southern England projected to experience a reduction in flows in all seasons. Despite wetter winters projected for northern catchments, studies have also highlighted an increase in future drought severity for the central estimate mainly due to lower summer flows and higher evaporative demand (Afzal et al., 2015; Afzal and Ragab, 2020). Using all 10,000 change factors may not be computationally feasible in practice. Christierson et al. (2012) found that a subset of 20 change factors is enough to capture climate model uncertainty, but the appropriate sample size is likely to differ for more extreme quantiles to understand uncertainty in projected change for hydrological extremes (Charlton and Arnell, 2014).

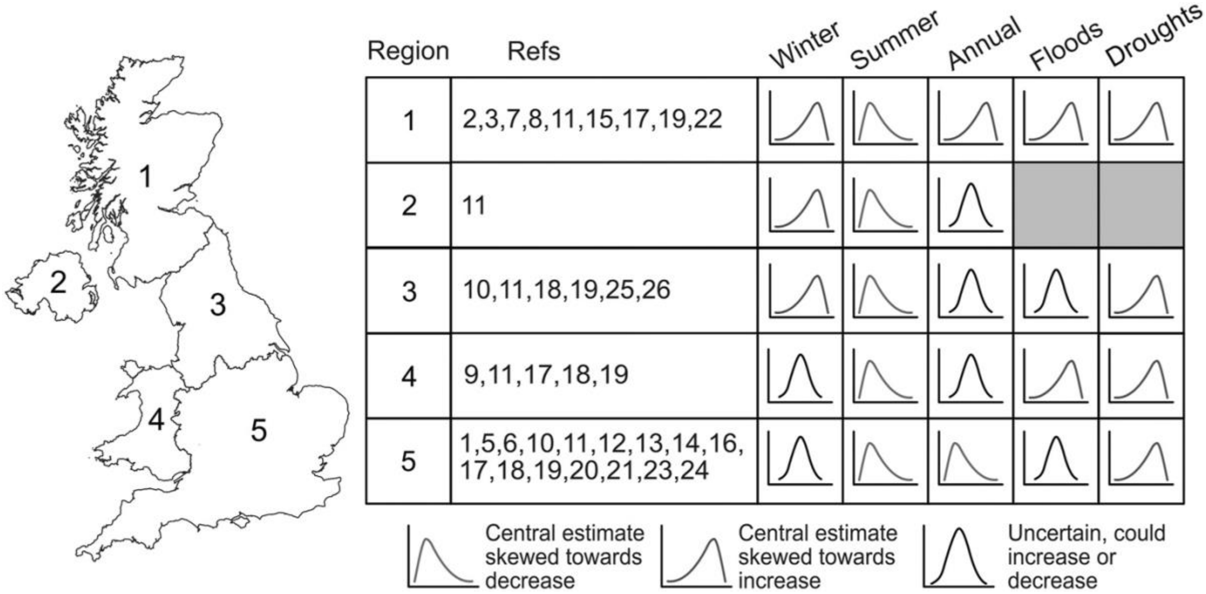

Figure 2.6 High level summary of the hydrological impacts of climate change from studies employing a probabilistic approach. Refer to Supplemental Table S2 for the corresponding citation to each reference index.

Probabilistic projections enable the adoption of what has been termed a "risk-based" approach in water resources planning (Hall et al., 2020). The large sample size from the probabilistic change factor sample sets and the UKCP09 stochastic weather generator allows for the generation of probability distributions to characterize the likelihood of projected changes exceeding certain thresholds (Hall et al., 2020; Borgomeo et al., 2014; Harris et al., 2013; Reynard et al., 2017). For example, Manning et al., (2009) employed a probabilistic approach with synthetic data generated from a stochastic weather generator to investigate the probability of exceeding water shortage thresholds for the River Thames in the 2050s and 2080s in accordance with current abstraction strategies. Similarly, Borgomeo et al. (2014) updated the risk of water shortages by using a weather generator fed with the UKCP09 probabilistic change factors. The authors found that climate change and population growth are likely to increase the probability of water shortage risk (failure to meet Level of Service for water shortage; the frequency of water use restrictions) even with demand and supply management measures. While studies have demonstrated the use of this approach in a number of catchments, the uptake of probabilistic projections in practice is challenging and limited by issues such as the treatment of uncertainties and spatial coherence which is further discussed in Section 2.4.

2.3.4 Scenario-neutral

The scenario-neutral (S-N) approach, first presented in Prudhomme et al. (2010), aims to invert the scenario-led, GCM-driven approach. Hydrological response from incremental changes in two user-defined dimensions are visualized on a response surface. The use of this approach in Prudhomme et al. (2010) was motivated by the need to consider changes beyond GCM projections and to explicitly consider system sensitivity against current guidance on climate change allowances for flood risk management. The scenario-neutral approach has since been used for different hydrological variables (peak flows - Prudhomme et al., 2013a, b; Kay et al., 2014 and low flows - Prudhomme et al., 2015) . In Prudhomme et al. (2010), response surfaces were constructed for 20-years flood peaks from incremental percentage changes in mean annual precipitation and seasonal precipitation variation. Results from different studies following the S-N approach confirmed the important role of precipitation seasonality in projected change in future floods and droughts on a national scale, as had been demonstrated in small subsets of UK catchments in earlier studies following the stylised approach.

The methodological framework of the S-N approach echoes the early stylised approach carried out two decades prior. It also has clear roots in early sensitivity experiments such as the "sensitivity surfaces" constructed in Arnell, (1996) for a small number of UK catchments and that of Němec and Schaake, (1982) for the Pease River, USA which was one of the first published studies to assess the impacts of climate change on river flows. Like the stylised approaches, studies are not directly driven and constrained by GCM model output. The S-N approach also quantifies hydrological response at finer increments rather than the discrete experiments in the stylised approach with the ability to consider dimensions beyond just changes in monthly means. Constructing response surfaces at a national scale for 154 catchments, Prudhomme et al. (2013a, 2013b) and Kay et al. (2014) defined nine flood sensitivity types for the UK by grouping flood peak response surfaces by signal and magnitude of change. Results from the flood sensitivity types further highlight differences in sensitivity to climatic change between different types of catchments, with certain sensitivity types more uncertain to future changes in peak flows (such as more variable and uncertain response at drier and slow-responding catchments in SE. England).

2.3.4.1 Summary of evidence

The ability to integrate GCM-driven and probabilistic approaches by overlaying projected changes from climate models or probabilistic outputs on the response surfaces further differentiates the S-N approach from previous approaches. Prudhomme et al. (2010) overlaid projected change from 46 GCMs on response surfaces of 20 years flood peaks to understand the validity of the widely used climate change allowance of +20% in flood peaks. The authors found that a considerable proportion of GCM projections match and exceed the allowance threshold and that a small deviation from some of the GCM projections would result in further increases in flood peaks beyond the allowance. Kay et al. (2014) subsequently combined the probabilistic projections from the full UKCP09 change factor set with S-N response surfaces. In this case, climate change allowances are revised on a catchment and regional basis by exploring the uncertainty range of the probabilistic projections within a “sensitivity-led” response surface framework for different flood sensitivity types (Kay et al., 2011; Reynard et al., 2017).

2.4 Methodological limitations

Table 2.3 summarizes the key characteristics of each approach and examples of their use in drought and water resources planning. The four approaches are subdivisions within the “top-down” and “bottom-up” categories. GCM-driven studies are “top-down” as their projections are constrained by the number or subset of GCMs selected. Although probabilistic projections are presented as an alternative way to navigate climate model uncertainty via a “risk-based” approach, they are also “top-down” as the probability distributions are dependent on the experimental setup, the climate model(s) used (e.g. PPEs based on single model) and the emission scenarios they follow. The stylised and scenario-neutral approaches can be considered “bottom-up” and “sensitivity-led” as they place particular emphasis on understanding system sensitivity without direct reliance on and can be developed independently from climate model output. The research-orientated objective of comprehensively assessing large numbers of uncertainty sources in GCM-driven studies differs from the more outcome-oriented focus of stylised and scenario-neutral approaches which explores a wider range of plausible futures through exploratory modelling.

Table 2.1 Advantages and disadvantages of the modelling approaches identified from peer reviewed literature since 1990s and examples of their use in water resources management

	Stylised scenarios (1990s)	GCM-driven (mid 1990s-present)	Probabilistic (2009-present)	Scenario-neutral (2010-present)
Direction of approach	Bottom-up – dependent on justification for perturbation ranges	Top-down	Top-down	Bottom-up
Number of scenarios	Small (<10)	Small (single model) to >40 (multi-model ensembles)	Depend on sampling strategy (10,000 for UKCP09 and 3000 for UKCP18)	Large (depend on sampling increments)
Advantages	- Simple generation of discrete sets of scenarios - Valuable for understanding system sensitivity	- Inter-comparison of GCMs and RCMs with finer spatial resolution - Quantification of GCM-related and other sources of uncertainty	- Drive for a risk-based approach using probabilistic information - Discrete output from single GCM does not cover all plausible futures	- Covers wide range of plausible futures - Emphasizes system sensitivity with information on vulnerability or system failure
Disadvantages	- Scenarios may not be realistic - Ad hoc changes in precip. and temp. separately may not be consistent with GHG-related changes - Applied at large domains (e.g. single or small set of perturbation across entire UK)	- Studies often use single or a limited set of models - GCMs do not cover all possible changes - Cascade of uncertainty due to long modelling chain - Bias correction applied based on baseline period may not hold in the future	- Large number of required model runs - Limited scope in water resources planning to fully incorporate probabilistic information - Attachment of probabilities may be misleading - Not temporally and spatially coherent	- Large number of required model runs - Difficult to analyze more than two dimensions in response surface - Range of possible futures may not narrow over time - Small sampling increments are computationally demanding
Example use in water resources planning	- Regional average monthly and annual flow factors estimated from subset of stylised scenarios (“wet”, “mid”, “dry”) applied to observed river flow (e.g. UKWIR 1997) - Employed by water companies in early water resources management plans	- Rainfall runoff modelling using UKCIP02, UKCP09 and UKCP18 - Future Flows Hydrology (Prudhomme et al., 2013b) - eFLaG ensemble (Hannaford et al., 2022; Parry et al., 2023)	- UKCP09 and UKCP18 - Risk estimates at probability levels (95^{th},50^{th} and 5^{th}) (Environment Agency, 2013) - “Smart sampling” of probabilistic sample at drier end of spectrum for drought (Environment Agency 2013)	- Catchment or regionalized response surfaces and typology (Kay et al., 2011; Environment Agency, 2015) - Drought vulnerability assessment framework (Environment Agency, 2020)

Each methodological approach is subject to several drawbacks. The number of scenarios (and model runs) required by studies following the different approaches can differ considerably. This ranges from the small number of discrete perturbations in the stylised approach to subsets (or full range) of climate models in GCM-driven studies and many possible simulations in both the probabilistic and scenario-neutral approaches. Although simple to apply, the stylised approach preserves the temporal variability of the observed time series as a single set of ad-hoc monthly perturbations are applied to observed data. The plausibility of such changes or combination of changes are difficult to verify with limited consideration of spatial variation. The scenario-neutral approach, which can be seen as a development from the stylised approach, is designed as a screening tool, and further detailed studies of individual "futures" within the response surface are still needed for adaptation and water resources planning (Prudhomme et al., 2015). Additionally, multiple or combined response surfaces are required if more than two dimensions (e.g. derived variables such as aridity) are considered at any one time which increases computational time and may potentially be confusing for practical use. Recent research also highlighted additional uncertainty from the wide variety of methods used to populate the response surfaces and the different choices of decision- or system-relevant impact variables (Keller et al., 2019; Culley et al., 2019). Another challenge is to define the boundaries over which the response surface is constructed: using climate model projections may help identify a "plausible" range as a first pass.

GCM-driven studies often aim to comprehensively analyze as many sources of uncertainty as possible. The lengthening of the cascade of uncertainty has led to what has been termed "ensemble fatigue" (Benestad et al., 2017) where choices made along the impact modelling chain result in an abundance of available information and wide uncertainty ranges. Even the most comprehensive study cannot fully analyze all sources of uncertainty and choices made along the impact modelling chain are often made by the modellers instead of the decision-makers (Smith et al., 2018). Additional uncertainty is introduced from "method uncertainty" characterized by differences in the experimental setups of different MIPs particularly for projections for changes in precipitation and patterns of drying (Uhe et al., 2021). The need for analyses to be repeated whenever new projections are published means that the subsequent uncertainty range may become larger with successive generations of climate change projections. This characterizes a "predict-then-manage" philosophy where decisions may be made from a single or few projections and represented through an ensemble mean, which may be both inaccurate and implausible (Arnell, 2011b; Smith et al., 2018; Løhre et al., 2019).

Probabilistic projections explore a larger range of plausible futures and in principle can represent different sources of uncertainty. However, the range of plausible futures depends on choices made about what sources of uncertainty to include and which sources of information to use – such as which climate models are used. For example, GCM-related uncertainty mainly stems from uncertainty in the atmospheric circulation response to climate change between different climate models (Shepherd, 2014). The estimated probability distribution is therefore not an objective estimate of the likelihood of some climate outcome (Arnell, 2011a; Beven, 2011). The treatment of climate model uncertainty in the UKCP09 probabilistic projections is largely the result of a science-led process. The assumption was made that estimating the full range of model uncertainty would lead to better decision-making. However, scientists' perceptions of user needs and actual user needs may differ (Skelton et al., 2017; Porter and Dessai, 2017). Current UK probabilistic projections are also not spatially coherent and cannot be used to analyze the spatial extent of hydrological extremes across multiple catchments, an often-neglected aspect in current studies (Brunner et al., 2021). Decision-makers could find it difficult to interpret probabilistic information as they may be unaware of the underlying assumptions and uncertainty when generating probability distributions (Reeder and Ranger, 2011). Although the inclusion of probabilistic information may be seen as more scientifically accurate with wider uncertainty ranges (i.e. more likely to include the actual outcome), probabilistic projections may be perceived as being less informative (i.e. lower level of precision) and therefore less useful for decision-making (Løhre et al. 2019).

2.5 Implications for methodological approaches

High-level summaries of projected change from the different approaches show good agreement over the general direction of changes projected for different regions of the UK and between catchments with different characteristics (e.g. slow vs fast-responding catchments). However, detailed comparisons of the magnitude of change are difficult due to the inconsistent and uneven selection of emission scenarios, catchments, hydrological models and variables (and indicators) between different studies. This inconsistency mainly arises from different methodological aims of the different approaches. For example, studies following stylised and S-N approaches may be able to focus on many catchments due to their relatively simple perturbations. Conversely, GCM-driven studies may choose to comprehensively analyze a single source of uncertainty (e.g. using climate model ensembles or multiple hydrological models) but may only be able to select a few catchments and may not be able to comprehensively analyze other sources of uncertainties. Consequently, the studies reviewed show an unequal geographical spread with certain regions (or catchments) that are studied more often than others (e.g. SE England). Studies are also dominated by a few hydrological models which can limit our understanding of the heterogeneity of hydrological behaviour and their responses to climate change. Recent advances to tackle this include flexible, modular modelling frameworks (Lane et al., 2019) and improvements to national-scale gridded hydrological models (e.g. inclusion of abstraction processes; Rameshwaran et al., 2022).

Figure 2.7 shows the uneven use of emission scenarios and future time period in studies using different generations of UK climate change projections. The largest number of studies using UKCIP02 and UKCP09 products focused on the medium emissions pathway. A previous synthesis by Gawith et al., (2009) found that users often saw the medium scenario as the "middle road" or "safe" choice. In practice, water companies rely on the medium scenario for estimates of climate change effects on water supply and use the high and low scenarios to incorporate uncertainty through a target headroom – a buffer to be maintained between water supply and demand (Environment Agency, 2013). In contrast to this, GCM-driven studies disproportionately employed the highest emissions RCP8.5 pathway. This was also identified in O'Neill et al., (2020) where the greatest number of studies globally across different sectors used RCP8.5. Some have contested that the use of RCP8.5 could be misleading, especially if interpreted – incorrectly – as a "business as usual" scenario (Hausfather and Peters, 2020). However, its use in practice is often because RCP8.5 has the strongest climate change signal and because it often has the most information available (e.g spatial coherence). Recent studies have demonstrated that other sources of information could be more suited for decision-making such as quantifying the impacts avoided from lower emission pathways or from mitigation strategies and policy targets (Arnell et al., 2014; Orr et al., 2021). Even though probabilistic projections are designed to tackle a wider range of climate model uncertainty, a number of studies have used and reported only the central estimate (i.e. 50th probability level) of the UKCP09 probabilistic projections. However, both probable and non-probable information are required from a risk perspective for effective adaptation (Lawrence et al., 2020). Adaptation and management measures based on the studies reviewed may therefore require further information on low-likelihood outcomes to reduce the risk of maladaptation where findings based on a single level of probability could be overly cautious and optimistic (Harris et al., 2013, 2014; Lawrence et al., 2020).

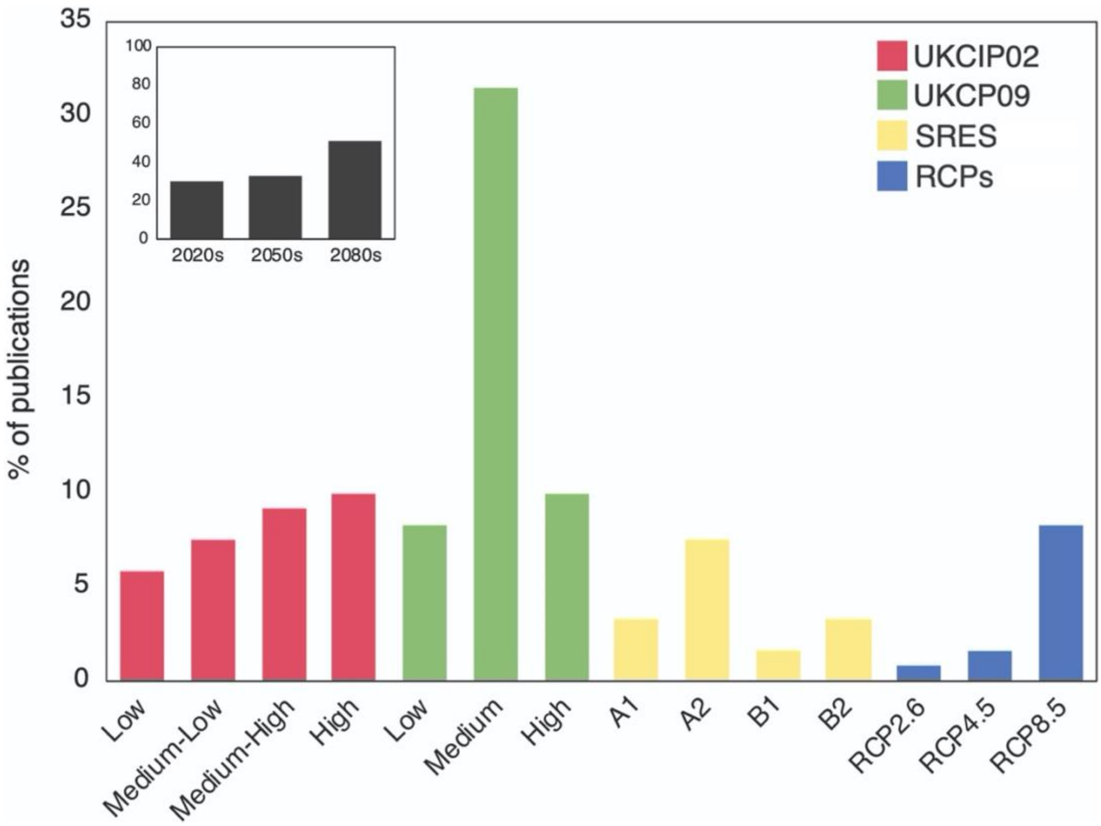

Figure 2.7 Percentage of total publications using each emission scenario from UKCIP02, UKCP09, IPCC SRES and RCP climate change scenarios. Inset plot shows percentage of total publications considering the three most commonly used future time slice (2020s, 2050s and 2080s).

Ensuring adopted approaches can provide meaningful information for decision-making emerges as a key research priority. Falloon et al. (2014) recommends a more flexible selection of approaches, such as the selection of "top-down" approaches if there are relative certainty across climate projections and selecting "bottom-up" approaches if there are widespread uncertainties in both magnitude and direction in projected change. Emerging approaches can be considered as "hybrid" or "pluralistic" where different techniques complement each other and "top-down" projections can be explored within a wider "bottom-up" framework led by the intended aims of specific applications (also as reflected in Weaver et al., 2013 in review of the use of climate projections in decision-making). They aim to circumvent and navigate aspects of the uncertainty cascade in different ways to provide additional lines of evidence in future climate change impact assessments.

Future research could draw on a combination of existing approaches and emerging approaches outlined in this section in a pluralistic and complementary way such that different approaches may be used for different purposes according to the aims of individual applications.

Alternative ways have been proposed to extract additional information from the cascade of uncertainty. Smith et al. (2018) identified three different strategies to characterize uncertainty: 1) Analyze, 2) Bound and 3) Crystallize. GCM-driven studies identified in this chapter tend to fall within the first strategy as their aim is to analyze as many sources of uncertainty as possible. The latter two strategies require a more focused investigation by presenting the upper and lower bounds or by searching for specific outcomes within the uncertainty cascade. Both strategies may be able to better consider plausible worst cases and high-impact, low-likelihood events (Sutton, 2019; Arnell et al., 2021). An example of this is the H++ climate change scenarios, which created high-impact scenarios for high/low river flows, floods and droughts. The high-end scenarios were created by combining multiple lines of evidence (e.g. process understanding, historical observations, paleo-climate analogues and GCM projections) to define the physical limits of plausible worst-case scenarios beyond the upper uncertainty range of GCM projections (Wade et al., 2015). Similarly, the UNprecedented Simulation of Extremes with ENsembles (UNSEEN) approach aims to characterize low-likelihood extreme events using retrospective forecasts or large ensemble climate model data to search for events which are beyond the observed record (Thompson et al., 2017; Kelder et al., 2020). Borgomeo et al., (2015) and Brunner and Tallaksen, (2019) are also examples of this strategy where the sample size is increased through direct stochastic simulation of synthetic river flows in order to robustly assess the probability of severe droughts at UK catchments.

Testing hydrological systems against a wider range of plausible outcomes echoes the motivations of the robust decision-making (RDM) framework and has previously been applied for the Thames basin to identify acceptable mixes of management options to severe drought (Matrosov et al., 2015; Huskova et al., 2016). Alongside the exploration of low-likelihood, high impact events with information from climate model projections, studies have also explored consequences of "what-if" experiments that are in many ways are conceptually similar to the storyline approach as introduced in Section 1.6. For example, an early application of "what-if" experiments in the UK was Whitehead et al. (2006) where a water quality model was used to test different adaptation strategies (e.g. land use change, reduced fertilization) against water quality outcomes for the River Kennett in southern UK. Similarly, Harrigan et al. (2014) used hydrological models to assess multiple hypotheses to attribute past river flow trends to different plausible climatological and anthropogenic drivers of change. Dessai and Darch (2014) showed that the adoption of such sensitivity-led frameworks is indicative of the increasing influence of RDM principles in practice, and that overcoming challenges such as computational resources and the "predict-then-manage" philosophy in the water resources industry could enable a fuller adoption of RDM principles.

2.6 Chapter summary

This chapter presented a review which has identified 122 papers investigating the hydrological impacts of climate change in the UK from the 1990s to 2021. Four modelling approaches are identified from the reviewed papers. A GCM-driven, "top-down" approach is the most widely adopted approach to date, but alternatives have emerged as the limitations of top-down approaches become more widely recognized. GCM-driven studies are often characterized by an aim to quantify the relative contribution of different sources of uncertainty using multiple methods to apply climate change scenarios, showing that circulation-related uncertainty between different GCMs is the dominant source of uncertainty. However, they incur the cascade of uncertainty which results in a large amount of information that may not be conducive to decision-making. Probabilistic approaches provide an alternative way to treat climate-model uncertainty through advances in perturbed physics ensembles. However, they are still "top-down" with outstanding challenges related to their practical use in water resources planning. The scenario-neutral approach echoes the earliest stylised approach with a "bottom-up" focus on system sensitivity and more explicit consideration of how results can be informative from a decision-making perspective. Both approaches have contributed to the fundamental understanding of how different types of hydrological systems respond to a wide range of climatic changes.

Synthesis of studies employing each approach showed that the magnitude and sign of change in different hydrological variables remain uncertain between different regions of the UK. High-level summaries of projected change in river flows do not significantly differ between the approaches although direct comparisons between studies following different approaches are difficult and limited due to their methodological differences and consequently different choices made along the impact modelling chain (e.g. catchments, emission scenarios and hydrological models). Major limitations across the different approaches included issues related to wide uncertainty ranges, limited consideration of high-impact outcomes and practical challenges in their use in water resources planning.

3 DATA AND METHODS

3.1 Introduction

This chapter presents the various data sources used in this thesis, approaches to analyse meteorological drivers of drought, the framework for hydrological modelling and hydrological drought analyses. Section 3.2 introduces the observational data used to drive and calibrate catchment hydrological models. Section 3.3 presents various sources of model data that are used to perturb and drive hydrological models and to explore the meteorological drivers of hydrological droughts in present and future climate. Section 3.4 introduces the catchment hydrological models that are employed to simulate river flows for catchments across Great Britain and the model calibration strategy employed. Section 3.5 describes the methods to extract hydrological drought events from simulated river flows and the selected hydrological drought metrics.

3.2 Observed data

3.2.1 Catchment selection and river flows

In this thesis, the catchments selected for investigation include catchments in the NRFA's Low Flow Benchmark Network (LFBN) as they comprise of catchments that are suitable for the low flow analysis given their near-natural conditions (Harrigan et al., 2018). To focus on Great Britain (GB), the 100 catchments within the LFBN that are in England, Scotland, and Wales and which overlap with catchments selected in previous drought studies by Smith et al., (2019) and

Barker et al., (2019) are selected. In addition to the catchments within the LFBN, an additional set of 16 catchments within the East Anglian region are chosen in collaboration with Anglian Water. The chosen catchments are representative of key abstraction catchments and catchments linked to key reservoirs such as the Ardleigh Reservoir (e.g. River Colne at Earls Colne – ID 37042) and the Grafham Reservoir (e.g. Bedford Ouse at Offord – ID 33026). Figure 3.1 shows the catchments selected in the LFBN and the additional catchments in the Anglian region.

Daily observed river flow (m3 s−1) and catchment properties listed in Table 3.1 are extracted via the *rnrfa* R package (Vitolo et al., 2016) from the UKCEH National River Flow Archive (NRFA) for each selected catchment. As seen from Figure 3.1, the catchments selected are representative of the broad range of climate and catchment characteristics across the UK. Catchments in southern England underlain by permeable aquifers have a higher baseflow index (BFI) and receives lower standardised annual average rainfall (SAAR) compared to catchments in Scotland and western GB. Variation in BFI across the UK is associated with catchment characteristics (predominantly the presence of permeable and productive aquifers) with relatively higher water abstraction also playing a role at groundwater-dominated catchments (Bloomfield et al., 2021).

Table 3.1 Description of selected catchment properties

Catchment properties	Description
Catchment area (km^2)	Total area of the catchment (km^2)
DPSBAR (m/km) – catchment steepness	Mean drainage path slope (DPSBAR) is an index for catchment steepness calculated as the mean inter-nodal slopes within a catchment. Higher values indicate steeper terrain and lower values flatter terrain.
PROPWET (%)	Proportion of time soils within a catchment are designated as being wet (i.e. higher values indicate wetter). PROPWET varies from <20% to >80% across the UK.
Proportion of horticultural/arable land (%)	Land use information derived from the Land Cover Map 2000 and the NRFA Land Cover Classes 2000
BFI	Baseflow Index (BFI) is a measure of the proportion of river flow that derives from groundwater and subsurface storage. Higher values indicate more permeable catchments with high groundwater contribution to river flow, particularly during dry periods.
SAAR 1961-1990 (mm)	Standardized Annual Average Rainfall (SAAR) over 1961-1990 30-year period

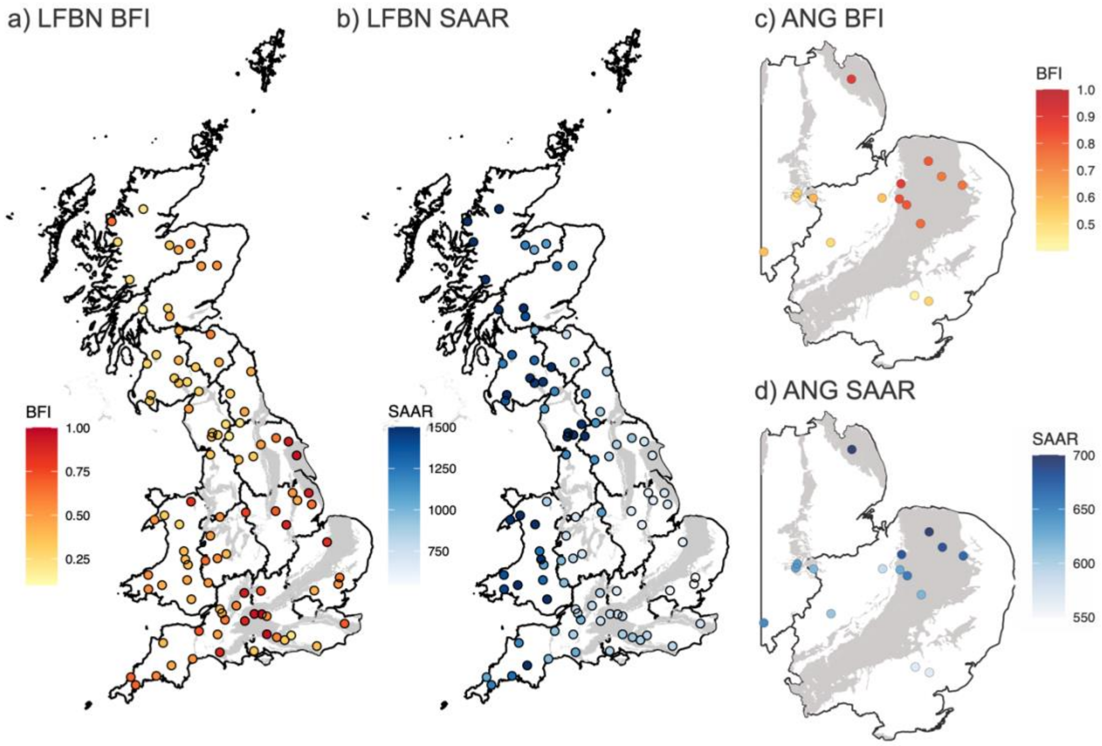

Figure 3.1 Selected catchments in the Low Flow Benchmark Network (LFBN) coloured by a) baseflow index (BFI) and b) SAAR (1961-1990) and additional catchments in the East Anglia (ANG) region coloured by c) BFI and d) SAAR (mm). Shading indicates regions of permeable aquifers from the hydrogeology map of the British Geological Survey.

3.2.2 Precipitation and temperature

Observed daily precipitation is taken from the CEH-GEAR dataset (Tanguy et al. 2021). CEH-GEAR provides 1km daily and monthly gridded observed precipitation across the UK derived from the UK rain gauge network and interpolated following the natural neighbour approach. Observed daily mean temperature is extracted from the CEH CHESS dataset (CHESS-met) at 1km resolution across the UK from 1961 to 2017 (Robinson et al. 2020). As the CEH CHESS dataset do not provide temperature data beyond 2017, analyses of the 2022 drought in this thesis (Chapter 5) and climate extremes in 2022 (Chapter 6) also make use of the HadUK-Grid dataset which provides up to date daily maximum and minimum temperature at the same resolution (1km) (Hollis et al., 2019). Observed daily and monthly estimates of potential evapotranspiration (PET) are available in Tanguy et al., (2018) which was produced as part of the UKCEH Historic Droughts programme. Tanguy et al. (2018) compared a number of temperature-based equations and calibration approaches to estimate PET and compared their results with the physically-based Penman-Monteith equation on a national scale. The study found that the McGuiness-Bordne equation (original equation in Eq.1 - Mcguinness and Bordne 1972) performed the best when specifically calibrated nationally across UK catchments against PET estimates using the Penman-Monteith equation.

$$PE\ [mm\ day^{-1}] = \frac{1}{\lambda} S_0 (\frac{T+5}{68}) \quad 3.1$$

where λ refers to the latent heat of vaporisation (MJ Kg^{-1}), T refers to temperature (°C) and S_0 refers to extraterrestiral radiation (MJ m^{-2} day^{-1}). In this thesis, PET is calculated from observed daily mean temperature from the CEH CHESS dataset (Chapters 4 and 6) and the HadUK-Grid dataset (Chapter 5) using the McGuinness–Bordne equation with parameters tuned specifically for the UK as set out in Tanguy et al. (2018). Given the need to ensure relevance with existing practice in climate change assessment and drought planning within water companies, a temperature-based method to estimate PET is chosen as such methods are relatively simple to apply and regularly used by water companies. The choice of PET estimation method can affect simulated river flows when used to drive hydrological models (Prudhomme and Williamson, 2013) although some studies have suggested that PET-related uncertainty is less than GCM-related uncertainty, in particular in relation to the wide range of projected change in precipitation across climate models (e.g. Kay and Davies, 2008; Thompson et al., 2014).

3.3 Model data

This thesis makes use of various sources of model datasets to understand hydrological droughts in both present and future climate. This includes climate model simulations (UKCP18 and EC-Earth large ensemble) and seasonal hindcasts from a weather forecasting system (ECMWF SEAS5). Figure 3.2 presents a schematic showing the sources of modelled meteorological data contributing to various parts of this thesis and key methods for data processing prior to the application of model simulations in hydrological modelling. The following section presents the data sources and processing methodology in detail.

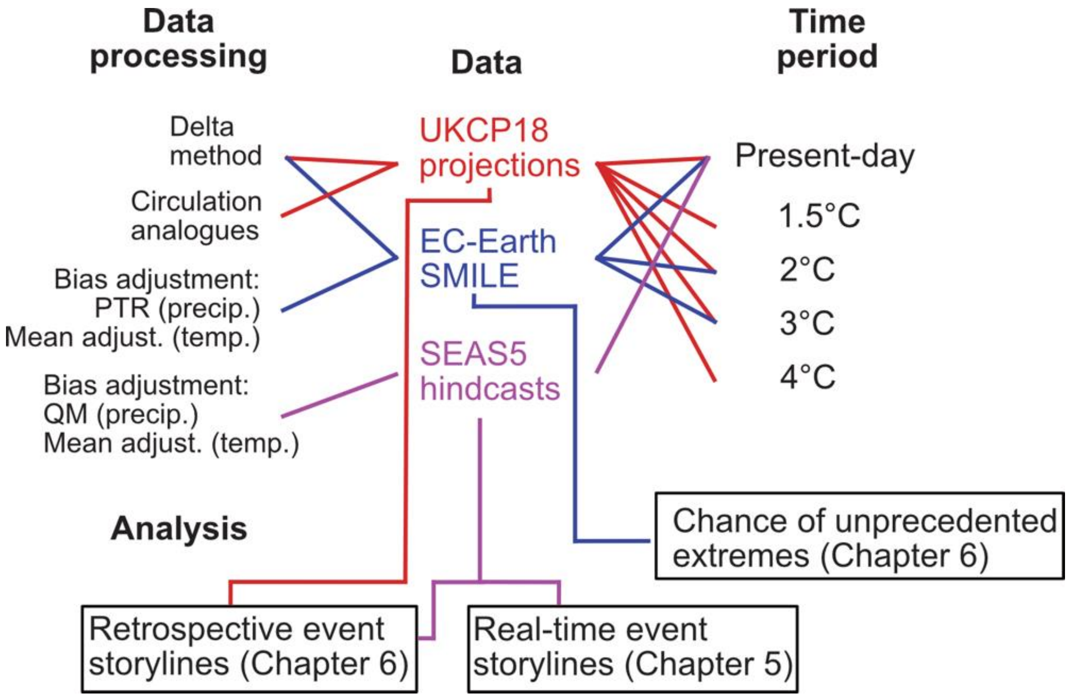

Figure 3.2 Schematic showing the various model data sources used in this thesis, the data processing undertaken for precipitation and temperature and the time periods in both present and future climate each data source considered. PTR refers to power transformation and QM refers to quantile mapping.

3.3.1 Atmospheric reanalysis

An atmospheric reanalysis system uses data assimilation to combine available historical observations of climate variables and past weather forecasts that is then used to drive a weather forecasting model to produce a spatially and temporally coherent gridded dataset of estimated atmospheric variables in near real time at the global scale (Hersbach et al. 2020). Although reanalysis provides data at the global scale without any gaps, there is a degree of uncertainty associated with the estimated variables, particularly in areas with poor coverage and quality of observations. A series of meteorological indices describing past atmospheric circulation patterns are calculated from the ERA5 reanalysis dataset and used throughout this thesis as proxy observations. The ERA5 reanalysis, produced by ECMWF, has a horizontal resolution of 31km and provides atmospheric variables from 1940 and in near real time (within 5 days) (Hersbach et al., 2020). In Chapter 5, monthly mean sea level pressure (MSLP) anomalies from ERA5 for the European/North Atlantic region is used to calculate the North Atlantic Oscillation (NAO) index and the East Atlantic (EA) index. The NAO and EA indices are represented by the first two leading modes calculated through empirical orthogonal functions (EOF) analysis respectively. The NAO is the leading mode of variability in the North Atlantic and describes the difference in pressure between the Azores and Iceland. The Nino3.4 index is calculated from average sea surface temperature anomalies in the region (5°S-5°N, 120-170°W) to represent the phases of the El-Nino Southern Oscillation (ENSO). In addition to the NAO, EA and ENSO, polar vortex strength is calculated based on average wind speed (U10) at 60°N and the North Atlantic sea surface temperature (SST) tripole index is calculated by SST anomaly averaged over ta northern box (40°-55°N, 60°-40°W) minus SST anomaly averaged over a southern box (25°-35°N, 80°-60°W).

3.3.2 UKCP18 climate projections

The UK Climate Projections 2018 (UKCP18) 12-member HadRM3 perturbed parameter ensemble (PPE) regional climate projections at 12 km resolution following the high emissions RCP8.5 scenario is used in Chapter 5. UKCP18 is the latest generation of national climate change projections for the UK. The 12-member PPE was created by exploring the plausible ranges of the climate model parameter space and driven by the boundary conditions of the global projections (Lowe et al., 2018). The regional projections are provided as spatially coherent projections which is important, given the spatial characteristics of drought events. The UKCP18 projections also provide a suite of other datasets in various other strands with each spanning a different range in the overall uncertainty in projected changes and with data provided at different resolutions (Lowe et al., 2018; Arnell et al., 2021). For example, the probabilistic projections consist of in total 3,000 plausible samples and samples the broadest range of plausible outcomes at different emissions pathways but the projections are not spatially coherent.

Figure 3.3 shows that the UKCP18 regional projections point towards, in general, wetter winters and drier summers with increasing temperature. This climate-change-induced change in the seasonality of precipitation is particularly noticeable at 3 and 4 °C warming, with general agreement among the 12 ensemble members over the sign of change. Projections also point to increased seasonality in temperature, with the greatest change in temperature in the summer, reaching 6 °C higher relative to 1981–2010 in the summer in a 4 °C warmer world. The UKCP18 global and regional projections project increases in average temperature at the warmer end of the probabilistic strand and are generally on the warmer and drier range of the CMIP5 projections under the RCP8.5 emissions scenario (Arnell et al., 2021; Arnell and Freeman, 2022). It should be noted that the RCP8.5 emissions scenario can be considered as a "worst-case" scenario and should not be interpreted as a "business-as-usual" scenario (Hausfather and Peters, 2020). However, its use is justified for risk assessment purposes as it provides the strongest climate change signal and often has the most information available (e.g. spatially coherent projections).

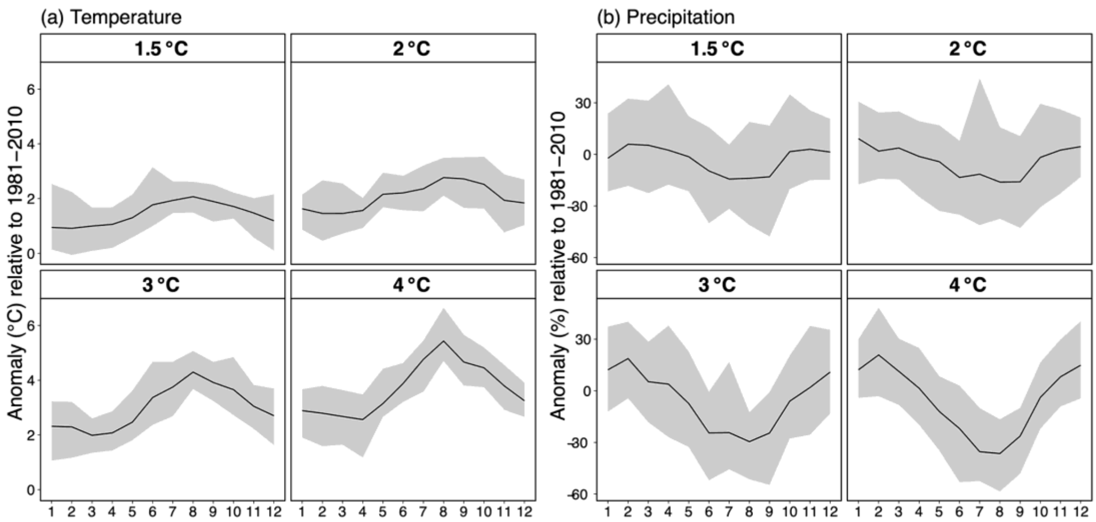

Figure 3.3 Average monthly projected change in a) temperature (°C) and b) precipitation (%) (relative to 1981-2010) across the 12 ensemble members of the UKCP18 regional projections at each global warming level. The shading is the spread across the 12 ensemble members and the solid line is the ensemble mean.

Delta change method

The literature review in Chapter 2 showed that various approaches have been taken in the literature to apply climate change scenarios in hydrological models. In Chapter 4, a time-sampling approach (James et al., 2017) is used to select the 10-year time period starting from the year that each UKCP18 ensemble member reaches conditions equivalent to four global warming levels (1.5, 2, 3, and 4°C) relative to 1981–2010. The delta change method is used perturb the observed time series with climate change factors. Monthly change factors for precipitation (%) and temperature (°C) are generated by comparing projections for a baseline period (1981–2010) to projections of the designated 10-year future periods for each river basin region and applied either additively (for temperature) or multiplicatively (for precipitation) to the baseline temperature and precipitation for each catchment. The delta change method is widely and consistently employed in studies projecting the impacts of climate change across UK catchments (Arnell, 2003; Kay et al., 2020; Wilby and Harris, 2006). In its standard form, this method retains the historical variability in the observations, and changes in dry/wet spell lengths are not considered. Variations in the delta change approach have been proposed to calculate percentile- or quantile-based change factors to represent different magnitudes of relative changes in wet and dry days and short-duration rainfall intensity (see Anandhi et al., 2011 for overview of various varients of the delta method).

Alternative statistical downscaling techniques correct for different biases, but all techniques share the assumption that the biases corrected for and the bias correction technique itself remain valid for future time periods. It is also challenging to validate the plausibility of analogue events found in bias corrected data due to uncertainty over the realism of climate model simulations for persistent circulation extremes (important for multi-year droughts; Ault et al., 2014; Moon et al., 2018) and how atmospheric circulation patterns will change under climate change (Shepherd, 2014). In Chapter 4, the delta method is used to place historical events in a future climate. Retaining the observed drought sequence, the meteorological conditions driving the observed drought remain consistent and plausible. This is an assumption that sacrifices the ability to generalise over all droughts, but focuses on the specificity of individual drought events. A comparison between projections of future change in drought characteristics across Great Britain using the delta method and the direct use of bias-adjusted climate model data is further explored in Chapter 6 (with methods described in Section 3.3.3).

Circulation analogues

The circulation analogue approach, first introduced in Yiou et al., (2007), aims to search within historical observations or climate model simulations to find days with similar circulation patterns to an historical event. In Chapter 5, the circulation analogues approach is applied by using both the global and regional strands of the UKCP18 projections in conjunction. The circulation analogue approach can be an alternative approach to the delta change method to understand the possible impacts of climate change on individual drought events. A past drought event is selected and for any given day in the selected event, the day in the UKCP18 global projections with the most similar MSLP anomalies pattern in the Euro-Atlantic domain to that observed day is identified as the circulation analogue. This selection process is carried out within a 30-day time window centred on each day of the selected event. The ERA5 reanalysis dataset is used to calculate observed MSLP anomalies, relative to 1965-2015, and simulated MSLP anomalies are calculated for each ensemble member in the UKCP18 global projections for the baseline (1980-2020) and future (2050-2080) periods. As an example for the first day of summer 1976 (June 1st 1976), days in the UKCP18 projections within a 30-day time window centred on June 1st 1976 are selected, and Euclidean distance is calculated between the SLP anomalies of the selected days and the observed SLP anomalies of June 1st 1976. The day with the closest Euclidean distance in the UKCP18 projections to the observed SLP anomaly of the day is subsequently identified and the mean precipitation over eastern England associated with that day is obtained from the corresponding 12km regional projections. This procedure is repeated for every day of the selected event, separately for the baseline and future periods and for each of the 12 ensemble members of the UKCP18 projections.

3.3.3 EC-Earth large ensemble

To mitigate the challenge of short observational records and to better understand the influence of natural climate variability, studies have increasingly made use of large ensemble simulations (Bevacqua et al., 2023; Kelder et al., 2022; Thompson et al., 2017). For example, Thompson et al. (2017) introduced the UNprecedented Simulation of Extremes using ENsembles (UNSEEN) technique to explore unprecedented events beyond what has been observed in the historical record using initialised large ensemble simulations. Single model initial condition large ensembles – SMILEs – have emerged as a particular source of data to expand the sample size. SMILEs are climate model simulations generated from perturbations made to the initial conditions of each ensemble member (Maher et al., 2021). Chapter 6 of this thesis uses the EC-Earth time-slice SMILE based on the EC-Earth GCM v2.3 (van der Wiel et al., 2019) to estimate the chance of unprecedented hydrological extremes. The large ensemble used was run for present-day (equivalent to the climate with observed global mean surface temperature for the period 2011-2015) and pre-industrial plus 2°C and 3°C global warming conditions. Figure 3.4 illustrates the set-up of the large ensemble taken from van der Wiel et al. (2019). 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 climate data for each global warming level (i.e. 16 ensemble members x 25 realizations x 5 years = 2000 years). The spatial resolution of the large ensemble is 1.1° x 1.1°. As with previous regional studies which employed this large ensemble data (e.g. van der Wiel et al. 2019; van der Wiel et al. 2020; Bonekamp et al. 2020; Goulart et al. 2021), the data is re-gridded to 0.5° x 0.5° via bilinear interpolation.

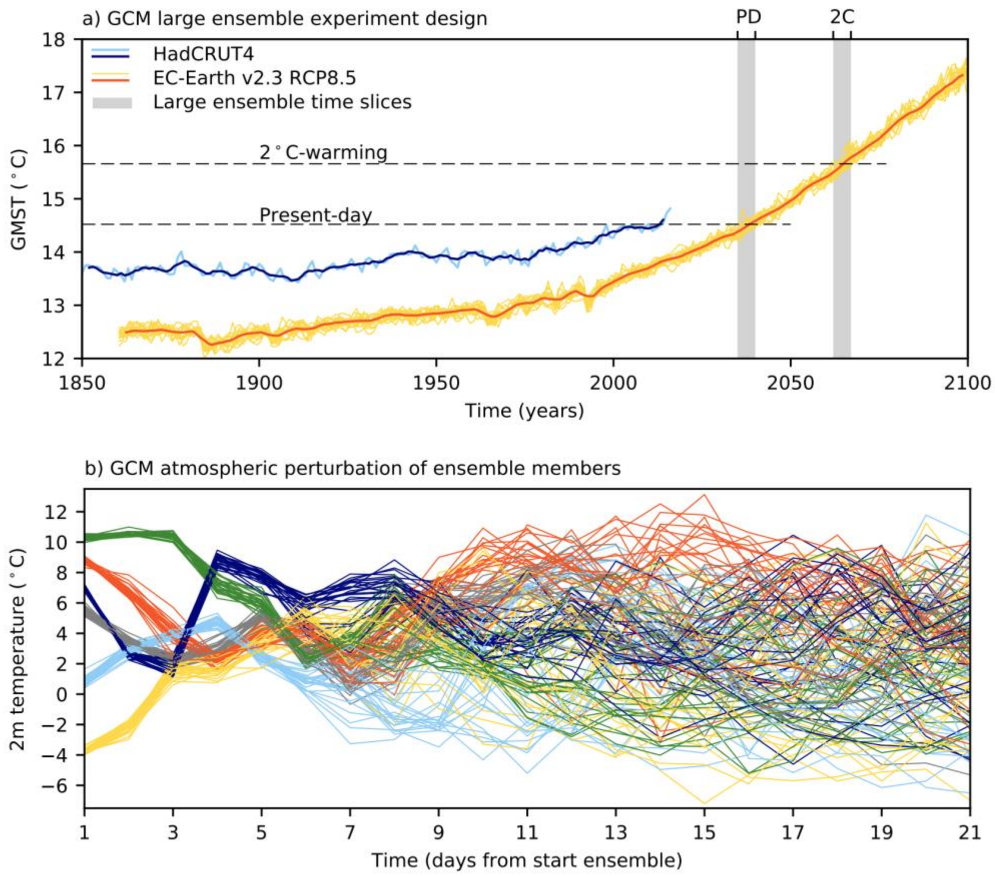

Figure 3.4 Design of the EC-Earth large ensemble (Source: van der Wiel et al. 2019). Panel a) shows global mean surface temperature in the EC-Earth transient simulations (yellow shading indicates different ensemble members). Grey shadings show the 5-year time slices at present day (PD) and 2°C warming. Panel b) shows simulated temperature for the first 21 days of a 5-yer time slice with different initial conditions illustrated by the 6 example ensemble members.

The same large ensemble has been widely used for climate impact modelling with the application of both global and regional hydrological models (Kelder et al., 2022a; van der Wiel et al., 2019; van Kempen et al., 2021) and crop yield models (Goulart et al., 2021; van der Wiel et al., 2020; Vogel et al., 2021). Compared to existing SMILEs, the time-slice simulations have the advantage of a stationary climate and are more representative of present-day conditions of the recent past rather than transient simulations over a baseline period which may include a forced trend from anthropogenic climate change over time. 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). This introduces 399 (out of 1999) spurious December to January transitions and the implication of this choice is discussed accordingly. Additionally, SMILEs also enable the exploration of the physical meteorological drivers of climate extremes. In Chapter 6, geopotential height anomalies at 500 hPa (Z500) are also extracted from the EC-Earth SMILE to explore differences in the meteorological drivers of dry seasons in the present-day and future simulations. Z500 is a commonly used variable to describe deviations in atmospheric circulation and is defined as the height in the atmosphere before reaching an air pressure of 500hPa. High pressure, anticyclonic conditions are associated with positive Z500 anomalies.

Bias adjustment

In addition to the delta method described in section 3.3.2, a second method to apply climate projections is by bias adjusting the model simulations so they can be directly used as input to hydrological models. In Chapter 6, bias adjustment is performed for each catchment in the LFBN and Anglian Water region. Modelled precipitation is adjusted to match monthly observed means using multiplicative correction factors for precipitation and additive factors for temperature. Initial tests found that the modelled GB-averaged mean monthly precipitation has a lower standard deviation compared to the observations. 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 in the method set out in Leander and Buishand (2007) which aims to adjust the variance statistics of precipitation data (Eq. 3.2).

$$P^* = aP^b \tag{3. 2}$$

where P^* refers to adjusted daily precipitation. Parameter b is determined by matching monthly mean coefficient of variation (CV) of the modelled precipitation with the CV of the observed precipitation. Parameter a subsequently scales the modelled precipitation so that it matches monthly mean observed precipitation. The simulated data is also corrected for excessive "drizzle", a well-known problem for GCMs, by setting precipitation below a threshold to zero. The threshold is 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 of the EC-Earth SMILE.

Modified delta method

As described previously, the delta change method scales or shifts the observed time series by change factors representative of projected climate change in the 2°C and 3°C large ensemble.

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, in addition to the standard delta change method, a modified delta change method based on the resampling methodology in Ledbetter et al., (2012) is also applied in Chapter 6 to give an indication of the possible range of change. For each original ensemble member of the EC-Earth large ensemble simulations, a resampling procedure randomly selects with replacement a block of monthly precipitation in the future period to form a new 30-year time series. Given that temperature values exhibit higher dependence between months, only one change factor set for temperature is created. 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. 2011). The modified delta method is repeated 30 times to create 30 change factor sets for each ensemble member for each catchment (30 change factor sets x 16 ensemble members = 480 change factor sets per catchment).

Projected change

Figure 3.5 shows the projected change in precipitation from the large ensemble obtained from the delta method and directly from the bias-adjusted precipitation across the 16 ensemble members. Projected changes in precipitation over the selected catchments in the EC-Earth large ensemble show drier summers and wetter winters with increasing temperature rise. The expanded set of change factors in the modified delta method incorporates a greater degree of climate variability and therefore shows a greater range of changes compared to a single set of change factors per ensemble member. Variations in the estimated rainfall changes for the latter two estimates mainly correspond to the spread across the selected catchments.

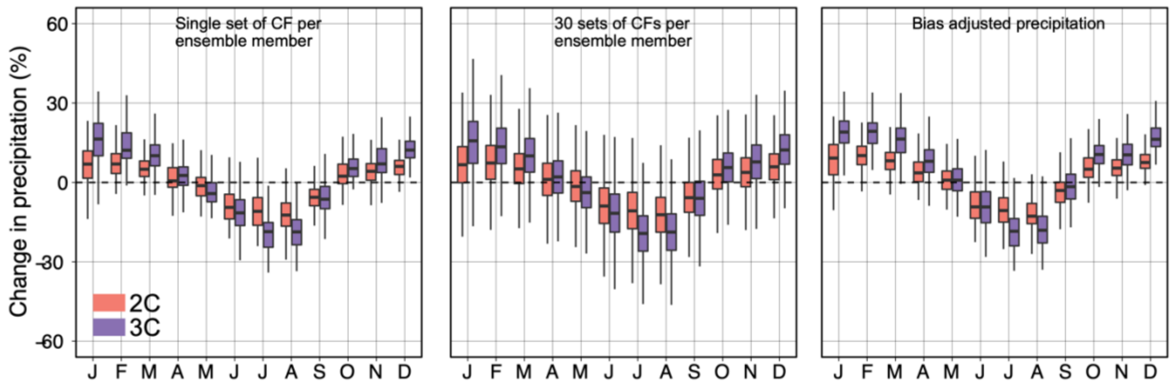

Figure 3.5 Projected change in precipitation across all LFBN and ANG catchments for 2°C warming (orange) and 3°C warming (purple) using a) a single set of change factors per ensemble member for each catchment, b) 30 sets of change factors per ensemble member from resampled precipitation for each catchment, and c) bias-corrected precipitation across ensemble members.

3.3.4 SEAS5 seasonal hindcasts

To further explore the utility of large ensemble datasets, the ECMWF SEAS5 hindcast dataset (1982-2021) is used to provide a large sample of plausible winters (Dec, Jan, Feb - DJF) to be investigated in Chapters 5 and 6. The winter season is chosen as the focus as it is the season where groundwater aquifers and reservoirs are usually recharged in the UK. In total, there are 2850 winters in the hindcast dataset across 25 ensemble members and three lead times (Sep, Oct and Nov) (comprising of 38 complete winters between 1983 and 2020 x 25 ensemble members x 3 lead times). SEAS5 ensemble members are generated by perturbations made to their initial atmospheric and oceanic conditions (Johnson et al., 2019). Similar to the use of the EC-Earth large ensemble as detailed in Section 3.3.3, the use of SEAS5 hindcasts follow recent studies advocating for the use of initialised large ensemble simulations consisting of multi-thousand years of simulations to explore a larger range of plausible outcomes. For example, the use of seasonal hindcasts to improve risk estimates of extreme events was previously demonstrated by van den Brink et al. (2004) which used 1500-years of hindcast simulations from a previous generation of the ECMWF seasonal prediction system to improve estimates of storm surge levels in the Netherlands. Figure 3.6 shows observed total winter rainfall for the East Anglia region over the 1983-2016 period from the CEH-GEAR dataset and the spread of modelled rainfall from the hindcasts across all ensemble members and lead times over the same period. The observational data points fall within the spread of modelled rainfall for roughly one-half of the years and fall within the maximum and minimum in all years. Standardising the observed rainfall against the modelled rainfall distribution shows that for 22 out of the 38 years, the observed value is within one standard deviation of the modelled rainfall of that year, showing that the SEAS5 hindcasts are reliable and useful for the East Anglia region over the selected period. Following the procedure employed by Anglian Water for operational drought forecasting, the hindcast winter rainfall was bias-adjusted for each catchment using quantile mapping (initiated via the qmap R package – Gudmudsson 2016) and scaled to match monthly mean observed catchment-averaged rainfall. The NAOI, EAI, SST tripole index and the Nino 3.4 index are calculated for each winter in the SEAS5 hindcasts following the same procedure as outlined for the ERA5 reanalysis.

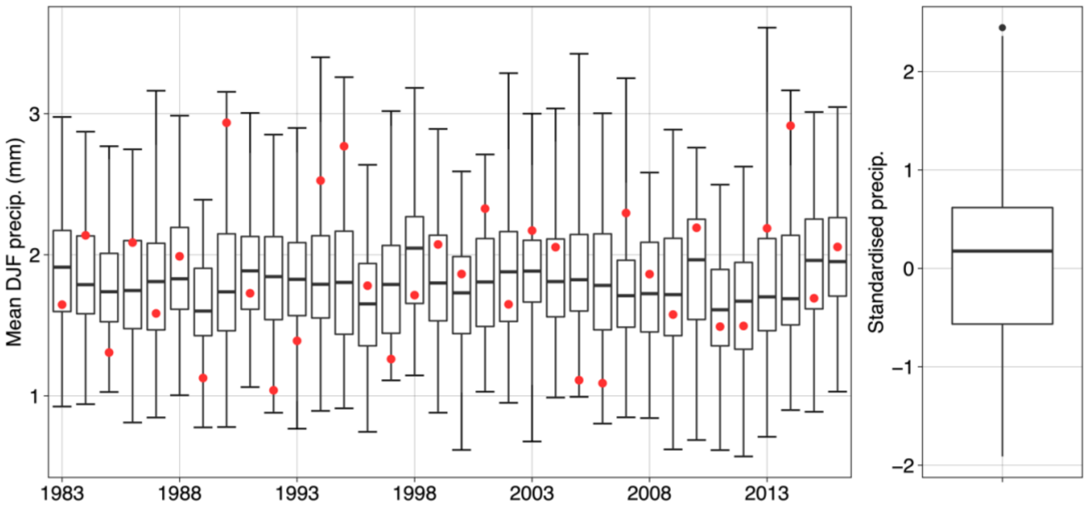

Figure 3.6 (Left) Observed (CEH-GEAR) (red dots) and simulated (box) mean winter (DJF) rainfall over 1983-2016 from the SEAS5 hindcasts across 25 ensemble members and three lead times over the Anglian region. The whiskers of the boxplots extend to the maximum and minimum modelled value. (Right) Distribution of observed winter rainfall for each year over the 1983-2016 period standardised against the distribution of simulated rainfall of the same year.

3.3.5 Model fidelity tests

Model simulations should be evaluated and deemed credible compared to the observations before they can be used. The model fidelity test set out in Thompson et al. (2017) is employed in this thesis to check 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 then 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. The model fidelity test is applied for all the considered catchments for both the EC-Earth large ensemble simulations and the SEAS5 seasonal hindcasts. Only the catchments where the fidelity test is passed are considered appropriate for use in further analyses.

EC-Earth large ensemble

Figure 3.7 shows the model fidelity test applied for the EC-Earth large ensemble at an example catchment in SE England and the 95 catchments that have passed the fidelity test and retained for subsequent analysis in Chapter 6. As the bias adjustment procedure corrects for mean and standard deviation, the fidelity test is applied to skewness and kurtosis. Catchments that did not pass the fidelity test include ones in central Wales, northwest England and northwest Scotland. These catchments fail after the standard deviation remains outside the 95% of model distribution after the subsequent adjustment of the mean. 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.

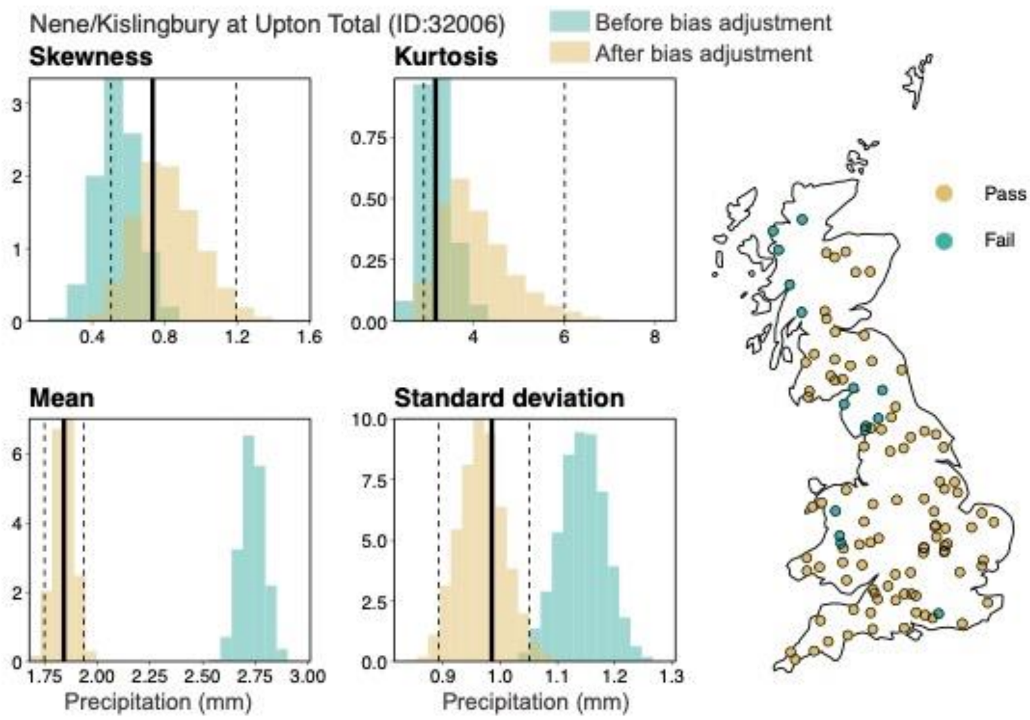

Figure 3.7 a) The distribution of statistical moments of monthly mean precipitation (mm) from bootstrapped samples of EC-Earth SMILE for an example catchment in SE England before (green) and after (yellow) bias adjustment compared to the observed value (1965-2015) (black line). The dotted lines indicate the 5th and 95th percentiles. b) Fidelity result for all selected catchments across GB.

SEAS5 seasonal hindcasts

The credibility of the SEAS5 hindcasts following the model fidelity test in Thompson et al. (2017) is presented in Figure 3.8a. Winter rainfall for the SEAS5 winters over the Anglian Water region is deemed statistically indistinguishable from the observations as the observed mean winter rainfall lies within 95% of the distribution of the mean-adjusted winter rainfall from the subsamples. Additional tests on ensemble member stability and independence are conducted following Kelder et al. (2020, 2022). Stability refers to the potential for ensemble members to drift towards their (biased) climatology from their observation-based initial conditions, and can be assessed by comparing the distribution of simulated variables across lead times (Figure 3.9b). Independence refers to whether individual ensemble members for each lead time are independent of each other and can be assessed by calculating the Spearman rank correlation of modelled rainfall for every distinct pair of ensemble members (Figure 3.9c). The tests show no evidence of model drift and that the ensemble members are independent of each other across the different lead times.

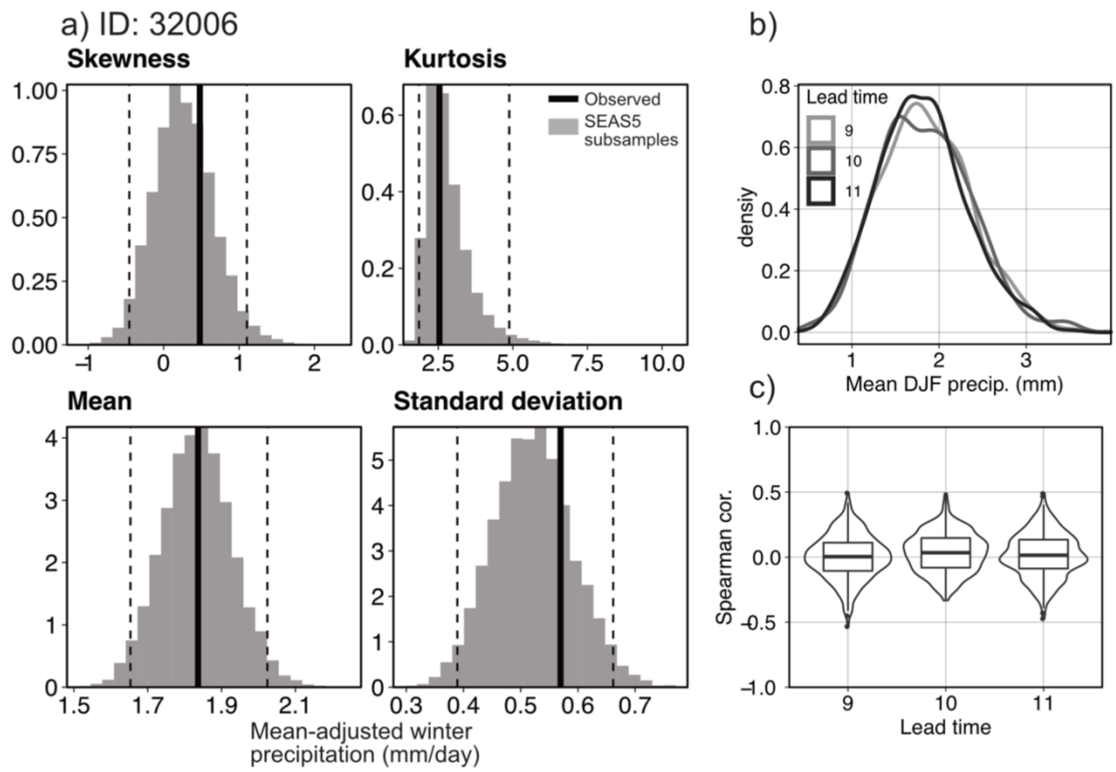

Figure 3.8 Example of the model fidelity test for one catchment (ID: 32006) using the SEAS5 seasonal hindcasts. a) The statistical moments of observed DJF rainfall and of 10,000 subsamples of the modelled rainfall in SEAS5. Hindcast winters are scaled to match the mean observed rainfall. b) Test for model stability and c) ensemble member independence across three lead times.

3.4 Hydrological modelling and model calibration

3.4.1 Hydrological models

In this thesis, the GR4J and GR6J hydrological models are used to simulate the river flow for the baseline and storylines at each catchment. GR4J and GR6J are daily lumped, bucket-type hydrological models with four and six model parameters available for calibration respectively (Perrin et al., 2003; Pushpalatha et al., 2011). Both models take catchment-averaged daily precipitation and PET as the primary input. The GR4J hydrological model has previously been used extensively in the UKCEH Historic Droughts project to reconstruct past UK droughts with newly digitised pre-1961 meteorological records (Smith et al. 2019; Barker et al. 2019). Both GR models have also been applied in the eFLaG ensemble at catchments across the UK to investigate the impacts of climate change on hydrological droughts using the latest UKCP18 projections (Hannaford et al., 2022; Parry et al., 2023). Additionally, both models are widely used for streamflow forecasting, such as within the UK Hydrological Outlook (Harrigan et al., 2018; Prudhomme et al., 2017) and used in practice by water companies for both forecasting and long-term water resources planning under climate change (e.g. Anglian Water Drought Plan 2022).

Figure 3.9 shows a schematic of the structure of the GR4J and GR6J models respectively, which is briefly described in this section. Catchment-averaged daily precipitation and PET are separated into net rainfall and net PET (i.e. net rainfall is P-E if P>E and net PET is E-P if P<E). The production store (maximum capacity determined by parameter **X1**) gains water from net rainfall and loses water from evaporation and percolation to the routing store. Percolated water is split into fixed proportions of which 90% is routed via a unit hydrograph (UH1) into a non-linear routing store (maximum capacity determined by parameter **X3**) while 10% is routed by a single unit hydrograph (UH2). UH1 and UH2 converts rainfall to streamflow and is characterised by the time taken from initial rainfall to subsequent streamflow peak (time lag determined by parameter **X4**). UH1 has a time base determined by X4 while UH2 has a time base that is 2 times the value of X4. A groundwater and inter-catchment exchange determining losses or gains (coefficient determined by parameter **X2**) that is applied to water routed through both UH1 and UH2. Inter-catchment groundwater exchange refers to the possibility that precipitation at one catchment results in streamflow response in the adjacent catchment via subsurface groundwater flow (e.g.

Oldham et al., 2023). The GR6J model has two additional parameters designed to capture river flow recession (i.e. drainage from aquifers) and has been shown to improve simulation of low flows. This means that GR6J could be more appropriate in simulating flows in slower responding catchments underlain by permeable aquifers, such as catchments in the East Anglia region and across southeast England. In GR6J, the groundwater exchange component in GR4J is modified to include the direction of groundwater exchange (gains or loss) within the year (determined by parameter **X5**). GR6J also includes an additional exponential routing store that is more efficient in simulating long streamflow recession (storage coefficient determined by parameter **X6**). Table 3.2 shows the parameters available for calibration of the GR4J and GR6J models and their plausible ranges as used in previous studies for UK catchments.

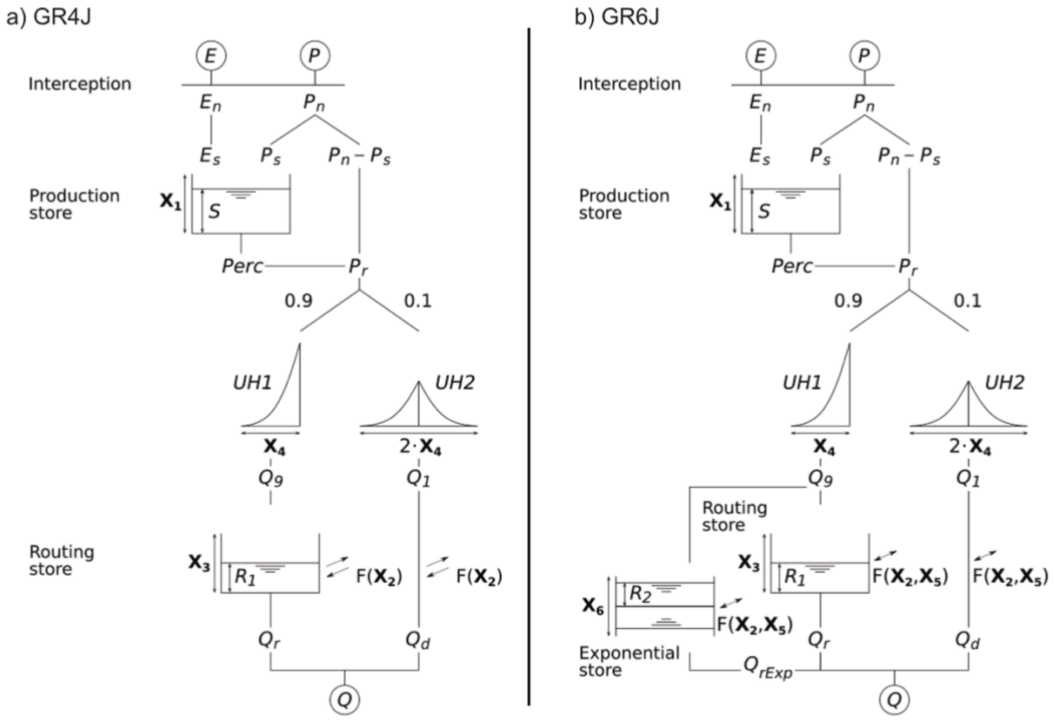

Figure 3.9 Model structure of the a) GR4J (Perrin et al. 2003) and b) GR6J (Pushpalatha et al. 2011) catchment hydrological models. The available parameters for model calibration are indicated by X1-6.

Table 3.2 Parameters available for calibration of the GR4J and GR6J hydrological models. Range refers to the plausible ranges of these parameters which are varied according to the hydrological modelling strategy outlined in the next section (Section 4.3.2)

Parameter	Name	Lower range	Upper range
X1	Maximum capacity of the production store (mm)	0.0001	3000
X2	Groundwater exchange coefficient (mm)	-20	20
X3	Maximum capacity of the non-linear routing store (mm)	0.0001	2000
X4	Time base of the unit hydrograph (days)	0.5	15
Additional parameters for GR6J			
X5	Direction of groundwater exchange (dimensionless)	0	1
X6	Exponential storage coefficient (mm)	0.1	100

Aquimod

Aquimod is used to simulate groundwater levels at selected boreholes in the East Anglia region in Chapter 5. Aquimod is a lumped, bucket-type model developed by the British Geological Survey to simulate groundwater levels at selected boreholes (Mackay et al., 2014). Aquimod is increasingly used in research and industry, including by Anglian Water operationally for their drought forecasts and long-term water resources planning. In brief, Aquimod is modular in structure and provides simplified representations of water movement through the unsaturated zone that is partitioned into groundwater recharge and groundwater flow in the saturated zone. In Chapter 5, Aquimod is driven by catchment-averaged precipitation and PET averaged across the closest 40km MORECS grid to the borehole location (Hough and Jones 1997) in the same way as employed operationally by Anglian Water. A Monte Carlo parameter sampling approach is used to generate a random set of parameters and model performance is assessed using NSE by comparing simulated and observed groundwater levels at individual boreholes (Mackay et al. 2014). The model was previously calibrated for 10 selected boreholes (Bunting et al., 2020) (Table 3.3) and the top parameter set from that study is used.

Table 3.3 Details of the selected groundwater boreholes within the Anglian Water region. The Environment Agency code, borehole name, latitude, longitude and the Nash-Sutcliffe Efficiency (NSE) score for the top performing parameter set are provided. NSE is calculated over the period when observational records area available and based on Bunting et al. (2020).

Environment Agency code	Observation borehole	Latitude	Longitude	MORECS grid	NSE
TM04/695	Castle Farm	52.10	1.01	141	0.79
TL65/050	Dullingham	52.21	0.36	140	0.78
1/610	Grange de Lings	53.29	-0.53	108	0.76
5/108	Horkstow Rd Barton	53.67	-0.45	101	0.59
2/544	Leasingham	53.02	-0.43	118	0.71
TG13/765A	Old Hall Thurgarten	52.89	1.23	120	0.51
TL66/094	Springhead Farm	52.25	0.34	140	0.70
2/566	Stow to Oakholt	53.21	-0.43	109	0.80
TL76/110	Tank Hall	52.26	0.54	140	0.77
TF 81/010	Washpit Farm	52.74	0.69	130	0.78

3.4.2 Calibration strategy

Calibration of the GR4J and GR6J hydrological models follows the multi-objective calibration strategy introduced in Smith et al. (2019). The same calibration strategy is employed for both the GR4J and GR6J models in this thesis for each catchment. Both models are used to simulate river flow over a baseline period (1965-2015) and parameters are calibrated against observed river flows for each catchment. The calibration strategy uses Latin Hypercube Sampling (LHS) to identify suitable parameter sets based on a number of model performance metrics designed to measure model performance for high, mean and low flows (Table 3.4). 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.

Table 3.4 The six evaluation metrics used to select the top parameter set for GR6J at each catchment based on Smith et al. (2019).

Metric	Focus	Range
Nash-Sutcliffe efficiency (NSE)	High flows	-∞ to 1 (perfect)
Nash-Sutcliffe efficiency on logarithmic river flows (logNSE)	Low flows	-∞ to 1 (perfect)
Absolute percent bias (PBIAS)	Overall water balance	0 (perfect) to ∞
Mean absolute percent error (MAPE)	Overall water balance	0 (perfect) to ∞
Q95 (low flows) absolute percent error ($Q95_{APE}$)	Low flows	0 (perfect) to ∞
APE in mean annual minimum (30-day moving average) (MAM30)	Low flows	0 (perfect) to ∞

GR4J simulations (Chapter 4)

GR4J simulations in Chapter 4 relies on the parameter sets calculated in Smith et al. (2019), In Smith et al. (2019), the authors generated 500,000 parameters using LHS and derived the top 500 parameter sets (LHS500) to reconstruct historic river flows and showed that they were able to simulate and reproduce characteristics (timing and magnitude) of key historic droughts. In Chapter 4, the top 500 parameter sets (LHS500) from Smith et al. (2019) are re-ranked based on a differential split-sample experiment. For each catchment, the 10 driest years are selected based on mean annual precipitation (1965–2015). Model performance for each of the driest years is calculated using daily observed and simulated river flow for four of the metrics in Table 3.4, namely NSE, logNSE, MAPE, and PBIAS. The metrics selected are unweighted as the high flows, timing of low flows, flow variability, and overall water balance should be considered equally important for river flows during the driest years to ensure that the full range of flow response during dry years is considered, including the potential for wet interludes or wet antecedent conditions before dry years. The parameter sets are then ranked from best to worst for each metric and given a score (1 to 500, where a higher score implies worse performance). Finally, the LHS500 is re-ranked based on the total score to obtain the sum of scores for each parameter set for each metric. Retaining the new ranking, the performance metrics are re-calculated for each catchment, first for the 10 wettest years and again for all years. The split-sample differential test aimed to investigate how parameter rankings change under different conditions. As seen from Figure 3.10a, model performance is comparable between the new (dry rank) and the original rank (LHS500). NSE and logNSE values show high values across most catchments (Figure 3.10c and d). Notable outliers with relatively poorer performance are fast-responding catchments in northern Scotland, identified in Smith et al. (2019) as catchments with flashy river regimes that are difficult to capture with possible snowmelt processes not incorporated in GR4J. The split-sample experiment indicated that optimising the LHS500 parameter ranking based on dry conditions does not result in significant differences, although, for some catchments, the top parameter set in the dry rank results in a marginally better performance during the driest years. The top-ranked parameter set in the original LHS500 ranking remained unchanged in the dry rank for 17 out of the 100 catchments. For most catchments (54 out of 100), the top parameter set in the new dry rank is within the top 10 of the original LHS500 rankings. For the remaining catchments, the top parameter set in the new dry rank are all found in the top 100 of the original LHS500 rankings (Fig. 3.10e). The top-ranked parameter set from the dry rank is used for GR4J simulations in Chapter 4.

GR6J simulations (Chapters 4, 5 and 6)

GR6J is used in sections of Chapter 4 and for Chapters 5 and 6. In Chapters 4 and 5, GR6J models are driven by ECMWF seasonal hindcasts as described in Section 3.3.4. In Chapter 6, GR6J catchment models are driven by the EC-Earth large ensemble climate model data as described in Section 3.3.3. GR6J model simulations are carried out for all LFBN catchments as for the GR4J but also including the additional catchments in the East Anglia region. For GR6J model calibration, 10,000 parameter sets for the six model parameters of GR6J are generated using LHS within the parameter limits outlined in Table 3.2. The 10,000 parameter sets are ranked for each of the evaluation metrics in Table 3.4 from best to worst and a total score based on the sum of the ranks for each metric is assigned for each parameter set. Similar to GR4J, the metrics selected are unweighted to ensure that the performance for a full range of flow response is captured. For each catchment, the parameter set with the lowest total score (i.e. top performing) is then used to simulate river flows in the respective chapters. Figure 3.11 shows the performance of the top GR6J parameter set across the selected catchments for the six evaluation metrics.

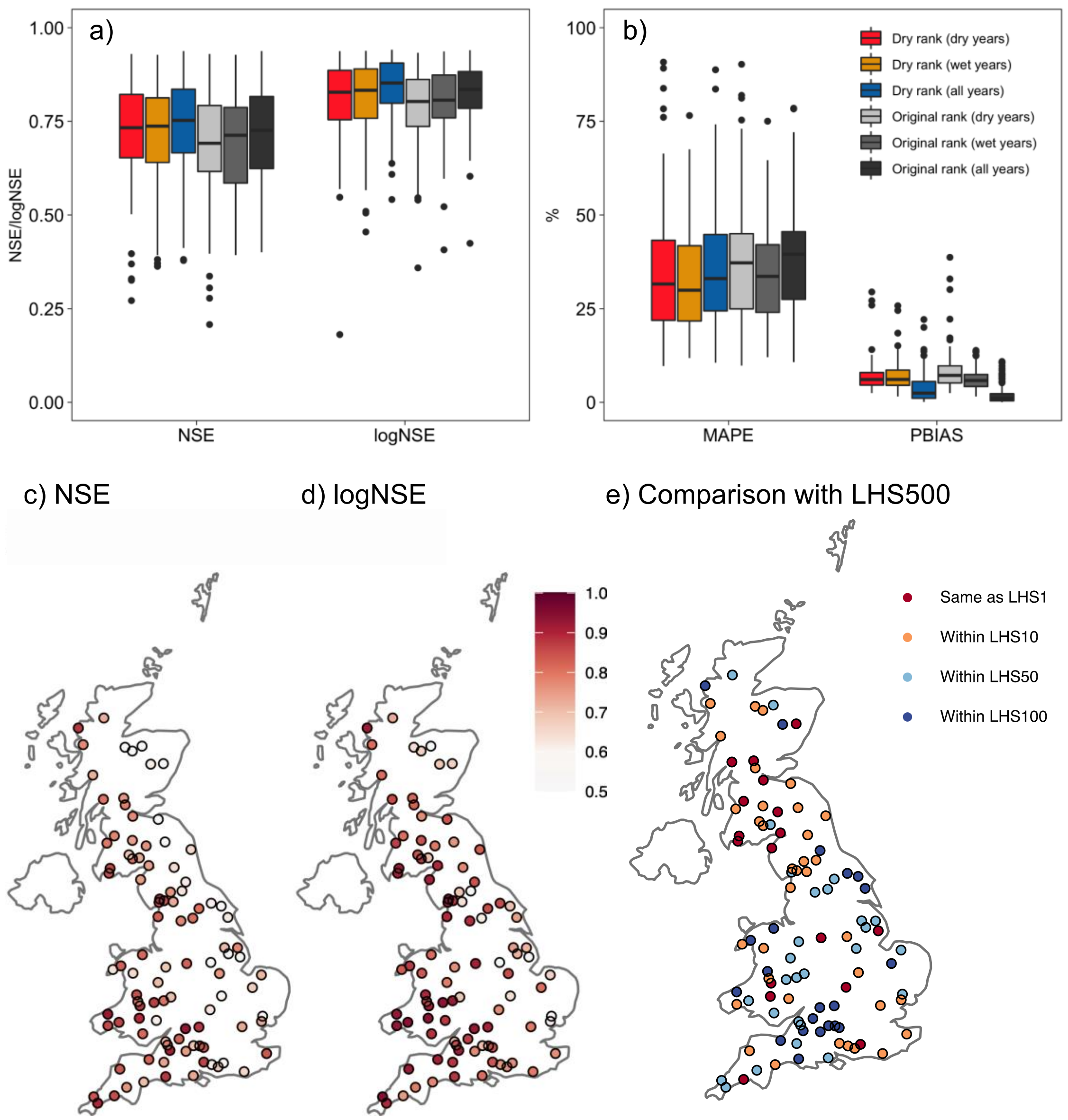

Figure 3.10 Differential split-sample test based on the top 500 GR4J parameter sets for the LFBN catchments in Smith et al. (2019). Panels a) and b) shows model performance of the top-ranked parameter set across the selected catchments between parameter sets ranked based on the 10 driest years (dry rank) and the original LHS500 rank (original rank). Comparison is made for the top-ranked parameter set in either the dry rank or the original rank when the model performance metrics are calculated for the 10 driest years, 10 wettest years, and all years. Panels c) and d) shows distribution of NSE and logNSE values across the selected catchments. Panel d) shows a comparison of the top ranked parameter set in the dry rank compared to LHS500.

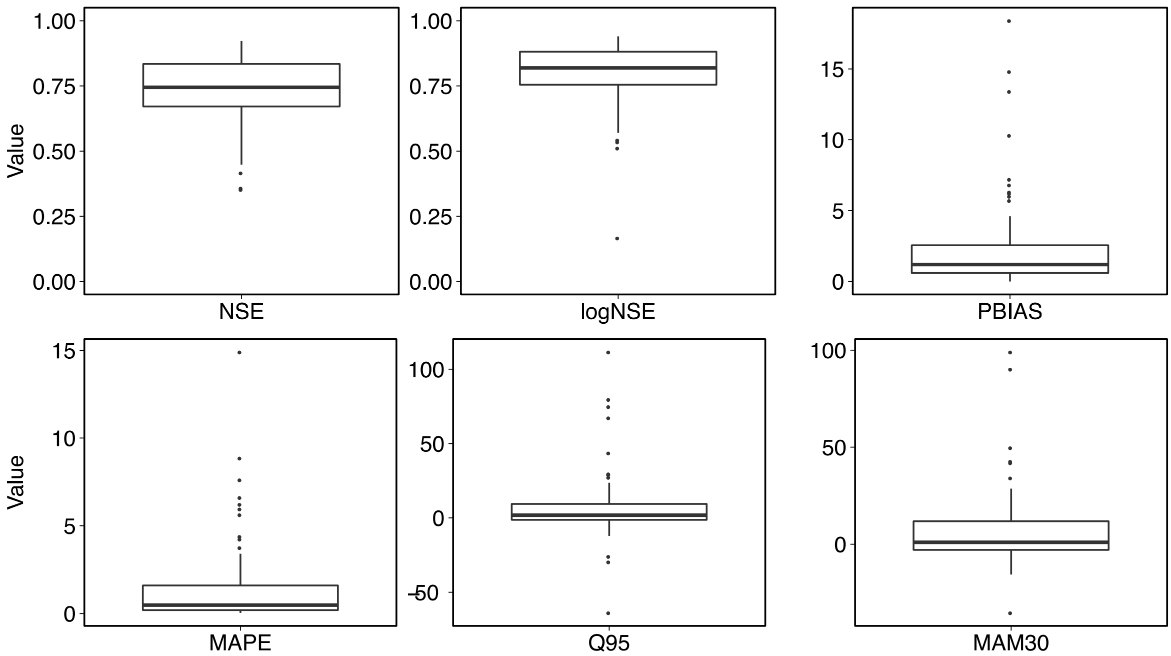

Figure 3.11 Model performance for the top GR6J parameter set across all LFBN and ANG catchments for the six model performance metrics.

3.5 Hydrological drought analysis

3.5.1 Standardised drought indices

Standardised indices such as the standardised precipitation index (SPI) and standardised streamflow index (SSI) are widely used indices to extract events and examine meteorological and hydrological drought characteristics (Vincente-Serrano et al., 2012). The SSI is calculated by accumulating monthly river flows across a user-defined n number of months and fitting a probability distribution function to the accumulated monthly flow for each calendar month and standardised by transformation to a standard normal distribution. Comparing different probability distribution functions, Svensson et al. (2017) concluded that the Tweedie distribution is most suitable for a wide variety of UK catchments and the same procedure to calculate SSI is used in this thesis. SSI fitted using the Tweedie distribution has previously been used for hydrological drought analysis in Barker et al. (2016, 2019) and Arnell et al. (2021). The usefulness of employing standardised drought indices for the UK was demonstrated in Barker et al. (2016). The authors showed how standardised precipitation and streamflow indices can shed light on the propagation from meteorological to hydrological droughts in a wide variety of UK catchments. For example, in the south and east of England where river catchments are groundwater-dominated and underlain by major permeable aquifers, cross-correlation analysis showed that SSI accumulated over 1 month is most strongly correlated with SPI accumulated over multiple months (up to SPI accumulated over 19 months for catchments with slow response times). Standardised drought indices are increasingly used in research and industry in the UK. Water companies may employ SSI to identify thresholds during drought onset before management interventions are required. The identification of catchment response time using standardised indices also allow water resources planners to determine when accumulated precipitation deficit over a critical period are reflected in streamflow response. For example, an accumulated deficits of up to 18-months (including two winters) are deemed the critical period for several reservoir systems within East Anglia (Anglian Water Drought Plan 2022).

Figure 3.12 shows a schematic from Barker et al. (2019) illustrating the methodology used in this thesis to extract various drought characteristics from a time series of the SSI for individual catchments (Chapter 4 and 5). Drought events are defined as periods of consecutive negative SSI with at least one month reaching severe drought (SSI < -1.5). Drought duration, maximum intensity and mean deficit are calculated for each of the extracted drought events. Table 3.5 shows the derivation method for each drought characteristic. Sub-seasonal droughts with a duration of less than 3-months are removed as they are unlikely to incur significant water resources impact. Chapters 4 and 5 employs the SSI to derive drought characteristics from simulated river flows.

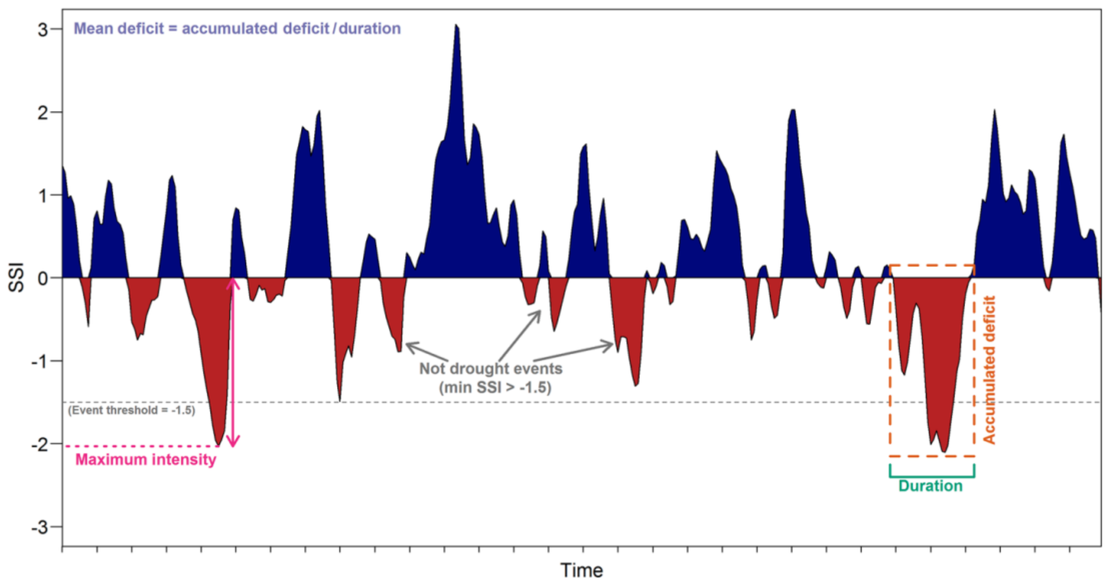

Figure 3.12 Schematic from Barker et al. (2019) showing the approach taken to extract drought events and their characteristics using the standardised stream index (SSI).

Table 3.5 Drought characteristics calculated from events extracted using monthly SSI time series. The same characteristics are calculated for SSI accumulated over various accumulation periods.

Drought characteristic	**Method**
Drought duration	Total number of months across all periods of identified drought conditions within event time frame
Mean deficit	Sum of all SSI/SPI values within periods of drought conditions (accumulated deficit) divided by drought duration
Max. intensity	Minimum SSI/SPI value across all identified periods of drought conditions within the event time frame

3.5.2 Variable threshold method

A second method to extract hydrological drought events is used in this thesis to identify drought events in Chapter 6. The variable threshold method outlined in Van Loon (2015) is selected given its ease of use and quick application to a large sample of simulated river flow time series (schematic of approach shown in Figure 3.13). This is considered advantageous to calculating SSI given the computational demand associated with fitting Tweedie distributions to simulated streamflow derived from the EC-Earth large ensemble in Chapter 6. The variable threshold level method can be applied to different variables of interest, such as precipitation, groundwater level and streamflow to consider different types of droughts. Hydrological drought events are defined as the total period of time when the river flow falls below a user-defined threshold. The threshold can be selected by the user to extract drought events that are most likely to incur high impacts relevant to their sector (for example, water resources managers may select specific thresholds representative of their abstraction licenses). More commonly, the threshold is taken as the percentiles of the flow duration curve in the absence of detailed data on specific drought impacts. In Chapter 6, the 70th percentile of the flow duration curve (Q70) for each month is chosen as the threshold and any period below the monthly varying Q70 is defined as a drought.

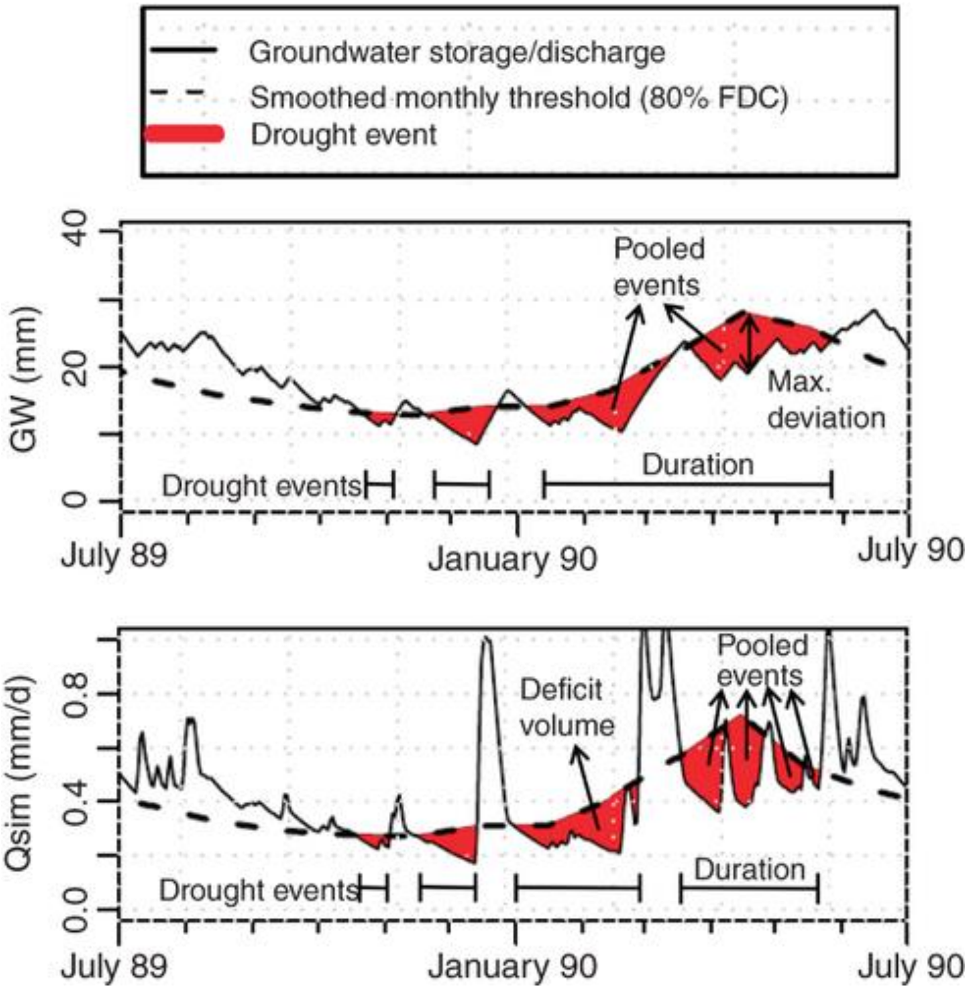

Figure 3.13 Schematic from van Loon (2015) showing the application of the variable threshold method to extract drought events and their characteristics from simulated river flows and groundwater level. Drought duration represents the total time below the threshold and deficit volume and maximum intensity is calculated in relation to the threshold. Events that are close together in time are pooled to form a singular event.

The variable threshold method is widely used and has previously been used to extract droughts at GB catchments from simulated river flows across many studies (e.g. Fleig et al., 2011; Parry et al., 2023; Rudd et al., 2019; Tanguy et al., 2023). 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. The pooling procedure is important to allow for potential wetter interludes within longer prolonged droughts and removes short, sub-seasonal droughts which are unlikely to incur significant water resources impacts.

3.5.3 Historic droughts and river flow reconstructions

Reconstructed standardised streamflow index from 1891 to 2015 is used to place the results of this thesis within a wider historical context in both Chapters 4 and 6. In the UKCEH Historic Droughts project, pre-1961 river flows were reconstructed by driving the GR4J hydrological models at 303 catchments across the UK using newly digitised temperature and precipitation data. Based on simulated river flows from the top performing parameter set for 108 catchments in the LFBN in Smith et al. (2019), historic SSI was reconstructed and the characteristics of notable historic drought episodes were extracted (Barker et al. 2019). Historic drought reconstructions allowed for an improved understanding of drought variability and a re-evaluation of the worst-historic droughts, highlighting droughts more severe than post-1961 events which could serve as additional stress tests for water resources systems. SSI reconstructions from the LFBN catchments from the 1920-21 drought are used in Chapter 4 to compare against simulated river flows of different alternative counterfactual storylines of the 1975-76 drought. River flow reconstructions of various post-1891 droughts (including the 1890-1910 "Long Drought" and the 1920-21 droughts) are used in Chapter 6 to compare with simulated droughts from the large ensemble climate model for both present and future climate.

3.6 Chapter summary

This chapter has presented the data and methods used in this thesis. Observed precipitation and temperature data is used to drive GR4J and GR6J hydrological models at selected catchments across Great Britain and are calibrated against observed river flows. Various sources of model data are also used to analyse the meteorological drivers of climate extremes and drive hydrological models to simulate river flows in present and future climate. This included the UKCP18 projections (Chapter 4), SEAS5 seasonal hindcasts (Chapters 4 and 5) and the EC-Earth large ensemble climate model (Chapter 6). Model data were applied in hydrological models in various ways, either through the delta method, a circulation analogue approach or the direct use of bias-adjusted model data following a series of model fidelity tests. Hydrological drought events are extracted either directly using simulated daily river flows via a variable threshold approach or by converting simulated monthly mean river flows into the monthly standardised streamflow index (SSI) by fitting the Tweedie distribution. Drought characteristics, such as duration, maximum intensity and mean deficit, are calculated to provide further context to understanding the unfolding of hydrological droughts and to infer possible water resources and other environmental impacts.

4 RETROSPECTIVE EVENT STORYLINES

Section 4.3 of this chapter (Storylines of the 2010-12 drought) is published as a paper in the journal *Hydrology and Earth System Sciences,* with the following reference:

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

4.1 Introduction

The literature review in Chapter 2 identified approaches to understand the hydrological impacts of climate change in the UK and showed that they have developed from an initially simple stylised approach focused on system sensitivity but have been dominated, since the mid-1990s, by global climate model (GCM)-driven approaches using a variety of techniques to apply climate change scenarios. Existing research gaps relate to the lack of consideration of plausible high-impact outcomes beyond GCM projections; particularly those related to the sequencing and clustering of meteorological variables which may not be adequately considered. The review also highlighted the limitations of existing approaches and showed that the methodological differences between the approaches present a challenge to fully understanding the hydrological impacts of climate change. As introduced in Chapter 1, storylines are an emerging approach to navigate the cascade of uncertainty which can be used to complement existing practices in hydrological climate change assessment to increase risk awareness of plausible worst cases and explore a wider range of plausible outcomes. Event storylines, in particular, seek to understand the processes and drivers leading up to an event and consider multiple counterfactuals of the event. Section 1.2.3 in Chapter 1 described the event storyline approach and presented recent examples of drought storylines in the literature. This chapter aims to identify opportunities to create event storylines of UK drought, basing analyses on selected past droughts. In particular, this chapter explores the application of downward counterfactual thinking to create event storylines of UK drought. Downward counterfactual thinking explores ways in which observed events could have turned out worse and can identify the combination of conditions that could exceed critical thresholds or result in unprecedented events not seen in the observations (i.e. black swans) (De Bruijn et al., 2016; Woo, 2019; Lin et al., 2020; Woo, 2021). Downward counterfactuals can be motivated by stakeholders' concerns about system vulnerability by specifying plausible changes to an event that could elevate its impacts (Albano et al., 2021). To systematically create downward counterfactuals, Woo (2019) and Lin et al. (2020) proposed a framework consisting of several steps. These steps involve identifying a past historical event, defining acceptable changes to the event's parameters, and determining an "end-of-search" criteria. The end-of-search criteria signify the point at which the consequences of the counterfactual events created can be compared to the historic event. The authors also suggested a range of parameters that can be altered for any given event to create plausible downward counterfactuals. Key parameters proposed by Lin et al. (2020) are summarised in Table 4.1 with amendments in relation to creating downward counterfactuals specifically for hydro-meteorological events which is the focus of this thesis.

Following some of the criteria set out to search for downward counterfactuals in Lin et al. (2020), Table 4.2 presents a selection of notable past UK drought events and examples of potential event storylines that can be created to explore downward counterfactuals and plausible worst cases to inform both current and future risk. Different methods and data may be used to quantify the event storylines of UK droughts, forming multiple lines of evidence to strengthen understanding of the drivers and hydrological impacts of droughts.

Table 4.1 Key parameters to create downward counterfactuals adapted from Lin et al. (2020) with reference to example downward counterfactuals of hydro-meteorological events.

Parameter	Explanation and example
Change in space	Shift in geographical space of the hazard (such as change in the location of impact)
Change in time	Shift in timing of hazard (such as change in seasonal sequences of precipitation deficits)
Change in intensity	Enhanced intensity of hazard (such as greater precipitation deficits from similar atmospheric circulation patterns) resulting in larger impacts
Cascading consequences	Secondary events triggered directly or indirectly from initial hazard (such as change in water quality succeeding a drought leading to water supply interruptions or intense floods after a drought - WSP 2020)
Coinciding consequences	Multiple hazards coincide at the same time which can lead to larger impacts than if hazards occurred individually (such as impact on water supply from hot and dry conditions)
Environmental change	Widespread changes in the overall environment (such as global warming)

Table 4.2 Selected past UK droughts and example event storylines to explore downward counterfactuals and plausible worst cases under both present and future climate.

Drought	Key characteristics	Example event storylines
1890-1910 "Long drought"	Sequences of dry winters with particular dry winters in 1898, 1902, 1905 and 1909	1. What if wet interludes such as 1903 were drier? 2. What if the annual precipitation totals were distributed more evenly throughout the year? 3. Could the hydrological volatility observed be an analogue of future climate?
1921-22	Dry autumn-winter followed by dry spring-summer over southern England exacerbated by hot and dry summer	1. What if the drought occurred in a warmer climate – how severe could the drought be with future drier summers? 2. How might future compound dry spring-summer or autumn-winter sequences unfold and how would it compare with the 1921-22 drought?
1975-76	Dry winter 1975-76 followed by dry spring-summer and abrupt termination in autumn	1. The less severe 1973 drought was terminated in 1974. What was the plausibility of the 1973 drought persisting into the 1975-76 drought? 2. What are the meteorological conditions required for the jet stream to persist in a northerly position beyond autumn?
2003	Short single-season drought characterised by the hot and dry summer	1. Winter 2002/03 was characterised by heavy rainfall. What if the preconditions to summer 2003 were drier? 2. How much more severe would a 2003-like summer be in a warmer climate?
2010-12	Multi-year event with two dry winters and abrupt drought termination in spring	1. What if the drought was preceded or succeeded by a third dry winter? 2. What if the northerly jet stream and dry conditions persisted beyond spring 2012?
2022-23	Driest spring-summer sequence since 1976	1. What were the meteorological conditions required for continued drought development or drought termination?

Using two notable droughts as a case study, this chapter demonstrates various ways in which counterfactual event storylines can provide information on both current and future risk and highlight conditions leading to different types of high-impact drought events. Section 4.2 investigates downward counterfactuals of the relatively short-lived but extreme 1975-76 drought from simple perturbations made to the observed event and its possible unfolding in a warmer climate. Section 4.3 presents an exploration of downward counterfactuals for the relatively more protracted, multi-year 2010-12 drought, including the case of three consecutive dry winters and the occurrence of the event in a warmer world using the UKCP18 projections.

4.1.1 Aims and objectives

The objective of this chapter is to demonstrate the creation of event storylines to explore the hydrological impacts of plausible worst cases and climate change. The 1975-76 and the 2010-12 droughts are selected as the basis to create counterfactual event storylines. The 1975-76 drought is selected as it is widely seen as a "benchmark" drought used by multiple water companies across the UK to stress test their water resources systems, specifically to a dry spring-summer sequence. The 2010-12 drought is selected as it is the most recent spatially extensive multi-year drought event spanning two consecutive dry winters.

4.2 Storylines of the 1975-76 event

The 1975-76 drought was a relatively short-lived but intense drought that affected large parts of the UK and placed significant stress on water resource systems at the time (Rodda and Marsh 2011). The drought remains a 'benchmark' drought that water companies use to stress-test some of their water resource systems, particularly systems that are sensitive to single-season precipitation deficits (i.e. typically smaller reservoirs). Drought conditions began in spring 1975 with large precipitation deficits in the 16 months prior to August 1976, including the dry winter of 1975-76. The maximum intensity of the drought was reached in the hot and dry summer of 1976. High evaporative losses during the summer of 1976 significantly influenced drought severity and led to strong soil moisture deficits. Slow-responding, groundwater-dominated catchments in eastern England were comparatively less affected during the drought compared to other catchments across the UK, as river flows and groundwater levels were well stocked from above-average precipitation over winter 1974/75 (Durant, 2015; Lister et al., 2018). It should be noted that although intense, the maximum intensity of the 1920-21 drought was more severe at several of the selected catchments (as shown by Barker et al., 2019), and the impacts of the 1976 drought on water resources from a demand restriction perspective were less severe than the more protracted 1989-93 drought with longer periods of accumulated precipitation and river flow deficits (Anglian Water Drought Plan 2022).

Table 4.3 presents the three sets of storylines created for catchments within the Anglian Water region (catchments described in Chapter 3: Section 3.2.1). These storylines serve as demonstrations of how relatively simple perturbations to an observed event can be used to explore downward counterfactuals of hydrological drought events. The river flows for each storyline are simulated using the calibrated GR6J hydrological models for each catchment (model described in Chapter 3: Section 3.4.1). Drought characteristics of the storylines are derived from calculating the standardised streamflow index (as described in Chapter 3: Section 3.5.1) and compared to the baseline simulation of the observed 1975-76 drought.

Table 4.3 Storylines considered for the 1975-76 drought and research questions for each storyline.

Storyline	Research questions	Method	Section
Extension in geographic space	What if autumn 1975 in East Anglia matched the rainfall deficit in neighboring East Midlands?	Autumn 1975 rainfall deficit in East Anglia region reduced to match rainfall deficit observed in East Midlands	Section 4.2.1
Enhanced intensity	What if winter 1975-76 was drier than observed given similar circulation patterns?	Sample for winters with similar circulation patterns observed in winter 1975-76 in the SEAS5 hindcasts	Section 4.2.2
Climate change	What might happen if similar circulation patterns to the 1975-76 drought occur in a warmer world?	Circulation analogues approach applied using the 12-member UKCP18 regional climate projections	Section 4.2.3

4.2.1 Expansion in geographic space

The first storyline relates to a geographical shift in the precipitation deficit observed in autumn 1975. Figure 4.1 shows the meteorological conditions over the Euro-Atlantic region during autumn 1975 (SON). September 1975 was particularly wet for eastern England, which received 176% of the long-term average (LTA) precipitation due to cyclonic conditions and the meandering of the jet stream, bringing rain-bearing systems to southern England (Figure 4.1a). Reservoir levels at some reservoirs rose or declined at a slower pace due to the wetter conditions (Marsh and Rodda 2011). Perry (1976) hypothesized that anomalously warm sea surface temperatures south of Greenland could have been a driver of high September precipitation. Research has found that warmer than average SSTs in that region can influence the North Atlantic Oscillation, the leading mode of variability that explains the variability in UK rainfall and favour NAO phases associated with increased precipitation (Rodwell et al., 1999). In comparison, the East Midlands region received moderate precipitation (98% of the LTA September). October and November 1975 were dry across the UK, but the precipitation deficit in eastern England was not as severe as in the East Midlands region. Throughout the season, the greatest deficit was observed in the East Midlands region (Figure 4.2a), amounting to 63% of the LTA autumn precipitation. In contrast, eastern England experienced relatively wetter conditions throughout the season, with 91% of the LTA autumn precipitation. This storyline considers what if the same level of precipitation deficit observed in autumn 1975 in the East Midlands region was also observed in the eastern England region. The storylines were created for each catchment by reducing autumn 1975 precipitation over eastern England to match the precipitation anomalies observed in the East Midlands for each month.

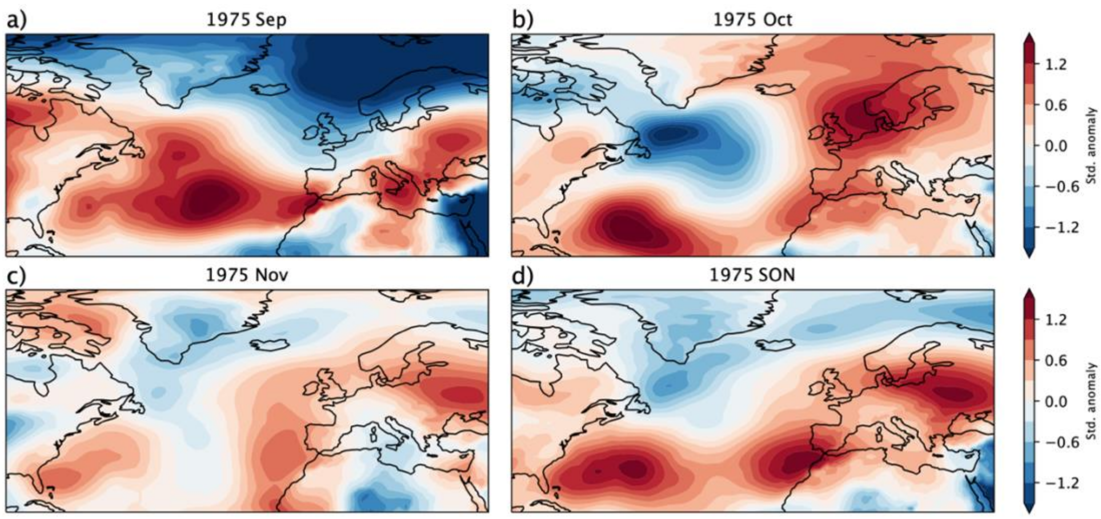

Figure 4.1 Mean sea level pressure (SLP) anomalies (relative to 1965-2015) from the ERA5 dataset for autumn (SON) 1975. The mean SLP anomalies across the whole season is shown in panel d).

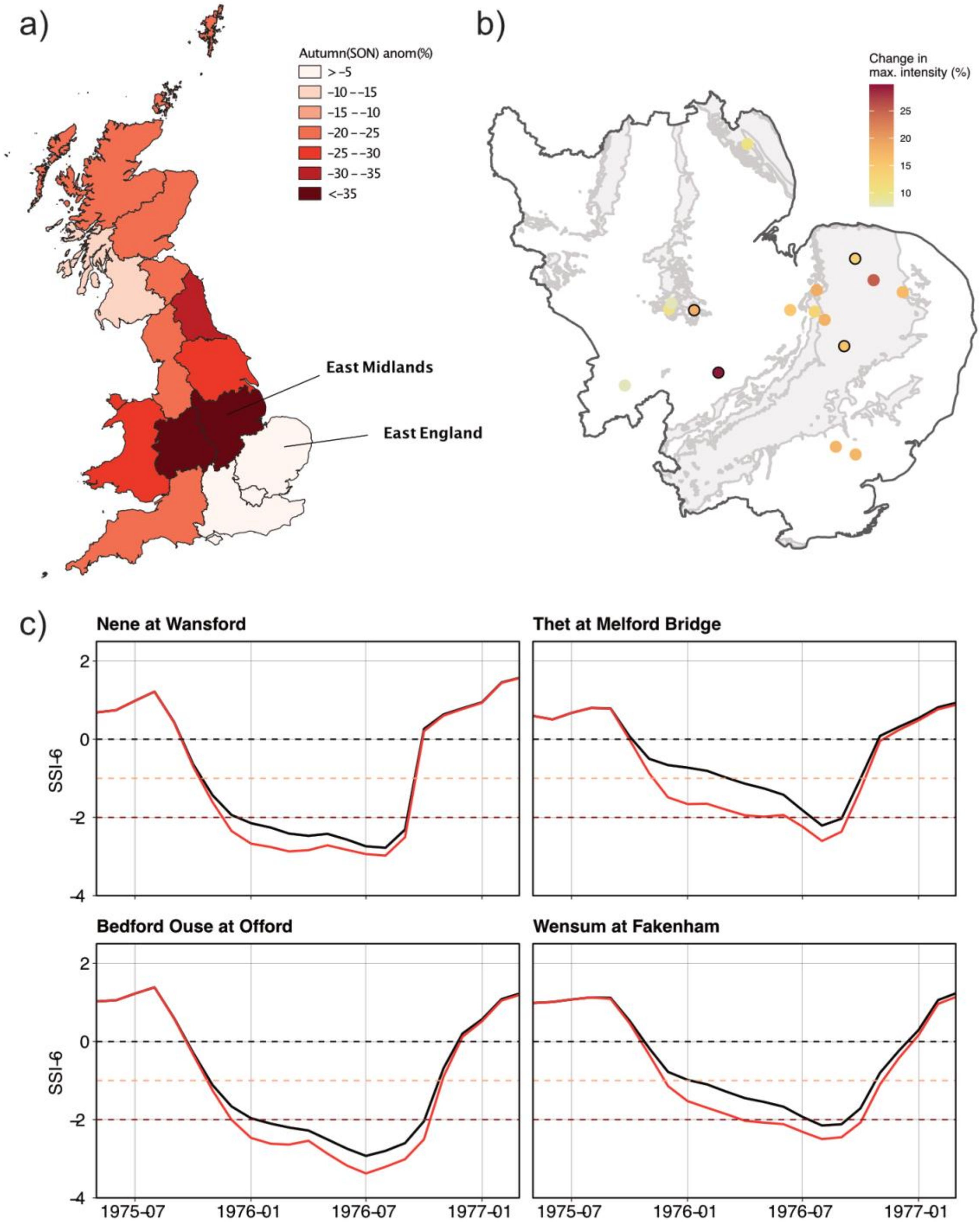

Figure 4.2 Downward counterfactuals of the 1975-76 drought given a geographic shift in precipitation deficit during autumn 1975 for the East England region to match the precipitation deficit observed in the East Midlands. Panel a) shows observed precipitation anomalies (%) during autumn 1975. Panel b) shows the change in max. intensity of the 1975-76 counterfactual storylines calculated from SSI-6 relative to the baseline observed event in catchments within eastern England. Panel c) shows SSI-6 over the drought period for the observed baseline (black) and simulated storyline (red) for four example catchments. The four example catchments are highlighted with black borders in the map in panel b.

Figure 4.2b shows that the maximum intensity of the drought across all selected catchments could have been worse given a change in autumn 1975 conditions. Table 4.4 shows the 12-month accumulated flow (Oct 1975 to Sep 1976) of the baseline and counterfactual storyline for each catchment. A more severe precipitation deficit in autumn 1975 would lead to a reduction in river flows ranging from 14% to up to 58% in 12-month accumulated flows. The evolution of SSI-6 shows the importance of autumn conditions in the observed event in prolonging drought inception (Figure 4.2c). Compared to catchments in other parts of the UK, there was a lag in drought inception for southeast and eastern England due to a combination of higher river flows and groundwater levels before spring 1975 and the slow-responding nature of groundwater-dominated catchments (Parry et al., 2012). Although the exceptionally high observed precipitation in autumn 1976 would still have been enough to terminate the drought, the downward counterfactual shows that groundwater-dominated catchments could have been placed under further water resources stress as they are more susceptible to prolonged precipitation deficiencies.

Reconstructed SSI-6 since 1891 from Barker et al. (2019) are available from some of the selected catchments. For these catchments, the 1920-21 drought holds the highest rank in terms of maximum intensity, while the 1975-76 drought is regarded as the worst in terms of mean deficit. As seen from Table 4.5, it is evident that, for some catchments, the downward counterfactual storyline's estimated maximum intensity surpasses that of the 1920-21 drought. (e.g. Lud at Louth, Bedford Ouse at Offord) This suggests that by making a simple adjustment to the autumn 1975 precipitation, which could plausibly have arisen from natural climate variability, it would have been possible for the 1975-76 drought to surpass the 1920-21 drought and become the most severe drought since 1891, considering both maximum intensity and mean deficit.

Table 4.4 12-month accumulated flow (Oct 1975 – Sep 1976) and deficit relative to the long-term average for the baseline 1975-76 drought and the counterfactual storyline for each catchment

ID	Name	Observed accumulated flow (mm)	Counterfactual accumulated flow (mm)	Observed % of LTA	Counterfactual % of LTA
37024	Colne at Earles Colne	76.0	56.0	48.2	35.6
31007	Welland at Barrowden	37.1	26.1	22.1	15.6
33026	Bedford Ouse at Offord	20.0	8.3	11.6	4.8
37005	Colne at Lexden	50.6	27.9	35.1	19.3
31010	Chater at Fosters Bridge	91.2	74.0	37.3	30.3
33035	Ely Ouse at Denver Complex	45.5	23.9	33.0	17.4
32006	Nene at Upton Total	71.3	53.4	31.3	23.4
32010	Nene at Wansford	73.0	62.2	34.8	29.7
34014	Wensum at Swanton Morley Total	117.3	94.0	53.4	42.8
34004	Wensum at Costessey Mill	116.1	92.5	54.6	43.5
33019	Thet at Melford Bridge	110.0	79.4	59.5	43.0
33006	Wissey at Northwold Total	126.4	95.8	57.9	43.9
34011	Wensum at Fakenham	61.3	43.5	40.5	28.8
33029	Stringside at Whitebridge	54.3	32.9	33.3	20.2
33007	Nar at Marham	89.3	60.5	42.6	28.9
29003	Lud at Louth	66.4	43.9	25.8	17.1

Table 4.5 Max. intensity calculated from SSI-6 of the 1921-22 drought and the counterfactual storyline of the 1975-76 drought and relative change at catchments where reconstructed SSI-6 of the 1921-22 drought from Barker et al. (2019) is available.

Catchment ID	Catchment name	1921-22 drought	Storyline 1975-76 drought	Change (%)
29003	Lud at Louth	-2.54	-2.76	8.7
31010	Chater at Fosters Bridge	-3.09	-2.61	18.7
32006	Nene at Upton Total	-2.67	-3.00	12.2
33026	Bedford Ouse at Offord	-2.90	-3.37	16.2
33029	Stringside at Whitebridge	-2.73	-2.90	5.6
34011	Wensum at Fakenham	-3.09	-2.54	-17.6
34014	Wensum at Swanton Morley Total	-3.15	-2.62	-16.6
37005	Colne at Lexden	-3.45	-2.72	-21.4

4.2.2 Enhanced intensity

The winter half-year 1975-76 (October to March) experienced less than 50% of long-term average precipitation and was characterized by strong La Niña conditions (Folland et al., 2015). Insufficient replenishment of river flows and groundwater levels occurred during the winter season, leading to the intensification of drought conditions following the hot and dry summer of 1976 (which received only 57% of the long-term average winter precipitation over East England). A plausible downward counterfactual would be what if winter 1975-76 was even drier than observed. This hypothetical scenario could arise due to natural climate variability, whereby similar atmospheric circulation patterns to those observed during the winter could plausibly result in even drier conditions. However, quantifying this scenario is challenging due to the limited length of observations. This section utilizes a large sample of plausible winters in the SEAS5 seasonal hindcast dataset (as described in Chapter 4; Section 4.3.3). This dataset is used to identify plausible winters where atmospheric circulation patterns resemble those observed during the winter of 1975-76 but exhibit even greater precipitation deficits. This approach follows previous work which uses seasonal hindcasts or large ensemble climate model simulations to expand the observational record and search for unprecedented climate extremes that may arise from internal climate variability (Brunner and Slater, 2022; Kelder et al., 2020; Thompson et al., 2017).

Based on the NAO index and EA index calculated from the ERA5 reanalysis dataset, the observed winter 1975-76 exhibited NAO+/EA- atmospheric circulation patterns (Figure 4.3a). Out of the 2850 plausible winters in the SEAS5 hindcasts, 238 La Niña winters showed similar atmospheric circulation patterns to winter 1975-76. The composite mean meteorological conditions during winters in the hindcast dataset with NAO+/EA- atmospheric circulation patterns show conditions similar to those observed during the winter of 1975-76 although the high pressure was more pronounced in the observed 1975-76 winter (Figure 4.3b). The associated surface response show precipitation deficit across the UK and warmer than average temperatures (Figure 4.3c-d). Winters which had lower precipitation anomalies over the east England region compared to winter 1975-76 show similar SLP anomalies as seen in the observed winter but with the high pressure further shifted eastwards centred over the British Isles rather than to the west (Figure 4.3e). This eastward shift would result in a diversion of the jet stream, potentially bringing even drier and warmer conditions across the UK, with western Scotland experiencing the highest temperature anomalies.

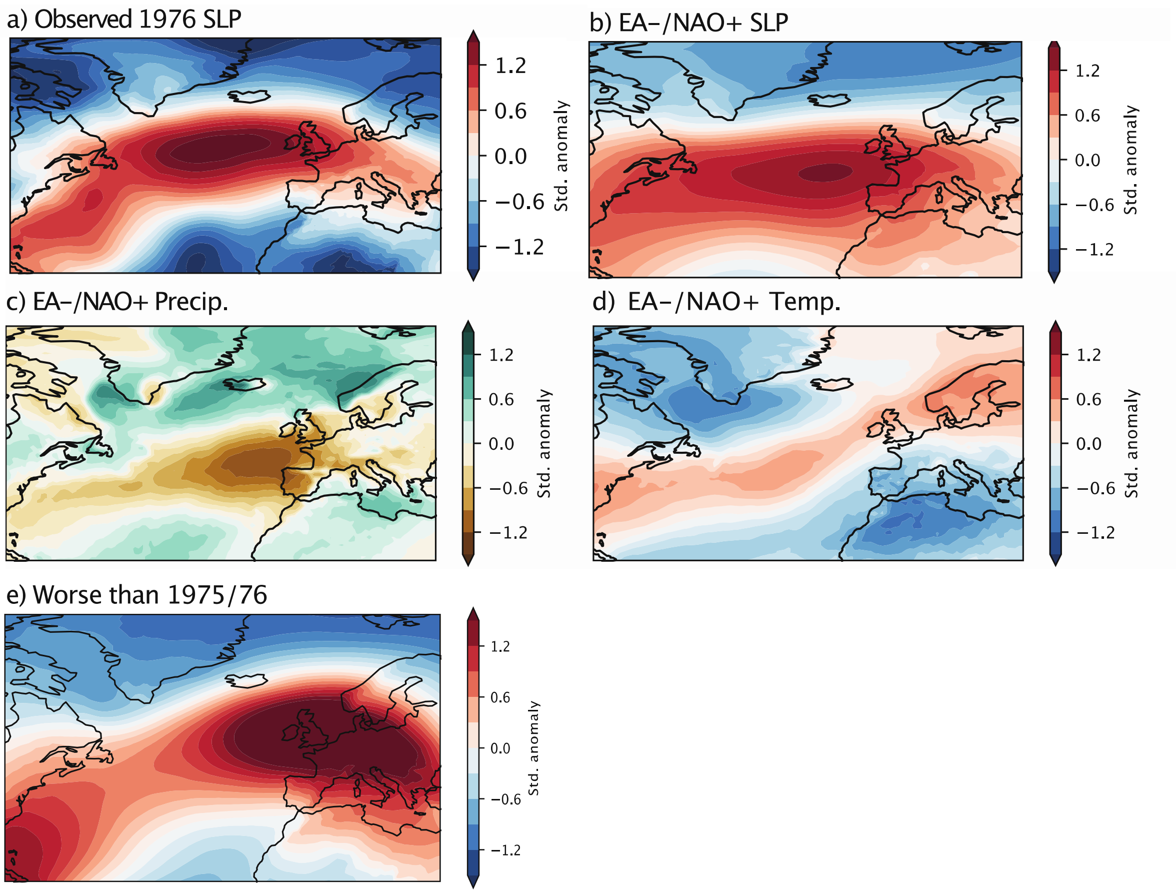

Figure 4.3 Composite mean a) precipitation, b) temperature and c) sea level pressure anomalies (relative to 1965-2015) for all winters in the SEAS5 hindcasts with NAO+/EA- atmospheric circulation patterns. Panel d) shows ERA5 SLP anomalies for the observed 1975-76 winter. Panel e) shows SLP anomalies associated with winters in the hindcasts which have lower precipitation anomalies over the Anglian Water region relative to the observed 1975-76 winter.

Counterfactual storylines are created by running hydrological model simulations using the precipitation and temperature of the NAO+/EA- winters in the hindcast dataset in place of the observed winter 1975-76. Figure 4.4 illustrates SSI-6 at four example catchments with contrasting BFI values, comparing the observed 1975-76 drought with the simulated storyline in which the winter of 1975-76 is replaced by all winters in the hindcast dataset that share similar NAO+/EA- atmospheric circulation patterns. Across all catchments, there exist winters in the hindcast dataset with comparable atmospheric circulation patterns that could have resulted in even drier conditions and thus more severe drought episodes. The response of river flows to the counterfactual storyline underscores the significance of winter precipitation for catchments in this region, particularly in slow-responding groundwater-dominated catchments. Although autumn precipitation in 1976 would still be enough to terminate the drought, the slow response nature of groundwater-dominated catchments could have meant a lagged response to a drier winter 1975-76 and a delay in drought termination. For example, the river flows at Wensum at Costessey Mill (BFI: 0.76) and Nar at Marham (BFI: 0.9) both show long persistence times with river flow response to alternative winter conditions lasting into late 1976 and early 1977.

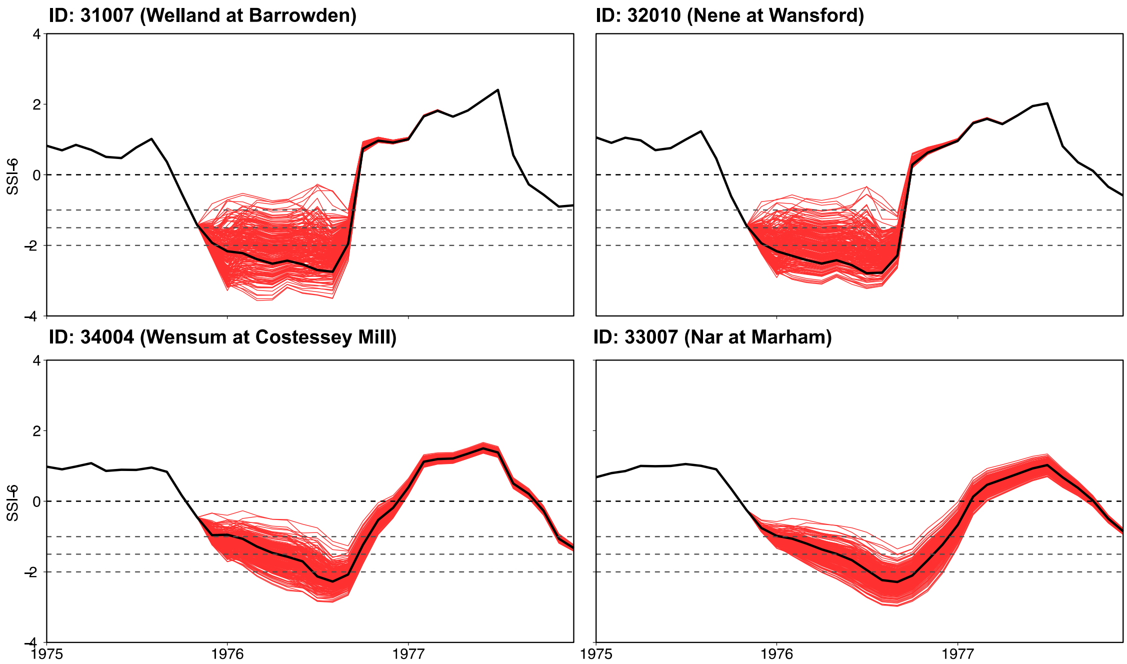

Figure 4.4 Simulated storylines of the 1975-76 drought (red) compared to the baseline simulation of the observed 1975-76 drought (black) at four example catchments. In each storyline simulation, winter 1975-76 is replaced with winters in the SEAS5 hindcast dataset with similar atmospheric circulation patterns.

Previous studies have attempted to quantify the return period of the 1975-76 drought using extreme value analysis (Burke et al., 2010; Rodda and Marsh, 2011). Storyline analyses enhance these probabilistic estimates by providing a contextual understanding of the winter 1975-76 precipitation deficits, thereby quantifying the range of potential impacts that could have transpired. Figure 4.5 shows the distribution of three drought characteristics of the counterfactual storyline compared to characteristics calculated from the observed event for each catchment. The results show the likelihood of more severe drought conditions with winter 1975-76 being drier even with similar atmospheric circulation patterns than observed. There is a higher chance of exceeding the observed drought characteristics at groundwater-dominated catchments with higher BFI. This is exemplified by several catchments with high BFI, where more than half of the hindcast winters featuring similar atmospheric circulation patterns could have resulted in more severe drought conditions than observed. On the other hand, catchments that exhibit relatively faster response times are less affected by an even drier winter in 1975-76, which makes surpassing the record of the observed drought less likely.

As with the quantification presented in Table 4.5 in the previous section, Table 4.6 compares the maximum intensity of the counterfactual storyline with the top-ranked drought (1920-22 drought) at catchments where reconstructions of post-1891 SSI-6 are available. For some catchments such as Lud at Louth (ID: 29003), there is a high chance of the counterfactual storyline exceeding the 1921-22 drought by up to 36% to become the top-ranked drought in terms of maximum intensity since 1891. Although a drier 1975-76 is estimated to lead to a worsening of the drought and a delay in drought termination for catchments such as the Wensum (ID: 34011 and 34014), results show that this is not enough to lead to the exceedance of the maximum intensity record set during the 1921-22 drought.

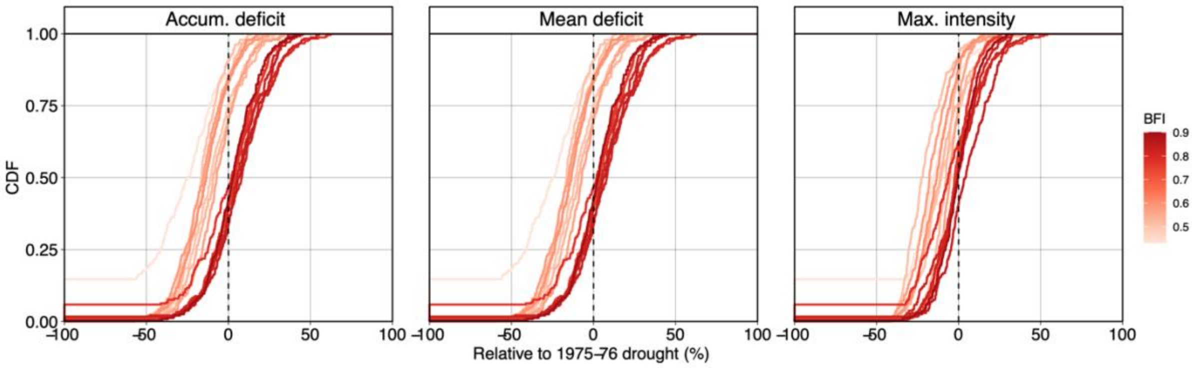

Figure 4.5 Distribution of drought characteristics calculated from SSI-6 relative to the baseline 1975-76 drought. Each line represents a catchment in the Anglian Water region and is coloured by baseflow index (BFI). Positive values on the x-axis mean worse than the 1975-76 drought.

Table 4.6 Likelihood of exceeding the max. intensity calculated from SSI-6 of the 1921-22 drought at catchments where reconstructed SSI-6 of the 1921-22 drought from Barker et al. (2019) is available. Percentage change in max. intensity relative to the 1921-22 drought is also presented (5 to 95% range).

ID	Catchment name	% of winters within SEAS5 ensemble exceeding max. intensity of 1921-22	Change in max. intensity relative to 1921-22 (%) [5 – 95% range]
29003	Lud at Louth	53.8	1.2 – 36.5
31010	Chater at Fosters Bridge	36.6	1.1 – 34.6
32006	Nene at Upton Total	14.7	0.8 – 25.5
33026	Bedford Ouse at Offord	8.8	0.2 – 14.1
33029	Stringside at Whitebridge	14.3	0.3 – 7.6
34011	Wensum at Fakenham	0	0
34014	Wensum at Swanton Morley Total	0	0
37005	Colne at Lexden	0	0

4.2.3 Climate change

As described in Chapter 1, water companies regularly use climate model projections to inform their understanding of how drought events may change in a future climate. However, given the challenges associated with traditional climate change attribution, it remains difficult to understand the impacts of climate change should historical events occur again in a warmer climate. This section uses the circulation analogue approach (as described in Section 3.3.2) to condition on the observed circulation patterns of 1975-76 and create storylines of how the event could unfold with future climate change. Circulation analogues were generated by searching for days with similar circulation patterns to each day of the observed 1976 drought (December 1975 to August 1976) for the 12 ensemble members of the UKCP18 regional projections at a baseline (1980-2020) and future (2050-2080) periods. To account for biases in precipitation and temperature, the modelled data is adjusted to match the mean observed precipitation and temperature over the eastern England region. Taking summer 1976 as an example, in the baseline period, the precipitation variability from day to day of the circulation analogues differ between ensemble members (Figure 4.6a). Although the ensemble mean total precipitation is similar to the observed, estimated precipitation from the circulation analogues is in general higher than observed. The ensemble mean temperature anomalies from the circulation analogues generally capture the observed temperature variability but underestimate the peak temperatures in late June 1976 (Figure 4.6b). Days with similar circulation patterns to JJA 1976 in the future period are associated with drier and warmer conditions compared to the baseline. This is evident in lower cumulative precipitation across the summer for the future analogues (Figures 4.6c and d). The mean summer precipitation in the future analogues is estimated to decline across all ensemble members with some decreasing by over 70% (Figure 4.6e).

Figure 4.7a and b shows projected change in mean precipitation and temperature for the future analogues relative to the baseline analogue for all seasons of the 1975-76 drought. Future analogues are associated with a wide range of precipitation and temperature responses, representing the uncertainty range sampled by the perturbed parameter ensemble. All members agree on a reduction in summer precipitation as seen in Figure 4.6 with more uncertainty for winter and spring. Unsurprisingly, all ensemble members project an increase in temperature in the future analogues with the largest increase in temperature for summer. Variation in response is due to epistemic uncertainty over the response of atmospheric circulation to climate change, such as jet stream latitude across the ensemble members as shown by Harvey et al., (2023). The results imply that should similar circulation patterns to the 1975-76 drought occur in a warmer climate, the event seen in summer 1976 would likely be even drier (precipitation reduce by up to >-75%) and hotter (temperature increase by up to >5°C). While more ensemble members project for winter 1975-76 to become wetter, some ensemble members show a reduction in precipitation (up to -25%). Figure 4.7c shows simulated river flows at four example stations with observed precipitation and temperature perturbed by the monthly changes in precipitation and temperature between the future and baseline analogues. Compared to the observed event, the maximum intensity of the drought is projected to lessen for most ensemble members across the selected catchments with a warmer climate. As many of the selected catchments depend on groundwater recharge in winter, the fact that more ensemble members are projecting an increase in precipitation for winter 1975-76 results in overall wetter conditions across the drought period. Despite this, most ensemble members show that the 1975-76 drought in a warmer world would still reach the severe drought threshold of SSI <-1.5. For some catchments (e.g. Wensum at Fakenham), ensemble members which projected moderate change in winter precipitation and a reduction in spring precipitation could increase in maximum intensity.

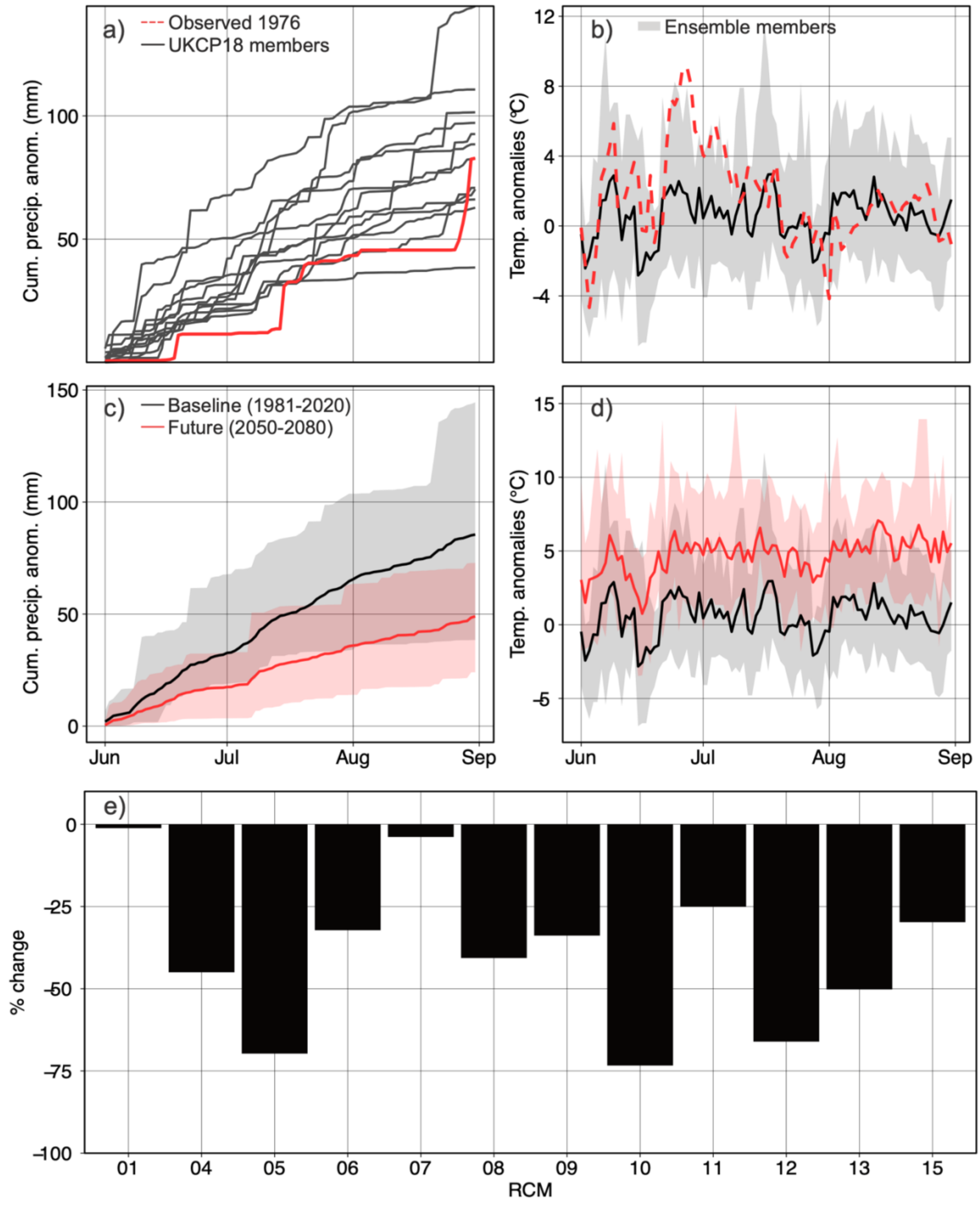

Figure 4.6 Circulation analogues of summer 1976 in the baseline (1981-2020) and future (2050-2080) period across the 12 ensemble members of the UKCP18 regional projections. Panels a) and b) compares cumulative precipitation and temperature anomalies associated with the baseline circulation analogues and observed precipitation and temperature for each day of summer 1976. Panels c) and d) shows cumulative precipitation and temperature anomalies of the baseline and future circulation analogues over summer and panel e) shows the change in mean precipitation in the future analogues compared to the baseline analogues across each ensemble member.

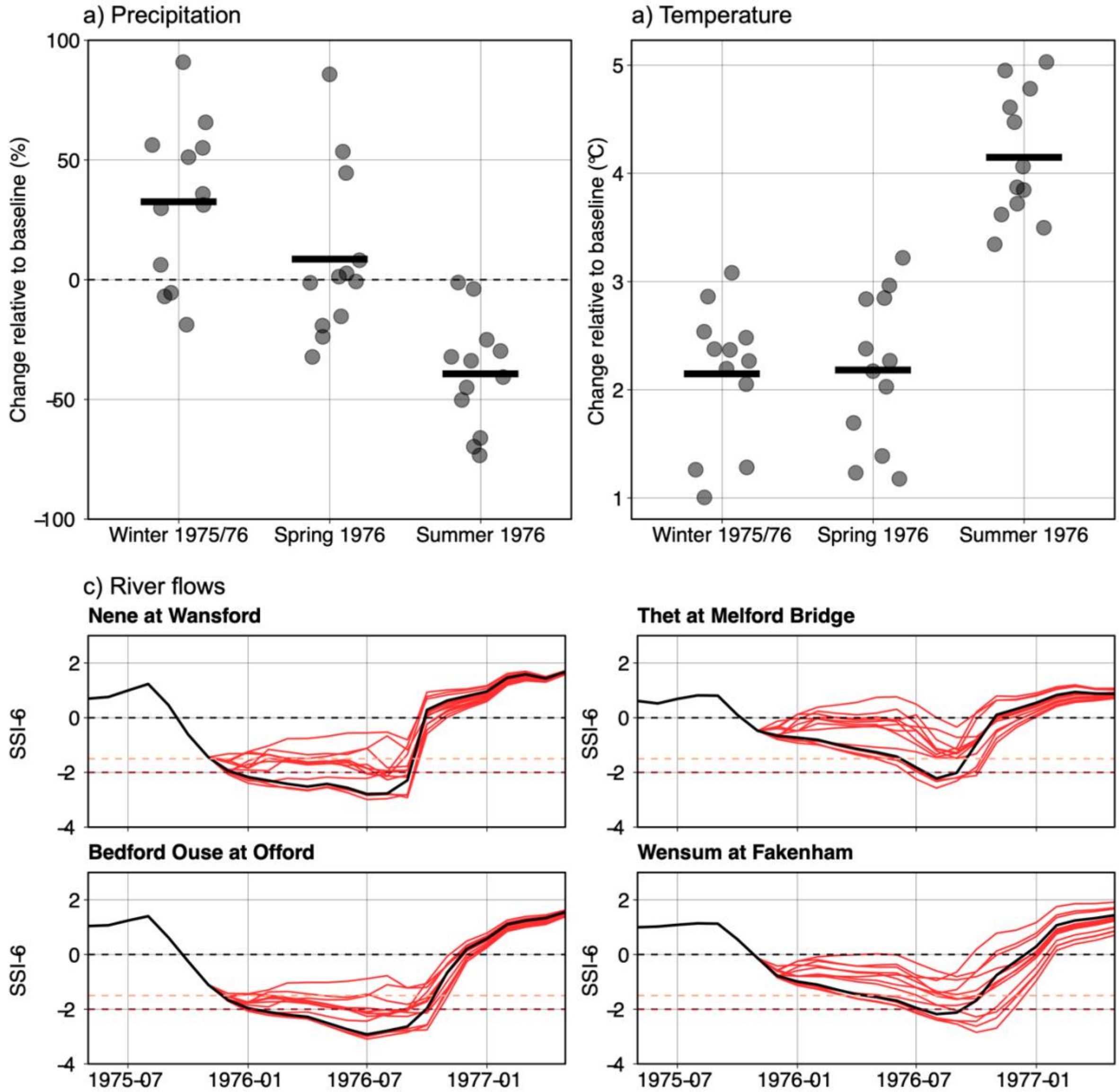

Figure 4.7 Change in precipitation (a) and temperature (b) in the future analogues relative to the baseline analogues for each of the 12 regional projections (dots) and the ensemble mean (line). Panel c) shows simulated river flows across four example catchments with the observed meteorological input perturbed by the monthly changes in precipitation (%) and temperature (°C) in panels a) and b).

The circulation analogues show that, in a warmer world, the re-occurrence of similar circulation patterns to the 1975-76 drought may lead to less severe river flow response for most ensemble members. However, these results do not imply a reduction in drought severity in the future or that a future drought as severe as the 1975-76 drought is less likely. Sampling for hazard analogues based on similar or worse meteorological extremes (such as similar precipitation deficits) can further inform the future risk. For example, Baker et al., (2021) used climate model simulations to show that the joint probability of a hot summer preceded by a dry winter-spring sequence like

1976 and a hot and dry summer similar to summer 1976 has increased since the 1970s. van der Wiel et al. (2022) also demonstrated an approach to sample for analogues similar in precipitation deficit as the 2018 drought by searching within a large ensemble. The robustness of the results depends on the quality of the circulation analogues. The average Euclidean distance between the observed SLP anomalies and the baseline and future analogues does not differ significantly (Figure 4.A.1, Appendix). This analysis does not consider the possibility that circulation patterns observed in 1975-76 may occur less frequently in the future.

4.2.4 Synthesis and summary of the 1975-76 event storylines

Section 4.2 has presented storylines of the 1975-76 drought to explore downward counterfactuals in various ways from simple perturbations made to the observed event. Key results from Section 4.2 are presented below:

- A more severe precipitation deficit in autumn 1975 could have led to a significant reduction in river flows across the selected catchments. If autumn 1975 in eastern England were as dry as the Midlands, catchments across the region would have been further stressed due to their susceptibility to prolonged precipitation deficits. This storyline showed that the 1975-76 drought could have surpassed the 1920-21 drought at slow-responding catchments by >15% to become the most severe drought since 1891 in terms of both maximum intensity and mean deficit.
- The dry winter 1975-76 led to insufficient replenishment of river flows. A storyline considering even drier conditions, using a large number of plausible winters with similar atmospheric circulation patterns to winter 1975-76 showed that more severe drought conditions could have occurred. The response of river flows to this storyline is particularly significant for groundwater-dominated catchments (up to 36% more intense than 1920-21), highlighting their vulnerability to low winter recharge. Flow response at fast-responding catchments was less likely to be affected as they were more impacted by the extreme spring-summer sequence.
- A circulation analogues approach showed that similar circulation patterns to the 1975-76 drought could lead to less severe drought conditions in a warmer world compared to the observed event. There is uncertainty across different ensemble members of the UKCP18 projections for the different seasons but members agree that similar circulation patterns to

summer 1976 would result in a reduction in summer precipitation in a warmer world. It may remain possible for an event as severe or worse than the 1975-76 drought to occur due to other circulation patterns in the future. Sampling for events as severe or worse than 1975-76 in model simulations can determine their likelihood.

4.3 Storylines of the 2010-12 event

Storylines for the 1975-76 drought showed that relatively simple shifts in an event's characteristics can be valuable to understand worst cases and the magnitude of plausible impacts. This section explores counterfactuals for the longer, 2010-12 multi-year drought on a national scale. This section uses river flow simulations at LFBN catchments in Great Britain (as described in Chapter 4: Section 4.2.1). The 2010–2012 drought is ranked among the top 10 most significant multi-year droughts in the English lowlands for the past 100 years (Folland et al., 2015). The precipitation during winters 2009/2010, 2010/2011, and 2011/2012 were all below average. The exceptionally cold and dry winter of 2009/2010 was the precursor to the drought, with below-average precipitation across western UK. However, for the worst affected catchments in southern England, winter 2009/10 was wetter than average. The drought was characterised by persistent blocked weather patterns and a northward shift of the jet stream in 2010 and across 2011, leading to a significant NW/SE precipitation gradient (Kendon et al., 2013). The drought was notable for its dramatic termination due to anomalously wet conditions over spring 2012, leading to a drought termination rate that was almost 4 times quicker than other droughts in the observed record (Parry et al., 2016, 2013).

Storylines of the 2010-12 drought explore a combination of plausible changes to the observed event (such as changes in both time and intensity). Drought characteristics of the storylines are derived from calculating the standardised streamflow index (as described in Chapter 3: Section 3.5.1) In particular, storylines of the 2010-12 drought are created with a "bottom-up" focus motivated by concern within the water resources sector about the consequences for water supply arising from three or more consecutive dry winters. Table 4.7 shows the various storylines considered in this case study and example research questions that each storyline aims to address.

Table 4.7 Storylines of the 2010-12 drought and a description of research questions for each storyline

Storyline	**Research questions**	**Method**	**Section**
Precondition severity			
Drier preconditions (DP)	How sensitive is the drought to progressively drier preconditions?	3- and 6-months prior to 2010-12 drought altered by estimated return periods (10, 20, 50 and 100-years)	Section 4.3.3
Temporal sequence			
Seasonal contributions (SC)	What were the seasonal contributions to the development and termination of the drought?	Winter and autumn within event replaced with daily climatological precipitation and temperature (1965-2015)	Section 4.3.2
Dry year before (DB)	What if the 2010-12 drought was preceded or succeeded by another	Replace 2009 with a dry year (2010) before the 2010-2012 drought	Section 4.3.4
Dry year after (DA)	dry year with dry winter conditions (i.e. a third dry winter situation)?	Replace 2012 with a dry year (2010) after the 2010-2012 drought	Section 4.3.4
Climate change			
UKCP18 regional projections (GW)	What would happen if the 2010-12 drought occurred in a warmer world?	UKCP18 projections applied to all months at 4 warming levels	Section 4.3.5

4.3.1 Anatomy of the drought event

Agglomerative hierarchical clustering based on the SSI-6 time series between January 2010 and March 2012 is used to group catchments with similar drought responses using the *TSclust* R package (Montero and Vilar, 2014) (Figure 4.8). Similar SSI hydrographs accumulated over 6 months (SSI-6) are grouped using Ward's minimum variance method to minimise total within-cluster variance (Ward, 1963). Cluster numbers between 2–10 are tested; five clusters are chosen as an appropriate number as this provides a clear distinction between hydrogeological units across southern England. The diversity of hydrological response to droughts in groundwater-dominated catchments in southern England has been shown by Merchant and Bloomfield, (2018), and differences in hydrological drought response among catchments in this region should be considered. The use of five clusters also divides northern catchments into east and west Scotland and distinguishes catchments in east Scotland where the influence of snowmelt processes may be more prevalent (also catchments with relatively poorer model performance). SSI-6 was selected to delineate clusters because it allows for a greater separation of catchments based on a larger variation in short-term drought response. SSI calculated with longer accumulation periods leads to a grouping of the hydrological response where only two clusters can be qualitatively identified. Subsequent storyline analyses employ SSI-6, SSI-12, and SSI-24 to consider catchment memory.

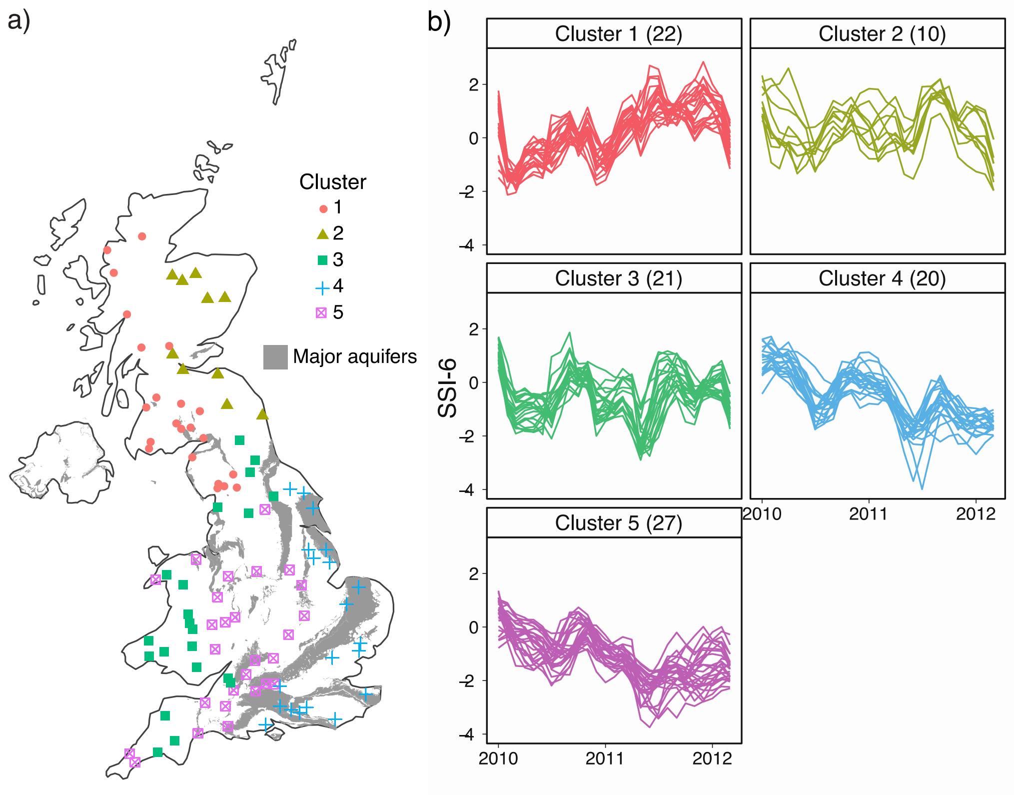

Figure 4.8 Hierarchical clustering of SSI-6 during the 2010–2012 drought event. (a) Spatial variation in the five identified clusters. (b) SSI-6 between January 2010 and December 2012 for the catchments in each cluster (with the number of catchments indicated in parentheses).

Initial streamflow response was uniform in response to precipitation deficit in early 2010 for all clusters with moderate to severe drought conditions (SSI < -1.5). Severe drought conditions developed for catchments in Clusters 4 and 5 (southern and southeastern England) because of a second consecutive dry winter. Most catchments in Cluster 4 are underlain by chalk aquifers and are slow-responding catchments with significant groundwater storage. Catchments in Cluster 3 (southwestern England) saw severe drought conditions develop over late 2010 and 2011, but the impacts did not persist as long and were not as severe as in Clusters 4 and 5. Although mean SSI-6 was not particularly severe, the SSI-6 time series for Clusters 1 and 2 show mild to severe conditions in the initial response to precipitation deficit over winter 2009/2010, after which streamflow recovered and did not return to drought conditions.

4.3.2 Storylines of seasonal contributions

To investigate the relative importance of individual seasons in drought development, storylines of seasonal contributions were created by prescribing daily climatological average precipitation and temperature for winter 2010/2011 and 2011/2012 and for autumn 2010 and 2011, while retaining observed values for the rest of the time series. The difference between the storylines and the baseline is indicative of the individual contribution of winter/autumn. Storylines of seasonal contributions reveal the relative importance of individual seasons in the development of the 2010–2012 drought (Fig. 4.9). The storylines confirm the importance of dry winters in the development of multi-year droughts. Drier than average winters 2010/2011 and 2011/2012 were a major determinant of the severe drought conditions observed across all clusters apart from Cluster 1. Baseline drought conditions across 2011, particularly for catchments in southern England (Clusters 4 and 5), can be attributed to the abnormally cold and dry winter in 2010/2011. The drier-than-average winter of 2011/2012 prolonged drought termination for all clusters, apart from Cluster 1. For Cluster 1, winter 2011/2012 was wetter than average, and the replacement of winter 2011/2012 with climatology would have meant that catchments could have experienced short-term minor drought conditions before recovery due to the wet conditions in 2012.

4.3.3 Storylines of precondition severity

Storylines of precondition severity assess the sensitivity of the 2010-2012 event to progressively drier preconditions. The preconditions are altered based on an estimation of the return periods of precipitation for 3 and 6 months preceding the observed event. Specified return periods (10, 20, 50 and 100-year) are estimated from annual average 3-month (October–December) and 6-month (July–December) precipitation for each of the LFBN catchments for 1900–2015 and fitted with the generalised extreme value (GEV) distribution. Observed precipitation for the 3 and 6 months before the 2010–2012 drought is then reduced or increased to match the estimated precipitation at each return period. The temporal variability is thereby unchanged from the observed precipitation of the specified 3- or 6-month period. The influence of the perturbed preconditions is characterised by the precondition persistence time. This is defined as the number of days needed for river flow at each catchment to return to values close to the baseline simulation (< 1 %) calculated from the start of the perturbation until the influence of the perturbation is no longer detected. The precondition persistence time is not indicative of the time taken for catchments to entirely recover from drought to non-drought conditions but is instead indicative of how long the influence of precondition perturbations lasts for each catchment. This is consistent with indices used in Staudinger and Seibert (2014) and Stoelzle et al. (2020) to assess hydrological response following initial condition perturbations.

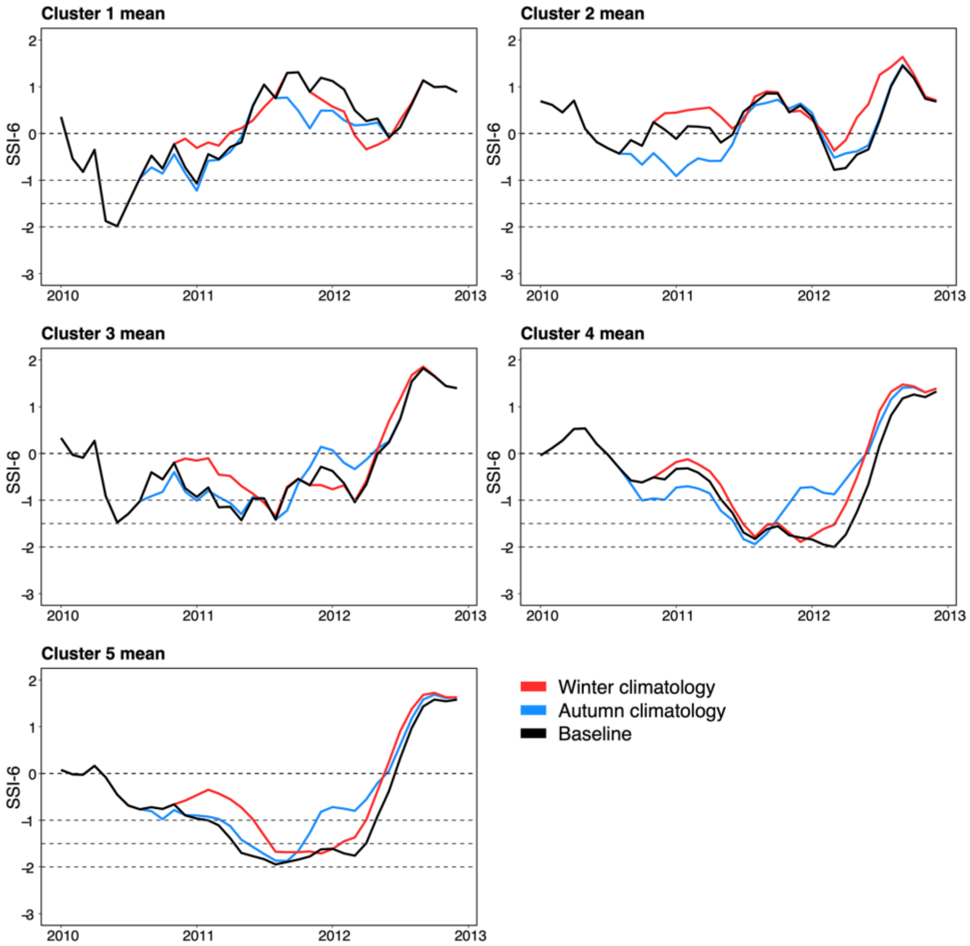

Figure 4.9 Cluster mean SSI-6 for the storylines of seasonal contributions with winter 2010/2011 (red) and with autumn 2010 and 2011 (blue) replaced by daily climatological values.

The creation of this storyline accounts for the possibility of perturbations affecting the correlation structures between potential evapotranspiration (PET) and precipitation, both of which are inputs for subsequent hydrological modelling. Perturbing the precipitation before the observed drought independently of PET is plausible, as observed precipitation and PET for the period 1965–2015 exhibit no correlation, except for a weak negative correlation in spring and early summer (Figure 4.A.2). The perturbations applied to monthly precipitation do not introduce outliers to the observed relationship between precipitation and PET (Figure 4.10). The creation of similar storylines in locations other than the UK may have to consider potential changes to the correlation structures if a strong correlation between different variables of interest is found. The precondition perturbations also do not violate existing autocorrelation structures as autocorrelation among successive monthly UK precipitation values decays rapidly after the first few months (also noted during the development of stochastic weather generators; (Chun et al., 2013; Kilsby et al., 2007; Ledbetter et al., 2012; Serinaldi and Kilsby, 2012).

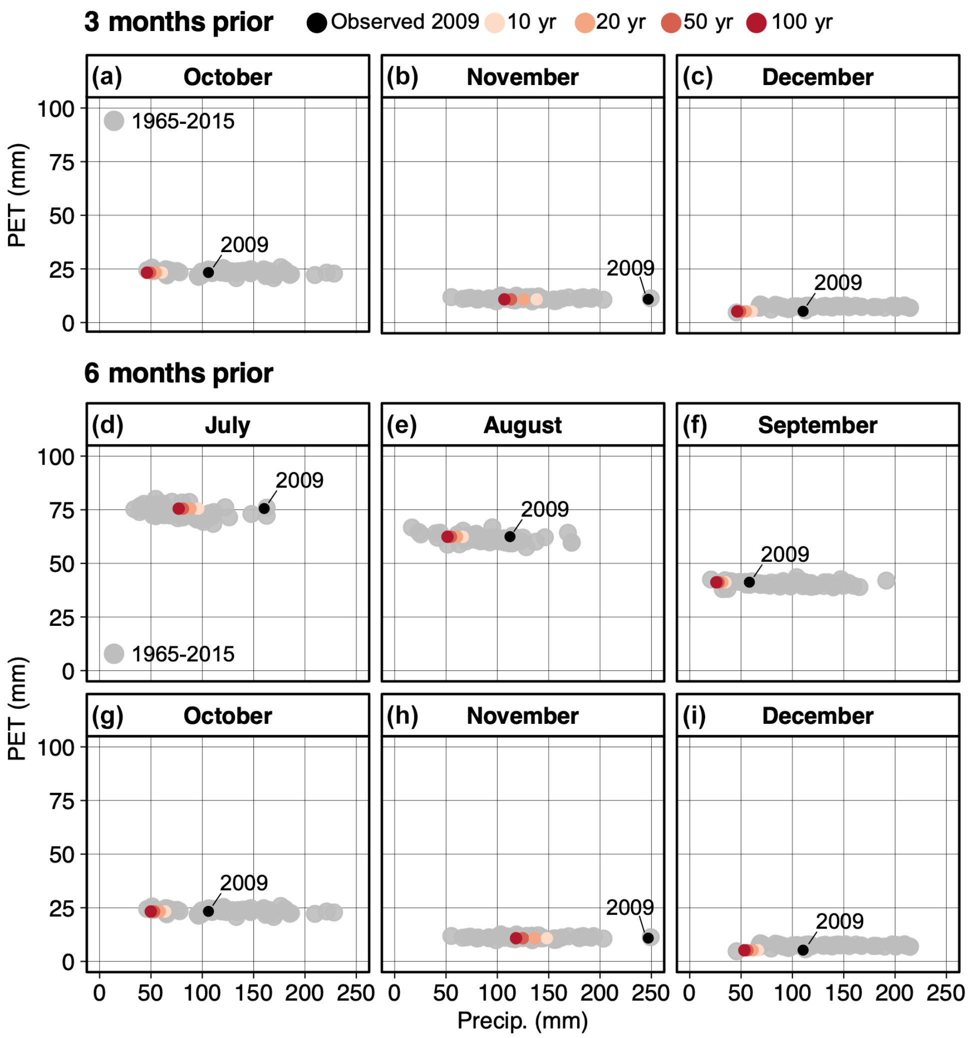

Figure 4.10 October to December (top) and July to December (bottom) monthly precipitation and PET (1965–2015) at an example catchment in southern England (grey circles). The black circle indicates the observed value in 2009, and the coloured circles indicate the value after precipitation 3 and 6 months prior to the 2010–2012 drought is reduced at four return periods.

Prescribing drier preconditions at varying severity for the 3 and 6 months prior to the 2010–2012 drought reveals the influence of preconditions on the baseline event (Figure 4.11). Drier preconditions led to 12-month precipitation before the drought varying between 65 % and 107 % (48 % and 90 %) relative to the long-term average for the 3-month (6-month) precipitation precondition reduction, with a significantly greater deficit for catchments in Clusters 4 and 5 (Figure 4.A.3). The 12-month precipitation deficit of the storylines of precondition severity is comparable to the range considered in the H++ climate change scenarios for low rainfall and droughts (Wade et al., 2015). Unsurprisingly, both drought characteristics worsen in most cases for all clusters, with an increase in precondition severity. The exception is Cluster 2, where changes in precondition precipitation with 10- and 20-year return periods lead to a reduction in drought intensity and deficit, meaning that the dryness observed in the 3- and 6-month precipitation before the 2010–2012 event had a return period of more than 20 years. The difference between the two precondition lengths is notable, especially at longer return periods, where a 6-month precondition length results in much greater change. Maximum intensity for the catchments in Cluster 5 is less sensitive to the influence of drier preconditions at shorter return periods, indicating that the conditions that developed prior to 2010 (i.e. winter 2009/2010) were already dry enough for the development of severe drought conditions, and only preconditions with longer return periods would result in significant differences to the eventual drought characteristics.

The spatial variation in the precondition persistence time shows that catchments in southern England generally show the longest persistence time, coinciding with regions of major aquifers (Figure 4.12). There is a positive relationship between persistence time and both the BFI and the proportion of arable/horticultural land. These catchments have high groundwater storage, which contributes to surface streamflow during drought and are associated with more agricultural/horticultural activities compared to impermeable catchments. Catchments with longer persistence times also tend to be larger in size, less steep, receive lower annual average precipitation, and exhibit dry soil moisture for a larger proportion of the time. This confirms that permeable lowland catchments are more vulnerable to long drought propagation, with a lag (and lengthening) between meteorological and hydrological droughts. Catchment sensitivity to drier preconditions reflects a combination of spatial characteristics of the drought and catchment properties and particularly the influence of hydrogeology.

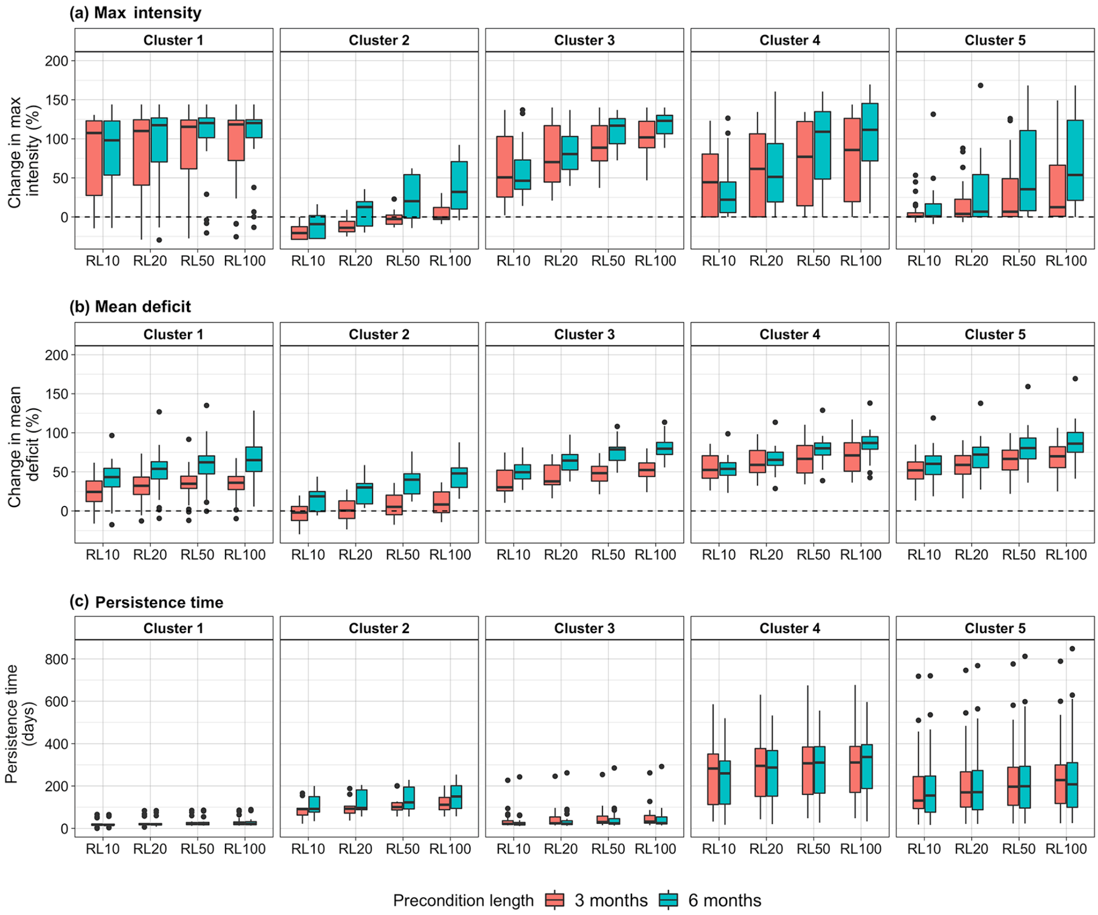

Figure 4.11 Change in mean drought deficit (%), max drought intensity (%), and persistence time (days) from the storylines of precondition severity at different return levels calculated from SSI-6.

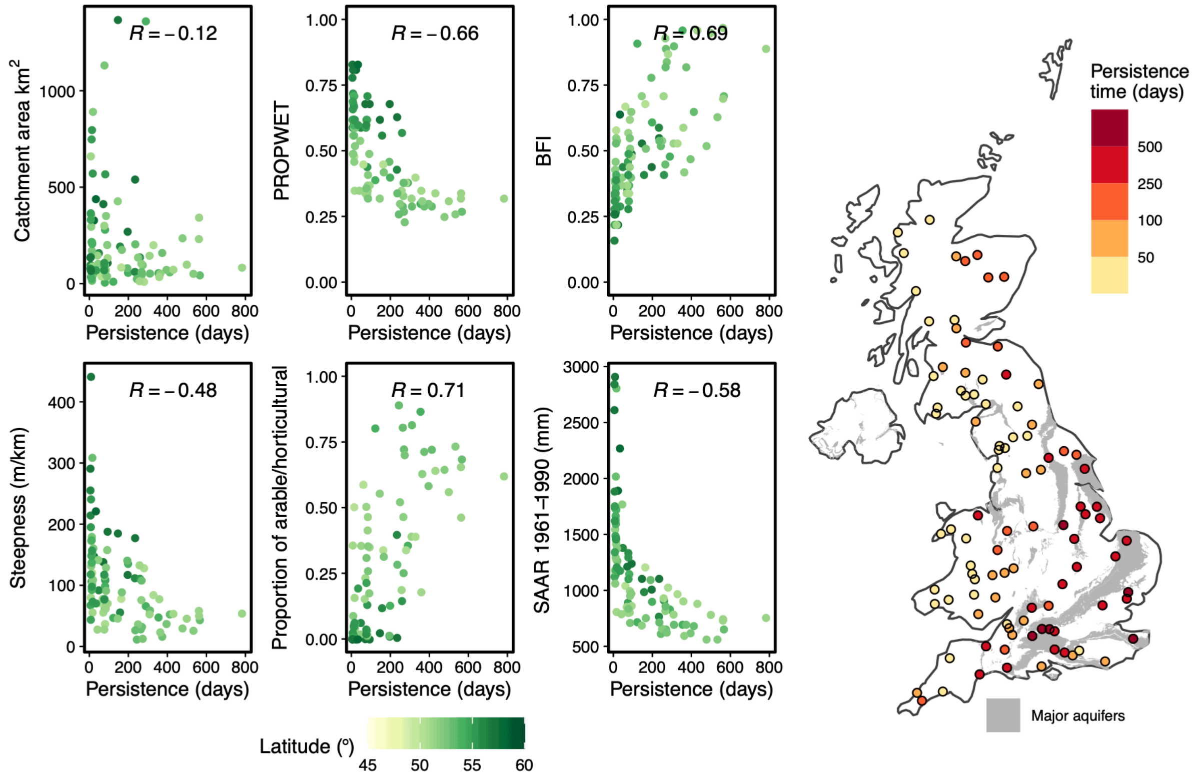

Figure 4.12 (a) Relationship between the persistence time (d) of the 6-month precondition storyline (100-year return period) with selected catchment characteristics. (b) Spatial variation in persistence time for the selected catchments.

4.3.4 Storylines of three dry winters

Although climate projections indicate average changes in a future period – for example, drier summers and wetter winters – these changes do not necessarily occur concurrently and may not be true for all years. Consecutive dry seasons are possible, and the hydrological response to long dry sequences merits further investigation. Successive dry winters are shown to have caused significant reduction in river flows and reservoir storage in both observations and river flow reconstructions (Barker et al., 2019; Spraggs et al., 2015; Watts et al., 2012). Quantifying historical transition probabilities of consecutive dry half-years in England and Wales, (Wilby et al., 2015) found that the longest consecutive dry half-years spanned 4 years (including four dry winters) and that even longer dry sequences are possible.

Drought orders were used by water companies to supplement reservoir stocks, and temporary hosepipe and water use bans affecting over 20 million customers were ordered, in early

2012, in anticipation of continued drought stress across another dry winter, before its abrupt termination (Kendon et al., 2013). Storylines were created using historical climate analogues to explore a "third dry winter" situation. The "dry year before" storyline replaces the year preceding the drought (i.e. 2009), whereas the "dry year after" storyline replaces the year succeeding the drought (i.e. from March 2012 to 2013) to explore the consequences if the drought was not terminated by anomalously wet conditions in spring 2012. 2010 was selected as the year to be repeated, as it was notable for its cold and dry conditions. These storylines are inspired by the Hydrological Outlook UK historical climate approach (after Day, 1985), where projections of river flows are produced by driving hydrological models with ensemble meteorological sequences sampled from the historical record combined with up-to-date observations (Prudhomme et al., 2017).

The storylines of three dry winters illustrate how much worse the 2010–2012 drought could have been, given another dry year with dry winter conditions (Figure 4.13). The drought defined by SSI-6 is estimated to worsen for the dry year before the storyline for all clusters, except for the mean drought deficit for Cluster 4. This anomaly for Cluster 4 can be explained by an increase in drought duration that is greater than the increase in accumulated deficit and maximum intensity. For this storyline, changes in drought characteristics are the greatest for Clusters 1 and 3, with a larger increase with longer accumulation periods. This indicates that the addition of a dry year prior to the observed event increases the risk of abrupt and intense drought conditions in these catchments. Changes in drought conditions are significant enough that they are noticeable at longer accumulation periods, despite the relatively fast precondition persistence times for catchments in these clusters. Conversely, the change in drought conditions for catchments in Clusters 4 and 5 is notable only at longer accumulation periods. The larger change for SSI-24 is particularly important for Clusters 4 and 5, as long accumulation periods are often used to assess drought impacts at these slow-responding catchments with significant catchment storage.

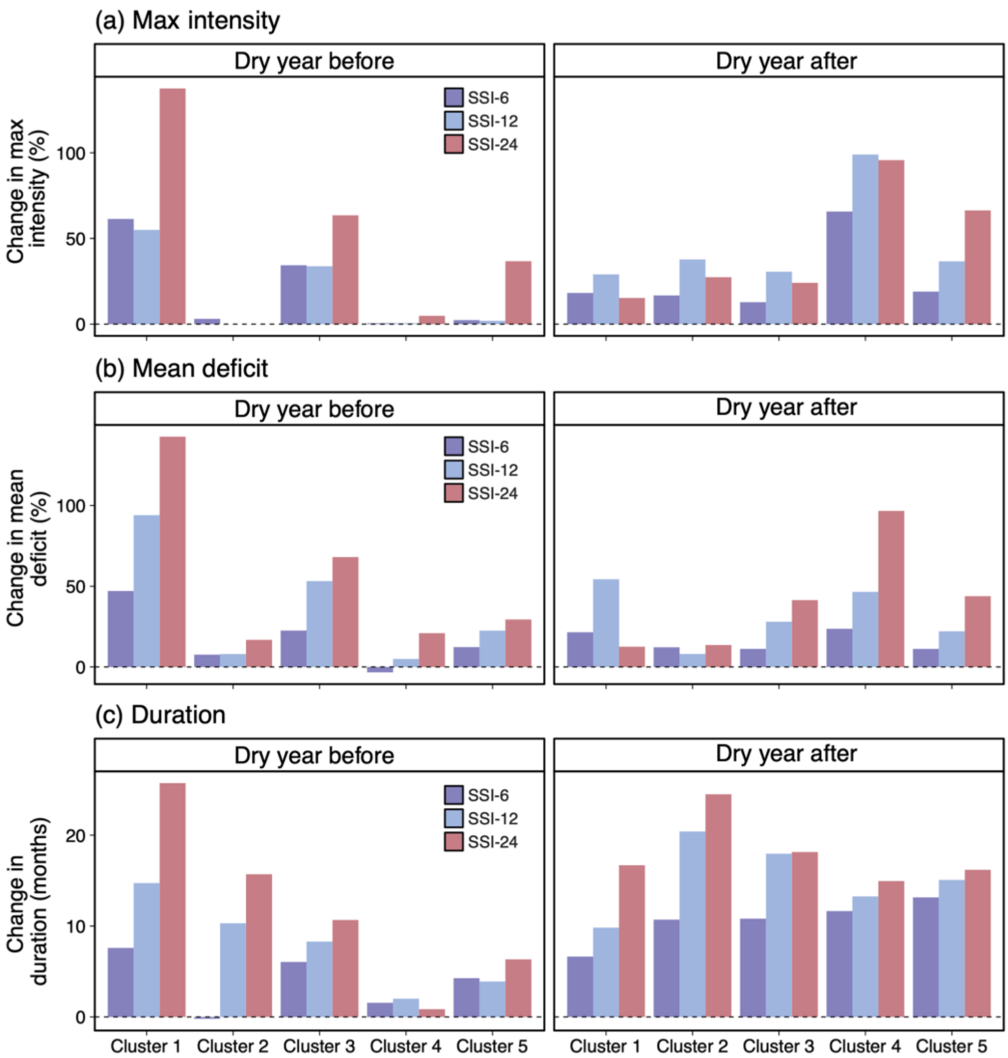

Figure 4.13 Mean change in the (a) max drought intensity (%), (b) mean drought deficit (%), and (c) duration (months) relative to the baseline for each cluster for the repetition of a dry year (2010) either before (left) and after (right) the 2010–2012 drought.

Compared to the dry year before storyline, the dry year after the storyline has a greater effect in the worst affected catchments in southern England. Without the dramatic drought termination in 2012, drought duration would have increased significantly for catchments in all clusters. The max intensity and mean deficit are estimated to increase for all clusters, with larger increases for Clusters 4 and 5 at all accumulation periods. This suggests that there is still considerable scope for worse drought conditions to develop if dry conditions persisted, as had been expected. The change in maximum intensity is greatest for SSI-12 for all clusters, except Cluster 5, while the magnitude of change in mean deficit increases with the accumulation period and is greatest (smallest) for SSI-24 for Clusters 3–5 (Clusters 1–2). This indicates the importance of assessing drought conditions at multiple accumulation periods and highlights the importance of catchment and water resource memory. For Clusters 1-2, SSI-6 and SSI-12 are useful for capturing changes in drought conditions from the storylines, but, for Clusters 3–5, SSI-12 or longer are needed to fully assess the drought response.

Individual catchment responses to an additional dry winter can be grouped by categories based on catchment response time (Fig. 4.14). First are the relatively fast-responding catchments (e.g. 81002 – Cluster 1; 7001 – Cluster 2) that recover from both the dry year before and dry year after storylines relatively quickly, with drought conditions more vulnerable to a dry year before storyline. Second are slow-responding catchments (e.g. 38026 and 42 008 – Cluster 4), where the streamflow response from the dry year before storyline persists across 2010 but not significantly beyond 2011. Third are slow-responding catchments (e.g. 43 014 and 39 019 – Cluster 5), where the streamflow response to the dry year before the storyline persists across 2010 and beyond into 2011. The dry year after storyline also shows that continued dry conditions over 2013 could have particularly challenging for the slow-responding catchments in southern and eastern England. However, the meteorological conditions over 2013 would still have been wet enough to allow most of the affected catchments to recover and exit drought conditions.

4.3.5 Climate change

The UKCP18 12-member HadRM3 perturbed parameter ensemble (PPE) regional climate projections at 12 km resolution was used to place the 2010–2012 event in a future climate following the delta method at different global warming levels. Projected change in precipitation across the 12 UKCP18 regional projections ensemble members is shown in Chapter 3: Section 3.3.2). River flow across the 2010–2012 drought is projected to decrease for most catchments (Figure 4.15). In fast-responding catchments (Clusters 1 and 2), winter river flows increase due to the projected increase in winter precipitation. In these catchments, the buffer effects of wetter winters compensate for increased evaporative demand from increased temperature. Mean river flows across the drought event for catchments in southern England and Wales are projected to decline substantially, with larger declines at higher warming levels. River flow is projected to decrease in all seasons, for even a 1.5 °C rise in temperature, with increasingly drier conditions at high warming levels, particularly for slow-responding catchments (Clusters 4 and 5). In these catchments, river flow is also projected to decrease progressively over the event timescale.

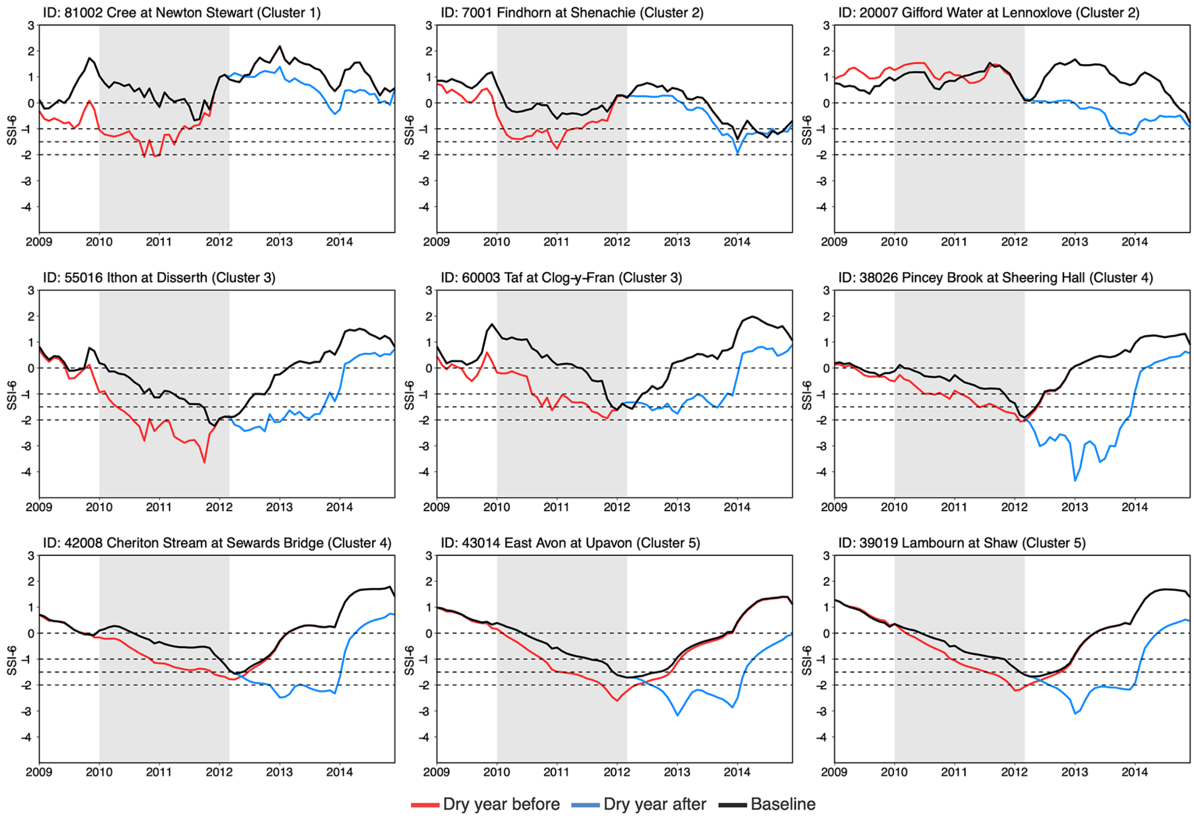

Figure 4.14 Baseline (black) and simulated SSI-6 for a repetition of a dry year before (red) or after (blue) the 2010–2012 drought for nine example catchments spanning the five hydrograph clusters. The shaded region indicates the duration of the baseline 2010–2012 drought event (January 2010 to March 2012). See Fig. S11 for the locations of the nine example catchments. See Figures. 4.A.4 and 4.A.5 for the SSI-12 and SSI-24.3.5 storylines of climate change.

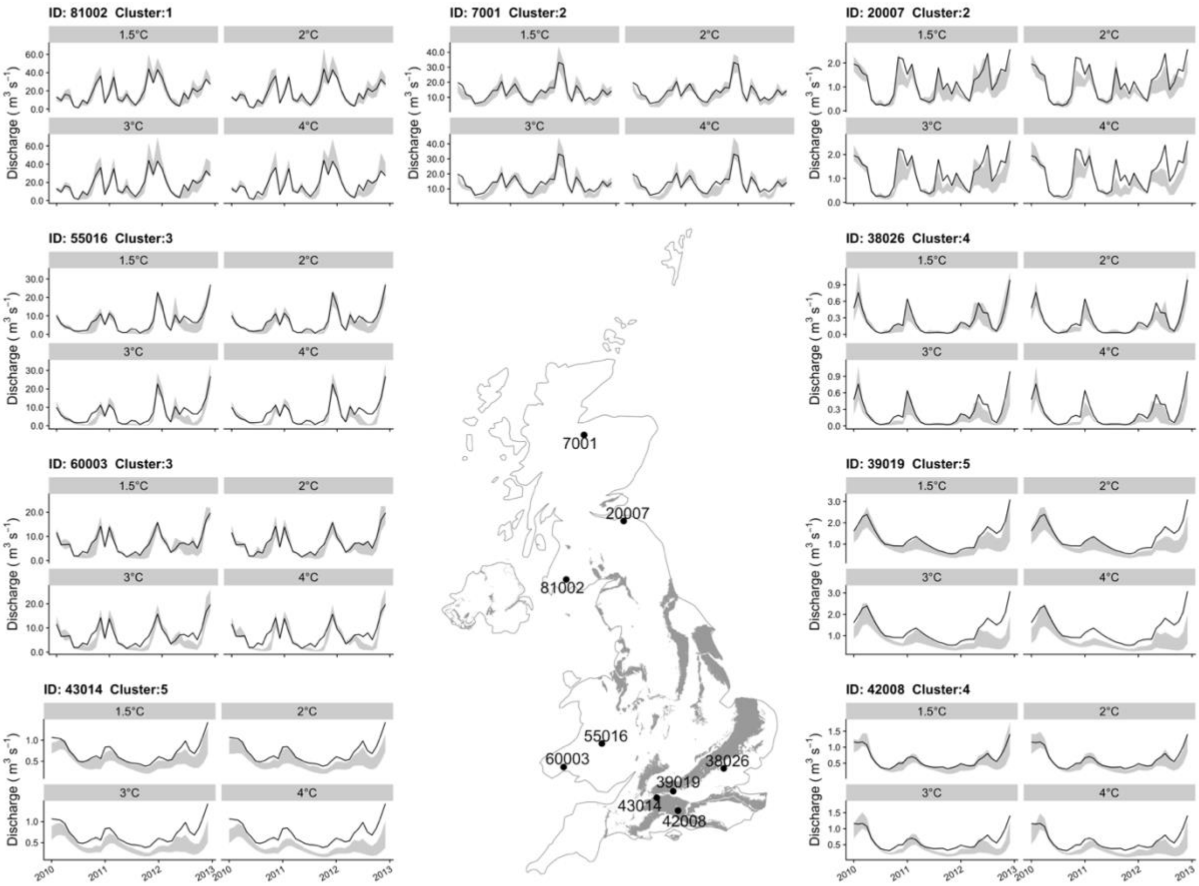

Figure 4.15 Projected change in river flows across 2010-2012 at four warming levels. Nine example catchments spanning the five hydrograph clusters are presented here. The solid line represents the baseline simulation, and the shaded region represents the uncertainty range of the 12 UKCP18 regional projections. Shaded regions on the map indicate the location of major aquifers.

Given the observed drought sequence, the conditions of the 2010–2012 drought are projected to worsen with global warming (Fig. 4.16). The change in drought characteristics for the initial temperature rise (1.5 and 2 ˚C) is greater for Clusters 3–5 compared to Clusters 1 and 2. Beyond 2˚C, drought characteristics are projected to worsen by a similar magnitude for all clusters and at longer accumulation periods, except Cluster 1. For SSI-12 and SSI-24, the magnitude of change in drought characteristics is larger compared to shorter accumulation periods for all clusters, except Cluster 1. Although drought characteristics are projected to increase with the temperature rise for Cluster 1, the increase in drought duration at 4°C is smaller compared to lower warming levels, indicating more severe drought conditions despite a smaller increase in drought duration. At longer accumulation periods, the projected change for Cluster 1 also does not follow the progressive increase with the warming levels seen in SSI-6. This reflects the fast response times and limited catchment memory for the catchments in Cluster 1, where drought conditions are better captured using short accumulation periods. The anomalous behaviour from Cluster 1 could be attributed to wetter winters for northwest Scotland, especially at high warming levels, which provide wet interludes and mitigate drought conditions.

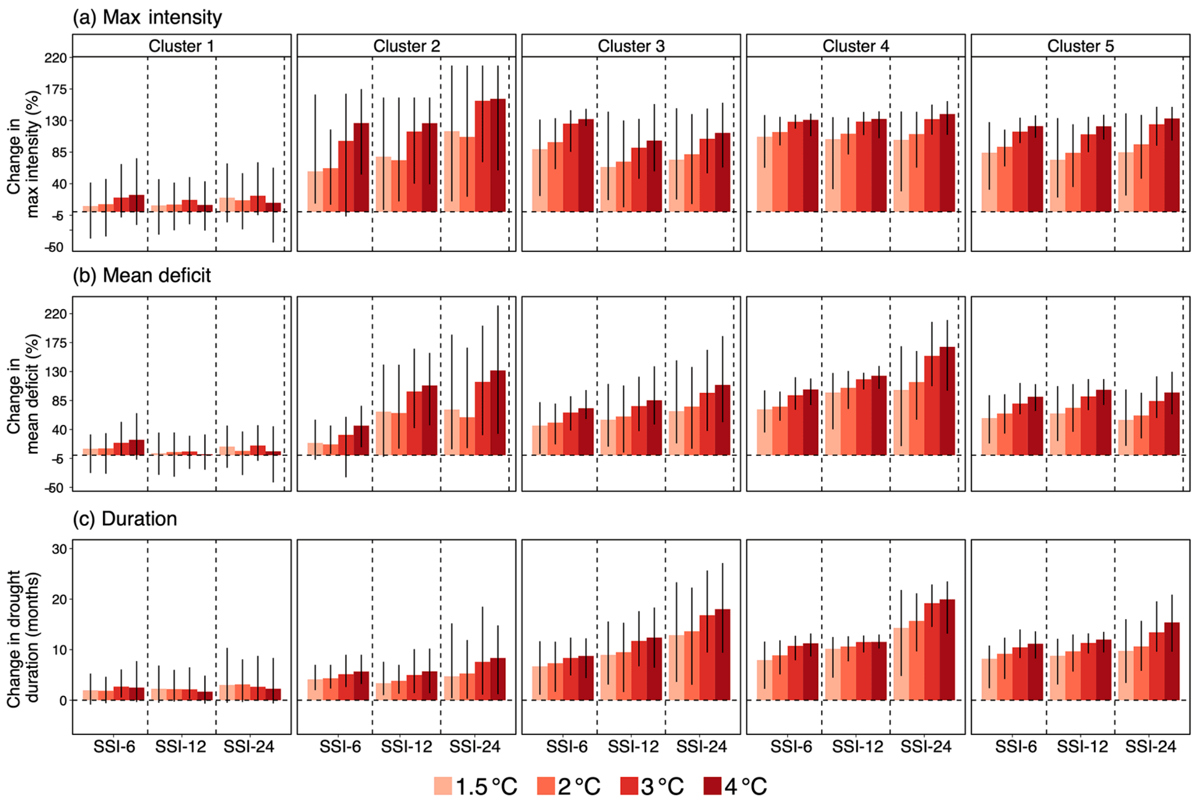

Figure 4.16 Mean change across the 12 UKCP18 regional projections in (a) max drought intensity (%), (b) mean drought deficit (%), and (c) drought duration (months) for the 2010–2012 drought across four warming levels for each cluster and SSI accumulation period. The error bar indicates the spread across the 12 regional projections.

4.3.6 Comparison with past droughts

To place the storylines of the 2010-12 drought in historical context, they are compared with the relatively short-lived 1975–1976 drought and the more protracted 1989–1993 drought. Four storylines are selected to compare with past droughts, namely (1) dry year before, (2) dry year before, (3) driest preconditions, and (4) 2°C warming. Figure 4.17 shows the percentage change in max intensity and mean deficit of the four storylines relative to the two past droughts. First, compared to the 1975–1976 event, drought conditions assessed using SSI-6 are generally less severe across all storylines, except for Cluster 1. In Cluster 1, drought conditions match the 1975–1976 drought for the dry year before and driest precondition storylines. However, when considering longer timescales with SSI-24, the drought conditions of all four selected storylines exceed those of the 1975–1976 drought for Clusters 3–5. Notably, the 2˚C warming storyline (and warming levels beyond that) results in the largest increase out of the selected storylines. For Clusters 1 and 2, drought conditions calculated using SSI-12 and 24 are less severe than both the 1975–1976 drought and SSI-6. The only exception is the dry year before storyline for Cluster 1, where drought conditions exceed that of the 1975–1976 drought for SSI-24 even though catchments in this cluster are fast responding.

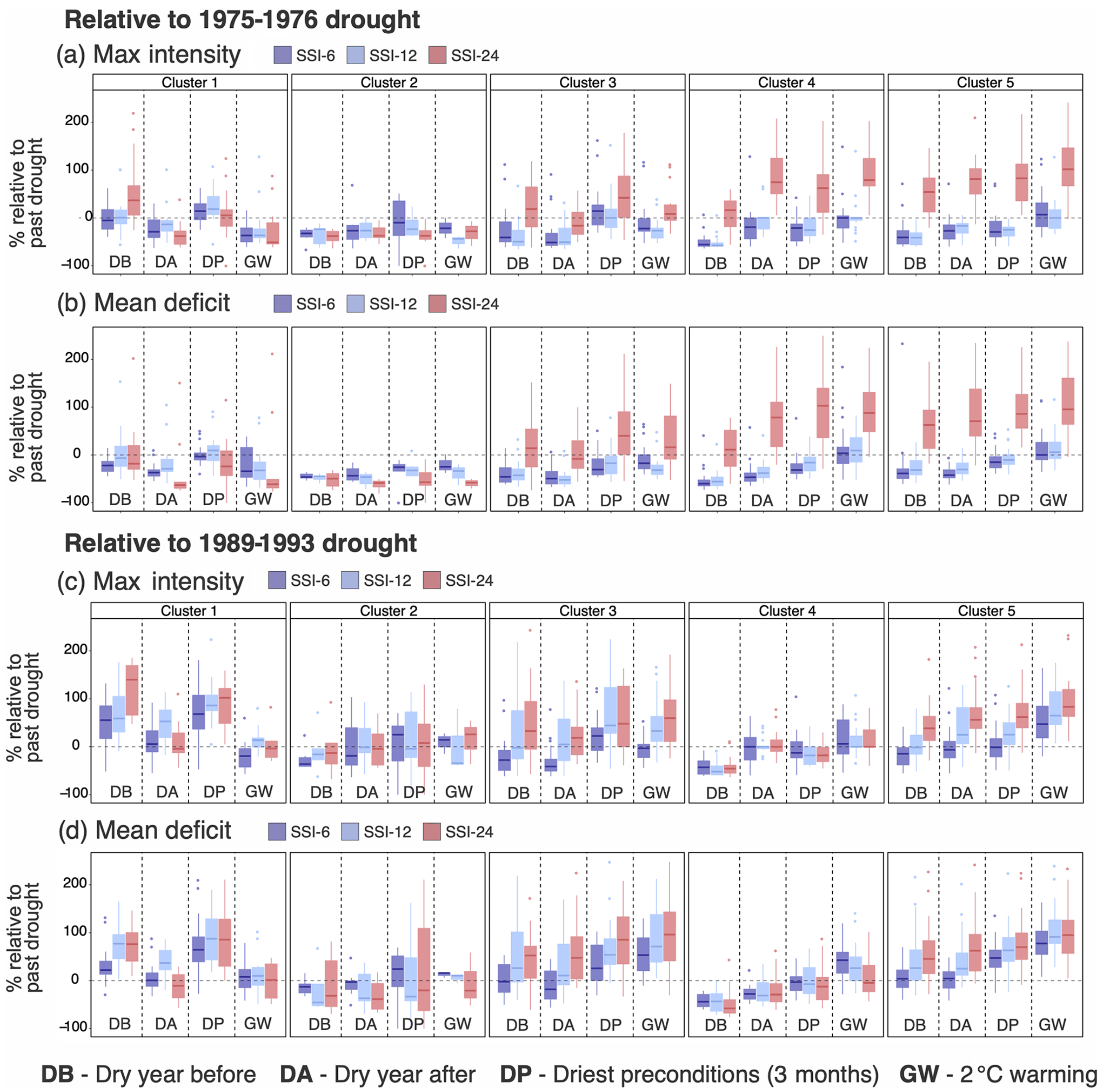

Figure 4.17 Percentage difference in max intensity (a, c) and mean deficit (b, d) calculated from SSI-6, SSI-12, and SSI-24 of the selected storylines of the 2010-12 drought relative to the 1976–1976 drought (top) and the 1989–1993 drought (bottom).

Second, conditions across the four selected storylines are estimated to be more severe than the 1989–1993 drought, apart from Cluster 4. Catchments in Cluster 4 were the most affected during the observed 1989–1993 drought, and only storylines with the more extreme changes could have matched or exceeded observed conditions (i.e. driest preconditions and 2°C and beyond). Out of the four storylines, a 2°C warming is estimated to result in the largest deviation from the 1989–1993 drought for Clusters 3–5. The 2°C warming storyline is less severe for Clusters 1 and 2, where, respectively, the dry year before and the driest preconditions instead result in greater deviations from the 1989–1993 drought. For all selected storylines, the magnitude of change relative to the 1989–1993 drought increases with accumulation period and is greatest for SSI-24 for Clusters 3 and 5, indicating the importance of catchment memory.

In summary, all four storylines are all capable of leading to more severe drought conditions compared with the two past droughts for all clusters. Conditions across the storylines are estimated to match the 1975–1976 drought, with comparatively more severe conditions for southern catchments at longer accumulation periods. Conditions are estimated to match or exceed the 1989–1993 drought for all clusters. Drier preconditions and a third consecutive dry winter, in particular, would have matched 1988-93 conditions for catchments in Cluster 4, which was the most affected in the observed event. Drought conditions decrease (increase) in severity with longer SSI accumulation periods for Clusters 1–2 (Clusters 3–5). The 2010-12 drought in a 2°C warmer climate is estimated to exceed conditions in both the 1975-76 and the 1988-93 drought for all clusters, especially when considering longer accumulation periods.

4.3.7 Synthesis and summary of the 2010-12 event storylines

Counterfactual storylines of the multi-year 2010-12 drought were created to explore the impacts on drought characteristics given discrete changes in the events' drivers and characteristics. Key results from each storyline are summarised below:

- Storylines of seasonal contributions showed that the drought was driven by drier than average winters in 2010/11 and 2011/12 which worsened drought conditions. Autumn conditions were a determinant of the timing of drought inception, while winter conditions were important in determining the drought's eventual length

- Drier preconditions before the 2010-12 drought could lead to a worsening of drought conditions except for catchments in eastern Scotland. Catchment sensitivity to drier preconditions was influenced by a combination of drought characteristics, catchment properties, and hydrogeology with the greatest influence for lowland catchments with longer response times underlain by permeable aquifers.
- Impacts of the dry year before and dry year after storylines vary spatially. The dry year before storyline is particularly severe for northern catchments and slow-responding catchments. The dry year after storyline is particularly severe for slow-responding catchments with high catchment storage, highlighting the remaining vulnerability to a "three dry winter" situation.
- The UKCP18 projections applied using the delta method show that the 2010-12 drought is projected to be more severe with temperature rise across the selected catchments. The magnitude of change in drought characteristics is greater at longer river flow accumulation periods.

4.4 Chapter summary

This chapter created retrospective event storylines for two contrasting drought events, namely the relatively short but intense 1975-76 drought and the longer, multi-year 2010-12 drought. Event storylines created based on past observed events can be used to explore downward counterfactuals and the impacts of climate change, thus informing plausible worst cases in both current and future climate. Key results from the storylines developed for the 1975-76 and the 2010-12 drought are given below:

- Precipitation in autumn 1975 was drier in East Midlands compared to East Anglia. Catchments in East Anglia could have been further stressed if the region was as dry as East Midlands across autumn 1975. Additionally, the drought was characterised by a dry 1975-76 winter and analysis of a large sample of winters showed that the prevailing atmospheric circulation patterns could plausibly have resulted in even drier conditions with greater impacts for groundwater-dominated catchments crucial for water supply. Given similar circulation patterns, climate change is projected to lead to a worsening of summer drought conditions with more uncertain changes in other seasons. In all cases, it is plausible for the

1975-76 drought to surpass the 1920-21 drought as the worst-ranked drought in terms of maximum intensity for some catchments in the region given each of the storylines.

- The multi-year 2010-12 drought was driven by two consecutive dry winters. The occurrence of three consecutive dry winters is a particular concern within the water resources industry. The plausible occurrence of a third dry consecutive winter instead of the rapid termination as observed would lead to particularly severe conditions for catchments across southern England. Conversely, plausible drier preconditions before the drought would be particularly impactful for catchments in Scotland. In all cases, the storylines are estimated to exceed the drought characteristics of the 1975-76 drought and the benchmark prolonged 1988/93 drought.

In conclusion, both sets of storylines complement existing studies by devoting greater emphasis to the pathways and impacts of plausible events and placing traditional top-down climate projections in a wider decision-relevant framework. These storylines enable a better understanding of the plausible drivers and unfoldings of downward counterfactuals or near-misses to improve risk awareness. Storylines based on observed events are familiar to stakeholders and increase realism among decision-makers. Storylines created in this chapter can be used in water resources planning to stress test UK catchments against unrealised droughts.

4.5 Appendix

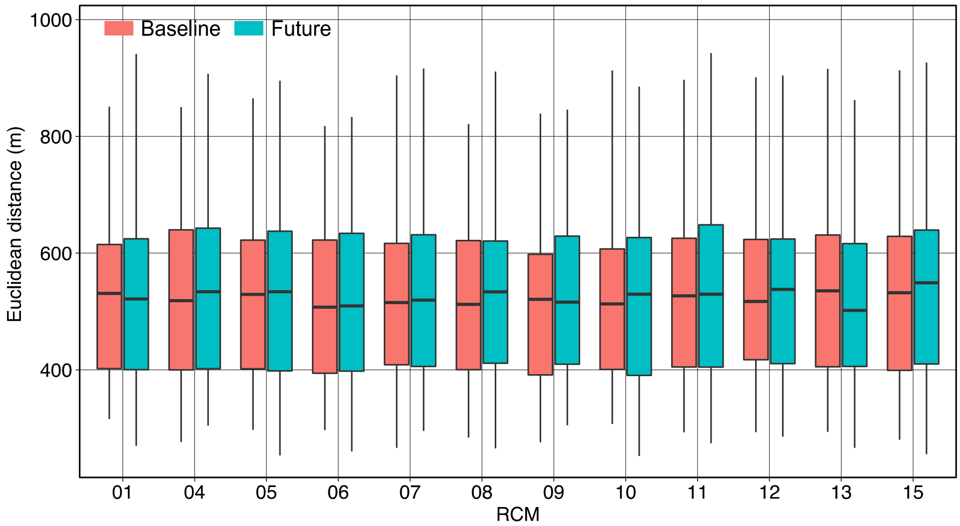

Figure 4.A.1 Analogue quality (Euclidean distance) across the 1975-76 event (Dec 1975 to Aug 1976) in the baseline and future period for each ensemble member of the UKCP18 regional projections.

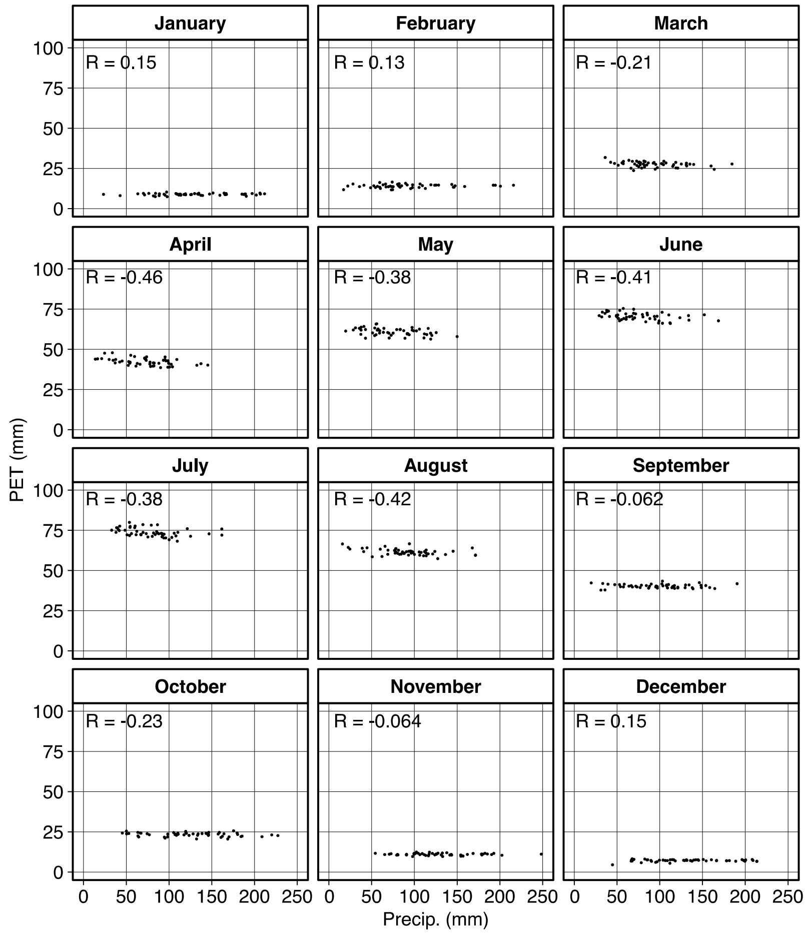

Figure 4.A.2 Observed relationship between PET and precipitation for each month (1965-2015) averaged across the LFBN catchments. The correlation coefficient value is shown for each month.

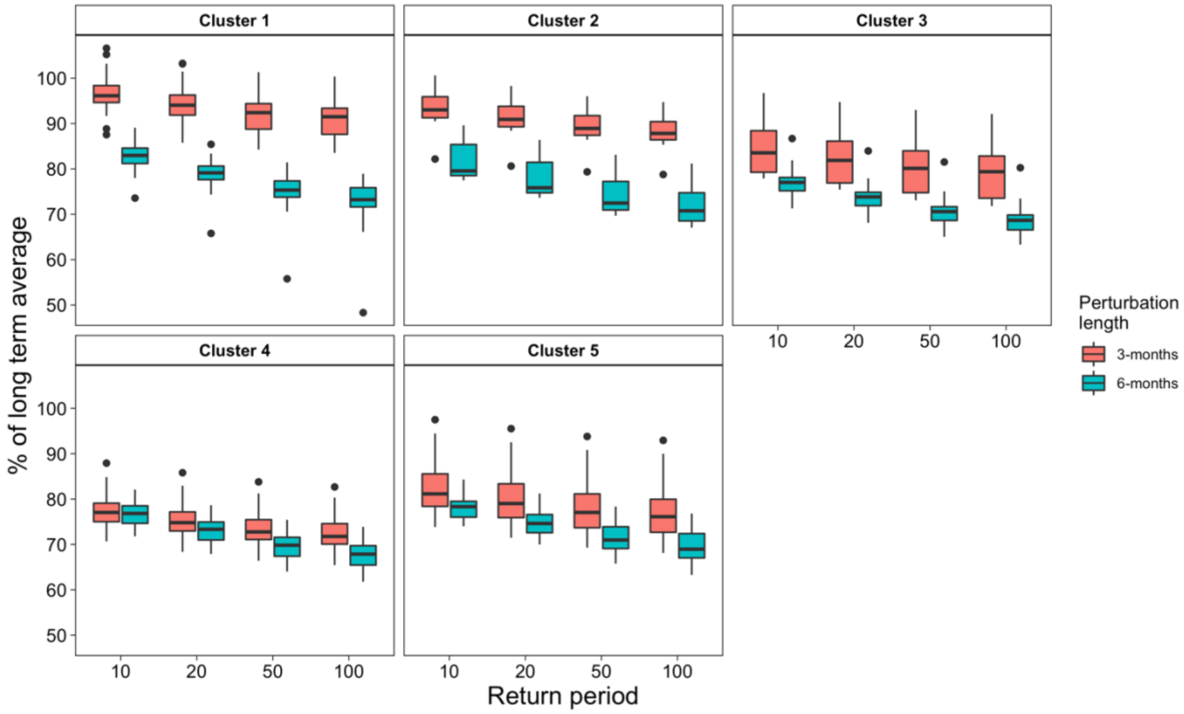

Figure 4.A.3 12-month precipitation deficit relative to the long-term average for each return period and each cluster for the storylines of precondition severity with a 3- and 6-month perturbation before the 2010-12 drought.

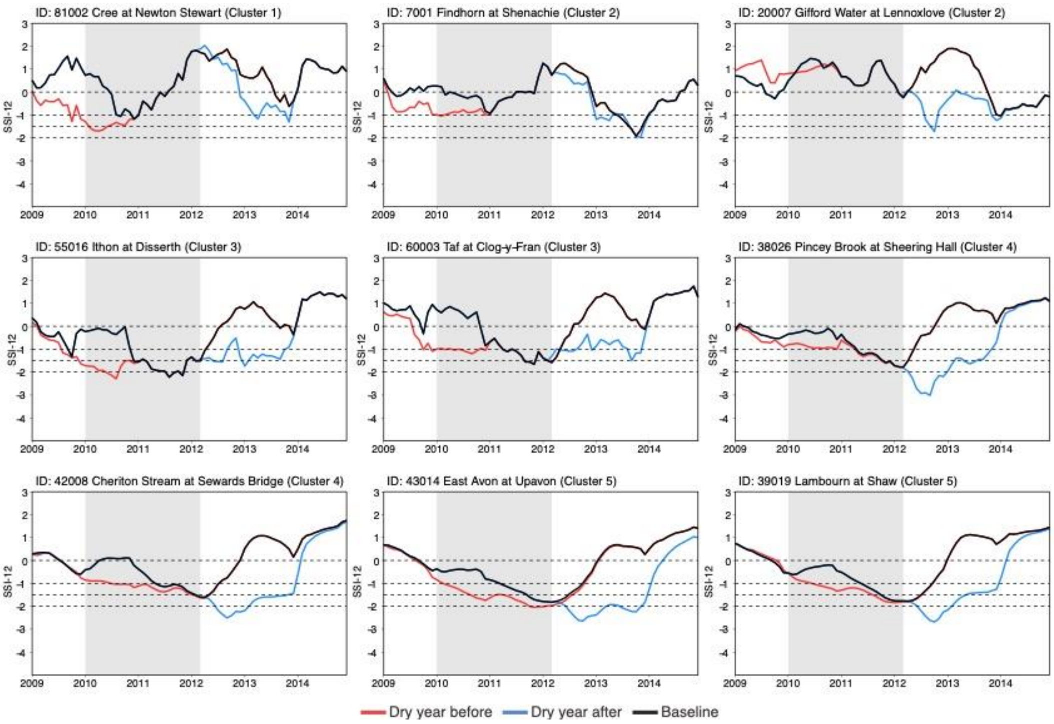

Figure 4.A.4 Baseline (black) and simulated SSI-12 for either a repetition of a dry year before (red) or after (blue) the 2010-12 drought for nine example catchments spanning five hydrograph clusters. The shaded region indicates the duration of the baseline 2010-12 drought (Jan 2010 to Mar 2012).

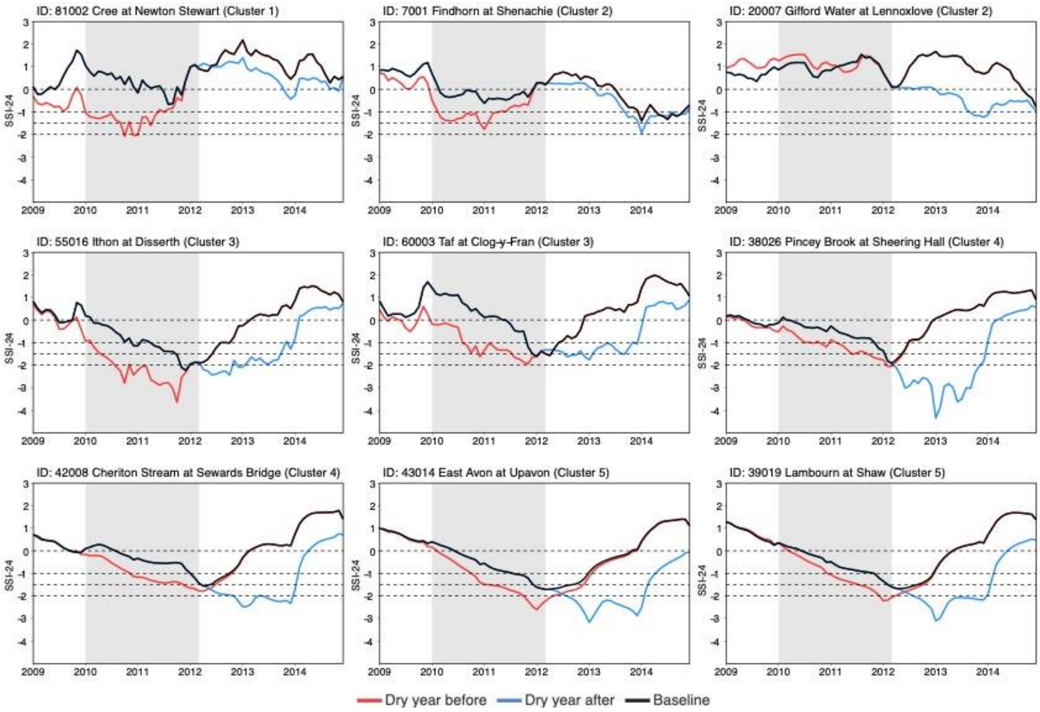

Figure 4.A.5 Same as Figure 4.A.4 but for SSI-24.

5 REAL TIME EVENT STORYLINES

A version of this chapter has been published at the journal *Natural Hazards and Earth System Sciences,* with the following reference:

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

5.1 Introduction

The previous chapter demonstrated different techniques to create retrospective event storylines exploring downward counterfactuals and the impacts of climate change. The two case studies of the 1975-76 and 2010-12 droughts showed the value of case study analyses based on past observed events to assess the current and future risk of plausible worst cases. This chapter extends the storyline approach to consider the use of event storylines as a complementary tool to traditional weather forecasts to aid water resources planning during an ongoing event. As described in Chapter 1, water companies are required to outline demand and supply management actions in their water resources management plans and to prepare for the application of drought permits and drought orders during an event. The main advantage of a storyline approach is a high degree of conditionality (e.g. atmospheric circulation patterns, management measures etc.) which can provide information with sufficient specificity rather than generalising across dissimilar events.

Storylines can thus complement existing practices when planning for an ongoing event by adding a dynamical perspective based on our knowledge of the meteorological drivers of precipitation.

The approach taken to plan for ongoing events differs between water companies but existing approaches can be separated into three strands. First, weather forecasts are used for operational drought forecasting. For example, the ECMWF SEAS5 forecasts provide seasonal (up to 215 days) forecasts which can be used as input to hydrological models. Dynamical climate simulations from the GloSEA5 global seasonal predictions using the Met Office HadGEM3 coupled model are also used directly in the UK Hydrological Outlook, the national operational seasonal forecasting service for the UK. Previous studies have highlighted that probabilistic forecasts have limited skill in the forecasting of meteorological droughts on a sub-seasonal and seasonal timescale as precipitation is challenging to predict at long lead times (Richardson et al., 2020). Second, trajectories of river flows can be created through catchment hydrological model simulations assuming that rainfall over the next month reaches a specific percentage of long term average (LTA) rainfall (e.g. 60%, 80% or 100% of LTA). This approach is taken by the Environment Agency in their monthly water situation reports (e.g. Environment Agency, 2022b).

Third, forecasts can be provided using information from historical climate. For example, the UK Hydrological Outlook issue forecasts by assuming the repetition of individual notable historical years (such as benchmark events like 1975-76 or La Niña drought years like 2011) or by repeating all available years in an Ensemble Streamflow Prediction (ESP) approach (Prudhomme et al., 2017; Harrigan et al., 2018). Operational forecasts are also issued using statistical methods based on past streamflow observations, such as persistence forecasts based on flow anomaly in the most recent month and historical analogue forecasts using the most similar historical river flow sequences based on the assumption that the latest streamflow anomaly remains unchanged for the forecast lead time (1-3 months) (Svensson, 2016). ESP was first developed in the U.S. and is now a widely used approach worldwide for operational river flow prediction (Twedt et al., 1977; Day, 1985). ESP and the repetition of selected historical years are representative of a storyline approach which aims to describe and quantify pathways and developments of past or future events conditioned on changes to the event's drivers. However, these approaches are subject to some drawbacks. The relatively simple assumption of rainfall as a percentage of long term average do not consider physical plausibility and cannot be traced to climate drivers while the ESP approach is hampered by the limited length of observations, constraining the range of outcomes.

All three strands produce forecasts and outlooks at different scales and employ different datasets to drive hydrological and statistical models. Each methodological approach achieves different levels of predictability for different parts of the UK. For example, as shown by Svensson et al. (2015), persistence forecasts are most skilful for catchments in the south and east due to the slow-responding nature of groundwater-dominated catchments. Forecasts driven by dynamical climate or seasonal forecasting models may achieve greater skill in winter, particularly for catchments in the north and west, due to greater predictability of winter circulation patterns such as the North Atlantic Oscillation (NAO) (e.g. Dunstone et al., 2016; Svensson et al., 2015). Harrigan et al. (2018) examined the skill of ESP for catchments across the UK and found that the approach provided skilful forecasts over lowland England with a strong association between BFI and forecast skill with higher seasonal to annual skill if forecasts are initiated in winter and autumn.

Forecasts of atmospheric circulation characteristics (or weather regimes) are often considered more reliable than forecasts of winter precipitation. For example, skilful forecasts of interannual variability in winter NAO initialised in November have been demonstrated by Scaife et al., (2014) on a seasonal timescale using the GloSea5 forecasting system. The authors highlight the influence on the NAO via the stratosphere, North Atlantic SST anomalies prior to winter, Arctic sea ice extent and ENSO state (i.e. tropical SSTs) as main sources of predictability. For example, the timing of a sudden stratospheric warming or a strong polar vortex event may provide an indication of winter NAO phase and magnitude (Scaife et al., 2016; Monnin et al., 2022). For regions where there is a strong relationship between NAO phase and precipitation, the predictability of the winter NAO can enable skilful seasonal prediction of river flows (Bierkens and Beek, 2009). Moore et al. (1989) have suggested that improved prediction of river flows can be achieved where additional information can be used to inform whether precipitation from a particular year is more likely and thus given greater weight. The improved knowledge of the drivers of winter precipitation can be incorporated via a modified ESP approach. As demonstrated in Stringer et al. (2020) and Donegan et al. (2021), NAO-conditioned hydrological outlooks can be created where instead of assuming the repetition of all years, only historical years which match hindcast prediction of the NAO are used. Moulds et al., (2023) recently showed that skilful predictions of mean winter high flows several years ahead can be achieved by driving a statistical model with sub-samples of climate model hindcast predictions from members representative of inter-annual NAO variability. Other studies have used winter circulation characteristics (NAO, North Atlantic SSTs) to predict river flows of the subsequent summer and beyond (e.g. Wilby, 2001; Wedgbrow et al., 2002; Wilby et al., 2004; Wedgbrow et al., 2005; Svensson and Prudhomme, 2005). Summarising the relationship between North Atlantic circulation indices and winter precipitation and temperature in different regions of the UK, Hall and Hanna (2018) noted that seasonal forecasts of EA and other circulation indices should be prioritised to further increase seasonal predictability of winter precipitation given the importance of winter precipitation to river flows, aquifers and groundwater in southern and central England. For example, Dawkins et al. (2022) recently described the construction of a stochastic weather generator to simulate synthetic, spatially coherent daily precipitation over East Anglia that includes the EA pattern as a predictor of monthly winter precipitation given its role as a stronger driver of precipitation variability in this region compared to the NAO.

5.1.1 Aims and objectives

This chapter aims to demonstrate the use of seasonal hindcasts from the ECMWF SEAS5 dataset to aid water resources planning during ongoing events. This provides an opportunity to complement existing ESP methods in two ways. First, there is a larger sample of plausible winter weather sequences in seasonal hindcasts which can be used to better consider plausible outcomes. Second, the use of seasonal hindcasts takes advantage of the predictability of atmospheric circulation patterns from dynamical simulations. The use of seasonal hindcasts thus aims to combine the advantages of both strands 1 and 2 of the UK Hydrological Outlook. The specific aims of this chapter are to:

- Investigate the drivers of winter rainfall for the region of eastern England supplied by Anglian Water using a large sample of plausible winters from the ECMWF seasonal forecasting system SEAS5;
- Use knowledge of winter rainfall drivers (e.g. atmospheric circulation patterns) to group SEAS5 hindcast winters into conditional storylines representing plausible winter rainfall trajectories based on various combinations of atmospheric circulation patterns;
- Create drought storylines of river flows and groundwater levels for the 2022 drought representative of what the drought could have looked like if winter 2022/23 resembled the hindcast winters within each winter circulation storyline. Calculate the mean deficit and maximum intensity of each drought storyline using simulated river flows.

It should be noted that this chapter is not attempting to verify or assess the skill of SEAS5 in forecasting rainfall and droughts. Instead, the use of seasonal hindcasts aims to explore the utility of the storyline approach as a complementary tool to traditional forecasting methods to assist water resources planning.

5.2 SEAS5 hindcasts

The main limitation of the ESP approach is that long observational records are often not available and thus the repetition of historical years may miss plausible high-impact outcomes or are not representative of plausible meteorological conditions that could arise. Given the fact that historical observations only represent one out of many plausible alternative realisations, there is a growing use of large ensemble simulations or seasonal hindcasts to explore a larger sample of plausible events to mitigate this challenge (Kelder et al., 2020; Brunner and Slater, 2022). Operational drought forecasting is often done within water companies using calibrated hydrological models of key catchments and some companies already make use of seasonal forecasts. The level of resources required to extend existing methodologies to include a large sample of seasonal hindcasts is minimal and could provide greater context with more robust evidence to inform the short to medium-term hydrological situation.

The SEAS5 hindcast dataset (1982-2021) is used to provide a large sample of plausible winters (Dec, Jan, Feb - DJF) (2850 winters are available, comprising 38 complete winters between 1983-2020 x 25 ensemble members x 3 lead times). Details of the SEAS5 dataset and fidelity of the hindcast winters are outlined in the methods chapter (SEAS5 described in Chapter 3; Section 3.3.4 and fidelity test described in Section 3.3.5). Statistical tests on range, stability and independence confirms the reliability of the SEAS5 forecasts for the aims of this study. A number of meteorological indices described in Chapter 3: Section 3.3.1 is calculated from both the SEAS5 hindcasts and the ERA5 reanalysis. Figure 5.1(a)-(c) shows the relationship between precipitation anomalies over the East Anglia region for both observed and hindcast winters with the average winter Nino3.4, NAO and EA index. There is no clear relationship between ENSO phase and rainfall anomalies. There is a weak negative relationship between the NAO index and rainfall anomalies and a positive relationship between the EA index and rainfall anomalies. For each year between 1982 and 2020, there are 75 simulated winters in the hindcasts across ensemble members and lead times. There is considerable variability in the NAO and EA phases across the hindcast winters each year which often spans the four possible combinations of NAO and EA (hence the high variability in rainfall anomalies). Conversely, there is little variability in ENSO phase across the hindcast winters for each year as ENSO is comparatively slowly evolving and hence more predictable several months ahead. For example, winters 2015/16, 1997/98 and 1982/83 all exhibited particularly strong El Niño conditions and the hindcasts issued prior to each of those winters all had a similarly high Niño.4 index value (as shown by the vertical cluster of points in Figure 5.1a). Figure 5.1d shows the rainfall anomalies associated with combination of NAO and EA phases. Table 5.1 shows the conditional probabilities of below average precipitation in the East Anglia region based on various combinations of NAO and EA given La Niña conditions. NAO+/EA- are most likely associated with drier than average conditions and NAO-/EA+ winters with wetter than average conditions although there are also outliers with notable dry winters in both the observations and the hindcast. The relationships between rainfall and meteorological indices for the hindcast winters are consistent with past work showing the influence of opposing phases of the NAO and EA on observed UK rainfall (e.g. West et al. 2021, 2022; Parry et al. 2012). The interaction between both modes of variability has resulted in distinct spatial patterns observed in past severe hydrological droughts across Europe (Hannaford et al., 2011; Parry et al., 2012). The multi-annual variability in EA and NAO phases also contributes to variability in groundwater levels across England notably at ~7 years (NAO) and 16-32 years (EA) (Rust et al., 2019).

Table 5.1 Conditional probabilities of below average precipitation in the East Anglian region for different combinations of EA and NAO state given La Niña conditions in the hindcast winters. The NAO and EA indices are represented by the first two leading modes calculated through empirical orthogonal functions (EOF) analysis using monthly mean sea level pressure (MSLP) anomalies from ERA5 of the Europe/North Atlantic region. The Nino3.4 index is calculated from average sea surface temperature anomalies (ERA5) in the region (5°S-5°N, 120-170°W) to represent the phases of the El-Nino Southern Oscillation (ENSO).

	EA+	**Neutral**	**EA-**
NAO+	0.38	0.72	0.91
Neutral	0.27	0.60	0.78
NAO-	0.22	0.45	0.60

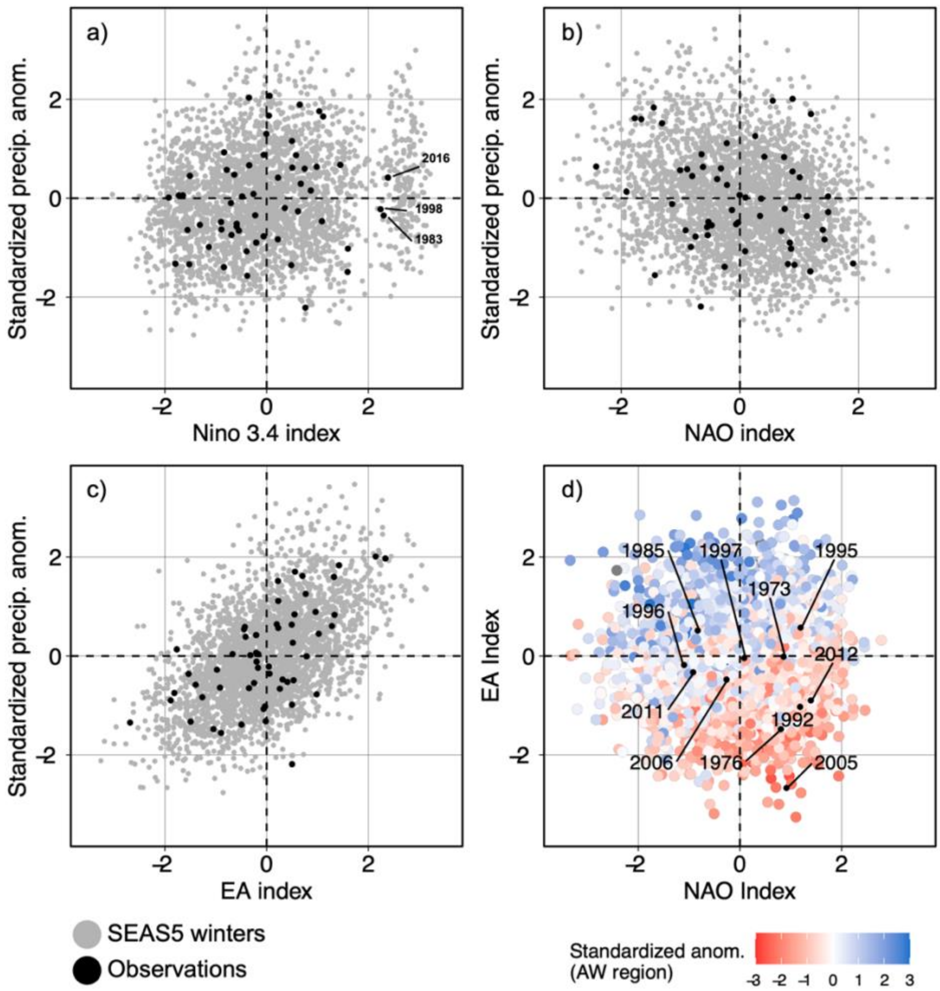

Figure 5.1 Relationship of a) Niño 3.4, b) NAO, and c) EA index with standardised precipitation anomalies in the Anglian Water region for the SEAS5 winters (grey) and observed winters (black). Panel d) shows the NAO index and EA index for each SEAS5 winter together with the precipitation anomalies over the Anglian Water (AW) region associated with each winter (colours). The cluster of strong El Niño hindcast winters in panel a) relates to hindcast winters issued prior to winters 2015/16, 1997/98 and 1982/83 (black dots in panel a), which were three of the strongest El Niño winters in the observations. Selected dry winters in the observations are shown in panel d) by the black dots and the year labels.

5.2.1 Circulation storylines

K-means clustering of all the calculated indices (NAO, EA, SST tripole, polar vortex strength) was used to create clusters of winters with similar circulation characteristics. Figure 5.2 shows four clusters defined for La Niña winters in the hindcast. Winter clusters were created separately for La Niña and El Niño winters. The clusters show little difference between El Niño and La Niña for clusters 1 and 3 but La Niña winters are in general drier than El Niño winters for clusters 2 and 4 (Figure 5.3). This is consistent with previous findings on the influence of ENSO on UK rainfall, as reviewed in Chapter 1. Clusters 2 and 4 are associated with NAO+ conditions and a strong polar vortex (Figure 5.2). Cluster 1 is associated with colder than average temperatures over East Anglia while Cluster 4 is associated with warmer than average temperatures. The temperature signal for Clusters 2 and 3 are less clear with normal temperature anomalies over East Anglia. Four clusters were chosen as they primarily reflect the four possible combinations of opposing phases of the NAO and EA as discussed in Section 5.2, including where opposing phases of the EA pattern may reverse the precipitation and temperature signal given a particular NAO phase. For example, both Clusters 2 and 4 are characterised by NAO+ conditions but exhibit different precipitation and temperature response given the effects of the EA phase (dry and mild for Cluster 2 and wet and warm for Cluster 4). The clusters also consider the range of circulation response and climate anomalies such as changes in polar vortex strength. Using the same SEAS5 hindcasts, Kolstad et al. (2022) showed the wide range of winter surface temperature responses that can arise from a given vortex state due to confounding factors such as NAO and ENSO.

Clusters 1 and 2 (3 and 4) are generally associated with drier (wetter) than average precipitation over the Anglian Water region although drier than average winters can occur for all clusters Figure 5.4 shows composite mean SLP anomalies for each cluster and four examples of dry observed winters exhibiting the same NAO and EA characteristics as each cluster across the NAO/EA phase space. As described in Wollings et al. (2010), NAO+/EA+ (NAO-/EA-) conditions are associated with the strongest (slowest) zonal wind speeds. The observed dry winters of 2011/12 and 1975-76 closely resemble the composite mean SLP anomalies of clusters 1 and 2, respectively. For clusters 3 and 4, the composite mean shows low pressure over the British Isles, which results in generally wetter winters as seen in Figure 5.2, meaning that the dry winters in the observations with these conditions are less similar to the composite mean. Observed winter 1984/85 resembles cluster 3 but with an extension of the high pressure eastwards with the pressure centre over Scandinavia leading to drier than average conditions in eastern England. Similarly, winter 1972/73 resembles the composite mean for cluster 4 but with a northward extension of the high pressure over southern UK, leading to drier, settled weather conditions over East Anglia. It should be noted that circulation patterns for individual years are not expected to fully resemble the composite mean patterns given the large range of variability but should exhibit similar features to the cluster with the same NAO/EA phase combination .

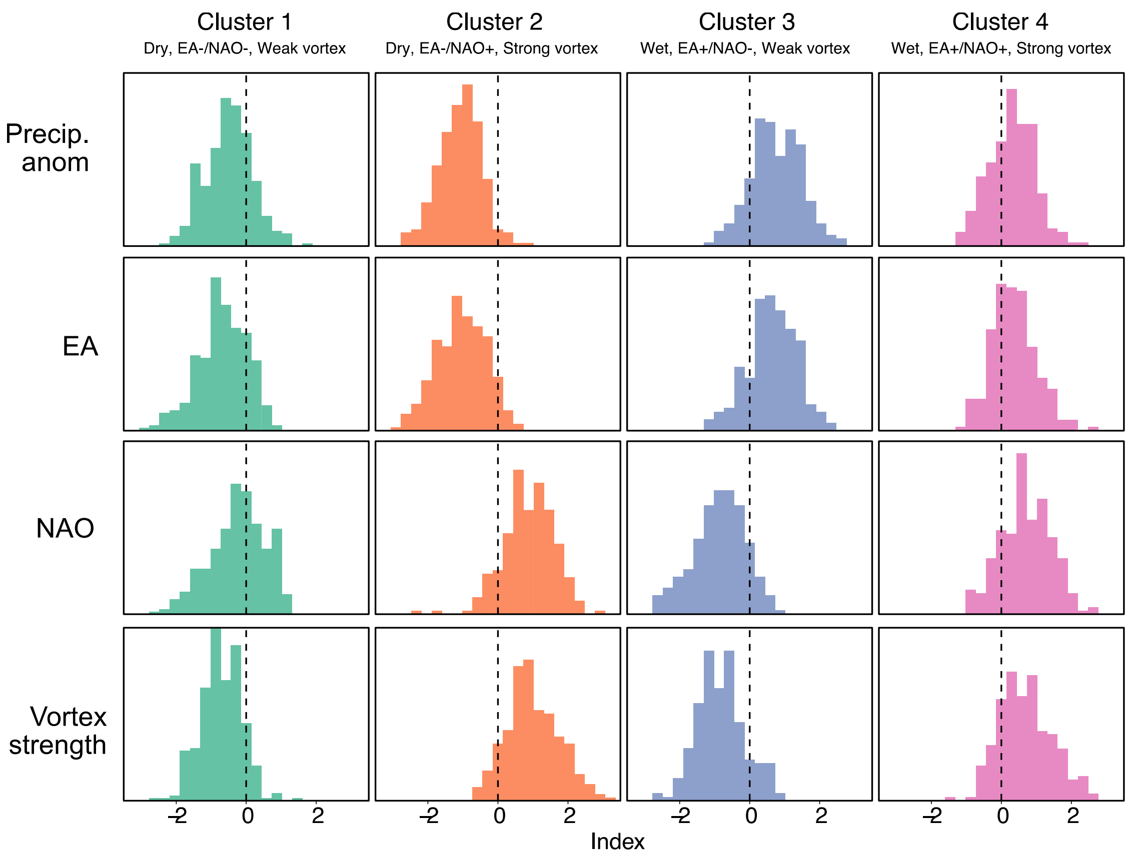

Figure 5.2 Winter clusters defined from hindcast winters with La Niña conditions using k-means clustering and the precipitation anomalies and meteorological indices associated with each cluster.

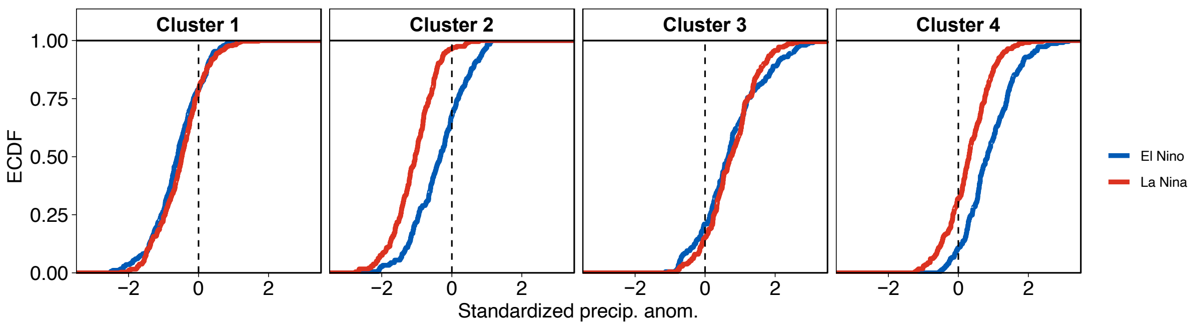

Figure 5.3 Standardised precipitation anomalies associated with La Niña (red) and El Niño (blue) winters in each circulation storyline.

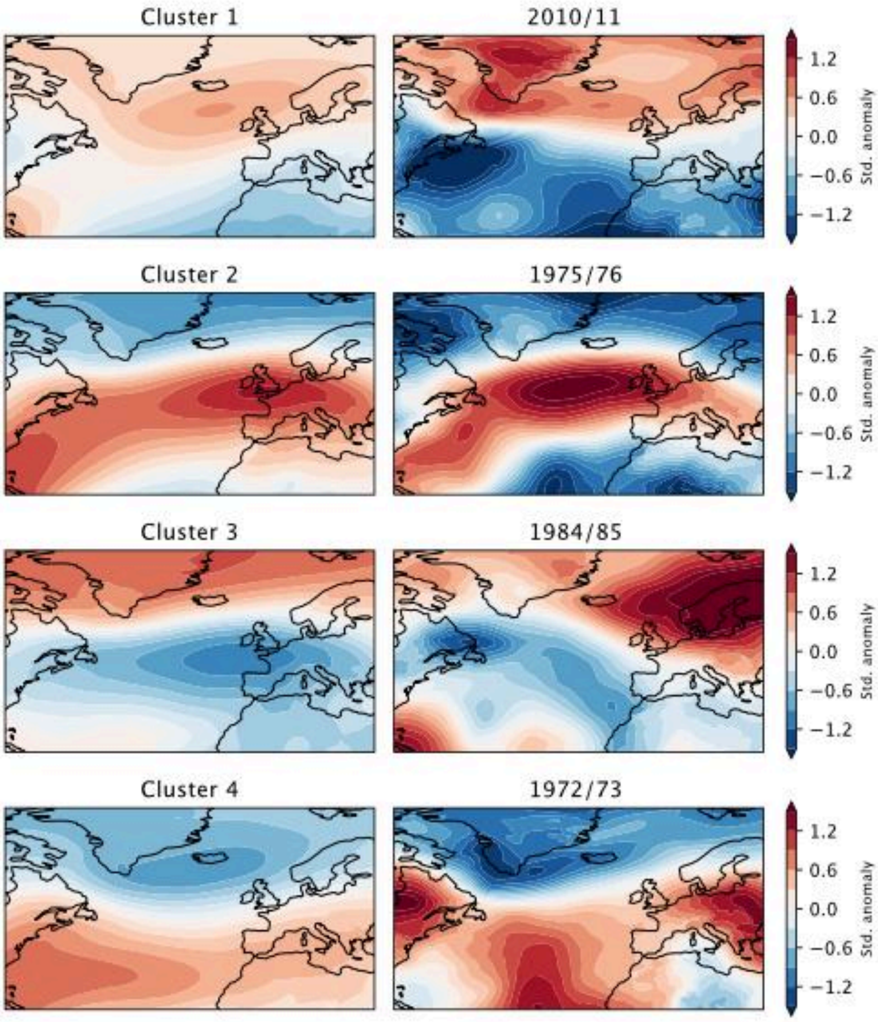

Figure 5.4 Composite mean sea level pressure (SLP) anomalies for SEAS5 winters within each of the four circulation storylines (left) and SLP anomalies (ERA5) for selected observed dry winters associated with similar NAO and EA pattern combinations for each cluster (right).

5.3 Case study – 2022 drought

5.3.1 2022 drought

The 2022 drought was declared in summer 2022 across England and Wales (Environment Agency, 2022b). The drought was most notable for a dry spring-summer sequence (51% of LTA March to August precipitation in East Anglia). The drought also followed an unusual pattern of precipitation in winter 2021/22 with average precipitation in December 2021, settled and dry conditions in January 2022 and wetter than average conditions in February 2022. Total winter precipitation was slightly below normal across East Anglia (97% LTA) with drier conditions concentrated in the southeast of the region (e.g. southeast Suffolk). Exceptional soil moisture deficits during the summer 2022 heatwave also exacerbated agricultural drought conditions. East Anglia experienced slightly above average rainfall in autumn 2022 (117% of LTA) which saw recovery of river flows at some catchments. However, above average precipitation was mostly concentrated in western parts of the region with river flows in the northeast remaining below normal entering winter 2022/23 (Environment Agency, 2022a). Figure 5.5 shows SPI-12 over Norfolk from 2021 to November 2022, showing the inception of drought conditions across winter 2021/22 and prolonged precipitation deficit across 2022. Figure 5.6a shows the regression slope of cumulative precipitation anomalies over East Anglia from May to August for each year in the HadUK-Grid precipitation dataset and Figure 5.6b highlights the temporal evolution of cumulative precipitation anomalies for 1921, 1976 and 2022. The regression slope for spring-summer 2022 is notable as the third steepest decline in cumulative precipitation anomalies after 1976 and 1921. Exceptional soil moisture deficits during the summer 2022 heatwave also exacerbated drought conditions when mean temperatures reached 18.26°C and maximum temperature reached 24.25°C for East Anglia (warmest since 1884).

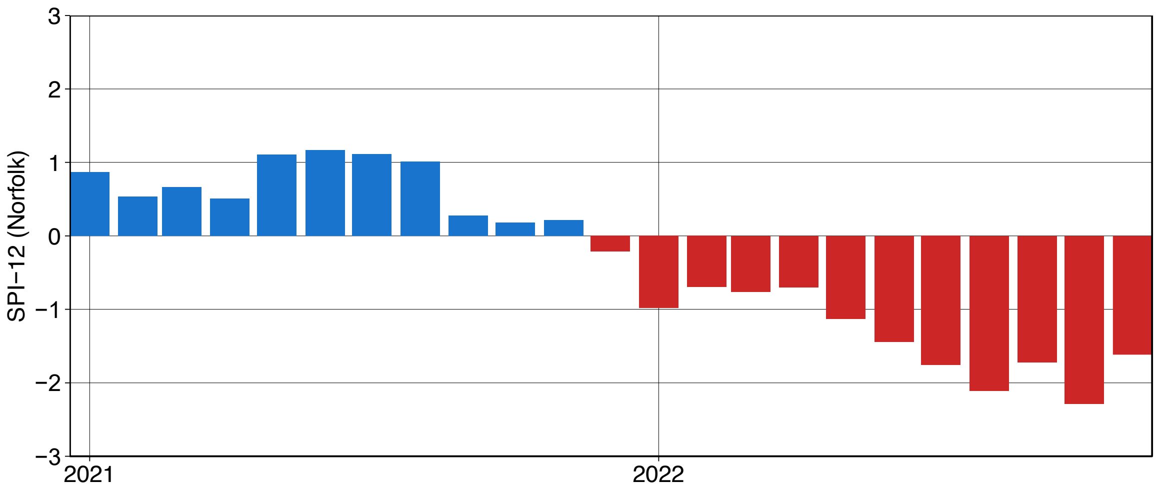

Figure 5.5 Standardised precipitation index (SPI) accumulated over 12 months for the Norfolk region of East Anglia from January 2021 to November 2022 (Data from the UK Water Resources Portal – Barker et al., 2022)

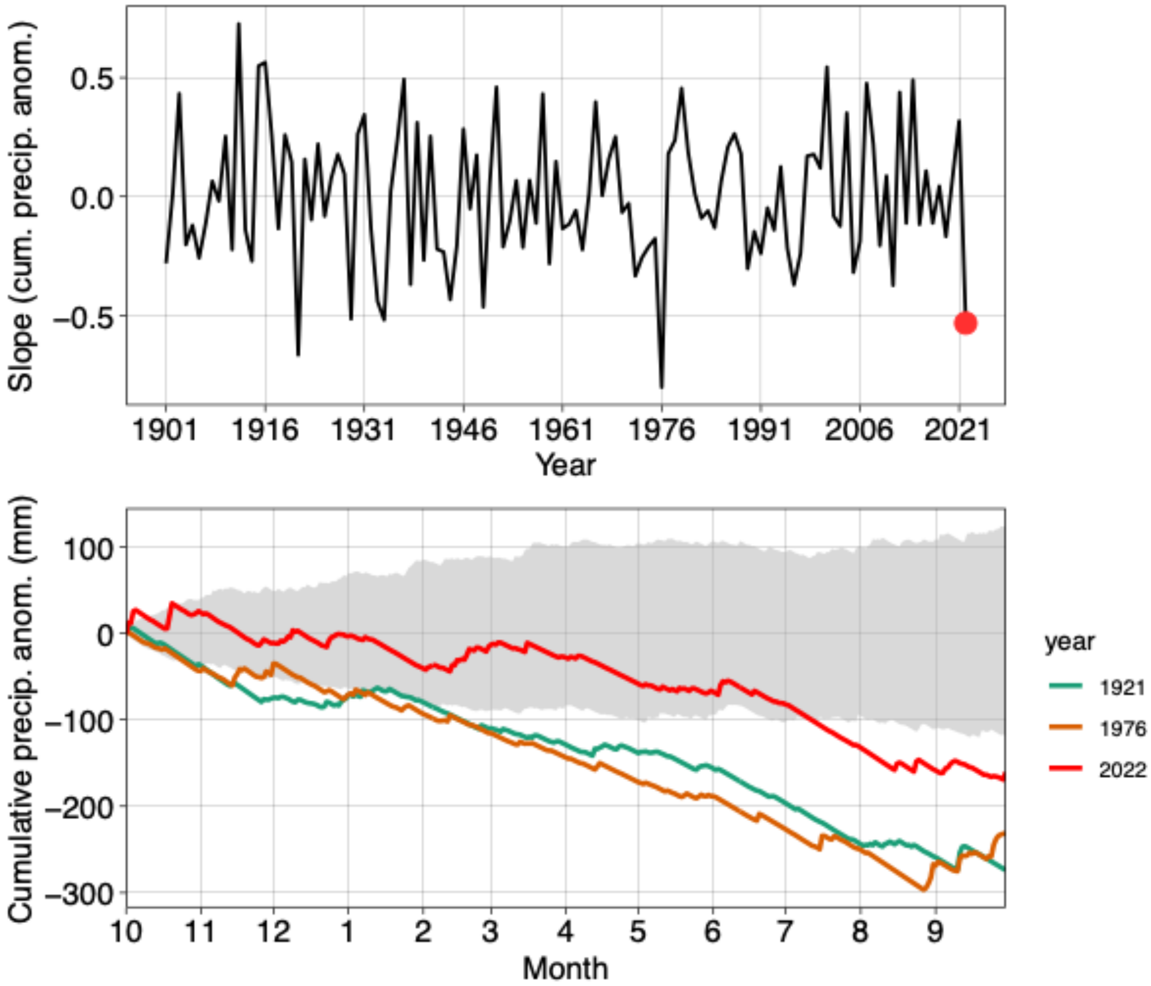

Figure 5.6 a) Regression slope of cumulative precipitation anomalies over March to August for years 1901-2022 (HadUK-Grid dataset) over East Anglia with the red dot highlighting the 2022 value. b) Cumulative precipitation anomalies (mm) over East Anglia for 1921, 1976 and 2022. The grey shading represents the 10-90th percentile calculated from observed precipitation over the historical 1965-2015 period.

5.3.2 Storylines of the 2022 drought

As opposed to retrospective storylines created based on past droughts as demonstrated in Chapter 4, this section details the conditioned drought storylines created in real time during the 2022 event. Specifically, storylines in this chapter were created in autumn 2022 without prior knowledge of winter 2022/23 to represent plausible pathways of the 2022 drought assuming winter 2022/23 resembled each of the four winter circulation storylines as described in Section 5.3. It should be noted that the storylines should not be considered as predictions, but instead are plausible pathways which can be used to understand the range of uncertainty and to explore plausible worst cases to assist water resources planning. Additionally Given the variety of approaches used for water resources planning during an event, storylines combine the advantages of ESP and dynamical simulations to condition storylines based on circulation patterns and knowledge of the drivers of winter precipitation in the East Anglia region. The GR6J hydrological model and Aquimod groundwater level model were used to simulate river flows at 16 river catchments and groundwater levels at 10 boreholes within the Anglian Water region as described in Chapter 4 (Section 4.2.1). Simulations were run for the baseline period up until November 2022 using GR6J and Aquimod after which hindcast precipitation and PET data for each winter (DJF) in the four winter clusters were appended in place of winter 2022/23. Focus is given to La Niña winters given that La Niña conditions were observed over 2022. precipitation. Spring (MAM), summer (JJA) and autumn (SON) 2023 were assumed to have 100% long-term average (LTA) precipitation by selecting the closest years matching 100% LTA precipitation in the observations.

River flows

Figure 5.7 shows simulated river flow response over winter 2022/23 for each circulation storyline. All catchments were estimated to experience below normal river flows when entering spring 2023 given winters in clusters 1 and 2 with particularly severe flow deficits in groundwater-dominated catchments in the northeast of the region. Despite the wetter weather for winters in clusters 3 and 4, the groundwater-dominated catchments in the northeast were still estimated to experience below normal to low flows by spring 2023. This is likely due to the combined effect of insufficient winter precipitation to overcome dry conditions and the slow response nature of groundwater-dominated catchments. Each storyline was contrasted with the unclustered distribution of simulated flows across all 2850 winters, analogous to the traditional ESP approach (unclustered map in Figure 5.7). Using all 2850 winters highlights the confidence of below normal flows in the northeast but does not consider the dynamical drivers of winter precipitation that could lead to a different likelihood of possible flow response as shown in the conditional subsets of each storyline. Results from cluster 1 show that it was likely for flows to remain below normal by spring 2023 with the potential to reach severe drought conditions over 2023, particularly for groundwater-dominated catchments, even with spring to autumn 2023 receiving 100% LTA precipitation.

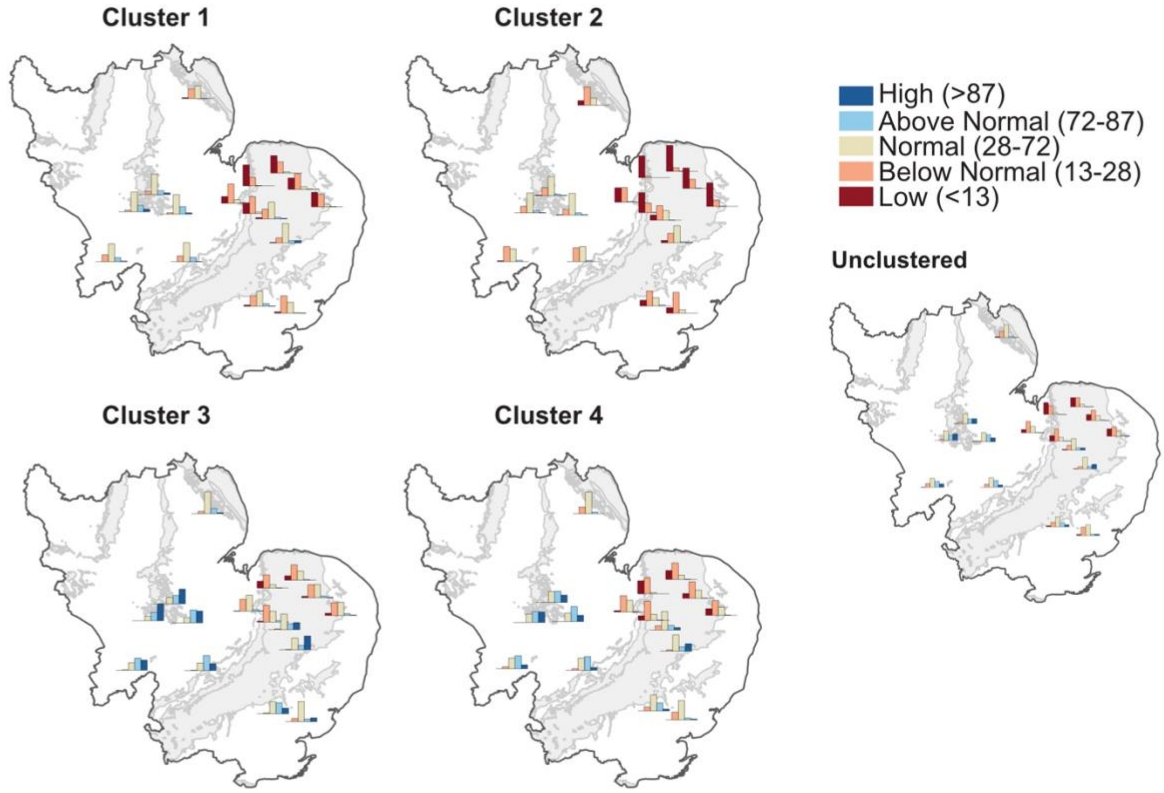

Figure 5.7 Distribution of river flows for each circulation storyline represented in percentile terms (percentile value in parenthesis in the legend) relative to 1965-2015. Each storyline assumes winter 2022/23 follows hindcast winters in one of the La Niña winter clusters. Individual plots show the distribution of hindcast winters for each percentile category as indicated by the colour key. Grey shading shows major aquifers in eastern England from the hydrogeology map of the British Geological Survey. The unclustered map shows the distribution across all 2850 hindcast winters (i.e. spanning both El Niño and La Niña winters).

Figure 5.8 compares drought evolution (characterised by the standardised streamflow index accumulated over 3 months – SSI-3) during 1975-76 and 2021-22 with storyline estimates of SSI-3 for 2023 for four example catchments. Similar to 2022, 1976 was characterised by a dry spring-summer sequence (50% LTA rainfall in East Anglia). The decline to drought conditions in 2022 was generally later in the year and less severe with river flows generally recovering later in the autumn compared to 1975-76. Simulated river flows from the driest (cluster 2) and wettest (cluster 3) storylines show the continued vulnerability of catchments in the Anglian Water region in 2023. For groundwater-dominated catchments such as the Nar at Marham (33007) and Ely Ouse at Denver Complex (33035), drought intensity could plausibly match that seen in summer 1976 by summer 2023 given a dry winter in cluster 2 (mostly associated with NAO+/EA-). For these catchments, drought conditions could plausibly decline to similar drought intensity as seen in summer 2022 even with a wet winter in cluster 3 (mostly associated with NAO-/EA+).

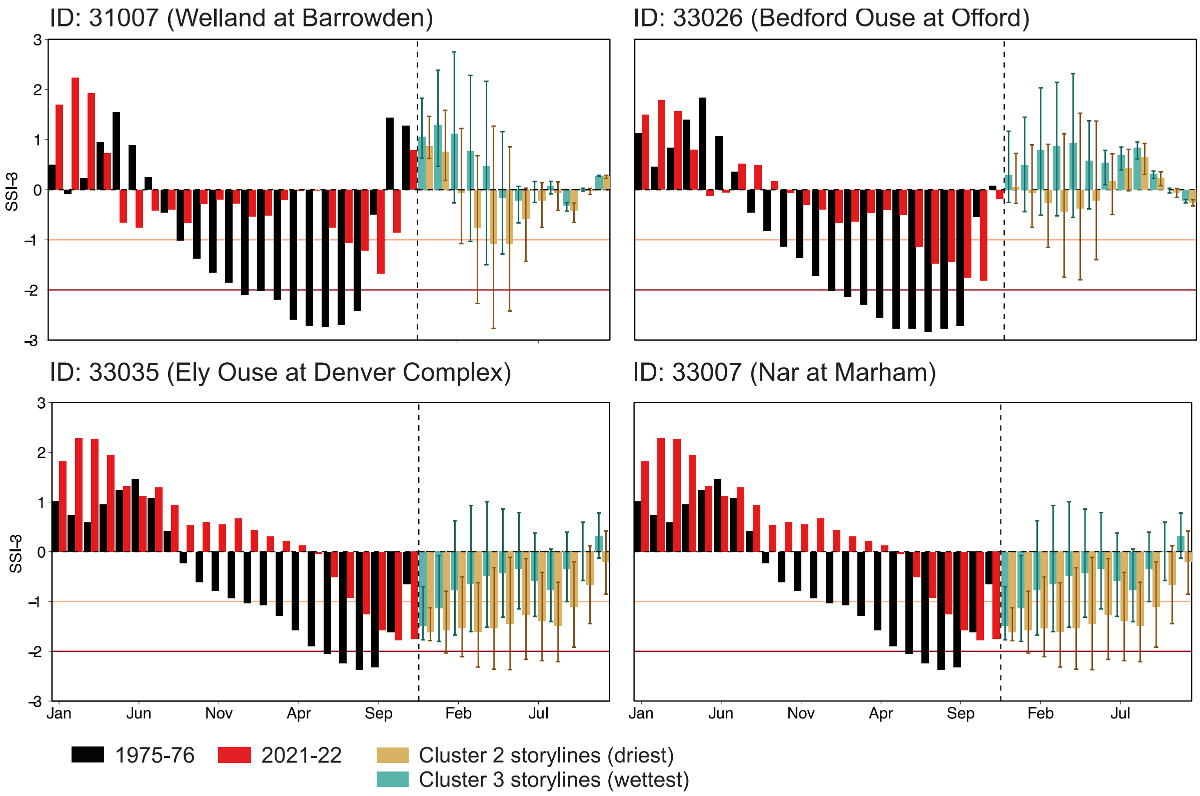

Figure 5.8 Standardised streamflow index accumulated at 3-months (SSI-3) over 2021-2022 and beyond following the driest and wettest circulation storyline at four example catchments compared with SSI-3 over 1975-1975. Spring to autumn 2023 is assumed to have 100% LTA precipitation.

To understand the importance of winter precipitation and the effect of a second consecutive dry summer, an additional sensitivity test assumed summer (JJA) 2023 to follow 60% LTA seasonal precipitation. Figure 5.9 shows the influence of a second consecutive dry summer in 2023 on the development of severe drought conditions (SSI-3 < -1.5). An accumulation of three months is used here to provide an indication of the shorter-term seasonal effects. Slow responding catchments are more influenced by the effect of a dry winter in clusters 1 and 2 with a comparatively higher likelihood of reaching severe conditions. A dry summer with 60% LTA rainfall (similar to summer 2018) results in a higher likelihood for severe drought conditions to develop, especially following a dry winter characterised by circulation patterns in clusters 1 and 2. Given the higher likelihood of a wetter than average winter in clusters 3 and 4, fewer catchments reach severe drought conditions if summer 2023 receives 100% LTA rainfall. For groundwater-dominated catchments, it is likely that severe drought conditions will be reached even with 100%

LTA rainfall in summer 2023 across all four storylines, even for clusters 3 and 4 with wetter than average winters. This is reflected previously in Figure 5.7, showing that river flows were estimated to be unlikely to recover to normal levels for all four storylines.

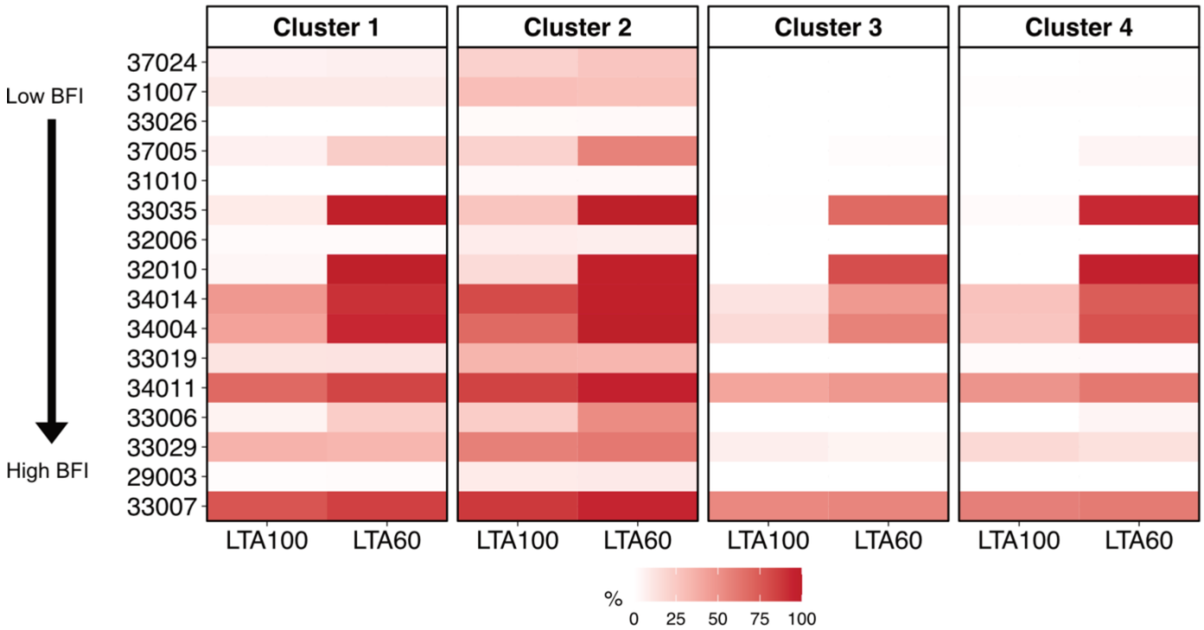

Figure 5.9 Likelihood of reaching SSI-3 below -1.5 from winter 2022/23 to autumn 2023 for each circulation storyline. In the LTA100 experiment, spring to autumn 2023 is assumed to have precipitation at 100% long-term seasonal average whereas the LTA60 experiment assumes summer 2023 to receive 60% LTA precipitation with 100% LTA precipitation for the other seasons. Catchments are ordered by increasing baseflow index (BFI) from the top.

Groundwater levels

Figure 5.10 shows storylines of groundwater levels given each cluster. Given drier winters in clusters 1 and 2, groundwater levels were estimated to be normal to below normal across all boreholes by spring 2023. Wetter conditions over winter associated with circulation patterns in clusters 3 and 4 were estimated to lead to groundwater level recovery to above normal levels, particularly for boreholes in Lincolnshire (the more northerly catchments on the map) as groundwater levels at these relatively faster responding boreholes were already recovering after sufficient rainfall in autumn 2022. Figure 5.11 shows the standardised groundwater index (SGI) accumulated over 12 months for four example boreholes with different responses to the circulation storylines. Similar to the pattern for some slow-responding river catchments , some boreholes in East Anglia (such as Washpit Farm and Old Hall Thurgaton) were still estimated to have a high likelihood of remaining at below normal levels by spring 2023 even with the wetter conditions from winters in clusters 3 and 4.

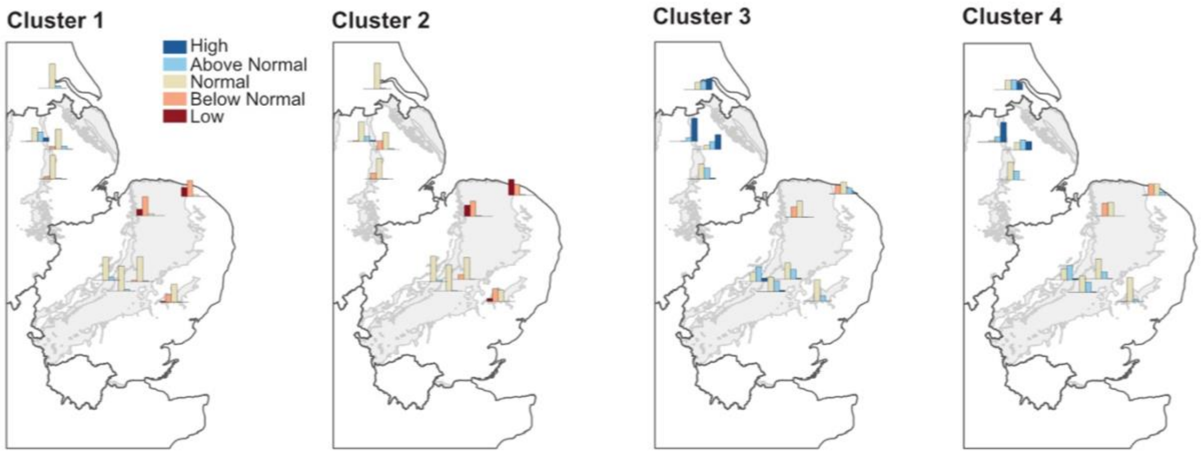

Figure 5.10 Storylines of groundwater levels for each borehole in different categories (percentiles relative to 1965-2015) by spring 2023 for each storyline. Individual plots show the distribution of hindcast winters for each percentile category as indicated by the colour key in Figure 3. Grey shading shows major aquifers in eastern England from the hydrogeology map of the British Geological Survey

5.3.3 Drought termination

It is often of interest to water resources managers to understand the conditions required for drought recovery. Drought termination refers to the return of river flows or groundwater levels from drought to normal conditions (Parry et al., 2016a, b). Each circulation storyline thus provides an indication of the mechanisms and magnitude of precipitation over winter 2022/23 that would be required for both abrupt and gradual drought terminations. Parry et al. (2018) previously demonstrated two approaches to create storylines of groundwater drought termination during the 2018/19 UK drought. The first approach assumes a linear rate of change in the latest groundwater level anomaly until conditions return to normal while the second approach assumes the repetition of drought terminations observed in past events. The circulation storylines created in this chapter add a dynamical perspective to the previous approaches to shed light on drought termination characteristics.

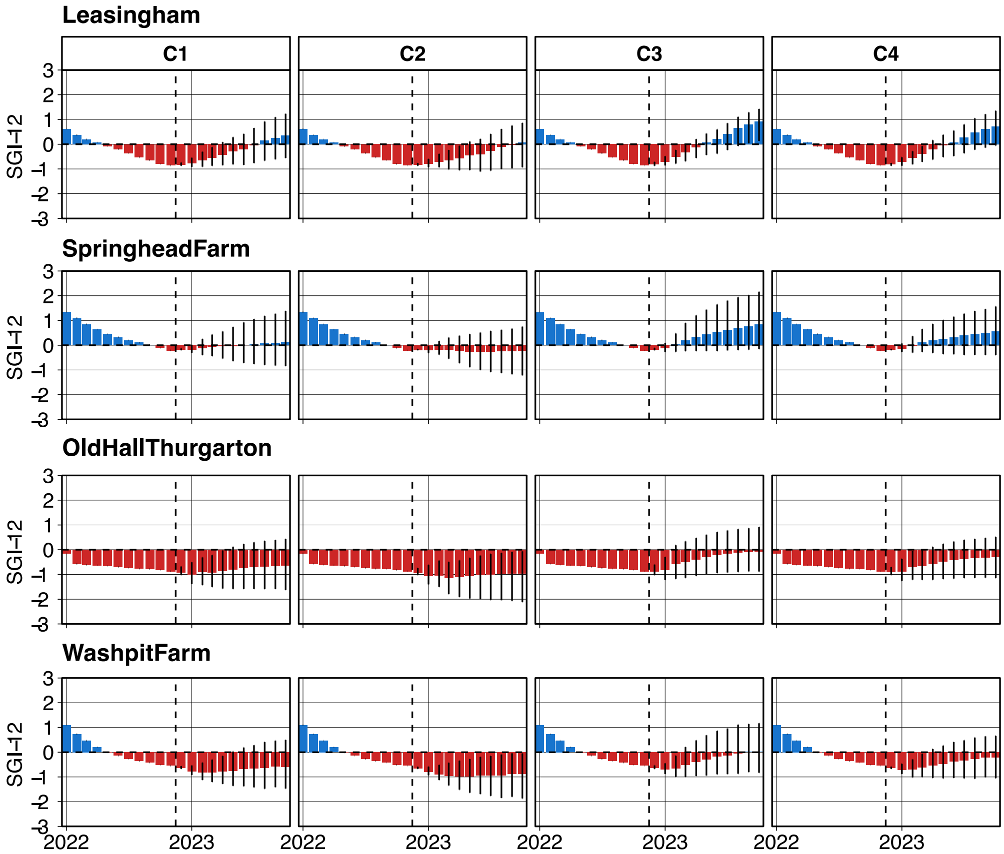

Figure 5.11 Examples of four boreholes and simulated groundwater response (SGI-12) to each winter circulation storyline over winter 2022/23 and beyond. Red (blue) colours represent negative (positive) SGI values.

The physical processes involved in drought recovery and termination have received relatively little attention in the UK until recently. Parry et al. (2016a, b) created an inventory of drought terminations from past UK events. The studies show that precipitation alone is not the only driver and termination can be a long-lasting process influenced by the physical driving characteristics of the drought (such as the temporal and seasonal distribution of precipitation) and physical catchment characteristics. The framework presented by Parry et al. (2016a, b) determines drought termination rate and drought termination duration from monthly river flows. In brief, the start of the drought termination period is defined as the period when the minimum monthly river flow anomaly within a drought event is reached (i.e. drought magnitude) and ends when the flow anomaly is positive for a user-defined number of consecutive time steps (i.e. termination magnitude). The drought termination rate (DTR) can be calculated by the difference between the drought magnitude and the termination magnitude divided by the total duration (months) of the drought termination period (DTD).

Drought termination characteristics at four catchments and boreholes for each storyline are shown in Figures 5.12 and 5.13 respectively. Given the higher likelihood of wet conditions, drought termination is estimated to be more likely if winter 2022/23 resembled hindcast winters in clusters 3 (EA+/NAO-) and 4 (EA+/NAO+) compared to clusters 1 and 2. Clusters 3 and 4 also include a larger number of winters that could have resulted in a rapid DTR. Conversely, given the slow response nature of groundwater-dominated catchments and insufficient precipitation, it is less likely for drought terminations to occur if winter 2022/23 resembles winters in Cluster 2. DTR is generally faster for river flows compared to groundwater levels. Unsurprisingly, a faster DTR is more likely to be caused by higher total winter precipitation. A fast DTR is associated with a short DTD as catchments rapidly exit drought conditions after reaching maximum drought magnitude whereas a slow DTR is often associated with a long DTD either because the catchment takes longer to recover from a significant drought magnitude or if moderate drought conditions continue after reaching maximum drought magnitude before termination.

The relationship between DTR and DTD is clearer for groundwater compared to river flows. There are anomalous cases for river flows where the event is terminated with a moderate DTR over a short DTD. For example, at the Bedford Ouse of Offord, there are winters in Cluster 3 that could have resulted in both slow and fast DTR over the same DTD at 2 months. Similarly, there are outcomes where the drought terminates at the same DTR but over different DTDs. One hypothesis for this behaviour could be dependence on the temporal distribution of precipitation within a given winter (i.e. prolonged precipitation across the whole winter versus anomalously high precipitation in specific winter months) and a possible role for physical catchment characteristics. For example, a slow DTR could occur over a short DTD if the drought magnitude is less severe, allowing the drought to terminate quickly even with a moderate DTR or if a small termination magnitude is reached shortly after maximum drought magnitude. The simulated drought terminations shows that DTR for the 2022 event is more likely to be quicker in relatively faster responding systems. As shown in Parry et al. (2016a) across past UK droughts, there is a negative relationship between DTR and BFI, indicating that less responsive catchments are more likely to have slower DTR.

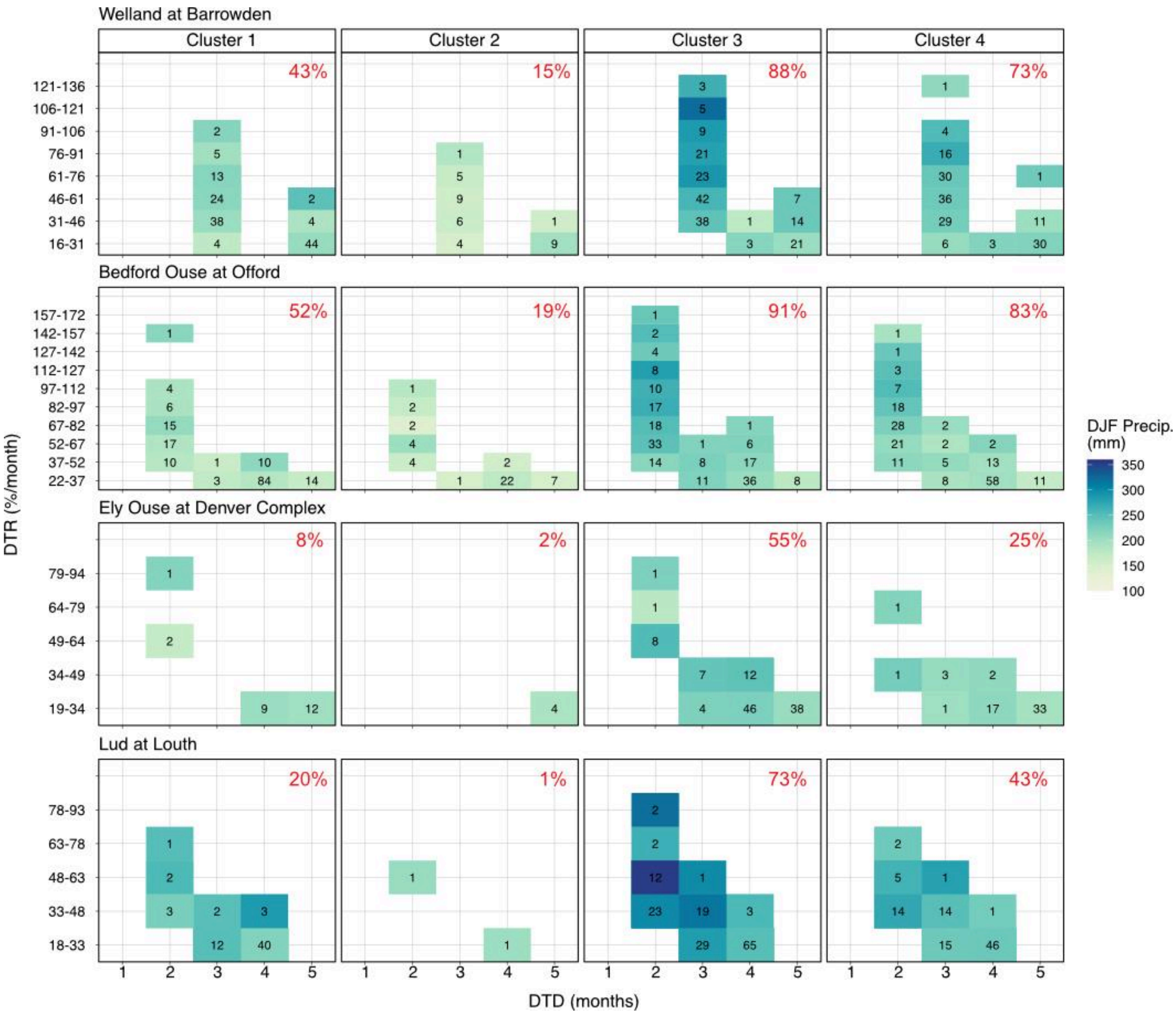

Figure 5.12 Drought termination characteristics of the 2022 hydrological drought at four example catchments for each circulation storyline. DTD refers to drought termination duration (months) and DTR refers to drought termination rate (%/month). The number of terminations within each DTD and DTR category is shown for each tile. The colours refer to the total winter precipitation required for termination within each tile. The likelihood of termination for each circulation storyline is shown on the top right of each panel.

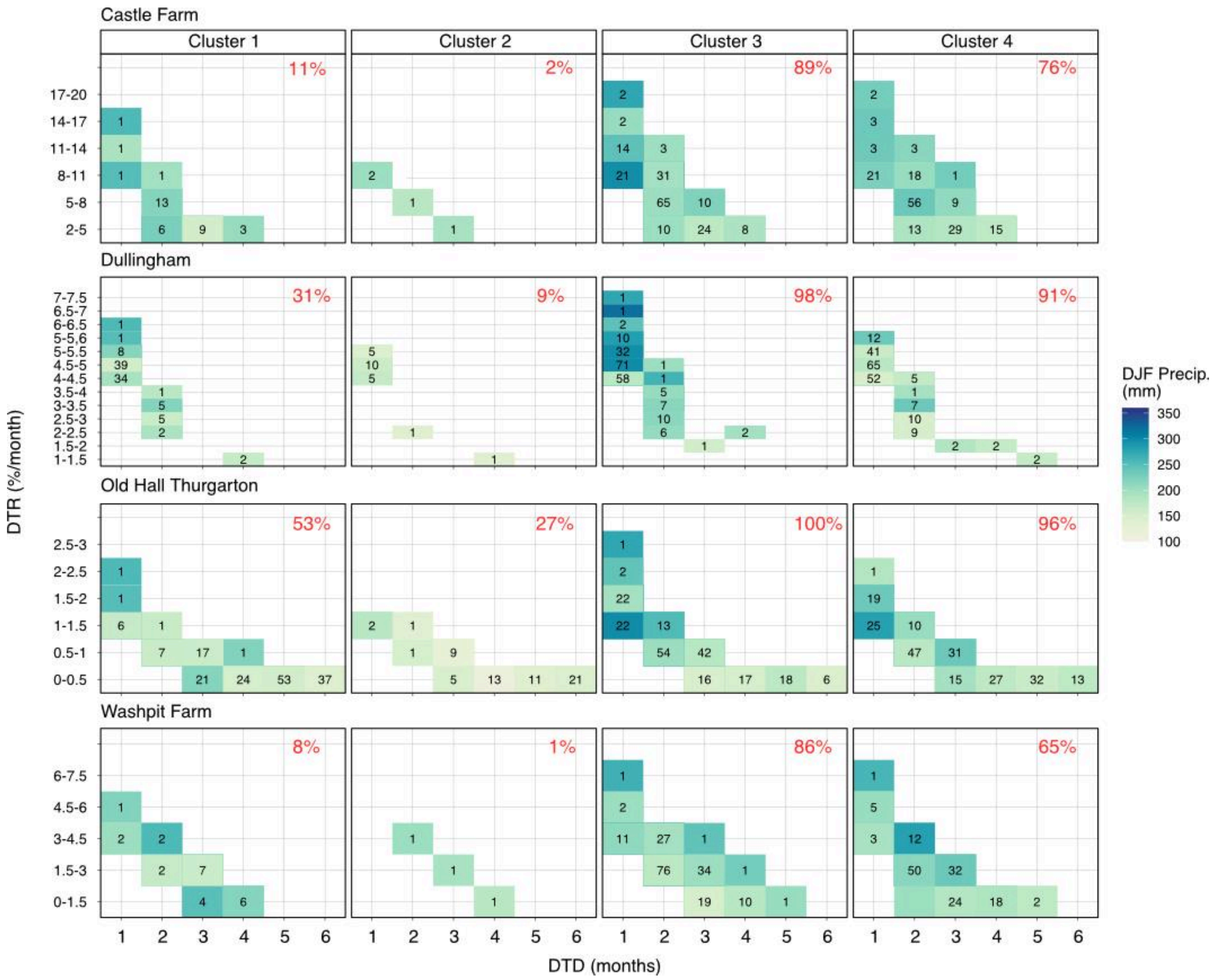

Figure 5.13 Drought termination characteristics of the 2022 groundwater drought at four example boreholes for each circulation storyline. DTD refers to drought termination duration (months) and DTR refers to drought termination rate (%/month). The number of terminations within each DTD and DTR category is shown for each tile. The colours refer to the total winter precipitation required for termination within each tile. The likelihood of termination for each circulation storyline is shown on the top right of each panel.

5.4 Winter 2022/23

This section provides a brief exploration of how the winter 2022/23 turned out and further knowledge that could be gained from conditional storylines created for the 2022 drought. The storylines were created in autumn 2022 before winter 2022/23 and without knowledge of how the winter would transpire. The observed winter exhibited an NAO-/EA- pattern, resembling the atmospheric circulation patterns for winters in cluster 1. Similar to the composite mean SLP anomalies of cluster 1, winter 2022/23 saw high pressure conditions over the UK leading to drier than average conditions with the high pressure centre shifted further westwards (Figure 5.14). The

East Anglia region received 69% of LTA winter precipitation with a notably dry February which received only 15% of LTA precipitation. Following the extremely low precipitation in February 2023, Anglian Water noted the continued vulnerability of catchments in this region in 2023 may result in a return of water use restrictions (Anglian Water, 2023). This was also reflected in a statement from the National Drought Group which stated that England is "one hot, dry spell away from drought returning this summer" following the dry February (National Drought Group, 2023). Indeed, the results from cluster 1 show that it was likely for flows to remain below normal by spring 2023 with the potential to reach severe drought conditions over 2023, particularly for groundwater-dominated catchments, assuming that spring to autumn 2023 receive 100% LTA precipitation. The descent into further drought conditions was somewhat alleviated by a wetter than average observed spring 2023 with 144% of LTA precipitation although East Anglia remain under drought conditions as of June 2023. March 2023 was particularly wet with East Anglia receiving over double the LTA March precipitation (214%). The observed summer 2023 was wetter than average nationally, with a notably wet July. East Anglia received 95% of LTA rainfall with patches of slightly below average rainfall in parts of Norfolk. Parts of East Anglia remained in drought status over summer 2023 and official drought status was only lifted in October 2023 after river flows and ecological impacts recovered sufficiently.

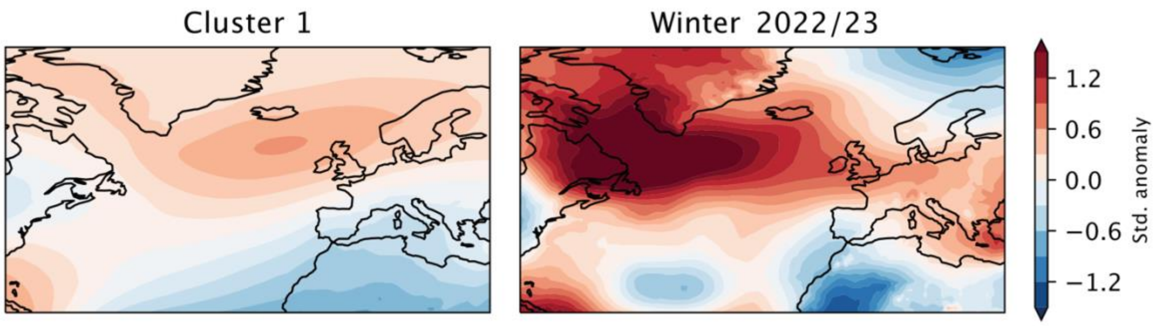

Figure 5.14 Composite mean sea level pressure (SLP) anomalies for winters in cluster 1 compared to mean SLP anomalies from ERA5 over observed winter 2022/23 (relative to 1965-2015).

Although the circulation storylines did not include a likelihood of a particular storyline for winter 2022/23, further subsets to the hindcast winters can be made to provide weights for particular storylines that are considered more likely than others over time (e.g. based on prevailing atmospheric circulation patterns). Given the large sample size of the hindcast winters, future work could condition storylines based on their preconditions. For example, for the 2022 drought, storylines can be created by selecting only winters in the hindcasts with a wetter than average preceding November (as was observed in November 2022).

5.5 Chapter summary

This chapter demonstrated the use of seasonal hindcasts to create drought storylines conditioned on atmospheric circulation patterns. These storylines enabled a more detailed focus on the drivers of winter precipitation in eastern England compared to existing approaches. The circulation storylines were created from a large sample of hindcast winters and covered a range of possible combinations of the various atmospheric circulation indices relevant to winter precipitation in East Anglia. The resulting storylines spanned all possible combinations of NAO and EA conditions and a wide range of surface precipitation and temperature response. Applying the circulation storylines to the ongoing 2022 drought in November 2022 without prior knowledge of winter 2022/23 highlighted the large-scale atmospheric circulation patterns that are likely to result in continued drought conditions in 2023 or drought recovery and termination. Assuming a second consecutive dry summer in 2023, drought conditions were estimated to return across most selected catchments, especially following a dry winter storyline which transpired in the observed winter 2022/23.

Although this chapter focused on the winter season, a similar approach can be taken for other seasons. This may be particularly useful for seasons where other forecasting approaches may be less informative and when it may be useful to consider a wider range of outcomes to explore plausible worst cases (e.g. during a prolonged dry weather period prior to drought onset). While existing practice includes exploring the repetition of key individual years (such as the La Niña year of 2011), conditional storylines consider a wider range of outcomes, including the combined effects of large-scale circulation patterns, such as the combination of NAO and EA patterns during La Niña years. Assuming that an upcoming season resembles certain atmospheric circulation patterns through a storyline framing increases risk awareness. This can include enabling water managers to plan for water resources provisions, and to explore plausible worst cases that are possibly outside the range of historical years. Decision-makers can prioritise and re-direct operational resources such as borehole maintenance in key areas where the large sample of hindcast winters show continued drought conditions or areas where plausible worst cases within each circulation storyline exceed certain thresholds (e.g. relative to past reference droughts).

6 LINKING PROBABILISTIC ESTIMATES WITH STORYLINES

A version of this chapter has been published in the *Journal of Hydrology,* with the following reference:

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

6.1 Introduction

The thesis so far has shown that event storylines are a valuable tool to explore current and future risk of a particular event. Discrete storylines of past events can increase risk awareness and assist in stress testing water resources systems against downward counterfactuals. Chapters 5 and 6 have shown that both retrospective and real-time event storylines can address some of the identified research gaps in existing approaches to better understand the unfolding of hydrological droughts in the UK. This chapter aims to address a number of further outstanding research gaps. First, as introduced in Chapter 1, internal climate variability dominates for near-term projections, and it is challenging to untangle the climate change signal from natural variability (i.e. signal-to-noise ratio). Understanding the nature of severe hydrological droughts is hampered by short observational records that are insufficient to robustly sample for plausible worst-case events that could arise due to internal climate variability. Second, while previous chapters demonstrated that storylines need not have probabilities attached to them, there remains an opportunity to combine probabilistic approaches with storylines to add value to existing risk-based estimates by increasing process understanding of low-likelihood, high-impact events and decision-relevant outcomes.

6.1.1 Current and future risk

There is a need to better understand current risk and consider the full range of possible outcomes that could arise from internal climate variability in the current climate. Adaptation planning needs to prepare and guard against unprecedented or record-breaking events beyond those that have occurred in historical observations ,as variability can be larger than the trend or mask any emerging gradual trends towards more extreme events (Fischer et al., 2021; Satoh et al., 2022; Thompson et al., 2023). Additionally, sectors with adaptation plans for the short- to medium-term (such as water resources management plans or plans for sustainable abstractions) need to plan for projected reductions in low flows before such trend may be statistically detectable (Wilby, 2006; Wilby et al., 2011; Watts et al., 2015). For example, Brunner and Tallaksen (2019) found widespread vulnerability of European catchments to multi-year hydrological droughts in the current climate despite some catchments not having encountered such multi-year hydrological droughts in the observations.

In addition to the possibility of unprecedented extremes in the current climate, internal climate variability is also the dominant source of uncertainty in near-term climate projections (Hawkins and Sutton 2009; 2011). Hulme et al. (1999) found that the impacts of climate change on low flows would remain undetectable until at least the 2050s across large parts of Europe. Similarly, Wilby et al. (2006; 2008) suggested that a statistically significant trend in seasonal river flows is not likely to emerge within a typical planning timescale (e.g. looking ahead 25 years). Arnell (2003; 2011) found that projected change in low flows may still be within the range of natural variability in the medium term but the climate change signal relative to natural variability is greatest for increasing winter flows (decreasing summer flows) in northern (southern) UK. It is also possible for projected change within a short time slice to exhibit a trend opposite to that expected from anthropogenic climate change due to natural internal variability (Deser et al., 2012b; Shepherd, 2014). Past studies have shown that projected changes in drought characteristics are larger when accounting for the effects of year-to-year variability in precipitation (e.g. Ledbetter et al., 2012; Kay and Jones, 2012; Charlton and Arnell, 2014; Mankin et al., 2017), highlighting the need to consider a wide range of droughts to stress test hydrological and water supply systems.

6.1.2 Large ensemble climate impact modelling

Although uncertainty associated with internal climate variability is aleatoric and largely irreducible, its effects can be better sampled using large ensemble simulations. Previous chapters have demonstrated the advantages of using a large sample of plausible weather sequences by pooling seasonal hindcast data. Studies have increasingly used SMILE simulations to understand high-impact climate extremes (Bevacqua et al., 2023). van der Wiel et al. (2020) recommended following a large ensemble climate impact modelling approach (Figure 6.1) to sample for high-impact events to understand the non-linear and compound ways in which they can develop even from moderate meteorological drivers. Each SMILE is based on a single climate model with the same external forcings. Each ensemble member is run with different initial conditions to generate multiple realisations of plausible weather sequences (Deser, 2020). Following initial condition perturbations, simulations across ensemble members gradually diverge from each other representing a range of plausible outcomes and trends due to internal climate variability (Deser et al., 2012a). Some SMILEs, such as the EC-Earth time-slice large ensemble, represent stationary climate conditions at different global warming levels (van der Wiel et al., 2019). Jain et al. (2023) further highlighted the need to adequately sample for internal climate variability using SMILEs when evaluating climate model simulations as it can lead to differences between simulated and observed trends in the current climate where the presence of unprecedented extremes may overwhelm the trend forced by anthropogenic warming. Pooling simulations from all ensemble members results in thousands of years of plausible weather sequences, allowing for more robust probabilistic estimates of the chance of climate extremes. Large ensembles are physically-based and the simulated extreme events are spatially and internally consistent which allows for an investigation of drivers of climate extremes and compound events (van der Wiel et al., 2019; Mankin et al., 2020; Maher et al., 2021; Bevacqua et al., 2023).

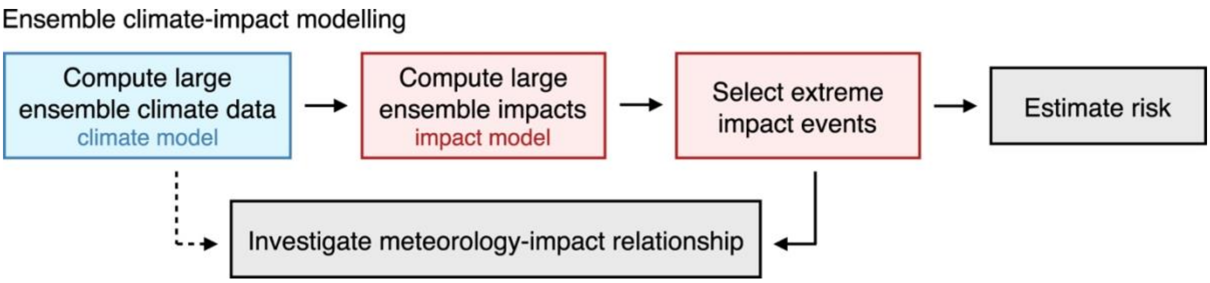

Figure 6.1 Flow chart of steps included in a large ensemble climate impact modelling approach. [taken from van der Wiel et al. (2020)]

One example of sampling for extreme events within SMILEs is the UNSEEN method by Thompson et al. (2017) as introduced in Chapter 3 (Section 3.3.3) The study used initialised climate model simulations from the Met Office Decadal Prediction System (DePreSys) to estimate the risk of high winter UK rainfall in the present-day climate. More recent studies have used initialized ensembles to explore different climate extremes such as high rainfall (Kelder et al., 2020; Kent et al., 2022), crop yields (van der Wiel et al., 2020; Coughlan de Perez et al., 2023), heatwaves (Kay et al., 2020), meteorological droughts (Kent et al., 2019; van der Wiel et al., 2021) and wildfires (Squire et al., 2021). In hydrology, initialised large ensembles have also been used in conjunction with hydrological models to understand hydrological extremes (van der Wiel et al., 2019; van Kempen et al., 2021; Kelder et al., 2022b; Brunner et al., 2021; Brunner and Slater, 2022).

6.1.3 Aims and objectives

This chapter employs SMILE simulations to estimate the chance of unprecedented events beyond the worst observed event and link probabilistic estimates with storylines of hydrological droughts in present and future climate. The specific aims of this chapter are to:

- Employ the EC-Earth time-slice SMILE data to account for the effects of internal climate variability in probabilistic estimates of 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
- Bridge probabilistic estimates with storylines sampled from the large ensemble 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.

6.2 Projected change

The set-up of the EC-Earth time slice large ensemble is outlined in Section 3.3.3. The bias-adjusted large ensemble precipitation and temperature data is used to drive the GR6J hydrological models at the Low Flow Benchmark Network (LFBN) and Anglian (ANG) catchments (see Chapter 3; Section 3.2.1 for catchment selection and Section 3.3.3 for the bias correction procedure and the impacts of bias adjustment). The EC-Earth large ensemble is used to drive hydrological models in two ways: 1) a modified delta change approach and 2) bias-adjustment of raw climate model data. Projected change in precipitation from the EC-Earth SMILE is shown in Chapter 3 (Section 3.3.3). Hydrological drought events are extracted using the variable threshold method as described in Chapter 3; Section 3.5.2. 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. Hydrological drought characteristics are calculated from simulated river flows over the baseline period (1965-2015) and simulated river flows driven by the large ensemble data. This threshold is chosen to maximise the number of extracted droughts in both the observations and the large ensemble. Although a higher threshold (e.g. Q90) may isolate the most extreme droughts, Q70 includes both moderate and extreme droughts to enable a more complete comparison between observed and simulated droughts.

6.2.1 Catchment clusters

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 occurrences is created based on the drought events extracted. Agglomerative hierarchical clustering, implemented using the TSclust R package (Montero and Vilar, 2015), is used to group catchments into clusters using the Ward's minimum variance method (Ward, 1963) based on the binary drought occurrence series. Figure 6.2 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 listed in Chapter 3; Table 3.1 (e.g. slower responding groundwater-dominated catchments in southern England - i.e. GB3 and some in GB4 with a high BFI). 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 ≥ 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. The bias-adjustment procedure applied to temperature and precipitation and the subsequent model fidelity check following Thompson et al. (2017) (as described in Chapter 3: Section 3.3.3) and that the large ensemble data is deemed credible and statistically indistinguishable from the observations. The impact of the bias adjustment on temperature and precipitation is shown in Figure 6.3 for the four defined catchment clusters.

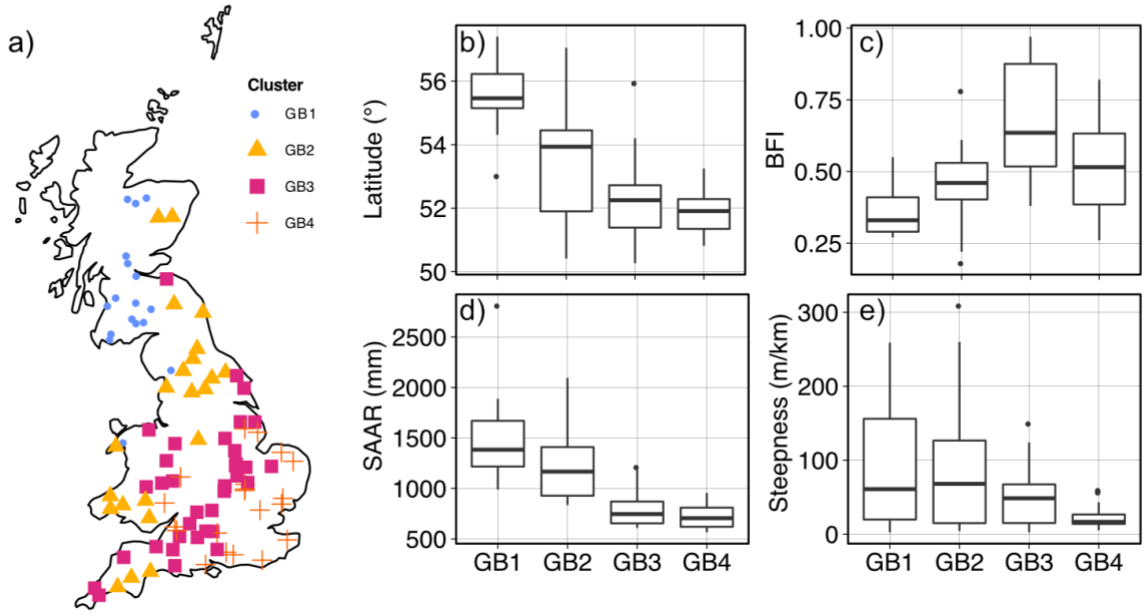

Figure 6.2 a) Catchment clusters defined from spatially extensive droughts using the regional drought index (RDI_{Q70}) over the baseline period (1965-2015). b) Distribution of four selected catchment characteristics according to latitude (°), c) SAAR – Standardised annual average rainfall (mm), d) BFI – Baseflow index, and e) catchment steepness (m/km) for catchments in each cluster.

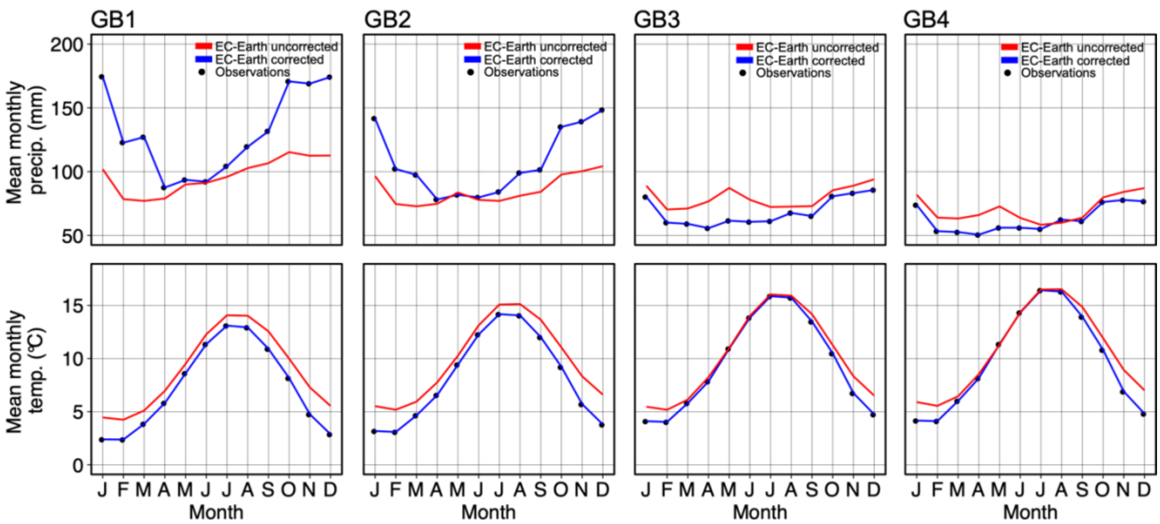

Figure 6.3 Mean monthly total precipitation (top) and temperature (bottom) in the baseline period (1965-2015) before and after the application of bias adjustment to the present-day large ensemble simulations.

6.2.2 River flows

The use of the traditional and modified delta method to explore projected change in precipitation is presented in Chapter 3 (Section 3.3.3). Figure 6.4 compares different estimates of projected change in monthly river flows from using delta-adjusted precipitation, the modified delta method and the direct use of bias-adjusted precipitation data to drive hydrological models. 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. 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. Monthly average river flows simulated with the bias-adjusted precipitation show a greater increase over spring and winter months compared to the delta method. The equivalent plot for catchments in GB2 and GB4 is presented in the Appendix (Figure 6.A.1)

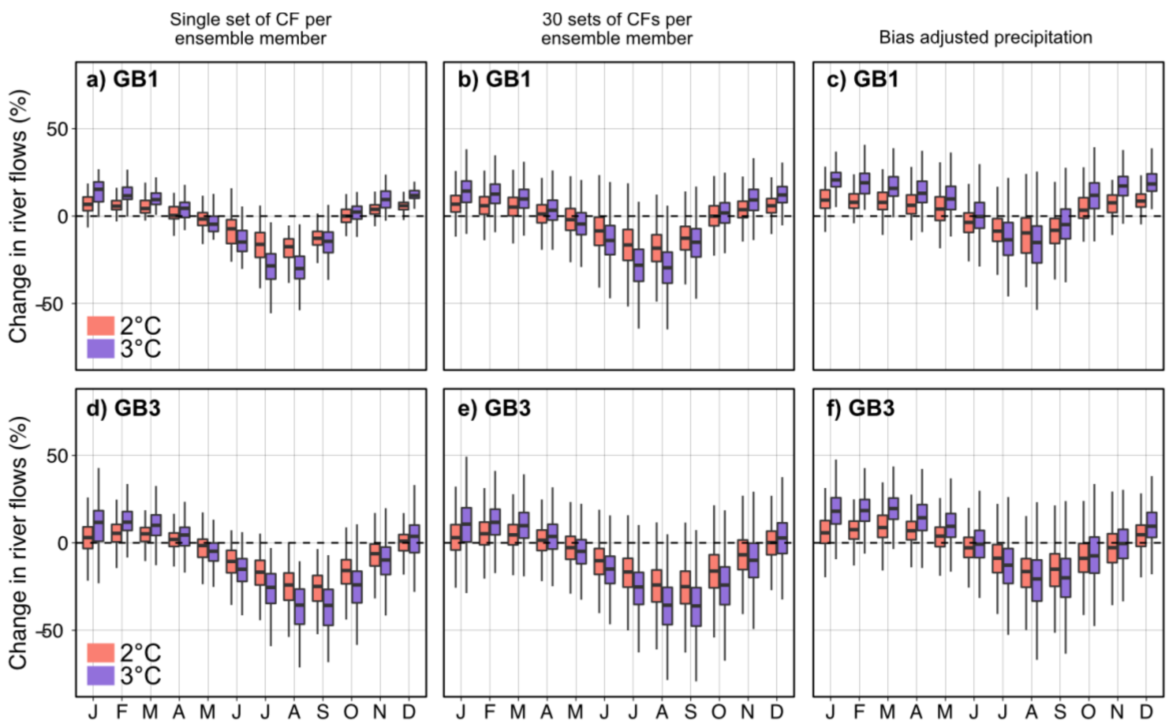

Figure 6.4 Projected change in monthly river flows across catchments in GB1 (top) and GB3 (bottom) for 2°C warming (orange) and 3°C warming (purple) using a single set of change factors per catchment (a and d), 30 sets of change factors from resampled precipitation per catchment (b and e) and bias-adjusted precipitation and temperature per catchment (c and f).

6.2.3 Hydrological drought characteristics

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 from across GB in Figure 6.5. 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.

Compared to the UKCP18 projections, the EC-Earth large ensemble project a larger increase in winter precipitation and a lesser decrease in summer precipitation with 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. The eFLaG ensemble recently used the UKCP18 projections to drive hydrological model simulations across the UK to investigate changes in hydrological drought characteristics. Drought characteristics are generally less severe in the EC-Earth large ensemble compared to the eFLaG ensemble where low, median and high flows were all projected to decline for catchments in southern and eastern England (Hannaford et al., 2023; Parry et al., 2023).

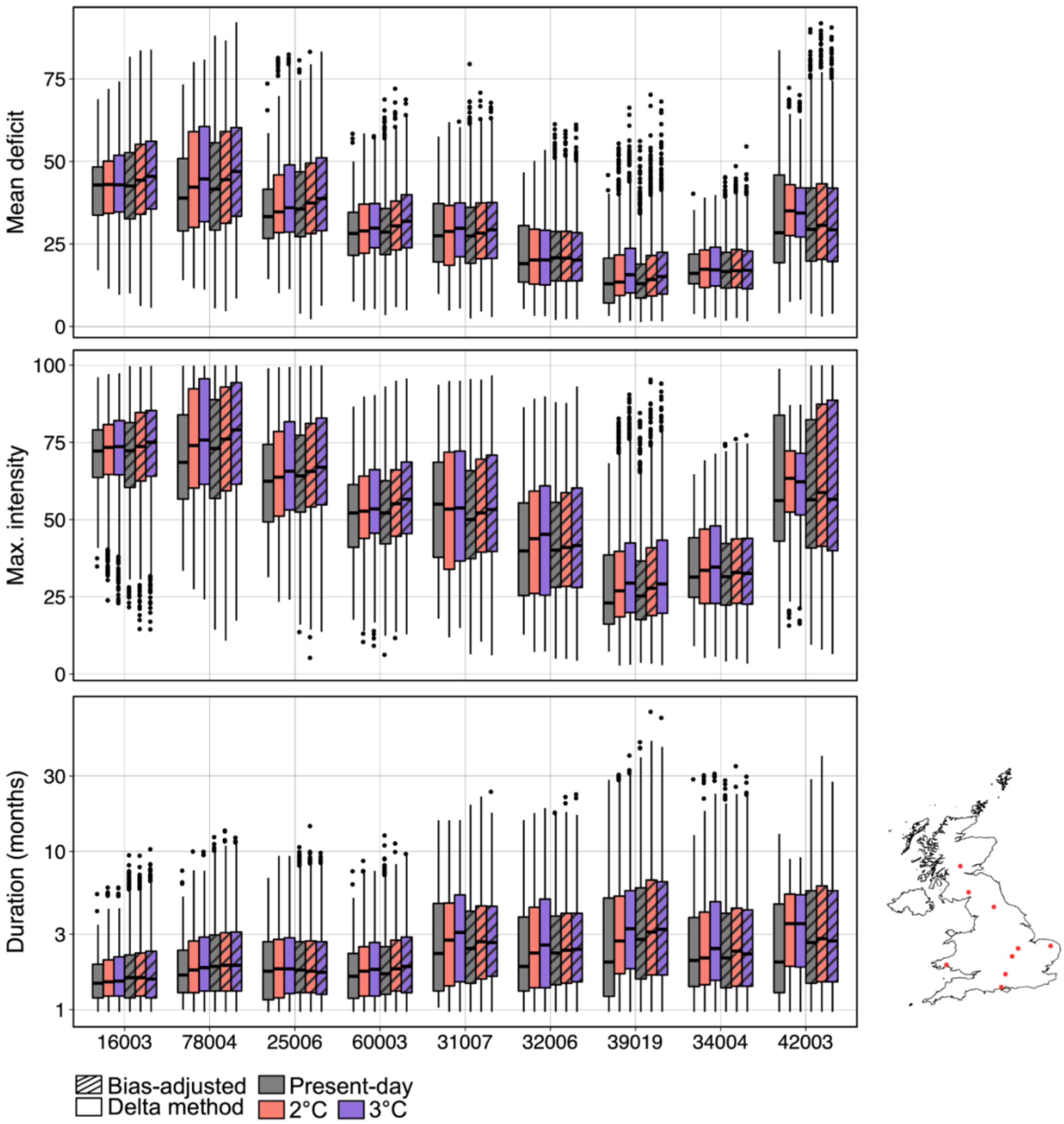

Figure 6.5 Projected mean drought deficit (top), max. drought intensity (middle), and drought duration (bottom) for present-day (grey), 2°C (orange) and 3°C (purple) extracted from simulated river flow using the delta method (solid colours) and the direct use of bias-adjusted temperature and precipitation (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. The location of the selected catchments is shown in the inset map.

6.3 Physical credibility

A common approach to assess the potential for dry periods to impact water supply is to calculate precipitation or river flow deficit accumulated over a user-defined n-months period.

Calculating the accumulation of precipitation and river flows across a user-defined period can provide evidence for the physical credibility of the modelled data by assessing whether there are notable outliers with unrealistic precipitation or river flow accumulations. Folland et al. (2015) previously found, for lowland England, the driest 12-month period between 1910 to 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 observed 12-month period in terms of accumulated river flows 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. Tables 6.1 and 6.2 present the top 10 driest accumulated precipitation and river flows respectively, over a 12- and 24-month period in the present-day large ensemble for catchments over lowland England (i.e. catchments in GB3 and GB4). As would be expected, there are 12-month and 24-month periods with lower precipitation and river flows compared to the driest observed event. Total precipitation as a percentage of the long-term average and total deficit for both precipitation and river flows are within the same order of magnitude as the driest event (i.e. grey shading) and there are no notable outliers that can be immediately discounted and considered unrealistic.

Different hydrological systems are vulnerable to different drought durations. Precipitation and river flow deficiency over a short period (~6 months) may be appropriate when assessing impacts in fast-responding systems. 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 one dry winter and two dry summers for several reservoir systems within East Anglia – Anglian Water Drought Plan 2022). Table 6.3 shows the top 10 driest accumulated river flow deficiency over an 18-months period with an April start showing a number of events in the present-day large ensemble which equals or exceeds the flow deficit in the driest 18-months period in the observations (i.e. 1975-76).

The physical credibility of the simulated events in the large ensemble can be further 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 (Figure 6.6 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 Figure 6.6).

Table 6.1 Top 10 a) 12- and b) 24-month periods with lowest accumulated bias-adjusted precipitation (mm) for catchments in southern England (GB3 and GB4) in the present-day large ensemble. The 12- and 24-month periods with the lowest accumulated observed precipitation (CEH-GEAR) over the baseline period is also indicated with a specific year in grey shading.

a) 12-months **Rank**	**Total precipitation (mm)**	**% of 1965-2015 average**	**Deficit (mm)**	**Start month**
1	410.2	51.5	-386.5	11
2	432.2	54.3	-364.1	12
3	444.0	55.7	-353.2	9
4	452.0	56.8	-344.4	12
5	455.2	57.2	-340.9	10
6	462.4	58.0	-335.5	1
7	463.1	58.2	-333.0	10
8 - 1975	464.2	58.2	-333.1	9
9	465.0	58.4	-331.7	11
10	465.9	58.4	-331.4	9
b) 24-months				
1	1033.6	65.0	-556.2	8
2	1089.9	68.5	-501.4	7
3	1096.9	69.0	-493.0	8
4	1100.6	69.3	-486.9	10
5	1104.7	69.5	-484.7	12
6	1109.4	69.8	-480.4	9
7	1115.1	70.1	-474.7	9
8	1126.2	70.7	-466.7	3
9	1126.3	70.7	-466.6	6
10	1126.6	70.8	-464.6	7
1990	1191.3	74.8	-401.6	3

Table 6.2. 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 grey shading).

a) 12-months **Rank**	**Total river flows (mm)**	**% of 1965-2015 average**	**Deficit (mm)**	**Start month**
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

Table 6.3. Top 10 18-months period (April start) with lowest accumulated river flows for catchments in southern England (GB3 and GB4) in the present-day large ensemble and the baseline period.

Rank	**Total river flows (mm)**	**% of 1965-2015 average**	**Deficit (mm)**
1	138.6	39.8	-209.7
2	140.5	40.3	-207.8
3	146.4	42.0	-201.9
4	160.2	46.0	-188.1
5	162.1	46.5	-186.2
6	162.6	46.7	-185.7
7	164.3	47.2	-184.0
8	166.4	47.8	-181.9
9	168.7	48.4	-179.6
10 - 1975	168.8	48.4	-179.6

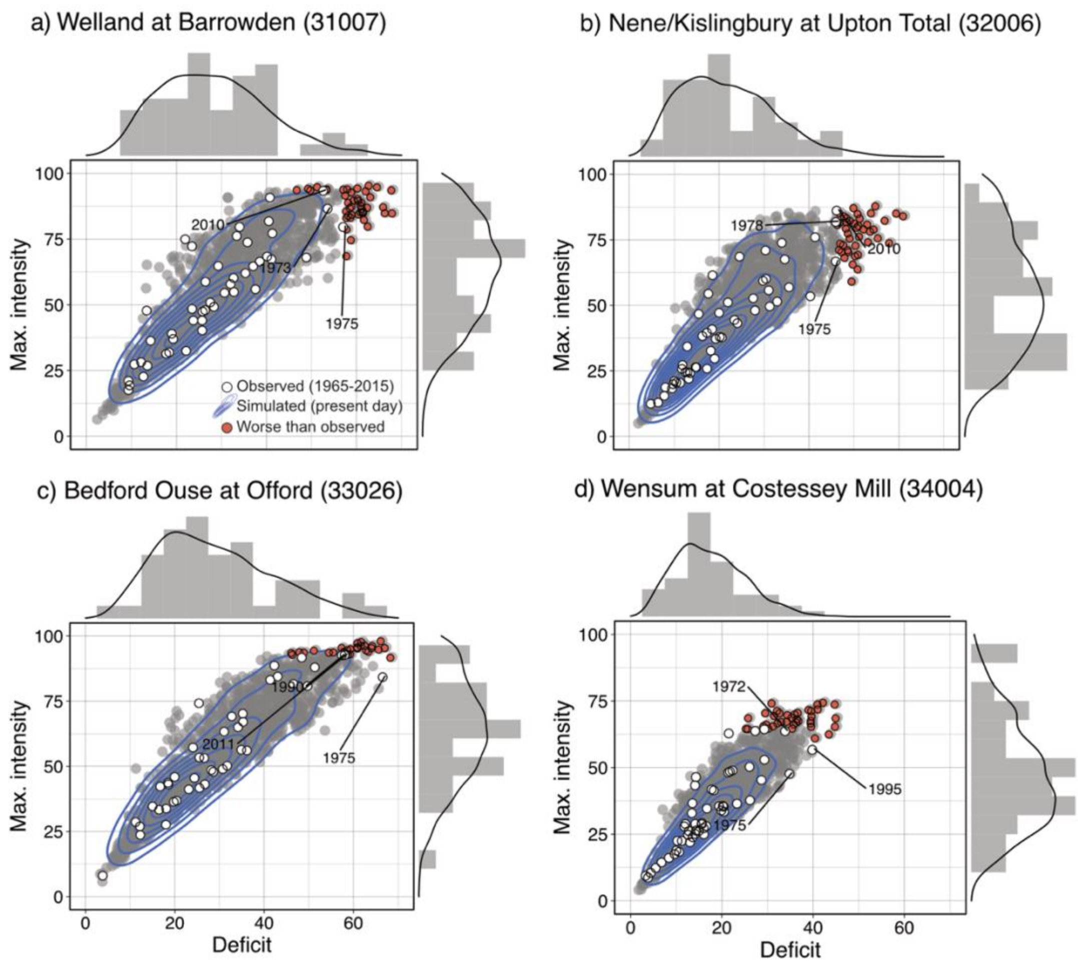

Figure 6.6 Max. intensity and deficit of droughts extracted from the present-day large ensemble and in the baseline observed period (1965-2015) at four example catchments in SE England. Notable severe droughts in the observations are labelled. Red dots represent unprecedented events with either a greater 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.

The driest years in the large ensemble are characterized by blocking conditions and high pressure across the British Isles and continental Europe as shown by geopotential height anomalies at 500hPa (Z500) for the driest summers and winters (Figure 6.7). Understanding the atmospheric circulation patterns driving precipitation deficits adds to the plausibility of simulated events within the large ensemble. The atmospheric circulation during both the driest years in the large ensemble and the driest observed years resembles patterns that are known to cause precipitation deficits across the UK, including the dipole (high pressure centred over eastern Atlantic with positive anomalies to the north and negative anomalies to the south) and Azores high (high pressure centred over western Europe) responsible for European droughts as identified in Kingston et al. (2015). The circulation patterns in the driest years of the large ensemble will not be the same as those observed in the driest years across the baseline period and are not meant to be comparable but the individual circulation patterns for each of the modelled years are associated with the synoptic conditions that would be expected to bring dry conditions to the UK. Due to the effects of internal variability, the patterns in the large ensemble show alternative patterns that may not have been observed before but could have been realised during droughts in the observed record.

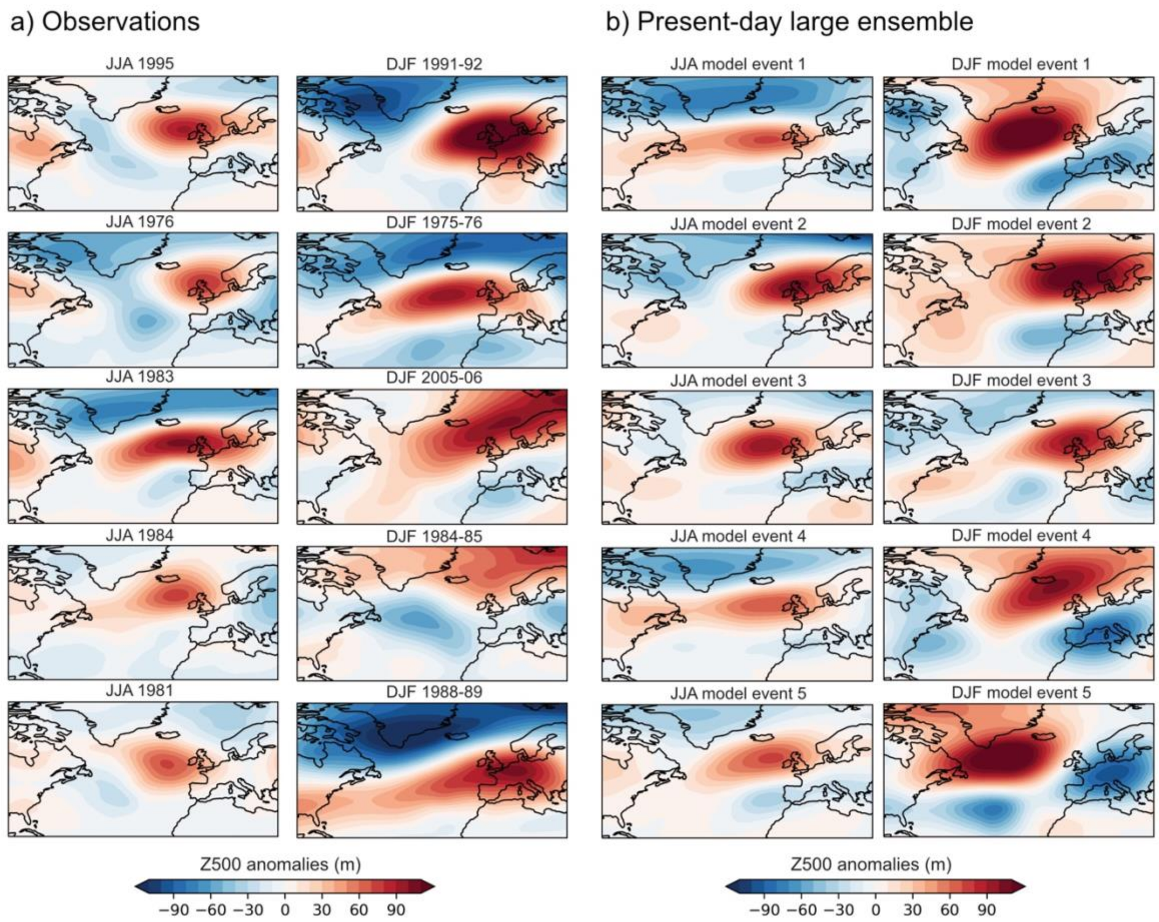

Figure 6.7 Geopotential height anomalies at 500hPa (ERA5 Z500) anomalies relative to 1965-2015 from the top 5 driest summers (JJA) and winters (DJF) in the observed baseline period (1965-2015) (a) and the Z500 anomalies of the top 5 driest summers and winters in the present-day large ensemble (b).

The temporal evolution of daily river flows during the driest years (12-months period from October to September with lowest river flow totals) in the present-day large ensemble also seems consistent with the hydrological behaviour in the driest year in the observations with similar flow timing (Figure 6.8 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. The driest hydrological years in the baseline period are all part of well-known drought episodes (Barker et al., 2019). The top 20 driest hydrological years in the present-day large ensemble include hydrological years which are close to or drier than the observed driest. These events seem consistent with the observations with similar flow timing, which adds to the physical credibility of the simulated events.

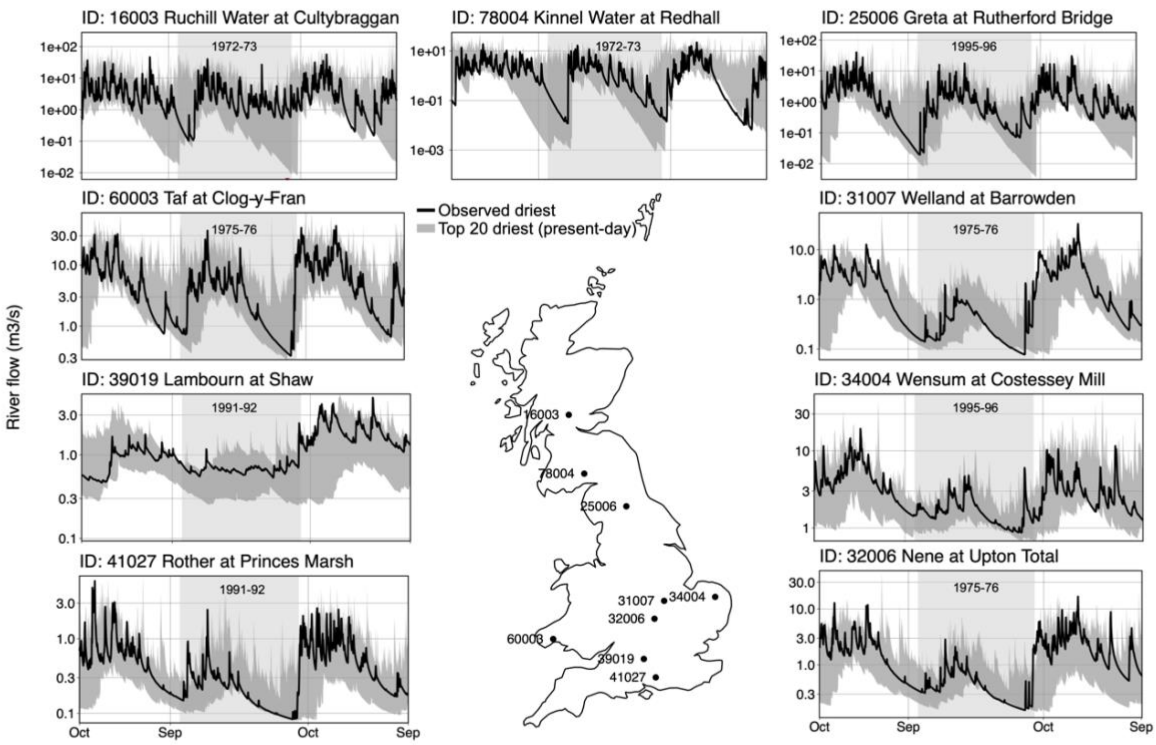

Figure 6.8 Comparison of simulated river flows during the driest 12-months (Oct-Sep) (grey box) in the observations (black line) and the top 20 driest in the present-day large ensemble (grey shading) at nine catchments spanning the clusters (map).

6.4 Chance of unprecedented extremes

6.4.1 Low precipitation and high temperature

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 the modelled temperature data 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.

Figure 6.9 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) (see Table 6.4 for estimates for all catchment clusters and Fig.6.A2 for the equivalent for 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 temperature over southeast England for summer 2022 in the HadUK-Grid dataset is 18.02°C (i.e. 0.2°C higher than 1976) (Met Office 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.

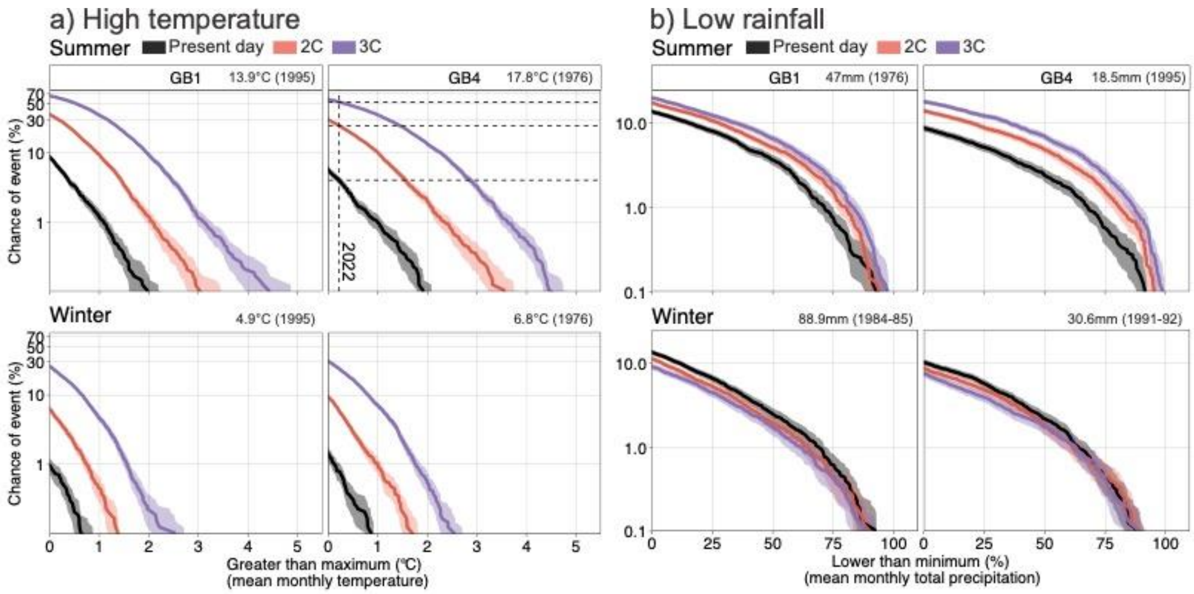

Figure 6.9 Estimate of the chance of any given summer or winter month with unprecedented a) high mean summer (JJA) and winter (DJF) temperature and b) low mean summer (JJA) and winter (DJF) precipitation, for a single year, in GB1 and GB4 for the present-day (grey), 2°C (orange) and 3°C (blue) large ensemble.

Table 6.4 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.

a) High temperature				
	GB1	GB2	GB3	GB4
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

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.

The increasing chance of unprecedented hot and dry summers with future warming is consistent with multiple generations of climate projections estimating a reduction in summer low flows and increased severity of summer droughts across the UK, including fast-responding catchments (Blenkinsop and Fowler, 2007; Rudd et al., 2019; Kay et al., 2021; Parry et al., 2023). Although winters are projected to become wetter in general in the EC-Earth large ensemble, the chance and magnitude of the driest winter occurring in any given year remain similar across the present-day, 2°C and 3°C large ensemble, indicating a continued risk of the most extreme dry winter months.

6.4.2 Hydrological droughts

The chance of any given drought exceeding the mean drought deficit of six past severe droughts is estimated to increase with future warming (Figure 6.10). 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.

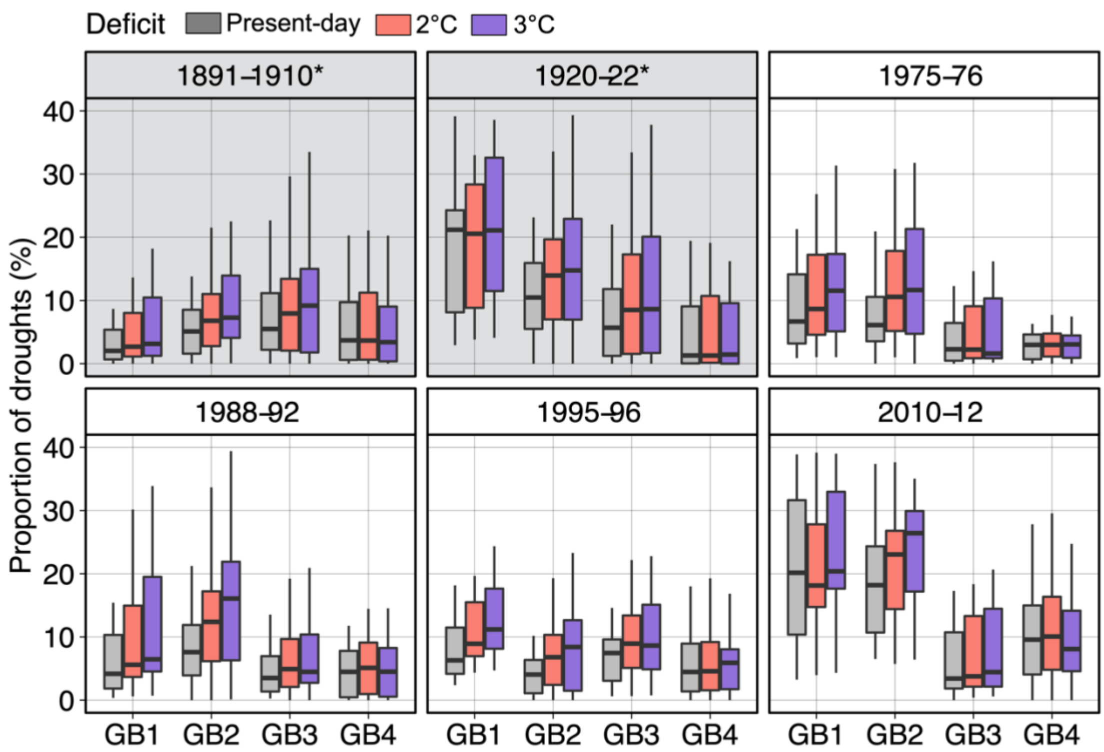

Figure 6.10 Estimate of the chance of a given drought exceeding mean drought deficit of past drought events for catchments across the catchment clusters for the present-day (grey), 2°C (orange) and 3°C (blue) large ensemble. *Data for the 1891-1910 and 1920-22 droughts are based on river flow reconstructions from Smith et al. (2019) using the GR4J model applied for the LFBN catchments.

The present-day chance of a given drought exceeding the characteristics of severe post-1891 droughts broadly reflects the spatial patterns of worst-case historic droughts found in Barker et al. (2019). 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 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. Although the chance of exceedance varies between catchments, the 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.

6.5 Storylines of specific drought conditions

This section aims to bridge the probabilistic estimates in Section 6.4 with storylines of specific drought sequences. Sampling for specific conditions within the large ensemble enables an investigation of plausible worst cases and the unfolding of future events with the same drivers (van der Wiel et al., 2021, 2022). For example, sampling for specific conditions enable a closer examination of the drivers of unprecedented events, such as events that may be exacerbated by increased summer temperatures and the associated elevation of evaporative demand (also suggested in Teuling et al., 2013; Brunner et al., 2021b and Reyniers et al., 2023). Although no probabilities are attached to each storyline, the relative frequency of climate sequences can also be informative to the construction of storylines. 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. The following storylines are considered: 1) dry springs (MAM) followed by dry summers (JJA), 2) dry autumns (SON) followed by dry winters (DJF) and 3) consecutive dry winters. 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) (Figure 6.11). Although the storylines do not explicitly sample for hot and dry events, the uncertainty in the variability of future droughts is determined by changes in precipitation trends as droughts will always coincide with hot extremes relative to the present day as the climate continues to warm (Diffenbaugh et al., 2015; Manning et al., 2019; Bevacqua et al., 2022).

The dry spring-summer and dry autumn-winter storylines resemble conditions of 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). Reviewing drought episodes in pre-industrial southeast England, Pribyl (2020) noted that severe summer droughts are often also coupled with warm and dry springs. On the other hand, the 1920-21 drought was characterized by a dry autumn followed by a dry winter (van der Schrier et al., 2021). The 1920-21 drought was notably severe in eastern England as explored in Chapter 5. 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) (e.g. 2010-12 drought). Storylines are selected by searching for consecutive negative mean precipitation anomalies relative to a 1965-2015 climatology for each catchment for the respective target seasons (e.g. spring and summer) within all years of the large ensemble and within years coinciding with hydrological drought events.

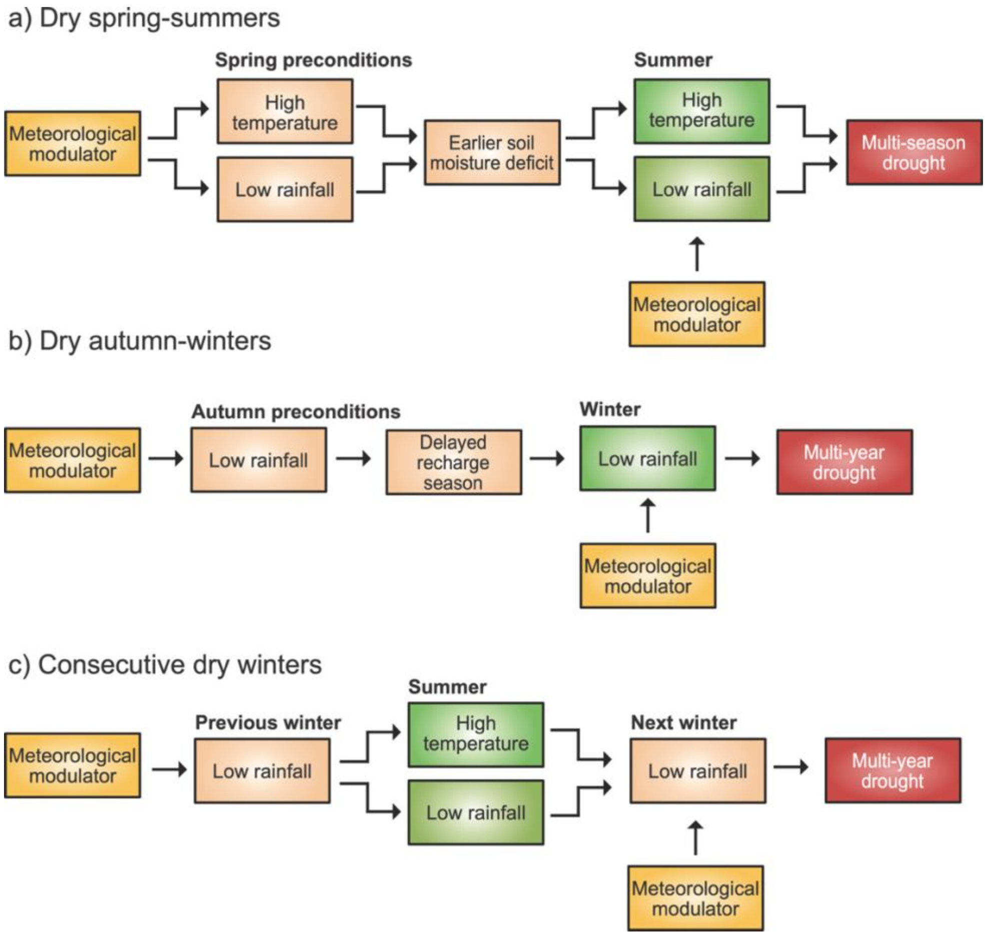

Figure 6.11 Schematic showing the physical elements of preconditioned compound drought events arising from a) dry spring followed by dry summer, b) dry autumn followed by dry winter and c) consecutive dry winters with an intervening hot and dry summer. The formulation of these storylines follows the compound event framework in Zscheischler et al. (2020) and case study examples in Bevacqua et al. (2021).

6.5.1 Dry spring-summers and autumn-winters

The selected dry spring-summers and dry autumn-winters in the present-day, 2C and 3C large ensembles are shown in Figure 6.12 for slow-responding catchments in southern England (i.e. GB3). As a comparison, the equivalent figure for contrasting catchments in GB1 is shown in Figure 6.A3. In the present-day, drought years (i.e. years coinciding with hydrological droughts) with dry spring-summers are more likely to have above average temperature anomalies, particularly in the summer months compared to all other years. Conversely, drought years with dry autumn-winters show no temperature signal in autumn and slightly below average temperatures in winter compared to all other years. The selected dry spring-summer and autumn-winter sequences are shown by the orange boxplots in Figure 6.12a and b respectively. The bottom row of Figure 6.12 shows dry spring-summers and autumn-winters in the 2C and 3C large ensemble. Unsurprisingly, the temperature anomalies across spring-summers and autumn-winters are projected to increase in all cases with future warming, with summer temperatures estimated to increase by the greatest magnitude. Summer months in future dry spring-summer sequences are estimated to become drier with warming. Apart from drier summers, there is a lack of change in the precipitation anomalies associated with dry springs and dry autumn-winter sequences in the 2C and 3C large ensemble.

The time series of cumulative precipitation, PET and precipitation minus PET (P-PET) anomalies of the top 20 driest dry spring-summers and autumn-winters show how future events with the same conditions could develop (Figure 6.13). 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 precipitation minus actual evapotranspiration (P-AET) anomalies for future dry spring-summers compared to the present day, which is more prominent for GB3 (Figure 6.A4). This result provides further context to recent work by Baker et al. (2021) which showed that he 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 1970s. The storylines in this study complement this result by showing that future dry spring-summers are estimated to generate greater deficit. For future dry autumn-winter sequences, the projected increase in precipitation for both autumn and winter is more apparent in GB1 with wetter conditions in both seasons. 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 is estimated to worsen with future warming (Figure 6.14). 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.

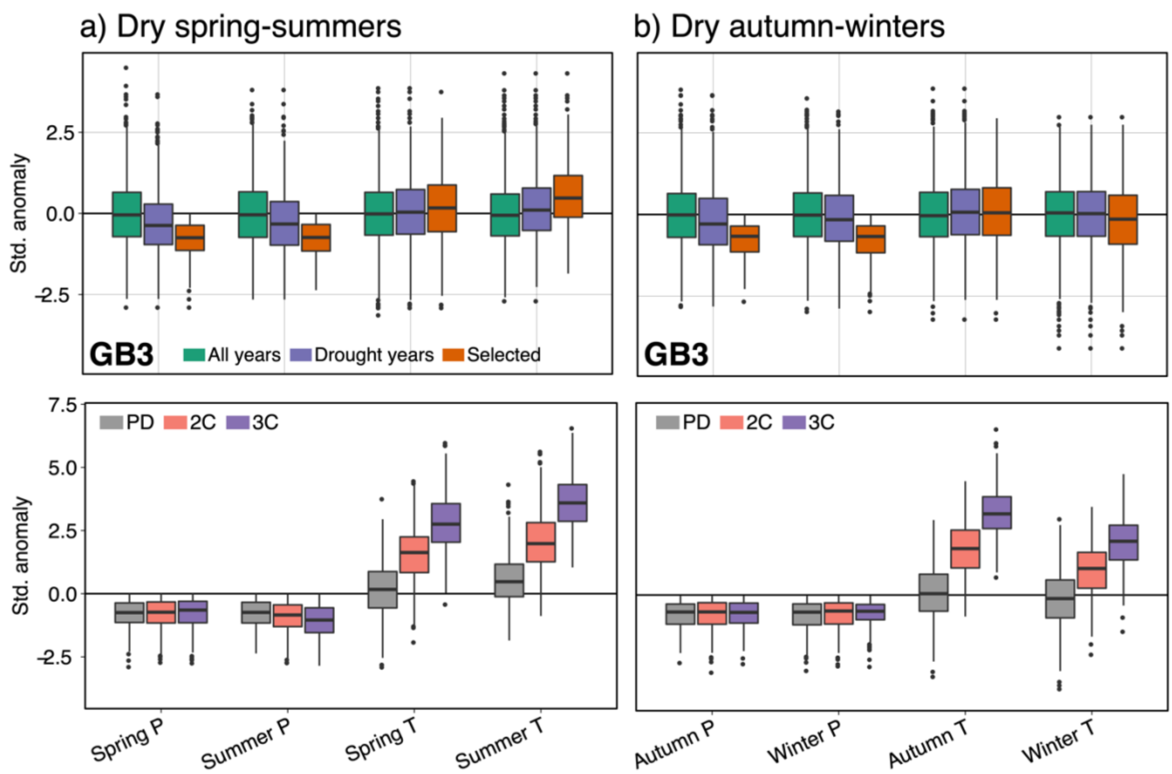

Figure 6.12 Standardised precipitation and temperature anomalies from dry spring-summers (left) and dry autumn-winters (right) averaged across catchments in GB3. The top panel compares temperature and precipitation in all 2000 years of the large ensemble (green), in years with hydrological droughts (purple) 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 (PD, grey), 2°C (orange) and 3°C (blue) large ensemble (standardised based on PD statistics).

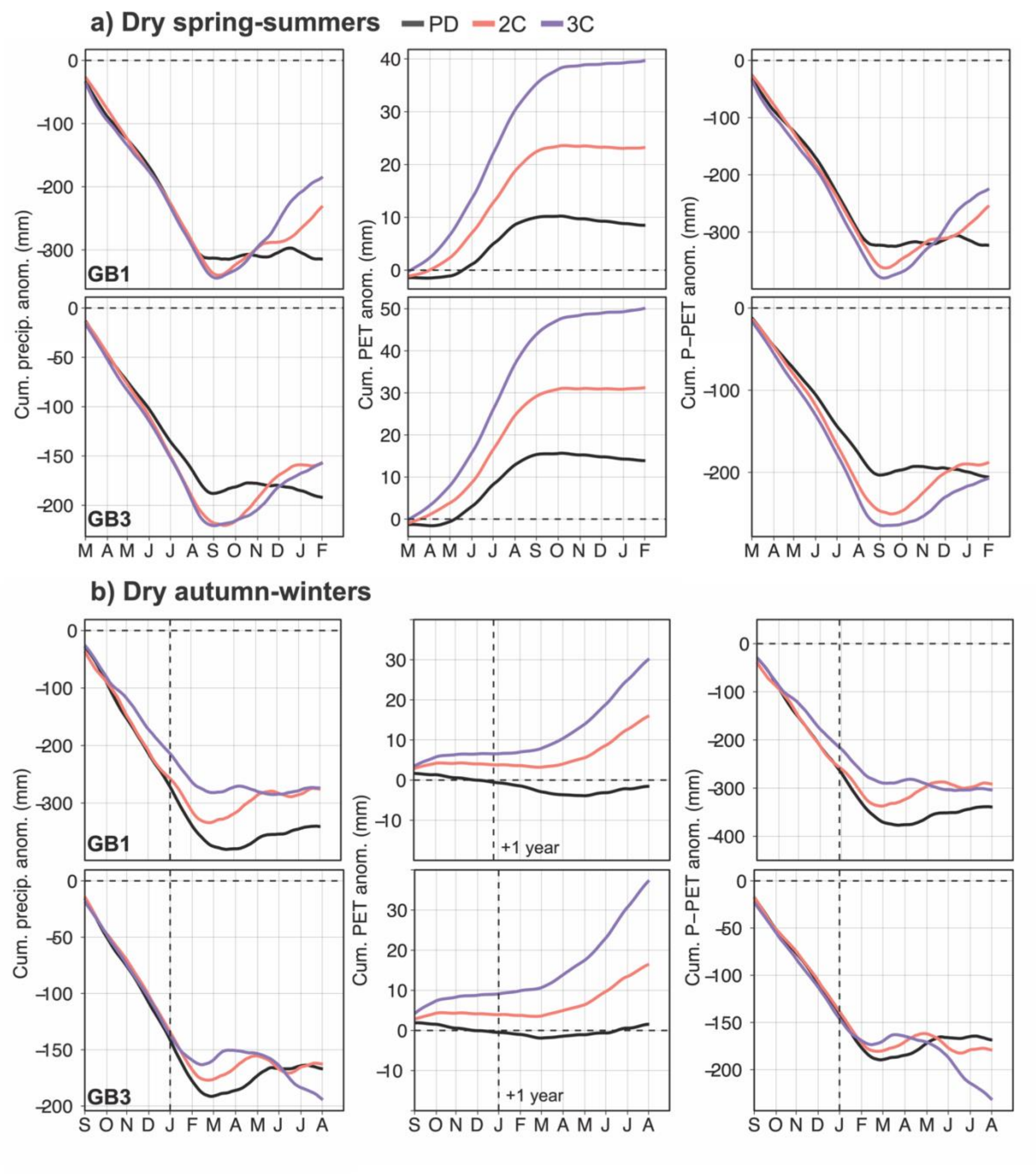

Figure 6.13 Time series of mean cumulative precipitation, PET and P-PET anomalies during the top 20 (i.e. ~1 in 100 year events) driest a) dry spring-summers and b) dry autumn-winters for catchments in GB1 and GB3 in the present-day (black), 2°C (orange) and 3°C (purple) large ensembles. A 30-day running mean is applied for all variables.

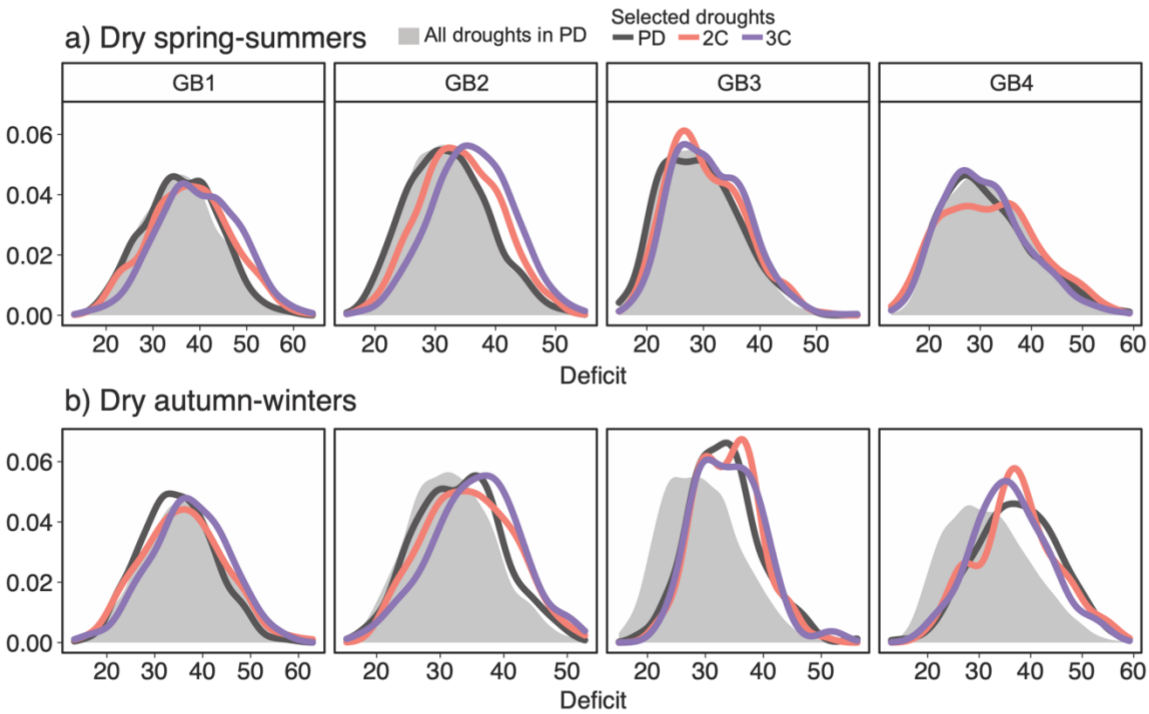

Figure 6.14 Mean deficit of selected spatially extensive droughts (RDIQ70) which coincides with dry spring-summers (top) and dry autumn-winters (bottom) in the present-day (PD), 2°C and 3°C large ensemble for each catchment cluster. The grey distribution represents the characteristics of all droughts in the present-day (PD) large ensemble.

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 (Figure 6.15). 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. 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.

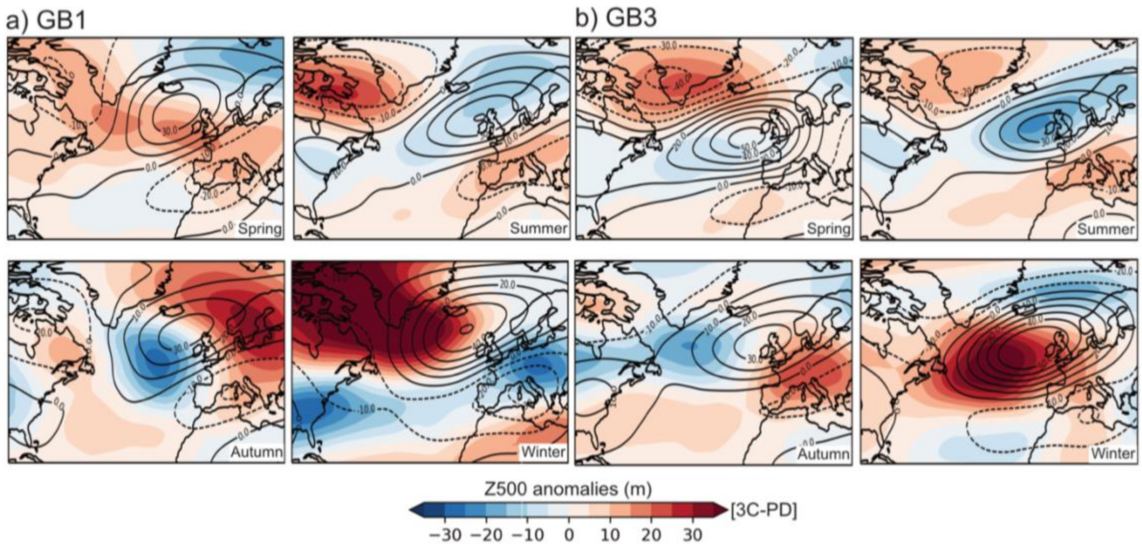

Figure 6.15 Composite mean Z500 anomalies relative to 1965-2015 (ERA5) during dry spring-summers (top row) and dry autumn-winters (bottom row) for GB1 (left) and GB3 (right). Contours are Z500 anomalies in the present-day and the colours represent the change in anomalies between events in the 3°C large ensemble minus the events in the present-day large ensemble.

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 during dry summers with future warming. This reflects the important influence of atmospheric circulation such as through changes in the persistence of weather patterns or changes in the latitude of the jet stream (e.g. Harvey et al. 2023). It may be possible that weaker pressure anomalies could lead to similar or higher levels of precipitation deficits. This could also reflect the role of land-atmosphere feedbacks with warming, such as heatwaves reinforcing anticyclonic conditions (e.g. Schumacher et al., 2019). 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.

6.5.2 Consecutive dry winters

Consecutive dry winters is the primary driver of multi-year droughts in the UK. Brunner and Tallaksen (2021) recently used stochastic simulations of synthetic river flows to highlight the proneness of catchments across southeast England to future multi-year hydrological droughts. 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).

Figure 6.16a and b show 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 (as described in Chapter 3; section 3.3.3). Sampling for consecutive dry winters within the large ensemble shows that there are consecutive winters in the present-day large ensemble with greater precipitation deficit for both the preceding and succeeding winter than the driest observed consecutive dry winter sequence. Figure 6.16c 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 probabilistic estimate of the chance of the driest winter remains relatively unchanged with future warming (see Figure 6.8). Drought years with consecutive dry winters show a large variation in the precipitation anomalies for intervening seasons. There is a 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 (Figure 6.15d). The equivalent figures for latent heat flux anomalies and cumulative P-AET anomalies also reflect this (Figure 6.A5). 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.

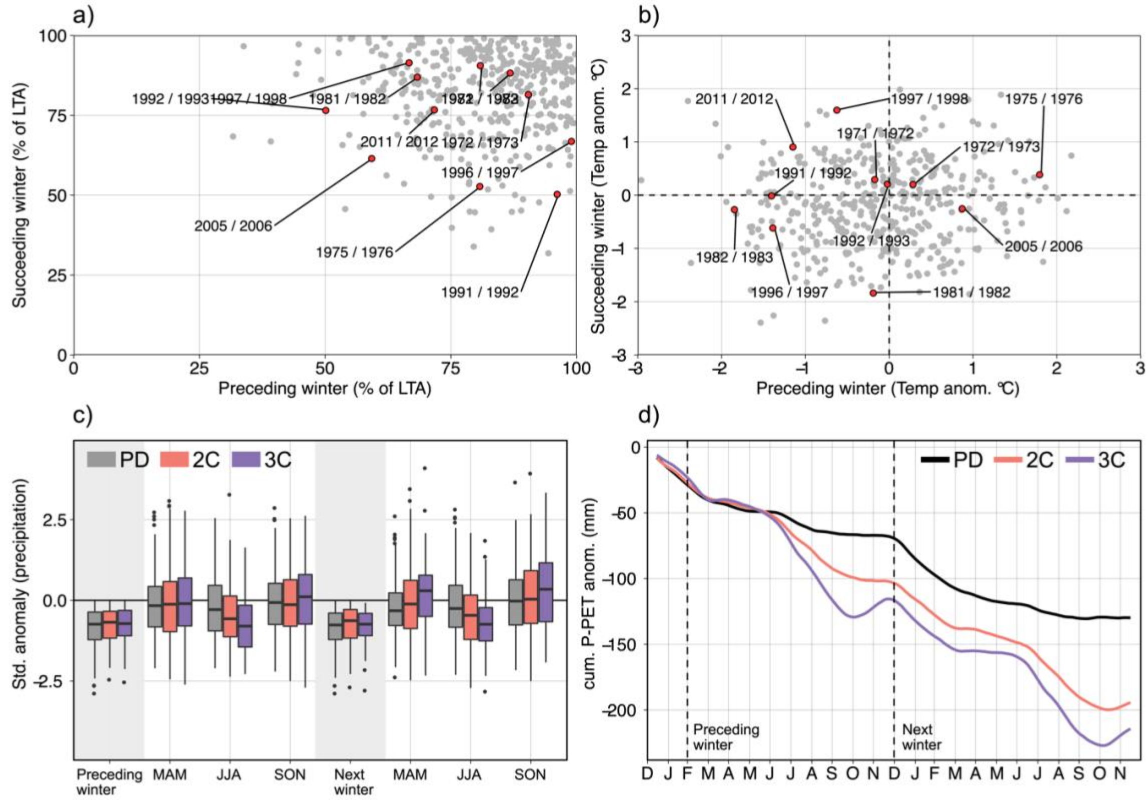

Figure 6.16 a) Precipitation (% of long term average 1975-2015) and b) temperature anomalies (°C) associated with all occurrences of consecutive dry winters in the present-day large ensemble (grey) and observation (red dots) averaged for catchments in GB3. The bottom row compares c) seasonal precipitation anomalies and d) cumulative P-PET anomalies during all drought years with consecutive dry winters in the present-day (PD, grey), 2°C (orange) and 3°C (purple) large ensemble.

Reviewing drought propagation of three past severe multi-year European droughts, Parry et al. (2012) noted that the distribution of dry seasons within a multi-year drought episode is crucial in determining eventual drought severity. The authors also note that there has not been a notable dry winter followed by a dry summer sequence since 1975-76. The results here demonstrate that such a combination is expected to increase in likelihood with future warming. Should a dry winter occur, the higher likelihood of a hot and dry summer is expected to increase the chance of a multi-year drought episode. Given the set-up of the EC-Earth 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 is not possible to specifically sample for three or more consecutive dry winters in the large ensemble. Alternative sources of information such as statistical models could be used to investigate the persistence of consecutive dry seasons (Wilby et al., 2015). Combining different large ensemble datasets may also increase understanding of the drivers of multi-year events (van der Wiel et al., 2022).

6.5.3 Stress testing

Storylines can be used to stress test hydrological systems by conditioning on different specified combinations of event drivers (Stoelzle et al., 2020; 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.

Figure 6.17 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 (based on BFI). 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 in East Anglia (Cambridgeshire) (Cluster 4) compared to the Greta in northern England (Cumbria) (Cluster 2), reflecting the persisting influence of precipitation deficits for slow-responding catchments. A shorter accumulation period may be more indicative of water resources implications for fast-responding catchments such as the Greta. 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 within the large ensemble (the crosses in Figure 6.17) clearly cover a large proportion of the response surface with seasonal combinations of precipitation deficits that are beyond those that have been observed (the yellow dots in Figure 6.17). 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.

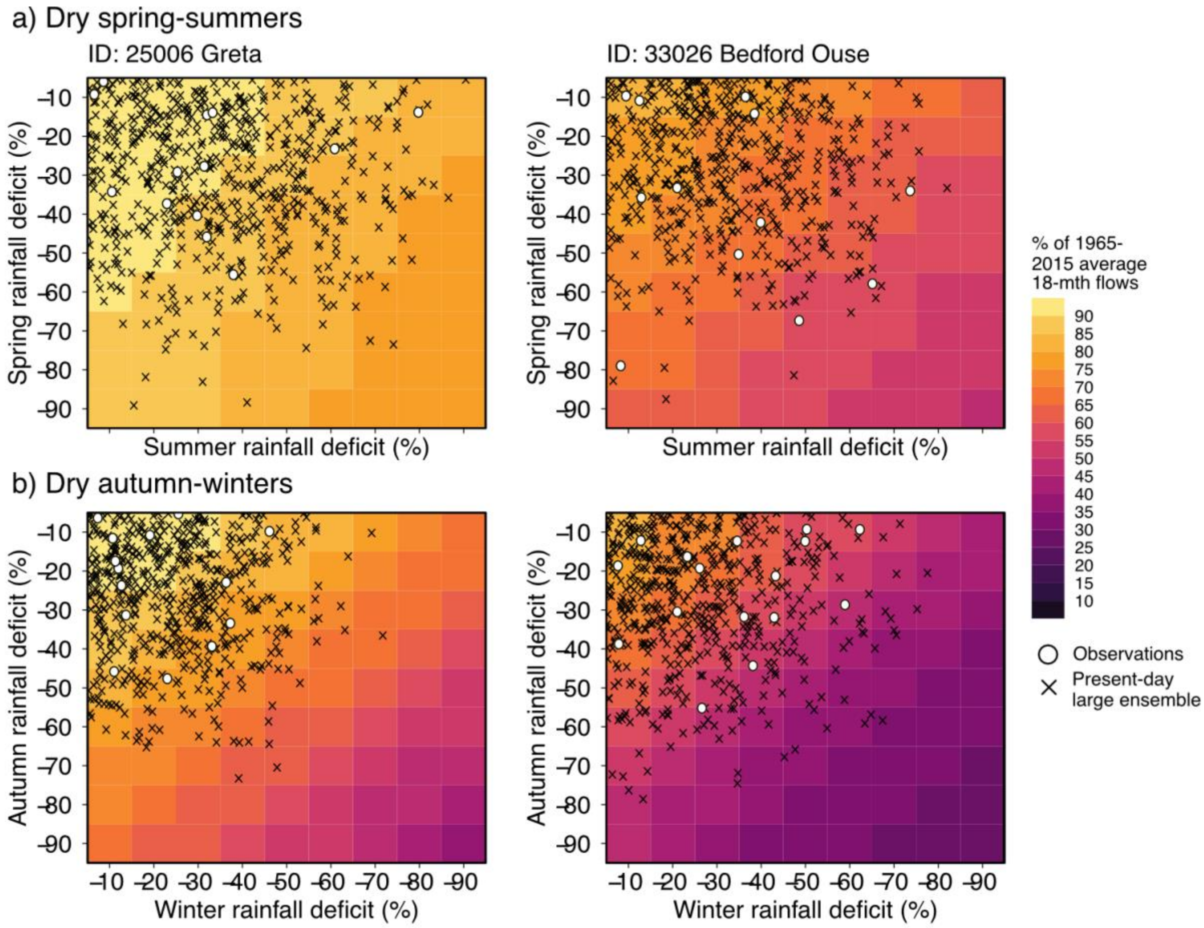

Figure 6.17 Stress tests of two contrasting catchments based on sequences of dry spring-summers (top) and dry autumn-winters (bottom) at varying precipitation deficit levels. The colour shading shows the resulting 18-month river flow deficit as a percentage of the 1965-2015 average (April start). White dots show observed events, and crosses the events from the present-day large ensemble.

6.6 Chapter summary

This chapter has used the EC-Earth time-slice large ensemble to estimate the current and future chance of unprecedented low rainfall, high temperature and hydrological droughts. Probabilistic estimates suggested 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 showed a worsening of drought characteristics for most catchments with warming. Comparing the much larger sample of plausible hydrological droughts with a selected number of severe post-1891 droughts highlighted the spatial signature of past drought episodes and identifies droughts that are especially hard records to break for different parts of Great Britain.

Table 6.5 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 6.4)	**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 6.5% 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 6.5)	**Dry spring-summers** are estimated to become drier with dry springs with deepening of high pressure and dry summers associated with enhanced evaporative demand. **Dry autumn-winters** may become wetter, due to wetter winters. 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. **Consecutive dry winters** leading to multi-year droughts may worsen 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. This implies that hydrological systems need to make up for the lack of rainfall and higher evaporative losses in the intervening summer.

Table 6.5 summarises the complementary insights gained in this chapter from the probabilistic estimates of unprecedented extremes and the different storylines of drought conditions. The probabilistic risk estimates were complemented by sampling for events with specific drought conditions in the large ensemble. Storylines of dry springs followed by dry summers, dry autumns followed by dry winters and consecutive dry winters were considered to understand the unfolding of future events driven by the same conditions. The formulation of storylines which resemble known conditions in past events is complementary to the retrospective event storylines presented in previous chapters and contributes to the growing use of event-based case studies to guide adaptation planning (Sillmann et al. 2021). Stress tests conditioned on different seasonal precipitation deficits based on the storyline conditions were designed to understand the effects of different distributions of seasonal precipitation on accumulated river flows over critical periods which are indicative of possible water resources implications.

6.7 Appendix

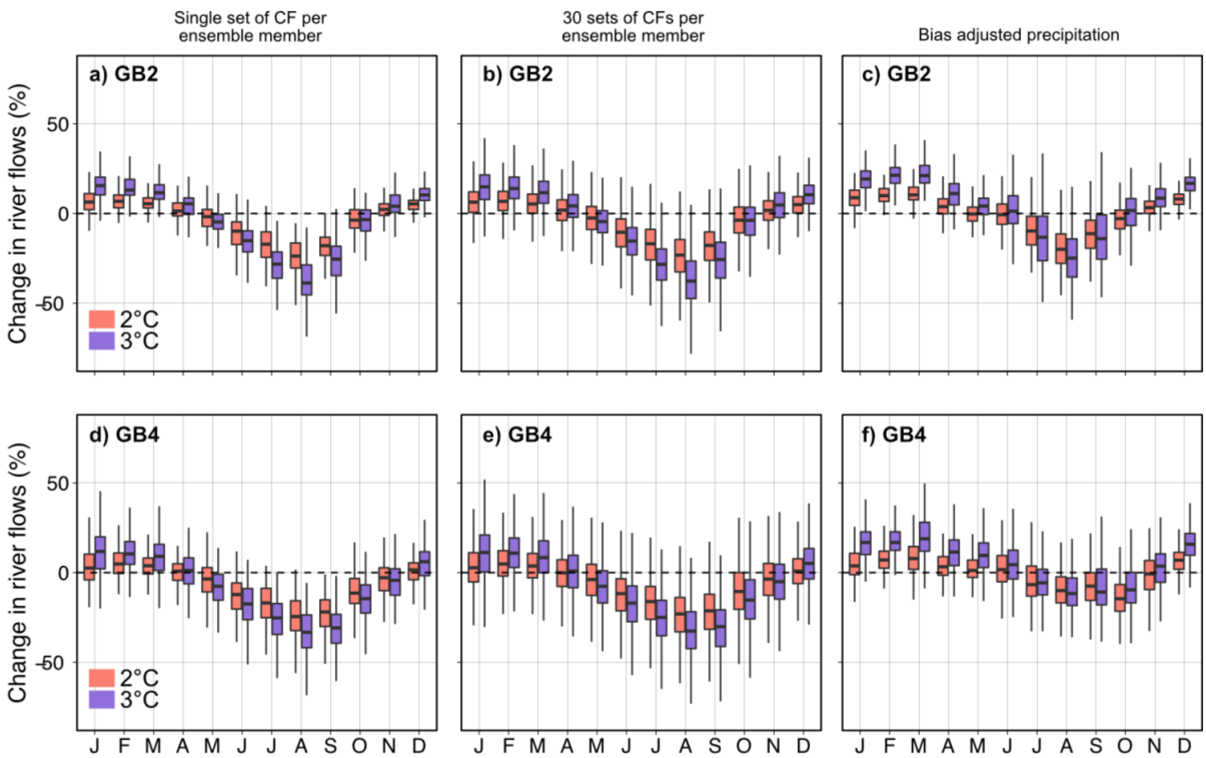

Figure 6.A1 Equivalent to Figure 6.3 but for GB2 and GB4.

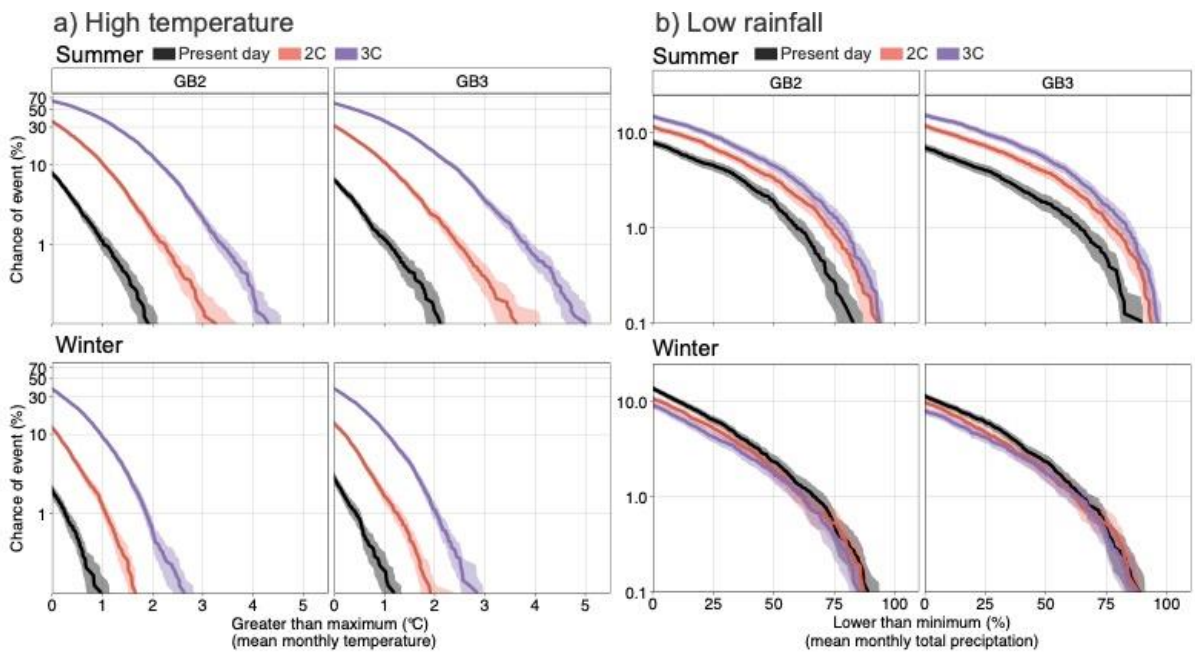

Figure 6.A2 Equivalent to Figure 6.8 but for GB2 and GB3.

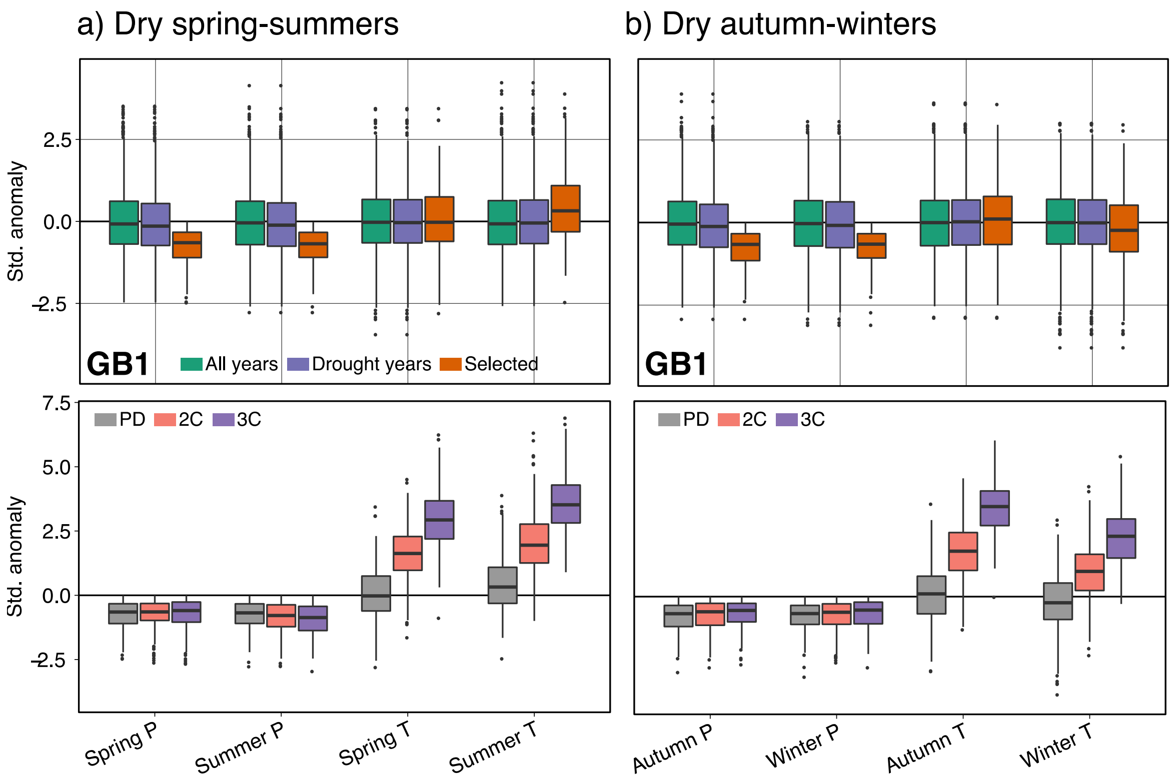

Figure 6.A3 Equivalent to Figure 6.11 but for GB1.

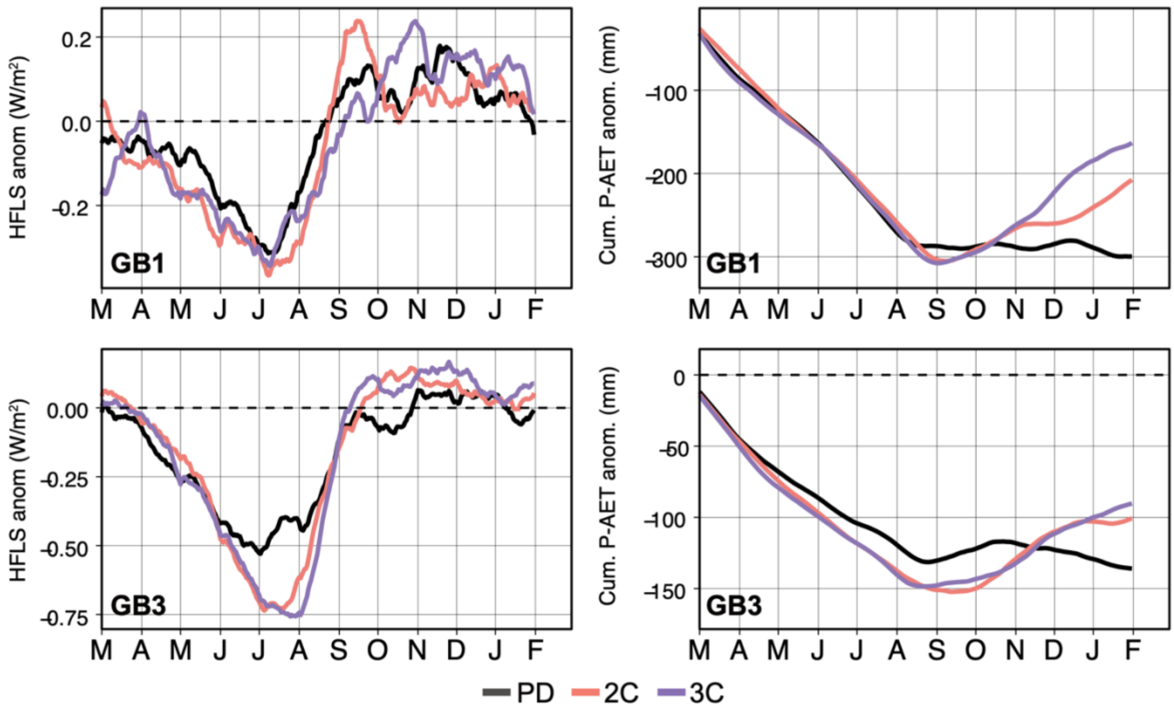

Figure 6.A4 Latent heat flux (W/m²) anomalies and cumulative precipitation minus actual evapotranspiration (AET) anomalies for dry spring-summers in present-day, 2C and 3C conditions at catchments in GB1 and GB3. AET is calculated from latent heat flux following FAO guidelines in Allen et al. (1998). A 30-day rolling mean is applied.

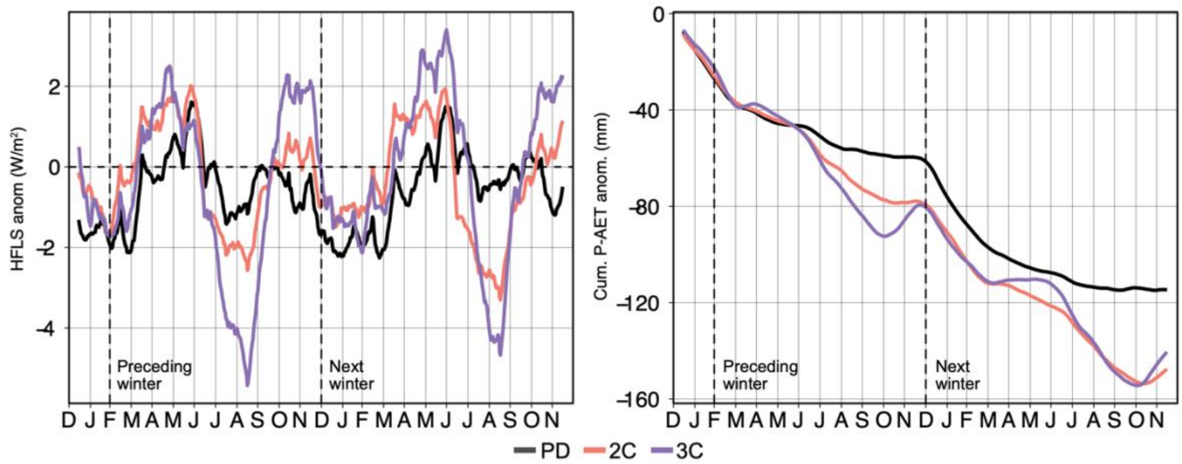

Figure 6.A5 Latent heat flux (W/m²) anomalies and cumulative precipitation minus actual evapotranspiration (AET) anomalies for consecutive dry winters in present-day, 2C and 3C conditions at catchments in GB3. AET is calculated from latent heat flux following FAO guidelines in Allen et al. (1998). A 30-day rolling mean is applied.

7 DISCUSSION AND CONCLUSIONS

7.1 Introduction

The UK has experienced periods of meteorological and hydrological droughts and risks future water shortages and other drought impacts due to climate change and increasing water demand. Hydrological droughts put pressure on public water supplies and incur significant impacts on the natural environment. Some of the most severe consequences of future climate change will be experienced through changes in the global water cycle and the frequency and severity of hydrological extremes. Existing approaches to understanding the impacts of climate change on UK droughts are hampered by large uncertainties in projected change, such as wide uncertainties in projected change in precipitation and drought magnitude. There is also insufficient understanding of low-likelihood, high-impact outcomes and how they might unfold in both current and future climate. This thesis aimed to advance our understanding of the current risk of hydrological droughts and explore the impacts of climate change on future UK droughts by applying a storyline framework to navigate the cascade of uncertainty and aid decision-making. This chapter discusses the main findings for each of the research questions defined in Chapter 1, drawing on the results from each chapter (Section 7.2-7.4). The chapter ends with an outlook on future research opportunities (Section 7.5) and concluding remarks on climate-driven changes in UK droughts and the applicability of the storyline approach (Section 7.6).

7.2 RQ1: How have approaches to understanding the hydrological impacts of climate change in the UK developed over time?

The first research question was addressed by the detailed review of past studies in Chapter 2 which tracked the usage of different approaches in the published literature since the 1990s. It was found that the approach to understanding the impacts of climate change on UK river flows has evolved over time and approaches were broadly motivated by either "top-down" or "bottom-up" aims. Early studies followed a stylised approach which applied ad hoc changes to observed climate variables using a delta method. Subsequent studies have benefited from the increasing availability of GCM projections and were characterised by a "top-down" approach and associated lengthening of the impact modelling chain with a motivation to quantify the various sources of uncertainties (such as differences between the delta method, statistical and dynamical downscaling). Probabilistic approaches emerged as an alternative way to treat climate-model uncertainty through advances in perturbed physics ensembles, starting with the UKCP09 climate change projections and an associated move towards a risk-based approach. More recently, the scenario-neutral approach emerged as a "bottom-up" technique to explore system sensitivity with clear roots from the early stylised approach but with a much more detailed focus on catchment scales, the ability to consider user-defined thresholds and improved consideration of physical plausibility.

Several drawbacks and limitations were identified for each methodological approach. Past studies following "top-down" GCM-driven and probabilistic approaches showed that there is considerable uncertainty over the magnitude of change in future river flows and hydrological extremes. The uncertainty range has not altered significantly through multiple generations of UK climate change projections and seems unlikely to reduce as studies further investigate climate model-related uncertainties through multi-model ensembles or perturbed parameter ensembles (Stainforth et al., 2007). Past studies have also highlighted challenges in quantifying the likelihood in probabilistic projections, which depends on the choice of climate models and how the estimated probability distribution is interpreted by decision-makers, which could lead to insufficient attention being paid to low-likelihood, high-impact outcomes. This has implications for a "predict-then-act" philosophy which has characterised decision-making framework and modelling approaches over the past decades, meaning water resources planners may opt to delay adaptation and investment options (such as infrastructure development or water transfer schemes) in the hope that a higher level of confidence in projected change can be achieved before major adaptation decisions are to be made. Several emerging approaches can be combined to complement existing approaches and address outstanding research gaps. For example, the storyline approach, robust decision-making and UNSEEN methodologies can explore "top-down" projections within a wider "bottom-up" framework led by the intended aims of specific applications. A common motivation of emerging approaches was the focus on identifying the robustness of hydrological systems against a wide range of outcomes which represented a move away from the "predict-then-act" philosophy. More generally, Chapter 2 helped put the storyline approach within a wider historical perspective. The storyline approach echoes "bottom-up" approaches in that impact assessments can be conducted independently of climate change projections and existing projections are used as additional information and not the only source of evidence. For example, the creation of downward counterfactual storylines echoes the sensitivity-focused motivation of the early stylised approach and the scenario-neutral approach but gains an advantage from a more detailed and regional exploration of the physical processes leading up to a drought event.

7.3 RQ2: How can the storyline approach be applied to construct plausible worst cases and understand extreme UK droughts in current and future climate?

This research question was addressed by the creation of drought storylines using different sources of information (climate model projections, seasonal hindcasts, river flow reconstructions and process understanding). Table 7.1 shows the different techniques used within this thesis to create storylines of UK drought under present and future climate. There were drawbacks to using different techniques, but their use highlighted the fact that the storyline approach is not a singular statistical tool or methodology but instead represents an alternative way of thinking that can include the application of various techniques. Some of the techniques used in this thesis are driven by emerging computational advances (e.g. UNSEEN and large ensemble climate model simulations) but others are already widely used techniques (e.g. delta change method and perturbations to past events) but applied within a sensitivity and vulnerability-focused framework. The remaining section aims to assess the advantages and drawbacks of each of the techniques used in this thesis to create drought storylines.

Table 7.1 Techniques applied in various chapters of this thesis to create storylines of UK drought.

Technique	Approach	Storyline(s)	Chapter	Data sources
Perturbations to observed event	Systematic perturbation	- What if the preconditions of the 2010-12 droughts were drier?	4	Process understanding and sensitivity-focused
		- What if autumn 1975 precipitation deficit in East Anglia matched neighbouring East Midlands?	4	Process understanding and sensitivity-focused
	Pooling seasonal hindcasts	- What if similar circulation patterns in winter 1975/76 led to drier conditions?	4	SEAS5 hindcasts
		- How bad could the 2022 drought have been if winter 2022/23 exhibited particular combinations of atmospheric circulation patterns?	5	SEAS5 hindcasts
	Delta change method	- What if the 2010-12 drought unfolded in a future climate at different global warming levels?	4	UKCP18 regional projections
Climate model simulations	Circulation analogues	- What if circulation patterns similar to those observed in the 1975-76 drought occur in present and future climate?	4	UKCP18 global and regional projections
	SMILEs	- How might dry spring-summers, autumn-winters and consecutive dry winters sequences unfold in present and future climate?	6	EC-Earth time-slice large ensemble, river flow reconstructions

7.3.1 Perturbations to an observed event

Various chapters demonstrated the creation of drought storylines based on resampling and perturbing the meteorological time series of observed past drought events, either based on incremental changes to specific event drivers or the replacement of the observed meteorological time series with plausible alternative weather sequences prior to their use in hydrological models. In Chapter 4, drought storylines were created to explore "downward counterfactuals" of the 1975-76 and 2010-12 events to explore possible impacts on river flows if the two selected events turned out worse. In Chapter 5, seasonal hindcasts of winter weather sequences clustered based on atmospheric circulation patterns were appended to the 2022 drought to explore how the drought could have turned out if winter 2022/23 exhibited specific configurations of atmospheric circulation patterns. The storylines explored the "anatomy" of past events by examining individual event drivers and are easier to understand and relate to, as they are based on perturbations to past events and rooted in realism. Creating event storylines by perturbing past observed events further contributed to their physical plausibility, compared to potential difficulties in verifying the physical plausibility of drought events simulated using other approaches from a climate driver perspective (such as synthetic droughts sampled from stochastic weather generators). Pooling seasonal hindcasts, in particular, further took advantage of the skilful simulation of winter circulation characteristics and weather regimes in the formulation of event storylines.

The delta method perturbs existing events with changes derived from climate models, as demonstrated by using the UKCP18 projections to place the 2010-12 event in a future climate at different global warming levels in Chapter 5. This was advantageous as it circumvents the uncertainty associated with different temperature responses to the same emissions scenario between different climate models with added policy relevance associated with the climate policy ambitions (e.g. Paris Agreement) (James et al., 2017; Arnell et al., 2019, 2021). The delta method also avoids having to deal with potential climate model biases in the representation of the persistent circulation anomalies that lead to drought. The main limitation of a delta change approach is that it retains the observed temporal variability in the observed drought. This is useful if studies aim to retain the characteristics of the observed event, such as attribution of individual specific events to climate change or imagining alternative unfolding of the events (e.g. Woo, 2021; Maraun et al., 2022). The temporal variability and sequencing of weather events may change under climate change, such as changes in the frequency of particular weather patterns. This would require alternative approaches such as sampling within large ensemble climate model simulations (as done in Chapter 5) to explore a wider diversity of drought events.

7.3.2 Climate model simulations

Instead of perturbing an observed event, climate model simulations can also be applied more directly in a transient matter to sample for event storylines. The UKCP18 projections were applied to the 1975-76 event following a circulation analogue approach to place the observed event in a warmer world. Circulation analogues provide an additional basis for imposing plausible perturbations to the observed event's drivers. It represents a more conditioned approach compared to the delta approach and thus provides a further basis for imposing additional plausible changes to the event's drivers. However, the use of circulation analogues does not consider the possibility that the circulation patterns observed in a past drought may occur less or more frequently in the future. This approach may be prone to under-estimating risk if observational datasets or traditional climate model simulations are used to sample for circulation analogues and if the circulation patterns associated with the target event are unusual. A larger sample of simulations, such as the large ensemble climate model used in Chapter 6 may be better suited to maximise the likelihood of finding analogue events with similar driving mechanisms to selected observed events. Furthermore, the approach was originally designed for short-duration (days) events. Conditioning the circulation analogues based on the observed preconditions, such as selecting analogues only when the previous day or season is dry, may enhance the quality of the analogues. Recent work by Faranda et al., (2023) modified the original approach by applying a moving average over nine months before identifying the closest circulation analogues to the 2022 European drought.

Advances in computational power have led to the emergence of initialized large ensemble model simulations, which provide an emerging way to understand high-impact, low-likelihood events (Kelder et al., 2022). As shown by this thesis, different types of initialized large ensemble simulations can be used to further understanding of present-day and future risk of hydrological droughts. Computational advances have led to the emergence of different types of large ensemble simulations with their respective strengths and limitations (also further discussed in section 7.4.3). Seasonal hindcasts (e.g. SEAS5) are often run at a higher resolution than global climate models with a large number of ensemble members at different lead times. Given their operational nature and the availability of reforecasts/hindcasts, they are ideal to tackle sampling uncertainty as the pooling of physically plausible, self-consistent hindcast simulations enables a large sample of weather sequences that could have happened in the current climate. On the other hand, SMILEs are often run on multi-decadal timescales (i.e. transient) with future projections and the large spread of ensemble members following initial condition perturbations is more robust indicator of the range of internal variability. By contrast, time-slice SMILEs (e.g. EC-Earth used in Chapter 6) aims to create a large sample of simulations representative of particular climate states at various time slices (e.g. present day and a 2°C warmer world), isolating climate variability from any trends and climate change signal that may be present in longer transient simulations. The large sample of simulations is ideal for exploring the effects of internal climate variability and may provide a more accurate estimation of the probability of extreme events. The larger sample size also means a greater likelihood of finding analogue events with either similar driving mechanisms to selected observed events or similar impacts to that incurred in past events (e.g. van der Wiel et al., 2021;

Goulart et al., 2021). Traditional climate model simulations used in a multi-model ensemble approach do not represent the full range of possible outcomes and studies generally do not consider outcomes beyond the range of the multi-model ensemble, thus under-sampling low-likelihood, high-impact outcomes (Sutton, 2019; Katzav et al., 2021). 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).

7.4 RQ3: What is the added value of a storyline approach to understand hydrological droughts in current and future climate and complement probabilistic estimates of drought hazard risk?

This thesis demonstrated two major contributions of applying the storyline approach to understanding UK droughts. The creation of event storylines contributes to navigating uncertainty in the hydrological impacts of climate change and represents an alternative way in which decision-makers can create and explore plausible worst cases in both current and future climate. Drought storylines further aimed to address outstanding research gaps identified in existing approaches to study past and future hydrological extremes by placing greater emphasis on the processes leading to extreme events and exploring traditional top-down projections in a wider vulnerability-driven and potentially more decision-relevant framework. It should be noted that physical climate storylines are not meant as precise predictions of what would happen in the near term or under future climate change but are instead pathways or event outcomes that are conditioned on plausible changes in physical climate drivers, including changes that could lead to high impacts but may be previously underexplored (e.g. van den Hurk et al., 2023). The following sections discuss the benefits and added value from retrospective event storylines and the use of large ensemble simulations to understanding current and future drought risk, and some of the key drawbacks from the different approaches and their wider implications for decision-making.

7.4.1 Current risk

Following the UK Water Act 2014, water companies were required to consider water supply reliability under plausible worst-case droughts (Environment Agency, 2015a). Additionally, the latest guidance also requires UK water companies to plan for a higher level of drought resilience

(1 in 500 years). Given that such a drought would surpass any event in the observed record, it is important to adopt approaches that can expand the sample size to consider a wide range of events that could arise. Historical river flow reconstructions have successfully expanded our knowledge of severe droughts in the late 19th and early 20th century (e.g. Barker et al. 2019). Tree ring studies on a longer, paleo-time scale have also uncovered particularly severe dry periods (or "mega-droughts") for the UK and Europe, such as the 1540 drought (Pribyl 2020; Cook et al. 2015). However, detailed hydrological simulations for these events are likely not achievable given large uncertainties and coarse resolution of meteorological reconstructions and hydrological non-stationaries (e.g. changes in catchment properties, land use change etc.). The full range of hydrological droughts that could arise from internal climate variability in the current climate thus remains under-explored. Event storylines, created by systematic perturbations to an observed event or by combining an observed event with large ensemble simulations, quantifies the possible impacts should the event turned out worse and represents a new way to interrogate the hydrological impacts of "near-miss" droughts.

A downward counterfactual way of thinking embedded in the storyline approach represents a move away from a "predict-then-act" paradigm in water management and could explore droughts not yet seen in the observations. Event storylines created for the 1975-76 and 2010-12 droughts in Chapter 4 enable water resources planners to explore plausible alternative unfoldings of past events from multiple perspectives, including demonstrating how process understanding and existing known vulnerabilities can be built into storylines. Storylines of the 1975-76 drought highlighted plausible ways in which the event could have turned out worse given changes to the processes leading up to the drought. Catchments across East Anglia could have experienced worse drought in terms of maximum intensity and mean deficit given more severe precipitation deficits in autumn 1975 and the possibility for a winter with similar atmospheric circulation patterns to winter 1975/76 to be even drier than observed. Storylines of the 2010-12 drought showed that the plausible occurrence of a third dry consecutive winter instead of the rapid termination as observed could have led to severe conditions, particularly for groundwater-dominated, slow-responding catchments across southern England. Given the reliance on recharge during the winter season for these catchments, this particular storyline showed that the 2010-12 drought was a "near-miss" event where severe impacts were avoided. In Chapter 5, appending a large sample of internally consistent, physically plausible winter weather sequences to the observed 2022 drought explored how bad the drought could have been given particular atmospheric circulation patterns, shedding light on the climate drivers (e.g. jet stream, circulation configurations, SST patterns) and the resulting surface precipitation and temperature responses.

Through identifying the sensitivity of hydrological systems against a wide range of outcomes, downward counterfactuals build on observed events and quantifies previously unseen conditions that may not be found in short observational records or from the limited sample of simulations in traditional multi-model climate model ensembles (e.g. CMIP6). Additionally, downward counterfactual storylines are developed based on selected observed events. This provides added value to climate risk communication as past studies have recommended that information provided or framed in relation to personal experiences or anchored on memorable events could be more effective for decision-making (e.g. Matthews et al. 2016). Testing management measures against long droughts by stacking multiple observed/reconstructed droughts, Watts et al. (2012) similarly noted that basing their analyses on actual events helped increase realism amongst decision-makers. A recent example of the storyline approach being used in practice was their inclusion in the latest UK Government National Risk Register, which stated that the reasonable worst-case drought for southeast England could arise from prolonged precipitation deficits consisting of three consecutive dry winters (HM Government, 2023). Event storylines of the 1975-76 drought and the 2022 droughts further demonstrated the value of initialized large ensemble simulations (such as seasonal hindcasts) in creating plausible worst cases in the current climate. The major added value is the addition of a dynamical perspective. The physical credibility of simulated events can be verified more easily compared to statistical methods such as stochastic weather generators. As seasonal hindcasts are based on a dynamical model that is physically self-consistent, the metrics describing the meteorological drivers of extreme events are more readily computable (e.g. Kay et al., 2020; Kelder et al., 2022a). Understanding plausible worst cases by pooling hindcasts and treating each hindcast sequence as individual plausible outcomes is valuable as a "perfect" probabilistic forecasts may not be attainable. In the case of the 2022 drought, pooling hindcasts to create explore different drought trajectories is valuable as the skill of available forecasts, though continuously improving, is currently not perfect. Having the information on what a plausible worst-case might look like is therefore useful for planning purposes.

7.4.2 Future risk

Analysis of droughts under a future climate requires driving hydrological models with climate model simulations. Initialized large ensemble simulations presents an emerging way to increase the sample size of hydrological drought events and sample for a wider variety of plausible droughts in a future climate compared to existing multi-model ensembles (e.g. CMIP6). Chapter 6 demonstrated an approach using the time-slice EC-Earth SMILE to bridge probabilistic estimates of future climate extremes with drought storylines, following the large ensemble climate impact modelling framework set out in van der Wiel et al. (2020). The approach is able to provide probabilistic estimates of climate extremes (i.e. estimates of UNSEEN likelihood of hot/dry extremes). Conditional probabilities calculated from SMILE simulations may be particularly useful in satisfying return period guidance from the regulator. For southeast England, the EC-Earth time-slice large ensemble suggested that the chance of a summer month in any given year with unprecedented high temperature increases from 6% in the present-day to 58% in a 3°C warmer world and the chance in winter increases from 2% to 31%. These estimates are consistent with previous estimates of the chance of present-day and future temperature extremes exceeding the observed record from both traditional climate model ensembles (e.g. Battisti and Naylor, 2009) and initialized large ensemble simulations (e.g. Kay et al., 2020). The chance of a dry summer month drier than the observed driest (1995) increases from 9% to 18% and the chance of an extremely dry winter month drier than winter 1991-92 slightly decreases from 10% in the present-day to 8% in a 3C warmer world. Although winter precipitation is projected to increase, the chance of the driest winter months in the large ensemble does not change significantly between present day and the future over southeast England, highlighting the continued risk of dry winters. The use of large ensembles to quantify the probability of record-breaking events increases risk awareness as estimates (e.g. return periods) calculated only based on observations may underestimate current risk and could lead to maladaptation or reduced effectiveness of current adaptation planning if extreme events in the observations can be easily surpassed (Kreibich et al., 2022; Thompson et al., 2023; Coughlan de Perez et al., 2023).

Combining insights from probabilistic and storyline approaches add value to understanding the roles of different event drivers that may be meaningful and informative for decision-making (Shepherd and Lloyd, 2021). Storylines sampled from the EC-Earth large ensemble provided a basis to understand plausible worst cases from the combination of specific meteorological conditions. van Garderen et al. (2021) demonstrated how storylines and a probabilistic approach can be complementary in the attribution of extreme events. As noted by Mankin et al. (2020), the "noise" within SMILE simulations is not just useful to quantify the role of internal climate variability but are all plausible outcomes around a mean state that includes low-likelihood outcomes valuable from a risk perspective. In the EC-Earth large ensemble, dry springs followed by dry summers were estimated to become drier with warming and are associated with a deepening of the high pressure in spring and enhanced evaporative demand in summer. Dry autumn-winters were shown to be generally wetter in a future climate compared to present-day although moderately dry sequences were more likely to be followed by a hot and dry summer in the succeeding year. There was no clear change in the precipitation anomalies associated with consecutive dry winters, reflecting that the probability of the driest winter months did not alter significantly. Should consecutive dry winters occur, multi-year droughts may worsen as the intervening summers are estimated to have a higher likelihood of being hotter and drier than present-day. These storylines had different hydrological implications for different catchments at different timescales and an extreme drought could feasibly be a combination of all three storylines considered, which could lead to droughts with spatial extents, duration and severity that are beyond observed and modelled droughts even in a large ensemble with a high number of ensemble members. Results were consistent with previous research showing that extreme droughts in the future are more likely to include precipitation deficits in the summer and flow responses are likely to be exacerbated by elevated summer temperatures (Brunner et al., 2021b; Reyniers et al., 2023). While precipitation trends are the key driver of variability in future droughts, the role of land–atmosphere feedbacks in influencing drought intensity in the UK remains unclear, such as the possibility that soil moisture deficit exacerbates hot extremes and reinforces low precipitation (e.g. Schumacher et al., 2019; Moravec et al., 2021).

7.4.3 Limitations of climate model simulations for assessing extreme droughts

As summarised in Section 7.3, different types of climate model simulations were used throughout this thesis. Each type of model simulations comes with their respective strengths and limitations. This section aims to discuss the limitations for the use of climate model simulations in creating drought storylines and in addressing outstanding research gaps. First, it should be noted that different sources of model simulations should be used to answer different research questions.

For example, large ensembles (i.e. SEAS5) holds potential to provide physically plausible weather sequences to explore downward counterfactuals when combined with observed droughts. However, although seasonal forecasts are released operationally at regular intervals, they are only run forwards for several months or seasons ahead (e.g. 7 months for SEAS5) and alternative sources of model data such as transient SMILEs would be required to sample for events in a future warmer world. The future unfolding of shorter-term extremes such as heatwaves (which enhances and potentially prolong dry conditions) or the clustering of storms (which could terminate drought events) could also be examined following recent advancement in forecast-based attribution approaches (e.g. Leach et al. 2024; Ermis et al. 2024).

The estimate of drought risk within large ensembles are highly conditioned on the underlying climate model data and are only reliable if climate models are accurate in reproducing observed climate drivers of drought. The value of insights into plausible worst-case droughts are highly dependent on whether the simulated events are judged to be physically credible. While SMILEs represent a new opportunity to expand the sample size of current and future climate extremes more robustly, the main limitation of most SMILEs is that they often have a relatively coarse spatial resolution. They are consequently subjected to biases as some atmospheric and oceanic processes are not well represented and sub-grid physical processes are simplified and parameterized. Studies have shown that CMIP5/CMIP6 models (including some large ensembles) under-estimate observed meteorological drought variability and the persistence of dry periods (e.g. Ukkola et al. 2018; Moon et al. 2018) and fails to capture the direction and magnitude of observed precipitation trends for several regions globally (e.g. Nasrollahi et al. 2015; Shaw et al. 2024). This may relate to model biases in variables such as land surface processes (e.g. plant physiology and land-atmosphere feedback – Lian et al. 2018) or atmospheric blocking frequency, which is underestimated by 10-30% in winter and 30-50% in summer in the Euro-Atlantic region for CMIP5 models (e.g. Wollings et al. 2018). More recently, CMIP6 models participating in the High Resolution Intercomparison Project (HighResMIP) showed that an increase in atmospheric resolution improves the simulation of blocking frequency for both summer and winter but limited improvement for blocking persistence (Schiemann et al. 2020). Model biases represents a drawback for using large ensembles for climate impact modelling as bias adjustment and statistical downscaling procedures are required. In Chapter 6, the bias correction factors applied to catchments, particularly in northern England and Scotland, 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. As highlighted for extreme floods in the Amazon River basin, Kelder et al. (2022b) showed that a large bias adjustment made to the climate data could lead to events that are physically implausible when used to drive hydrological models, meaning the estimated chance of unprecedented extremes at these catchments may be over- or under-estimated. Similarly, some researchers have cautioned that bias adjustment techniques may lead to misleading results if the physical drivers and regional feedbacks within the driving climate model itself are not credible (Maraun et al. 2017).

Biases in key atmospheric drivers of drought in climate model simulations may be improved with further increase in spatial resolution, improvements in physical parameterizations and enhanced model tuning approaches (Moreno-Chamarro et al. 2022; Wollings et al. 2018). Continued advancement in computing power have led to opportunities for climate model simulations at convective-permitting scales (e.g. UKCP18 2.2km simulations) with particular implications for changes in precipitation (e.g. summertime extreme rainfall) (Kendon et al. 2021). Given the large uncertainties in how atmospheric circulation responds to climate change, it is not certain that near-term improvements in climate model simulations would directly lead to a reduction in the spread of model projections for precipitation and droughts (e.g. Cook et al. 2020). The large computational demand also means that convective permitting simulations generally consists of only small numbers of ensemble members with limits to the simulation length or model domain (Kendon et al. 2021). However, the influence of internal variability on hydro-climate variables is large and extreme droughts (e.g. 1 in 500-year) are by definition rare events. The number of ensemble members needed to robustly assess future extreme drought risk therefore needs to be large and existing multi-model ensembles are too small to fully understand the risk and characteristics of extreme droughts (Coats and Mankin 2016). Although existing climate model simulations and hydroclimate projections remain imperfect, the workflow and the climate impact modelling approach demonstrated in Chapter 6 can readily ingest future improved climate model simulations and new generations of large ensembles which may have higher model fidelity or capable of providing robust quantitative estimates of the risk of extreme droughts at a much more local scale.

7.5 Observational data uncertainty and modelling improvements

There are several opportunities to incorporate modelling improvements in this thesis. The motivation of the storyline approach is to enable deep uncertainty to be managed by communicating climate information via discrete storylines. Choices made along the impact modelling chain are inevitably subjective. Throughout this thesis, the choices of observational data, climate models, hydrological models, calibration strategy and PET estimation were all motivated by their current use by water companies or previous use in UK hydrological drought analyses. This choice maximizes relevance to decision-makers by using tools they are already familiar with and allows for comparison with previous datasets or products (such as comparisons of event storylines with reconstructed hydrological droughts since 1891). However, any updates to the methodologies used by industry and decision-makers would have to be reflected and incorporated in the physical climate storylines developed in this thesis.

First, the physical credibility of drought storylines can be further enhanced by quantifying and constraining observational data uncertainty. New observational networks and techniques to obtain spatially distributed precipitation measurements and PET estimates could provide better inputs to hydrological models (Beven et al., 2019). In this thesis, PET was calculated using a temperature-based equation calibrated specifically for the UK which has been widely applied in hydrological drought analysis and used by water companies. Future work could test the sensitivity of the results from the various drought storylines to alternative PET estimation methods and test the validity of temperature-based PET equations under non-stationary conditions. Characterizing uncertainties in observed precipitation (e.g. gridded precipitation products such as HadUK-Grid or newly rescued/digitized data from the 19^{th} to early 20^{th} century) could further add confidence to the magnitude of drought storylines and their relation to past events. For example, Murphy et al. (2019) showed that winter (summer) precipitation in the 19^{th} century from the England and Wales Precipitation (EWP) series were likely too low (high) due to changes in the density of rain gauges and the presence of snow under-catch.

In addition to uncertainties in meteorological inputs, erroneous observations of river flows can also arise due to several factors, including errors in measurement instrumentation (e.g. location of river flow gauges), post-processing (e.g. infilling of missing data – particularly missing low and high flow values) and human influences which may alter the stage-discharge relationship (e.g. water management, land use change and urbanisation) (Wilby et al., 2017; Coxon et al. 2015). More generally, the modification of river flows and hydrological drought characteristics by anthropogenic activities is an increasingly active research field (Van Loon et al., 2016). Recent studies showed that surface and groundwater abstractions can lead to a worsening of hydrological droughts and influence drought termination characteristics (e.g. Margariti et al., 2019; Wendt et al., 2020; Van Loon et al., 2022). Other factors such as urbanization, wastewater discharges and land cover change in catchments can also be major drivers of change in observed river flow magnitude and variability. For example, Han et al. (2022) showed with a sample of urbanising catchments in the UK that high urban land uses had a significant impact on low flow quantiles, hence raising questions about the validity of hydrological models and projections that do not consider land cover change. A better estimation of the uncertainty associated with low flow measurements during extreme droughts could thus further ensure a more robust validation of simulated river flows for the drought storylines created in this thesis.

Second, to account for hydrological model uncertainty, the use of an ensemble of hydrological models and an ensemble of hydrological model parameters (such as the full LHS500 parameter sets in Smith et al. 2019) would increase the robustness of the hydrological modelling results. The choice of hydrological model code and the assessment of a plausible range of model parameters should be motivated by better understanding of model performance (such as the switch from GR4J to GR6J due to better performance for low flows at groundwater-dominated catchments or recent advances in national-scale spatially distributed SHETRAN hydrological model - Lewis et al., 2018). Physically based hydrological models and land surface models, in particular, aim to represent surface and subsurface hydrological processes more comprehensively. There is growing observational evidence globally that prolonged dry periods may alter the rainfall-runoff relationship at catchments, leading to a reduction in annual runoff generated for any given rainfall input and an intensification of drought propagation (e.g. Alvarez-Garreton et al. 2021; Saft et al. 2015; Fowler et al., 2022a). Reviewing the evidence for changes in rainfall-runoff relationships during Australia's "Millennium Drought", Fowler et al. (2022a) suggested that subsurface processes, such as changes to surface water-groundwater interactions after prolonged dry periods were among key factors leading to reduction in river flows. This highlights the importance of considering land surface processes and surface water-groundwater interactions for hydrological systems with long memory, such as the groundwater-dominated catchments considered in this thesis. Catchment hydrological models, such as GR6J and GR4J, may fail to represent the observed changes in precipitation-runoff relationships post-drought, which introduces further uncertainty in the magnitude of the simulated drought storylines and for river flow simulations in driven by future climate model projections (e.g. Fowler et al., 2022b). A case study comparing simulated river flows during the 2022 drought from lumped catchment models (e.g. GR) and physically-based models (e.g. SHETRAN) should be a priority for future work to diagnose hydrological model uncertainty during periods of low flows.

Third, future work could also relate each storyline with management decisions using water resource system models. This would require the consideration of factors such as water abstraction, reservoir yields. The calibration of the selected hydrological models using observed river flows indirectly accounts for anthropogenic influences but recent use of hydrological models with explicit inclusion of abstraction processes showed improvements in model performance (Rameshwaran et al., 2022). This would be an important advancement as Salwey et al. (2023) recently showed with a large sample of catchments that river flow volume and variability at downstream catchments can be significantly influenced by reservoir operations and their inclusion in hydrological models through stylised operating rules could improve model performance nationally (Salwey et al. 2024).

7.6 Future work

7.6.1 Trend detection of hydrological extremes

Various chapters of this thesis alluded to the fact that historical observations represent a single realization out of many other plausible alternative realizations that could have happened (hence the need to consider internal climate variability to sample for low-likelihood, high-impact droughts). Jain et al. (2023) recently highlighted the need to consider internal climate variability in climate model evaluation (i.e. avoid discounting models which seemingly do not reproduce trends in observations). Differences in the calculated river flow trends across past studies are complicated by the use of different study periods, where the presence of wetter periods at the start (or drier periods at the end) of the time series significantly influences the computed trends (Svensson et al., 2006; Hannaford, 2015; Rudd et al., 2017). As hydro-climate time series are often highly variable, a large change in the magnitude or frequency of the variable of interest (e.g. low flows) is needed for projected change to exceed the range of natural variability and for a statistically significant trend to be detected (Slater et al., 2021). Historical observations showed high temporal clustering of drought (or flood) events (such as the 1970s being a relatively drought-rich decade) (Marsh et al., 2007). Precipitation and river flow reconstructions for the pre-instrumental period also showed significant inter-annual variability in wet/dry periods including the clustering of meteorological droughts in the late 18th-century (Todd et al., 2013) and the presence of severe hydrological droughts in the early 20th-century (Rudd et al., 2017; Barker et al., 2019).

Studies have thus cautioned against assuming any significant trends calculated from observational river flow records as representative of climate change's effects (or similarly, assuming any non-significant trends as the absence of climate change) (Wilby, 2006; Arnell, 2011; Orlowsky and Seneviratne, 2013; Hannaford et al., 2013; Arnell, 2022; Environment Agency 2023). Deser and Phillips (2023) used a large ensemble climate model to show that a diversity of temperature and precipitation trends could have occurred in the past 50 years over Europe, including both wetting and drying trends over the UK across all ensemble members of a large ensemble. Additionally, very rare "record-shattering" events could also occur from the combination of anthropogenic climate change influence and internal variability in the absence of a long-term trend. Future work could extend this analysis by exploring the impacts of internal variability on hydrological drought trends. Such analysis could be valuable to reconcile the potential mismatch between the observed and expected trends with future warming. Results could complement emerging work on attributing changes in river flows to climate change (e.g. Gudmundsson et al., 2021) and assist the interpretation of global hydrological trends from past observations within reference hydrometric networks (e.g. https://www.ceh.ac.uk/our-science/projects/robin). Given that the majority of existing SMILEs are limited by relatively low spatial resolution, the emergence of dynamically downscaled SMILEs (e.g. ClimEx RCM - Poschlod et al., 2020; Brunner et al., 2021; Böhnisch et al., 2021) could provide further detailed regional information.

7.6.2 Plausible worst cases

7.6.2.1 Compound events

Building on the retrospective event storylines in Chapter 4 and the sampling of drought sequences within large ensemble simulations in Chapter 6, a similar approach can be taken to create plausible worst cases with a specific focus on compound events. For example, temporally compounding hydrological extremes can include rapid drought-flood transitions which can lead to flash flooding, significant impacts on infrastructure or deterioration in water quality. The processes in which these rapid transitions can occur in present and future climate, such as from a sequence of storm clusters or from an increase in storm intensity (Bevacqua et al. 2020) merit further investigation and studies can follow an event storyline approach to explore multiple counterfactuals. Drought-flood transitions can also be investigated using the drought termination framework in Parry et al. (2016) by pooling existing publicly available projections for UK catchments (such as eFLaG and MARUIS datasets) or by sampling within large ensemble simulations (especially emerging SMILEs based on RCMs such as Böhnisch et al. 2021 given that the spatial resolution remains a major constraint to their uptake in practice). Results from Chapter 6 showed that it is highly likely for warmer than average summer temperatures to occur concurrently with summer droughts in a future climate. The UK National Risk Register also recognizes the likelihood of concurrent and temporally compounding hazards which can cause disruptions to transportation and supply networks and potential socio-economic changes (HM Government, 2023). An example of this could be the impacts on levels and variability of water demand caused by changes in working patterns from the COVID pandemic and the coinciding occurrence of a widespread heatwave in August 2020 (Bunney et al., 2021). An event storyline approach is well suited to quantify such an event and imagine its counterfactuals to increase risk awareness and future resilience.

7.6.2.2 Multi-year droughts

The event storylines of the 2010-12 drought in Chapter 4 showed the utility of an event storyline approach to characterize "near-misses" and highlight the vulnerability of slow-responding, groundwater-driven catchments to multi-year drought conditions driven by three consecutive dry winters. However, the likelihood of three dry winters in present and future climate is poorly understood given high variability in UK rainfall, climate model biases in drivers of low rainfall (e.g. blocking persistence as previously discussed) and limited understanding of the remote drivers of low rainfall (e.g. ENSO) (Folland et al. 2015). Event storylines based on physically plausible perturbations of observed events, such as that demonstrated in Chapter 4, could serve as an interim approach to ensure risk awareness to dry winters and provide context for stress-testing to ensure informed decision-making. Further, sampling for multi-year droughts are limited by the set-up of climate model simulations. For example, the set-up of the EC-Earth time-slice large ensemble used in Chapter 6 meant that multi-year droughts, such as events arising from more than two consecutive dry winters were not well sampled. Depending on the set-up of individual SMILEs or differences in the lead-time of different hindcast datasets, their usefulness in assessing long-duration multi-year droughts may differ. For example, simulations may be truncated or require "stitching" together (e.g. Guillod et al. 2018) if they are reinitialized 12 months apart (e.g. the DePreSys3 dataset - Smith et al., 2007) or on seasonal timescales (the SEAS5 hindcasts used in Chapter 5).

Drought impact studies for catchments most vulnerable to multi-year droughts could benefit from more robust sampling of multi-year events in different SMILEs or longer (e.g. decadal) hindcasts. Transient CMIP5/CMIP6 SMILE simulations, such as those included in the Multi-Model Large Ensemble Archive (MMLEA) could be used to assess multi-year meteorological droughts (e.g. van der Wiel et al. 2023). The ensemble boosting approach to simulate trajectories more extreme than what was observed could also be applied to generate worst case multi-year drought simulations for Europe (Gessner et al. 2022). However, their coarse resolution precludes their use for detailed catchment hydrological modelling. Future generations of SMILEs, improved predictability of key climate drivers of winter rainfall (e.g. NAO) and the progress in convective permitting models contain new opportunities to improve understanding of the drivers and enable a more accurate estimation of the likelihood of consecutive dry winters and multi-year droughts. Future work could prioritize extending meteorological records and river flow simulations to consider climate drivers of the string of dry winters in the late 1880s and 1890s (part of the "Long Drought"). More work is also required to understand how multi-decadal variability (e.g. AMO) interacts with climate variability at the shorter time scales (e.g. ENSO and jet stream variability) and combine to lead to extreme droughts (Wilby 2019).

Additionally, researchers are increasingly advocating for climate impact research to focus more on understanding the risk of climate extremes in a stabilized climate (i.e. Paris Agreement target of stabilizing global temperatures well below 2°C) (King et al., 2021). Transient climate simulations are not suitable for understanding the effects of a stabilized climate for extremes that are characterised by long time-scales (e.g. multi-year droughts). Climate drivers impacting European climate and thus multi-year droughts (e.g. extreme heat, ENSO variability and sea ice extent) are also highly influenced by the rate of global warming (King et al. 2020; King et al. 2024). Using new climate model stabilization experiments, Dittus et al. (2024) showed that precipitation trends in a stabilized climate may be different to that projected by transient simulations. The results suggested that the decline in summer precipitation projected by transient projections could be reverse in a stabilized climate. The implications of this for the risk of hydrological droughts and extreme multi-year droughts is not known and is a key area for future work.

7.6.2.3 Counterfactual library of extreme droughts

There are significant benefits and scope for storylines to be included more routinely in operational planning. There are numerous examples of retrospective event analyses in academic publications and research reports (e.g. ad-hoc reports on UK flood and drought events by the National Hydrological Monitoring Programme). These reports provide an ideal avenue to include qualitative and quantitative counterfactual storyline analyses to build up a national counterfactual library of extreme droughts. As these reports often include detailed chronologies of how events unfolded (such as the mention of the meteorological drivers of notable wet months within long dry sequences), a logical extension would be to explore quantitatively "what-if" situations should the event unfolded in different ways or in a warmer climate. Indeed, Table 4.1 used information from such event reports and publications to propose a series of counterfactual storylines for past droughts. Routine analysis of counterfactual storylines echoes the recommendation in Woo (2021) to provide a database of counterfactual events to increase risk awareness. Leach et al. (2021) recently also demonstrated a near real-time approach to attribute the effects of global warming to a singular event by perturbing simulations from a weather forecast model that has successfully predicted the event (in this case, the 2019 winter heatwave). Including storyline analyses in routine event reporting means that water resources managers may be able to make more confident decisions as different lines of evidence are able to inform the severity of events at different levels of detail, thus more effectively navigate the cascade of uncertainty.

The spatial dimension of current and future droughts were not explicitly considered in this thesis. Changes in the spatial coherence of current and future droughts will likely have implications for water management measures such as regional water transfers (Tanguy et al., 2023). The methodology to obtain a 1 in 500-year drought differs between water companies and there can therefore be multiple definitions of such a drought and a large diversity of droughts could satisfy a 1 in 500 year statistical definition. A series of plausible worst cases with a focus on spatial coherence can therefore be created, such as event storylines of a severe regional drought versus a severe spatially extensive drought. Given the focus from a hazard perspective in this thesis, future work could also extend the existing analysis to include the dimensions of exposure and vulnerability to consider future changes in population, water demand and socio-economic development. For example, standardized indicators are recommended by the UNCCD to quantify the total population exposed to drought and the propensity of socio-economic sectors to be affected severely by droughts (Barker et al., 2021).

7.7 Concluding remarks

This thesis reviewed the historical development of approaches used to understand climate-driven changes to UK river flows and demonstrated the ways a storyline approach can add value to the understanding of UK hydrological droughts. Research findings highlighted the potential for storylines to navigate the cascade of uncertainty and provided useful regional and local information on the physical drivers and hydrological implications arising from near misses and worst-case droughts at different timescales. Key conclusions from this thesis include:

- Existing UK research on climate-driven changes in hydrology has evolved over recent decades. A GCM-based, scenario-driven approach has dominated the literature with wide uncertainty ranges remaining for many hydrological variables. Probabilistic approaches have been hampered by challenges in interpreting likelihoods for practical decision-making. Sensitivity-focused approaches can be applied independently from climate model projections. The storyline approach, placed within this historical perspective, was shown to help navigate the cascade of uncertainty and places emphasis on high-impact, low-likelihood outcomes relevant to risk management.
- Event storylines created for past and ongoing droughts explored alternative plausible unfoldings of the event that could have turned out worse. Modifying the observed event with changes to its climate drivers and temporal characteristics identified vulnerabilities of hydrological systems, placed historical events in context and enhanced understanding of plausible worst-case droughts in both present-day and future conditions. Case studies of the relatively short, but severe 1975-76 drought and the more protracted 2010-12 drought showed that there was considerable scope for both events to have been significantly more severe given storylines that could arise

from internal climate variability. The case studies identified the perturbations needed for impacts to reach and exceed past droughts, highlighting situations that can be considered near-misses. Both events are estimated to worsen with future warming.

- Storylines can be created routinely for ongoing events to represent plausible river flow and groundwater level trajectories conditional on atmospheric circulation patterns. Storylines created for the 2022 drought explored a wider range of possible outcomes than traditional outlooks and forecasting approaches that rely heavily on historical years. The storylines identified atmospheric circulation configurations that could have led to a gradual recovery, prolonged drought conditions or abrupt drought termination.
- Large ensemble simulations, such as SMILEs and seasonal hindcasts, can be used to obtain probabilistic estimates of climate extremes. Probabilistic estimates from the EC-Earth time-slice large ensemble showed a significant increase in the likelihood of summer and winter months with unprecedented high temperatures with warming, an increasing chance of extremely dry summer months and the enduring risk of dry winters across the UK. Combining large ensembles with observed events and additional sources of information, such as historical river flow reconstructions, allowed for a better understanding of plausible worst cases, which could lead to a re-evaluation of reference droughts.
- Sampling for drought storylines in large ensemble simulations enhanced understanding of record-breaking hydrological droughts, and enabled stress tests on hydrological systems. Storylines can be effective in providing further decision-relevant context to probabilistic estimates. Droughts with dry springs followed by dry summers were estimated to become drier with warming with an increased role of elevated summer temperatures, leading to an increased frequency of low flows or rapid river flow recessions. Dry autumn-winters become wetter, which could provide a buffer for drier summers in slow-responding catchments, but hydrological impacts may worsen if a moderately dry winter half-year is followed by a much drier summer. Consecutive dry winters could lead to intensified multi-year droughts due hotter and drier intervening summers. The approach to create probabilistic storylines of extreme UK drought risk can readily ingest future climate modelling products which may have improved model fidelity or confidence in local to regional climate projections to obtain more accurate probabilistic information.

The UK is expected to encounter more severe hydrological extremes and increased volatility with future warming. Building on the findings of this thesis, there is scope for regulator guidance to encourage the use of event storylines within water resources planning given the remaining limitations of the direct use of climate models to estimate the probability of extreme drought. Event storylines contribute to the general diversification of approaches to consider different ways extreme droughts could arise will benefit climate adaptation to hydrological extremes, safeguard the resilience of water supplies and balance the water resources needs of the natural environment.

REFERENCES

Aalbers, E. E., van Meijgaard, E., Lenderink, G., de Vries, H., and van den Hurk, B. J. J. M.: The 2018 west-central European drought projected in a warmer climate: how much drier can it get?, Natural Hazards and Earth System Sciences, 23, 1921–1946, https://doi.org/10.5194/nhess-23-1921-2023, 2023.

Afzal, M. and Ragab, R.: How do climate and land use changes affect the water cycle? Modelling study including future drought events prediction using reliable drought indices, Irrig. Drain., https://doi.org/10.1002/ird.2467, 2020.

Afzal, M., Gagnon, A. S., and Mansell, M. G.: The impact of projected changes in climate variability on the reliability of surface water supply in Scotland, Water Sci. Technol.-Water Supply, 15, 736–745, https://doi.org/10.2166/ws.2015.027, 2015.

Allan, R. P., Barlow, M., Byrne, M. P., Cherchi, A., Douville, H., Fowler, H. J., Gan, T. Y., Pendergrass, A. G., Rosenfeld, D., Swann, A. L. S., Wilcox, L. J., and Zolina, O.: Advances in understanding large‐scale responses of the water cycle to climate change, Ann. N.Y. Acad. Sci., 1472, 49–75, https://doi.org/10.1111/nyas.14337, 2020.

Anandhi, A., Frei, A., Pierson, D.C., Schneiderman, E.M., Zion, M.S., Lounsbury, D., Matonse, A.H., 2011. Examination of change factor methodologies for climate change impact assessment. Water Resources Research 47. https://doi.org/10.1029/2010WR009104

Anglian Water: Anglian Water Drought Plan 2022: https://www.anglianwater.co.uk/about-us/our-strategies-andplans/drought-plan/, last access: 6 March 2023.

Anglian Water: When it does rain, it pours, but still more's needed to boost water supplies in East Anglia for summer: https://www.anglianwater.co.uk/news/when-it-does-rain-it-pours-but-still-mores-needed-to-boost-water-supplies-in-east-anglia-for-summer/, last access: 6 March 2023.

Arnell, N. W. and Delaney, E. K.: Adapting to climate change: Public water supply in England and Wales, Climatic Change, 78, 227–255, https://doi.org/10.1007/s10584-006-9067-9, 2006.

Arnell, N. W. and Gosling, S. N.: The impacts of climate change on river flow regimes at the global scale, Journal of Hydrology, 486, 351–364, https://doi.org/10.1016/j.jhydrol.2013.02.010, 2013.

Arnell, N. W. and Reynard, N. S.: The effects of climate change due to global warming on river flows in Great Britain, J. Hydrol., 183, 397–424, https://doi.org/10.1016/0022-1694(95)02950-8, 1996.

Arnell, N. W., Brown, R. P. C., and Reynard, N. S.: Impact of climatic variability and change on river flow regimes in the UK, Rep. - UK Inst. Hydrol., 107, 1990.

Arnell, N. W., Charlton, M. B., and Lowe, J. A.: The effect of climate policy on the impacts of climate change on river flows in the UK, J. Hydrol., 510, 424–435, https://doi.org/10.1016/j.jhydrol.2013.12.046, 2014.

Arnell, N. W., Freeman, A., Kay, A. L., Rudd, A. C., and Lowe, J. A.: Indicators of climate risk in the UK at different levels of warming, Environ. Res. Commun., 3, 095005, https://doi.org/10.1088/2515-7620/ac24c0, 2021.

Arnell, N. W., Halliday, S. J., Battarbee, R. W., Skeffington, R. A., and Wade, A. J.: The implications of climate change for the water environment in England, Prog. Phys. Geogr. Earth Environ., 39, 93–120, https://doi.org/10.1177/0309133314560369, 2015.

Arnell, N. W., Kay, A. L., Freeman, A., Rudd, A. C., and Lowe, J. A.: 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, 2021.

Arnell, N. W., Lowe, J. A., Challinor, A. J., and Osborn, T. J.: Global and regional impacts of climate change at different levels of global temperature increase, Climatic Change, 155, 377–391, https://doi.org/10.1007/s10584-019-02464-z, 2019.

Arnell, N. W.: Factors controlling the effects of climate change on river flow regimes in a humid temperate environment, J. Hydrol., 132, 321–342, https://doi.org/10.1016/0022-1694(92)90184-W, 1992a.

Arnell, N. W.: Impacts of Climatic Change on River Flow Regimes in the UK, Water Environ. J., 6, 432–442, https://doi.org/10.1111/j.1747-6593.1992.tb00772.x, 1992b.

Arnell, N. W.: Incorporating Climate Change Into Water Resources Planning in England and Wales1, JAWRA Journal of the American Water Resources Association, 47, 541–549, https://doi.org/10.1111/j.1752-1688.2011.00548.x, 2011a.

Arnell, N. W.: 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, 2003.

Arnell, N. W.: The implications of climate change for emergency planning, International Journal of Disaster Risk Reduction, 83, 103425, https://doi.org/10.1016/j.ijdrr.2022.103425, 2022.

Arnell, N. W.: Uncertainty in the relationship between climate forcing and hydrological response in UK catchments, Hydrology and Earth System Sciences, 15, 897–912, https://doi.org/10.5194/hess-15-897-2011, 2011.

Arnell, N.: Global Warming, River Flows and Water Resources, Wiley, Chichester, 1996.

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. Journal of Hydrology 270, 195–213. https://doi.org/10.1016/S0022-1694(02)00288-3

Arnell, N.W., Freeman, A., 2022. The impact of climate change on policy-relevant indicators of temperature extremes in the United Kingdom. Climate Resilience 1. https://doi.org/10.1002/cli2.12

Ault, T.R., Cole, J.E., Overpeck, J.T., Pederson, G.T., Meko, D.M., 2014. Assessing the Risk of Persistent Drought Using Climate Model Simulations and Paleoclimate Data. Journal of Climate 27, 7529–7549. https://doi.org/10.1175/JCLI-D-12-00282.1

Baker, L., Shaffrey, L., and Hawkins, E.: Has the risk of a 1976 north-west European summer drought and heatwave event increased since the 1970s because of climate change?, Quart J Royal Meteoro Soc, 147, 4143–4162, https://doi.org/10.1002/qj.4172, 2021.

Barker, L. J., Fry, M., Hannaford, J., Nash, G., Tanguy, M., and Swain, O.: Dynamic High Resolution Hydrological Status Monitoring in Real-Time: The UK Water Resources Portal, Frontiers in Environmental Science, 10, 2022.

Barker, L. J., Hannaford, J., Chiverton, A., and Svensson, C.: From meteorological to hydrological drought using standardised indicators, Hydrology and Earth System Sciences, 20, 2483–2505, https://doi.org/10.5194/hess-20-2483-2016, 2016.

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

Barker, L. J., Rickards, N., Sarkar, S., Hannaford, J., King-Okumu, C., and Rees, G.: Good Practice Guidance for National Reporting on UNCCD Strategic Objective 3: To mitigate, adapt to, and manage the effects of drought in order to enhance resilience of vulnerable populations and ecosystems, UNCCD, Bonn, Germany, 2021.

Battisti, David. S. and Naylor, R. L.: Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat, Science, 323, 240–244, https://doi.org/10.1126/science.1164363, 2009.

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P., and Makowski, D.: Impact of extreme weather conditions on European crop production in 2018, Phil. Trans. R. Soc. B, 375, 20190510, https://doi.org/10.1098/rstb.2019.0510, 2020.

Bell, V. A., Kay, A. L., Jones, R. G., and Moore, R. J.: Use of a grid-based hydrological model and regional climate model outputs to assess changing flood risk, Int. J. Climatol., 27, 1657–1671, https://doi.org/10.1002/joc.1539, 2007.

Benestad, R., Sillmann, J., Thorarinsdottir, T. L., Guttorp, P., Mesquita, M. d S., Tye, M. R., Uotila, P., Maule, C. F., Thejll, P., Drews, M., and Parding, K. M.: New vigour involving statisticians to overcome ensemble fatigue, Nat. Clim. Change, 7, 697–703, https://doi.org/10.1038/nclimate3393, 2017.

Beran, M. and Arnell, N.: Effect of Climatic Change on Quantitative Aspects of United Kingdom Water Resources, Institute of Hydrology, Wallingford, 1989.

Betts, R. A., Boucher, O., Collins, M., Cox, P. M., Falloon, P. D., Gedney, N., Hemming, D. L., Huntingford, C., Jones, C. D., Sexton, D. M. H., and Webb, M. J.: Projected increase in continental runoff due to plant responses to increasing carbon dioxide, Nature, 448, 1037–1041, https://doi.org/10.1038/nature06045, 2007.

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A. F. S., Ramos, A. M., Vignotto, E., Bastos, A., Blesić, S., Durante, F., Hillier, J., Oliveira, S. C., Pinto, J. G., Ragno, E., Rivoire, P., Saunders, K., Wiel, K., Wu, W., Zhang, T., and Zscheischler, J.: Guidelines for Studying Diverse Types of Compound Weather and Climate Events, Earth's Future, 9, https://doi.org/10.1029/2021EF002340, 2021.

Bevacqua, E., Suarez-Gutierrez, L., Jézéquel, A., Lehner, F., Vrac, M., Yiou, P., and Zscheischler, J.: Advancing research on compound weather and climate events via large ensemble model simulations, Nat Commun, 14, 2145, https://doi.org/10.1038/s41467-023-37847-5, 2023.

Bevacqua, E., Zappa, G., and Shepherd, T. G.: Shorter cyclone clusters modulate changes in European wintertime precipitation extremes, Environ. Res. Lett., 15, 124005, https://doi.org/10.1088/1748-9326/abbde7, 2020.

Bevacqua, E., Zappa, G., Lehner, F., and Zscheischler, J.: 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, 2022.

Beven, K.: I believe in climate change but how precautionary do we need to be in planning for the future?, Hydrol. Process., 25, 1517–1520, https://doi.org/10.1002/hyp.7939, 2011.

Beven, K., Asadullah, A., Bates, P., Blyth, E., Chappell, N., Child, S., Cloke, H., Dadson, S., Everard, N., Fowler, H. J., Freer, J., Hannah, D. M., Heppell, K., Holden, J., Lamb, R., Lewis, H., Morgan, G., Parry, L., and Wagener, T.: Developing observational methods to drive future hydrological science: Can we make a start as a community?, Hydrological Processes, 34, 868–873, https://doi.org/10.1002/hyp.13622, 2020.

Bierkens, M. F. P. and Beek, L. P. H. van: Seasonal Predictability of European Discharge: NAO and Hydrological Response Time, Journal of Hydrometeorology, 10, 953–968, https://doi.org/10.1175/2009JHM1034.1, 2009.

Blenkinsop, S. and Fowler, H. J.: Changes in drought frequency, severity and duration for the British Isles projected by the PRUDENCE regional climate models, Journal of Hydrology, 342, 50–71, https://doi.org/10.1016/j.jhydrol.2007.05.003, 2007.

Bloomfield, J.P., Gong, M., Marchant, B.P., Coxon, G., Addor, N., 2021. How is Baseflow Index (BFI) impacted by water resource management practices? Hydrol. Earth Syst. Sci. 25, 5355–5379. https://doi.org/10.5194/hess-25-5355-2021

Böhnisch, A., Mittermeier, M., Leduc, M., and Ludwig, R.: Hot Spots and Climate Trends of Meteorological Droughts in Europe–Assessing the Percent of Normal Index in a Single-Model Initial-Condition Large Ensemble, Frontiers in Water, 3, 2021.

Boorman, D. B. and Sefton, C. E. M.: Recognising the uncertainty in the quantification of the effects of climate change on hydrological response, Clim. Change, 35, 415–434, https://doi.org/10.1023/A:1005372407881, 1997.

Borgomeo, E., Hall, J. W., Fung, F., Watts, G., Colquhoun, K., and Lambert, C.: Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties, Water Resour. Res., 50, 6850–6873, https://doi.org/10.1002/2014WR015558, 2014.

Borgomeo, E., Pflug, G., Hall, J. W., and Hochrainer-Stigler, S.: Assessing water resource system vulnerability to unprecedented hydrological drought using copulas to characterize drought duration and deficit, Water Resour. Res., 51, 8927–8948, https://doi.org/10.1002/2015WR017324, 2015.

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

Brunner, M. I. and Tallaksen, L. M.: Proneness of European Catchments to Multiyear Streamflow Droughts, Water Resources Research, 55, 8881–8894, https://doi.org/10.1029/2019WR025903, 2019.

Brunner, M. I. and Tallaksen, L. M.: Proneness of European Catchments to Multiyear Streamflow Droughts, Water Resour. Res., 55, 8881–8894, https://doi.org/10.1029/2019WR025903, 2019.

Brunner, M. I., Slater, L., Tallaksen, L. M., and Clark, M.: Challenges in modeling and predicting floods and droughts: A review, WIREs Water, 8, e1520, https://doi.org/10.1002/wat2.1520, 2021.

Brunner, M. I., Swain, D. L., Gilleland, E., and Wood, A. W.: Increasing importance of temperature as a contributor to the spatial extent of streamflow drought, Environ. Res. Lett., 16, 024038, https://doi.org/10.1088/1748-9326/abd2f0, 2021b.

Brunner, M. I., Swain, D. L., Wood, R. R., Willkofer, F., Done, J. M., Gilleland, E., and Ludwig, R.: 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, 2021a.

Bunney, S., Lawson, E., Cotterill, S., and Butler, D.: Water Resource Management: Moving from Single Risk-Based Management to Resilience to Multiple Stressors, Sustainability, 13, 8609, https://doi.org/10.3390/su13158609, 2021.

Bunting, S.Y., Jackson, C.R., Mackay, J.D., 2020. AquiMod modelling of groundwater level hydrographs in the Anglian Water Services' area (Commissioned Report No. CR/20/056). British Geological Survey.

Burke, E. J., Perry, R. H. J., and Brown, S. J.: An extreme value analysis of UK drought and projections of change in the future, Journal of Hydrology, 388, 131–143, https://doi.org/10.1016/j.jhydrol.2010.04.035, 2010.

Burt, T. P. and Howden, N. J. K.: North Atlantic Oscillation amplifies orographic precipitation and river flow in upland Britain: NAO Drives Double Orographic Enhancement, Water Resour. Res., 49, 3504–3515, https://doi.org/10.1002/wrcr.20297, 2013.

Charlton, M. B. and Arnell, N. W.: Adapting to climate change impacts on water resources in England—An assessment of draft Water Resources Management Plans, Global Environmental Change, 21, 238–248, https://doi.org/10.1016/j.gloenvcha.2010.07.012, 2011.

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

Christierson, B. v., Vidal, J.-P., and Wade, S. D.: Using UKCP09 probabilistic climate information for UK water resource planning, J. Hydrol., 424–425, 48–67, https://doi.org/10.1016/j.jhydrol.2011.12.020, 2012.

Chun, K. P., Wheater, H., and Onof, C.: Prediction of the impact of climate change on drought: an evaluation of six UK catchments using two stochastic approaches, Hydrological Processes, 27, 1600–1614, https://doi.org/10.1002/hyp.9259, 2013.

Clarke, B., Otto, F., and Jones, R.: When don't we need a new extreme event attribution study?, Climatic Change, 176, 60, https://doi.org/10.1007/s10584-023-03521-4, 2023.

Cloke, H. L., Jeffers, C., Wetterhall, F., Byrne, T., Lowe, J., and Pappenberger, F.: Climate impacts on river flow: projections for the Medway catchment, UK, with UKCP09 and CATCHMOD, Hydrol. Process., 24, 3476–3489, https://doi.org/10.1002/hyp.7769, 2010.

Cook, E. R., Seager, R., Kushnir, Y., Briffa, K. R., Büntgen, U., Frank, D., Krusic, P. J., Tegel, W., Van Der Schrier, G., Andreu-Hayles, L., Baillie, M., Baittinger, C., Bleicher, N., Bonde, N., Brown, D., Carrer, M., Cooper, R., Čufar, K., Dittmar, C., Esper, J., Griggs, C., Gunnarson, B., Günther, B., Gutierrez, E., Haneca, K., Helama, S., Herzig, F., Heussner, K.-U., Hofmann, J., Janda, P., Kontic, R., Köse, N., Kyncl, T., Levanič, T., Linderholm, H., Manning, S., Melvin, T. M., Miles, D., Neuwirth, B., Nicolussi, K., Nola, P., Panayotov, M., Popa, I., Rothe, A., Seftigen, K., Seim, A., Svarva, H., Svoboda, M., Thun, T., Timonen, M., Touchan, R., Trotsiuk, V., Trouet, V., Walder, F., Ważny, T., Wilson, R., and Zang, C.: Old World megadroughts and pluvials during the Common Era, Sci. Adv., 1, e1500561, https://doi.org/10.1126/sciadv.1500561, 2015.

Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E., and Anchukaitis, K. J.: Twenty-First Century Drought Projections in the CMIP6 Forcing Scenarios, Earth's Future, 8, e2019EF001461, https://doi.org/10.1029/2019EF001461, 2020.

Cole, J. A., Slade, S., Jones, P. D., and Gregory, J. M.: Reliable yield of reservoirs and possible effects of climatic change, Hydrol. Sci. J., 36, 579–598, https://doi.org/10.1080/02626669109492545, 1991.

Comas-Bru, L. and McDermott, F.: Impacts of the EA and SCA patterns on the European twentieth century NAO-winter climate relationship: Impacts of EA and SCA patterns on NAO-winter climate relationship, Q.J.R. Meteorol. Soc., 140, 354–363, https://doi.org/10.1002/qj.2158, 2014.

Conway, D., Nicholls, R. J., Brown, S., Tebboth, M. G. L., Adger, W. N., Ahmad, B., Biemans, H., Crick, F., Lutz, A. F., De Campos, R. S., Said, M., Singh, C., Zaroug, M. A. H., Ludi, E., New, M., and Wester, P.: The need for bottom-up assessments of climate risks and adaptation in climate-sensitive regions, Nat. Clim. Change, 9, 503–511, https://doi.org/10.1038/s41558-019-0502-0, 2019.

Cotterill, D. F., Pope, J. O., and Stott, P. A.: Future extension of the UK summer and its impact on autumn precipitation, Clim Dyn, https://doi.org/10.1007/s00382-022-06403-0, 2022.

Coughlan de Perez, E., Ganapathi, H., Masukwedza, G. I. T., Griffin, T., and Kelder, T.: Potential for surprising heat and drought events in wheat-producing regions of USA and China, npj Clim Atmos Sci, 6, 1–10, https://doi.org/10.1038/s41612-023-00361-y, 2023.

Counsell, C., Hunt, D., and Ledbetter, R.: Drought Vulnerability Framework, UK Water Industry Research, London, 2017.

Coxon, G., Freer, J., Westerberg, I. K., Wagener, T., Woods, R., and Smith, P. J.: A novel framework for discharge uncertainty quantification applied to 500 UK gauging stations, Water Resources Research, 51, 5531–5546, https://doi.org/10.1002/2014WR016532, 2015.

Culley, S., Bennett, B., Westra, S., and Maier, H. R.: Generating realistic perturbed hydrometeorological time series to inform scenario-neutral climate impact assessments, J. Hydrol., 576, 111–122, https://doi.org/10.1016/j.jhydrol.2019.06.005, 2019.

Dawkins, L. C., Osborne, J. M., Economou, T., Darch, G. J. C., and Stoner, O. R.: The Advanced Meteorology Explorer: a novel stochastic, gridded daily rainfall generator, Journal of Hydrology, 607, 127478, https://doi.org/10.1016/j.jhydrol.2022.127478, 2022.

Day, G. N.: Extended Streamflow Forecasting Using NWSRFS, J. Water Resour. Plann. Manage., 111, 157–170, https://doi.org/10.1061/(ASCE)0733-9496(1985)111:2(157), 1985.

De Bruijn, K. M., Lips, N., Gersonius, B., and Middelkoop, H.: The storyline approach: a new way to analyse and improve flood event management, Nat Hazards, 81, 99–121, https://doi.org/10.1007/s11069-015-2074-2, 2016.

De Luca, P., Harpham, C., Wilby, R. L., Hillier, J. K., Franzke, C. L. E., and Leckebusch, G. C.: Past and Projected Weather Pattern Persistence with Associated Multi-Hazards in the British Isles, Atmosphere, 10, 577, https://doi.org/10.3390/atmos10100577, 2019.

Defra and Environment Agency: Drought: how water companies plan for dry weather and drought, https://www.gov.uk/government/publications/drought-managing-water-supply/drought-how-water-companies-plan-for-dry-weather-and-drought. 2021.

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

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S.: Communication of the role of natural variability in future North American climate, Nature Clim Change, 2, 775–779, https://doi.org/10.1038/nclimate1562, 2012a.

Deser, C., Phillips, A., Bourdette, V., and Teng, H.: Uncertainty in climate change projections: the role of internal variability, Clim Dyn, 38, 527–546, https://doi.org/10.1007/s00382-010-0977-x, 2012b.

Deser, C.: "Certain Uncertainty: The Role of Internal Climate Variability in Projections of Regional Climate Change and Risk Management," Earth's Future, 8, e2020EF001854, https://doi.org/10.1029/2020EF001854, 2020.

Dessai, S. and Darch, G.: Robust decision-making? Managing uncertainties in adapting water resource systems to a changing climate in England and Wales, in: Climate Change Adaptation Manual: Lessons learned from European and other industrialised countries, edited by: Prutsch, A., Grothmann, T., McCallum, S., Schauser, I., and Swart, R., Routledge, Abingdon, 208–212, 2014.

Dessai, S., Lu, X., and Risbey, J.: On the role of climate scenarios for adaptation planning, Glob. Environ. Change, 15, 87–97, https://doi.org/10.1016/j.gloenvcha.2004.12.004, 2005.

Diaz-Nieto, J. and Wilby, R. L.: A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the River Thames, United Kingdom, Clim. Change, 69, 245–268, https://doi.org/10.1007/s10584-005-1157-6, 2005.

Diffenbaugh, N. S., Swain, D. L., and Touma, D.: Anthropogenic warming has increased drought risk in California, Proc. Natl. Acad. Sci. U.S.A., 112, 3931–3936, https://doi.org/10.1073/pnas.1422385112, 2015.

Dittus, A. J., Collins, M., Sutton, R., and Hawkins, E.: Reversal of Projected European Summer Precipitation Decline in a Stabilizing Climate, Geophysical Research Letters, 51, e2023GL107448, https://doi.org/10.1029/2023GL107448, 2024.

Donegan, S., Murphy, C., Harrigan, S., Broderick, C., Foran Quinn, D., Golian, S., Knight, J., Matthews, T., Prudhomme, C., Scaife, A. A., Stringer, N., and Wilby, R. L.: Conditioning ensemble streamflow prediction with the North Atlantic Oscillation improves skill at longer lead times, Hydrology and Earth System Sciences, 25, 4159–4183, https://doi.org/10.5194/hess-25-4159-2021, 2021.

Douville, H., K. Raghavan, J. Renwick, R.P. Allan, P.A. Arias, M. Barlow, R. Cerezo-Mota, A. Cherchi, T.Y. Gan, J. Gergis, D. Jiang, A. Khan, W. Pokam Mba, D. Rosenfeld, J. Tierney, and O. Zolina, 2021: Water Cycle Changes. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1055–1210, doi:10.1017/9781009157896.010

Dunstone, N., Smith, D., Scaife, A., Hermanson, L., Eade, R., Robinson, N., Andrews, M., and Knight, J.: Skilful predictions of the winter North Atlantic Oscillation one year ahead, Nature Geosci, 9, 809–814, https://doi.org/10.1038/ngeo2824, 2016.

Durant, M.: Description of groundwater droughts in the UK: 1890 to 2015, British Geological Survey, Nottingham, UK, 2015.

Ekström, M., Gutmann, E. D., Wilby, R. L., Tye, M. R., and Kirono, D. G. C.: Robustness of hydroclimate metrics for climate change impact research, WIREs Water, 5, https://doi.org/10.1002/wat2.1288, 2018.

Environment Agency: Climate Change Approaches in Water Resources Planning – Overview of New Methods., 2013.

Environment Agency: Understanding the Performance of Water Supply Systems during Mild to Extreme Droughts., 2015.

Environment Agency: Worked examples – testing your drought plan against a range of droughts scenarios, 2019.

Environment Agency: Water Resources Planning Guidance: Proposed Update., 2020.

Environment Agency: Water stressed areas – 2021 classification, Environment Agency, 2021.

Environment Agency: Environment Agency chairs National Drought Group as parts of country move into drought, 2022a.

Environment Agency: Monthly Water Situation Report: November 2022., 2022b.

Environment Agency: Annex to the review of the research and scientific understanding of drought. Environment Agency, Bristol. 2023.

Ermis, S., Leach, N. J., Lott, F. C., Sparrow, S. N., and Weisheimer, A.: Event attribution of a midlatitude windstorm using ensemble weather forecasts, Environ. Res.: Climate, 3, 035001, https://doi.org/10.1088/2752-5295/ad4200, 2024.

Falloon, P., Challinor, A., Dessai, S., Hoang, L., Johnson, J., and Koehler, A.-K.: Ensembles and uncertainty in climate change impacts, Front. Environ. Sci., 2, 2014.

Fan, M. and Schneider, E. K.: Observed Decadal North Atlantic Tripole SST Variability. Part I: Weather Noise Forcing and Coupled Response, Journal of the Atmospheric Sciences, 69, 35–50, https://doi.org/10.1175/JAS-D-11-018.1, 2012.

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

Fereday, D. and Knight, J.: The roles of atmospheric circulation and sea surface temperature in UK surface climate, Atmospheric Science Letters, https://doi.org/10.1002/asl.1139, 2022.

Fereday, D., Chadwick, R., Knight, J., and Scaife, A. A.: Atmospheric Dynamics is the Largest Source of Uncertainty in Future Winter European Rainfall, Journal of Climate, 31, 963–977, https://doi.org/10.1175/JCLI-D-17-0048.1, 2018.

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

Fleig, A. K., Tallaksen, L. M., Hisdal, H., and Hannah, D. M.: Regional hydrological drought in north-western Europe: linking a new Regional Drought Area Index with weather types, Hydrol. Process., 25, 1163–1179, https://doi.org/10.1002/hyp.7644, 2011.

Folland, C. K., Hannaford, J., Bloomfield, J. P., Kendon, M., Svensson, C., Marchant, B. P., Prior, J., and Wallace, E.: Multi-annual droughts in the English Lowlands: a review of their characteristics and climate drivers in the winter half-year, Hydrology and Earth System Sciences, 19, 2353–2375, https://doi.org/10.5194/hess-19-2353-2015, 2015.

Fowler, H. J. and Kilsby, C. G.: Precipitation and the North Atlantic Oscillation: a study of climatic variability in northern England, Int. J. Climatol., 22, 843–866, https://doi.org/10.1002/joc.765, 2002.

Fowler, H. J., Blenkinsop, S., and Tebaldi, C.: Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling, Int. J. Climatol., 27, 1547–1578, https://doi.org/10.1002/joc.1556, 2007.

Fowler, K., Peel, M., Saft, M., Peterson, T. J., Western, A., Band, L., Petheram, C., Dharmadi, S., Tan, K. S., Zhang, L., Lane, P., Kiem, A., Marshall, L., Griebel, A., Medlyn, B. E., Ryu, D., Bonotto, G., Wasko, C., Ukkola, A., Stephens, C., Frost, A., Gardiya Weligamage, H., Saco, P., Zheng, H., Chiew, F., Daly, E., Walker, G., Vervoort, R. W., Hughes, J., Trotter, L., Neal, B., Cartwright, I., and Nathan, R.: Explaining changes in rainfall–runoff relationships during and after Australia's Millennium Drought: a community perspective, Hydrology and Earth System Sciences, 26, 6073–6120, https://doi.org/10.5194/hess-26-6073-2022, 2022a.

Fowler, K., Peel, M., Saft, M., Nathan, R., Horne, A., Wilby, R., McCutcheon, C., and Peterson, T.: Hydrological Shifts Threaten Water Resources, Water Resources Research, 58, e2021WR031210, https://doi.org/10.1029/2021WR031210, 2022b.

Fraedrich, K.: An ENSO impact on Europe?, Tellus A, 46, 541–552, https://doi.org/10.1034/j.1600-0870.1994.00015.x, 1994.

Fung, F., Goddard, C., Matte, D., Ballinger, A., Hegerl, G., O'Reillly, C., Weisheimer, A., Croker, T., McSweeney, C., van der Wiel, K., and Wilcke, R.: Storylines of predictions and projections developed and assessed for potential applications, European Climate Prediction system (EUCP), 2022.

Fung, F., Watts, G., Lopez, A., Orr, H. G., New, M., and Extence, C.: Using Large Climate Ensembles to Plan for the Hydrological Impact of Climate Change in the Freshwater Environment, Water Resour. Manag., 27, 1063–1084, https://doi.org/10.1007/s11269-012-0080-7, 2013.

Garner, G., Hannah, D. M., and Watts, G.: Climate change and water in the UK: Recent scientific evidence for past and future change, Prog. Phys. Geogr. Earth Environ., 41, 154–170, https://doi.org/10.1177/0309133316679082, 2017.

Gawith, M., Street, R., Westaway, R., and Steynor, A.: Application of the UKCIP02 climate change scenarios: Reflections and lessons learnt, Glob. Environ. Change, 19, 113–121, https://doi.org/10.1016/j.gloenvcha.2008.09.005, 2009.

Gessner, C., Fischer, E. M., Beyerle, U., and Knutti, R.: Multi-year drought storylines for Europe and North America from an iteratively perturbed global climate model, Weather and Climate Extremes, 38, 100512, https://doi.org/10.1016/j.wace.2022.100512, 2022.

Ghosh, R. and Shepherd, T. G.: Storylines of Maritime Continent dry period precipitation changes under global warming, Environ. Res. Lett., 18, 034017, https://doi.org/10.1088/1748-9326/acb788, 2023.

Goulart, H. M. D., van der Wiel, K., Folberth, C., Balkovic, J., and van den Hurk, B.: Storylines of weather-induced crop failure events under climate change, Earth System Dynamics, 12, 1503–1527, https://doi.org/10.5194/esd-12-1503-2021, 2021.

Gudmundsson, L., Boulange, J., Do, H. X., Gosling, S. N., Grillakis, M. G., Koutroulis, A. G., Leonard, M., Liu, J., Müller Schmied, H., Papadimitriou, L., Pokhrel, Y., Seneviratne, S. I., Satoh, Y., Thiery, W., Westra, S., Zhang, X., and Zhao, F.: Globally observed trends in mean and extreme river flow attributed to climate change, Science, 371, 1159–1162, https://doi.org/10.1126/science.aba3996, 2021.

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., and Hall, J. W.: 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, 2018.

Hall, J. and Murphy, C.: Adapting Water Supply Systems in a Changing Climate, in: Water Supply Systems, Distribution and Environmental Effects, edited by: Quinn, S. and O'Neill, V., Nova Science Publishers, Inc, 2012.

Hall, J. W., Mortazavi-Naeini, M., Borgomeo, E., Baker, B., Gavin, H., Gough, M., Harou, J. J., Hunt, D., Lambert, C., Piper, B., Richardson, N., and Watts, G.: Risk-based water resources planning in practice: a blueprint for the water industry in England, Water Environ. J., 34, 441–454, https://doi.org/10.1111/wej.12479, 2020.

Hall, R. J. and Hanna, E.: 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, 2018.

Han, S., Slater, L., Wilby, R. L., and Faulkner, D.: Contribution of urbanisation to non-stationary river flow in the UK, Journal of Hydrology, 613, 128417, https://doi.org/10.1016/j.jhydrol.2022.128417, 2022.

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

Hannaford, J., Lloyd-Hughes, B., Keef, C., Parry, S., and Prudhomme, C.: Examining the large-scale spatial coherence of European drought using regional indicators of precipitation and streamflow deficit, Hydrological Processes, 25, 1146–1162, https://doi.org/10.1002/hyp.7725, 2011.

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., and Wilcox, A.: The enhanced future Flows and Groundwater dataset: development and evaluation of nationally consistent hydrological projections based on UKCP18, Earth System Science Data, 15, 2391–2415, https://doi.org/10.5194/essd-15-2391-2023, 2023.

Hannaford, J.: Climate-driven changes in UK river flows: A review of the evidence, Progress in Physical Geography-Earth and Environment, 39, 29–48, https://doi.org/10.1177/0309133314536755, 2015.

Hannaford, J.: Climate-driven changes in UK river flows: A review of the evidence, Prog. Phys. Geogr.-Earth Environ., 39, 29–48, https://doi.org/10.1177/0309133314536755, 2015.

Harrigan, S., Murphy, C., Hall, J., Wilby, R. L., and Sweeney, J.: Attribution of detected changes in streamflow using multiple working hypotheses, Hydrol. Earth Syst. Sci., 18, 1935–1952, https://doi.org/10.5194/hess-18-1935-2014, 2014.

Harrigan, S., Prudhomme, C., Parry, S., Smith, K., and Tanguy, M.: Benchmarking ensemble streamflow prediction skill in the UK, Hydrology and Earth System Sciences, 22, 2023–2039, https://doi.org/10.5194/hess-22-2023-2018, 2018.

Harris, C. N. P., Quinn, A. D., and Bridgeman, J.: Quantification of uncertainty sources in a probabilistic climate change assessment of future water shortages, Clim. Change, 121, 317–329, https://doi.org/10.1007/s10584-013-0871-8, 2013.

Harris, C. N. P., Quinn, A. D., and Bridgeman, J.: The use of probabilistic weather generator information for climate change adaptation in the UK water sector, Meteorol. Appl., 21, 129–140, https://doi.org/10.1002/met.1335, 2014.

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

Haslinger, K., Hofstätter, M., Kroisleitner, C., Schöner, W., Laaha, G., Holawe, F., and Blöschl, G.: Disentangling Drivers of Meteorological Droughts in the European Greater Alpine Region During the Last Two Centuries, JGR Atmospheres, 124, 12404–12425, https://doi.org/10.1029/2018JD029527, 2019.

Hausfather, Z. and Peters, G. P.: Emissions – the 'business as usual' story is misleading, Nature, 577, 618–620, https://doi.org/10.1038/d41586-020-00177-3, 2020.

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in projections of regional precipitation change, Clim. Dyn., 37, 407–418, https://doi.org/10.1007/s00382-010-0810-6, 2011.

Hazeleger, W., van den Hurk, B. J. J. M., Min, E., van Oldenborgh, G. J., Petersen, A. C., Stainforth, D. A., Vasileiadou, E., and Smith, L. A.: Tales of future weather, Nature Climate Change, 5, 107–113, https://doi.org/10.1038/nclimate2450, 2015.

Held, I. M. and Soden, B. J.: Robust Responses of the Hydrological Cycle to Global Warming, Journal of Climate, 19, 5686–5699, https://doi.org/10.1175/JCLI3990.1, 2006.

Hellwig, J., Stoelzle, M., and Stahl, K.: Groundwater and baseflow drought responses to synthetic recharge stress tests, Hydrology and Earth System Sciences, 25, 1053–1068, https://doi.org/10.5194/hess-25-1053-2021, 2021.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thépaut, J., 2020. The ERA5 global reanalysis. Q.J.R. Meteorol. Soc. 146, 1999–2049. https://doi.org/10.1002/qj.3803

HM Government: National Risk Register (2023 Edition), London, 2023.

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

HR Wallingford: Updated projections of future water availability for the third UK Climate Change Risk Assessment, HR Wallingford, 2020.

Hulme, M., Barrow, E. M., Arnell, N. W., Harrison, P. A., Johns, T. C., and Downing, T. E.: Relative impacts of human-induced climate change and natural climate variability, Nature, 397, 688–691, https://doi.org/10.1038/17789, 1999.

Hurrell, J. W.: Decadal Trends in the North Atlantic Oscillation: Regional Temperatures and Precipitation, Science, 269, 676–679, https://doi.org/10.1126/science.269.5224.676, 1995.

Huskova, I., Matrosov, E. S., Harou, J. J., Kasprzyk, J. R., and Lambert, C.: Screening robust water infrastructure investments and their trade-offs under global change: A London example, Glob. Environ. Change, 41, 216–227, https://doi.org/10.1016/j.gloenvcha.2016.10.007, 2016.

Ionita, M.: The Impact of the East Atlantic/Western Russia Pattern on the Hydroclimatology of Europe from Mid-Winter to Late Spring, Climate, 2, 296–309, https://doi.org/10.3390/cli2040296, 2014.

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

James, R., Washington, R., Schleussner, C.-F., Rogelj, J., and Conway, D.: Characterizing half-a-degree difference: a review of methods for identifying regional climate responses to global warming targets, WIREs Climate Change, 8, e457, https://doi.org/10.1002/wcc.457, 2017.

Johnson, S.J., Stockdale, T.N., Ferranti, L., Balmaseda, M.A., Molteni, F., Magnusson, L., Tietsche, S., Decremer, D., Weisheimer, A., Balsamo, G., Keeley, S.P.E., Mogensen, K., Zuo, H., Monge-Sanz, B.M., 2019. SEAS5: the new ECMWF seasonal forecast system. Geoscientific Model Development 12, 1087–1117. https://doi.org/10.5194/gmd-12-1087-2019

Katzav, J., Thompson, E. L., Risbey, J., Stainforth, D. A., Bradley, S., and Frisch, M.: On the appropriate and inappropriate uses of probability distributions in climate projections and some alternatives, Climatic Change, 169, 15, https://doi.org/10.1007/s10584-021-03267-x, 2021.

Kautz, L.-A., Martius, O., Pfahl, S., Pinto, J. G., Ramos, A. M., Sousa, P. M., and Woollings, T.: Atmospheric blocking and weather extremes over the Euro-Atlantic sector – a review, Weather Clim. Dynam., 3, 305–336, https://doi.org/10.5194/wcd-3-305-2022, 2022.

Kay, A. L. and Jones, R. G.: Comparison of the use of alternative UKCP09 products for modelling the impacts of climate change on flood frequency, Clim. Change, 114, 211–230, https://doi.org/10.1007/s10584-011-0395-z, 2012.

Kay, A. L., Bell, V. A., Guillod, B. P., Jones, R. G., and Rudd, A. C.: National-scale analysis of low flow frequency: historical trends and potential future changes, Clim. Change, 147, 585–599, https://doi.org/10.1007/s10584-018-2145-y, 2018.

Kay, A. L., Crooks, S. M., Davies, H. N., Prudhomme, C., and Reynard, N. S.: Probabilistic impacts of climate change on flood frequency using response surfaces I: England and Wales, Reg. Environ. Change, 14, 1215–1227, https://doi.org/10.1007/s10113-013-0563-y, 2014.

Kay, A. L., Davies, H. N., Bell, V. A., and Jones, R. G.: Comparison of uncertainty sources for climate change impacts: Flood frequency in England, Clim. Change, 92, 41–63, https://doi.org/10.1007/s10584-008-9471-4, 2009.

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

Kay, A. L., Lane, R. A., and Bell, V. A.: Grid-based simulation of soil moisture in the UK: future changes in extremes and wetting and drying dates, Environ. Res. Lett., 17, 074029, https://doi.org/10.1088/1748-9326/ac7a4e, 2022.

Kay, A. L., Rudd, A. C., Davies, H. N., Kendon, E. J., and Jones, R. G.: Use of very high resolution climate model data for hydrological modelling: baseline performance and future flood changes, Clim. Change, 133, 193–208, https://doi.org/10.1007/s10584-015-1455-6, 2015.

Kay, A. L., Rudd, A. C., Fry, M., Nash, G., and Allen, S.: Climate change impacts on peak river flows: Combining national-scale hydrological modelling and probabilistic projections, Clim. Risk Manag., 31, 100263, https://doi.org/10.1016/j.crm.2020.100263, 2021.

Kay, A., Crooks, S., and Davies, H.: Practicalities for implementing regionalised allowances for climate change on flood flows, NERC/Centre for Ecology & Hydrology, 2011.

Kay, A.L., Davies, H.N., 2008. Calculating potential evaporation from climate model data: A source of uncertainty for hydrological climate change impacts. Journal of Hydrology 358, 221–239. https://doi.org/10.1016/j.jhydrol.2008.06.005

Kay, A.L., Watts, G., Wells, S.C., Allen, S., 2020. The impact of climate change on U. K. river flows: A preliminary comparison of two generations of probabilistic climate projections. Hydrological Processes 34, 1081–1088. https://doi.org/10.1002/hyp.13644

Kay, G., Dunstone, N., Smith, D., Dunbar, T., Eade, R., and Scaife, A.: Current likelihood and dynamics of hot summers in the UK, Environ. Res. Lett., 15, 094099, https://doi.org/10.1088/1748-9326/abab32, 2020.

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

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

Kelder, T., Wanders, N., van der Wiel, K., Marjoribanks, T. I., Slater, L. J., Wilby, R. l, and Prudhomme, C.: Interpreting extreme climate impacts from large ensemble simulations—are they unseen or unrealistic?, Environ. Res. Lett., 17, 044052, https://doi.org/10.1088/1748-9326/ac5cf4, 2022b.

Keller, L., Rössler, O., Martius, O., and Weingartner, R.: Comparison of scenario-neutral approaches for estimation of climate change impacts on flood characteristics, Hydrol. Process., 33, 535–550, https://doi.org/10.1002/hyp.13341, 2019.

Kendon, E. J., Prein, A. F., Senior, C. A., and Stirling, A.: Challenges and outlook for convection-permitting climate modelling, Phil. Trans. R. Soc. A., 379, 20190547, https://doi.org/10.1098/rsta.2019.0547, 2021.

Kendon, E. J., Fischer, E. M., and Short, C. J.: Variability conceals emerging trend in 100yr projections of UK local hourly rainfall extremes, Nat Commun, 14, 1133, https://doi.org/10.1038/s41467-023-36499-9, 2023.

Kendon, M., Marsh, T., and Parry, S.: The 2010–2012 drought in England and Wales, Weather, 68, 88–95, https://doi.org/10.1002/wea.2101, 2013.

Kent, C., Dunstone, N., Tucker, S., Scaife, A. A., Brown, S., Kendon, E. J., Smith, D., McLean, L., and Greenwood, S.: Estimating unprecedented extremes in UK summer daily rainfall, Environ. Res. Lett., 17, 014041, https://doi.org/10.1088/1748-9326/ac42fb, 2022.

Kent, C., Pope, E., Dunstone, N., Scaife, A. A., Tian, Z., Clark, R., Zhang, L., Davie, J., and Lewis, K.: Maize Drought Hazard in the Northeast Farming Region of China: Unprecedented Events in the Current Climate, Journal of Applied Meteorology and Climatology, 58, 2247–2258, https://doi.org/10.1175/JAMC-D-19-0096.1, 2019.

Kilsby, C. G., Jones, P. D., Burton, A., Ford, A. C., Fowler, H. J., Harpham, C., James, P., Smith, A., and Wilby, R. L.: A daily weather generator for use in climate change studies, Environmental Modelling & Software, 22, 1705–1719, https://doi.org/10.1016/j.envsoft.2007.02.005, 2007.

King, A. D., Lane, T. P., Henley, B. J., and Brown, J. R.: Global and regional impacts differ between transient and equilibrium warmer worlds, Nat. Clim. Chang., 10, 42–47, https://doi.org/10.1038/s41558-019-0658-7, 2020.

King, A. D., Sniderman, J. M. K., Dittus, A. J., Brown, J. R., Hawkins, E., and Ziehn, T.: Studying climate stabilization at Paris Agreement levels, Nat. Clim. Chang., 11, 1010–1013, https://doi.org/10.1038/s41558-021-01225-0, 2021.

King, A. D., Ziehn, T., Chamberlain, M., Borowiak, A. R., Brown, J. R., Cassidy, L., Dittus, A. J., Grose, M., Maher, N., Paik, S., Perkins-Kirkpatrick, S. E., and Sengupta, A.: Exploring climate stabilisation at different global warming levels in ACCESS-ESM-1.5, EGUsphere, 1–38, https://doi.org/10.5194/egusphere-2023-2961, 2024.

Kingston, D. G., Fleig, A. K., Tallaksen, L. M., and Hannah, D. M.: Ocean–Atmosphere Forcing of Summer Streamflow Drought in Great Britain, Journal of Hydrometeorology, 14, 331–344, https://doi.org/10.1175/JHM-D-11-0100.1, 2013.

Kingston, D. G., Stagge, J. H., Tallaksen, L. M., and Hannah, D. M.: European-Scale Drought: Understanding Connections between Atmospheric Circulation and Meteorological Drought Indices, Journal of Climate, 28, 505–516, https://doi.org/10.1175/JCLI-D-14-00001.1, 2015.

Kreibich, H., Van Loon, A. F., Schröter, K., Ward, P. J., Mazzoleni, M., Sairam, N., Abeshu, G. W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garreton, C., Aznar, B., Balkhi, L., Barendrecht, M. H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyono, Y., Buytaert, W., Capewell, L., Carlson, H., Cavus, Y., Couasnon, A., Coxon, G., Daliakopoulos, I., De Ruiter, M. C., Delus, C., Erfurt, M., Esposito, G., François, D., Frappart, F., Freer, J., Frolova, N., Gain, A. K., Grillakis, M., Grima, J. O., Guzmán, D. A., Huning, L. S., Ionita, M., Kharlamov, M., Khoi, D. N., Kieboom, N., Kireeva, M., Koutroulis, A., Lavado-Casimiro, W., Li, H.-Y., LLasat, M. C., Macdonald, D., Mård, J., Mathew-Richards, H., McKenzie, A., Mejia, A., Mendiondo, E. M., Mens, M., Mobini, S., Mohor, G. S., Nagavciuc, V., Ngo-Duc, T., Thao Nguyen Huynh, T., Nhi, P. T. T., Petrucci, O., Nguyen, H. Q., Quintana-Seguí, P., Razavi, S., Ridolfi, E., Riegel, J., Sadik, M. S., Savelli, E., Sazonov, A., Sharma, S., Sörensen, J., Arguello Souza, F. A., Stahl, K., Steinhausen, M., Stoelzle, M., Szalińska, W., Tang, Q., Tian, F., Tokarczyk, T., Tovar, C., Tran, T. V. T., Van Huijgevoort, M. H. J., Van Vliet, M. T. H., Vorogushyn, S., Wagener, T., Wang, Y., Wendt, D. E., Wickham, E., Yang, L., Zambrano-Bigiarini, M., Blöschl, G., and Di Baldassarre, G.: The challenge of unprecedented floods and droughts in risk management, Nature, 608, 80–86, https://doi.org/10.1038/s41586-022-04917-5, 2022.

Kunimitsu, T., Baldissera Pacchetti, M., Ciullo, A., Sillmann, J., Shepherd, T. G., Taner, M. Ü., and van den Hurk, B.: Representing storylines with causal networks to support decision making: Framework and example, Climate Risk Management, 40, 100496, https://doi.org/10.1016/j.crm.2023.100496, 2023.

Laaha, G., Gauster, T., Tallaksen, L. M., Vidal, J.-P., Stahl, K., Prudhomme, C., Heudorfer, B., Vlnas, R., Ionita, M., Lanen, H. A. J. V., Adler, M.-J., Caillouet, L., Delus, C., Fendekova, M., Gailliez, S., Hannaford, J., Kingston, D., Loon, A. F. V., Mediero, L., Osuch, M., Romanowicz, R., Sauquet, E., Stagge, J. H., and Wong, W. K.: The European 2015 drought from a hydrological perspective, Hydrology and Earth System Sciences, 21, 3001–3024, https://doi.org/10.5194/hess-21-3001-2017, 2017.

Lafon, T., Dadson, S., Buys, G., and Prudhomme, C.: Bias correction of daily precipitation simulated by a regional climate model: A comparison of methods, Int. J. Climatol., 33, 1367–1381, https://doi.org/10.1002/joc.3518, 2013.

Lane, R. A., Coxon, G., Freer, J. E., Wagener, T., Johnes, P. J., Bloomfield, J. P., Greene, S., Macleod, C. J. A., and Reaney, S. M.: Benchmarking the predictive capability of hydrological models for river flow and flood peak predictions across over 1000 catchments in Great Britain, Hydrol. Earth Syst. Sci., 23, 4011–4032, https://doi.org/10.5194/hess-23-4011-2019, 2019.

Lawrence, J., Haasnoot, M., and Lempert, R.: Climate change: making decisions in the face of deep uncertainty, Nature, 580, 456–456, https://doi.org/10.1038/d41586-020-01147-5, 2020.

Leach, N. J., Watson, P. A. G., Sparrow, S. N., Wallom, D. C. H., and Sexton, D. M. H.: Generating samples of extreme winters to support climate adaptation, Weather and Climate Extremes, 36, 100419, https://doi.org/10.1016/j.wace.2022.100419, 2022.

Leach, N. J., Weisheimer, A., Allen, M. R., and Palmer, T.: Forecast-based attribution of a winter heatwave within the limit of predictability, Proc. Natl. Acad. Sci. U.S.A., 118, e2112087118, https://doi.org/10.1073/pnas.2112087118, 2021.

Leach, N. J., Roberts, C. D., Aengenheyster, M., Heathcote, D., Mitchell, D. M., Thompson, V., Palmer, T., Weisheimer, A., and Allen, M. R.: Heatwave attribution based on reliable operational weather forecasts, Nat Commun, 15, 4530, https://doi.org/10.1038/s41467-024-48280-7, 2024.

Leander, R., Buishand, T.A., 2007. Resampling of regional climate model output for the simulation of extreme river flows. Journal of Hydrology 332, 487–496. https://doi.org/10.1016/j.jhydrol.2006.08.006

Ledbetter, R., Prudhomme, C., and Arnell, N.: A method for incorporating climate variability in climate change impact assessments: Sensitivity of river flows in the Eden catchment to precipitation scenarios, Clim. Change, 113, 803–823, https://doi.org/10.1007/s10584-011-0386-0, 2012.

Lehner, F. and Deser, C.: Origin, importance, and predictive limits of internal climate variability, Environ. Res.: Climate, 2, 023001, https://doi.org/10.1088/2752-5295/accf30, 2023.

Lewis, E., Birkinshaw, S., Kilsby, C., and Fowler, H. J.: Development of a system for automated setup of a physically-based, spatially-distributed hydrological model for catchments in Great Britain, Environmental Modelling and Software, 108, 102–110, https://doi.org/10.1016/j.envsoft.2018.07.006, 2018.

Lian, X., Piao, S., Huntingford, C., Li, Y., Zeng, Z., Wang, X., Ciais, P., McVicar, T. R., Peng, S., Ottlé, C., Yang, H., Yang, Y., Zhang, Y., and Wang, T.: Partitioning global land evapotranspiration using CMIP5 models constrained by observations, Nature Clim Change, 8, 640–646, https://doi.org/10.1038/s41558-018-0207-9, 2018.

Lin, Y. C., Jenkins, S. F., Chow, J. R., Biass, S., Woo, G., and Lallemant, D.: Modeling Downward Counterfactual Events: Unrealized Disasters and why they Matter, Front. Earth Sci., 8, https://doi.org/10.3389/feart.2020.575048, 2020.

Lister, D., Osborn, T., Jones, P., and Darch, G.: Observed droughts in the greater Anglian region since 1920, 2018.

Lloyd-Hughes, B.: The impracticality of a universal drought definition, Theor Appl Climatol, 117, 607–611, https://doi.org/10.1007/s00704-013-1025-7, 2014.

Løhre, E., Juanchich, M., Sirota, M., Teigen, K. H., and Shepherd, T. G.: Climate Scientists' Wide Prediction Intervals May Be More Likely but Are Perceived to Be Less Certain, Weather Clim. Soc., 11, 565–575, https://doi.org/10.1175/WCAS-D-18-0136.1, 2019.

Lopez, A., Fung, F., New, M., Watts, G., Weston, A., and Wilby, R. L.: From climate model ensembles to climate change impacts and adaptation: A case study of water resource management in the southwest of England, Water Resour. Res., 45, https://doi.org/10.1029/2008WR007499, 2009.

Mackay, J.D., Jackson, C.R., Wang, L., 2014. A lumped conceptual model to simulate groundwater level time-series. Environmental Modelling & Software 61, 229–245. https://doi.org/10.1016/j.envsoft.2014.06.003

Maher, N., Milinski, S., and Ludwig, R.: Large ensemble climate model simulations: introduction, overview, and future prospects for utilising multiple types of large ensemble, Earth System Dynamics, 12, 401–418, https://doi.org/10.5194/esd-12-401-2021, 2021.

Mankin, J. S., Lehner, F., Coats, S., and McKinnon, K. A.: The Value of Initial Condition Large Ensembles to Robust Adaptation Decision-Making, Earth's Future, 8, e2012EF001610, https://doi.org/10.1029/2020EF001610, 2020.

Mankin, J. S., Viviroli, D., Mekonnen, M. M., Hoekstra, A. Y., Horton, R. M., Smerdon, J. E., and Diffenbaugh, N. S.: Influence of internal variability on population exposure to hydroclimatic changes, Environ. Res. Lett., 12, 044007, https://doi.org/10.1088/1748-9326/aa5efc, 2017.

Manning, C., Widmann, M., Bevacqua, E., Loon, A. F. V., Maraun, D., and Vrac, M.: Increased probability of compound long-duration dry and hot events in Europe during summer (1950–2013), Environ. Res. Lett., 14, 094006, https://doi.org/10.1088/1748-9326/ab23bf, 2019.

Manning, L. J., Hall, J. W., Fowler, H. J., Kilsby, C. G., and Tebaldi, C.: Using probabilistic climate change information from a multimodel ensemble for water resources assessment, Water Resour. Res., 45, https://doi.org/10.1029/2007WR006674, 2009.

Maraun, D., Knevels, R., Mishra, A. N., Truhetz, H., Bevacqua, E., Proske, H., Zappa, G., Brenning, A., Petschko, H., Schaffer, A., Leopold, P., and Puxley, B. L.: A severe landslide event in the Alpine foreland under possible future climate and land-use changes, Commun Earth Environ, 3, 1–11, https://doi.org/10.1038/s43247-022-00408-7, 2022.

Maraun, D., Shepherd, T. G., Widmann, M., Zappa, G., Walton, D., Gutiérrez, J. M., Hagemann, S., Richter, I., Soares, P. M. M., Hall, A., and Mearns, L. O.: Towards process-informed bias correction of climate change simulations, Nat. Clim. Change, 7, 764–773, https://doi.org/10.1038/nclimate3418, 2017.

Margariti, J., Rangecroft, S., Parry, S., Wendt, D. E., and Van Loon, A. F.: Anthropogenic activities alter drought termination, Elementa: Science of the Anthropocene, 7, 27, https://doi.org/10.1525/elementa.365, 2019.

Marsh, T., Cole, G., and Wilby, R.: Major droughts in England and Wales, 1800–2006, Weather, 62, 87–93, https://doi.org/10.1002/wea.67, 2007.

Marsh, T., Parry, S., Kendon, M., and Hannaford, J.: The 2010-12 drought and subsequent extensive flooding: a remarkable hydrological transformation, NERC/Centre for Ecology & Hydrology, Wallingford, 2013.

Matrosov, E. S., Huskova, I., Kasprzyk, J. R., Harou, J. J., Lambert, C., and Reed, P. M.: Many-objective optimization and visual analytics reveal key trade-offs for London's water supply, J. Hydrol., 531, 1040–1053, https://doi.org/10.1016/j.jhydrol.2015.11.003, 2015.

Matthews, T., Mullan, D., Wilby, R. L., Broderick, C., and Murphy, C.: Past and future climate change in the context of memorable seasonal extremes, Climate Risk Management, 11, 37–52, https://doi.org/10.1016/j.crm.2016.01.004, 2016.

Mellado-Cano, J., Barriopedro, D., García-Herrera, R., Trigo, R. M., and Hernández, A.: Examining the North Atlantic Oscillation, East Atlantic Pattern, and Jet Variability since 1685, Journal of Climate, 32, 6285–6298, https://doi.org/10.1175/JCLI-D-19-0135.1, 2019.

Merchant, B. and Bloomfield, J. P.: Spatio-temporal modelling of the status of groundwater droughts, Journal of Hydrology, 564, 397–413, https://doi.org/10.1016/j.jhydrol.2018.07.009, 2018.

Mindlin, J., Shepherd, T. G., Vera, C. S., Osman, M., Zappa, G., Lee, R. W., and Hodges, K. I.: Storyline description of Southern Hemisphere midlatitude circulation and precipitation response to greenhouse gas forcing, Clim Dyn, 54, 4399–4421, https://doi.org/10.1007/s00382-020-05234-1, 2020.

Mishra, A. K. and Singh, V. P.: A review of drought concepts, Journal of Hydrology, 391, 202–216, https://doi.org/10.1016/j.jhydrol.2010.07.012, 2010.

Monnin, E., Kretschmer, M., and Polichtchouk, I.: The role of the timing of sudden stratospheric warmings for precipitation and temperature anomalies in Europe, Intl Journal of Climatology, 42, 3448–3462, https://doi.org/10.1002/joc.7426, 2022.

Montanari, A., Nguyen, H., Rubinetti, S., Ceola, S., Galelli, S., Rubino, A., and Zanchettin, D.: Why the 2022 Po River drought is the worst in the past two centuries, Sci. Adv., 9, eadg8304, https://doi.org/10.1126/sciadv.adg8304, 2023.

Montero, P. and Vilar, J. A.: TSclust: An R Package for Time Series Clustering, Journal of Statistical Software, 62, 1–43, https://doi.org/10.18637/jss.v062.i01, 2015.

Moon, H., Gudmundsson, L., Seneviratne, S.I., 2018. Drought Persistence Errors in Global Climate Models. Journal of Geophysical Research: Atmospheres 123, 3483–3496. https://doi.org/10.1002/2017JD027577

Moore, G. W. K. and Renfrew, I. A.: Cold European winters: interplay between the NAO and the East Atlantic mode, Atmosph. Sci. Lett., 13, 1–8, https://doi.org/10.1002/asl.356, 2012.

Moore, R. J., Jones, D. A., and Black, K. B.: Risk assessment and drought management in the Thames basin, Hydrological Sciences Journal, 34, 705–717, https://doi.org/10.1080/02626668909491376, 1989.

Moravec, V., Markonis, Y., Rakovec, O., Svoboda, M., Trnka, M., Kumar, R., and Hanel, M.: Europe under multi-year droughts: how severe was the 2014–2018 drought period?, Environ. Res. Lett., 16, 034062, https://doi.org/10.1088/1748-9326/abe828, 2021.

Moulds, S., Slater, L. J., Dunstone, N. J., and Smith, D. M.: Skillful Decadal Flood Prediction, Geophysical Research Letters, 50, https://doi.org/10.1029/2022GL100650, 2023.

Murphy, C., Bastola, S., Hall, J., Harrigan, S., Murphy, N., and Holman, C.: Against a 'wait and see' approach in adapting to climate change, Irish Geography, 44, 81–95, https://doi.org/10.1080/00750778.2011.615707, 2011.

Nasrollahi, N., AghaKouchak, A., Cheng, L., Damberg, L., Phillips, T. J., Miao, C., Hsu, K., and Sorooshian, S.: How well do CMIP5 climate simulations replicate historical trends and patterns of meteorological droughts?, Water Resources Research, 51, 2847–2864, https://doi.org/10.1002/2014WR016318, 2015.

National Infrastructure Commission: Preparing for a drier future England's water infrastructure needs, National Infrastructure Commission, 2018.

Němec, J. and Schaake, J.: Sensitivity of water resource systems to climate variation, Hydrol. Sci. J., 27, 327–343, https://doi.org/10.1080/02626668209491113, 1982.

New, M., Lopez, A., Dessai, S., and Wilby, R.: Challenges in using probabilistic climate change information for impact assessments: an example from the water sector, Philos. Trans. R. Soc. Math. Phys. Eng. Sci., 365, 2117–2131, https://doi.org/10.1098/rsta.2007.2080, 2007.

O'Neill, B. C., Carter, T. R., Ebi, K., Harrison, P. A., Kemp-Benedict, E., Kok, K., Kriegler, E., Preston, B. L., Riahi, K., Sillmann, J., van Ruijven, B. J., van Vuuren, D., Carlisle, D., Conde, C., Fuglestvedt, J., Green, C., Hasegawa, T., Leininger, J., Monteith, S., and Pichs-Madruga, R.: Achievements and needs for the climate change scenario framework, Nat. Clim. Change, 10, 1074–1084, https://doi.org/10.1038/s41558-020-00952-0, 2020.

Oldham, L.D., Freer, J., Coxon, G., Howden, N., Bloomfield, J.P., Jackson, C., 2023. Evidence-based requirements for perceptualising intercatchment groundwater flow in hydrological models. Hydrology and Earth System Sciences 27, 761–781. https://doi.org/10.5194/hess-27-761-2023

Oliver, T. H., Marshall, H. H., Morecroft, M. D., Brereton, T., Prudhomme, C., and Huntingford, C.: Interacting effects of climate change and habitat fragmentation on drought-sensitive butterflies, Nature Clim Change, 5, 941–945, https://doi.org/10.1038/nclimate2746, 2015.

National Drought Group: One hot, dry spell away from drought returning this summer, National Drought Group warns: 390 https://www.gov.uk/government/news/one-hot-dry-spell-away-from-drought-returning-this-summer-national-droughtgroup-warns. 2023. last access: 6 March 2023.

Orlowsky, B. and Seneviratne, S. I.: Elusive drought: uncertainty in observed trends and short- and long-term CMIP5 projections, Hydrology and Earth System Sciences, 17, 1765–1781, https://doi.org/10.5194/hess-17-1765-2013, 2013.

Orr, H. G., Ekström, M., Charlton, M. B., Peat, K. L., and Fowler, H. J.: Using high-resolution climate change information in water management: a decision-makers' perspective, Philos. Trans. R. Soc. Math. Phys. Eng. Sci., 379, 20200219, https://doi.org/10.1098/rsta.2020.0219, 2021.

Parliamentary Office of Science and Technology: Water supply resilience and climate change, 2021.

Parry, S., Hannaford, J., Lloyd-Hughes, B., and Prudhomme, C.: Multi-year droughts in Europe: analysis of development and causes, Hydrology Research, 43, 689–706, https://doi.org/10.2166/nh.2012.024, 2012.

Parry, S., Mackay, J. D., Chitson, T., Hannaford, J., Bell, V. A., Facer-Childs, K., Kay, A., Lane, R., Moore, R. J., Turner, S., and Wallbank, J.: Divergent future drought projections in UK river flows and groundwater levels, Hydrol. Earth Syst. Sci. Discuss., 1–36, https://doi.org/10.5194/hess-2023-59, 2023.

Parry, S., Marsh, T., and Kendon, M.: 2012: from drought to floods in England and Wales, Weather, 68, 268–274, https://doi.org/10.1002/wea.2152, 2013.

Parry, S., Prudhomme, C., Wilby, R. L., and Wood, P. J.: Drought termination: Concept and characterisation, Progress in Physical Geography: Earth and Environment, 40, 743–767, https://doi.org/10.1177/0309133316652801, 2016b.

Parry, S., Wilby, R. L., Prudhomme, C., and Wood, P. J.: A systematic assessment of drought termination in the United Kingdom, Hydrology and Earth System Sciences, 20, 4265–4281, https://doi.org/10.5194/hess-20-4265-2016, 2016.

Parry, S., Wilby, R., Prudhomme, C., Wood, P., and McKenzie, A.: Demonstrating the utility of a drought termination framework: prospects for groundwater level recovery in England and

Wales in 2018 or beyond, Environ. Res. Lett., 13, 064040, https://doi.org/10.1088/1748-9326/aac78c, 2018.

Parry, S.: Dry summer pushes river flows to the brink of 1976 drought, 2022.

Pasten-Zapata, E., Jones, J. M., Moggridge, H., and Widmann, M.: Evaluation of the performance of Euro-CORDEX Regional Climate Models for assessing hydrological climate change impacts in Great Britain: A comparison of different spatial resolutions and quantile mapping bias correction methods, J. Hydrol., 584, 124653, https://doi.org/10.1016/j.jhydrol.2020.124653, 2020.

Perrin, C., Michel, C., Andréassian, V., 2003. Improvement of a parsimonious model for streamflow simulation. Journal of Hydrology 279, 275–289. https://doi.org/10.1016/S0022-1694(03)00225-7

Perry, A. H.: The long drought of 1975-76, Weather, 31, 328–336, https://doi.org/10.1002/j.1477-8696.1976.tb07448.x, 1976.

Pilling, C. and Jones, J. A. A.: High resolution climate change scenarios: implications for British runoff, Hydrol. Process., 13, 2877–2895, https://doi.org/10.1002/(SICI)1099-1085(19991215)13:17<2877::AID-HYP904>3.0.CO;2-G, 1999.

Pope, J. O., Brown, K., Fung, F., Hanlon, H. M., Neal, R., Palin, E. J., and Reid, A.: Investigation of future climate change over the British Isles using weather patterns, Clim Dyn, 58, 2405–2419, https://doi.org/10.1007/s00382-021-06031-0, 2022.

Porter, J. J. and Dessai, S.: Mini-me: Why do climate scientists' misunderstand users and their needs?, Environ. Sci. Policy, 77, 9–14, https://doi.org/10.1016/j.envsci.2017.07.004, 2017.

Poschlod, B., Willkofer, F., and Ludwig, R.: Impact of Climate Change on the Hydrological Regimes in Bavaria, Water, 12, 1599, https://doi.org/10.3390/w12061599, 2020.

Pribyl, K.: A survey of the impact of summer droughts in southern and eastern England, 1200–1700, Climate of the Past, 16, 1027–1041, https://doi.org/10.5194/cp-16-1027-2020, 2020.

Prudhomme, C., Jakob, D., and Svensson, C.: Uncertainty and climate change impact on the flood regime of small UK catchments, J. Hydrol., 277, 1–23, https://doi.org/10.1016/S0022-1694(03)00065-9, 2003.

Prudhomme, C. and Davies, H.: Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate, Clim. Change, 93, 197–222, https://doi.org/10.1007/s10584-008-9461-6, 2009.

Prudhomme, C., Wilby, R. L., Crooks, S., Kay, A. L., and Reynard, N. S.: 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, 2010.

Prudhomme, C., Young, A., Watts, G., Haxton, T., Crooks, S., Williamson, J., Davies, H., Dadson, S., and Allen, S.: The drying up of Britain? A national estimate of changes in seasonal river flows from 11 Regional Climate Model simulations, Hydrological Processes, 26, 1115–1118, https://doi.org/10.1002/hyp.8434, 2012.

Prudhomme, C., Crooks, S., Kay, A. L., and Reynard, N.: Climate change and river flooding: part 1 classifying the sensitivity of British catchments, Clim. Change, 119, 933–948, https://doi.org/10.1007/s10584-013-0748-x, 2013a.

Prudhomme, C., Haxton, T., Crooks, S., Jackson, C., Barkwith, A., Williamson, J., Kelvin, J., Mackay, J., Wang, L., Young, A., and Watts, G.: Future Flows Hydrology: an ensemble of daily river flow and monthly groundwater levels for use for climate change impact assessment across Great Britain, Earth Syst. Sci. Data, 5, 101–107, https://doi.org/10.5194/essd-5-101-2013, 2013b.

Prudhomme, C. and Williamson, J.: Derivation of RCM-driven potential evapotranspiration for hydrological climate change impact analysis in Great Britain: A comparison of methods and associated uncertainty in future projections, Hydrology and Earth System Sciences, 17, 1365–1377, https://doi.org/10.5194/hess-17-1365-2013, 2013.

Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., Fekete, B. M., Franssen, W., Gerten, D., Gosling, S. N., Hagemann, S., Hannah, D. M., Kim, H., Masaki, Y., Satoh, Y., Stacke, T., Wada, Y., and Wisser, D.: Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment, PNAS, 111, 3262–3267, https://doi.org/10.1073/pnas.1222473110, 2014.

Prudhomme, C., Sauquet, E., and Watts, G.: Low Flow Response Surfaces for Drought Decision Support: A Case Study from the UK, J. Extreme Events, 02, 1550005, https://doi.org/10.1142/S2345737615500050, 2015.

Prudhomme, C., Hannaford, J., Harrigan, S., Boorman, D., Knight, J., Bell, V., Jackson, C., Svensson, C., Parry, S., Bachiller-Jareno, N., Davies, H., Davis, R., Mackay, J., McKenzie, A., Rudd, A., Smith, K., Bloomfield, J., Ward, R., and Jenkins, A.: Hydrological Outlook UK: an operational streamflow and groundwater level forecasting system at monthly to seasonal time scales, Hydrological Sciences Journal, 62, 2753–2768, https://doi.org/10.1080/02626667.2017.1395032, 2017.

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. Journal of Hydrology 411, 66–76. https://doi.org/10.1016/j.jhydrol.2011.09.034

Rameshwaran, P., Bell, V. A., Brown, M. J., Davies, H. N., Kay, A. L., Rudd, A. C., and Sefton, C.: Use of Abstraction and Discharge Data to Improve the Performance of a National-Scale Hydrological Model, Water Resour. Res., 58, e2021WR029787, https://doi.org/10.1029/2021WR029787, 2022.

Rangecroft, S., Birkinshaw, S., Rohse, M., Day, R., McEwen, L., Makaya, E., and Van Loon, A.: Hydrological modelling as a tool for interdisciplinary workshops on future drought, Progress in Physical Geography: Earth and Environment, 42, 237–256, https://doi.org/10.1177/0309133318766802, 2018.

Reeder, T. and Ranger, N.: How do you adapt in an uncertain world?: lessons from the Thames Estuary 2100 project., World Resources Institute, Washington DC, USA, 2011.

Reynard, N. S., Kay, A. L., Anderson, M., Donovan, B., and Duckworth, C.: The evolution of climate change guidance for fluvial flood risk management in England, Prog. Phys. Geogr. Earth Environ., 41, 222–237, https://doi.org/10.1177/0309133317702566, 2017.

Reynard, N. S., Prudhomme, C., and Crooks, S. M.: The Flood Characteristics of Large U.K. Rivers: Potential Effects of Changing Climate and Land Use, Clim. Change, 48, 343–359, https://doi.org/10.1023/A:1010735726818, 2001.

Reyniers, N., Osborn, T. J., Addor, N., and Darch, G.: Projected changes in droughts and extreme droughts in Great Britain strongly influenced by the choice of drought index, Hydrology and Earth System Sciences, 27, 1151–1171, https://doi.org/10.5194/hess-27-1151-2023, 2023.

Richardson, D., Fowler, H. J., Kilsby, C. G., Neal, R., and Dankers, R.: Improving sub-seasonal forecast skill of meteorological drought: a weather pattern approach, Natural Hazards and Earth System Sciences, 20, 107–124, https://doi.org/10.5194/nhess-20-107-2020, 2020.

Rodda, M. and Marsh, T.: The 1975-76 Drought: a contemporary and retrospective review, UK Centre for Ecology and Hydrology, 2011.

Rodrigues, R. R. and Shepherd, T. G.: Small is beautiful: climate-change science as if people mattered, PNAS Nexus, 1, pgac009, https://doi.org/10.1093/pnasnexus/pgac009, 2022.

Rodwell, M. J., Rowell, D. P., and Folland, C. K.: Oceanic forcing of the wintertime North Atlantic Oscillation and European climate, Nature, 398, 320–323, https://doi.org/10.1038/18648, 1999.

Rossi, L., Wens, M., De Moel, H., Cotti, D., Sabino Siemons, A., Toreti, A., Maetens, W., Masante, D., Van Loon, A., Hagenlocher, M., Rudari, R., Naumann, G., Meroni, M., Avanzi, F., Isabellon, M. and Barbosa, P., European Drought Risk Atlas, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/33211, JRC135215

Rudd, A. C., Bell, V. A., and Kay, A. L.: National-scale analysis of simulated hydrological droughts (1891–2015), Journal of Hydrology, 550, 368–385, https://doi.org/10.1016/j.jhydrol.2017.05.018, 2017.

Rudd, A. C., Kay, A. L., and Bell, V. A.: National-scale analysis of future river flow and soil moisture droughts: potential changes in drought characteristics, Climatic Change, 156, 323–340, https://doi.org/10.1007/s10584-019-02528-0, 2019.

Rudd, A. C., Kay, A. L., Wells, S. C., Aldridge, T., Cole, S. J., Kendo, E. J., and Stewart, E. J.: Investigating potential future changes in surface water flooding hazard and impact, Hydrol. Process., 34, 139–149, https://doi.org/10.1002/hyp.13572, 2020.

Rust, W., Holman, I., Bloomfield, J., Cuthbert, M., and Corstanje, R.: Understanding the potential of climate teleconnections to project future groundwater drought, Hydrology and Earth System Sciences, 23, 3233–3245, https://doi.org/10.5194/hess-23-3233-2019, 2019.

Saft, M., Western, A. W., Zhang, L., Peel, M. C., and Potter, N. J.: The influence of multiyear drought on the annual rainfall-runoff relationship: An A ustralian perspective, Water Resources Research, 51, 2444–2463, https://doi.org/10.1002/2014WR015348, 2015.

Salwey, S., Coxon, G., Pianosi, F., Singer, M. B., and Hutton, C.: National-Scale Detection of Reservoir Impacts Through Hydrological Signatures, Water Resources Research, 59, e2022WR033893, https://doi.org/10.1029/2022WR033893, 2023.

Salwey, S., Coxon, G., Pianosi, F., Lane, R., Hutton, C., Bliss Singer, M., McMillan, H., and Freer, J.: Developing water supply reservoir operating rules for large-scale hydrological modelling, EGUsphere, 1–29, https://doi.org/10.5194/egusphere-2024-326, 2024.

Satoh, Y., Yoshimura, K., Pokhrel, Y., Kim, H., Shiogama, H., Yokohata, T., Hanasaki, N., Wada, Y., Burek, P., Byers, E., Schmied, H. M., Gerten, D., Ostberg, S., Gosling, S. N., Boulange, J. E. S., and Oki, T.: The timing of unprecedented hydrological drought under climate change, Nat Commun, 13, 3287, https://doi.org/10.1038/s41467-022-30729-2, 2022.

Scaife, A. A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R. T., Dunstone, N., Eade, R., Fereday, D., Folland, C. K., Gordon, M., Hermanson, L., Knight, J. R., Lea, D. J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A. K., Smith, D., Vellinga, M., Wallace, E., Waters, J., and Williams, A.: Skillful long-range prediction of European and North American winters, Geophys. Res. Lett., 41, 2514–2519, https://doi.org/10.1002/2014GL059637, 2014.

Scaife, A. A., Karpechko, A. Yu., Baldwin, M. P., Brookshaw, A., Butler, A. H., Eade, R., Gordon, M., MacLachlan, C., Martin, N., Dunstone, N., and Smith, D.: Seasonal winter forecasts and the stratosphere, Atmos. Sci. Lett., 17, 51–56, https://doi.org/10.1002/asl.598, 2016.

Schiemann, R., Athanasiadis, P., Barriopedro, D., Doblas-Reyes, F., Lohmann, K., Roberts, M. J., Sein, D. V., Roberts, C. D., Terray, L., and Vidale, P. L.: 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 and Climate Dynamics, 1, 277–292, https://doi.org/10.5194/wcd-1-277-2020, 2020.

Schumacher, D. L., Keune, J., van Heerwaarden, C. C., Vilà-Guerau de Arellano, J., Teuling, A. J., and Miralles, D. G.: Amplification of mega-heatwaves through heat torrents fuelled by upwind drought, Nat. Geosci., 12, 712–717, https://doi.org/10.1038/s41561-019-0431-6, 2019.

Serinaldi, F. and Kilsby, C. G.: A modular class of multisite monthly rainfall generators for water resource management and impact studies, Journal of Hydrology, 464–465, 528–540, https://doi.org/10.1016/j.jhydrol.2012.07.043, 2012.

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., and Wang, L.: Regional climate change: consensus, discrepancies, and ways forward, Front. Clim., 6, https://doi.org/10.3389/fclim.2024.1391634, 2024.

Shepherd, T. G. and Lloyd, E. A.: Meaningful climate science, Climatic Change, 169, 17, https://doi.org/10.1007/s10584-021-03246-2, 2021.

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., and Zenghelis, D. A.: Storylines: an alternative approach to representing uncertainty in physical aspects of climate change, Climatic Change, 151, 555–571, https://doi.org/10.1007/s10584-018-2317-9, 2018.

Shepherd, T. G.: A Common Framework for Approaches to Extreme Event Attribution, Curr Clim Change Rep, 2, 28–38, https://doi.org/10.1007/s40641-016-0033-y, 2016.

Shepherd, T. G.: Atmospheric circulation as a source of uncertainty in climate change projections, Nature Geoscience, 7, 703–708, https://doi.org/10.1038/ngeo2253, 2014.

Shepherd, T. G.: Storyline approach to the construction of regional climate change information, Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 475, 20190013, https://doi.org/10.1098/rspa.2019.0013, 2019.

Shorthouse, C. and Arnell, N.: The effects of climatic variability on spatial characteristics of European river flows, Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, 24, 7–13, https://doi.org/10.1016/S1464-1909(98)00003-3, 1999.

Sillmann, J., Shepherd, T. G., Hurk, B. van den, Hazeleger, W., Martius, O., Slingo, J., and Zscheischler, J.: Event-Based Storylines to Address Climate Risk, Earth's Future, 9, e2020EF001783, https://doi.org/10.1029/2020EF001783, 2021.

Simpson, I. R. and Jones, P. D.: 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, 2014.

Skelton, M., Porter, J. J., Dessai, S., Bresch, D. N., and Knutti, R.: The social and scientific values that shape national climate scenarios: a comparison of the Netherlands, Switzerland and the UK, Reg. Environ. Change, 17, 2325–2338, https://doi.org/10.1007/s10113-017-1155-z, 2017.

Slater, L. J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., Kelder, T., Kowal, K., Lees, T., Matthews, T., Murphy, C., and Wilby, R. L.: Nonstationary weather and water extremes: a review of methods for their detection, attribution, and management, Hydrology and Earth System Sciences, 25, 3897–3935, https://doi.org/10.5194/hess-25-3897-2021, 2021.

Smith, D. M., Cusack, S., Colman, A. W., Folland, C. K., Harris, G. R., and Murphy, J. M.: Improved Surface Temperature Prediction for the Coming Decade from a Global Climate Model, Science, 317, 796–799, https://doi.org/10.1126/science.1139540, 2007.

Smith, K. A., Wilby, R. L., Broderick, C., Prudhomme, C., Matthews, T., Harrigan, S., and Murphy, C.: Navigating Cascades of Uncertainty — As Easy as ABC? Not Quite…, J. Extreme Events, 05, 1850007, https://doi.org/10.1142/S2345737618500070, 2018.

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. Hydrology and Earth System Sciences 23, 3247–3268. https://doi.org/10.5194/hess-23-3247-2019

Spraggs, G., Peaver, L., Jones, P., and Ede, P.: Re-construction of historic drought in the Anglian Region (UK) over the period 1798–2010 and the implications for water resources and drought management, Journal of Hydrology, 526, 231–252, https://doi.org/10.1016/j.jhydrol.2015.01.015, 2015.

Squire, D. T., Richardson, D., Risbey, J. S., Black, A. S., Kitsios, V., Matear, R. J., Monselesan, D., Moore, T. S., and Tozer, C. R.: Likelihood of unprecedented drought and fire weather during Australia's 2019 megafires, npj Clim Atmos Sci, 4, 1–12, https://doi.org/10.1038/s41612-021-00220-8, 2021.

Stainforth, D. A., Downing, T. E., Washington, R., Lopez, A., and New, M.: Issues in the interpretation of climate model ensembles to inform decisions, Phil. Trans. R. Soc. A., 365, 2163–2177, https://doi.org/10.1098/rsta.2007.2073, 2007.

Staudinger, M., Weiler, M., and Seibert, J.: Quantifying sensitivity to droughts – an experimental modeling approach, Hydrology and Earth System Sciences, 19, 1371–1384, https://doi.org/10.5194/hess-19-1371-2015, 2015.

Sternberg, T.: Regional drought has a global impact, Nature, 472, 169–169, https://doi.org/10.1038/472169d, 2011.

Stoelzle, M., Stahl, K., Morhard, A., and Weiler, M.: Streamflow sensitivity to drought scenarios in catchments with different geology, Geophysical Research Letters, 41, 6174–6183, https://doi.org/10.1002/2014GL061344, 2014.

Stoelzle, M., Staudinger, M., Stahl, K., and Weiler, M.: Stress testing as complement to climate scenarios: recharge scenarios to quantify streamflow drought sensitivity, in: Proceedings of the International Association of Hydrological Sciences, Hydrological processes and water security in a changing world - Hydrological Processes and Water Security in a Changing World, Beijing, China, 6–9 November 2018, 43–50, https://doi.org/10.5194/piahs-383-43-2020, 2020.

Stott, P. A., Christidis, N., Otto, F. E. L., Sun, Y., Vanderlinden, J., Van Oldenborgh, G. J., Vautard, R., Von Storch, H., Walton, P., Yiou, P., and Zwiers, F. W.: Attribution of extreme weather and climate-related events, WIREs Clim Change, 7, 23–41, https://doi.org/10.1002/wcc.380, 2016.

Stringer, N., Knight, J., and Thornton, H.: Improving Meteorological Seasonal Forecasts for Hydrological Modeling in European Winter, Journal of Applied Meteorology and Climatology, 59, 317–332, https://doi.org/10.1175/JAMC-D-19-0094.1, 2020.

Sutton, R. T.: 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, 2019.

Svensson, C. and Hannaford, J.: Oceanic conditions associated with Euro-Atlantic high pressure and UK drought, Environ. Res. Commun., 1, 101001, https://doi.org/10.1088/2515-7620/ab42f7, 2019.

Svensson, C. and Prudhomme, C.: Prediction of British summer river flows using winter predictors, Theor. Appl. Climatol., 82, 1–15, https://doi.org/10.1007/s00704-005-0124-5, 2005.

Svensson, C., Brookshaw, A., Scaife, A. A., Bell, V. A., Mackay, J. D., Jackson, C. R., Hannaford, J., Davies, H. N., Arribas, A., and Stanley, S.: Long-range forecasts of UK winter hydrology, Environ. Res. Lett., 10, 064006, https://doi.org/10.1088/1748-9326/10/6/064006, 2015.

Svensson, C., Hannaford, J., Kundzewicz, A. W., and Marsh, T. J.: Trends in river floods: why is there no clear signal in observations?, Frontiers in flood research, 8th Kovacs Colloquium, UNESCO, Paris, 1–18, 2006.

Svensson, C.: Seasonal river flow forecasts for the United Kingdom using persistence and historical analogues, Hydrological Sciences Journal, 61, 19–35, https://doi.org/10.1080/02626667.2014.992788, 2016.

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., Prudhomme, C., Smith, K., Hannaford, J., 2018. Historical gridded reconstruction of potential evapotranspiration for the UK. Earth System Science Data 10, 951–968. https://doi.org/10.5194/essd-10-951-2018

Teuling, A. J., Van Loon, A. F., Seneviratne, S. I., Lehner, I., Aubinet, M., Heinesch, B., Bernhofer, C., Grünwald, T., Prasse, H., and Spank, U.: Evapotranspiration amplifies European summer drought: EVAPOTRANSPIRATION AND SUMMER DROUGHTS DROUGHTS, Geophys. Res. Lett., 40, 2071–2075, https://doi.org/10.1002/grl.50495, 2013.

Teutschbein, C. and Seibert, J.: Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions?, Hydrol. Earth Syst. Sci., 17, 5061–5077, https://doi.org/10.5194/hess-17-5061-2013, 2013.

Thompson, J. R., Iravani, H., Clilverd, H. M., Sayer, C. D., Heppell, C. M., and Axmacher, J. C.: Simulation of the hydrological impacts of climate change on a restored floodplain, Hydrological Sciences Journal, 62, 2482–2510, https://doi.org/10.1080/02626667.2017.1390316, 2017.

Thompson, J. R.: Modelling the impacts of climate change on upland catchments in southwest Scotland using MIKE SHE and the UKCP09 probabilistic projections, Hydrol. Res., 43, 507–530, https://doi.org/10.2166/nh.2012.105, 2012.

Thompson, J.R., Green, A.J., Kingston, D.G., 2014. Potential evapotranspiration-related uncertainty in climate change impacts on river flow: An assessment for the Mekong River basin. Journal of Hydrology 510, 259–279. https://doi.org/10.1016/j.jhydrol.2013.12.010

Thompson, V., Dunstone, N. J., Scaife, A. A., Smith, D. M., Slingo, J. M., Brown, S., and Belcher, S. E.: High risk of unprecedented UK rainfall in the current climate, Nat. Commun., 8, 107, https://doi.org/10.1038/s41467-017-00275-3, 2017.

Thompson, V., Mitchell, D., Hegerl, G. C., Collins, M., Leach, N. J., and Slingo, J. M.: The most at-risk regions in the world for high-impact heatwaves, Nat Commun, 14, 2152, https://doi.org/10.1038/s41467-023-37554-1, 2023.

Todd, B., Macdonald, N., Chiverrell, R. C., Caminade, C., and Hooke, J. M.: Severity, duration and frequency of drought in SE England from 1697 to 2011, Climatic Change, 121, 673–687, https://doi.org/10.1007/s10584-013-0970-6, 2013.

Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., and Sheffield, J.: Global warming and changes in drought, Nature Clim Change, 4, 17–22, https://doi.org/10.1038/nclimate2067, 2014.

Turner, S., Barker, L. J., Hannaford, J., Muchan, K., Parry, S., and Sefton, C.: The 2018/2019 drought in the UK: a hydrological appraisal, Weather, 76, 248–253, https://doi.org/10.1002/wea.4003, 2021.

Twedt, Schaake, J., and Peck, E. L.: National weather service extended streamflow prediction, in: Proceedings of the 45th Annual Western Snow Conference, 45th Annual Western Snow Conference, Albuquerque, New Mexico, 1977.

Uhe, P., Mitchell, D., Bates, P. D., Allen, M. R., Betts, R. A., Huntingford, C., King, A. D., Sanderson, B. M., and Shiogama, H.: Method Uncertainty Is Essential for Reliable Confidence Statements of Precipitation Projections, J. Clim., 34, 1227–1240, https://doi.org/10.1175/JCLI-D-20-0289.1, 2021.

Ukkola, A. M., Pitman, A. J., Kauwe, M. G. D., Abramowitz, G., Herger, N., Evans, J. P., and Decker, M.: Evaluating CMIP5 Model Agreement for Multiple Drought Metrics, Journal of Hydrometeorology, 19, 969–988, https://doi.org/10.1175/JHM-D-17-0099.1, 2018.

van den Brink, H.W., Können, G.P., Opsteegh, J.D., van Oldenborgh, G.J., Burgers, G., 2004. Improving 10000-year surge level estimates using data of the ECMWF seasonal prediction system. Geophys. Res. Lett. 31, n/a-n/a. https://doi.org/10.1029/2004GL020610

van den Hurk, B., Baldissera Pacchetti, M., Boere, E., Ciullo, A., Coulter, L., Dessai, S., Ercin, E., Goulart, H. M. D., Hamed, R., Hochrainer-Stigler, S., Koks, E., Kubiczek, P., Levermann, A., Mechler, R., van Meersbergen, M., Mester, B., Middelanis, R., Minderhoud, K., Mysiak, J., Nirandjan, S., van den Oord, G., Otto, C., Sayers, P., Schewe, J., Shepherd, T. G., Sillmann, J., Stuparu, D., Vogt, T., and Witpas, K.: Climate impact storylines for assessing socio-economic responses to remote events, Climate Risk Management, 40, 100500, https://doi.org/10.1016/j.crm.2023.100500, 2023.

van der Schrier, G., Allan, R. P., Ossó, A., Sousa, P. M., Van de Vyver, H., Van Schaeybroeck, B., Coscarelli, R., Pasqua, A. A., Petrucci, O., Curley, M., Mietus, M., Filipiak, J., Štěpánek, P., Zahradníček, P., Brázdil, R., Řezníčková, L., van den Besselaar, E. J. M., Trigo, R., and Aguilar, E.: The 1921 European drought: impacts, reconstruction and drivers, Climate of the Past, 17, 2201–2221, https://doi.org/10.5194/cp-17-2201-2021, 2021.

van der Wiel, K., Batelaan, T. J., and Wanders, N.: 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, 2022.

van der Wiel, K., Lenderink, G., and de Vries, H.: Physical storylines of future European drought events like 2018 based on ensemble climate modelling, Weather and Climate Extremes, 33, 100350, https://doi.org/10.1016/j.wace.2021.100350, 2021.

van der Wiel, K., Selten, F. M., Bintanja, R., Blackport, R., and Screen, J. A.: Ensemble climate-impact modelling: extreme impacts from moderate meteorological conditions, Environ. Res. Lett., 15, 034050, https://doi.org/10.1088/1748-9326/ab7668, 2020.

van der Wiel, K., Wanders, N., Selten, F. M., and Bierkens, M. F. P.: Added Value of Large Ensemble Simulations for Assessing Extreme River Discharge in a 2 °C Warmer World, Geophysical Research Letters, 46, 2093–2102, https://doi.org/10.1029/2019GL081967, 2019.

Van Garderen, L. and Mindlin, J.: A storyline attribution of the 2011/2012 drought in Southeastern South America, Weather, 77, 212–218, https://doi.org/10.1002/wea.4185, 2022.

van Garderen, L., Feser, F., and Shepherd, T. G.: A methodology for attributing the role of climate change in extreme events: a global spectrally nudged storyline, Natural Hazards and Earth System Sciences, 21, 171–186, https://doi.org/10.5194/nhess-21-171-2021, 2021.

van Kempen, G., van der Wiel, K., and Melsen, L. A.: The impact of hydrological model structure on the simulation of extreme runoff events, Natural Hazards and Earth System Sciences, 21, 961–976, https://doi.org/10.5194/nhess-21-961-2021, 2021.

Van Loon, A. F. and Van Lanen, H. a. J.: A process-based typology of hydrological drought, Hydrology and Earth System Sciences, 16, 1915–1946, https://doi.org/10.5194/hess-16-1915-2012, 2012.

Van Loon, A. F., Gleeson, T., Clark, J., Van Dijk, A. I. J. M., Stahl, K., Hannaford, J., Di Baldassarre, G., Teuling, A. J., Tallaksen, L. M., Uijlenhoet, R., Hannah, D. M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T., Rangecroft, S., Wanders, N., and Van Lanen, H. A. J.: Drought in the Anthropocene, Nature Geoscience, 9, 89–91, https://doi.org/10.1038/ngeo2646, 2016.

Van Loon, A. F., Rangecroft, S., Coxon, G., Werner, M., Wanders, N., Di Baldassarre, G., Tijdeman, E., Bosman, M., Gleeson, T., Nauditt, A., Aghakouchak, A., Breña-Naranjo, J. A., Cenobio-Cruz, O., Costa, A. C., Fendekova, M., Jewitt, G., Kingston, D. G., Loft, J., Mager, S. M., Mallakpour, I., Masih, I., Maureira-Cortés, H., Toth, E., Van Oel, P., Van Ogtrop, F., Verbist, K., Vidal, J.-P., Wen, L., Yu, M., Yuan, X., Zhang, M., and Van Lanen, H. A. J.: Streamflow droughts aggravated by human activities despite management, Environ. Res. Lett., 17, 044059, https://doi.org/10.1088/1748-9326/ac5def, 2022.

Van Loon, A. F.: Hydrological drought explained, WIREs Water, 2, 359–392, https://doi.org/10.1002/wat2.1085, 2015.

Van Tiel, M., Weiler, M., Freudiger, D., Moretti, G., Kohn, I., Gerlinger, K., and Stahl, K.: Melting Alpine Water Towers Aggravate Downstream Low Flows: A Stress-Test Storyline Approach, Earth's Future, 11, e2022EF003408, https://doi.org/10.1029/2022EF003408, 2023.

van Vliet, M. T. H., Sheffield, J., Wiberg, D., and Wood, E. F.: Impacts of recent drought and warm years on water resources and electricity supply worldwide, Environ. Res. Lett., 11, 124021, https://doi.org/10.1088/1748-9326/11/12/124021, 2016.

Viner, D.: A qualitative assessment of the sources of uncertainty in climate change impacts assessment studies, in: Climatic Change: Implications for the Hydrological Cycle and for Water Management, edited by: Beniston, M., Springer Netherlands, Dordrecht, 139–149, https://doi.org/10.1007/0-306-47983-4_8, 2002.

Visser-Quinn, A., Beevers, L., Collet, L., Formetta, G., Smith, K., Wanders, N., Thober, S., Pan, M., and Kumar, R.: Spatio-temporal analysis of compound hydro-hazard extremes across the UK, Adv. Water Resour., 130, 77–90, https://doi.org/10.1016/j.advwatres.2019.05.019, 2019.

Vogel, J., Rivoire, P., Deidda, C., Rahimi, L., Sauter, C.A., Tschumi, E., van der Wiel, K., Zhang, T., Zscheischler, J., 2021. Identifying meteorological drivers of extreme impacts: an application to simulated crop yields. Earth System Dynamics 12, 151–172. https://doi.org/10.5194/esd-12-151-2021

Wade, S., Sanderson, M., Golding, N., Lowe, J., Betts, R. A., Reynard, N., Kay, A., Stewart, L., Prudhomme, C., Shaffrey, L., Lloyd-Hughes, B., and Harvey, B.: Developing H++ climate change scenarios for heat waves, droughts, floods, windstorms and cold snaps., Committee on Climate Change, 2015.

Ward, J. H.: Hierarchical Grouping to Optimize an Objective Function, Journal of the American Statistical Association, 58, 236–244, https://doi.org/10.1080/01621459.1963.10500845, 1963.

Watts, G., Battarbee, R. W., Bloomfield, J. P., Crossman, J., Daccache, A., Durance, I., Elliott, J. A., Garner, G., Hannaford, J., Hannah, D. M., Hess, T., Jackson, C. R., Kay, A. L., Kernan, M., Knox, J., Mackay, J., Monteith, D. T., Ormerod, S. J., Rance, J., Stuart, M. E., Wade, A. J., Wade, S. D., Weatherhead, K., Whitehead, P. G., and Wilby, R. L.: Climate change and water in the UK - past changes and future prospects, Progress in Physical Geography-Earth and Environment, 39, 6–28, https://doi.org/10.1177/0309133314542957, 2015.

Watts, G., Christierson, B. von, Hannaford, J., and Lonsdale, K.: Testing the resilience of water supply systems to long droughts, Journal of Hydrology, 414–415, 255–267, https://doi.org/10.1016/j.jhydrol.2011.10.038, 2012.

Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., and Sarewitz, D.: Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks, WIREs Clim. Change, 4, 39–60, https://doi.org/10.1002/wcc.202, 2013.

Wedgbrow, C. S., Wilby, R. L., and Fox, H. R.: Experimental seasonal forecasts of low summer flows in the River Thames, UK, using Expert Systems, Climate Research, 28, 133–141, https://doi.org/10.3354/cr028133, 2005.

Wedgbrow, C. S., Wilby, R. L., Fox, H. R., and O'Hare, G.: Prospects for seasonal forecasting of summer drought and low river flow anomalies in England and Wales, Int. J. Climatol., 22, 219–236, https://doi.org/10.1002/joc.735, 2002.

Wendt, D. E., Van Loon, A. F., Bloomfield, J. P., and Hannah, D. M.: Asymmetric impact of groundwater use on groundwater droughts, Hydrology and Earth System Sciences, 24, 4853–4868, https://doi.org/10.5194/hess-24-4853-2020, 2020.

West, H., Quinn, N., and Horswell, M.: Monthly Rainfall Signatures of the North Atlantic Oscillation and East Atlantic Pattern in Great Britain, Atmosphere, 12, 1533, https://doi.org/10.3390/atmos12111533, 2021.

West, H., Quinn, N., and Horswell, M.: Regional rainfall response to the North Atlantic Oscillation (NAO) across Great Britain, Hydrology Research, 50, 1549–1563, https://doi.org/10.2166/nh.2019.015, 2019.

West, H., Quinn, N., and Horswell, M.: Spatio-temporal propagation of North Atlantic Oscillation (NAO) rainfall deviations to streamflow in British catchments, Hydrological Sciences Journal, 67, 676–688, https://doi.org/10.1080/02626667.2022.2038791, 2022a.

West, H., Quinn, N., and Horswell, M.: The Influence of the North Atlantic Oscillation and East Atlantic Pattern on Drought in British Catchments, Frontiers in Environmental Science, 10, https://doi.org/10.3389/fenvs.2022.754597, 2022b.

Whitehead, P. G., Wilby, R. L., Butterfield, D., and Wade, A. J.: Impacts of climate change on in-stream nitrogen in a lowland chalk stream: An appraisal of adaptation strategies, Sci. Total Environ., 365, 260–273, https://doi.org/10.1016/j.scitotenv.2006.02.040, 2006.

Wilby, R. L.: A global hydrology research agenda fit for the 2030s, Hydrology Research, 50, 1464–1480, https://doi.org/10.2166/nh.2019.100, 2019.

Wilby, R. L. and Dessai, S.: Robust adaptation to climate change, Weather, 65, 180–185, https://doi.org/10.1002/wea.543, 2010.

Wilby, R. L. and Harris, I.: A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK, Water Resour. Res., 42, https://doi.org/10.1029/2005WR004065, 2006.

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., and Wood, P. J.: 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, 2017.

Wilby, R. L., Fenn, C. R., Wood, P. J., Timlett, R., and LeQuesne, T.: Smart licensing and environmental flows: Modeling framework and sensitivity testing, Water Resour. Res., 47, https://doi.org/10.1029/2011WR011194, 2011.

Wilby, R. L., O'Hare, G., and Barnsley, N.: The North Atlantic Oscillation and British Isles climate variability, 1865-1996, Weather, 52, 266–276, https://doi.org/10.1002/j.1477-8696.1997.tb06323.x, 1997.

Wilby, R. L., Prudhomme, C., Parry, S., and Muchan, K. G. L.: Persistence of Hydrometeorological Droughts in the United Kingdom: A Regional Analysis of Multi-Season Rainfall and River Flow Anomalies, J. of Extr. Even., 02, 1550006, https://doi.org/10.1142/S2345737615500062, 2015.

Wilby, R. L., Troni, J., Biot, Y., Tedd, L., Hewitson, B. C., Smith, D. M., and Sutton, R. T.: A review of climate risk information for adaptation and development planning, Int. J. Climatol., 29, 1193–1215, https://doi.org/10.1002/joc.1839, 2009.

Wilby, R. L., Wedgbrow, C. S., and Fox, H. R.: Seasonal predictability of the summer hydrometeorology of the River Thames, UK, Journal of Hydrology, 295, 1–16, https://doi.org/10.1016/j.jhydrol.2004.02.015, 2004.

Wilby, R. L.: Seasonal Forecasting of River Flows in the British Isles Using North Atlantic Pressure Patterns, Water & Environment J, 15, 56–63, https://doi.org/10.1111/j.1747-6593.2001.tb00305.x, 2001.

Wilby, R. L.: Stress-Testing Adaptation Options, in: Climate Adaptation Modelling, Cham, 41–49, https://doi.org/10.1007/978-3-030-86211-4_6, 2022.

Wilby, R. L.: Uncertainty in water resource model parameters used for climate change impact assessment, Hydrol. Process., 19, 3201–3219, https://doi.org/10.1002/hyp.5819, 2005.

Wilby, R. L.: When and where might climate change be detectable in UK river flows?, Geophys. Res. Lett., 33, L19407, https://doi.org/10.1029/2006GL027552, 2006.

Wilby, R.: Evidence of enso in the synoptic climate of the British Isles since 1880, Weather, 48, 234–239, https://doi.org/10.1002/j.1477-8696.1993.tb05897.x, 1993.

Wilby, R.L., Harris, I., 2006. A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK. Water Resources Research 42. https://doi.org/10.1029/2005WR004065

Wilhite, D. A., Sivakumar, M. V. K., and Pulwarty, R.: Managing drought risk in a changing climate: The role of national drought policy, Weather and Climate Extremes, 3, 4–13, https://doi.org/10.1016/j.wace.2014.01.002, 2014.

Wilhite, D. A., Svoboda, M. D., and Hayes, M. J.: Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness, Water Resour Manage, 21, 763–774, https://doi.org/10.1007/s11269-006-9076-5, 2007.

Woo, G.: A counterfactual perspective on compound weather risk, Weather and Climate Extremes, 32, 100314, https://doi.org/10.1016/j.wace.2021.100314, 2021.

Woo, G.: Downward Counterfactual Search for Extreme Events, Frontiers in Earth Science, 7, 2019.

Woollings, T., Barriopedro, D., Methven, J., Son, S.-W., Martius, O., Harvey, B., Sillmann, J., Lupo, A. R., and Seneviratne, S.: Blocking and its Response to Climate Change, Curr Clim Change Rep, 4, 287–300, https://doi.org/10.1007/s40641-018-0108-z, 2018.

Woollings, T., Czuchnicki, C., and Franzke, C.: Twentieth century North Atlantic jet variability: Jet variability, Q.J.R. Meteorol. Soc., 140, 783–791, https://doi.org/10.1002/qj.2197, 2014.

Woollings, T., Hannachi, A., and Hoskins, B.: Variability of the North Atlantic eddy-driven jet stream: Variability of the North Atlantic Jet Stream, Q.J.R. Meteorol. Soc., 136, 856–868, https://doi.org/10.1002/qj.625, 2010.

Yiou, P., Vautard, R., Naveau, P., Cassou, C., 2007. Inconsistency between atmospheric dynamics and temperatures during the exceptional 2006/2007 fall/winter and recent warming in Europe. Geophysical Research Letters 34. https://doi.org/10.1029/2007GL031981

Young, H. R., Shepherd, T. G., Acidri, J., Cornforth, R. J., Petty, C., Seaman, J., and Todman, L. C.: Storylines for decision-making: climate and food security in Namibia, Climate and Development, 13, 515–528, https://doi.org/10.1080/17565529.2020.1808438, 2021.

Zaitchik, B. F., Rodell, M., Biasutti, M., and Seneviratne, S. I.: Wetting and drying trends under climate change, Nat Water, 1, 502–513, https://doi.org/10.1038/s44221-023-00073-w, 2023.

Zappa, G. and Shepherd, T. G.: Storylines of Atmospheric Circulation Change for European Regional Climate Impact Assessment, J. Climate, 30, 6561–6577, https://doi.org/10.1175/JCLI-D-16-0807.1, 2017.

Zappa, G., Bevacqua, E., and Shepherd, T. G.: Communicating potentially large but non-robust changes in multi-model projections of future climate, Intl Journal of Climatology, 41, 3657–3669, https://doi.org/10.1002/joc.7041, 2021.

Zappa, G., Ceppi, P., and Shepherd, T. G.: Time-evolving sea-surface warming patterns modulate the climate change response of subtropical precipitation over land, Proc. Natl. Acad. Sci. U.S.A., 117, 4539–4545, https://doi.org/10.1073/pnas.1911015117, 2020.

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., and Vignotto, E.: A typology of compound weather and climate events, Nat Rev Earth Environ, 1, 333–347, https://doi.org/10.1038/s43017-020-0060-z, 2020.