CS-N0W-D2 Task 5: Analysis of future scenarios

D2 – Future water availability for water intensive energy infrastructure

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About CS N0W

Commissioned by the UK Department for Energy Security and Net Zero (DESNZ), Climate Services for a Net Zero Resilient World (CS-N0W) is a 4-year, £5.5 million research programme, that will use the latest scientific knowledge to inform UK climate policy and help us meet our global decarbonisation ambitions.

CS-N0W aims to enhance the scientific understanding of climate impacts, decarbonisation and climate action, and improve accessibility to the UK's climate data. It will contribute to evidence-based climate policy in the UK and internationally, and strengthen the climate resilience of UK infrastructure, housing and communities.

The programme is delivered by a consortium of world leading research institutions from across the UK, on behalf of DESNZ. The CS-N0W consortium is led by Ricardo and includes research **partners Tyndall Centre for Climate Change Research**, including the Universities of East Anglia (UEA), Manchester (UoM) and Newcastle (NU); institutes supported by the **Natural Environment Research Council (NERC)**, including the British Antarctic Survey (BAS), British Geological Survey (BGS), National Centre for Atmospheric Science (NCAS), National Centre for Earth Observation (NCEO), National Oceanography Centre (NOC), Plymouth Marine Laboratory (PML) and UK Centre for Ecology & Hydrology (UKCEH); and **University College London (UCL)**.

Contents

1. Executive summary

This report presents a preliminary analysis of future water availability based on the outputs from WPD2. The analysis focuses on artificially influenced river flows and aims to shed light on potential water availability challenges and inform decision-making processes at regional and national levels. It should be noted that, in common with the scope of WPD2 and earlier reports, 'water availability' is used in this report in a general sense, in terms of average river flows, low flows and drought characteristics, rather than in a more tightly-defined sense used by the Environment Agency, that means water available for abstraction, after factoring in environmental flow requirements.

The analysis used future projected river flows from 626 catchments in England, simulated by Grid-to-Grid hydrological model driven by the UKCP18 regional climate projections, and applied various indicators and metrics to assess water availability under different Artificial Influence (AI) scenarios and warming levels. The analysis considered flow metrics, such as Q95, Q90, Q70, mean annual and monthly flows, as well as drought characteristics including duration, intensity, and severity over the period 1981-2080. The percentage changes for all these indicators between three warming levels (1.5°, 2 °C and 4 °C) and three AI scenarios were compared with a baseline. The baseline was defined as river flows from 1981-2010 for a 'mean AI' scenario (corresponding to the mean discharges minus abstractions over a 5-year period of the recent past).

Key findings from the analysis include:

1. Future Projection of Low River Flows (based on 16 catchments):

- Based on 16 example catchments picked for illustrative purpose distributed across England, we expect decrease in future projections of mean annual river flows by the end of the century for most southern catchments, with more contrasting and non-linear trends in mean annual flows in the northern half of England.
- For these same 16 example catchments, differences among AI scenarios are relatively minor (differences of -1.82 to $0.30 m^3/s$ between scenarios for the end of the 21^{st} century), but certain catchments (two out of the 16) show larger differences dependent on AI scenario.

2. Monthly Mean Flows (based on 16 catchments):

- Slight increase (median increase of 1%) in mean monthly flows during winter (DJF) and spring (MAM), with a decrease (median decrease of 33%) during summer (JJA) months for most example catchments.
- Some catchments in the south may experience decreased flows throughout the year, mostly driven by climate change.

3. Regional Differences (based on 626 catchments):

- Overall decrease of between 19%-24% (median for the regions), 26%-33%, and 46%-58% in Q95 flows across the five water regions (or water company regional groups) for warming levels of 1.5ºC, 2ºC and 4ºC respectively.
- Effect of climate change (warming levels) is stronger than the effect of AI scenarios.

4. Drought Characteristics (based on 626 catchments):

- Duration, intensity, and severity of drought events were analysed.
- Drought characteristics (duration, intensity and severity) are all expected to increase over all of England, and for all three warming levels considered (1.5ºC, 2ºC and 4ºC), though the magnitude of the expected increase is greater in the south and southeast, and the increase is larger for higher warming levels.

The analysis offers valuable insights into future water availability and highlights the potential challenges for water-intensive energy infrastructure. Notably, the water consumption associated with Hydrogen energy, favoured in the 'Sustainability' AI scenario that prioritises sustainability over economic growth, is high. This contributes to the exacerbation of water scarcity during future droughts: there were 83% of 626 catchments where the 'Sustainability' scenario leads to lower mean Q95 than the 'Economic Growth' scenario by the 4ºC warming level. However, it is worth noting that the impact of the changing climate on water availability outweighs the influence of any of the three AI scenarios considered. This emphasises the significance of considering both climate change and AI scenarios when assessing future water availability in a changing climate. However, large uncertainties are present in the analysis, stemming from the climate projections, the hydrological modelling and the simplified nature of the AI scenarios considered.

These preliminary findings offer some insights that could be considered by policymakers, water resource managers, and stakeholders in developing effective strategies for future water management, ensuring sustainability, and supporting decision-making processes at regional and national levels. While they may provide some initial guidance, it is important to recognise the study’s limitations and the need for further research to refine the analysis presented here.

2. Introduction

This report presents a preliminary analysis of future water availability based on the outputs of WPD2, that is, a gridded dataset of future river flow projections, that factors in both future anthropogenic climate change (using the latest UKCP18 regional climate projections) and future changes in water demand.

It should be noted that, in common with the scope of WPD2 and earlier reports, ‘water availability’ is used in this report in a general sense, in terms of average river flows, low flows and drought characteristics, rather than in a more tightly-defined sense used by the Environment Agency, that means water available for abstraction, after factoring in environmental flow requirements.

There have been numerous assessments of potential impacts of climate change on river flows for the UK. eFLaG (enhanced Future Flows and Groundwater, Hannaford et al., 2023) delivered an updated set of national, spatially consistent hydrological projections based on UKCP18. eFLaG uses the 12km regional projections to provide transient (daily) time series to 2080 using four hydrological models (GR4J, GR6J, PDM and Grid-to-Grid). An analysis of eFLaG outputs in respect of future drought risk and low flows can be found in Parry et al. (2023) and Tanguy et al. (2023).

eFLaG provides a useful gridded dataset of bias-corrected climatology, and river flow at key locations (200 catchments). However, eFLaG only considers changes in climate, when changes in water demand can also have significant impacts on river flows. eFLaG does not consider the net impact of abstractions (water withdrawals for public supply, irrigation, etc.) and discharges (return discharge from e.g. sewage treatment works) – it provides either naturalised flows (estimates of natural water availability not accounting for AIs) or flows calibrated to current conditions, including AIs implicitly. In both cases, it makes no assessment of possible future changes in abstractions/discharges - such assessments previously were unavailable. While some assessments of future artificially influenced water availability have been made in water company water resource management plans (WRMPs) and in EA plans (notably the National Framework; EA, 2020), these are typically at large regional scales using approximations and are not resolved at the local scale relevant for the Net Zero ambition. Projections at a high spatial resolution are essential to address fine scale differences in supply/demand, environmental impacts and adaptation strategies.

The objectives of WPD2 were twofold:

1. Provide daily time-series of projections of water availability and river flows in England to 2080, accounting for both climate change and future changes in abstractions and discharges at a 1km-gridded spatial scale.

2. Derive key indicators and statistics for historical, current and future timescales to 2080 and delivery of future flow/recharge metrics to other WPs as required.

This report aims, as per the second objective, to provide key indicators and statistics to describe current and future river flow conditions to the late 21st Century. The scope of the analysis encompasses a comprehensive study of 626 catchments in England, including a specific subset of the eFLaG catchments. The evaluation focuses on Artificial Influence (AI)-impacted flows and drought characteristics, using a set of indicators selected based on stakeholders' feedback (as described in Barker et al., 2023). Specifically, these were: key low flow percentiles used in water management (Q95, Q90, Q70), mean annual and monthly flows, along with drought metrics (duration, intensity, and severity). Notably, the analysis focuses solely on AI-impacted flows, as the eFLaG project has already conducted a thorough analysis of the G2G naturalised flows (Parry et al., 2023; Lane et al., in prep).

Due to space limitation in this report, a subset of 16 catchments distributed across the country were selected to illustrate the changes for individual catchments. Furthermore, regional-scale assessments were undertaken by clustering the study catchments within each water company regional groups (also known as water regions) outlined in the National Framework, as well as the water resources zones. While the report focuses on the regional/national-scale picture and case study catchments, we have produced analytics for all 626 catchments and have made these available as a supplementary graphical output (see Appendix 1).

In this report, we aim to provide a preliminary examination of future water availability as represented by the WPD2 dataset, shedding light on the potential challenges that lie ahead. By delving into a detailed analysis of these catchments and using drought indicators, we can enhance our understanding of future water resources management options at both regional and national levels.

The analysis presented here feeds through also into the development of tools for visualisation and data access (WPF2), that will eventually make it possible for users to explore these analytical outputs for the whole 1km gridded dataset.

3. Data and Methodology

This section outlines the data used and the methodology applied to conduct the analysis.

3.1 Study area

The analysis focuses on 626 catchments in England. The complete list of catchments, along with their corresponding metadata, can be found in the supplementary data that accompanies this report. Due to space limitations, it is not feasible to present results for all catchments within this report. Therefore, a subset of 16 catchments spread across England has been selected (Figure 3-1a), offering geographical diversity across the country, with a mixture of abstraction- and discharge-dominated catchments.

To present regional summaries of changes, we have used water company regional groups or water regions (WRs, Figure 3-1b), and at a more detailed scale, water resources zones (WRZs, Figure 3-1c). The figures also illustrate the distribution of study catchments across each region and zone.

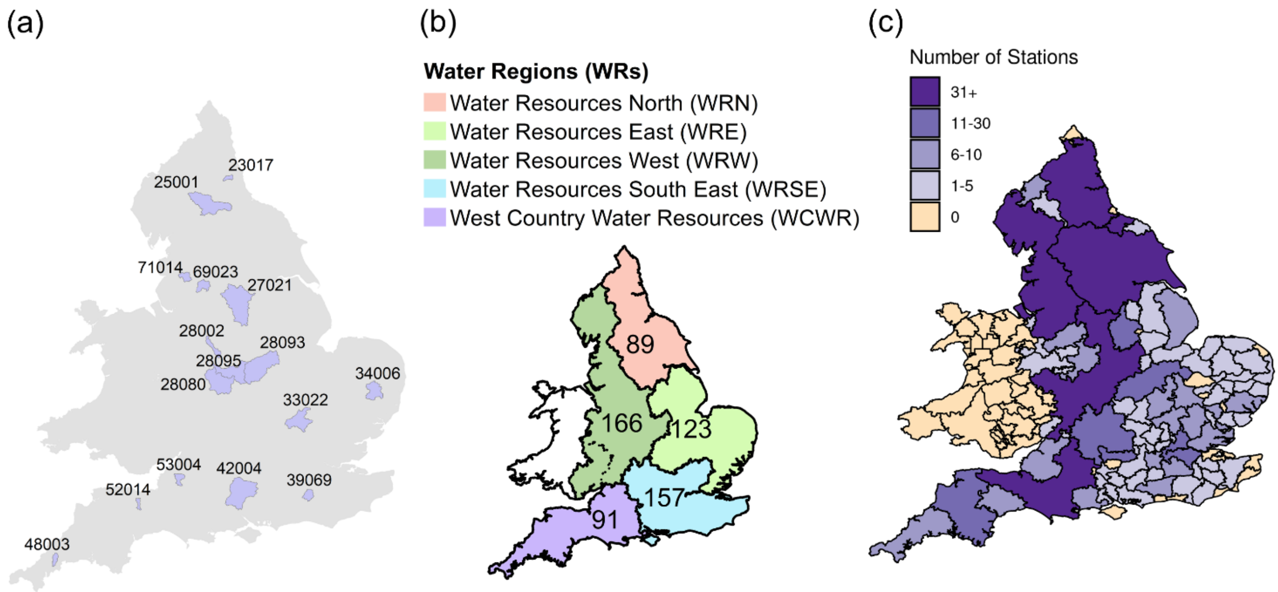


Figure 1(a) Map showing the location and NRFA catchment ID for a subset of 16 catchments used as example in this report; (b) Map of Water Regions (WRs) used in this study with their respective acronyms. These align with water company regional groups used in the National Framework. The number displayed within each region corresponds to the number of catchments used in each WR in this study; (c) Map of Water Resources Zones (WRZs) with corresponding number of catchments in each of them.

3.2 Artificial Influences (AI) scenarios

Three artificial influence (AI) scenarios, representing different water demand projections over the 21st century, were considered in this project. These are described in detail in Table 2 of the companion report, "Literature Review - Approaches to Construct Scenarios of Future Water Demand" (Baron et al., 2023), and are summarised as follows:

- **'Sustainability' AI scenario:** sustainability is prioritised, high levels of water efficiency are achieved, low population growth, innovation and societal change to achieve Net Zero energy production ahead of schedule, reduction in meat consumption and food waste, additional environmental constraints. Typically, this scenario results in lower surface-water and groundwater abstraction volumes than for the two other scenarios, but the overall change relative to the present day depends on individual catchments and the future time period.
- **'Business as Usual' AI scenario:** current ambitions for water efficiency are achieved with no further efficiencies implemented, best-estimate population growth, a move to green energy production consistent with current projections, and environmental considerations kept at current levels. 'Business as Usual' is typically (but not always) a "central" AI scenario, with abstractions higher than for the 'Sustainability' scenario, but the overall change relative to the present day depends on individual catchments and the future time period.
- **'Economic Growth' AI scenario:** economic growth is prioritised over sustainability, no water efficiencies, high population growth, continued use of fossil fuels and water-intensive agriculture (e.g. high meat consumption and increase of irrigated area), and some relaxation of environmental considerations. Typically (but not always), this scenario results in higher surface-water and groundwater abstraction volumes than for the 'Sustainability' and 'Business as Usual', but the overall change relative to the present day depends on individual catchments and the future time period. Note that the assumption that 'Economic Growth' is a high-abstraction scenario does not always hold, and for some catchments 'Sustainability' abstractions are higher than for 'Economic Growth' for some future time-periods.

For each of the three AI scenarios (above), corresponding future scenarios of discharge have been constructed by scaling present day discharges with the same factors used to scale abstractions (Baron et al., 2023). For example, discharges related to Public Water Supply (PWS), were scaled similarly to PWS abstractions but with adjustments to remove the effects of leakage change.

3.3 Future Streamflow Projections

Future projections of river flows were generated for the whole of England for each of the three AI scenarios (Bell et al. 2023). These were derived using the Grid-to-Grid (G2G) distributed hydrological model (Bell et al., 2009), which was driven by the eFLaG climate projections (Hannaford et al., 2023). The eFLaG climate projections are based on downscaled and bias-corrected data from the UKCP18 dataset. The UKCP18 dataset corresponds to the 'RCP8.5' emission scenario, representing the upper bound of projected global emission scenarios. The climate projections consist of a 12-member ensemble (12 Regional Climate Models or RCMs). G2G provides estimates of runoff at 1km resolution which are routed to enable estimates of river flow for specific catchments.

Therefore, for each catchment, there is a collection of 12 transient time-series of daily river flows (one for each climate ensemble member) for each of the three AI scenarios, spanning from 1980 to 2080. In this report, 'transient' refers to continuous time series.

To assess future changes in river flows, the baseline used for comparison was the run "Simrcm_MeanAI" defined in Bell et al. (2023) for the period 1981-2010. This run corresponds to river flows simulated by G2G when driven by the UKCP18 projected climate (12 RCMs) and using observed mean AI (between 2000 and 2014). For the baseline run, no seasonal changes in abstraction were considered, whereas for future projections, monthly abstractions were used.

For more details on the generation of the future projections of river flows, we refer the reader to the companion report, "Hydrological modelling and artificial influences: performance assessment & future scenarios" (Bell et al., 2023).

3.4 Flow metrics and drought characteristics

Based on the input from stakeholder workshops, various flow metrics and drought characteristics have been calculated and analysed. To assess changes under future climate conditions, two alternative approaches have been considered: time slices and warming levels.

3.4.1 Time slices vs. warming bands

1) Time slice approach: This approach uses 30-year periods as a basis for quantifying changes in flow metrics and drought characteristics under future climate conditions. The selected time slices for analysis are as follows:

- Baseline (BS): 1981-2010.

- Near Future (NF): 2020-2049.

- Far Future (FF): 2050-2079.

This approach aligns with other studies employing the eFLaG dataset, such as Hannaford et al. (2023), Parry et al. (2023) and Tanguy et al. (2023), though the baseline period chosen is different from these previous studies (which used 1989-2018), for consistency with the warming levels approach.

2) Warming level approach: In this approach, instead of using a fixed time period, we considered 30-year periods, which are RCM-specific, in which the mean global surface average temperature surpasses a specified warming level indicated in the climate projections. Table 1 displays the calculated warming levels and the start year of their corresponding 30-year period for the HadGEM3.02 ensemble (Arnell et al., 2021), which serves as the foundation for the UKCP18 projections used in the eFLaG dataset. The warming levels used in this study are 1.5ºC, 2ºC and 4ºC of warming, which were chosen in consultation with key stakeholders. One advantage of the warming level approach is its independence from emission scenarios, meaning that the analysis is not tied to a particular set of emissions assumptions, providing a more flexible and adaptable framework (Arnell et al., 2021). Furthermore, using a warming level approach provides a more consistent and comparable framework for analysing and comparing climate change impacts across different regions and studies, allowing for more standardised comparisons.

For simplicity, the subsequent sections of this report present results based on the warming levels approach only. However, all equivalent results based on the time slice approach can be found in the supplementary information. A list of all data provided in the supplementary information can be found in the Appendix A.

Table 1 First year of 30-year period with mean global surface average temperature exceeding specified warming level: HadGEM3.02 ensemble (source: from Arnell et al., 2021, supplementary data). In red, warming levels used in the current study. RCMs 2, 3 and 14 (greyed out in this table) from the original UKCP18 runs were not released by the Met Office, for various reasons explained in Murphy et al. (2018).

Level of warming	HadGEM3.02 Model number														
°C above pre-industrial	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1994	1993	1993	1993	1994	1994	1992	1993	1992	1995	1992	1996	1993	1994	1993
1.25	2000	1998	1999	1998	2001	2000	1998	1999	1998	2000	1998	2003	1999	2000	1999
1.5	2006	2003	2005	2003	2007	2005	2005	2006	2004	2008	2004	2010	2005	2006	2006
1.75	2011	2009	2010	2008	2012	2011	2011	2012	2010	2013	2010	2015	2010	2011	2013
2	2016	2015	2015	2013	2018	2016	2017	2018	2014	2018	2015	2020	2016	2017	2019
2.25	2021	2020	2020	2018	2023	2020	2023	2024	2019	2023	2020	2025	2021	2022	2024
2.5	2026	2025	2025	2023	2028	2025	2027	2029	2023	2027	2025	2030	2026	2027	2030
2.75	2030	2029	2029	2027	2033	2029	2032	2034	2027	2032	2030	2034	2031	2031	2034
3	2034	2033	2032	2031	2037	2034	2036	2038	2030	2036	2034	2038	2035	2035	2038
3.25	2038	2038	2036	2035	2041	2038	2039	2043	2034	2040	2038	2042	2039	2038	2042
3.5	2042	2041	2039	2039	2044	2042	2043	2047	2037	2045	2042	2045	2043	2042	2046
3.75	2045	2044	2042	2042	2048	2046	2047	2051	2040	2048	2046	2049	2046	2045	2050
4	2049	2048	2046	2046	2051	2049	2050	2055	2044	2052	2050	2052	2050	2049	2054
4.25	2053	2051	2049	2049	2055	2053	2053	2060	2047	2056	2053	2056	2053	2052	2058
4.5	2056	2055	2052	2052	2058	2057	2057	2064	2050	2060	2057	2059	2057	2055	2062
4.75	2060	2059	2055	2055	2061	2061	2061	0	2054	2064	2060	2063	2060	2059	2066

Please note that for the 4°C warming level, four of the 12 ensemble members do not have a full 30-year period covered by the dataset (RCMs 8, 10, 12 and 15 have 25-, 28-, 28- and 26-year period respectively for the 4°C warming level). This might affect the magnitude of the results slightly, though it will not change the overall conclusions of this analysis.

3.4.2 Flow metrics

For each warming level, a subset of hydrological indicators used in Hannaford & Buys (2012) were computed to capture changes in flow characteristics. The following indicators were calculated:

- Annual low flow: Q95 (5th percentile flow, the flow that is exceeded 95% of the time) and Q90 (10th percentile flow, flow exceeded 90% of the time).
- Annual medium flow: Q70 (30th percentile flow, flow exceeded 70% of the time).
- Annual mean flow.
- Monthly mean flow.

These flow indicators have been widely used to characterise flow regimes and detect trends in river flows in previous studies (e.g., Hannaford & Buys, 2012; Harrigan et al., 2018). To assess the impacts of warming levels, the percentage change in these indicators was calculated, and the results were summarised for the 12-member ensemble projection. The baseline used as reference to calculate the percentage change is the 1981-2010 period for each RCM for river flows simulated with mean observed AI over a 5-year period (2010-2014), for both the time-slice and the warming level approaches. The baseline period was chosen to minimise the overlap between the reference baseline and the first warming level (1.5ºC).

For each of the 626 catchments, the different indicators were calculated for each RCM separately, for the various 30-year periods considered (either time slices or warming levels). These values were then juxtaposed against the previously defined baseline to determine the percentage change in these indicators for each catchment and RCM. Subsequently, these percentage changes were averaged across RCMs for each catchment to yield an ensemble mean of percentage change in drought characteristics for each catchment. To provide a spatial summary of the results, we computed the averages of these ensemble means for all catchments falling within each Water Resource Zone (WRZ). A catchment was classified as part of a WR or a WRZ when its outlet was situated within the respective geographical region.

3.4.3 Drought identification and characterisation

To extract drought events, the threshold level method, as described in Rudd et al. (2017), was employed and summarised below. Figure 2 illustrates the method conceptually.

The threshold level method involves comparing a time series of the variable X (in this case, streamflow) to a threshold value, Xthresh, which can be fixed or varying. A drought event initiates when the variable falls below the threshold and continues until the threshold is surpassed again. However, there is no universally defined method for determining Xthresh.

In this study, a monthly variable threshold approach was used, employing three different thresholds:

- **Moderate droughts:** Q70 or the 70 percent exceedance.
- **Severe droughts:** Q90 or the 90 percent exceedance
- **Extreme droughts:** Q95 or the 95 percent exceedance

A "drought" is then defined as a period during which X is consistently below the threshold (or X – Xthresh < 0).

Furthermore, after identifying individual drought events, if there is only one month of above-threshold flows between two events, they are combined into a single event, as long as the magnitude by which flows exceed the threshold is not greater than the accumulated deficit of the first event.

Once the drought events have been identified, three characteristics are assessed for each event (Barker et al., 2019):

i) **Duration:** The number of months over which a drought occurs.

ii) **Intensity or maximum deficit:** The largest flow deficit relative to the drought threshold observed during any month of the drought.

iii) **Severity or total deficit:** The accumulated flow deficit across all months of the drought.

For each of the 626 catchments, we computed time series of drought events, characterising each individual drought with their duration, intensity and severity. Subsequently, we determined the average characteristics of droughts over 30-year periods (either time slices or warming levels) for each catchment and RCM. Following this, we compared these average drought characteristics to the baseline established in section 3.4.2 to calculate the percentage change in drought characteristics for each catchment and RCM. These percentage changes were then averaged across RCMs for each catchment to obtain an ensemble mean of the percentage change in drought characteristics for each catchment. To provide a spatial summary of our findings, we computed the average values of these ensemble means for all catchments falling within each Water Resource Zone (WRZ).

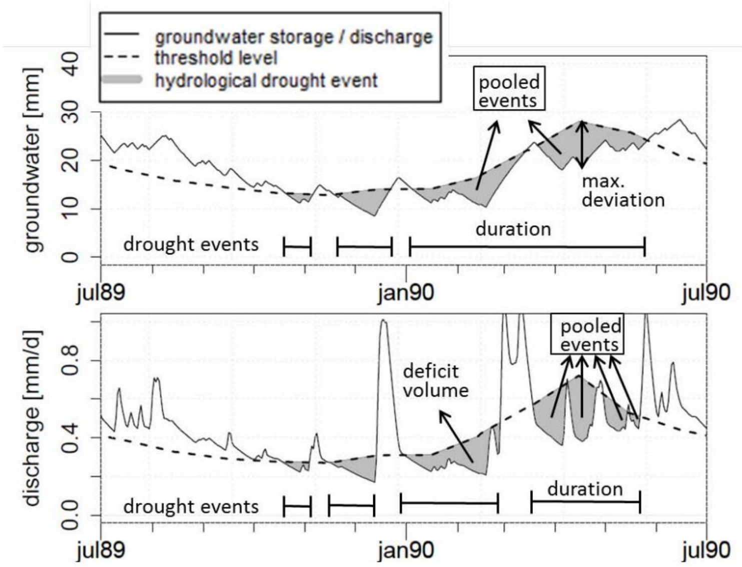


Figure 2 Conceptual diagram of threshold level method with variable threshold, illustrated for groundwater level (top) and river flow (discharge, bottom), including an illustration of pooling method and drought characteristics duration, maximum deviation (maximum deficit) and deficit volume (total deficit). Figure taken from Van Loon and Van Lanen (2012).

4. Results

This section presents the key findings of the analysis, beginning with the projected changes in flow metrics and then focusing on drought characteristics. The baseline used to calculate percentage change in all results shown in this section is the river flow simulations for each RCM for the period 1981-2010 using mean AI (2010-2014), as described in section 3.4.2. This will be referred to as the *baseline flow* in the rest of the report.

4.1 Future projection of low river flows

4.1.1 Transient mean annual flows

Figure 3 illustrates the yearly time series of transient mean annual flows (calculated as 30-year moving averages) from 1981 to 2080 for the selected subset of 16 example catchments shown in Figure 3-1a. The results indicate a clear decrease in mean annual flows for most of the southern catchments (e.g., 33022, 39069, 42004, 52014, 53004). In contrast, trends in the northern half of the country are less definitive, with some catchments expected to experience a decrease in mean annual flow (e.g., 27021), while others exhibit minimal change or a slight increase (e.g., 71014).

In general, the differences anticipated between the various AI scenarios are relatively minor for most catchments, with a few exceptions where the AI scenario has the potential to significantly influence the trajectory of future flows, e.g., 28080, 28095. Both of these are discharge dominated catchments, for which the net balance between discharge minus abstractions are expected to increase substantially for the “Economic Growth” scenario (Figure 4 and Table 2.1).

Interestingly, it is observed that the “Sustainability” AI scenario (prioritising sustainability over economic growth) is often associated with lower flows compared to the “Economic Growth” AI scenario (prioritising economic growth over sustainability) in certain catchments, such as 28080, 28095, and 39069. This seems counterintuitive, and would need further investigating, but can be at least partially explained by the fact that the “Sustainability” AI scenario includes the use of certain “clean” energies (e.g., Hydrogen heating) that have higher water consumption requirements. Overall, the differences among AI scenarios are small, with the variations in annual flows between the "Sustainability" and "Economic Growth" scenarios for the 16 catchments during the 2051-2080 time slice ranging from -1.82 to 0.30m^3/s.

In Figure 4, we show the evolution of the net balance between discharge minus abstractions for the 16 example catchments for the three AI scenarios. For these example catchments, we observe that the sustainability scenario is always the one with a net balance closer to zero. This means that for discharge dominated catchments (positive net balance), the sustainability scenario will exhibit lower flows, whereas for abstraction dominated catchments (negative net balance), it will have higher flows than the other AI scenarios. Table 4.1 provides the detail of discharge and abstractions for the three AI scenarios for the 16 example catchments in 2000, 2040 and 2080.

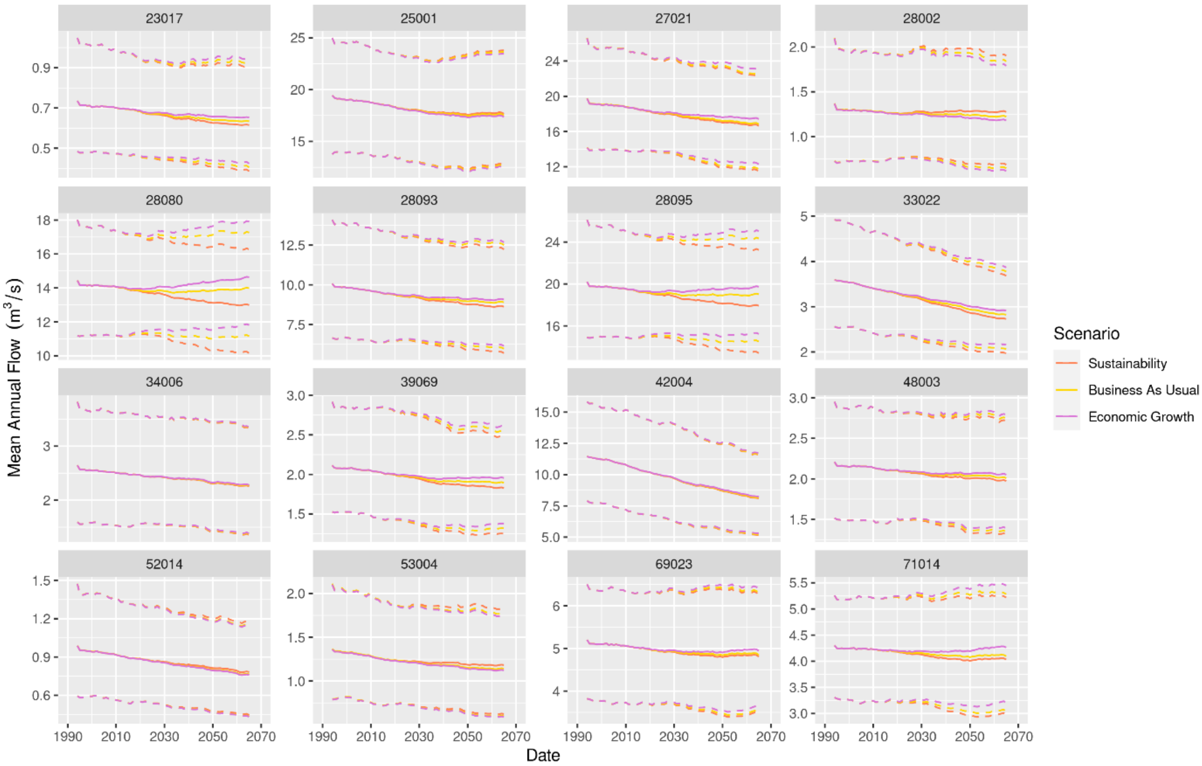


Figure 3: Transient mean annual flow (30-year moving average) for the subset of 16 example catchments shown in Figure 3-1a. The coloured lines represent the three AI scenarios (Section 3.2). The solid lines show the mean of the 12 RCMs, whereas the dashed lines show the maximum and minimum of the ensemble. The year shown on the x-axis corresponds to the central year of the 30-year moving average.

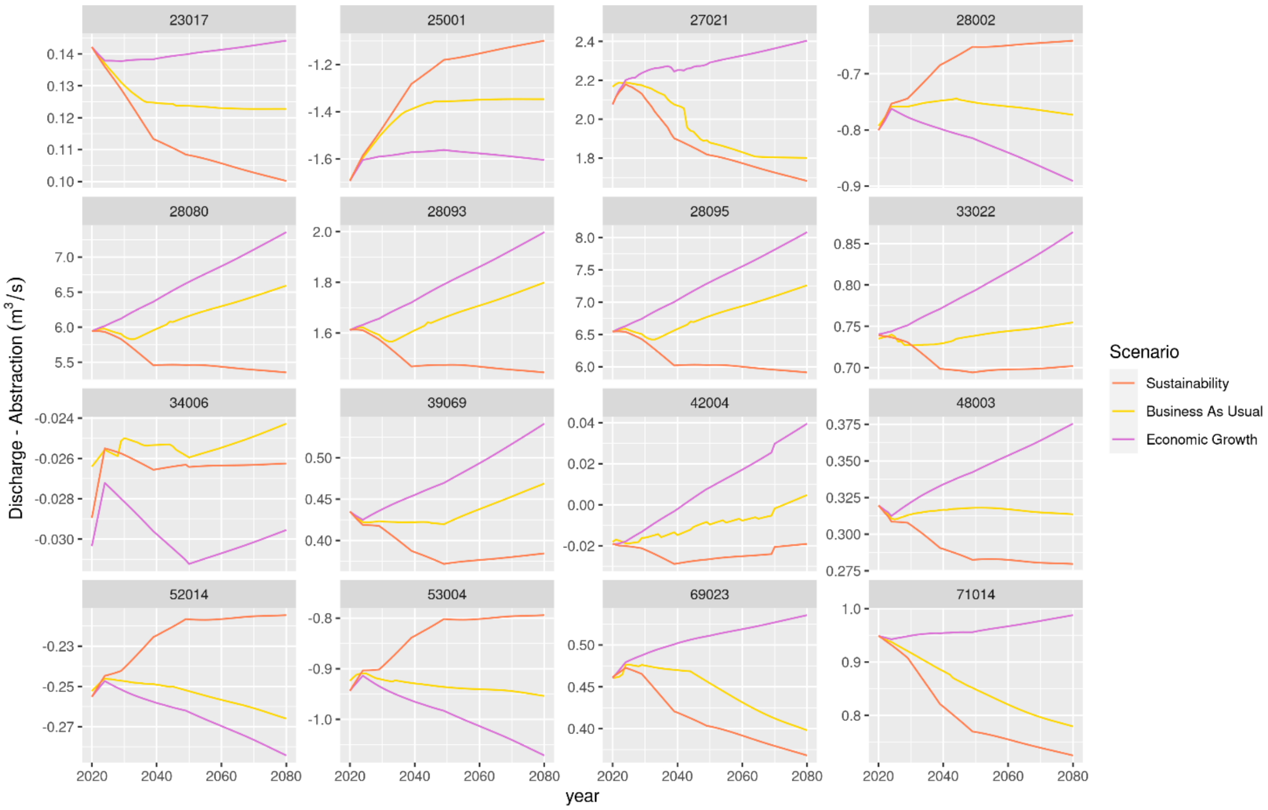


Figure 4: Transient mean annual net balance between discharge minus abstractions for the three AI scenarios for the subset of 16 example catchments shown in Figure 3-1a.

Table 2: Discharge; Abstraction (in m^3/s) for the three AI scenarios for the 16 example catchments shown in Figure 3-1a. (AI scenarios abbreviation: SUS = sustainability; BAU = Business As Usual; EG = Economic Growth).

Catchment ID	2020			2050			2080		
	SUS	BAU	EG	SUS	BAU	EG	SUS	BAU	EG
23017	0.142; 0.000	0.142; 0.000	0.142; 0.000	0.108; 0.000	0.124; 0.000	0.140; 0.000	0.100; 0.000	0.123; 0.000	0.144; 0.000
25001	0.124; 1.818	0.124; 1.815	0.124; 1.818	0.110; 1.288	0.116; 1.472	0.123; 1.687	0.107; 1.206	0.116; 1.463	0.125; 1.729
27021	3.82; 1.75	3.83; 1.66	3.83; 1.75	3.23; 1.42	3.64; 1.76	3.93; 1.65	3.04; 1.36	3.51; 1.70	4.08; 1.68
28002	0.00857; 0.80894	0.00857; 0.80109	0.00857; 0.80896	0.00839; 0.66061	0.00873; 0.76013	0.00891; 0.82590	0.00834; 0.64948	0.00880; 0.78186	0.00922; 0.90003
28080	6.46; 0.52	6.46; 0.52	6.46; 0.52	5.90; 0.44	6.65; 0.49	7.19; 0.54	5.79; 0.44	7.10; 0.51	7.93; 0.57
28093	1.84; 0.22	1.84; 0.22	1.84; 0.23	1.67; 0.20	1.88; 0.22	2.04; 0.24	1.64; 0.20	2.02; 0.22	2.25; 0.26
28095	7.28; 0.74	7.28; 0.74	7.28; 0.74	6.66; 0.64	7.49; 0.70	8.09; 0.78	6.54; 0.63	7.99; 0.73	8.91; 0.83
33022	0.958; 0.219	0.958; 0.223	0.960; 0.220	0.884; 0.189	0.963; 0.224	1.034; 0.240	0.896; 0.194	1.008; 0.254	1.133; 0.269
34006	0.114; 0.143	0.114; 0.140	0.113; 0.143	0.098; 0.124	0.110; 0.136	0.123; 0.155	0.099; 0.126	0.117; 0.142	0.139; 0.169
39069	0.435; 0.00006	0.435; 0.00006	0.435; 0.00006	0.372; 0.00006	0.422; 0.00007	0.472; 0.00008	0.384; 0.00006	0.469; 0.00007	0.542; 0.00008
42004	0.458; 0.477	0.458; 0.476	0.458; 0.478	0.373; 0.400	0.422; 0.432	0.486; 0.478	0.391; 0.410	0.452; 0.447	0.559; 0.519
48003	0.376; 0.057	0.376; 0.057	0.376; 0.057	0.339; 0.057	0.375; 0.057	0.400; 0.057	0.336; 0.057	0.370; 0.057	0.432; 0.057
52014	0.00544; 0.26060	0.00544; 0.25769	0.00544; 0.26060	0.00521; 0.22191	0.00584; 0.25820	0.00616; 0.26892	0.00515; 0.21977	0.00622; 0.27219	0.00676; 0.29102
53004	0.0632; 1.0069	0.0632; 0.9871	0.0632; 1.0069	0.0586; 0.8608	0.0661; 1.0027	0.0709; 1.0569	0.0580; 0.8521	0.0675; 1.0213	0.0779; 1.1492
69023	1.19; 0.73	1.19; 0.73	1.19; 0.73	0.93; 0.52	1.05; 0.60	1.20; 0.69	0.86; 0.49	0.95; 0.56	1.25; 0.71
71014	1.00; 0.05	1.00; 0.05	1.00; 0.05	0.81; 0.04	0.90; 0.06	1.01; 0.05	0.77; 0.04	0.83; 0.05	1.04; 0.05

4.1.2 Monthly mean flows

Figure 4a illustrates the predicted monthly mean flows for the 16 example catchments across the three warming levels (1.5, 2, and 4ºC) and three AI scenarios (Sustainability, Business as Usual, and Economic Growth).

Figure 4b presents the percentage change in monthly mean flows compared to the baseline flow for the same warming levels and AI scenarios. The results indicate a slight increase in mean monthly flows during winter and spring for most catchments (median increase of 1%). Conversely, there is a decrease in mean monthly flows during the summer months (median decrease of 33%). Although the decrease may appear relatively small when considering absolute values (Figure 4a), it represents a large percentage difference (Figure 4.1-3b), reaching up to -60% for certain catchments in the South (e.g., 53004).

It is noteworthy that for some catchments in the South, monthly flows are expected to decrease throughout the year, including winter and spring (e.g., 33022, 42004).

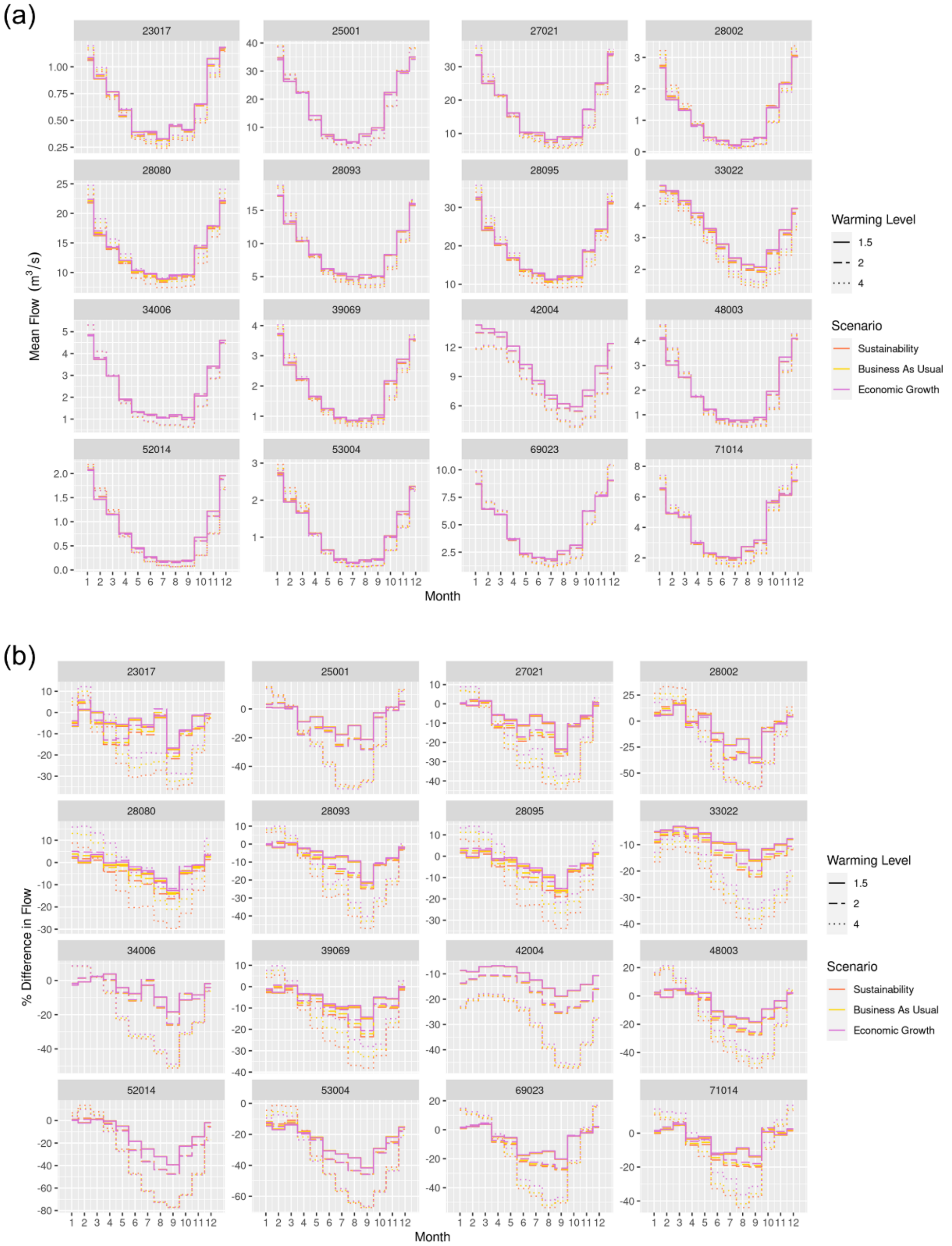


Figure 4: (a) Monthly mean flows for the three warming levels (1.5, 2 and 4ºC) shown by the different type of line, and three AI scenarios (Sustainability, Business as Usual, and Economic Growth) shown by the different coloured line, for the 16 example catchments (Figure 3-1a); (b) Same as (a) but showing the percentage difference in mean flows compared to the baseline flows.

4.1.3 Regional Differences

Water regions

Figure 5 shows a summary of the percentage change in various percentile flows at the Water Region (WR) level, compared to the baseline flows. Each boxplot corresponds to a specific pairing of warming level and AI scenario within each WR. These boxplots illustrate the range of percentage change encompassing all catchments situated within each WR, as well as across the 12 RCMs. For all regions, an overall decrease in low flows is expected as the warming level increases, and this decrease is more pronounced for the more extreme droughts (Q95, Figure 5c).

Figure 5 also indicates, especially for the warming level of 4ºC (blue boxplots), that the percentage changes expected under the 'Economic Growth' AI scenario are smaller than under the 'Sustainability' AI scenario. As mentioned earlier, the drivers of these differences should be investigated further, but could be partially explained by the high water demand of certain 'cleaner' energy sources, such as Hydrogen. However, it is important to note that the effect of climate change (the difference between warming levels) is much stronger than the effect of AI scenarios.

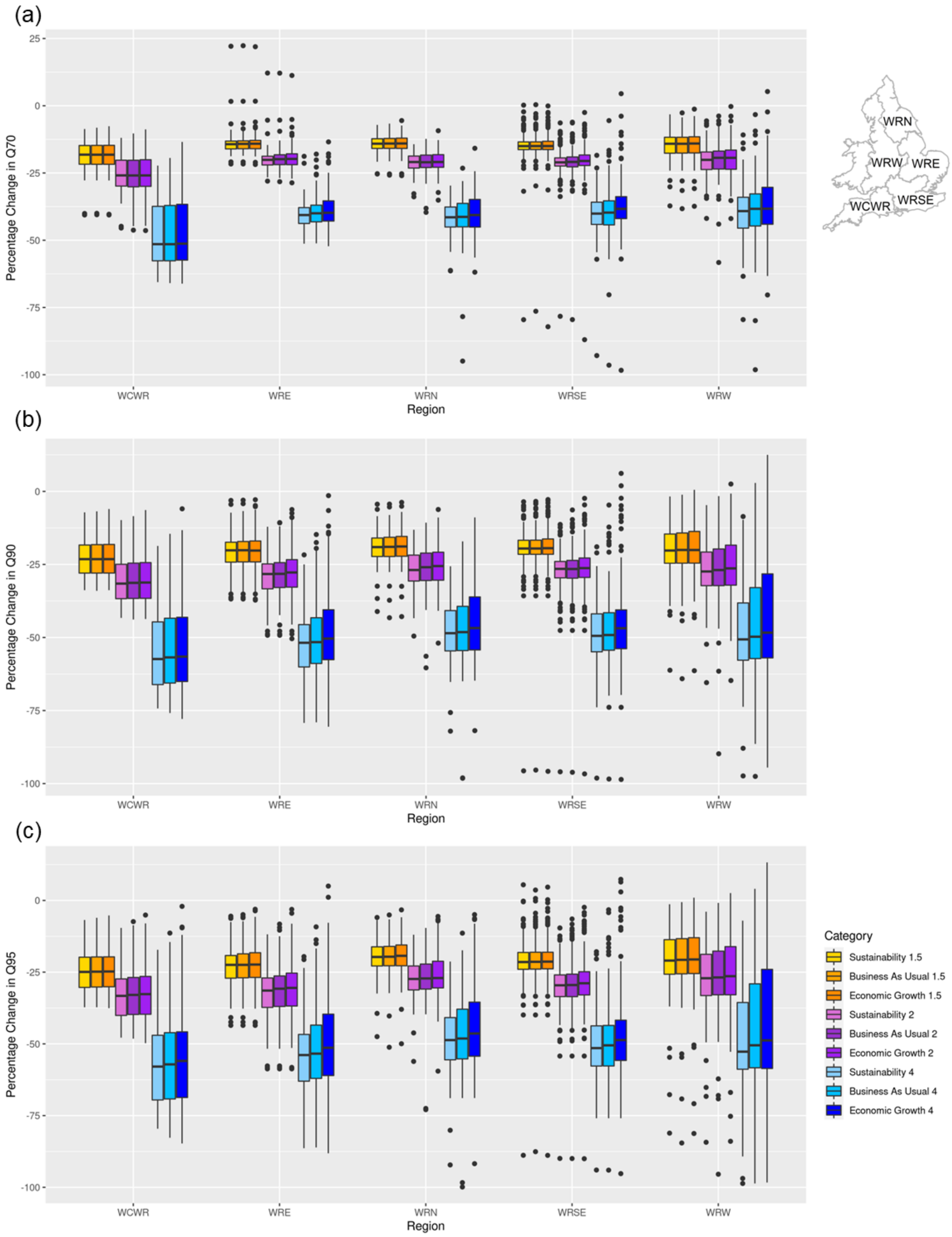


Figure 5: Range of change in river flows for (a) moderate droughts (Q70), (b) severe droughts (Q90) and (c) extreme droughts (Q95), across all RCMs and catchments within each WR. Different warming levels are indicated by colours, with variations in colour shade representing AI scenarios. The percentage change is calculated relative to the baseline flows. Each boxplot illustrates the extent of percentage change in flows for each warming level, considering all catchments and RCMs individually. The box displays the range between the 25th and 75th percentiles, while outliers (denoted by dots) represent values that deviate by more than 1.5 times the interquartile range from the box.

Water resources zones

Figure 6 shows maps of the mean percentage difference in Q90 flow between the baseline flows and each combination of warming level and AI scenario. The way the percentage changes have been calculated is explained in section 3.4.2. The equivalent maps for other percentile flows (Q70 and Q95) can be found in the supplementary data.

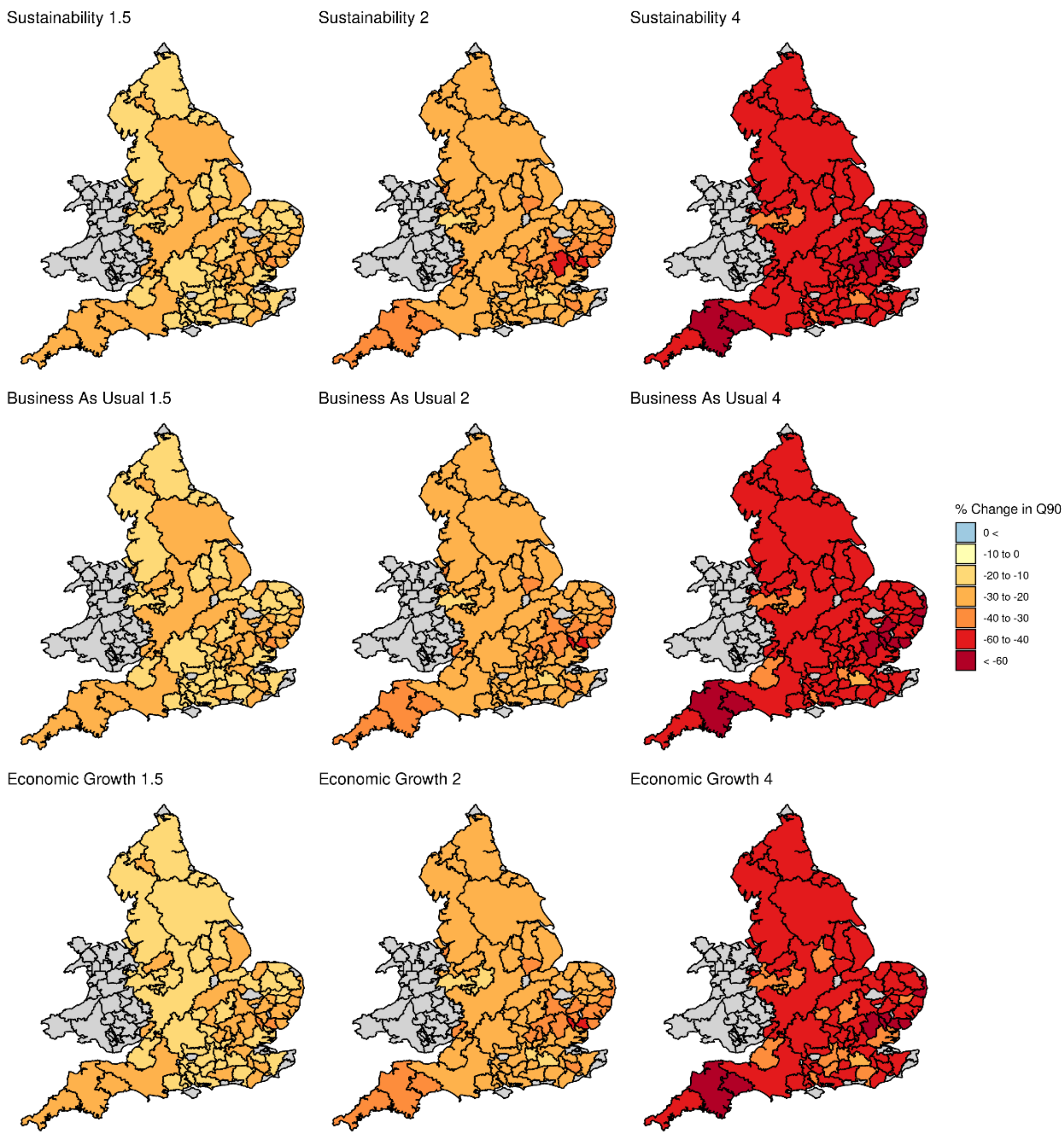


Figure 6: Map showing mean percent difference between the combination of each AI scenario (rows) and warming level (columns) with the baseline flows for Q90 (severe droughts) for each WRZ.

In Figure 6, it is evident that for a warming level of 1.5ºC (first column), a moderate decrease in Q90 flow can be expected in all of England. There is little difference observed between the three AI scenarios.

As the warming level increases (second and third columns in Figure 6 for 2ºC and 4ºC, respectively), the decrease in Q90 flow becomes increasingly more pronounced in all Water Resource Zones (WRZs) compared to baseline flows. These changes are observed quite uniformly across all WRZs. The differences between AI scenarios are much smaller than the differences observed between warming levels. For the highest level of warming (4ºC), the 'Economic Growth' AI scenario leads to a lower percentage change than the 'Sustainability' AI scenario in some WRZs, especially in central and southern England.

4.2 Drought characteristics

Individual catchments

Figure 7 displays the mean percentage change in drought duration for the subset of 16 example catchments, while Figures 4-2.2a and 4-2.2b illustrate the mean percentage change in maximum deficit (drought intensity) and in total deficit (drought severity), respectively, all for moderate droughts (Q70 threshold). The percentage change displayed in these figures (4-2.1 and 4-2.2) reflect mean differences between the characteristics of individual drought events identified within the 30-year period associated with each warming level and AI scenario, as compared to the baseline flows, for every catchment and RCM. The boxplots show the range of these mean differences. Equivalent plots for severe (Q90) and extreme (Q95) droughts can be found in the supplementary material.

Regarding drought duration, the outcomes are quite varied among the 16 catchments. For most, a slight increase in drought duration relative to the baseline is expected for the ensemble median with a warming level of 1.5ºC, although the full ensemble shows a great variability with some RCM suggesting an increase, and some a decrease in duration. This increasing trend continues for higher levels of warming, although with notable uncertainties (e.g., 33022, 42004), especially for the 4ºC warming level.

Similar observations can be made for drought maximum deficit (Figure 8a) and total deficit (Figure 8b), where all example catchments are expected to experience an increase in these values at a warming level of 1.5ºC, with the largest increase observed for 4ºC warming level.

The influence of AI scenarios on future changes in drought characteristics varies among different catchments. In some cases, the disparities between AI scenarios are minimal (e.g., 25001, 52014). Conversely, for certain other catchments, the scenarios significantly affect future drought characteristics, particularly at the 4ºC warming level, such as in the case of catchments 28080 and 27021. In certain catchments, the 'Sustainable' scenario results in more severe drought characteristics than the other AI scenarios in the future, as seen in catchments like 28095 and 33022. In contrast, in other catchments, it is the 'Economic Growth' scenario that leads to more severe droughts, for example in catchments 52014 and 25001.

These observations generally apply to severe (Q90) and extreme (Q95) droughts as well (see supplementary material) and are consistent with the broader patterns observed at the national scale in the subsequent sections. This suggests that, despite the initial selection of the 16 catchments primarily based on their geographical location, they seem to provide a relatively representative depiction of the entire country.

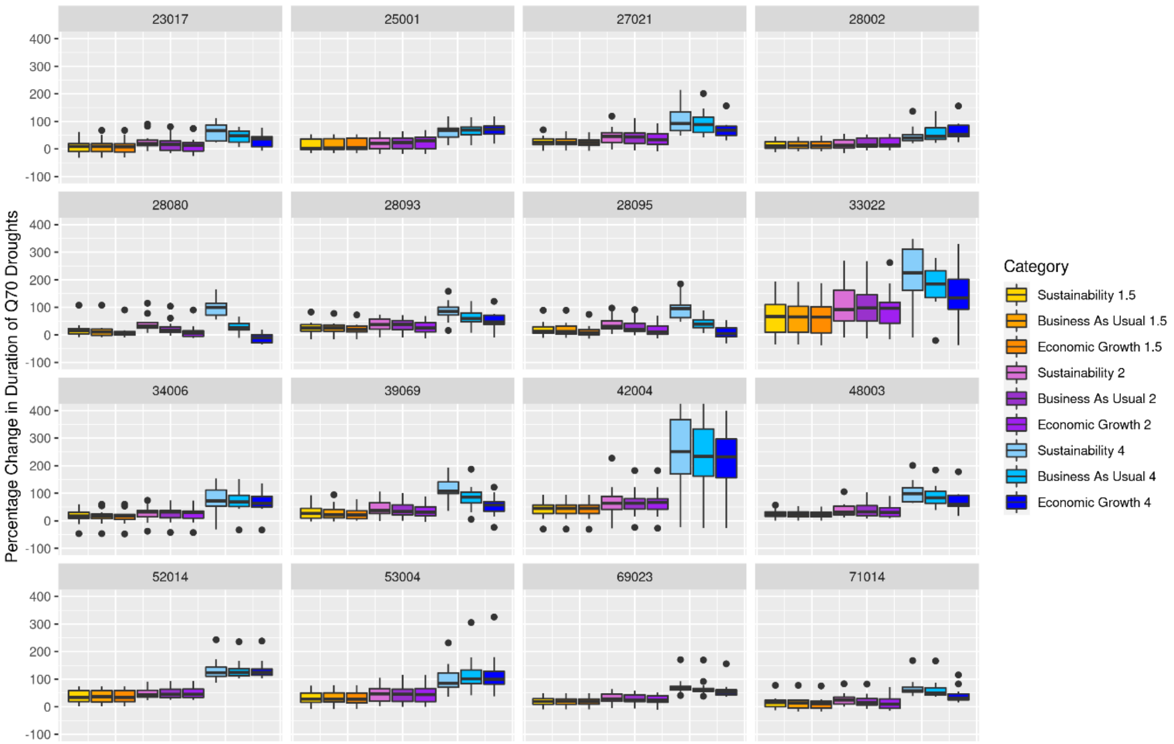
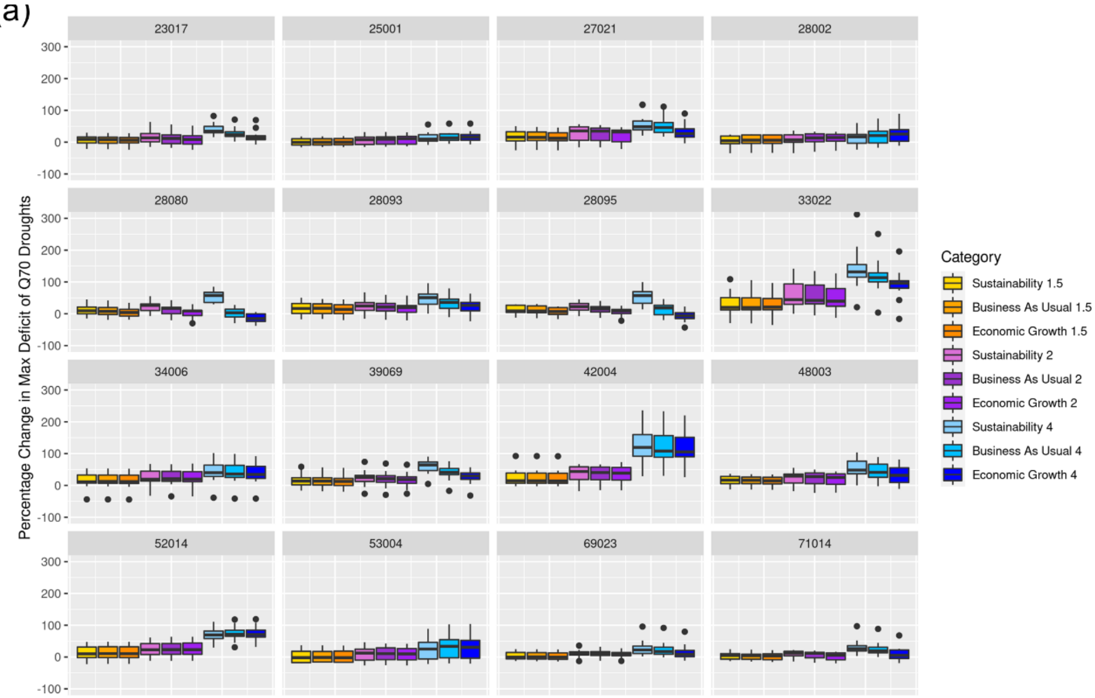


Figure 7: Range of mean percentage change in drought duration for Q70 threshold drought for the subset of 16 example catchments. Colours show different warming levels, whereas shade of colour denotes AI scenarios. Percentage change calculated against baseline flows. The box displays the range between the 25th and 75th percentiles, while outliers (denoted by dots) represent values that deviate by more than 1.5 times the interquartile range from the box.

(a)


23017
25001
27021
28002
28080
28093
28095
33022
34006
39069
42004
48003
52014
53004
69023
71014
Percentage Change in Max Deficit of Q70 Droughts
300
200
100
0
-100
Category
Sustainability 1.5
Business As Usual 1.5
Economic Growth 1.5
Sustainability 2
Business As Usual 2
Economic Growth 2
Sustainability 4
Business As Usual 4
Economic Growth 4

(b)

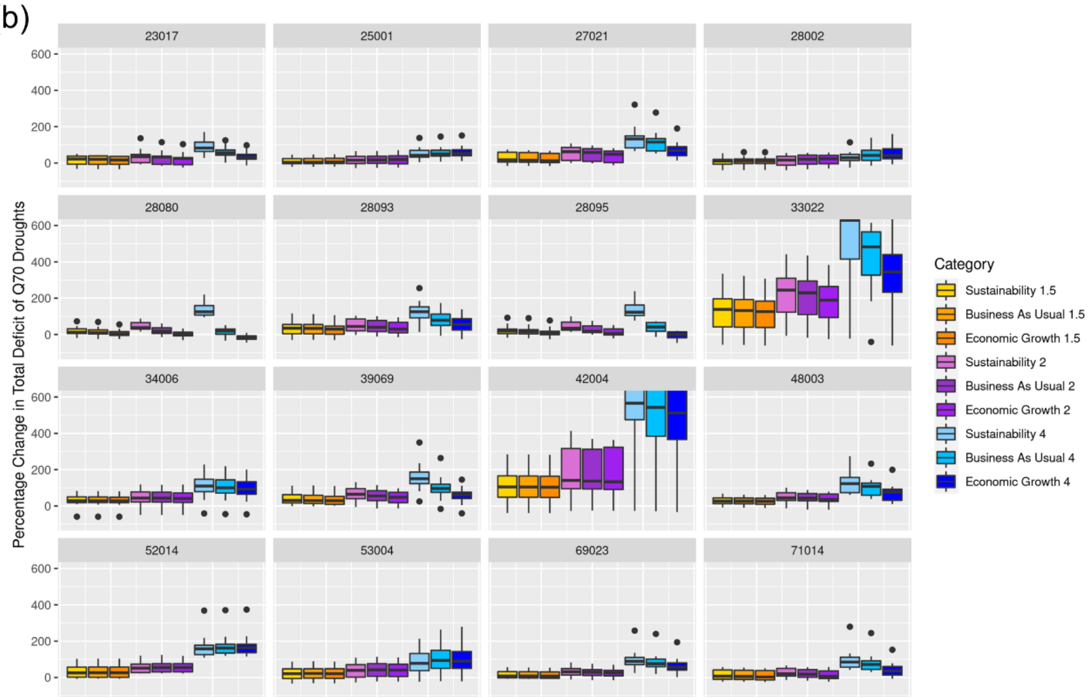

23017
25001
27021
28002
28080
28093
28095
33022
34006
39069
42004
48003
52014
53004
69023
71014
Percentage Change in Total Deficit of Q70 Droughts
600
400
200
0
Category
Sustainability 1.5
Business As Usual 1.5
Economic Growth 1.5
Sustainability 2
Business As Usual 2
Economic Growth 2
Sustainability 4
Business As Usual 4
Economic Growth 4

Figure 8: Range of mean percentage change in (a) drought intensity (maximum deficit) and (b) drought severity (total deficit) for Q70 threshold drought for the subset of 16 example catchments. Colours show different warming levels, whereas shade of colour denotes AI scenarios. Percentage change calculated against equivalent baseline drought. The box displays the range between the 25th and 75th percentiles, while outliers (denoted by dots) represent values that deviate by more than 1.5 times the interquartile range from the box.

Regarding AI scenarios, the impact on drought characteristics is once again highly varied depending on the catchment. In certain cases, the scenarios have minimal influence on the drought characteristics (e.g., 52014), while for others, the 'Economic Growth' AI scenario leads to greater values of drought characteristics compared to the 'Sustainability' AI scenario (e.g., 28002, 53004). Conversely, in some catchments, the 'Sustainability' AI scenario results in higher values of drought characteristics compared to the 'Economic Growth' AI scenario (e.g., 39069, 33022, 48003).

Water regions

Figure 9 shows the percentage change expected in drought characteristics for severe droughts (Q90 threshold) compared to the equivalent baseline drought for each WR. To derive this plot, first the ensemble mean percentage change in drought characteristics were calculated for each catchment and each RCM, and the boxplots in Figure 9 shows the range of values for all catchments within each WR. The equivalent figure for moderate (Q70) and extreme (Q95) droughts can be found in the supplementary material. Overall, as the warming level increases, all drought characteristics are expected to worsen, though the magnitude of change is variable for different catchments within each WR, as displayed by the range of the boxplots, particularly at 4ºC warming level. The largest changes are projected to occur in WRE (Water Resources East) and WRSE (Water Resources South East) regions.

Changes under the 'Economic Growth' AI scenario are anticipated to be smaller than changes under the 'Sustainability' AI scenario. However, once again, it is evident that warming levels have a much stronger influence on drought characteristics than AI scenarios, emphasising the dominance of climate-driven factors over AI scenario variations. The degree of variation displayed in the plots reflects the variety of catchments within each WR and the uncertainty from the climate ensemble, showing a greater divergence as we progress in the future (warming levels).

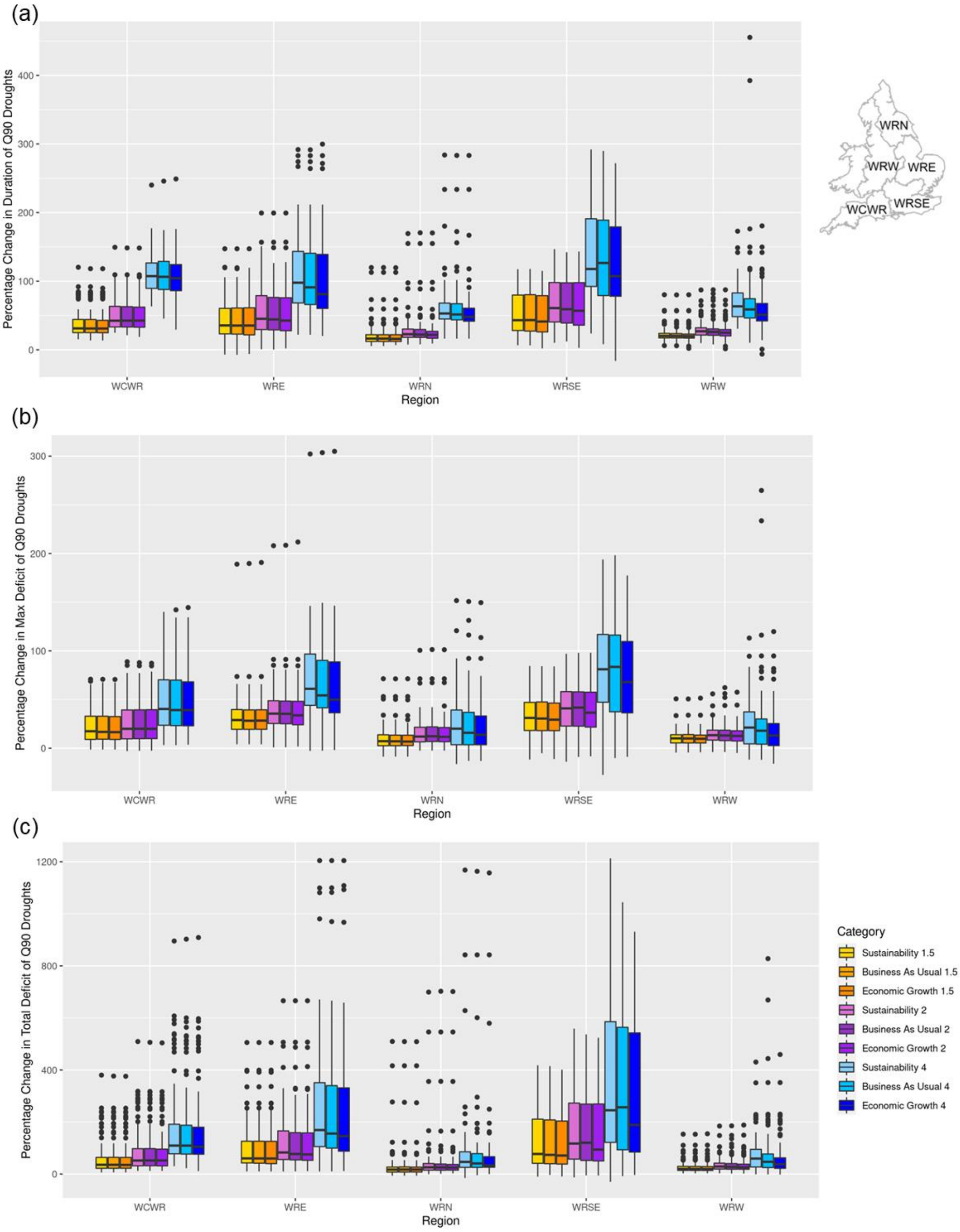


Figure 9: Range of percentage change in drought characteristics for Q90 threshold drought, summarised for each WR. (a) Percentage change in drought duration; (b) Percentage change in drought intensity (maximum deficit); and (c) Percentage change in drought severity (total deficit). Colours show different warming levels, whereas shade of colour denotes AI scenarios. Percentage change calculated against equivalent baseline drought for each individual catchment and RCM. The box displays the range between the 25th and 75th percentiles, while outliers (denoted by dots) represent values that deviate by more than 1.5 times the interquartile range from the box.

Water Resources Zones

For the Water Resources Zones (WRZ) analysis, the maps in Figures 4-2.4, 4-2.5, and 4-2.6 show the percentage change in mean drought characteristics for severe droughts (Q90 threshold) across different WRZs. The equivalent maps for moderate droughts (Q70) and extreme droughts (Q95) can be found in the supplementary information. The values in Figure 10, 4-2.5 and 4-2.6 were derived by averaging the ensemble mean drought characteristics for all catchments within each WRZ, and is explained in detail in section 3.4.3.

In all Water Resource Zones (WRZs), drought duration (Figure 10) is projected to increase with higher warming levels, though the magnitude of change varies in space. Notably, the southern and south-eastern part of the country is projected to endure the most significant increase in drought duration.

Drought intensity (maximum deficit, Figure 11) and severity (total deficit, Figure 12) are also predicted to increase across the country, with the most pronounced increase expected again in the south and southeast, and with higher warming levels.

As warming levels rise further, these indicators are expected to continue increasing.

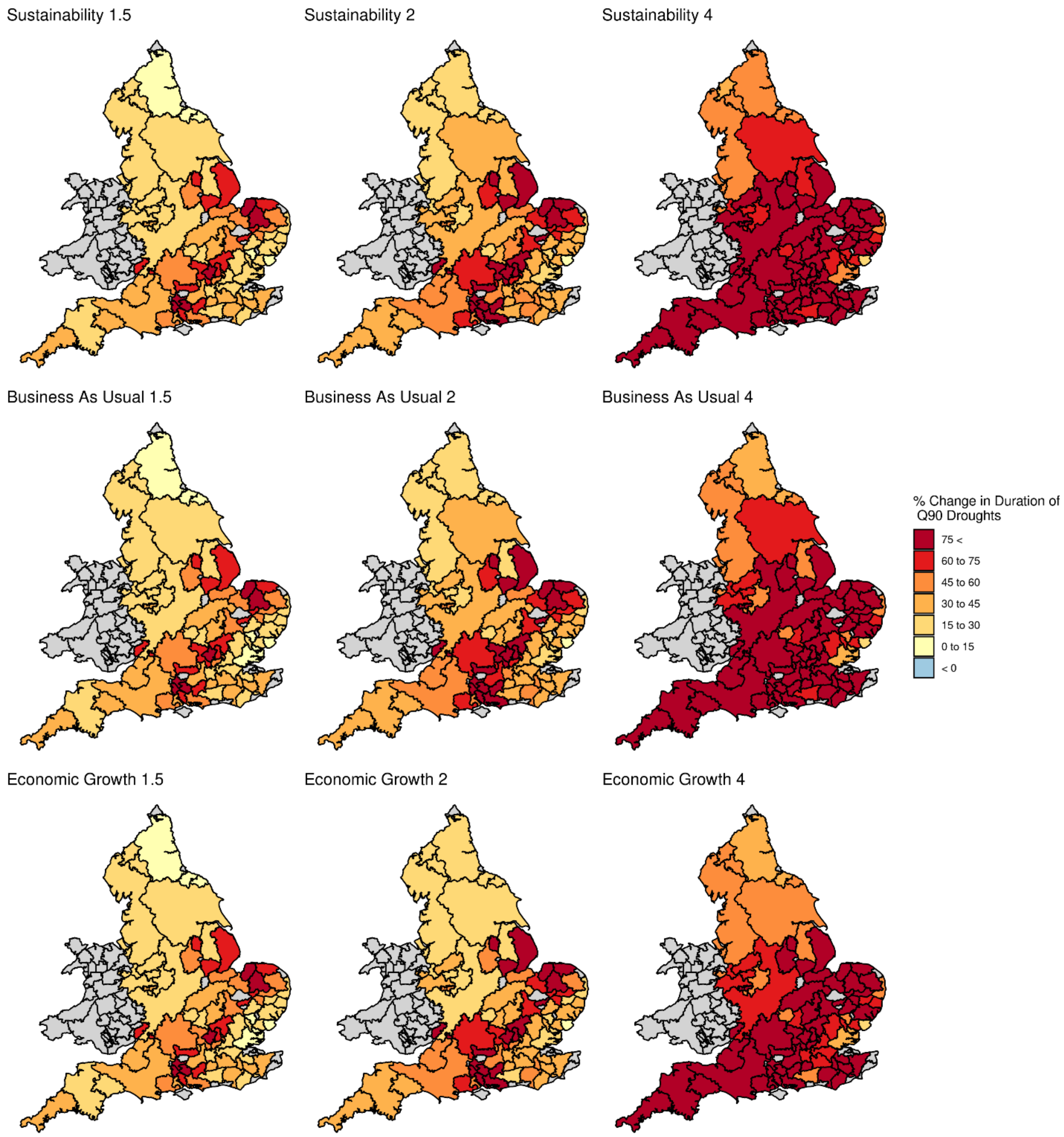


Figure 10: Map showing mean percent difference in drought duration between Q90 (severe droughts) for each combination of AI scenario (rows) and warming level (columns) with the equivalent baseline drought for each WRZ.

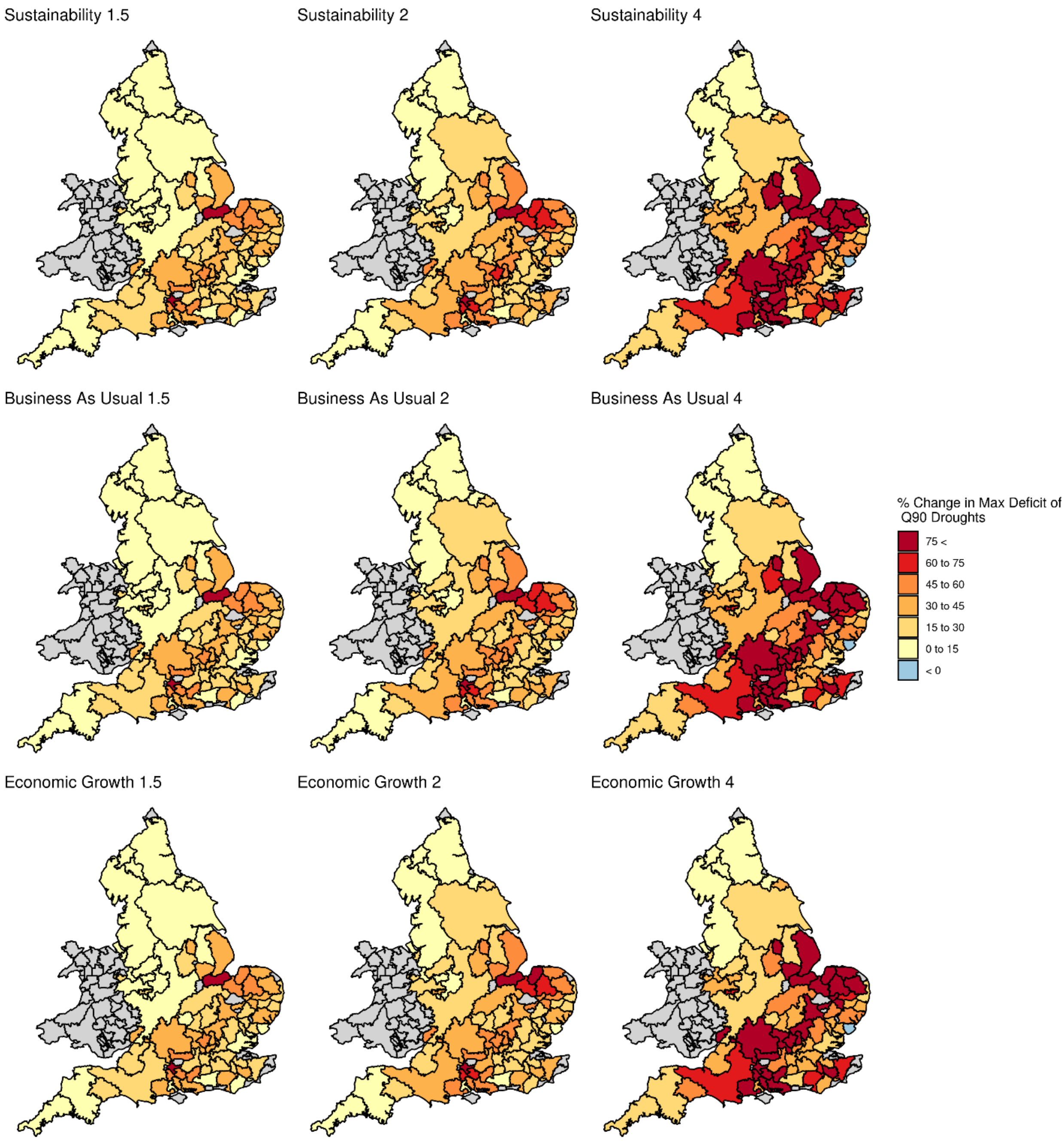


Figure 11: Map showing mean percent difference in drought intensity (maximum deficit) between Q90 (severe droughts) for each combination of AI scenario (rows) and warming level (columns) with the equivalent baseline drought for each WRZ.

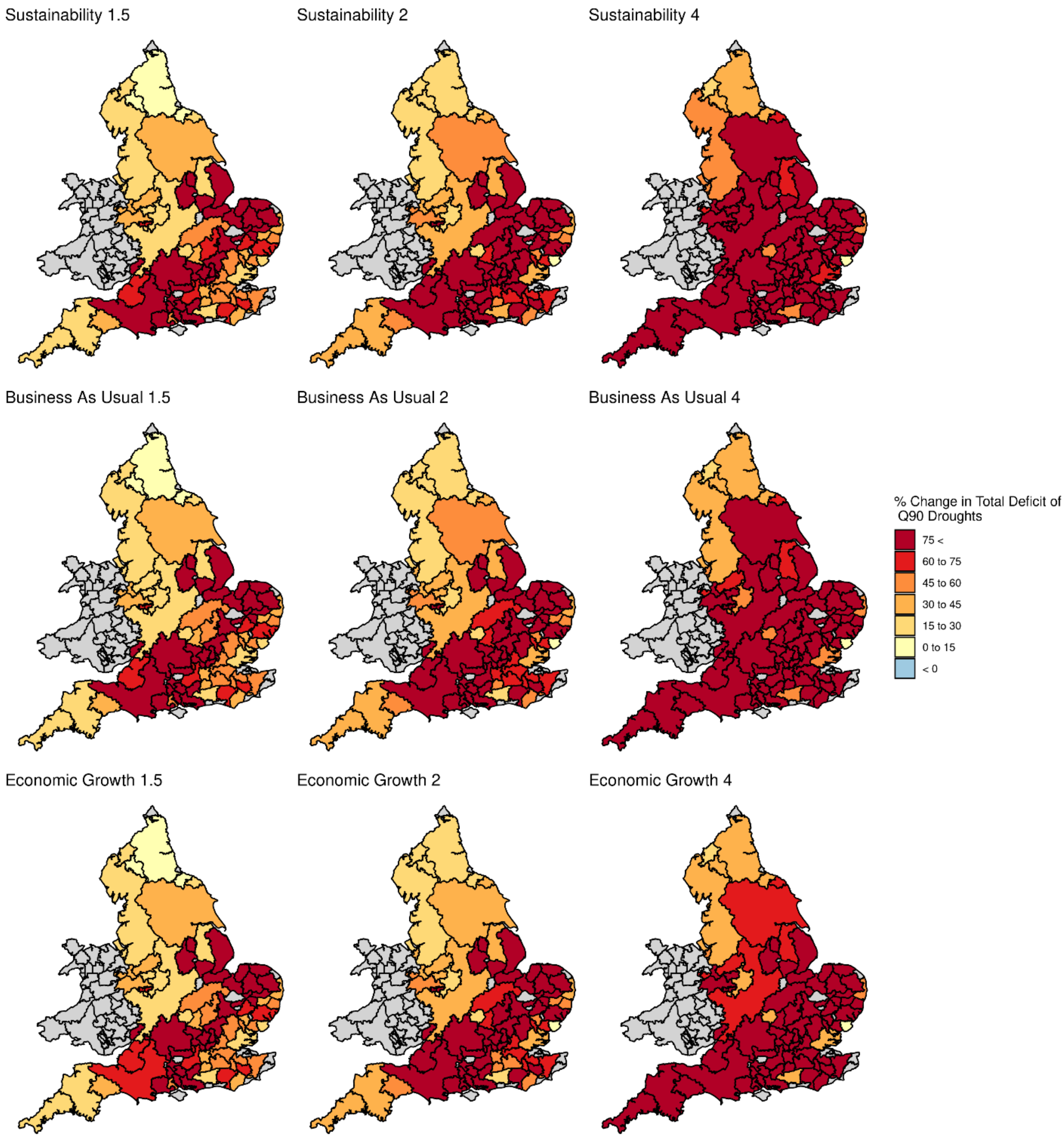


Figure 12: Map showing mean percent difference in drought severity (total deficit) between the combination of each AI scenario (rows) and warming level (columns) with the BSO flows for Q90 (severe droughts) for each WRZ.

5. Discussion and Conclusions

5.1 Main Findings and Implications for Water Management

The analysis presented in this report provides valuable insights into future water availability and its potential implications for policy makers and water managers. Most of our findings align with prior climate change assessments on water availability (e.g., Parry et al., 2023). What sets this study apart is its pioneering inclusion of high-resolution artificial influence scenarios in the context of England's water resources. The key findings can be summarised as follows:

- **Decrease in mean annual flows:** The analysis indicates a clear expected decrease from 1981 to 2080 in mean annual flows for most southern catchments, while trends in the northern half of the country are less definitive. This projected decrease in mean annual flows has significant implications as it suggests potential water scarcity issues in the affected regions.
- **Seasonal variations in monthly mean flows:** The analysis shows a slight increase (median increase of 1%) in mean monthly flows during winter and spring, while a decrease (median decrease of 33%) is expected during the summer months. This seasonal variation in monthly flows could impact water management practices, such as reservoir management and irrigation planning.
- **Regional differences:** The analysis highlights regional variations in the projected changes in flow metrics and drought characteristics. Different water regions and water resource zones exhibit distinct patterns of change in low flows and droughts. This regional variability necessitates tailored water management strategies that consider the specific challenges and opportunities in each region. The southern and south-eastern parts of England is expected to see the more pronounced changes in drought characteristics.
- **AI scenarios:** Furthermore, the analysis reveals an intriguing finding regarding the influence of different AI scenarios on water availability. Contrary to expectations, the 'Economic Growth' AI scenario, which prioritises economic growth over sustainability, demonstrates relatively less change compared to the baseline in contrast to the 'Sustainability' AI scenario, which emphasises sustainability over economic growth, particularly at higher warming levels. This unexpected outcome can be attributed at least partially to the significant water consumption associated with certain 'cleaner' energy sources, notably Hydrogen. However, it is important to note that throughout the analysis, the impact of warming levels on drought characteristics is significantly stronger than the influence of the AI scenarios. It is worth

considering that a 'Sustainability' AI scenario emphasising sustainability and 'clean' energy adoption might have the potential to mitigate the adverse effects of warming, potentially leading to greater and wider benefits. However, this hypothesis requires further investigation – the precise nature of this offsetting is very complex and further work would be needed (including detailed local-scale modelling of particular energy developments) to explore this, building on this initial analysis.

5.2 Limitations

While this analysis provides valuable insights into future water availability, it is important to acknowledge certain limitations that may affect the interpretation of the results. These limitations include:

- **Climate and hydrological uncertainties:** The projections of future flows are subject to uncertainties associated with climate models and hydrological modelling. The analysis is based on downscaled and bias-corrected climate data from the UKCP18 dataset, used to drive one single hydrological model (Grid-to-Grid) to produce future projections of river flows. However, alternative climate and hydrological models may yield different results. The inherent uncertainties in climate projections and hydrological modelling should be considered when interpreting the findings. Some recent studies discuss in more detail the uncertainties involved in eFLaG projections (Hannaford et al., 2023; Parry et al., 2023; Aitken et al., 2023), and highlight the relative role of hydrological versus climate model uncertainty.
- **Simplified representation of AI scenarios:** The analysis considers three AI scenarios representing different priorities and assumptions regarding water demand and usage. However, as noted in Baron et al. (2023), these scenarios may not capture the full range of possible future developments and policy pathways. The AI scenarios presented in this study should be seen as simplified representations and further refinement and inclusion of additional scenarios could provide a more comprehensive understanding of future water availability. Moreover, the AI scenarios are based on averages, and they do not account for seasonal or event-based variations (i.e. hot summer droughts), which is a major limitation given the focus on droughts and low flows of this analysis. Abstractions can vary significantly during drought periods and therefore our results are likely to be biased.

- **Limited spatial representation:** Although the study includes a substantial number of catchments (626 in total), there are still gaps that prevent a comprehensive representation of the entire nation. The underlying data is gridded at a 1km resolution, which presents an opportunity for future exploration of spatial differences in a more comprehensive and fully distributed manner.

5.3 Future work

Future work should aim to address the limitations mentioned previously.

Firstly, a larger ensemble of climate projections derived from multiple climate models would provide a more robust assessment of the potential future climate conditions and associated uncertainties. Additionally, incorporating multiple hydrological models into the analysis would enhance the understanding of the uncertainties associated with hydrological modelling.

Furthermore, improving the AI scenarios by allowing seasonal and event specific variations, as well as expanding the range of AI scenarios by incorporating, for example, additional combinations of policy pathways and alternative population growth projections would provide a more comprehensive evaluation of the potential impacts and trade-offs.

Future work could also consider targets such as environmental flows. Analysing whether environmental flow thresholds will be crossed more frequently in the future can help identify potential risks to aquatic ecosystems and guide the formulation of mitigation measures.

Finally, leveraging the distributed nature of the Grid-to-Grid model, future work should focus on conducting a more comprehensive analysis of the spatial patterns of future river flows, allowing a better understanding of localised impacts and vulnerabilities.

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7. Appendix 1: Content of the supplementary material

Supplementary information is available in the form of a compressed zipped folder that includes all figures that could not be accommodated within this report due to space constraints. The structure of the zipped folder is elaborated in Figure A1 below.

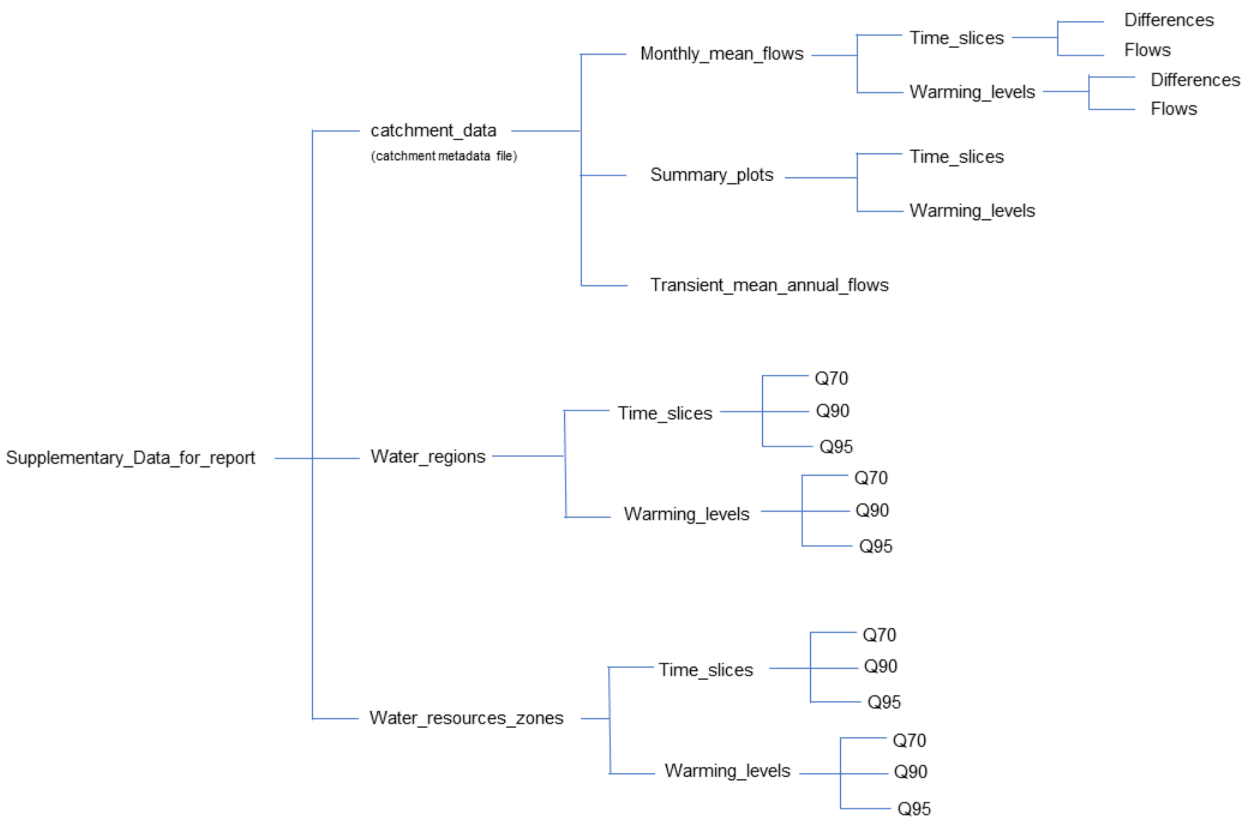

Figure A1: Folder structure of the zipped supplementary material.

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Climate services for a net zero resilient world