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Climate change effects on indicators of high and low river flow across Great Britain

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Abstract

Changes in river flows, especially extreme high and low flows, could be a particularly important impact of climate change in terms of the hazard to people and the environment. Here, a national-scale grid-based hydrological model is applied, with ensembles of global and regional climate projections from UK Climate Projections 2018, to investigate the potential future changes in both floods and droughts in a consistent way across the whole of Great Britain (gauged and ungauged locations). Using hydrological model outputs for the climate projection ensembles, a clustering technique is applied to highlight 'typical' sets of changes in individual indicators of floods or droughts, but also to look at concurrent changes in pairs of flood and drought indicators. The results for regions across the country generally indicate decreases in low flows combined with increases in high flows up to the end of the 21st century. There is significant variation in results for different regions, with those to the south/east tending to show greater decreases in low flows and a greater range of uncertainty in the projections for high flows. A grid-based cluster analysis also shows potentially important variation within regions, likely related to catchment properties. The potential future changes in derived climate hazards, such as the frequency or severity of floods and droughts, is a key piece of information required for adaptation planning, and the consideration of potential concurrent changes in a range of related hazards/risks, rather than viewing each in isolation, could be vital to avoid maladaptation.

Keywords

Climate change; hydrological impacts; rainfall-runoff; UKCP18; flood; drought

1 Introduction

The impact of projected climate change on the hydrological cycle is likely to be particularly apparent in changes in river flows, with extreme high and low flows potentially presenting a hazard for people, infrastructure, and the natural environment. There is some evidence that climate change has already affected occurrence of both floods (Razavi et al. 2020, Blöschl et al. 2019) and hydrological droughts (Dai 2013) in some parts of the world. In Britain, a series of recent floods (e.g. winters 2019/20, 2015/16 and 2013/14, summer 2012) and droughts (e.g. summer 2018, 2010-2012) have led to questions about the role climate change may already be having in such events (e.g. Pall et al. 2011, Kay et al. 2018b). The potential for future increases in magnitude and/or frequency of floods and droughts is a major concern (Jiménez Cisneros et al. 2014).

Much of the research into the impacts of climate change on river flows in Britain has applied the UK Climate Projections 2009 (UKCP09; Murphy et al. 2009), which provided information about potential future climatic change via a range of products. For example, Prudhomme et al. (2012) looked at changes in mean seasonal river flows across Britain by the 2050s (medium emissions), simulated with the CERF hydrological model using change factors derived from the UKCP09 11-member perturbed parameter ensemble (PPE) of a Regional Climate Model (RCM). They showed consistent decreases in summer flows but both increases and decreases in winter flows, depending on location and ensemble member. Christierson et al. (2012) investigated changes in mean annual and monthly flow for 70 catchments by the 2020s (medium emissions), simulated with two catchment-based hydrological models using sub-samples of the UKCP09 probabilistic projections. There was a high likelihood of a significant decline in summer flows. Charlton and Arnell (2014) simulated changes in high flow (Q5) and low flow (Q95) (respectively, the flow exceeded 5% and 95% of the time) for 6 catchments in England with the Cat-PDM hydrological model and the UKCP09 probabilistic projections. All 10,000 projections showed a decrease in low flows by the 2050s (medium emissions), while the proportion of projections giving an increase in high flows varied significantly between catchments, ranging from 20% to 80% by the 2050s.

Studies specifically focussing on floods using UKCP09 projections include Cloke et al. (2013), who show likely increases in annual maximum flows in the upper Severn catchment using the HBV hydrological model and the UKCP09 RCM PPE, and Bell et al. (2016), who show likely increases in 5- and 20-year return period peak flows across much of Britain using the Grid-to-Grid national-scale hydrological model with the UKCP09 RCM PPE. Similarly, Collet et al. (2017) show typical increases in the 100-year return period flood by the 2080s, using data for 281 catchments across GB. Kay and Jones (2012b) compare the use of alternative UKCP09 products to assess potential impacts on floods by the 2080s (medium emissions) for nine catchments in Britain. The results suggest likely future increases in 2- and 20-year return period peak flows in most cases, with relatively good agreement between methods, but with potential decreases in peak flows for some catchments in the south.

Studies specifically looking at droughts or water shortages using UKCP09 projections include Harris et al. (2013), who considered metrics related to triggering of reservoir controls for the North Staffordshire Water Resource Zone, using the HySim hydrological model and Aquator water resource model with time-series data from the UKCP09 weather generator. They showed that climate change was likely to significantly increase the threat of water scarcity. Similarly, Gosling (2014) modelled 22 catchments across Scotland using the UKCP09 RCM PPE, and showed an increase in summer water resource scarcity by the 2050s. More recently, the MaRIUS project (Managing the Risks, Impacts and Uncertainties of drought and water Scarcity) produced large numbers of RCM simulations (initial condition ensembles for baseline, near-future and far-future periods under RCP8.5 emissions) specifically designed for analysis of droughts (Guillod et al. 2018). Using these data to drive the Grid-to-Grid hydrological model, Rudd et al. (2019) showed that the severity of hydrological droughts is projected to increase in the future, while the peak intensity is projected to increase in south-eastern regions but decrease for much of the rest of Britain. Similarly, Kay et al. (2018a) showed future reductions in 7- and 30-day low flows of 2- and 20-year return periods, which are generally larger in the south, and Dobson et al. (2020) showed a worsening of extreme droughts in the future, using a water resource system model for England and Wales.

One factor highlighted by the above selection of papers is that floods and droughts are typically studied separately, and that differences in the models, methods and datasets applied make comparisons between studies difficult. A rare exception is Collet et al. (2018), who look at potential future changes in floods and droughts using a consistent method based on simulated data available for 281 catchments across Britain. They highlight 'hotspots' where future changes in the frequency, magnitude and duration of both floods and droughts increase by at least a certain amount. Catchments in the west of the country are more likely to be identified as hotspots. Visser-Quinn et al. (2019) use a similar technique to look at compound flood and drought hazard for 239 catchment across the UK simulated using three hydrological models and five Global Climate Models (GCMs).

This paper investigates potential future changes in both floods and droughts in a consistent way across the whole of Great Britain (GB) — gauged and ungauged locations — using a national-scale grid-based hydrological model. It also applies the recent UK Climate Projections 2018 (UKCP18; Murphy et al. 2018), which were released by the UK Met Office to update the UKCP09 projections and similarly provide information about potential future climatic change via a range of products. Using hydrological model outputs for the climate projection ensemble, a novel application of a clustering technique is used to highlight 'typical' sets of changes in individual indicators of floods or droughts, but also to look at concurrent changes in pairs of flood and drought indicators. The methods are described in Section 2, with results presented Section 3, discussion in Section 4 and conclusions in Section 5.

2 Methods

2.1 Hydrological model

The Grid-to-Grid (G2G) is a national-scale grid-based rainfall-runoff and routing model that typically operates on a 1km grid across GB at a 15-minute time-step (Bell et al. 2009), and includes an optional snow module (Bell et al. 2016). The model is parameterised using spatial datasets (e.g. soil grids) rather than catchment calibration.

Bell et al. (2009) looked at model performance for 42 catchments across GB and showed that use of soil datasets enabled good performance, even for those with a higher proportion of baseflow. This was confirmed by an analysis for 34 catchments in the Thames basin, which also highlighted the differences between modelled and observed flows when the latter are affected by factors like abstractions and discharges (Bell et al. 2012); anthropogenic influences are currently not included in the model, although work is underway to do so. The analysis of Bell et al. (2016) for 13 upland catchments showed that the incorporation of a snow module improved performance, enabling the delay of water inputs from snow until melt occurs. Rudd et al. (2017) investigated model performance for low flows in 61 catchments across GB, showing reasonable performance for most (albeit better for monthly mean flows than daily mean flows). No clear relationships were found between model performance and catchment properties, suggesting that the use of spatial datasets by G2G is effective in enabling differences in hydrological response due to different physical characteristics. Formetta et al. (2018) looked at estimation of the index flood for 550 catchments across GB, and showed good correspondence between the model-derived values and those derived from observed data. Similar to Rudd et al. (2017), no clear relationships were found between model performance and catchment properties, suggesting that the model provides estimates of consistent quality across various types of catchment. In summary, G2G has been shown to perform well for a wide range of catchments across GB, particularly those with a relatively natural flow regime. As such, the model is well-suited to the consistent simulation of river flows across the whole country, at gauged and ungauged locations, under potential future changes in climate.

G2G requires gridded input time-series of precipitation and potential evaporation (PE), as well as temperature data if the snow module is applied. Here, 1km grids of daily precipitation and min and max temperature are used (HadUK-Grid v1.0.0.0; Met Office et al. 2019), along with 40km grids of monthly short grass PE from the UK Met Office (MORECS; Hough and Jones 1997). The daily precipitation data are divided equally over each model time-step within a day, while the temperature data are interpolated through the day using a sine curve. The monthly PE data are copied down to the 1km grid and divided equally over each model time-step within a month.

The model produces estimates of daily mean 'river flow' for every 1km grid box but only data from grid boxes with a catchment area of at least 50km^2 are analysed here, as use of daily precipitation divided equally over the model time-step is unlikely to be appropriate for smaller catchments (Formetta et al. 2018). Tidal river points are also excluded. One feature of the model setup which is useful in this application is the ability to save a file of model 'states' (typically values of water storage) at a given time, for use as an initial condition for subsequent model runs.

2.2 Climate change projections

The UK Climate Projections 2018 (UKCP18; Lowe et al. 2018, Murphy et al. 2018) provide a range of products to enable assessment of the impacts of climate change in the UK over the 21st century. Two products are applied here — UKCP18 Global (60km) and UKCP18 Regional (12km) projections (Met Office Hadley Centre 2018a,b).

The UKCP18 Global projections comprise a 28-member ensemble, with 15 members (01-15) from a PPE of the Met Office Hadley Centre GCM and the other 13 (16-28) from alternative GCMs taken from CMIP5 (see Murphy et al. 2018 Table 3.1). The inclusion of data from other GCMs enables investigation of climate model structure uncertainty (although ensemble member 27 is excluded here, due to problems with the wind data), while the 15-member Hadley PPE covers climate model parameter uncertainty, and together they also cover natural internal variability. Ensemble member 01 represents the standard parameterisation of the Hadley Centre GCM. These projections are for Dec 1899–Nov 2099 under RCP8.5 emissions (Riahi et al. 2011).

The UKCP18 Regional projections comprise a 12-member PPE of the Met Office Hadley Centre RCM, with each member nested in the equivalent GCM PPE member (note that there are no RCM members corresponding to GCM members 02, 03 and 14). Ensemble member 01 represents the standard parameterisation of the RCM. These projections are for Dec 1980–Nov 2080, also under RCP8.5 emissions.

The UKCP18 Global and Regional data are available re-projected from the native grids, to provide data covering the UK aligned with the GB national grid at 60km and 12km resolutions respectively. The re-projected monthly precipitation and temperature data are used here.

PE for short grass is not available directly from the climate models, but is estimated from other monthly climate variables (net downward surface long- and short-wave radiation, relative humidity, wind speed and temperature) using the Penman-Monteith formulation (Monteith 1965), including future changes in stomatal resistance under higher atmospheric CO_2 concentrations (Rudd and Kay 2016, Guillod et al. 2018). For some of the 13 CMIP5 GCMs, not all of the data required to estimate PE are available at the monthly time-step so the available seasonal data have been interpolated to monthly. This applied to multiple GCMs: members 16-18 and 22 lack wind speed; 20, 22 and 26 lack relative humidity; and 16-28 are missing long- and short-wave radiation. In all cases, a cubic spline was used to interpolate seasonal data to monthly intervals (following tests comparing monthly data with interpolated seasonal data for ensemble members with data at both time-steps). PE is also only estimated for climate model grid boxes classed as ‘land’, with PE for other boxes initially set to missing because direct estimation of PE using climate data for ‘sea’ boxes can lead to unrealistic values. However, some coastal 1km G2G grid boxes are located within climate model ‘sea’ boxes; in these locations, PE data are copied from the nearest climate model ‘land’ box.

2.3 Application of climate change projections

While RCM data can be used to directly drive hydrological models (e.g. Fowler and Kilsby 2007, Dankers and Feyen 2008, Bell et al. 2016), GCM data are generally considered too coarse for direct use in hydrological modelling in Britain, where even the largest catchment would only be covered by about three 60km grid boxes. Thus to enable use of both the UKCP18 Global and Regional projections, the delta change approach (sometimes called the change factor method) has been adopted. This involves the application of monthly change factors for a climate variable to a baseline time-series for that variable (e.g. Arnell 2003, Kay et al. 2020). While this gives perturbed time-series similar to the baseline in terms of relative size and ordering of events (Cloke et al. 2013), it has the advantage of avoiding potential issues with bias in climate model variables because it only uses changes rather than absolute values. The approach was used instead of more complex methods because a) it means that the baseline time-series is the same for each simulation, and b) bias-adjustment of climate model data generally lacks a sound physical basis, does not satisfy conservation laws, and adds uncertainty (e.g. Ehret et al. 2012, Teng et al. 2015, Maraun et al. 2017).

Previous applications of the delta change approach have typically involved use of fixed baseline and future time-slices, where the model is run with baseline observed climate time-series data, then re-run with the baseline data adjusted using monthly change factors derived to represent the mean monthly changes for a specific future time-slice relative to the baseline time-slice. Previous applications have also typically involved use of lumped or semi-distributed catchment-based hydrological models, with the same delta changes usually applied for the whole catchment. The change factors are multiplicative for precipitation and PE, and additive for temperature.

Here though, a transient grid-based approach was taken. This involves deriving grids of change factors for each month and year from the climate projection data, using multiple future 30-year time-slices moving on one year at a time, relative to a fixed baseline time-slice (Dec 1980–Nov 2010); the monthly change factors for a specific year are therefore calculated from the mean change over the 30 years centred on that year. The gridded observed climate time-series data (daily precipitation, daily min and max temperature and monthly PE; Section 2.1) for the baseline period are copied three times to cover the period up to Nov 2100, then the change factors are applied to the copied baseline data at the centre of the future 30-year time-slice (Figure 1). That is,

- the delta change grids derived as a mean change for Decembers 1995–2024 (relative to Decembers 1980–2009) are applied to data for Dec 2010 (copied from Dec 1980);
- the delta change grids derived as a mean of Januarys 1996–2025 (relative to Januarys 1981–2010) are applied to data for Jan 2011 (copied from Jan 1981);
- and so on, up to
- the delta change grids derived as a mean change for Novembers 2085–2114 (relative to Novembers 1981–2010) are applied to data for Nov 2100 (copied from Nov 2010).

The change factors applied to the baseline data in each 1km grid box are those from the Global 60km or Regional 12km grid box within which it sits. A similar transient delta change approach was taken by Arnell et al. (2020).

The change factors for a year are constructed from 30-year mean changes. To estimate change factors for the last few (15) years it is therefore necessary to extrapolate for 15 years beyond the last year to calculate the 30-year mean. For example, to derive delta changes for Nov 2100, data are required for Novembers 2085–2114. For the Global projections, this extrapolation was done by simply fitting a linear regression to the last 40 years of data. The Regional projections only extend to 2080, so the change factors beyond 2080 were estimated from the corresponding Global projection ensemble member (scaled to account for differences between the Global and Regional model anomalies in the overlap period). Supp. Figure 1 presents examples of the derivation of extrapolated delta changes.

The derived delta changes show that precipitation tends to increase in winter and decrease in summer, particularly for later time-slices (e.g. Supp. Figure 2). Temperature generally increases throughout the year (e.g. Supp. Figure 3). PE typically increases in the late spring, summer and early autumn, with some potential decreases at other times of year, although winter changes are noisier since PE then is fairly low (e.g. Supp. Figure 4).

To achieve full transient outputs without repeating the baseline part of each run, and to enable use of water years for annual maxima (see Section 2.4), the G2G model's state initialisation ability is used. Firstly, a spin-up run is completed for 1st Jan 1970 to 31st Sep 1980, with the end states saved. Then the baseline run is completed for 1st Oct 1980 to 31st Nov 2010, initialised using the states from the spin-up run, and writing a states file for 31st Sep 2010. Then, for each Global and Regional ensemble member, the three 30-year time-slices of delta change runs are completed (1st Oct 2010 to 31st Nov 2040, 1st Oct 2040 to 31st Nov 2070, and 1st Oct 2070 to 31st Nov 2100, using the baseline data for 1st Oct 1980 to 31st Nov 2010 in each case, and initialised using the states files output on 31st Sep of the previous time-slice in each case). In this way, the delta change runs are effectively continuous transient runs, but split to enable easier setup and processing.

2.4 High and low flow indicators

G2G is run with the transient delta change grids derived for each Global and Regional ensemble member. To analyse potential future changes in high flows, the annual maxima (AMAX) of daily mean flows are extracted for each water year (Oct-Sep) during each run. The water year is used to try to avoid extraction of the same high flow event in two consecutive years. To analyse potential future changes in low flows, the annual minima (AMIN) of running 7-day and 30-day mean flows are extracted for each Dec-Nov 12-month period during each run. AMIN extraction would usually use calendar years, but Dec-Nov is used here to match with the climate model data running from December of the first year to November of the final year, whilst still likely avoiding extraction of the same low flow event in two consecutive years.

Moving window analysis is then used to investigate transient changes in high and low flows, in a similar way to Kay et al. (2012a, 2018a). A 30-year moving window is applied, moved on by one year at a time, with high (low) flow frequency curves fitted to the 30 AMAX (AMIN) covered by each position of the window. As recommended for GB, the high flow frequency curve is fitted using the generalised logistic distribution (Robson and Reed 1999), while the low flow frequency curve is fitted using the generalised extreme value distribution (Zaidman et al. 2002). From each fitted curve, 5- and 20-year return period flows are derived.

To enable regional averaging, the 5- and 20-year return period high (low) flows for each 1km cell are standardised by dividing by the baseline 2-year return period high (low) flow (referred to subsequently as 'scaled magnitude'). This scaling is analogous to use of growth curves (e.g. Hosking and Wallis 1997). Regional averages are then calculated for each indicator (high flow and low flow of a specific return period) and each ensemble member, for the UKCP18 river-basin regions (Figure 2). The baseline performance of the standardised 5- and 20-year return period high and low flows, compared to gauged flows, is relatively good (Supp. Section 1.2).

2.5 Cluster analysis

For each indicator and each region (Section 2.4), there are time-series results for 27 GCM and 12 RCM ensemble members (Section 2.2); a large amount of data. To reduce this, time-series clustering is applied as described below, to derive a small number of exemplar ensemble members for each indicator in each region. Note that the selection of exemplars does not imply greater probability – they are simply representative of a cluster of similar possible outcomes.

The time-series clustering is performed using Dynamic Time Warping (DTW; Sakoe and Chiba 1971) and DTW Barycenter Averaging (DBA) implemented in R using the *dtwclust* package (Sara-Espinosa 2019). In this method, the distance between each time-series is computed using DTW, designed to give small distances to time-series which have similar features even if the features are offset in time, by trying to "warp" the time-steps of one time-series to make it match a second as closely as possible (Supp. Section 1.3). Then clusters of time-series are generated such that within-cluster distances are minimised and between-cluster distances are maximised, using DBA by adjusting and optimising the clusters' centres-of-mass by reassigning time-series to different clusters. To summarise each cluster, the time-series closest to the centre of the cluster (as measured using DTW) is selected as an exemplar. This exemplar should be considered representative of the “average” behaviour of a cluster, but a cluster may vary in how close together members are in DTW distance, and some within-cluster variability is likely. To determine the optimal number of clusters in each region, the process is tried for two to five clusters, and the number of clusters is chosen which maximises the Calinski-Harabasz score, a ratio of between-cluster and within-cluster variance (Calinski and Harabasz 1974).

As well as applying the cluster analysis to individual indicators, the methodology is applied to pairs of indicators. Combinations of indicators can tell a more nuanced story of possible hydrological changes due to climate change than single indicators in isolation. For example, some regions may experience worse droughts and worse floods while others may experience worse droughts but reduced flooding. To understand how pairs of high and low flow indicators jointly change over time in each region, the clustering procedure was performed for bivariate time-series to identify sets of ensemble members with similar response for both the high and the low flow indicators. DTW was computed component-wise and summed to give distances, as different indicators were assumed to not directly depend on each other; rather the indicators all depend on a set of underlying climatic, meteorological and hydrological processes.

Finally, to examine spatial similarity in the hydrological response to projected future changes in climate, a grid-based clustering is performed to identify geographical regions (sets of 1km grid cells) with a similar response. This is used to highlight areas with differing response (e.g. due to chalk vs clay soils/geology), which may be masked by use of regional averaging of indicators. For computing reasons, this 1km grid-based analysis is done for a subset of indicators and for a single climate ensemble member (RCM 01), keeping the number of clusters fixed to five.

3 Results

3.1 Regional average high flow changes

The results for 5-year and 20-year return period high flows typically show an increase over time in response to climate change, across all regions and both return periods, although regions to the south/east (e.g. SE England, Thames and Anglian) can show decreases and tend to have a greater range of climate projection uncertainty (Figure 3). This is consistent with the typical increases in winter precipitation (Supp. Figure 2). The cluster analysis identifies only two clusters for the majority of regions; the North Highland region is unique in having four clusters at both return periods.

For 5-year return period high flows in the most south-easterly regions (Anglian, Thames and South East England), one exemplar indicates an increase in high flows but the other exemplar indicates a decrease in high flows by the end of the time period (Figure 3). In contrast, regions across the rest of the country almost exclusively display multiple clusters with exemplars that indicate increased high flows, although some regions (e.g. Severn and Dee) have clusters with exemplars showing an initial decrease and then an increase. For two regions (West Highland and Severn) a small cluster (fewer than three members) is identified which indicates greatly increased high flows. In contrast, the two small clusters in the North Highland region (each with fewer than five members) indicate relatively little change in high flows by the end of the time period.

For 20-year return period high flows the geographic split seen for 5-year return period high flows shifts location (Figure 3). While northern and north-western regions still primarily display clusters that tend towards increases in high flows, eastern regions from Tweed southwards display one cluster with decreasing high flows, and the Severn shows a similar pattern. Only two regions display clusters with fewer than five members: North Highlands, in which the small cluster again shows relatively little change in high flows by the end of the time period, and Severn, in which the small cluster is meandering in nature but generally reflects large increases in high flows. The future changes for 20-year return period high flows are generally less smooth in their progression through time than for 5-year return period high flows, due to inherent greater uncertainty in estimation of higher return period flows.

3.2 Regional average low flow changes

The results for 5-year and 20-year return period low flows typically show a decrease over time in response to climate change, across all regions and both return periods for both 7-day and 30-day durations (Figure 4). Decreases tend to be larger in regions to the south/east. This is consistent with the typical decreases in summer precipitation and increases in PE (Supp. Figures 2-4). As for high flows, the cluster analysis identifies only two clusters for the majority of regions. The exemplars of the clusters identified within each region generally display similar behaviour for both 7-day and 30-day low-flows.

For 5-year return period low flows the cluster exemplars generally indicate a decrease in low flows throughout the analysed time period (Figure 4). The exceptions are in regions that display a higher than average number of clusters, where smaller clusters (fewer than five members) can show small increases in low flows (e.g. Tay and Northumbria). For the Tay for example, there are four clusters identified for the 30-day duration low flows, one of which indicates increasing low flows. The northern Scottish regions (West Highlands, North Highlands and North East Scotland) all have one cluster indicating a decrease in low flows and a second cluster with a flatter response through the time period.

There are similar overall patterns for the 20-year return period low flows (Figure 4); most regions display two clusters that both indicate a decrease in low flows. However, the only region with a cluster showing a (marginal) increase in low flows is Northumbria (for 30-day duration), although Anglia has a smaller cluster showing a flat response. While the West Highland region still displays a cluster with a flatter response, the other northern Scottish regions now display multiple clusters with decreasing low flows.

3.3 Regional average high and low flow changes

The paired clustering results, performed for selected pairs of high and low flow changes (i.e. 5-year return period high flows with 5-year return period 7-day low flows, and 20-year return period high flows with 20-year return period 7-day low flows) show some significant differences between regions (Figure 5 and Supp. Section 2.1).

Most regions have only two clusters, with only Argyll and SW England (5-year) and NW England, Northumbria and West Wales (20-year) giving three clusters. For all eastern regions, the cluster exemplars are in the same order for both high and low flows. Specifically, the cluster exemplar with the greatest decrease in low flows also has the least increase (or greatest decrease) in high flows, while the cluster with the least decrease in low flows also has the greatest increase (or least decrease) in high flows (e.g. SE England, Figure 5). In contrast, western regions are much more variable in high vs low flow response. For example, for 5-year return period flows, while the two clusters in West Highland behave similarly to those for the eastern regions, the two clusters in NW England have exemplars that swap order over time but end up in the same order for high and low flows, and the two clusters in West Wales have exemplars consistently of opposite order for high and low flows — the cluster with the greatest decrease in low flows also has the greatest increase in high flows. For Argyll, for 5-year return period flows, all three cluster exemplars show relatively similar increases in high flows, but they show very different changes in low flows — two show decreases, of different amounts, but one shows a small increase. Results for 20-year return period flows can differ to some extent from those for 5-year return period flows, particularly in terms of number of clusters, but the general pattern is similar.

Many of the cluster exemplars show changes over time that are roughly monotonic, particularly for low flows and the lower return period, although with varying rates so the cluster order can change over time. However, some cluster exemplars show highly non-monotonic behaviour, with a period of increases followed by a period of decreases, or vice-versa (Figure 5 and Supp. Section 2.1).

These results indicate that the nature of the combined response of high and low flows to climate change is variable across the regions, and that there is significant variability between climate ensemble members.

3.4 Analysis of cluster exemplars and membership

To assess whether specific ensemble members are commonly chosen as exemplars across different regions, the number of times each ensemble member is chosen is counted for each indicator. This shows that there are no ensemble members consistently selected, across all regions, for any indicator (Figure 6a). Every ensemble member is selected at least once as a regional exemplar, for at least one high or low flow indicator, but GCM/RCM 05 occurs frequently for low flows, and some ensemble members (GCM/RCM 01 and 10 and GCM 22) are selected in at least one region for all indicators. However, there is a tendency for the largest two clusters to have one exemplar from the Hadley PPE (either RCM or GCM 01-15) and one from the CMIP5 GCMs (16-28), particularly for low flows (Figure 6b).

Even though no ‘universal’ exemplars are identified, there may be subsets of ensemble members which are repeatedly found in the same cluster, which may lead to simpler summaries of future changes in indicators. Examining the clusters as a whole, a simple similarity metric was computed by summing, across all considered indicators and regions, the number of times a pair of climate ensemble members has different cluster labels. There is a clear distinction between the Hadley PPE and the CMIP5 GCMs, showing great similarity within these groups and high dissimilarity between them (Supp. Section 2.2). Using a hierarchical ordering, high similarity can also be seen between equivalent RCMs and GCMs (e.g. RCM 08 and GCM 08), shown through close proximity on the axes.

3.5 Grid-based high and low flow changes

The results of the national 1km clustering for 5-year return period high flows (for RCM 01) highlight a high level of spatial variability in the response (Figure 7a). Although some clusters are generally more dominant in the west and others are more dominant in the east, areas covered by the same cluster can be far apart and relatively disconnected from each other. This suggests that spatial variation in catchment properties (which can occur at relative small spatial scales), as well as spatial differences in climatic change (which generally only occur at larger spatial scales), affect the spatial pattern of response. As an example, analysis of a proxy baseflow index derived from soil data (BFIHOST; Boorman et al. 1995) for the 1km points within each cluster shows that cluster 1, which has the largest change in scaled high flow magnitude over time, is more likely to have higher baseflow (Figure 7a). Previous work has shown a relationship between catchment properties and potential future changes in flood peaks in Britain (Kay et al. 2014).

The results of the national 1km clustering for 5-year return period low flows (for RCM 01) show less spatial variability in the response than for high flows (Figure 7b). Areas covered by the same cluster show a general north/north-west to south/south-east pattern and are relatively spatially coherent, suggesting that low flow changes are perhaps more affected by spatial variations in climatic change than catchment properties. However, previous work has suggested that potential future changes in droughts in Britain could be worse in groundwater-dependent areas (Rudd et al. 2019), and the low flow results in Figure 7b are consistent with that as cluster 1 shows the largest decrease in scaled low flow magnitude over time and is also more likely to have higher baseflow (using BFIHOST).

4 Discussion

The simulated future decreases in low flows are consistent with previous studies using UKCP09 projections (e.g. Charlton and Arnell 2014, Christierson et al. 2012) and later large ensemble projections for GB (Visser-Quinn et al. 2019, Kay et al. 2018a). Similarly, the typical increases in high flows, with potential decreases in some locations, are consistent with previous studies using UKCP09 (e.g. Collet et al. 2018, Bell et al. 2016, Kay and Jones 2012b) and a recent study using the UKCP18 probabilistic projections in a sensitivity-based approach (Kay et al. 2021).

The UKCP18 Global and Regional projections are only available for the RCP8.5 emissions scenario, which is a high scenario (Riahi et al. 2011) but should not be considered implausible, particularly up to mid-century (Schwalm et al. 2020). Lower scenarios should lead to lower eventual impacts (e.g. Kay et al. 2021). Also, all of the UKCP18 Regional projections and 15 of the 27 UKCP18 Global projections are from the same climate model — that of the Met Office Hadley Centre (Section 2.2) — and there is high similarity between equivalent Regional and Global PPE members. The remaining 12 global projections are each derived from different GCMs, which is very valuable in terms of assessing climate model uncertainty as the Global multi-model ensemble tends to cover a broader range of potential climatic changes than the Regional PPE (Supp. Section 1.1). Future work could apply projections from other climate modelling projects (e.g. EuroCORDEX, Jacob et al. 2020). The use of only one hydrological model is an additional potential source of uncertainty, particularly for low flows (e.g. Vetter et al. 2017), but climate models are generally considered to be the main source of uncertainty in projected hydrological changes (e.g. Thober et al. 2018, Marx et al. 2018).

Rather than directly using the climate model data to drive the hydrological model, the delta change method is used to apply climatic changes derived from climate models to baseline observed climate data. As well as enabling the application of the coarser resolution Global multi-model ensemble alongside the Regional PPE, this method has a number of advantages, including the typically higher spatial resolution of available observed data (Section 2.3), however it does not allow for future changes in the variability or sequencing of events (Cloke et al. 2013). Future work could apply more complex delta change methods (e.g. van Pelt et al. 2012), and compare results to direct use of RCM data. Use of future climate time-series has been shown to lead to a broader impact range than use of delta changes when modelling future change in flood peaks, although ensemble median impacts were similar (Kay and Jones 2012b).

Other factors that are likely to affect future changes in river flows include changes in land-cover, and changes in patterns and amounts of abstractions and discharges. Such factors are highly complex to project into the future, and not included in the hydrological modelling here. A further factor not included here is the effect of a possible increase in leaf area index (due to carbon fertilisation of vegetation) on future PE, although stomatal closure under higher CO_2 concentrations is included (Rudd & Kay 2016).

Further work will look at clustering for a wider range of indicators of change in river flow, and how clusters relate to catchment properties. Using fuzzy clusters, which assign probabilities of being in one cluster or another, would give more flexibility in cluster membership so that nearby clusters could be more easily identified. If uncertainty in the indicator time-series is well described, then this could be included. If exact timings of regime changes are of interest, a Euclidean metric could replace the Dynamic Time Warping approach to give stronger weight to temporal coincidence of features.

5 Conclusions

The analysis presented here shows the potential impacts of climate change on extreme high and low flows across Great Britain. The impacts are modelled in a consistent way, using a grid-based hydrological model with a transient delta change approach and Global and Regional climate projections from UKCP18 – the latest climate projections for the UK. Clusters are used to summarise the results from the climate projection ensembles. The results generally indicate decreases in low flows combined with increases in high flows up to the end of the 21st century. There is significant variation in cluster exemplars for different regions of the country, with regions to the south/east tending to show greater decreases in low flows and a greater range of uncertainty in the projections for high flows (including potential decreases in some regions). The paired cluster analysis shows that the nature of the combined response of high and low flows varies between regions. The grid-based cluster analysis also shows potentially important variation within regions, likely related to the properties of individual catchments.

The simulation of potential future changes in derived climate hazards, such as the frequency or severity of floods and droughts, is a key first step required for adaptation planning. The subsequent translation of hazard into risk (e.g. numbers of people/properties affected by floods or water use restrictions) could be as important for policy-makers. However, many other factors affect the exposure component of risk (e.g. presence of flood defences, land use on flood plains, population change, construction of new reservoirs etc.), each of which is highly complex to project into the future. Indeed, factors like urbanisation could potentially have a greater effect on future flood risk than climate change, particularly for smaller catchments (Poelmans et al. 2011), while the relative importance of climate change and population growth for exposure to future extreme droughts has been shown to vary globally (Smirnov et al. 2016). The consideration of potential concurrent changes in a range of related hazards/risks, rather than viewing each in isolation, could be vital to avoid maladaptation (e.g. Huntjens et al. 2012).

The results here demonstrate that climate change as represented by the new UKCP18 Global and Regional climate projections will have clear effects on both high and low flows across Britain, and that some regions may experience an increase in both floods and droughts. However, there is considerable uncertainty in the magnitude of change at a place, due to uncertainty in projected climate changes, and spatial variability in catchment properties increases the variability in the hydrological response to climate change across Britain.

Acknowledgements

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Figures

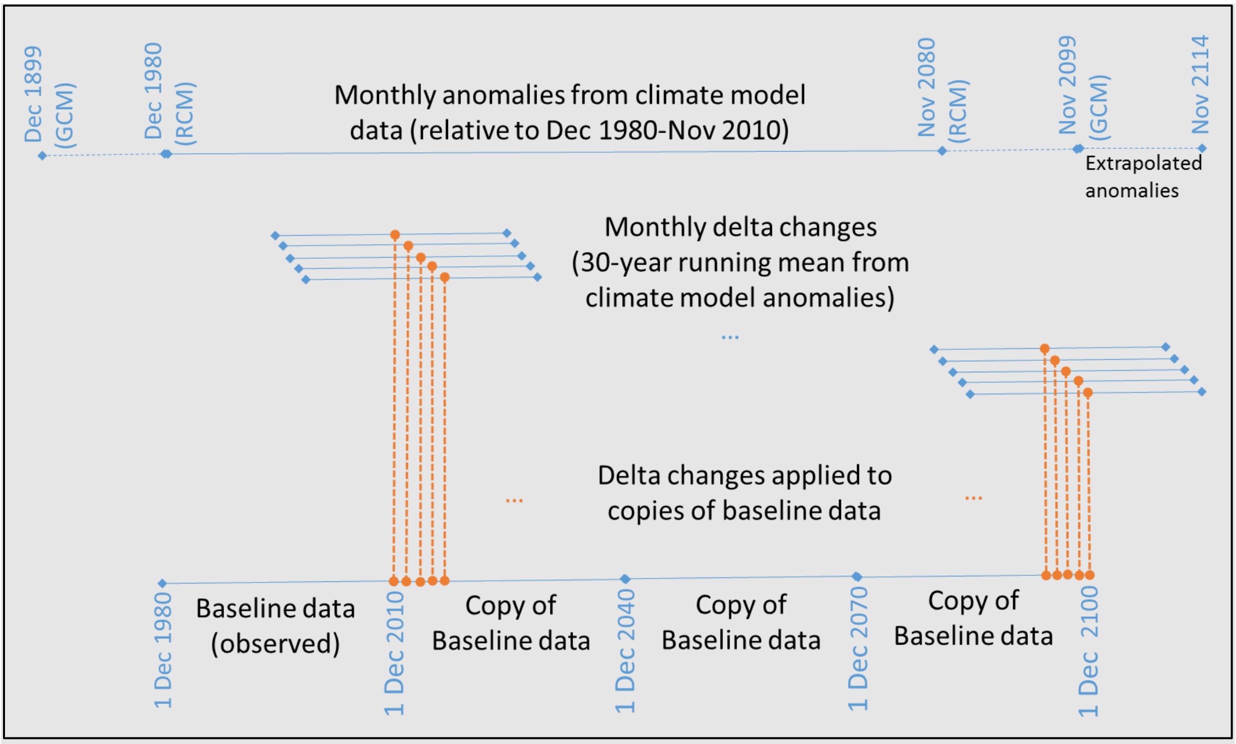

Figure 1 Schematic of the transient delta change approach (Section 2.3). The time period of the available (GCM and RCM) climate projection anomalies is represented by the top line, with the derivation of transient delta changes from multiple 30-year sub-periods of the anomalies shown by the middle horizontal lines. The baseline observed data, copied three times to cover the period up to Dec 2100, are represented by the bottom line. The application of each set of monthly delta changes to a year of the copied baseline data is represented by the vertical dashed lines.

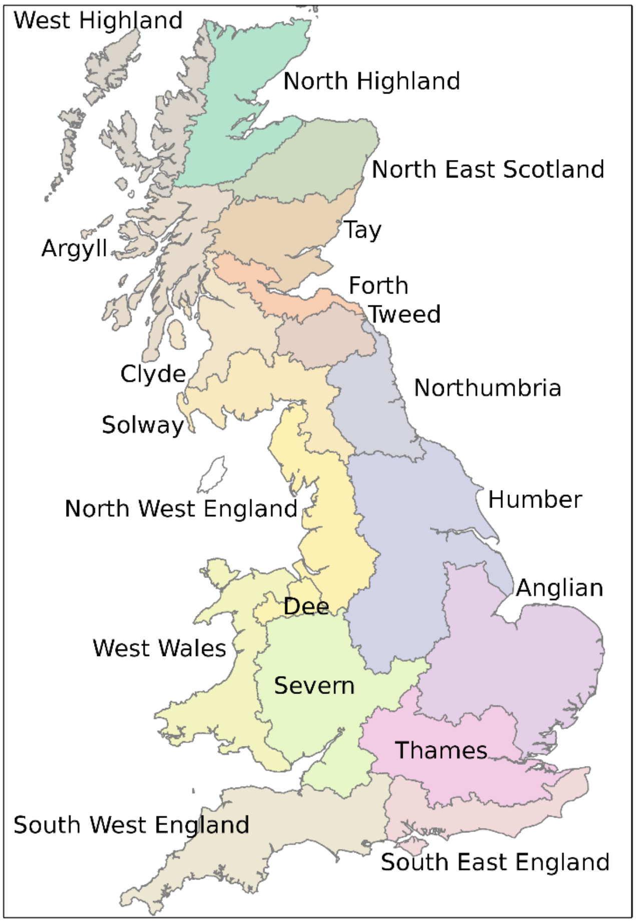

Figure 2 Map of the river-basin regions.

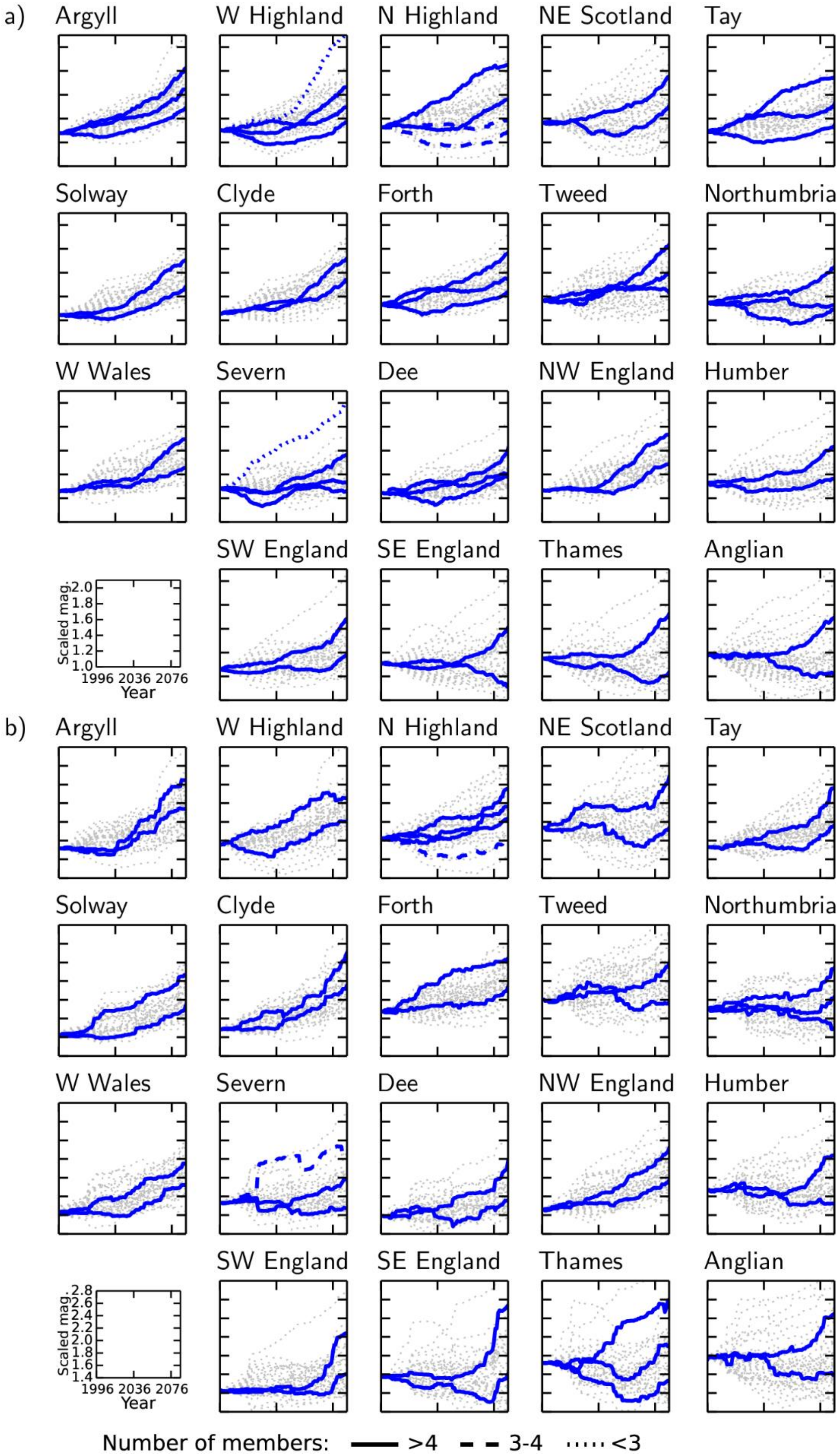

Figure 3 Projected change in the scaled magnitude of high flow indicators across river basin regions for a) 5-year return period high flows and b) 20-year return period high flows. Each plot shows all ensemble data (grey dotted lines) and the selected cluster exemplars (blue lines, with the line style indicating cluster size; solid for larger clusters and dashed or dotted for smaller clusters - see legend).

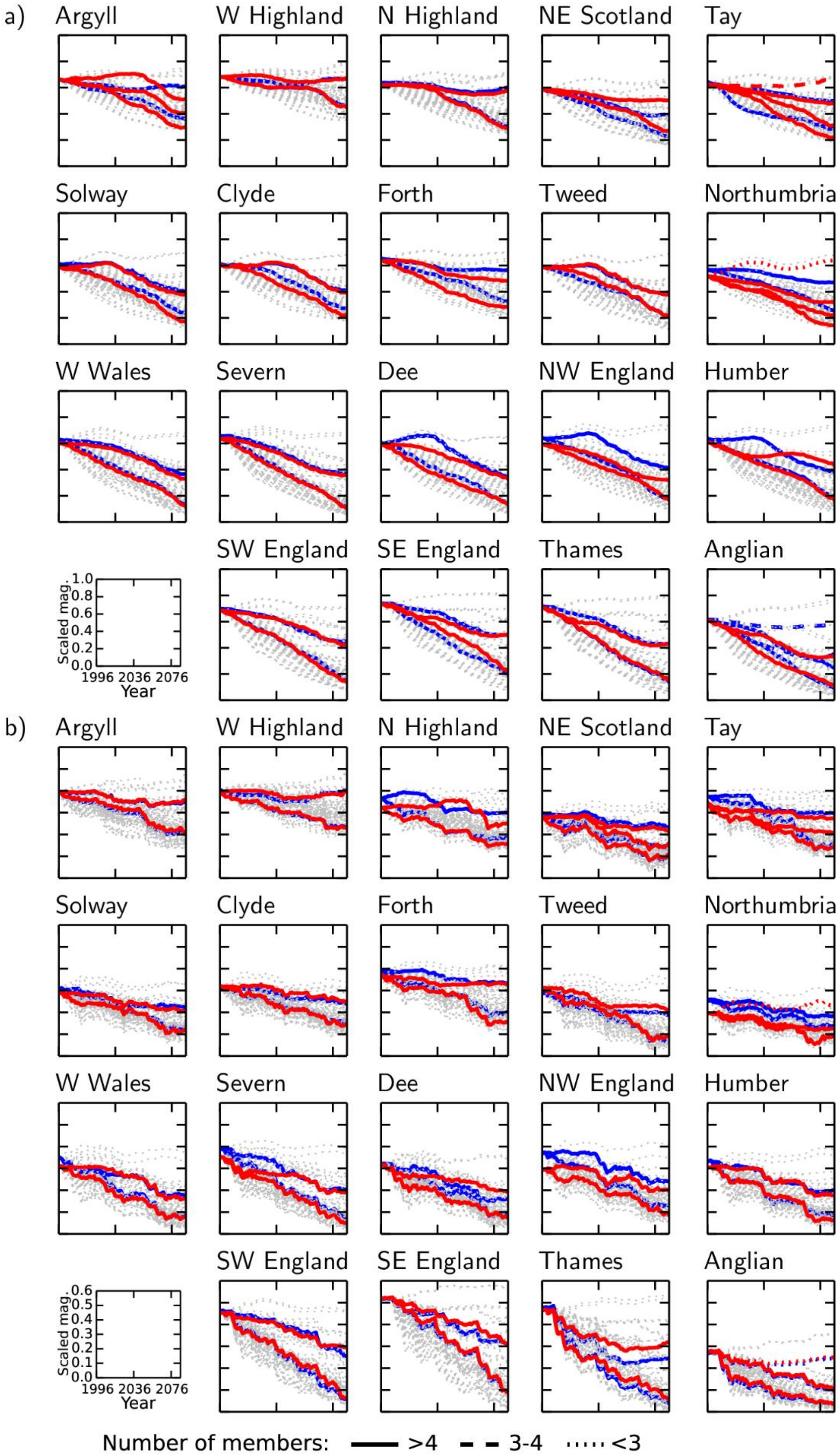

Figure 4 Projected change in the scaled magnitude of low flow indicators across river basin regions for a) 5-year return period low flows and b) 20-year return period low flows. Each plot shows all ensemble data (grey dotted lines) and the selected cluster exemplars for 7-day duration and 30-day duration (blue and red lines respectively, with the line style indicating the cluster size; see legend).

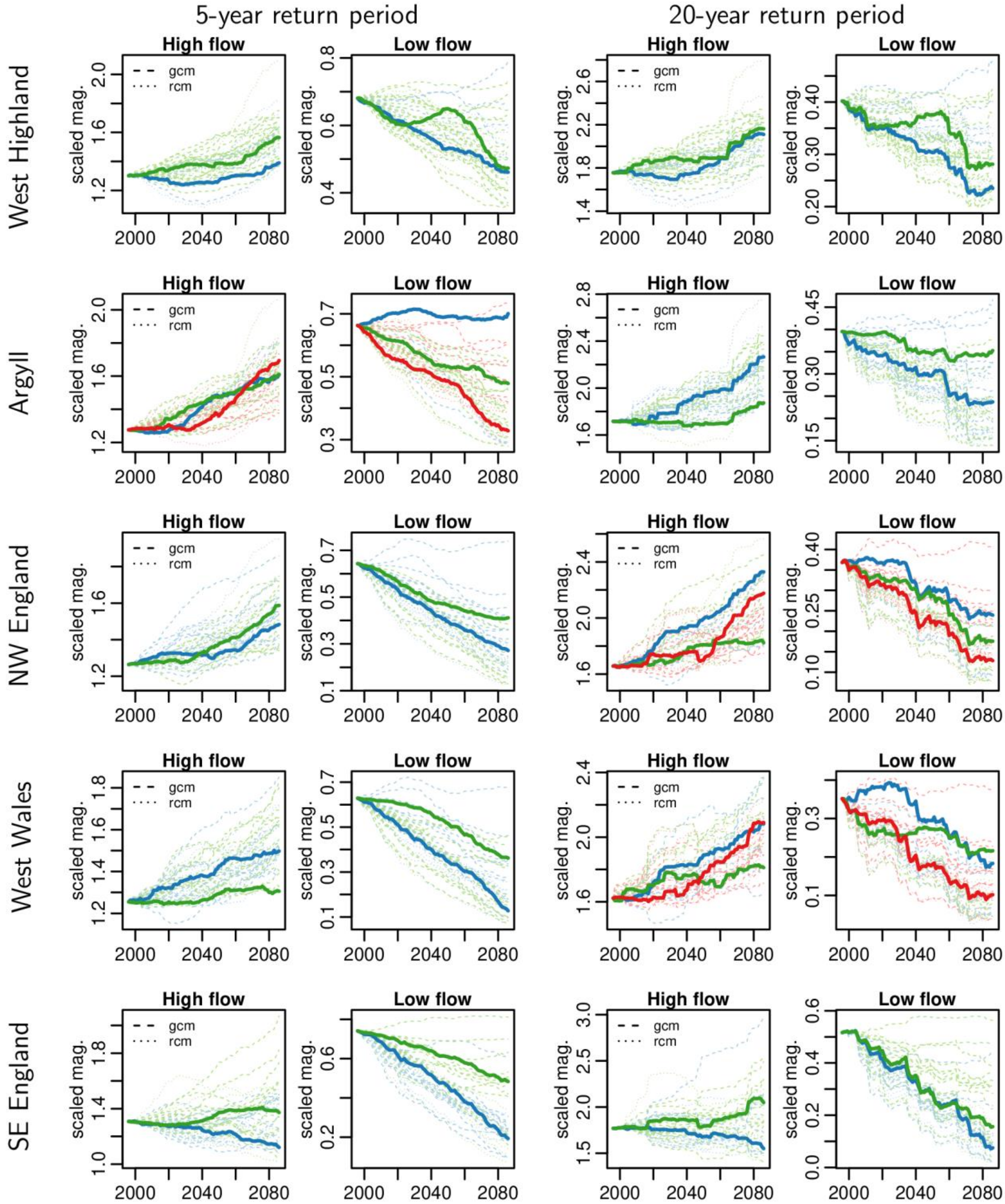

Figure 5 Clustering results for five regions, for paired high flows and 7-day low flows (5- and 20-year return period). The coloured lines indicate the same cluster for the indicator pair in a region, but there is no equivalence in colours between regions or for 5- and 20-year return period results. See Supp. Section 2.1 for the paired cluster results for all 19 regions.

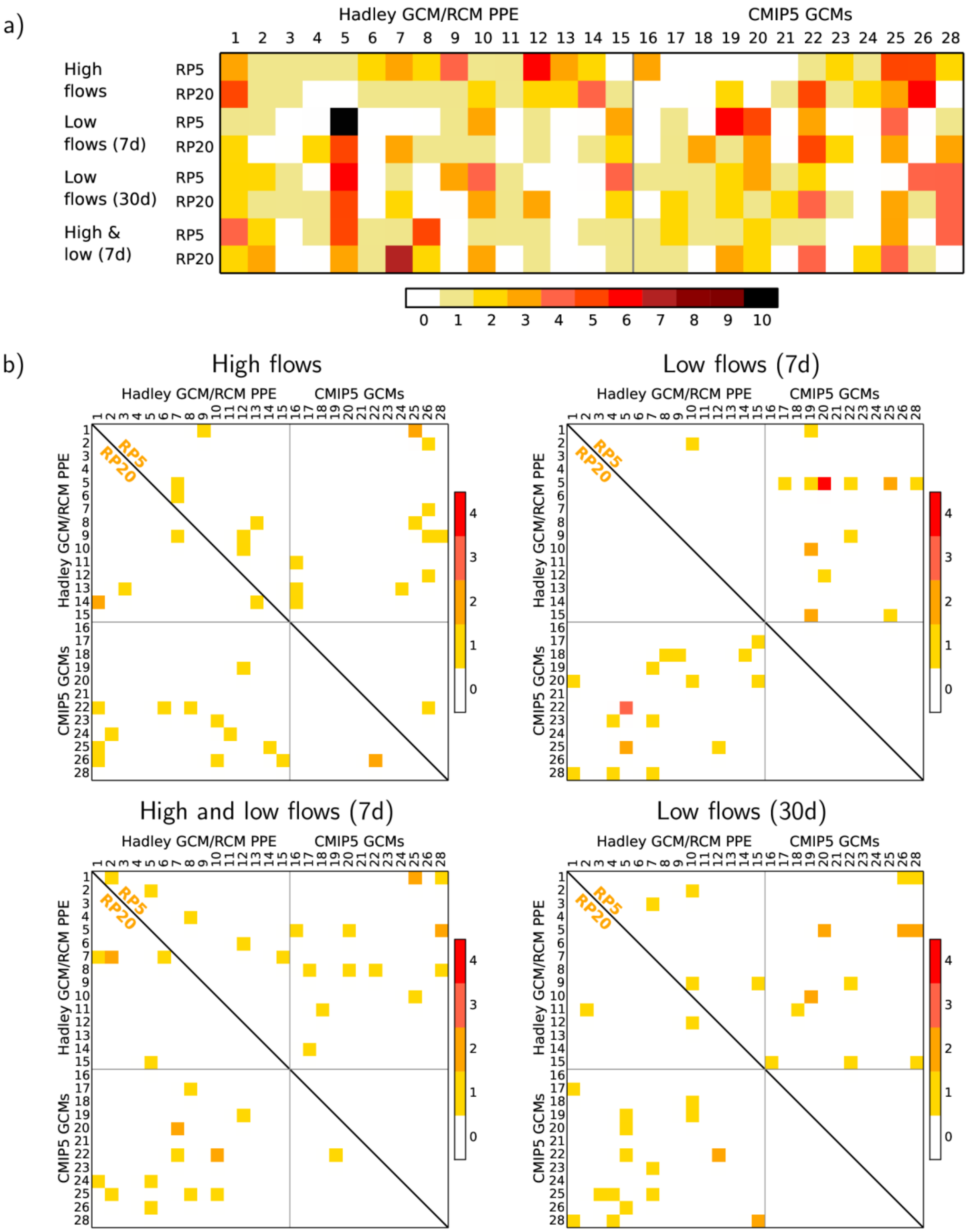

Figure 6 Counts of a) the number of times each climate ensemble member is selected as a cluster exemplar for a region, and b) the number of times each pair of climate ensemble members is selected as the exemplars for the largest two clusters in a region, for the high and low flow indicators separately and paired. The equivalent Hadley GCM and RCM PPE members are grouped together for simplicity in each case.

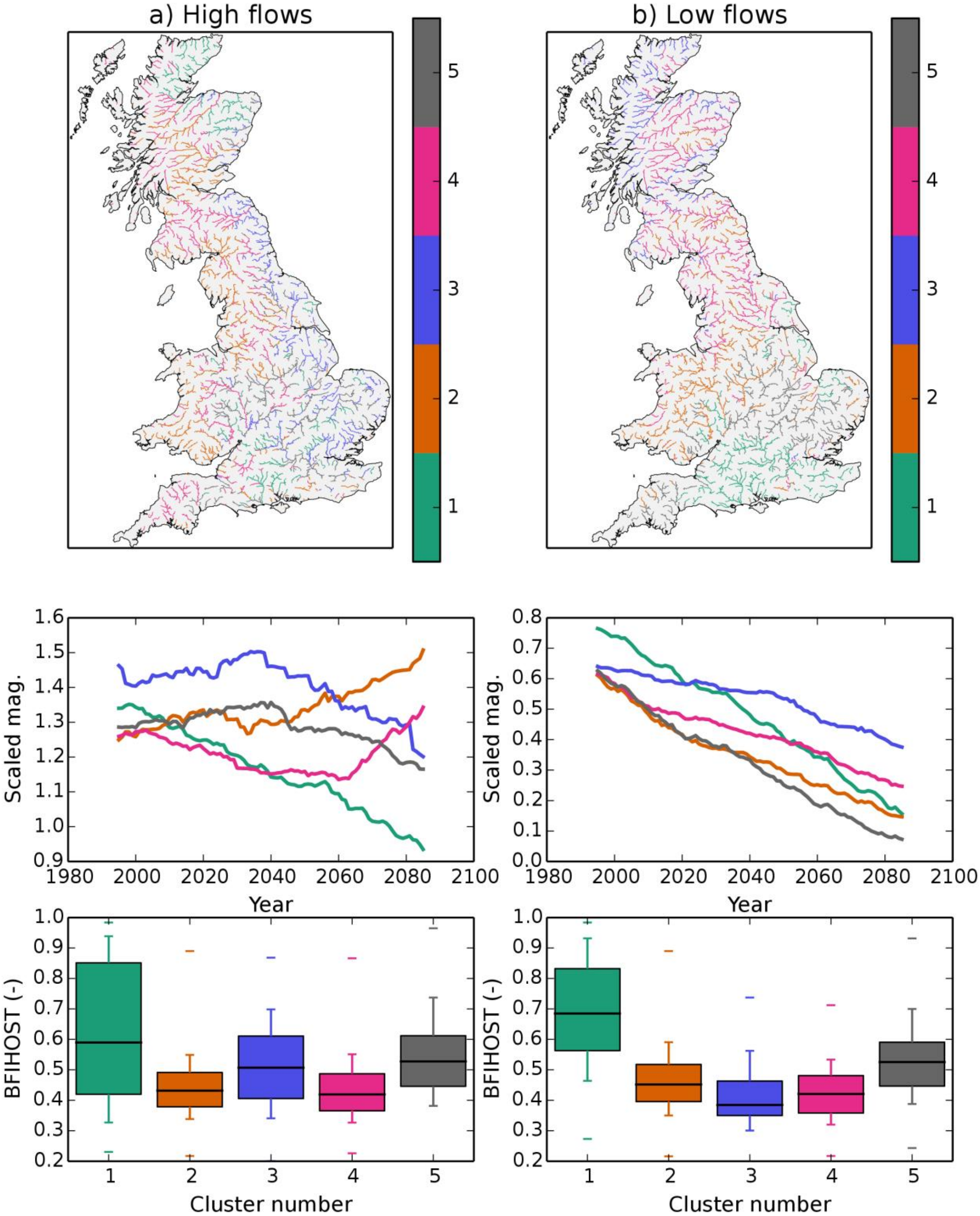

Figure 7 Results of 1km clustering across GB for a) 5-year return period high flows and b) 5-year return period 7-day low flows. Note that in this case there is no equivalence between the clusters for high and low flows.

Climate change effects on indicators of high and low river flow across Great Britain

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Supplementary Material

1 Methods

1.1 Application of climate change projections

Figure 1 shows examples of the derivation of extrapolated GCM and RCM delta changes, for two months and for a single grid box and ensemble member in each case.

The derived delta changes show that precipitation tends to increase in winter and decrease in summer, particularly for later time-slices (e.g. Figure 2). Temperature generally increases throughout the year (e.g. Figure 3). PE typically increases in the late spring, summer and early autumn, with some potential decreases at other times, although winter changes are noisier since PE then is fairly low (e.g. Figure 4).

Figure 3 also shows that the temperature increases from the Regional PPE tend towards the higher end of the Global multi-model ensemble range, particularly for summer (c.f. Murphy et al. 2018 Fig. 5.2) and autumn. The increases in PE from the Regional PPE also tend towards the higher end of the Global multi-model ensemble range (Figure 4). Differences between the Global and Regional ensembles are less obvious for changes in precipitation, but the Global multi-model ensemble does tend to cover a broader range of changes than the Regional PPE (Figure 2). In particular, some Global ensemble members can give increases in summer precipitation.

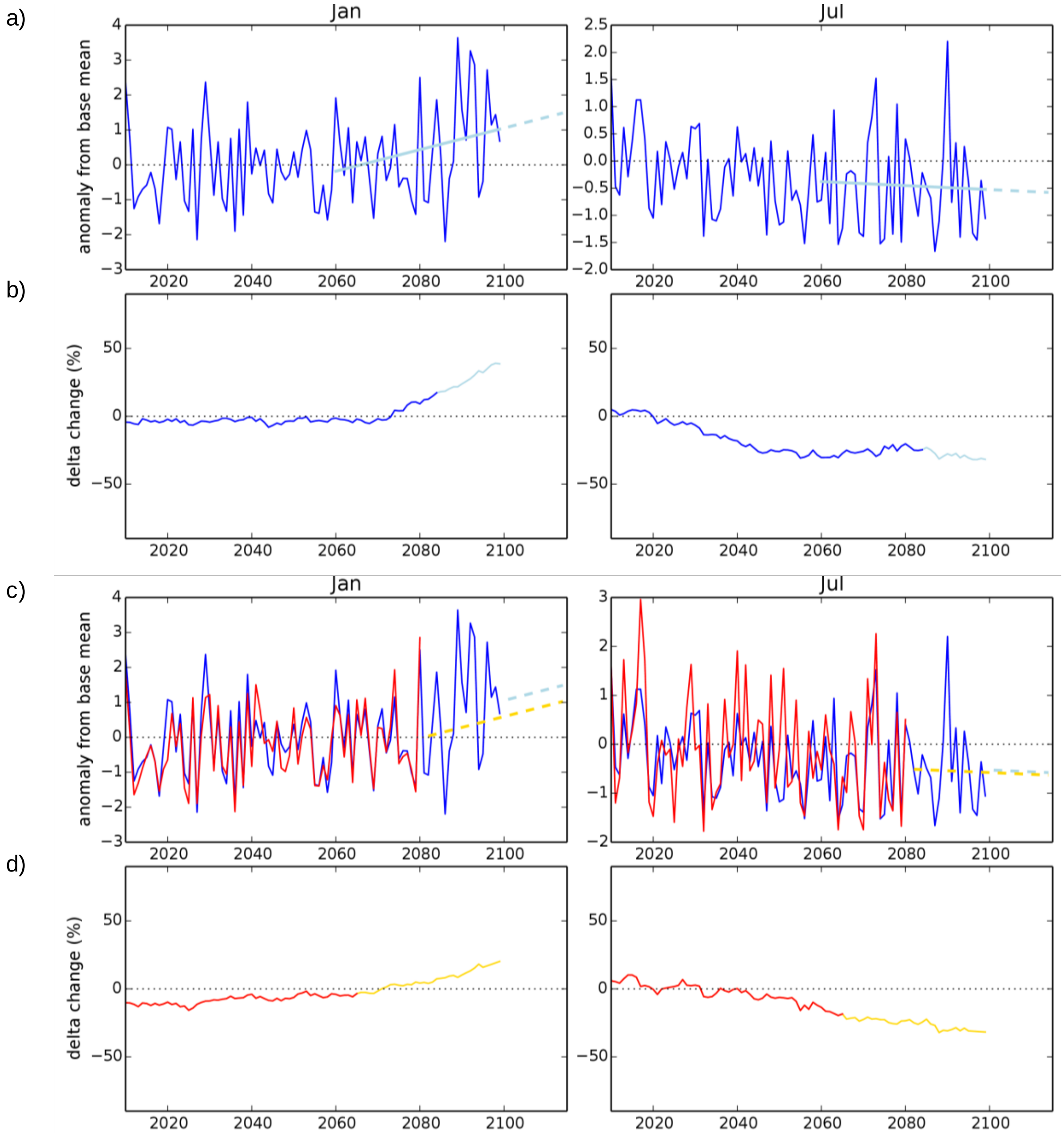

Figure 1 Example derivation of precipitation delta changes for January and July, for a single climate ensemble member and grid box. a) Yearly GCM anomalies from the baseline mean (blue; mm/day), with a linear trend fitted to the last 40 years of data (light blue solid) used to extrapolate to 2114 (light blue dashed). b) GCM delta changes for 30-year time-slices (blue, with those that include extrapolated data in light blue). c) Yearly RCM anomalies from the baseline mean (red) and their extrapolation to 2114 (gold dashed) using the slope of the trend from the equivalent GCM ensemble member and location (as in a)). d) RCM delta changes for 30-year time-slices (red, with those that include extrapolated data in gold).

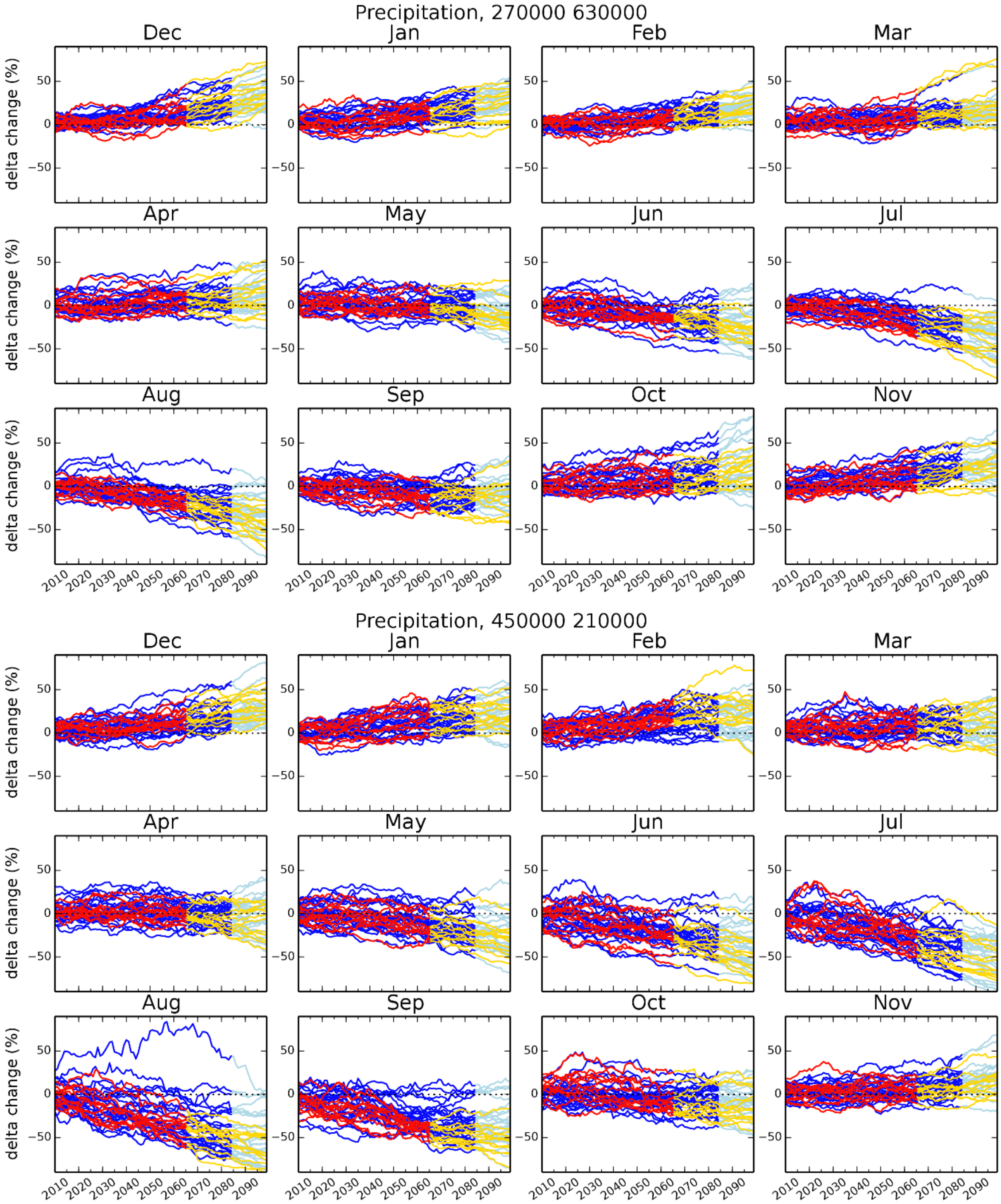

Figure 2 Monthly delta changes in precipitation for locations in Scotland (top) and southern England (bottom). Changes are shown for each GCM ensemble member (blue, with those that include extrapolation in light blue), and each RCM ensemble member (red, with extrapolation in gold). The grid box Easting and Northing are shown above each set of plots.

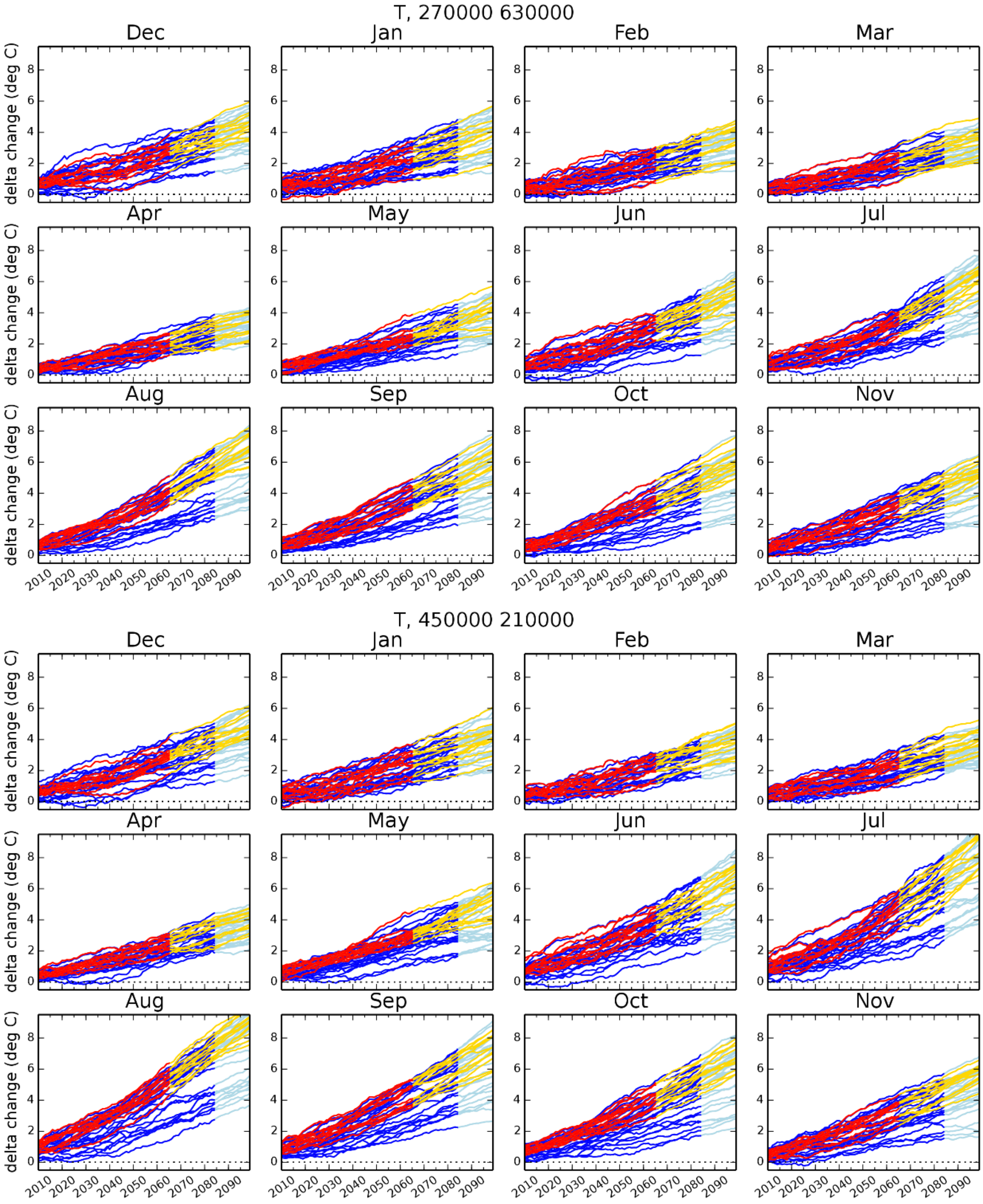

Figure 3 As Figure 2, but for changes in temperature.

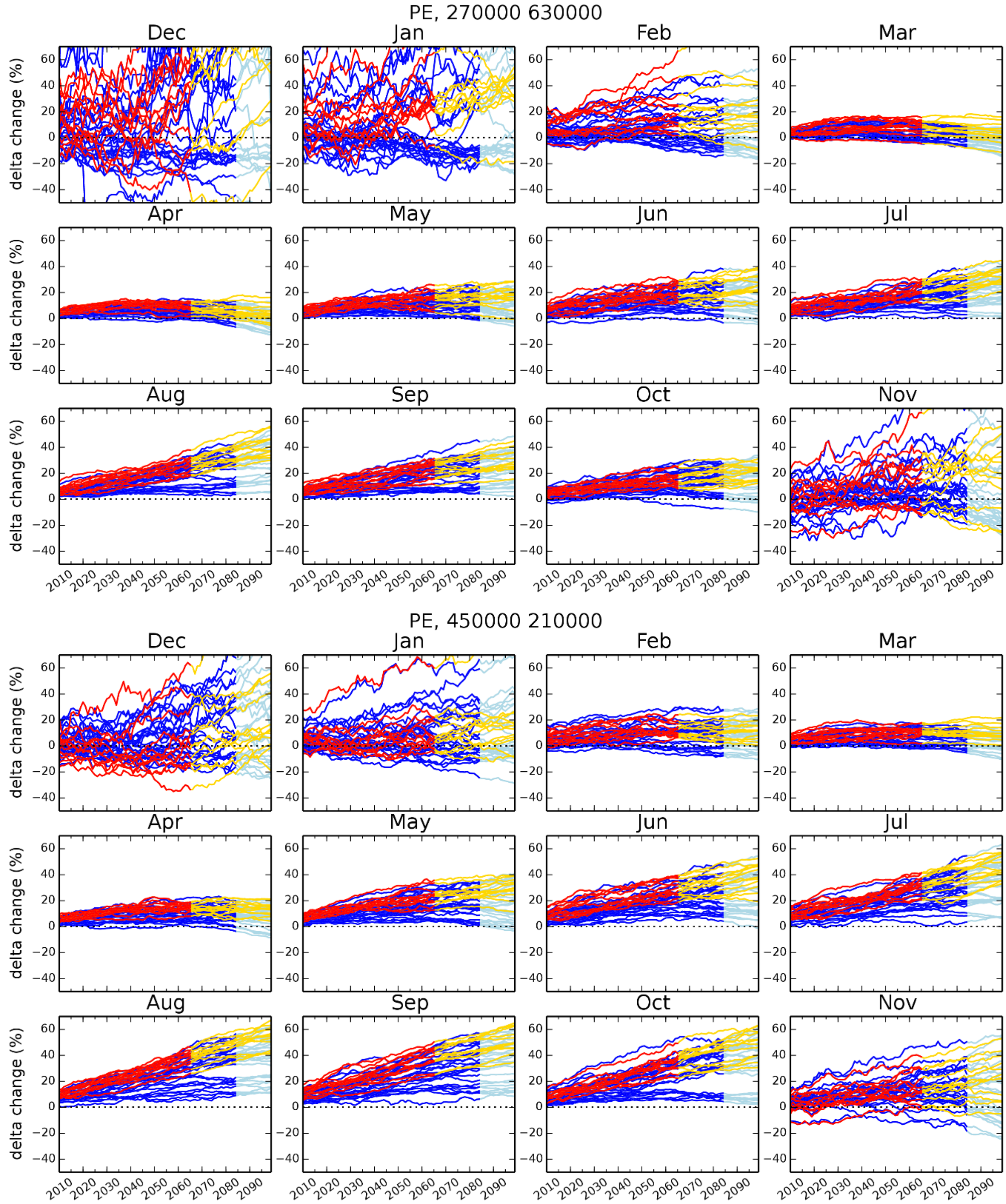

Figure 4 As Figure 2, but for changes in PE.

1.2 Baseline performance of simulated high and low flows

The simulated standardised 5- and 20-year return period high and low flows for the baseline period, for locations corresponding to gauged catchments, are compared to values derived in the same way from gauged flow data held by the National River Flow Archive (NRFA; www.ceh.ac.uk/data/nrfa/).

The first comparison uses data for locations corresponding to a set of benchmark catchments (UKBN2; Harrigan et al. 2018), which was specifically designated as a set of 146 catchments across the UK where human disturbance to flows is considered minimal and flow gauging is considered reliable. Simulated data are available for 97 of the benchmark catchments, after discounting those that are too small (<50km^2), have a large proportion of missing data (>20%) in the baseline period (Dec 1980-Nov 2010) or are located in Northern Ireland. A subset of 75 of these is used for the high flow comparison and a subset of 71 is used for the low flow comparison, based on information available with the benchmark list about potential issues with high and low flow gauging respectively (Figure 5). The second comparison uses data for locations corresponding to 703 NRFA gauging stations (again discounting catchments by the above criteria on area, missing data and location) (Figure 5).

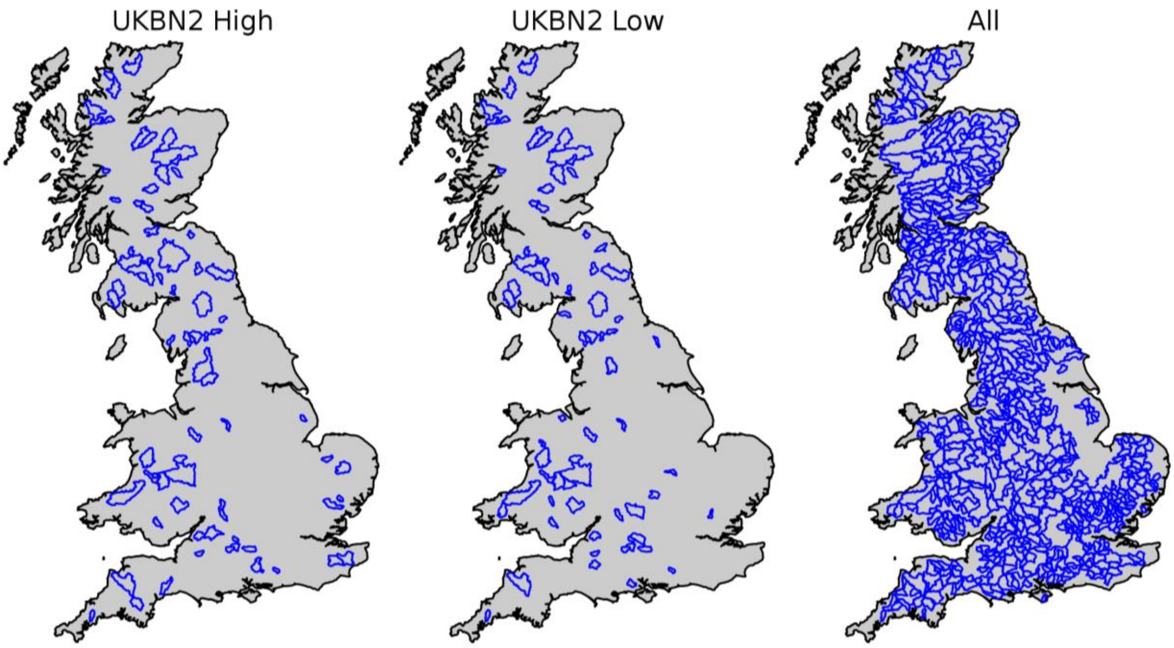

Figure 5 The catchments used for the baseline performance assessment; UKBN2 catchments used for high flows (left), UKBN2 catchments used for low flows (middle), and the full set of catchments assessed (right).

Figure 6a presents boxplots of the range of the percentage differences between the simulated and observed values for each indicator, across the appropriate set of benchmark catchments in each case. Performance for high flows is good, with median values close to zero and differences mostly within ±10%. For low flows, the median difference between modelled and observed flows is negative, indicating more under-estimation, and some catchments show large percentage differences, but this is because small differences in small numbers can give large percentage differences. The median difference for the actual (not standardised) 7-day low flows is -0.07 m^3s^{-1} for both the 5- and 20-year return period, while the largest magnitude differences are less than 3 m^3s^{-1}. There are also particular issues with the gauging of low flows that could lead to large percentage differences between simulated and gauged flows (e.g. even a small error in the datum, or seasonal growth of algae; nrfa.ceh.ac.uk/accuracy-fitness-for-purpose).

When assessed across the much larger set of NRFA catchments (Figure 6b), the median performance for high flows is very similar to that for the benchmark catchments, with a small increase in the 25th–75th percentile range. The median performance for low flows is slightly more negative than for the benchmark catchments, with a similar 25th–75th percentile range. For both high and low flows, the overall spread of differences increases substantially for the larger set of NRFA catchments compared to that for the benchmark catchments. This is unsurprising as some of the additional catchments will have substantial artificial influences to flows, whereas the G2G essentially simulates natural flows.

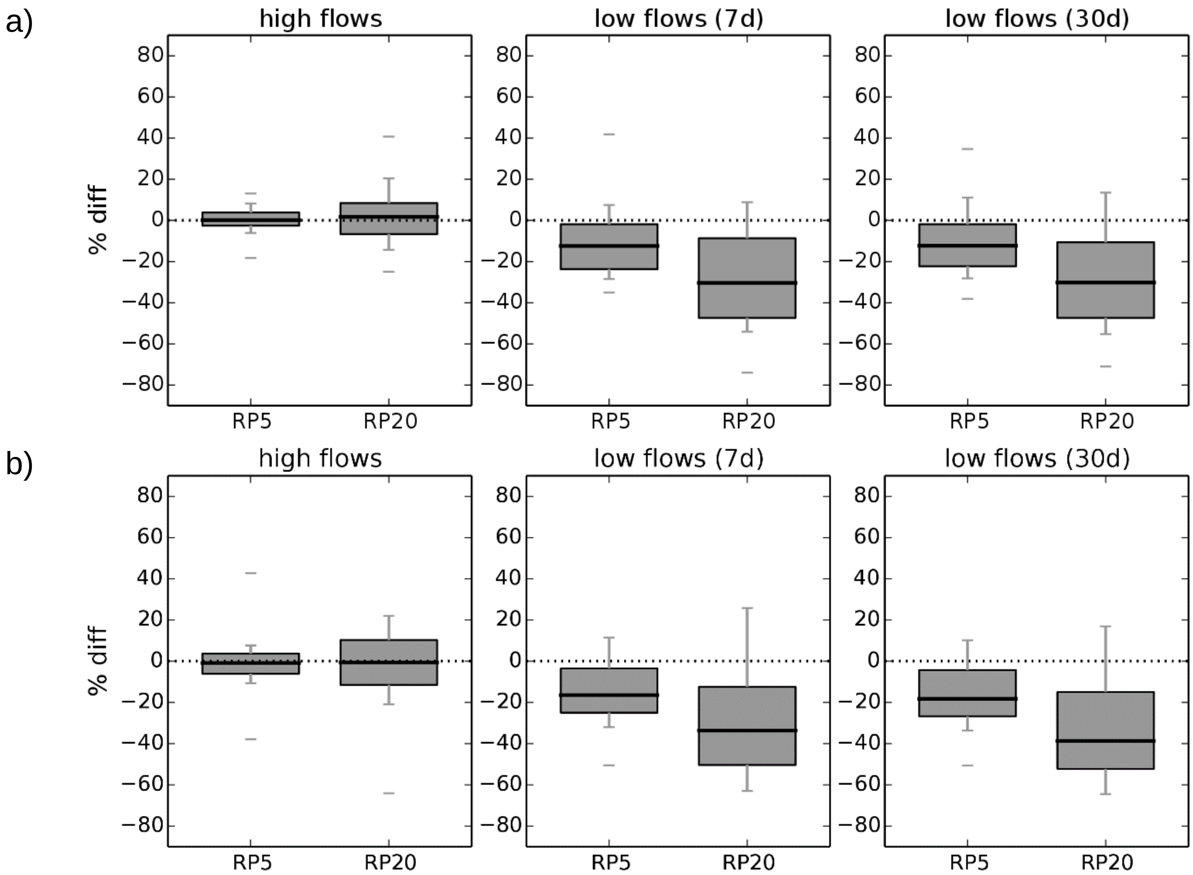

Figure 6 Boxplots summarising the comparison of the simulated and observed standardised 5- and 20-year return period (RP5 and RP20) high and low flows, across a) the set of benchmark catchments, and b) the set of 703 NRFA catchments. Each box shows the 25th-75th percentile range, with the line showing the 50th percentile and the whiskers the 10th-90th percentiles. Lines outside the box show the overall min and max (if within the plotted range).

1.3 Cluster analysis

To generate clusters for a single indicator and region, the distance between each pair of time-series must be computed. Dynamic Time Warping is used to measure the distance between time-series with a focus on highlighting feature similarity (rather than the precise timing of features). Figure 7 shows how DTW distance is computed, with examples of close and distant pairs of time-series. Once distance has been computed between each pair of time-series, clusters are generated by choosing groups which minimise within-group distances and maximise between-group distances. Cluster exemplars are chosen as the member closest to the "centre-of-mass" of the cluster.

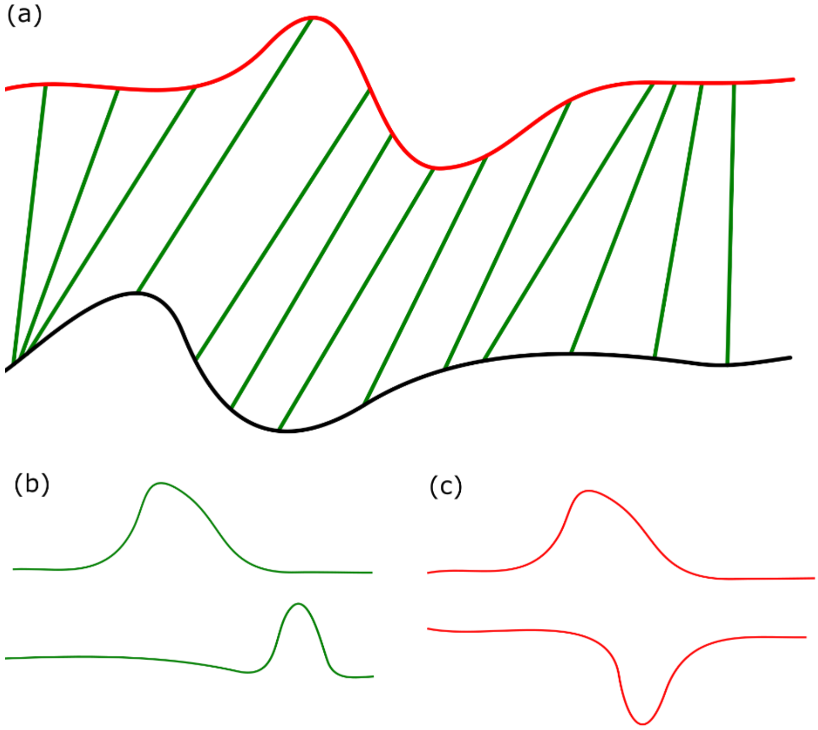

Figure 7 Schematic of Dynamic Time Warping. a) Time points are matched to minimise distance between two time-series (green lines show matched time points). b) A pair of time-series close in DTW space. c) A pair of time-series distant in DTW space.

2 Results

2.1 Regional average high and low flow changes

Figure 8 shows the clustering results for each river-basin region for 5-year return period high flows paired with 5-year return period 7-day low flows. Figure 9 shows the equivalent clustering results for 20-year return period high flows paired with 20-year return period 7-day low flows. Note that there is no equivalence in colours between regions or for 5- and 20-year return period results.

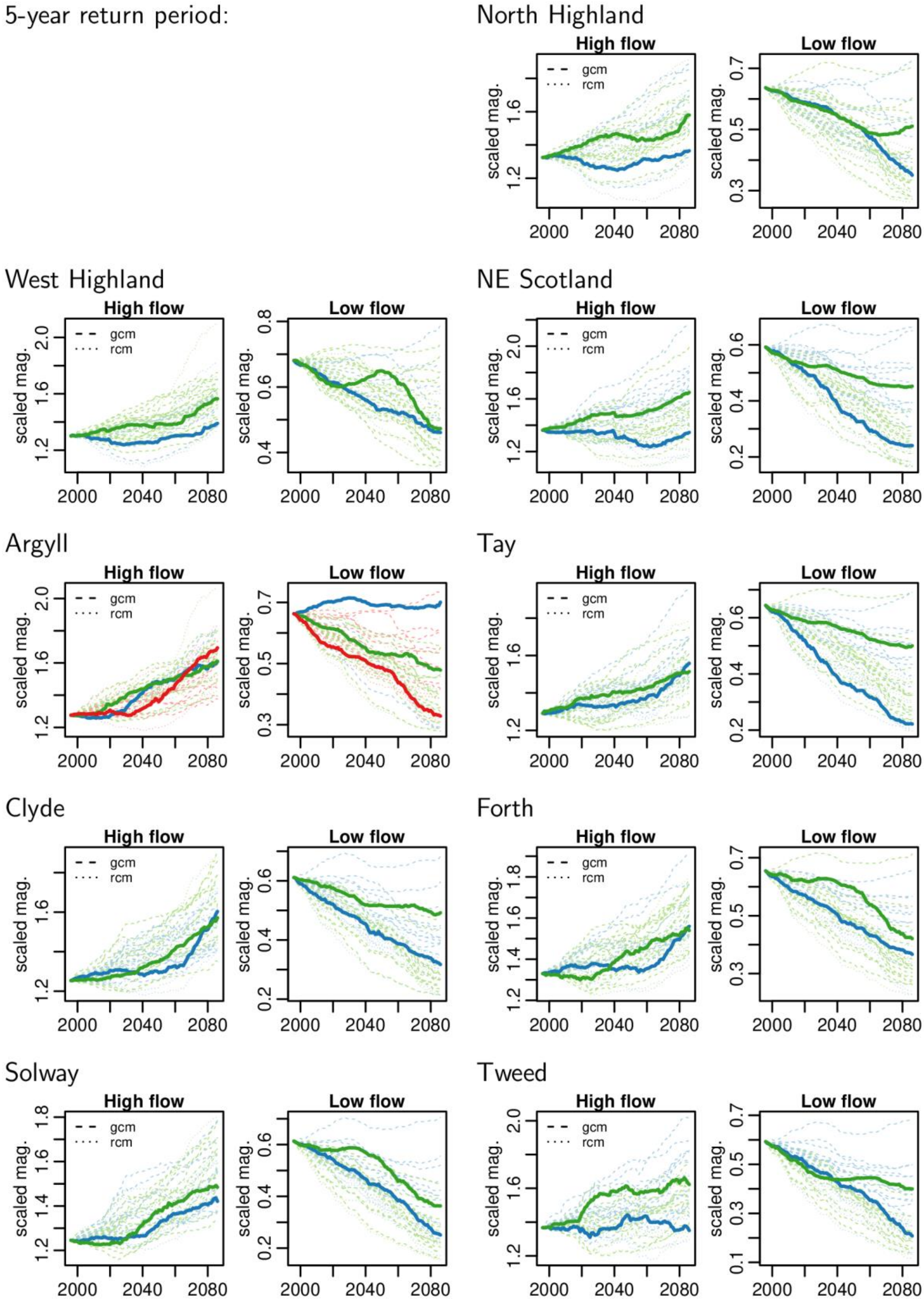

Figure 8 Clustering results for paired high flows and 7-day low flows (5-year return period). The coloured lines indicate the same cluster for the indicator pair in a region, but there is no equivalence in colours between regions.

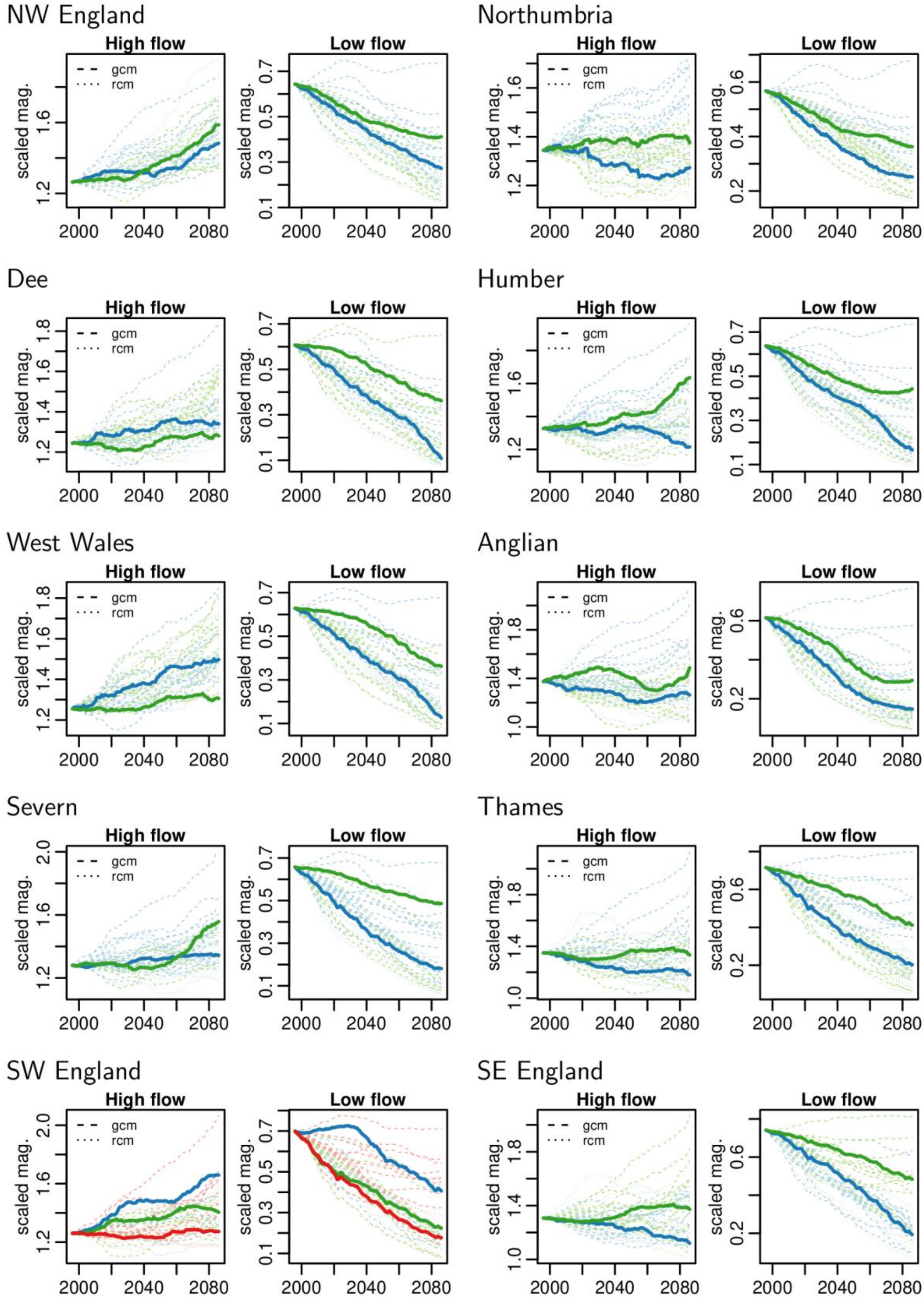

Figure 8 continued.

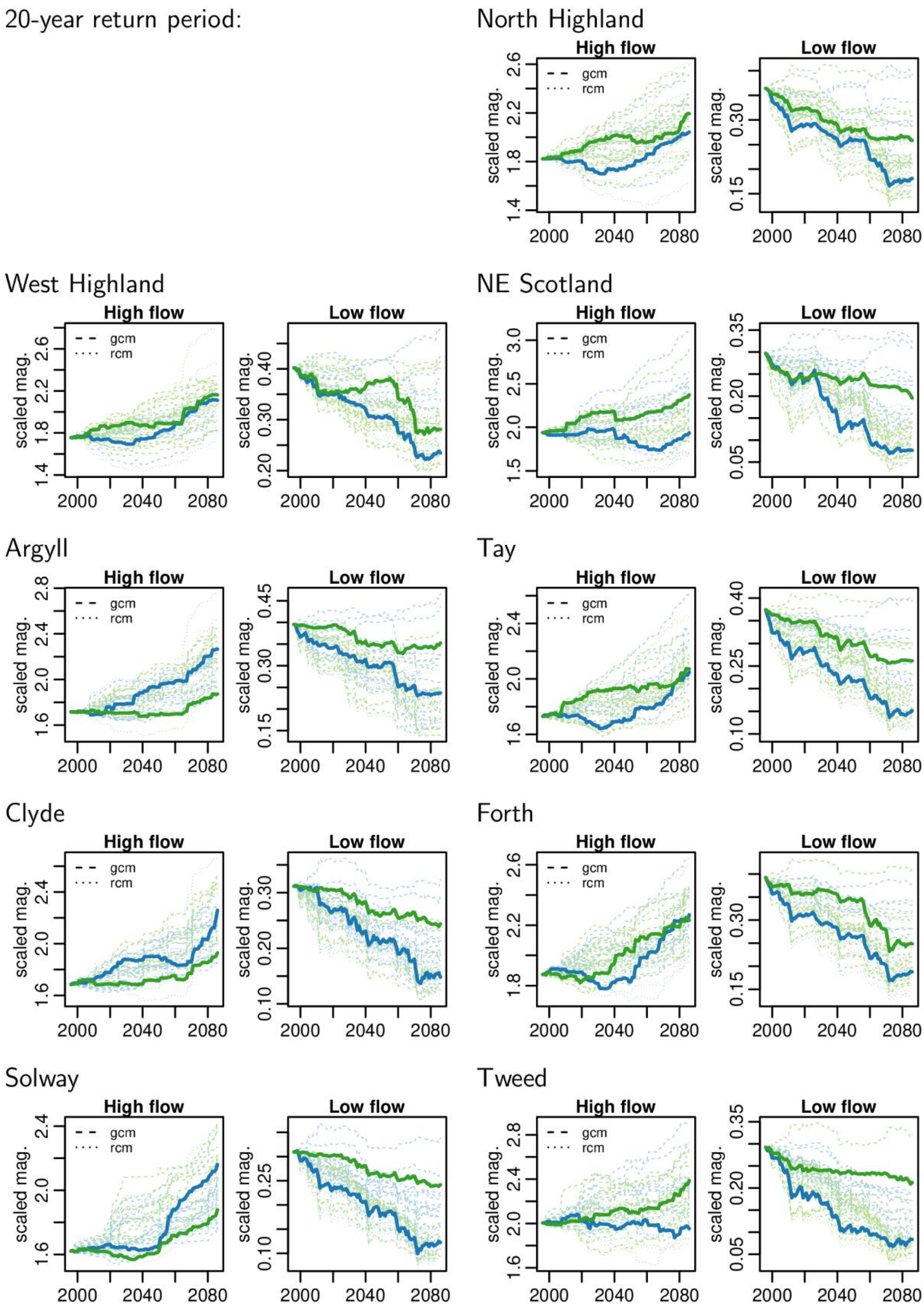

Figure 9 Clustering results for paired high flows and 7-day low flows (20-year return period). The coloured lines indicate the same cluster for the indicator pair in a region, but there is no equivalence in colours between regions.

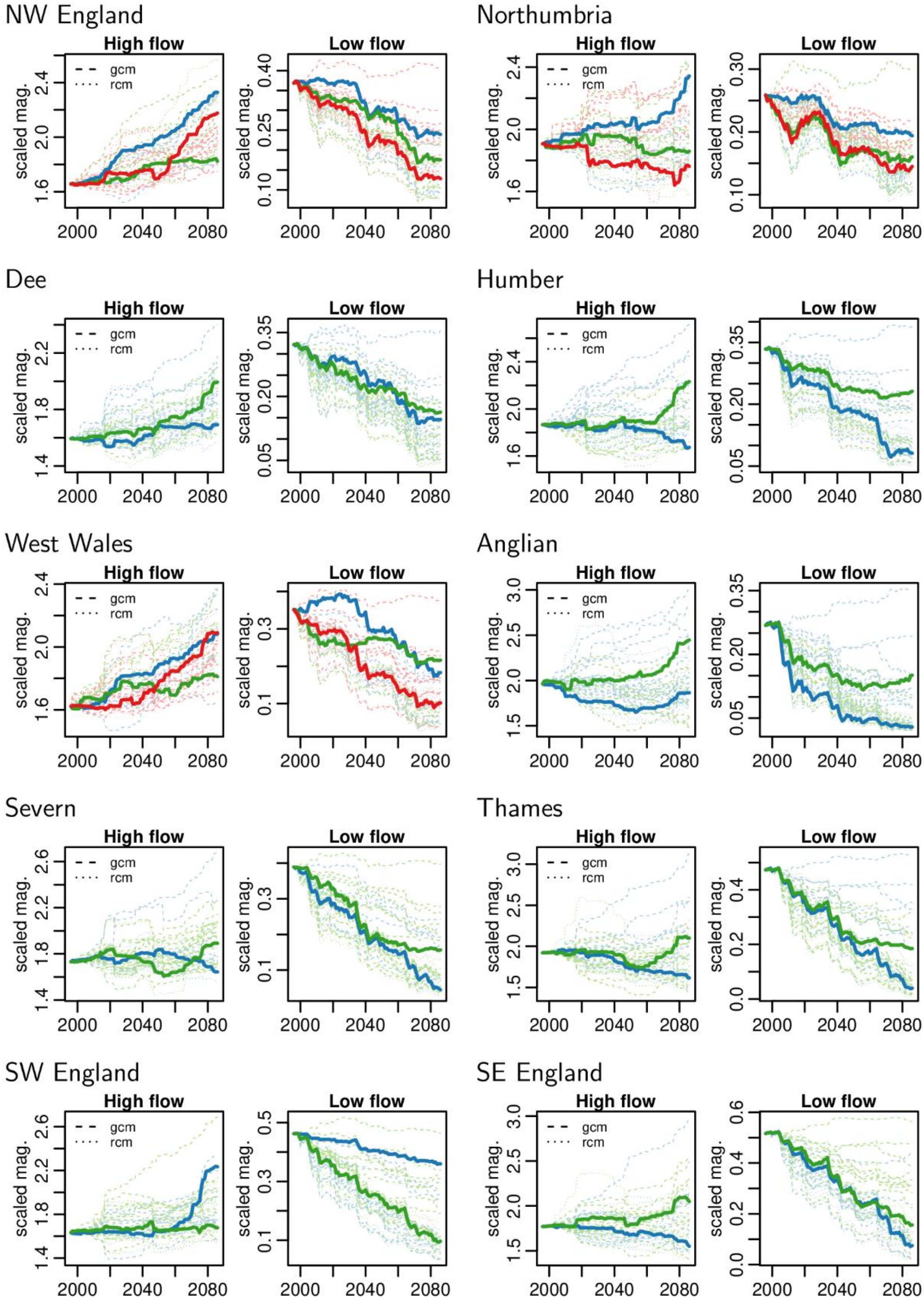

Figure 9 continued.

2.2 Analysis of cluster exemplars and membership

An examination of the number of times a pair of climate ensemble members has different cluster labels, across all considered indicators and regions, shows that there is a clear distinction between the Hadley PPE and the CMIP5 GCMs, with high similarity within these groups and high dissimilarity between them (Figure 10). Using a hierarchical ordering, high similarity can also be seen between equivalent RCMs and GCMs (e.g. RCM 08 and GCM 08), shown through close proximity on the axes.

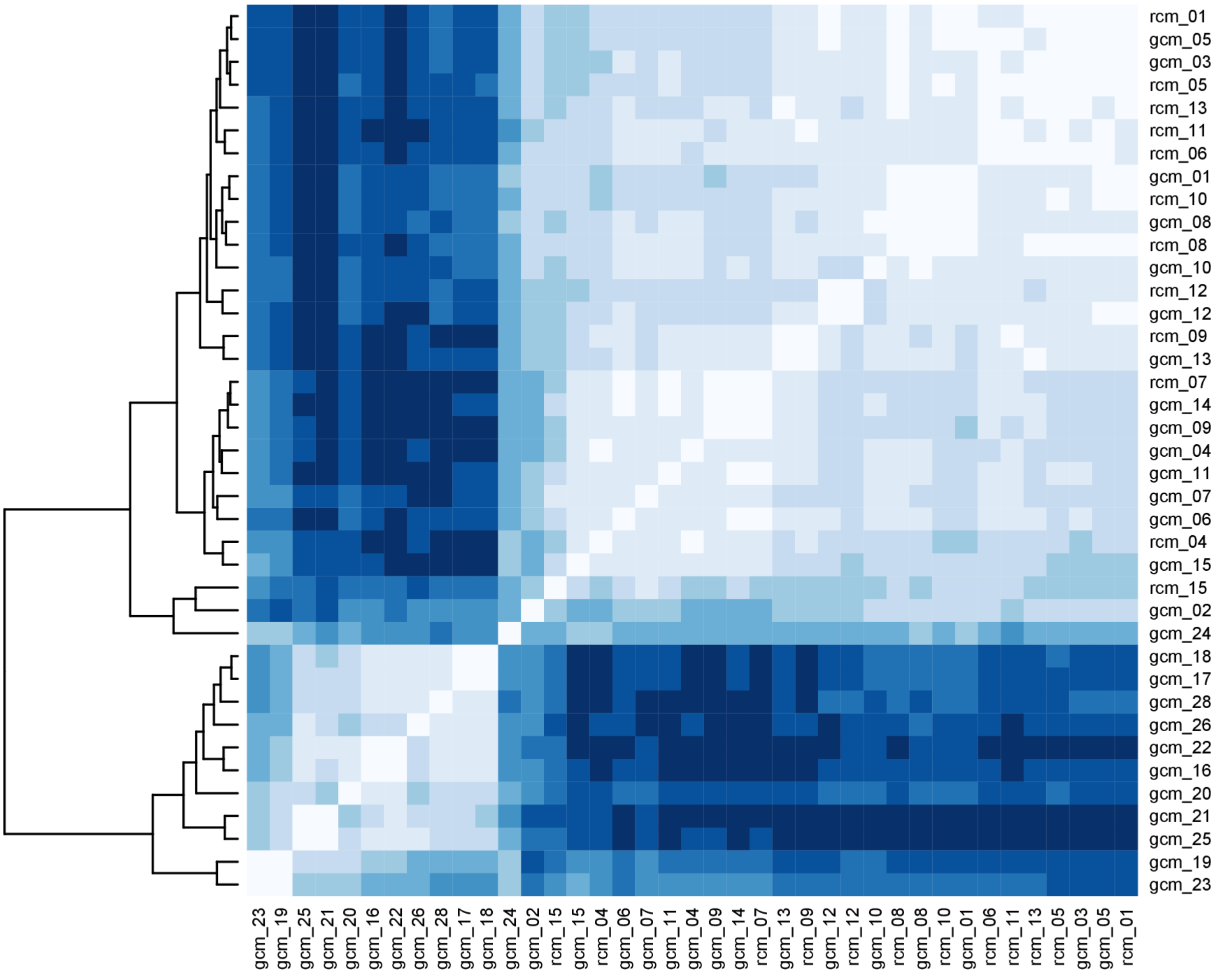

Figure 10 Symmetric heatmap showing pairwise similarity of clustering between climate ensemble members. Darker colours indicate ensemble members appearing more frequently in different clusters. Ensemble members are reordered by similarity using a hierarchical dendrogram (left); nearby ensemble members are more frequently in the same cluster.

References

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