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Circulation-driven streamflow variability in Great Britain and its representation by UKCP18 climate models

James G. Carruthers[1], Anna Murgatroyd[1], Hayley J. Fowler[1]

[1]School of Engineering, Newcastle University, Newcastle upon Tyne, UK

Correspondence to: James G. Carruthers (james.carruthers@newcastle.ac.uk)

Abstract. Interannual to decadal seasonal streamflow variability has major implications for flood risk, drought management, water resources and hydropower production across Great Britain. A substantial component of this variability is linked to large-scale atmospheric circulation, particularly over the North Atlantic, but its contribution to seasonal streamflow variability remains insufficiently quantified. Here, we use a dynamical adjustment framework based on multiple linear regression to quantify the contribution of synoptic-scale weather regimes to seasonal Standardised Streamflow Index (SSI) variability across Great Britain. The method is applied to reconstructed SSI series for 167 non-overlapping catchments, which are aggregated to the UKCP18 river regions.

The strongest dynamical contribution occurs in winter, especially across western and northern Great Britain, where weather-regime-driven SSI explains around 70% of interannual winter SSI variance in several regions. The dynamically driven contribution to SSI also explains a substantial fraction of spring and autumn variability, but the relationship is weaker in summer, consistent with the reduced influence of synoptic-scale circulation on warm-season rainfall. In one third of GB regions, including the Clyde, Solway, and North-West England, dynamically driven SSI captures much of the observed interannual and decadal variability, including several historically wet and dry winters. This strong circulation–streamflow relationship provides useful information for seasonal forecasting, climate-model evaluations and historical reconstruction.

Applying the same framework to weather-regime sequences from the UKCP18 global climate models ensemble shows that the ensemble systematically under-represents interannual variance in winter dynamically driven SSI, with an ensemble-mean bias of approximately -20% relative to observations and substantial spatial and inter-member variation. These results show that atmospheric circulation biases can propagate into climate-model-driven assessments of seasonal streamflow variability, with implications for hydrological projections, model evaluation, and process-informed bias correction.

1 Introduction

Seasonal streamflow variability has significant impacts on human and natural systems. Extreme seasonal high flows are often associated with flood impacts, particularly when persistent rainfall or snowmelt occurs over catchments with already wet antecedent conditions (Staudinger et al., 2025). In the United Kingdom, the winter of 2013/2014 provides a notable example, with widespread flooding and record-breaking seasonal streamflow across many parts of the country (Muchan et al., 2015).

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Conversely, prolonged periods of low flows can affect water resources, abstraction (Murgatroyd et al., 2022), hydropower production (Golgojan et al., 2025), navigation, agriculture and ecosystems. The UK has experienced several major seasonal to multi-annual droughts with widespread impacts (Barker et al., 2019, 2024). Even when individual seasons are not extreme, sequences of below-average seasons can produce cumulative impacts, especially in catchments that depend strongly on winter recharge (Chan et al., 2022).

A substantial component of seasonal streamflow variability is linked to seasonal precipitation variability, which itself is primarily driven by variability in large-scale atmospheric circulation (Hall & Hanna, 2018). Over the UK, atmospheric circulation modulates the frequency, persistence, and tracks of synoptic weather systems, thereby influencing seasonal precipitation and streamflow anomalies. The best-known example is the North Atlantic Oscillation (NAO), which describes variability in the sea-level pressure gradient across the North Atlantic. During positive NAO phases, the North Atlantic jet stream is typically stronger and more zonal, favouring enhanced baroclinicity, more frequent extra-tropical cyclones, and increased atmospheric-river activity around the UK (Brown, 2018). These conditions are often associated with wetter anomalies, particularly in northern and western regions. During negative NAO phases, the jet stream is typically more meridional or meandering, and UK weather tends to be more variable. Depending on the location and persistence of Rossby wave breaking, negative NAO conditions can be associated with severe cold outbreaks (Burgess & Klingaman, 2015), drier conditions (West et al., 2022) or locally enhanced precipitation (Barnes et al., 2022).

Although the NAO is the dominant mode of North Atlantic circulation variability affecting the UK, other circulation patterns, including Scandinavian Blocking and the East Atlantic Pattern, also influence UK hydroclimate variability (Hall & Hanna, 2018; Lavers et al., 2010). These modes can be affected by remote drivers in the Atlantic, Pacific and Indian oceans (Chevuturi et al., 2025; Davies et al., 2021; Scaife et al., 2017), and there is evidence that North Atlantic circulation varies on decadal to multi-decadal timescales in association with sea-surface temperature variability (Börgel et al., 2020). Previous studies have improved understanding of links between atmospheric circulation, sea-surface temperature variability, rainfall, drought and streamflow in the UK (Chevuturi et al., 2025; Lavers et al., 2010; Svensson et al., 2015). However, a gap remains between this process understanding and its practical use in hydrological forecasting, historical reconstruction, and climate-impact assessment.

This gap is important because the mean state, variability and persistence of North Atlantic atmospheric circulation are expected to change under anthropogenic forcing (Folland et al., 2009; Priestley & Catto, 2022). This is supported by observed changes in the North Atlantic jet stream and related circulation features attributable to anthropogenic climate change (Blackport & Fyfe, 2022; Vacca et al., 2026). However, climate models have known biases in their representation of North Atlantic circulation. These include biases in the position and structure of the jet stream, underestimation of observed jet strengthening (Blackport & Fyfe, 2022) and systematic biases in the underestimation of the variability and persistence of large-scale circulation regimes, including atmospheric blocking (Priestley et al., 2020; Schiemann et al., 2020; Simpson et al., 2020). Such biases may affect the reliability of climate-model-driven hydrological simulations, particularly where seasonal streamflow variability is strongly controlled by atmospheric circulation.

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Although the general impact of atmospheric model circulation biases on hydrological modelling outputs is recognised (Teutschbein & Seibert, 2012), conventional bias-correction methods often mask these structural circulation errors rather than resolving their underlying physical impact on streamflow variability. In part, this is because the contribution from atmospheric circulation variability is typically not constrained in the bias correction of climate model outputs, which may conflate and correct for biases in dynamical (i.e. atmospheric circulation) and non-dynamical precipitation processes simultaneously. Improvements have been shown if circulation biases are taken into account (Photiadou et al., 2016).

The UKCP18 climate projections are widely used to inform flood-risk, drought, water-resource, and adaptation planning in the UK. The UKCP18 modelling framework includes global, regional, and convection-permitting simulations, with the global 60 km parameter-perturbed ensemble providing boundary conditions for the higher-resolution regional projections (Murphy et al., 2018). Recent work has used synoptic-scale weather patterns to separate dynamical and non-dynamical contributions to UK winter rainfall variability, showing that UKCP18 global climate models under-represent the dynamical contribution to winter rainfall variance by approximately 20% (Carruthers et al., 2026). If similar circulation-related biases propagate into streamflow, this would have important implications for interpreting hydrological projections based on UKCP18 since these models form the foundation of the national climate projections used in multiple sectors.

Here, we extend this dynamical adjustment framework from seasonal rainfall to seasonal streamflow. We use observed weather-regime sequences and reconstructed Standardised Streamflow Index (SSI) series to quantify the contribution of synoptic-scale atmospheric circulation to seasonal streamflow variability across Great Britain. We then apply the same framework to UKCP18 global climate model weather-regime sequences to assess whether the models reproduce observed dynamically driven winter streamflow variability. Here, we use the observed relationship between synoptic-scale weather regimes and seasonal streamflow as a fixed transfer function and apply it to the weather-regime sequences simulated by each UKCP18 GCM. This allows us to isolate the contribution of differences in simulated atmospheric circulation to the variance of dynamically driven streamflow, independently of other sources of hydrological model uncertainty.

Specifically, we address three questions:

1. How much of seasonal SSI variability across Great Britain can be explained by synoptic-scale weather regimes?
2. How does this dynamical contribution vary by season and region, and how does it compare with the dynamical contribution to rainfall variability?
3. Do UKCP18 global climate models reproduce the observed interannual variance of dynamically driven winter streamflow when evaluated using a common, observation-based relationship between weather regimes and streamflow?

By quantifying the dynamically driven component of streamflow variability, this study provides a process-based diagnostic for interpreting historical hydrological variability, evaluating climate model performance, and informing the use of UKCP18 climate-model-driven hydrological projections in Great Britain.

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2 Data and Methodology

Figure 1 provides an overview of the datasets and analytical framework used to quantify the dynamically driven component of seasonal streamflow variability. The analysis combines reconstructed Standardised Streamflow Index (SSI) series for Great Britain, daily synoptic-scale weather regimes, HadUK-Grid precipitation, and weather-regime simulations from the UKCP18 Parameter Perturbed Ensemble (PPE). The dynamical adjustment framework is first calibrated using observed weather regimes and historical SSI, before being applied to the UKCP18 weather-regime sequences.

2.1 Data

1.1.1 Standardised Streamflow Index

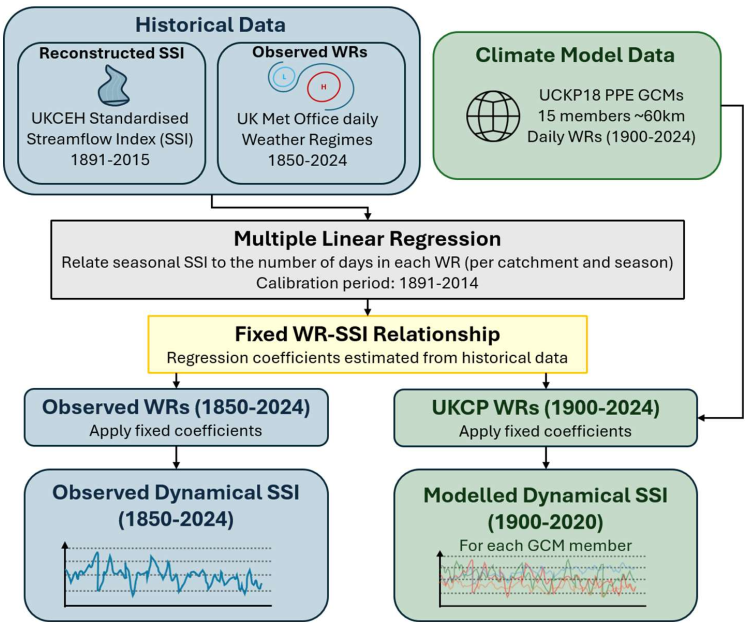

Figure 1: Schematic overview of the dynamical adjustment framework used to estimate and evaluate the dynamically driven component of seasonal streamflow variability. The relationship between weather-regime (WR) frequency and seasonal Standardised Streamflow Index (SSI) is estimated from observations using multiple linear regression. The resulting regression coefficients are held fixed and applied to both observed WR sequences and those from each UKCP18 Parameter Perturbed Ensemble (PPE) member to estimate observed and modelled dynamically driven SSI, respectively. This approach isolates differences in dynamically driven SSI arising from differences in simulated WR sequences rather than changes in the WR–SSI relationship. Dynamically adjusted HadUK-Grid precipitation, calculated following Carruthers et al. (2026), is included for comparison.

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2.1 Data

2.1.1 Standardised Streamflow Index

Historical streamflow estimates are available from the UK Centre for Ecology & Hydrology (UKCEH) for 303 catchments across Great Britain (GB) for 1891-2015 (Barker et al., 2019). The estimates are derived from historical daily river flow reconstructions (Smith et al., 2016) produced using an ensemble of hydrological models. For each catchment, the best performing hydrological model is selected for the construction of the Standardised Streamflow Index (SSI) time series.

The SSI is primarily used as a drought indicator and is calculated using a methodology analogous to the Standardised Precipitation Index (SPI; McKee et al, 1993). A Tweedie distribution is fitted to the streamflow data over the 1961-2010 calibration period. The fitted distribution is then transformed to a standard normal distribution, with SSI expressed as a dimensionless standardised anomaly. Positive SSI values therefore indicate above-average streamflow, while negative values indicate below-average streamflow.

For the dynamical adjustment analysis, seasonal SSI values are used to represent seasonal streamflow variability. The analysis is restricted to 167 non-overlapping catchments, selected from the full set of 303 catchments to avoid spatial duplication when aggregating results to the UKCP18 river regions (Sect. 2.2.2).

2.1.2 Weather regimes

Daily weather regimes (WRs) are used to represent the synoptic-scale atmospheric circulation associated with seasonal streamflow variability. The WR classification was developed by the UK Met Office for use in seasonal forecasting (Neal et al., 2016). It consists of eight circulation regimes derived from an underlying classification of 30 weather patterns (WPs).

The 30 WPs were initially identified using k-means clustering of mean sea level pressure (MSLP) over the domain 30° W-20° E, 35° N-70° N for 1850-2003 using the EMSLP dataset. The 30 WPs were subsequently grouped into eight WRs using spatial correlations together with expert-informed decisions regarding the number and characteristics of the regimes. The WP and WR datasets were extended beyond 2003 using MSLP from ERA-Interim.

The eight WRs represent distinct configurations of North Atlantic and European atmospheric circulation and are summarised in Table 1. They comprise NAO-negative, NAO-positive, northwesterly, southwesterly, Scandinavian High, high pressure over the UK, low pressure close to the UK, and Azores High regimes.

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WR	Name	Description
1	NAO negative	Positive/negative MSLP to the north/south of the UK
2	NAO positive	Negative/positive MSLP to the north/south of the UK
3	Northwesterly	Negative/positive MSLP to the north east/south west of the UK
4	Southwesterly	Negative/positive MSLP to the north west/south east of the UK
5	Scandinavian High	Negative/positive MSLP to the west/east of the UK
6	High pressure over UK	Positive MSLP over the UK
7	Low close to UK	Negative MSLP close to the UK
8	Azores high	Negative MSLP extended from the Azores high

Table 1: Description of the eight weather regimes used in this study.

2.1.3 Climate Models

The climate models assessed in this study are drawn from the UKCP18 Parameter Perturbed Ensemble (PPE) (Murphy et al., 2018). The PPE comprises 15 Global Climate Model (GCM) simulations covering 1900-2100. The ensemble is based on perturbed versions of the Hadley Centre GC3.05 coupled ocean atmosphere model, with a horizontal resolution of approximately 60 km.

The parameters perturbed within the PPE were selected through expert elicitation and subsequently filtered to improve model performance while retaining diversity across the ensemble. The resulting GCMs provide boundary conditions for the UKCP18 12km Regional Climate Model (RCM) ensemble, which in turn provides boundary conditions for the 2.2km convection-permitting model (CPM) ensemble. The PPE therefore forms the basis of the UKCP18 regional climate projections used for UK climate-impact assessments.

Daily WP and WR time series have been derived for the UKCP18 PPE by McSweeney & Thornton (2020). These simulated WR sequences provide the circulation information required to estimate the dynamically driven component of seasonal SSI for each GCM.

2.2 Methodology

2.2.1 Dynamical adjustment of seasonal streamflow

Dynamical adjustment quantifies the component of variability in a local or regional climate variable that can be attributed to changes in large-scale atmospheric circulation. The approach has previously been applied to rainfall (Fereday et al., 2018; Guo et al., 2019; Carruthers et al., 2025, 2026) and temperature (Lehner et al., 2020). Here, the methodology is adapted to quantify the circulation-driven component of seasonal streamflow variability.

Previous applications to rainfall have estimated accumulated seasonal precipitation totals from the frequency of individual weather patterns and the rainfall climatology of each weather pattern. This approach cannot be directly applied to SSI because

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SSI is a standardised index rather than an accumulated quantity. Instead, we use multiple linear regression to relate seasonal SSI to the number of days spent in each of the eight WRs.

Instead, a multiple linear regression methodology is used here:

$$DYN_t = \beta_0 + \sum_{WR=1}^{8} \beta_{WR} X_{WR,t}$$

Where DYN_t is the dynamical contribution to seasonal SSI for season t, β_{WR} represents the effect of a one day increase in the WR count and $X_{WR,t}$ is the count of the WR in t. DYN_t contributes to total SSI for the season such that:

$$SSI_t = DYN_t + \epsilon_t$$

The remaining component is represented by the regression residual, ϵ_t, capturing the non-dynamically explained component of seasonal SSI. This residual may contain other dynamical influences that aren't captured by the eight WRs.

This formulation provides a direct interpretation of the contribution of each WR to seasonal streamflow. For example, a positive regression coefficient indicates that an increase in the number of days assigned to that WR is associated with higher seasonal SSI, while a negative coefficient indicates an association with lower seasonal SSI.

This regression model is fitted independently for each catchment and season using the historical SSI record for 1891-2015. The fitted regression coefficients are then combined with the full observed WR record to estimate the dynamically driven contribution to SSI over 1850-2020.

To assess the extent to which dynamically-driven variability is also present in precipitation, the dynamical adjustment methodology of Carruthers et al. (2026) is applied to the HadUK-Grid regionalised precipitation dataset. Unlike SSI, HadUK-Grid precipitation is available as a daily accumulated quantity, allowing the daily resampling approach used by Carruthers et al. (2026) to be applied directly. This provides a consistent comparison between the dynamically driven components of seasonal precipitation and seasonal streamflow variability.

The fitted SSI regression coefficients are subsequently applied to the WR sequences from each member of the UKCP18 PPE for 1900-2020. Importantly, the regression coefficients estimated from the observed SSI-WR relationship are held fixed for all UKCP18 simulations. Only the frequency and temporal sequence of the WRs are replaced by those simulated by each climate model. This design isolates the effect of differences in simulated atmospheric circulation on dynamically driven streamflow variability.

Consequently, differences between the observed and modelled dynamically driven SSI time series arise from differences in WR occurrence and frequency, rather than from differences in the assumed relationship between a given WR and streamflow. The resulting modelled dynamically driven SSI therefore provides a process-based diagnostic of the extent to which climate models reproduce the circulation-driven component of observed streamflow variability.

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2.2.1 Catchment aggregation

The dynamical adjustment methodology is applied independently to each of the 167 unique, non-overlapping catchments selected from the UKCEH dataset. The catchments are subsequently aggregated to the UKCP18 river regions (Met Office, 2026) by calculating the mean dynamically driven SSI across all catchments located within each region.

A simple arithmetic mean is used because SSI is already standardised within each catchment and is therefore independent of the absolute magnitude of streamflow and catchment area. This approach gives each catchment equal weight in the regional estimate. However, the number of catchments contributing to each river region differs, and this is considered when interpreting regional results.

The resulting regional time series represent the mean dynamically driven SSI across the contributing catchments and are used to assess the spatial and seasonal variability of the circulation-driven component of streamflow across Great Britain.

3 Results

3.1 Dynamically explained variance in seasonal streamflow and precipitation

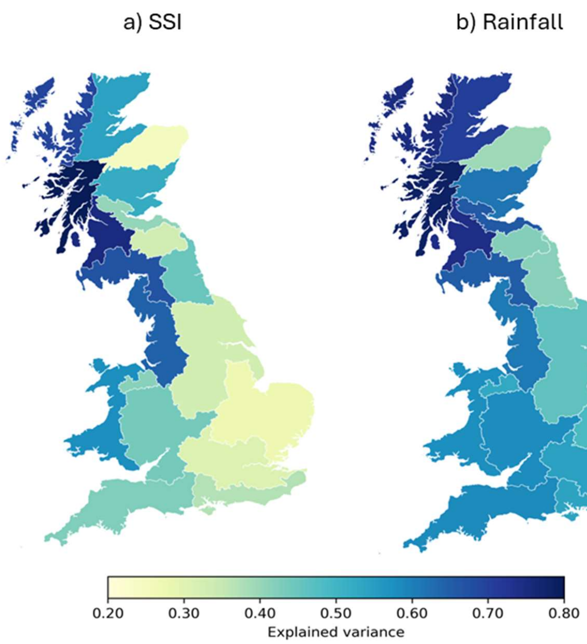

Figure 2: (a) Proportion of interannual winter Standardised Streamflow Index (SSI) variance explained by dynamically driven SSI and (b) proportion of interannual winter precipitation variance explained by dynamically driven precipitation.

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Figure 2a shows the proportion of interannual winter SSI variance explained by dynamically driven SSI. The explained variance varies substantially across Great Britain, with clear west-east and north-south spatial gradients. The largest fractions of explained variance occur across western Wales, north-west England and western Scotland. Argyll has the highest explained variance, with ~80 % of interannual winter SSI variance explained by the dynamical component. In contrast, explained variance is generally lower across eastern Scotland and south-east England, reaching a minimum of ~25% in north-east Scotland.

The spatial distribution of explained winter SSI variance broadly corresponds to that of dynamically explained winter precipitation variance (Figure 2b). For precipitation, explained variance is also generally greatest in western and northern regions and lower towards the east and south-east. This correspondence is further demonstrated in Figure S1, which shows a strong spatial relationship between the regional fractions of dynamically explained SSI and precipitation variance.

Despite this broad correspondence, differences between the spatial patterns of precipitation and SSI indicate that atmospheric circulation alone does not determine the streamflow response. Regional differences in catchment characteristics, including geology, groundwater storage, catchment size, and human influence, may modify the translation of precipitation anomalies into streamflow variability (Chiverton et al., 2015; Tijdeman et al., 2018; Van Loon et al., 2019). These influences are considered further in Sect. 4.

The fraction of SSI variance explained by atmospheric circulation also varies seasonally (Fig. S2). Dynamically driven SSI explains the largest proportion of total SSI variance in winter, with approximately 50% explained across Great Britain on average, compared with approximately 25% in summer. Spring and autumn show intermediate levels of explained variance. A similar seasonal cycle is evident for precipitation, for which dynamically explained variance is substantially lower in summer than in winter. Relationships between total and dynamically driven SSI for individual regions and seasons are shown in Figures S3-6. Overall, these results demonstrate that the influence of synoptic-scale atmospheric circulation on streamflow variability is strongest in winter and weakest in summer, consistent with previous studies of atmospheric circulation and UK streamflow variability (Rust et al., 2021; Svensson et al., 2015)

3.2 Dynamically driven SSI in flood- and drought-sensitive regions

The results in Section 3.1 show substantial regional differences in the influence of large-scale atmospheric circulation on winter streamflow in Great Britain. We therefore examine three regions in greater detail: Clyde, Solway and North West England. These regions have relatively high fractions of dynamically explained winter SSI variance, with R2 values of 0.75, 0.67 and 0.64, respectively, and contain major urban areas exposed to both flood and water resource risks.

Figure 3 compares total and dynamically driven winter SSI in these regions. Dynamically driven SSI reproduces a substantial proportion of the interannual variability in total SSI, consistent with the high explained variance in each region. The correspondence is also evident at longer timescales: the decadal time series in Figure S2 show much of the observed decadal variability in winter SSI is reproduced by the dynamical component.

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Dynamically driven SSI captures winters with high total SSI across all three regions, although the magnitude of individual extremes is not always reproduced. For example, in Solway, the dynamically driven component of the 2013/2014 winter SSI anomaly is approximately 50% smaller than the total SSI anomaly. Differences are also apparent at the dry end of the distribution, where the dynamically driven component tends to be less negative than total SSI during some extreme low-flow winters. These departures indicate that processes not represented by contemporaneous seasonal WR frequencies contribute to the magnitude of some hydrological extremes. One possibility is that autumn SSI has a lagged effect on winter SSI, which may be more pronounced for dry extremes.

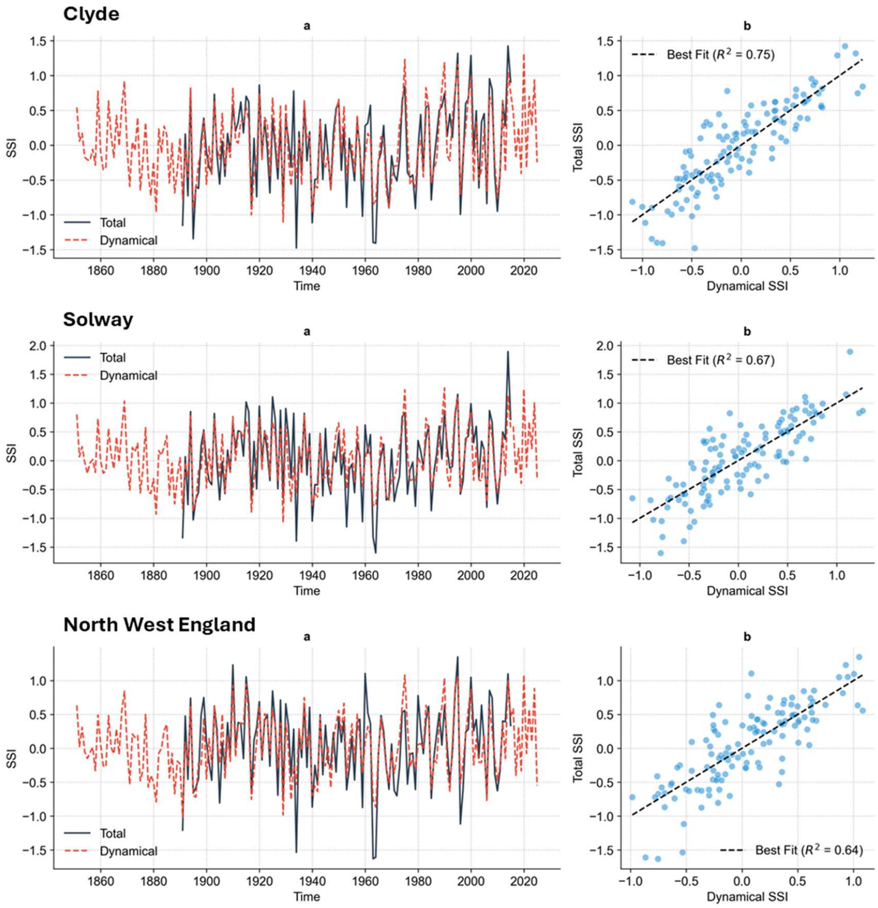

Figure 3: (a) Time series of total winter SSI (1891-2014) and dynamically driven winter SSI (1851-2024) SSI and (b) relationship between total and dynamically driven SSI over their common period (1891–2014) for the Clyde (top), Solway (middle) and North West England (bottom) regions.

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Owing to their geographical proximity, the three regions share many of the same dynamically driven wet and dry SSI winters. The five wettest winters in the dynamically driven winter SSI record are 2019/20, 1974/1975, 1989/1990, 1994/1995 and 2013/2014. Four of these winters are associated with reported flooding within the three regions. For example, flooding during winter 1994/1995 affected approximately 700 homes in Glasgow (Black and Bennett, 1994).

The five driest dynamically driven SSI winters are 1928/29, 1916/17, 1939/40, 1880/81 and 1894/95. Several of these periods coincide with documented drought impacts in Scotland (UKCEH, n.d.).

At decadal timescales, the dynamically driven SSI component also identifies drought-rich periods during the late nineteenth century and the 1940s, 1960s and 1970s (Barker et al., 2019), as well as the relatively flood-rich period since the 1990s (Blöschl et al., 2020) (Figure S7).

3.3 Representation of dynamically driven SSI in UKCP18

Having established that atmospheric circulation variability explains a substantial proportion of total winter SSI variability, particularly across northern and western Great Britain, we next assess whether the UKCP18 GCMs reproduces the observed variance of dynamically driven winter SSI.

Figure 4 shows the percentage bias in variance in winter dynamically driven SSI variance for each UKCP18 PPE member relative to observations. Because the observation-derived WR–SSI regression coefficients are held fixed when applied to each PPE member, differences in dynamically driven SSI variance arise solely from differences in the simulated WR sequences within this framework. The comparison therefore isolates the influence of the modelled atmospheric circulation on dynamically driven streamflow variability.

Most UKCP18 PPE members underestimate observed dynamically driven SSI variance, although both the magnitude and spatial distribution of the bias vary considerably among ensemble members. Several members, including members 1, 5, 9, 12, and 14, exhibit pronounced spatial variation in their biases. For example, member 9 underestimates dynamically explained SSI variance by approximately 20% in south-east England but exhibits considerably smaller biases in north-western regions. Other members, including members 2, 4, 6, 8, 10, and 11 show more spatially uniform biases. In some regions, individual members underestimate dynamically explained SSI variance by as much as 50% (members 10 and 14). Member 3 is the only ensemble member to overestimate variance in part of GB, with positive biases confined primarily to the south-east while variance remains underestimated in the north-west.

At the ensemble mean level, winter dynamically explained SSI variance is approximately 20% lower than observed. This magnitude is comparable to the approximately 20% underestimation of dynamically driven winter precipitation variance reported for the UKCP18 PPE by Carruthers et al. (2026). Together, these results indicate that biases in the representation of atmospheric circulation variability propagate from precipitation to the circulation-driven component of seasonal streamflow variability.

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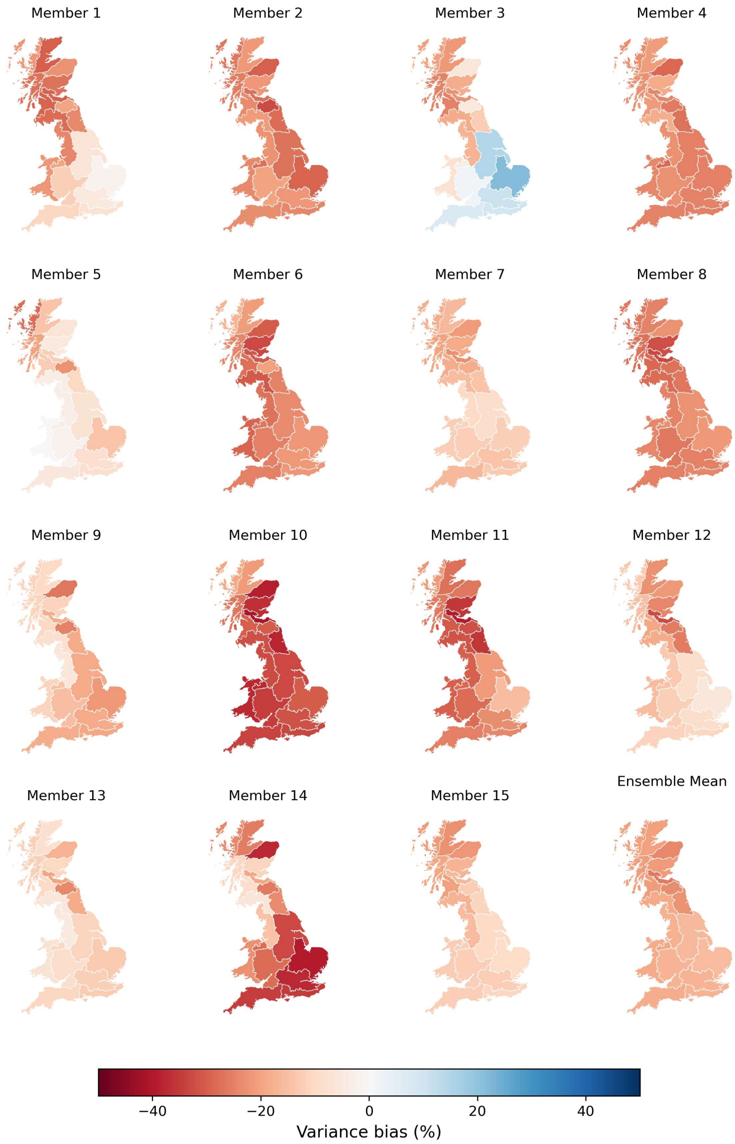

Figure 4: Percentage bias in winter dynamically driven SSI variance for individual UKCP18 PPE members and the ensemble mean relative to observations over 1901-2024. Negative values (red) indicate that the model underestimates observed dynamical SSI variance, while positive values (blue) indicate overestimation.

Regional results for Clyde, Solway and North West England are summarised in Table 2. Consistent with the GB-wide results, ensemble-mean dynamically explained SSI variance is approximately 20% lower than observed in these regions. However, the ensemble mean masks substantial inter-member variability. North West England shows the largest range in model performance, from a bias of only 3% in member 5 to 32% in member 10.

Model performance is also spatially dependent. The member with the smallest variance bias in one region is not necessarily the best-performing member elsewhere. For example, member 5 has the smallest bias in Solway and North-West England but ranks fourth in the Clyde region. Conversely, member 14 has the smallest bias in the Clyde but ranks sixth in North-West England. These results demonstrate that the ability of individual PPE members to reproduce dynamically driven streamflow variability varies geographically and that ensemble-mean behaviour can obscure substantial regional and inter-member differences.

Ensemble member	Clyde (%)	Solway (%)	NW England (%)
1	-29	-28	-25
2	-23	-21	-22
3	-25	-19	-17
4	-21	-18	-23
5	-13	-4	-3
6	-28	-31	-27
7	-18	-15	-10
8	-29	-28	-25
9	-10	-8	-6
10	-30	-32	-32
11	-31	-31	-30
12	-19	-19	-13
13	-10	-6	-5
14	-9	-6	-15
15	-20	-17	-16
Ensemble mean	-21	-19	-18

Table 2: Percentage bias in winter dynamically driven SSI variance for individual UKCP18 PPE members and the ensemble mean relative to observations in the Clyde, Solway and North West England regions over 1901-2024.

4 Discussion

4.1 Atmospheric circulation as a driver of seasonal streamflow variability

This study extends the dynamical adjustment framework previously applied to UK precipitation (Fereday et al., 2018; Carruthers et al. 2026) to seasonal streamflow. The results demonstrate that synoptic-scale atmospheric circulation explains a substantial proportion of winter SSI variability across Great Britain, although the strength of this relationship varies considerably between regions and seasons. Dynamically driven SSI explains more than 50% of winter SSI variability in approximately half of the regions considered and up to approximately 80% in some western regions. These results are

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consistent with previous studies demonstrating strong relationships between North Atlantic atmospheric circulation and UK streamflow variability (Svensson et al., 2015; Rust et al., 2021), but provide a direct quantitative estimate of the contribution of discrete weather regimes to seasonal streamflow variability.

The spatial distribution of dynamically explained SSI variance closely resembles that of dynamically explained precipitation variance, with the strongest relationships occurring across western and northern Great Britain. This correspondence indicates that the spatial dependence of streamflow on atmospheric circulation is partly inherited from the influence of circulation on precipitation. Westerly circulation regimes exert a particularly strong control on winter precipitation across western Great Britain, where orographic enhancement increases precipitation on windward slopes while rain-shadow effects reduce the influence of westerly circulation further east. The resulting spatial structure in dynamically driven precipitation therefore propagates into seasonal streamflow.

However, dynamically explained SSI variance is generally lower than dynamically explained precipitation variance, indicating that the translation of precipitation into streamflow introduces additional sources of variability. Catchment characteristics including geology, groundwater storage, catchment size, antecedent conditions and human modification influence both the magnitude and timing of the streamflow response to precipitation (Chiverton et al., 2015; Tijdeman et al., 2018). For example, catchments in south-east England are strongly influenced by Chalk aquifers, groundwater storage and abstraction, which can delay and attenuate the response of streamflow to contemporaneous atmospheric forcing. In contrast, many catchments in north-western Great Britain have shorter hydrological response times and less groundwater storage, producing a more direct response to precipitation. These differences may partly explain why atmospheric circulation accounts for a greater proportion of seasonal SSI variability in some western regions than in parts of southern and eastern Great Britain.

Hydrological memory may also contribute to departures between dynamically driven and total SSI. Antecedent soil-moisture and groundwater conditions can influence seasonal streamflow independently of circulation during the season itself. This may be particularly important during hydrological extremes. For example, the difference between total and dynamically driven SSI during the extreme winter of 2013/2014 in Solway suggests that contemporaneous winter WR frequencies alone do not explain the full magnitude of the event. Similarly, differences between dynamically driven and total SSI during some dry winters may reflect antecedent conditions or nonlinear catchment responses. Incorporating lagged atmospheric or hydrological predictors, such as autumn WR frequencies or antecedent SSI, may therefore provide a useful extension of the framework.

The seasonal dependence of explained variance provides further evidence of the importance of the precipitation–streamflow pathway. Dynamically driven SSI explains substantially more variability in winter than in summer, consistent with the corresponding seasonal dependence of dynamically explained precipitation. Summer precipitation is more strongly influenced by local and mesoscale processes, including convection, which are not fully represented by the synoptic-scale WR classification. In addition, higher evapotranspiration and greater soil-moisture limitation during summer further weaken the direct relationship between atmospheric circulation, precipitation and streamflow. The weaker performance of the dynamical adjustment in summer therefore reflects both reduced synoptic control of precipitation and greater hydrological modulation of the precipitation signal.

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At longer timescales, dynamically driven SSI reproduces much of the observed decadal variability in regions such as Clyde, Solway and North-West England. This is consistent with evidence that North Atlantic circulation, including the NAO, exhibits substantial decadal variability associated with variability in North Atlantic sea-surface temperatures (Woollings et al., 2015). The strong correspondence between dynamically driven and total SSI at decadal timescales suggests that variations in the frequency and persistence of circulation regimes contribute not only to individual wet and dry winters but also to multi-year periods characterised by enhanced flood or drought occurrence.

4.2 Potential applications of dynamically adjusted streamflow

The ability of the dynamical adjustment framework to explain a substantial proportion of seasonal SSI variability suggests three potential applications: seasonal forecasting, extension of the historical context of streamflow variability, and diagnosis of climate-model-driven hydrological projections.

First, the framework could contribute to seasonal streamflow forecasting. The weather patterns used here were originally developed by the UK Met Office for seasonal forecasting and are used operationally for predicting seasonal anomalies in variables including precipitation and temperature (Neal et al., 2016). Representing atmospheric circulation using a relatively small number of discrete regimes provides a physically interpretable link between predictable large-scale circulation and regional hydrological response. In regions where the relationship between WR frequency and SSI is particularly strong, such as the Clyde, forecasts of seasonal WR occurrence could therefore provide information on the likelihood of anomalously high or low winter streamflow. Such information could complement existing approaches to seasonal hydrological forecasting (Chan et al., 2026), particularly for water-resource planning and flood preparedness. This may be especially valuable where winter precipitation and streamflow make an important contribution to annual groundwater and reservoir recharge.

Second, the long observational WR record allows dynamically driven SSI to be reconstructed beyond the period covered by the historical SSI dataset (Figure 3). Although such a reconstruction cannot replace observed or hydrologically reconstructed streamflow, it provides an independent circulation-based estimate with which to place recent hydrological variability in a longer-term context. Several of the largest dynamically driven wet winters occur in recent decades, including 1989/90, 2013/14, 2019/20, while the reconstruction also identifies historically drought-rich periods during the late nineteenth and twentieth centuries. The particularly strong relationship between total and dynamically driven SSI at decadal timescales suggests that the framework may be especially useful for investigating longer-term variations in hydrological conditions. However, interpretation of individual extremes should remain cautious because the dynamical reconstruction represents only the component associated with the WR classification and does not account explicitly for antecedent hydrological conditions or other processes affecting streamflow.

Third, the framework provides a computationally efficient means of diagnosing the atmospheric-circulation contribution to streamflow variability in climate-model ensembles. Once WRs have been identified from modelled sea-level pressure, dynamically driven SSI can be estimated without running an additional hydrological model for every ensemble member. This could facilitate analysis of larger climate-model ensembles and provide improved sampling of model uncertainty and internal

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climate variability (Chan et al., 2025). Importantly, this application should be viewed primarily as a process-based diagnostic rather than as a replacement for conventional hydrological projections. Dynamically driven SSI does not represent changes in all processes controlling future streamflow, but instead isolates the component associated with changes in large-scale circulation.

Application of the framework to future climates also requires an assumption that the historical relationship between WR occurrence and streamflow remains sufficiently stationary. This assumption may become less valid under substantial warming. The precipitation, temperature, humidity and evapotranspiration associated with a given circulation regime may change even if the large-scale pressure pattern remains similar. Changes in land use, abstraction, catchment management, soil moisture and groundwater storage could further modify the hydrological response to a particular WR. Consequently, future dynamically driven SSI should be interpreted as the streamflow component implied by changes in circulation under the historical WR–SSI relationship, rather than as a complete projection of future streamflow.

4.3 Representation of dynamically driven streamflow variability in UKCP18

A central result of this study is that the UKCP18 PPE systematically under-represents the observed variance of dynamically driven winter SSI, with ensemble mean variance approximately 20% lower than observed. Individual ensemble members exhibit substantially larger biases in some regions, reaching 50%. These biases are particularly relevant because atmospheric circulation explains a large proportion of winter streamflow variability in several GB regions exposed to flood risk and containing nationally important water resources. The UKCP18 PPE is used to develop many flood risk and water resource plans in GB.

The experimental design allows this bias to be interpreted more specifically than would be possible from a direct comparison of modelled and observed streamflow. The WR–SSI regression coefficients are estimated once from observations and held fixed when applied to every UKCP18 PPE member. The models are therefore not permitted to generate different WR–streamflow relationships. Within this framework, differences between observed and modelled dynamically driven SSI arise solely from differences in the simulated WR sequences. The underestimation of dynamically explained SSI variance can therefore be interpreted as evidence that the PPE does not fully reproduce the atmospheric-circulation variability required to generate the observed variance in circulation-driven seasonal streamflow.

This finding is consistent with known biases in the representation of North Atlantic circulation by climate models. GCMs commonly simulate a North Atlantic jet stream that is too equatorward and too zonal (Priestley et al., 2020), while GCMs also under-represent recent strengthening trends in the North Atlantic jet stream, and the increasing frequency of NAO positive conditions (Blackport & Fyfe, 2022). Climate models additionally exhibit biases in the persistence of circulation regimes, particularly atmospheric blocking (Schiemann et al., 2020; Simpson et al., 2020). Because seasonal hydrological anomalies depend not only on individual weather events but also on the frequency and persistence of circulation regimes over weeks to months, these circulation biases can affect seasonal precipitation totals (Blackport & Fyfe, 2022; Carruthers et al., 2025) and variability (Carruthers et al., in review), and ultimately streamflow variability.

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The similarity between the approximately 20% ensemble-mean underestimation of dynamically driven SSI variance identified here and the approximately 20% underestimation of dynamically driven precipitation variance reported by Carruthers et al. (2026) is particularly noteworthy. It suggests that biases in atmospheric circulation variability can propagate through the hydroclimatic system from precipitation to streamflow. This provides a physical link between previously identified circulation and precipitation biases and the hydrological variability investigated here.

This result also highlights an important distinction between the simulation of local meteorological processes and large-scale atmospheric circulation. At daily timescales, accurate hydrological simulations require climate models to reproduce the distributions of precipitation, temperature and other meteorological variables. Improvements in model resolution can improve the representation of processes such as convection and orographic precipitation (Kendon et al., 2017). However, accurate representation of these local processes does not necessarily ensure realistic seasonal variability. Weekly to seasonal precipitation and streamflow anomalies also depend on whether the model reproduces the frequency, persistence and sequencing of the large-scale circulation regimes that generate those conditions (Addor et al., 2016; Maraun et al., 2021). The results presented here therefore demonstrate the value of evaluating atmospheric circulation alongside conventional meteorological variables when assessing climate models for hydrological applications.

4.4 Implications for climate-model selection and bias correction

The substantial inter-member and regional variation in dynamically explained SSI variance bias has implications for the interpretation of UKCP18 hydrological projections. Ensemble-mean behaviour masks considerable differences between individual PPE members, and the member with the smallest circulation-related streamflow bias differs between regions. This means that a model performing well for dynamically driven streamflow variability in one part of Great Britain cannot necessarily be assumed to perform equally well elsewhere.

These results suggest that process-based diagnostics of atmospheric circulation could provide useful additional information when evaluating climate models for regional hydrological applications. However, low historical dynamically explained SSI variance bias alone would not justify assigning greater weight to an ensemble member for future projections. Model weighting would require evidence that the diagnostic is relevant to the projected quantity of interest and that historical performance provides meaningful information about future projection skill. Nevertheless, the substantial differences identified here provide a strong rationale for examining circulation-related performance alongside more conventional metrics of precipitation and temperature when assessing model suitability for flood and water-resource applications.

The results also have implications for bias correction. Climate-model output is commonly bias-corrected before being used to drive hydrological models because biases in precipitation, temperature and other variables can otherwise propagate into simulated streamflow (Addor and Seibert, 2014; Teutschbein and Seibert, 2012). However, statistical agreement in a meteorological variable does not necessarily imply that the physical processes generating that variable are represented correctly. For example, a bias in seasonal precipitation may arise from errors in the precipitation generated within a given circulation regime, errors in the frequency or persistence of the circulation regimes themselves, or a combination of both.

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Correcting the seasonal precipitation distribution without distinguishing between these sources of error can therefore conflate dynamical and thermodynamic biases. As argued by Maraun et al. (2017) bias correction is most defensible when informed by an understanding of the physical origin of model errors. Dynamical adjustment provides one means of making this distinction. By separating the component of hydroclimatic variability associated with atmospheric circulation from the remaining variability, it can help identify whether a model bias originates primarily from the representation of circulation or from processes operating within a given circulation state. Such information could ultimately support more process-informed approaches to climate-model evaluation and bias correction for hydrological impact assessment.

Overall, the results demonstrate that large-scale atmospheric circulation is an important source of seasonal and decadal streamflow variability across Great Britain and that this contribution is not fully represented by the UKCP18 PPE. Dynamical adjustment provides a relatively simple and physically interpretable framework for isolating this component of hydrological variability. Its greatest value may therefore lie not in replacing conventional hydrological modelling, but in complementing it: providing a process-based diagnostic for understanding historical variability, exploiting predictable atmospheric circulation, and identifying circulation-related biases in climate-model-driven hydrological projections.

5 Conclusions and outlook

This study demonstrates that weather-regime-based dynamical adjustment (Carruthers et al. 2026) can isolate a substantial component of seasonal streamflow variability across GB. The approach is most effective in winter and in western and northern regions, where large-scale atmospheric circulation exerts a strong influence on precipitation and streamflow. Applying the observation-derived WR–SSI relationships to UKCP18 weather-regime sequences shows that the ensemble systematically under-represents dynamically driven winter SSI variance, by approximately 20% in the ensemble mean. This demonstrates how biases in simulated atmospheric circulation can propagate into the hydrological variability represented by climate models. These results highlight the value of separating circulation-related variability from other sources of hydrological variability when evaluating climate-model-driven projections. Dynamical adjustment provides a computationally inexpensive, process-based diagnostic that can complement conventional hydrological modelling and help identify the physical origins of biases relevant to flood, drought and water-resource assessments.

Future work could exploit long weather-regime records and large climate-model or hindcast ensembles to investigate hydrological extremes beyond those observed historically, including through UNSEEN approaches (Chan et al., 2024). Particular attention should be given to the persistence and sequencing of extreme seasons, especially consecutive dry winters in catchments dependent on winter recharge (Chan et al., 2022). Incorporating antecedent hydrological conditions and developing circulation diagnostics better suited to summer rainfall may further extend the applicability of the framework.

Crucially, these results highlight the need for careful interpretation of GCM driven hydrological simulations, particularly when assessing seasonal variability. We show that the UKCP18 PPE systematically underestimates the interannual variability of dynamically driven winter streamflow, indicating that biases in large-scale atmospheric circulation can propagate into

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hydrological projections. Distinguishing biases associated with atmospheric dynamics from those arising from thermodynamic and local precipitation processes is therefore an important step towards more process-informed climate model evaluation and bias correction prior to hydrological modelling, particularly given the role of these simulations in informing long-term climate adaptation and investment decisions.

Code and data availability

Data used in this study is publicly available. SSI data is available at UKCEH: https://catalogue.ceh.ac.uk/documents/58ef13a9-539f-46e5-88ad-c89274191ff9, historical weather patterns are available at: https://doi.pangaea.de/10.1594/PANGAEA.942896 , UKCP18 weather patterns are available at: https://catalogue.ceda.ac.uk/uuid/6e61f79cb6b0457eb84edaffcf0aab3a/ and UK precipitation data is available at: https://catalogue.ceda.ac.uk/uuid/4dc8450d889a491ebb20e724debe2dfb/.

Supplement

The supplementary material is provided as separate file and available with this article.

Author contributions

J.G.C. was responsible for data analysis and writing. A.M. and H.J.F. were responsible for supervision and writing.

Competing interests

There are no conflict of interests to declare.

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