Reply to Comments by Referee #3

Review of "Evolution of nonstationary hydrological drought characteristics in the UK under warming" by Jha et al.

Comment This manuscript proposes an analysis of the probability of occurrence of rare hydrological droughts in the UK under different warming levels. It makes use of state-of-the-art multimodel hydrological projections over the 21st century and of an extreme value analysis of drought characteristics (duration, intensity, severity). Note that hydrological drought are defined through daily anomalies with respect to an average daily regime and the manuscript topic is therefore not about low-flows. The manuscript is well written and well organised. Methods, results, and corresponding conclusions are sound. Moreover, such an analysis is timely when climate change adaptation is more and more organised around Global or Regional Warming Levels (see e.g. Sauquet et al., 2025). **I have however one concern about the seasonal approach chosen to present results**. It is detailed -- with suggestions of improvements -- along another general comment below. Specific comments are also detailed afterwards. I would therefore recommend a revision to be made on this point before publication.

Reply: We sincerely thank the reviewer for their thorough reading and detailed evaluation of our manuscript. We greatly appreciate your positive recommendations, questions, and suggesting constructive changes for improvement. Below, we provide point-wise responses to each of your comments.

General comments

Comment 1: L244-249: This is where the methodological choices seem rather strange. I do not understand why results are artificially broken by seasons after an event-based analysis. Indeed, any physical continuity across seasons is lost while this continuity is of uttermost importance when analysing seasonal shifts in drought development. Furthermore, analysing seasons separately leads inevitably to an artificial upper bound for duration (and therefore severity). **I would strongly suggest considering instead e.g. the proportion of each individual event in each season (possibly considering also different consecutive years/seasons for a single multiyear event).** This would only slightly alter the analysis and bring much more insight into drought changes.

Reply 1: Thank you for raising this very important point. We would like to clarify that in our study, event detection is performed on the full continuous time series in reference period and warming level periods, not within seasons. Seasonal metrics are calculated only after drought events and their onset are identified, so physical continuity is preserved, and duration or severity are not artificially capped by seasonal or yearly boundaries except in the last year of the period. We have calculated the drought characteristics based on the starting point of the event and assigned the season based on starting month. While considering the proportion of each event across seasons could add another dimension and provide additional insights, it might also complicate both the representation and interpretation of drought events, especially for some long or severe events that span multiple seasons. This might also require different approaches for allocating proportionality to duration, severity, and intensity, potentially leading to multiple representations of the same event. For example, a 150-day event might need to be expressed as 70% in one season, 20% in another, and 10% in a third based on its duration distribution. However, the same event could show a different distribution in terms of severity or deficit volume such as peaking in the final season which would then need to be accounted for. In some cases, this potentially dilute the key message that the event is after all fundamentally only one long and continuous event.

For these reasons, we assign the season based on the starting month of each drought event. Additionally, the use of a 30-day rolling-window and variable threshold methods allows us to incorporate smooth intra-annual variability and ensures that hydrological droughts are identified only when flows fall below the seasonally expected level for that day.

In the revised manuscript, we aim to clarify our seasonal approach more clearly by mentioning the above points in **L244-249** and also include an additional analysis comparing the distribution of drought characteristics using alternative metrics as suggested alongside the approach we adopted to assess the suitability and sensitivity of the two different methods.

Comment 2: The warming level analysis is rather attractive, but **associated uncertainties are barely discussed** in the manuscript although they are crucial for adaptation purposes. Some specific comments below detail a few aspects of that, but the main question arising here is the relative importance of **the diversity of climate projections, the diversity of hydrological models, and GEV parameter estimation**. I may have missed corresponding explanations, but it is unclear **how pooling is done across climate projections** (and or not across hydrological models) to derive GEV estimates. **Making hypotheses even clearer** is a major point of potential improvement for the manuscript.

Reply 2: Thank you for the important observation and suggestions. We agree that associated uncertainty is one of the important aspects on our analysis and needs more discussion in the manuscript. In the revised version, we intend to include points to explain the methodological basis of addressing this and more discussion based on the results we obtained. More specifically:

<u>on the importance of the 'diversity of climate projections'-</u>

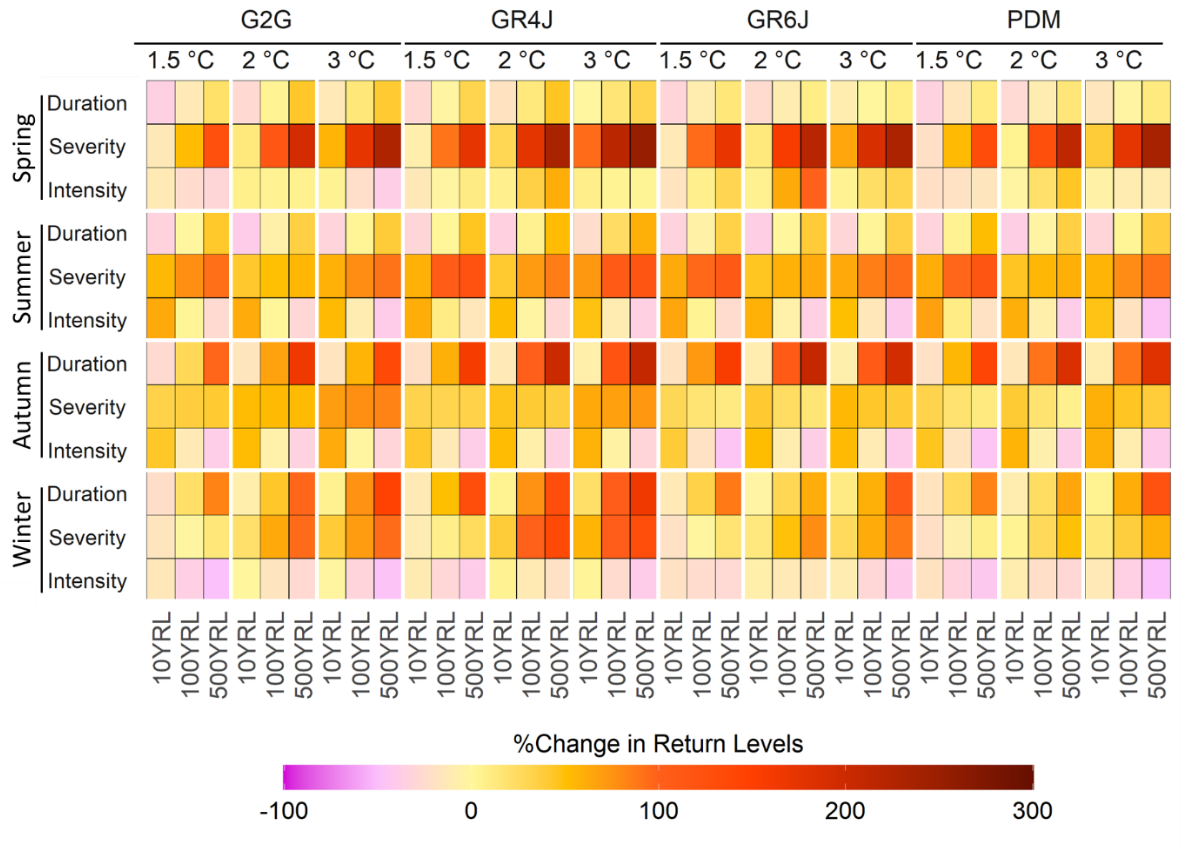
we will modify **L131-135** in Section 2.1 explaining eFLaG 'simrcm' projections data as following:

The 'simrcm' projections consist of a 12-member ensemble generated using perturbed-parameter runs of the Hadley Centre global climate model (GCM, HadGEM3-GC3.05) and regional climate model (RCM, HadREM3-GA705) (Murphy et al., 2018). Each ensemble member represents a plausible variation in model parameters to capture uncertainty in the climate response, while all members share the same underlying model framework and follow the high-emissions scenario (RCP8.5). We focus exclusively on the RCP8.5 pathway in this study because it represents a worst-case, but varying warming trajectories, allowing a clear assessment of the upper bound of potential changes in extremes under climate change.

<u>on the importance of the 'diversity of hydrological models'-</u>

In the manuscript, we provide a brief description of the structure and characteristics of the hydrological models used (**L136-144**). In our analysis, we observe that the uncertainty in return-level changes is driven primarily by the rarity and the characteristic of the hydrological drought events rather than by differences between the individual hydrological models. We illustrate this in Figure 6 (main text) and Figure S4a-f (supplementary material), where we compare stationary and nonstationary return-level changes across UK. Since these figures show that inter-model differences are relatively smaller as compared to the factors mentioned above, we chose not to discuss the results of each hydrological model separately and clarified this point in **L406-408**.

However, in the revised manuscript, we will introduce a more detailed analysis of uncertainty by including additional results. We will incorporate and discuss a new figure in the main text (shown below) illustrating changes across models, seasons, characteristics, warming levels, and return periods, providing a comprehensive perspective on the associated uncertainties and explicitly highlighting inter-model differences for nonstationary return levels. This will help readers better understand the range of possible deviations and uncertainties in hydrological drought projections across different layers, with particular emphasis on variations between models.



On the importance of ‘GEV parameter estimation’-

Parameter uncertainty is a key aspect of the nonstationary hydrological drought risk assessment. As discussed in the manuscript (Figure S1), we obtain robust posterior distributions of parameters using a Bayesian MCMC approach. To illustrate the impact of parameter uncertainty, we computed results using four different summaries of the parameter distribution: the 25th percentile (Q25), the 75th percentile (Q75), the mean, and the median. The estimates of return level changes, as well as the differences between nonstationary and stationary return levels across these four summaries, demonstrate consistency and robustness throughout the analysis, as shown in Figures S2 and S3. In the revised manuscript, we will provide a more detailed description of these points and will also discuss the possible implications of the same.

In addition to explaining the three factors individually, we will also discuss their relative importance in the revised manuscript.

On pooling procedure:

In the revised manuscript, we will modify **L230-238** as follows to provide a clearer and more precise explanation:

For each of the 12 ensemble members of each hydrological model, we first calculated the daily mean flow values for every day of the reference period using the eFLaG dataset**.** We then applied a 30-day rolling window centred on each day of the year. For example, for 15 January, the window includes flows from 15 days before to 15 days after. This smoothing method helps capture natural variability in daily flows and prevents the resulting statistics from being overly influenced by short-lived extreme events. Using these rolling-window values, we derived 365 Q90 thresholds, one for each day of the year, representing the 90th percentile exceedance flow for the reference period. These thresholds were then used as the baseline against which projected flow levels at different warming levels were compared. Specifically, we calculated the difference between projected flows and the corresponding daily Q90 threshold to identify high-flow anomalies or deficits relevant for drought analysis. The resulting drought characteristics for each warming level were subsequently pooled across all 12 ensemble members, and this pooled dataset was used to fit GEV distributions to assess changes in extremes under future climate conditions.

<u>On Making hypotheses clearer:</u>

As also requested by Reviewer 2, we propose to modify **L186** and include the following lines in the revised manuscript to provide additional clarification:

The null hypothesis in our study assumes that drought characteristics extremes are stationary, meaning their statistical properties do not change over time or with temperature. Using the likelihood ratio test, this hypothesis is evaluated by comparing the fit of stationary and nonstationary GEV models. The null hypothesis is rejected when the p-value falls below 0.05, indicating that including temperature as a covariate significantly improves the model. Such an approach is consistent with standard methods in extreme value analysis for hydrological data (Salas and Obeysekera, 2014; Das and Umamahesh, 2017).

Specific comments

Comment 3: L146-150: Does eFlag use CHESS-SCAPE as forcings for hyrological models? Please make it clear.

Reply 4: L146-150 will be modified as follows:

The CHESS-SCAPE temperature records used in this analysis are derived from UKCP18 projections that have been downscaled to 1 km resolution using methods that account for local topographic effects and pattern scaling properties for different scenarios. It should be noted that the eFLaG dataset is based directly on the original UKCP18 projections.

Comment 4: L159-161: How is the daily temperature anomaly defined in CHESS-SCAPE? What is the reference period? How is seasonality taken into account? What is the spatial scale considered for computing the anomalies: local, UK, global? Please detail the answers explicitly in the manuscript.

Reply 5: Thank you for the suggestion. More clarification at **L161** will be added in the revised version of the manuscript as below:

Here, daily temperature anomaly for each period were calculated relative to the mean temperature over the UK for the reference period (1989-2018). After identifying drought events, we matched the timestamp of each drought characteristic with the corresponding temperature time series and used the mean reference-period to compute the anomalies, which were then used as covariates. Please refer to Section 2.4 for further details on the event-calculation methodology to understand how seasonality and continuation of events have been considered.

Comment 5: L 220-224: Please define exactly what these warming levels refer to. Are they Global Warming Levels (GWLs)? Are they Regional (UK) Warming Levels (RWLs)? In the first case, how GWLs translate into RWLs?

Reply 5: We agree that clearer explanation of the considered warming levels is needed. In addition to replacing the word 'global' with 'regional warming levels/UK warming levels', we propose to add the following statements with suitable references at **L220-224** in the revised manuscript clarifying warming level's relationship to the underlying global temperature used during CHESS-SCAPE dataset:

The warming levels in this analysis should be interpreted as regional UK warming levels rather than global warming levels, since CHESS-SCAPE provides only UKCP18 climate projections over the UK. While the CHESS-SCAPE framework does use global mean air temperature from UKCP18 GCMs and uses time shifting and pattern scaling, the downscaled dataset contains only UK specific surface variables (Robinson et al., 2022a). However, these warming levels are broadly aligned with GWLs as UKCP18 assumes seasonal UK climate anomalies scale linearly with global mean temperature, and it is known that UK temperature changes generally track global land-surface warming (Kendon et al., 2023).

Comment 6: L238-251: How does this pooling procedure compare with the Sequent Peak Algorithm (SPA) traditionally used with a fixed threshold?

Reply 6: The pooling methodology used in our analysis differs from the traditional Sequent Peak Algorithm (SPA). In SPA, a fixed threshold is applied, and a new drought event is recognized only when the cumulative deficit returns to zero. In contrast, our approach allows two drought events separated by a single day to be pooled if the flow on that day does not exceed the cumulative deficit accumulated beforehand. This ensures that longer droughts with short interruptions are properly captured, which might otherwise be overlooked by the SPA-based method.

Comment 7: L242: What does "standard" refer to? 30 days sound already quite long for a drought event, even with a daily varying threshold. Please comment on that. Plus, this introduces a hard lower bound for duration, which may hide some signal on "flash droughts". I would therefore recommend not censuring a priori such short events which might (depending on catchment storage) bring in some extreme values of e.g. intensity.

Reply 7: Thank you for the comment and recommendation. In the revised manuscript, we will clarify this and discuss its implications, including the potential exclusion of flash droughts. We propose to include the following clarification at **L242:**

To reduce uncertainty arising from very short, potentially non-significant drought events caused by daily variability in the threshold, we excluded events with a duration of less than 30 days. Given that we focus on Q90 to derive these events, even after applying precautionary measures such as a 30-day moving window and a 12-member ensemble pool to ensure smoother and larger sample sizes, extreme value analysis remains challenging, particularly for rare, small drought events. We acknowledge that this threshold effectively imposes a hard lower bound on drought duration and may also exclude smaller events such as flash droughts. Nevertheless, we chose 30 days which has widely been used in similar analyses (Anderson et al., 2025; Brunner and Chartier-Rescan, 2024), as compromise to balance robustness of event statistics with capturing meaningful hydrological droughts.

Comment 8: Section 3.1. and Fig. 2.: Fig. 2 presents strong fluctuations of stationarity properties across warming levels with e.g. the number of nonstationary catchments declining from 1.5°C to 2°C and increasing to 3°C. This demonstrates the limits of pattern scaling properties and what is striking is that this is barely commented in the corresponding text of Sect. 3.1. Please at least add such comments on that, as pattern scaling is indeed one of the foundations of this manuscript. What is also missing here is the corresponding spatial patterns of such nonstationarity, which would be interesting for understanding the limits of pattern scaling across the UK.

Reply 8: We agree that limitations of pattern scaling properties and spatial patterns of nonstationary should be discussed in more detail in Section 3.1. In the revised manuscript, we will modify this section and **L266-270** as following for more clarity and explanation:

Further, the fluctuations in the stationarity properties of catchments specifically, the number of nonstationary catchments declining from 1.5°C to 2°C warming but then increasing at 3°C highlight the limitations of the pattern scaling assumption. This is central to CHESS-SCAPE and UKCP18 data considered, which is based on the assumption that local or regional climate responses scale linearly with global mean temperature (Robinson et al., 2022a). The observed variations suggest that this assumption may break down for certain warming levels or in specific regions, as illustrated in Figures 2 and 3. Examining the spatial distribution of nonstationarity across the UK provides insight into where pattern scaling might hold and where caution is needed, highlighting regions dominated by nonlinear responses. Therefore, changes in nonstationary properties, their dependence on warming levels, catchment characteristics, and seasonal variability must be considered with full caution when modelling the evolution of future hydrological droughts.

Comment 9: L.288: Fig. S1 is rather required in the main text in my view.

Reply 9: Figure S1 will be included in the main text in the revised manuscript.

Comment 10: Fig. 3: This is clearly unreadable as such, for several reasons. One, the color scale is non linear, which is definitely against perceptual rules (Hawkins, 2015 ; Stoelze and Stein, 2021). Two, maps are way too small. Three, using catchment surface as the support for colors is not appropriate for such small figure dimensions, as it perceptually highlights only large catchments. I would therefore strongly suggest using shapes at the outlet of each catchment. Four, colorscale label sizes are not homogeneous across facets, and the colorscale titles "location paramater" are redundant.

Reply 10: Thank you for the constructive feedback. Here we have included the modified figure based on your recommendations for your reference. If suggested, we will replace Figure 3 in the revised manuscript with this new figure.

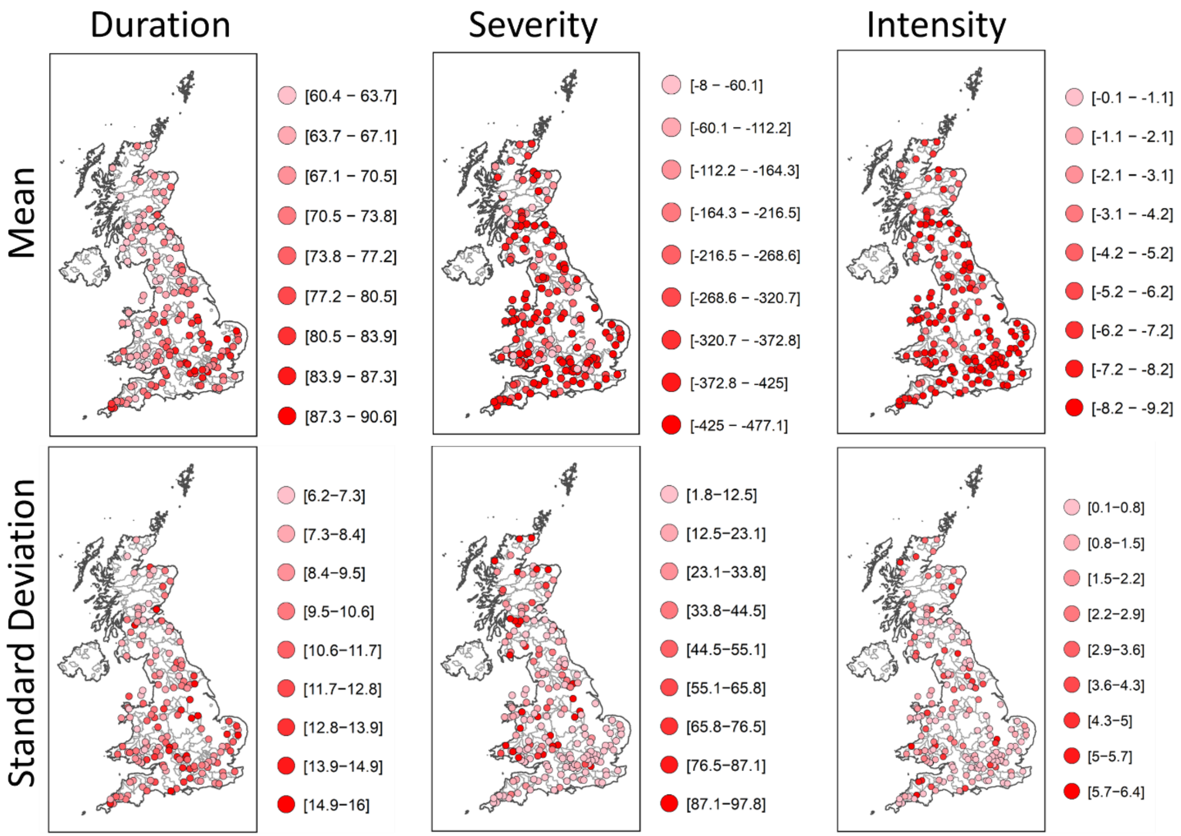


Figure 3. Mean and standard deviation of location parameter samples for GR4J model during summer season at 3°C warming level.

Comment 11: Fig. 4: This is again much too small for being readable. And again, I would strongly recommend using e.g. disc shapes, and also using grey instead of black for UK coastlines. A discrete color scale might also be more effective.

Reply 10: Thank you for your recommendation. We understand that it may be challenging for readers to interpret the distribution of changes in return levels for smaller catchments in the current form of plot. Main aim of our analysis is to provide an overall picture of changes in different drought characteristics, seasons, warming levels, and return periods across the UK. Each figure combination therefore contains multiple smaller plots of the UK, resulting from iterative analyses providing readers an opportunity to compare multiple cases. However, we do understand that this can be improved based on your suggestions. Below we have included a sample modified Fig. 4 incorporating the recommendations about using discs instead of colouring the catchment shapefiles, a discrete color scale and grey for UK coastlines in this document. We also propose to split Fig. 4a and Fig 4b into two separate and larger figures as given below. This, if preferred, may replace Fig. 4 in the revised manuscript, and similar updates mat be applied to the other figures in the supplementary information:

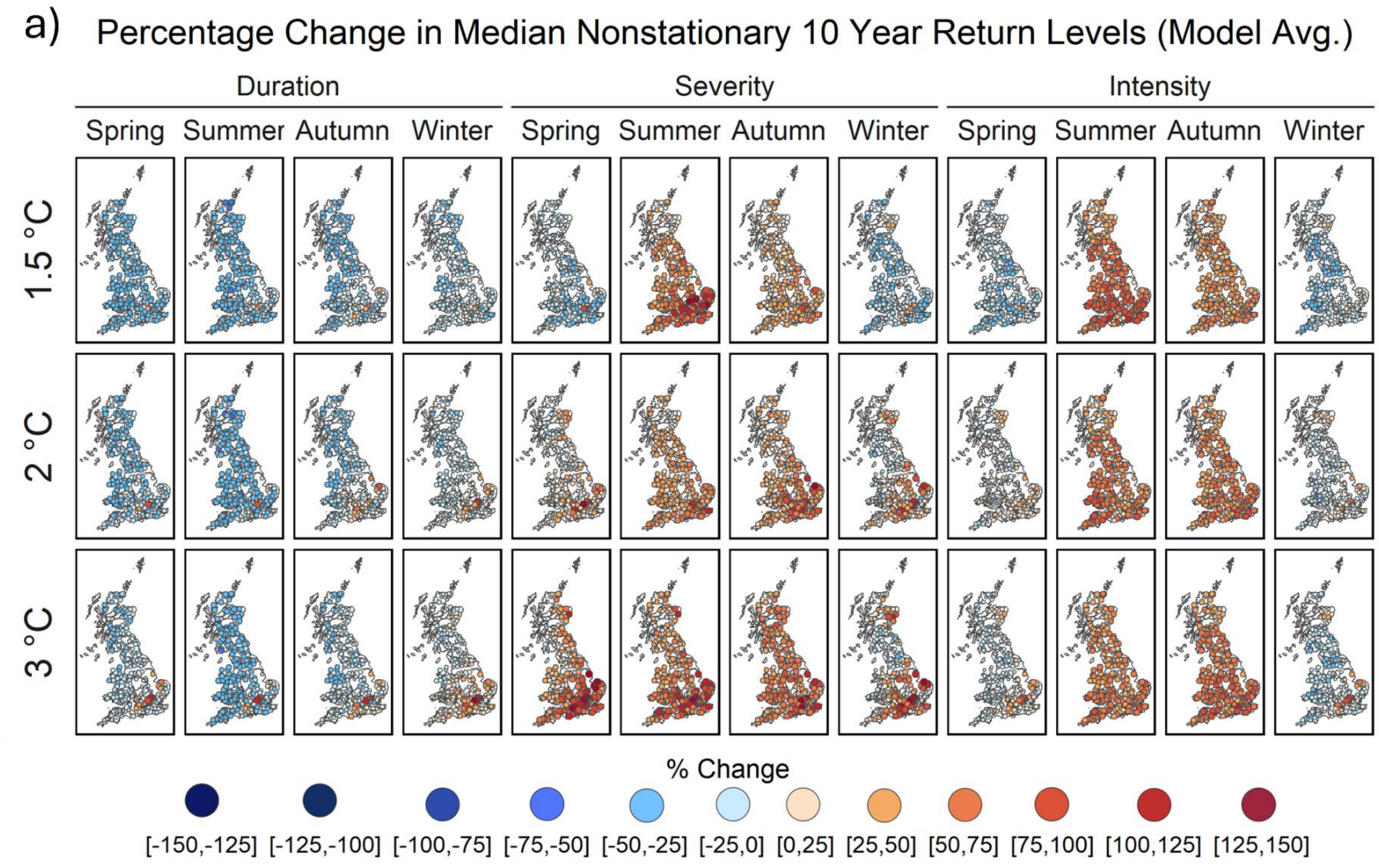


Figure 4a. Percentage change in mean nonstationary 10-year return levels for different drought characteristics across all warming levels and seasons.

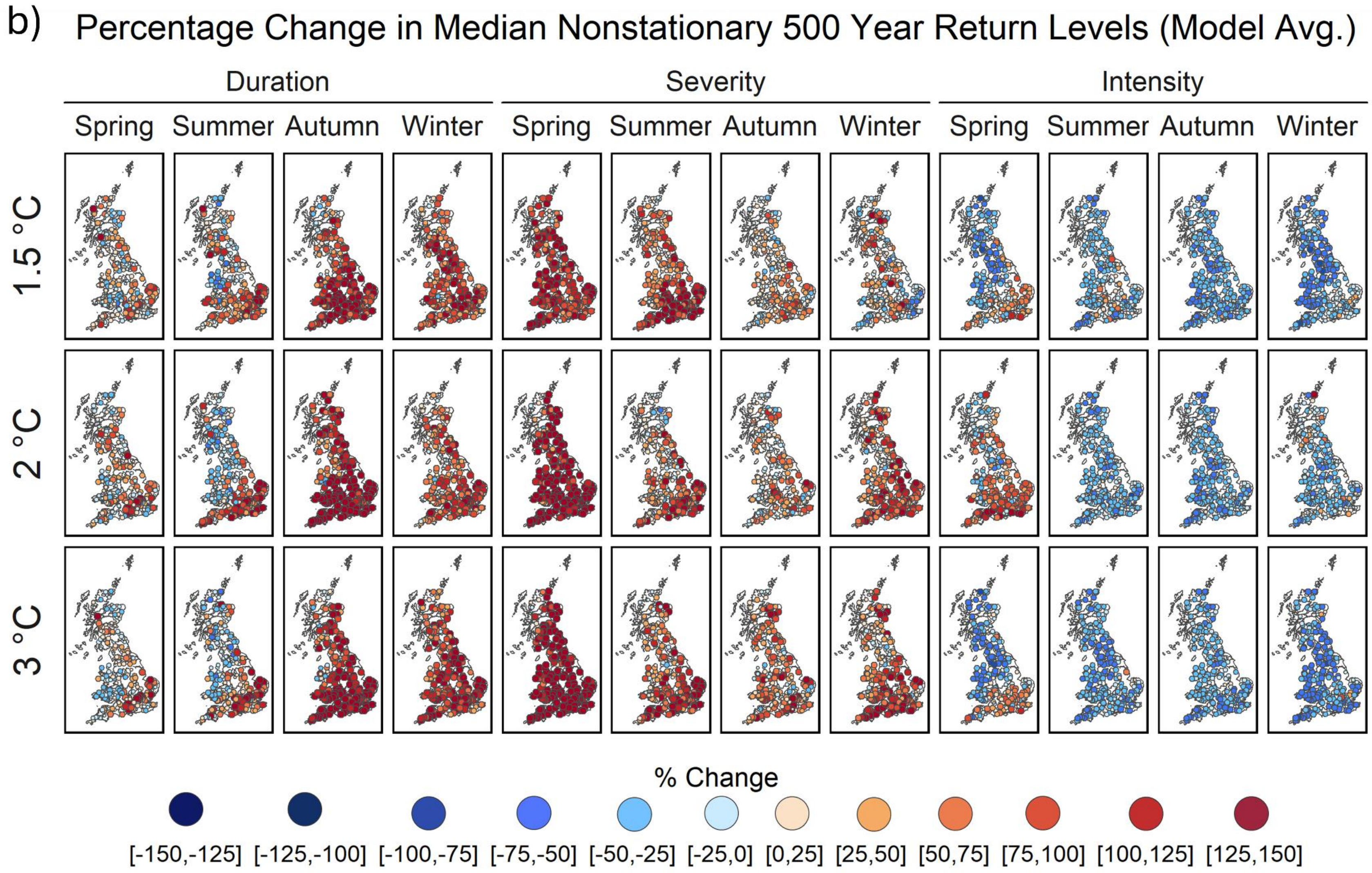


Figure 4b. Percentage change in mean nonstationary 500-year return levels for different drought characteristics across all warming levels and seasons.

Comment 12: Fig. 5: Please confirm (in the legend) that boxplots show differences across catchments only (and not across climate/hydrological models).

Reply 12: Thank you for the suggestion. We will further clarify that the boxplot represent difference across catchments in the revised manuscript.

Comment 13: L371-372: What can the reader refer to when reading that rarer droughts are accompanied by large variability? Across what? Spatial? Parameter estimation? Other?

Reply 12: These lines describe Figure 5a,b, showing that the variability in percentage change of return level estimates increases with increasing return period. To add more explanation, we propose to modify line **L371-L372** as follows:

It can also be concluded from Figure 5a,b that rarer droughts, which are inherently associated with larger uncertainty contributed by factors such as event identification, estimation of distribution parameters, or an interaction of these factors, are not only associated with larger changes but also with greater overall spatial variability across catchments.

Comment 14: L421: Please provide factual elements to comfort the assertion of "robust estimates of uncertainty".

Reply 14: Thank you for the comment, in the revised version of the manuscript, we will modify the **L418-423** as following:

Despite this, the findings from this analysis give crucial insights about the changing future hydrological drought characteristics in the UK under climate change. The results not only quantify the changes in the return level of drought duration, severity, and intensity but also provide explicit estimates of uncertainty in the GEV distribution parameters and associated return levels centred on the methodological framework adopted in this study. The Bayesian approach allows full posterior distribution of the GEV parameters to be explored, enabling return level estimates to be assessed across a wide range of parameter values. This is further supported by using MCMC simulations whose convergence is diagnosed with the Heidelberger-Welch test, which helps to ensure that the posterior distributions are stable and reliable. These elements along with moving window approach and pooling procedure to identify drought events ensure that thorough attention has been given from the initial drought identification through to the estimation of return levels, resulting in reliable and transparently quantified estimates of return level across temporal scales, models, seasons and warming levels.

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