

1 Evolution of nonstationary hydrological drought characteristics 2 in the UK under warming

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10
11 **Abstract.** Although the United Kingdom (UK) is relatively wet, there is an increasing awareness of the
12 impacts of droughts, and an expectation that droughts will become worse in the future. This has
13 motivated studies that have developed projections of future UK drought characteristics. To date,
14 however, very few have addressed future changes in terms of probability of occurrence, and none
15 have quantified the evolution of rare nonstationary hydrological drought characteristics under
16 different warming conditions. This study investigates future changes in the hydrological drought
17 characteristics under varying regional warming levels (1.5°C, 2°C, and 3°C), using nonstationary
18 extreme value analysis combined with a Bayesian uncertainty framework across 200 river catchments
19 in the UK. The analysis utilizes the enhanced future Flows and Groundwater (eFLaG) dataset, which is
20 based on the most recent UKCP18 climate projections, and incorporates outputs from four
21 hydrological models (G2G, PDM, GR4J, and GR6J). The findings indicate that rising temperatures will
22 significantly influence future drought duration, severity, and intensity across a majority of catchments,
23 with rare droughts (return period of 100-500 years) projected to be more severe in all seasons,
24 particularly in the southern UK. Further, relatively frequent summer droughts (return periods of 10
25 years) are expected to become shorter but more severe and intense, particularly at higher warming.
26 We observe notable differences between stationary and nonstationary return periods across seasons,
27 with the change becoming more pronounced at longer return periods, particularly for drought
28 severity. Although the trends remain consistent across models under stationary and nonstationary
29 conditions, the results underscore the role of rarity, nonstationarity, and seasonal controls on the
30 future evolution of hydrological droughts in the region. Furthermore this framework could be used to
31 support similar analyses in other environments where analogous datasets of transient hydroclimate
32 projections are available.

34 **1. Introduction**

35 With ongoing global climate change the United Kingdom (UK) is experiencing a pronounced
36 warming trend, with the most recent decade (2015-2024) averaging 1.24 °C above the 1961-
37 1990 baseline(Climate Change Committee, 2021; Kendon et al., 2024). Many notable drought
38 events have been recorded in the UK during the periods of 1975-76, 1988-89, 1990-92, 1995-
39 97, 2004-06, 2010-12, and 2022 Barker et al., 2024; Murphy et al., 2020; Turner et al., 2021).
40 Projections indicate that by 2050, several regions could face frequent water shortages, driven
41 by extended spells of hot and dry weather, which are expected to significantly affect river
42 flows and soil moisture levels (Bevan, 2019). In addition to the adverse impacts of climate
43 change, the increasing demand will pose water management challenges in the future, which
44 is particularly crucial for the south-eastern part of the UK, which is expected to experience
45 more significant changes in the long-term climate (Bevan, 2022). However, droughts are not
46 only expected to become more frequent, but also more spatially coherent, especially during
47 the summer season, which could further complicate drought management strategies(Raut
48 and Ganguli, 2024; Tanguy et al., 2023b). River-flow projections in the UK are known to be
49 sensitive to seasonal variations in precipitation and potential evapotranspiration, owing to
50 their influence on the seasonal wetting and drying cycles of the land surface (Parry et al.,
51 2024). Chan et al., (2024) further highlighted that the likelihood of experiencing a summer
52 month drier than the historically driest recorded month is expected to rise with future
53 warming in certain regions of UK. And yet, deficits in the winter half-year have been a key
54 driver of historical droughts, especially in southeast England where faltering winter
55 replenishment of groundwater resources also impacts river flows. Hence it has been argued
56 that it is important to consider hydrological droughts in all seasons, and the interactions
57 between them. Although these and other studies highlight the importance of seasonal
58 controls on UK droughts, a comprehensive probabilistic analysis of drought return levels
59 across characteristics and warming levels is still needed.

60

61 The growing awareness of drought as a major and increasing hazard and its impacts has
62 prompted a significant acceleration of research on changing drought risk in the UK, and
63 parallel changes in water resource management practices. In particular, the financial
64 regulators (OFWAT) and environmental regulators (Environment Agency) of the water
65 industry set out a 'duty of resilience' stipulates that water utilities must plan to ensure

66 security of supply to very extreme events (OFWAT, 2015; Environment Agency, 2023) in
67 practice, 1:500-year droughts. Understanding and preparing against these extreme
68 hydrological events is of most societal importance for the UK due to their disproportionate
69 impacts on water resources, agriculture, ecosystems, and public health. For instance, the cost
70 of relying on emergency drought measures in the UK is projected at £40 billion, whereas
71 proactively building water resilience would cost £21 billion over the same period (National
72 Infrastructure Commission, 2018). Furthermore, the annual cost to maintain resilience to
73 severe droughts is estimated at £60–600 million. For extreme droughts, this rises to £80–800
74 million per year (Climate Change Committee, 2019).

75 Given the relative brevity of most hydrological records, the need to ensure resilience to very
76 rare extremes has prompted the widespread adoption of stochastic simulation methods to
77 generate long time series from which we can sample such rare events. However, several lim-
78 itations and complexities arise from using such methods when understanding extreme event
79 evolution under anthropogenic climate change (Counsell and Durant, 2023; Environment
80 Agency, 2025), chief of which is the need to apply post-hoc climate change adjustments to
81 stochastic simulations based on the present day. There is therefore merit in directly analysing
82 climate change projections to assess the changing return levels of events of a given rarity,
83 including those very extreme events of the most importance for water resources planning. In
84 this study, return levels have been defined as the values of a variable (here duration, severity,
85 and intensity) expected to be exceeded on average once every T years, where T is the return
86 period. However, the complicated nature of the drought hazard and its relatively infrequent
87 occurrence, and the diverse and uncertain spatiotemporal patterns of hydrological droughts
88 make severity and rarity assessments complicated (Brunner et al., 2021). Further, under-
89 standing future changes in hydrological drought, in particular, remains limited for the UK, as
90 the majority of studies have primarily focused on analysing changes in drought magnitude
91 between current and future periods, using threshold-based metrics rather than exploring the
92 evolving nonstationary dynamics of various drought characteristics in the future (Barker et
93 al., 2019; Chan et al., 2022; Kay et al., 2021). More recently, Parry et al., (2024) utilised a newly
94 developed nationally consistent, multi-model ensemble of hydrological projections enhanced
95 future Flows and Groundwater (eFLaG) dataset (Hannaford et al., 2022a) to quantify future
96 UK hydrological droughts which consists of transient time series (continuous daily data from

97 1980 to 2080), to explore changes in drought characteristics. These transient analyses capture
98 how river flows evolve over time, rather than only comparing baseline and future time slices.
99 However, they do not account for the probabilistic assessment of droughts or changes in their
100 likelihood under future warming. Also, there has been a lack of research focusing on under-
101 standing the evolution of hydrological droughts in the UK under different warming conditions
102 (1.5°C, 2°C, 3°C, and so on), which is very important from a risk planning point of view(Tanguy
103 et al., 2023a). Warming level assessments can be used to support timely adaptation of
104 drought management strategies, inform policy decisions aligned with global targets, and en-
105 sure resilience under plausible future warming scenarios.

106 The analysis in most of the previously mentioned research for the UK is based on the analyses
107 of extreme events relying on the assumption of stationarity, which assumes that the
108 probability distribution parameters of a drought characteristic remain constant over time (Wu
109 et al., 2024). However, it is well-accepted that rising temperatures introduce nonstationarity
110 into hydrological systems, challenging the conventional approaches to drought analysis. This
111 nonstationarity might lead to inaccuracies in estimating the return levels of extreme events
112 for any design return period under evolving climatic conditions. Coles, (2001) highlighted that
113 assuming stationarity can lead to an underestimation of extreme event probabilities.
114 Therefore, incorporating nonstationarity, particularly due to rising temperatures, is crucial for
115 accurately modelling future drought characteristics (Salas and Obeysekera, 2014). One of the
116 important aspects of probabilistic modelling of extreme hydroclimatic events is the
117 uncertainty in estimated parameters (Leng et al., 2024; Onyutha, 2017). Traditional methods,
118 such as L-moments (Parvizi et al., 2022), method of moments (Lück and Wolf, 2016) and
119 maximum likelihood estimation (Jha et al., 2022), typically rely on point estimates of
120 parameters, without adequately addressing this issue. However, Bayesian methods have
121 found their utility for addressing these challenges in parameter estimation processes (Baykal
122 et al., 2024; Liu et al., 2024). This approach allows for obtaining the posterior distribution of
123 parameters by integrating over the existing parameter space. Additionally, the introduction
124 of Markov Chain Monte Carlo (MCMC) methodology facilitates the approximation of integrals
125 by using a Markov chain with the posterior distribution (Chandra et al., 2015). This paper uses
126 a nonstationary extreme value analysis (EVA) framework with Bayesian uncertainty
127 assessment to analyse the evolution of future hydrological drought characteristics in the UK

128 with specifically including rare droughts (return period ≥ 100 years). Leveraging the benefits
129 of the eFLaG river flow datasets, which comprise four hydrological models' (GR4J, GR6J, PDM,
130 and G2G) outputs, this study analyses transient, in this case daily continuous, century-long
131 projections data over 200 catchments in the UK. It examines the evolution of future
132 hydrological drought characteristics under three different warming levels (WLs): 1.5°C, 2°C,
133 and 3°C, with a particular focus on extreme droughts. By focusing on a range of warming
134 scenarios, we aim to capture the full spectrum of possible future hydrological drought
135 conditions under different climatic conditions. In doing so, this study provides critical insights
136 for policymakers and water resource managers to better understand and prepare for future
137 hydrological drought risks and their uncertainties under the influence of climate change. In
138 summary, the objectives of this study are: (i) to investigate the projected changes in key
139 hydrological drought characteristics (duration, severity, and intensity) across 200 UK
140 catchments under three future warming scenarios. (ii) to apply and compare results from
141 nonstationary and stationary EVA using a Bayesian framework to quantify the role of
142 nonstationarity in governing future hydrological drought risks. (iii) to understand the future
143 evolution of hydrological drought characteristics in UK, specifically for rare events with robust
144 estimation of uncertainty.

145

146 **2. Data and methods**

147 **2.1. eFLaG data set: hydrological models and future river flow projections**

148 This paper utilizes the eFLaG dataset which are nationally consistent and spatially coherent
149 hydrological river flow projections for the UK based on UKCP18 - the latest climate projections
150 from the UK Climate Projections programme (Hannaford et al., 2022a; Lowe et al., 2018;
151 Murphy et al., 2018). The eFLaG dataset are hydrological projections derived from a range of
152 hydrological models (Grid-to-Grid, PDM, GR4J and GR6J) and groundwater recharge model
153 ZOODRM (zooming object-oriented distributed-recharge model). However, in this paper we
154 have only focussed on the river flow projections for our analysis and did not consider the
155 groundwater data. We considered the hydrological model simulations of river flow ('simobs'
156 and 'simrcm') for over 200 catchments in the UK. In this context, 'simobs' refers to
157 observation-driven simulations (1989-2018), while 'simrcm' denotes outputs generated from
158 hydrological modelling using 12km UKCP18 RCM (Regional Climate Models) projections (up
159 to 2080). The 'simrcm' projections consist of a 12-member ensemble generated using

160 perturbed-parameter runs of the Hadley Centre global climate model (GCM, HadGEM3-
161 GC3.05) and regional climate model (RCM, HadREM3-GA705)(Murphy et al., 2018). Each
162 ensemble member represents a plausible variation in model parameters to capture
163 uncertainty in the climate response, while all members share the same underlying model
164 framework and follow the high-emissions scenario (RCP8.5). The 12-member RCM perturbed-
165 parameter ensemble is therefore valuable for representing parameter uncertainty; however,
166 because all members are based on the same model structure and emissions scenario, they do
167 not capture the full range of climate or scenario uncertainties.

168 GR4J and GR6J, members of the 'airGR' family, are lumped catchment rainfall-runoff models
169 known for their simplicity and efficient calibration function (Kuana et al., 2024). The
170 Probability Distributed Model (PDM) offers configurable options for catchment rainfall-runoff
171 modelling, allowing for various permutations to be tested across catchments (Moore, 2007).
172 Grid-to-Grid (G2G) is a distributed hydrological model utilized for simulating natural river
173 flows across Great Britain at a 1km resolution, providing consistent national-scale flow
174 estimates (Bell et al., 2018). These models have been successfully applied in diverse
175 hydrological studies, and several publications detail their versatility and wide-ranging
176 applicability (Kuana et al., 2024; Ndiaye et al., 2024; Tanguy et al., 2023b). Detailed metadata
177 and site listings are stored and accessible through the Environmental Informatics Data Centre,
178 which can be referred for more information(Hannaford et al., 2022b). For the nonstationary
179 modelling of drought characteristics for each catchment, we utilised the CHESS-SCAPE
180 temperature datasets, which are bias-corrected 1km resolution gridded data also derived
181 from UKCP18 projections (Robinson et al., 2022a) as a covariate. The CHESS-SCAPE
182 temperature records are derived from UKCP18 projections that have been downscaled to 1
183 km resolution using methods that account for local topographic effects and pattern scaling
184 properties for different scenarios(Robinson et al., 2022a), however, the eFLAG dataset is
185 based directly on the original UKCP18 projections.

186

187 **2.2. Nonstationary analysis of future drought characteristics**

188 The impact of adverse climate change effects has prompted scrutiny of the stationary
189 assumption regarding hydroclimatic variables, leading to heightened interest in the concept
190 of nonstationarity within the research community. The concept is also pertinent to planners
191 using projections of hydrological information and data in their decision-making. In this study,

192 the drought characteristics were fitted with the generalized extreme value (GEV) distribution
 193 with a cumulative distribution function given by Eq. (1) (Coles, 2001):

$$194 \quad G(x; \mu, \sigma, \xi) = \begin{cases} \exp \left\{ - \left[1 + \left(\frac{(x-\mu)\xi}{\sigma} \right) \right]^{-\left(\frac{1}{\xi}\right)} \right\}, \sigma > 0, \quad 1 + \left(\frac{(x-\mu)\xi}{\sigma} \right) > 0, \xi \neq 0 \\ \exp \left\{ - \exp \left[-\frac{x-\mu}{\sigma} \right] \right\}, \sigma > 0, \xi = 0 \end{cases} \quad (1)$$

195 Here, μ, σ and ξ are the location, scale, and shape parameters of the distribution. Daily
 196 temperature anomaly (ΔT) from the CHES-SCAPE data (Robinson et al., 2022a) was selected
 197 as the covariate to quantify the temperature-dependent signals for future river flow. Here,
 198 daily temperature anomaly for each period were calculated relative to the mean temperature
 199 over the UK for the reference period (1989-2018). After identifying drought events, we
 200 matched the timestamp of each drought characteristic with the corresponding temperature
 201 time series and used the mean reference-period temperature to compute the anomalies,
 202 which were then used as covariates. Please refer to Section 2.4 for further details on the
 203 event-calculation methodology to understand how seasonality and continuation of events
 204 have been considered.

205 The incorporation of linear dependency in the location parameter is a common practice in
 206 nonstationary modelling, and similar applications to the scale parameter have been
 207 advocated by Yilmaz and Perera, (2014). However, Gilleland and Katz, (2016) argue against
 208 introducing covariates solely to the scale parameter without corresponding variations in the
 209 location parameter. Further, the estimation of the shape parameter under a time-varying
 210 framework is challenging due to the uncertain tail behaviour of the distribution, especially in
 211 limited data settings, and is therefore often kept constant (Ragulina and Reitan, 2017). In our
 212 study, only the location parameter for historical and future streamflow extremes was
 213 assumed to be a linear function of temperature. Hence, the parameter set takes the form of
 214 $\mu(t) = \mu_0 + \mu_1 c(\Delta T), \sigma(t) = \sigma$ and $\xi(t) = \xi$. Parameter estimation was conducted utilizing
 215 the maximum likelihood function, chosen for its capability to incorporate nonstationarity into
 216 the distribution parameter (Strupczewski et al., 2001) as given by Eq. (2):

$$217 \quad L(\theta) = -n \log \sigma - \left(1 + \frac{1}{\xi}\right) \sum_{i=1}^n \log \left[1 + \xi \left(\frac{x_i - \mu}{\sigma} \right) \right] - \sum_{i=1}^n \left[1 + \xi \left(\frac{x_i - \mu}{\sigma} \right) \right]^{-\left(\frac{1}{\xi}\right)}, \quad 1 + \xi \left(\frac{x_i - \mu}{\sigma} \right) > 0 \quad (2)$$

218
 219 Here, $L(\theta)$ is the likelihood function of the parameter vector θ and n is the sample size. By
 220 minimizing the above function, the distributions of parameters for both stationary and

221 nonstationary cases were formulated. The comparative statistical significance of stationary
 222 and nonstationary models was assessed by using the likelihood ratio test (L.R. test) (Posada
 223 and Buckley, 2004) which is derived using Eq. (3):

$$224 \quad 2[nllh_s - nllh_{(NS)}] > c_\alpha \quad (3)$$

225 Here, $nllh_s$ and $nllh_{(NS)}$ are the negative log-likelihood values of stationary and
 226 nonstationary models. Further, c_α represents the $(1 - \alpha)$ quantile of the Chi-square
 227 distribution. The difference between the stationary and nonstationary models is expected to
 228 conform to an approximate chi-squared distribution at a specific significance level α (5% in
 229 this case). The null hypothesis in this study assumes that drought characteristics extremes are
 230 stationary, meaning their statistical properties do not change over time or with temperature.
 231 Using the likelihood ratio test, this hypothesis is evaluated by comparing the fit of stationary
 232 and nonstationary GEV models. The null hypothesis is rejected when the p-value falls below
 233 0.05, indicating that including temperature as a covariate significantly improves the model.
 234 Such an approach is consistent with standard methods in extreme value analysis for
 235 hydrological data (Das and Umamahesh, 2017; Salas and Obeysekera, 2014). The percentage
 236 of catchments showing nonstationary characteristics for different combinations of seasons,
 237 metrics, models and warming levels are mentioned in Table S1 in the supplementary
 238 information.

239 **2.3. Bayesian framework for parameter uncertainty**

240 As discussed above, parameters for both stationary and nonstationary methods are derived
 241 using the maximum likelihood approach, which only provides point estimates without
 242 accounting for uncertainty. Bayesian analysis aims at updating parameter uncertainty
 243 through a prior distribution using Bayes' theorem (Sarhadi et al., 2016). This approach
 244 combines the prior distribution and the data's likelihood function to form the posterior
 245 distribution, incorporating additional information to enhance predictive modelling. The
 246 posterior distribution is obtained by multiplying the likelihood function by the prior
 247 distribution of the parameter (Eq. 4):

$$248 \quad p(\theta | y) \propto p(y|\theta) p(\theta) \quad (4)$$

249 Here, $p(\theta | y)$ denotes the posterior distribution of the parameter vector $\theta = (\mu, \sigma, \xi)$, $p(\theta)$
 250 represents the prior distribution, and $p(y|\theta)$ denotes the likelihood function corresponding
 251 to the GEV distribution evaluated at $y_{i...n}$ where n is the number of observations. We utilised
 252 a non-informative prior distribution for location parameter modelling. Given the complexity

253 of solving Eq. (4) analytically, numerical methods like MCMC sampling are utilized to produce
 254 numerous realizations from the posterior distribution (Reis and Stedinger, 2005). Further, we
 255 can estimate desired return levels for a given probability of occurrence (p) by employing Eq.
 256 (5):

$$257 \quad Z_p(\hat{\mu}, \hat{\sigma}, \hat{\xi}) = \hat{\mu} - \frac{\hat{\sigma}}{\hat{\xi}} \left\{ 1 - [-\log(1 - p)]^{-\hat{\xi}} \right\} \quad \text{for } \xi \neq 0 \quad (5)$$

$$258 \quad Z_p(\hat{\mu}, \hat{\sigma}) = \hat{\mu} - \hat{\sigma} \log[\log(1 - p)] \quad \text{for } \xi = 0$$

259 The Metropolis-Hastings algorithm is used to sample the parameter vector using the specified
 260 prior and likelihood function. It is crucial to monitor the convergence of the MCMC chain to
 261 ensure it accurately represents the posterior distribution. In this study, Heidelberger and
 262 Welch's convergence diagnostic is used to determine the necessary length of each simulation
 263 (Sharma and Mujumdar, 2022).

264

265 **2.4. Analysis of future drought return levels**

266 The whole analysis is set up to calculate the percentage changes in the return level of the
 267 hydrological drought characteristics in the warming level period as compared to the reference
 268 period. The 30-year reference period was 1989-2018, i.e., the available historical period in
 269 the eFLaG dataset. Relative to this reference period, three warming level periods (also 30-
 270 year) were calculated based on the recently developed CHES-SCAPE temperature data
 271 projections for the UK (Robinson et al., 2022a). In alignment with the objectives and directives
 272 of the Paris Agreement about limiting global warming, a +1.5°C and +2°C rise in temperature
 273 was considered (Jha et al., 2023). Moreover, a warming level of +3°C was also considered,
 274 corresponding to the projected warming expected to be attained by the year 2100 under
 275 existing nationally determined mitigation goals (Seneviratne and Hauser, 2020). The starting
 276 year of each warming level period is defined as the initial year of the 30-year interval wherein
 277 the mean warming exceeds the respective warming level. We considered the last 30-year time
 278 period, in case, the +3°C warming period exceeded the end of the century. For example, in
 279 cases where the warming period is identified as 2080-2110, we instead use the 2070-2100
 280 window to remain within the 21st-century bounds. The warming levels in this analysis should
 281 be interpreted as regional UK warming levels rather than global warming levels, since CHES-
 282 SCAPE provides only UKCP18 climate projections over the UK. While the CHES-SCAPE
 283 framework does use global mean air temperature from UKCP18 GCMs and uses time shifting

284 and pattern scaling, the downscaled dataset contains only UK specific surface variables.
285 However, these warming levels are broadly aligned with global warming levels as UKCP18
286 assumes seasonal UK climate anomalies scale linearly with global mean temperature, and it
287 is known that UK temperature changes generally track global land-surface warming (Kendon
288 et al., 2024).

289 To identify hydrological drought events, we used a variable threshold-based approach that
290 has been widely applied for drought identification (Sarailidis et al., 2019). In the reference
291 period, for each of the 12 ensemble members of each hydrological model, a 30-day moving
292 window centred on each day of the year was applied. Several approaches exist for
293 implementing rolling window smoothing; here, we adopted the method similar to used by
294 Ahmadi and Moradkhani, (2019) and Van Loon and Laaha, (2015). For example, for 15
295 January, the window includes flows from 14 days before to 15 days after that date (including
296 the centre day), resulting in a total of 30 days.

297 This smoothing method helps capture natural variability in daily flows and prevents the
298 resulting statistics from being overly influenced by short-lived extreme events. Using these
299 rolling-window values, we derived 365 Q90 thresholds, one for each day of the year,
300 representing the 90th percentile exceedance flow for the reference period. These thresholds
301 were then used as the baseline against which projected flow levels at different warming levels
302 were compared. Specifically, we calculated the difference between projected flows and the
303 corresponding daily Q90 threshold to identify high-flow anomalies or deficits relevant for
304 drought analysis. The resulting drought characteristics for each warming level were
305 subsequently pooled across all 12 ensemble members, and this pooled dataset was used to
306 fit GEV distributions to assess changes in extremes under future climate conditions. We
307 selected the 90th percentile (Q90) threshold to ensure that the analysis captures instances
308 characterised by extremely low historical flows. This choice allows us to focus on severe low-
309 flow anomalies that are hydrologically meaningful, rather than relatively normal variations in
310 streamflow. The Q90 threshold has also been widely used in previous hydrological drought
311 assessments, providing both consistency and comparability with earlier studies (Hasan et al.,
312 2020; Janicka-Kubiak, 2025; Prudhomme et al., 2014). Furthermore, Q90 is sufficiently
313 stringent to minimise the influence of short-term fluctuations, ensuring that the identified
314 drought events represent genuine low-flow conditions rather than transient anomalies. An

315 additional motivation for adopting the Q90 threshold is our emphasis on addressing
316 uncertainties associated with estimating rare drought characteristics. Using a high-percentile
317 threshold such as Q90 demonstrates that the methodology is robust for detecting extremely
318 low-occurrence drought events, thereby supporting the reliability of our drought
319 characterisation approach. Further, we have demonstrated the drought characteristics
320 distribution for one model (G2G) and one warming level 3°C using both Q90 and Q80
321 thresholds in Figure S1a-c in the supplementary information. A catchment was considered to
322 be in drought on any given day when the flow dropped below the baseline Q90 threshold for
323 that day. A pooling procedure across drought events was also applied, where two distinct
324 events separated by a single day were combined into a single drought event, provided the
325 magnitude above the threshold did not exceed the accumulated deficit before this single day
326 similar to the methodology used by Van Loon and Van Lanen, (2012) and Parry et al., (2024).
327 To reduce uncertainty arising from very short, potentially non-significant drought events
328 caused by daily variability in the threshold, we excluded events with a duration of less than
329 30 days. Given that we focus on Q90 to derive these events, even after applying precautionary
330 measures such as a 30-day moving window and a 12-member ensemble pool to ensure
331 smoother and larger sample sizes, extreme value analysis remains challenging, particularly for
332 rare, small drought events. We acknowledge that this threshold effectively imposes a hard
333 lower bound on drought duration and may also exclude smaller events such as flash droughts.
334 Nevertheless, we chose 30 days which has widely been used in similar analyses by Anderson
335 et al., (2025) and Brunner and Chartier-Rescan, (2024), as compromise to balance robustness
336 of event statistics with capturing meaningful hydrological droughts.

337 Figure 1 schematically represents the derivation of drought characteristics using the variable
338 threshold method and a flow chart of the methodology used. We chose the variable threshold
339 method as a more suitable and increasingly popular approach compared to the constant
340 (fixed) threshold method for defining hydrological droughts (Anderson et al., 2025; Brunner
341 and Chartier-Rescan, 2024). This method allows for smooth intra-annual variability and
342 identifies drought events when flows fall below the historically expected level on a given day,
343 which would be overlooked by a constant threshold. This is important when we consider
344 drought is relative phenomenon, and especially as we are looking at hydrological deficits in
345 all seasons as argued in the introduction. A variable approach allows the identification of

346 multi-season and indeed multi-year droughts, whereas in strongly seasonal regimes a fixed
347 threshold typically only identifies 'absolute' droughts in the 'low flow' period (in the summer
348 half-year in the case of the UK), and these naturally terminate in the autumn/winter simply
349 given the fact flows in these seasons are always higher than summer - even if they are in fact
350 low for the season in question relative to historical norms, and potentially part of multi-annual
351 ongoing droughts. Wider discussion on the use of both fixed and variable approaches is
352 provided elsewhere (see e.g. (Stahl et al., 2020; Tallaksen and Van Lanen, 2023) and
353 quantitative comparisons have been made to highlight the impacts of such decisions e.g. for
354 the US, (Hammond et al., 2022).

355 Having identified individual events, three event characteristics were computed for each
356 season (i.e. winter: December-February, spring: March-May, summer: June-August and
357 autumn: September-November) which are duration(number of days)- the number of days
358 over which a drought occurs, severity - the accumulated flow deficit across all days(cumecs),
359 and intensity (cumecs per day) - the ratio of drought severity and duration of a drought event.
360 It should be noted that event detection is performed on the full continuous time series in
361 reference period and warming level periods, not within seasons. Seasonal metrics are
362 calculated only after drought events and their onset are identified, so physical continuity is
363 preserved, and duration or severity are not artificially capped by seasonal or yearly
364 boundaries except in the last year of the period. We have calculated the drought
365 characteristics based on the starting and end points of the event and assigned the season
366 based on starting month.

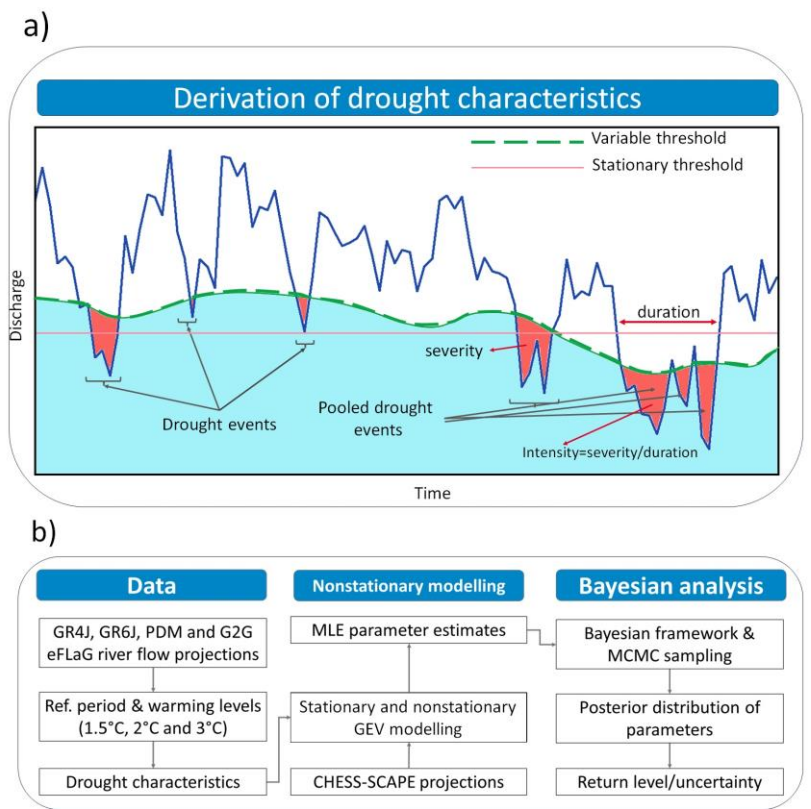


Figure 1. a) Variable threshold methodology used to identify and characterise drought events, b) Methodological framework utilized in the analysis.

368

369 **3. Results and discussion**

370 **3.1. Nonstationary properties and Bayesian parameter estimates**

371 Once the drought characteristics for all four models across all four seasons were calculated,
 372 the nonstationarity was assessed using the likelihood ratio test. Figure 2 and Table S1 in the
 373 supplementary information represent the percentage of nonstationary catchments for each
 374 drought characteristic across three warming levels and seasons. It shows that the
 375 nonstationary properties of catchments depend on the combination of the drought event
 376 characteristics, warming levels, and seasons. Future hydrological drought duration is found
 377 to be nonstationary in most catchments across warming levels and seasons. This is most
 378 noticeable at 3°C warming, where almost all catchments across seasons are depicting
 379 nonstationarity in future hydrological drought duration. Interestingly, future drought
 380 intensity at lower warming levels appears to be stationary. Only during the winter season
 381 does drought severity exhibit a trend of rising nonstationarity as the warming increases.

382 Further, at least half of the catchments display nonstationary hydrological drought severity
 383 characteristics across warming levels, except during the summer season at lower warming
 384 levels. The fluctuations in the nonstationarity properties of catchments specifically, the
 385 number of nonstationary catchments declining from 1.5°C to 2°C warming but then increasing
 386 at 3°C highlight the limitations of the pattern scaling assumption. This is central to CHES-
 387 SCAPE and UKCP18 data considered, which is based on the assumption that local or regional
 388 climate responses scale linearly with global mean temperature (Robinson et al., 2022a). The
 389 observed variations suggest that this assumption may break down for certain warming levels
 390 or in specific regions, as illustrated in Figure 2, 3. Examining the spatial distribution of
 391 nonstationarity across the UK provides insight into where pattern scaling might hold and
 392 where caution is needed, highlighting regions dominated by nonlinear responses. Therefore,
 393 changes in nonstationary properties, their dependence on warming levels, catchment
 394 characteristics, and seasonal variability must be considered with full caution when modelling
 395 the evolution of future hydrological droughts. Finally, the trend across models remains overall
 396 similar, and no noticeable difference in the ability to capture nonstationarity was observed.

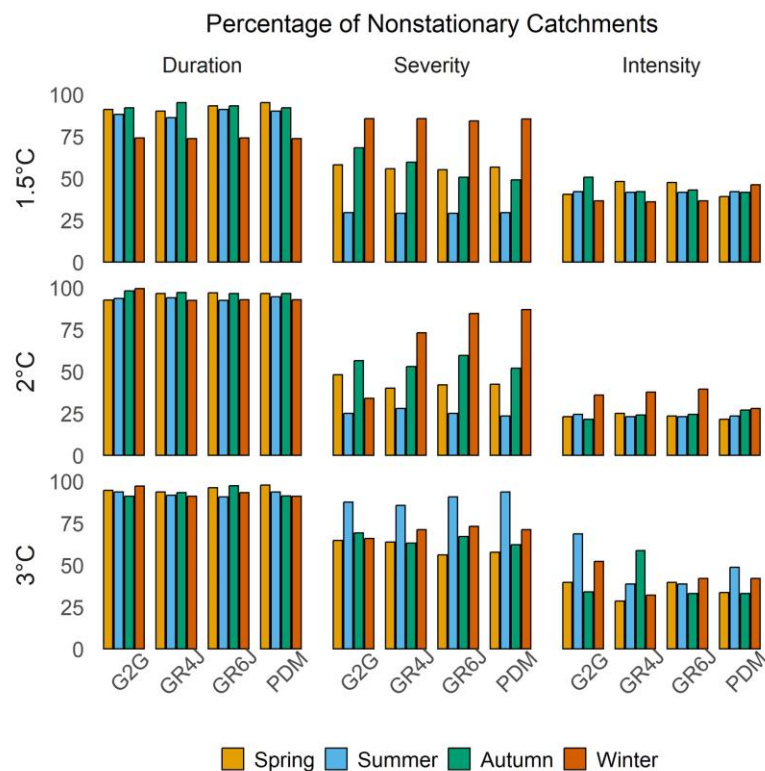


Figure 2. Percentage of nonstationary catchments for each event characteristics, hydrological models and warming levels.

397

398 Once the nonstationarity was assessed, we derived the parameter distribution for calculating
399 the return levels of future and historical drought duration, intensity, and severity. Figure 4
400 demonstrates the mean and standard deviation of the posterior distribution of parameters
401 obtained using the Bayesian framework for the GR4J model during the summer season at
402 +3°C. The spatial distribution of parameter means and standard deviation, particularly for
403 duration, suggests that there is relatively higher uncertainty in the location parameter in the
404 south-eastern catchments. The south-east not only experiences a higher magnitude of mean
405 location parameter but also higher uncertainty which is in agreement with previous studies
406 depicting more significant changes in future drought conditions in this region (Kay et al.,
407 2021). The variation of the location parameter across catchments for drought intensity and
408 severity exhibits more or less similar behaviour. It can also be observed that catchments with
409 a higher magnitude of the location parameter exhibit a higher standard deviation. This is
410 crucial and calls for more caution as it denotes, for e.g., a catchment with a higher duration
411 of drought might show higher uncertainty in the estimates. We also demonstrate the
412 robustness of the employed method by comparing the curves of posterior distributions of
413 location parameters for a sample catchment (Dee in Scotland, NRFA ID: 67018) for the
414 reference period and +3°C warming (Figure 3). The location parameter for future drought
415 duration shows a lower value, whereas intensity and severity are generally higher. This
416 pattern is consistent with the findings from the return level analysis, which are presented in
417 the next sections. Figure 3 also shows that the possible spread of location parameters for
418 future drought characteristics is well constrained. This is critical as it ensures that the model
419 provides robust estimates of parameters, especially for understanding future changes in
420 drought characteristics under projected warming.

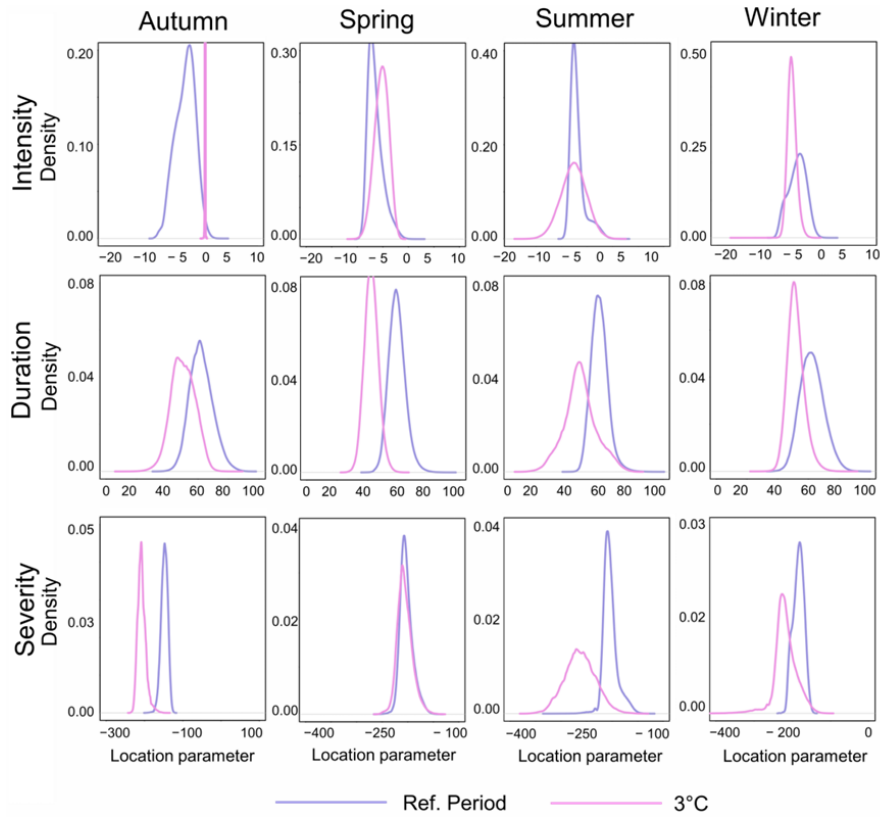


Figure 3. Posterior distribution of parameters for different drought characteristics for a sample (Dee in Scotland, NRFA ID: 67018) catchment in reference period and at 3°C warming level.

421

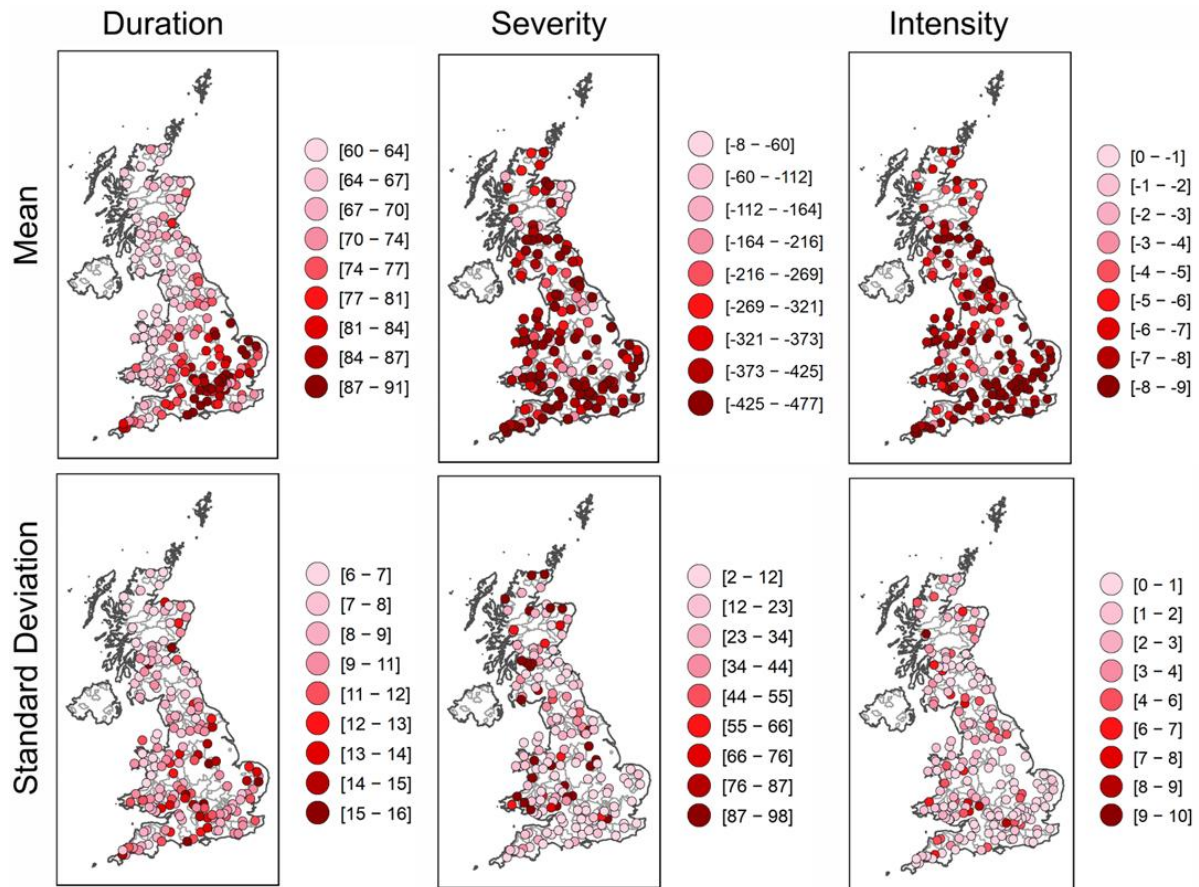


Figure 4. Mean and standard deviation of duration- number of days, severity - cumecs, intensity - cumecs/day parameter samples for GR4J model during summer season at 3°C warming level.

422

423 **3.2. Return levels of different drought characteristics**

424 Next, we calculated the return levels of drought duration, severity and intensity at different
 425 return periods (10, 100, and 500 years) using parameter samples from the posterior
 426 distribution obtained through Bayesian analysis. The return levels were calculated for both
 427 the reference period and the warming level periods, considering the stationary case as well
 428 as nonstationary case. As discussed, parameter uncertainty is a key aspect of the
 429 nonstationary hydrological drought risk assessment. To illustrate that the results are
 430 consistent, we computed results using four different summaries of the parameter
 431 distribution: the 25th percentile (Q25), the 75th percentile (Q75), the mean, and the median.
 432 The estimates of return level changes, as well as the differences between nonstationary and
 433 stationary return levels across these four summaries, demonstrate consistency and
 434 robustness throughout the analysis, as shown in Figures S2 and Figure S3. For the sake of
 435 brevity the results presented in the main text of this paper focus exclusively on the mean
 436 return levels.

437 Figure 5,6 shows the model average percentage change in mean nonstationary return levels
438 for 10-year (frequent droughts) and 500-year (rare droughts) return levels, respectively. The
439 return level is dependent on the rarity of the drought, as changes in return levels are more
440 pronounced for a 500-year drought compared to a 10-year drought, with the former
441 exhibiting more distinct spatial characterisation. The overall distribution of percentage
442 changes in the mean 100-year return level is shown in the supplementary information
443 (FigureS2b, S3b, S4a-f). For drought duration, the overall return levels are expected to be
444 higher for 500-year droughts during the autumn and winter seasons, whereas they are
445 expected to be lower for 10-year droughts in the same seasons. This increase in the risk of
446 prolonged extreme droughts in autumn and winter is concerning, given that the winter half-
447 year is the critical time for replenishment of aquifers (in the south-east) and reservoirs(Barker
448 et al., 2019; Environment Agency, 2011). The shorter duration of 10-year droughts may
449 slightly ease water stress during more frequent droughts in these seasons however, any
450 potential benefits could be offset by increased drought intensity, making the overall water
451 management plan in the country still challenging. In Fig. 6, which shows longer drought
452 durations, regions in the north and west, which rely almost entirely on surface water and lack
453 the buffering capacity of groundwater, might be significantly affected, whereas areas in the
454 south-east dominated by groundwater-fed systems might experience delayed drought
455 impacts, offering a degree of resilience during prolonged dry periods. Previous studies have
456 also shown significant variability in hydrometeorological drought characteristics, both in the
457 current period and in future projections, specifically in the southern part of the country
458 (Barker et al., 2019; Di Nunno and Granata, 2024; Reyniers et al., 2022). Compared to
459 intensity, duration return levels have more distinct regional attributes for rare droughts -
460 particularly in the spring and summer season where some of the catchments show abrupt
461 negative changes in return levels. Studies suggest that the UK is likely to experience warmer
462 and wetter winters alongside hotter and drier summers in the future(Lowe et al., 2018).

463

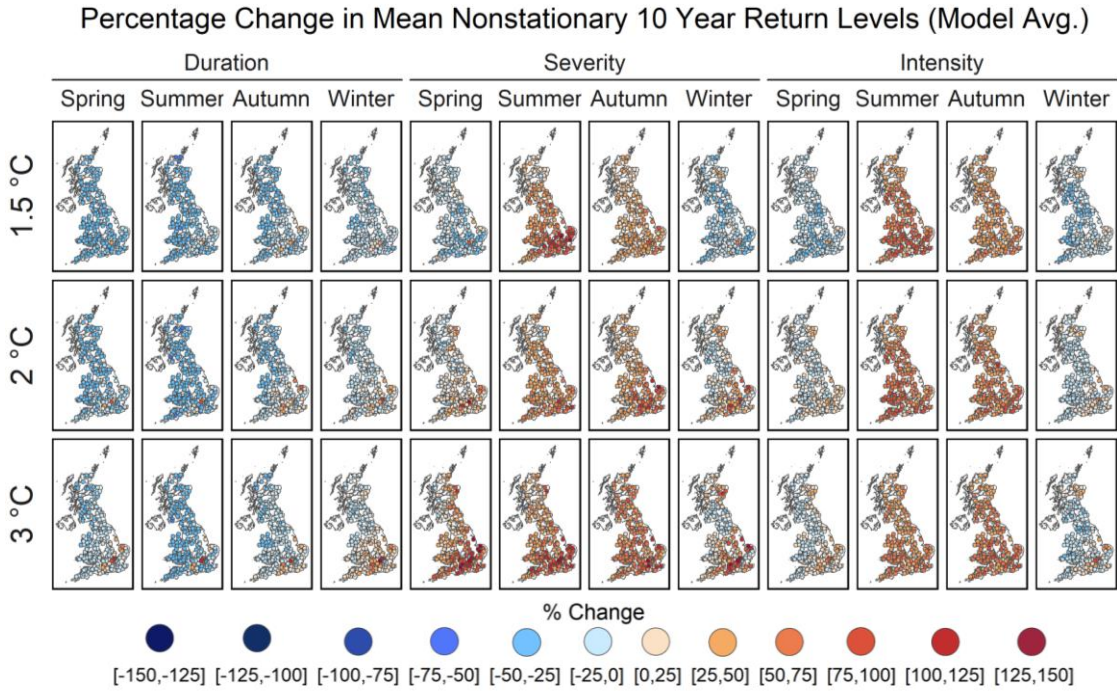


Figure 5. Percentage change in mean nonstationary 10-year return levels for different drought characteristics across all warming levels and seasons.

464

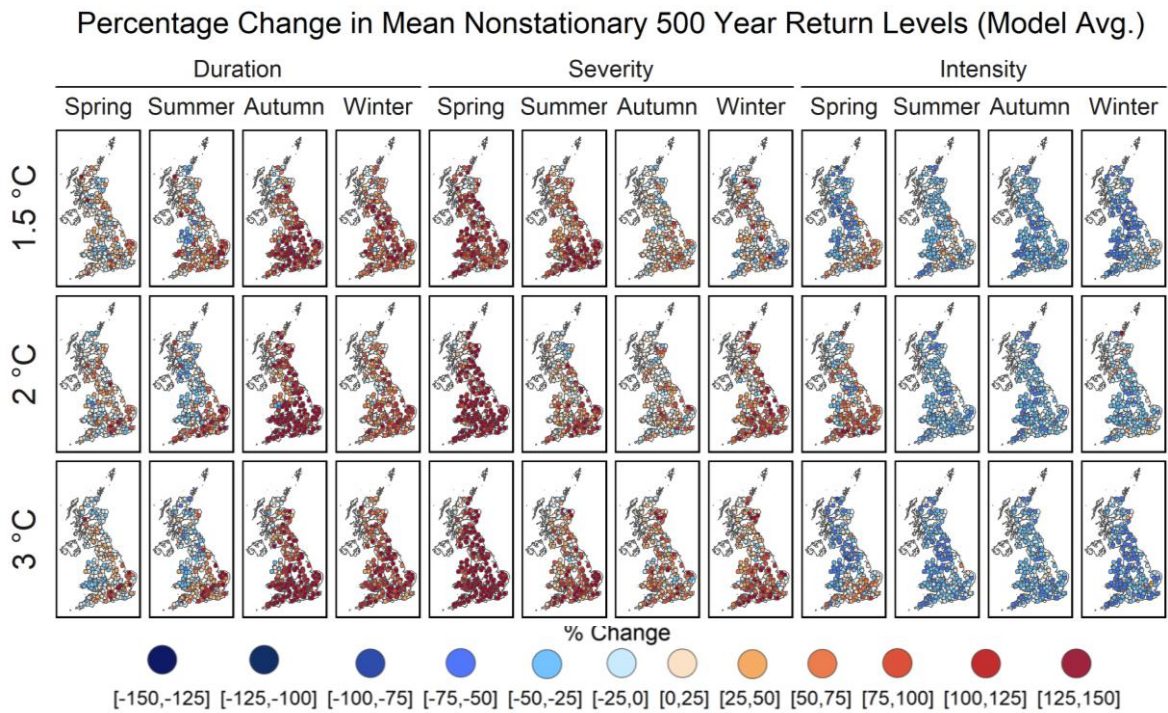


Figure 6. Model average percentage change in mean nonstationary 500-year return levels for different drought characteristics across all warming levels and seasons.

465

466 Additionally, most projections indicate an overall increase in potential evapotranspiration,
467 with seasonal variations in the rate of change, but a consistent upward trend on an annual
468 basis (Robinson et al., 2022b). This could be one of the possible drivers of longer future
469 drought durations for frequent droughts or higher severity of rarer droughts, particularly in
470 the summer season (Kay et al., 2020; Murphy et al., 2018). Future severity is observed to be
471 increasing for both frequent and rare droughts in most catchments, except during the winter
472 season for frequent droughts at lower warming levels. Season-wise, the increasing changes
473 in the severity of rare droughts in the spring are highest, followed by summer, winter, and
474 autumn. This increase is more substantial at higher warming levels, which indicates that both
475 rare and frequent droughts are, in general, expected to be more severe in the future under
476 the influence of rising temperature (Parry et al., 2024). Further, the intensity of droughts with
477 a 10-year recurrence interval is projected to increase during the autumn and summer
478 seasons. Conversely, the intensity of droughts with a 500-year return period is found to be
479 decreasing in most seasons across all warming levels. It should be noted that we have
480 considered the mean intensity, which is a function of both duration and severity, and highly
481 intense frequent droughts in the future, particularly in autumn and summer seasons, could
482 be due to highly severe droughts over a smaller duration (Figure 5).

483

484 **3.3. Difference between stationary and nonstationary return levels**

485 To understand the role of temperature in governing changes in future drought characteristics,
486 we compared the stationary return levels with the nonstationary return levels. Figure 7a,b
487 shows the distribution of model-average percentage change in nonstationary and the
488 stationary return levels for seasons and warming levels. The difference in percentage change
489 in hydrological drought intensity return levels for the stationary and nonstationary cases is
490 negative, particularly for higher return periods and warming levels across seasons. This might
491 be because most catchments for drought intensity exhibit stationary characteristics (Figure 2)
492 and show similar spatial patterns for stationary return levels as well (Figure S3a-c). For
493 drought severity, the changes in return levels tend to show a decreasing trend with increased
494 rarity. However, this is exclusive to the autumn season as drought severity in other seasons
495 exhibits higher return levels with higher return periods of droughts. Similar results were
496 observed for the stationary return levels; however, while the overall trend remains
497 consistent, there is a significant difference in the magnitude of the stationary and

498 nonstationary return levels. Figure S3a-c in the supplementary information shows the spatial
 499 patterns of stationary return levels.

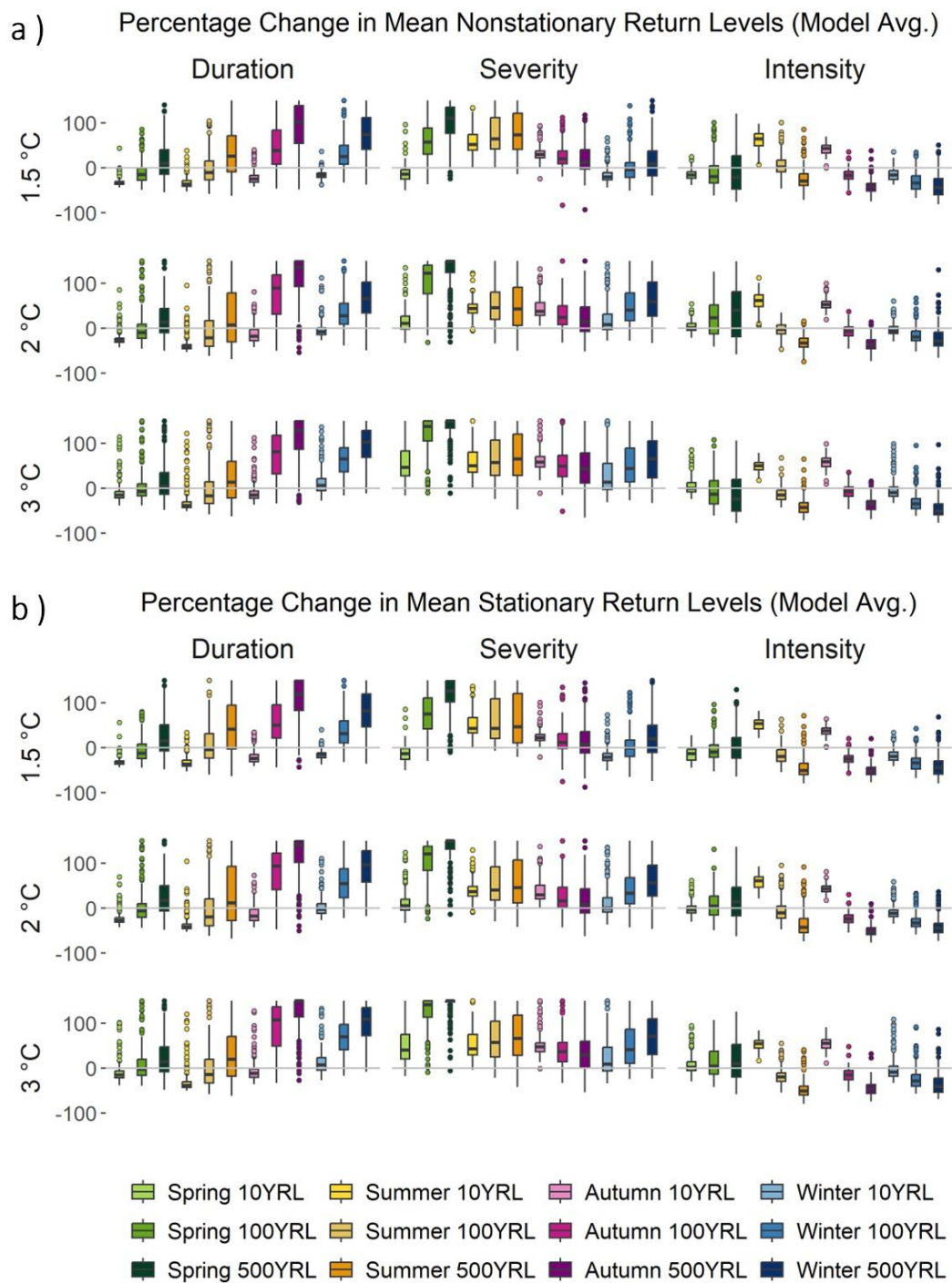


Figure 7. Spatial average percentage change in mean a) nonstationary and b) stationary return levels (10,100 and 500 years) for different drought characteristics across all warming levels and seasons.

500

501 The incorporation of 100-year return levels also confirms the trends in the results, showing
502 that as droughts become less frequent, the changes in return levels become more
503 pronounced. It can also be concluded from Figure 7,8 that rarer droughts, which are
504 inherently associated with larger uncertainty contributed by factors such as event
505 identification, estimation of distribution parameters, or an interaction of these factors, are
506 not only associated with larger changes but also with greater overall spatial variability across
507 catchments. This heightened variability underscores the need for robust modelling
508 approaches to better understand the impacts of rare hydrological droughts in the UK under
509 climate change. Most previous studies in the UK have considered different climate model
510 outputs or hydrological models but did not take into account the variability induced due to
511 warming on different drought events on the seasonal scale (Parry et al., 2024; Rudd et al.,
512 2019). Therefore, the results of this analysis provide more comprehensive insights into the
513 varying uncertainty of future return levels.

514 **3.4. Inter-model differences in return levels**

515 In Further, Figure 9 shows the magnitude of the difference between the percentage changes
516 in nonstationary and stationary return levels for 3°C warming level. Results are shown for
517 each model to demonstrate the variability among models. The difference between the
518 nonstationary and stationary return levels is smaller for drought intensity compared to
519 drought duration and severity. This outcome was expected due to the relatively lower level
520 of nonstationarity detected in the drought intensity projections (Figure 2) and a higher
521 severity and lower duration compared to the reference period (Figure 5). This suggests that
522 the mean flow deficit relative to the historical drought threshold on any given day in the
523 future is less likely to be related to temperature change than for duration and severity.
524 However, the number of days over which drought might occur and the total accumulated flow
525 deficit across all days of a drought are more likely to be affected by these factors at higher
526 warming levels. Moreover, the duration of more frequent droughts being less affected by
527 rising temperatures is also confirmed by minimal difference between stationary and
528 nonstationary return levels across seasons, which changes significantly when higher return
529 levels are considered (Figure 9).

530 Overall, the results demonstrate that neglecting temperature effects in modelling drought
531 duration for longer return periods leads to significant uncertainty in projected return levels,
532 as clearly evidenced by the pronounced differences between stationary and non-stationary

533 estimates particularly for higher return periods (Figure. 9). This underestimation and
 534 variability are most amplified for future drought severity, where it is evident that temperature
 535 influences across models, seasons, and warming levels might lead to more severe droughts.
 536 To further confirm this, we analysed the distribution of the 25th, 75th quantiles, and the
 537 median return levels for different warming levels (Figure S4a-f), which shows a similar trend.
 538 Further, assessing model performance for future periods compared to a baseline period is
 539 challenging because different hydrological models capture processes and uncertainties based
 540 on their individual structure and operational specifications. Therefore, it is important to
 541 incorporate multiple models for more confident estimates of future changes in drought
 542 characteristics (Hannaford et al., 2023; Lane et al., 2022). In this setting, with four hydrological
 543 model outputs assessed, for each drought characteristic, the return levels across the UK are
 544 primarily driven by the rarity of the event in different seasons rather than the model itself.

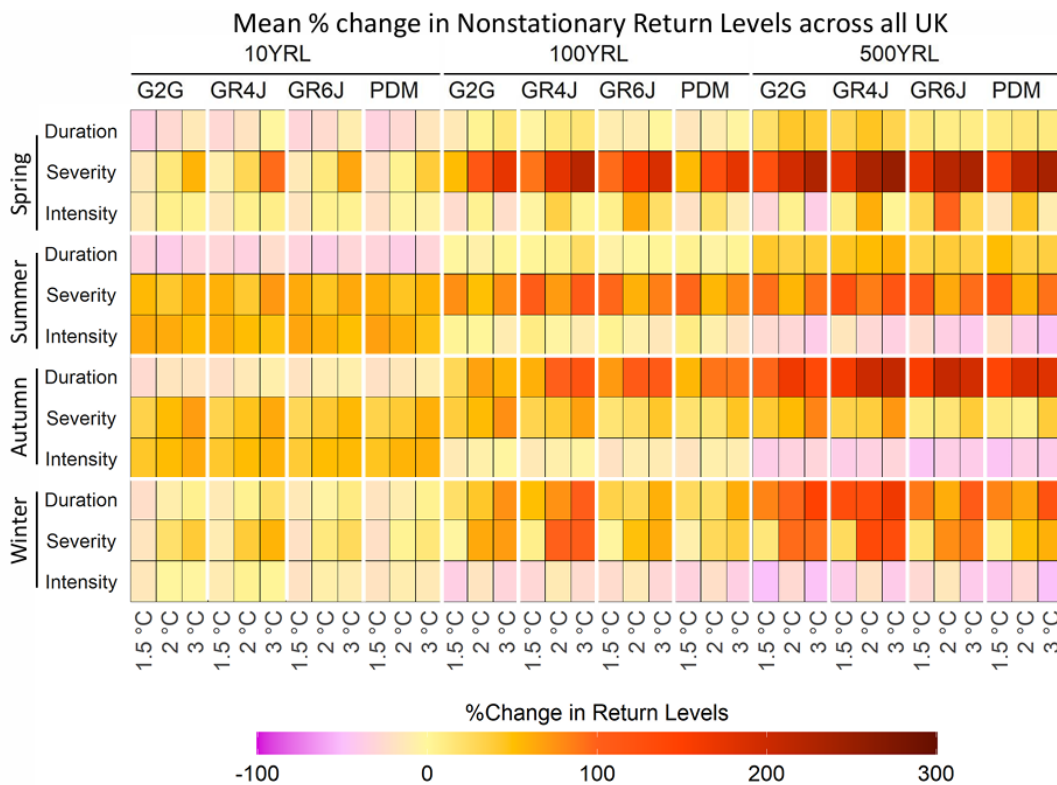


Figure 8. Mean Percentage change in nonstationary return levels for duration, severity and intensity across different models, seasons and return periods.

545

Diff. in % Change in Mean Nonstationary vs Stationary Return Levels at 3 °C

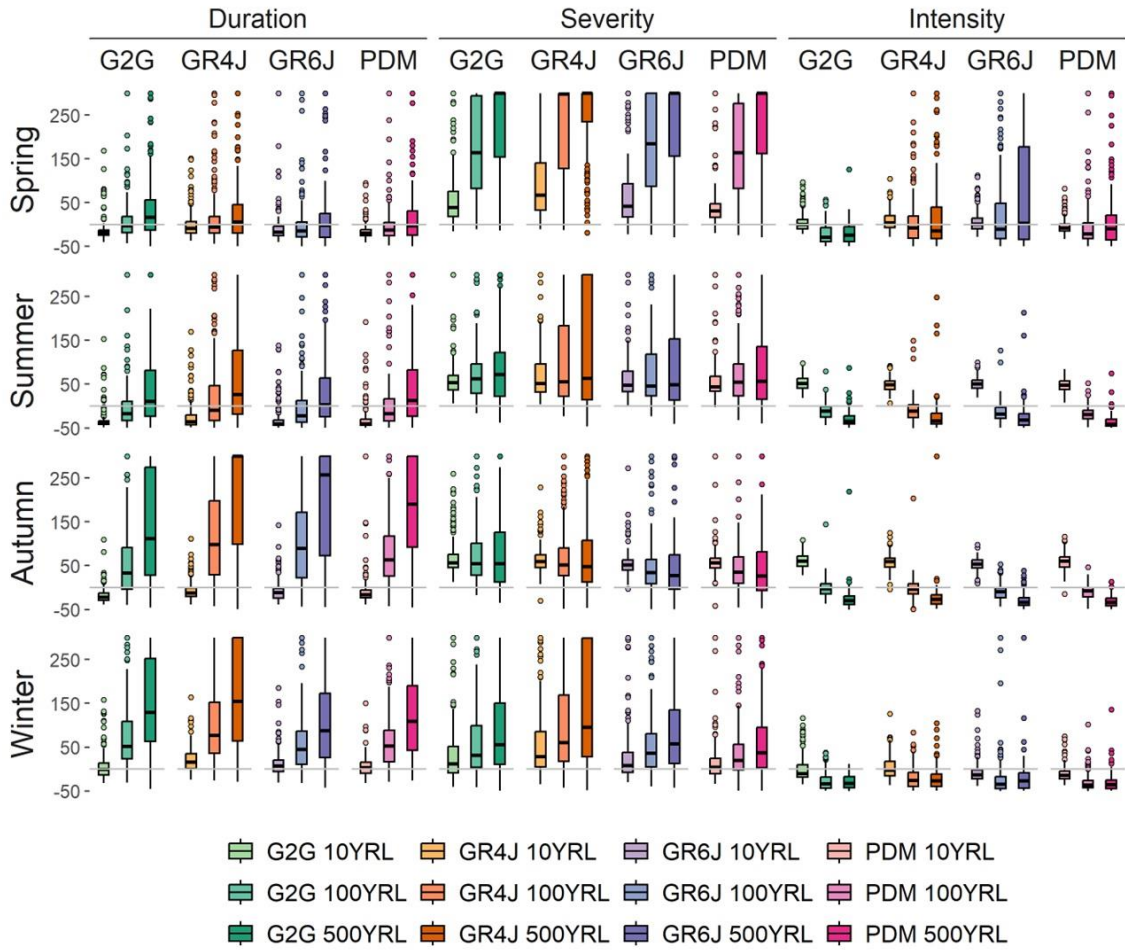


Figure 9. Difference in spatial average percentage change in return levels for mean nonstationary and stationary return levels for different drought characteristics across all seasons and 3°C warming levels.

546

547 Although the results from this analysis are consistent across the hydrological models, a more
 548 detailed uncertainty partition analysis could be conducted in the future to gain a deeper
 549 understanding of the inter-model differences in the projected characteristics of future
 550 droughts. Further studies could also incorporate catchment hydrometeorological
 551 characteristics in the nonstationary modelling set-up to understand the role of changing
 552 catchment conditions in governing the drought characteristics. In this study, we have looked
 553 at the drought characteristics independently, however, the dependence of drought
 554 characteristics over time, as well as their evolution in a compound setting could give more
 555 useful insights about their interrelation in the future. Despite this, the findings from this
 556 analysis give crucial insights about the changing future hydrological drought characteristics in
 557 the UK under climate change. The results not only quantify the changes in the return level of

558 drought duration, severity, and intensity but also provide explicit estimates of uncertainty in
559 the GEV distribution parameters and associated return levels centred on the methodological
560 framework adopted in this study. The Bayesian approach allows full posterior distribution of
561 the GEV parameters to be explored, enabling return level estimates to be assessed across a
562 wide range of parameter values. This is further supported by using MCMC simulations whose
563 convergence is diagnosed with the Heidelberger-Welch test, which helps to ensure that the
564 posterior distributions are stable and reliable. These elements along with moving window
565 approach and pooling procedure to identify drought events ensure that thorough attention
566 has been given from the initial drought identification through to the estimation of return
567 levels, resulting in reliable and transparently quantified estimates of return level across
568 temporal scales, models, seasons and warming levels.

569

570 **4. Conclusions**

571 This study attempts to understand the evolution of future hydrological droughts in the UK
572 under different warming conditions, utilising nonstationary extreme value analysis with a
573 Bayesian framework for parameter uncertainty. We used the recently developed eFLaG
574 projections to investigate changes in drought characteristics in terms of return levels. The
575 findings indicate that future temperature changes contribute significantly and uniquely to
576 hydrological droughts' characteristics - duration, severity, and intensity. Results demonstrate
577 that the future changes in these characteristics are highly dependent on the season and the
578 rarity of droughts. Drought severity in most cases, irrespective of rarity and season, appears
579 to be increasing in the future at higher warming levels. However, future drought duration and
580 intensity are showing both increasing and decreasing trends depending on the season and
581 return period of droughts. This also underscores the varying degrees of nonstationarity
582 exhibited by different drought characteristics, which should be carefully considered while
583 planning measures against future drought risks in the UK. The projected return levels,
584 particularly for rare and high-impact events, also show a higher level of uncertainty in their
585 magnitude as compared to more frequent events, which can be critical for risk management
586 and adaptation strategies. Overall, this research underlines the importance of considering the
587 influence of temperature-induced nonstationarity in modelling future changes in hydrological
588 drought characteristics. Results from both stationary and nonstationary cases across different

589 seasons, rarities, and warming levels provide comprehensive insights that can be utilised by
590 policymakers and water managers to develop effective strategies against future risks.

591 We conclude that the most critical policy considerations for future hydrological droughts will
592 revolve around adapting to projected nonstationary changes in the nature of risk. As
593 mentioned, the finding that drought severity consistently increases across the majority of
594 catchments under higher warming adds to previous assessments of decreasing future water
595 availability, reaffirming that that policy reviews of water resource infrastructure and
596 management plans are necessary to create buffers against larger future deficits, as well as to
597 mitigate impacts of worsening hydrological droughts on the environment. However our
598 analysis provides greater granularity in terms of providing fine-detail spatial appraisals as well
599 as a multi-seasonal viewpoint as well as considering multiple characteristics of drought
600 (duration, severity and intensity) which is important given the widely varying nature and
601 timing of droughts which catchments, water resource systems and ecosystems alike are
602 vulnerable to around the UK (e.g. Barker et al. 2016; Counsell and Durant, 2023; Stubbington
603 et al. 2024).

604 As noted in our introduction, various reviews of the current frameworks for water resources
605 management have highlighted some of the limitations of current stochastic-based planning
606 approaches (Counsell & Durant, 2023; Environment Agency, 2025). Durant and Counsell
607 (2024) argued that ‘the future is transient’ and that more efforts should be directed towards
608 the use of continuous, transient projections like eFLaG, rather than focusing on change point
609 analyses based on time-slices. Here we provide a test-case further highlighting the added
610 value of such transient projections, although we acknowledge that our emphasis is on
611 hydrological droughts and further work is needed to look at the onward impacts on complex
612 water supply systems. Furthermore, our observation that changes in drought duration and
613 intensity are highly dependent on the season points toward a required shift from uniform,
614 year-round planning to seasonally specific risk management strategies. This bolsters the
615 argument (e.g. Environment Agency, 2025) for further investigation of ‘bottom-up’ storyline
616 approaches to stress tests systems according to the types of drought they are vulnerable to,
617 in terms of seasonality and duration (e.g. Chan et al. 2022). Finally, the higher uncertainty
618 observed, particularly for rare high-impact droughts, such as the 1:200 and 1:500 year events
619 that are a cornerstone of planning indicates that future policy must explicitly integrate the

620 possibility of extreme outcomes beyond currently accepted limits of uncertainty, requiring
621 robust, nonstationary modelling in all risk management and adaptation strategies.

622

623 **Code and data availability**

624 The eFLaG river flow projections analysed in this study are stored at the UKCEH's
625 Environmental Information Data Centre and can be freely accessed as DOI datasets. Please
626 ensure these data are cited in full when used in any application:

627 <https://catalogue.ceh.ac.uk/documents/1bb90673-ad37-4679-90b9-0126109639a9>. The
628 CHESS-SCAPE dataset can be downloaded from the NERC Environmental Data Service (EDS)
629 Centre for Environmental Data Analysis (CEDA) via the following link:

630 <https://doi.org/10.5285/8194b416cbee482b89e0dfbe17c5786c>. The R scripts used for
631 analysis were developed using publicly available packages, such as 'extRemes', 'evir', 'coda',
632 'foreach', and 'doparallel', which support extreme value analysis, Markov Chain Monte Carlo
633 diagnostics in a parallel environment.

634

635 **Author contribution**

636 Conceptualization was done by SJ, JH, MT, and LB. Methodology development and analysis
637 were carried out by SJ. The original draft was written by SJ and JH. Reviewing and editing of
638 the manuscript were performed by LB, JH, and MT. Supervision of the work was provided by
639 JH, LB, and MT.

640

641 **Competing interests statement**

642 The authors declare that they have no conflicts of interests.

643

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647 Technology Facilities Council on behalf of the Natural Environment Research Council.

648

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