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Precipitation and temperature timings underlying bioclimatic variables rearrange under climate change globally

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Abstract

Modeling how climate change may affect the potential distribution of species and communities typically utilizes bioclimatic variables. Distribution predictions rely on the values of the bioclimatic variable (e.g., precipitation of the wettest quarter). However, the ecological meaning of most of these variables depends strongly on the within-year position of a specific climate period (SCP), for example, the wettest quarter of the year, which is often overlooked. Our aim was to determine how the within-year position of the SCPs would shift (SCP shift) in reaction to climate change in a global context. We calculated the deviations of the future within-year position of the SCPs relative to the reference period. We used four future time periods, four scenarios, and four CMIP6 global climate models (GCMs) to provide an ensemble of expectations regarding SCP shifts and locate the spatial hotspots of the shifts. Also, the size and frequency of the SCP shifts were subjected to linear models to evaluate the importance of the impact modeler's decision on time period, scenario, and GCM. We found ample examples of SCP shifts exceeding 2 months, with 6-month shifts being predicted as well. Many areas in the tropics are expected to experience both temperature and precipitation-related shifts, but precipitation-related shifts are abundantly predicted for the temperate and arctic zones as well. The combined shifts at the Equator reinforce the likelihood of the emergence of no-analogue climates there. The shifts become more pronounced as time and scenario progress, while GCMs could not be ranked in a clear order in this respect. For most SCPs, the modeler's decision on the GCM was the least important, while the choice of time period was typically more important than the choice of scenario. Future predictive distribution models should account for SCP shifts and incorporate the phenomenon in the modeling efforts.

KEYWORDS
bioclimatic variable, climate change, climate pattern, impact assessment, no-analogue climate, phenology, quarter, specific climate period, within-year distribution

1 | INTRODUCTION

It is beyond doubt that climate change is ongoing (IPCC, 2021). This phenomenon has already affected a wide range of domains of the environment, including geomorphology by enhancing erosion, vegetation, and human-constructed landscape elements (IPCC, 2022). Although the impacts of climate change are already apparent and wide-ranging (e.g., Corwin, 2021; Dupuy et al., 2020; Xi et al., 2023), they are expected to become even more abundant (IPCC, 2022). Furthermore, it is clear by now that even if emission targets would be instantly achieved, climate change would proceed for a while (IPCC, 2021). Consequently, in addition to mitigation, adaptation planning is of crucial importance (Arneth et al., 2020; Ito et al., 2020; Papadimitriou et al., 2019). This in turn requires the estimation of impacts under a range of scenarios (Bede-Fazekas & Somodi, 2023).

Climate change impact assessments regarding species and communities, including predictive distribution models, most typically involve the use of bioclimatic variables (Hijmans et al., 2005; Porfirio et al., 2014). The bioclimatic variables were defined by Nix (1986) and further refined by Busby (1991) to represent the physiological requirements of species (Deblauwe et al., 2016; Title & Bemmels, 2018; Watling et al., 2012). These variables rely on monthly values of temperature and precipitation either separately or in combination. Some of the bioclimatic variables (e.g., temperature of the wettest quarter of the year) involve the selection of a specific climate period (SCP; e.g., wettest quarter), which is already calculated from the climate data (e.g., precipitation). It is evident from climate studies that climate change encompasses not only quantitative changes, such as an increase in temperature but also the rearrangement of climate patterns, such as the within-year distribution of the precipitation. The rearrangement of patterns can in turn reflect spatial relocation of climate types (Barredo et al., 2018; de Castro et al., 2007; Garcia et al., 2014) or even the emergence of novel climates patterns (IPCC, 2022). Bioclimatic variables appear to have the potential to handle the novelty in climate patterns, as they do not rely on a predefined month or season but are dynamically calculated for the new climate by default (Bede-Fazekas & Somodi, 2020). However, this dynamic feature also involves potential pitfalls. Particularly, it assumes that the major impact of climate change originates from a quantitative change. While it does consider, for instance, the increase in the temperature of the wettest quarter, it fails to address the magnitude of the shift of the wettest quarter within the year (Bede-Fazekas & Somodi, 2020; Merkenschlager et al., 2023).

The reshuffling of the within-year distribution of the temperature or precipitation may result in the shift of an SCP one or more months earlier or later within the year (hereinafter referred to as 'SCP shift'). A visual demonstration of a four-month SCP shift is provided in Figure 1c. SCP shifts can range from a few months to half a year. Bede-Fazekas and Somodi (2020) have shown examples of half-year SCP shifts for Hungary by the end of the 21st century. As long as the SCP shifts gradually, we can expect the adaptation of plants and animals to the new situation (Roslin et al., 2021). It may even be possible that the new circumstances do not extend beyond the fundamental niches of the organism in focus (Veloz et al., 2012).

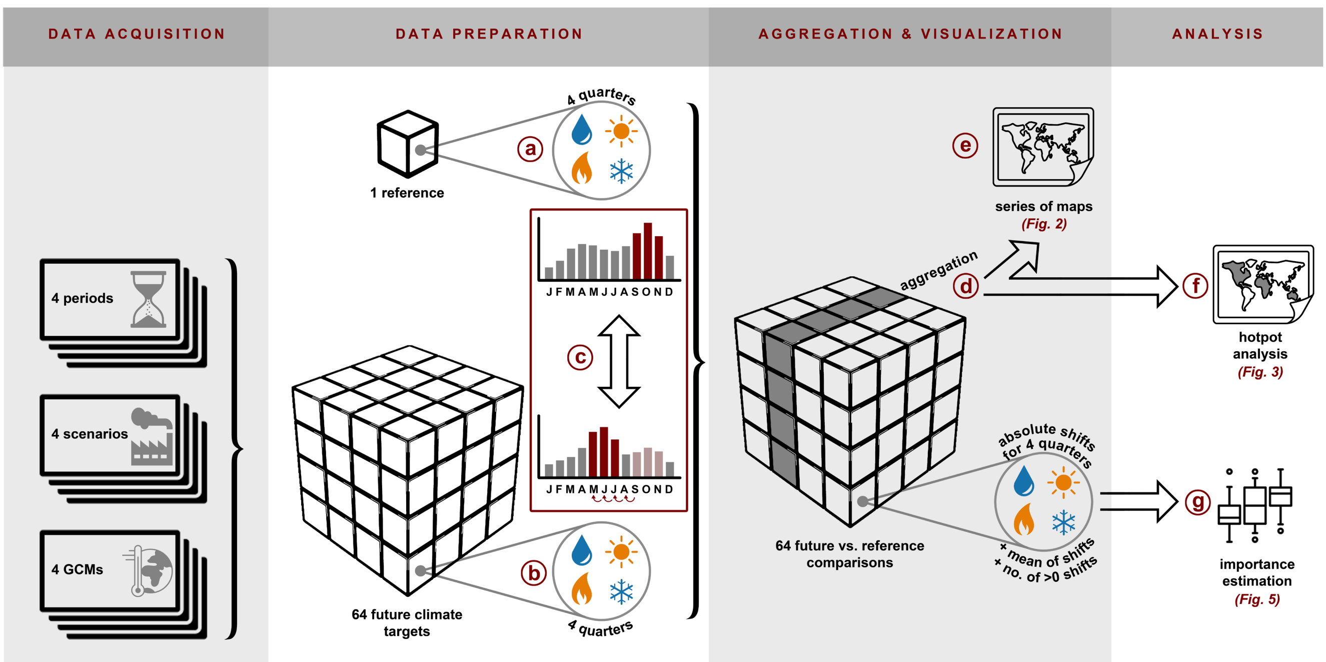

FIGURE 1 The framework of the data processing and analyses. Data preparation is shown on the left side: (a) determination of the quarters for the reference period, (b) determination of quarters for the 64 future targets; and (c) SCP shift calculation. Data aggregation, visualization, and analyses are shown on the right side: (d) aggregation; (e) visualization on maps; (f) hotspot analysis; and (g) importance estimation of modeler's decisions. Although the figure displays the four specific quarters as SCPs, the same analyses were conducted for the four specific months as well. Figure numbers in dark red color refer to subsequent figures of the Results section derived from steps e–g.

However, if the reshuffling of the within-year distribution means a leap over former seasons, physiological plasticity cannot necessarily bridge the gap to tolerate or exploit the climate features of the future period in the same way as in the original period. In such cases, a redistribution of biodiversity is expected (Pecl et al., 2017).

Climate research has already warned of the likely emergence of areas with yet-unknown climates as a consequence of climate change (Fitzpatrick & Hargrove, 2009; Sales et al., 2019; Veloz et al., 2012). Furthermore, it is known that climates that are not analogous to the current climate have existed in the past (Birks, 2019; Faith et al., 2020; Sunderlin et al., 2011; Williams & Jackson, 2007). Additionally, assessments regarding the expectations of no-analogue climates have also been conducted (Mahony et al., 2017; Torres-Amaral et al., 2023), however, have not spanned the globe yet. Moreover, restructuring of climate pattern does not necessarily result in no-analogue climates. The replacement of one climate type with another (e.g., Barredo et al., 2018) can also result in a shift in the SCPs. These SCP shifts have an effect on organisms nonetheless and must be considered when constructing predictive models as well. Additionally, while no-analogue climates are anticipated in the tropics mainly (Sales et al., 2019; Torres-Amaral et al., 2023; Williams & Jackson, 2007), reshuffling of the within-year distribution of temperature/precipitation, and consequently, the shift of SCPs are expected elsewhere as well. Information on whether these involve SCP shifts that require unrealistic or particularly challenging phenological shifts from the species is not available yet.

The objective of this study was to ascertain the prevalence of SCP shifts on a global scale. Therefore, we conducted an integrated and multifaceted global analysis of SCP shifts. Specifically, we aimed at identifying the temporal shifts (measured by the number of months) of the specific within-year periods on which the bioclimatic variables rely, namely, the wettest/driest/warmest/coldest months and quarters. We posed the following questions:

- What is the magnitude of the SCP shifts on the Earth's surface?
- What is the spatial pattern of these SCP shifts?
- To what extent do the SCP shifts depend on (1) the temporal distance of the investigated future time period to the present; (2) the climate change scenario used; and (3) the global climate model employed?

2 | MATERIALS AND METHODS

2.1 | Climate data

Monthly downscaled climate data (i.e., minimum temperature, maximum temperature, and precipitation sum) were obtained from the WorldClim 2.1 database (Fick & Hijmans, 2017), which is one of the most widely used sources of future climate for predictive distribution models (Cerasoli et al., 2022). Data were downloaded at 2.5′ (ca. 5 km) resolution for the reference period (1970–2000) and four future periods (2021–2040, 2041–2060, 2061–2080, and 2081–2100). Four scenarios of the projected global changes were used that combine different shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs): SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-85. The radiative forcing in the year 2100 expected by the scenarios spans from 2.6 to 8.5 W/m^2. Among the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016) global climate models (GCMs) available in the WorldClim database for all scenarios, four GCMs were selected based on their effective climate sensitivity (ECS; Zelinka et al., 2020): MIROC6 (ECS: 2.60; Tatebe et al., 2019), BCC-CSM2-MR (ECS: 3.02; Wu et al., 2019), IPSL-CM6A-LR (ECS: 4.56; Boucher et al., 2020) and CanESM5 (ECS: 5.64; Swart et al., 2019).

2.2 | Research framework

The data processing and analysis framework is summarized in Figure 1. Monthly mean temperatures were calculated as the mean of the minimum and maximum temperatures. The selection of the coldest and warmest months and quarters was based on the monthly mean temperatures, while the selection of the driest and wettest months and quarters was based on the monthly precipitation sum. Quarters mean three consecutive months instead of predefined seasons. In the following, our study and the embedded figures focus on quarters and the results based on months are provided as supplementary material. The four specific quarters were selected separately for each spatial unit (2.5′×2.5′ terrestrial raster cell) for both the reference period (Figure 1a) and all the 4×4×4 future period×scenario×GCM combinations (hereinafter 'future targets'; Figure 1b). The quarters of the future were then compared with those of the reference period per spatial unit, and the deviations (i.e., the 'SCP shifts', which span from 0 to ±6 months) were registered (Figure 1c; Bede-Fazekas & Somodi, 2024). The calculated SCP shift thus measures how the within-year distribution of the wettest/driest/warmest/coldest quarters is predicted to change according to a selected future target (compared with the reference period) at a selected spatial location.

Due to a large number of future targets (64), quarters (4), and spatial units (12,532,612 cells), SCP shifts were spatially and non-spatially aggregated in several different ways: minimum, mean, and maximum, and the number of the non-zero shifts were calculated (Figure 1d). Cellwise aggregations, which preserve spatial information, are suitable for map visualization (Figure 1e) and for locating the regions of climate disruption, that is, where most of the quarters deviate the most from those of the reference period. Aggregations are able to characterize the future targets with one or more numbers, that (1) make the future targets comparable to each other and (2) are needed as input for subsequent hotspot analysis.

2.3 | Analyses

A hotspot analysis was performed to identify the locations around the globe where SCP shifts are expected to be most pronounced (Figure 1f). To serve as a reference for the severity of SCP shifts, intra-annual climate variability was estimated for each location. Estimation was carried out separately regarding precipitation and temperature. For precipitation, the ratio of the range of monthly precipitations to the precipitation of the wettest quarter ($\frac{P_{\text{wettestQ}} - P_{\text{driestQ}}}{P_{\text{wettestQ}}} \times 100$; %) was calculated, for temperature, the range of monthly temperatures ($T_{\text{warmestQ}} - T_{\text{coldestQ}}$;°C). Hotspots were defined as regions where any of the wettest or driest quarters or any of the warmest or coldest quarters is prone to shift ≥2 months compared with the within-year position of the SCP in the reference period according to the mean of all the 64 future targets. Hotspots were generalized for visualization by raster aggregation, geometry simplification, and boundary smoothing.

The importance of period, scenario, and GCM choice (i.e., the importance of the modeler's decisions in climate change impact studies) were estimated in a nested model comparison framework using the following six response variables separately: the shift of the four quarters, their mean shift, and the number of the quarters prone to shift >0 month (Figure 1g). The full linear model described the response variable with five covariates: the period, the scenario, the GCM, and the two coordinates according to the WGS-84 system (i.e., longitude and latitude). The coordinates were included to deal with the spatial heterogeneity of the dataset and to eliminate the residual spatial autocorrelation of the models, allowing us to focus on the importance of the period, the scenario, and the GCM. This procedure yielded six types of models representing the six response variables, each containing five covariates. For each full model, three partial models were also created by removing the period, scenario, and GCM, respectively from the covariate set, and was compared with the full model. The *F* statistic and its significance were calculated. Due to the balanced study design where the number of the periods, scenarios, and GCMs is the same (i.e., the level of each categorical covariate is 4), the degrees of freedom are the same for the three model comparisons (i.e., d.f. = 3). Therefore, the F statistics are directly comparable and can be interpreted as the importance of the covariate under study. Due to computational limitations, models were built using n = 802,087 samples representing one thousandth of the full dataset (n = 802,087,168). To compensate for the drawbacks of using a subsample, we repeated the sampling (with replacement) and the subsequent model building 50 times. Accordingly, the importance of the modeler's decisions was estimated by the mean of 50 *F* statistics.

All analyses were performed in R statistical software (R Core Team, 2023) using the 'raster' (Hijmans, 2021) and 'sf' (Pebesma, 2018; Pebesma & Bivand, 2023) packages.

3 | RESULTS

3.1 | Spatial patterns of SCP shifts

Spatial patterns of the mean shift of the quarters for all the 64 future climate targets are shown in Figure 2a, minimum and maximum shifts are shown in Figure S1. For all four quarters, the minimum shift was 0 months at almost every geographic point (except for the warmest and coldest quarters, for example, in Greenland and South America; please refer to Figures S2.3 and S2.4). The 0 minimum value means that there is at least one of the 64 climate targets that do not predict a shift in the specific SCP compared with the reference period. However, the mean and maximum shifts for the 64 future climate targets revealed potential for remarkable reshuffling of the within-year distribution of the SCPs on all continents. The most extended and most remarkable shift was predicted for the wettest quarter (with a spatial mean of the maximum shift more than 1 month). The driest quarter was less prone to the change, with Europe, Eastern North America, South America, and South Australia predicted to experience the most remarkable shifts. The regions expected to experience the most shift of precipitation-related quarters in the future show some overlap with the regions with the lowest intra-annual variability of precipitation within the reference period (Figure 2b; e.g., South Australia). Low intra-annual variability might indicate a homogeneous climate where SCP shifts have a limited impact on the ecosystem due to the relatively small difference between the monthly precipitation values. However, other regions might be considered vulnerable to SCP shifts, that is where either (1) the intra-annual variability is high (e.g., Central Africa, Central America, the northern part of South America, and the Malay Archipelago), or (2) the low variability is associated with the very limited annual precipitation sum (e.g., Central Asia).

Spatial patterns of the shift of the warmest and the coldest quarters showed similarities. The tropical region was predicted to be the most vulnerable. The mean shift was mainly concentrated in tropical South America and Africa, while the maximum shift included also the Malay Archipelago. If the spatial distribution of the predicted shift of the temperature-related quarters is compared with the intra-annual variability of the monthly temperatures within the reference period, co-locations, and spatial mismatches also occur. While, as expected, most of the regions vulnerable to the shift of the coldest or warmest quarter have limited within-year temperature variability (e.g., the Malay Archipelago and the tropical region of Africa and South America), high-variability regions also experience such shifts. Central America, the northernmost part of South America, the Sahel region, and Southeast Asia might experience remarkable SCP shifts even though the intra-annual temperature variability in these regions is far from negligible.

The four monthly alternatives to the quarters revealed the same spatial patterns but more remarkable shifts (Figure S1.2).

3.2 | Hotspots of the expected SCP shift

The hotspot analysis revealed that the shift of the precipitation-related months and quarters was scattered: all continents and all climate zones were predicted to be affected (Figure 3a). The areas with >2 month mean shift were somewhat focused on those regions where the relative annual range of the precipitation was low or moderate. At the same time, several subtropical, temperate, and polar regions with high relative annual range were predicted to be subject to remarkable structural change in the future (Figure 2). This finding was more pronounced when studying months rather than quarters (Figure S1.2).

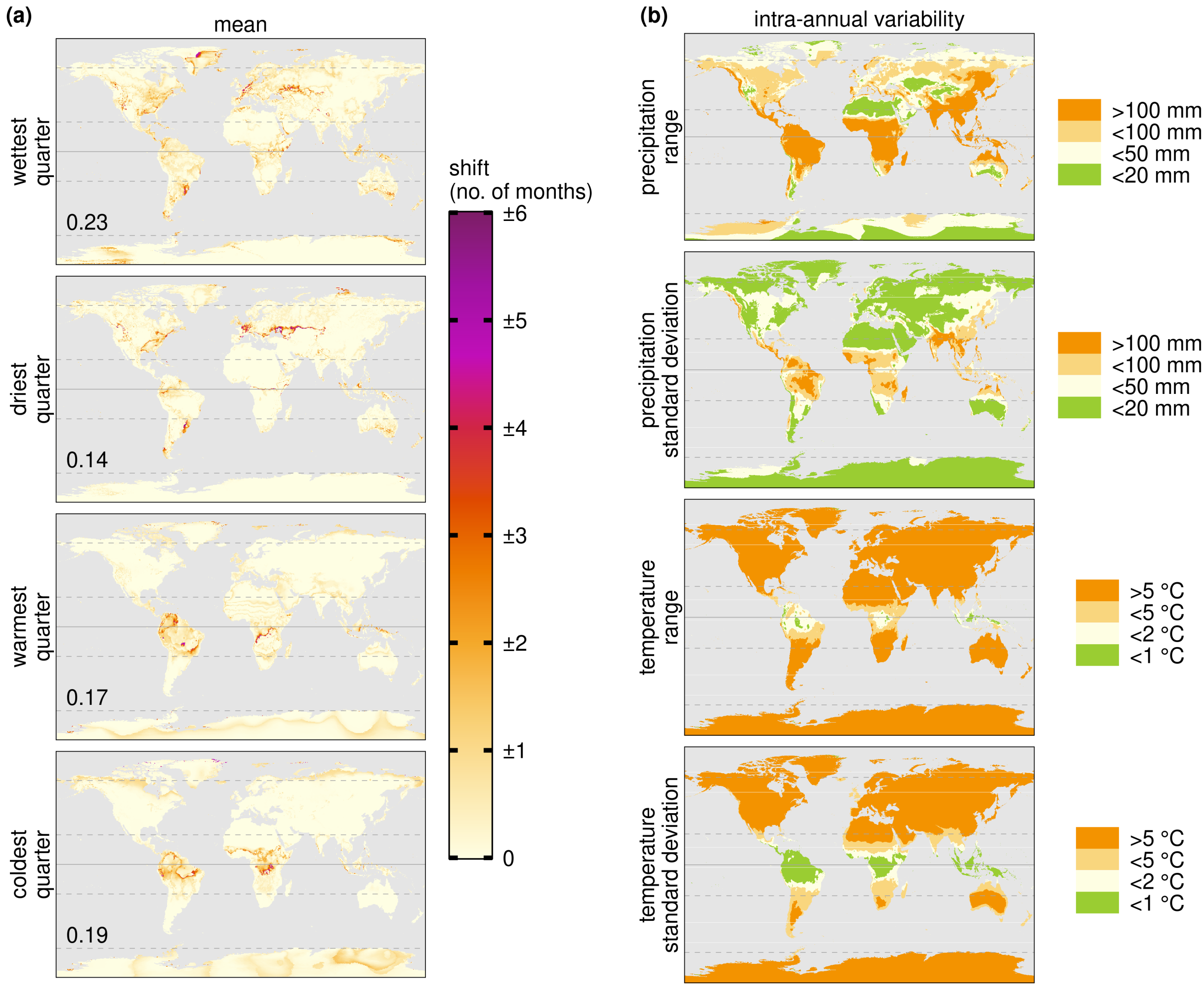

FIGURE 2 (a) Deviation of the within-year position of the four specific quarters in the future from their position in the reference period (i.e., SCP shift). Results are aggregated by their mean across the 64 future climate targets. For aggregation by their minimum and maximum, please refer to Figure S1.1. Spatial means of all the terrestrial cells are displayed in the bottom left corner of the subfigures, indicating the average global magnitude of the SCP shift. (b) Spatial distribution of the intra-annual variability (range and standard deviation) of the monthly precipitation and temperature values in the reference period. For months instead of quarters, please refer to Figure S1.2.

Hotspots of the shift of the temperature-related months and quarters mostly concentrated in the tropics (Figure 3b), where the temperature range is relatively small, which is consistent with previous findings (Figure 2; Figure S1). However, the polar regions (both in the Arctic and the Antarctic) were predicted to be subject to shifts of the coldest and warmest quarters (Figure 2)—although lower in magnitude (<2 month). For the coldest and warmest months, also large areas of the temperate region were involved (Figure S1.2).

3.3 | Overall differences between periods, scenarios, and GCMs

Different periods, scenarios, and GCMs showed similar spatial patterns but different magnitudes of the SCP shifts (Supplementary Material S2). In addition, the inter-model variability of the patterns was much greater than the inter-period and inter-scenario variability. The spatial means of the SCP shifts and the number of the quarters with >0 shifts are visualized in Figure 4 for comparison purposes. The wettest quarter was predicted to deviate the most from the reference period, while the driest quarter was predicted to remain the most in place within the year. The most obvious and homogeneous gradient was observed in the case of the scenarios and periods. The order of the GCMs was more heterogeneous. The difference between the BCC-CSM2-MR and IPSL-CM6A-LR climate models was negligible, although their ECS values are remarkably different (3.02 vs. 4.56, respectively; Zelinka et al., 2020). Also, the mean of the shifts of the wettest quarter suggested a different order of the GCMs compared with the other three quarters. Similar conclusions could be drawn when studying months instead of quarters (Figure S1.3),

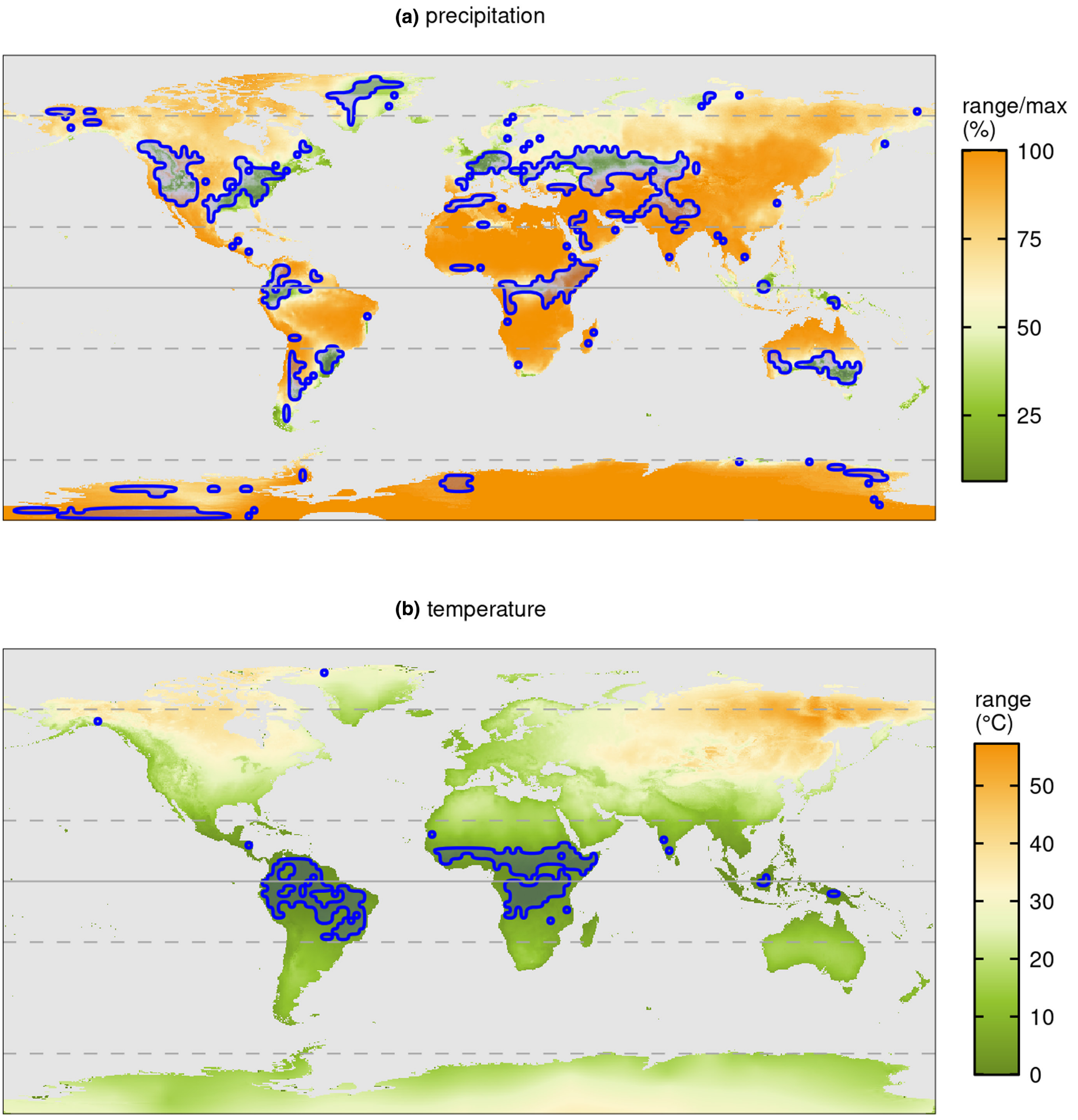

FIGURE 3 Intra-annual (a) precipitation variability (range/maximum; %) and (b) temperature variability (range;°C) and hotspots (blue polygons) of the expected SCP shift. Hotspots were defined as regions where (a) any of the wettest or driest quarters or (b) any of the warmest or coldest quarters is prone to shift ≥2 months compared with the within-year position of the quarter in the reference period according to the mean of all the 64 future targets.

but the magnitude of the predicted shifts usually exceeded their quarterly equivalent. The wettest, driest, and coldest months, and the number of the >0 shifts calculated for months ranked the GCMs in the same way as the wettest quarter did: the BCC-CSM2-MR climate model predicted more SCP shifts than CanESM5. This means that among the specific months, only the warmest month ranked the GCMs according to their ECS value.

3.4 | Relative importance of the distribution modeler's decisions

Variable importance estimation revealed that each of the three decisions of the distribution modeler, that is, the choice of the period, the choice of the scenario, and the choice of the GCM, had highly significant ($p < .001$) impact on all the six studied aspects of the SCP

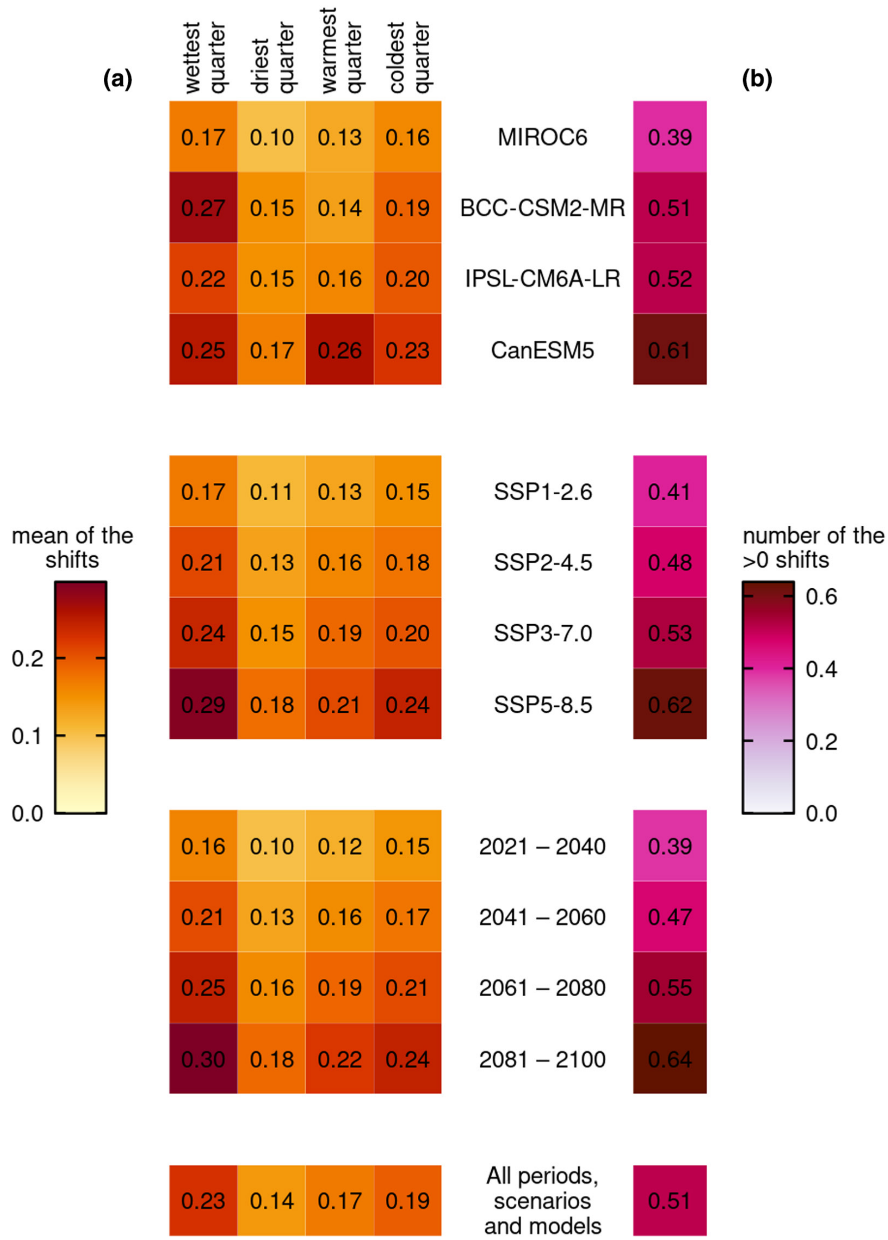

FIGURE 4 (a) Spatial mean of the shifts and (b) the number of the quarters with >0 shifts averaged over all the 4×4 period×scenario combinations, all the 4×4 period×GCM combinations, all the 4×4 scenario×GCM combinations, and all the 4×4×4 period×scenario×GCM combination (from top to bottom, respectively). Larger numbers suggest a higher potential for the reshuffling of the within-year distribution pattern of the climate. For months instead of quarters please refer to Figure S1.3.

shifts (i.e., all the six response variables): on the shift of the wettest, driest, warmest, and coldest quarters, on their mean shift, and also on the number of quarters with >0 shifts.

The order of importance of the variables showed some heterogeneity (Figure 5). For most of the response variables, the period choice is the most important, followed by the scenario and then by the GCM choice. However, for the shift in the warmest quarter, GCM choice was found to be the most important covariate. The period choice was the variable with the highest impact on the number of the >0 shifts, but the order of the scenario and GCM choice were not clear.

Comparing the linear models of the months (Figure S1.4) with those of the quarters revealed remarkable differences. The order of importance of the covariates was reversed for the wettest month: choice of the GCM was found to be the most important for this response variable. For the number of the SCPs with >0 shifts, the order of the covariates was clearly period > GCM > scenario. For the other four response variables, the order of importance remained unchanged.

4 | DISCUSSION

4.1 | Magnitude of SCP shifts and their ecological relevance

For all SCPs and for all continents, shifts were observed in at least one of the periods studied. Shifts were more pronounced for quarters than for months. Even shifts reaching 6 months were detected. In the case of such long shifts, the distribution modeler should definitely consider whether the shift can be followed by phenology.

Phenological shifts in response to climate change have been identified in several organisms (Auffret, 2021; Inouye, 2008; Inouye, 2022).

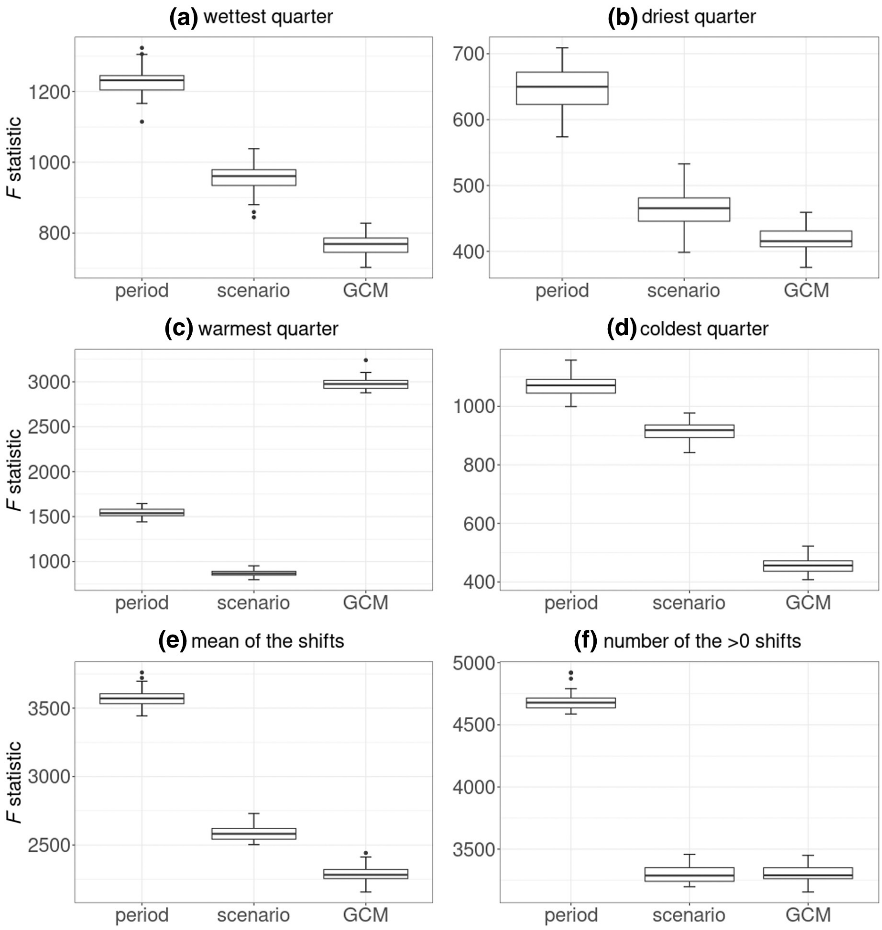

FIGURE 5 Estimation of the importance of the period, scenario, and GCM choice on the shift of the (a) wettest, (b) driest, (c) warmest, and (d) coldest quarters, (e) on their mean shift, and (f) on the number of quarters with >0 shifts using the *F* statistics (d.f. = 3, for each of the three covariates). The higher the *F* statistic, the more important the choice of the covariate. The response variables are displayed as subfigure titles. For months instead of quarters please refer to Figure S1.4.

The shifts studied are mostly related to temperature (Auffret, 2021; Inouye, 2008; Inouye, 2022). Examples of responses to within-year distribution reshuffling of the precipitation pattern are less common, although it has been shown that the timing of precipitation can also be an influential factor on phenology, especially in arid environments (Currier & Sala, 2022; Lesica & Kittelson, 2010; Shen et al., 2015). As we have shown, reshuffling of both seasonal temperature and precipitation patterns is widely expected. However, in the already observed cases of the shift in a climate parameter, the species was able to adapt to the change in the climatic feature by phenological shift (De Valpine & Harte, 2001; Dunne et al., 2003; Ingty et al., 2023). The consequence of climate reshuffling and SCP shifts depends on whether plants or communities are likely to be able to adapt to the change (Richardson et al., 2017). There is evidence that adaptation may not always be possible. For instance, Inouye (2008) described cases when earlier flowering was associated with higher frost damage, indicating that phenological shift may not be adaptive without limits.

Clearly, some of the phenology can shift earlier as has already been observed in the case of earlier greening or flowering related to the climate change that has occurred so far (Piao et al., 2019). Also, some of the physiological processes can be delayed, such as the leaf senescence before the winter (Gordo & Sanz, 2010; Piao et al., 2019). However, as the size of the shift increases, the likelihood of a phenological adaptation decreases. An SCP shift >2 months widely encountered in our study, likely exceeds the phenological plasticity of most of the living organisms, particularly since plasticity has yet been observed in the range of days/decade, that is, weeks/century, rather than in the range of months/century (e.g., Auffret, 2021; Inouye, 2022; Moore & Lauenroth, 2017; Richardson et al., 2017). Thus, it is safe to say that >2 month shift in phenology is unlikely to be feasible for species to adapt to and needs to be addressed if occurs in bioclimatic variables calculations for assessing climate change impact.

It is recommended to interpret SCP shifts together with (1) the expected change in the precipitation/temperature values, and (2) the intra-annual variability of the climate observed in the reference period. The latter is particularly important from the point of view of the studied species since it describes the within-year distribution of the climate to which the species has long adapted to. If the intra-annual variability is high, species living in the area are likely to adapt to the seasonal patterns. In such a situation, it will be more challenging to cope even with smaller SCP shifts. On the other hand, if the intra-annual variability is relatively low (e.g., the precipitation is evenly distributed), even a significant SCP shift (e.g. in the timing of the small precipitation peak) might pose only minor problem for the organisms present.

4.2 | Spatial patterns of SCP shifts

The expected emergence of no-analogue climates with climate change has been voiced repeatedly (Birks, 2019; Maguire et al., 2015; Williams

& Jackson, 2007). Shifts in the timing of the SCPs clearly foreshadow the emergence of a no-analogue climate. However, it is also possible, that climate shifts occur in concert, resulting in an analogous climate that is different from the previous one at the specific location, but similar to another currently known climate. Thus, the emergence of a no-analogue climate necessarily involves the shift of at least one SCP, but the shifts do not predict a no-analogue climate in themselves.

The emergence of no-analogue climates has already been predicted for the tropics (Torres-Amaral et al., 2023; Williams & Jackson, 2007). Consequently, we would expect most of the climate shifts to occur there. This coincides with part of our results. In particular, temperature-related shifts are expected there according to our results. Nevertheless, a remarkable proportion of the SCP shifts, mostly those related to precipitation changes, have been observed in the temperate regions in our study.

For ecologists and modelers, it has a crucial significance whether the SCP shift coincide with the emergence of a no-analogue climate or reflects the emergence of a known climate pattern in a new area. For ecologists in general, SCP shifts indicate the expected reassembling of communities (le Roux & McGeoch, 2008; Thorson et al., 2021), the possible shift of species' ranges (e.g., Hannah et al., 2002; Lecomte et al., 2004; Mátyás et al., 2010), or even extirpations (Erb et al., 2011). For modelers specifically, SCP shifts that exceed the limits of phenological plasticity have important implications for the use of bioclimatic variables. It is noteworthy not only if a no-analogue climate arises, but also in the case of a shift of a climate zone. For example, the shift of the Mediterranean climate toward the north (Barredo et al., 2018) replacing the continental climate would mean the rescheduling of precipitation maxima to winter from summer. Such a possibility can also be observed in our results, which identify precipitation timing shift hotspots in Southern Europe.

Precipitation and temperature are inter-correlated (Sillero et al., 2021; Vrac et al., 2023). GCMs seek to describe the physical state of the climate as a system, including the correlation and interaction of temperature and precipitation (Randall et al., 2007; Zhou et al., 2020). The simultaneous use of correlated bioclimatic variables to train predictive distribution models should be avoided (De Marco & Nóbrega, 2018; Dormann et al., 2013; Porfirio et al., 2014). A widely applied modeling practice is to subject available bioclimatic variables to correlation analysis and to use a less correlated subset of the original variables for model training (Dormann et al., 2013; Sillero et al., 2021; Zhang et al., 2020). However, the reference period is usually used to calculate the correlation, while the correlation structure may change over time, which causes transferability issues (Chen et al., 2024; Feng et al., 2019). The change in the correlation structure is likely to be only slightly influenced by a gradual (but spatially heterogeneous) change in the value of the precipitation or temperature variable, and more significantly by a shift of the underlying SCP, although further research is needed to investigate this issue. In such cases, the default dynamic calculation method of bioclimatic variables for predictive distribution models will likely result in artifacts (Bede-Fazekas & Somodi, 2020). In such cases, a static approach, whereby the SCP is fixed for the future, is less susceptible to the aforementioned issues. Alternatively, variables that depend on the affected SCP should be eliminated. Particular attention should be paid to bioclimatic variables that combine temperature and precipitation (i.e., the temperature of the wettest/driest quarter and precipitation of the warmest/coldest quarter; Escobar et al., 2014, Booth, 2022). Predictive distribution models involving combined variables are outstandingly vulnerable to transferability issues, as there is a significant risk that one or the other aspect shifts outside the limits of the realistic phenotypic adaptation.

4.3 | Hotspots of the expected SCP shift

The significance of shifts for community ecology depends on the capacity of species to adapt to the new circumstances (Veloz et al., 2012). Species can have wider tolerance than perceived under the climate of one period (Veloz et al., 2012) and thus they can survive in no-analogue climates as well. Phenological plasticity is a mechanism by which species can survive under new climatic conditions without genetic modifications, too. Therefore, its amplitude is relevant in assessing the severity of the SCP shift. Our results indicate that large areas within the temperate regions will experience more than a 2-month shift, which exceeds the observed phenological shifts of species studied so far (Auffret, 2021; Inouye, 2022). Even 6-month shifts are frequent. For example, a change from winter precipitation maximum to summer precipitation maximum in the temperate zone is unlikely to be bridged by adaptation, particularly given that temperatures will rise there as well. We argue that special attention should be paid to those regions where the deviation is larger than 2 months ("hotspots" of SCP shifts, Figure 3) both with regards to monitoring the ecological response to the emerging shifts and when building models to predict consequences.

In the temperate regions, hotspots of shifts are related more to precipitation, while in the tropics hotspots of shifts are both related to temperature and precipitation. It was unexpected that such prominent SCP shifts would be experienced in the temperate zone, as these fall outside the tropics and subtropics that were identified as candidates for no-analogue climates earlier (Williams & Jackson, 2007). While these do not necessarily indicate the presence of no-analogue climate yet, the occurrence of such shifts suggests the potential for climate patterns to challenge the plasticity of the resident communities. Hotspots of precipitation shifts appear to affect very diverse current biomes. Many of these hotspots are centered in the Mediterranean and neighboring areas globally, which is in good accordance with warnings that the area of the Mediterranean climate might contract or shift in space (Barredo et al., 2018) and the indication of no-analogue climate emergence in California (Mahony et al., 2017). Further hotspots emerge in the current territory of grassland and desert biomes. While grasses have the potential to utilize precipitation from a different period in the year, restructuring the precipitation timing may prove to be transformative for deserts.

The significance of the expected SCP shifts for the wet tropics remains to be determined. One could argue that shifts in temperature or precipitation maxima or minima during the year are not significant in a climate, where the temperature is rather evenly warm and precipitation is present throughout the year (Cobb et al., 2003). Here the mere fact that temperatures are rising can have a higher effect (e.g. Huey et al., 2009) and can lead to no-analogue climate in itself as already signaled by Williams and Jackson (2007). Also, Mahony et al. (2017) found that the southernmost part of the US, characterized by tropical climate, is the most prone to the emergence of no-analogue climates. Nevertheless, even in the wet tropics, there are climatic cues during the year that regulate the pattern of leaf senescence (Borchert, 1992; Cleveland et al., 2006; dos Santos et al., 2022). Disruption of these by major shifts within the year may still present an adaptation challenge that is not necessarily feasible to overcome for all species (Veloz et al., 2012).

The found spatial patterns and hotspots of SCP shift might be altered by mesoclimate and microclimate in mountainous regions if studied at a finer resolution. Due to computational constraints, the spatial resolution of the input climate data used in our analysis was limited to 2.5′ (ca. 5 km). Although interpolation of temperature and precipitation to this resolution relied heavily on elevation (Fick & Hijmans, 2017), the resulting climate surface and our findings on the SCP shifts are relevant only for regional to global studies. Uncertainty of the climate is usually more pronounced in topographically heterogeneous regions (Brown et al., 2018; Gillingham et al., 2012; Kemppinen et al., 2024; Slavich et al., 2014), which is true also for the input climate data (Fick & Hijmans, 2017), hence, for our findings as well. This requires due diligence in local studies, where fine-resolution topography should be incorporated in the analysis.

4.4 | Overall differences between periods, scenarios, and GCMs

The size of the shifts was larger with more pessimistic climate change scenarios and further time periods as it was expected. Also, the GCMs followed the expected order according to the shifts of the temperature-related quarters. However, the ECS was not found to be the determining factor of the magnitude of the shifts when we studied the wettest quarter (Figure 4) or the wettest, driest, and coldest months (Figure S1.3). This might be partially attributed to the warming-focused definition of ECS (Zelinka et al., 2020) and other climate model sensitivity indices (Grose et al., 2018).

In contrast to periods and scenarios, different GCMs expressed the alteration of the climate structure in different ways. It is not possible to predict with certainty the shift of all the other quarters and months based on the shift of a single quarter or month. Therefore, transferability assessments and estimations of the magnitude of extrapolation should take all the quarters/months (i.e., the annual distribution pattern) into account. Relying on the value of a climatic variable (e.g., temperature values of the wettest quarter) alone can be misleading. A parallel investigation of the shift of the underlying quarter or month (e.g., wettest quarter) is essential to avoid artifacts (Bede-Fazekas & Somodi, 2020; Booth, 2022; Merkenschlager et al., 2023).

In summary, while periods and scenarios can be consistently ordered by the severity of SCP shifts, the same does not hold for the GCMs due to the heterogeneous results. This warns distribution modelers that for an analysis involving SCPs, which is automatically the case when using the popular bioclimatic variables, diversifying the selected GCMs to represent various ECS is not sufficient. A preliminary analysis of expected SCP shifts may be more informative.

4.5 | Relative importance of the distribution modeler's decisions

There is no scientific consensus on the order of the relative importance of the three decisions, that is, the choice of the period, the scenario, and the GCM (Blanusa et al., 2023; Iizumi et al., 2017; Olesen et al., 2007). Our variable importance estimations often found the period > scenario > GCM order, suggesting that the choice of the study period was the primary source of variation, followed by the scenario. The choice of the GCM was found to be the least important decision of the modeler in the case of five of the eight SCPs (wettest, driest, and coldest quarters, driest, and coldest months). These findings are in concert with previous research on the importance/impact of the choice of the period, scenario, and GCM, and their contribution to the uncertainty of impact assessments (Bede-Fazekas & Somodi, 2020; Hawkins & Sutton, 2009; Hawkins & Sutton, 2011).

It is reasonable that the degree of shifts progressed with time and thus the greatest variation was found across time periods. The results imply that the size and direction of expected SCP shifts are even more pronounced than humans can mitigate climate change, even in optimistic scenarios. However, it is a reassuring finding of our study that GCMs are responsible for the least of the variation suggesting that the choice of the climate model has the least influence on the prediction outcomes. Some earlier studies found comparable variation regarding GCMs vs. periods (Chen et al., 2015; Ziter et al., 2012). However, improvement of GCMs could have contributed to a change in the situation. Furthermore, differences in the values of climate variables (e.g., precipitation sum) may be less robust than the location of precipitation maxima/minima within the year, which was the target of our study.

5 | CONCLUSIONS

Our results indicated severe reshuffling of the within-year distribution of the climate patterns measured by the shift of the SCPs, which bioclimatic models rely on. While the reshuffling did affect the tropics as expected, SCP shifts are widely predicted elsewhere as well on the globe. The scale of SCP shifts frequently exceeds 2-month shifts, well beyond the known phenological plasticity of species. Thus, besides being technically relevant in the process of the calculation of bioclimatic variables, the findings also call for ecological considerations in the variable choice and calculation of bioclimatic variables.

Therefore, we advise predictive distribution modelers to account for SCP shifts and incorporate the phenomenon in the modeling efforts.

Based on our results, we anticipate the most pronounced temperature-related shifts along the Equator, while precipitation-related shifts are likely to affect the areas affected by temperature-related shifts as well as the temperate zone on both hemispheres and the Arctic. GCMs exhibit high agreement regarding the position and magnitude of SCP shifts, and are more uniform than scenarios and periods.

The variable importance estimation revealed that the modeler's choice from the available time periods and scenarios significantly influences the identification of the expectable SCP shifts. However, scenarios explained a slightly smaller proportion of the variation than the choice of time period. This suggests that SCP shifts are inevitable, regardless of human interventions.

Thus, our study makes a significant contribution to the understanding of the impact of climate change on biological distributions. However, the findings serve to raise awareness rather than to provide a detailed and local-scale picture of the change ahead. There is a clear need for continued research and the development of adaptation strategies in the face of the inevitable SCP shifts. In line with this, we urge further investigations into the effects of the interaction of temperature and precipitation shifts.

AUTHOR CONTRIBUTIONS

Ákos Bede-Fazekas: Conceptualization; formal analysis; methodology; visualization; writing – original draft. **Imelda Somodi:** Conceptualization; methodology; supervision; writing – original draft.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Dryad at https://doi.org/10.5061/dryad.6m905qg8j. Raw climate data is available from the WorldClim 2.1 database at https://www.worldclim.org/data/worldclim21.html and https://www.worldclim.org/data/cmip6/cmip6_clim2.5m.html.

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