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Climate change impacts on the distribution of deciduous forests in the Central Highlands of Vietnam

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Abstract

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The spatial distribution of deciduous forests (DF) in Vietnam is relatively restricted. However, these ecosystems play a pivotal role in overall ecosystem structure and function. This study aimed to assess the environmental drivers governing the distribution of DF in Vietnam under climate change scenarios. Our results show that DF currently occupies a relatively narrow climatic niche spanning approximately 10,496.49 km^2, predominantly in the Central Highlands. Precipitation of the driest month, temperature seasonality, and elevation emerged as the dominant predictors of DF distribution. Projected climatic niche contraction for the period 2081–2100 ranged from 7.6% (SSP245) to 33.2% of the current climatically suitable area (SSP585). This decline is primarily associated with increased precipitation during the coldest quarter and greater temperature variability. These findings underscore the need for targeted and proactive conservation strategies for DF in the Central Highlands of Vietnam, where the already limited suitable habitats are particularly susceptible to climate-driven range contractions.

Keywords

ACCESS-CM2, habitat suitability, MaxEnt, vegetation community distribution

Introduction

Climate is the primary determinant of terrestrial biome distribution at broad spatial scales (Loidi et al., 2022). Shaped by distinct climatic regimes and evolutionary histories, terrestrial biomes are increasingly vulnerable to the impacts of global climate change (Luna-Aranguré et al., 2025). Consequently, identifying the key drivers of biome distributions is essential for anticipating and assessing the effects of global environmental change (Moncrieff et al., 2016a). Future predictions of terrestrial biomes are crucial for guiding conservation planning and management, particularly in contexts where safeguarding vulnerable biomes and the species they support over the long term is a key priority (Allen et al., 2024). Although the effects of climate change on the ranges of individual plant species have been widely modeled, its impact on the spatial distribution of vegetation at the community level been relatively understudied (Hadinejad et al., 2025; Suzuki et al., 2024). Methods for predicting how vegetation community patterns might change in response to future climate conditions are typically grouped into two categories: a) dynamic vegetation models (DVMs) and b) statistical distribution models (SDMs). SDMs, also known as species distribu-

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tion models (SDMs). SDMs, also known as species distribution models, niche models or habitat suitability models, link observed species or vegetation distributions to current environmental variables, using presence–absence records and spatially explicit environmental datasets (Moncrieff et al., 2016b).

SDMs are subject to several well-recognized limitations, including the assumption that current distributions of forest trees reflect equilibrium with environmental conditions, reduced reliability when extrapolated to novel climates, and the omission of biotic interactions such as competition (Guisan and Thuiller, 2005). Nevertheless, owing to their relatively modest data requirements, flexibility, and strong predictive performance, SDMs remain among the most widely applied approaches for assessing potential impacts of climate change on species and vegetation distributions (Safdar et al., 2025; Srivastava et al., 2019). Typically, SDMs have been used to model climate change effects on the distribution of vegetation communities in the Zayandeh-Rud Basin, Iran (Hadinejad et al., 2025), Mongolian rangeland vegetation (Suzuki et al., 2024), and to assess the global potential distribution of vegetation community (Bonannella et al., 2023). Among SDMs, maximum entropy modeling (MaxEnt) has emerged as one of the most widely applied and well-established methods for analyzing species–environment relationships (Safdar et al., 2025; Wang et al., 2024). One of the principal strengths of MaxEnt lies in its capacity to generate robust predictions using presence-only data, which are often the most readily available type of ecological information (Dad and Rashid, 2025). In addition, MaxEnt performs reliably when occurrence records are sparse or sample sizes are small, making it particularly suitable for species distribution modeling in data-limited regions (Phillips et al., 2017).

Tropical forests occupy only about 6% of the world's land area, but they contain the greatest biodiversity on the planet (Henry et al., 2024). They are also essential components of the global carbon cycle, storing around 25% of all terrestrial carbon and accounting for roughly 34% of Earth's gross primary production (Kafy et al., 2023). Within tropical forest ecosystems, tropical deciduous forests are the most widespread, representing almost 42% of the total forest cover in the tropical zone (Ocón et al., 2021). Although they occupy a broad geographical range, these forests rank among the most imperiled biomes worldwide, while still maintaining high levels of species richness (Riggio et al., 2020). In Vietnam, deciduous forests are largely comprised of dry dipterocarp forests, which occur mainly in the Central Highlands, with the greatest extent in Dak Lak and Gia Lai provinces. Smaller, more fragmented stands of these forests also appear in other provinces, including Lam Dong, Ninh Thuan, Binh Thuan, Binh Phuoc, and Tay Ninh (Averyanov et al., 2003; Lung et al., 2011).

Deciduous forests of Vietnam are important for conserving biodiversity, regulating water and air quality, cycling carbon and nutrients, preventing soil erosion, and sustaining habitats for many endemic animal species (Tuan et al., 2021b). Deciduous forests are undergoing substantial degradation and decline as a result of intense anthropogenic disturbance and continuing climate change. This situation in the fragmented forests highlights the urgent necessity of placing their protection at the forefront of environmental management and policy agendas (Nguyen and Baker, 2016; Van Quy et al., 2025). A rigorous delineation of the spatial extent and geographic distribution of the tropical dry forest biome is critical for the reliable monitoring of spatiotemporal dynamics in forest cover. Such spatially explicit information is foundational for quantifying and evaluating major anthropogenic and natural stressors, including deforestation, wildfire, and climate change, as well as for assessing the overall conservation status of this biome. This assessment includes analyses of the occurrence and spatial distribution of threatened and endangered species, the identification and cartographic characterization of remaining old-growth forest remnants, and the evaluation of the effectiveness, ecological representativeness, and landscape connectivity of existing protected areas (Ocón et al., 2021).

Despite this urgency, our scientific understanding of how climate change influences the spatial distribution of plant communities in Vietnam is largely unexplored. The documented results mostly focused on modeling the distribution of individual plant species (Dinh et al., 2022; Pham et al., 2024a; Pham et al., 2025; Tuan et al., 2021a) or groups of specific species groups (Van Quy et al., 2025). Although its usefulness for predicting plant species distributions at the community scale has already been demonstrated (Raney and Leopold, 2018; Suzuki et al., 2024), patterns at the community level have been much less thoroughly investigated. Further research is required to enhance our current understanding of vegetation community distribution in deciduous forests, because changes in plant communities greatly affect the structure and functioning of entire forest ecosystems, including the animal species that inhabit them. To address this critical knowledge gap, this study aimed to investigate the effects of climate change on the spatial distribution of deciduous forest communities in the Central Highlands and Southern Vietnam. Specifically, we aimed to address the following questions: (i) which key climatic variables determine the current distribution of DF in Vietnam; (ii) how the distribution of DF may change in the future under different climate change scenarios; and (iii) how climatic variables and their projected changes contribute to shaping the future distribution of DF. Our findings offer important guidance for forest conservation planning and ecosystem management in Vietnam's deciduous forest ecosystems.

Materials and methods

Study site

This study was conducted in the Central Highlands and southern regions of Vietnam, spanning latitudes from 8°33'30.00"N to 14°36'30.00"N and longitudes from

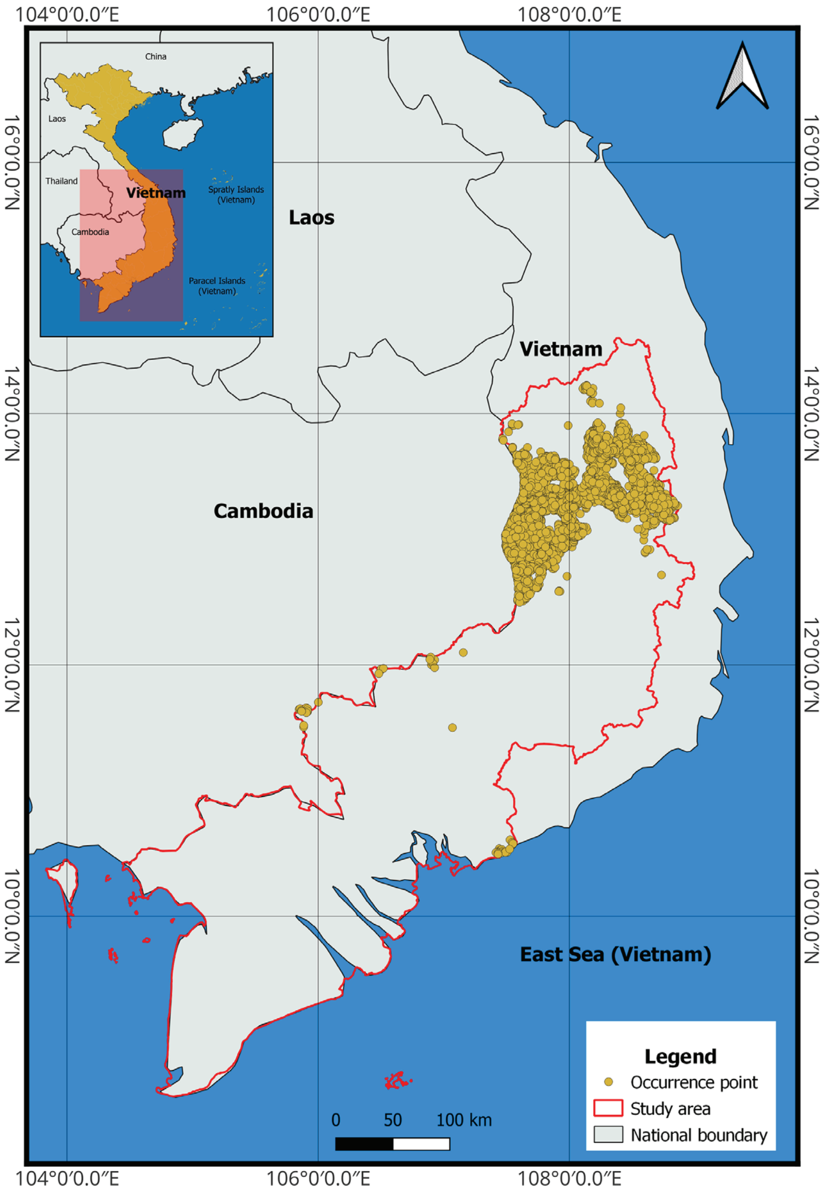

Fig. 1. Location of the deciduous forest in Central Highland and Southern Vietnam

103°25'60.00"E to 109°0'0.00"E. The climatic features of the study region comprise: (i) a monsoon tropical climate characterized by warm winters and summer rainfall in the Central Highlands; (ii) a monsoon tropical climate associated influenced by mountainous conditions in the Central Highlands at elevations above 1,400–1,500 m asl; and (iii) a monsoon sub-equatorial climate with summer rainfall in southern Vietnam (Averyanov et al., 2003). The angiosperm flora of deciduous forests encompasses 204 genera distributed among 68 families, with a marked predominance of taxa belonging to the family Dipterocarpaceae. This assemblage includes more than 90 timber species, 54 of which are categorized as large- and medium-sized timber trees (Lung et al., 2011). Other prominent families commonly associated with these forests include Combretaceae, Fabaceae, Phyllanthaceae, and Leguminosae (Tuan et al., 2021b). Under favorable site conditions, several high-value timber species such as *Pterocarpus macrocarpus* and *Dalbergia bariensis* are also present (Averyanov et al.. 2003; Lung et al., 2011).

Data collection

We used Vietnam's national forest inventory dataset, which consists of 500–1,000 m^2 sample plots collected from 2018 to 2024, to identify occurrence locations of deciduous forests in the Central Highlands and Southern Vietnam. The inventory is organized hierarchically into compartments, sub-compartments, and parcels, with parcels forming the smallest homogeneous mapping units (≥0.5 ha). Occurrence points were derived from plots situated at the centers of parcels classified as deciduous forest, whereas parcels labeled as mixed or transitional forest types were omitted to maintain class consistency. The environmental predictors comprised elevation and nineteen bioclimatic variables. A total of twenty predictor layers were sourced from the WorldClim database (version 2.1) at a spatial resolution of 30 arc-seconds (Fick and Hijmans, 2017). Spatial rarefaction was applied to occurrence data to reduce sampling bias. Using SDMtoolbox, closely spaced records were filtered to retain only one occurrence within a 1 km radius (Brown, 2014). This approach reduces the influence of spatially clustered observations by limiting redundancy in densely sampled areas, thereby improving the independence of occurrence points and reducing spatial autocorrelation in the dataset. After these steps, a total of 5,666 occurrence points were retained for subsequent species distribution modeling (Fig. 1).

Projected shifts in the geographical distribution of DF were simulated for the future time slices (2061–2080) and 2100 (2081–2100) under three climate change scenarios: SSP126, SSP245 and SSP585, representing low, intermediate, and high levels of global radiative forcing, respectively. The ACCESS-CM2 global circulation model was used to project future climate change scenarios. This model has demonstrated superior performance in representing wet and dry climate conditions across Southeast Asia (Soe et al., 2025). Models from the ACCESS family have been widely applied in species distribution studies, including in South Asia (Ali et al., 2024), Southeast Asia (Deb et al., 2017), and Vietnam (Pham et al., 2024a; Pham et al., 2025; Pham et al., 2024b; Van Quy et al., 2025). For each pair of bioclimatic variables, Pearson's correlation coefficient was computed, and variables exhibiting substantial multicollinearity (>0.8) were excluded from subsequent analyses (Hadinejad et al., 2025; Van Quy et al., 2025). Subsequently, eight environmental predictor variables were selected for inclusion in the species distribution models (SDMs): elevation, mean diurnal temperature range (bio2), isothermality (bio3), temperature seasonality (bio4), annual temperature range (bio7), annual precipitation (bio12), precipitation of the driest month (bio14), and precipitation of the coldest quarter (bio19) (Table S1).

Data analyses

Modeling the distribution of DF

We employed the MaxEnt algorithm within the ENMeval 2.0 framework (Kass et al., 2021; Phillips et al., 2017) to model the potential distribution of DF. The modeling procedure was implemented as follows: (i) Data preparation – Initially, the delineation of the background extent was carried out, a step that is critical in MaxEnt modeling because it defines the environmental domain against which occurrence conditions are contrasted. The spatial scope of the background area exerts a strong influence on model outputs, including predicted suitability patterns and associated evaluation metrics (VanDerWal et al., 2009). Using an excessively broad background extent can artificially inflate model performance, whereas an overly restricted background may fail to represent the full range of environmental conditions experienced by the species. Consequently, delineating a biologically meaningful and spatially appropriate background is critical. In accordance with these principles, we constrained the background to an area surrounding known occurrence records by applying a 50 km buffer. This distance was chosen to balance the need to encompass sufficient environmental heterogeneity while minimizing the inclusion of distant or ecologically irrelevant regions. Moreover, the buffer facilitated the exclusion of offshore islands in the East Sea, which lie outside the intended study area. Finally, we generated 10,000 randomly sampled background points, a practice that has been widely adopted in previous studies modeling the spatial distribution of plant species (Dinh et al., 2022, Liu et al., 2025). This sample size is generally adequate to characterize environmental conditions within the specified background extent while preserving computational efficiency. Moreover, MaxEnt commonly employs a default of 10,000 background points; (ii) Spatial partitioning – To incorporate spatial structure into the occurrence data, we applied the "block" partitioning method implemented in ENMeval 2.0.5. The study area was divided into four spatially distinct groups based on latitude and longitude, and both occurrence and background records were assigned to these groups accordingly. This approach, also referred to as "masked geographically structured" partitioning (Radosavljevic and Anderson, 2014), reduces spatial autocorrelation between training and validation datasets and supports a more robust and realistic assessment of model performance, particularly when occurrence data are geographically biased (Roberts et al., 2017); (iii) Model tuning and selection – For MaxEnt models, the two principal parameters tuned using ENMevaluate were (1) the range of regularization multiplier values and (2) the combinations of feature classes (Merow et al., 2013). In this study, candidate models were systematically assessed by varying the feature class configurations (L, H, LQ, LQH) and the regularization multipliers, which ranged from 1 to 5 in increments of 0.5, thereby ensuring a comprehensive and balanced exploration of the trade-off between model complexity and predictive performance (Dinh et al., 2022). The optimal model was selected based on the lowest delta AICc to prioritize parsimony and avoid overfitting (Velasco and González-Salazar, 2019), and (iv) Null Model Evaluation – Null model with 100 iterations was implemented to assess the statistical significance of model performance (Bohl et al., 2019; Kass et al., 2020). This allowed us to determine whether the model's performance (AUC) was significantly better than expected by chance, thereby ensuring that the results meaningfully represent the species' niche rather than random spatial patterns.

Suitability mapping and classification

The output format of the MaxEnt model was configured as logistic, which can be interpreted as an estimate of the relative probability of species occurrence across geographic space (Elith et al., 2006). We generated the current habitat suitability map using the 10th percentile training presence logistic threshold (10% TP). This threshold was used to convert the continuous suitability predictions into a binary classification, whereby all values below the 10% TP were designated as unsuitable. The areas classified as suitable (values ≥ 10% TP) were further stratified using the 25th and 50th percentiles of the presence data. This procedure yielded three discrete suitability classes: low suitability (10th–25th percentile), medium suitability (25th–50th percentile), and high suitability (>50th percentile).

To evaluate future habitat dynamics, we defined four categories of change by comparing current and projected distributions: Stable Suitable, comprising areas predicted to remain suitable across both time periods, and Stable Unsuitable, comprising areas predicted to remain unsuitable. In addition, we quantified habitat gain as the area currently classified as unsuitable that is projected to become suitable under future climatic conditions, and habitat loss as the area currently classified as suitable that is projected to become unsuitable. These spatiotemporal dynamics were assessed for the years 2080 and 2100 under three climate change scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. The percentage change in suitable habitat area under climate change was then calculated as:

Change (%) = (1 – (Future suitable area / Current suitable area)) × 100, where the current suitable area is defined as:

Current suitable area = Future suitable area + Loss – Gain.

Identifying drivers of range change

We investigated the mechanisms underlying projected range contraction using a two-stage spatial sensitivity framework: (i) Limiting factor analysis: Within areas classified as projected "Loss" (i.e., locations transitioning from suitable to unsuitable conditions), we implemented a One-Factor-At-A-Time (OFAT) procedure. By varying individual future predictor variables while holding all others at their baseline values, we quantified each variable's specific proportional contribution to local habitat collapse, thereby distinguishing the primary drivers of range loss from variables that are merely important for overall model performance. (ii) Environmental niche shift analysis: We compared the probability density functions (PDFs) of key environmental variables between the currently suitable range and the future loss areas. Divergence in these distributions, including shifts in modal values beyond the limits of the present realized niche, was interpreted as evidence of exceeded biological thresholds, thus providing a mechanistic basis for understanding future habitat unsuitability. All analyses were implemented in R version 4.3.1 (R Core Team, 2025).

Results

Model evaluation and significant explanatory variables

Among the 40 candidate models, the configuration with a regularization multiplier of 0.5 and a combination of linear, quadratic, and hinge (LQH) feature classes exhibited the lowest ΔAICc value; therefore, this model was selected to predict the potential distribution of DF in this study (Table S2). The average training and validation AUC values of the selected model were 0.92 and 0.93, respectively. The empirical training AUC (solid red line) was substantially higher than expected under random conditions, exceeding the 99th quantile of the null distribution (dashed purple line) (Fig. 2), indicating that the selected model achieved strong discriminatory performance and is suitable for predicting the spatial distribution of DF.

Precipitation in the driest month (bio14) and temperature seasonality (bio4) were the dominant predictors of the current distribution of deciduous forests, each accounting for 30.8% of the overall model contribution. Elevation represented the next most influential predictor (14.5%), followed by annual precipitation (bio12, 9.2%) and mean diurnal range (bio2, 8.1%). The remaining variables, including temperature annual range (bio7, 3.5%), isothermality (bio3, 2.0%), and precipitation of the coldest quarter (bio19, 1.2%), exhibited comparatively minor contributions. Taken together, the three most important predictors (bio14, bio4, and elevation) accounted for 76.1% of the total model contribution (Fig. 3).

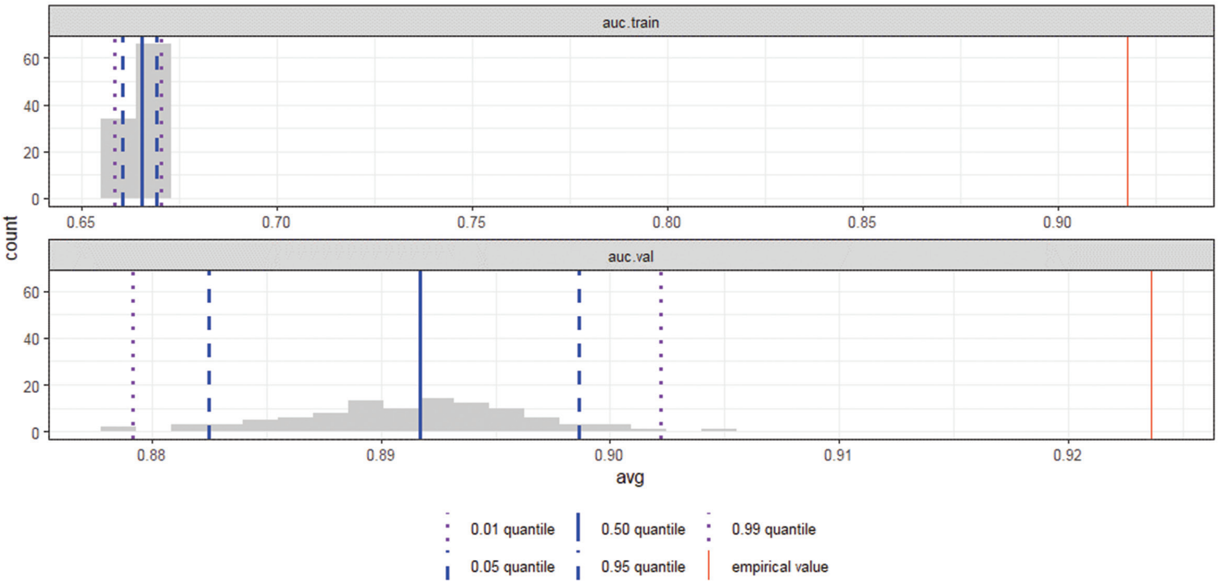

Fig. 2. The histogram of AUC value of null models

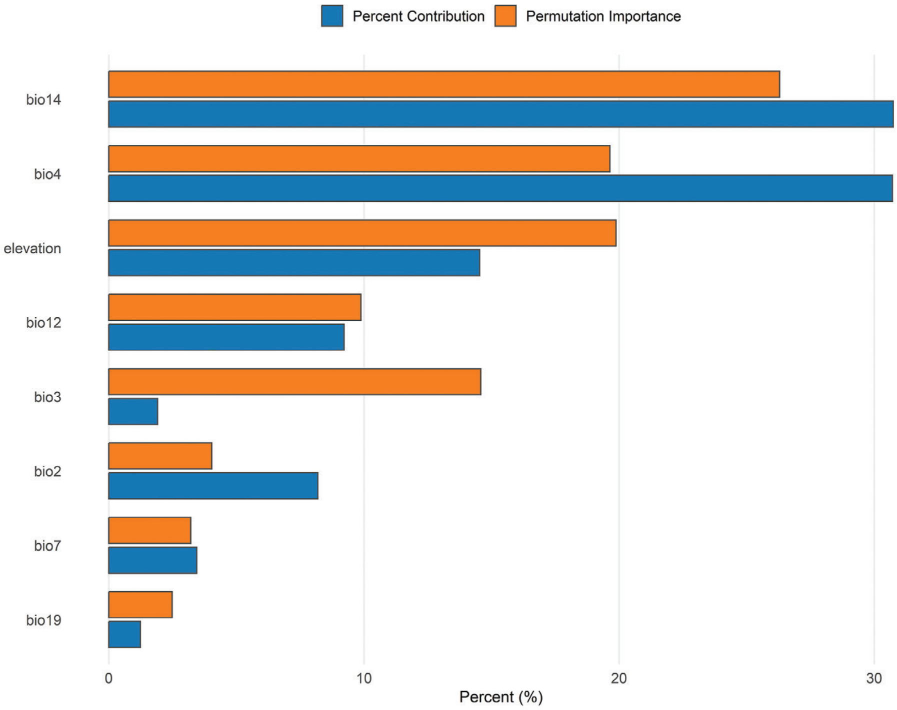

Fig. 3. Contribution of variables in the selected MaxEnt model for DF distribution.

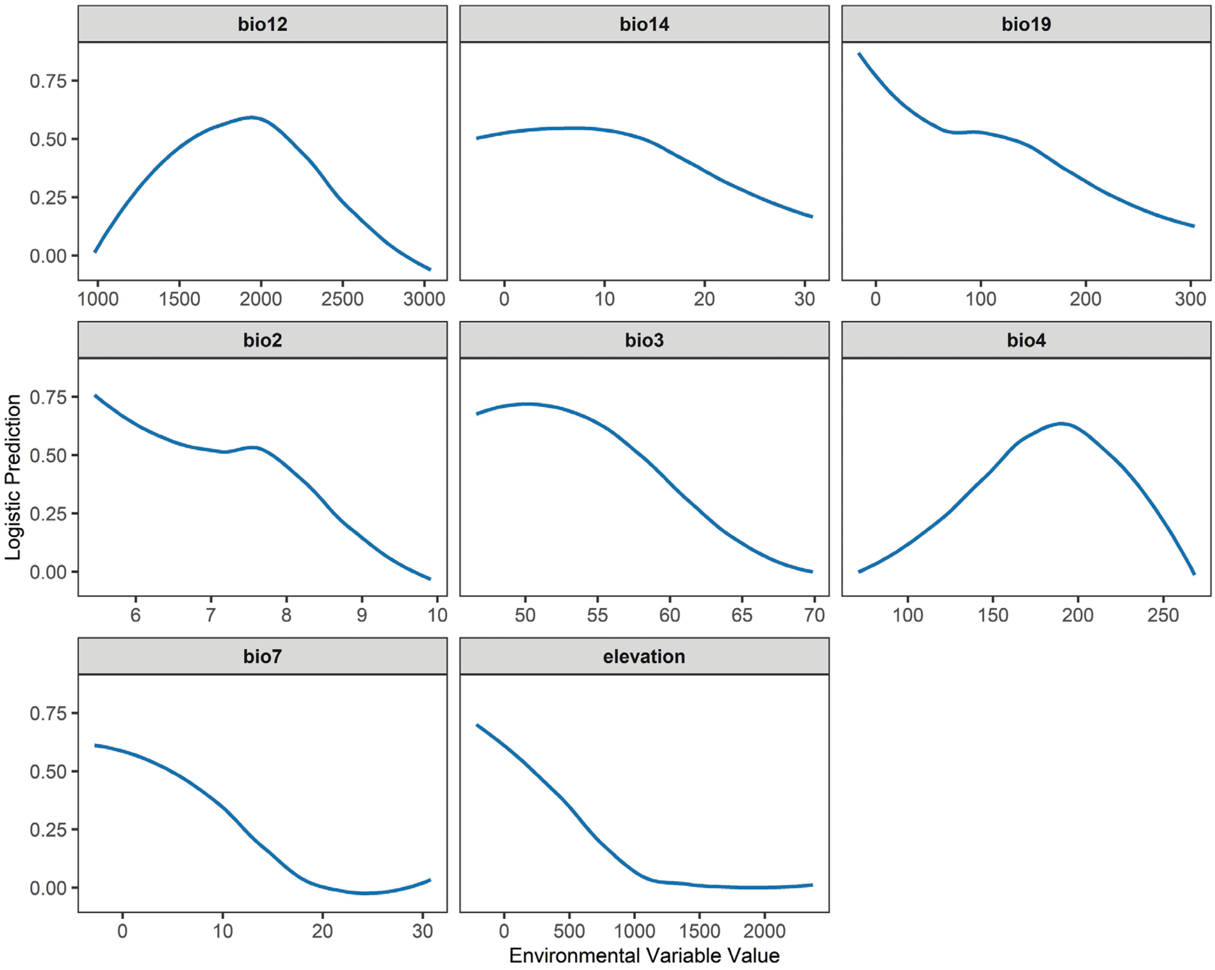

Fig. 4. Response curves of environmental variables for the DF distribution.

The response curves for annual precipitation (bio12) and temperature seasonality (bio4) exhibited unimodal (hump-shaped) patterns, suggesting that only a relatively narrow range of values is suitable for the species, with optimal responses occurring at approximately 2,000 mm and 180–190 (%) for bio12 and bio4, respectively. Likewise, isothermality (bio3) and precipitation of the driest month (bio14) displayed an initial modest increase towards an optimum, followed by a gradual decline beyond this peak. In contrast, precipitation of the coldest quarter (bio19) and mean diurnal range (bio2) showed a rapid initial decrease in predicted suitability, followed by a minor localized increase and a final steep decline. Finally, both temperature annual range (bio7) and elevation demonstrated a consistently decreasing relationship with suitability across their observed gradients (Fig. 4).

Current and future distribution for deciduous forests

The logistic thresholds derived from the presence data indicated values of 0.32, 0.43, and 0.54 for the 10%, 25%, and 50% (median) percentiles, respectively. Based on these thresholds, the predicted habitat suitability for deciduous forests was divided into four classes: unsuitable (0–0.32), low suitability (0.32–0.43), moderate suitability (0.43–0.54), and high suitability (0.54–1.00). Unsuitable areas dominate the region at 90.1% (95,113.72 km^2), while the remaining 9.9% (10,496.49 km^2) of suitable habitat is concentrated in the Central Highlands of Dak Lak and Gia Lai provinces (Fig. 5). Within these suitable zones, medium and high suitability areas comprise 4.2% and 3.9%, respectively, while low suitability areas represent the smallest portion at 1.9%.

Assuming that the current suitable area of deciduous forests is 100%, it is projected to decrease by 4.5%, 0.5% and 20.2% by 2080, and by 22.5%, 7.6% and 33.2% by 2100 under the scenarios SSP126, SSP245, and SSP585, respectively (Fig. 6 and Table S3).

Importance of environmental variables for the future distribution of deciduous forests

In all scenarios, precipitation from the coldest quarter

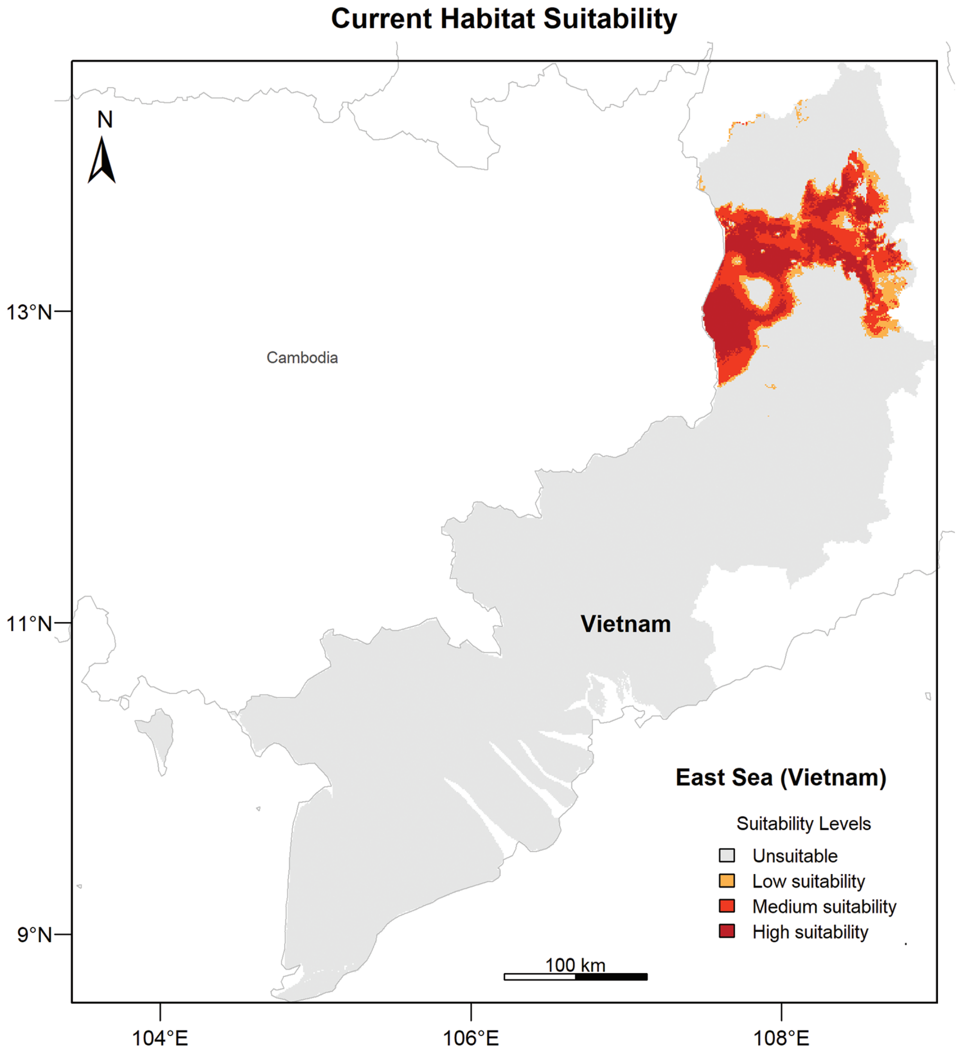

Fig. 5. Modeling of the predicted current habitat suitability for the DF in Central Highlands and Southern Vietnam on the MaxEnt model.

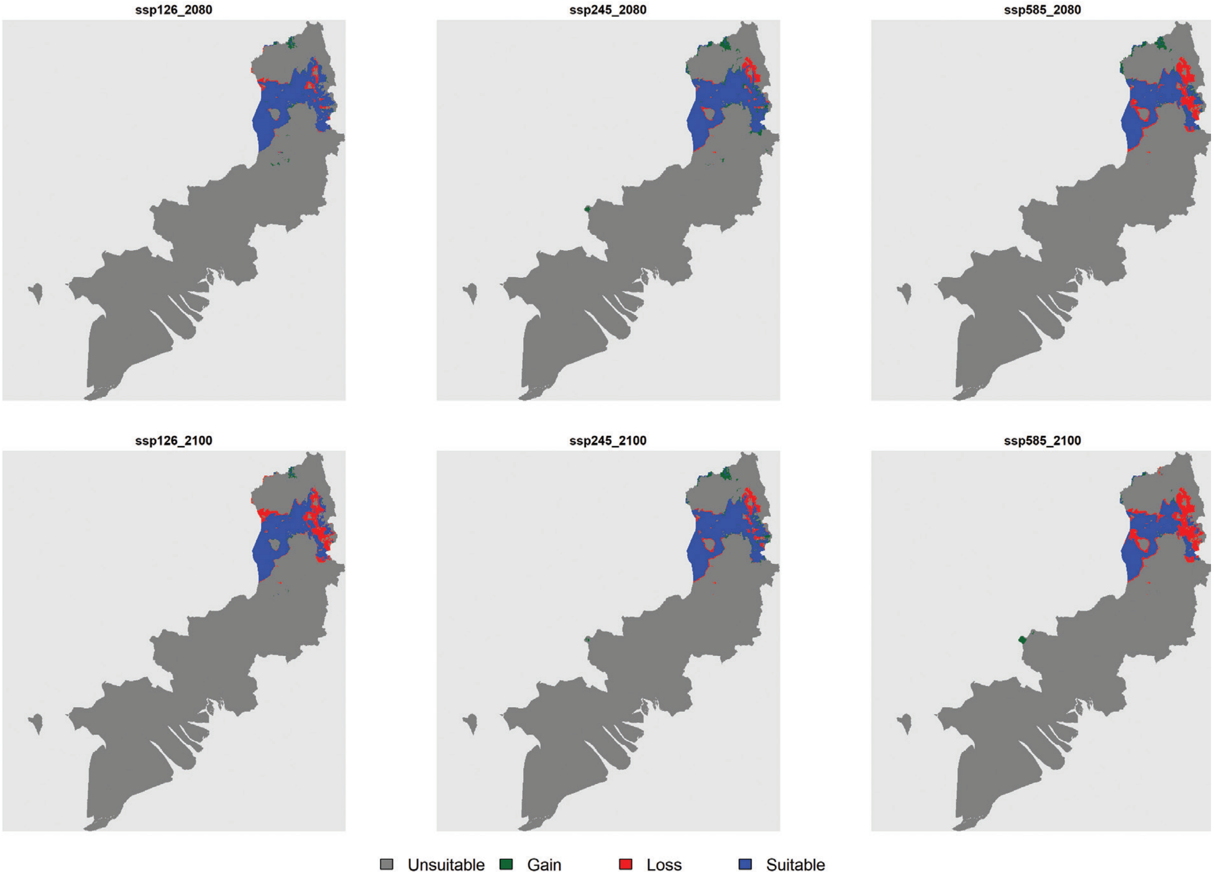

Fig. 6. Projected changes in habitat suitability for DF under three climate scenarios (SSP126, SSP245 and SSP585) for 2080 and 2100. Colours indicate transitions relative to the current distribution: blue = areas remaining suitable, red = areas projected to become unsuitable (habitat loss), green = areas projected to become newly suitable (habitat gain), and grey = areas unsuitable under both current and future conditions.

(bio19) is the dominant limiting factor, contributing 38–72% to model performance. Annual precipitation (bio12) is influential under SSP126, particularly in 2080 (24.8%) and 2100 (19.2%), but plays a minor role (3–6%) under SSP245 and SSP585. The temperature seasonality (bio4) is the primary driver in SSP245_2080 (45.1%) and remains important in SSP245 and SSP585 by 2100. The mean diurnal range (bio2) showed the strongest influence under SSP585 (24.3–26.6%) and a moderate contribution (10–18%) under SSP245 (Figs S1–S6).

Discussion

Climatic and topographic constraints on the distribution of deciduous forests

Our results indicate that deciduous forests in Vietnam occupy a comparatively narrow climatic niche, implying a high degree of sensitivity to ongoing and future climate change. Their distribution is largely confined to the northern Central Highlands of Vietnam, predominantly at elevations below 600 m asl, and under conditions where precipitation in the driest month is less than 12 mm. Low-elevation environments, characterized by higher mean temperatures and a pronounced dry season, appear to provide the most favorable ecological conditions for the persistence and conservation of these deciduous forest ecosystems. These observations are consistent with previous research demonstrating that deciduous forests in southern Vietnam are associated with semi-arid climatic zones, experiencing 5–7 months of drought and occurring primarily at elevations between 0 and 500 m (occasionally up to 700 m) asl (Averyanov et al., 2003; Lung et al., 2011; Tran et al., 2021).

In tropical dry deciduous forests, precipitation during the driest month constitutes a key climatic variable governing forest distribution, as it provides a direct indicator of the severity of seasonal drought (Xie et al., 2015). Prolonged water deficit induces foliar abscission and constrains tree growth and survival. Together with a pronounced dry season of approximately 5 to 6 months per year, this variable defines the ecological niche typical of tropical dry deciduous forests (Van Bloem et al., 2004). Deciduous forest species are adapted to pronounced dry seasons through drought-avoidance strategies such as leaf shedding; however, their persistence depends on a limited but sufficient level of moisture during the driest period (de Souza et al., 2020; Yan et al., 2025). Under conditions of moderately reduced dry-season precipitation, deciduous phenological strategies are selectively favored, leading to a concomitant decrease in competitive pressure exerted by co-occurring evergreen species (Vico et al., 2017; Xie et al. 2015). Our results indicate that precipitation of the driest month (<12 mm) is a critical limiting factor driving the narrow spatial distribution of deciduous forest. Precipitation in the driest month plays a critical role in shaping the dynamics of deciduous forest, as extremely low values impose severe water stress, triggering leaf shedding, restricting tree growth and regeneration, and increasing deciduousness with dry season severity (Ouédraogo et al., 2016). Relative to other regions, the climatic niche of deciduous forests in Vietnam appears to be more constrained. Across Southeast Asia, deciduous forests are typically associated with environments receiving less than 50 mm of precipitation during the driest month (Van Bloem et al., 2004).

Annual precipitation represents a broad-scale climatic constraint that delineates the distributional limits of deciduous forests (Ouédraogo et al., 2016). Precipitation regimes also modulate the phenological schedule of leaf abscission and dormancy (Zhang et al., 2025). Although temperature is typically identified as the primary driver of leaf dormancy, precipitation related stressors, including summer drought and extreme rainfall events, have been shown to significantly affect the onset and duration of autumn dormancy in deciduous forests in New Hampshire (Xie et al., 2015). Deciduous forests in Vietnam are characterized by comparatively high annual precipitation relative to many other deciduous forest systems globally. Within the prevailing classification of tropical deciduous forests, semi-arid forests are associated with low annual rainfall, whereas dry forests occur under intermediate precipitation regimes. With annual precipitation ranging from 1,200 to 2,400 mm, Vietnamese deciduous forests are therefore categorized as dry forests (Van Bloem et al., 2004). By contrast, reported annual rainfall in other dry deciduous forests, such as those in India, Mexico, Puerto Rico, Venezuela, and Thailand, ranges from approximately 516 to 1,200 mm (Ratnam et al., 2019; Van Bloem et al., 2004), indicating that many analogous systems occur under substantially drier conditions and generally receive less precipitation than the lower bound documented for Vietnam. Only a limited number of systems, including those in the Republic of Congo (1,273 mm), the Bahamas (1,300 mm), Guyana (1,520 mm), and Costa Rica (1,750 mm), approach the precipitation regime characteristic of Vietnamese deciduous forests (Adams et al., 2019; Van Bloem et al., 2004). Collectively, these comparisons indicate that, despite broadly comparable seasonal dynamics, deciduous forests in Vietnam operate under relatively high water availability. In this context, the seasonal distribution of precipitation, rather than total annual rainfall, appears to exert the predominant control on their spatial distribution and ecological functioning.

With respect to temperature conditions, the observed suitability of deciduous forests in Vietnam within a temperature seasonality range of 160–220% suggests that this vegetation type is well adapted to pronounced intra-annual temperature variability. This degree of seasonality reflects marked contrasts between warm and cool periods, which, in conjunction with strong dry–wet seasonal cycles, regulate key phenological processes, including leaf flushing and abscission (Lai et al., 2025). The interaction between temperature seasonality and severe dry-season water limitation likely reinforces the deciduous growth strategy by synchronizing dormancy and active growth with periods of favorable climatic conditions, thereby restricting the occurrence of deciduous forests to climatically stable yet strongly seasonal environments (Gupta and Krishnamurthy, 2023). Collectively, our findings underscore the critical role of pronounced seasonal fluctuations in both temperature and precipitation in governing the spatial distribution of deciduous forests in Vietnam.

Key climatic factors shaping the future decline in deciduous forest distribution

Our results show a substantial decline in the appropriate habitat for deciduous forests in future climate scenarios. This pattern is consistent with previous studies on dipterocarp species, which also expect reductions in appropriate areas under future climate change (Deb et al., 2017; Tumaneng et al., 2019; Van Quy et al., 2025). Similarly, over the past five decades (1971–2020), long-term precipitation and temperature changes have been associated with a decline in the forest cover of tropical deciduous forests in Central India (Kumar et al., 2026).

Based on the One-Factor-At-A-Time (OFAT) analysis, the projected reduction in climatically suitable habitat for deciduous forests under future climate scenarios can be primarily attributed to alterations in precipitation regimes and increased temperature variability. Increased precipitation during the coldest quarter is likely to decrease habitat suitability, given that these forest systems rely on well-defined dry seasons to regulate key phenological processes, including leaf abscission and the induction and maintenance of dormancy (Murali and Sukumar, 1993). Similarly, elevated levels of mean annual precipitation may surpass the ecological tolerance thresholds of deciduous species, which are generally adapted to environments characterized by moderate seasonality, comparatively low moisture availability (Van Quy et al., 2025). Increased temperature seasonality and expanded diurnal temperature ranges may further exacerbate physiological stress by amplifying thermal variability, thereby influencing organismal growth dynamics and modulating interspecific competitive interactions (Appanah and Turnbull, 1998; ICHIE et al., 2023). Collectively, these projections indicate that forthcoming climatic regimes may surpass the ecological niche tolerance of deciduous forest ecosystems, thereby constraining their long-term persistence and spatial distribution across the landscape.

In total, these climatic perturbations reduce the extent of environmentally suitable habitats for deciduous forests in Vietnam under projected future climate scenarios. These results are consistent with a broader body of evidence demonstrating that climate change, driven by rising atmospheric CO_2 concentrations, rising air temperatures, and increasing variability in precipitation regimes, exerts a direct influence on the growth, physiological functioning, and overall dynamics of tropical deciduous forests. At community and ecosystem scales, shifts in climatic conditions modify phenological patterns, successional trajectories, and plant–animal interaction networks, which in turn alter forest structural attributes and productivity (Sinha, 2022). Comparable patterns have been documented in temperate deciduous forests, where increases in precipitation intensity have been associated with declines in the productivity of deciduous broadleaf forest systems (Hai et al., 2025).

Study limitations

Several limitations of this study should be acknowledged. First, the modeling framework relied exclusively on climatic and topographic predictors and did not account for land-use dynamics or direct anthropogenic disturbances, including deforestation, agricultural expansion, and forest management interventions. Given that these human-driven processes exert substantial control over forest distribution in Vietnam, the projected suitable areas should be interpreted as indicating potential climatic suitability rather than realized future species distributions.

Furthermore, future climate conditions were simulated using a single global circulation model (ACCESS-CM2). The absence of a multi-model ensemble constrains the capacity to represent the range of uncertainty arising from differences in climate model structures, parameterizations, and regional climate responses. Consequently, the findings should be interpreted with caution, particularly regarding the magnitude of the projected changes in climatically suitable habitat.

Conclusions

Our results demonstrate that the spatial distribution of deciduous forests in Vietnam is strongly constrained by seasonal climatic conditions, in particular by the interplay between dry periods and interannual temperature variability. Projected future climate change is likely to disrupt this climatic equilibrium, resulting in a contraction of climatically suitable areas for deciduous forests, with the most pronounced reductions occurring under high-emission scenarios. Alterations in precipitation regimes and increasing temperature variability emerge as key drivers of this projected decline, as they are expected to shift environmental conditions beyond the ecological tolerance thresholds of these forest systems. Although the analysis solely relied on a single climate model and the exclusion of non-climatic drivers such as land-use change, edaphic factors, and biotic interactions, our findings consistently indicate that future climate change is likely to exert adverse effects on the potential distribution of deciduous forests in Vietnam. These results underscore the need to prioritize conservation and climate-adaptive management interventions, particularly in the Central Highlands, where remaining suitable habitats are projected to be highly vulnerable. Priority actions include safeguarding extant climatically suitable areas, enhancing landscape connectivity, and explicitly integrating climate adaptation considerations into forest management and conservation planning.

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Supplementary materials

Table S1. Pearson’s correlation matrix between the remaining environmental variables used for SDMs

Variables	elevation	bio19	bio14	bio12	bio7	bio4	bio3	bio2
elevation	1							
bio19	–0.36	1						
bio14	0.21	–0.14	1					
bio12	-0.22	0.16	–0.73	1				
bio7	0.22	0.38	–0.28	0.23	1			
bio4	0.33	–0.40	0.72	–0.78	–0.28	1		
bio3	–0.55	0.29	–0.43	0.62	0.13	–0.69	1	
bio2	–0.20	0.45	–0.46	0.55	0.78	–0.63	0.72	1

Table S2. Different 40 Maxent models with different combinations of regularization multipliers and feature classes

№.tune.args	auc. train	cbi. train	auc. diff. avg	auc. diff. sd	auc. diff. avg	auc. val. sd	cbi. val. avg	cbi. val. sd	or.10 val.	or.10 p.avg	AICc p.sd	delta. AICc	w.AIC	n coef
1 fc.LQH_rm.0.5	0.92	1.00	0.02	0.01	0.92	0.02	0.94	0.08	0.17	0.07	101,167.23	0.00	0.997	71
2 fc.H_rm.0.5	0.92	1.00	0.02	0.01	0.92	0.02	0.94	0.08	0.17	0.07	101,178.86	11.63	0.003	70
3 fc.H_rm.1	0.92	1.00	0.02	0.01	0.92	0.02	0.91	0.11	0.15	0.06	108,276.62	7,109.39	0	51
4 fc.LQH_rm.1	0.92	1.00	0.02	0.01	0.92	0.02	0.91	0.11	0.15	0.06	108,619.28	7,452.05	0	50
5 fc.LQH_rm.1.5	0.92	1.00	0.02	0.01	0.92	0.02	0.89	0.14	0.14	0.05	112,152.83	10,985.60	0	45
6 fc.H_rm.1.5	0.92	1.00	0.02	0.01	0.92	0.02	0.90	0.14	0.14	0.05	112,152.83	10,985.60	0	45
7 fc.LQH_rm.2.5	0.92	1.00	0.02	0.01	0.91	0.02	0.88	0.17	0.14	0.06	112,828.94	11,661.71	0	37
8 fc.H_rm.2.5	0.92	1.00	–	–	–	–	–	–	–	–	112,828.94	11,661.71	0	37
9 fc.H_rm.3	0.92	1.00	–	–	–	–	–	–	–	–	112,892.20	11,724.97	0	36
10 fc.LQH_rm.3	0.92	1.00	0.02	0.01	0.91	0.02	0.86	0.19	0.14	0.06	112,894.13	11,726.90	0	37
11 fc.LQH_rm.3.5	0.92	1.00	0.02	0.01	0.91	0.02	0.86	0.19	0.14	0.07	113,032.85	11,865.62	0	33
12 fc.H_rm.3.5	0.92	1.00	–	–	–	–	–	–	–	–	113,032.85	11,865.62	0	33
13 fc.LQH_rm.4	0.92	1.00	0.02	0.01	0.91	0.02	0.86	0.19	0.14	0.08	113,142.20	11,974.97	0	30
14 fc.H_rm.4	0.92	1.00	–	–	–	–	–	–	–	–	113,142.20	11,974.97	0	30
15 fc.LQH_rm.4.5	0.92	1.00	0.02	0.02	0.91	0.02	0.87	0.17	0.14	0.09	113,244.10	12,076.87	0	27
16 fc.H_rm.4.5	0.92	1.00	–	–	–	–	–	–	–	–	113,244.10	12,076.87	0	27
17 fc.LQH_rm.5	0.92	1.00	0.02	0.02	0.91	0.02	0.86	0.17	0.14	0.10	113,344.94	12,177.71	0	24
18 fc.H_rm.5	0.92	1.00	–	–	–	–	–	–	–	–	113,344.94	12,177.71	0	24
19 fc.LQH_rm.2	0.92	1.00	0.02	0.01	0.92	0.02	0.89	0.16	0.14	0.05	113,885.94	12,718.71	0	39
20 fc.H_rm.2	0.92	1.00	0.02	0.01	0.92	0.02	0.89	0.16	0.14	0.05	113,885.94	12,718.71	0	39
21 fc.L_rm.5	0.91	0.98	0.03	0.02	0.92	0.03	0.93	0.06	0.11	0.12	127,490.81	26,323.58	0	6
22 fc.L_rm.4.5	0.91	0.98	0.03	0.02	0.92	0.03	0.93	0.06	0.11	0.12	127,707.09	26,539.86	0	6
23 fc.L_rm.4	0.91	0.98	0.03	0.02	0.92	0.03	0.92	0.07	0.11	0.12	127,933.15	26,765.92	0	7
24 fc.L_rm.3.5	0.91	0.98	0.03	0.02	0.92	0.03	0.92	0.07	0.11	0.12	128,332.81	27,165.58	0	8
25 fc.LQ_rm.5	0.91	0.99	0.03	0.01	0.92	0.02	0.93	0.06	0.11	0.12	128,91,0.18	27,742.95	0	9
26 fc.L_rm.3	0.91	0.98	0.03	0.02	0.92	0.03	0.92	0.07	0.11	0.12	128,928.62	27,761.39	0	7
27 fc.LQ_rm.4.5	0.91	0.99	0.02	0.01	0.92	0.02	0.93	0.06	0.11	0.12	129,502.48	28,335.25	0	9
28 fc.L_rm.2.5	0.91	0.98	0.03	0.02	0.92	0.03	0.92	0.08	0.11	0.12	129,542.32	28,375.09	0	7
29 fc.LQ_rm.4	0.91	0.99	0.02	0.01	0.92	0.02	0.92	0.06	0.11	0.11	130,130.76	28,963.53	0	9
30 fc.L_rm.2	0.91	0.98	0.03	0.02	0.92	0.03	0.91	0.08	0.11	0.12	130,216.32	29,049.09	0	7
31 fc.LQ_rm.3.5	0.91	0.99	0.02	0.01	0.92	0.02	0.92	0.06	0.12	0.11	130,785.81	29,618.58	0	9
32 fc.L_rm.1.5	0.91	0.98	0.03	0.02	0.92	0.03	0.91	0.08	0.11	0.12	130,949.15	29,781.92	0	7
33 fc.L_rm.1	0.91	0.99	0.03	0.02	0.92	0.03	0.91	0.09	0.11	0.11	131,759.65	30,592.42	0	8
34 fc.LQ_rm.3	0.91	0.99	0.02	0.01	0.92	0.02	0.92	0.07	0.12	0.11	131,904.88	30,737.65	0	11
35 fc.L_rm.0.5	0.91	0.98	0.03	0.02	0.92	0.03	0.91	0.09	0.11	0.11	132,937.00	31,769.76	0	8
36 fc.LQ_rm.2.5	0.91	0.99	0.02	0.01	0.92	0.02	0.92	0.07	0.12	0.11	133,044.48	31,877.24	0	11
37 fc.LQ_rm.2	0.92	0.99	0.02	0.01	0.92	0.02	0.92	0.08	0.11	0.09	134,306.25	33,139.02	0	11
38 fc.LQ_rm.1.5	0.92	0.99	0.02	0.01	0.92	0.02	0.93	0.08	0.10	0.08	135,424.30	34,257.07	0	11
39 fc.LQ_rm.1	0.92	1.00	0.02	0.01	0.92	0.02	0.93	0.08	0.10	0.07	135,532.82	34,365.59	0	12
40 fc.LQ_rm.0.5	0.92	1.00	0.02	0.01	0.92	0.02	0.94	0.09	0.10	0.06	136,,062.79	34,895.56	0	13

Table S3. Predicted range changes of DF under future climate change scenarios at SSP 126, SSP 245 and SSP 585 for 2080 and 2100 across Central Highlands and Southern Vietnam

Scenario	Class	Area (km^2)	Percent
ssp126_2080	Unsuitable	94,721.35	89.7
ssp126_2080	Gain	392.37	0.4
ssp126_2080	Loss	851.64	0.8
ssp126_2080	Suitable	9,644.85	9.1
ssp245_2080	Unsuitable	94,124.94	89.1
ssp245_2080	Gain	988.78	0.9
ssp245_2080	Loss	1,036.07	1.0
ssp245_2080	Suitable	9,460.43	9.0
ssp585_2080	Unsuitable	94,480.22	89.5
ssp585_2080	Gain	633.5	0.6
ssp585_2080	Loss	2,624.43	2.5
ssp585_2080	Suitable	7,872.07	7.5
ssp126_2100	Unsuitable	94,913.59	89.9
ssp126_2100	Gain	200.13	0.2
ssp126_2100	Loss	2,517.38	2.4
ssp126_2100	Suitable	7,979.12	7.6
ssp245_2100	Unsuitable	94,425.68	89.4
ssp245_2100	Gain	688.04	0.7
ssp245_2100	Loss	1,434.84	1.4
ssp245_2100	Suitable	9,061.66	8.6
ssp585_2100	Unsuitable	94,831.76	89.8
ssp585_2100	Gain	281.96	0.3
ssp585_2100	Loss	3,675.17	3.5
ssp585_2100	Suitable	6,821.33	6.5

The percentage change in suitable area was calculated as: Change suitable = (1 – (Future suitable area / Current suitable area)) × 100, where the current suitable area is defined as: Current suitable area = Future suitable area + Loss – Gain.

Fig. S1. Ridgeline plots showing the distribution of the climatic data for present and Shared Socioeconomic Pathway (SSP 126) projected scenarios for the year 2080.

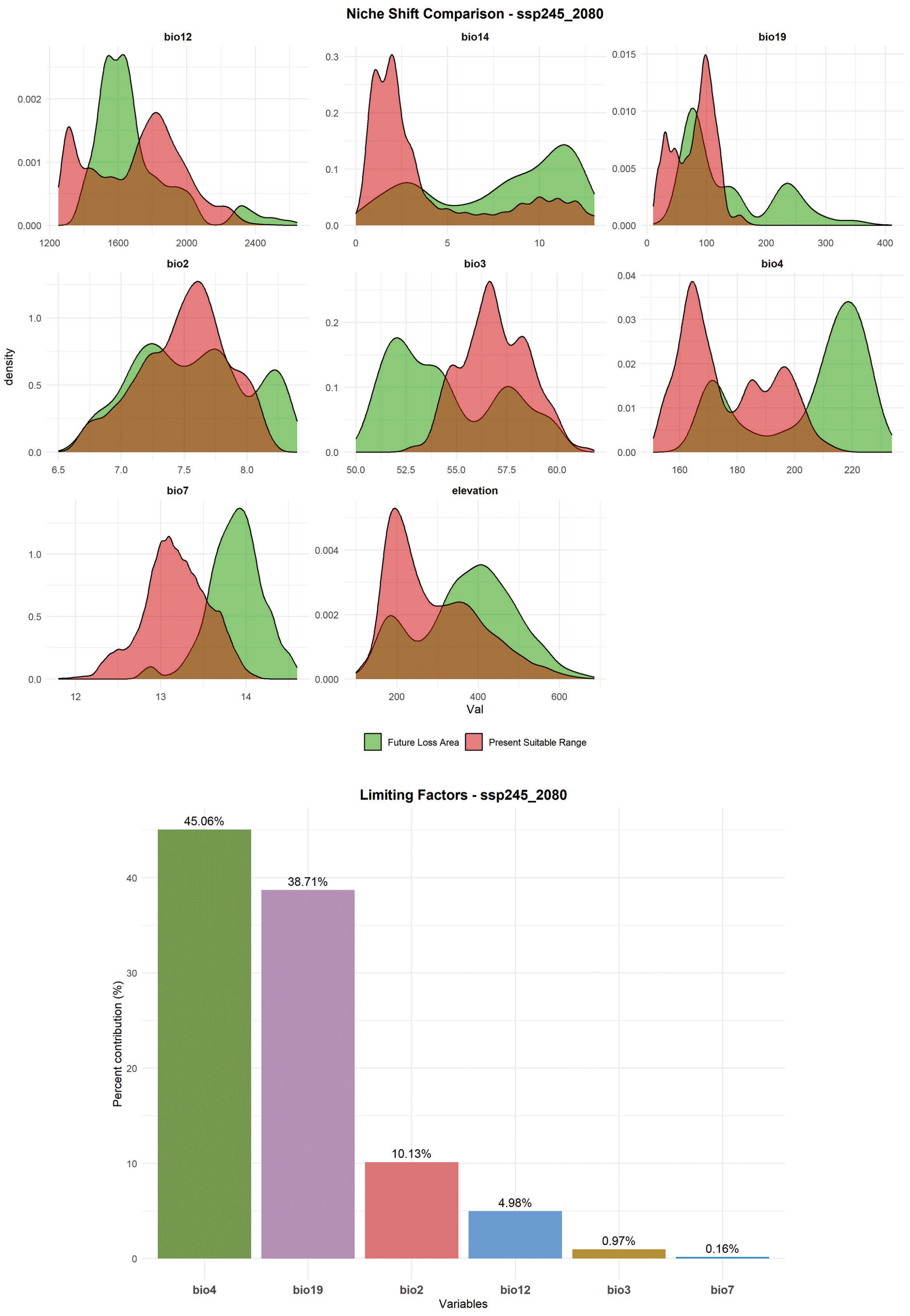


Fig. S2. Ridgeline plots showing the distribution of the climatic data for present and Shared Socioeconomic Pathway (SSP 245) projected scenarios for the year 2080.

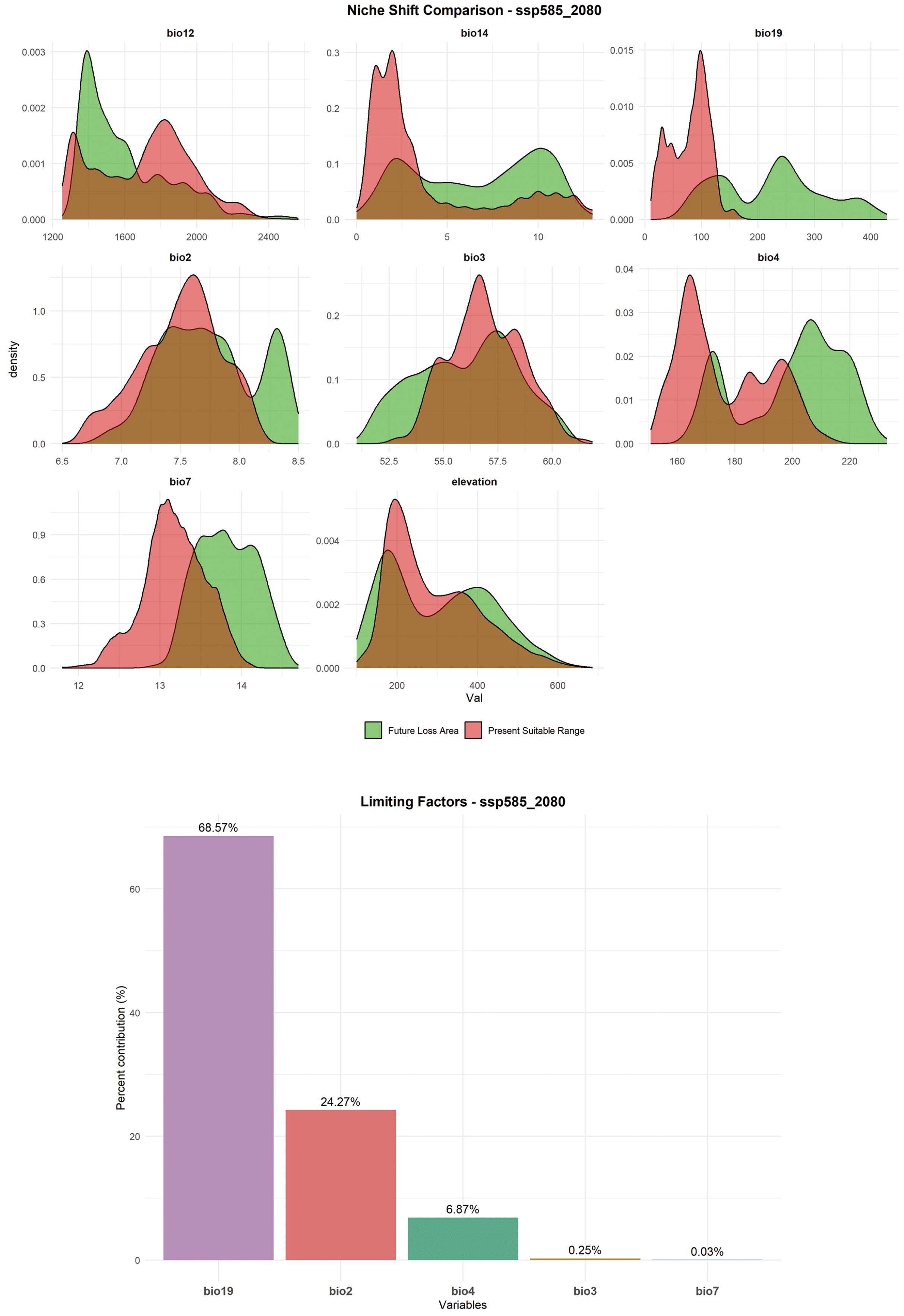
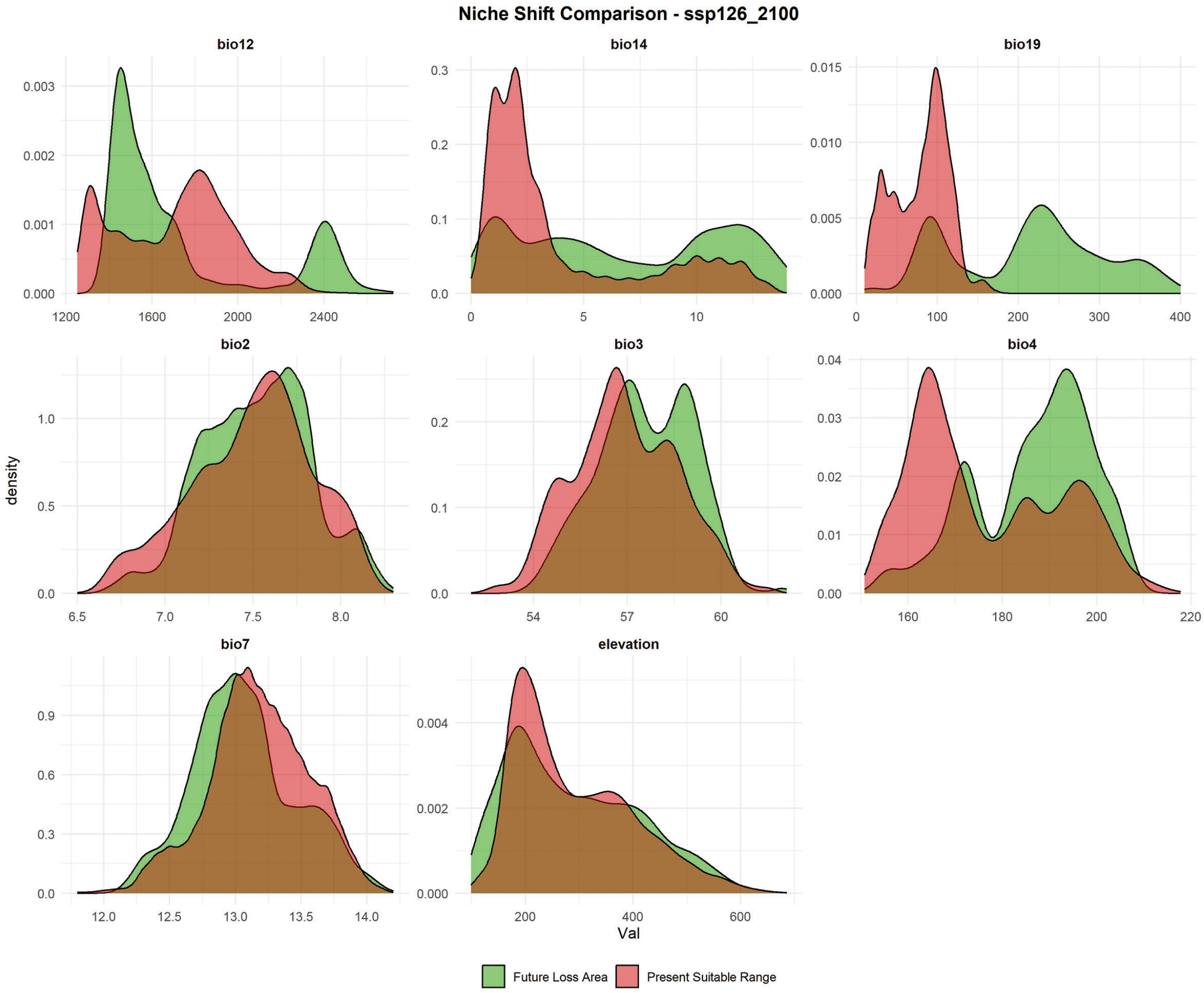


Fig. S3. Ridgeline plots showing the distribution of the climatic data for present and Shared Socioeconomic Pathway (SSP 585) projected scenarios for the year 2080.



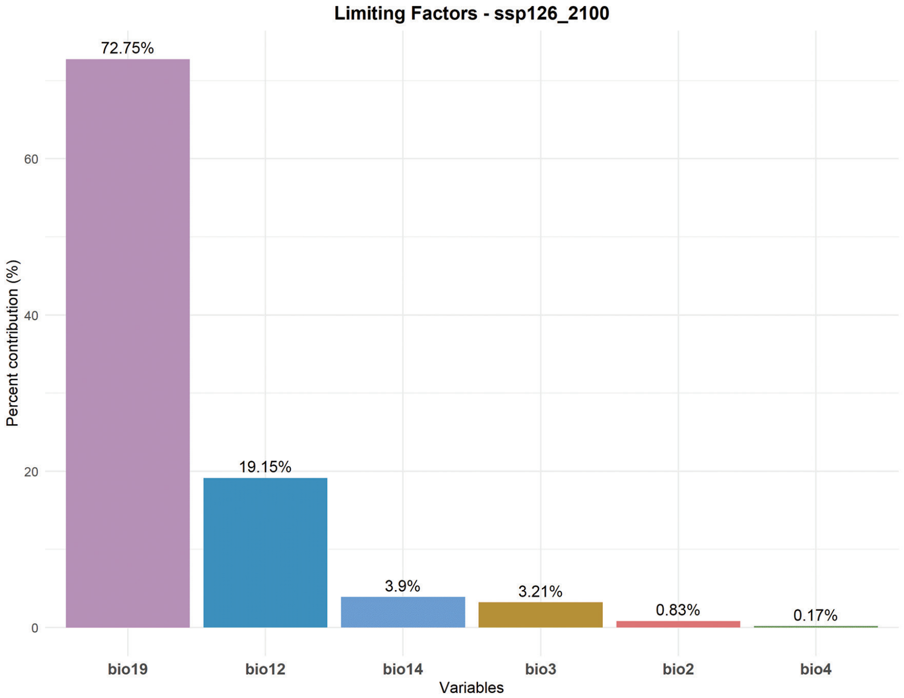


Fig. S4. Ridgeline plots showing the distribution of the climatic data for present and Shared Socioeconomic Pathway (SSP 126) projected scenarios for the year 2100.

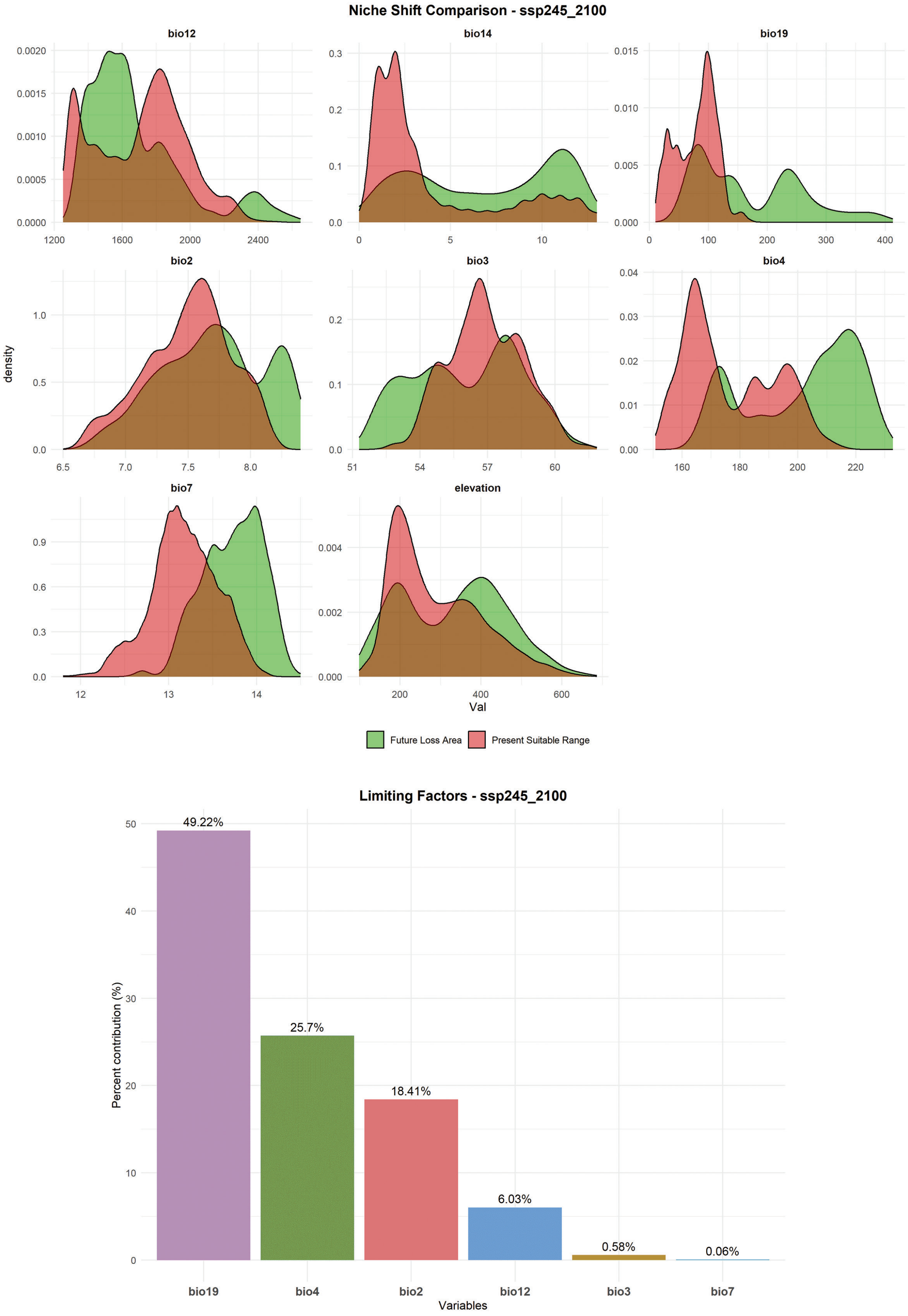


Fig. S5. Ridgeline plots showing the distribution of the climatic data for present and Shared Socioeconomic Pathway (SSP 245) projected scenarios for the year 2100.