

Article

Climate-Driven Changes in Potential Suitable Habitats of Moso Bamboo (*Phyllostachys edulis*) in China: An Optimized MaxEnt Approach

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Abstract

Phyllostachys edulis (Moso bamboo) is a subtropical bamboo species endemic to China and holds substantial economic and ecological value. Ongoing climate change is reshaping the geographic distribution of its suitable habitats. To reveal these climate-driven dynamics, we calibrated the maximum entropy (MaxEnt) species distribution model using the ENMeval R package version 4.5.2 and evaluated model robustness via spatially independent block cross-validation. We identified nine critical environmental predictors to model spatiotemporal variations in suitable habitats for Moso bamboo, examining both present-day climate and four future periods under four Shared Socioeconomic Pathway (SSP) scenarios. Model performance was optimized at regularization multiplier (RM) of 1.5 with the feature class combination LQHPT, yielding a spatial validation AUC of 0.9104 and robust predictive capacity. Environmental controls were dominated by mean temperature of the coldest quarter (bio11, 63.9% relative contribution) and precipitation of the driest quarter (bio17, 31.2%), while soil clay and organic carbon content modulated suitability at local scales. Under current conditions, the total suitable habitat area encompasses approximately $218.88 \times 10^4 \text{ km}^2$, with the majority distributed throughout the subtropical zone of southeastern China. Under nearly all future scenarios, high-suitability habitats showed a general contracting trend of 20.94%–95.29% relative to the current baseline, while moderate-suitability habitats exhibited a fluctuating expansion trend, reaching a peak increase of 47.90% in the 2030s under SSP585, but contracted by 18.65% in the 2090s. Meanwhile, habitat centroids underwent small-scale oscillatory shifts in multiple directions and remained entirely within Hunan Province across all periods. MESS analysis confirmed that 90.60%–99.82% of China's land area fell within climate-analogous ranges, indicating low extrapolation risk for core habitat projections. Core climate refugia with high cross-scenario stability were primarily concentrated in the traditional bamboo-producing regions of southeastern China. This study provides a scientific basis for the sustainable management of Moso bamboo resources, biodiversity conservation, and ecological risk prevention in the context of ongoing climate change.

Keywords: *Phyllostachys edulis*; MaxEnt model; climate change; habitat suitability; parameter optimization; centroid shift



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1. Introduction

Phyllostachys edulis, widely recognized as Moso bamboo, is an endemic species native to subtropical China and holds remarkable economic and ecological value [1,2]. Characterized by rapid growth and a short rotation period, Moso bamboo produces high-value timber and edible shoots, which are widely used in construction, food processing, and handicraft production [2–4]. As a vital component of forest ecosystems in southern China, Moso bamboo forests provide irreplaceable ecological services including carbon sequestration, soil and water conservation, and regional climate regulation [5–7]. Moreover, this species has strong clonal growth and dispersal ability. When introduced into marginal regions, it may exhibit invasive traits and pose threats to native plant communities and biodiversity [8,9]. Therefore, accurately defining its suitable habitat range and spatial pattern is essential for reconciling sustainable resource use with ecological risk management [8].

Species distribution models (SDMs), which combine occurrence records with environmental predictors, are widely used to infer niche requirements and project potential geographic ranges, making them particularly useful for evaluating climate change impacts [10]. The maximum entropy (MaxEnt) model stands among available SDM frameworks as one that constructs ecological niche representations through the application of maximum entropy theory. It operates with presence-only data and maintains robust predictive accuracy even with limited sample sizes, making it one of the most widely adopted models for plant habitat simulation and endangered species conservation planning [10]. Previous studies have confirmed that MaxEnt outperforms conventional models such as Bioclim, Domain and Genetic Algorithm for Rule-set Production (GARP) in predictive accuracy and stability [11]. However, the model's predictive performance is strongly influenced by its parameter settings, and default configurations are rarely optimal for a given study system. Default parameter combinations are rarely optimal for a given taxon or study region, a mismatch that frequently induces model overfitting and ultimately undermines the credibility and spatial transferability of projections.

Two parameters play central roles in determining MaxEnt model complexity and goodness of fit: the regularization multiplier (RM) and feature class (FC) settings. The regularization multiplier (RM) smooths response curves by penalizing parameter estimates, whereas FC defines the functional forms of environmental responses, including linear (L), quadratic (Q), hinge (H), product (P), and threshold (T) features [10,12,13]. Under default settings, RM and FC rarely achieve the global optimum. Systematic parameter tuning is therefore a prerequisite for achieving the optimal trade-off between model complexity and goodness of fit and for improving the reliability of MaxEnt projections [14–16].

Most existing MaxEnt assessments of Moso bamboo distribution use default parameters without systematic calibration, making models prone to overfitting and undermining the reliability of future climate projections. Additionally, mainstream analyses rely almost exclusively on climatic variables, overlook edaphic and topographic factors, and lack rigorous multicollinearity control, which limits the ecological realism of model outputs. To fill these gaps, in this study, MaxEnt model parameters were systematically optimized using the ENMeval package to minimize overfitting and improve predictive performance and spatial transferability. Three primary objectives were pursued: (1) to determine the optimal parameterization scheme for Moso bamboo distribution modeling; (2) to characterize the spatial pattern of suitable Moso bamboo habitats across China under current climatic conditions and identify the key environmental variables governing its distribution; (3) to project future trajectories of Moso bamboo habitat suitability through the end of the 21st century under four Shared Socioeconomic Pathway (SSP) scenarios, and quantify centroid migration dynamics and the restructuring dynamics of habitat suitability classes.

Our findings provide a scientific basis for the sustainable management of Moso bamboo resources and ecological risk prevention under ongoing climate change.

2. Materials and Methods

2.1. Study Area

The study covered the entire land area of China (Figure 1). Moso bamboo is primarily distributed in southeastern China, covering Zhejiang, Fujian, Jiangxi, Hunan, Guangdong, Guangxi, Anhui, and Hubei provinces. China's Moso bamboo forests occupy more than 5.0 million hectares, accounting for approximately 70% of the national bamboo forest area [6]. Moso bamboo mostly forms pure stands, and can also develop stable mixed forests with Chinese fir (*Cunninghamia lanceolata*), Masson pine (*Pinus massoniana*), and *Liquidambar formosana* [16].

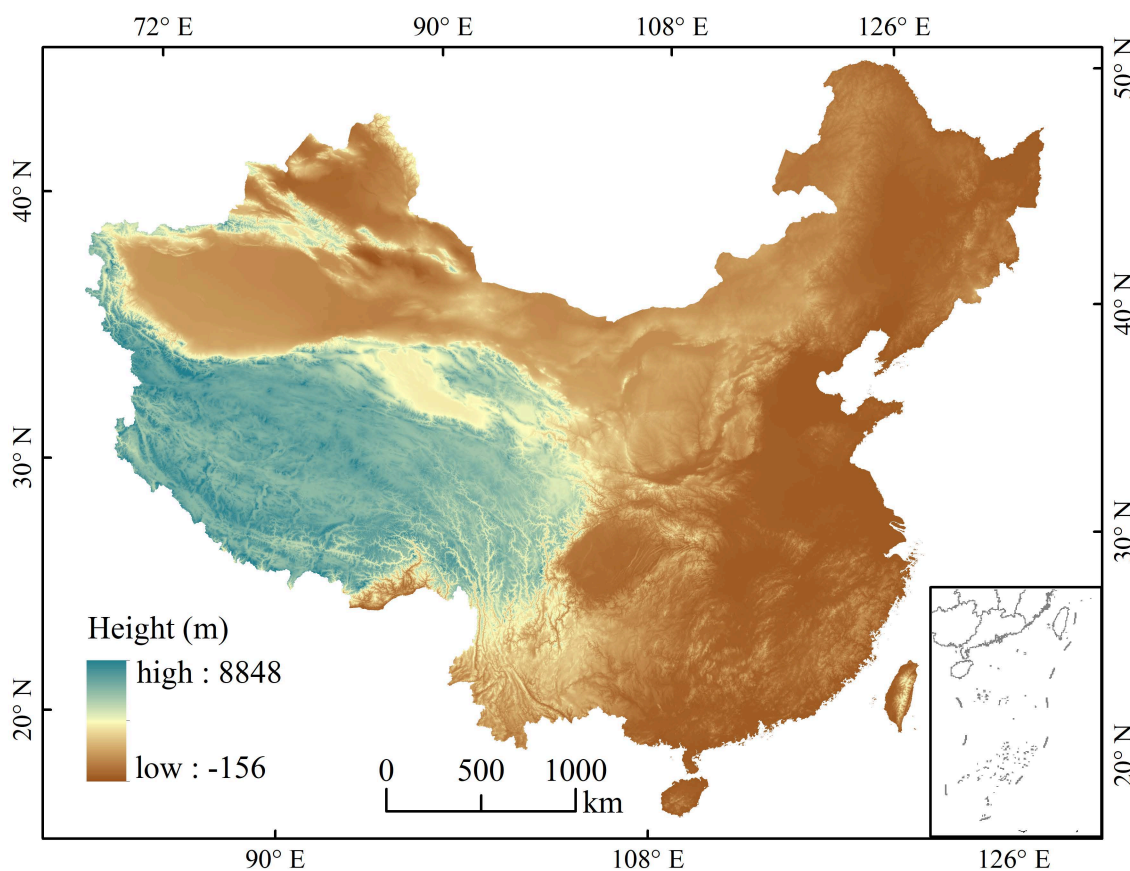


Figure 1. Geographical distribution of Moso bamboo occurrence records used in this study.

The core distribution range of Moso bamboo lies in the subtropical monsoon climate zone of southeastern China, with mean annual precipitation ranging from 800 to 2000 mm. Approximately 70%–80% of annual precipitation falls in the wet season from April to September, whereas the winter dry season receives markedly lower rainfall. For land use characteristics, forestland dominates the core suitable habitats, comprising both natural Moso bamboo stands and intensively managed plantations for timber and edible shoot production. These forests are interspersed with agricultural fields, shrublands, and native evergreen broad-leaved forests, creating a mosaic landscape that shapes the dispersal and colonization dynamics of Moso bamboo at local scales. In China, Moso bamboo has been cultivated and utilized as a multipurpose forest resource for over 2000 years. Although its natural distribution was originally limited to subtropical mountainous areas, large-scale

planting and introduction over recent decades have expanded its range into climatically marginal regions.

2.2. Data

2.2.1. Distribution Data

The geographical distribution data of Moso bamboo were compiled from database retrieval, literature collation, and field surveys. A total of 548 occurrence records were retrieved from four biodiversity databases, including the Chinese Virtual Herbarium (<http://www.cvh.ac.cn/>), the National Specimen Information Infrastructure of China (<http://www.nsii.org.cn/>), the Global Biodiversity Information Facility (<https://www.gbif.org/>), and the Discover Life biodiversity platform (<https://www.discoverlife.org/>). Another 427 occurrence records were extracted from published literature [17]. Field surveys were conducted from 2023 to 2025 to fill spatial gaps in the existing records and to verify occurrences in climatically marginal regions. Route reconnaissance and typical stand verification were carried out across both core distribution provinces and peripheral zones. Geographic coordinates were recorded for each confirmed stand, whether naturally growing or managed, using a handheld GPS. To avoid niche bias, isolated individuals that had been artificially planted in urban green spaces were excluded. A total of 4410 georeferenced occurrence points were produced from this field campaign.

All records were checked for taxonomic consistency to exclude misidentified specimens, and georeferencing accuracy was verified against county-level boundary data; records with coordinate errors > 1 km or ambiguous locality descriptions were removed. Subsequently, spatial thinning at a 1 km distance threshold was applied to filter raw occurrence records, removing redundant points within 1 km to reduce spatial autocorrelation. This threshold was selected to match the resolution of environmental predictors, and aligns with standard ENM practice to minimize artificial inflation of model performance caused by spatially clustered samples. Finally, a total of 533 valid occurrence records of Moso bamboo were retained for further analysis (Figure 1).

2.2.2. Environmental Variables

A total of 37 environmental variables, including climatic, edaphic, and topographic factors, were adopted in this study (Table 1). The current bioclimatic variables were obtained from the WorldClim database (<http://www.worldclim.org/>). Future climate data came from the BCC-CSM coupled climate system model, developed at the Beijing Climate Center by the National Climate Center of China. Four Shared Socioeconomic Pathway (SSP) scenarios were selected, representing different greenhouse gas emission trajectories corresponding to alternative socioeconomic development pathways: SSP126 (low emission intensity), SSP245 (moderate emissions), SSP370 (high emissions), and SSP585 (very high emissions). Nineteen environmental variables were extracted for four future periods: the 2030s (2021–2040), 2050s (2041–2060), 2070s (2061–2080), and 2090s (2081–2100). Soil variables, including volumetric percentage of soil gravel (t_gravel) and soil sand content (t_sand), were derived from Food and Agriculture Organization (FAO; <https://www.fao.org/>) datasets, comprising 15 soil indicators in total. Elevation data were acquired from WorldClim (<http://www.worldclim.org/>), from which slope and aspect were further calculated. Consequently, three topographic variables were generated in total.

Table 1. Summary of environmental variables used in this study.

Category	Number	Code	Variable Description	Unit
Climatic	1	bio1	Annual mean temperature	°C
	2	bio2	Mean diurnal temperature range	°C
	3	bio3	Isothermality	–
	4	bio4	Temperature seasonality	–
	5	bio5	Max temperature of warmest month	°C
	6	bio6	Min temperature of coldest month	°C
	7	bio7	Temperature annual range	°C
	8	bio8	Mean temperature of wettest quarter	°C
	9	bio9	Mean temperature of driest quarter	°C
	10	bio10	Mean temperature of warmest quarter	°C
	11	bio11	Mean temperature of coldest quarter	°C
	12	bio12	Annual precipitation	mm
	13	bio13	Precipitation of wettest month	mm
	14	bio14	Precipitation of driest month	mm
	15	bio15	Precipitation seasonality	–
	16	bio16	Precipitation of wettest quarter	mm
	17	bio17	Precipitation of driest quarter	mm
	18	bio18	Precipitation of warmest quarter	mm
	19	bio19	Precipitation of coldest quarter	mm
Topographic	20	Ele	Elevation	m
	21	Slope	Slope	°
	22	Aspect	Aspect	–
Edaphic	23	t_bs	Soil base saturation	%
	24	t_Caco3	Soil calcium carbonate (lime) content	%
	25	t_Caso4	Soil sulfate content	%
	26	t_ece	Soil electrical conductivity	dS/m
	27	t_clay	Soil clay proportion	%
	28	t_cec_clay	Cation exchange capacity of clay soil	cmol/kg
	29	t_cec_soil	Cation exchange capacity of soil	cmol/kg
	30	t_esp	Soil exchangeable sodium	%
	31	t_gravel	Soil gravel proportion	%
	32	t_oc	Soil organic carbon content	%
	33	t_ref_bulk	Soil bulk density	g/cm ³
	34	t_sand	Soil sand proportion	%
	35	t_silt	Soil silt proportion	%
	36	t_teb	Soil exchangeable bases	–
	37	t_usda_tex	USDA soil texture classification	–

Note: Nine variables selected for final modeling (bio2, bio8, bio11, bio17, bio18, slope, t_bs, t_clay, t_oc) are shaded in gray.

2.3. Methods

2.3.1. Environmental Variables Selection

Multicollinearity among environmental variables is a common issue in species distribution models, and its effects are especially problematic in MaxEnt applications. Strongly correlated predictors can distort the estimated contributions of individual variables, produce unreliable response curves, and reduce both model transferability and ecological interpretability—not merely predictive performance [18]. When predictors are highly correlated, the model may assign importance arbitrarily among them, resulting in unstable contribution estimates and diminished spatial transferability. To address these issues and ensure robust inference, a standardized analytical workflow was implemented in R, integrating data cleaning, spatial thinning of occurrence records, and multicollinearity screening of environmental variables [19]. Raw occurrence records of Moso bamboo were manually checked and georeferenced, then spatially thinned at a resolution of 1 km × 1 km. This

thinning procedure reduced sampling bias and mitigated spatial autocorrelation among occurrence points, which could otherwise inflate apparent collinearity among predictors.

An initial MaxEnt model was first built using all 37 environmental variables to identify and remove those with zero contribution. This step reduced computational redundancy and eliminated non-informative noise before formal collinearity assessment, thereby avoiding spurious correlation results. A rigorous two-step screening approach was then applied, combining Pearson correlation analysis and variance inflation factor (VIF). This combined strategy was adopted because it addresses both bivariate and multivariate collinearity, offering a more comprehensive evaluation than single-method screening. Pairwise correlations were assessed using Pearson's coefficient, which is suitable for the continuous climatic and topographic variables used here. A threshold of $|r| \geq 0.8$ was applied to detect strongly collinear pairs, following standard practice in MaxEnt-based studies. For any pair exceeding this threshold, the variable with the smaller contribution to the preliminary model was excluded (Figures S1 and S2).

After bivariate screening, 16 variables were retained for multivariate collinearity assessment using VIF. While $VIF < 10$ is generally considered acceptable and $VIF < 5$ ideal in regression modeling [20], a more conservative stepwise elimination strategy was adopted here. Variables with the highest VIF were removed sequentially until all remaining variables met a strict threshold of $VIF < 2$. This stringent cutoff was chosen for two reasons: (1) Moso bamboo occupies a wide range of climatic and topographic gradients, where overlapping environmental factors may obscure independent ecological effects; and (2) strict collinearity control is essential for reliable interpretation of variable importance and response curves, which are central to this study's ecological inferences. Beyond statistical criteria, the ecological relevance of each candidate variable was also evaluated based on known ecophysiological and biogeographical characteristics of Moso bamboo. Variables recognized as important limiting factors for its growth and distribution were prioritized. Through this combined statistical-ecological procedure, nine key environmental variables were finally selected for subsequent modeling (shaded in Table 1). All selected variables had VIF values below 2 (range: 1.56–1.98), confirming that multicollinearity was effectively controlled and that the variables satisfied the independence requirements for reliable MaxEnt parameter estimation and ecological interpretation [21].

2.3.2. Model Construction and Parameter Optimization

MaxEnt models built with default settings tend to overfit due to excessive complexity, which compromises both predictive accuracy and spatial transferability. Default parameters are calibrated for general applications and are seldom suitable for particular species or study regions. Their uncritical adoption can produce inflated area under the receiver operating characteristic curve (AUC) values that reflect overfitting to clustered occurrence records rather than genuine niche relationships. To address this issue, the ENMeval R package was used to optimize the feature class (FC) and settings within the MaxEnt framework, aiming to improve model reliability and predictive performance while reducing overfitting risk [13,14,22]. A range of regularization multiplier (RM) values from 0.5 to 4.0 was tested at 0.5 increments, in combination with six FC settings: L, H, LQ, LQH, LQHP, and LQHPT. The optimal configuration was selected based on the minimum $\Delta AICc$ value, while also ensuring low values for both the 10% omission rate (OR_{10}) and the AUC difference metric (diff.AUC). $\Delta AICc$ quantifies the trade-off between model complexity and goodness-of-fit; lower values indicate a better balance between fitting training data and generalizing to new data [23]. OR_{10} reflects the proportion of test occurrence points incorrectly predicted as unsuitable, which directly affects the extrapolation reliability of the model to novel environments [24]. The AUC difference represents the prediction variability among 10 replicate runs, with smaller values indicating a more robust model with lower overfitting risk [25].

Using the optimal parameter combination, a species distribution model for Moso bamboo was constructed in MaxEnt. A random subset of 75% of the occurrence records was used for calibration, and the remaining 25% was held aside for independent validation. To further enhance model robustness, a 5-fold spatially independent block cross-validation procedure was implemented. Calibration data were divided into five spatially separated folds; four folds were used for training and one for validation in each iteration. Final predictions were generated by averaging the results of the ten replicate runs. Outputs were produced in logistic format, providing continuous suitability scores from 0 to 1 for each grid cell, with higher scores indicating more favorable conditions.

Model performance was evaluated using AUC, a threshold-independent metric of model discrimination ability. AUC values range from 0.5 (no discrimination beyond random chance) to 1.0 (perfect classification). Higher AUC values denote stronger capacity to distinguish suitable from unsuitable habitats, indicating more reliable predictions [26].

2.3.3. Habitat Suitability Classification and Centroid Shift Analysis

To define ecologically meaningful suitability boundaries while avoiding arbitrary thresholds, the 1% omission threshold ($T_1\% = 0.0954$) was adopted to differentiate suitable from unsuitable habitats. This threshold was derived from the spatially independent 5-fold block cross-validation presence points [27,28] and was calculated from the training occurrence records, excluding 1% of spatially extreme outliers while retaining 99% of the confirmed distribution range. All terrestrial grid cells within China were included in the analysis; inland water bodies and areas with missing data were classified as unsuitable.

Within the suitable range (suitability ≥ 0.0954), habitat suitability was further divided into three categories based on the tertiles (33.3rd and 66.7th percentiles) of suitability values extracted from all verified occurrence records. The resulting classes were: low suitability (0.0954–0.5663), moderate suitability (0.5663–0.8213), and high suitability (0.8213–1.0000). This empirically based classification ensures that each tier corresponds to approximately one-third of the known occurrence records, thereby reflecting the actual habitat quality gradient experienced by wild Moso bamboo populations rather than an artificial division of the entire landscape.

To quantify the spatiotemporal dynamics of suitable habitats under climate change, we conducted centroid shift analysis by comparing the spatial distribution patterns of suitable habitats under current and future climate scenarios [29,30]. Specifically, we calculated the geographic centroid coordinates of the total suitable habitat for the baseline period and for each of the four future periods under the four SSP scenarios. We then analyzed the migration direction and displacement distance of the centroids to characterize the overall shifting trend of Moso bamboo's potential geographical range [4,31].

2.3.4. Multivariate Environmental Similarity Surface (MESS) Analysis

To rigorously assess potential model extrapolation risks and climate novelty when projecting MaxEnt models into future horizons, we conducted a MESS analysis [27]. The analysis was calibrated using the nine key environmental variables retained in the final MaxEnt model as the baseline environmental envelope, which ensures that the extrapolation assessment is fully aligned with the actual predictor space used for model training.

The MESS framework quantifies the environmental congruence between multidimensional future climatic conditions and the baseline calibration space across all grid cells. Negative values (MESS < 0) identify “novel climates” (non-analog conditions) where at least one bioclimatic variable falls outside the range observed during model training, signifying potential model extrapolation risks. Conversely, positive values (MESS ≥ 0) designate analogous climates where model projections maintain high predictive fidelity [32].

To enable a nuanced, gradient-level evaluation of climate similarity and extrapolation risk, we further categorized MESS values into five ordered grades: severe novel climate (<-20), moderate novel climate (-20 to -10), mild novel climate (-10 to 0), moderate climate similarity (0 to 20), and high climate similarity (>20). This fine-grained classification supports regional-level reliability assessment of habitat projections and provides a methodological foundation for the subsequent multi-scenario climate refugia analysis.

2.3.5. Climate Refugia Identification Based on Multi-Scenario Consensus

To address the inherent uncertainties across future SSPs and time horizons, we followed the climate refugia consensus framework proposed by Beaumont et al. [33], building on the scenario-specific habitat suitability classification results to quantify long-term habitat stability via multi-scenario ensemble averaging.

To reduce interference from numerical fluctuations in individual projections and improve the robustness of long-term stability assessment, we performed pixel-wise ensemble averaging on the reclassified categorical suitability layers (scoring: 0 = unsuitable, 1 = low suitability, 2 = moderate suitability, 3 = high suitability), rather than directly averaging raw continuous suitability scores. The 16 future projections were overlaid and averaged to derive the Climate Refugium Average Suitability Index (R), calculated as:

$$R(x, y) = \frac{1}{N} \sum_{i=1}^N S_i(x, y) \quad (1)$$

where $N = 16$ denotes the total number of future climate projections, and $S_i(x, y)$ is the predicted suitability score of grid cell (x, y) under the i -th scenario.

The resulting index ranges continuously from 0.0 to 3.0 . We further classified habitat stability into three tiers based on the index values. Core climate refugia ($R > 2.0$): areas that consistently maintain moderate-to-high suitability across all scenarios, with the highest cross-scenario consensus and the strongest habitat stability and resilience. Moderate-stability buffer zones ($1.0 \leq R \leq 2.0$): areas that maintain medium long-term suitability with moderate cross-scenario consensus, serving as transition zones between core and marginal habitats. Marginal transition habitats ($0 < R < 1.0$): areas that are suitable under only a few scenarios, with low cross-scenario consensus, weak stability, and high climatic sensitivity.

3. Results

3.1. Parameter Optimization and Model Accuracy Evaluation

Under default parameters ($RM = 1$, $FC = LQHPT$), the MaxEnt model yielded a $\Delta AICc$ of 21.45 , a mean AUC difference (diff.AUC, Figure 2c) of 0.0496 , a mean 10% omission rate (OR_{10} , Figure 2b) of 0.2328 , and a validation AUC value of approximately 0.9076 (Figure 2a).

Parameter optimization was conducted through the ENMeval package, which determined $RM = 1.5$ and $FC = LQHPT$ as the optimal configuration for the MaxEnt model. Figure 2 illustrates the variations in model performance metrics for the six feature class combinations across the RM range of 0.5 – 4.0 . Overall, OR_{10} and diff.AUC for high-complexity feature classes decreased rapidly and then stabilized with increasing RM , while validation AUC first increased and then plateaued. $\Delta AICc$ increased monotonically with RM for all combinations, and the LQHPT feature set consistently maintained the lowest $\Delta AICc$ across all RM levels. At the optimal parameter combination $RM = 1.5$, $FC = LQHPT$, the $\Delta AICc$ value was 27.78 , confirming the best trade-off between model complexity and goodness-of-fit.

The global minimum $\Delta AICc$ occurred at $RM = 0.5$ for LQHPT, but this configuration suffered from severe overfitting with excessively high OR_{10} and diff.AUC. We therefore selected $RM = 1.5$ and $FC = LQHPT$ as the optimal parameterization based on a comprehensive trade-off among $\Delta AICc$, OR_{10} , and diff.AUC. Compared with default parameters, the

optimized model reduced diff.AUC to 0.0456 (8.06% reduction) and OR_{10} to 0.2141 (8.07% reduction), while increasing validation AUC to 0.9104, achieving the best balance between predictive accuracy and generalization ability.

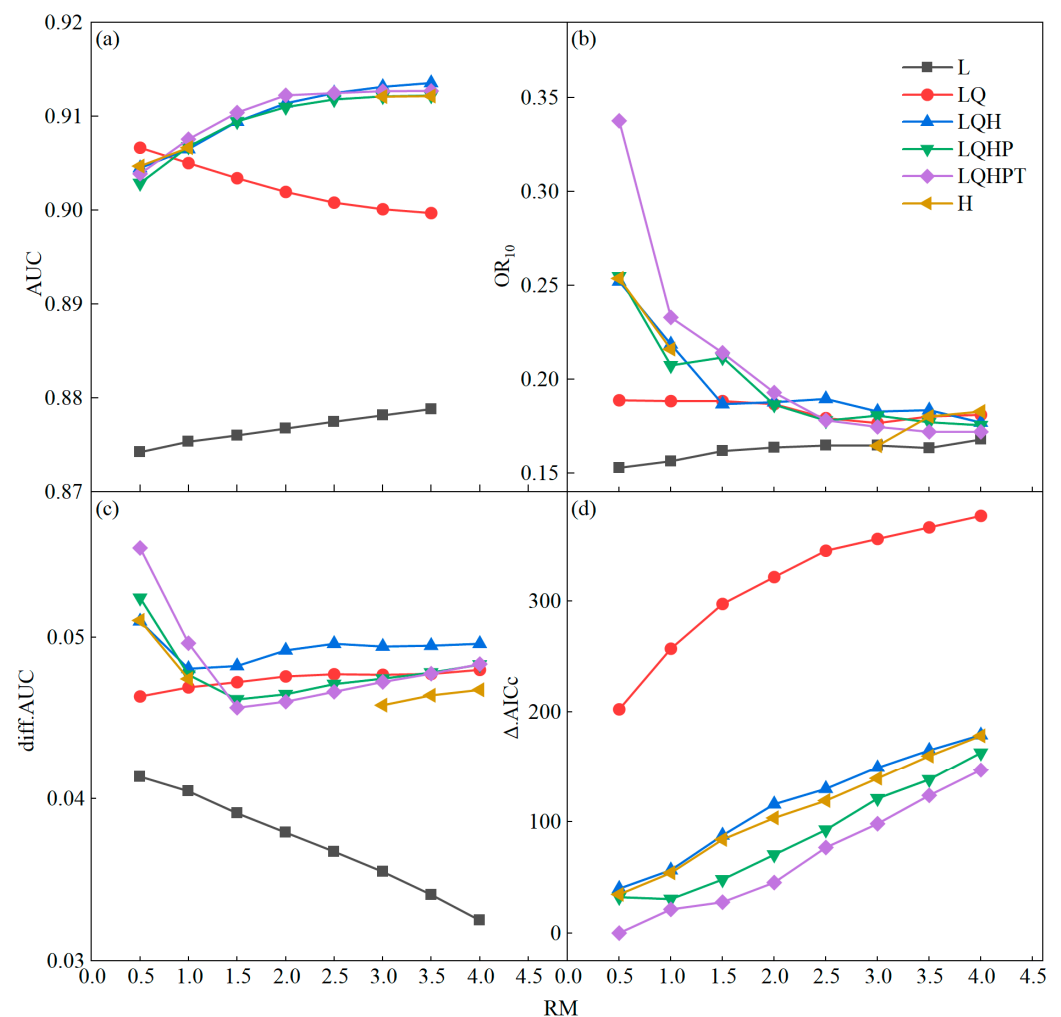


Figure 2. Performance metrics of the MaxEnt model under different RM values and feature class combinations: (a) mean AUC, (b) mean 10% omission rate, (c) mean AUC difference, and (d) $\Delta AICc$. Note: The line for the hinge (H) feature is disconnected at RM 1.5–2.5 due to non-convergence under spatial block partitioning.

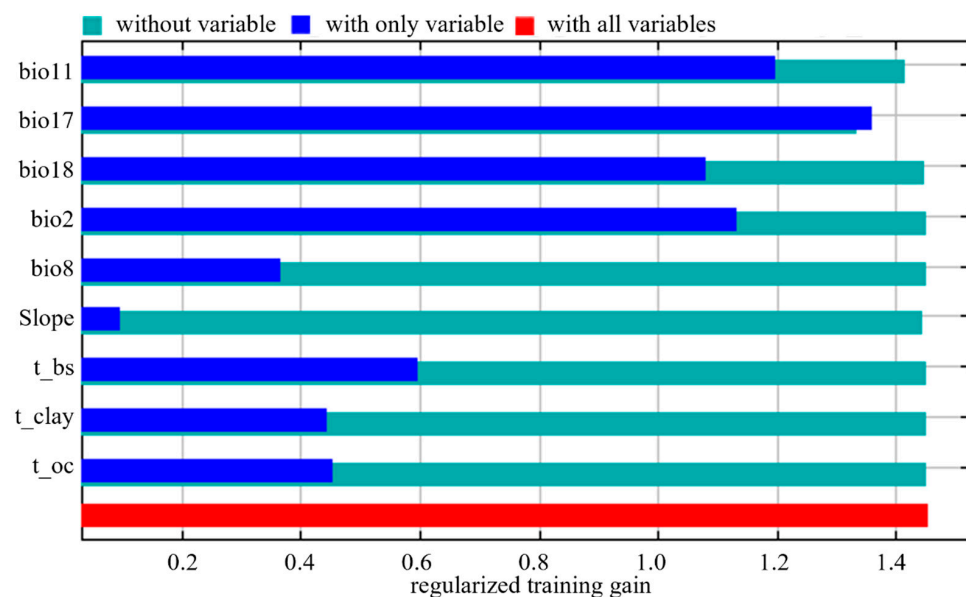
Compared with the default parameters, the optimized mean AUC difference decreased to 0.0456, representing an 8.06% reduction, and the optimized mean 10% omission rate decreased to 0.2141, representing an 8.07% reduction. Overall, as the RM value increased, OR_{10} and diff.AUC for complex feature combinations showed a trend of rapid initial decline followed by stabilization, while validation AUC values exhibited a slight upward trend toward stability. This pattern indicated that appropriately increasing the regularization multiplier could effectively reduce the risk of model overfitting. These results confirm that appropriate regularization effectively mitigates overfitting, and systematic parameter calibration is critical for improving the reliability of species distribution model projections.

3.2. Contribution and Response of Key Environmental Variables

The relative contributions and limiting effects of nine key environmental variables on suitable habitat distribution of Moso bamboo in China were comprehensively quantified using percent contribution, permutation importance (Table 2), and Jackknife test (Figure 3).

Table 2. Contribution rate and permutation importance of key environmental variables.

Code	Percent Contribution (%)	Permutation Importance (%)
bio2	0.6	0.5
bio11	63.9	38.9
bio8	0.5	1.0
bio17	31.2	53.6
bio18	1.6	2.2
Slope	0.9	1.4
t_bs	0.8	0.4
t_clay	0.4	1.1
t_oc	0.1	0.8

**Figure 3.** Jackknife test results of the relative importance of environmental variables.

According to the relative contribution rates, the three variables with the highest relative explanatory power for the modeled distribution pattern were mean temperature of the coldest quarter (bio11, 63.9%), precipitation of the driest quarter (bio17, 31.2%), and precipitation of the warmest quarter (bio18, 1.6%). Notably, the top two climatic variables together accounted for 95.1% of the total contribution, confirming the dominant role of hydroclimatic factors in governing the broad-scale distribution of Moso bamboo. Permutation importance reflects the dependence of the model on input variables, and yields a broadly consistent yet slightly different ranking of variable importance; the top three variables were precipitation of the driest quarter (bio17, 53.6%), mean temperature of the coldest quarter (bio11, 38.9%), and precipitation of the warmest quarter (bio18, 2.2%). Notably, these metrics quantify relative importance within the MaxEnt modeling framework and should not be interpreted as direct measures of the absolute ecological impact of each factor on natural populations.

The Jackknife test results showed that the three environmental variables that contributed most to regularized training gain were precipitation of driest quarter (bio17), mean temperature of coldest quarter (bio11), and mean diurnal range (bio2). This indicated that these three variables contain the highest amount of unique information independent of other predictors, and thus contribute most strongly to improving model discriminatory ability. The divergence in ranking across the three metrics arises from differences in their calculation logic: percent contribution reflects cumulative gain during model training, permutation importance reflects predictive sensitivity, and the Jackknife test quantifies unique information content.

The response curves of the nine key environmental variables are presented in Figure 4. For temperature variables, mean temperature of the coldest quarter (bio11) exhibited a typical unimodal response pattern, with occurrence probability peaking at 1.2 °C and decreasing on both sides, verifying that low temperature is the core constraint limiting the northward distribution of Moso bamboo. Mean diurnal range (bio2) showed a trend of initial decrease followed by slow recovery, with the lowest probability occurring in the 5–7 °C interval. Mean temperature of the wettest quarter (bio8) showed an overall increasing trend with rising temperature. For precipitation variables, precipitation of the driest quarter (bio17) displayed a unimodal distribution, peaking at approximately 150 mm; both seasonal drought and excessive dry-season precipitation restricted habitat suitability. Precipitation of the warmest quarter (bio18) also presented a unimodal characteristic, reaching its peak at around 500 mm and declining gradually under higher precipitation. For topographic and edaphic variables, slope showed a unimodal response that rose rapidly first and then declined slowly, with the peak at approximately 12°, and suitability remained at a relatively high level at 30°. Soil base saturation (t_bs) increased initially and then stabilized, with probability leveling off when the value exceeded 20. Soil clay content (t_clay) followed a unimodal pattern, peaking at 14% and decreasing slightly with further increase in clay proportion. Soil organic carbon content (t_oc) was positively associated with occurrence probability, which rose sharply in the 0–10% range and then stabilized at a high level, reflecting the promoting effect of soil organic matter on Moso bamboo survival.

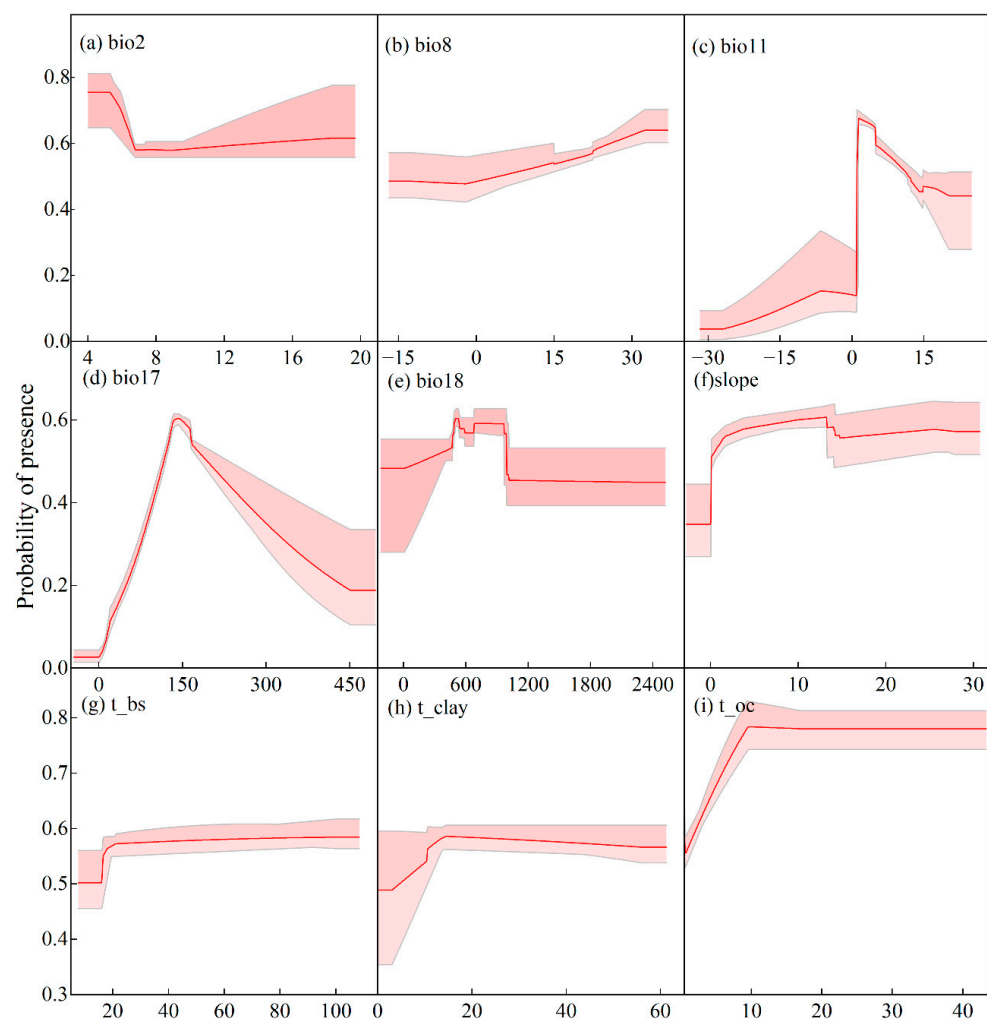


Figure 4. Response curves of main environmental factors. The red solid line represents the predicted suitable probability; the pink shaded area denotes the confidence interval.

3.3. Spatial Distribution Pattern of Suitable Habitats Under Current Climate

Under present-day climatic conditions, the total potential suitable habitat area for Moso bamboo across China was estimated to be $218.88 \times 10^4 \text{ km}^2$, accounting for 22.80% of the national terrestrial land area. Suitable habitats were largely concentrated in subtropical southeastern China, with suitability gradually declining towards the northwestern and southwestern inland margins (Figure 5).

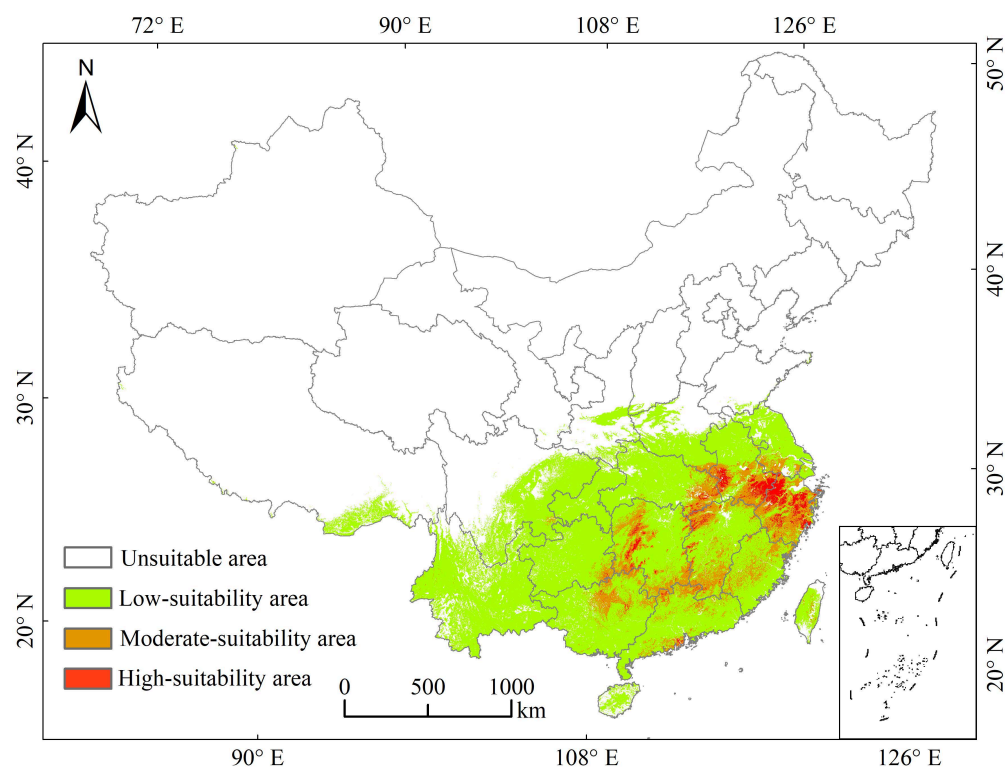


Figure 5. Potential suitable area of Moso bamboo under current climate conditions.

The high-suitability habitat, covering $5.14 \times 10^4 \text{ km}^2$ (2.35% of the total suitable area), represents the optimal core bioclimatic envelope. This class was tightly clustered in the provinces of East and Central South China, predominantly occurring in western and southern Zhejiang, northern and central Fujian, eastern and western Jiangxi, central and western Hunan, southern Anhui, with sporadic patches in northern Guangdong.

Radiating outward from these core clusters, the moderate-suitability habitat encompassed $40.97 \times 10^4 \text{ km}^2$, representing 18.72% of the total suitable area. This intermediate class formed a broad, continuous buffer belt across southern China, extensively covering Jiangxi, Hunan, Fujian, Zhejiang, Guangdong, northern and central Guangxi, southern Anhui, southeastern Hubei, eastern Guizhou, and southern Chongqing.

In contrast, the low-suitability habitat was the most spatially expansive, spanning $172.77 \times 10^4 \text{ km}^2$ —accounting for 78.93% of the total suitable habitat and 18.00% of the national territory. It was widely dispersed along the outer peripheral transition zones, notably the northern climatic boundary, including southern Henan, central and northern Hubei, southern Shaanxi, and Jiangsu, as well as southwestern inland regions, including most of Guizhou, Sichuan, central and southern Yunnan, Guangxi, Hainan, and the southeastern edge of Xizang.

The remaining $741.12 \times 10^4 \text{ km}^2$ (77.20% of the country) was classified as unsuitable habitat (UA), distributed across the arid, semi-arid, and alpine frigid regions of northern, northwestern, and western China, where severe winter thermal deficits and moisture constraints strictly inhibit the survival and regeneration of Moso bamboo.

3.4. Spatiotemporal Changes of Suitable Habitats and Centroid Shift Under Future Scenarios

Suitable habitat areas of Moso bamboo underwent pronounced restructuring across future climate scenarios (Table 3). Across all four emission pathways (SSP126, SSP245, SSP370, and SSP585), the total suitable habitat area (SA) consistently expanded relative to the current baseline, with net gains ranging from +7.97% to +25.98%, peaking in the late 21st century (2090s) under high radiative forcing under SSP370 and under SSP585. However, internal suitability composition revealed a distinct qualitative degradation: core high-suitability habitats suffered persistent and severe contractions, whereas low-suitability habitats (LA) expanded steadily, and moderate-suitability habitats (MA) exhibited significant early-stage surges followed by scenario dependent fluctuations.

Table 3. Area changes of suitable habitats under different climate scenarios.

Scenarios	Period	SA	UA	LA		MA		HA		
		Area (10 ⁴ km ²)	Area (10 ⁴ km ²)	Rate (%)	Area (10 ⁴ km ²)	Rate (%)	Area (10 ⁴ km ²)	Rate (%)	Area (10 ⁴ km ²)	Rate (%)
Current	2000	218.88	741.12	/	172.77	/	40.97	/	5.14	/
SSP126	2030	243.51	716.49	−3.32	178.84	3.51	60.61	47.94	4.06	−20.94
	2050	252.33	707.67	−4.51	193.74	12.13	55.66	35.85	2.94	−42.82
	2070	248.54	711.46	−4.00	194.91	12.81	52.63	28.45	1.01	−80.44
	2090	253.06	706.94	−4.61	205.16	18.74	46.47	13.42	1.43	−72.12
SSP245	2030	244.28	715.72	−3.43	190.77	10.42	50.35	22.9	3.16	−38.48
	2050	254.8	705.2	−4.85	210.9	22.07	42.8	4.46	1.1	−78.52
	2070	257.84	702.16	−5.26	207.95	20.36	47.72	16.48	2.16	−57.91
	2090	258.5	701.5	−5.35	216.35	25.22	40.72	−0.61	1.43	−72.09
SSP370	2030	236.33	723.67	−2.36	173.63	0.50	59.93	46.28	2.77	−46.06
	2050	247.11	712.89	−3.81	188.09	8.87	56.63	38.22	2.39	−53.4
	2070	263.65	696.35	−6.04	218.81	26.64	43.8	6.90	1.04	−79.7
	2090	275.65	684.35	−7.66	227.61	31.74	47.00	14.71	1.04	−79.8
SSP585	2030	244.41	715.59	−3.45	178.63	3.39	60.59	47.90	5.19	1.02
	2050	256.21	703.8	−5.04	204.75	18.51	49.43	20.63	2.03	−60.54
	2070	270.65	689.35	−6.99	227.07	31.43	42.34	3.36	1.24	−75.92
	2090	275.74	684.26	−7.67	242.17	40.17	33.33	−18.65	0.24	−95.29

Note: SA, total suitable area; UA, unsuitable area; LA, low-suitability area; MA, moderate-suitability area; HA, high-suitability area. Change rate is calculated relative to the current baseline.

Under SSP126, total suitable habitat expanded from +11.25% in the 2030s to +15.62% in the 2090s. Low-suitability areas increased steadily by 3.51%–18.74%. Moderate-suitability areas expanded sharply in the early period (+47.94% in the 2030s) before leveling off to ±13.42% by the 2090s, while high-suitability areas contracted substantially by 20.94%–80.44%. Under SSP245, total suitable habitat increased steadily to +18.10% by the 2090s. Low-suitability habitats expanded by 10.42%–25.22%. Moderate-suitability habitats fluctuated during the 2030s–2070s but slightly declined in the 2090s (−0.61%). Concurrently, high-suitability habitats declined markedly by 38.48%–78.52%, with core habitats shifting downward into moderate and low-suitability classes.

Under SSP370, total suitable habitat displayed continuous growth over time, reaching +25.94% in the 2090s. Low-suitability areas expanded markedly, particularly in the 2070s (+26.64%) and 2090s (+31.74%). Moderate-suitability areas expanded significantly in the 2030s (+46.28%) and maintained moderate gains (+6.90%–14.71%) through the late century, whereas high-suitability areas experienced severe losses of 46.06%–79.80%. Under SSP585, habitat restructuring was most drastic under extreme warming. Total suitable habitat expanded by +11.66% in the 2030s and culminated in a +25.98% expansion by the 2090s. Low-suitability areas expanded aggressively, surging by +40.17%. Moderate-suitability

areas rose markedly by +47.90% in the 2030s but dropped sharply by −18.65% in the 2090s as thermal stress intensified. High-suitability habitats underwent near complete depletion, declining from +1.02% in the 2030s to a −95.29% collapse by the 2090s.

Under current climatic conditions, the centroid of suitable Moso bamboo habitats is located in central-western Hunan Province (110.841, 27.788). Across all four SSP scenarios, the centroid consistently moved in a northward to northeastward direction, yet remained within Hunan Province throughout all periods (Figure 6). Under SSP126, the centroid shifted north-northeastward during the 2030s–2050s, then retreated slightly southeastward in the 2070s, before moving further north by the 2090s. Under SSP245, it advanced north-eastward to its easternmost position in the 2050s, then shifted westward in the 2070s–2090s, with a total displacement of 139.97 km. Under SSP370, the centroid followed a “northeast then northwest” trajectory, reaching northern Hunan by the 2090s. Under SSP585, the largest migration was observed: the centroid moved steadily north-northeastward before turning northwestward in the late century, ultimately reaching its northernmost latitude (29.466° N) and maximum displacement of 186.73 km in the 2090s—a clear indication of poleward tracking of suitable habitats under extreme warming.

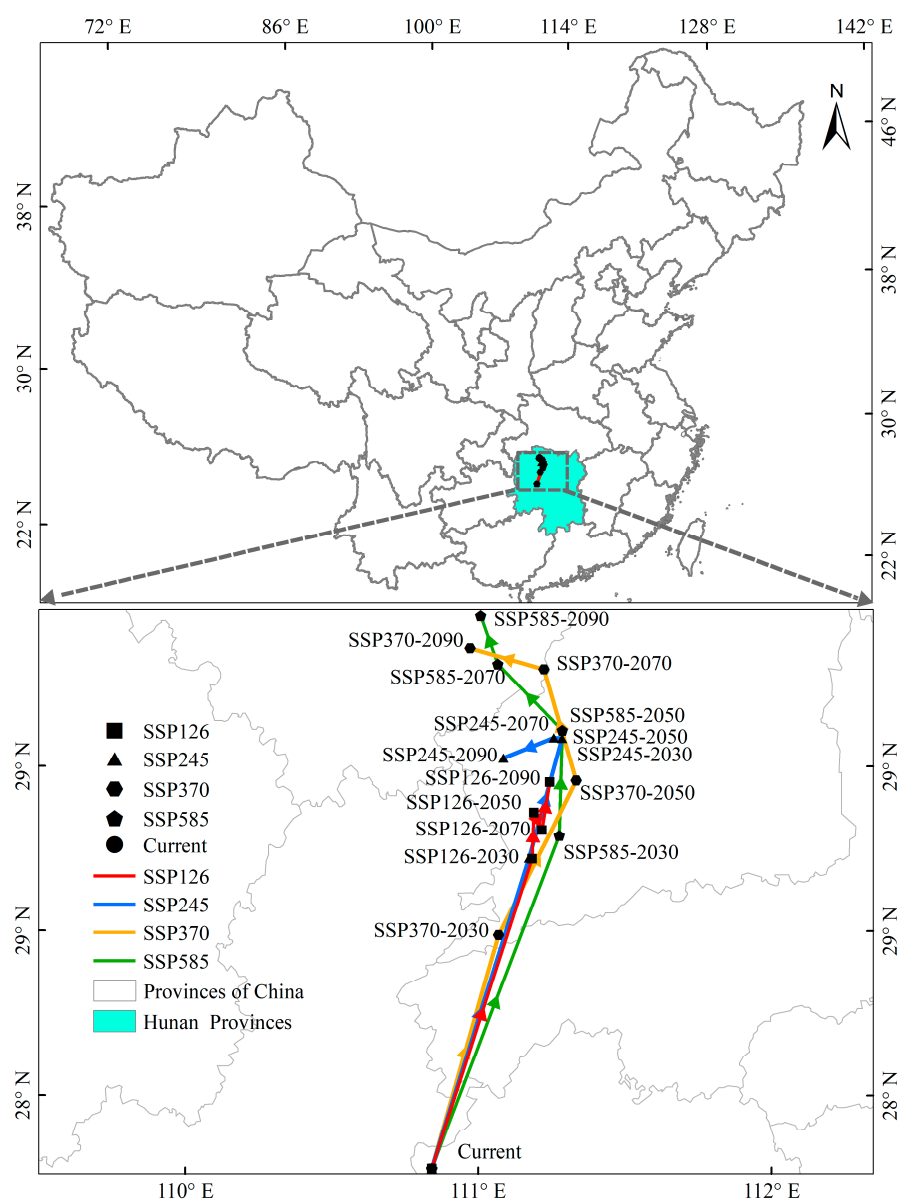


Figure 6. Centroid migration trajectories of potential suitable habitats under different climate.

3.5. Extrapolation Risk Assessment of Future Climate Projections

Across all 16 future scenarios, 90.60% to 99.82% of China's land area was covered by climate-analogous regions ($\text{MESS} \geq 0$) (Table 4). Specifically, the moderate similarity class (0~20, orange) formed the broad climatic matrix of China (~73.55%–77.37%), while the high-similarity class, covering 17.05%–25.18% of the territory, was predominantly concentrated in southern provinces such as Fujian, Jiangxi, Hunan, Guangdong, and Zhejiang. This high-similarity zone precisely overlaps with the primary modern distribution and projected suitable habitats of Moso bamboo, confirming that core bamboo regions will maintain highly analogous environmental conditions with minimal physiological stress.

Table 4. Proportions of novel and analogous climates under different SSP scenarios based on MESS analysis.

Scenario	Period	Novel Climate Proportion (%)	Analogous Climate Proportion (%)
SSP126	2030s	0.22	99.78
	2050s	0.25	99.75
	2070s	0.27	99.73
	2090s	0.3	99.7
SSP245	2030s	0.2	99.8
	2050s	0.36	99.64
	2070s	0.47	99.53
	2090s	0.53	99.47
SSP370	2030s	0.18	99.82
	2050s	0.32	99.68
	2070s	0.75	99.25
	2090s	5.52	94.48
SSP585	2030s	0.25	99.75
	2050s	0.48	99.52
	2070s	3.22	96.78
	2090s	9.4	90.6

Conversely, areas with potential extrapolation risks ($\text{MESS} < 0$) were extremely limited under low- and moderate-emission scenarios (SSP126 and SSP245), occupying less than 0.53% of China's territory throughout the 21st century (Figure 7a–h, Table 4). Under high-emission warming pathways (SSP370 and SSP585), novel climates expanded notably in the late 21st century (2070s–2090s), reaching 5.52% and 9.40% of total land area under SSP370 and SSP585 in the 2090s, respectively (Table 3). Notably, this expansion was almost entirely contributed by the mild novel climate tier, which accounted for 9.21% of the 9.40% total share under SSP585–2090s. These areas were mainly distributed in northern high-latitude regions including Heilongjiang, Jilin, and eastern Inner Mongolia, with scattered patches in northern North China (Figure 7l,p). Severe and moderate novel climates remained negligible nationwide. These findings demonstrate that future climate anomalies are largely mild deviations at the climatic periphery, statistically confirming the high reliability of MaxEnt habitat projections for Moso bamboo.

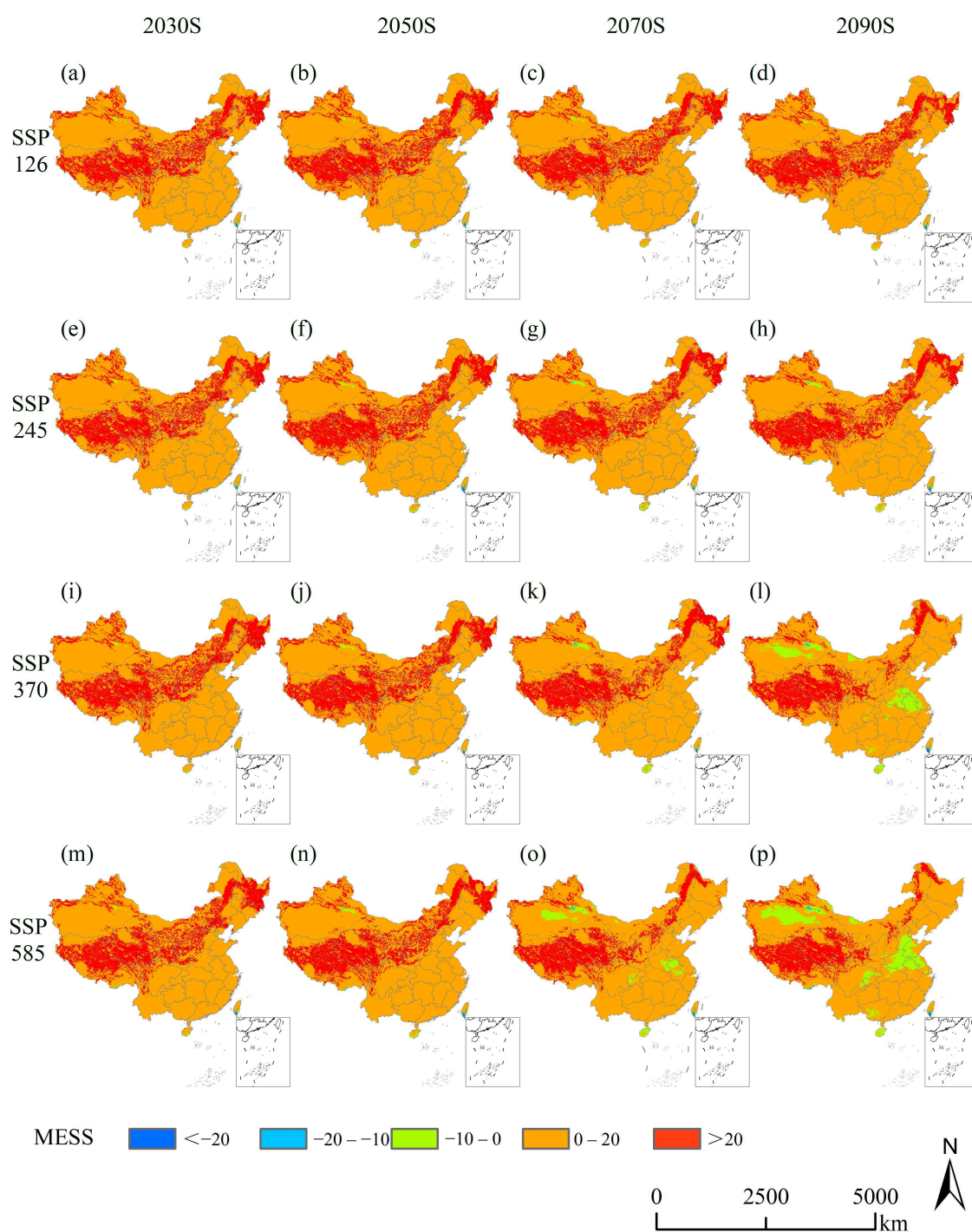


Figure 7. MESS analysis across China under 16 future climate scenarios. Panels (a–d), (e–h), (i–l), and (m–p) represent SSP126, SSP245, SSP370, and SSP585 across the 2030s, 2050s, 2070s, and 2090s, respectively.

3.6. Spatial Pattern of Climate Refugia Under Multi-Scenario Consensus

The ensemble average across all 16 projections revealed a clear three-tiered spatial hierarchy of habitat stability for Moso bamboo in China, with stability declining gradually from the southeastern core to the northern and western peripheries (Figures 8 and S3).

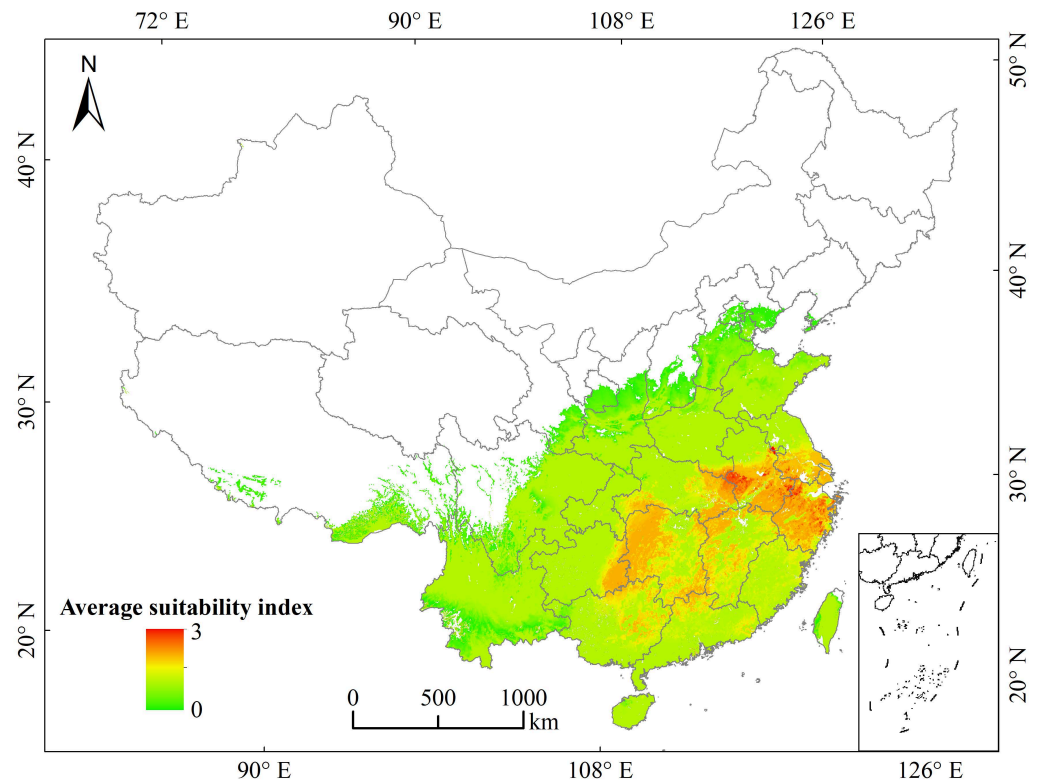


Figure 8. Climate refugia map based on ensemble averaging across 16 future projections.

Core climate refugia ($R > 2.0$) represent high-stability habitats with the highest cross-scenario consensus. They are concentrated in contiguous patches across the traditional core bamboo-producing regions in southeastern China, covering the main areas of Fujian, Jiangxi and Hunan provinces, as well as the hilly and mountainous zones of southern Zhejiang, northern Guangdong, southern Anhui and eastern Hubei. These areas maintain stable moderate-to-high habitat suitability across all future climate scenarios, and serve as core priority areas for the in situ conservation of Moso bamboo under climate warming.

Moderate-stability buffer zones ($1.0 \leq R \leq 2.0$) encircle the core climate refugia in a ring-like pattern, and are widely distributed across the low hilly regions of the middle and lower Yangtze River, most of South China, and the marginal zones of the Sichuan Basin. These areas sustain a medium level of long-term habitat suitability, acting as key ecological transition zones linking core refugia and marginal habitats, and providing spatial support for natural population dispersal and secondary conservation planning.

Marginal transition habitats ($0 < R < 1.0$) extend in strips along two major climatic transition zones. The northern belt stretches along the Funiu Mountain–Huaihe River line, covering southern Henan, northern Anhui, northern Jiangsu and southern Shandong; the southwestern belt lies in the peripheral areas of the Yunnan–Guizhou Plateau. These regions have relatively low cross-scenario consensus, representing climate-driven potential expansion habitats with generally weak habitat stability and high sensitivity to climate change.

4. Discussion

4.1. Optimization Performance and Reliability Validation of the Model

Parameter calibration is a core component of the species distribution modeling workflow, which directly governs the degree of overfitting and the predictive transferability of the model. In this study, the RM and FC settings of the MaxEnt model were systematically optimized using the ENMeval package in conjunction with a spatially independent 5-fold

block cross-validation framework. This approach effectively balanced model goodness-of-fit against complexity, providing a robust methodological basis for evaluating current suitable habitats and projecting future dynamics of Moso bamboo.

The optimal parameter combination was identified as $RM = 1.5$ and $FC = LQHPT$. Compared with the default settings ($RM = 1$, $FC = LQHPT$; $\Delta AICc = 21.45$), the optimized model achieved a substantially improved trade-off between goodness-of-fit and complexity, with a $\Delta AICc$ of 27.78. Under spatial block cross-validation, the optimized configuration reduced diff.AUC from 0.0496 to 0.0456 and OR_{10} from 0.2328 to 0.2141, while maintaining a high spatial validation AUC of 0.9104 (Figure 2). These results indicate that moderate penalization of model complexity through an increased regularization multiplier effectively limits localized over-parameterization and improves spatial transferability [13]. A similar optimization pattern has been reported for other subtropical species, such as the medicinal orchid *Cremastra appendiculata*, for which parameter calibration reduced overfitting in complex terrains [4].

For the current baseline period, the model achieved a validation AUC of 0.9104, indicating excellent predictive performance [34]. This calibrated model was then applied directly to all future climate scenarios. No independent AUC values were calculated for future periods, as validation occurrence data were unavailable for those time horizons. The accuracy obtained falls within the range reported for congeners of *Phyllostachys* and *Bambusa* (AUC 0.95–0.98), supporting the reliability of our modeling approach [35]. Spatially, the predicted high-suitability areas were mainly concentrated in Zhejiang, Fujian, Jiangxi, and Hunan provinces, closely matching the documented natural distribution of Moso bamboo and providing empirical support for our projections. Compared with previous global distribution projections that lacked systematic parameter calibration [36], our optimized framework reduced overfitting bias and enhanced the spatial transferability of future projections. Overall, this optimized modeling approach offers a more robust basis for dynamic assessments of Moso bamboo habitat suitability under climate change.

4.2. Key Environmental Factors Regulating the Potential Distribution of Moso Bamboo

Our results indicate that, within the present modeling framework, the mean temperature of the coldest quarter (bio11 , relative contribution 63.9%) and precipitation of the driest quarter (bio17 , relative contribution 31.2%) are the dominant explanatory variables governing the large-scale distribution pattern of Moso bamboo. Jointly accounting for 95.1% of the total relative contribution in the model, this finding reflects those hydrothermal conditions, serving as the primary environmental constraints shaping the species' geographic range. This finding aligns well with earlier studies reporting that the species distribution is largely governed by the combined effects of temperature and precipitation regimes [36]. Notably, although edaphic and topographic variables (t_{clay} , t_{oc} , slope) were included in the model, their individual contributions were consistently low (<1%), indicating that soil and terrain factors only modulate habitat suitability at local scales rather than altering the overarching climatic constraints. This pattern reinforces the robustness of hydroclimatic dominance, demonstrating that including nonclimatic predictors does not overturn the primary climatic control but rather substantiates it.

The response curve characteristics show that when the mean temperature of coldest quarter ranges from 2 °C to 5 °C and precipitation of driest quarter ranges from 150 mm to 200 mm, the habitat presence probability of Moso bamboo maintains a high level above 0.6, and the suitability drops significantly beyond the optimal threshold range. Physiologically, the rhizome buds of Moso bamboo must survive through the winter dormancy period, during which extremely low temperatures in the coldest quarter can inflict direct frost injury on these buds. This cold sensitivity is widely recognized as the key physiological bottleneck

limiting the northward range expansion of Moso bamboo [29]. Although Moso bamboo has a certain tolerance to seasonal drought and low temperature, both extreme drought and excessive precipitation can inhibit its growth and development. Especially in the dry season, moderate precipitation supply is a key condition for maintaining the physiological metabolic activity and population stability of Moso bamboo [29]. This physiological characteristic also explains the spatial distribution pattern that the high-suitability habitats of Moso bamboo are concentrated in the subtropical regions of southeastern China and are difficult to expand to higher latitudes.

Precipitation of warmest quarter (bio18) and mean diurnal range (bio2) also surfaced as key determinants of Moso bamboo distribution, with permutation importance values of 2.2% and 0.5%, respectively, second only to mean temperature of coldest quarter. Moso bamboo habitat suitability remained relatively stable when warm-season precipitation was between 500 mm and 1000 mm, indicating that it has a wide ecological amplitude for precipitation in the growing season. The suitability is highest when the mean diurnal range is between 4 °C and 7 °C, reflecting that Moso bamboo is sensitive to temperature fluctuations. Under extremely humid conditions (e.g., precipitation of the warmest quarter > 1200 mm), Moso bamboo suitability declined, possibly due to poorer soil aeration, root hypoxia, or higher pathogen loads associated with excessive rainfall [37].

In addition, the relative contribution rates of soil clay content (t_clay) and soil organic carbon content (t_oc) are both less than 1%, but their permutation importance values are 1.1% and 0.8%, respectively. This indicates that soil texture and fertility do not determine the large-scale distribution pattern, but can regulate the habitat suitability of Moso bamboo at a local scale. The response curve shows that the occurrence probability of Moso bamboo rises rapidly to a peak of 0.586 with increasing soil clay content, and then decreases slowly, suggesting that Moso bamboo prefers light to medium loamy soils, and excessive clay proportion will hinder root respiration and water infiltration. Soil organic carbon content shows a positive correlation with Moso bamboo suitability: within the range of 0–10%, the occurrence probability increases continuously from 0.556 to 0.783 and then stabilizes, indicating that Moso bamboo tends to distribute in soil environments rich in organic matter. Higher organic carbon levels can provide sufficient nutrients for its growth and maintain favorable soil aggregate structure.

4.3. Research Uncertainties and Management Implications

Although parameter optimization via ENMeval improved the performance and robustness of the MaxEnt model, our projections still have certain limitations. First, the model only includes climatic, edaphic, and topographic factors, while biotic factors (e.g., interspecific competition, pathogens) and anthropogenic factors (e.g., forest management, landuse change) are not considered. These factors play important regulatory roles in the actual distribution and population dynamics of Moso bamboo at local scales [38]. Second, future climate data are derived from a single GCM (BCC-CSM), without multi-model ensemble analysis. The systematic bias of climate models and the hypothetical nature of emission scenarios will both introduce uncertainties into the projections. In addition, static species distribution models assume niche conservatism and do not account for adaptive evolution and dispersal limitations, which may also cause deviations between projected and actual distribution dynamics. Future studies can integrate multi-model ensemble simulations via the Biomod2 platform and incorporate factors such as land use and biotic interactions to further improve the reliability of projections [39].

Regarding environmental extrapolation risks, our 5-class MESS analysis quantitatively demonstrated that over 90.60% to 99.78% of China's land area resides firmly within the climate-analogous domain (MESS $\geq$ 0, classes 4 and 5) across all 16 future scenarios

(Figure 8). Crucially, the high-similarity class (>20 , red), which covers 17.05%–25.18% of the territory, precisely coincides with the primary modern distribution and projected suitable habitats of Moso bamboo across southern and central China. This strong environmental alignment indicates that the calibrated response curves adequately reflect the fundamental climatic niche of *P. edulis* under most future pathways. However, the emergence of novel climates (reaching 9.40% under SSP5-8.5 in the 2090s), although predominantly consisting of mild anomalies ($-10\sim 0$, class 3), indicates that extreme thermal and moisture regimes in late-century high-emission trajectories will locally exceed historical calibration boundaries [32,40]. Following the conservative interpretation principles proposed by Chen, habitat expansions or contractions projected within or adjacent to these novel climate zones should be interpreted with caution.

With the explicit caveat that our projections reflect modeled climatic habitat suitability rather than realized on-ground habitats or confirmed actual conservation risks, the results presented here offer forward-looking practical guidance for addressing two key management concerns: maintaining sustainable Moso bamboo resources and preventing unwanted expansion into vulnerable ecosystems. On one hand, the contraction of core high-suitability habitats indicates that traditional major production areas such as Zhejiang, Fujian and Jiangxi provinces may face the risk of declining climatic suitability in the future. In situ conservation of germplasm resources and artificial tending measures are recommended in these regions to maintain the stability of bamboo forest productivity [41]. On the other hand, the outward expansion of moderately suitable habitats demonstrates the climatic potential rather than the confirmed likelihood for Moso bamboo to spread into current marginal areas such as southern Henan, southern Shaanxi and eastern Guizhou. Most of these regions are ecologically sensitive zones, and should natural dispersal or unregulated introduction occur, the strong clonal reproductive invasiveness of Moso bamboo may pose threats to local forest community structure and biodiversity [8]. Therefore, it is recommended to establish a long-term monitoring and early warning mechanism in potential expansion areas and strictly regulate blind introduction to prevent ecological invasion risks.

Beyond regional implications for China, this study carries broader relevance for global readers engaged in forest ecology, species distribution modeling, and invasive species management. Methodologically, our standardized optimization workflow coupling ENMeval with MaxEnt offers a replicable framework for reducing model overfitting and improving projection transferability, which can be readily extended to habitat assessments of other bamboo species and subtropical woody plants worldwide. Empirically, the identified dominant climatic constraints—cold-quarter temperature and dry-season precipitation—and the corresponding suitability thresholds provide a quantitative baseline for introduced Moso bamboo plantations across Southeast Asia, Africa, and the Americas, supporting regional cultivation zoning and productivity estimation. From a management perspective, the dual strategy of in situ conservation in core production areas and risk monitoring in marginal zones provides a generalizable paradigm for balancing economic utilization and ecological risk of fast-growing forest resources under global climate change.

5. Conclusions

In this study, we employed MaxEnt for habitat suitability modeling, with parameter tuning performed via the ENMeval package and spatially independent 5-fold block cross-validation. Nine climatic, edaphic, and topographic variables were input to project spatiotemporal dynamics of suitable habitats across the current period and four future time slices (2030s–2090s) under four SSP climate scenarios. Dominant limiting environmental variables, habitat response curves and centroid migration trajectories, climate refugia, and

environmental extrapolation risks were quantified. The main findings are summarized as follows:

(1) Model performance was substantially improved after systematic parameter tuning. The optimal combination (RM = 1.5, FC = LQHPT) achieved a mean spatial validation AUC of 0.9104, while decreasing the diff.AUC by 8.06% and OR₁₀ by 8.07%, demonstrating excellent predictive capacity and effective suppression of overfitting.

(2) Hydroclimatic conditions governed broad-scale distribution. Mean temperature of coldest quarter (bio11, 63.9% relative contribution) and precipitation of driest quarter (bio17, 31.2% relative contribution) were the primary drivers, jointly accounting for 95.1% of the total contribution. Soil clay and organic carbon presented low contribution rates (<1%) and only modulated suitability at local spatial scales.

(3) Climate warming restructured habitat suitability patterns. The total current suitable area is $218.88 \times 10^4 \text{ km}^2$, concentrated in subtropical southeast China. High-suitability habitats contracted by 20.94%–95.29% under all SSP scenarios, while moderate-suitability habitats expanded fluctuantly, reaching a peak increase of 47.90% in the 2030s under SSP585, but later contracted by 18.65% in the 2090s. Habitat centroids underwent minor reciprocal shifts and remained entirely within Hunan Province throughout projections.

(4) Multi-scenario consensus and extrapolation assessments verified the high reliability of projections. The ensemble average suitability index successfully identified long-term in situ climate refugia ($R > 2.0$) primarily concentrated in Zhejiang, Fujian, Jiangxi, Hunan, Anhui, and northern Guangdong provinces. Concurrently, MESS analysis demonstrated that analogous climates ($\text{MESS} \geq 0$) dominated 90.60% to 99.78% of the national territory, confirming that core Moso bamboo habitats operate within robust environmental bounds with minimal extrapolation risk.

Supplementary Materials: The following are available online at <https://www.mdpi.com/article/10.3390/f17091077/s1>, Figure S1: Correlation matrix of environmental variables, Figure S2: Variance inflation factor (VIF) of environmental variables, Figure S3: Spatiotemporal patterns of suitable habitats for moso bamboo in China under different future climate scenarios.

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