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Author-formatted, not peer-reviewed document posted on 11/11/2025

DOI: https://doi.org/10.3897/arphapreprints.e177651

Modeling climate-change impacts on suitable habitats of *Myristica yunnanensis*

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Abstract

Myristica yunnanensis is an endangered, China-endemic tree of medicinal and spice value whose habitat is threatened by climate change and human disturbance. We provide the first quantitative habitat-suitability assessment to guide conservation. We compiled 21 vetted occurrences and environmental predictors (19 bioclimatic variables, ASTER GDEM topography, HWSD v2.0 soils, and GLC-SHARE land use) across China, focusing interpretation on Yunnan. We modelled current suitability and future projections (2050s, 2070s) under SSP126, SSP245, and SSP585 using a MaxEnt model and a biomod2 ensemble (GLM, GAM, RF, GBM), with cross-validation. Model performance was evaluated with AUC; variable importance used jackknife/permutation; and robust areas were identified by overlap between binarized MaxEnt and ensemble outputs. All models performed well (AUC > 0.90); MaxEnt performed best (AUC = 0.997) but produced more conservative suitable areas, whereas the ensemble predicted a broader extent. Temperature-related variables dominated importance: Temperature Seasonality (bio3), Max Temperature of Warmest Month (bio4), and Mean Temperature of Driest Quarter (bio9). Under current climate, unsuitable area predominates. Under SSP126/245, suitable area slightly contracts; under SSP585, moderate and high suitability expand, most strongly in the 2070s. Overlap mapping identifies stable core refugia concentrated in southeastern Yunnan and southern Hainan. Our results clarify thermal controls on *M. yunnanensis* distributions, quantify model-dependent uncertainty, and translate consensus into spatial priorities. The identified refugia provide actionable targets for habitat protection, restoration, and assisted management under warming. The workflow—integrating single-model and ensemble SDMs with consensus overlap—offers a transferable template for conservation planning of other threatened tropical–subtropical plants.

Keywords: climate change; conservation biogeography; habitat suitability; MaxEnt; *Myristica yunnanensis*; species distribution model.

1. Introduction

Biodiversity is a fundamental basis for maintaining ecological balance, promoting economic development, and addressing climate change, and it is therefore of vital significance to the sustainable development of human society(Qian et al. 2020; Bianchi et al. 2022; Wang et al. 2024d). Located in the transition zone between the tropics and subtropics, Yunnan Province is a global biodiversity hotspot due to its complex landforms and diverse climate types, and is praised as a 'kingdom of plants' a ‘gene bank of species’ and a ‘world garden’(Zhang & Sun 2010; Qian et al. 2020; Bianchi et al. 2022). Among its flora, plant species with extremely small populations, both endemic and endangered, not only play important roles in maintaining ecosystem functions (such as water conservation, soil retention, and climate regulation) but also possess unique genetic and medicinal value. Conducting conservation research on these species is key to safeguarding regional biodiversity(Volis 2016; Crane 2020; Willi et al. 2021; Sun et al. 2024; Wang et al. 2025b).

However, climate change poses an unprecedented threat to biodiversity. According to the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), global warming and changes in precipitation patterns have significantly increased species' survival risks of species, especially for species with extremely small populations and limited ecological adaptability, for which habitat loss and extinction risks are particularly pronounced(Trisos et al. 2020; Lee et al. 2023). *M. yunnanensis*, a nationally protected Class II endangered plant endemic to southwestern China, is mainly distributed in southern Yunnan and is extremely sensitive to thermal environments. Due to its small population size, narrow distribution, and strong dependence on specific habitats, this species has become an important target for conservation research on endangered tree species(Wu et al. 2019). However, current studies focus mainly on its chemical constituents, pharmacological activities, cultivation, and genetic diversity, while systematic research on the response of its potential distribution to climate change remains lacking(Mao et al. 2019; Brewer et al. 2023; Wang et al. 2024c).

Currently, species distribution models (SDM) are commonly used to simulate suitable habitats for species. SDMs are statistical tools used to simulate the spatial distribution and abundance of specific species(Park et al. 2020). The main purpose of SDMs is to analyze the relationships between environmental variables (such as climate, topography, and land use/land cover) and species observations, and to use statistical or machine learning methods to build models that simulate suitable habitats in unsampled areas(Mainali et al. 2015; Guo et al. 2017; Gleich et al. 2022). Common SDM methods include the maximum entropy model (MaxEnt), generalized additive models (GAM), and random forests (RF). These models are widely applied in ecology, conservation biology, and climate change research, allowing researchers to gain deeper insights into ecological processes, assess the impacts of human activities on species, and formulate corresponding conservation strategies, thus providing an important scientific basis for species conservation, habitat management, and biodiversity assessment(Valavi et al. 2021; Ahmadi et al. 2023; Li et al. 2023; Xie et al. 2023).

Among existing modeling approaches, MaxEnt is widely used for endangered species with scarce occurrence data due to its adaptability and stability for presence data, yet it is still prone to instability caused by parameter settings and the selection of pseudo-absence points(Wang et al. 2024a; Wang et al. 2024b). On the contrary, ensemble modeling can integrate the strengths of different models by combining the results of multiple algorithms, thus reducing the uncertainty of a single model and improving predictive robustness. Traditional modeling methods often rely on climatic variables, but relying on a single type of factor can fail to fully capture the ecological requirements of tree species, potentially leading to biased predictions and an incomplete representation of the complexity of species distributions, which can in turn result in overestimation or underestimation of distribution ranges(Ariyanto et al. 2024; Koc et al. 2024; Wang et al. 2025a). Previous studies have shown that combining climatic factors with topographic and soil factors can significantly improve model explanatory power and ecological realism, thereby enhancing predictive accuracy(Rota et al. 2024).

Therefore, this study takes *M. yunnanensis* as the research object, integrates climatic, topographic, land use/land cover, and soil factors to construct a multidimensional niche model, and compares the performance of a single model (MAXENT) with that of an ensemble model (BIOMOD2 that integrates GLM, GAM, RF, and GBM). We predicted the potential distribution of *M. yunnanensis*, compared and overlayed the results of different models, and examined key environmental factors, future distribution trends, and conservation implications. The findings provide a scientific basis for the conservation planning and management of this species and offer a reference for suitable habitat simulation and conservation research on plant species with extremely small populations.

2. Materials and Methods

2.1 Data acquisition

2.1.1 Acquisition of distribution data for M. yunnanensis

The known geographic distribution data of *M. yunnanensis* were obtained through the following channels: published literature, Global Biodiversity Information Facility (GBIF, https://www.gbif.org/),Chinese Virtual Herbarium (CVH, https://www.cvh.ac.cn), and China's Plant Photo Bank (https://ppbc.iplant.cn/). To reduce the impact of spatial autocorrelation, records with duplicate coordinates, obvious identification errors, unreliable distributions, or those outside the designated range were filtered out. In total, 21 *M. yunnanensis* distribution records were retained (Figure 1), and the data was saved in CSV format.

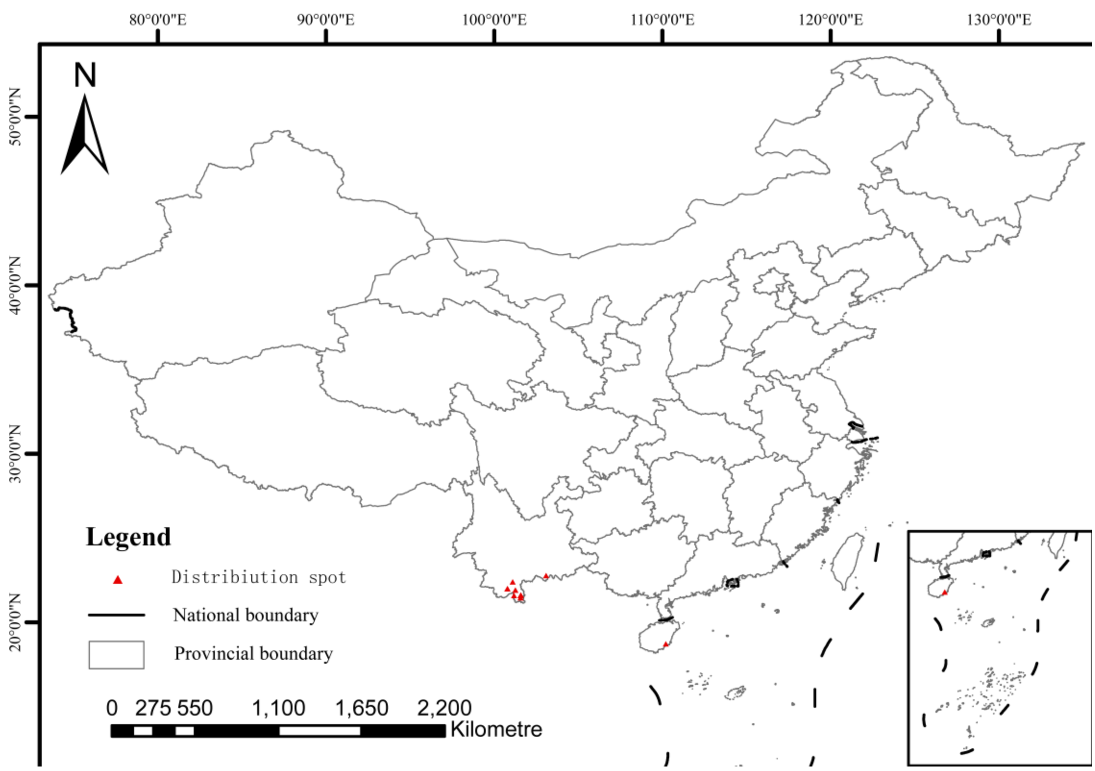

Fig. 1 Geographic distribution of *M. yunnanensis*

2.1.2 Acquisition and processing of ecological factor data

Bioclimatic, topographic, soil, and land use/land cover factors were selected to simulate current and future climate scenarios. The climate variables used in this study were sourced from the WorldClim database (http://www.worldclim.org). DEM (Digital Elevation Model) data were obtained from the China Geospatial Data Cloud (http://www.gscloud.cn/) using ASTER GDEM at 30 m resolution. The slope and aspect were extracted from DEM in ArcGIS 10.8.1 (https://www.esri.com/). Soil data were taken from the Harmonized World Soil Database version 2.0 (HWSD v2.0), jointly released by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA). This database integrates soil survey data from multiple countries and regions, provides global soil physicochemical attribute information with a spatial resolution of approximately 1 km, and is widely used in studies of agriculture, ecosystem services and biodiversity conservation (FAO/IIASA, 2023; https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/). Land use/land cover data were derived from the FAO Global Land Cover-SHARE (GLC-SHARE) database (FAO, 2014; https://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1036355/). Compiled by FAO Land and Water through integration of multiple national and regional high-resolution land cover datasets, GLC-SHARE provides 11 major land cover types (including artificial surfaces, cropland, grassland, forest, shrubland, wetlands, mangroves, sparse vegetation, bare soil, snow/ice, and water bodies) at a spatial resolution of approximately 30 arc-seconds (\~1 km), and is widely applied in ecosystem services and biodiversity research.

All datasets were standardized in ArcGIS 10.8.1 (https://www.esri.com/) to a uniform resolution (0.0083333333 × 0.0083333333) and coordinate system (GCS_WGS_1984). For the current period, climate data comprised the 19 key bioclimatic variables for 1970–2000. For future climate scenarios, two key periods were selected:2041–2060 and 2061–2080, in three scenarios: SSP126 (the sustainable development pathway, representing the most proactive and optimistic climate-change response scenario), SSP245 (a medium-low emissions scenario simulating significantly reduced future greenhouse gas emissions to limit global warming) and SSP585 (a high-emissions scenario simulating continued increases in future greenhouse gas emissions

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that can lead to substantial global temperature rise), to comprehensively assess the impact of climate change on the suitable habitat of *M. yunnanensis*(Joshi et al. 2024).

To address multicollinearity between variables and reduce model overfitting, variable selection was a key step to improve model performance. Using R 4.4.3 (https://cran.r-project.org), correlation analysis was performed on 40 ecological factors (Figre2) and factors with |r| < 0.7 were retained, resulting in the selection of 20 ecological factors (Table 1).

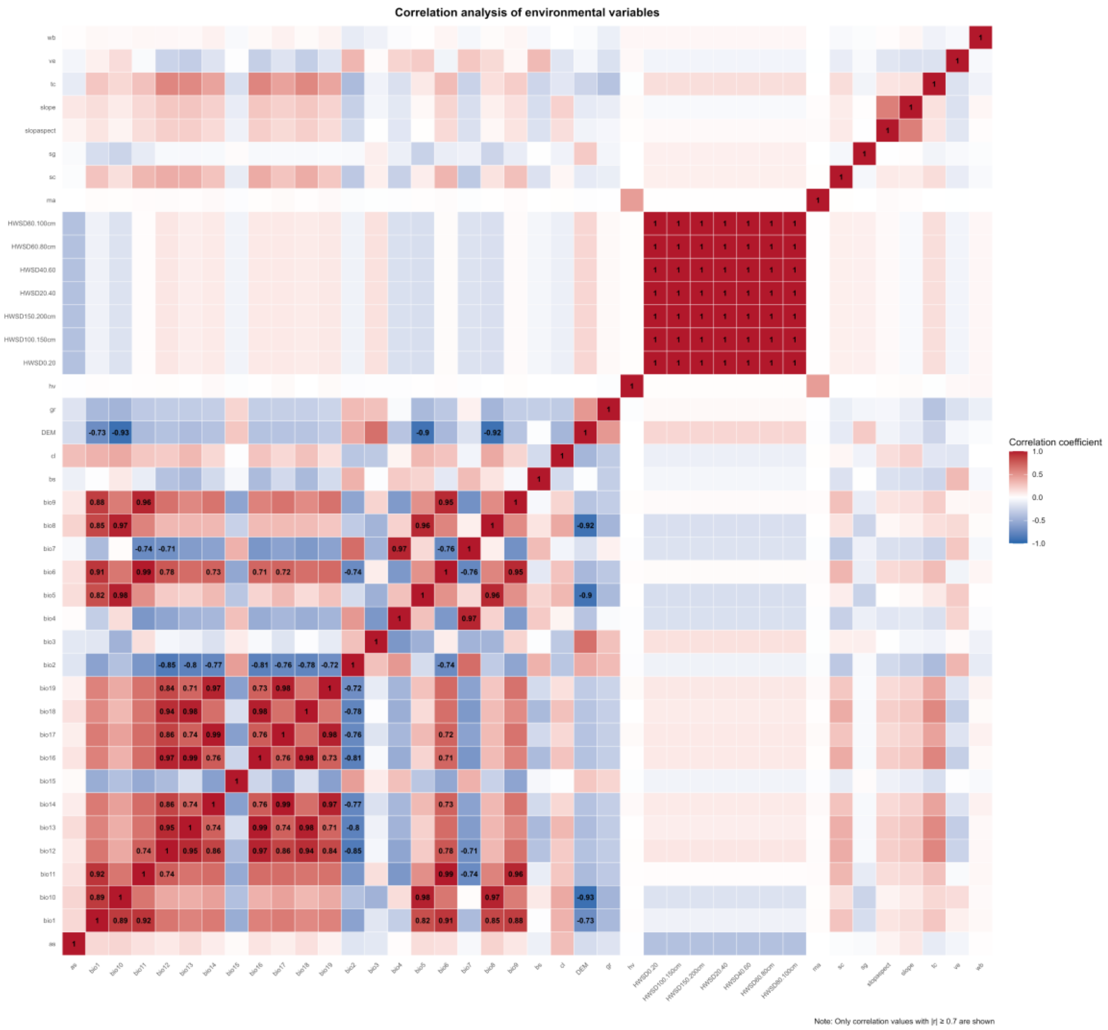

Fig. 2 Correlation analysis of 40 ecological factors

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Table 1. Environmental variables affecting *M. yunnanensis*

Abbreviation	Abbreviated name	Unit
as	Artificial surfaces	
bs	Bare soil	
cl	Crop land	
hv	Herbaceous vegetation, aquatic or regularly flooded	
ma	Mangroves	
sc	Shrubs covered area	
sg	Snow and glaciers	
tc	Trees covered area	
ve	Vegetation	
wb	Water bodies	
bio3	Isothermality	
bio4	Temperature Seasonality	
bio7	Temperature Annual Range	
bio9	Mean Temperature of Driest Quarter	℃
bio11	Mean Temperature of Coldest Quarter	℃
bio13	Precipitation of Wettest Month	mm
bio15	Precipitation Seasonality	mm
slope	Slope	°
slopeaspect	Slope aspect	°
HWSD20-40	HWSD2.0 20-40cm data	

2.1.3 Overview and baseline of the study area

This study adopts China as the overall extent of the investigation, with Yunnan province as the focal region for the assessment of suitability and spatial visualization. A nationwide extent was used for modeling and projection to capture the full environmental gradient available to this rare species, reduce edge effects, and facilitate comparison with potentially suitable areas outside Yunnan (for example, tropical islands such as Hainan). The map of China was obtained from the National Geoinformation Public Service Platform (https://www.tianditu.gov.cn/); the visualization of administrative regions of provincial level carries the map approval number GS (2024)0650.

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2.2 Modeling and Evaluation

2.2.1 MaxEnt

The MaxEnt model was run in MaxEnt 3.4.4 software (http://biodiversityinformatics.amnh.org/open_source/maxent/). Based on 21 distribution records and the environmental data screened, these were imported into MaxEnt 3.4.4 with the following settings: 75% of the samples were randomly selected as the training data set and the remaining 25% as the test data set to validate the model; the maximum number of iterations was set to 1000. To avoid instability caused by random selection, the modeling was repeated ten times and “Subsample” was chosen as the replication type(Barbet-Massin et al. 2012; Ito 2020).

To assess the relative contributions of environmental variables to the prediction of the distribution of *M. yunnanensis*, the Jackknife test was used. This approach measures the importance of variables by sequentially removing each variable and comparing changes in model performance. After removing a given climatic factor each time, the model was rerun and the contribution and importance of the permutation of that variable to the prediction of species distribution were calculated. This analysis helps identify the key environmental factors for the potential distribution of the species. The predictive accuracy of the model was evaluated using the area under the receiver operating characteristic curve (AUC)(Wang et al. 2024b). The AUC ranges from 0.5 to 1.0, with values closer to 1 indicating a stronger discriminative ability. In general, AUC values of 0.5 to 0.6 indicate low predictive ability, 0.6 to 0.7 indicate fair, 0.7 to 0.9 indicate good, and values above 0.9 indicate very high predictive accuracy(Wang et al. 2021; Anibaba et al. 2022; Treves et al. 2022; Xu et al. 2022).

The MaxEnt model output files were in ASC format. The prediction results were imported into ArcGIS 10.8.1 and converted to raster data, then overlayed with the administrative boundaries of China for visualization. The predictions were subsequently reclassified according to the suitability index (representing the probability of species occurrence), dividing the potential suitable habitat of *M. yunnanensis* into four classes: unsuitable (0–0.2), low suitability (0.2–0.4), moderate suitability (0.4–0.6), and high suitability (>0.6)(Ye et al. 2021). Different classes correspond to differences in the potential probability of species occurrence in specific areas, with higher probabilities indicating areas more suitable for the survival of *M. yunnanensis*.

2.2.2 Ensemble model

The modeling was carried out in R 4.4.3 (https://cran.r-project.org) using the biomod2 package (v4.2.5-2). The algorithms included generalized linear models (GLM), random forests (RF), gradient boosting machines (GBM), and generalized additive models (GAM)(Zhang et al. 2024). The response variable was binary presence/absence data (0/1) for *M. yunnanensis*, with coordinates standardized to longitude–latitude (WGS84), and missing values removed with standardized formatting prior to modeling. Environmental predictors came from 20 raster variables.asc, all standardized to a common projection, resolution, and spatial extent. To avoid numerical instability of GAM on near constant predictors, the number of unique values was counted at species occurrence sites was counted; if the number of unique values was fewer than 6, that variable was excluded from the predictors for GAM only, while all other models used the full set of variables.

Pseudo absence (PA) points were generated using a random strategy: 300 PA points were drawn each time and repeated twice to reduce uncertainty from a single sampling. Cross-validation used random splits, with 80% of the data as the training set and 20% as the validation set in each run, repeated 5 times to enhance model robustness. Class weights were balanced by setting prevalence = 0.5. Evaluation metrics included AUC, True Skill Statistic (TSS), and Cohen Kappa, with averages calculated from cross-validation results. The importance of variables was assessed by permutation (repeated 3 times). Finally, univariate response curves were generated with other variables fixed at their median values to reveal the potential effects of each environmental factor on species distribution.

3. Results

3.1 Model evaluation

The evaluation results showed that all algorithms achieved high predictive accuracy (AUC > 0.90) (figure 3). Among them, the MaxEnt model performed the best (AUC = 0.997), slightly higher than the ensemble model (AUC = 0.92).

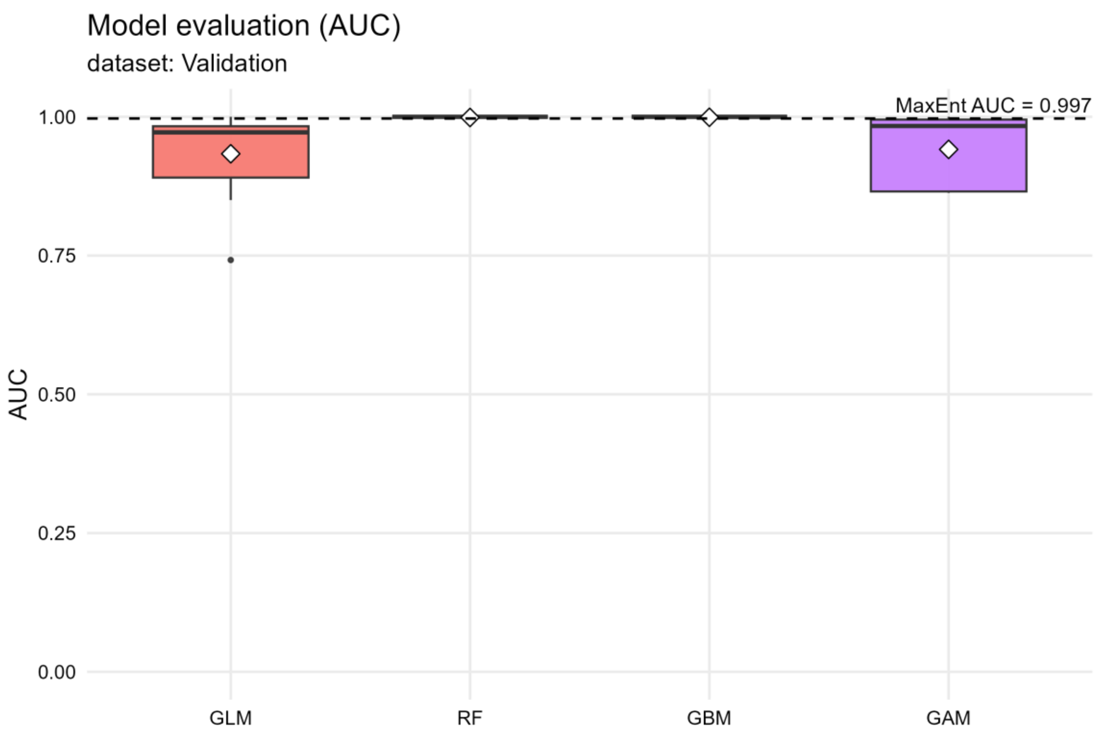

Fig. 3 Comparative AUC across algorithms (boxplot)

3.2 Contribution of environmental variables

The Jackknife analysis of variable importance (based on test gain; figure 4) indicated that the seasonality of the temperature (bio3), the maximum temperature Warmest Month (bio4), and The mean temperature of Driest Quarter (bio9) are the most critical factors influencing the potential distribution of *M. yunnanensis*. When modeled as single variables, these factors produced the highest test gains, indicating strong explanatory power; conversely, when these variables were removed, overall model performance decreased more markedly, further confirming their important role in determining the species' distribution.

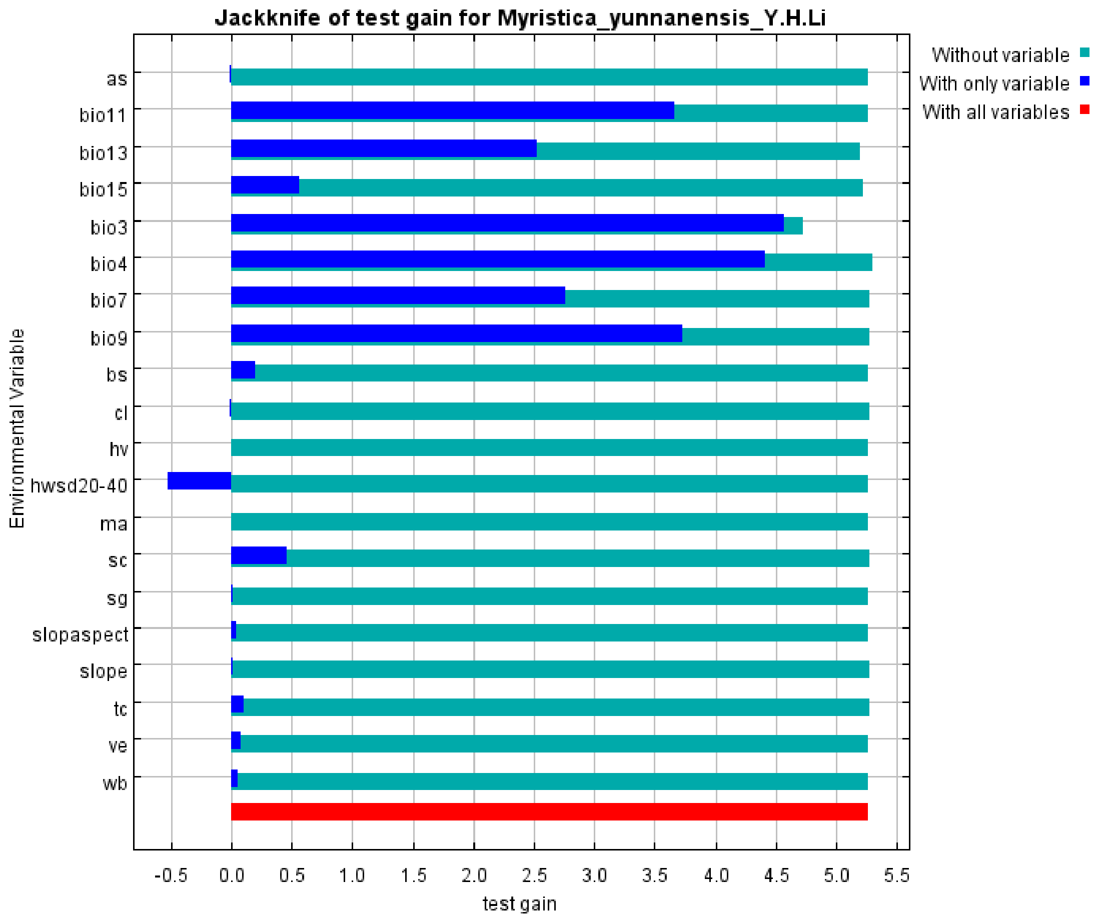

Fig. 4 Variable importance (jackknife) comparison: *M. yunnanensis* MaxEnt model

3.3 Current Potential Distribution

Under current climatic conditions, both MaxEnt and the ensemble model predict that unsuitable areas dominate the potential distribution of *M. yunnanensis*. MaxEnt predicts a high suit area of 0.78 × 10^4 km², a moderate suit area of 0.84 × 10^4 km², a low suit area of 3.08 × 10^4 km², and an unsuitable area of 956.83 × 10^4 km² (Figure 5a); whereas the ensemble model predicts a high suit area of 3.04 × 10^4 km², a moderate suit area of 5.08 × 10^4 km², a low suit area of 10.10 × 10^4 km², and an unsuitable area of 942.40 × 10^4 km² (Figure 5A). This indicates that the ensemble model produces a broader predicted range, whereas MaxEnt provides a more conservative estimate of suitable areas.

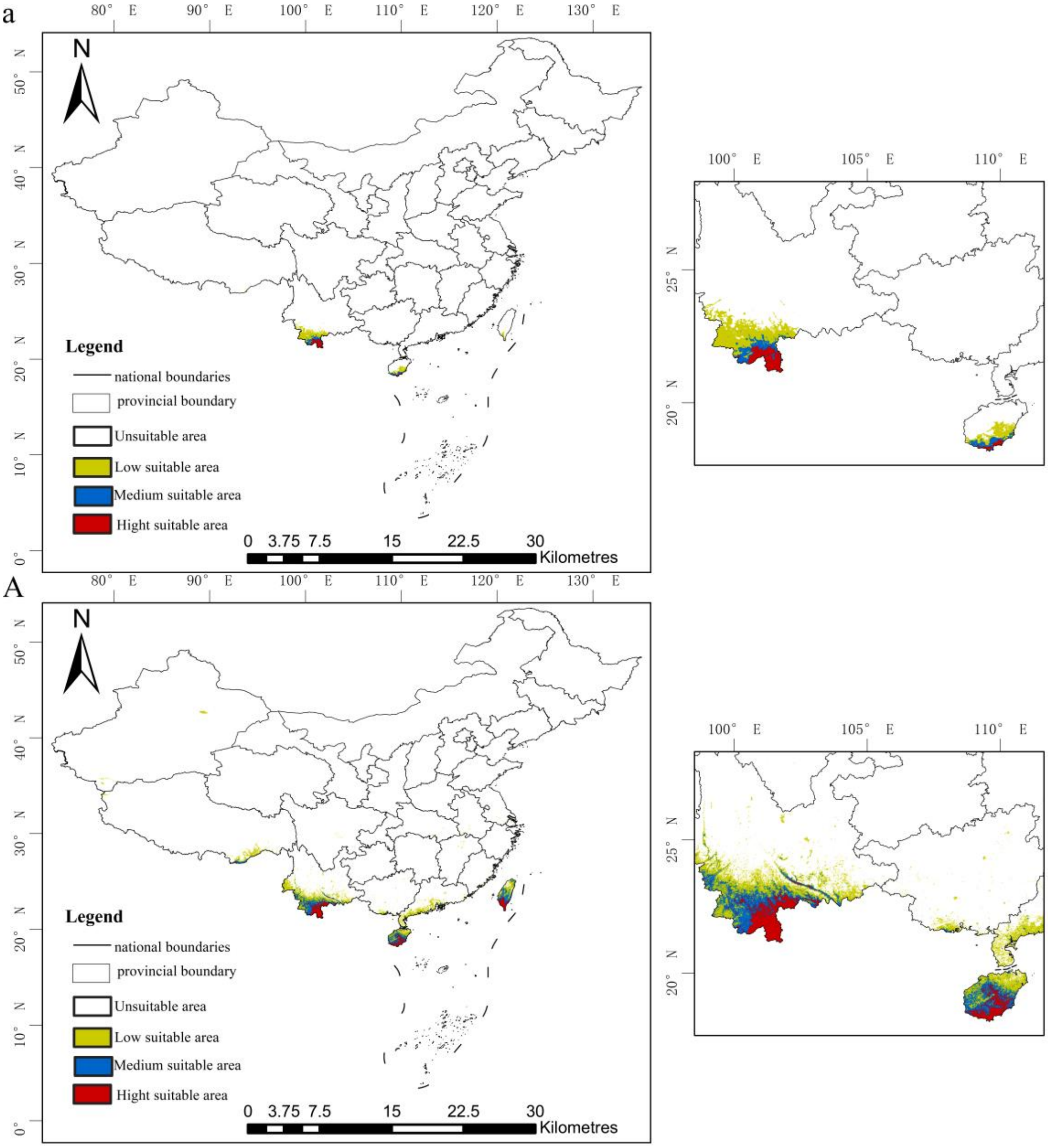

Fig. 5 Current predicted suitable habitat for *M. yunnanensis*. a: MaxEnt result; A: ensemble model result.

3.4 Future potential distribution

Under future climate scenarios, the trends predicted by MaxEnt and the ensemble model are generally consistent, with unsuitable areas dominating across all scenarios (Figure 6-9). Under SSP126 and SSP245, the area of suitable habitat is slightly reduced

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compared with the current period; whereas under SSP585, moderate and high suitability zones exhibit an expansion trend, which is most pronounced in the 2070s. For example, in the scenario 2070-SSP585, the moderate-suitability area predicted by MaxEnt is 1.29×10^4 km^2, while that predicted by the ensemble model reaches 10.11×10^4 km^2 (Table 2). These results indicate that under the high-emission scenario, the potential distribution of *M. yunnanensis* may expand, but the magnitude of expansion varies by model.

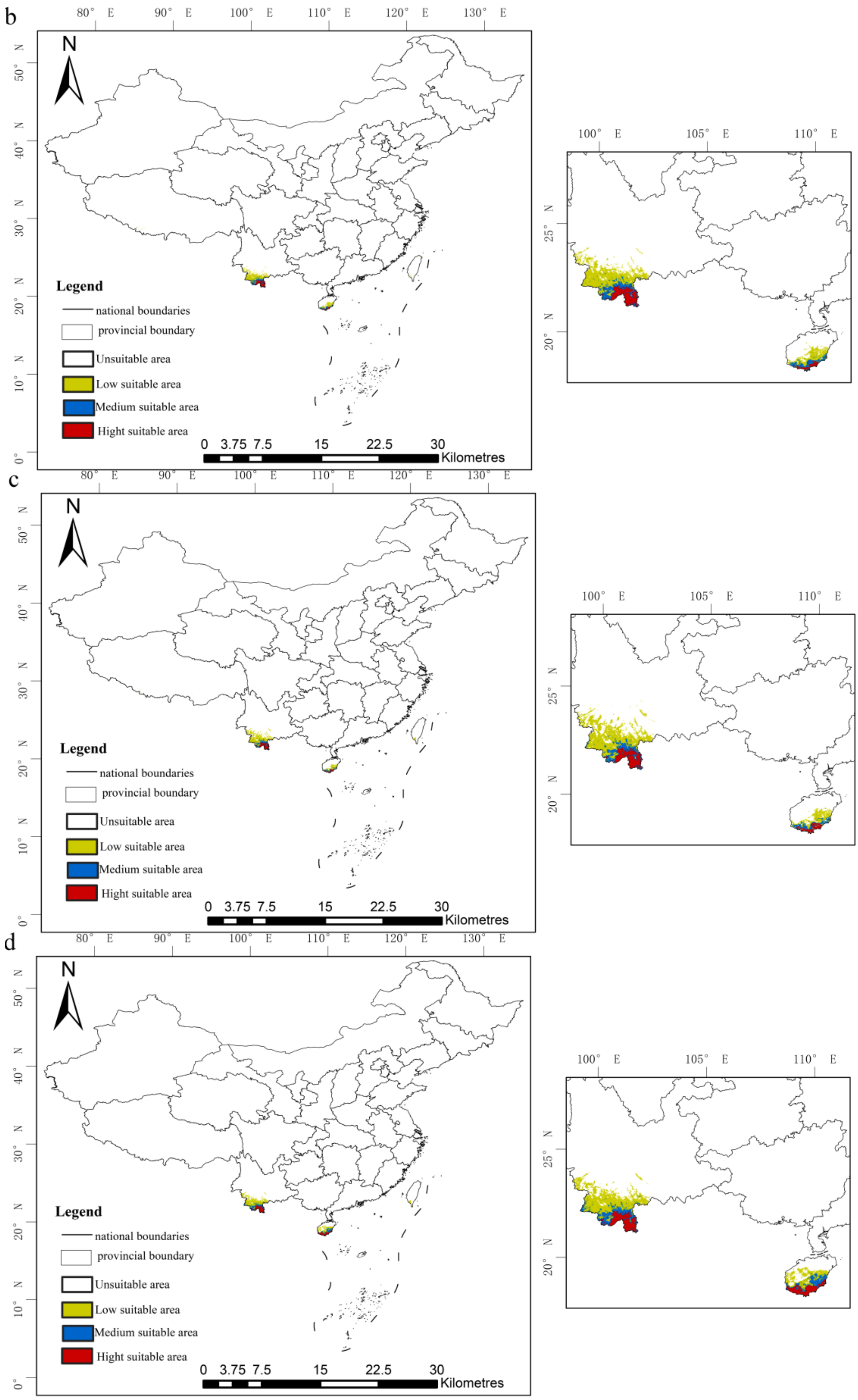

Fig. 6 MaxEnt results for the 2050s, a: SSP126, b: SSP245, c: SSP585.

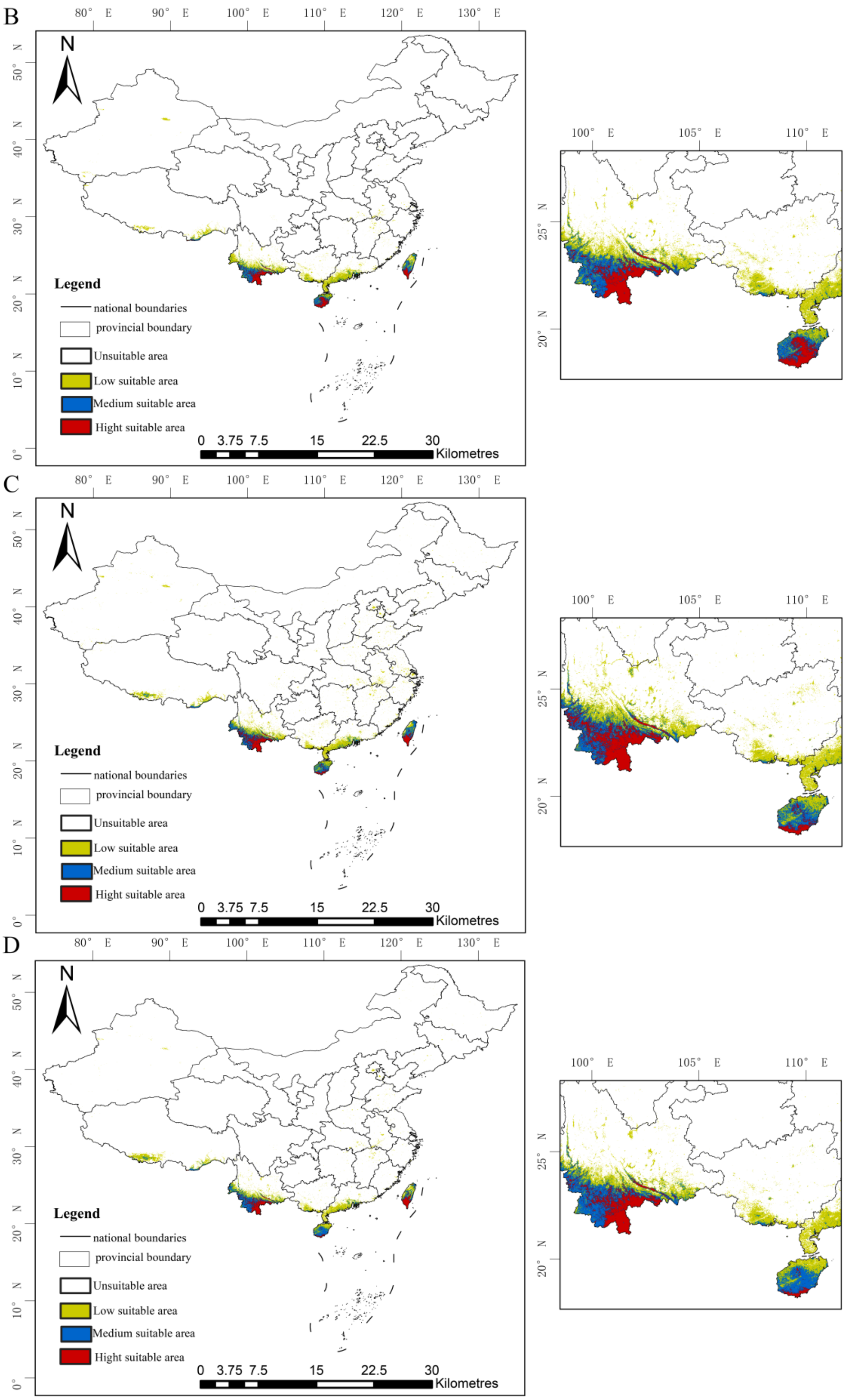

Fig. 7 Results of the ensemble model for the 2050s, A: SSP126, B: SSP245, C: SSP585.

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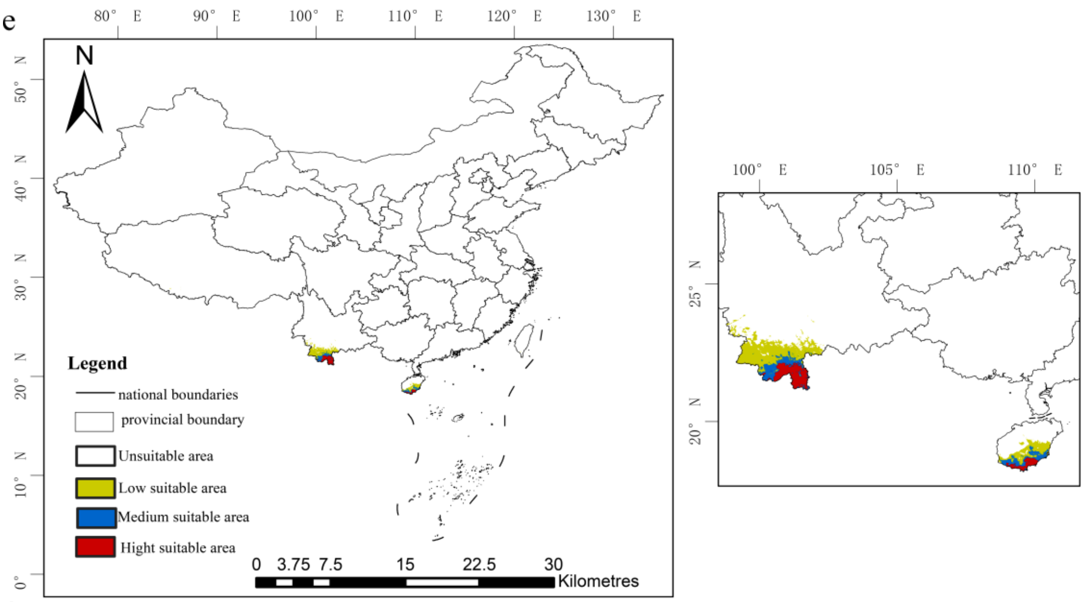
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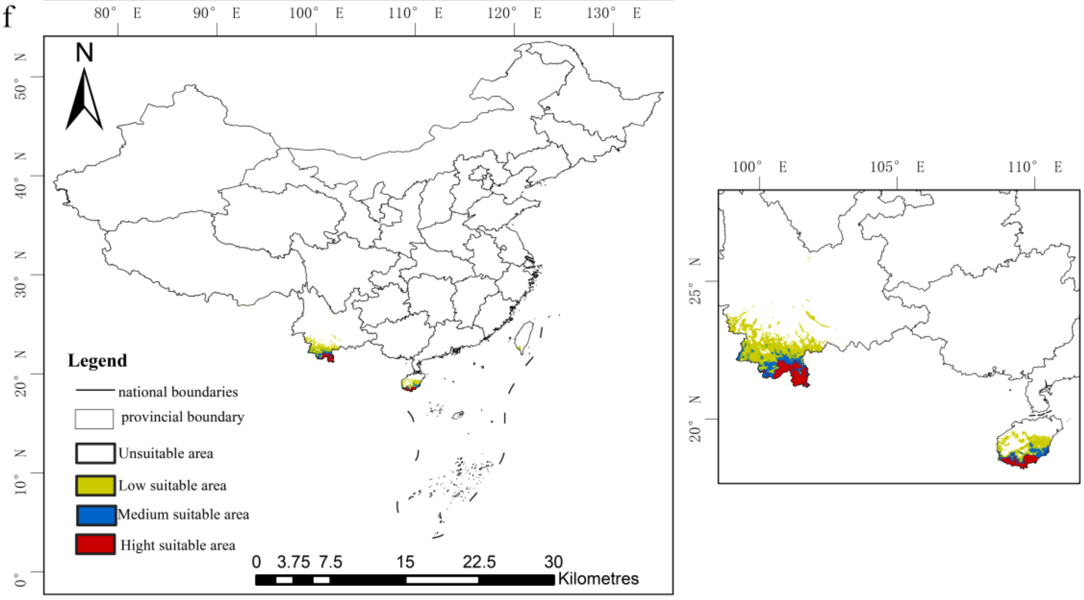
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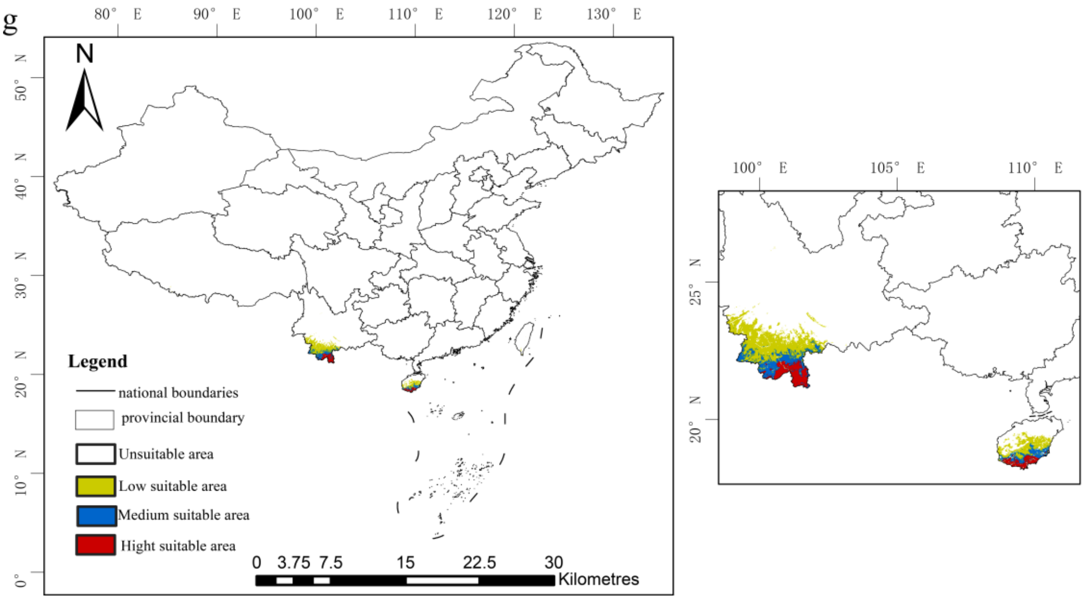
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Fig. 8 MaxEnt results for the 2070s, d: SSP126, e: SSP245, f: SSP585.

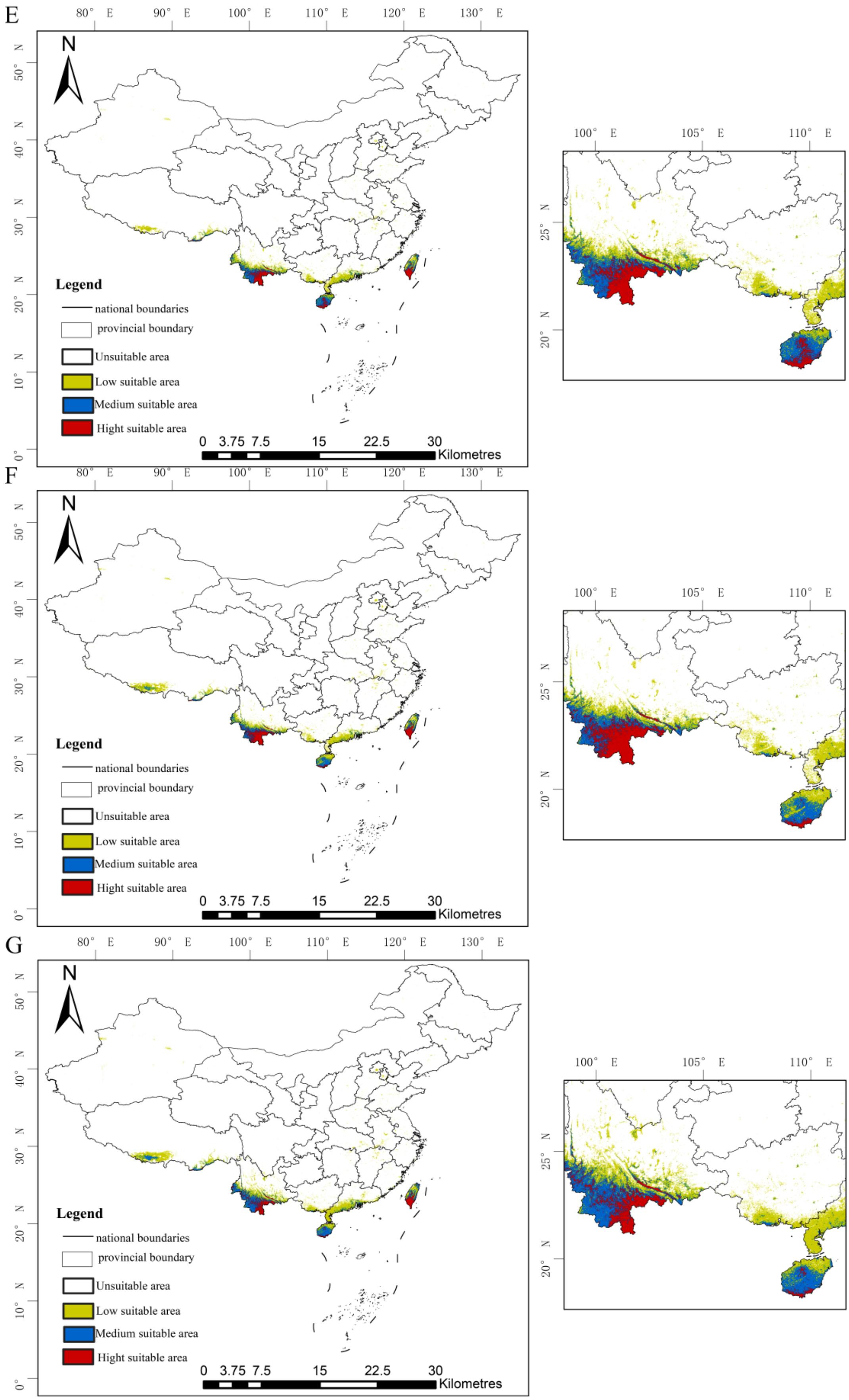

Fig. 9 Ensemble model results for the 2070s, E: SSP126, F: SSP245, G: SSP585.

3.5 Trends in the suitable habitat of M. yunnanensis under climate change

Table 2 summarizes the area predictions for unsuitable, low, moderate, and high-suitability zones under current and future climate scenarios by MaxEnt and the ensemble model. The MaxEnt results show that under current conditions, the unsuitable area is overwhelmingly dominant (956.83 $\times 10^4$ km^2), while the areas of low, moderate, and high suitability are 3.08 $\times 10^4$ km^2, 0.84 $\times 10^4$ km^2, and 0.78 $\times 10^4$ km^2, respectively. Both models indicate that the unsuitable zone occupies an absolute majority (exceeding 940 $\times 10^4$ km^2), whereas the areas of low, moderate, and high-suitability are relatively limited. In the 2050s, under SSP126 and SSP245, the MaxEnt results show a slight decline in the areas of low and moderate suitability, with the area of high suitability also decreasing (0.72–0.76). However, under SSP585, the high-suitability zone expands to 1.04 $\times 10^4$ km^2, and the moderate-suitability zone increases to 1.06 $\times 10^4$ km^2, indicating that extreme warming can promote the near-term expansion of suitable habitats. In the 2070s, under SSP126, the MaxEnt results show a further contraction of the low-suitability zone (2.52 $\times 10^4$ km^2), while the moderate- and high-suitability areas increase (0.88 $\times 10^4$ km^2 and 0.90 $\times 10^4$ km^2). Under SSP245, the moderate and high suitability areas further increase (0.96 $\times 10^4$ km^2 and 0.91 $\times 10^4$ km^2). Under SSP585, expansion is most pronounced, with the moderate suit zone increasing to 1.29 $\times 10^4$ km^2 and the high suit zone reaching 0.94 $\times 10^4$ km^2.

Compared to MaxEnt, the ensemble model predicts larger suitable areas across

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scenarios, with more pronounced differences in the moderate and high suitability categories. In the 2050s, under SSP126 and SSP245, both models predict a slight decrease in the areas of moderate and high suitability compared with the current period, whereas under SSP585 both show an expansion trend. In the 2070s, the expansion of suitable areas is more marked, especially under SSP585, where the ensemble model predicts a moderate suitability area of 10.11 $\times 10^4$ km^2, while MaxEnt predicts only 1.29 $\times 10^4$ km^2. The two models exhibit generally consistent trends across climate scenarios, but the range of suitable areas predicted by the ensemble model is clearly larger than that of MaxEnt.

Overall, although unsuitable areas remain dominant, under the high-emissions scenario (especially SSP585), the moderate and high-suitability zones show a sustained expansion trend, with the magnitude of expansion in the 2070s being notably greater than in the 2050s.

Table 2. Suitable habitat area statistics (×10^4 km²) under current and future climate scenarios predicted by MaxEnt and the ensemble model.

			Unsuitable survival	Low fitness	Medium fitness	High fitness
current		maxent model	956.826	3.082569	0.837986	0.784792
		ensemble model	942.4039	10.99847	5.082292	3.046736
2050s	SSP126	maxent model	957.2601	2.719375	0.829306	0.722639
		ensemble model	936.0383	14.5409	6.731736	4.220486
	SSP245	maxent model	956.9413	3.009653	0.816944	0.763472
		ensemble model	931.4899	16.94431	8.147014	4.950139
	SSP585	maxent model	956.3852	3.041944	1.06	1.044236
		ensemble model	935.1104	14.61396	7.816528	3.990486
2070s	SSP126	maxent model	957.234	2.522153	0.876319	0.898889
		ensemble model	936.033	13.67125	7.296805	4.530347
	SSP245	maxent model	956.3903	3.272431	0.958403	0.910278
		ensemble model	934.4186	15.41875	6.959583	4.734444
	SSP585	maxent model	955.9837	3.318403	1.292639	0.936597
		ensemble model	928.6468	18.5066	10.10563	4.272361

3.6 Overlap of Suitable Areas

To compare the differences in predicted distributions between MaxEnt and the ensemble model, we used the ‘Mosaic to New Raster’ tool in ArcGIS 10.8.1 (with the LAST option) to overlay binarized (presence/absence) outputs of the two models, generating an overlap map (figure). After classifying suitability within the overlap and conducting area statistics, we found that the locations and areas of each suitability class in the final overlap region were consistent with the MaxEnt results.

4 Discussion

4.1 Performance and differences of the model

Both the MaxEnt model and the ensemble model achieved high predictive accuracy, with MaxEnt performing slightly better, reflecting its advantages in handling presence–background data and capturing species–environment relationships. The differences between MaxEnt and the ensemble model highlight the inherent uncertainty in species distribution modeling. This uncertainty arises from algorithmic assumptions, data-processing procedures, and the choice of evaluation metrics. While multi model ensembles help reduce the bias of single methods, they may also lead to broader predicted ranges(Rose et al. 2024). Therefore, identifying areas of agreement between MaxEnt and the ensemble results is especially important, as these overlap regions represent the most reliable core suitable habitats. This approach aligns with best practices in climate impact assessment, i.e., enhancing robustness through multimodel consensus. In addition, the differences between the two are not substantial, and this consistency increases the robustness and credibility of the study's conclusions (Harris et al. 2023; Rose et al. 2024; Zipkin & Doser 2024).

The greatest difference between the two models lies in the estimation of the suitable-area extent. MaxEnt consistently predicts smaller and more conservative moderate- and high-suitability areas, whereas the ensemble model predicts a markedly larger expansion. This mainly stems from methodological differences: MaxEnt tends to identify a narrower niche range with higher specificity, while the ensemble model, integrating multiple algorithms (GLM, RF, GAM, GBM) captures broader ecological tolerance and may thus overestimate suitable areas, yielding more generalizable predictions with wider extent. Such differences underscore the complementary value of the two modeling strategies and have been reported in recent studies, where ensemble models often provide more comprehensive but relatively less conservative predictions (Hosseini et al. 2024; Zhang et al. 2024).

Despite differences in magnitude, the two models show consistent temporal trends. Across all scenarios, unsuitable areas remain dominant, while moderate- and high-suitability areas expand under high-emissions pathways, especially SSP585 in the 2070s. For example, MaxEnt predicts that the high-suitability area will increase from 0.78×10^4 km^2 to 0.94×10^4 km^2, whereas the ensemble model projects a larger expansion, from 3.05×10^4 km^2 to 4.27×10^4 km^2. This suggests that *M. yunnanensis* may experience an expansion of the potential distribution under future warming, although the extent of expansion remains uncertain(Nan et al. 2024; Shen et al. 2024).

4.2 Response of M. yunnanensis to ecological factors

The high contribution of temperature seasonality (bio3) indicates that *M. yunnanensis* tends to occur where interannual temperature fluctuations are small and seasonality is moderate, which may be relate to its physiological and ecological traits: stable temperature conditions favor seed germination and seedling establishment, whereas frequent or intense temperature fluctuations increase exposure of seedlings to adverse climates (late spring frost or summer heat), thereby reducing population renewal rates. The maximum temperature of the warmest month (bio4) is directly related to extreme heat events: excessively high maxima can affect seed physiological function, lower germination rates, and severely affect seedling photosynthesis and water balance, increasing mortality; recent SDM applications similarly highlight bio3–

bio4 as dominant constraints in warm regions(He et al. 2024).

The mean temperature of the driest quarter (bio9) reflects the combined effects of heat and drought stress; several studies indicate that its joint action exerts a synergistically negative effect on seedling growth and survival, leading to increased seedling mortality and regeneration failure. Consistent with this, recent modeling work identifies BIO9 as a key predictor of future distributional change in tree species and a common important variable across taxa(Shi et al. 2024).

4.3 Overlap Regions

The overlap of suitable areas jointly predicted by MaxEnt and the ensemble model represents the most robust habitat, as it minimizes uncertainty due to model-specific characteristics. Although ensemble models often predict broader ranges and MaxEnt is more conservative, the ‘complete overlap’ observed here essentially means that the suitable core area predicted by MaxEnt is entirely contained within the broader potential suit predicted by the ensemble model. The MaxEnt result forms the most reliable ‘kernel’ of model consensus. In conservation planning, this overlap region can be regarded as the area with the highest likelihood of species occurrence and the best environmental match. Consequently, integrating overlap results from different models yields predictions that are less sensitive to modeling choices and highly robust, helping to delineate core protected areas and providing a tiered reference for future habitat management(Harris et al. 2023; Rose et al. 2024).

4.4 Significance of the Ecological and Conservation Environment

From a conservation perspective, the expansion of suitable areas under high-emission scenarios offers potential opportunities for *M. yunnanensis*. However, such expansion may not translate into stable population distributions, as it may be constrained by habitat fragmentation, limited dispersal, and human disturbance. Recent studies show that fragmentation can reduce plant functional diversity and compromise ecosystem functioning, while dispersal assumptions (limited vs. unlimited) strongly condition 2061–2080 projections (Ortega et al. 2024; Yu et al. 2024); intensive human activities also degrade habitat quality in vulnerable regions(Sun et al. 2024).

To reduce risk, priority should be given to areas consistently predicted as suitable by both MaxEnt and the ensemble model. These areas are most likely to remain suitable under future climates and should therefore be focal regions for habitat protection and management planning; in particular, management that identifies and safeguards climate change refugia provides a practical pathway to maintain populations under warming(Keppel et al. 2024).

5 Conclusions

Using the MaxEnt model and an ensemble modeling framework (GLM, RF, GAM, GBM), this study predicted the potential distribution of *M. yunnanensis* in current and multiple future climate scenarios. The results indicate that temperature-related factors (temperature seasonality, extreme high temperatures in the growing season, and mean temperature of the dryest quarter) are the key drivers affecting their distribution, underscoring the species’ high sensitivity to thermal environments. Both approaches demonstrated high predictive accuracy, with MaxEnt performing slightly better on evaluation metrics, while the ensemble model predicted larger suitable areas. Despite differences in magnitude, both consistently indicate an expansion trend in moderate- and high-suitability areas under high-emission scenarios, particularly SSP585 in the 2070s.

The differences between MaxEnt and the ensemble predictions highlight the importance of considering the uncertainty of the model in species distribution research. Multi-model ensembles can enhance robustness, and the overlap region where both models agree can be regarded as the most reliable core suitable area. From a conservation point of view, our findings suggest prioritizing stable, overlapping habitats as key targets for future habitat management and protection. Overall, this study provides new insights into how climate change may affect the potential distribution of *M. yunnanensis* and offers a scientific basis for developing conservation strategies under future environmental change.

Statements and Declarations

Acknowledgments: This study was funded by the Research Start-up Fund (A2032023917) and the Basic Research Project for Young Talents of Yunnan Provincial Department of Education (KBA3012023045026).

The authors declare that they have no competing interests.

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Data Availability

The research data, software, code, and results have been uploaded to Zenodo, DOI: https://doi.org/10.5281/zenodo.17174837

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