RESEARCH ARTICLE

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Projecting the Potential Distribution of Pinus Taiwanensis Under Climate Change Using Ensemble Modeling in Biomod2

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Abstract

The continuous rise in global atmospheric carbon dioxide has profoundly altered climate patterns and the spatiotemporal balance of hydrothermal conditions at regional scales. Understanding species' responses to climatic factors is thus critical for biodiversity conservation. This study focuses on Pinus taiwanensis, analyzing changes in its suitable habitat using distribution data and environmental variables. Employing the biomod2 ensemble model, potential habitats were predicted under three climate scenarios (SSPs126, SSPs370, SSPs585) for the present, 2050, and 2090. Results show: (1) Model performance is excellent (AUC > 0.9, TSS > 0.8). (2) Temperature-related factors (isothermality, diurnal range) play dominant roles, followed by precipitation. (3) Future climate changes may lead to moderate habitat expansion. (4) The centroid of suitable habitat is projected to shift northeastward, with higher probability of a northwestward shift. (5) The SSPs585 scenario shows the greatest deviation from the current climate, with diurnal range as the least similar variable in 2050 and isothermality in 2090. In conclusion, climate change will reshape the potential distribution of Pinus taiwanensis, with habitat dynamics driven by the combined effects of dominant and secondary environmental factors.

Keywords: biomod2 model, pinus taiwanensis, climate change, potential habitat suitability.

1 Introduction

Climate change has disrupted the regional hydrothermal balance, severely impacting species' reproduction, growth, and distribution [1–3]. It poses a significant threat to species survival and development, particularly for those with restricted habitats, forcing them to adapt to new environments

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or undergo geographical migration [4]. Therefore, investigating how species respond to climate change under global climate change scenarios has become a key issue of international concern.

Species' responses to climate change are typically reflected in shifts in geographical range and phenological changes, while climate change directly affects the spatiotemporal variation of climatic factors associated with species' climatic niches [5]. During habitat adaptation, species often alter their original distributions through migration and dispersal processes to recolonize suitable habitats [6]. In response to climate change, many species have already modified their original horizontal (latitudinal, longitudinal) and vertical (altitudinal) distribution ranges, particularly those already inhabiting high-latitude and high-altitude regions. Changes in species distribution ranges are often multidirectional and exhibit more complex responses to climate change than anticipated [7].

Species Distribution Models (SDMs) are critical and effective tools based on niche theory for studying the impact of climate change on species distributions [8]. These models correlate known species occurrence data with corresponding habitat variables to probabilistically reflect habitat suitability, explaining species occurrence probability, habitat suitability, or species richness. They further serve as quantitative models to assess changes in species distribution ranges and their driving factors [9]. Currently, commonly used SDMs include Generalized Linear Models (GLM), Boosted Regression Trees (GBM), Classification and Regression Trees (CTA), Artificial Neural Networks (ANN), Surface Range Envelopes (SRE), Flexible Discriminant Analysis (FDA), Random Forests (RF), Ecological Niche Factor Analysis (ENFA), Genetic Algorithm for Rule-set Prediction (GARP), Bioclimatic Envelope (BIOCLIM), and Maximum Entropy (MaxEnt) models [10–13]. However, most species distribution prediction studies rely on single-model approaches. Due to differences in theory, assumptions, algorithms, data independence, and representativeness—as well as varying applicability across species—single-model predictions often lack stability and exhibit certain biases [14].

The Biomod2 species distribution modeling framework, implemented on the R platform, integrates 10 common SDMs. By applying an Ensemble Model (EM) strategy, it performs multiple independent runs under different initial conditions, parameter optimizations, and constraints. This approach comprehensively analyzes the commonalities, discrepancies, and uncertainties across all model outputs. By separating the "signal" (true species-environment relationships) from the "noise" (data errors and model uncertainties), it reduces uncertainties arising from different modeling methods and non-independent evaluation samples, thereby improving predictive accuracy [15, 16]. This framework addresses the challenge of selecting appropriate SDMs for predicting species' potential distributions [17] and has gained widespread recognition and application due to its ability to overcome the limitations of single-model approaches [18–21].

Pinus taiwanensis, an endemic tree species in China, is an important afforestation and ecological restoration species in subtropical regions, as well as a valuable timber resource. It plays a vital ecological and economic role in mountain vegetation recovery, carbon sequestration, water conservation, and medicinal exploitation of coniferous traits [22]. Pinus taiwanensis forests often exist as pure stands fragmented by plains and lakes, forming discontinuous "island-like" distributions. Due to severe threats from climate change and pine wilt disease, Pinus taiwanensis communities are exhibiting declining trends [23]. Thus, this species warrants special attention in biodiversity conservation under global climate change. Current research on Pinus taiwanensis primarily focuses on spatial patterns [24], ecological niches [25], community characteristics and succession dynamics [26], and pest control [27], with relatively few studies on its response to climate change. Although some scholars have used the MaxEnt model to predict its potential distribution under climate change based on occurrence records and habitat factors [28], MaxEnt as a single model carries risks of overfitting and inherent limitations [29].

Therefore, this study employs the Biomod2 ensemble modeling framework to predict shifts in suitable habitats for Pinus taiwanensis under future climate scenarios using known distribution data. The objectives are to identify range contraction zones, determine future migration centers, and provide a theoretical basis for developing conservation and sustainable utilization strategies to alleviate China's severe timber shortages.

2 Data Sources and Methods

2.1 Data Source and Processing of Pinus taiwanensis Distribution

Distribution point data for Pinus taiwanensis were obtained through the following methods: Firstly, electronic databases, primarily the Global Biodiversity Information Facility (GBIF[1]), China Field Herbarium (CFH[2]), Chinese Virtual Herbarium (CVH[3]), National Specimen Information Infrastructure (NSII[4]), and Flora of China Data (FRPS[5]). Secondly, literature searches were conducted using electronic literature databases like China National Knowledge Infrastructure (CNKI) and Web of Science (WOS), filtering by keywords to retrieve target information. The obtained coordinate data were processed using ArcGIS 10.8 and saved in .csv format as required by the biomod2 model for future use. The distribution of Pinus taiwanensis was showed in Figure 1.

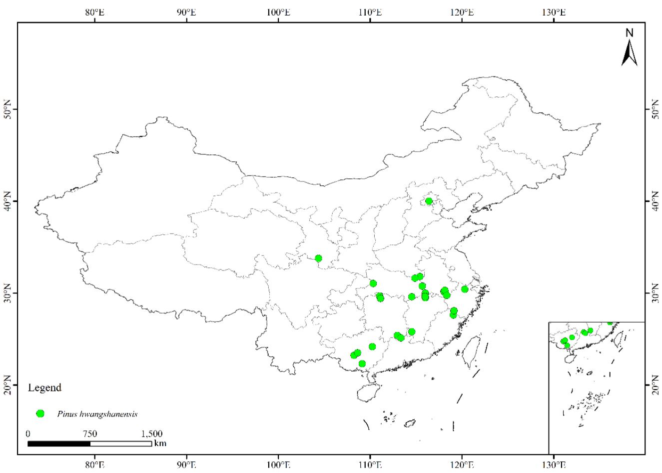

Figure 1. Distribution of pinus taiwanensis.

2.2 Acquisition of Environmental Factor Data

The relevant environmental factor data used in this study are listed in Table 1, including climate, soil, topography, and other related factors. Climate factor data with a resolution of 30 arc-seconds were obtained from the WorldClim climate database[6]. Future climate data were derived from the BCC-CSM1-1 model under three Shared Socioeconomic Pathway scenarios: SSPs126 (low greenhouse gas emissions), SSPs370 (medium greenhouse gas emissions), and SSPs585 (high greenhouse gas emissions) [?]. Elevation data (Digital Elevation Model, DEM) with a resolution of 30m were obtained from the Geospatial Data Cloud[7]. Aspect and slope were extracted using ArcGIS 10.8 [30]. Relevant soil data were acquired from the World Soil Database[8] [31].

When building species distribution models, multicollinearity among environmental factors can lead to model overfitting, affecting the reliability of prediction results. To optimize variable selection, the following screening steps were applied: First, identify highly correlated environmental variables based on a Pearson correlation coefficient matrix (threshold $|r| > 0.8$). Second, evaluate the importance of each variable through the factor contribution rate output by the models. Finally, retain factors with high contribution rates and low correlation with other variables, eliminating redundant variables. Constructing the biomod2 model using the screened environmental variables effectively reduces interference from redundant information, thereby enhancing model predictive performance.

2.3 Biomod2 Model Construction and Evaluation

This study used the biomod2 package within the R platform (v4.3.3). Distribution points of Pinus taiwanensis and the selected environmental factors were imported into biomod2 to construct 12 species distribution models. The models used include: Generalized Additive Model (GAM), Maximum Entropy Neural Network Model (MaxNet), Flexible Discriminant Analysis (FDA), Generalized Boosted Regression Tree Model (GBM), Classification Tree Analysis (CTA), Multivariate Adaptive Regression Splines (MARS), Surface Range Envelope (SRE), Extreme Gradient Boosting Model (XGBOOST), Maximum Entropy Model (MaxEnt), Generalized Linear Model (GLM), Random Forest Model (RF), and Artificial Neural Network Model (ANN). Using environmental background sampling, 500 pseudo-absence background points were randomly generated within the species distribution raster data. The data were randomly split into training and validation sets at a 3:1 ratio. To account for sample size differences, appropriate weighting was applied to both sets during model training [32]. Model prediction performance was comprehensively evaluated using the Receiver Operating Characteristic (ROC) curve and the True Skill Statistic (TSS) metrics. The Area Under the Curve (AUC) of the ROC curve is one of

[1]https://www.gbif.org/
[2]http://www.cfh.ac.cn/
[3]https://www.cvh.ac.cn/
[4]http://www.nsii.org.cn/
[5]http://www.iplant.cn/frps
[6]https://www.worldclim.org/
[7]http://www.gscloud.cn/
[8]https://www.fao.org/

Table 1. Environmental factors.

Factor type	Code	Environmental factor description
Climate	AMT	Annual Mean Temperature
	DATR	Daily average temperature range
	Iso	Isothermality
	SVCT	Seasonal variation coefficient of temperature
	MTWAM	Max Temperature of Warmest Month
	MTCM	Min Temperature of Coldest Month
	TAG	Temperature Annual Range
	MTWEQ	Mean Temperature of Wettest Quarter
	MTDQ	Mean Temperature of Driest Quarter
	MTWAQ	Mean Temperature of Warmest Quarter
	MTCQ	Mean Temperature of Coldest Quarter
	AP	Annual Precipitation
	PWEM	Precipitation of Wettest Month
	PDM	Precipitation of Driest Month
	SVCP	Seasonal variation coefficient of Precipitation
	PDQ	Precipitation of Driest Quarter
	PWEQ	Precipitation of Wettest Quarter
	PWAQ	Precipitation of Warmest Quarter
	PCQ	Precipitation of Coldest Quarter
Topography	altitude	altitude
	aspect	aspect
	slope	slope
Soil	awc_class	Soil Available Water Content
	s_ph_h2o	Subsoil pH
	s_oc	Subsoil Organic Carbon Content
	t_oc	Topsoil Organic Carbon Content
	t_ph_h2o	Topsoil pH
Other	ndvi	Normalized Difference Vegetation Index
	lucc	Land Use Type

the most widely accepted and effective indicators for evaluating SDMs. AUC is independent of specific diagnostic thresholds and shows low sensitivity to changes in species presence frequency, ensuring objective and accurate assessment. The AUC value ranges from 0.5 to 1, with higher values indicating better predictive accuracy. The True Skill Statistic (TSS) serves as an improved model evaluation metric, retaining the strengths of the Kappa statistic while overcoming issues with unimodal species presence distributions. A TSS value approaching 1 indicates superior model prediction performance [32].

After establishing the single models, those with TSS $\geq$ 0.8 were selected based on accuracy requirements. An ensemble model was constructed using the weighted mean method (EMwmean), and the model with the highest accuracy was chosen for subsequent research [33]. Utilizing the model ensemble module of the biomod2 package, a performance-based weighted combination scheme was implemented. This strategy uses the AUC evaluation value of each single model as the weight parameter and applies a weighted averaging algorithm to generate the ensemble prediction, giving greater weight to models with higher predictive accuracy in the final combined model. Based on the maximum TSS threshold method, the potential distribution area of Pinus taiwanensis was classified into two major habitat types: suitable ($P \geq$ threshold) and non-suitable ($P <$ threshold). The suitable area was further subdivided into three grades using the Jenks Natural Breaks classification method, generating high, medium, and low suitability levels, thus classifying the potential suitable habitat of Pinus taiwanensis into four categories. Through the ensemble model's variable response curves and contribution rate analysis, the relative importance of various ecological factors to distribution prediction was determined [10]. Model prediction results can be classified according to the following AUC grades: No predictive value ($0 \leq \text{AUC} < 0.6$); Limited predictive ability ($0.6 \leq \text{AUC} < 0.7$); Moderate predictive accuracy ($0.7 \leq \text{AUC} < 0.8$); Good predictive performance ($0.8 \leq \text{AUC} < 0.9$); Excellent predictive performance ($0.9 \leq \text{AUC} \leq 1.0$) [34].

2.4 Multivariate Environmental Similarity Surfaces (MESS) and Most Dissimilar Variables (MOD)

This study used Multivariate Environmental Similarity Surfaces (MESS) and Most Dissimilar Variable (MOD) methods to quantitatively assess the differences between future climate scenarios and the current climate scenario. By calculating the climate similarity index (S), key driving factors influencing the potential distribution area of Pinus taiwanensis under future climate scenarios were explored. If $S > 0$, a larger positive S value indicates a greater difference between the future climate conditions in the study area and the current conditions. When $S = 0$, it signifies that future climate conditions are identical to the current ones. If $S < 0$, at least one environmental variable in the future climate scenario exceeds the current climate range. This point is a climate anomaly point, and a larger absolute value indicates a greater difference in climate conditions. This study established a reference baseline using the climate metrics from the current suitable range of Pinus taiwanensis. By integrating MESS and MOD spatial algorithms, it analyzed the correlation between future climate factors and current climate conditions, thereby identifying areas where climate anomalies may occur within the suitable habitat of

Pinus taiwanensis under future climate change and the corresponding anomalous climate factors [35].

2.5 Suitability Grading for Pinus taiwanensis Habitat

Using the raster data of species distribution probability output from the biomod2 ensemble model, the study area for Pinus taiwanensis was classified into four ecological response units based on suitability gradients using the Raster Reclassification tool in the Spatial Analyst module of ArcGIS 10.8: Non-suitable area (0.0-0.2), Low suitability zone (0.2-0.6), Medium suitability zone (0.6-0.8), and High suitability zone (0.8-1.0) [36]. A spatial measurement matrix was constructed to characterize the spatial occupancy characteristics of each suitability grade under different climate scenarios. Using spatial overlay analysis tools, the current suitable distribution range was spatially erased with the potential distribution range under future climate conditions to obtain spatial distribution patterns of habitat reduction rate (future range minus current range) and expansion rate (current range minus future range).

2.6 Centroid Shift of Pinus taiwanensis Habitat

Based on the distribution centroid extraction tool in ArcGIS 10.8, this study extracted the spatial geometric centroid coordinates of high suitability areas (probability value ≥ 0.8) under the three climate scenarios (SSPs126, SSPs370, SSPs585). The spatial transformation characteristics along the climate pathway were compared across three time periods: baseline (2020s), mid-century (2050s), and end-century (2090s). By constructing migration trajectories of the geometric center under multidimensional climate scenarios, the dynamic shift patterns of the spatial centroid of the ecologically suitable core area were analyzed. Specifically, continuously distributed suitable habitat patches were merged into a single vector point. A geographic vector field model was established based on the spatiotemporal offset of the centroid coordinates, enabling the visualization of its spatial migration.

3 Results and Analysis

3.1 Selection of Environmental Predictors and Ensemble Modeling

To prevent model overfitting due to multicollinearity among environmental variables, which affects model precision, species distribution sample points were plotted onto 29 contemporary climate factor layers. Pearson correlation analysis of environmental factors was performed in R software. When the correlation coefficient $|r|$ between two climate factors exceeded 0.8, the climate factor with the highest contribution value was retained. The correlation analysis result of environmental factors was showed in Figure 2. Consequently, this study selected 7 climate factors (Precipitation of Driest Month (PDM), Min Temperature of Coldest Month (MTCM), Mean Diurnal Range (DATR), Precipitation of Warmest Quarter (PWAQ), Temperature Annual Range (TAG), Seasonal variation coefficient of Precipitation (SVCP)), 4 soil factors (Soil Available Water Content (awc_class), Subsoil pH (s_ph_h2o), Topsoil Organic Carbon Content (t_oc)), 3 topographic factors (Elevation (altitude), Slope (slope), Aspect (aspect)), and Land Use/Land Cover (lucc), Normalized Difference Vegetation Index (ndvi). Comprehensive analysis within the biomod2 ensemble model highlighted PWAQ, PDM, Iso, and TAG, indicating that temperature and precipitation are the most influential factors on the distribution of Pinus taiwanensis (see Figure 3).

Figure 2. The correlation analysis result of environmental factors.

Model outputs revealed that the average AUC values for Pinus taiwanensis in future periods (2050s and 2090s) were all greater than 0.9 (see Figure 4), and TSS values reached above 0.85. The model validation results demonstrate that the biomod2 modeling framework exhibits high reliability in predicting suitable habitats.

After creating pseudo-absence points twice and

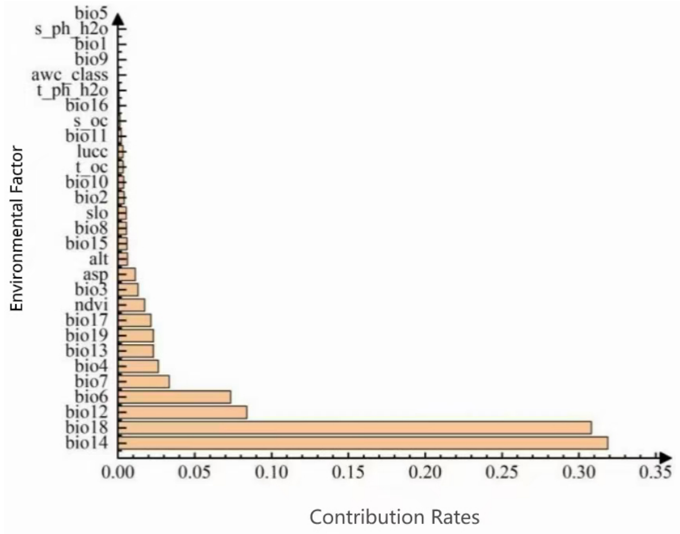

Figure 3. Environmental factor contribution rates.

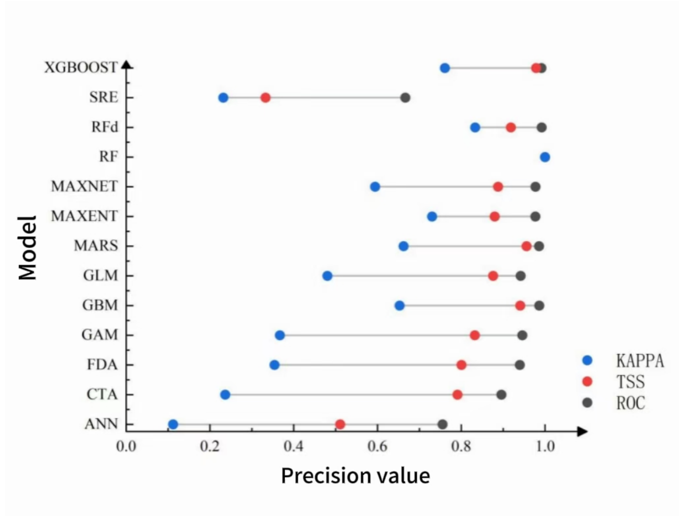

Figure 4. Model accuracy evaluation.

running each single model 10 times, evaluation results (KAPPA, TSS, AUC) for 13 single models were obtained (Figure 4). The Artificial Neural Network model (ANN) had AUC, TSS, and KAPPA values of 0.75, 0.51, and 0.11, respectively. The Surface Range Envelope model (SRE) had AUC, TSS, and KAPPA values of 0.66, 0.33, and 0.23, respectively. Both failed the model accuracy test. The remaining single models all had AUC and TSS values above 0.8 and 0.6, respectively, indicating excellent model performance. To further optimize the algorithm, models with AUC > 0.90 and TSS > 0.80 were selected for ensemble model (EM) construction, including GBM, GLM, MARS, RF, and XGBOOST. The resulting EM achieved a mean AUC of 0.97 and a mean TSS of 0.85, representing improvements of 0.05 and 0.08 over the average AUC and TSS values of the single models. These data indicate that this ensemble model has a clear advantage in predicting the suitable growth area for Pinus taiwanensis.

3.2 Potential suitable habitats of Pinus taiwanensis under current climatic scenarios

The Biomod2 output results were visualized using ArcGIS 10.8 (see Figure 5). Calculate the raster data of the layer through the Raster to Polygon tool (Table 2). Table 2 and Figure 5 show that the total area of ecologically suitable habitat for Pinus taiwanensis is 257.62 ten thousand square kilometers, exhibiting significant spatial heterogeneity with gradient characteristics. Specifically, the High Suitability (HS) distribution area covers 86.53 ten thousand square kilometers, the Medium Suitability (MS) area is 71.35 ten thousand square kilometers, and the Low Suitability (LS) area spans 99.73 ten thousand square kilometers. Overall, high suitability areas account for approximately 33.59% of the total suitable area. In contrast, low suitability areas, constituting 38.71%, are the dominant type. Non-suitable areas, lacking suitable biological conditions, dominate the study region, covering approximately three-quarters (76%) of the total study area. Furthermore, by reclassifying the raster data within the study area in ArcGIS 10.8, it is visually evident that the high suitability zones for Pinus taiwanensis are primarily concentrated in southeastern China.

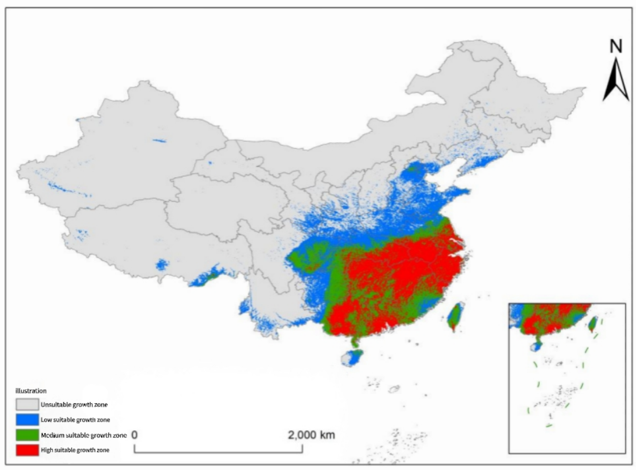

Figure 5. Classification of habitat suitability grades for pinus taiwanensis under current climate scenario.

3.3 Prediction of Suitable Habitat for Pinus taiwanensis under Future Climate Scenarios

The distribution of Pinus taiwanensis in the future was predicted using the biomod2 ensemble model and visualized for suitability in ArcGIS 10.8 (see Figure 6).

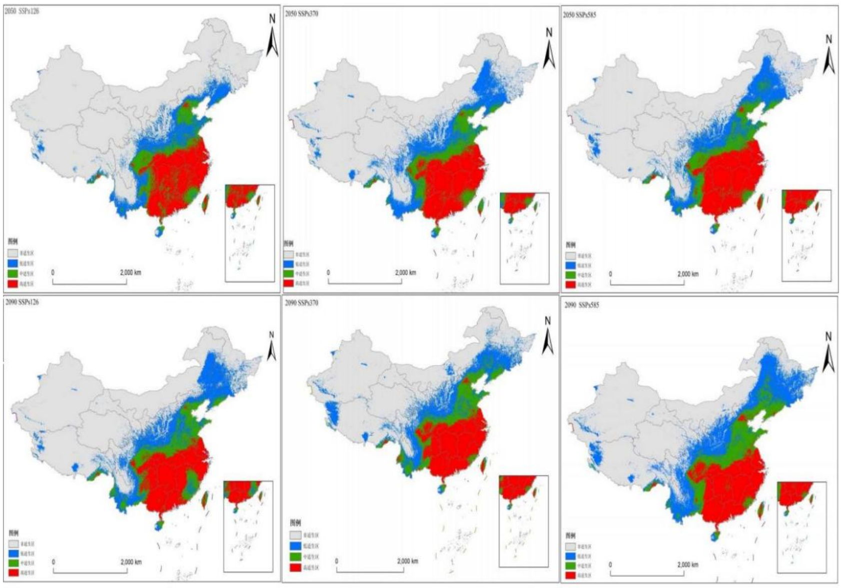

Figure 6. Suitability grading of pinus taiwanensis habitat under future climate scenarios.

Table 2. Area of contemporary suitable habitat for pinus taiwanensis.

Index	Type	Value
Suitable Area (km^2)	Non-suitable	8238143.6
	Low suitability	997330.7
	Medium suitability	713530.3
	High suitability	865326.1
	Total Suitable	2576187.1
Proportion of Suitable Area (%)	Low suitability	38.71%
	Medium suitability	27.70%
	High suitability	33.59%

The area was subsequently calculated by converting raster to polygon (see Table 3).

Based on SSPs126 scenario simulations, the total potential suitable habitat area for Pinus taiwanensis by 2050 could reach 325.95 ten thousand square kilometers. Compared to the present, the medium suitability, high suitability, and total suitable areas show increases of 0.16%, 0.19%, and 0.19%, respectively. By 2090 under this scenario, the total suitable area expands to 4,083,676.5 km^2, with the high suitability area increasing by 0.21%, and the medium suitability and total suitable areas increasing by 0.19% and 0.18%, respectively.

Based on SSPs370 scenario simulations, by 2050, the total potential suitable habitat area for Pinus taiwanensis is projected to reach 395.40 ten thousand square kilometers. Compared to the current climate baseline, medium suitability, high suitability, and total suitable areas show increases of 0.19%, 0.18%, and 0.17%, respectively. Extending to 2090, the suitable habitat area expands to 441.94 ten thousand square kilometers, with the medium suitability increase rising to 0.21%, the high suitability increase reaching 0.24%, and the total suitable area increasing by 0.19%.

Under the SSPs585 scenario simulation, by 2050, the total potential suitable habitat area is projected to be 398.87 ten thousand square kilometers. Compared to the current baseline, the medium suitability area increases by 0.19%, the high suitability area increases by 0.23%, and the total suitable area increases by 0.18%. By 2090 under this scenario, the suitable area further expands to 479.25 ten thousand square kilometers, with the medium suitability increase reaching 0.20%, the high suitability increase reaching 0.24%, and the total suitable area increasing by 0.20%.

3.4 Analysis of Centroid Shift in High Suitability Areas of Pinus taiwanensis under Different Climate Scenarios

Raster data layers for the current period and for the 2050s and 2090s under the three climate scenarios were imported into ArcGIS 10.8. Each layer was reclassified into four categories. Features with attribute value 4 (High suitability) were selected. Each layer was converted from raster to polygon, renamed accordingly. The Mean Center tool was then used to visualize the centroid of the high suitability area for each layer, which were then plotted (see Figure 7).

According to Table 4 and Figure 7, the centroid position of the high suitability area for Pinus taiwanensis in the current period is (111.821652°E, 31.294436°N). Under the SSPs126 scenario, the predicted centroid positions for the 2050s and 2090s are (111.100804°E, 32.378402°N) and (111.559171°E, 35.076825°N), with migration directions of northeast and northwest, respectively. Under the SSPs370 scenario, the predicted centroid positions for 2050s and 2090s are (110.695562°E, 35.099849°N) and (110.226264°E, 36.175191°N), both shifting northwest. Under the SSPs585 scenario, the predicted centroid positions for 2050s and 2090s are (110.889082°E, 34.890013°N) and (110.515474°E, 36.293402°N). Spatial distribution modeling reveals that the centroid of the high suitability area for Pinus taiwanensis exhibits a characteristic northwestward latitudinal shift.

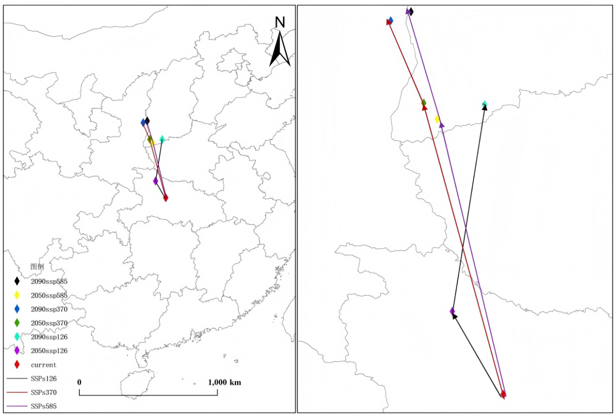

Figure 7. Centroid shift of high suitability areas for pinus taiwanensis.

3.5 Multivariate Environmental Similarity Surfaces (MESS) and Most Dissimilar Variable (MOD) Analysis

The "density.tools.Novel" analysis tool within MaxEnt was used to analyze the Multivariate Environmental Similarity Surfaces (MESS) and the Most Dissimilar Variable (MOD) for the 2050s and 2090s periods. Based on the spatial heterogeneity distribution of future climate scenarios constructed by MESS and MOD models (see Figure 8), differences between future and current climate environments were analyzed, and the main environmental factors driving changes in the suitable habitat of Pinus taiwanensis were identified.

Under different climate scenarios in the 2050s, the average MESS values were 4.17, 4.68, and 6.21. Climate anomalies primarily occurred in the northeastern and southern parts of the current suitable area. The corresponding MOD was the daily average temperature range (DATR).

Under different climate scenarios in the 2090s, the average MESS values were 5.18, 5.72, and 6.53. Climate factor anomalies mainly appeared in the northeastern and southern parts of the current suitable area. The corresponding MOD was isothermality (Iso).

4 Discussion

4.1 Model Evaluation and Analysis of Environmental Factor Influence

The excellent performance of various evaluation metrics for the biomod2 ensemble model indicates a high degree of credibility and reliability for this study [37]. Further optimization of the biomod2 model results showed that the AUC values for predictions in the 2050s and 2090s were all above 0.9, and TSS values were above 0.85. This confirms that the biomod2 model simulation performs "excellently" in predicting the potential distribution area of Pinus taiwanensis.

The environment determines plant growth and geographical distribution patterns [38]. Different tree species have distinct biological characteristics and ecological habits, resulting in different responses to climate. The adaptability and dispersal capacity of plants to their environment often determine the distribution patterns of their groups. Simultaneously, biotic and abiotic environmental factors can also cause changes in these distribution patterns [39]. Various ecological factors influence the animals, plants, and microorganisms living within them, while the presence of these organisms also alters the natural environment to some extent. Considering current climate change trends, shifts in global climate patterns profoundly impact the distribution and

Table 3. Suitable habitat area for pinus taiwanensis under future climate scenarios.

Climate scenario	Period	Areas of suitable are/km²					Area change rate of the suitable area/%					
		Non-suitable area	Low suitable area	Mid-natural area	High fitness area	Total suitable area	Mid-natural area		High fitness area		Total suitable area	
							Increased	Decreased	Increased	Decreased	Increased	Decreased
SSPs126	2050	7555056.5	1142415.7	818897.6	1298212.5	3259525.8	0.16	0.15	0.19	0.09	0.19	0.14
	2090	6731287.1	1648453.5	1002540.6	1432682.4	4083676.5	0.21	0.14	0.19	0.09	0.18	0.12
SSPs370	2050	6860763.9	1609480.2	871774.4	1472713.1	3953967.8	0.19	0.14	0.18	0.09	0.17	0.12
	2090	6395480.7	1726087.8	1056213.2	1637061.1	4419362.1	0.21	0.13	0.24	0.10	0.19	0.12
SSPs585	2050	6826127.3	1517074.4	926105.8	1545508.1	3988688.3	0.19	0.13	0.23	0.10	0.18	0.12
	2090	6021998.6	2014946.4	1201795.4	1575788.9	4792530.7	0.21	0.12	0.24	0.11	0.20	0.24

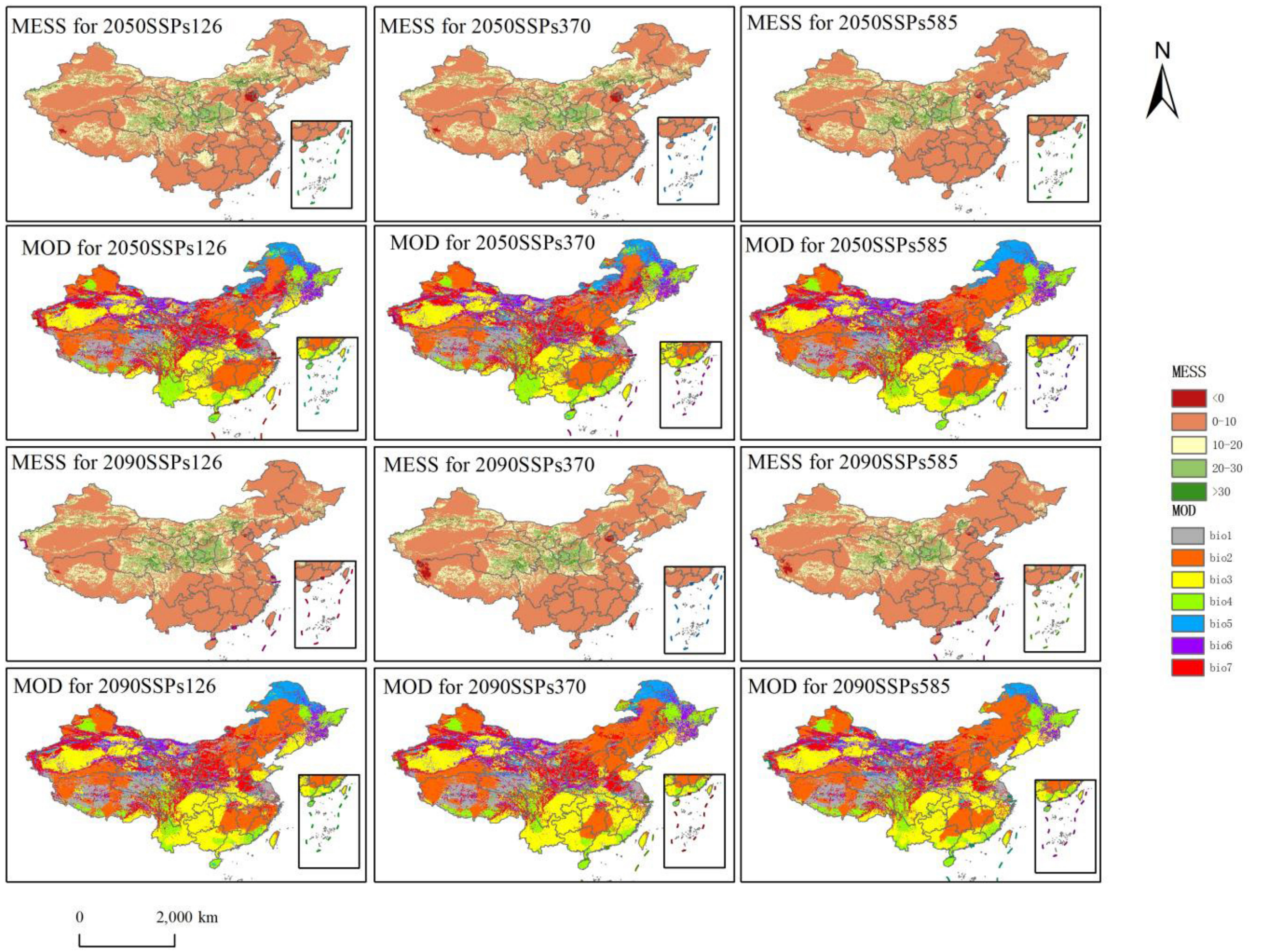

Figure 8. Multivariate environmental similarity surfaces (MESS) and most dissimilar variable.

Table 4. Centroid Position and Migration Direction of High Suitability Areas for Pinus taiwanensis under Future Climate Scenarios.

Climate scenario	Period	Centroid position	The direction of centroid migration
Current		111.821652E, 31.294436N	
SSPs126	2050	111.100804E, 32.378402N	Northeast
	2090	111.559171E, 35.076825N	Northwest
SSPs370	2050	110.695562E, 35.099849N	Northwest
	2090	110.226264E, 36.175191N	Northwest
SSPs585	2050	110.889082E, 34.890013N	Northwest
	2090	110.515474E, 36.293402N	Northwest

survival of Pinus taiwanensis and related tree species. Furthermore, given the important ecological roles of Pinus taiwanensis, such as climate amelioration and soil improvement, this study focused on the influence of various environmental factors on its potential distribution area. Analysis using the biomod2 ensemble model revealed that temperature factors have the greatest impact on its distribution, followed by precipitation patterns. This should be the focus for protection, development, and utilization efforts concerning Pinus taiwanensis.

4.2 Distribution of Pinus taiwanensis Suitable Habitat under Various Climate Scenarios

Analyzing changes in potential species distribution patterns under climate change is critical for assessing the impact of environmental changes on species and formulating corresponding conservation strategies to maintain ecosystem balance [40]. By importing seven potential suitable habitat distribution maps into ArcGIS 10.8, the centroid migration path of Pinus taiwanensis was analyzed. The analysis shows that the high suitability area of Pinus taiwanensis will shift northwestward. This provides some theoretical guidance for the prevention and control of pine wilt disease (Bursaphelenchus xylophilus) in Pinus taiwanensis. Predicting the distribution of Pinus taiwanensis is significant for pine wilt disease control and regional zoning.

According to the analysis, the direction and path of centroid migration for the high suitability area of Pinus taiwanensis are not entirely identical but generally trend northwest. However, this study has limitations. Economic conditions, social conditions, historical evolution, and biological relationships within the same species or between different species within the study area were not fully considered. For example, interspecific competition among different tree species or intraspecific competition within Pinus taiwanensis, and anthropogenic disturbances damaging ecological habitats can alter the geographic location and various biological characteristics of Pinus taiwanensis to some extent. Future research should pay more attention to the influence of anthropogenic factors on the distribution of Pinus taiwanensis to further improve the accuracy and credibility of distribution predictions.

This study, by analyzing the suitable growth areas of Pinus taiwanensis under current and future climate conditions, provides scientific support for the resource conservation and sustainable utilization of this species nationwide. When formulating ecological conservation strategies, the dynamic impact of climate change on species geographic distribution must be prioritized. Differentiated management approaches can be adopted: firstly, strengthening the protection of core habitats relying on the natural protected area system; secondly, promoting population restoration through scientifically planned artificial breeding. This holds positive significance for biodiversity maintenance and ecosystem protection.

5 Conclusion

This study on predicting the potential distribution area of Pinus taiwanensis was primarily based on species distribution point data and biomod2 ensemble model simulations. It examined changes in the spatial location and suitable habitat area of Pinus taiwanensis for the contemporary period and the future periods (2050s and 2090s) under three climate scenarios (SSPs126, SSPs370, SSPs585). This allowed the identification of future migration trends and changes in occupied area for Pinus taiwanensis. Based on this, various environmental factors were screened and analyzed to determine the main factors influencing Pinus taiwanensis, providing a solid basis and scientific guidance for the protection and rational development and utilization of this species.

1. The TSS values for both current and future periods in the biomod2 ensemble model simulation results were greater than 0.8, and AUC values were all greater than 0.9, indicating high accuracy and reliability of the model for predicting the potential distribution area of Pinus taiwanensis.
2. Using R software for correlation analysis of various habitat factors, combined with factor contribution rates, the habitat factors with the highest contribution rates were retained. Analysis confirmed that temperature and precipitation are the main environmental factors influencing the potential distribution area of Pinus taiwanensis.
3. Research analysis indicates that under the three climate scenarios in future periods, the suitable habitat area for Pinus taiwanensis may expand to some extent.
4. Under different future climate scenarios, the centroid of Pinus taiwanensis is predicted to migrate mainly northwestward. This can provide guidance and basis for zoning the distribution area of Pinus taiwanensis and related pest and disease control.
5. According to Multivariate Environmental Similarity Surfaces (MESS) and Most Dissimilar Variable (MOD) analysis, the SSPs585 climate scenario in future periods differs the most from the current climate scenario. The most dissimilar variable for the 2050s is the mean diurnal temperature range (DATR), and for the 2090s, it is isothermality (Iso).

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Ning Zhang is an employee of Henan Yuanzhi Forestry Planning and Design Co., Ltd, Zhengzhou 450003, China.

Ethical Approval and Consent to Participate

Not applicable.

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