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# Analysis of Potential Suitable Areas and Environmental Factor Responses for Four Species in Sichuan

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**Abstract** *Quercus glauca*, *Phyllostachys edulis*, *Phoebe zhennan*, and *Camphora officinarum* are the primary species constituting Sichuan Province's forest resources. To analyze the key environmental factors influencing their distribution and explore their ecologically suitable ranges, this study employed Geographic Information Systems (GIS) and an optimized Maximum Entropy (MaxEnt) model to simulate their ecological niches based on geographic distribution point data and 37 environmental factors. Results indicate the MaxEnt model achieved high accuracy with AUC values exceeding 0.8. The most influential environmental factors for the distribution of *Q. glauca*, *P. edulis*, *P. zhennan*, and *C. officinarum* were minimum temperature of the coldest month, elevation, precipitation of the wettest month, and elevation, respectively. Their suitable ranges were 1-7 ℃, 447-991 m, 247-426 mm, and 6-490 m. The potential suitable areas for these four species are primarily distributed in basins and their surrounding mountainous regions, with *Q. glauca* exhibiting the largest distribution area of $10.2\times10^4$ $km^2$. This study aims to provide references for resource conservation and utilization, as well as the selection of cultivation sites.

**Key words** Forest resources; Optimizing the Maximum Entropy model; Environmental factors; Suitable areas

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Forest ecosystems are complex systems dominated by trees and other woody plants, serving as vital components of terrestrial ecosystems and essential foundations for national economic development and ecological conservation. They deliver significant economic, ecological, and social benefits[1]. Rising temperatures, shifting precipitation patterns, and frequent extreme weather events driven by global climate change are profoundly altering species' potential spatial distributions and dynamic structures[2]. Against the backdrop of national initiatives promoting scientific greening and reserve forest development, Sichuan Province, serving as an ecological barrier in the upper reaches of the Yangtze River, faces multiple challenges. Its terrain descends in a stepped pattern from west to east: the western region lies along the eastern edge of the Qinghai-Tibet Plateau, with an average elevation exceeding 4 000 m and a cold and arid climate; the central Hengduan Mountains feature steep peaks and deep valleys, significantly influenced by monsoons, exhibiting characteristics of both alpine and warm-humid climates; while the eastern Sichuan Basin and surrounding hills exhibit a subtropical humid monsoon climate with annual precipitation around 1 000 mm[3]. This complex topography and climatic diversity foster rich vegetation, ranging from alpine meadows and coniferous forests to evergreen broadleaf forests[4]. As vegetation growth depends on ecological conditions, industrial civilization—while advancing human society—has also brought severe environmental issues, leading to degraded environmental quality and ecological imbalance[5].

The relationship between environmental factors and organisms has long been a focus across various disciplines including climatology, ecology, and geography. The connection between species distribution and environmental data is equally a central issue explored by these fields. Modeling approaches for analyzing species distribution—the process of quantifying species-environment relationships—link flora and fauna to their environmental factors through diverse niche models[6]. Species distribution models (SDMs) employ diverse algorithms to integrate quantified biological distribution data with environmental information. This enables the assessment of environmental factors essential for species survival. Based on the relative importance of these factors, existing actual distribution areas are extrapolated to similar spatial regions, thereby determining the species' potential distribution range[7]. Numerous SDM variants and software packages have emerged, including the Bioclimatic Analysis and Prediction System (BIOCLIM), Genetic Algorithm for Rule-based Prediction (GARP), Ecological Niche Factor Analysis (ENFA), Random Forest (RF), and Maximum Entropy (MaxEnt) models[6-8]. Elith *et al.* were among the first to introduce MaxEnt into species habitat modeling. Since then, MaxEnt models have been widely applied in assessing the potential habitat quality for endangered flora and fauna[9]. Recent studies have pointed out that research based on MaxEnt models often relies on default parameter settings, frequently neglecting model parameter optimization. Unoptimized MaxEnt models exhibit certain fitting biases, which can lead to errors in species distribution predictions[10-11]. Under default settings, MaxEnt models are often suboptimal. Optimizing the regularization multiplier (RM) and feature combination parameter

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(FC) can yield more precise interpretations and inferences[10-12]. To better integrate multidimensional data such as climate, soil, topography, and remote sensing for more precise tree species distribution predictions, researchers have employed optimized MaxEnt models to forecast species like *Euglandina rosea*[12], *Simulium equinum*[13], *Juniperus przewalskii*[14], and *Firmiana kwangsiensis*[15].

Therefore, based on the geographic distribution data of four species in Sichuan, combined with environmental factors such as climate, soil, and topography, this study employed the R language to optimize the Maximum Entropy (MaxEnt) models for modeling and prediction. The study delves into the complex interrelationships between the probability of species suitability zone distribution and environmental factors. Its core objective is to provide scientific theoretical foundations and data support for resource conservation, rational introduction, and cultivation of Sichuan's primary timber tree species. This research aims to deliver more precise and actionable decision support for sustainable forestry development and ecological restoration in the region.

## 1 Materials and methods

**1.1 Data of species distribution** Historical plot survey archives and field survey data of Sichuan Province (Fig. 1) were collected. To accurately describe the distribution of four species, only pure stand survey data were retained. Additional data were supplemented from the China Digital Herbarium (https://cvh.ac.cn/), the China National Resource Specimen Platform (https://nsii.org.cn/), the Global Biodiversity Information Facility (https://www.gbif.org/), and relevant Chinese literature. To accurately depict the actual distribution patterns of each tree species, anomalous distribution points were excluded based on ecological characteristics[15]. Ultimately, a total of 1 194 distribution points of species *Q. glauca*, *P. edulis*, *P. zhennan*, and *C. officinarum* were collected.

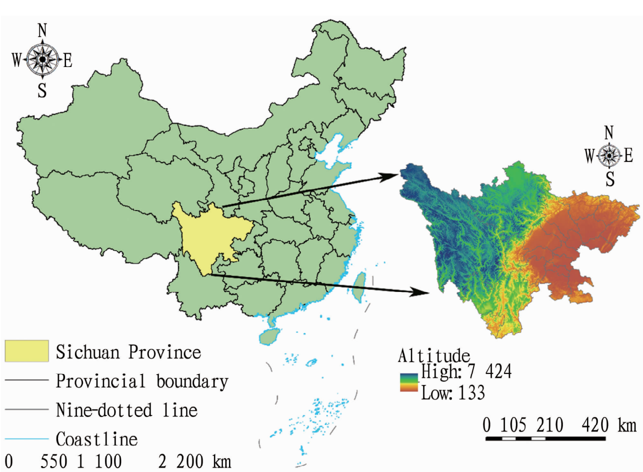



**Fig. 1 Study area**

**1.2 Data of environmental factors** This study integrated multi-source environmental data to construct potential distribution models for six major tree species in Sichuan. The selected variables encompassed three major categories: climate, soil, and topography. Nineteen bioclimatic variables (Bio1-Bio19) were sourced from the WorldClim v2.1 dataset (https://www.worldclim.org/). Soil characteristics were selected from 15 key variables provided by the Chinese Soil Database, including organic matter content, pH, and sand, silt, and clay particle size composition, at a 1 km resolution. Topographic factors such as elevation, slope gradient, and aspect were extracted from the Digital Elevation Model (DEM) in the Geospatial Data Cloud at a 12.5 m resolution. To ensure consistent spatial scales, all variables were uniformly resampled to 1 km resolution using ArcGIS and converted to ASCII raster format for subsequent analysis[12].

During species distribution modeling, a rigorous screening process is essential to effectively mitigate the impact of multicollinearity among environmental factors. First, tree species distribution points and all environmental factors are imported into the MaxEnt model for an initial run. Based on the results of 10 iterations, factors with a contribution rate below 1% are eliminated. Subsequently, ArcGIS software is used to precisely extract the variable values corresponding to each distribution point from the filtered environmental factors. Finally, Pearson correlation analysis is performed on these variable values using the Python 3.10 platform. When the absolute value of the correlation coefficient between any two variables exceeds 0.8, their contribution rates are further compared, and the variable with the lower contribution rate is removed. This ensures that the final selected factors are both significantly influential and relatively independent of each other[16].

**Table 1 Environmental factors**

| Data category | Title | Name | Unit |
|---|---|---|---|
| Bioclimatic variables | Bio1 | Annual mean temperature | ℃ |
| Bioclimatic variables | Bio2 | Mean diurnal range | ℃ |
| Bioclimatic variables | Bio3 | Isothermality (Bio2/Bio7) (*100) | - |
| Bioclimatic variables | Bio4 | Temperature seasonality (standard deviation *100) | ℃ |
| Bioclimatic variables | Bio5 | Maximum temperature of the warmest month | ℃ |
| Bioclimatic variables | Bio6 | Minimum temperature of the coldest month | ℃ |
| Bioclimatic variables | Bio7 | Temperature annual range (Bio5-Bio6) | ℃ |
| Bioclimatic variables | Bio8 | Mean temperature of the wettest quarter | ℃ |
| Bioclimatic variables | Bio9 | Mean temperature of the driest quarter | ℃ |
| Bioclimatic variables | Bio10 | Mean temperature of the warmest quarter | ℃ |
| Bioclimatic variables | Bio11 | Mean temperature of the coldest quarter | ℃ |
| Bioclimatic variables | Bio12 | Annual precipitation | mm |
| Bioclimatic variables | Bio13 | Precipitation of the wettest month | mm |
| Bioclimatic variables | Bio14 | Precipitation of the driest month | mm |
| Bioclimatic variables | Bio15 | Precipitation seasonality (coefficient of variation) | - |
| Bioclimatic variables | Bio16 | Precipitation of the wettest quarter | mm |
| Bioclimatic variables | Bio17 | Precipitation of the driest quarter | mm |
| Bioclimatic variables | Bio18 | Precipitation of the warmest quarter | mm |
| Bioclimatic variables | Bio19 | Precipitation of the coldest quarter | mm |

(To be continued)

(Continued)

| Data category | Title | Name | Unit |
|---|---|---|---|
| Terrain variables | Altitude | Altitude | m |
| Terrain variables | Slope | Slope | ° |
| Terrain variables | Aspect | Aspect | – |
| Soil variables | T_gravel | Topsoil gravel content | % vol |
| Soil variables | T_sand | Topsoil sand fraction | % wt |
| Soil variables | T_silt | Topsoil silt fraction | % wt |
| Soil variables | T_clay | Topsoil clay fraction | % wt |
| Soil variables | T_usda_tex | Topsoil USDA texture classification | name |
| Soil variables | T_ref_bulk | Topsoil reference density bulk | $kg/dm^3$ |
| Soil variables | T_oc | Topsoil organic carbon | % weight |
| Soil variables | T_ph_h2o | Topsoil pH ($H_2O$) | $-log(H^+)$ |
| Soil variables | T_cec_clay | Topsoil CEC (clay) | cmol/kg |
| Soil variables | T_cec_soil | Topsoil CEC (soil) | cmol/kg |
| Soil variables | T_bs | Topsoil base saturation | % |
| Soil variables | T_teb | Topsoil TEB | cmol/kg |
| Soil variables | T_caco3 | Topsoil calcium carbonate | % weight |
| Soil variables | T_esp | Topsoil sodicity (ESP) | % |
| Soil variables | T_ece | Topsoil salinity (Elco) | dS/m |

**1.3 Model construction** In constructing species distribution models, this study employed the MaxEnt model for simulation analysis. The specific workflow is as follows. First, the preprocessed tree species distribution point data and the selected environmental factor variables were imported into the MaxEnt model. To assess the model's generalization ability and robustness, the distribution point data were randomly partitioned in each run. 75% of the samples were used as the training subset to build the model, while the remaining 25% served as the testing subset for validation. This process was repeated 10 times to obtain more stable and reliable average prediction results[12-15].

The evaluation of model performance employs the widely adopted area under the receiver operating characteristic curve (AUC value) as the core metric. AUC serves as a crucial standard for evaluating a model's ability to distinguish between positive and negative points, with values ranging from 0 to 1[17]. An AUC value of 0.5 indicates that the model's predictive capability is no better than random guessing, while values closer to 1 signify higher predictive accuracy and stronger discrimination ability. In practical applications, the effective interpretation range for AUC falls between 0.5 and 1. Generally, an AUC value between 0.5 and 0.7 indicates low predictive accuracy or poor discrimination capability; values between 0.7 and 0.9 signify good and acceptable discrimination accuracy; an AUC value reaching 0.9 to 1.0 indicates excellent predictive performance, capable of highly accurate predictions of species' suitable distribution ranges[14].

**1.4 Model optimization** During the optimization of the MaxEnt model, this study systematically tuned two key parameters—the regularization multiplier (RM) and feature combination (FC)—using the ENMeval package in R to enhance the model's predictive accuracy and interpretability[12-15]. The specific settings are as follows: the search range for the regularization multiplier (RM) was set from 0.5 to 4 with a step size of 0.5. Feature combinations (FC) encompassed five basic types—linear (L), fragmented (H), product (P), quadratic (Q), and threshold (T)—along with their combinations, forming multiple parameter combination schemes through permutations. During the model selection phase, the Akaike Information Criterion (AICc) serves as the primary evaluation metric. This indicator effectively balances model complexity and goodness-of-fit, prioritizing the model with the smallest AICc value[10]. The results of model optimization are shown in Table 2.

**Table 2 Results of model optimization**

| Species | FC | RM | AICc | or.10p.avg | auc.diff.avg | AUC |
|---|---|---|---|---|---|---|
| *Q. glauca* | LQHPT | 3.5 | 0 | 0.223 2 | 0.095 9 | 0.880 5 |
| *P. edulis* | LQ | 0.5 | 0 | 0.203 2 | 0.027 6 | 0.958 6 |
| *P. zhennan* | LQHP | 3.0 | 0 | 0.167 9 | 0.027 3 | 0.972 4 |
| *C. officinarum* | LQ | 0.5 | 0 | 0.057 7 | 0.029 5 | 0.920 1 |

**1.5 Analysis of dominant environmental factors** Different species exhibit significant variations in their natural habitat requirements, with their potential suitable areas often dominated by a few key environmental factors[18]. To identify these dominant factors, this study screened the primary influencing factors for the distribution of suitable areas of each tree species based on the contribution rate outputs from the MaxEnt model, combined with the ecological characteristics of the four tree species. The specific methodology is as follows: the top three environmental factors ranked by cumulative contribution rate are defined as dominant environmental factors, with the single factor exhibiting the highest contribution rate regarded as the most dominant environmental factor. Concurrently, the response curves generated by the MaxEnt model are utilized to analyze the patterns of species presence probability as environmental factors vary, thereby determining the suitable value ranges for each dominant environmental factor. Typically, the environmental factor value range corresponding to a presence probability of no less than 0.5 is determined as the suitable survival range for that tree species[19].

**1.6 Classification of suitable areas** After completing 10 repeated simulation predictions in the MaxEnt model, the averaged results were imported into ArcGIS Pro software as a raster layer. The original ASCII format output file was converted into a raster layer suitable for spatial analysis. Pixel values ranged from 0 to 1, with higher values indicating greater habitat suitability and values closer to 1 representing a higher probability of species presence[10]. Referencing the definition of probability (P) of existence from the United Nations Intergovernmental Panel on Climate

Change (IPCC) report, and incorporating the maximum train sensitivity plus specificity logistic threshold (MTSS) output from the MaxEnt model, the Reclassify tool was used to classify the potential habitat for the six tree species within the study area into three suitability levels: $P < MTSS$ was classified as unsuitable areas, $MTSS \leqslant P < 0.66$ as moderately suitable areas, and $P \geqslant 0.66$ as highly suitable areas[20].

## 2 Results and analysis

**2.1 Evaluation of MaxEnt model prediction accuracy** After optimizing the MaxEnt models using the R package ENMeval, the optimal parameters for the Quercus glauca model were FC = LQHPT and RM = 35; for *Phyllostachys edulis* model, FC = LQ and RM = 0.5; for *Phoebe zhennan* model, FC = LQHP and RM = 3; and for the *Camphora officinarum* model, FC = LQ and RM = 0.5. As shown in Fig.2, the optimized model parameters yielded an average AUC value exceeding 0.880 5. This indicates that the model provides highly reliable predictions for the potential suitable distribution ranges of the four species, demonstrating strong predictive capability and suitability for further analysis of leopard distribution areas.

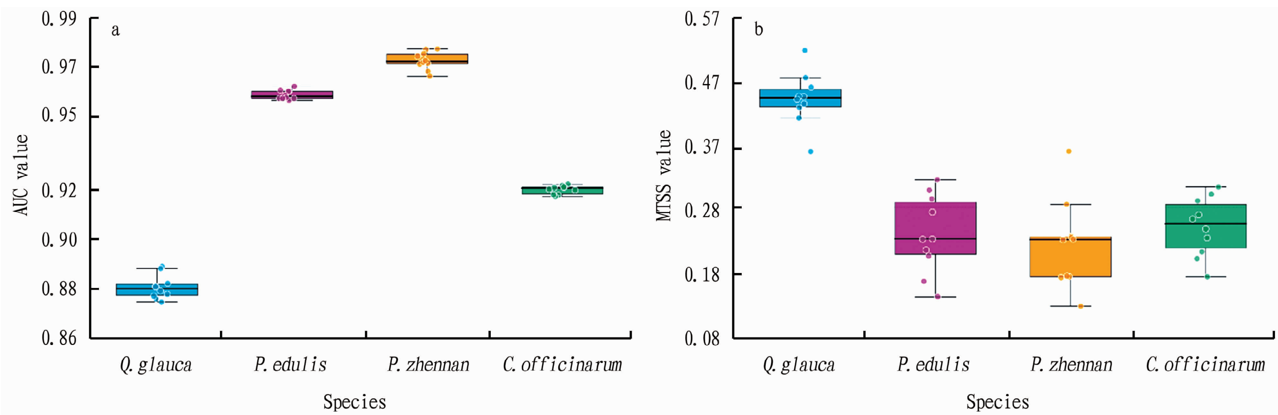



**Fig.2 Distribution of AUC (a) and MTSS (b) values across different plant species**

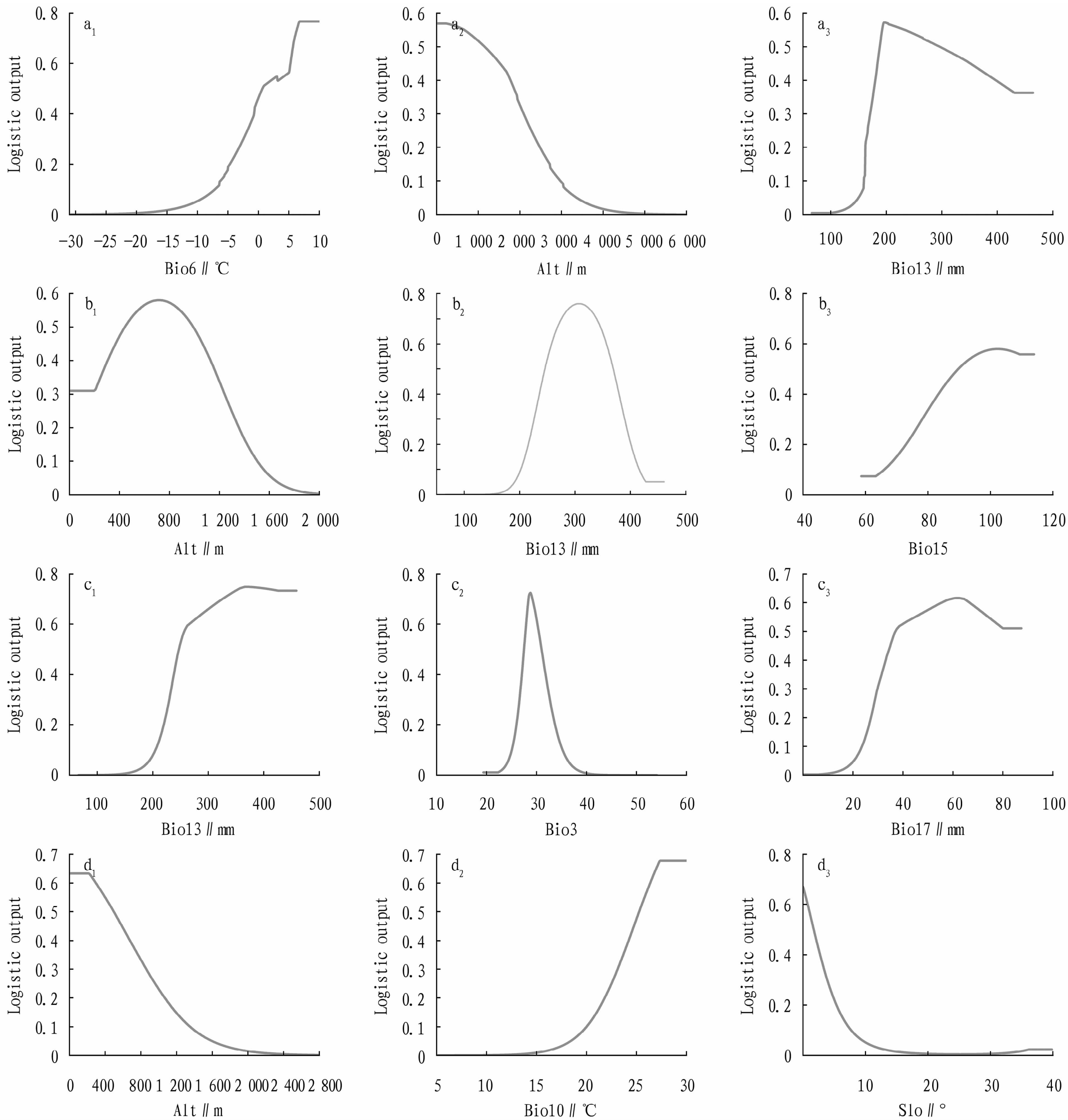
**2.2 Analysis of dominant environmental factors** To clarify the relationship between key environmental factors and species, threshold values of environmental variables affecting the distribution of species were determined through response curve analysis. The factors most significantly influencing the distribution contribution rate of *Q. glauca* are the coldest month's minimum temperature (BIO6 = 55.3%), elevation (ALT = 21.2%), and the wettest month's precipitation (Bio3 = 10.4%). Specifically, the coldest month's minimum temperature range: 1 – 7 ℃, with peak contribution at 7 ℃; altitude range: 0 – 1 152 m, with peak occurrence at 1 152 m; the wettest month's precipitation range: 189 – 216 mm, with peak occurrence at 196 mm.

The primary factors influencing the distribution contribution rate of *P. edulis* are altitude (ALT = 47.9%), precipitation in the wettest month (Bio13 = 18%), and seasonal coefficient of variation in precipitation (Bio15 = 12.2%). Specifically, altitude range: 447 – 991 m, with peak contribution at 727 m; the range for the wettest month's precipitation is 66 – 100 and 245 – 369 mm, with the peak occurring at 100 mm. The range for seasonal coefficient of variation in precipitation is 90 – 114, with the peak occurring at 109.

The primary factors influencing the distribution contribution rate of *P. zhennan* are the wettest month's precipitation (Bio13 = 55.6%), isothermality (Bio3 = 19.4%), and the driest season's precipitation (Bio17 = 11.6%). Specifically, the wettest month's precipitation range is 247 – 426 mm, with peak contribution at 426 mm; the isothermality range is 27 – 31, with the peak occurring at 29; the driest season's precipitation range is 37 – 80 mm, with the peak occurring at 80.

The primary factors influencing the distribution contribution rate of *C. officinarum* are elevation (ALT = 45.6%), the warmest season's mean temperature (Bio10 = 35.5%), and slope (Slo = 4.9%). Within the elevation range of 6 – 490 m, peak contribution occurs at 6 m. The optimal mean temperature range for the warmest season is 25 – 30 ℃, with peak contribution occurring at 27 ℃. The optimal slope range is 0 – 2°, with peak contribution occurring at 0°.

**2.3 Analysis of latent distribution** *Q. glauca* is primarily distributed in eastern and southern Sichuan, with its high-suitability zones concentrated in eastern Dazhou City, northern Luzhou City, Panzhihua City, and eastern Liangshan Yi Autonomous Prefecture. The total suitable area spans $10.2 \times 10^4$ km$^2$, while the high-suitability zone covers $0.50 \times 10^4$ km$^2$. *P. edulis* is primarily distributed in central Sichuan. Its highly suitable areas are mainly located in Ya'an City, Leshan City, Meishan City, Neijiang City, western Zigong City, western Yibin City, and southern and western Chengdu City. The suitable area covers $4.86 \times 10^4$ km$^2$, while the highly suitable area spans $0.49 \times 10^4$ km$^2$. *P. zhennan* is primarily distributed in central Sichuan. Its highly suitable areas are mainly located in southern Mianyang City, central Deyang City, western Chengdu City, eastern Ya'an City, Meishan City, Leshan City, and western Yibin City. The suitable area is $2.88 \times 10^4$ km$^2$, and the highly suitable area is $0.50 \times 10^4$ km$^2$. *C. officinarum* is primarily distributed in central and eastern Sichuan. The highly suitable areas are mainly located in Chengdu City, northern Meishan City, eastern Yibin City, and northern Luzhou City. The suitable area is $7.91 \times 10^4$ km$^2$, and the highly suitable area is $0.51 \times 10^4$ km$^2$.

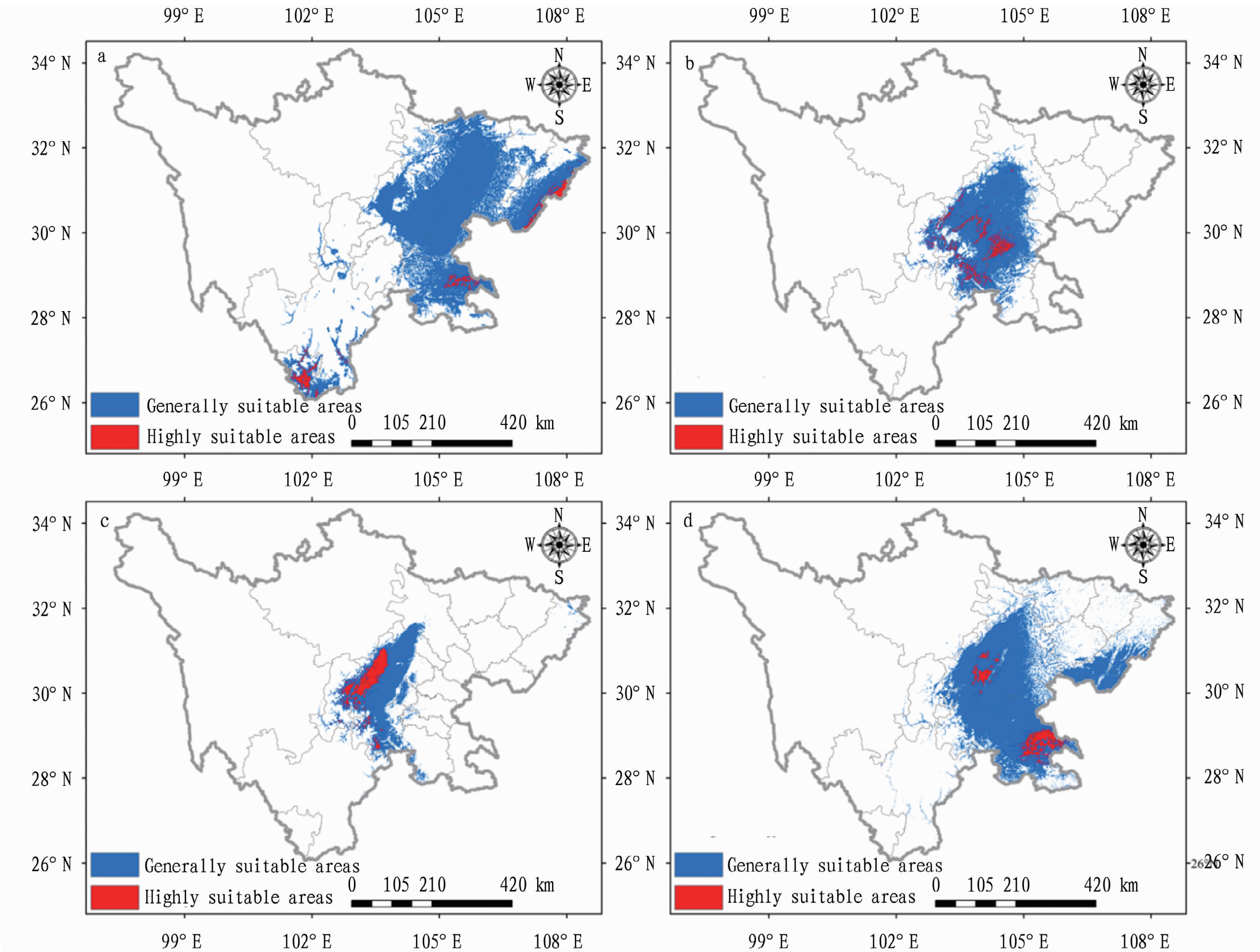



Note: a. *Q. glauca*; b. *P. edulis*; c. *P. zhennan*; d. *C. officinarum*.

**Fig. 3 Distribution of logistic output of different plant species**

## 3 Discussion

In research on plant ecology, studying the geographical distribution characteristics of species forms the foundation for biodiversity conservation[21]. Clarifying the spatial distribution patterns of species can reveal the relationship between species distribution and environmental factors. This study conducted ecological suitability zoning for four species in Sichuan. The AUC values of the predictive models exceeded 0.9, indicating that the optimized MaxEnt model accurately predicts species' potential distribution areas. By integrating MaxEnt modeling with ArcGIS technology, the study comprehensively considered the influence of various environmental factors, ultimately identifying the environmental factors most significantly affecting species growth and their optimal value ranges. Comprehensive analysis indicates that temperature, elevation, and precipitation all exert primary influences on ecological suitability distribution. The study identifies climate and elevation as the key determinants of species distribution. This confirms that climate, through factors like temperature and precipitation, synergistically drives plant physiological metabolic rates, morphogenesis, and adaptation strategies, ultimately shaping their geographic distribution patterns. Climate thus represents a fundamental environmental factor influencing plant survival and evolution[22]. Additionally, increasing elevation leads to decreasing temperatures and altered precipitation patterns. Lower temperatures directly inhibit plant physiological metabolism and shorten the growing season, while precipitation changes interact synergistically with temperature to jointly determine soil water availability and nutrient cycling rates[23]. Ultimately, the combination and variation of these two core factors—temperature and moisture—along the elevation gradient collectively drive plant growth strategies, morphological adaptations, and the distribution patterns of mountain vegetation vertical zonation.




Note: a. *Q. glauca*; b. *P. edulis*; c. *P. zhennan*; d. *C. officinarum*.

**Fig. 4 Distribution of suitable areas of different plant species**

However, while this study represents progress over previous similar research by incorporating soil data alongside the climate data commonly used in niche modeling, the niche modeling approach itself retains inherent limitations[24]. Therefore, subsequent related work should refine niche model construction and prediction by integrating aspects such as species population genetic structure, evolutionary dynamics, and genetic variation composition[25]. Consequently, future investigative efforts will focus on thoroughly exploring the impacts of non-natural factors on species' spatio-temporal distributions. Through more scientific and rigorous field surveys, data collection, and the integration of multiple distribution models for ensemble analysis, the aim is to fill gaps in this research field and provide a more robust, scientific basis for effective conservation strategies addressing species' responses to climate change[26]. The study delineated ecologically suitable areas for four Sichuan species, primarily distributed across the Sichuan Basin and surrounding mountainous regions. These areas predominantly feature a subtropical monsoon climate, characterized by suitable temperatures, abundant precipitation, and significant elevation gradients—aligning well with documented distributions[27]. This indicates high simulation fidelity. Although the modeled suitable distribution ranges are broader than actual historical distributions, the cultivable ranges for these four Sichuan species exceed their current real-world distribution areas.

## 4 Conclusions

This study employed an optimized MaxEnt model to predict the distribution of four species in Sichuan. Results indicate the model exhibits high accuracy, with AUC values exceeding 0.8 for all species. This demonstrates that the MaxEnt model effectively utilizes environmental variables and known distribution point data to accurately predict potential suitable habitats. Simulated actual and potential species suitability areas showed considerable similarity, though potential suitability areas covered larger regional areas. The primary environmental factors influencing the distribution of *Q. glauca*, *P. edulis*, *P. zhennan*, and *C. officinarum* were the minimum temperature of the coldest month, elevation, the precipitation of the wettest month, and elevation. All four species predominantly occur in basins and their surrounding mountainous areas. The potential habitat areas for *Q. glauca*, *P. edulis*, *P. zhennan*, and *C. officinarum* are $10.2\times10^4$, $4.86\times10^4$, $2.88\times10^4$, and $7.91\times10^4$ $km^2$, respectively. This study explored species potential suitability zones from an ecological factor perspective; however, species planting should consider multiple influencing factors. Therefore, subsequent research should also analyze species quality and chemical composition content across different regions to identify more suitable production areas. This approach ensures both yield and high-quality forest resources, promoting sustainable ecological development.

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