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Authors: He, Yunling, Xiong, Qiaoli, Yu, Lan, Yan, Wenbo, and Qu, Xinxing

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Impact of Climate Change on Potential Distribution Patterns of Alpine Vegetation in the Hengduan Mountains Region, China

Yunling He*, Qiaoli Xiong, Lan Yu, Wenbo Yan, and Xinxing Qu
* Corresponding author: hy610@126.com
School of Earth Sciences, Yunnan University, Kunming 650500, China

Assessing the impacts of climate change on geographic distribution by identifying how biological response relates to environmental conditions is important for addressing the adverse effects of climate change. Using the maximum entropy algorithm and spatial analysis module of ArcGIS, we construct a habitat prediction model for the geographic distribution of alpine vegetation in the Hengduan Mountains of southwestern China. We use the model to identify how alpine vegetation has responded to climatic changes during the period 1980–2018, and to predict responses to possible temperature and precipitation changes in the future. The results indicate that the geographic distribution of alpine vegetation in the Hengduan Mountains is most sensitive to annual mean minimum temperature variation. The most suitable habitat for alpine vegetation under climate change is in northermost Sichuan, in the Hengduan–Himalayan mountain area, at elevations from 4500 to 5000 masl. The current area of alpine vegetation in the Hengduan Mountains accounts for 8.20% of their total area. As the annual mean temperature increases, the area suitable for alpine vegetation increases by 0.32–1.27%, regardless of changes in precipitation. When the temperature increases by 1–2°C, the area unsuitable for alpine vegetation decreases by 1.64–2.97%. These results indicate that a temperature increase influences the geographic distribution pattern of alpine vegetation in the Hengduan Mountains. The most notable effect was under the 2°C increase scenario. The predictions suggest that under future climate change, the geographic distribution of alpine vegetation will continue to shift toward middle and higher elevations. To protect endemic alpine vegetation, the best habitats should be protected from interference and destruction by human activities.

**Keywords:** alpine vegetation; potential distribution; climate change; MaxEnt; Hengduan Mountains.

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Introduction

The average global air temperature increased by 0.85°C during the last century. Warming has significantly accelerated since the 1990s and is predicted to rise by 1.0–3.7°C in the 21st century, with the temperature increase reaching 2°C between 2026 and 2060 (IPCC 2013). Climate is a decisive factor for biological growth, so it plays a critical role in the potential distribution of species (Zhang et al 2019). Climate change, and its strong influence on the distribution of species, is therefore an important topic in the field of biogeography (Zhu et al 2018). Mountainous and highland ecosystems are particularly sensitive and vulnerable to long-term climatic changes (Fan et al 2011).

The Hengduan Mountains are a globally acknowledged biodiversity hotspot with a high level of endemic species (Xu et al 2014). The area of alpine vegetation in the Hengduan Mountains accounts for more than one tenth of the total area of alpine vegetation in China. However, fragmentation and loss of habitat threaten its survival. Furthermore, the region is vulnerable to climate change (Li et al 2010). Scholars have studied the impact of climate change on individual species, providing many inconsistent results (He et al 2019). Some studies show that species in mountain areas will shift upward in a warming climate (Zhao and Wu 2014), and some indicate that range size of montane species could increase (Elsen and Tingley 2015). However, the form of ecological response driven by environmental change has not been systematically addressed in this region.

There are many types of species distribution models, including the bioclimatic prediction system, generalized additive model, generalized linear model, and maximum entropy (MaxEnt), of which the MaxEnt algorithm is increasingly used (Abdelaal et al 2019). It has been widely used in the fields of invasion, conservation, and evolutionary biology and to investigate the impact of climate change on species distribution (Silva et al 2019). Extensive reference materials and field survey data were used in this study to investigate potentially suitable habitats for alpine vegetation under current and future climatic conditions, including their main changes in area. Using the MaxEnt model and ArcGIS, the importance of climate variables in influencing their distribution was evaluated in terms of range size and elevation in response to climate change. The results are an important step in the development of a feasible conservation
strategy for alpine vegetation in the Hengduan Mountains of southwest China.

Material and methods

Study area
The Hengduan Mountains are of great significance because of their orientation and geographic location. They are located in the southeast Tibetan Plateau (Figure 1), covering an area of 493,334.82 km². They are the major source of the Yangtze River, which is the longest river in Asia. Active tectonism in this region has resulted in varied topography and the development of special ecosystems influenced by unique environmental patterns. Tectonic collision between the South Asian and the Eurasian continental plates created a series of north–south–oriented ranges in the Hengduan Mountains. The mountains are mostly 4000–5000 m high, with an average elevation of more than 4000 masl. Alpine vegetation is mainly distributed between the mountain forest line and the zone annually covered with snow, and it is usually distributed in patches (Dirnböck et al 2003). The alpine vegetation in the Hengduan Mountains largely consists of 2 subtypes of vegetation: alpine cushion vegetation and alpine sparse vegetation. The climate is influenced by westerly circulation and Indian and Pacific monsoon circulation. Precipitation is uneven throughout the year. The rainy season (from May to October, accounting for 85–90% of precipitation for the year) has abundant rainfall, whereas the dry season (from December to April) has little precipitation (He et al 2016). The average annual temperature is 9.0°C, with a mean temperature of 3.4°C in the coldest month and an average annual maximum temperature of 16.7°C.

Climate and vegetation data
To provide a robust dataset, all 35 meteorological stations in the study area were selected. Their general situation and location details are shown in Appendix S1 (Supplemental material, https://doi.org/10.1659/MRD-JOURNAL-D-20-00010.1S1). A dataset of monthly mean surface air temperature, monthly precipitation, and sunshine duration series (1980–2018) was used. The data were obtained from the China Meteorological Administration (National Meteorological Information Centre, n.d.). By performing paired sample t-tests, we confirmed that there were no significant differences between the WorldClim dataset and the dataset derived from the meteorological stations in the Hengduan Mountains. The Pearson correlation coefficient (r) was used to test the degree of cross-correlation (Yang et al 2013) using SPSS 19.0 to avoid overfitting the model variables. When the coefficient of the 2 variables was greater than 0.75, the variables with less ecological significance were excluded. The resolution of all climate datasets was 1 × 1 km based on the ANUSPLIN interpolation method (Xu and Hutchinson 2013), which can introduce multiple covariates. In particular, it considers the influence of elevation on data sequence. Elevation was extracted from a digital elevation model (DEM), and the data were extracted from the Shuttle Radar Topography Mission DEM (Jarvis et al 2008).

The geographic distribution data of vegetation types were obtained from a 1:100,000 vegetation map of China (IGSNRR 2017) and field validation. The geographic distribution data of alpine vegetation in the Hengduan Mountains were extracted using ArcGIS, removing small patches with an area of less than 5 km², and randomly selecting points among the remaining patches. The minimum distance between 2 points in the same patch was 20 km. This produced 125 geographic distribution points of alpine vegetation (Figure 1).

All climate and vegetation data were preprocessed using ArcGIS tools, including data format conversion, tessellation, definition projection, and clipping, before they were converted into the ASCII format required by MaxEnt 3.4.1 software.

MaxEnt model procedure
The MaxEnt model is a probability model that predicts the potential distribution of species based on the principle of ecological niche. In practice, the MaxEnt model evaluates habitat suitability for species by using species occurrence points and environmental variables. It selects the distribution with the maximum entropy as the optimal distribution from all eligible distributions. The predicted result is the relative probability that a species will exist in an area. The output range of the model is 0–1, and the larger the value, the more suitable the area is for the species (Franklin et al 2013; Merow and Silander 2014; Hu et al 2019). Based on the MaxEnt machine learning method, habitat suitability was modeled using existing data on alpine vegetation and the current environmental variables of the research area. Using the ArcGIS conversion tool, environmental factors were extracted into ASCII format,
and climate and vegetation sampling data were divided into 2 datasets: 75% of the randomly selected data were used for verification training, and the remaining 25% were used to test the ability of the model to predict vegetation distribution. Threshold-independent receiver-operating characteristic (ROC) analysis was conducted to calibrate the model. The area under the ROC curve (AUC) value is provided by the model. AUC and Kappa values were selected as criteria for judging the applicability and accuracy of the MaxEnt model simulation. The simulation process of the MaxEnt model is shown in Appendix S2 (Supplemental material, https://doi.org/10.1659/MRD-JOURNAL-D-20-00010.1).

Climate variables were included in fitting the model: First, climate factors with a contribution rate of 0 in the simulation results were eliminated. The remaining climate factors were added to the model, which was then run 10 times to check whether the results still contained climate factors with a contribution rate of 0. This was done until no climate factor with a contribution rate of 0 appeared. After these repeated runs, 7 climate factors were retained: annual mean temperature ($T$), annual mean maximum temperature ($T_{\text{max}}$), annual mean minimum temperature ($T_{\text{min}}$), annual mean sunshine duration (SSD), dry season precipitation (DP), rainy season precipitation (WP), and annual relative variability of precipitation ($R$). During model development and operation, the model was cross-validated. A jackknife test and an ROC test were used to assess the relative importance of each variable.

### Division of climate suitability

Different studies have used different methods to classify the results predicted by the MaxEnt model, including by suitability. Among them, the method of division according to the natural break point achieved results closest to the actual geographic distribution range and area of alpine vegetation shown in the vegetation type map for the base period (1980–1999) in the Hengduan Mountains. Therefore, the natural break point method was used to divide the simulation results of habitat suitability into 4 grades as follows: unsuitable, 0–0.10; low suitability, 0.10–0.28; moderate suitability, 0.28–0.5; and high suitability, 0.50–1. The climatic suitability grade distribution map showing the potential geographic distribution of alpine vegetation in the Hengduan Mountains was obtained using ArcGIS. The elevation distribution of alpine vegetation in the fully suitable climate area was extracted from the DEM layer, and the variation with elevation was statistically calculated.

### Results

**Prediction accuracy of the MaxEnt model and contribution of climate variables**

The average AUC value of the training set run through the model was 0.934, showing that the MaxEnt model can accurately predict suitable regions for the distribution of alpine vegetation in the Hengduan Mountains. Climate variables ($T_{\text{min}}$, $T$, SSD, and $R$) explained most of the variability of the data (Table 1). The cumulative contribution rate of these 4 environmental variables was 88.57%, indicating that they play a decisive role in the potential distribution of alpine vegetation in the Hengduan Mountains. $T_{\text{min}}$ was a potent factor among the 7 climate variables, indicating that colder temperatures over the year play a decisive role in the broad distribution of alpine vegetation in the Hengduan Mountains.

**Potentially suitable areas for alpine vegetation under current climate factors**

The unsuitable areas are mainly distributed in the southern regions of the Hengduan Mountains (Figure 2), including central Yunnan and southern Sichuan. The areas with low and moderate suitability are mainly in the northern regions of the Hengduan Mountains, including northern Sichuan. The region that is most suitable for alpine vegetation lies in the high mountain area of the Tibetan Plateau.

From 1980 to 1999, the highly suitable areas for alpine vegetation accounted for 8.61% of the entire region, the moderately suitable areas accounted for 11.34%, and the areas of low suitability accounted for 28.86%. The proportion of highly suitable areas for alpine vegetation increased by about 1% from this period to the period 2000–2018, and the proportion of unsuitable areas decreased by 3%.

The relationships between potential geographic distribution of alpine vegetation and individual environmental factors are shown in Figure 3. The moderately and highly suitable zones are mainly in regions with elevations between 4500 and 5000 masl; the low suitability zone is found between 3500 and 4500 masl, and the unsuitable zone is mostly below 3500 masl. The highly suitable zone for alpine vegetation is mainly in areas where

### Table 1: Contribution rate and permutation importance of climate variables in the MaxEnt model.

| Variable | Climatic factors | Contribution (%) | Permutation importance (%) |
|----------|------------------|------------------|---------------------------|
| $T_{\text{min}}$ | Annual mean minimum temperature | 43.08 | 15.66 |
| $T$ | Annual mean temperature | 29.99 | 41.22 |
| SSD | Annual sunshine duration | 9.23 | 10.27 |
| $R$ | Annual relative variability of precipitation | 6.27 | 13.31 |
| WP | Rainy season precipitation | 5.86 | 10.56 |
| DP | Dry season precipitation | 4.38 | 0.55 |
| $T_{\text{max}}$ | Annual mean maximum temperature | 1.19 | 8.43 |
$T_{\text{min}}$ ranges between $-15$ and $-8^\circ C$. In the zones of moderate and low suitability, $T_{\text{min}}$ ranges between $-8$ and $-2^\circ C$. In the unsuitable zone, it is greater than $-2^\circ C$.

**Potentially suitable areas for alpine vegetation under future climate change**

The model was used to predict areas potentially suitable for alpine vegetation under future climate scenarios. The increased temperatures led to an increase in the proportion of highly suitable areas for alpine vegetation and a slight decrease the proportion of unsuitable areas, regardless of changes in precipitation. The proportion of highly suitable areas for alpine vegetation increased and the proportion of unsuitable areas decreased slightly compared with the present situation. In all future climate change scenarios, when $T$ rises by $2^\circ C$ and the annual precipitation decreases by 20%, the proportion of unsuitable areas decreases by at least 2%. Therefore, taking this climate change scenario as the model estimate for the lowest change of alpine vegetation in response to future climate change scenarios (Figure 4), the range of potentially suitable areas will increase in the Hengduan Mountains.

Compared with the current period, the pattern of highly suitable areas for the geographic distribution of alpine vegetation under future climate change scenarios shifts from the highest and the lowest elevations toward the middle of the elevation gradient (Table 2). This is reflected by a decrease in the proportion of this zone below 4500 masl and above 5000 masl and an increase in its proportion in the range of 4500–5000 masl.

**Discussion**

**Analyzing the geographic distribution of climate suitable for vegetation using the MaxEnt model**

The MaxEnt model is a biological climate envelope model (or bioclimatic envelope model). In ecology, the MaxEnt model offers better predictive power, faster operation, and higher
availability of sample data than other models of this type. It is mostly applied at the species scale but can be used to study the distribution range of plant functional types and community sets (relative to individuals) (Chapman and Purse 2011). Based on an in-depth analysis of its principles, the present study expanded the application field of the MaxEnt model from species scale to climate suitability analysis to predict the geographic distribution of vegetation categories. We carried out strict repeated trials and applicability tests during the model simulation. The results simulate well habitat for the large category of alpine vegetation in the Hengduan Mountains. This means that it is possible to predict the geographic distribution of climate suitable for vegetation based on the MaxEnt model to help understand the functional diversity of ecosystems.

In recent years, studies have also shown that the MaxEnt model has shortcomings. For example, Yang et al (2013) pointed out that the model overestimates the potential distribution area compared with the realized ecological niche of a species. In this study, data recorded by meteorological stations were used for interpolation using the ANUSPLIN method, thus improving interpolation accuracy. Furthermore, the model was cross-validated during development. To analyze the influence of the random training ratio of different current distribution points on the prediction accuracy of MaxEnt model, the standard deviation of AUC was used as an evaluation criterion. AUC and Kappa values were selected as criteria for judging the applicability and accuracy of MaxEnt model simulation. The average AUC was 0.934. A Kappa consistency test was carried out between the potential distribution of alpine vegetation in the study area after model simulation and the existing status point map to test the accuracy of the simulation. The sample points obtained were extracted from the numerical values of the simulation results from 1980 to 1999. If the sample points are in suitable areas, the simulation results are consistent with the actual distribution. The Kappa coefficient is 0.627, indicating that the accuracy of the simulation is good.

Comparing the AUC values of different sample sizes showed that the maximum and minimum AUC values of the training and test data generally appeared when the sample size was small. When the sample size is small, the AUC value of the model varies greatly and has poor stability. As sample size increases, the AUC value becomes more stable. We found that a sample size of 120 provided relatively stable model predictions.

According to the vegetation type chart data of China (1:100,000) compiled in 2001, the alpine vegetation area in the Hengduan Mountains is 25,652 km². This represents about 8.2% of the total area of the study area, mainly distributed in Qinghai Province, Tibet Autonomous Region. Model simulation results show that the highly suitable areas for alpine vegetation during the period of 1980–1999 accounted for 8.61% of the total area. This shows that the MaxEnt model can well simulate the potential distribution area of alpine vegetation in the Hengduan Mountains. The MaxEnt model predicted areas with environmental conditions similar to those of current areas of alpine vegetation, indicating which areas would be suitable for growth in the future. The model only considers growth and succession of the vegetation to form the most stable and mature top-level vegetation type, according to current climate conditions. It reflects the overall trend of vegetation development in a specific region under specific climate conditions (Jiang et al 2017). It excludes the impact of human activities (Pearson et al 2007). Although the change of alpine vegetation in the Hengduan Mountains cannot be completely attributed to climate change, there is no doubt that climate change has accelerated the process and changed the distribution pattern of vegetation. Compared with other natural ecosystems, the Hengduan Mountains area is more sensitive to climate change. The results of this study present potential alpine vegetation changes based on climate suitability on a regional scale. Further studies are needed to consider land uses, combined with soil types, human activities, and other factors.

Species distribution models are not a substitute for field surveys but are useful tools for data exploration, helping to

![FIGURE 4](image_url) Potential geographic distribution of climate suitable for alpine vegetation in the Hengduan Mountains under different temperature and precipitation scenarios. T+1.0 represents annual average temperature increases of 1.0°C, P−20% means annual precipitation decreases by 20%; T+2.0 represents annual average temperature increases of 2.0°C, P−20% means annual precipitation decreases by 20%.

### TABLE 2

| Elevation (m) | 1980–1999 (%) | 2000–2018 (%) | T+1.0 (%) | T+1.5 (%) | T+2.0 (%) |
|--------------|---------------|---------------|-----------|-----------|-----------|
|              | P0 P+20% P−20% | P0 P+20% P−20% | P0 P+20% P−20% | P0 P+20% P−20% | P0 P+20% P−20% |
| >5000        | 45.98 40.58   | 39.70 38.68 37.86 | 38.91 39.41 40.08 | 39.39 38.68 40.02 |
| 4500–5000    | 43.67 50.11   | 52.83 53.84 54.75 | 52.44 52.03 52.97 | 52.65 53.81 53.18 |
| 3500–4500    | 10.35 9.30    | 7.47 7.49 7.40 | 8.65 8.56 6.95 | 7.96 7.52 6.80 |
| <3500        | 0.00 0.00     | 0.00 0.00 0.00 | 0.00 0.00 0.00 | 0.00 0.00 0.00 |

Note: T+1.0, T+1.5, and T+2.0 represent annual average temperature increases of 1.0, 1.5, and 2.0°C, respectively. P0, P−20%, and P+20% represent unchanged annual precipitation, precipitation decreased by 20%, and precipitation increased by 20%, respectively.
identify potential knowledge gaps and providing guidance for designing field surveys of rare species.

Changes in potential geographic distribution of vegetation in response to climate change

The range sizes of mountain species were predicted to shrink in response to climate warming, moving upslope (Salick et al. 2014; Seddon et al 2016). Species may adapt to climate change by shifting their ranges to higher elevations, but the lack of suitable habitats can have a profound effect on alpine plant species (He et al 2019). Studies have shown that ranges can increase with elevation in some mountain areas (Elsen and Tingley 2015), so the range of many mountain species may increase, rather than decrease, under climate warming (Liang et al 2018).

The contribution of climate factors to the geographic distribution of species differs according to regional environment, reflecting the sensitivity and accuracy of the MaxEnt model to the input parameters (Radosavljevic and Anderson 2013). For each temperature change scenario, the geographic distribution of climatically suitable areas for alpine vegetation in the Hengduan Mountains does not differ significantly according to precipitation level. This suggests that precipitation is not the main factor affecting the geographic distribution of alpine vegetation. The growth of alpine vegetation in the Hengduan Mountains has a strong response to temperature, and $T_{	ext{min}}$ has the most obvious effect on the geographic distribution of vegetation. Key to the adaptation of alpine plants to an adverse environment is their ability to develop and maintain normal metabolism at low air temperatures (Larcher 1980).

Positive growth trends have been found at high elevations, suggesting that temperature is a strong limit on tree growth at alpine tree lines (Panthi et al 2019; Singh et al 2019). The onset of cell division has a low threshold temperature. Warming tends to drive the upward shift of alpine tree lines, but their shift rate is mediated by species interaction (Astudillo-Sánchez et al 2019). Each plant species evolves under long-term pressures from the external environment, and various strategies may develop in response to rapid environmental change. The species interaction mechanism explains spatial differences of tree line shift under a warming climate. The rise in temperature alleviates the restriction of low temperatures on the growth and distribution of organisms. However, the changes in the distribution of plant species in response to climate change are more complex than expected.

Combining a regional map of temperature and the distribution map predicted by the MaxEnt model, it can be seen that alpine vegetation can grow in areas where the annual average lowest temperature is $-15$ to $-8^\circ$C. This is important for biogeographic research and species conservation management in terms of introduction and cultivation.

Conclusion

Alpine vegetation has been significantly influenced by climate change, and this is likely to continue. The model predicts that the future climatically suitable space for alpine vegetation will continue to shift toward middle and higher elevations. In the Hengduan Mountains, the area with a suitable climate for alpine vegetation is predicted to expand, increasing range sizes, in response to climate warming.

Our results suggest that under climate warming, a greater available land area may regulate the range lost by alpine plants because of the elevation gradient and heterogeneity of the adjacent Tibetan Plateau topography. Our findings have important implications for estimating the future viability of vegetation and for biodiversity conservation and management in mountain ecosystems in the face of expected global warming. To protect endemic alpine species in the Hengduan Mountains from the effects of climate change, the optimal habitat for alpine vegetation, ranging from 4500 to 5000 masl, should be protected from interference and destruction by human activities.

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Supplemental material

APPENDIX S1 General situation and location details.
APPENDIX S2 The simulation process of the MaxEnt model.

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