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Predicting Potential Distribution of Tibetan Spruce (*Picea smithiana*) in Qomolangma (Mount Everest) National Nature Preserve Using Maximum Entropy Niche-based Model

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Abstract: Tibetan spruce (*Picea smithiana*) is an endemic species of the Himalayas, and it distributes only in a restricted area with very low number. To address the lack of detailed distributional information, we used maximum entropy (Maxent) niche-based model to predict the species′ potential distribution from limited occurrence-only records. The location data of *P. smithiana*, relative bioclimatic variables, vegetation data, digital elevation model (DEM), and the derived data were analyzed in Maxent. The receiver operating characteristic (ROC) curve was applied to assess the prediction accuracy. The Maxent jackknife test was performed to quantify the training gains from data layers and the response of *P. smithiana* distribution to four typical environmental variables was analyzed. Results show that the model performs well at the regional scale. There is a potential for continued expansion of *P. smithiana* population numbers and distribution in China. *P. smithiana* potentially distributes in the lower reaches of Gyirong Zangbo and Poiqu rivers in Gyirong and Nyalam counties in Qomolangma (Mount Everest) National Nature Preserve (QNNP), China. The species prefers warm temperate climate in mountain area and mainly distributes in needle-leaved evergreen closed to open forest and mixed forest along the river valley at relatively low altitudes of about 2000–3000 m. Model simulations suggest that distribution patterns of rare species with few species numbers can be well predicted by Maxent.

Keywords: *Picea smithiana*; maximum entropy niche-based model; potential distribution; Qomolangma (Mount Everest) National Nature Preserve (QNNP)

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1 Introduction

Rare species often distribute in limited geographic areas or in a very small number of habitats, which need to be well preserved. Developing effective methods for identifying the factors that shape the distribution and abundance of rare species is a prime concern for conservation (Guisan *et al*., 2006; Williams *et al*., 2009). Models of the distribution of rare species are important tools in monitoring and management efforts. Because of their rarity, presence data of such species that are used to build distribution models are generally limited. Many rare species inhabit remote regions which are difficult to observe, and there is an urgent need to assess the status of these species. However, until recently such regions have been little explored by biologists, and most available information is based on visual surveys in existing or proposed reserves (Schaller, 1977; Harris and Loggers,

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2004). Although these surveys can not provide reliable estimations of population distribution, they provide an opportunity to focus sampling effort and refine the estimations of distribution within the broader population range. This can be achieved by understanding the fundamental ecological requirements of the species, based on the environmental characteristics of known occurrence sites (Kadmon and Heller, 1998; Peterson *et al*., 1999).

It is widely accepted that the geographic distribution of species and their diversity or richness depend on how well their ecological niche is understood (Whittaker *et al*., 2001). The measurement of environmental requirements to quantify the range size and patterns of species distribution and richness is an important step towards this understanding (Woodward, 1987). The niche is an abstract characterization of the intra-community position of the species that depends on time, space, and differences in resource gradients that cause the species evolution. The majority of niche-based models published in the literature have been developed on common plant and animal species or biodiversity (Rouget *et al*., 2004; Poutsma *et al*., 2008). To date, relatively few successful applications of this approach for rare plant species have been found (Miller, 1986; Brigham and Schwartz, 2003; Engler *et al*., 2004).

Maximum entropy (Maxent) niche-based model can be applied to analyzing the coordinates of species presence-only geographic locations and associated environmental data to produce distributions by expressing suitability of each grid cell as a function of the environmental variables at that grid cell. A high value of the function indicates that the grid cell is predicted to have suitable conditions for that species (Phillips *et al*., 2005). Compared with other existing models, such as the bioclimatic prediction system (BIOCLIM) (Beaumont *et al*., 2005), domain model (DOMAIN) (Carpenter *et al*., 1993), genetic algorithm for rule-set prediction modeling system (GARP) (Stockwell *et al*., 2006; Sanchez-Flores, 2007) and multivariate adaptive regression splines (MARS) (Elith *et al*., 2006), Maxent has a number of features that make it very useful for modeling species distribution (Vidal-Garcia and Serio-Silva, 2010), including a deterministic frame work, hence, stability as well as the ability to run with presence-only point occurrences; high performance with few point localities; better computing efficiency enabling the use of large-scale high-resolution data layers; continuous output from least to most suitable conditions; and an ability to model complex responses to environmental variables (Phillips *et al*., 2005).

Tibetan spruce (*Picea smithiana*) is a Himalayan endemic conifer species with very few species number and limited distribution areas, and as a habitat specialist, very sensitive to climate change. Confirming the distribution of *P. smithiana* is of great importance for species conservation and facing the challenge of species conservation under the threat of climate change. This paper, using maximum entropy (Maxent) niche-based model, predicted the potential distribution area of *P. smithiana* in the Qomolangma (Mount Everest) National Nature Preserve (QNNP), China, with the purpose of providing reliable spatial prediction of *P. smithiana* for its conservation and identifying the suitable site conditions for its reintroduction.

2 Materials and Methods

2.1 Study area

The Qomolangma (Mt. Everest) National Nature Preserve (3.3×10^4 km^2), one of the most important protected area in the world (Cidanlunzhu, 1997), is located at the junction of the Tibet Autonomous Region, China and Nepal. It covers the whole area of Tingri, Gyirong, Nyalam counties and most area of Dinggyê County (27°48′–29°19′N, 84°28′– 88°23′E) (Zhang *et al*., 2007). We take the whole area of the four counties (3.6×10^4 km^2) as the study area. It is composed of two big plateau geomorphic units of high Himalayan Mountains, and the lake basin on the plateau. The former has towering snowy peaks and deep river valleys with great divergence of altitude (1800–8800 m). In the southern QNNP, at increasing altitudes, are the following climate types: mountain warm temperate, subalpine cold temperate, alpine sub-frigid, and alpine frigid. In the northern part, the climate is cold and dry, which are the typical characteristics of the plateau continental climate. The soil distribution shows significant horizontal and vertical zonation. Mountain yellow brown soil, mountain acid brown soil, and mountain bleached podzolic soil, subalpine meadow soil, alpine meadow soil, subalpine steppe soil and alpine meadow-steppe soil are distributed in turn from bottom to top. The QNNP is very diverse in ecosystems and its vertical zones are remarkable. The vegetation is mainly composed of mountain subtropical evergreen broad-leaved forests, mountain warm-temperate needle-leaved and broad-leaved mixed forests, mountain cold-temperate needle-leaved forests, subalpine frigid shrubs and meadows, alpine frigid meadows and cushion vegetation, and alpine frigid moraine lichens. The QNNP is rich in biodiversity; there are 2176 species of vascular plants, among them more than 10 species are national key protected plants, such as *P. smithian Alcimandra cathcartii* and *Trillium govanianum*, and 263 species of animals including more than 30 species of national key protected animals, such as *Presbytis entellus*, *Macaca assamensis*, and *Ailurus fulgens* (Tibet Bureau of Statistics, 2008).

2.2 Data and processing

2.2.1 Occurrence data of P. smithiana

P. smithiana belongs to genus *Picea*, which is native to the Himalayas, giving rise to its alternative name, the 'West Himalayan Spruce'. It is an evergreen tree growing to 30–50 m at a slow rate. *P. smithiana* has the longest needles of any spruce, up to 5 cm in length. It is in leaf all year, and the seeds ripen from October to November. The flowers are monoecious and are wind pollinated. The plant prefers a climate with distinct seasons and acid mountain brown soil. It requires sufficient humidity during growing season and has a large root system. The plant can resist cold, drought and strong wind, and it has a strong shade tolerance, but it can not tolerate atmospheric pollution and maritime exposure. It often mixes with *Pinus griffithii* and *Quercus semicarpifolia. P. smithiana* grows mainly at an altitude of 2400–3200 m, and it is one of the endemic species of the Himalayas. According to the former literature references and documentation (Wu, 1980), in China, it only appears (with low abundance) in the Gyirong Zangbo River Basin in Gyirong County, located in the south of the Qinghai-Tibetan Plateau. However, the Poiqu and Pumqu River basins located in the three other counties of QNNP have extremely similar environmental conditions and are distributed relatively close to the Gyirong Zangbo River Basin. As such, there is a high probability of *P. smithiana* occurring in these regions.

The distribution data of *P. smithiana* were obtained from Chinese Virtual Herbarium applied by the Qinghai-Tibetan Plateau Museum of Biology in the Northwest Institute of Plateau Biology, Chinese Academy of Sciences. The database contains the information of the location, associated environment and morphological features of the samples collected from the 1970s to present. A total of 36 *P. smithiana* samples were available, including eight replicate samples. We eliminated the replications and used the remaining 28 points (18 for training, 10 for testing) as the occurrence data to be analyzed in this study.

2.2.2 Bioclimatic variables

The environmental layers 'Bioclimatic Variables' were used in the predicting procedures. These consist of important ecological factors and global climatic features. The data supplied by World Climate Project were downloaded from http://www.worldclim.org/, and comprised 19 layers (Table 1). The data layers were generated through interpolation of monthly average climate data from weather stations on a 30 arc-second resolution grid (often referred to as '1 km' resolution) during 1950–2000 and calculation of the annual mean values (Hijmans *et al*., 2005). We scaled down the environmental layers to 30 m resolution to match with the elevation and vegetation data, as finer resolution data was not available.

Table 1 Bioclimatic variables description

Variable	Description
Bio1	Mean annual temperature
Bio2	Mean diurnal range
Bio3	Isothermality
Bio4	Temperature seasonality
Bio5	Max temperature of warmest month
Bio6	Minimum temperature of coldest month
Bio7	Temperature annual range
Bio8	Mean temperature of wettest quarter
Bio9	Mean temperature of driest quarter
Bio10	Mean temperature of warmest quarter
Bio11	Mean temperature of coldest quarter
Bio12	Annual precipitation
Bio13	Precipitation of wettest month
Bio14	Precipitation of driest month
Bio15	Precipitation seasonality
Bio16	Precipitation of wettest quarter
Bio17	Precipitation of driest quarter
Bio18	Precipitation of warmest quarter
Bio19	Precipitation of coldest quarter

2.2.3 Elevation data

All the spatial data was handled in ArcGIS version 9.2 (ESRI) with the spatial analyst extension. Digital elevation model (DEM) was obtained from Earth Remote Sensing Data Analysis Centre with a resolution of 30 m (http://www.gdem.aster.ersdac.or.jp/search.jsp). Aspect and slope values were derived from DEM.

2.2.4 Vegetation data

The vegetation data used in this study were derived from the land cover data obtained through the interpretation of Advanced Wide Field Sensor (AWiFS) satellite imagery in 2007, by the method of object-oriented classification. The land cover data (Zhang *et al*., 2010) encompass the whole QNNP with a spatial resolution of 56 m (Fig. 1). The classification system of the land cover was established by the Land Cover Classification System 2 published by FAO (Table 2) (Zhang *et al*., 2010).

2.2.5 Auxiliary data

The auxiliary data include the topographic maps at the scale of 1∶100 000 covering the whole QNNP; the vector layers of county boundaries, main rivers, important cities and counties, main road lines and main railway lines of China were obtained from National Fundamental Geographic Information System.

2.3 Maximum entropy (Maxent) niche-based model

Maxent is a machine learning algorithm that generates predictions or inferences of species′ ecological requirements from an incomplete set of information. The Maxent approach is based on a probabilistic framework. It relies on the assumption that the incomplete empirical probability distribution (based on the species occurrences) can be approximated with a probability distribution of maximum entropy subject to certain environmental constraints, and that this distribution approximates a species potential geographic distribution (Phillips *et al*., 2005; Suarez-Seoane *et al*., 2008). Maxent models do not predict the actual limits of a species′ range; they can identify regions with similar environmental conditions to occurrence localities. The input data includes a set of environmental layers for a geographical region and a set of species presence data inside that region. The model evaluates the suitability of each grid

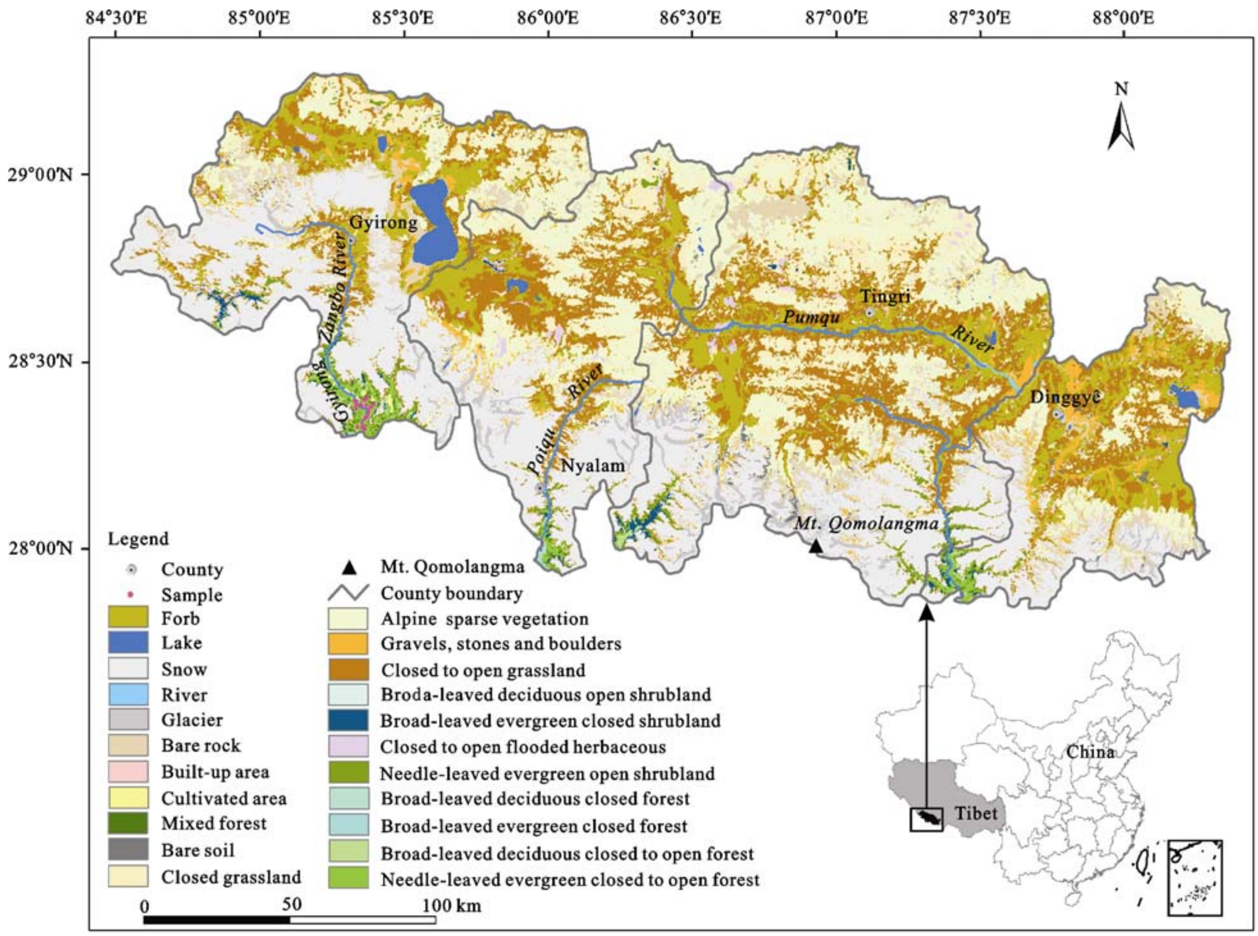


Fig. 1 Land cover map of study area (Zhang *et al*., 2010)

Table 2 Classification system of land cover

ID	Class Division	Description
1	Bare soil	Bare soil and/or other unconsolidated material(s)
2	Bare rock	Bare rock(s)
3	Built-up area	Built up area(s)
4	Cultivated area	Herbaceous crop(s); crop gype: food crops
5	River	Natural waterbodies (flowing)
6	Lake	Natural waterbodies (standing)
7	Snow	Snow
8	Glacier	Ice (moving)
9	Gravels, stones and boulders	Gravels, stones and boulders
10	Alpine sparse vegetation	Sparse perennial short forbs
11	Forbs	Open annual forbs; floristic: *Artemisia wellbyi*
12	Closed to open grassland	Closed to open grassland, single layer; floristic: *Kobresia*
13	Closed grassland	Closed perennial short grassland; floristic: *Kobresia*
14	Closed to open flooded herbaceous	Vegetation grow on permanently flooded land
15	Broad-leaved evergreen closed shrubland	Broad-leaved evergreen with medium height and thickness
16	Broad-leaved deciduous open shrubland	Broad-leaved deciduous shrubland
17	Needle-leaved evergreen open shrubland	Needle-leaved evergreen medium high shrubland
18	Broad-leaved evergreen closed forest	Broad-leaved evergreen high trees
19	Broad-leaved deciduous closed forest	Broad-leaved deciduous high trees
20	Mixed forest	Multi-layered mixed high trees
21	Broad-leaved deciduous closed to open forest	Broad-leaved deciduous woodland
22	Needle-leaved evergreen closed to open forest	Needle-leaved evergreen woodland

cell as a function of environmental variables at that cell. The suitability value provided by Maxent range is from 0 (unsuitable habitat) to 100 (optimal habitat). In addition, Maxent is equipped with several features aimed at supporting the interpretation of the model results. It has a built-in jackknife option, which allows the estimation of the significance of individual environmental data layers in computing the species distributions. It also can provide response curves for each environmental layer showing how the Maxent prediction depends on a particular environmental variable. Maxent version 3.3.2 was obtained from http://www.cs.princeton.edu/~schapire/maxent/. We followed recently published best practice approaches to tune its parameters (Phillips and Dudik, 2008) and carried out the jackknife test and response curves to further analyze the model results.

The Receiver Operating Characteristic (ROC) curve was applied to verifying the result of Maxent modeling. Maxent provides statistical measures for model performance such as omission rates and the areas under the ROC curve. The ROC curve provides a quantitative representation of the tradeoffs between no omission (sensitivity) and commission error (1-specificity). The sensitivity represents the absence of the omission error, and the quantity 1-specificity represents the commission error. The ROC curve is obtained by plotting the sensitivity on the y-axis and 1-specificity on the x-axis for all possible thresholds. The area under the ROC curve (AUC) is an important measurement of the model performance. The larger the AUC is, the higher the sensitivity rate and the lower the 1-specificity rate. An AUC equal to 1.0 represents an ideal diagnostic test because it achieves both 100% sensitivity and 100% specificity (Zweig and Campbell, 1993).

3 Results

3.1 Identification of main bioclimatic variables

There are close correlations among the 19 bioclimatic variables. Such correlations can increase the difficulty of identification of the main influencing factors, at the same time, the modeling requirements of logistic regression (applied in Maxent) that the variables should be normal and independent can not be met. In addition, if the environmental variables layers have a high resolution, the Maxent could not run because of the large amount of data. Therefore, we ran the Maxent for the first time to calculate the contribution of each bioclimatic variable to the predicted probability. We chose six bioclimatic variables with high contribution values ($\geqslant 1$) as the modeling variables, which include Bio3, Bio6, Bio7, Bio14, Bio11 and Bio1, with the contribution percent of 67.00%, 17.10%, 9.60%, 1.90%, 1.10%, 1.00%, respectively.

3.2 Potential distribution of *P. smithiana*

Maxent models for the potential distribution of *P. smithiana* were generated using the geo-referenced species presence data and 10 environmental variable layers, including six bioclimatic variable layers, three elevation layers and one vegetation layer. The potential distribution of *P. smithiana* is shown in Fig. 2.

P. smithiana mainly distributes in the lower reaches of Gyirong Zangbo and Poiqu in Gyirong and Nyalam Counties, where the altitude is comparatively lower than the other areas in QNNP, and the climate is mountain warm temperate. It often appears along the river valley and mixes with *Pinus griffithii* and *Quercus semicarpifolia* which are the dominant species of subtropical mountain needle-leaved forest and mixed forests of subtropical mountain evergreen broad-leaved forests, needle-leaved forest and deciduous broad-leaved forest. Its distribution area is parallel to the buffer zone of the rivers. The distribution probability becomes lower as the distance from the river increases.

3.3 Result evaluation using ROC test

We used two indicators to examine the performance of the model: the fraction of predicted area and extrinsic omission rate as the threshold-dependent test and the area under the ROC curve (AUC) as the threshold-independent test (Table 3). The indicators were obtained using approximately 30% of the training data as

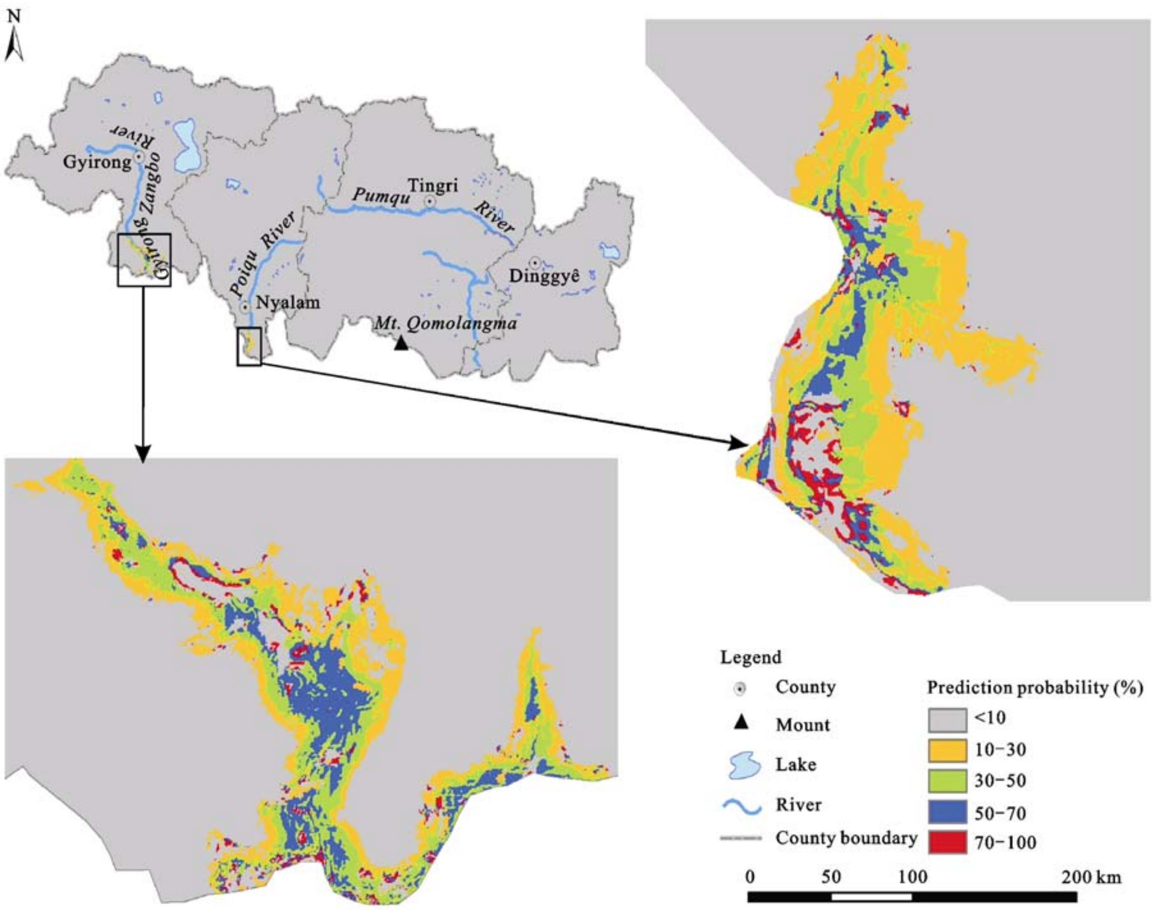


Fig. 2 Prediction of distribution of *P. smithiana*

Table 3 Results of threshold-dependent omission test and threshold-independent ROC test

Threshold-dependent test		Threshold-independent test
Fractional predicted area	Test omission rate	AUC test (training)
0.004	0.001	0.998 (0.999)

test localities for evaluating the performance statistics. The AUC value (0.998) was significantly better than random (0.5). This result was obtained for both the training and the test data, with the small difference in AUC values suggesting a robust performance of the Maxent algorithm to capture the changes in environmental variables over point localities. The omission test was calculated at a 10% threshold value. At this threshold, the fractional predicted area shows the fraction of all the pixels that are predicted suitable for the species. The omission rate was quite low (0.001), indicating that only a small fraction of the test locations fell into pixels not predicted as suitable for *P. smithiana*. The overall accuracy of the model for *P. smithiana* was high, implying that the Maxent-derived distributions are a close approximation of the distribution probability that represents the reality.

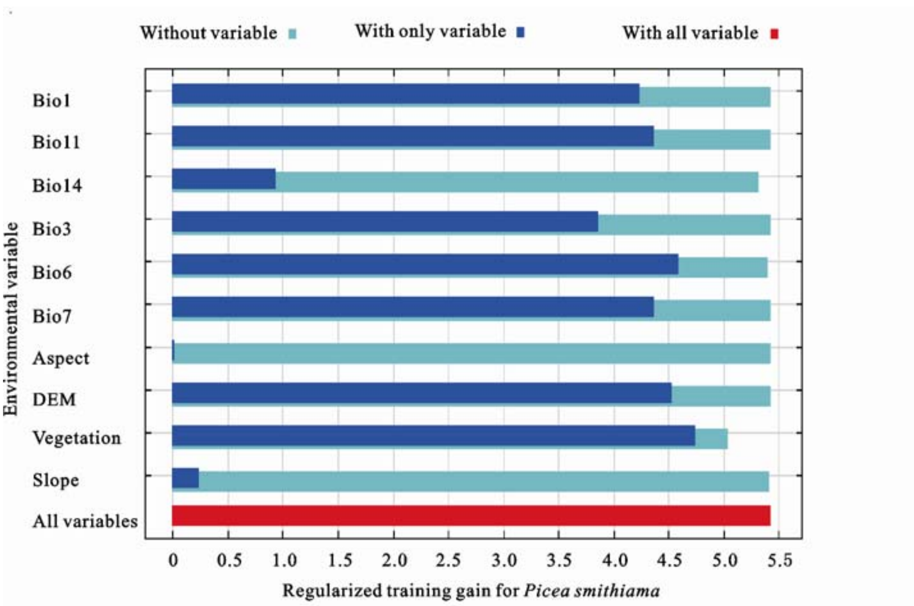
3.4 Jackknife analysis of environmental variables

The jackknife training gains for the environmental variables were performed for all individual runs and showed almost the same results with slight variability in gain values (Fig. 3). Six variables have notable influences on the distribution pattern of *P. smithiana*: vegetation, DEM, temperature annual range, minimum temperature of the coldest month, mean temperature of the coldest quarter and mean annual temperature. The variables with low gain and thus less contribution to model generation were: aspect, slope and precipitation of the driest month.

3.5 Response curves of environmental variables

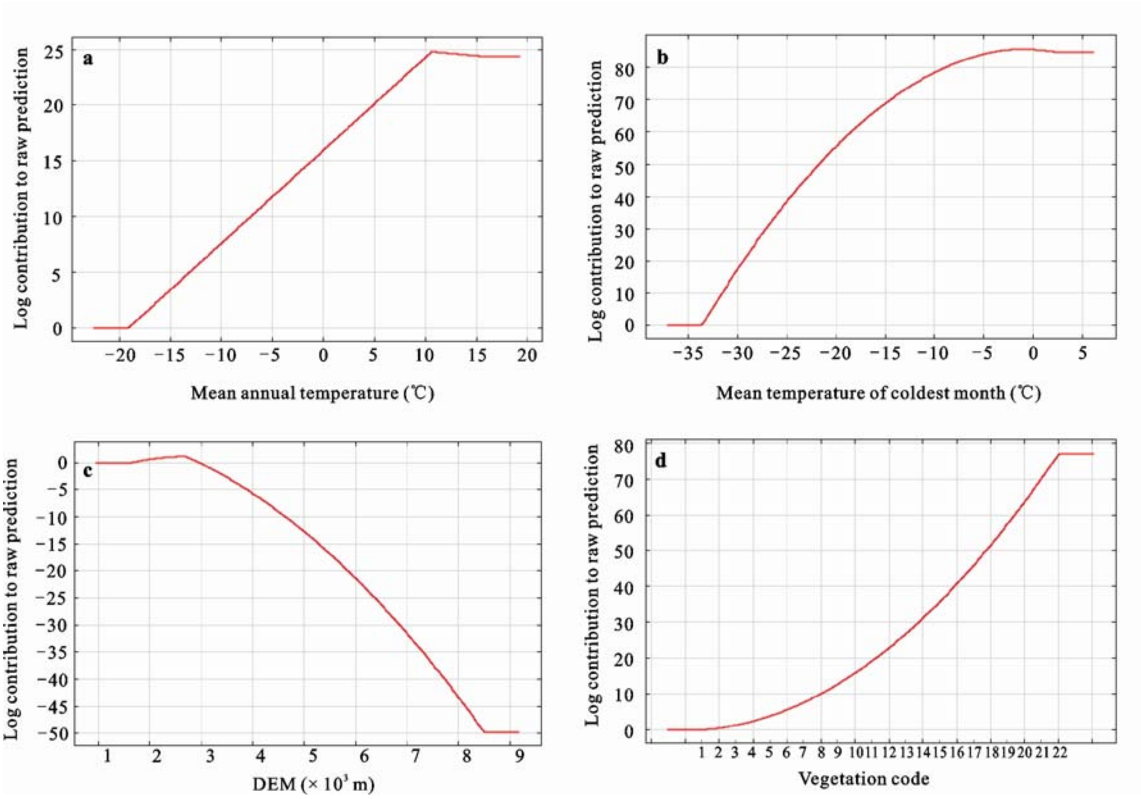
We chose four response curves of environmental variables, including vegetation, DEM, mean annual temperature and minimum temperature of the coldest month to analyze the response of *P. smithiana* distribution to each typical environmental variable (Fig. 4).

Based on these response curves, *P. smithiana* prefers the ecological environment with high forest cover, comparatively low altitude and warm temperature, and is more likely to choose needle-leaved evergreen closed to open forest and mixed forest. It is worth noting that certain patches of cultivated area are distributed quite close to the potential distribution area of *P. smithiana*. The further expansion of cultivated land will probably alter the habitat of *P. smithiana*. As for the DEM, *P. smithiana* appears to mainly distribute from 2000 m to 3000 m. The distribution probability decreases with the increase



Bio1: mean annual temperature; Bio3: isothermality; Bio6: minimum temperature of coldest month; Bio7: temperature annual range; Bio11: mean temperature of coldest quarter; Bio14: Precipitation of driest month

Fig. 3 Jackknife test for environmental variables significance performed by Maxent



Vegetation code: 1, bare soil; 2, bare rock; 3, built-up area; 4, cultivated area; 5, river; 6, lake; 7, snow; 8, Glacier; 9, gravels, stones and boulders; 10, alpine sparse vegetation; 11, forbs; 12, closed to open grassland; 13, closed grassland; 14, closed to open flooded herbaceous; 15, broad-leaved evergreen closed shrubland; 16, broad-leaved deciduous open shrubland; 17, needle-leaved evergreen open shrubland; 18, broad-leaved evergreen closed forest; 19, broad-leaved deciduous closed forest; 20, mixed forest; 21, broad-leaved deciduous closed to open forest; 22, needle-leaved evergreen closed to open forest

Fig. 4 Response curves of environmental variables

of elevation (> 3000 m). *P. smithiana* prefers a warm temperate climate in mountainous area. The distribution probability increases as the mean annual temperature and minimum temperature of the coldest month increase.

4 Discussion and Conclusions

This study employed maximum entropy (Maxent) niche-based model to generate a predictive distribution of *P. smithiana*. The model performed well at the regional scale. Results indicate that for *P. smithiana*, the number and distribution might continue to expand in China. *P. smithiana* prefers a warm temperate climate in mountain area and mainly distributes in the needle-leaved evergreen closed to open forest and mixed forest along the valley at comparatively low altitudes of about 2000–3000 m. According to the results of this study, aside from the lower reaches of the Gyirong Zangbo River, which is considered to be the only distribution area in China, *P. smithiana* may potentially distribute in the lower reaches of the Poiqu River.

Although the Maxent performed well with few point localities and enabled the use of large-scale high-resolution data layers, there remained several limitations in this study. The data used in the model are from a variety of sources with different resolutions. The vegetation (56 m) and DEM data (30 m) have high resolution; however, the bioclimatic variables only have a resolution of about 1 km, errors may exist during the downscaling process which will reduce the accuracy of the prediction. There are only a small number of location data of *P. smithiana* because of its rareness. Most of the recorded location data were collected during the 1970s and these locations were only distributed near roads because they were easier to reach. The lack of surveys in some habitats may result in a bias in prediction and lead to the weak validation because few location data were used for testing. Moreover, the validity of training dataset for the model is based on the assumption that current species distributions are in equilibrium with the current climate. The impact of global climate change on species distribution is not considered. Another important defect is that the niche selection does not necessarily reflect the quality of the habitat (Johnson and Seip, 2008). It describes the realized niche of the species, which results from competition with natural disaster (e.g., fire), human disturbance and several other biotic and abiotic factors. It is quite difficult to take account of all the possible factors.

There is great potential to build upon the foundation of this project. Possible distributions of other rare species can be predicted using specific location data and relative environmental variable layers for each species. If more location data and layers with higher resolution are available, it would lend even greater support to the predictions and might also provide a stronger foundation for validity of the prediction. As the global climate changes, the surrounding environment of rare species will inevitably be affected, leading to changes in habitats. The influence of global climate change on species distribution presents a challenge because it requires continuing data refinement as environmental variables change along with climate change. Another challenge for future research will be to develop an integrated approach to incorporate human influence factors, such as land-use changes, and reproduction mechanisms to improve the precision of species distribution simulations. Furthermore, more field work for identifying *P. smithiana* in the lower reaches of the Poiqu River and related conservation planning needs to be considered.

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