Predicting distribution of *Zanthoxylum bungeanum* Maxim. in China

Zhihang Zhuo¹,³, Danping Xu¹²*, Biao Pu²*, Rulin Wang⁴ and Meng Ye⁵

**Abstract**

**Background:** With the growth of economic benefits brought by *Zanthoxylum bungeanum* Maxim. and the increasing market demand, this species has been widely introduced and cultivated in China. It is important to scientifically select suitable areas for artificial planting and promotion, and to understand the status and potential of *Z. bungeanum* resources.

**Results:** The maximum entropy (MaxEnt) model and ArcGIS technologies were used to analyze the climatic suitability of *Z. bungeanum* based on known distribution data, combined with environmental data in China. *Z. bungeanum* was mainly distributed in subtropical and mid-eastern warm temperate regions. The total suitable area (high and medium suitability) accounted for 32% of China’s total land area, with high suitability areas composing larger percentage, reaching \( 1.93 \times 10^6 \) km². The suitable range (and optimum value) of the key environmental variables affecting the distribution of *Z. bungeanum* were the maximum temperature in February of 2.8–17.7 °C (10.4 °C), the maximum temperature in March of 8.6–21.4 °C (16.3 °C), the maximum temperature in December of 2.5–17.1 °C (9.9 °C), the maximum temperature in November of 7.7–22.2 °C (14.5 °C) and the mean temperature in March of 3.2–16.2 °C (12.0 °C).

**Conclusions:** The model developed by MaxEnt was applicable to explore the environmental suitability of *Z. bungeanum*.

**Keywords:** Environmental variables, MaxEnt model, *Zanthoxylum bungeanum* Maxim., Distribution area

**Background**

*Zanthoxylum bungeanum* Maxim. is a small deciduous tree that belongs to the Rutaceae family. The fruit is purple-red and scattered with slightly raised oil spots. Its roots, stems, fruit and leaves can be used as raw materials for biomedicine, with antibacterial, anti-tumor, anti-inflammatory, analgesic and anti-oxidation effects [1–3]. The pericarp is famous for its pungent and numbing flavor, so it is also widely used as a seasoning. With the growth of economic benefits brought by *Z. bungeanum* and the increasing market demand, this species has been widely introduced and cultivated. In the process of introduction and cultivation, it is necessary to consider *Z. bungeanum*’s adaptability to local climatic conditions, to avoid the quality degradation and resource waste caused by inappropriate introduction. It is also important to scientifically select suitable areas for artificial planting and promotion, to understand the status and potential of *Z. bungeanum* resources.

Species distribution models use species distribution data and environmental data to estimate the distribution of a species based on a specific algorithm and to reflect the preference of a species to a habitat in the form of probability [4]. Although a variety of distribution models have been established, studies have shown that MaxEnt model is superior to other models in predicting with accuracy, especially in the case...
of incomplete species distribution data [5–7]. Maxent model is a niche model with good prediction effect. It demonstrates a strong capacity to distinguish the interaction of variables and cope with sampling deviation. It is simple and fast to operate and requires only a small sample size. The MaxEnt model has been applied in the simulation of pest and disease spread [8], the potential habitat quality estimation of endangered animals and plants [9], the prediction of invasive alien species [10], the prediction of suitable habitats for crop planting [11], the adaptation response to climate change [12], and good simulation results have been achieved. The MaxEnt model uses Jackknife to judge the importance of environmental factors and to quantitatively describe the effects of environmental factors on species habitats. However, there are few reports on the prediction of the suitable area of *Z. bungeanum* by MaxEnt in China which will restrict the future development of this species to a certain extent. We hypothesize that climate and topographical variables could be used to predict the suitable area of *Z. bungeanum*, and key environmental variables affecting the distribution would be obtained.

In this work, Maxent and ArcGIS technologies were used to analyze the environmental suitability of *Z. bungeanum* based on known distribution data, combined with environmental data in China. The key environmental variables affecting distribution and suitable growing areas were identified, which provided a scientific basis for practical introduction and cultivation of *Z. bungeanum* in the future.

### Results

#### Dominant environmental factors

The contribution of each environmental factor to the suitable distribution area of *Z. bungeanum* was quantitatively calculated by the Jackknife test (Table 1). Variables with zero contribution were removed. Prec8 contributes the most to the distribution, reaching 21.3%. The other main contribution factors contributing more than 10% are *tmax*3 (20.3%), *tmax*11 (15.1%) and *tmax*2 (14.4%) with an accumulated percent contribution accounting for more than half of the total contribution (71.1%). The single factor contribution rate of all twelve main contribution factors is more than 0.3% with accumulated percent contribution reaching 99.9%.

To eliminate the influence of collinearity on the modeling process and results interpretation, a strong correlation factor with a correlation coefficient higher than 0.8 was eliminated. Pearson correlation analysis was carried out on the twelve main contribution factors in Table 1, and the results are shown in Table 2. The correlation coefficients of the twelve variables in Table 2 are less than 0.8. The twelve variables were selected as the dominant environmental variables affecting the distribution of *Z. bungeanum*. The MaxEnt model was reconstructed based on the selected dominant environmental variables.

#### Model optimization and validation

The settings of regularization multiplier (RM) and feature classes (FC) in the Maxent algorithm are used to balance model fitting and complexity, and determine the types of constraints allowed in the model [13]. Akaike information criterion (AIC) quantity reflects the fitting and complexity of the model, which is an excellent standard to measure the performance of the model. A model

### Table 1 The contribution of each main contribution factor in MaxEnt modeling

| Code   | Environmental variables                               | Percent contribution/ % | Accumulated Percent contribution/ % |
|--------|--------------------------------------------------------|-------------------------|-------------------------------------|
| prec8  | Precipitation of August                                | 21.3                    | 21.3                                |
| *tmax*3| Maximum Temperature of March                           | 20.3                    | 41.6                                |
| *tmax*1| Maximum Temperature of November                        | 15.1                    | 56.7                                |
| *tmax*2| Maximum Temperature of February                        | 14.4                    | 71.1                                |
| bio15  | Precipitation Seasonality (Coefficient of Variation)   | 9.7                     | 80.8                                |
| bio4   | Temperature Seasonality (standard deviation *100)      | 7.2                     | 88                                  |
| *tmax*12| Maximum Temperature of December                      | 6                       | 94                                  |
| *tmean*3| Mean Temperature of March                            | 2.5                     | 96.5                                |
| *tmin*1| Minimum Temperature of January                         | 1.2                     | 97.7                                |
| alt    | Elevation                                             | 1                       | 98.7                                |
| *tmean*0| Mean Temperature of September                    | 0.9                     | 99.6                                |
| *tmean*1| Mean Temperature of January                          | 0.3                     | 99.9                                |
with a minimum AICc value (i.e., delta AICc = 0) is considered the best model [14]. The area under the ROC curve (AUC), true skill statistic (TSS) and Cohen’s Kappa (Kappa) were used to evaluate model accuracy [15]. In the mode of default setting (RM = 1.0, FC = LQHPT), the delta AICc was 206.7, AUC DIFF was 0.052 and TSS was 0.521 (Table 3). The goodness of model fitting is not enough, and the accuracy is not very high. Under optimized settings (RM = 2.5, FC = LQHP), the delta AICc value was the lowest, the AUC DIFF value (difference between the training AUC value and the test AUC value) reduced to 0.031, and the value of mean AUC, mean TSS, mean Kappa increased to 0.989, 0.803, 0.789, respectively. The degree of over fitting and complexity of the optimized model were reduced and model performed “excellent” after optimization.

**Potential suitable distribution areas**

The potential suitable distribution regions are shown in Fig. 1 (map source: modified from Yuan et al. [16]) and the predicted areas in different provinces are listed in Table 4. The potential area suitable for distribution was divided into four grades. *Z. bungeanum* is distributed in the subtropical and mid-eastern warm temperate regions. It is located in the east of the Qinghai-Tibet Plateau, mainly in the area of the eastern part of the Yunnan-Guizhou Plateau, Qinling Mountains, Daba Mountains, Taihang Mountains and Dabie Mountains. The high suitable areas are mainly in the Yangtze River and Yellow River basins. The total area of suitable habitat (high and medium suitability) is 3.05 *10^6 km^2*, occupying 32% of China’s total land area. The area of high suitability (1.93 *10^6 km^2) is larger than that of medium suitability (1.13 *10^6 km^2). The provinces with large areas of high suitability are Sichuan, Shaanxi, Guizhou, Henan, Hubei and Gansu.

**Relationship between environmental variables and geographical distribution**

The Jackknife test (Fig. 2) showed that the distribution of *Z. bungeanum* was mainly restricted by temperature. Maximum temperature of March (tmax3), February (tmax2), November (tmax11), December (tmax12), and mean temperature of March (tmean3) are the key environmental variables affecting distribution. The training gains are all above 2.4.

According to the response curves of key environmental variables affecting distribution. The training gains are all above 2.4.

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### Table 2 Pearson correlation coefficient of dominant environmental variables

| Code | alt | prec8 | tmax12 | bio4 | tmax11 | bio15 | tmean3 | tmax3 | tmax2 | tmin1 | tmean9 |
|------|-----|-------|--------|------|--------|-------|--------|-------|-------|-------|--------|
| prec8 |     | 0.064^b |       |      |        |       |        |       |       |       |        |
| tmax12 | 0.723^a | 0.400^b |       |      |        |       |        |       |       |       |        |
| bio4  | 0.341^b | −0.504^b | 0.611^b |      |        |       |        |       |       |       |        |
| tmax11 | 0.281^a | 0.302^b | 0.709^b | −0.677^b |        |       |        |       |       |       |        |
| bio15 | 0.003^b | 0.021^b | −0.107^b | 0.110^b | −0.045^b |       |        |       |       |       |        |
| tmean3 | 0.041^b | 0.120^b | 0.601^b | −0.584^b | 0.657^b | −0.052^b |       |       |       |       |        |
| tmax3 | 0.651^a | 0.122^b | 0.572^b | −0.560^b | 0.629^b | −0.051^b | 0.552^b |       |       |       |        |
| tmax2 | 0.703^b | 0.259^b | 0.736^b | −0.712^b | 0.747^b | −0.088^b | 0.709^b | 0.636^b |       |       |        |
| tmin1 | 0.258^b | 0.342^b | 0.774^b | −0.734^b | 0.714^b | −0.107^b | 0.609^b | 0.577^b | 0.690^b |       |        |
| tmean9 | 0.534^b | −0.020^b | 0.380^b | −0.240^b | 0.307^b | −0.008^b | 0.262^b | 0.406^b | 0.311^b | 0.389^b |        |
| tmean1 | 0.410^b | 0.385^b | 0.768^b | 0.769^b | 0.703^b | −0.066^b | 0.603^b | 0.596^b | 0.691^b | 0.776^b | 0.381^b |

*Means the difference is significant at the 0.05 level; ^Means the difference is extremely significant at the 0.01 level.

### Table 3 Model performance under default and optimized settings

|             | Default | Optimization |
|-------------|---------|--------------|
| RM          | 1.0     | 2.5          |
| FC          | LQHPT   | LQHP         |
| Mean AUC    | 0.965   | 0.989        |
| AUC DIFF    | 0.052   | 0.031        |
| Mean TSS    | 0.521   | 0.803        |
| Mean Kappa  | 0.752   | 0.789        |
| delta AICc  | 206.7   | 0            |

**RM** regularization multiplier, **FC** feature combination, **AUC** area under the ROC curve, **AUC DIFF** the difference between the training AUC and the test AUC, **TSS** true skill statistic, **AIC** Akaike information criterion.
The distribution probability rises with the increase of the value of each key environmental variable before optimum value and drops after optimum value.

**Discussion**

In this work, the MaxEnt model was used to model the potential distribution of *Z. bungeanum* in China based on the selected dominant environmental variables. The model accuracy was high (AUC = 0.989, TSS = 0.803, Kappa = 0.789). The high and medium suitability areas are similar to the actual main production areas of *Z. bungeanum* in China. The veracity of the model is influenced not only by types of environmental factors but also by the amount of species distribution points [17]. The result of effects of sample size on accuracy of species distribution models reported by Stockwell and Peterson [18] shows that the average success rate of coarse surrogate model and machine-learning methods is 90% of maximum at ten sample points and reaches maximum accuracy at 100 sample points. The number of sample points used to construct the model reached 127 in this
work, which may be the reason for the high accuracy of the simulation results. However, the equilibrium degree of the distribution of samples, and the spatial scale and limitations of the model itself will bring some uncertainties to the modeling results [5, 19–21], which need further study and improvement in the future.

According to the results of the MaxEnt model, the distribution of *Z. bungeanum* is mainly in the subtropical and mid-eastern warm temperate regions, which is consistent with the report in *Flora Reipublicae Popularis Sinicae* [22]. In the subtropical climate region, the solar elevation angle is large and the temperature is high in summer. Southern monsoons bring abundant precipitation, and the rain and heat occur in the same period. The warm temperate zone in the central and eastern part of the country is characterized by hot and rainy summers, cold and dry winters, and distinct seasons. These climatic conditions may be an important factor limiting the distribution of *Z. bungeanum*. This species also has a certain suitable range in the western plateau climate areas of

| Province  | No suitability | Low suitability | Medium suitability | High suitability |
|-----------|----------------|-----------------|--------------------|-----------------|
|           | Area ratio (%)a | Area ratio (%)a | Area ratio (%)a    | Area ratio (%)a |
| Sichuan   | 0.33           | 6.59            | 11.04              | 27.58           |
| Shaanxi   | 0.00           | 0.29            | 0.39               | 19.70           |
| Guizhou   | 0.00           | 0.70            | 0.47               | 14.79           |
| Henan     | 0.00           | 0.00            | 2.66               | 13.47           |
| Hubei     | 0.00           | 0.18            | 3.93               | 13.45           |
| Gansu     | 19.89          | 5.07            | 4.43               | 12.14           |
| Tibet     | 39.57          | 50.08           | 12.83              | 11.85           |
| Shanxi    | 0.07           | 4.28            | 0.98               | 10.62           |
| Yunnan    | 1.64           | 17.93           | 5.38               | 9.33            |
| Shandong  | 0.01           | 0.18            | 7.00               | 8.22            |
| Chongqing | 0.00           | 0.00            | 0.04               | 7.69            |
| Hebei     | 1.63           | 5.29            | 5.06               | 7.66            |
| Jiangxi   | 0.01           | 2.81            | 4.84               | 7.62            |
| Anhui     | 0.00           | 1.45            | 5.57               | 6.34            |
| Hunan     | 0.00           | 1.11            | 12.86              | 5.41            |
| Inner Mongolia | 91.89  | 31.17           | 2.80               | 3.26            |
| Fujian    | 0.01           | 5.45            | 3.16               | 2.38            |
| Guangxi   | 0.00           | 17.42           | 1.24               | 2.30            |
| Qinghai   | 40.62          | 21.34           | 7.60               | 1.79            |
| Ningxia   | 0.05           | 2.06            | 1.54               | 1.61            |
| Jiangsu   | 0.06           | 2.26            | 5.84               | 1.60            |
| Zhejiang  | 0.03           | 2.18            | 5.86               | 1.39            |
| Beijing   | 0.00           | 0.26            | 0.15               | 1.32            |
| Guangdong | 0.04           | 14.72           | 0.30               | 0.56            |
| Liaoning  | 0.01           | 10.06           | 5.28               | 0.32            |
| Tianjin   | 0.00           | 0.00            | 1.11               | 0.11            |
| Taiwan    | 0.97           | 2.06            | 0.14               | 0.02            |
| Shanghai  | 0.00           | 0.56            | 0.03               | 0.00            |
| Heilongjiang | 49.05  | 5.39            | 0.00               | 0.00            |
| Xinjiang  | 174.92         | 0.70            | 0.00               | 0.00            |
| Jilin     | 2.28           | 18.95           | 0.06               | 0.00            |
| Hong Kong | 0.00           | 0.09            | 0.00               | 0.00            |
| Hainan    | 0.73           | 2.18            | 0.00               | 0.00            |
| Total area| 423.88         | 112.56          | 192.50             |                 |

* Refers to the ratio of predicted area to the corresponding province's total land area

Table 4 Predicted area suitable for distribution of *Zanthoxylum bungeanum Maxim*
western Sichuan, eastern Tibet and eastern Qinghai. The plateau climate is characterized by strong solar radiation, significant diurnal temperature difference, low temperature, high wind and harsh climate [23], which indicates that *Z. bungeanum* has relatively strong adaptability. The Qinling Mountains-Huaihe River line is the boundary between temperate monsoon climate and subtropical monsoon climate in China, as well as between semihumid and humid regions. *Z. bungeanum* has high adaptability in this area, with high quality and yield represented by places such as Wudu and Qinan in Gansu Province, Hancheng and Fengxian in Shaanxi Province, Laiwu in Shandong Province, Ruicheng in Shanxi Province and Shexian in Hebei Province. This further illustrates that *Z. bungeanum* can adapt to a variety of ecological environments. Western Sichuan and Guizhou provinces in southwest China present a warm and humid climate, small daily temperature difference, abundant rainfall, and warmth in winter and heat in summer, which provides an appropriate ecological environment for plant growth [24]. There are places in this area with a long cultivation history and high quality of *Z. bungeanum*, such as Hanyuan, Maoxian and Mianning in Sichuan Province, and Zunyi and Bijie in Guizhou Province. The model predicted results are consistent with the actual growth range.

The results of the MaxEnt model showed that the distribution of *Z. bungeanum* was mainly restricted by temperature, especially the maximum temperature of February, March, December, and November and the mean temperature of March. The period of February to March is the germination stage of *Z. bungeanum*. When the average temperature is above 6 °C in spring, buds begin to germinate; when above 10 °C, new shoots begin to grow [25]. The average maximum temperature in February and March is too low, which may easily cause flower organs to be frozen and the fruit to be insufficiently developed. If the temperature is too high, it may lead to premature development, excessive growth of new branches, unbalanced nutrition and underdevelopment of fruits. Therefore, the maximum temperatures of 10.4 °C in February and 16.3 °C in March are the optimum temperatures for the full development of *Z. bungeanum*. The *Z. bungeanum* is not tolerant to severe cold [26]. November to December is the winter season in China. At this time, the temperature directly determines whether *Z. bungeanum* can safely pass through the dormancy period and whether freezing damage occurs [27], which influences the quality and yield to a certain extent. Thus, the maximum temperatures of 9.9 °C in December and 14.5 °C in November are the optimum values for growth.

The species distribution under the ideal state is almost impossible in reality, so it may occur that the predicted area is larger than the actual distribution area. On the other hand, due to the self-adaptability of plants as well as the influence of human activity, plants can survive in areas beyond the original basic niche [17, 28]. In this situation, the modeled species distribution area may be smaller than the actual distribution area. As a horticultural plant affected by human activity, such as irrigation, variety improvement, cultivation management, and market demand, it is possible to expand the distribution area of *Z. bungeanum*, resulting in the predicted distribution
area being smaller than the actual. The adoption of more key ecological factors restricting species distribution will undoubtedly improve the accuracy of model simulation. In this work, only the effects of 70 environmental variables on the distribution are considered. The effects of interspecies interaction and human activity are not considered, which may have a certain negative impact on the accuracy of prediction results. It is impossible to consider all environmental factors in a particular model analysis, so it may be more realistic to regard the model as an ideal distribution model [29]. Since data related to impact factors such as artificial introduction, cultivation management, and market demand are difficult to obtain, how to incorporate these factors into the model is a matter that needs to be taken into account in the future.

**Conclusions**

The suitable habitat for *Z. bungeanum* were predicted successfully by the MaxEnt based on known distribution data and environmental variables in China. Suitable areas for *Z. bungeanum* to introduction and cultivation were mainly distributed in subtropical and mid-eastern warm temperate regions with a total suitable area of $3.05 \times 10^6$ km$^2$. The maximum temperature of February,
March, December, and November and the mean temperature of March are the key environmental variables limiting the distribution. Only climate and topographical variables were considered for modeling in this work. More environmental variables such as human activity, soil type, vegetation types and interspecies interaction should be concerned in the future to improve the accuracy and precision of model prediction.

Methods
Species occurrence data
The natural distribution data of *Z. bungeanum* was derived from the sample records of the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/), the Chinese Virtual Herbarium (CVH, http://www.cvh.ac.cn/) and field investigations. The distribution sites with insufficient accuracy and repetition were eliminated. It’s likely that samples near roads and towns would be heavily sampled which cause sampling bias [30]. In this work, the sampling bias was corrected according to the attribute of environment variable. Specifically, in the same cell grid, only one distribution point closest to the center point was reserved. A total of 127 effective sites were obtained in China (Fig. 4, map source: modified from Yuan et al. [16]). The input files in CSV format were generated according to the requirements of the software MaxEnt 3.3.3 k (http://www.cs.princeton.edu/schapire/Maxent/) [31].

Environmental variables
*Zanthoxylum bungeanum* is a kind of shade-intolerant tree species, with the characteristics of preferring warmth, not cold tolerance, and poor water tolerance of root system [22]. Its growth process is mainly influenced by temperature, precipitation, sunshine, and topography. In this work, a total of 70 environmental variables including 19 bioclimatic variables (bio1-bio19), 48 monthly climatic variables, and three topographical factors were selected based on the biological characteristics of *Z. bungeanum*. The monthly climatic variables were minimum temperature (tmin), maximum temperature (tmax), mean temperature (tmean) and precipitation (prec) of each month. The topographical factors were elevation (alt), slope (slo) and aspect (asp). The environmental

![Figure 4](image-url)
Set [15]. The value of Kappa higher than 0.75 means the model performs excellent. TSS is the difference between omission and commission errors [38]. The range of TSS is from -1 to 1. Value of TSS closes to 1 means high accuracy, and value closes to -1 means low accuracy. TSS = 0 means the model is unable to differentiate between omission and commission errors.

The distribution map of *Z. bungeanum* in China was then extracted by spatial analysis technology in ArcGIS. The criteria for classification of habitat suitability according to existence probability were as follows: high suitability (0.6–1), medium suitability (0.4–0.6), low suitability (0.2–0.4) and no suitability (0–0.2) [39].

**Supplementary information**

*Supplementary information* accompanies this paper at https://doi.org/10.1186/s12898-020-00314-6.

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**Establishment, optimization and evaluation of model**

MaxEnt 3.3.3 k software was used for modeling the potential distribution of *Z. bungeanum*. Repeat the operation for 10 times, and cross validation was selected to extract test samples. The contribution rate of environmental variables to the distribution of *Z. bungeanum* was quantitatively studied by the Jackknife method. RM and FC were optimized by calling ENMeval R package (http://www.R-project.org) to avoid overfitted models and improve the accuracy [34, 35].

The model was built with RM changing from 0.5 to 4.0 (increments of 0.5) and several FC combinations (L, LQ, H, LQH, LQHP, LQHPT; where L = linear, Q = quadratic, H = hinge, P = product and T = threshold). ENMeval was used to test the above 48 parameter combinations. AIC was used as a criterion to select the best model. The receiver operating characteristic (ROC) curve was used to evaluate and verify the accuracy of the model operation results. The value of area (0–1) under the ROC curve (AUC) can well reflect the accuracy of model prediction. Thus, the model was optimized according to the AIC values (delta AIC) and the difference between the training AUC value and the test AUC value (AUC_Diff) [14, 36].

The accuracy of model simulation results is proportional to AUC. AUC evaluation criteria were divided into five cases: failed (0.50–0.60), poor (0.60–0.70), fair (0.70–0.80), good (0.80–0.90), and excellent (0.90–1.00) [37]. Besides, TSS and Kappa were also selected to evaluate the accuracy because of their characteristic of being not affected by the size of the validation set [15]. The value of Kappa higher than 0.75 means the model performs excellent. TSS is the difference between omission and commission errors [38]. The range of TSS is from -1 to 1. Value of TSS closes to 1 means high accuracy, and value closes to -1 means low accuracy. TSS = 0 means the model is unable to differentiate between omission and commission errors.

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**Supplementary information**

*Supplementary information* accompanies this paper at https://doi.org/10.1186/s12898-020-00314-6.

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**Abbreviations**

MaxEnt: The maximum entropy; ROC: Receiver operating characteristic curve; AUC: Area under the ROC curve; RM: Regularization multiplier; FC: Feature classes; AIC: Akaike information criterion; TSS: True skill statistic; Kappa: Cohen’s Kappa.

**Acknowledgements**

We thank Zhiqing Zhang for reviewing the draft and providing language help of this work.

**Authors’ contributions**

DX, BP and MY: made substantial contributions to the conception; DX and BP: design of the work; ZZ, DX and RW: acquisition, analysis, and interpretation of data; ZZ, DX and RW: the creation of new software used in the work; ZZ, DX, RW: drafted the work and substantively revised it; BP and MY: approved the submitted version. All authors read and approved the final manuscript.

**Funding**

This work is financially supported by Department of Science and Technology of Hainan Province (319QN163), Chinese State Forestry Administration (2015LY-184), Sichuan Science and Technology Department (18ZDYF1175), and the Technological Development of Meteorological Administration/Heavy Rain and Drought-Flood Disasters in Plateau and Basin Key Laboratory of Sichuan Province (2018-Key-05-08).

**Availability of data and materials**

All data generated or analyzed during this study are included in this published article and its supplementary information files.

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare that they have no competing interests.

**Author details**

1 College of Life Science, China West Normal University, 1 Shida Road, Nanchong 637002, China. 
2 College of Food Science, Sichuan Agricultural University, 46 Xinkang Road, Yaan 625014, China. 
3 College of Forestry, Hainan University, 58 Renmin Avenue, Haikou 570228, China. 
4 Sichuan Provincial Rural
References

1. Nooreen Z, Singh S, Singh DK, Tandon S, Ahmad A, Luqman S. Characterization and evaluation of bioactive polyphenolic constituents from Zanthoxyllum armatum DC, a traditionally used plant. Biomed Pharmacother. 2017;89:366–75.

2. Kumar V, Kumar S, Singh B, Kumar N. Quantitative and structural analysis of amides and lignans in Zanthoxylum armatum by UPLC-DAD-ESI-QTOF–MS/MS. J Pharmaceut Biomed. 2014;94:23–31.

3. Thakur M, Asaria RK, Thakur S, Sharma PK, Patil RD, Lal B, Parkash O. Observations on traditional usage of ethnomedicinal plants in humans and animals of Kangra and Chamba districts of Himachal Pradesh in North-Western Himalaya, India. J Ethnopharmacol. 2016;191:280–300.

4. Coro G, Vilas LG, Magiloizzi C, Effenbroek A, Scarponi P, Pagano P. Predicting the ongoing invasion of Lagochilus scleratus in the Mediterranean Sea. Ecol Model. 2018;371:37–49.

5. Yi Y, Cheng X, Yang Z, Wieprecht S, Zhang S, Wu Y. Evaluating the ecological influence of hydraulic projects: a review of aquatic habitat suitability models. Renew Sustain Energy Rev. 2017;68:748–62.

6. Saatchi S, Buermann W, ter Steege H, Mori S, Smith TB. Modeling distribution and habitat connectivity modelling. J Environ Manage. 2017;204:367–77.

7. Phillips SJ, Anderson RP, Schapire RE. Maximum entropy modeling of species geographic distributions. Ecol Model. 2006;190:231–59.

8. Saatchi S, Buermann W, ter Steege H, Mori S, Smith TB. Modeling distribution and habitat connectivity modelling. J Environ Manage. 2017;204:367–77.

9. Zheng H, Shen G, Shang L, Lu X, Wang Q, McLaughlin N, He X. Efficacy of conservation strategies for endangered oriental white storks (Ciconia boyciana) under climate change in Northeast China. Biol Conserv. 2016;204:367–77.

10. Rodríguez-Merino A, García-Murillo P, Cirujano S, Fernández-Zamudio R. Predicting the risk of aquatic plant invasions in Europe: how climatic factors and anthropogenic activity influence potential species distributions. J Nat Conserv. 2018;45:58–71.

11. Sharma S, Arunachalam K, Bhavsar D, Kala R. Modeling habitat suitability of Perilla frutescens with MaxEnt in Uttarakhand—A conservation approach. J Appl Res Med Arom Plants. 2018;10:99–105.

12. Muscarella R, Galante PJ, Soley Guardia M, Boria RA, Kass JM, Uriarte M, Anderson RP. ENM eval: an R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. Methods Ecol Evol. 2014;5:1198–205.

13. Phillips SJ, Dudzik M. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography. 2008;31:161–75.

14. Tarabon S, Bergles L, Dutoto T, Iselin-Nondedifu F. Environmental impact assessment of development projects improved by merging species distribution and habitat connectivity modelling. J Environ Manage. 2019;241:439–49.

15. Van H, Feng L, Zhao Y, Feng L, Wu D, Zhu C. Prediction of the spatial distribution of Alternanthera philoxeroides in China based on ArcGIS and MaxEnt. Glob Ecol Conserv. 2020;1:e02856.

16. Yuan H, Wei Y, Wang X. Maxent modeling for predicting the potential distribution of Sanghuang, an important group of medicinal fungi in China. Fungal Ecol. 2015;17:140–5.

17. Walden-Schreiner C, Leung Y, Kuhn T, Newburger T, Tsai W. Environmental and managerial factors associated with high fish stock distribution in high elevation meadows: case study from Yosemite National Park. J Environ Manage. 2017;193:52–63.

18. Stockwell DRB, Peterson AT. Effects of sample size on accuracy of species distribution models. Ecol Model. 2002;148:1–13.

19. Machado-Machado EA. Empirical mapping of suitability to dengue fever in Mexico using species distribution modeling. Appl Geogr. 2012;33:82–93.

20. Bosso L, Luchi N, Maresi G, Cristinigo G, Smeraldo S, Russo D. Predicting current and future disease outbreaks of Diploida sapinea shoot blight in Italy: species distribution models as a tool for forest management planning. Forest Ecol Manag. 2017;400:655–64.

21. Jones MC, Dye SR, Pinnegar JK, Warren R, Cheung WWL. Modelling commercial fish distributions: prediction and assessment using different approaches. Ecol Model. 2012;225:133–45.

22. Huang C. Flora Repubbliche Popolari Siciliane, Volume 43, Volume 2 Angiospermi Phylum, Decotyledon Class, Rutaceae. In. Flora Repubbliche Popolari Siciliane. Beijing: Science Press; 1997. p. 13–53.

23. Liu Z, Zhou P, Zhang F, Liu X, Chen G. Spatiotemporal characteristics of dryness/wetness conditions across Qinghai Province, Northwest China. Agric Forest Meteorol. 2013;182–183:101–8.

24. Yin ZY, Cai Y, Zhao X, Chen X. An analysis of the spatial pattern of summer persistent moderate-to-heavy rainfall regime in Guizhou Province of Southwest China and the control factors. Theor Appl Climatol. 2009;97:205.

25. Liu L, Zhang Y, Sun C, Pu J. Pepper in Wudu District, Gansu: meteorological condition analysis and climate adaptability regionalization. China Agric Sci Bull. 2017;33:126–32.

26. He X, Yang T, Wei A, Yang H, Rui Z. Changes of Physiological Indexes of Zanthoxylum bungeanum Related to Cold Resistance during Natural Over-wintering. J Northeast For Univ. 2009;67–69.

27. Yang TX, Wei AZ, Xiao L. Changes of cold resistance and tissue water and osmoregulation substances of Zanthoxylum bungeanum Maxim. during Winter. Plant Physiol Commun. 2010;4:175.

28. Li G, Xu G, Guo K, Du S. Geographical boundary and climatic analysis of Pinus tabuliformis in China: insights on its afforestation. Ecol Eng. 2016;86:75–84.

29. Chakraborty A, Joshi PK, Sachdeva K. Predicting distribution of major forest tree species to potential impacts of climate change in the central Himalayan region. Ecol Eng. 2016;97:593–609.

30. Merow C, Smith MJ, Silander JA. A practical guide to Maxent for modelling species’ distributions: what it does, and why inputs and settings matter. Ecosphere. 2013;3:1058–69.

31. Wang P, Li Q, He S, Liu Y, Wang M, Jiang G. Modeling and mapping the current and future distribution of Pseudomonas syringae pv. actinidiae under climate change in China. PLoS ONE. 2018;13:e0192153.

32. Sharma S, Arunachalam K, Bhavsar D, Kala R. Modeling habitat suitability of Perilla frutescens with MaxEnt in Uttarakhand—A conservation approach. J Appl Res Med Arom Plants. 2018;10:99–105.

33. Worthington TA, Zhang T, Logue DR, Mittelstet AR, Brewer SK. Landscape and flow metrics affecting the distribution of a federally-threatened fish: improving management, model fit, and model transferability. Ecol Model. 2016;342:1–18.

34. Muscarella R, Galante PJ, Soley Guardia M, Boria RA, Kass JM, Uriarte M, Anderson RP. ENM eval: an R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. Methods Ecol Evol. 2014;5:1198–205.

35. Phillips SJ, Anderson RP, Dudzik M, Schapire RE, Blair ME. Opening the black box: an open-source release of Maxent. Ecography. 2017;40:887–93.

36. Warren DL, Seifert SN. Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. Ecol Appl. 2011;21:335–42.

37. Walden-Schreiner C, Leung Y, Kuhn T, Newburger T, Tsai W. Environmental and managerial factors associated with high fish stock distribution in high elevation meadows: case study from Yosemite National Park. J Environ Manage. 2017;193:52–63.

38. Velasco JA, González-Salazar C. Akaike information criterion should not be a “test” of geographical prediction accuracy in ecological niche modelling. Ecol Inform. 2019;31:25–32.

39. IPCC: Contribution of Working Groups I, II, III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change 2007. Geneva; 2007.