Geographic distribution and impacts of climate change on the suitable habitats of Rhamnus utilis in China

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Abstract

Rhamnus utilis (Rhamnaceae) is an ecologically and economically important tree species. The growing market demands and recent anthropogenic impacts to *R. utilis* forests has negatively impacted its populations severely. However, little is known about the potential distribution of this species and environmental factors that affect habitat suitability for this species. By using 219 occurrence records along with 51 environmental factors, present and future suitable habitat were estimated for *R. utilis* using MaxEnt modelling; the important environmental factors affecting its distribution were analyzed. The results indicate that January water vapor pressure, the normalized difference vegetation index, mean diurnal range, and precipitation of the warmest quarter represented the critical factors explaining the environmental requirements of *R. utilis*. The potential habitat of *R. utilis* included most provinces from central to southeast China. Under climate change scenario SSP 245, MaxEnt predicted a cumulative loss of ca. 0.73×10^5 km^2 for suitable habitat for *R. utilis* by the 2060s while an increase of ca. 0.65×10^5 km^2 occurred in the 2010s. Furthermore, under this climate change scenario, the suitable habitat will geographically expand to higher elevations. The findings of our study provide a foundation for targeted conservation efforts and inform future research on *R. utilis*. By considering the identified environmental factors and anticipating the potential impacts of climate change, conservation strategies can be developed to preserve and restore suitable habitats for *R. utilis*. Protecting this species is not only crucial for maintaining biodiversity but also for sustaining the economic benefits associated with its ecological services.

Introduction

Climate is one of the most crucial elements affecting plant life cycles and fitness [1, 2], niche construction [3, 4], species coexistence [5], community composition [6], and the geographic distribution of species [7, 8]. The Fifth Assessment Report of the IPCC states that global climate warming will continue indefinitely, and by 2100 the mean temperature of earth will increase by 0.3–4.5°C compared with that during 1986–2005 [9]. Changes in the effects of climate change on the world's biota are creating a critical issue for scientists, conservationists, and decision-makers [10]. Plant species are unlikely to be able to migrate sufficiently quickly. They will, therefore, have to respond *in situ*, e.g. through local adaptation, which may often fail [11]. Therefore, in order for forest managers to assess the susceptibilities of ecosystems and species to climate change, it is critical to study how climate change effects the spatial distribution of species on the landscape.

One method of simulating the probable geographic range and ecological needs of a species is species distribution model (SDM) [8]. There are various kinds of SDMs, such as CLIMEX [12], maximum entropy (MaxEnt) [7], Genetic Algorithm for Rule-set Production [13–15], Ecological Niche Factor Analysis [16], and bioclimate envelope [17], which are used to forecast the geographic distribution, ecological reactions, and ecological needs of various species. Among those models, MaxEnt, a general-purpose machine learning method, only requires information on the presence of species, not their absence because absence data is difficult to gather [18]. It has proven to be one of the most reliable habitat modeling methods in terms of predictive capability [19]. In addition, MaxEnt can match complex relationships between species and environmental factors, which could improve our understanding of how species interact with their surroundings [20].

Rhamnus utilis (Rhamnaceae) is an ecological and economical important shrub species occurring in forests, thickets, mountains, and hills below an elevation of 3300 m in southern China [21]. This species thrives on light sandy to medium loamy soil that is moist and well-drained and has an important effect on boosting the water retention capacity of soils and decreasing soil loss to surface runoff [21]. The fruits of *R. utilis* are a valuable resource, containing high levels of protein and a yellow pigment that is used in the manufacture of lubricating oil, printing ink, and soap. [22, 23]. Furthermore, several pharmaceutical research studies have shown that the bark, leaves, and seeds of this species have anti-inflammatory, and anti-allergic properties [24, 25].

In recent decades, a growing market demand has threatened *R. utilis* together with the unprecedented anthropogenic disturbance to its natural habitat. However, heretofore, little has been known about the suitable geographic range of this species and the environmental conditions that influence habitat appropriateness for it. Due to the economically and ecologically significant species, understanding how a changing climate will affect this species' favourable habitat is critical.

In present study, MaxEnt modeling was to project the potential geographical ranges of this species by using database recent historical and geo-referenced occurrence records as well as to evaluate habitat suitability and important environmental factors that shape its distribution. The objectives of the present study include: (1) modeling the potential suitable habitat for this species under current and further climate change scenarios, (2) identifying important environmental factors that shape its distribution; and (3) using projected future climate conditions to quantify the changes in its geographical ranges in a way that will help researchers to create suitable habitat.

Material and methods

Species distribution data

The species occurrence data of *R. utilis* were gathered from the online herbaria databases shown below: the Chinese Virtual Herbarium (http://v5.cvh.org.cn/), Tropicos (http://www.tropicos.org/), and the GBIF (http://www.gbif.org). Inaccurate locations without precise geo-coordinates in the occurrence records were excluded. For specimens with mere village locations documented in the Chinese Virtual Herbarium, we identified their longitude and latitude via Google Earth (http://ditu.google.cn/). Duplicate data points were eliminated, while the remaining points were subjected to spatial filtering. Hence, a maximum of one point per 1.0 × 1.0 km grid cell was mapped. The total number of geo-referenced occurrence records used was 219. (Fig. 1).

Environmental variables

The 51 environmental factors that can potentially affect the distribution of *R. utilis* were used. Those include 19 bioclimatic along with 12 solar radiation and water vapor pressure variables acquired from the World Climate Database [26]. Data related to three topographic variables of slope, aspect, and elevation were acquired from the RESDC website (http://www.resdc.cn/Default.aspx) covering 1984–1995 were used. Also, data for seven soil variables including soil organic carbon content, soil pH, soil buck density, soil conductivity, along with soil sand, silt and clay content were obtained from the Harmonized world soil database v1.2 [27]. Moreover, normalized difference of vegetation index (NDVI) data were acquired from the China Meteorological Data Sharing Service System.

With regard to future climate scenarios, the climate change modeling data of the Beijing Climate Center climate system model version 2 (BCC-CSM2)-MR of the CMIP6 model were adopted from the Shared Socio-economic Pathways (SSPs) 245 put forward by Intergovernmental Panel on Climate Change to predict the distribution of *R. utilis* in 2041–2060 and 2081–2100. The suppliers of BCC-CSM advised it should be used for research related to short-term operational climate prediction and change within China [see 28 and references listed therein]. The SSP 245 scenario indicates possible radiative forcing in 2100 relative to the optimistic + 4.5 W/m^2 pre-industrial value [29]. Other variables, such as those related to soil and topography, should be included when modeling. However, the changes expected in those variables were not available for modeling with future climate change scenarios. Therefore, those variables were left unchanged for the current analysis of the future potential suitable habitat for *R. utilis*. To ensure consistent results among diverse layers, we processed all environmental layers with identical cell size, spatial extent, while using WGS84 projection under the ArcGIS 10.0 scenario.

Principal component analysis (PCA) along with Pearson correlation analysis were performed for minimizing model overfitting while decreasing high collinearity. Only one factor with a high correlation coefficient (|r| >0.85) from every set was maintained in subsequent analysis. Factors enrolled into the final environmental dataset used here included April and August solar radiation (SRAD4 and SRAD8), aspect, average diurnal temperature range (BIO2), elevation, isothermality (BIO3), January, July, and November water vapor pressure (VAPR01, VAPR7, and VAPR11, respectively), NDVI, precipitation of driest month (BIO14), precipitation of warmest quarter (BIO18), slope, soil buck density, soil sand and clay content, and annual range of temperature (BIO7) (Table 1).

Table 1
Percentage contributions and permutation importance of the variables included in the Maxent models for *Rhamnus utilis*.

Code	Environmental Variables	%Contribution	Permutation importance
VAPR01	Water vapor pressure of January	37.7	32.8
NDVI	Normalized difference of vegetation index	27.3	25.5
BIO2	Mean diurnal range	15	11.7
BIO18	Precipitation of warmest quarter	4.5	10.3
SLOPET	Slope degree	4.3	3.1
VAPR07	Water vapor pressure of July	2.4	2.2
ASPECT	Aspect	1.8	1.6
ELEV	Elevation	1.7	5.8
SRAD11	Solar radiation of November	1.2	1.5
BIO14	Precipitation of driest month	0.7	1.5
BIO3	Isothermality	0.7	0.6
CLAY	Soil clay content	0.5	0.6
SAND	Soil sand percentage	0.5	1
SRAD4	Solar radiation of April	0.5	0.1
BIO7	Temperature annual range	0.4	0.4
SRAD8	Solar radiation of August	0.4	1
SRAD9	Solar radiation of September	0.3	0.2
BUCK	Soil buck density	0.2	0.2

Model simulation and evaluation

Models were established with MaxEnt version 3.3.3 k [30] based on species records together with bioclimatic factors. We used 25% and 75% of occurrence records for model testing and training, respectively. It is well known that sampling bias significantly affects presence-background distribution models, which was avoided by using one bias file layer in the present work [31]. A bias file layer was produced based on occurrence point through the derivation of one Gaussian kernel density map according to the description by [19]. We used a bias file in MaxEnt to create maps. Recent study indicated that the default setting of MaxEnt may not necessarily be suitable at all time, especially if only a few species occurrence records can be obtained [20]. Consequently, we examined diverse regularization multiplier values, and discovered that default option had the most favorable performance. We restricted the background point number to 10,000 during sampling. However, a further increase in background point number (e.g., 100,000) made no difference to the model. The maximal iteration number was set to 1,000, which provided sufficient time for model convergence, and a convergence threshold was selected at 1×10^{-6} (8, 32). In addition, default "autofeatures," namely, linear, quadratic, hinge, threshold, and product features were used [20].

Response curves were used to interpret MaxEnt output patterns. A Jackknife test was performed to analyze the relative importance of the environmental variables. The evaluation of robustness of the MaxEnt model's was calibrated and then validated using tests of threshold-independent receiver operating characteristics (ROCs). For increase the precision of the analyses further, the area under the ROC curve (AUC) was used. Four types of potential habitats were developed based on the final potential distribution map, having values ranging from 0 to 1, where habitat was classified as highly (> 0.75), moderately (0.50–0.75) or poorly suitable (0.25–0.50) or as providing no potential habitat (< 0.25). Moreover, by comparing this data with the currently known suitable habitat, future potential distribution maps were re-categorized as, (i) becoming suitable, (ii) becoming unsuitable, and (iii) remaining suitable; the spatial extents of areas in each category were calculated and are presented.

Results

Current potential habitat and model accuracy

The models for the potential habitat of *R. utilis* performed better than random data when using the given sets of training and test data. The average for the training AUC was 0.978, with a standard deviation of 0.001, suggesting good model performance. Areas in provinces such as southeastern Gansu, southern Shanxi, eastern along with central to western Sichuan, Sichuan, northwester Henan, western Chongqing, eastern Hubei, southern Jiangxi, southeast Fujian, central to northern Zhejiang, and northern Taiwan were appropriate for the growth of *R. utilis* (Fig. 2). The current areas of moderately and highly suitable habitat for *R. utilis* encompasses ca. 3.16×10^5 and 1.18×10^5 km^2, respectively, accounting for 3.41% and 1.28% of China's land area.

Important environmental factors

Based on the contributions of the various environmental factors to the MaxEnt model (Table 1), the mainly factors contributing to the *R. utilis* distribution model were VAPR01 (37.7% of variation), NDVI (27.3%), BIO2 (15.0%), and BIO18 (4.5%) (Table 1), yielding a cumulative contribution as high as 84.5% (Table 1). In contrast, additional factors had smaller contributions, indicating their restricted impact on the distribution of appropriate *R. utilis* habitat (Table 1).

The response curves (marginal responses generated through keeping the remaining bioclimatic factors in the mean sample values) of the four critical factors in MaxEnt for examining the *R. utilis* climatic preference are shown in Fig. 3. Overall, VAPR01 and BIO18 showed a nonlinear logistic response pattern, with the probability of presence increasing when VAPR01 < 0.2 KPa and BIO18 > 250 mm; in contrast, NDVI and BIO2 both showed an increasing and then decreasing pattern, with the maximum probability of presence occurring at 0.4 and 10.6°C (Fig. 3).

Future changes in suitable habitat area

Under the SSP245 climate change scenario, MaxEnt predicted *R. utilis* would lose a cumulative amount of appropriate habitat area ca. 0.73×10^5 km^2 by the 2060s. The loss area mainly occurred at Guangxi, Guangdong, Fujian, eastern Sichuan, southern Gansu, and Ningxia Hui Autonomous Region (Fig. 4). In contrast, under the same climate change scenario and by 2100s, MaxEnt predicted the cumulative gain of ca. 0.65×10^5 km^2 in appropriate habitat area. The increased area mainly occurred in central Sichuan Province; at the same time, MaxEnt predicted ca. 0.08×10^5 km^2 of area loss in southern Gansu and Ningxia Hui Autonomous Region.

Discussion

Understanding the distribution of a species is one of the prerequisites for employing it during ecosystem restoration. Although *R. utilis* is a fast-growing species that has been frequently applied in the ecological rehabilitation of temperate forests and riverbanks in eastern and central China, the influences of alterations in climate on its distributions have never been evaluated. Our current work modeled the distributions of *R. utilis* in the present and future climatic contexts, and thus will provide a reference for using this species to allowing land managers to develop improved forest management practices and species protection strategies.

Distribution and prediction of R. utilis

R. utilis has an extensive distribution; areas with suitable habitat exist in the provinces of Jiangsu, Jiangxi, Shaanxi, Shanxi, Sichuan, Fujian, Gansu, Guizhou, Hebei, Henan, Hubei, Hunan, Jiangxi, Shaanxi, Shanxi, and Zhejiang. The results of our model suggested that under present climate conditions, moderately and highly suitable habitat for *R. utilis* spanned around 14.82×10^5 km^2. Our results are generally consistent with previous reports [21]. In addition, some areas of Yunnan, and Ningxia Hui Autonomous Region were also shown to be suitable for this species and would have areas that would be suitable for introducing this plant in the future. The introduction of *R. utilis* to these areas would not only support the preservation and growth of this valuable species, but also provide opportunities for soil improvement, resource utilization, and potential medicinal applications. This would support the conservation of this important species and help to promote its continued growth and success in new habitats.

Environmental factors affecting R. utilis distribution

Factors affecting the geographic distribution of species are a critical issue in ecology and evolution. Of the 18 environmental factors incorporated into our model, VAPR01, NDVI, BIO2 and BIO18 (Table 1) yielded cumulative contributions of as high as 84.5%. However, it should be noted that the response curve was created by using the average sample value for all other bioclimatic variables. In actuality, variables are not maintained at their means. The appropriateness of changes as a result of interactions between components can change in ways that marginal response curves completely conceal. Nevertheless, this method allowed us to examine the relationships between particular factors and the likelihood of finding suitable habitat [15].

The probability of presence of *R. utilis* peaked when VAPR01 ≥ 0.2 KPa. This means that the plant is able to grow and survive best in areas with relatively high humidity. Water vapor pressure is a measure of the amount of water vapor in the air, and it plays a critical role in determining the overall moisture content of an ecosystem. For *R. utilis*, a water vapor pressure of 0.2 KPa or greater provides the ideal level of humidity for the plant to grow and thrive. This can help to ensure that the plant has access to the moisture it needs to survive, while also providing the ideal conditions for photosynthesis, growth, and reproduction [33, 34].

The effect of vegetation indices, i.e. NDVI, also indicated these indices have a significant contribution to the existence of *R. utilis*, demonstrating that NDVI has the capacity to influence the distribution of *R. utilis*. This might be due to the fact that the majority of *R. utilis* populations are found in broad-leaved deciduous forests, degraded tropical evergreen forests, and even may occur on farms and otherwise managed regions. In addition, past research has shown that a link exists between NDVI and features of the canopy including net primary production [35], the percentage of absorbed photosynthetically active radiation [36], the leaf area index [37], and evapotranspiration [37, 38]. However, the habitat parameters will need to be studied in detail in future to draw a clear-cut conclusion.

BIO2 (mean diurnal range) and BIO18 (precipitation of warmest quarter) also are important environmental factors that affect the presence of *R. utilis.* The mean diurnal range (BIO2) indicates the variation in temperature over a day, and changes in temperature may have a significant impact on plant growth, especially photosynthesis and respiration of the plant, contributing to nutrient buildup [39]. In addition, drought stress has been reported to result in a significant decrease in plant height, leaf area, the number of branches produced, and photosynthesis of *R. utilis.* Furthermore, water availability may directly affect the emergence and development of seedlings [40]. To mitigate the negative impact of drought stress on *R. utilis*, it is important to manage water resources in a sustainable manner and to conserve natural water sources that support the growth of this species. Additionally, efforts to enhance the drought tolerance of *R. utilis*, such as through breeding programs or the use of drought-tolerant cultivars, can help to ensure its persistence in areas that are prone to drought.

Impact of climate change on the distribution of R. utilis and related forest ecosystems

Global warming will result in some species migrating to high latitudes or elevations [7, 15], while other species may use physiology or phenology adapt to climate change [41]. Our study adopted the climate change scenario SSP 245. This scenario is an intermediate scenario that assumes that CO_2 emissions begin to decline in 2045, and by 2100, they will be virtually half of what they were in 2050. The SSP 245 scenario also requires a peak in methane (CH_4) emissions by 2050 and that they should then decline to about 75% of 2040 levels; meanwhile, by 2040 sulphur dioxide (SO_2) emissions should fall to around 20% of 1980–1990 levels [42] and references therein). Our result predicted that in the 2060s, the cumulative loss of appropriate habitat for *R. utilis* should be ca. 2.0×10^5 km^2. Consistent with former studies, the lost areas would mainly occur at low elevations, with the increased areas would mainly occur at high elevations. Such result may indicate *R. utilis* would be unable to tolerate continuously increasing temperatures. Furthermore, changes of precipitation and temperature regimes may induce a phenological shift of *R. utilis* species, thus having indirect effects on the dependent flora and fauna. Additionally, such alterations would adversely affect numerous terrestrial insects, birds, and mammals with a direct or indirect dependence on *R. utilis* seeds, flowers, and fruits. In contrast, by the 2010s, MaxEnt predicted the cumulative gains for *R. utilis* would be ca. 0.73×10^5 km^2 in appropriate habitats. This, as state above, may be due to the scenario we selected, i.e. a predicted decline in CO_2 and CH_4 in 2010s.

Implications for conservation plans

According to our model predictions, the potential suitable habitat of *R. utilis* increased in high elevations under the future climate scenarios. In addition, *R. utilis* plantations in appropriate habitats could serve as a preservation strategy allowing the species to respond to future climate change. In addition, our findings might be adopted to categorize natural habitats of *R. utilis* from those of low to high risk for this species based on predicted climate change during conservation planning, i.e. only introduce this species in areas of suitable habitat. Moreover, natural regeneration must be maximally conserved in high-risk regions under the future climate scenarios. The unchanged appropriate habitat may provide underlying refugia for climate change, and preserving these habitats is an important option for the conservation and protection of in-situ and ex-situ *R. utilis* forests.

Limitations of modeling and future research directions

Species distribution modeling has been widely adopted and have been proven to be an effective method for providing related guidelines for forest management under future global climate change. However, there are uncertainties in the use of different climate change scenarios for projecting possible plant distribution. The BCC-CSM1.1 model was used in the present work, but it showed the uncertain nature of future climate change, even though it is recommended for studying climate change in China, thus leading to uncertainties in projected habitat distribution/suitability. Consequently, future studies must adopt diverse GCMs. Additionally, although MaxEnt models are commonly used, several restrictions should be highlighted [43]. The current study compiles with the need for presence-only data derived from a number of sources. As a result, when compared with the range of other native species, a larger amount of species occurrence data may need to be included within relatively well-known locations [44]. Nevertheless, the sampling bias layer used in our models reflects only a near approximation of actual species distribution. In addition, some biologically important factors, such as human activities, dispersal capability, and competition, were not included in the model because robust data were lacking.

Conclusions

Our results indicate that January water vapor pressure, the normalized difference vegetation index, mean diurnal range, and precipitation of the warmest quarter represented the critical factors explaining the environmental requirements of *R. utilis*. The potential habitat of *R. utilis* included most provinces from central to southeast China. Under climate change scenario SSP 245, MaxEnt predicted a cumulative loss of ca. 0.73×10^5 km^2 for suitable habitat for *R. utilis* by the 2060s while an increase of ca. 0.65×10^5 km^2 occurred in the 2100s. Furthermore, under this climate change scenario, the suitable habitat will geographically expand to higher elevations. Our results will assist land managers in avoiding the blind introduction of *R. utilis* into unsuitable habitat and enhance its quality and production.

Declarations

Authors' contributions

Song G and Jiang X designed and supervised the study; Zhao S, Zhao Y, Kong X conducted the field work with the help of Feng J, Gong S, Hao W. Song G and Jiang X wrote the first draft and various revisions of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

All relevant data can be found within the manuscript.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Figures

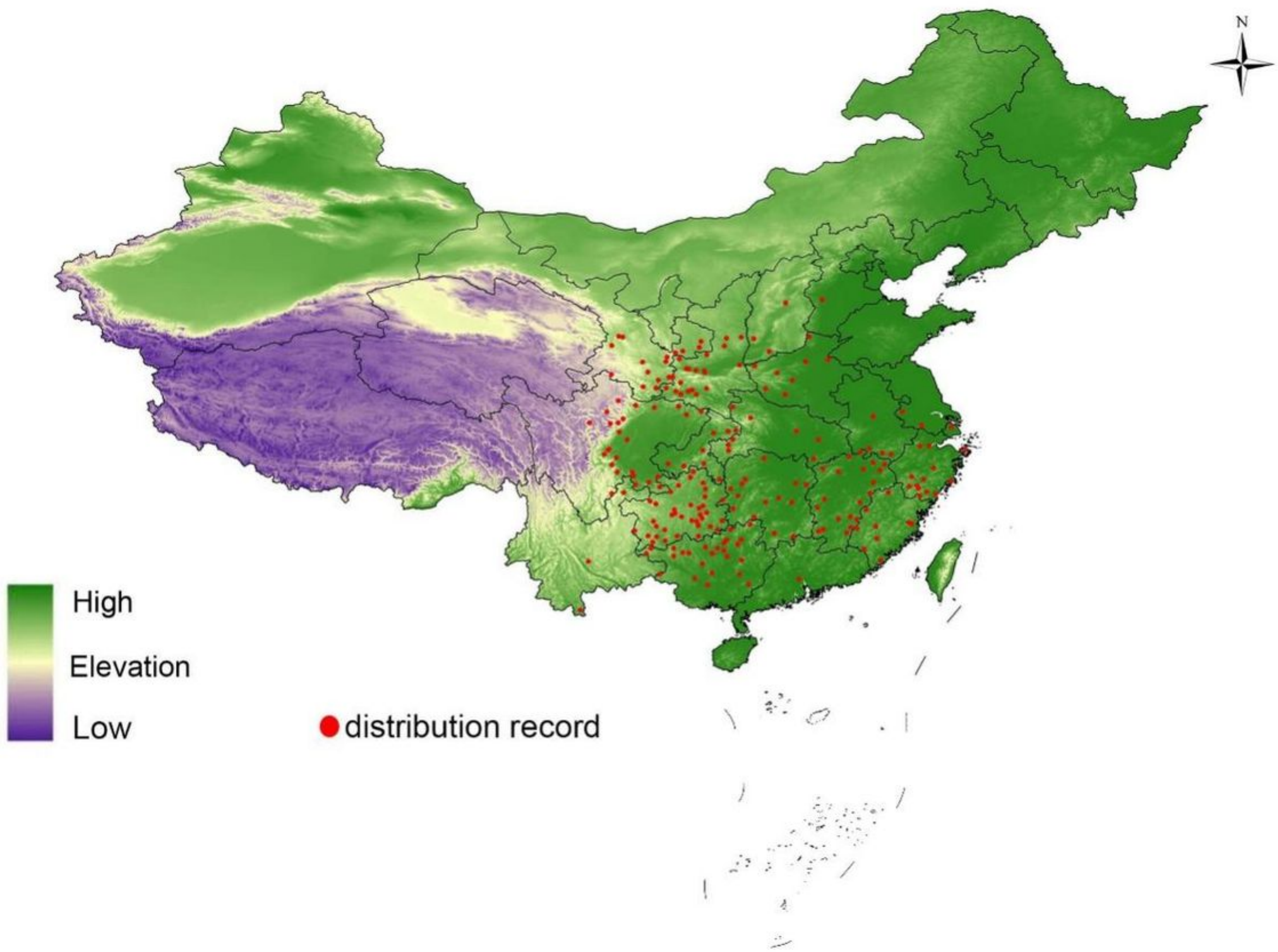

Figure 1

Distribution records of *Rhamnus utilis* in China.

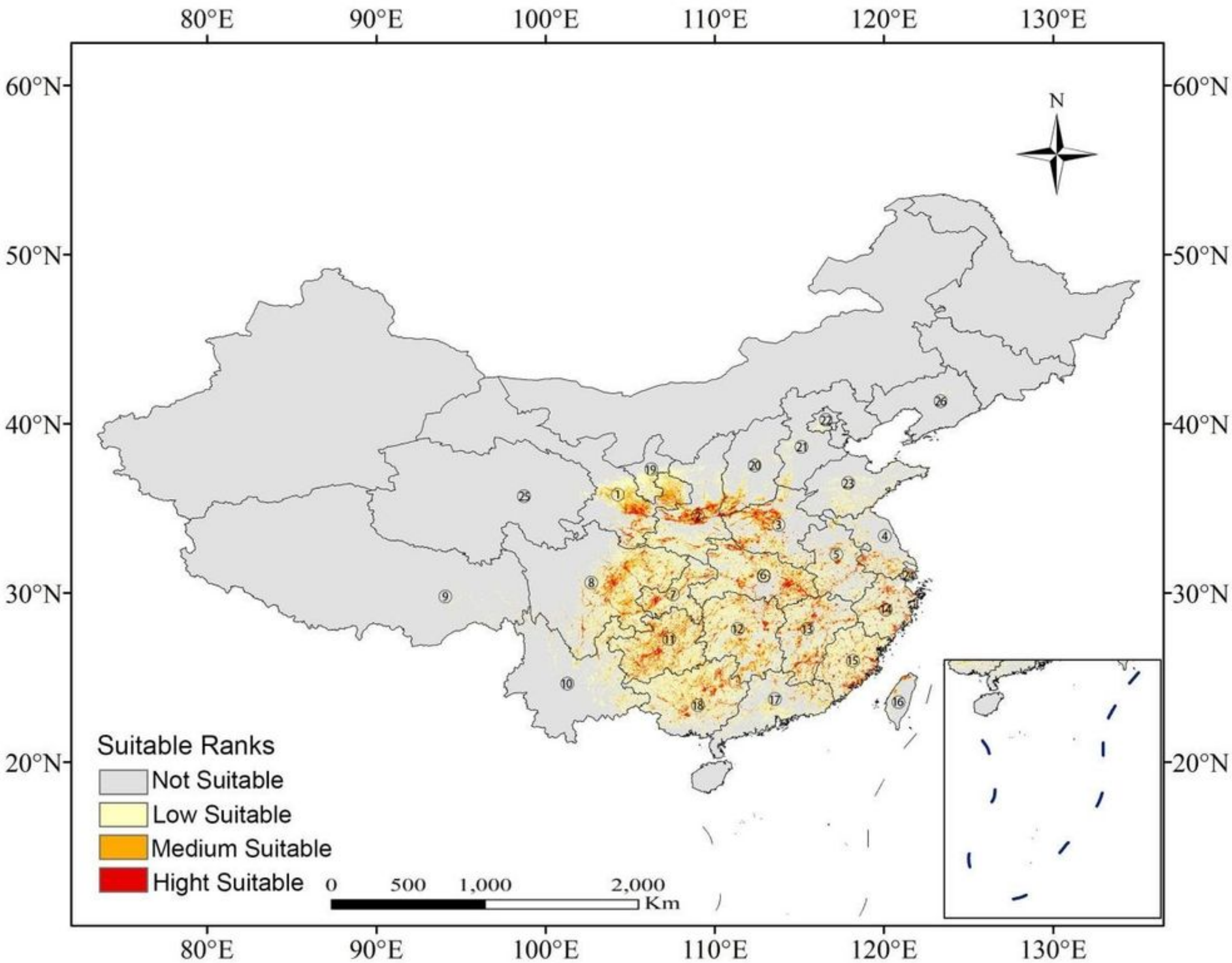

Fig. 2. Predicted potential distribution map of *Rhamnus utilis* under current climate scenario. ① Gansu; ② Shaanxi; ③ Henan; ④ Jiangsu; ⑤ Anhui; ⑥ Hubei; ⑦ Chongqing; ⑧ Sichuan; ⑨ Xizang; ⑩ Yunnan; ⑪ Guizhou; ⑫ Hunan; ⑬ Jiangxi; ⑭ Zhejiang; ⑮ Fujian; ⑯ Taibei; ⑰ Guangdong; ⑱ Guangxi; ⑲ Ningxia Hui Autonomous Region; ⑳ Shanxi; ㉑ Hebei; ㉒ Beijing; ㉓ Shandong; ㉔ Shanghai; ㉕ Qinghai; ㉖ Liaoning.

Figure 2

See image above for figure legend

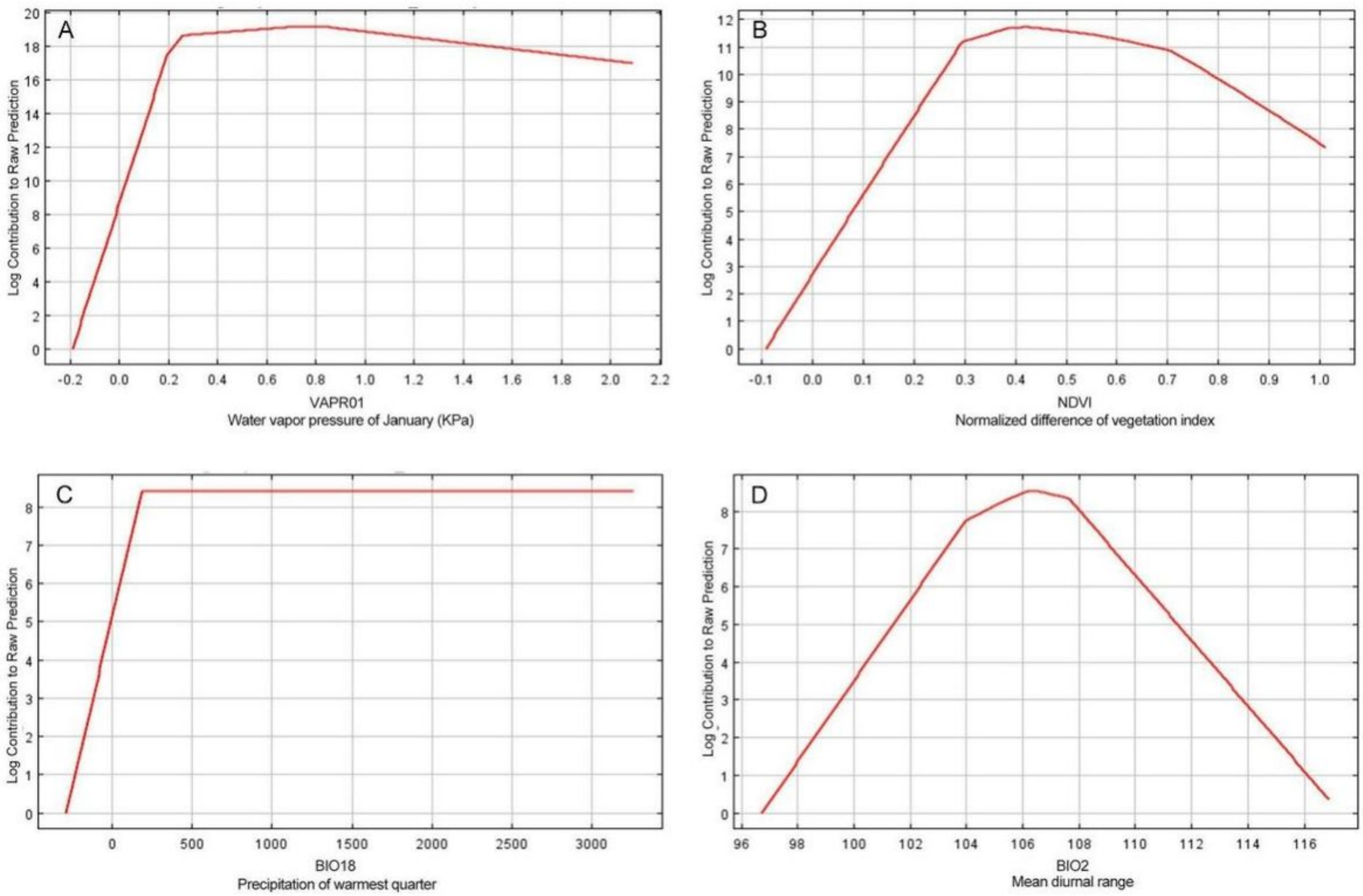

Figure 3

Response curves for important environmental predictors in the species distribution model for *Rhamnus utilis.*

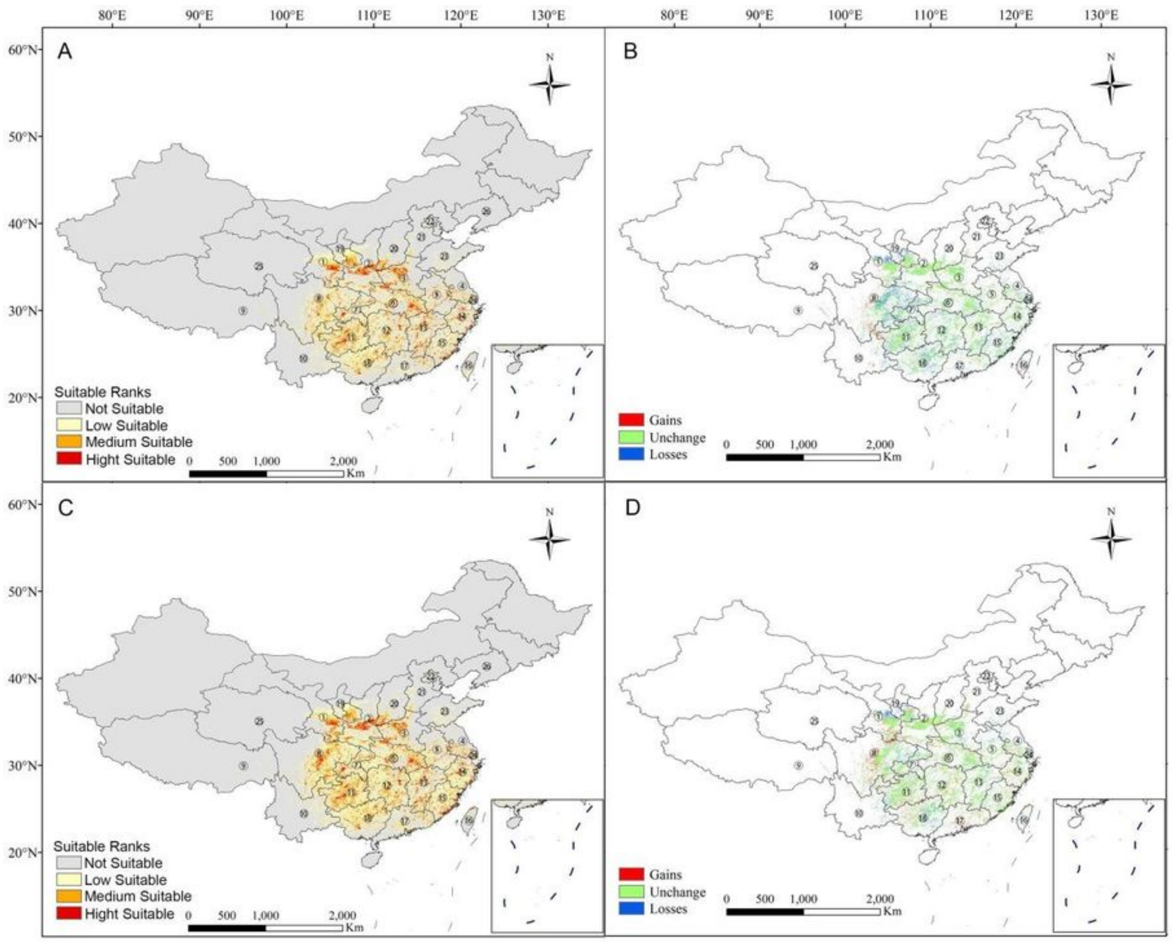

Fig. 4. Predicted potential distribution map of *Rhamnus utilis* under future climate change scenario. ① Gansu; ② Shaanxi; ③ Henan; ④ Jiangsu; ⑤ Anhui; ⑥ Hubei; ⑦ Chongqing; ⑧ Sichuan; ⑨ Xizang; ⑩ Yunnan; ⑪ Guizhou; ⑫ Hunan; ⑬ Jiangxi; ⑭ Zhejiang; ⑮ Fujian; ⑯ Taibei; ⑰ Guangdong; ⑱ Guangxi; ⑲ Ningxia Hui Autonomous Region; ⑳ Shanxi; ㉑ Hebei; ㉒ Beijing; ㉓ Shandong; ㉔ Shanghai; ㉕ Qinghai; ㉖ Liaoning.

Figure 4

See image above for figure legend