Potential distribution and habitat suitability of *Picea crassifolia* with climate change scenarios

Journal:	<i>Canadian Journal of Forest Research</i>
Manuscript ID	cjfr-2020-0507.R1
Manuscript Type:	Article
Date Submitted by the Author:	21-Jun-2021
Complete List of Authors:	Gao, Yuan; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences; University of Chinese Academy of Sciences He, Zhibin; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Zhu, Xi; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Chen, Longfei; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Du, Jun; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Lin, Pengfei; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Tian, Quanyan; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences Kong, Junqia; Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences; University of Chinese Academy of Sciences
Keyword:	<i>P. crassifolia</i> , Climate change, Potential distribution, Habitat suitability, MaxEnt
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)
Note: The following files were submitted by the author for peer review, but cannot be converted to PDF. You must view these files (e.g. movies) online.	
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Potential distribution and habitat suitability of *Picea crassifolia* with climate change scenarios

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Draft

Number of tables: 1

Number of figures: 8

Abstract: The Qinghai-Tibet Plateau in China is a region strongly impacted by climate change, yet its effects are unknown on the keystone endemic forest species, *P. crassifolia*. Understanding changes in potential distribution and habitat suitability of *P. crassifolia* forest with the climate change will contribute to water conservation, forest management, and ecological protection in the upper reaches of the Yellow River. A total of 129 records of species distribution data and 19 environmental variables were chosen for modeling. The MaxEnt model was used to analyze the main environmental factors affecting the potential distribution of *P. crassifolia* in two periods (2050s and 2070s) and four representative emission pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5). The main results are follows: (1) the most important environmental variables affecting distribution of *P. crassifolia* and percentage variance explained were: altitude (41.85%), precipitation of driest month (19.76%), slope (12.35%), annual precipitation (6.56%), precipitation of wettest month (5.73%), and precipitation of warmest quarter (5.12%), (2) habitat suitability of *P. crassifolia* shifted to the northwest and into high-altitude areas under climate change scenarios, but its core distribution areas were concentrated in northeastern Qinghai-Tibet Plateau, Qilian Mountains, southern Ningxia, and Helan Mountains, (3) total area of potential suitable habitat of *P. crassifolia* will change significantly in the future, and change of habitat area of not suitable, low, moderate, and high suitability exceed 60%.

Keywords: *P. crassifolia*, Climate change, Potential distribution, Habitat suitability, MaxEnt.

1 Introduction

In recent decades, climate change impacted natural and human systems on all continents and oceans. Impacts include continuous retreat and accelerated melting of glaciers all over the world, decreases in grain yield in many regions, and increase in the frequency of extreme weather events (such as rainstorms, floods, droughts, heat waves, and wildfires). Many terrestrial, freshwater, and marine species exhibits altered seasonal activities, migration patterns, abundances, and species interactions in response to ongoing climate change (Becklin et al. 2016; Chen et al. 2011; Koundinya et al. 2018; Ma et al. 2017; Parmesan 2006). In addition, studies have shown that with the increase of the global temperature, the forest vegetation belt in the middle and high latitudes will change significantly (Lenoir et al. 2008; Parmesan and Yohe 2003), such as the upward movement of the vegetation vertical zone and the area expanding. The biodiversity and habitat suitability of many species will be affected, and that it may lead to degradation of many ecosystems and extinction of

some species (Cámara-Leret et al. 2019; Cao et al. 2020; Driouech et al. 2010; OECD 2012). Therefore, a greater understanding of the impacts of climate change on the distribution pattern of habitat suitability and biodiversity will contribute to the development of new insights into the potential ecological risk and its assessment (Wan and Wang 2019), help decision makers understand sensitivity of species to climate change, and provide fundamental data for species conservation and re-introductions (Yi et al. 2016).

Ecological niche refers to the minimum threshold of habitat necessary for the survival of each organism in the ecosystem. Specifically, it describes the conditions (including matter, energy, space, time) that are required for a species to survive and evolve at a specific scale, and the effect of a species on the 'ecological environment' within that scale (Zhang and Xie 1997). The ecological niche model (ENM) is a common method for predicting potential geographical distribution and evaluating habitat suitability of species based on the ecological niche theory (Lu et al. 2012; Phillips et al. 2004). Among the existing ENMs, the maximum entropy (MaxEnt) algorithm offers relatively high prediction accuracy while using a small amount of data to determine the occurrence of species based on environmental variables (Pramanik et al. 2018). It is widely regarded as one of the best non-integrated approaches in ecological niche modeling (Phillips and Dudik 2008; Phillips et al. 2006).

P. crassifolia, also known as Qinghai spruce, is a coniferous species in the Pinaceae family and a dominant tree species in the Qilian Mountains (QLM) of China (Chang et al. 2014). It prefers cold and humid environments and often forms large pure forests on shaded and semi-shaded slopes. However, on semi-sunny slopes and in humid valleys, this species occurs mostly as scattered or isolated trees with poor growth. It is mainly distributed in the subalpine zone of Gansu, Qinghai, Ningxia, and Inner Mongolia at an altitude of 1750-3500 m (Zhao et al. 2006). The cones and kernels are edible, and seed scales can be used as fuel. Wood material is flexible, and it can be used as raw materials in construction, and furniture and fiber industry. Because of its strong drought resistance, persistent foliage, and attractive shape, *P. crassifolia* is often used as street and garden trees (FOC, 1999), and forests are often designated as scenic forests. It has become an important afforestation tree species in eastern Qinghai, northern Gansu, and Qilian Mountains (QLM). Because of its dominant in the mountain ecosystem, it is a key element for the ecosystem continuum of "mountains-rivers-forests-farmlands-lakes-grasslands-deserts", and it can regulate river runoff,

prevent soil erosion, protect land resources, and contribute to ecological protection in the upper reaches of the Yellow River. At present, research on *P. crassifolia* mainly focuses on its biological characteristics (Chang et al. 2017; Zeng et al. 2020), population distribution pattern (He et al. 2018; Wang et al. 2018), and seedling cultivation and afforestation (Lin et al. 2019; Zhu et al. 2017), but potential distribution of *P. crassifolia* with climate change is largely unknown. Furthermore, *P. crassifolia* is an important barrier of glacier, wetland reserves, and ecological security in the inland river basins of the Hexi Corridor in China. It plays a dominant position in the strategic policy of “protecting water resources in the south, developing oasis in the middle, and preventing sandstorm in the north”. It is also an important water source and runoff producing area in the Yellow River Basin and a priority area for biodiversity conservation in China. A greater understanding of the distribution of habitat suitability of *P. crassifolia* under climate change is critical to the protection and development of *P. crassifolia* population and plantation establishment. Therefore, strengthening the ecological environment protection in the QLM has great strategic significance for protecting the national ecological security and promoting the sustainable development of Gansu and the Hexi Corridor. At the same time, it can also effectively promote the implementation of national strategies for ecological protection and high-quality development in the upper reaches of the Yellow River Basin.

In this study, we used the MaxEnt algorithm (Evans et al. 2010) in the ecological niche model to predict the distribution of suitable habitat for *P. crassifolia* under climate change scenarios. Bioclimatic and terrain variables were selected as modeling parameters. The main influencing factors were determined using the Jackknife method. By comparing the current and future changes in key areas of *P. crassifolia* distribution, we can evaluate the increase or decrease in the area of its potential distribution. Finally, we predicted the potential distribution of *P. crassifolia* in the 2050s and 2070s climate change scenarios. We used SDM tools in ArcGIS, which provides an effective means for us to quantitatively analyze the changes of habitat suitability of *P. crassifolia*. Our objectives were to (1) analyze the relationships between the distribution of *P. crassifolia* and main environmental variables and determine key environmental factors affecting potential distribution of *P. crassifolia*; (2) predict potential distribution and habitat suitability changes of *P. crassifolia* under current climate conditions and climate change scenarios.

2 Materials and methods

2.1 Occurrence records of *P. crassifolia*

An occurrence record is the species sampling point, which documents geographic coordinates and growth environment of *P. crassifolia*. Information about the current distribution of *P. crassifolia* in China was collected from several sources including (1) 42 occurrence records of *P. crassifolia* sample sites from the Global Biodiversity Information Facility (GIBF, <https://www.gbif.org/>), an international network and research infrastructure funded by the world's governments and aimed at providing anyone, anywhere, open access to data about all types of life on Earth, (2) 250 occurrence records from the National Plant Specimen Resource Center, also known as Chinese Virtual Herbarium (CVH, <http://www.cvh.ac.cn/>), (3) 207 records from the Plant Photo Bank of China (PPBC, <http://ppbc.iplant.cn/>) and 461 from the Chinese Field Herbarium (CFH, <http://www.cfh.ac.cn/>), respectively. In addition, 57 occurrence records were obtained by searching the Chinese National Knowledge Infrastructure (CNKI, <https://www.cnki.net/>), and we conducted field surveys in the summer of 2019 and 2020. A total of 1017 records of *P. crassifolia* were extracted using the above-listed sources. To reduce the error that may be caused by the aggregation effect in modeling, we screened the data to remove possible identification errors and duplicate entries. Since the study of species distribution relies on high location accuracy, we excluded some records which contained non-specific descriptions of the location (e.g., a town or a mountain). Google Earth was used to determine specific geographic coordinates of the record with specific location when no longitude or latitude were given. Furthermore, we used the buffer analysis in ArcGIS 10.2 (ESRI, Redlands, California, USA, <http://www.esri.com>) to ensure that there was only one record in the grid cell with 30 arc-seconds (approximately 1km×1km) spatial resolution. Finally, 129 records of species distribution data were screened for modeling and analysis (Fig.1). Records were saved in the order of species name, longitude, and latitude as a CSV format. The number of occurrence records met the requirements of modeling to ensure the stability of simulation (Wisz et al. 2008).

2.2 Environmental variables

Temperature and precipitation are key environmental factors that affect growth and distribution of vegetation, and these factors have important biological significance for determining the environmental niche of species (Yi et al. 2016). Bioclimatic variables are derived from the monthly temperature and rainfall values to generate more biologically-meaningful variables (Hijmans et al.

2005). Bioclimatic variables represent annual trends (e.g., mean annual temperature, annual precipitation), seasonality (e.g., annual range in temperature and precipitation), and extreme environmental factors (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters) from 1960 to 2000. These are often used in species distribution modeling and related ecological modeling techniques (Cámara-Leret et al. 2019). To investigate potential distribution and habitat suitability of *P. crassifolia* under different climate change scenarios, we selected 19 bioclimatic variables of current climate (average for 1960-2000) and future climate (2050s and 2070s, average for 2041-2060 and 2061-2080, respectively) from the WorldClim database for modeling (<https://www.worldclim.org/>; Fick and Hijmans 2017; Hijmans et al. 2005). The spatial resolution of these data was at 30 arc-seconds (approximately 1 km at the equator). Because large-scale climatic averages may not necessarily represent differences in topography well (Pironon et al. 2019), we also downloaded Digital Elevation Model (DEM) data with a horizontal grid spacing of 30 arc-seconds (approximately 1 km) from the USGS GTOPO30 (<https://earthexplorer.usgs.gov/>), and used 3D analyst tools in ArcGIS 10.2 to extract aspect and slope data from GTOPO30.

For the different future climate change scenarios, we selected the Community Climate System Model version 4 (CCSM4, <https://www.worldclim.org/>) in the Global Climate Models (GCMs) with strong simulation capability for China (Williams et al. 2007), taken from the Coupled Model Inter-comparison Project Phase 5 (CMIP5). The model was developed by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC 2013; Meinshausen et al. 2011), and it contains four future greenhouse gas (GHG) Representative Concentration Pathways (RCPs) that represent an estimated range of GHG concentration up to 2100 (Reisinger et al. 2011). Different RCPs (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) represent the radiative forcing value peaks at approximately (2.6, 4.5, 6.0 and 8.5 W/m², respectively) and CO₂ concentration equivalents for each scenario are 490, 650, 850, and 1370 mL/m³ before year 2100. They are defined as ideal scenario (RCP2.6), intermediate stabilization pathways (RCP4.5 and RCP6.0) and extreme GHG emission scenarios (RCP8.5) (IPCC 2013). Finally, in this work, we selected two periods (2050s and 2070s), four RCPs emission scenarios in future climate change scenarios and combined with current climate information. We used the Maxent model to simulate potential suitability distribution areas and changes in *P. crassifolia* under climate change scenarios.

Research has shown strong multi-collinearity among bioclimatic variables in the WorldClim database (Yang et al. 2013). We took the following steps to avoid overfitting of highly correlated environmental variables (19 bioclimatic and 3 topographic variables) in the simulation process. First, we used Pearson correlation analysis in IBM-SPSS software (Statistical Product and Service Solutions, version 26.0, Chicago, USA) to conduct multi-collinearity test (Pearson et al. 2007) for the 22 environmental variables used in this study (Fig.2); we also imported all environmental variables into the model, and those environmental variables which contributed $> 0.05\%$ were included (environmental variables with percentage contribution $\leq 0.05\%$ have very little impact on species, therefore they can be ignored and eliminated). Second, if the correlation coefficient between two environmental variables was $> |0.8|$, then the environmental factors with low contribution should be eliminated (Liu et al. 2005). Finally, 19 environmental variables were selected as modeling parameters (Table 1). We used ArcGIS 10.2 to convert these environmental variables into ASCII file format for model simulation.

2.3 Species distribution modeling

Machine learning algorithms (MaxEnt and Random Forests) are superior to regression-based methods (Beaumont et al. 2016) for species distribution modeling. The so-called maximum entropy model is based on the principle of maximum entropy, using known information in the processing of unknown events as probabilistic events without making any unknown assumptions (Jaynes 1991). It often uses pixels of known species distribution points as sample points, and environmental variables at sample points as constraints, identifying the maximum value under such constraints (Ren et al. 2020). Therefore, accuracy of prediction results is guaranteed (Yue et al. 2019), and model performance is stable even with small sample sizes (Elith et al. 2006; Morales et al. 2017; Shcheglovitova and Anderson 2013). This model has been widely used in many fields, including biological invasions, the spread of infectious diseases, and habitat suitability research (Filazzola et al. 2020; Gao and Cao 2019; Ghareghan et al. 2020; Hosni et al. 2020). Thus, we used the maximum entropy (MaxEnt, version 3.4.1, <https://www.cs.princeton.edu/ws-chapire/maxent>; Phillips et al. 2006), model to investigate potential distribution of *P. crassifolia*.

We imported 19 environmental variables and the occurrence records of *P. crassifolia* into the MaxEnt software to create the initial model (Wang et al. 2019), then randomly selected 75% of the occurrence records of *P. crassifolia* as training data for modeling and 25% as model validation data

(Phillips and Dudik 2008; Phillips et al. 2006). Other settings of MaxEnt model were as follows: the maximum number of background points and the maximum number of iterations were 10,000 and 500, respectively; ‘create response curves’, ‘make pictures of predictions’, ‘do jackknife to measure variable importance’; other options were set to default values. Data selection process and modeling were repeated 10 times (mean of 10 simulations as the final result) to avoid uncertainty of simulation results generated by splitting data into the training and validation portions (Guo et al. 2019).

2.4 Model evaluation

We used true skill statistic (TSS), sensitivity, specificity, and the area under the curve (AUC) of the receiver operating characteristic curve (ROC) to evaluate the fitting degree of the model. ROC curve is a common method for evaluating accuracy of prediction of the Maxent model (Angelieri et al. 2016; Fourcade et al. 2014). As a general rule, AUC ranges from 0 to 1, with AUC value closer to 1 indicating higher accuracy of prediction (Evans et al. 2010; Ihlow et al. 2012). The specific evaluation criteria were as follows: at $0.5 \leq \text{AUC} < 0.6$, the simulation failed, at $0.6 \leq \text{AUC} < 0.7$, simulation results were poor, at $0.7 \leq \text{AUC} < 0.8$, simulation results were acceptable, at $0.8 \leq \text{AUC} < 0.9$ simulation results were good, and at $0.9 \leq \text{AUC} < 1$ simulation results were excellent (Swets 1988).

2.5 Habitat suitability classification

The output file generated by the MaxEnt software was a continuous probability layer in ASCII format, which cannot be directly visualized. The spatial analysis tool of ArcMap software was used to convert the format from ASCII to raster, and then the habitat suitability distribution map of *P. crassifolia* in China was constructed. The fifth and tenth percentile training presence are two commonly used thresholds in the simulation of species distribution (Pearson et al. 2002). We examined the thresholds, and maximum sensitivity and specificity of the above two percentiles, and found that the fifth percentile was consistent with the actual conditions in the study area. Species below the threshold were often considered as ‘absent’, that is, *P. crassifolia* did not exist. Therefore, we selected the minimum of the training presence (MTP) with the fifth percentile average value of 0.3 as a threshold for every climate change scenario (Hijmans and Graham 2006). Based on the division scheme of habitat suitability developed by Xu et al. (2019), we defined habitat suitability of *P. crassifolia* under different climate change scenarios at four levels: not suitable (0-0.3), low

suitability (0.3-0.5), moderate suitability (0.5-0.7), and high suitability (0.7-1).

3 Results

3.1 Model performance and contribution of environmental variables

The AUC values of multiple simulations were higher than 0.9, with average AUC values at 0.976 (Fig.3). The mean value of AUC indicated that the performance of the maximum entropy model (MaxEnt) was excellent (Merow et al. 2013; Swets 1988), and hence the results of the simulation of potential distribution and habitat suitability of *P. crassifolia* using the MaxEnt can be considered credible. Analysis of the relative percentage contribution of environmental variables and the permutation importance of individual variables used in the MaxEnt model for *P. crassifolia* showed that altitude (alt, 41.85% of variation), precipitation of driest month (bio14, 19.76% of variation), slope (slo, 12.35% of variation), annual precipitation (bio12, 6.56% of variation), precipitation of wettest month (bio13, 5.73% of variation), precipitation of warmest quarter (bio18, 5.12% of variation), temperature seasonality (bio4, 4.11% of variation), and aspect (asp, 1.46% of variation) were the main environmental factors affecting the distribution of *P. crassifolia*, with a cumulative percentage contribution of 96.95% (Table 1). Other environmental variables had little influence on the distribution of *P. crassifolia*.

3.2 Potential distribution of habitat suitability of *P. crassifolia* in current climate conditions

The MaxEnt model showed that habitat suitable for *P. crassifolia* under current climate conditions was mainly distributed in arid and semi-arid regions of northwestern China (northeast of Qinghai-Tibet Plateau), with scattered areas in the Helan Mountains and the southern mountains of Ningxia Hui Autonomous Region (Fig. 4). This was consistent with the actual distribution of *P. crassifolia* (Zhao et al. 2006). The distribution range of potential suitability was larger than that of actual distribution of *P. crassifolia*. As shown in Fig.4, the middle part of Tianshan Mountains contained a potentially suitable area of *P. crassifolia* in current climate conditions. However, there were no occurrence points in the region. High-suitability area of *P. crassifolia* was located in eastern Qinghai and middle and eastern parts of QLM in Gansu, with an area of $1.72 \times 10^4 \text{ km}^2$, accounting for about 0.18% of the total land area of China. Moderate and low suitability areas were distributed around high suitability areas, mainly located in Gannan, Linxia, and Dingxi of Longzhong Plateau and east of Qinghai, with an area of $5.05 \times 10^4 \text{ km}^2$ and

9.01×10⁴ km², respectively. Because moderate and high suitability areas in our study exhibited logistic probability of > 0.5, we defined those areas as the core areas of *P. crassifolia* habitat suitability, with an area of 6.76×10⁴ km², accounting for 0.7% of the national area.

3.3 Potential suitability distribution of *P. crassifolia* under multiple climate change scenarios

The spatial pattern of *P. crassifolia* and its potential suitability distribution under climate change scenarios were similar to those in current climate conditions (Fig.5). Furthermore, suitable habitat for *P. crassifolia* will expand to the northwest and to high elevation areas.

When current climate was used as the base condition, simulation results indicated that potential distribution range of habitat suitability of *P. crassifolia* in China had an increasing trend from 2050s to 2070s, and main locations were northeast of the Qinghai-Tibet Plateau, namely the middle of QLM and Tianshan Mountains, southwestern Gansu Province, and eastern Qinghai Province and southeastern of Qaidam Basin (Fig.5). The high suitability area is mainly located in the middle of QLM and around Qinghai Lake. By the 2050s, the total potential habitat suitability area of *P. crassifolia* in the other three scenarios (RCP2.6, RCP6.0, and RCP8.5) increased, except for RCP4.5, the intermediate greenhouse gas concentration pathways. The largest increase in suitable habitat area was 72.19% (11.39×10⁴km²) with RCP2.6. However, the total area of potential habitat suitability for *P. crassifolia* continued to increase in the 2070s under all GHG emission scenarios, but the rate of suitable area expansion decreased in the 2070s compared to the previous period (Fig.6).

3.4 Effects of several key environmental variables on occurrence probability of *P. crassifolia*

Most of the environmental variables followed Gaussian distribution, one notable exception was aspect (Fig.7). When the values of logistic output were ≥0.3, the corresponding environmental variables were suitable for growth of species, while the maximum values of logistic output indicated the optimum environmental conditions for the growth of species (Phillips et al. 2006; Swets 1988).

At altitudes < 1958 m and > 3832 m, the probability of *P. crassifolia* occurrence was < 0.3. With an increase in altitude, the probability occurrence increased, and reached maximum at 2802 m. The response curve of annual precipitation was similar to those of precipitation of driest month,

precipitation of wettest month, and precipitation of warmest quarter. In that, when annual precipitation was < 210 mm or > 671 mm, the probability of *P. crassifolia* occurrence was < 0.3 . With an increase in slope steepness, the probability of *P. crassifolia* occurrence exhibited an inverted V-shape pattern, with a maximum at 14° . However, probability of occurrence of shaded and semi-shaded slopes was significantly higher than that of sunny and semi-sunny slopes, affecting distribution of *P. crassifolia*.

Our results showed that *P. crassifolia* preferred to grow at the altitude of 2253-3455 m, precipitation of driest month of 0-2 mm, slopes of $8-44^{\circ}$, annual precipitation of 290-519 mm, precipitation of wettest month of 74-112 mm, precipitation of warmest quarter of 184-298 mm, temperature seasonality of 764-935, aspect (5° - 45° and 265° - 360° , that is northwestern, northern and northeastern slopes). This indicated that the distribution of *P. crassifolia* was mainly affected by elevation, slope, aspect, and precipitation. These results were consistent with previous studies and field surveys.

4 Discussion

Understanding potential distribution of suitable habitat of *P. crassifolia* in China is of great significance for efficient cultivation and conservation, management and sustainable utilization of the species. In this research, we selected 129 *P. crassifolia* occurrence records and 19 environmental variables, and predicted habitat suitability of *P. crassifolia* in China using the MaxEnt model. Under the present climatic conditions, the potential suitable habitat of *P. crassifolia* was mainly located in QLM, eastern Qinghai Province, southwestern Gansu, the middle part of Tianshan Mountains, HLM and Liupan Mountains in Ningxia. The overall accuracy of the potential distribution of *P. crassifolia* simulated by MaxEnt model was very high, but it does not mean that the potential distribution is completely consistent with the actual distribution of *P. crassifolia*. The maximum theoretical geographic distribution of *P. crassifolia* was obtained using model simulation. However, on one hand, the species distribution is affected by abiotic factors such as climate, topography, soil types and texture; on the other hand, it is also affected by competition, growth characteristics, dispersion and migration capabilities, natural renewal capabilities, herbivory, and human activities (deforestation, overgrazing, tourism behavior, industrial and mining construction, etc.) (Boulangeat et al. 2012; Takahashi and Okuhara 2013). For example, forest vegetation in the QLM decreased by 33.5% from 1989 to 1998 due to

increased human activities (Guo et al. 2003), and forest ecosystem was degraded. In addition, a deviation can be expected between simulation results and actual species location when species occurrence data are limited. Differences in the resolution of selected environmental variables during the modeling process may also affect results of estimated geographic distribution range of species.

Geographic distribution of species at a specific scale is mainly restricted by climatic conditions, in which hydrothermal conditions (moisture and heat) play a leading role. We found that altitude, mean temperature of wettest quarter, and precipitation of wettest month were the main climatic factors affecting distribution of *P. crassifolia*. However, Xu et al. (2009) concluded that mean temperature in the wettest quarter and highest temperature in the warmest month were the main climatic factors affecting potential distribution of *P. crassifolia* in the QLM. These differences may be related to the spatial scale of the selected study area. In this study, potential habitat suitability of *P. crassifolia* was based on the national scale, which is much larger than the regional scale (QLM) used in Xu et al. (2009). Some authors have pointed out that the response of *P. crassifolia* to climatic variables may be altered by topographical factors (altitude, slope, and aspect), and the distribution of mountain forests in arid areas is controlled by low temperature at higher altitudes and precipitation at lower altitudes, but that large differences may be present in different regions (He et al. 2016; Luo et al. 2011). We conclude that *P. crassifolia* is limited at the national scale by altitude and precipitation. Specifically, the most suitable habitat for *P. crassifolia* comprise altitudes of 2253-3455 m, precipitation of wettest month of 74-112 mm, and precipitation of warmest quarter of 189-298 mm. This conclusion is consistent with Wang et al. (2020) who used the V.S. model to determine that precipitation from May to September directly affected the growth of *P. crassifolia*. Results of small and medium-scale research, however, may be affected by combined altitude, temperature, and precipitation.

The total area of potential suitable habitat of *P. crassifolia* will change significantly under future climate change scenarios. The area of habitat suitability of *P. crassifolia* will increase by more than 60% with all climate change scenarios. However, the distribution range of *P. crassifolia* is quite different in different habitat suitability levels. This may be related to our classification of potential habitat suitability of *P. crassifolia*. The simulated area of the highest habitat suitability (moderate and high suitability) was $6.76 \times 10^4 \text{ km}^2$ under current climate conditions. Area of highest

habitat suitability exhibited an increasing trend for four climate change scenarios and two periods (2050s and 2070s), but the rates of increase declined with the continuous increase in greenhouse gas concentration (Fig.6). At RCP8.5 (2070s), the area with moderate and high suitability decreased by 6,336.3 km², compared with the same period for RCP6.0 (Fig.5, 6). It is generally believed that the direction of species migration is connected with their location and with emission scenarios (Liao et al. 2020). We found that the new range of suitable habitat of *P. crassifolia* may be gradually expanded in the future to the interior of the Qinghai-Tibet Plateau and high-altitude mountainous areas. We expect that *P. crassifolia* will migrate to the northwest under four climate change scenarios. This result is consistent with the IPCC conclusion that climate change will have a positive feedback on ecosystems in some areas of the low latitudes of the northern hemisphere (IPCC, 2014). As well as the results of Dakhil et al. (2019) and Gao et al. (2016), who showed that alpine coniferous forests migrated westward as the climate continued to warm.

The area of forest plantations in arid and semi-arid areas of China has increased significantly in recent years, due in large part to a series of ecological projects, such as the Three-North Shelterbelt System, the Natural Forests Protection Project, and Returning Farmland to Forests and Grasslands (Chen et al. 2019). Although our research results indicate that many areas are suitable for *P. crassifolia* in a future climate, it is entirely unknown what scale and pattern of plantation establishment will support natural restoration and ecological and hydrological regulation of mountain ecosystems. Such knowledge is critical to the establishment of national parks, security of water supply in inland river basins, protection of mountain biodiversity, and construction and management of ecological projects. Therefore, future research must address the scale effect (individual, patch, watershed, regional, etc.) and distribution patterns when using high-resolution remote sensing images and geographic information system (GIS), combined with landscape ecological pattern and species distribution models (He et al. 2016). Understanding the scale-effects will provide scientific basis and decision support for mountain ecological engineering construction and planning.

As one of the most common used methods for simulating potential distribution and evaluating the habitat suitability of species, MaxEnt also has some shortcomings. There are mainly the following three aspects: (1) uncertainty of species distribution models (SDMs), which is mainly reflected in the uncertainty of species distribution data, environmental variables. The uncertainty of

the location information of species sampling points may cause inaccurate estimation of the species-environmental relationship, which is closely related to the degree of auto-correlation of environmental variables participating in the modeling (Naimi et al. 2014). Some studies have pointed out that environmental variables are often used in current species distribution model, such as the collinearity of some variables in WorldClim and HWSD (Harmonized World Soil Database) (Fick and Hijmans 2017; Zhang and Zhang 2012), which results in redundancy of statistics information during modeling and have a negative impact on the simulation results. Therefore, Principal Component Analysis (PCA), Pearson correlation coefficient or Variance Inflation Factor (VIF) should be used to reduce the dimensionality of environmental variables during modeling (Fourcade et al. 2018; Guisan et al. 2017). (2) model validation and evaluation. The frequently used verification and evaluation methods are True Skill Statistic (TSS), F-Score, Kappa coefficient, and the area under the curve (AUC) of the receiver operating characteristic curve, etc. (Angelieri et al. 2016; Phillips and Dudik 2008; Radosavljevic and Anderson 2014). The evaluation methods of different SDMs only evaluate some aspects of the model, and there is no universal model evaluation method (Guillera-Arroita et al. 2015). (3) threshold selection and extrapolation of simulation results. The selection of appropriate classification threshold is critical to the accuracy of the results. Jiménez-Valverde and Lobo (2007) concluded that there is no so-called universal optimal threshold division method. However, when there are uncertainties in the modeling data itself, the setting of the habitat suitability threshold of the species should be taken into account the characteristics of the species' niche and research purpose. The extrapolation of simulation results refers to the extrapolation of the model on the spatial-temporal scale (Anderson 2013). There are still difficulties in transforming the prediction results of the SDMs on the spatial scale. At different spatial scales, the niche of target species exhibits different characteristics, so the environmental threshold for species growth is also different, especially in the downscaling study in the SDMs, other information is needed (Guisan et al. 2017). Temporal extrapolation should include factors such as species dispersal ability, soil, vegetation changes, and human activities into the modeling process.

5 Conclusions

In this study, we established a species distribution model that comprehensively considered climate and topographic factors, to provide a scientific basis for the assessment of habitat suitability of *P. crassifolia* in China. The results show that climate change will affect the distribution of *P.*

crassifolia in four RCPs and two periods, which varies in different regions. We found that the potential suitable area of *P. crassifolia* will increase and migrate to the interior of the Qinghai-Tibet Plateau and high-altitude mountain areas by the 2070s. Due to the increase in precipitation with climate warming, habitat suitability of *P. crassifolia* in some areas is expected to exhibit little change, while habitat suitability on the edge of the Qaidam Basin and in southeastern Qinghai will increase. In future research, we plan on including effects of human disturbance on habitat suitability modeling of *P. crassifolia*. Additionally, we propose to include more abundant environmental variables (land cover types, evaporation, soil temperature, humidity and texture, etc.) as modeling parameters to predict potential habitat distribution of species on a small scale.

Acknowledgments

This research was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (No. XDA23060301), the Science and Technology Service Network Initiative of the Chinese Academy of Sciences (No. KFJ-STS-QYZD-175), and the National Key Research and Development Program of China (No. 2019YFC0507403).

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Table captions:

Table 1 Percentage contribution and permutation importance of the environmental variables included in the Maxent model for *P. crassifolia*

Figure captions:

Fig.1 Geographic distribution of *P. crassifolia* in China (green dots); data obtained from various sources (see section 2.1). The base map used in the mapping comes from the Chinese standard map service (<http://bzdt.ch.mnr.gov.cn/>).

Fig.2 Multi-collinearity test for environmental variables using Pearson correlation analysis.

Fig.3 Receiver operating characteristic (ROC) curve of Maxent for *P. crassifolia*. The upper red curve indicates the mean AUC of 0.976, the blue area indicates the sample standard deviation, and the diagonal black line indicates random prediction.

Fig.4 Potential suitability distribution of *P. crassifolia* in China under current climate. The base map used in the mapping comes from the Chinese standard map service (<http://bzdt.ch.mnr.gov.cn/>).

Fig.5 Future habitat suitability distribution of *P. crassifolia* in China under four representative GHG concentration pathways (RCP2.6, 4.5, 6.0, 8.5) of climate change scenarios in 2050s (left panels) and 2070s (right panels). Red indicates high suitability areas with probability > 0.7; green indicates moderate suitability with probability of 0.5-0.7; yellow indicates low suitability with probability of 0.3-0.5, and white indicates no suitability with probability of < 0.3. The base map used in the mapping comes from the Chinese standard map service (<http://bzdt.ch.mnr.gov.cn/>).

Fig.6 Area of *P. crassifolia* under current and future climate change scenarios.

Fig.7 Response curves of the major environmental variables in the MaxEnt model. Values of logistic output (probability presence) range from 0 to 1; generally, values of logistic output ≥ 0.5 indicate a better performance than random simulation. The shaded part of each response curve is the most suitable distribution range of *P. crassifolia* for that environmental variable.

Fig.8 Jackknife test of environmental variables affecting potential suitability distribution of *P. crassifolia*.

Table 1 Percentage contribution and permutation importance of the environmental variables included in the Maxent model for *P. crassifolia*

Variable Code	Variable Description	Unit	Percent contribution (%)	Permutation importance (%)
alt	Altitude	m	41.85	22.45
bio14	Precipitation of driest month	mm	19.76	3.60
slo	Slope	%	12.35	6.03
bio12	Annual precipitation	mm	6.56	4.65
bio13	Precipitation of wettest month	mm	5.73	17.09
bio18	Precipitation of warmest quarter	mm	5.12	0.07
bio4	Temperature seasonality (standard deviation*100)	°C	4.11	12.57
asp	Aspect	°	1.46	1.65
bio5	Maximum temperature of warmest month	°C	0.60	1.21
bio17	Precipitation of driest quarter	mm	0.55	9.11
bio7	Temperature annual range (bio5-bio6)	°C	0.51	2.96
bio19	Precipitation of coldest quarter	mm	0.34	10.92
bio15	Precipitation seasonality (coefficient of variation)	/	0.34	0.70
bio6	Minimum temperature of coldest month	°C	0.17	2.00
bio1	Annual mean temperature	°C	0.16	0.71
bio2	Mean diurnal range (Mean of monthly (max temp-min temp))	°C	0.14	0.29
bio8	Mean temperature of wettest quarter	°C	0.13	2.32
bio10	Mean temperature of warmest quarter	°C	0.07	1.08
bio3	Isothermality (bio2/bio7)	/	0.05	0.61

285x206mm (300 x 300 DPI)

229x178mm (300 x 300 DPI)

285x198mm (300 x 300 DPI)