

## Article

# The Influence of Climate Change on Three Dominant Alpine Species under Different Scenarios on the Qinghai–Tibetan Plateau

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**Abstract:** The Qinghai–Tibetan Plateau (QTP) with high altitude and low temperature is one of the most sensitive areas to climate change and has recently experienced continuous warming. The species distribution on the QTP has undergone significant changes especially an upward shift with global warming in the past decades. In this study, two dominant trees (*Picea crassifolia* Kom and *Sabina przewalskii* Kom) and one dominant shrub (*Potentilla parvifolia* Fisch) were selected and their potential distributions using the MaxEnt model during three periods (current, the 2050s and the 2070s) were predicted. The predictions were based on four shared socio-economic pathway (SSPs) scenarios, namely, SSP2.6, SSP4.5, SSP7.0, SSP8.5. The predicted current potential distribution of three species was basically located in the northeastern of QTP, and the distribution of three species was most impacted by aspect, elevation, temperature seasonality, annual precipitation, precipitation of driest month, Subsoil CEC (clay), Subsoil bulk density and Subsoil CEC (soil). There were significant differences in the potential distribution of three species under four climate scenarios in the 2050s and 2070s including expanding, shifting, and shrinking. The total suitable habitat for *Picea crassifolia* shrank under SSP2.6, SSP4.5, SSP7.0 and enlarged under SSP8.5 in the 2070s. On the contrary, the total suitable habitat for *Sabina przewalskii* enlarged under SSP2.6, SSP4.5, SSP7.0 and shrank under SSP8.5 in the 2070s. The total suitable habitat for *Potentilla parvifolia* continued to increase with SSP2.6 to SSP8.5 in the 2070s. The average elevation in potentially suitable habitat for *Potentilla parvifolia* all increased except under SSP8.5 in the 2050s. Our study provides an important reference for the conservation of *Picea crassifolia*, *Sabina przewalskii*, *Potentilla parvifolia* and other dominant plant species on the QTP under future climate change.

**Keywords:** climate change; potential distribution; MaxEnt model; suitable habitat; average elevation

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## 1. Introduction

Climate change is considered to be one of the most important driving factors of species distribution [1–3]. According to the report of the sixth Coupled Model Intercomparison Project (CMIP6), the global temperature will continue to increase by the end of the 21st century [4]. The Qinghai–Tibetan Plateau (QTP), famous as the “third pole” in the world with high altitude and low temperature, is one of the most sensitive regions to climate change [5]. With global warming, many species shift their suitable habitats especially upward in altitude in order to adapt to changes in environmental conditions [6,7].

However, it remains unclear what influences climate change will have on alpine species at large regional scales and whether alpine species respond uniformly on the QTP. Two dominant and representative alpine trees (*Picea crassifolia* Kom, *Sabina przewalskii* Kom) and one dominant and representative alpine shrub (*Potentilla parvifolia* Fisch) on

the QTP were used in this study, *Picea crassifolia* favors shady slopes, semi-shady slopes and humid valleys in the mountains with an altitude of 1750–3100 m (a.s.l), is endemic to China, and is distributed in the Qilian Mountains, Qinghai, Gansu, Ningxia, Inner Mongolia. *Sabina przewalskii* grows on sunny slopes of 2600–4000 m (a.s.l), is endemic to China, and is distributed in Qinghai, Gansu Hexi Corridor, and the north of Sichuan. *Potentilla parvifolia* favors dry hillside, rock crack, forest edge and forest with an altitude of 900–5000 m (a.s.l), and it is distributed in Heilongjiang, Inner Mongolia, Gansu, Qinghai, Sichuan and Tibet in China. Species on shady slopes are more sensitive to the magnitude of temperature fluctuations, and species on sunny slopes can tolerate larger temperature fluctuations [8]. The previous study was conducted on potential distribution for *Picea crassifolia*, *Sabina przewalskii* and *Potentilla parvifolia*, but they only focused on the potential distribution under different climate scenarios without considering the influence of geographical factors [9].

Species distribution models are popular methods in modeling the potential distributions of species in response to climate change in the past few decades [10]. Many species distribution models are used to predict potential distributions, such as maximum entropy (MaxEnt) [11], random forests (RFs) [12], CLIMEX, and genetic algorithm for rule set production (GARP) [13]. Among them, MaxEnt is widely selected because it performs excellently with a small number of sample records compared to other models [14]. This research used MaxEnt to predict potential distribution for three species under different shared socio-economic pathways (SSPs) scenarios.

SSPs can be selected to predict greenhouse gas emission scenarios under different climate conditions [15]. SSPs consider the effects of land use and socio-economic with the development of regional climate change and are different from representative concentration pathways (RCPs) [16]. SSPs have a higher beginning point than RCP and the result of prediction is near to the true value [17]. SSP2.6 (Low forced scenario), SSP4.5 (Medium forced scenario), SSP7.0 (Medium-high forced scenario), SSP8.5 (High forced scenario) were selected to predict the potential distribution of three species during the period of the 2050s and 2070s in this study.

The aims of this research are: (1) to predict the potential distribution of three species under different climate scenarios; (2) to assess the key environment variables affecting the distribution of three species; (3) to analyze the area and elevation changes of the suitable habitat of three species in the future climate change. The results of this study will provide an important reference for the conservation of *Picea crassifolia*, *Sabina przewalskii*, *Potentilla parvifolia* and other dominant plant species on the QTP under climate change.

## 2. Materials and Methods

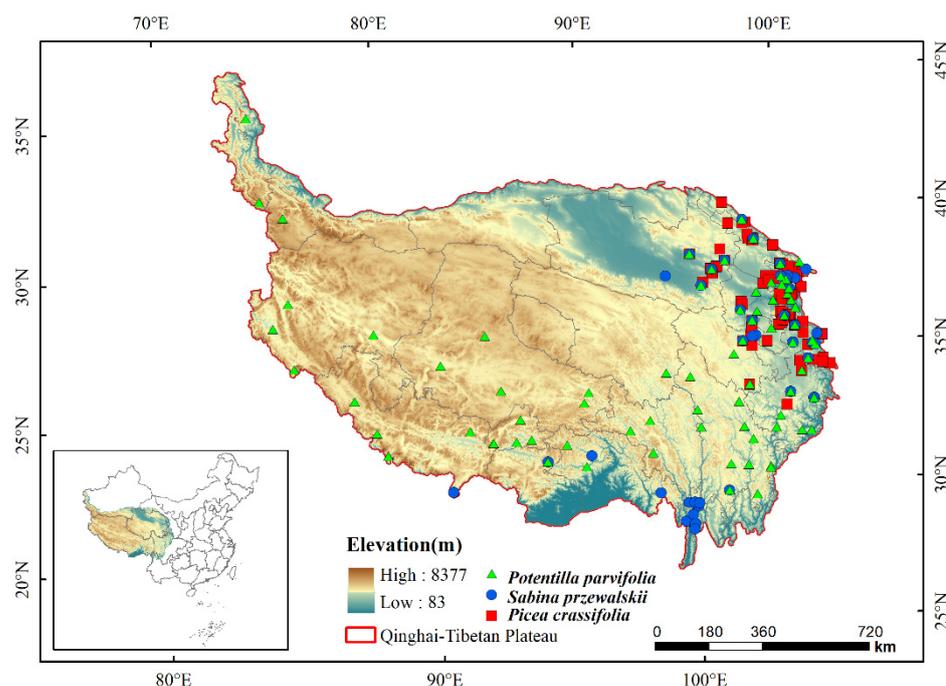
### 2.1. Study Area

The Qinghai–Tibetan Plateau (QTP), located in western China, is famous as the “Roof of the World” with the highest and one of the most extensive plateaus on earth [18]. It lies between 26° N to 39° N and 73° E to 104° E, and covers a total area of approximately 2.5 million km<sup>2</sup> with an average elevation above 4000 m (a.s.l). Alpine desert ecosystems, alpine meadow, alpine grassland, shrub and forest are distributed from the southwestern to the northeastern of QTP, which is characterized by low annual temperature differences, high daily temperature differences, low air temperature and strong solar radiation [19]). Climate change probably affect species on the QTP more than those in other regions with the same latitude [20,21]).

### 2.2. Occurrence Data

As the accurate location information of species distribution is the basis of high precision simulation and prediction, the geographical distribution information of *Picea crassifolia*, *Sabina przewalskii* and *Potentilla parvifolia* were obtained from: (1) Chinese Virtual Herbarium (CVH, <https://www.cvh.ac.cn/>, accessed on 23 September 2021); (2) Global Biodiversity Information Facility (GBIF, <http://www.gbif.org/>, accessed on 24 September

2021); (3) Relevant literature reports (CNKI, Web of Science, <https://www.cnki.net/> <https://apps.webofknowledge.com/>, accessed on 15 November 2021). Google Earth (<http://ditu.google.cn/>, accessed on 22 November 2021) was used to proofread specimen distribution information and the duplicate records were removed [22]. Finally, the 172 records of *Picea crassifolia* distribution data, 69 records of *Sabina przewalskii* distribution data and 146 records of *Potentilla parvifolia* distribution data were used (Figure 1). The longitude and latitude of the distribution data and the species name were entered into Excel and converted to csv format for modeling.



**Figure 1.** Locations of three species on the Qinghai–Tibetan Plateau.

### 2.3. Environment Variables

#### 2.3.1. Climate Data

The data used for climate assessment were downloaded from the WorldClim global climate database [23] (<http://www.worldclim.org>, accessed on 15 November 2021).

Current climate data included 19 Bioclimatic variables with 30'' spatial resolution during 1970–2000 [24], which reflect temperature and precipitation.

Future Bioclimatic data were obtained from BCC\_CSM1.1 (Beijing Climate Center, China Meteorological Administration, Beijing, China) global circulation model [8]), which is available for predicting the global climate response to increasing greenhouse gas concentration [22]). Bioclimatic data (at 2.5' spatial resolution) for four scenarios of Shared Socioeconomic Pathways (SSPs) provided by the sixth Coupled Model Intercomparison Project (CMIP6) were used for modeling [25]). Each SSP includes scenarios of SSP2.6, SSP4.5, SSP7.0, SSP8.5, and analyses the spatial and temporal changes of the annual temperature and precipitation during 2021–2100 [26]). The future climate variables were resampled to the same spatial resolution with current data using ArcGIS 10.7 [27]).

#### 2.3.2. Topographic Data

The DEM data with a cell size of 90 m × 90 m were downloaded from the WIST geodatabase of NASA (<http://srtm.csi.cgiar.org/>, accessed on 15 November 2021). The variables of slope, aspect and elevation were derived from DEM using ArcGIS 10.7.

### 2.3.3. Soil Property Data

Soil data used in this study were collected from Harmonized World Soil Database (HWSD, <http://www.fao.org/soils-portal>, accessed on 15 November 2021).

### 2.3.4. Processing and Selection of Environment Variables

All environment variables were resampled to 30'' spatial resolution and were processed to the same geographic bounds. In the modeling process, high correlation variables and environment variables that contribute less to the model were removed to improve the accuracy of the model [28,29]. The correlation coefficient was calculated to account for the influence of collinearity on the model accuracy. The variables with  $r$  below 0.8 were selected [30]. The 16 variables with low correlation coefficients and high contribution rates were selected for distribution modeling (Table 1).

**Table 1.** The selection of environmental variables used in this study.

Data Source	Symbol	Variables	Unit	Important Variables for Modelling
WorldClim	Bio1	Annual mean temperature	°C	
	Bio2	Mean diurnal range	°C	
	Bio3	Isothermality (BIO2/BIO7) ( $\times 100$ )	%	
	Bio4	Temperature seasonality (standard deviation $\times 100$ )	°C	✓
	Bio5	Max temperature of warmest month	°C	
	Bio6	Min temperature of coldest month	°C	
	Bio7	Temperature annual range (BIO5-BIO6)	°C	✓
	Bio8	Mean temperature of wettest quarter	°C	
	Bio9	Mean temperature of driest quarter	°C	
	Bio10	Mean temperature of warmest quarter	°C	
	Bio11	Mean temperature of coldest quarter	°C	
	Bio12	Annual precipitation	mm	✓
	Bio13	Precipitation of wettest month	mm	
	Bio14	Precipitation of driest month	mm	✓
	Bio15	Precipitation seasonality (coefficient of variation)	1	✓
	Bio16	Precipitation of wettest quarter	mm	
	Bio17	Precipitation of driest quarter	mm	
	Bio18	Precipitation of warmest quarter	mm	✓
	Bio19	Precipitation of coldest quarter	mm	✓
DEM	ASL	Elevation	m	✓
	SLOP	Slope	°	✓
	ASPE	Aspect	°	✓

Table 1. Cont.

Data Source	Symbol	Variables	Unit	Important Variables for Modelling
HWSD	S_GRAVEL	Subsoil gravel content	%vol	
	S_SAND	Subsoil sand fraction	%wt	
	S_SILT	Subsoil silt fraction	%wt	
	S_CLAY	Subsoil clay fraction	%wt	√
	S_USDA_TEX_CLASS	Subsoil USDA texture classification	name	
	S_REF_BULK_DENSITY	Subsoil reference bulk density	kg/dm <sup>3</sup>	
	S_BULK_DENSITY	Subsoil bulk density	kg/dm <sup>3</sup>	√
	S_OC	Subsoil organic carbon	% weight	
	S_PH_H <sub>2</sub> O	Subsoil pH (H <sub>2</sub> O)	−log(H <sup>+</sup> )	
	S_CEC_CLAY	Subsoil CEC (clay)	cmol/kg	√
	S_CEC_SOIL	Subsoil CEC (soil)	cmol/kg	√
	S_BS	Subsoil base saturation	%	√
	S_TEB	Subsoil TEB	cmol/kg	
	S_CACO <sub>3</sub>	Subsoil calcium carbonate	% weight	
	S_CASO <sub>4</sub>	Subsoil gypsum	% weight	√
	S_ESP	Subsoil sodicity (ESP)	%	
S_ECE	Subsoil salinity (Elco)	dS/m		

#### 2.4. Distribution Modeling

MaxEnt with advantages in performance and stability was used to predict the potential distribution of three species (Figure 2) [11,31]. In addition, MaxEnt has the advantage of utilizing continuous and classified data and integrating the interaction between variables [14]. MaxEnt software version 3.4.4k was used to identify the species potential habitat distribution. The MaxEnt was set to run 500 iterations with a maximum of 10,000 background points, a convergence threshold (0.00001), a regularization multiplier of 1, a logistic output grid format, and the algorithm parameters set to “auto feature”. The other parameter values were kept in the default settings [32]. A total of 70% of the distribution point data were selected for training, and the rest were used for testing [33]. The Jackknife was used for testing the importance of environmental variables in a model with a small amount of the distribution point records [34].

##### 2.4.1. Accuracy Assessment

The value of the area under the receiver operating characteristic curve (AUC) was selected to assess model accuracy [11]). Model performance can be regarded as fail when it is between 0.5 and 0.6, poor when it is between 0.6 and 0.7, fair when it is between 0.7 and 0.8, good when it is between 0.8 and 0.9; and excellent when it is between 0.9 and 1 [35].

##### 2.4.2. The Area and Elevation Changes of the Habitat Suitability

SDMtoolbox of ArcGIS 10.7 was used to convert the current and future results. The asc format files in the model result were converted to the raster format and reclassified into four suitable habitats, and we calculated the area and average altitude of potential distribution by zonal statistic tool [36]. The area and average altitude changes in the suitable habitat for species distribution were used as an indicator to evaluate the impact of climate change on the distribution of species [8]. The intersection distributions of the three species were obtained through the raster calculator and extracted by attributes tools.

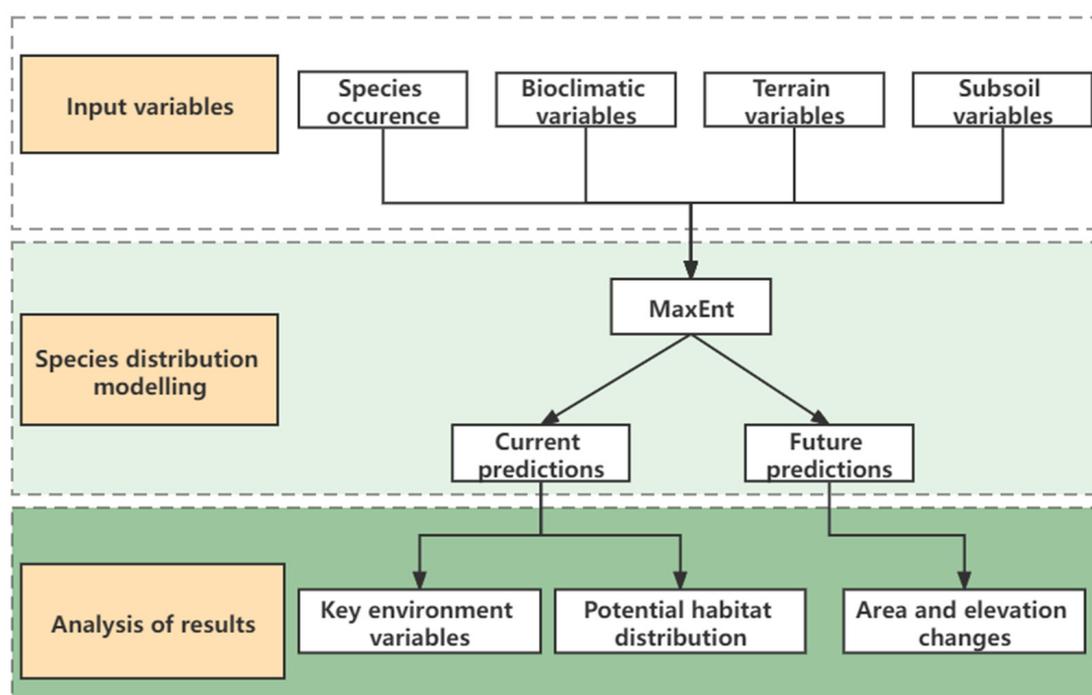


Figure 2. Flow diagram of methodology adopted.

### 3. Results

#### 3.1. Model Assessment and Key Environmental Variables

The mean AUC of three species in training and testing all exceeded 0.9 in current and future modeling. The model for the geographic distribution prediction performed excellently and had high accuracy.

We selected the variables whose contribution rate for three species is more than 0.1 for analysis. The internal jackknife test of the MaxEnt model for environmental variables' importance showed that aspect was the most critical factor determining the distribution of the three species. Aspect contributed 33.9% to model output for *Picea crassifolia*, 51.7% for *Sabina przewalskii* and 56.1% for *Potentilla parvifolia* (Table 2). In addition, elevation contributed 20.2% to model output for *Picea crassifolia*, 26% for *Sabina przewalskii* and 15.9% for *Potentilla parvifolia*. The following factors were precipitation of driest month (Bio14: 23.1% for *Picea crassifolia*, 3.4% for *Sabina przewalskii* and 3.5% for *Potentilla parvifolia*), annual precipitation (Bio12: 10.7% for *Picea crassifolia*, 4.9% for *Potentilla parvifolia*) and temperature seasonality (Bio4: 6% for *Picea crassifolia*). The total contributions of three subsoil variables (S\_CEC\_CLAY, S\_BULK\_DEN, S\_CEC\_SOIL) did not exceed 3% (Table 2). The results indicated that subsoil conditions had very limited impacts on the potential distribution of *Picea crassifolia*, *Sabina przewalskii* and *Potentilla parvifolia*. The cumulative percentage of aspect, elevation, Bio14, Bio12, Bio4, S\_CEC\_CLAY, S\_BULK\_DEN, and S\_CEC\_SOIL was 95.6% for *Picea crassifolia*, 82.5% for *Sabina przewalskii* and 83.5% for *Potentilla parvifolia*, respectively.

#### 3.2. Potential Distribution of Three Species at Current Climate Scenarios

The total suitable habitat area for *Picea crassifolia* was 99,203.04 km<sup>2</sup> (account for 3.86% of QTP), and was mainly concentrated in the northeastern of QTP. The total suitable habitat area for *Potentilla parvifolia* was 102,179.35 km<sup>2</sup> (account for 3.98% of QTP) and was mainly distributed in the southern and northeastern of QTP. While the total suitable habitat area (21,283.4 km<sup>2</sup>) for *Sabina przewalskii* was much lower than *Picea crassifolia* and *Potentilla parvifolia* (only account for 0.82% of QTP) (Table 3, Figure 3).

**Table 2.** The contribution and cumulative percentage of key environmental variables.

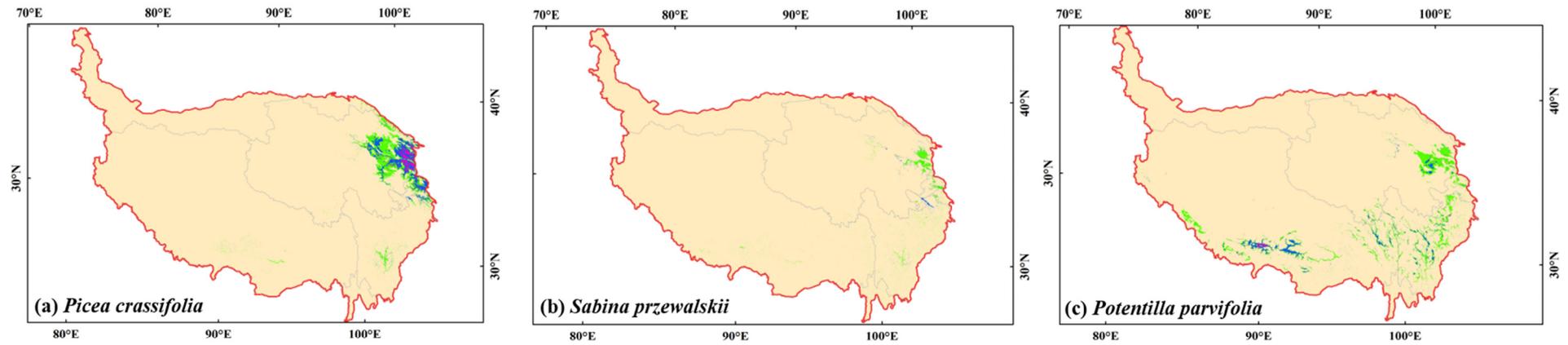
Symbol	Variables	<i>Picea crassifolia</i>		<i>Sabina przewalskii</i>		<i>Potentilla parvifolia</i>	
		Contribution (%)	Cumulative Percentage (%)	Contribution (%)	Cumulative Percentage (%)	Contribution (%)	Cumulative Percentage (%)
ASPE	Aspect	33.9	33.9	51.7	51.7	56.1	56.1
Bio14	Precipitation of driest month	23.1	57.0	3.4	55.1	3.5	59.6
ASL	Elevation	20.2	77.2	26.0	81.1	15.9	75.5
Bio12	Annual precipitation	10.7	87.9	0.0	81.1	4.9	80.4
Bio4	Temperature seasonality	6.0	93.9	0.0	81.1	0.2	80.6
S_CEC_CLAY	Subsoil CEC (clay)	1.2	95.1	0.4	81.5	0.5	81.1
S_BULK_DEN	Subsoil bulk density	0.3	95.4	0.9	82.4	2.3	83.4
S_CEC_SOIL	Subsoil CEC (soil)	0.2	95.6	0.1	82.5	0.1	83.5

**Table 3.** The area of suitable habitat for three species under different climate scenarios.

Suitable Habitat	The Area of Potential Suitable Habitat for Three Species (km <sup>2</sup> )								The Area at Current (km <sup>2</sup> )	
	2050s				2070s					
	SSP2.6	SSP4.5	SSP7.0	SSP8.5	SSP2.6	SSP4.5	SSP7.0	SSP8.5		
<i>P. crassifolia</i>	High	10,271.02	10,171.20	8483.41	10,813.65	6294.73	4882.79	9386.29	4767.55	8830.95
	Moderately	33,347.47	34,940.89	42,712.89	30,644.28	4143.71	34,927.27	26,032.80	54,663.53	32,876.52
	Low	55,668.94	47,247.23	57,771.42	53,073.74	43,502.34	58,147.09	48,217.26	48,614.71	57,495.57
	Total	99,287.43	92,359.32	108,967.72	94,531.67	53,940.78	97,957.15	83,636.35	108,045.79	99,203.04
<i>S. przewalskii</i>	High	625.21	1883.79	361.15	0	774.02	1046.25	232.30	120.69	194.19
	Moderately	7243.89	4968.09	3235.84	1260.40	3468.14	4416.38	6272.95	1838.42	3327.49
	Low	32,359.29	18,678.21	16,681.90	13,747.32	26,963.81	22,868.65	31,810.31	18,537.56	17,761.72
	Total	40,228.39	25,530.09	20,278.89	15,007.72	31,205.97	28,331.28	38,315.56	20,496.67	21,283.40
<i>P. parvifolia</i>	High	3047.10	991.80	2301.20	1096.16	1153.32	3744.90	2755.82	915.58	3167.78
	Moderately	20,949.47	13,109.41	18,451.36	9,434.38	14,813.53	15,636.56	13,672.01	19,009.42	21,045.65
	Low	86,588.17	83,692.61	92,607.04	59,658.84	81,386.87	80,101.97	99,566.01	99,144.06	77,965.92
	Total	110,584.74	97,793.82	113,359.60	70,189.38	97,353.72	99,483.43	115,993.84	119,069.06	102,179.35

### 3.3. Potential Distribution of Three Species under Future Climate Scenarios

There were significant differences in the distribution area of low suitable habitat, moderately suitable habitat and high suitable habitat under future climate scenarios as compared to current. The high suitable habitat for *Picea crassifolia* decreased under SSP2.6, SSP4.5 and SSP8.5 in the 2070s. Especially, the high suitable habitat for *Sabina przewalskii* declined to zero under SSP8.5 in the 2050s. The total suitable habitat for three species all decreased under SSP8.5 in the 2050s (Figure 4). The total suitable habitat for *Picea crassifolia* shrank under SSP2.6, SSP4.5 and SSP7.0 and enlarged under SSP8.5 in the 2070s. On the contrary, the total suitable habitat for *Sabina przewalskii* enlarged under SSP2.6, SSP4.5 and SSP7.0 and shrank under SSP8.5 in the 2070s. The total suitable habitat for *Potentilla parvifolia* continued increasing from SSP2.6 to SSP8.5 in the 2070s (Table 3, Figure 5)).



**Habitat Suitability**

0-10%	Unsuitable Habitat	10%-20%	Low Suitable Habitat
20%-40%	Moderately Suitable Habitat	40%-100%	High Suitable Habitat

**Figure 3.** The current potential geographical distribution of the three species.

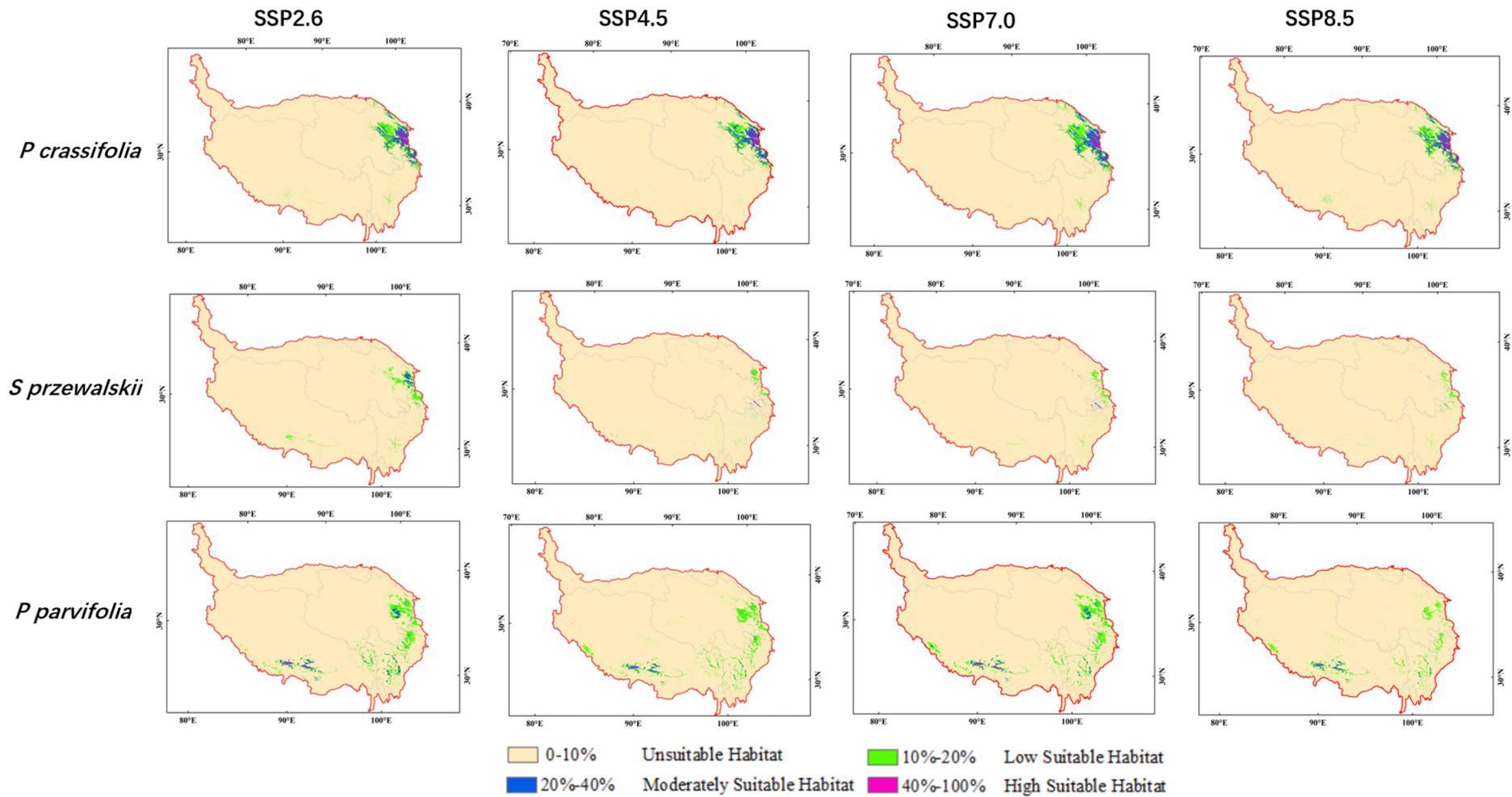


Figure 4. Prediction results of potential geographical distribution of three species in 2050s.

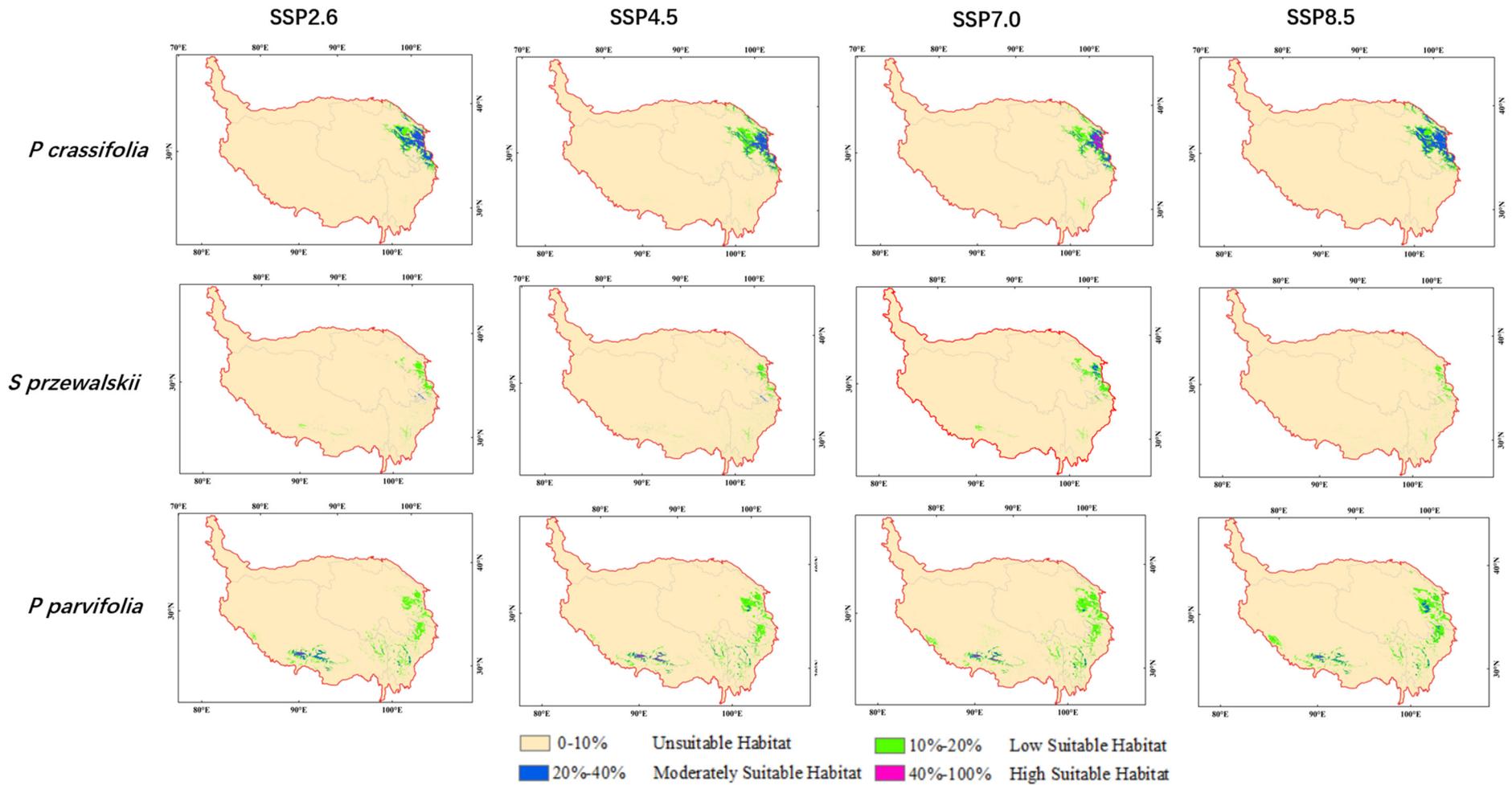


Figure 5. Prediction results of potential geographical distribution of three species in 2070s.

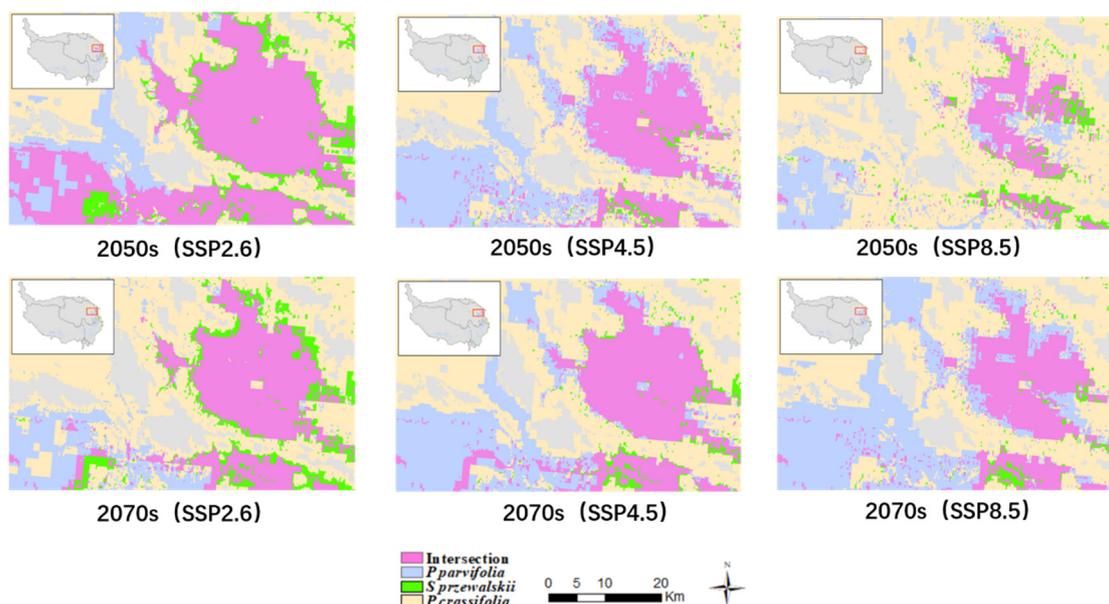
The average elevation in potentially suitable habitat for three species showed a slight upward shift under many climate scenarios in the 2050s and 2070s as compared to the average elevation of their potential distribution at current. For instance, the average elevation in potentially suitable habitat for *Potentilla parvifolia* all increased except under SSP8.5 (3552 m) in the 2050s. The average elevation of high suitable habitat for *Picea crassifolia* was 2758 m at current. However, the average elevation of highly suitable habitat for *Picea crassifolia* varied from 2773 m (SSP2.6) to 2849 m (SSP8.5) in the 2050s and increased to 2961 m (SSP2.6), 2891 m (SSP4.5) and 3043 m (SSP8.5) in the 2070s. The average elevation of highly suitable habitat, medium suitable habitat and low suitable habitat for *Sabina przewalskii* was 2951 m, 3175 m and 3083 m, respectively, at current. However, the average elevation of potentially suitable habitat for *Sabina przewalskii* varied from 2597 m to 3487 m in future climate scenarios. The changes of the average elevation in potentially suitable habitat for *Picea crassifolia* and *Sabina przewalskii* under different climate scenarios were not obvious, while the mean elevation in potentially suitable habitat for *Potentilla parvifolia* basically rose from the current period to the 2070s (Table 4).

**Table 4.** The average elevation of suitable habitat for three species under different climate scenarios.

	Suitable Habitat	The Average Elevation under Different Climate Scenario (m)								Average Elevation at Current (m)
		2050s				2070s				
		SSP2.6	SSP4.5	SSP7.0	SSP8.5	SSP2.6	SSP4.5	SSP7.0	SSP8.5	
<i>P. crassifolia</i>	High	2773	2834	2790	2849	2961	2891	2691	3043	2758
	Moderately	3033	3000	3124	3022	2972	2964	2987	3077	3031
	Low	3353	3333	3374	3383	3298	3335	3077	3375	3359
<i>S. przewalskii</i>	High	2597	3093	3103	—	3090	2894	2764	2649	2951
	Moderately	2765	3487	3305	3149	3334	3224	2775	2878	3175
	Low	3079	3312	3130	3049	3066	3081	3090	2996	3083
<i>P. parvifolia</i>	High	3712	3987	3795	3552	3831	3728	3640	4220	3617
	Moderately	3578	3597	3537	3717	3822	3605	3625	3586	2636
	Low	3499	3539	3502	3711	3587	3482	3520	3629	3475

### 3.4. The Changes of the Intersection Distribution of Three Species

Due to the large distribution area in the northeastern of QTP for three species, we analyzed the changes of intersection distributions for three species under future climate scenarios. Figure 6 showed the modeled vegetation fractional cover and spatial distribution of suitable habitat under future climate scenarios in the 2050s and 2070s in the northeastern of QTP. There was a decreasing trend for the intersection distribution area of three species (34,745 km<sup>2</sup> for SSP2.6, 15,441 km<sup>2</sup> for SSP4.5 and 7822 km<sup>2</sup> for SSP8.5 in the 2050s; 18,584 km<sup>2</sup> for SSP2.6, 17,060 km<sup>2</sup> for SSP4.5 and 15,440 km<sup>2</sup> for SSP8.5 in 2070s), which expanded their distribution area to the northeast. Under SSP8.5, the distribution for *Potentilla parvifolia* enlarged but the distribution for *Picea crassifolia* and *Sabina przewalskii* contracted. The total suitable habitat area for *Potentilla parvifolia* in the QTP would increase from 97,353.72 km<sup>2</sup> under SSP2.6 to 119,069.06 km<sup>2</sup> under SSP8.5 in the 2070s. However, the total suitable habitat area for *Sabina przewalskii* in the QTP would shrink from 31,205.97 km<sup>2</sup> under SSP2.6 to 20,496.67 km<sup>2</sup> under SSP8.5 in the 2070s.



**Figure 6.** Intersection for *Picea crassifolia*, *Sabina przewalskii* and *Potentilla parvifolia* under SSP2.6, SSP4.5 and SSP8.5 scenarios.

#### 4. Discussion

##### 4.1. Influence of Environmental Variables on the Potential Distribution of Three Species

It is widely known that the species distributions are not only determined by climatic factors but also impacted by local topography, human activities and species interactions [37]. Terrain characteristics, i.e., slope, altitude, and aspect are key environmental variables for shaping the vegetation distribution by changing moisture and heat especially for alpine trees [38,39]. In this study, analyses of environmental variables showed that aspect and elevation are critical factors restricting the distribution of the three species. The three species live in different aspects and their suitable habitats so they have their own ecological characteristics. Species distribution is primarily affected by elevation and aspect in alpine forest ecosystems [40]. According to the results of this study, *Picea crassifolia* is distributed between 2691 and 3375 m. The mean elevation of the highest habitat Suitability of *Picea crassifolia* under SSP8.5 in the 2050s is about 2849 m, which is similar to the previous study [41].

Temperature and precipitation are two major climate factors affecting the species distribution, especially growth-season temperatures, cold tolerance and the available water supply for alpine trees [42]. The results showed that precipitation of driest month (Bio14), annual precipitation (Bio12), temperature seasonality (Bio4) are major climatic factors that influence the distribution of *Picea crassifolia*, *Sabina przewalskii* and *Potentilla parvifolia*. Higher precipitation of the driest month and annual precipitation have a positive impact on species distribution. Temperature and precipitation are the key factors influencing species distribution in the drier upper sites. However, species distribution is more restricted by precipitation than the temperature in the wetter upper sites [37]). Temperature seasonality is positively related to elevation and strong seasonal variation in temperature may inhibit the growth of trees [43].

Soil provides the necessary space and nutrients for species to survive and limits their distributions [44]. The soil thickness at different sites is the reason for the spatial difference of species distribution [45]. Soil thickness  $\geq 40$  cm can store enough available water to allow trees to survive during drought periods [40]. In this study, we used physical and chemical characteristics of subsoil (30–100 cm) variables to further evaluate the suitable distribution of three species. We found subsoil CEC (clay), subsoil bulk density and subsoil CEC (soil) have a little influence on species distributions the QTP.

#### 4.2. Average Elevation Changes of Potential Suitable Habitat for Three Model Species

The average elevation in potentially suitable habitat for three species showed a slight upward shift under many climate scenarios in the 2050s and 2070s as compared to the average elevation of their potential distribution at current. Especially the average elevation in potentially suitable habitat for *Potentilla parvifolia* all increased except under SSP8.5 (3552 m) in the 2050s. These results are similar to other studies, which show plant species shift to higher elevation and cooler habitats responding to climate warming [46,47]. In order to adapt to climate change at local, regional, and global scales, alpine species shape the mechanism of shifting suitable climatic niches to relatively cooler habitats [48]. For three species in this study, the modeled predictions indicate species would shift to a higher elevation to occupy the current climate niche by the 2070s.

The changes of the average elevation in potentially suitable habitat for trees (*Picea crassifolia* and *Sabina przewalskii*) under different climate scenarios were not obvious, while the mean elevation in potentially suitable habitat for shrub (*Potentilla parvifolia*) had a basically rising from current to 2070s. The modeling results suggested there would be a competitive relationship between shrubs and trees. The existence of shrubs restricts the growth of trees to higher altitudes, so the average altitude of *Picea crassifolia* and *Sabina przewalskii* did not increase further with climate warming. The previous study found the changes in the mean elevation could be influenced by other factors rather than climate alone [49].

#### 4.3. Influence of Other Factors on the Potential Distribution of Three Species

The vegetation is currently growing to a higher altitude [50,51], and this expansion will probably go on in the future. It is mainly responsible for climate change due to temperature or water availability [52,53]. In this study, we found that the positive interaction between shrubs and trees can promote the upward movement of vegetation. These interactions occur at slightly higher altitudes [54,55]. Shrubs are expected to expand to a higher elevation than trees with the same critical survival temperature. The snow cover is the protection of shrubs because it alleviates the influence of the temperature on shrubs [56]. The interaction between shrubs and trees may become more and more important to explain changes in the species composition and structure on the QTP. The expansion of shrubs could be discontinuous spatially and temporally which actually covers up tree expansion.

In addition, the two *Ips* species (*Ips nitidus* Eggers and *Ips shangrila* Cognato and Sun) are the most destructive secondary bark beetles on *Picea crassifolia* and always cause mortality of trees by their cooperation [57]. Increasing human interventions, such as harvesting, grazing and mining, may also result in distribution changes of the three species. The human population on the QTP has expanded dramatically in the past decades. Some suitable habitats for alpine species were converted to other land uses, such as pastures or settlements [40].

## 5. Conclusions

In this study, we explored the influence of climate change on two dominant alpine trees (*Picea crassifolia* Kom and *Sabina przewalskii* Kom) and one dominant alpine shrub (*Potentilla parvifolia* Fisch) under different climate scenarios on the Qinghai–Tibetan Plateau. The predicted current potential distribution of three species was basically located in the northeastern of Qinghai–Tibetan Plateau, and the distribution of three species was most impacted by aspect, elevation, temperature seasonality, annual precipitation, precipitation of driest month, Subsoil CEC (clay), Subsoil bulk density and Subsoil CEC (soil). There were significant differences in the potential distribution of the three species under four climate scenarios in the 2050s and 2070s including expanding, shifting, and shrinking. The mean elevation in potentially suitable habitat for *Potentilla parvifolia* basically rose from the current period to the 2070s. Our study provides an important reference for the conservation of *Picea crassifolia*, *Sabina przewalskii*, *Potentilla parvifolia* and other dominant plant species under climate change. However, our research only used the friendly MaxEnt model without considering other models. In future studies, we will select the ensemble

model which can improve the reliability and accuracy of forecast results to further predict species distribution.

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