# PREDICTING POTENTIAL DISTRIBUTION OF STELLERA CHAMAEJASME UNDER GLOBAL CLIMATE CHANGE IN CHINA

LI, L.<sup>1,2</sup> – Zhang, B.<sup>1\*</sup> – Wen, A. M.<sup>3</sup> – Yao, X. J.<sup>1</sup>

<sup>1</sup>College of Geographical and Environmental Science, Northwest Normal University, Lanzhou 730070, China

<sup>2</sup>Lanzhou Resources & Environment Voc-Tech University, Lanzhou 730021, China

<sup>3</sup>State Key Laboratory of Cryosphere Sciences, Northwest Institute of Eco-Environment and Resources, CAS, Lanzhou 730000, China

> \**Corresponding author e-mail: zhangbo@nwnu.edu.cn; phone:* +86-138-9313-6515

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Abstract. The impact and feedback of climate-vegetation interaction on the potential habitat of plants is one of the focuses of terrestrial ecosystem and global climate change research. Based on 246 occurrence records of S. chamaejasme and 28 environmental variables (climate, topography and soil), we predicted and analyzed the suitable habitat distributions and shifts of S. chamaejasme under current and future (by 2050 and 2070) climate scenarios using the maximum entropy (Maxent) model. The Area Under the receiver operating characteristics Curve (AUC) was used to evaluate the model performance. The key environmental factors were screened by Jackknife tests. The results showed the following: 1) AUC values indicated better performance of MaxEnt modeling. 2) Altitude, annual precipitation, extreme moisture conditions (including precipitation of the wettest and the driest month) and mean temperature of the coldest quarter were the most predominant environmental factors influencing S. chamaejasme's habitat suitability. 3) In the current scenario, S. chamaejasme distributed in Oinghai–Tibet plateau, Loess Plateau, Inner Mongolia plateau and Yungui plateau (covering 44.16% of total land of China), especially in Sichuan (37.25%) and Gansu (34.65%) province. 4) With climate change, an increasing trend for the distribution (except in 2050\_RCP2.6 and 2050\_RCP8.5) had taken place in the area of all suitable classes comparing current and future scenarios overall, while the trends of variation are insignificant. At the same time, the centroid of highly suitable distribution regions shifted to northeast China, and the distribution regions moderately extended to the south. This paper may provide a deep insight for further research and practice management on S. chamaejasme.

**Keywords:** *climate change, Maxent modeling, environmental variables, habitat distribution, S. chamaejasme* 

### Introduction

The interaction between vegetation and climate change is the focus of many academic fields (in botany, geography, ecology and meteorology) (Zhang et al., 2011). Vegetation and ecosystem change are consistent with the climate variability (Shuman et al., 2019). The most direct reflection of vegetation to climate change is the change of species distribution pattern (Fang et al., 2013; Bradshaw et al., 2016). According to AR6 report, the global surface temperature in the first two decades of the 21<sup>st</sup> century (2001–2020) is higher than 1850–1900 (IPCC, 2021). The structure and function of terrestrial ecosystems may be altered substantially (Bertrand et al., 2011). Climate change has changed the ecological environment and has a huge impact on the biodiversity and distribution of species that grow on different spatial and temporal

scales and their ecosystems (Rahman et al., 2017; Jiang et al., 2021). More and more attention has been attracted to accurately forecasting the geographical distribution of species and their response to climate change and put forward scientific solutions.

Species habitat is the integration of their living space and biotic factors, including abiotic and biological environments. Species distribution model (SDM) is the main niche model for assessing the response to climate change on species habitat distribution (Georgopoulou et al., 2016), which estimates habitat suitability based on species distribution points and environmental data. Recent years, SDM has been widely used for the study of biodiversity loss in future climate change scenarios (Penner et al., 2017), biological invasion (Wan et al., 2017) and management and conservation of threatened species (Remya et al., 2015; Yi et al., 2016). Currently, SDM models for predicting species distribution are widely used, such as ENFA, GARP, DOMAIN, BIOCLIM, and Maxent (Maximum Entropy) (Wen et al., 2022). Among the above available algorithms, Maxent modeling could predict species' habitat range relatively accurately, based on simplified and constrained species occurrences and environmental variables. It has come into particularly common use (Humphreys et al., 2017; Zhao et al., 2021; Su et al., 2021).

Stellera chamaejasme L. (S. chamaejasme for short), a perennial poisonous herbaceous plant widely inhabits China, Russia, Mongolia, North Korea and other countries. Its poisonous nature, high competition and adaptability pose great threat to the growth of healthy vegetation in the degraded grasslands where the ecosystem is extremely fragile, particularly in the farming-pastoral ecotones over China (Liu et al., 2021; Guo et al., 2021). Previous research on S. chamaejasme mainly concentrated on biological and pharmacological traits (Grey, 1995; Li et al., 2014), impact on soil physical and chemical properties (An et al., 2016; Wei et al., 2017), spatial association and distribution pattern (Zhao et al., 2010), remote sensing monitoring and detecting in larger scale (Guo et al., 2017) and weed control techniques and uses (Zhang et al., 2011). However, the detailed actual spatial distribution of this weed species in China is unclear. It has been reported that the niches, range and reproduction of S. chamaejasme population were greatly affected by climate warming (Zhang et al., 2010), but the responses of climate change on the distribution of the suitable habitat are ignored. Additionally, S. chamaejasme have been shown to have notable effect on soil nutrient pools and dynamics, but the soils properties' influence on its habitat distribution is unknown (Yin et al., 2012; Yang et al., 2018). Moreover, it is verified that topography changes have clear response mechanism on spatial association and distribution pattern of S. chamaejasme, but only based on point pattern analysis (Gao et al., 2014). So, it became necessary and vital to ascertain the species distribution pattern, habitat suitability, the extent of expansion, and relationship with natural and environmental factors, which also provide bedrock for conservation, restoration and weed control for grassland ecosystem diversity.

This aim of this study include: (1) exploring the key ecological factors and their suitable range of affecting the potential distributions; (2) delineating the potential geographical distribution and shifts of *S. chamaejasme* under current and future climatic scenarios; (3) assessing whether the overall global distribution and habitat suitability expand or contract as a result of climate change.

### Materials and methods

#### Occurrence records

S. chamaejasme's occurrences in China were acquired and collected from the Chinese Virtual Herbarium (CVH, http://www.cvh.ac.cn), the China Species Information Service (CSIS, http://www.chinabiodiversity.com) and extensive literature. Then the presence samples databases of S. chamaejasme were deleted and filtered spatially, within 10 km×10 km, to ensure that there are no duplicate points. Finally, in general, 246 samples, representing the total known distribution of this plant in China (*Fig. 1*), were finally saved as .csv file format for further modeling.



Figure 1. Presence samples of S. chamaejasme in China

# Environmental variables

Taking into account the biological relevance to habitat distributions and niches of *S. chamaejasme* (Nybom, 2004), 28 environmental variables (climate, topography, soil, *etc.*) were used to predict the potential geographical distribution and shifts of *S. chamaejasme* under current and future (2050s and 2070s) climate scenarios (*Table 1*). 19 bioclimatic variables (bio01–bio19) of present climate condition were collected from the WorldClim database (http://www.worldclim.org/bioclim), which represents seasonality, extremities and annual trends of climate (Hijmans et al., 2005). Additionally, these climate variables under four representative concentration pathway of RCP2.6, RCP4.5, RCP6.0 and RCP8.5 (BCC-CSM1-1) scenarios during 2050s and 2070s released by IPCC Assessments Report 5 (AR5) were downloaded from the Climate Change, Agriculture and Food Security Web site (http://www.ccafs-climate.org); Topographical factors (including elevation, slope and aspect) were generated from DEM data (ca.1 km, http://westdc.westgis. ac.cn) using surface analysis function of ArcGIS 9.3 software; Moreover, five soil variables within topsoil (0–30 cm; t\_oc, t\_sand, t\_clay, t\_bden, t\_ph and t\_gravel) were downloaded from HWSD database

(http://webarchive.iiasa.ac.at) (Nachtergaele et al., 2008; Guo et al., 2015); Geographical base map of China was acquired from http://nfgis.nsdi.gov.cn. All above environmental variables were resampled to 2.5' longitude/latitude (ca. 5 km at ground spatial resolution) for the study area, and then converted to the ASCII format (.asc) for further Maxent modeling. The projections of all variables were set to WGS 1984 projection.

Cada	Environmental variables	Percent	Permutation	
Code	Environmental variables	contribution	importance	
alt	Altitude	25.3	13.6	
bio12	Annual Precipitation	22.3	29.7	
bio13	Precipitation of Wettest Month	13.5	4.6	
bio14	Precipitation of Driest Month	9.7	1.4	
bio11	Mean Temperature of Coldest Quarter	8.8	2.3	
t_oc	Topsoil organic carbon	2.0	0.5	
bio04	Temperature Seasonality (standard deviation *100)	1.7	8.5	
t_sand	Topsoil sand fraction	1.7	4.7	
slo	Slope	1.6	1.6	
t_clay	Topsoil clay fraction	1.5	0.9	
asp	Aspect	1.5	1.4	
bio01	Annual Mean Temperature	1.4	0.0	
bio03	Isothermality (BIO2/BIO7) (*100)	1.4	2.4	
t_bden	Topsoil reference bulk density	1.3	2.1	
t_ph	Topsoil pH (H <sub>2</sub> O)	1.2	2.2	
bio02	Mean Diurnal Range (Mean of monthly (max temp - min	1.0	26	
01002	temp))	1.0	2.0	
t_grave	Topsoil gravel content	0.8	0.8	
1	ropson graver content	0.0	0.0	
bio16	Precipitation of Wettest Quarter	0.7	10.7	
bio15	Precipitation Seasonality (Coefficient of Variation)	0.6	1.3	
bio07	Temperature Annual Range (BIO5-BIO6)	0.5	0.1	
bio19	Precipitation of Coldest Quarter	0.4	5.8	
bio05	Max Temperature of Warmest Month	0.3	0.8	
bio09	Mean Temperature of Driest Quarter	0.3	0.3	
bio06	Min Temperature of Coldest Month	0.2	0.0	
bio17	Precipitation of Driest Quarter	0.2	1.0	
bio10	Mean Temperature of Warmest Quarter	0.2	0.0	
bio08	Mean Temperature of Wettest Quarter	0.2	0.7	
bio18	Precipitation of Warmest Quarter	0.0	0.0	

Table 1	Contributions	of each	environmental	l variahle in	Maxent	modeling
I uvic I.	Commonitions	oj cucn	environmenia	variable in	mareni	moucing

# Predicting potential distribution

MaxEnt software 3.4.0 k (available at http://www.cs.princeton.edu/\*schapire/ maxent) was used for habitat suitability simulation, which performed relatively better than other SDMs (Phillips et al., 2006; Elith et al., 2011; Trisurat et al., 2011). Occurrence locations and its related environmental variables were required by Maxent. Of the 246 samples of *S. chamaejasme*, 75% were used for the training, and 25% for testing. The Jacknife analysis, under current condition, was performed in order to evaluate the contribution and response of each environmental variable to potential geographical distribution of *S. chamaejasme*. And the performance of MaxEnt was evaluated by AUC (Area Under the receiver operating characteristics Curve) value, which ranged from 0.5 (random) to 1.0 (perfect discrimination) (Swets, 1988; Weber, 2011).

The modeling outputs of ASCII format were imported into ArcGIS9.3 for further spatial analysis and statistics. Potential distribution regions were reclassified into five classes by referring to Zhang et al. (2016): (1) unsuitable (p < 0.1); (2) marginally suitable ( $0.1 \le p < 0.3$ ); Low–level suitable ( $0.3 \le p < 0.5$ ); (4) moderately suitable ( $0.5 \le p < 0.7$ ); and (5) highly suitable ( $p \ge 0.7$ ).

# Results

# Model performance

The average AUC data in MaxEnt model for 28 environmental variables under current scenario indicated good performance (*Fig. 2a*) (Swets, 1988). Similarly, the AUC values for the training data and test data of eight future climatic projections (2050s and 2070s) ranged from 0.891 to 0.897, and 0.851 to 0.856, respectively (*Fig. 2b*). These results suggested that Maxent had a high predictive power for the distribution of *S. chamaejasmes* over China.



*Figure 2.* AUC results of Maxent modeling: Left) AUC curve of current scenario; Right) box plot showing changes in AUC values based on current and eight future climatic projections (2050-RCP2.6, 2050-RCP4.5, 2050-RCP6.0, 2050- RCP8.5, 2070-RCP2.6, and 2070-RCP4.5, 2070-RCP6.0, 2070-RCP8.5)

# Contribution of environmental variables

Jackknife tests gave estimates of contribution percentage and permutation importance of the environmental variables (*Table 1*). Overall, the total contribution of precipitation is 47.4%, topography is 28.4%, temperature is 16% and soil is 8.5%. Among 28 environmental variables, altitude, annual precipitation (bio12), extreme moisture conditions (including precipitation of the wettest and the driest month *i.e.*, bio13 and bio14) and mean temperature of the coldest quarter mainly influenced the geographic distribution and habitat suitability of *S. chamaejasme*. Precipitation had a large influence on the spatial distribution of *S. chamaejasme*. The boxplots of the five suitable habitat type maps also indicated that the annual precipitation of suitable habitat regions is smaller than unsuitable habitat regions. It can be found that *S. chamaejasme* is mainly distributed in regions with 500 mm annual precipitation (*Fig. 3*). Meanwhile,

annual precipitation is strongly correlated with precipitation of the wettest and the driest month. Average altitude of suitable distribution regions extracted and calculated in ArcGIS dedicated that suitable habitat of *S. chamaejasme* distributed from 1400 m in the Inner Mongolia Plateau to 1900 m in the Loess Plateau, 2300 m in the Yungui Plateau, to 3500 m in the Qinghai-Tibet Plateau (*Fig. 4*), and sunny slope. The high contribution of elevation was similarly reported in other papers (Zhang et al., 2016; Tang et al., 2017), for that it closely related to temperature, light and precipitation. Thus, precipitation and temperature were the key factors of influencing potential distributions, colonizing, and growing potentials of *S. chamaejasme*. Importing mean precipitation and temperature data of 12 months into MaxEnt model for further simulating; it was further found that the precipitation in April and May, and average temperature of July and August, had the highest contributions for the potential distribution (*Fig. 5*). Additionally, soil properties in root zone played an important role next to hydrothermal conditions and topographical conditions, but this was not obvious.



Figure 3. Box plots showing variation range in occurrence annual precipitation



Figure 4. Box plots showing variation range in occurrence elevation values of S. chamaejasme in different provinces over China



*Figure 5.* Jackknife test for variable importance of S. chamaejasme habitat suitability distribution: (a) precipitation; (b) average temperature

Scatter graphs (*Fig. 6*) further illustrated the climate niches of *S. chamaejasme* in two dimensions for four key bioclimatic variables (bio11\_bio13 and bio12\_bio14). In the potential distribution regions, this weed species was suitable for the extremely hydrothermal conditions:  $-1 - -17^{\circ}$ C mean temperature of the coldest quarter (even -24.5°C), 80-160 mm precipitation of the wettest month (*Fig. 6a*), 300–750 mm annual precipitation and 0–5 mm precipitation of the driest month respectively (*Fig. 6b*).



*Figure 6.* Scatter graphs for two-dimensional climate niches: (a) precipitation of wettest month (bio13) and mean temperature of coldest quarter (bio11); (b) annual precipitation (bio12) and precipitation of driest month (bio14)

### Predicted current potential distribution

From the MaxEnt modeling result in *Fig.* 7 under current climate scenario, the potential distribution regions of *S. Chamaejasme* mainly located in Q–T plateau, loess plateau, Inner Mongolia plateau and Yungui plateau, which extends from the northeast to the southwest (covering 44.16 % of total land of China) along the Hu Line in general.

Cities of moderately and highly suitable habitat were further extracted and conducted. Overall, the core distribution areas were located in the Eastern Monsoon Geo–Eco Region and Q–T Plateau Geo–Eco Region (*Table 2*). The environmental factors in these regions suited the growth and niches of *S. chamaejasme*. Highly suitable regions mainly concentrated in Sichuan (20.62%), Gansu (20.49%), Yunnan (17.83%), Tibet (13.80%), Shanxi (11.28%) and Qinghai (8.09%) province, respectively; and the moderately

suitable areas are mainly in Shanxi (19.35%), Sichuan (16.63%), Tibet (15.80%) and Gansu (14.16%).



Figure 7. Potential distribution of S. chamaejasme under current climatic condition

Table 2	. Analysis	of highly	and	moderately	suitable	distribution	areas	of S.	chamaejasm	e
under cı	ırrent clim	uatic condi	tion							

Ducation	High	nly suitable		Moderately suitable				
Province	Area $(10^4  \text{km}^2)$	P/P (%)	P/C (%)	Area $(10^4  \text{km}^2)$	P/P (%)	P/C (%)		
Sichuan	3.7292	8.27	20.62	13.6233	30.22	16.63		
Gansu	3.7066	8.99	20.49	20.49 11.6007		14.16		
Yunnan	3.2257	9.59	17.83	7.7639	23.08	9.48		
Tibet	2.4965	2.31	13.80	12.9444	11.96	15.80		
Shanxi	2.0399	5.62	11.28	15.8524	43.65	19.35		
Qinghai	1.4635	2.18	8.09	6.5347	9.72	7.98		
Ningxia	0.6389	12.51	3.53	1.8090	35.42	2.21		
Inner Mongolia	0.4583	0.36	2.53	5.5521	4.38	6.78		
Hebei	0.1962	1.01	1.08	3.6163	18.67	4.41		
Heilongjiang	0.0538	0.10	0.30	0.9392	1.77	1.15		
Guizhou	0.0260	0.16	0.14	0.2726	1.73	0.33		
Jilin	0.0260	0.12	0.14	0.4253	2.04	0.52		
Tibet	0.0156	0.01	0.09	0.5712	0.34	0.70		
Beijing	0.0087	0.52	0.05	0.1563	9.31	0.19		
Henan	0.0017	0.01	0.01	0.1059	0.66	0.13		
Liaoning	0.0017	0.01	0.01	0.1510	1.00	0.18		

Note: P/P is percentage of suitable areas of the province; P/C is percentage of suitable areas in China

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### Spatial pattern changes under global warming scenarios

In order to evaluate the influence of climate warming on the spatial distribution pattern of S. chamaejasme, potential distributions under future periods (2050s, 2070s) were predicted and illustrated in Fig. 8. In general, slight changes had taken place in the area of all suitable classes for current and future scenarios at large spatial scale, which also were analyzed by spatial analysis and statistics in ArcGIS (*Table 3*). Contrast to current scenario, by 2050s, the total area of suitable regions for RCP2.6 and RCP8.5 reduced and increased for RCP4.5 and RCP6.0, however increased for all RCPs by 2070s. In 2050s, the ratio of highly suitable areas only increased by 0.01% in a stringent mitigation scenario (RCP6.0), and fall in all others (RCP2.6, RCP4.5 and RCP8.5), but moderately suitable class under those three scenarios showed a substantially increasing trend. In 2070s, moderately suitable and high suitable classes increased overall under all RCPs (excepting the highly suitable under RCP2.6). Contrary to the negative effect of global warming on ecosystem, this study verified that the uplift of Qinghai-Tibet Plateau, and climate transformation from warm-dry to warm-humid in northwestern China, accelerated and favored the expansion of S. chamaejasme. This competitive advantage could improve invasion capability of S. chamaejasme and affect grassland ecosystems functioning and biodiversity in the coming years.

Climate	Unsuitable		Marginally suitable		Low-level suitable		Moderately suitable		Highly suitable		Total suitable regions
scenario	Area/	Ratio	Area/	Ratio	Area/	Ratio	Area/	Ratio	Area/	Ratio	Area
	$ imes 10^4 km^2$	/%	$ imes 10^4 km^2$	/%	$ imes 10^4 km^2$	/%	$ imes 10^4 km^2$	/%	$ imes 10^4 km^2$	/%	$/\times 10^4 km^2$
Current	504.951	54.36	204.227	21.99	119.663	12.88	81.929	8.82	18.089	1.95	423.908
RCP2.6(2050)	512.047	55.13	197.894	21.31	122.597	13.20	78.597	8.46	17.726	1.91	416.814
RCP2.6(2070)	499.477	53.77	207.326	22.32	118.566	12.76	85.552	9.21	17.939	1.93	429.383
RCP4.5(2050)	497.974	53.61	209.637	22.57	117.616	12.66	86.405	9.30	17.229	1.85	430.887
RCP4.5(2070)	498.635	53.68	207.226	22.31	119.915	12.91	84.835	9.13	18.250	1.96	430.226
RCP6.0(2050)	491.769	52.94	211.639	22.78	121.885	13.12	85.405	9.19	18.163	1.96	437.092
RCP6.0(2070)	490.099	52.76	218.649	23.54	119.628	12.88	81.962	8.82	18.524	1.99	438.763
RCP8.5(2050)	507.060	54.59	200.403	21.58	119.531	12.87	84.288	9.07	17.578	1.89	421.800
RCP8.5(2070)	490.415	52.80	216.823	23.34	120.555	12.98	82.564	8.89	18.505	1.99	438.447

**Table 3.** Areas and percentage of suitable habitats distribution of S. chamaejasme under different climate change scenarios

Additionally, in order to reveal the location changes of core potential distribution regions and to indicate recent population expansions of *S. chamaejasme* associated with global climate changes, centroid of geographic distribution was calculated to characterize the position change based on un-regular and un-tidy habitat distribution edges, which was more visual and representative. The analyses for centroid changes of highly suitable and moderately suitable regions are showed in *Fig. 9*. In different RCPs scenarios by 2050s and 2070s, the centroid shifted with a distance of 5.31-5.76 km (longitudinal distances) to the northeast of China against current climate scenario for highly suitable distribution regions (*Fig. 9a*); extended to south (4.01-4.65 km) for moderately suitable regions (*Fig. 9b*), which is generally the same as the view of Zhang et al. (2010). Specifically, the city with the biggest highly suitable distribution area shifted from Sichuan to Gansu, while from Shanxi to Sichuan for moderately suitable region. The south–north parallel valleys and mountain chains would provide an ecological corridor for the immigration of *S. chamaejasme*.



*Figure 8.* Future habitat distribution of S. chamaejasme under different RCPs climate change scenarios for 2050s and 2070s based on BCC-CSM1.1



*Figure 9.* Centroids distribution under different climate change scenarios: (a) highly suitable distribution areas; (b) moderately suitable distribution areas. (Number beside the mark of centroid represents the longitudinal distances between the mark and current centroid)

### Discussions

Maxent is the most popularized SDMs for analyzing the relationship between climate change and potential geographical distribution of species (Khanum et al., 2013; Qin et al., 2017). AUC was usually utilized for evaluating model accuracy; however, there exist some controversy for the accuracy measurement using AUC in distribution models, even may be misleading, so the test AUC values in this paper only provided a reference to some extent (Lobo et al., 2010). Both sample sizes and environmental variables could influence the accuracy of most SDMs in various degrees. However, distinguished from other SDMs, MaxEnt is little affected by sample sizes, while remains fairly robust for that the simpler models are fitted with smaller samples (Wisz et al., 2008; Ray et al., 2017), while influenced by the quality of occurrence data (West et al., 2016). Additionally, the results of MaxEnt modeling demonstrated that the accuracy of the dataset integrated soil and DEM variables with climate factors was better than that of using climate variables alone, but too many predictor variables may result in poor performance of the model (Barry and Elith, 2006; Vanderwal et al., 2009). Apart from the influence of climatic factors, soil properties and topography, inter-species interactions and the local microclimate also affect species distribution; however existing niche models couldn't well couple the relationships for predicting distribution with high accuracy (Engler et al., 2013). The adaptability of species to environmental factors and specific competition were not considered into Maxent, which may greatly affect the prediction accuracy. Besides, climate change scenarios also influenced the model accuracy, but Maxent model only considered the greenhouse gases emission, and ignored the greenhouse gas feedback.

The area change tendency of potential distribution for S. chamaejasme is 2070 > 2050 > current (Garcia et al., 2013; Chen et al., 2014). Additionally, centroid shifted to northeast for highly suitable distribution regions and extended to the south of China for moderately suitable distribution regions are influenced by global warming and ecosystem shifts with uplift of the Qinghai-Tibet Plateau (Zhang et al., 2010). *S. chamaejasme* will be breeding to places with more suitable "big atmosphere" and "small environment". According to Jackknife results of MaxEnt, climate is the key

environmental factor for species niches and cover at large scale. Vegetation, a link of soil, atmosphere and moisture, acts as an "indicator" in global change. Firstly, climate change determines the dynamics of changes of vegetation types and distribution, vegetation is also actively feedback on climate change (Lambin and Strahler, 1994; Ichii et al., 2002; Pang et al., 2016). The abiotic factors that determine vegetation niches and shifts are hydro-thermal conditions. Thermal condition is the energy source of plant, and hydro condition affect the plant's physiological structure (Yi et al., 2013). Throughout the growing seasons (5-9) of S. chamaejasme, our results showed that precipitation in April and May facilitates the grow at the mid of growing season (precipitation has the characteristic of lag), while at the silique mature period, the decline stage, average temperature in July and August plays a leading role. Accordingly, for the response of vegetation to precipitation and temperature a suitable threshold exists (-1-17°C for mean temperature of coldest guarter, 80-160 mm for precipitation of wettest month, 300–750 mm annual precipitation and 0–5 mm precipitation of driest month respectively). Thus, temperature and precipitation could both promote and decrease the growth of vegetation. Secondly, the edaphic factors in this paper, including the content of organic carbon, sand, clay, bulk density, pH and gravel within topsoil (0-30 cm), had different attribution for potential distribution of S. chamaejasme. Climate warming changes the micro-environmental condition, especially changing soil condition or microclimate, which helps to provide better soil nutrient environment (Gao et al., 2016; Yang et al., 2018).

Much work can be done to refine the use of Maxent for modeling geographic distributions of S. chamaejasme in the future. In order to make an adequate prediction, research should further determine the quality and quantity of occurrence data, and screen how much environmental variables will be needed by testing their significance and correlation for avoiding over-fitting and redundancy (Bradie et al., 2017). Additionally, expression of biological factors of S. chamaejasme (such as interspecies interactions) in MaxEnt should be replaced by the spatial distribution and density of upper and lower levels in its food chain. AUC method is also necessary to be improved and replaced by PAUC (Slater and Michael, 2012) or AIC index (Riddle and Stratford, 1999). Besides, multiple evaluation techniques, such as remote sensing (RS) technique and field validation should be concerned and integrated in the results assessment of MaxEnt modeling rather than relying on AUC only (Park et al., 2017). Lastly, this paper is the only research to date that have been conducted for predicting potential geographical distribution and shifts of S. chamaejasme in response to climate change using MaxEnt model, the results may provide a reference to make a detailed reference for ecological conservation and sustainable management of this plant in the future.

# Conclusions

This paper delved the response of *S. chamaejasme* to climate change regarding geographical distributions and habitat suitability based on MaxEnt and GIS in China. Maxent model performance under 9 climate scenarios consistently performed significantly well for *S. chamaejasme*. Average AUC values ranged from 0.851 to 0.897. Predicting performance of MaxEnt was improved by using multiple environmental variables (including climate, soil and topography), but limited likely due to the quantity and quality of sample. The results showed that the distributions of *S. chamaejasme* were largely determined by the hydrothermal conditions: annual precipitation, precipitation

of the wettest and the driest month, and mean temperature of the coldest quarter; precipitation in April and May and average temperature in July and August. Overall, topography, soil and bioclimatic variables are inherently spatially and temporally auto correlated.

Potential distribution region of *S. chamaejasme* mainly distributed in Q-T plateau, loess plateau, Inner Mongolia plateau and Yungui plateau (mainly in Eastern Monsoon Geo-Eco Region and Q–T Plateau Geo–Eco Region) along the Hu line. Specifically, mid-high suitable regions mainly distributed in Sichuan (37.25%) and Gansu (34.65%) province. Maxent logistic predictions for present and future (2050s and 2070s) geographic distribution of suitable habitat of *S. chamaejasme* with climate changing showed that areas of suitable habitats increased (except in 2050\_RCP2.6 and 2050\_RCP8.5), while not significantly. Results of centroid changes demonstrated that highly suitable distribution regions shifted to northeast China, and moderately suitable distribution regions extended to the south. The results were consistent with global warming, and geographical and ecological alterations that followed the uplift of the Q-T Plateau.

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