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*Original Research*

# A Simulation Study of the Geographical Distribution of *Actinidia arguta* in China

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## Abstract

The aim of this study was to conduct an ecological regionalization and suitability evaluation of *Actinidia arguta* in China. The methods of maximum entropy have been deployed for some years to address the problem of species abundance distributions. In this approach, the ecological niche modeling software MaxEnt (the maximum entropy model), combined with ArcGIS (geographic information system), was applied to predict the potential geographic distribution of *A. arguta* in China. Bioclimatic dominant factors and the appropriate ranges of their values were also investigated. Our results showed that training data AUC (Area area under the ROC curve) of the 10 replicates was 0.992, which indicated a better forecast. The highly suitable area of *A. arguta* in China can be divided into three parts: the southwest, northeast, central and eastern regions. The moderately suitable areas are distributed around the most suitable areas, and the total area is $178.59 \times 10^4$ $km^2$, with a wider distribution than that of the most suitable areas. The important environmental factors affecting the distribution of *A. arguta* were Precipitation precipitation in July, temperature seasonality, altitude, mean temperature in April, and precipitation of the warmest quarter. The above results provide valuable references for wildlife tending, plantation regionalization, and standard cultivation of *A. arguta*.

**Keywords**: *Actinidia arguta*, MaxEnt, environmental factors, potential distribution

## Introduction

The interaction between plants and climate is reflected in the adaptation of plants to climatic factors and the feedback of plants to climate [1-2]. Climate is the dominant factor affecting plant distribution. Climate is expressed in the fact that heat is the source of energy for plant life activities, and water is the basic component of plants and can affect plant physiological activities. Climate change will have a great impact on the growth, geographical distribution, diversity and richness of plants. In global climate change, the most important ecological factors influencing the plant-ecosystem are

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enhanced air temperature, changed precipitation and elevated atmospheric carbon dioxide, which are mainly exerted on the physiological processes of water transport, photosynthesis, respiration and substance metabolism in plants [3-4]. Previous studies have shown that for every 1ºC increase in temperature during crop growth, the growth period of rice will be shortened by 7-8 days, and the growth period of winter wheat will be shortened by 17 days, which reduces the time for photosynthesis to accumulate dry matter [5]. Temperature is the main ecological factor limiting the distribution of plants, and climate warming has changed the distribution boundaries of plants. Lucht et al's [6] model shows that vegetation in the northern hemisphere tends to move to higher latitudes, which indicates the response of plant growth to temperature rise. The increase or decrease of precipitation will change the evaporation of water in the soil and the transpiration of water in the plant canopy, which in turn will affect the function of the plant [7]. Many studies have proved that under drought stress, plants would transport more assimilation products to the root system, resulting in an increase in root biomass [8-9]. The increase in atmospheric carbon dioxide has significant effects on the photosynthesis of different types of plants. C3 plants are generally more sensitive to the increase in carbon dioxide than C4 plants [10-11].

Systematically analyzing the relationship between plants and climatic factors and accurately predicting the impacts of climate change on plant distribution will be of great theoretical and practical significance to scientifically understand the impacts of climate change on biodiversity and to formulate effective countermeasures [12-13].

The geographical distribution and spatial distribution of species are closely related to changes in the climate and the environment, and they have a profound impact on the distribution and reproductive development of species [14]. Therefore, the biological climate demand and its relationship with the geographical distribution of species have become an important basis for the development of species introduction strategies. At present, a model analysis is widely used in species distribution prediction [15], in which the MaxEnt model can be used to reveal the distribution of species or unknown populations and has been widely used in the prediction of endangered species, climate and environment suitability, and the evaluation of species conservation priority, for species such as *Bretschneidera sinensis* [16], *Amygdalus mongolica* [17], *Abies chensiensis* [18], *Canacomyrica monticola* [19], and *Thuja sutchuenensis* [20].

*Actinidia arguta* (Sieb. And Zucc), which belongs to the *Actinidiaceae* family and the genus *Actinidia*, is a perennial deciduous vine [21]. *A. arguta* is one of kiwifruit's widespread cultivars in China and is suitable for growing in cool, moist and fertile soil. It is an ideal healthcare fruit because it is rich in nutritious and healthy functional ingredients, and its fruits, seeds and roots can be used as medicine [22-23]. Hou's experimental results indicate that AASP extracted from *A. arguta* can stimulate significantly the immune functions in mice, and thus can be used as an effective immunological regulator [24]. Liu's study confirmed that alkaloids extracted from *A. arguta* serve as a novel anti-fatigue and exercise performance agent with physiological benefits [25].

At present, the research on *A. arguta* mainly focuses on genetic breeding, cultivation techniques, composition analysis, health care, storage and processing, etc., but the research on its geographical distribution pattern has not been reported [26-272829]. Therefore, for the first time, MaxEnt was used to predict the potential natural distribution of *A. arguta* to reveal habitat needs and to identify suitable growing areas. The results can provide a scientific basis for the rational introduction and cultivation of *A. arguta* in the future.

## Materials and Methods

### Species Data

To obtain the occurrence records of *A. arguta* in the world, we accessed the Global Biodiversity Information Facility (GBIF, https://www.gbif.org/) and consulted the literature [21, 30-313233]. According to Zhou's method of filtering the distribution records, we used Google Earth to proofread the latitude and longitude [34]. In strict accordance with the requirements of MaxEnt, duplicate records, fuzzy records and neighboring records were removed. Finally, 785 valid records were retained for constructing the models (Fig. 1). Occurrence records were processed in Microsoft Excel and saved in CSV format.

### Environmental Variables

Plant growth is restricted by a variety of environmental factors, and climate factors are the main factors for determining the large-scale distribution of plants [35-36]. In this study, to analyze the climatic suitability regionalization of *A. arguta* in China, we chose climatic factors and altitude factors as initial environmental variables. Climate variables, including month-average meteorological data and bioclimatic data, as well as altitude data (Table S1), were downloaded from the official website of Worldclim. There may be multiple collinearity between environmental variables, which affect the model's evaluation of response relationships and contribution rates, which in turn affect the accuracy of the simulation. Therefore, in this study importance analyses and multi-collinearity tests were used to screen key environmental variables based on Worthington's method [37]. The impact of various environmental factors on the distribution should be considered as comprehensively as possible, and the most relevant variable factors should be selected for prediction and evaluation. Finally, 6 environmental factors were retained to build the final model, including

Fig. 1. Spatial distribution of occurrence records of *A. arguta*.

Table S1. List of environmental variables used for this study, with type and measurement unit.

| Code | Environmental variables | Unit |
|---|---|---|
| Bio1 | Annual Mean Temperature | ºC |
| Bio2 | Mean Diurnal Range (Mean of monthly (max temp - min temp) | ºC |
| Bio3 | Isothermality (BIO2/BIO7) (* 100) | - |
| Bio4 | Temperature Seasonality (standard deviation *100) | - |
| Bio5 | Max Temperature of Warmest Month | ºC |
| Bio6 | Min Temperature of Coldest Month | ºC |
| Bio7 | Temperature Annual Range (BIO5-BIO6) | ºC |
| Bio8 | Mean Temperature of Wettest Quarter | ºC |
| Bio9 | Mean Temperature of Driest Quarter | ºC |
| Bio10 | Mean Temperature of Warmest Quarter | ºC |
| Bio11 | Mean Temperature of Coldest Quarter | ºC |
| Bio12 | Annual Precipitation | mm |
| Bio13 | Precipitation of Wettest Month | mm |
| Bio14 | Precipitation of Driest Month | mm |
| Bio15 | Precipitation Seasonality (Coefficient of Variation) | mm |
| Bio16 | Precipitation of Wettest Quarter | mm |
| Bio17 | Precipitation of Driest Quarter | mm |
| Bio18 | Precipitation of Warmest Quarter | mm |
| Bio19 | Precipitation of Coldest Quarter | mm |
| Prec1, 2,..... 12 | Precipitation in January, February..... December | mm |
| Tmax1, 2..... 12 | Maximum temperature in January, February..... December | ºC |
| Tmin1, 2,..... 12 | Minimum temperature in January, February..... December | ºC |
| Tmean1, 2,..... 12 | Mean temperature in January, February..... December | ºC |
| Alt | Altitude | m |

altitude (Alt), precipitation in July (Prec7), temperature seasonality (Bio4), precipitation of the warmest quarter (Bio18), mean temperature in March (Tmean3) and mean temperature in April (Tmean4).

## Modeling Method and Statistical Analysis

MaxEnt, based on the maximum entropy theory, uses species distribution data and environmental data to analyze the distribution of species when maximum entropy occurs. MaxEnt is an ideal tool for studying the geographical distribution of species and has unique advantages. For example, Petitpierre et al. [38] applied MaxEnt to verify the niche conservativeness of invasive organisms, which suggests that MaxEnt is an effective tool for this study and is suitable for analyzing the relationship between species geographic distribution and climate; Elith et al. [15] compared the accuracy of 16 niche models, and the results showed that MaxEnt had a higher prediction accuracy than other models; Zhang et al. [39] used several niche models to predict the potential suitable habitats of *Pomacea canaliculata* in China. The results showed that the simulation accuracy of MaxEnt was higher than GARP, BIOCLIM and DOMAIN. Therefore, MaxEnt is selected as a simulation software to predict the potential distribution of *A. arguta* in China and to analyze the impact of environmental variables on its distribution.

MaxEnt mines the relationship between a set of sample locations and the corresponding grid cell of climatic layers based on climatological resemblance and then assumes the probability of the presence of the species in other cells of the study area [40-41]. MaxEnt software (Version 3.4.1), which is now open source and was downloaded from the website of the American Museum of Natural History (http://biodiversityinformatics.amnh.org/open_source/maxent/), has excellent predictive performance for plants [42].

The specific operational steps of MaxEnt are as follows: First, we import the occurrence points of

Table 1. Standards of probability (P) in this research.

| Habitat type | Standards | Colour |
|---|---|---|
| Unsuitable area | P≤0.05 | White |
| Lowly suitable area | 0.05<P≤0.33 | Yellow |
| Moderately suitable area | 0.33<P≤0.66 | Orange |
| Most suitable area | P>0.66 | Red |

*A. arguta* and 67 climatic variables into the MaxEnt software to create the initial model, in which 'random test percentage' was set as 25; 'make pictures of predictions' and 'do jackknife to measure variable importance' were all chosen; and the remaining model values were set to default values. Then we evaluated the percentage contribution and permutation contribution of the environmental variables by using the jackknife test to select key environmental variables for modeling. Finally, the occurrence points and the key environmental variables were uploaded to MaxEnt to simulate the distribution of *A. arguta* in China. In the final model, 'random seed' was chosen and 10 replicate models were run. We selected the best model with the highest AUC value. The remaining model settings were set to the same as those of the initial model [43-44].

The file output by the MaxEnt model is in ASCII format, and it cannot be visually displayed on the map. ArcGIS conversion tools were used to convert the file from ASCII to raster format, and the extraction function was used to extract the probability distribution map of *A. arguta* in China. We reclassified the distribution threshold and divided the suitable area into 4 categories and displayed them in different colors according to Wang's method [45]. The specific description is shown in Table 1.

The receiver operating characteristic curve (ROC) is an effective method for evaluating the accuracy of the species distribution model. The method sets the area under curve (AUC) as the index to measure accuracy [46-47]. The theoretical value range of AUC is 0.5~1, and the closer the AUC value is to 1, the higher the prediction accuracy of the model. The evaluation criteria are: simulation failure (fail), 0.5≤AUC<0.6; poor simulation results (poor), 0.6≤AUC<0.7; the simulation results are generally (fair), 0.7≤AUC<0.8; the simulation results are good (good), 0.8≤AUC<0.9; the simulation result is excellent (excellent), 0.9≤AUC<1.

## Results and Discussion

### Model Performance of the Initial Model

Fig. 2a) shows the ROC curve of the initial model. The AUC values of the training data and the test data are 0.995 and 0.994, respectively. According to the evaluation criteria in 1.3, the accuracy of the initial model is "excellent".

### Selecting Key Environmental Factors

MaxEnt is a mathematical model based on the principle of climate similarity to explore the correlation between geographical distribution and climatic factors. The choice of climatic factors is the key to determining the accuracy of the simulation. Therefore, referring to the method in the 'materials and methods' section, we screened the key environmental factors. The results showed that the percentage contribution of precipitation in July, mean temperature in April, temperature seasonality, mean temperature in March, precipitation of the warmest quarter and altitude were 29.1%, 25.4%, 13.5%, 8.6%, 2.8% and 1.5% respectively, and the cumulative sum was 80.9%, which was significantly higher than the residual climatic factors (Table 2). Comparing the permutation importance, the values of precipitation in July, temperature seasonality, altitude, mean temperature in April, and precipitation of the warmest quarter were 24.1%, 16.4%, 10.5%, 9%, 8.7% (Table 2), which played a key role in the modeling process.

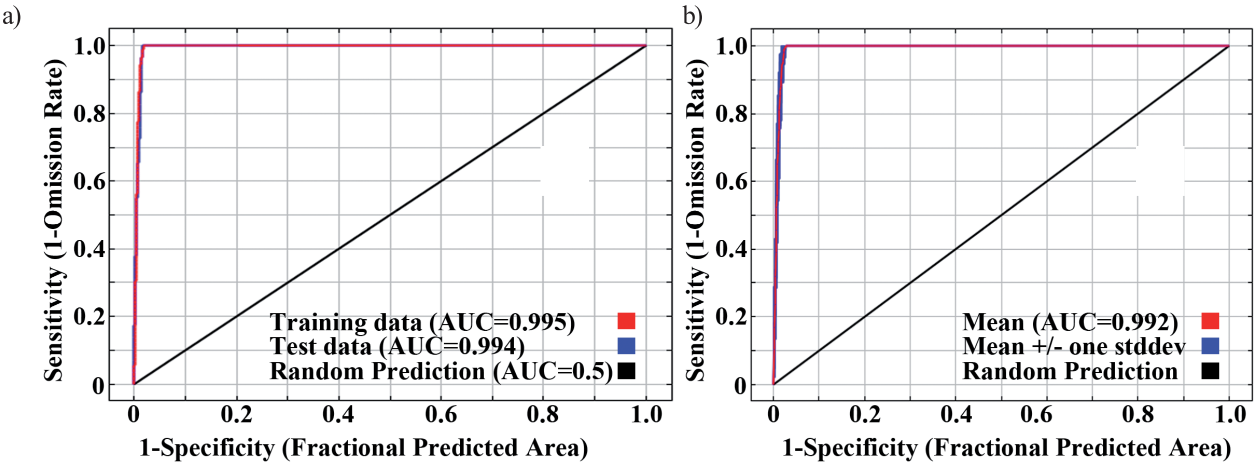


Fig. 2. ROC curve and AUC value for initial model a) and reconstruction model b).

Table 2. Percentage contribution and permutation importance of the environmental variables to the Maxent model.

| Environmental variables | Percent contribution | Permutation importance |
|---|---|---|
| Precipitation in July | 29.1 | 24.1 |
| Mean temperature in April | 25.4 | 9 |
| Temperature Seasonality | 13.5 | 16.4 |
| Mean Temperature in March | 8.6 | 0.3 |
| Precipitation of the Warmest Quarter | 2.8 | 8.7 |
| Altitude | 1.5 | 10.5 |
| Total | 80.9 | 69 |

The correlation between the 6 environmental factors was calculated using Pearson's correlation to eliminate the influence of collinearity on the modeling process. If the absolute value of the correlation coefficient between the two environmental variables is greater than 0.8, there is a strong correlation. It was shown that the correlation coefficients among the 6 environmental factors were all less than 0.8 and were selected as the dominant variables in this study. On this basis, the MaxEnt model of the distribution of *A. arguta* in China was reconstructed, and the accuracy of the simulation results was evaluated.

In this study, the geographic information data of *A. arguta* were screened by a query database and literature search. The occurrence records of the missing coordinate information needs to query the specific latitude and longitude through Google Earth, so it will produce a certain error. In the process of selecting environmental variables, the author uses Pearson's correlation coefficient (r) to test the multicollinearity between climate variables. If the correlation coefficient is high (r>0.8), only one variable is selected for model prediction, which reduces the error caused by multicollinearity to some extent. The extensive application of the MexEnt model in ecology illustrates the effectiveness of the model algorithm.

Due to the autocorrelation of the 19 bioclimatic variables provided by worldclim, to avoid the introduction of redundant information in the simulation process and to reduce the accuracy of the simulation, the environmental variables need to be effectively screened. To improve the accuracy of prediction, this study refers to the method of Zhang et al. [48], compares the percentage contribution rate of each variable to the modeling by using the knife-cut method, uses Pearson's correlation coefficient to eliminate the collinearity effect, and, finally, retains six variables for modeling.

## Model Performance of the Reconstruction Model

Fig. 2b) shows the ROC curve of the reconstruction model. The results showed that the mean AUC value was 0.992, which indicated that the prediction result was "excellent" and proves that the model can be used to study the potential distribution simulation of kiwifruit in China. The above results prove that the model can be used to study the potential distribution simulation of *A. arguta* in China.

## Potential Distribution of *A. arguta* in China

Combining the selected 6 environmental variables, the MaxEnt model was used to obtain a suitable index distribution map of *A. arguta* in China. ArcGIS software was used to superimpose the index distribution map on China's administrative division map to obtain the suitability regionalization map of *A. arguta* (Fig. 3 and Table 3).

The results showed that the highly suitable area of *A. arguta* in China can be divided into the following parts: the southwest, northeast, central and east regions. The southwest region includes central and northeastern Sichuan, most of the Guizhou, western Hubei, middle eastern Chongqing, southern Shaanxi and southeastern Tibet. The area reached $45.5\times10^4$ km$^2$ in this region. Among them, Sichuan has the largest area, $14.62\times10^4$ km$^2$, and Tibet has the smallest at $1.38\times10^4$ km$^2$. The northeast region includes eastern Jilin, eastern and western Liaoning, and sporadic regions of Heilongjiang. The area is $12.64\times10^4$ km$^2$ in this region. The area is $6.54\times10^4$ km$^2$, $5.97\times10^4$ km$^2$ and $0.14\times10^4$ km$^2$, respectively. The central region of

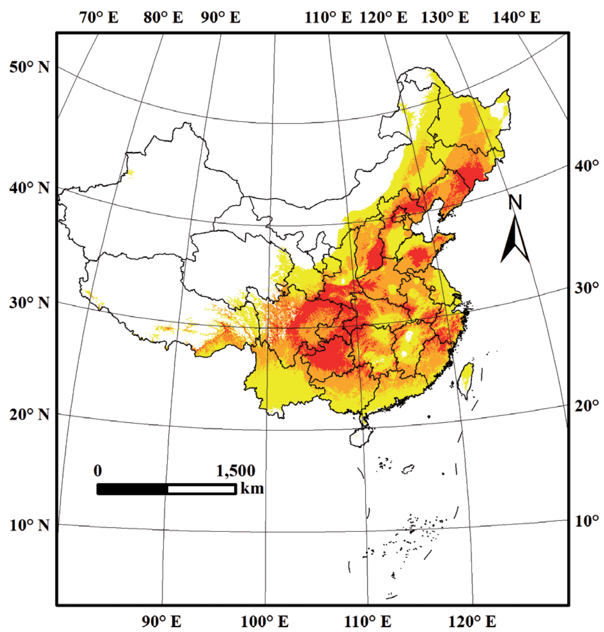


Fig. 3. Potential suitable distribution of *Actinidia arguta* in China based on the MaxEnt model.

Table 3. Suitable area of *A. arguta* in China.

| Region | Province | Area ($\times 10^4$km) | | |
|---|---|---|---|---|
| | | Lowly suitable | Moderately Suitable | Most suitable |
| Southeast | Sichuan | 4.57 | 20.82 | 14.62 |
| | Guizhou | 0.02 | 4.71 | 11.23 |
| | Hubei | 3.79 | 6.87 | 6.90 |
| | Chongqing | 0.01 | 2.64 | 6.22 |
| | Shaanxi | 8.66 | 4.84 | 5.09 |
| | Tibet | 12.15 | 5.43 | 1.38 |
| Northeast | Liaoning | 0.74 | 8.38 | 6.54 |
| | Jilin | 6.21 | 8.88 | 5.97 |
| | Heilongjiang | 31.94 | 11.97 | 0.14 |
| Central | Hebei | 6.99 | 7.80 | 4.85 |
| | Shanxi | 3.36 | 7.86 | 4.73 |
| | Anhui | 4.15 | 6.92 | 2.29 |
| | Henan | 1.55 | 11.93 | 2.65 |
| East | Shandong | 4.57 | 7.09 | 3.73 |
| | Zhejiang | 2.98 | 3.07 | 3.30 |
| | Fujian | 2.50 | 6.45 | 1.84 |
| | Jiangsu | 6.10 | 3.54 | 0.05 |

the highly suitable area includes northeast Hebei, southeastern Shanxi, western Henan and southern Anhui, with an area of $4.85\times10^4$ km$^2$, $4.73\times10^4$ km$^2$, $2.65\times10^4$ km$^2$ and $2.29\times10^4$ km$^2$, respectively. The eastern region includes central Shandong, most of Zhejiang, northern Fujian and sporadic regions of Jiangsu, and the area is $3.73\times10^4$ km$^2$, $3.3\times10^4$ km$^2$, $1.84\times10^4$ km$^2$ and $0.05\times10^4$ km$^2$, respectively. The total area of the highly suitable areas of China is $92.87\times10^4$ km$^2$, which occupied 9.67% of the national territory area. The moderately suitable areas are distributed around the most suitable areas, mainly in the Heilongjiang, Liaoning, Jilin, Hebei, Shanxi, Henan, Shandong, Jiangsu, Sichuan, Chongqing, Guizhou, Guangxi, Guangdong, and Fujian provinces. The total area of the moderately suitable area is $178.59\times10^4$ km$^2$, with a wider distribution than that of the most suitable area. The total suitable area (the most suitable area and the moderately suitable area) is $271.46\times10^4$ km$^2$, which accounts for 28.22% of China's total area.

In this study, ArcGIS software was used to visualize the calculation results of MaxEnt and to extract the suitable distribution area of kiwifruit in China. At present, the main producing provinces of *A. arguta* in China are Sichuan, Jilin, Liaoning, and Hubei. Although it has been planted in other areas, a scale has not yet formed. According to the results of a Maxent analysis, Hebei, Shandong, Jiangsu, Anhui, Zhejiang, Henan, Hunan, Guizhou, Chongqing, Ningxia, and Yunnan also have a large area of *A. arguta* ($P\geq33\%$). In these areas, small-scale planting areas can be expanded in combination with actual conditions, and areas that have not yet been cultivated can be considered for introduction and cultivation. Using MaxEnt to simulate the geographical distribution of species requires data on the occurrence of species. Studies have shown that the more species occurrence data, the higher the accuracy of the MaxEnt prediction. Under the background of global warming, many areas that are not suitable or have low suitability are likely to become suitable areas for this plant as the climate changes.

## Environmental Factors Affecting the Existence of *A. arguta*

We used the spatial analyst tools of ArcGIS to extract the niche parameters of each suitable area and to calculate the ecological range (minimum to maximum) and the majority and mean of the 6 environmental variables (Table 4). The results showed that with the increase of suitable grade, the change range of each environmental variable showed a unified and gradually narrowing trend, and the majority and mean of each variable in the moderately suitable area and the most suitable area had little difference; that is, the concentration trend of the niche parameters was basically the same.

Table 4. Statistical analysis of the niche parameters in different suitable classes of *A. arguta*.

| Variables | Marginally suitable | | | Moderately suitable | | | Most suitable | | |
|---|---|---|---|---|---|---|---|---|---|
| | Range | Majority | Mean | Range | Majority | Mean | Range | Majority | Mean |
| Prec7 | 73-999 | 139 | 173 | 80-908 | 158 | 191 | 78-678 | 200 | 207 |
| Bio4 | 25-168 | 85 | 97 | 40-161 | 95 | 90 | 42-147 | 75 | 85 |
| Bio18 | 182-2624 | 482 | 469 | 235-2426 | 523 | 515 | 271-1824 | 516 | 547 |
| Tmean3 | -11-25.7 | -1.5 | 5.4 | -10.7-22.9 | 10.5 | 7.4 | -10.3-20.4 | 12.9 | 8.2 |
| Tmean4 | -2-28.6 | 18.6 | 12.7 | -6.8-25.8 | 16.9 | 13.9 | -5.4-23.7 | 16.8 | 14 |
| Alt | -2-6338 | 0 | 965 | 0-6019 | 40 | 889 | 0-5352 | 538 | 960 |

Prec7: Precipitation in July; Bio4: Temperature Seasonality; Bio18: Precipitation of the Warmest Quarter; Tmean3: Mean Temperature in March; Tmean4: Mean temperature in April; Alt: Altitude.

Fig. 4 is the response curve drawn by MaxEnt between the key environmental variables and the probability of presence. In this study, the range of environmental variables suitable for the distribution of *A. arguta* was divided by a probability value of 0.33. The results showed that the suitable range of the precipitation in July was 142.3-408.2 mm, and the optimum value was 213.2. When the rainfall is 142.3-213.2 mm, the probability of presence increases with the increase of rainfall. While at 213.2-408.2 mm, the probability of presence decreases with the increase of rainfall. The suitable range of the mean temperature in March was -2.1-16.1ºC, and the optimum value was 7.3ºC. This finding indicates that when the mean temperature in March is -2.1-7.3ºC, the probability of presence of *A. arguta* will increase with increasing temperature. When the temperature is higher than 7.3ºC, the probability will decrease as the temperature increases. The response curves of the 6 key environmental variables were similar to that of the normal distribution, but the suitable range and the variation range were different (Table 5). Within the suitable range, the change of the key environmental variables has a certain influence on the probability of presence, but outside the suitable range the influence decreases gradually.

The results of the MaxEnt model operation indicated that the main environmental factors affecting the geographical distribution of *A. arguta* were precipitation of July, mean temperature of April, temperature seasonality, mean temperature of March, precipitation of the warmest quarter and altitude, in which the percent contribution and permutation importance of precipitation of July were 29.1% and 24.1%, respectively, and were the most important climatic factors. The flowering period of *A. arguta* is from May to July, and the fruiting period is from June to August. July is the most vigorous period of *A. arguta*, and it is also the month with the largest water demand. This indicates that the precipitation in July has a crucial impact on the growth and distribution of *A. arguta*. This study shows that the optimum value of precipitation in July is 142.3-408.2 mm, which not only satisfies the water requirement of *A. arguta* but also does not cause excessive root water to rot. The temperature factors affecting the distribution of *A. arguta* include tmean3, tmean4 and bio4. It is reported that when the temperature is above 6ºC in early March, the sap of *A. arguta* begins to flow. In mid-March, when the temperature was above 8.5ºC, it begins to germinate. The leaf spreading period is from mid-March to early April, when the temperature is above 10ºC [49]. In this

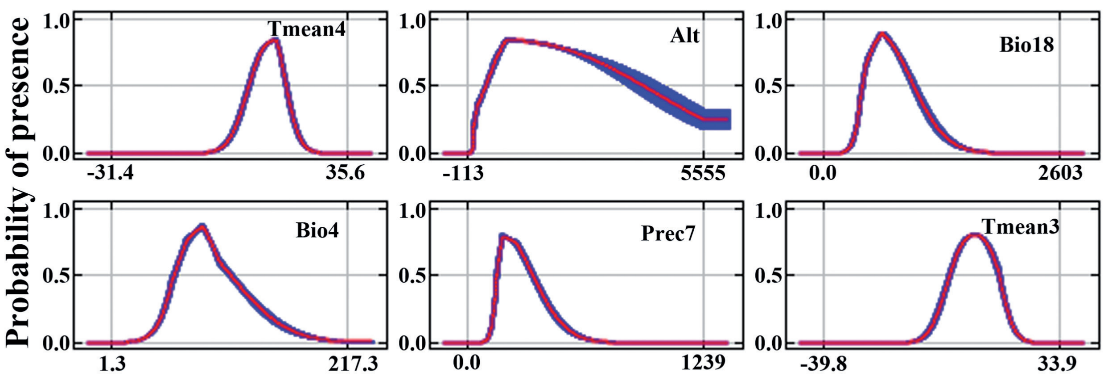


Fig. 4. Response curves of the variables contributing most to the prediction by MaxEnt for *A. arguta*.

Table 5. Suitable range of dominant environmental variables affecting the potential distribution of *A. arguta*.

| Environmental variables | Suitable range | Optimum value |
|---|---|---|
| Precipitation in July | 142.3-408.2 mm | 213.4 mm |
| Temperature seasonality | 54.5-123.9 | 84.4 |
| Precipitation of the warmest quarter | 392.2-1126 mm | 662.3 mm |
| Mean temperature in March | -2.1-16.1ºC | 7.3ºC |
| Mean temperature in April | 6.5-19.1ºC | 15.3ºC |
| Altitude | 140.8-3929.6 m | 845.1 m |

paper, the suitable range of tmean3 and tmean4 are -2.11-16.1ºC and 6.5-19.1ºC, respectively, and the optimum values are 7.3ºC and 15.3ºC, respectively, which are in good agreement with the above results. The temperature seasonality is an important environmental factor affecting the distribution of *A. arguta,* which reflects the average temperature and its variation range, and its percentage contribution and permutation importance are 13.5% and 16.4%, respectively. The niche parameter analysis showed that the majority and the average of bio4 gradually decreased with the increase of the suitable grade, and the range of the most suitable area was narrower than that of the moderately suitable area, which indicated that the seasonal variation of the average temperature of the most suitable area was not significant. The southwestern region is one of the main distribution areas of *A. arguta* in China. The climate of this region is controlled and influenced by the southwest monsoon, the westerly circulation and the Tibetan High. Its main features are low heat, small annual temperature differences and a large daily temperature difference, which is in line with the characteristics of *A. arguta,* which is cool and resistant to yin and good moisture [50].

## Conclusions

Studies have shown that the more comprehensive the species distribution data, the higher the accuracy of the model simulation when using the niche model to simulate the geographical distribution of species. In this study, the occurrence data of *A. arguta* mainly comes from specimens, the literature and cvh, and the number is much lower than the actual quantity. Therefore, the results of this study have certain limitations and shortcomings. First, the field survey is conducted only in Sichuan Province, although it is relatively systematic, but due to the limitations of the scope of the survey, the work is not comprehensive and accurate. Among the distribution points obtained by retrieving the CVH and consulting the literature, the distribution points without clear latitude and longitude need to determine the relevant information through the coordinate positioning software, so there is inevitably a certain geographic error.

The environmental variables used in this study are from the World Climate Database, which is the average of data from 1950 to 2000. Studies have shown that in the past 20 years, with increasing global warming, the growth and distribution patterns of the species have changed significantly [51]. The lack of climate data in the past 20 years may lead to a deviation from the actual situation. Therefore, to ensure more reliable prediction results, more comprehensive and accurate distribution data of kiwifruit should be used, and the corresponding missing climate data should be supplemented in the next step. The basic niche refers to the largest niche that is occupied by a species under the most ideal living conditions. The niche model only analyzes the influence of abiotic factors on species distribution, so it can be inferred that the niche predicted by the model is wider than the actual niche occupied by kiwifruit. The results show that the growth of kiwifruit is not only affected by climate but is also closely related to topographic characteristics, soil types, soil physical and chemical properties, and kiwifruit cultivation density. In the next step, consideration of the interaction between species and other biological factors expressed would improve the prediction effect of the model.

Based on MaxEnt software and certain environmental data, this paper predicts the geographical distribution of *A. arguta* in China and aims to provide a scientific reference for the introduction and cultivation of *A. arguta*. However, there are many factors that affect the distribution of plants, and each model has its advantages and disadvantages. Therefore, in the specific operation of expanding the introduction to consider factors such as the economy and the planting land, it is necessary to carry out trial planting before large-scale introduction.

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## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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