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Redistribution of *Qiongzhuea tumidinoda* in Southwest China under Climate Change: A Study from 1987 to 2012

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Abstract: *Qiongzhuea tumidinoda* stands out as an endemic bamboo species of significant conservation importance in Southwest China, particularly in the upper reaches of the Yangtze River. It holds a pivotal role in poverty alleviation through the commercialization of its wood and bamboo shoots. However, the suitable area of this species is undergoing rapid changes due to climate change, resulting in species redistribution and potential losses for bamboo farmers. We utilized 209 presence records and 25 environmental variables from 1987 to 2012 to predict the potentially suitable habitats for *Q. tumidinoda* using MaxEnt (version 3.4.1), ArcGIS (version 10.8.2), and R (4.3.3). We rigorously screened the recorded data for reliability and accuracy through expert consultations and observer interviews. We performed pre-processing to select the variables with high contributions for modeling, and 11 variables were selected for the final modeling. Our findings reveal that the top three most influential variables associated with *Q. tumidinoda*'s distribution were the mean monthly potential evapotranspiration (Pet), annual range of air temperatures (Bio7), and mean diurnal air temperature range (Bio2), and the rates of contributions from 1987 to 2012 were 4.8333, 3.5833, and 1.7000. There was a southeastward shift and an elevation increase in the potentially suitable habitats for *Q. tumidinoda*. The area of potentially suitable habitats in the study region exhibited fluctuating growth, expanding from 3063.42 km^2 to 7054.38 km^2. The mean monthly potential evapotranspiration (Pet) emerged as a critical determinant shaping the distribution of potentially suitable habitats for *Q. tumidinoda*. Our study sheds light on the response of *Q. tumidinoda* to climate change, offering valuable insights for the development and management of plantation industries associated with this species. In the future, to enhance prediction accuracy, researchers could equally consider both organic and inorganic environmental variables. For better preservation of environment and development, *Q. tumidinoda* could be introduced into nature restoration projects in areas with a suitable habitat or as a commodity that participates in forest carbon sink trading.

Keywords: climate change; potential habitats; redistribution; *Qiongzhuea tumidinoda*; MaxEnt; GIS

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1. Introduction

Comprehending the responses of organisms to climate change is of paramount importance, often serving as a cornerstone for successful conservation and management strategies [1]. The impact of climate change on the geographical distribution of plants has been acknowledged for a significant amount of time [2]. Consequently, plants are anticipated to manifest discernible changes in their reactions to climate shifts, encompassing phenotypic plasticity, genetic adaptation, and redistribution [3–5].

Indeed, more than 80% of species undergoing changes are shifting in the expected direction, aligning with the recognized physiological constraints of each species [6]. The alterations in the distributions and differentiations of plants in the Himalayan region and Hengduan Mountains are conspicuous and attributed to climate change [7]. Since the Last Glacial Maximum (LGM), plants have begun to expand toward higher elevations following climate changes in the Hengduan Mountains [8,9]. Moreover, plants exhibit a tendency to ascend to higher altitudes and dimensions in pursuit of more favorable climatic conditions amid climate warming scenarios [10].

Bamboos play a significant role as woody grass species in mitigating climate change and are considered a nature-based solution (NbS) to climate change [11]. Similar to many understory plants [12,13], understory bamboo species constitute a vital component of various forest ecosystems [14,15]. However, due to their limited seed dispersal ability [16] and unusually extended sexual reproduction intervals, many bamboo species are susceptible to the impacts of climate change [17]. Conversely, Moso bamboo (*Phyllostachys pubescens* Mazel ex J. Houz.) in the Tianmu Mountain region of southeastern China has shown an average upward shift of 9.8 m over the past decade, potentially leading to biodiversity reduction by altering the species composition of the ecosystem [18]. Despite the vulnerability and potential impact of bamboo species on climate change, studies on bamboo redistribution have not received adequate attention.

China serves as a significant origin and distribution center for bamboos, with the highest concentration found in the region south of the Yangtze River [19]. A total of 500 species in 40 genera have been recorded in China, and 250 species in 29 genera have been discovered in Yunnan [20]. *Qiongzhuea tumidinoda* J. R. Xue & T. P. Yi is an endemic species restricted to Southwest China and the upper reaches of the Yangtze River [21], listed as endangered by the Chinese government [22]. Dong reported that populations of *Q. tumidinoda* are facing severe degradation due to human activities [23]. However, there have been few studies on the responses of *Q. tumidinoda* to climate change [24].

For endemic species, MaxEnt has been widely used for modeling habitat-endemic species and is considered a very useful tool for modeling rare or narrowly endemic species [25]. The distributions of two endemic species (*Varanus palawanensis* and *Caprimulgus manillensis*) were modeled in the Philippines using MaxEnt [26]. The new distribution areas of two crayfish (*Procambarus reimeri* and *Fallicambarus harpi*), two narrowly endemic species, were found in western Arkansas also using MaxEnt [27]. The potential distribution habitat of *Salsola junatovii* (a Chinese endemic species) was predicted in Southern Xinjiang with this tool [28].

In this study, our objective was to investigate the changes in the potentially suitable distribution areas of *Q. tumidinoda* and the occurrence or absence of this species using data collected by our continuous forest inventory system over the past 30 years (1987, 1992, 1997, 2002, 2007, and 2012). Furthermore, we hope the results revealed by our study will provide some contributions to stakeholders, thus countering climate change and alleviating poverty.

2. Materials and Methods

2.1. Study Area

Q. tumidinoda is naturally distributed in the mountainous areas from the northeast edge of the Yunnan Plateau to the Sichuan Basin in the upper reaches of the Yangtze River with a subtropical monsoon climate [29]. The largest distribution area of *Q. tumidinoda* is located in the Zhaotong area of northeastern Yunnan Province. Our survey was mainly conducted in the Zhaotong area. The landform in the study area belongs to the uplift of the plateau–mountain system; the area of the mountain accounts for 96%. The terrain is high in the southwest and low in the northeast. The highest elevation in the study area is 4041.6 m, mainly distributed on Yaoshan Mountain. The lowest elevation in the study area is 267.0 m, mainly distributed in the Shuifu area [30].

2.2. Study Procedure

In this study, the research methodology unfolded as follows: Firstly, we compiled occurrence records of *Q. tumidinoda* from multiple sources, including our own surveys, a continuous forest resource inventory system, and the pertinent literature. Secondly, a rigorous data-screening process ensued, wherein the reliability and accuracy of the compiled data were meticulously assessed through expert consultations and interviews with observers familiar with the species. Thirdly, we obtained bioclimatic data comprising 19 variables and environmental data comprising 7 variables from publicly available datasets. Fourthly, employing a combination of MaxEnt and ArcGIS, we delineated the distribution of *Q. tumidinoda* across various temporal intervals, leveraging both occurrence records and environmental variables. Fifthly, we identified key climatic variables pertinent to our focal species within the study area, elucidating climate trends spanning from 1987 to 2012. Finally, utilizing the data derived from the continuous forest inventory system, we identified 20 specific locations where occurrences of *Q. tumidinoda* were documented between 1987 and 2012, facilitating an assessment of its presence or absence within those delineated points.

2.3. *Qiongzhuea Tumidinoda* Occurrence Data

We compiled 209 occurrence records from our continuous inventory system, literature review [22,29], publicly accessible databases, and personal communication with experts and observers (Figure 1). The continuous inventory system was sampled in the whole province, which was evenly distributed in a 6 km $\times$ 8 km grid system, and each monitoring point was a square with 28.28 m long sides. Each point was screened out once the *Q. tumidinoda* occurrence was recorded in our continuous inventory system. The occurrences from publicly accessible databases were located in the mainland only. The occurrences with geographic coordinates were examined in a GIS after consulting with the authors. The geographic coordinate system was CGCS2000 (China Geodetic Coordinate System 2000). The records were arranged in a manner appropriate for input into the MaxEnt package as an Excel file.

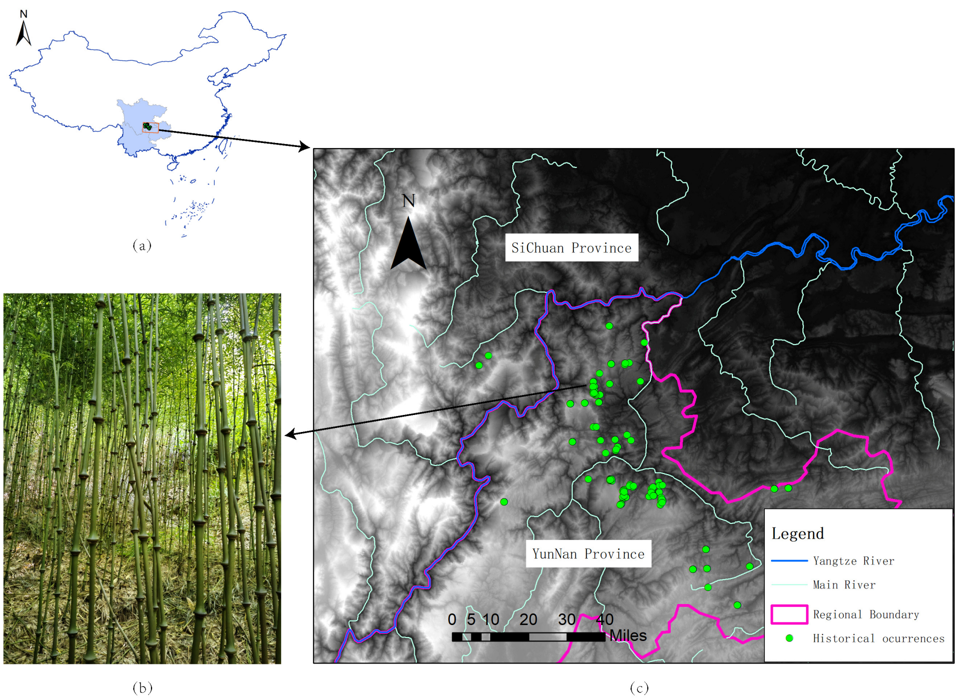

Figure 1. (**a**) The study area in China. (**b**) A close shot of natural habitat of *Q. tumidinoda*. (**c**) Surveyed points in distribution areas of *Q. tumidinoda*.

2.4. Environmental Variables and Pre-Processing

We used 19 bioclimatic and 7 environmental variables (i.e., elevation, aspect, slope, the mean monthly climate moisture index, the mean monthly potential evapotranspiration, the mean monthly climate moisture index, and the human influence indicator) as predictors.

The 19 bioclimatic variables were derived from the monthly temperature and precipitation layers [31]. The 19 variables involved different statistical calibers, including annual statistics (e.g., the mean annual air temperature, the mean diurnal air temperature range, and the annual precipitation amount), quarterly statistics (e.g., the mean daily mean air temperatures in the wettest quarter, the mean daily mean air temperatures in the driest quarter, and the mean daily mean air temperatures in the warmest quarter), monthly statistics (e.g., the mean daily maximum air temperature in the warmest month, the mean daily minimum air temperature in the coldest month, and the precipitation amount in the wettest month). The 9 bioclimatic variables were coded as follows:

Bio 1 = the mean annual air temperature (the mean annual daily mean air temperatures averaged over 1 year).

Bio 2 = the mean diurnal air temperature range (the mean diurnal range of temperatures averaged over 1 year).

Bio 3 = the isothermality (the ratio of the diurnal variation to annual variation in temperatures).

Bio 4 = the temperature seasonality (the standard deviation in the monthly mean temperatures).

Bio 5 = the mean daily maximum air temperature in the warmest month (the highest temperature of any monthly daily mean maximum temperature).

Bio 6 = the mean daily minimum air temperature in the coldest month (the lowest temperature of any monthly daily mean maximum temperature).

Bio 7 = the annual range of air temperatures (the difference between the maximum temperature in the warmest month and the minimum temperature in the coldest month).

Bio 8 = the mean daily mean air temperatures in the wettest quarter (the wettest quarter of the year is determined).

Bio 9 = the mean daily mean air temperatures in the driest quarter (the driest quarter of the year is determined).

Bio 10 = the mean daily mean air temperatures in the warmest quarter (the warmest quarter of the year is determined).

Bio 11 = the mean daily mean air temperatures in the coldest quarter (the coldest quarter of the year is determined).

Bio 12 = the annual precipitation amount (the accumulated precipitation amount over 1 year).

Bio 13 = the precipitation amount in the wettest month (the precipitation in the wettest month).

Bio 14 = the precipitation amount in the driest month (the precipitation in the driest month).

Bio 15 = the precipitation seasonality (the coefficient of variation is the standard deviation in the monthly precipitation estimates expressed as a percentage of the mean of those estimates).

Bio 16 = the mean monthly precipitation amount in the wettest quarter (the wettest quarter of the year is determined).

Bio 17 = the mean monthly precipitation amount in the driest quarter (the driest quarter of the year is determined).

Bio 18 = the mean monthly precipitation amount in the warmest quarter (the warmest quarter of the year is determined).

Bio 19 = the mean monthly precipitation amount in the coldest quarter (the coldest quarter of the year is determined).

The Shuttle Radar Topographic Mission (SRTM) Digital Terrain Model (DTM) with a 90 m resolution, downloaded from the www.srtm.usgs.gov website, was used to generate the topographic variables. Human influence was assessed using the Human Influence Indicator (HII), obtained from the Last of the Wild Data Version 2 (2005). The HII integrates four proxy data types: human settlement, land transformation, accessibility, and electrical power infrastructure. The values of the HII range from 0 to 64, representing the absence or maximum extent of human influence [32]. The other variables, with a 30 s (ca. 1 km) spatial resolution, were downloaded from the Chelsa climate dataset (www.chelsa-climate.org accessed on 19 January 2024). All variables were re-sampled to a spatial resolution of 10 arc seconds (300 m).

To avoid the overfitting problem in predictions caused by multi-collinearity between the 19 bioclimatic variables [33], first, we conducted a pretest in MaxEnt to calculate the contribution rates of the 19 bioclimatic variables to the prediction of suitable growth areas for *Q. tumidinoda* (Table 1).

Table 1. The contribution rates of the 19 bioclimatic variables.

Variable	Percentage Contribution	Variable	Percentage Contribution
Bio5	26.4%	Bio13	0.9%
Bio2	24.1%	Bio19	0.5%
Bio14	10.1%	Bio1	0.4%
Bio10	7.2%	Bio11	0.3%
Bio15	7.1%	Bio6	0.3%
Bio16	7%	Bio18	0.2%
Bio12	6.7%	Bio8	0.2%
Bio7	3.5%	Bio4	0.1%
Bio17	3%	Bio9	0

Then, we used "Extract value to point" tools to extract the corresponding climate data in ArcGIS by the distribution point data for correlation analysis [34]. The distribution point data were merged with the distribution points at the same spatial resolution. Ninety-three distribution point data were engaged to extract the climate data.

Pearson's correlation coefficient (R) was used to examine the cross-correlations, and the bioclimatic variables with cross-correlation coefficient (R) values of <∣0.8∣ were kept (Figure 2). We picked the bioclimatic variables with high contribution rates in the pretest when the bioclimatic variables had cross-correlation coefficient values of ≥∣0.8∣.

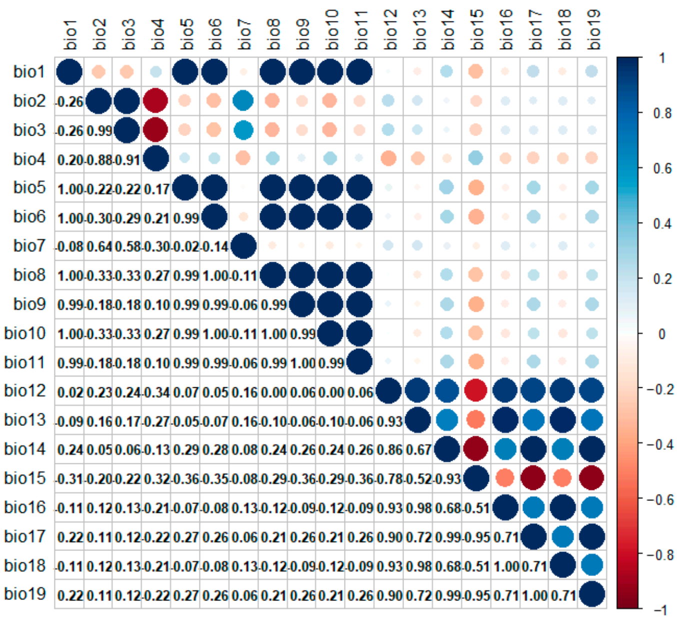

Figure 2. Multi-collinearity test using cross-correlations between the bioclimatic variables.

Bio2, Bio5, Bio10, and Bio14 were selected by the pretest in MaxEnt. Bio7 was selected due to its Pearson correlation coefficient. Pet, Cmi, Ele, Slo, Asp, and Hii were chosen due to their biological significance for the target species [33]. Finally, 11 environmental variables were selected for the modeling (Table 2).

Table 2. Environmental variables used in this study and their percentage contributions.

Variable	Environmental Variable	Unit
Bio2	Mean diurnal air temperature range	°C
Bio5	Mean daily maximum air temperature in the warmest month	°C
Bio7	Annual range of air temperatures	°C
Bio10	Mean daily mean air temperatures in the warmest quarter	°C
Bio14	Precipitation amount in the driest month	$kg{\cdot}m^{-2}{\cdot}month^{-1}$
Pet	Mean monthly potential evapotranspiration	$kg{\cdot}m^{-2}{\cdot}month^{-1}$
Cmi	Mean monthly climate moisture index	$kg{\cdot}m^{-2}{\cdot}month^{-1}$
Ele	Elevation	m
Slo	Slope	°
Asp	Aspect	°
Hii	Human influence indicator	

2.5. Spatial Modeling

MaxEnt (maximum-entropy models) is a machine learning program rooted in maximum entropy principles, tasked with estimating the probability distribution of a species' occurrence by discerning the environmental constraints [35]. Central to this methodology is the notion that the observed distribution of a species yields valuable insights into its environmental preferences and requirements [36]. MaxEnt is among the most robust and accurate SDM techniques [37].

The selected environmental variables and the distribution data were input into the MaxEnt model to predict the suitable growth areas for *Q. tumidinoda*. All the variables in ASCII file format were used with the same resolution of 10 arc seconds (300 m). The Jackknife test was used to reflect the contributions of the environmental variables to the species distribution [33]. The regularization multiplier value was set as 1 [38]. A total of 10 runs were set for the model building [39]. We selected 70% of the data for training and the other 30% for testing. Other values were kept as default. We used the mean area under the receiver operating characteristic curve (ROC or AUC) to evaluate the model performance, which is regarded as one of the best assessments of performance [40]. The model with the highest AUC value was considered the best performer [41]. The final potential species distribution value ranged from 0 to 1, and we regrouped it into four classes of potential habitats, viz., high potential (AUC value > 0.8), good potential (0.6 < AUC value ≤ 0.8), moderate potential (0.4 < AUC value ≤ 0.6), and least potential (AUC value ≤ 0.2).

2.6. The Influence of Climate Change

The data including 20 points from a continuous inventory system were used to reveal the presence or absence of *Q. tumidinoda*. *Q. tumidinoda* was recorded at each point at least once from 1987 to 2012. The continuous inventory system was built in 1978, and the inventory stations in the system were distributed in a 6 km × 8 km grid to directly record the changes in forest resources. The data belong to our occurrence records (209 points) and range from 1987 to 2012.

The ASCII-formatted data outputs derived from the spatial modeling AUC analyses were utilized to delineate the alterations in the distribution patterns and the corresponding spatial extents across distinct habitat classifications. The changes in distribution were characterized in terms of latitude, longitude, and altitude. Furthermore, the potential habitat areas were categorized into four distinct groups, namely, high potential, good potential, moderate potential, and least potential. The final predictive maps were generated in the following steps: Firstly, the Card Conversion Tool within ArcGIS facilitated the conversion of the format of the 11 environmental variables from TIFF to ASCII format. Subsequently, MaxEnt was employed to compute the final ASCII datasets, incorporating the AUC values derived from the integration of the 11 environmental variables. Finally, the Classification Tool within ArcGIS was employed to partition each raster layer into four classes based on predetermined thresholds established within the framework of this study.

ArcGIS was used to calculate the areas and the distributions in two dimensions (latitude and longitude). The area of each group was calculated by the number of rasters in different groups. The area of each raster was 90,000 m^2 (300 × 300 m). The exhibition of the distribution each year was located in the same picture frame and scale. The Sankey package in R was used to calculate the presence/absence and the distribution in terms of altitude.

The system with 973 points was used to extract the climate variables to show the trend of climate change in the study area. The positions of points were the same as the points in our continuous inventory system. The points were evenly distributed in our study area.

3. Results

3.1. Model Performance and Contributions of Environmental Variables

The ROC estimate showed that the mean AUC values of the test datasets were 0.981 (the year 1987), 0.984 (the year 1992), 0.988 (the year 1997), 0.973 (the year 2002), 0.976 (the year 2007), and 0.952 (the year 2012), which revealed the high level of accuracy in the model prediction (Figure 3). The model was considered to be sensitive and descriptive.

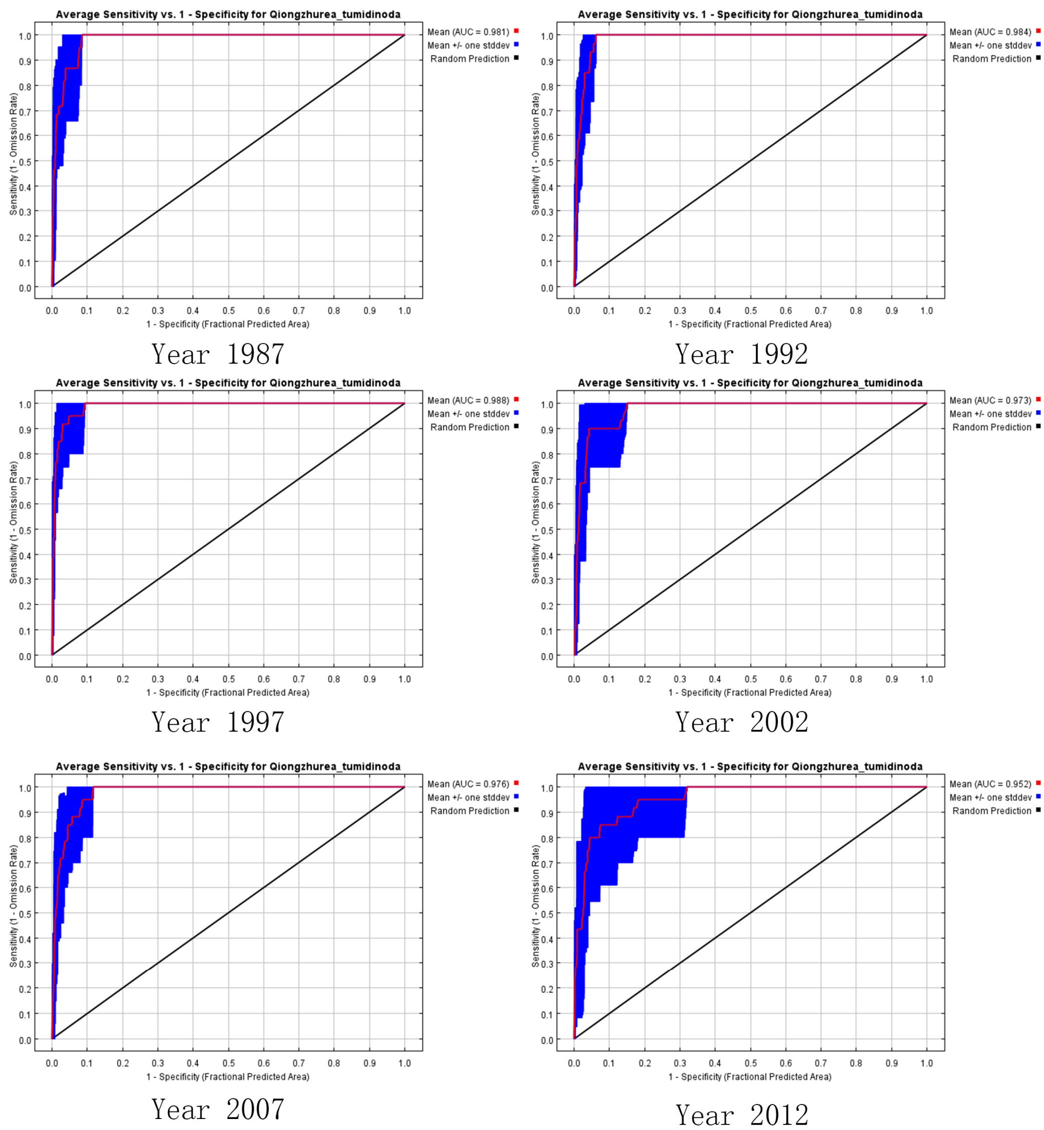

Figure 3. The results of the AUC (area under ROC) curves for *Q. tumidinoda* habitat suitability model from 1987 to 2012.

The results of the jackknife test of the variables' contributions to the model are shown in Figure 4. The different ranks in terms of the frequency of each environmental variable are listed in Table 3. The rank was determined by the contribution. The point was calculated by the rank and frequency. Among the 11 environmental variables used to establish the model, the mean monthly potential evapotranspiration (Pet), the annual range of air temperatures (Bio7), and the mean diurnal air temperature range (Bio2) had very high contributions when used independently from 1987 to 2012, and the point of each environmental variable was 4.8333, 3.5833, and 1.7000. The mean daily mean air temperatures in the warmest quarter (Bio10), the mean monthly climate moisture index (Cmi), the mean daily maximum air temperature in the warmest month (Bio5), the elevation (Ele), and the precipitation amount in the driest month (Bio14) had moderate contributions when used separately, and the points of each environmental variable were between 1.4833 and 0.9262. The human influence indicator (Hii), slope, and aspect showed low contributions, and the points of each environmental variable were 0.6556, 0.5818, and 0.5747. The contribution shows the variable's influence on the habitat suitability distribution of *Q. tumidinoda*.

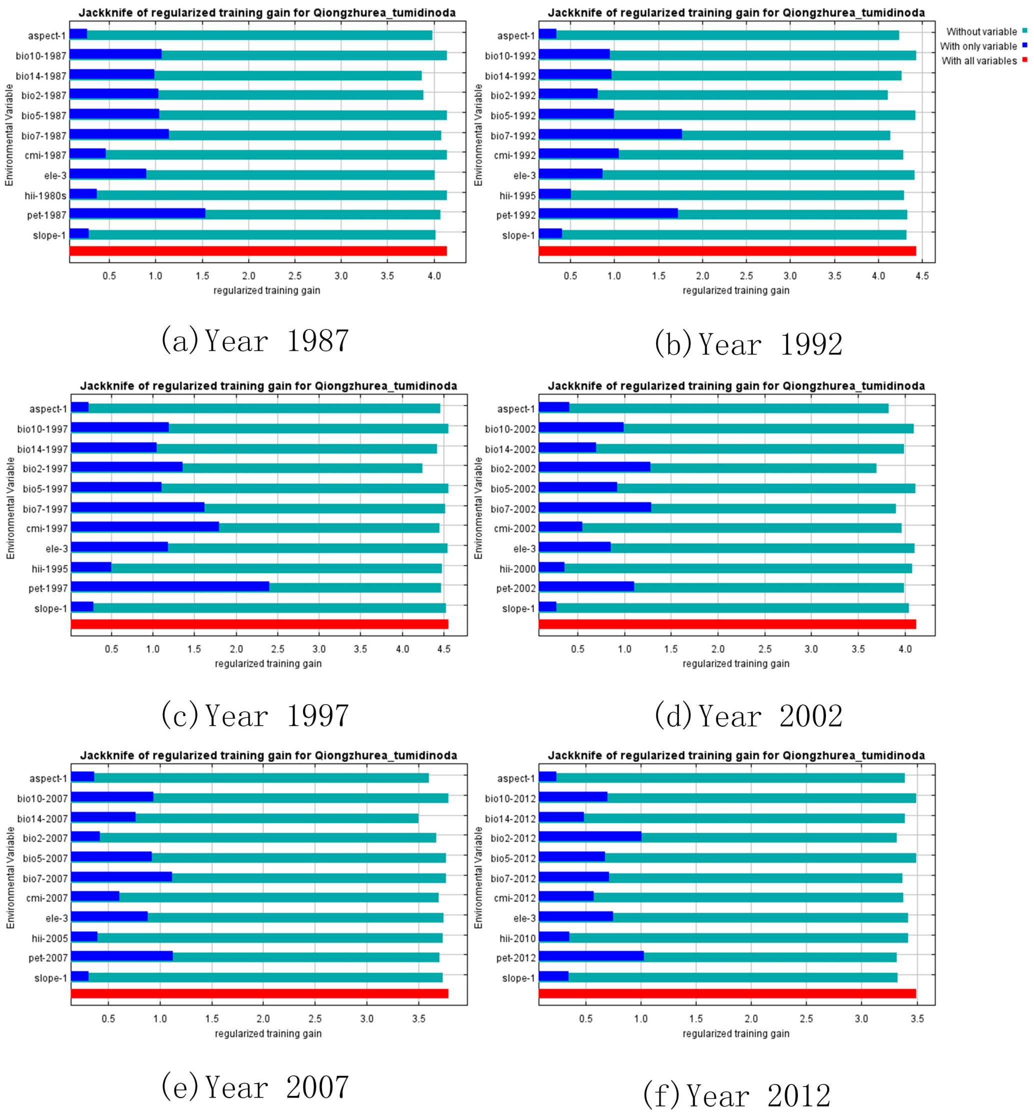

Figure 4. Jackknife test results of the variables in the model.

Table 3. The frequency of each environmental variable listed in descending order by contribution.

	Pet	Cmi	Bio7	Bio2	Bio10	Ele	Bio5	Bio14	Hii	Slope	Aspect
Rank1	4	0	2	0	0	0	0	0	0	0	0
Rank2	1	1	2	2	0	0	0	0	0	0	0
Rank3	1	1	1	0	2	1	0	0	0	0	0
Rank4	0	0	1	1	1	0	3	0	0	0	0
Rank5	0	0	0	1	2	1	1	1	0	0	0
Rank6	0	0	0	0	1	2	1	2	0	0	0
Rank7	0	2	0	0	0	2	1	1	0	0	0
Rank8	0	2	0	2	0	0	0	2	0	0	0
Rank9	0	0	0	0	0	0	0	0	5	0	1
Rank10	0	0	0	0	0	0	0	0	1	4	1
Rank11	0	0	0	0	0	0	0	0	0	2	4
Point	4.8333	1.3690	3.5833	1.7000	1.4833	1.1524	1.2595	0.9262	0.6556	0.5818	0.5747

Note: The points were calculated by the formula $Point = \sum_{1}^{i} Frequency_i \times Rank_i^{-1}$. i represents the number of the rank.

3.2. Distribution and Prediction of *Q. tumidinoda* under Climate Change

The predicted habitat suitability was classified into four groups (Figure 5): high potential (0.8–1) indicated a very highly suitable habitat, good potential (0.6–0.8) indicated a highly suitable habitat, moderate potential (0.4–0.6) indicated a moderately suitable habitat, and least potential (0–0.4) indicated an unsuitable habitat.

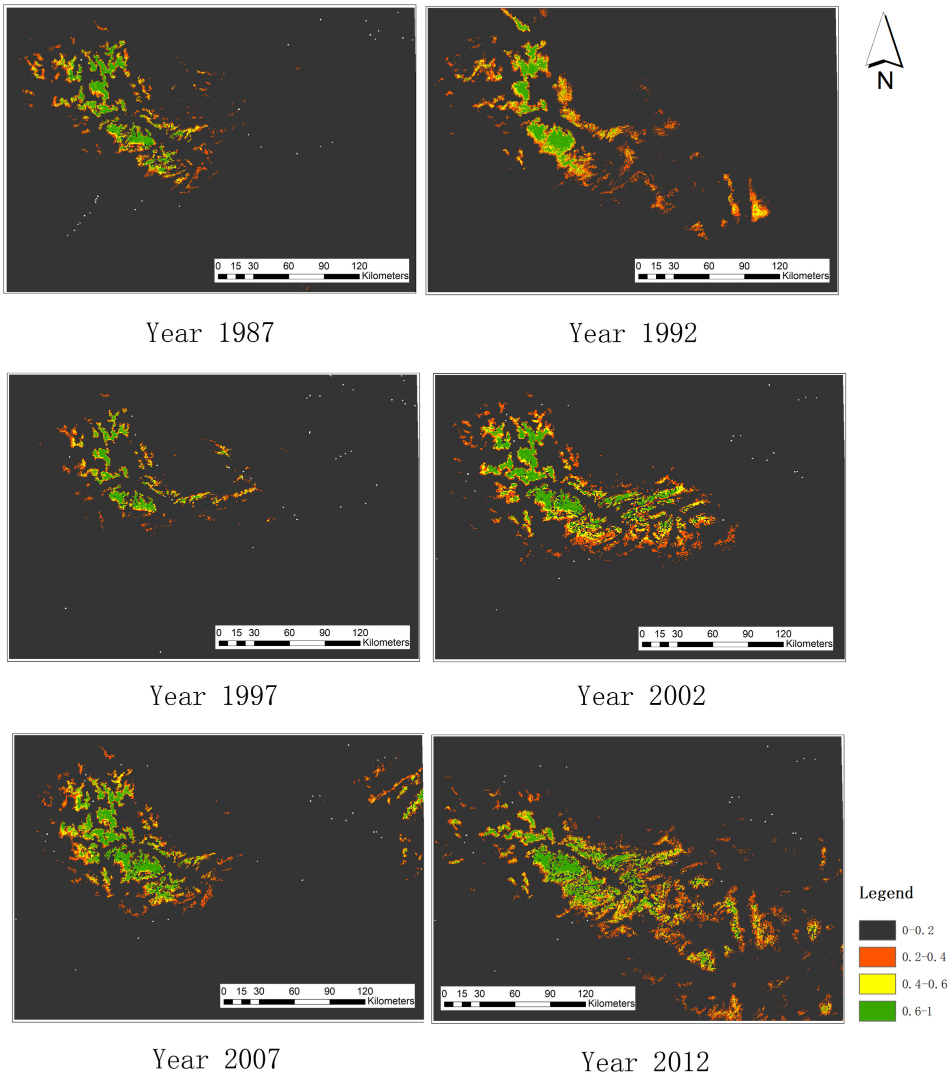

Figure 5. The geographical distributions of potential habitats for *Q. tumidinoda* from 1987 to 2012.

The potentially suitable habitats for *Q. tumidinoda* expanded southeastward. The southeastward distribution band changed from 27°24′37.604″ N 104°54′27.949″ E to 26°37′16.342″ N 106°30′51.500″ E. The northwestward distribution band changed from 28°36′12.149″ N 103°21′46.960″ E to 28°24′58.913″ N 103°18′23.743″ E.

The statistics of the geographical distributions of *Q. tumidinoda* from 1987 to 2012 in different groups are shown in Table 3. Less than 1.5% of the area was suitable for *Q. tumidinoda* to grow. Except for least-potential groups, the rates of high-potential and good-potential groups were all less than 0.31%, and the rates of moderate-potential groups were all less than 0.69%. Except for least-potential groups, the areas in each group followed the order of moderate potential > high potential > good potential. The trends in the areas and rates exhibited fluctuating growth, and the potentially suitable area changed from 3063.42 km^2 to 7054.38 km^2 (Table 4, Figure 6a,b).

The trend in Pet from 1987 to 2012 exhibited a fluctuating decrease. The trend in Bio7 from 1987 to 2012 exhibited a fluctuating increase. The trend in Bio2 from 1987 to 2012 exhibited a fluctuating decrease. The ranges of the three factors (Pet, Bio3, and Bio7) between the minimum and maximum values exhibited expansions (Figure 6c–e).

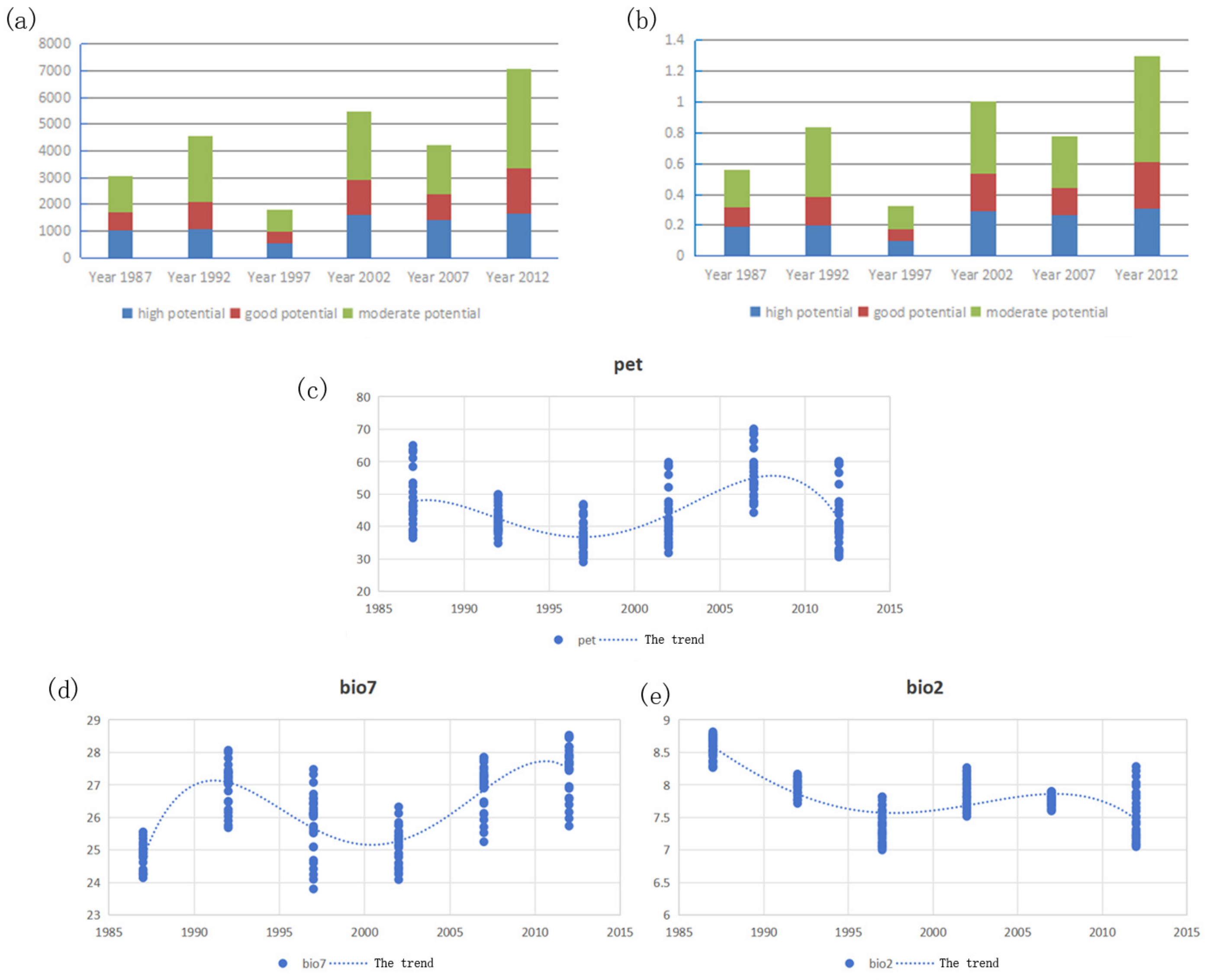

Figure 6. (**a**) The trend in the areas suitable for *Q. tumidinoda* to grow. (**b**) The trend in the rates of areas suitable for *Q. tumidinoda* to grow. (**c**) The trend in Pet from 1987 to 2012. (**d**) The trend in Bio7 from 1987 to 2012. (**e**) The trend in Bio2 from 1987 to 2012.

Table 4. The statistics of the geographical distribution of *Q. tumidinoda*.

		Year 1987	Year 1992	Year 1997	Year 2002	Year 2007	Year 2012
High potential	Area (km^2)	1042.920	1091.880	562.050	1603.710	1435.680	1665.360
	Rate (%)	0.192	0.201	0.103	0.295	0.264	0.306
Good potential	Area (km^2)	668.430	976.410	408.150	1286.190	964.350	1665.270
	Rate (%)	0.123	0.179	0.075	0.236	0.177	0.306
Moderate potential	Area (km^2)	1352.070	2465.280	809.100	2562.840	1838.790	3723.750
	Rate (%)	0.248	0.453	0.149	0.471	0.338	0.684
Least potential	Area (km^2)	541,151.460	539,681.310	542,435.580	538,762.140	539,976.060	537,160.500
	Rate (%)	99.437	99.167	99.673	98.998	99.221	98.704

3.3. Presence or Absence of *Q. tumidinoda*

The trends in changes varied between covers in the intervals of the study period (Figure 7). The differences in covers were significant during the six research periods (1987, 1992, 1997, 2002, 2007, and 2012). *Q. tumidinoda* was recorded in nine samples in 1987. The presence of *Q. tumidinoda* increased from 1987 to 2007 and decreased in 2012. The number of points that possessed *Q. tumidinoda* increased to 11 in 2012. The number of samples that recorded the presence of *Q. tumidinoda* was 15 in 2007. *Q. tumidinoda* was recorded continuously from 1987 to 2012 in five samples (S4796, S4782, S4691, S4604, and S4554). No *Q. tumidinoda* was recorded in six samples (S4827, S4800, S4664, S4649, S4576, and S4537) in 1987, but *Q. tumidinoda* was recorded in 2012. *Q. tumidinoda* was recorded in five samples (S4692, S4646, S4616, S4555, and S4545) in 1987; however, it disappeared in 2012, and the *Q. tumidinoda* in S4646 was naturally replaced by *Chimonobambusa utilis* (Keng) P. C. Keng. No *Q. tumidinoda* was recorded in four samples (S4812, S4797, S4663, and S4641) in 1987 and 2012, but *Q. tumidinoda* occurred in the period between 1987 and 2012, and the *Q. tumidinoda* in S4641 was finally replaced by *Chimonobambusa pachystachys* J. R. Xue & T. P. Yi.

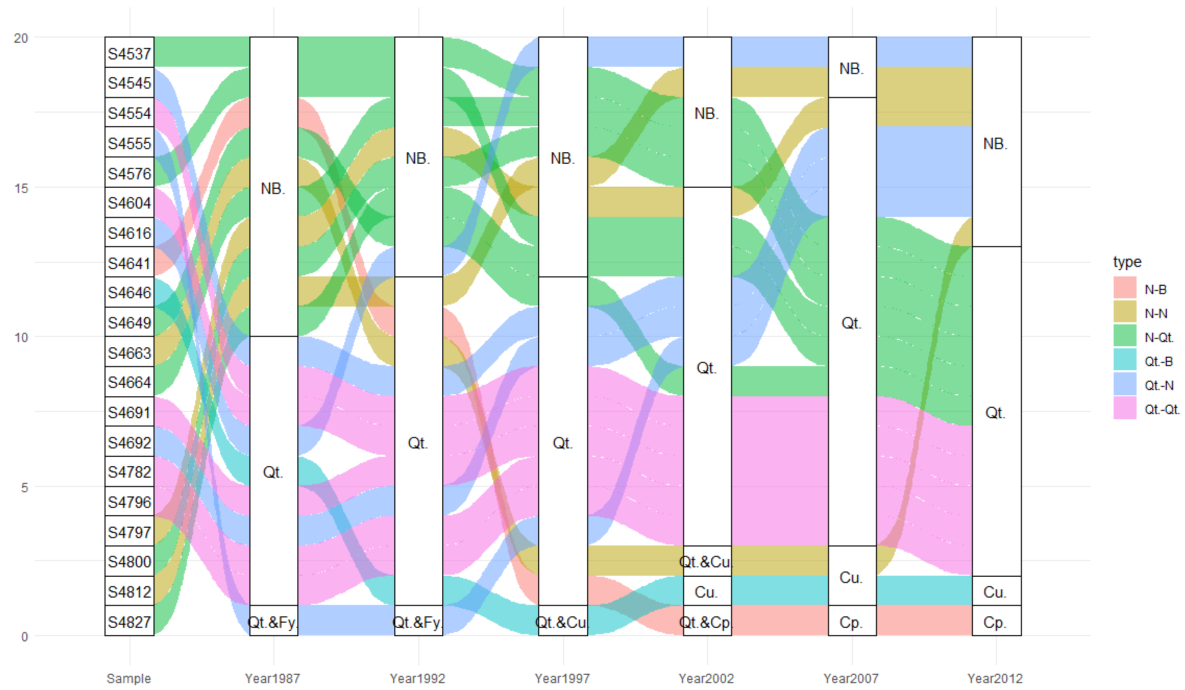

Figure 7. The occurrence or absence of *Q. tumidinoda* from 1987 to 2012. NB. indicates that no bamboo was recorded in the sample. Qt. represents *Q. tumidinoda*. Fy. represents Fargesia yunnanensis. Cu. represents *Chimonobambusa utilis*. Cp. represents *Chimonobambusa pachystachys*. Type represents covers recorded in 1987 and 2012: the left half represents covers recorded in 1987, and the right half represents covers recorded in 2012. B indicates bamboos occurred in the sample, but not *Q. tumidinoda*. N indicates no bamboos were recorded in the sample.

The presence and absence of *Q. tumidinoda* had significant differences between elevations. *Q. tumidinoda* was absent at nine points, and the nine points were distributed in an area with a relatively low elevation, where the average elevation was 1536 m. *Q. tumidinoda* was present at 11 points, and the 11 points were distributed in areas with a relatively high elevation, where the average elevation was 1720 m. *Q. tumidinoda* was recorded at six points over the whole period, and the average elevation was 1893.6 m (Figure 8).

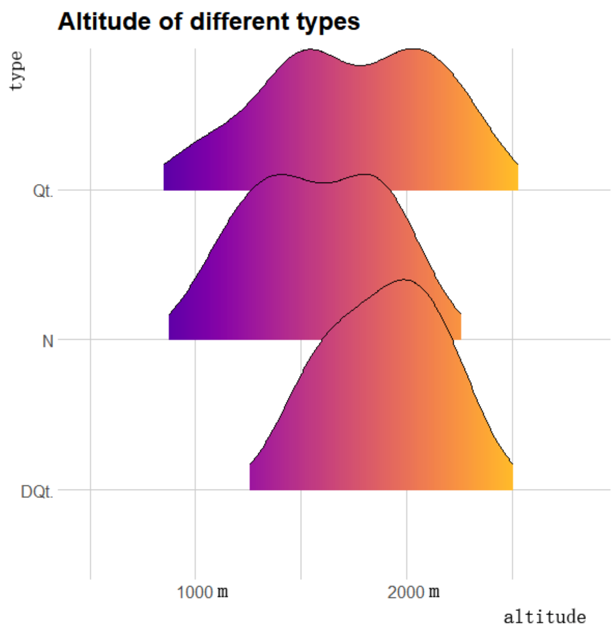

Figure 8. The distributions of points at different types of altitude. Qt. indicates the covers at that point changed from no bamboo to *Q. tumidinoda*. DQt. indicates *Q. tumidinoda* was recorded at points over the whole period. N indicates *Q. tumidinoda* occurred at that point but was finally absent.

4. Discussion

4.1. Influence of Climate Change

Analyzing the potentially suitable habitats for a species in a chronological sequence is essential for understanding the developmental trend (prosperity or extinction) of the species [42]. This constitutes a critical aspect of the better management (utilization or conservation) of the species [43]. Bamboo forests are recognized as important resources in mitigating climate change [11], encompassing approximately 0.8% of the total global forest area [44]. *Q. tumidinoda*, an endemic bamboo species in Southwest China, holds significant potential for mitigating climate change and alleviating poverty through wood and bamboo shoot utilization. Predicting the potentially suitable habitats for *Q. tumidinoda* in a chronological sequence is imperative for understanding and enhancing the developmental trend of the species.

The receiver operating characteristic curve (ROC or AUC) is a key tool in MaxEnt to evaluate the model performance. The AUC values tend to be lower for species that have a broad distribution scope [45]. It is important to note that the larger the AUC value, the higher the reliability. The AUC values were classified into five levels to represent the reliability of prediction, which were as follows: failed ($0.5 \leq AUC < 0.6$), poor ($0.6 \leq AUC < 0.7$), moderate ($0.7 \leq AUC < 0.8$), good ($0.8 \leq AUC < 0.9$), great ($0.9 \leq AUC < 1$) [46]. The AUC values of the test datasets in our study were all greater than 0.95 from 1987 to 2012, which revealed a high level of accuracy in the model prediction.

In this study, three main environmental factors (the mean monthly potential evapotranspiration, the annual range of air temperatures, and the mean diurnal air temperature range) were selected by the jackknife test and were considered key factors contributing to the distribution of the target species. The annual range of air temperatures was also a key climate variable associated with the potentially suitable habitats of *Dendrocalamus sinicus* [47]. Many studies have revealed that the distributions of bamboos (*Phyllostachys edulis*, *Phyllostachys bambusoides*, and *Yushania alpina*) are dominated by temperature, for example, isothermality, temperature seasonality, the mean temperature in the wettest quarter, and so on [42,48]. However, the mean diurnal air temperature range was not a key factor in these studies. Furthermore, the mean monthly potential evapotranspiration, the most important factor for *Q. tumidinoda*, was rarely reported as an important one for other bamboos.

Our study unveiled the chronologically extensive areas in Southwest China where *Q. tumidinoda* may potentially occur. The area of potentially suitable habitats showed an increasing trend from 1987 to 2012, consistent with the conclusion that global warming is facilitating the distribution shift of bamboos to new areas [49,50]. Similarly, the potentially suitable habitats for other bamboo species, such as Moso bamboo (*Phyllostachys edulis*), madake bamboo (*Phyllostachys bambusoides*), and Highland bamboo (*Yushania alpina*), also exhibited an increasing trend under the influence of climate change [42,48].

The trends in the mean monthly potential evapotranspiration (a fluctuating decrease) and the annual range of air temperatures (a fluctuating increase) in our study area from 1987 to 2012 possessed the same trends as the evapotranspiration and annual range of temperature changes in the Qinghai–Tibet Plateau [51]. The trend in the mean diurnal air temperature range exhibited a fluctuating decrease, and the trend in this factor has also exhibited a decrease across China during from 1961 to 2000 [52]. The key factors that have dominated the distributions of creatures are different because of different biological properties, but the key factors for creatures could be summarized as heat and water.

Previous research indicates that climate change-induced redistribution will widely occur in latitudinal and altitudinal directions [6,53]. Statistics from existing studies reveal that out of 4000 species, half, including bamboos, are shifting toward higher latitudes and altitudes [54–56]. In our study, the potentially suitable habitats for *Q. tumidinoda* also experienced a shift to higher altitudes. However, we observed an expansion in the potentially suitable habitats for *Q. tumidinoda* from 1987 to 2012, accompanied by a southeastward shift. These differences from other bamboos [39,47,48] may be attributed to variations in key environmental factors influencing the potentially suitable habitats. Notably, the potentially suitable habitats for *Q. tumidinoda* are primarily influenced by the mean monthly potential evapotranspiration (Pet), whereas the potentially suitable habitats for other bamboos are predominantly influenced by temperature.

4.2. Future Research Directions and Possible Applications

Future climate change scenarios are a hot topic introduced by the Intergovernmental Panel on Climate Change (IPCC) [57]. The Shared Socioeconomic Pathways (SSPs), introduced within the CMIP6 framework, serve to delineate diverse social, economic, and technological narratives, encompassing a spectrum of plausible futures characterized by challenges related to mitigation and adaptation [58]. These pathways offer four distinct scenarios for the future: SSP1-2.6 (sustainability), which targets a warming scenario significantly below 1.5 °C by 2100; SSP2-4.5 (middle of the road), projecting a radiative forcing of approximately 4.5 W/m^2 by 2100; SSP3-7.0 (regional rivalry), depicting scenarios marked by high social fragility alongside significant anthropogenic radiative forcing; and SSP5-8.5 (fossil-fueled development), envisaging the most extreme scenario with a radiative forcing reaching 8.5 W/m^2 by 2100 [59,60]. The four scenarios envisaging climate change under different socioeconomic development situations provide more precise projections for *Q. tumidinoda* in the future, such as its redistribution in different scenarios and its role in countering climate change because of its possible expansion.

Based on the findings of this study, the potential habitats for *Q. tumidinoda* exhibited an expansion from 1987 to 2012, indicating the species' adaptability to climate change. However, our observations reveal a shift in potential habitats toward areas characterized by lower latitudes and higher altitudes. This shift may result in the absence of *Q. tumidinoda* in regions where suitability has declined, potentially causing losses for bamboo farmers operating in these areas. Consequently, we recommend that introduction and conservation planning initiatives should incorporate considerations of climate impacts, along with strategies aimed at enhancing both current and future suitable habitats. Furthermore, to avoid the excessive bamboo shoot harvesting of natural *Q. tumidinoda* populations in the distribution area, we call for more management activities from the government and social organizations, such as delimitating enclosure areas for natural populations following the levels of suitability established in this research, creating harvesting rules in the region via the government or organizations granted license, and developing new ways to participate in the forest carbon sink trade in the market to alleviate poverty, thus protecting *Q. tumidinoda* populations.

4.3. Limitations

The MaxEnt model is considered the predominant way to reveal the effects of climate change on species distributions [61]. However, MaxEnt also has several limitations, for example, the need for high-quality data, appropriate environmental variables, optimal parameters, and uncertainty assessments [62,63]. In our study, some factors were still overlooked, for example, interspecies interactions, extreme disturbances, and diffusion processes [64]. Furthermore, the default parameters and the multiple environmental variables could have complicated the model, thus limiting the accuracy of predictions [56]. There were still several environmental variables with low contributions to predictions, although we performed pre-processing to select the better variables among all. In the future, to improve the accuracy of predictions, more inner factors could be involved, such as the relationship between competition and cooperation in species and the tolerance of species, and more ways could be developed to screen the good environmental variables.

In our study, the environmental variables were extracted from the Chelsa climate dataset. The Chelsa climate dataset is a public dataset consisting of downscaled model output temperature and precipitation estimates at a horizontal resolution of 30 arc sec. However, the dataset does not include annual data from 2012 onward, just average data from 2012 to 2040. Furthermore, there are currently no substitute environmental data products in the publicly available database. Therefore, our study was limited to the period from 1987 to 2012.

5. Conclusions

This study focused on an endemic bamboo (*Q. tumidinoda*) in China, which is facing rapid changes in its suitable habitat under climate change. These changes will result in species redistribution and potential losses for bamboo farmers. Our study was dedicated to revealing the changes in *Q. tumidinoda* to prevent possible losses to the environment and bamboo farmers. In this study, we employed the MaxEnt model to predict the potential habitat distribution of *Q. tumidinoda* in Southwest China from 1987 to 2012. Our projections indicate an expansion in the potentially suitable habitat for *Q. tumidinoda*, along with a likely shift southeastward and toward higher altitudes. The potentially suitable area exhibited fluctuating growth during the period from 1987 to 2012. The mean monthly potential evapotranspiration (Pet) emerged as a critical determinant influencing the distribution of potentially suitable habitats for *Q. tumidinoda*. These findings have significant implications for the introduction and cultivation efforts of *Q. tumidinoda*. The integration of a GIS and MaxEnt modeling would provide opportunities for poverty alleviation through the development of *Q. tumidinoda* plantations. In the future, research endeavors should aim at enhancing prediction accuracy, and it is imperative to accord equal consideration to both organic and inorganic environmental variables. Furthermore, *Q. tumidinoda* is a good way for nature restoration, the manager aimed at better environment and poverty alleviation could consider it as a plant to restoration. This would also be a great method to protect *Q. tumidinoda* from possible extinction in the areas defined as potentially suitable habitats for *Q. tumidinoda* in our study. Meanwhile, the government could introduce forest carbon sink trading events for bamboo farmers, thus increasing the income from bamboo and protecting the natural populations of *Q. tumidinoda*.

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