

Article

Projected Distribution of Five Invasive *Ipomoea* Species in China Under Climate Change

Zhengxuan Wei , Wende Chen, Jie Ran, Zhijia Wang  and Yuelin Wang *

College of Geography and Planning, Chengdu University of Technology, Chengdu 610059, China; 19828948319@163.com (Z.W.); chenwende@mail.cdut.edu.cn (W.C.); 18884238912@163.com (J.R.); wzjhjia04@163.com (Z.W.)

* Correspondence: wangyuelin19@cdut.edu.cn; Tel.: +86-178-2808-0908

Abstract

In recent years, increasing attention has been paid to the influence of climate change on the distribution and spread of invasive species. However, projections of the future distributions of invasive *Ipomoea* species remain limited, despite their strong reproductive capacity, ecological adaptability, and competitive ability. In this study, 34 environmental variables were initially considered, and highly correlated variables were removed before fitting Maximum Entropy (MaxEnt) models, with model settings selected according to species-specific sample sizes, to predict the potential distributions of five invasive *Ipomoea* species (*Ipomoea nil*, *Ipomoea purpurea*, *Ipomoea quamoclit*, *Ipomoea lacunosa*, and *Ipomoea alba*) across China under current and future climate scenarios (SSP126, SSP370, and SSP585). Model performance and the contributions of environmental variables were evaluated, and changes in suitable areas and distribution centroids were compared among climate scenarios. All five models showed high predictive performance, with AUC values exceeding 0.9. Snow cover days (SCD) was the main predictor for *I. nil* and *I. purpurea*, while Bio9, elevation, and Bio11 were the dominant predictors for *I. quamoclit*, *I. lacunosa*, and *I. alba*, respectively. Compared with the baseline climate period (1981–2010), suitable areas for all five species were projected to expand under future climate scenarios, with varying shifts in distribution centroids. These results indicate that climate warming may increase the potential invasion risk and ecological impacts of invasive *Ipomoea* species in China, highlighting the need for strengthened monitoring and management to support biodiversity conservation.

Keywords: alien species; future climate scenarios; environmental driver; suitable area; MaxEnt model



Academic Editor: Rodolfo Gentili

Received: 13 August 2026

Revised: 4 September 2026

Accepted: 6 September 2026

Published: 9 September 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Invasive species are organisms that come from outside the local ecosystem, including plants, animals, and microorganisms [1,2]. With ongoing globalization and a changing climate, biological invasions have increased competition for resources and disturbed ecological balance, increasing competitive pressure on native species and contributing to global declines in biodiversity and ecosystem decline worldwide [3,4]. On the other hand, invasive species can reduce crop yields, increase agricultural management costs, and negatively affect socio-economic development [5,6]. In China, several invasive species, including *Bemisia tabaci* [7], *Bursaphelenchus xylophilus* [8], and *Ageratina adenophora* [9], have been reported to cause crop yield reductions, timber losses, and livestock poisoning [10]. Between 1965 and 2017, the aggregate economic burden of biological invasions in China

was estimated at US\$174.7 billion (in 2017 constant dollars), with an average annual loss of approximately US\$3.30 billion [11–13]. Moreover, climate change may further complicate the management and control of invasive species by altering their dispersal processes and rates [14,15]. Therefore, accurately predicting the potential range and invasion mechanisms of invasive plants under future climate change can help guide early prevention and control measures.

Ipomoea represents the largest genus within the *Convolvulaceae* family, known for its high reproductive potential, strong adaptability, and rapid growth, and is widely found across tropical and subtropical regions worldwide [16,17]. In China, 13 invasive *Ipomoea* species have been recorded and are widely distributed in southern China and parts of eastern China, most of which are herbaceous vines [18,19]. Some *Ipomoea* species can establish stable populations in a variety of habitats, including croplands, forest margins, riverbanks, roadsides, and wastelands [20,21]. Their rapid growth and twining habit may form dense vegetation cover, suppress native plant growth, and alter plant community structure, with potential consequences for ecosystem stability and biodiversity [22]. In agricultural systems, invasive *Ipomoea* species may also compete with crops for light, water, and nutrients, increasing field management costs and potentially causing agricultural production losses [23,24]. Therefore, assessing the future range of *Ipomoea* species under climate change is important for informing effective invasion management.

Currently, models of species distribution (SDMs) have been widely applied to species distribution prediction, endangered species conservation, and invasion risk assessment of non-native species because they can effectively integrate species occurrence records with environmental factors such as climate, topography, and soil, quantify the relationships between species and environmental conditions, and predict potential suitable areas under current and future environmental conditions [25,26]. In addition, SDMs can overcome the spatial limitations of existing occurrence records and facilitate the assessment of changes in species distributions and their responses to climate change [27]. Many researchers use methods such as MaxEnt (Maximum Entropy Model), RF (Random Forest), GAM (Generalized Additive Model), GBM (Generalized Boosted Model), and GLM (Generalized Linear Model) to simulate the nonlinear relationship between species and environmental variables, all of which have good generalization ability and prediction accuracy [28–30]. However, relative to other approaches for modeling species distributions, MaxEnt has a key advantage in requiring only presence-only data, while still achieving high accuracy and stability with limited samples [31,32]. Furthermore, MaxEnt can quantify the relative contributions of environmental variables and generate spatially explicit habitat suitability predictions, making it an effective tool for identifying potential suitable habitats and their environmental drivers [33]. Early studies have used MaxEnt models to predict various invasive plants, such as *Alternanthera philoxeroides* [34], *Eriochloa villosa* [35], and *Cenchrus spinifex* [36]. In addition, researchers have also used this model to predict multiple plants of the same family or genus, such as the *Avena* genus [37], the *Asteraceae* family [38], and the *Bidens* genus [39]. However, previous research has largely focused on individual species or a few families and genera, and systematic assessments of the potential range and invasion risk of highly invasive *Ipomoea* species are still lacking.

In this study, we employed the MaxEnt model (version 3.4.4; Princeton University, Princeton, NJ, USA), together with occurrence data from five *Ipomoea* species in China and 34 environmental factors (such as climate, topography, soil, and UV-B radiation), to assess how climate change influences their distribution patterns (Figure S1). The specific objectives are: ① Identify the key environmental factors influencing the invasion of five *Ipomoea* species; ② Construct the current distribution patterns (1981–2010) of five invasive plants in the *Ipomoea* and further predict their future distribution trends under three climate scenarios;

③ Quantify the centroid migration and rate of five *Ipomoea* species under three future climate scenarios, and propose monitoring strategies for specific regions.

2. Materials and Methods

2.1. Data Source for the Distribution Sample

To identify *Ipomoea* species occurring in China, data were obtained from the Chinese Information System on Invasive Alien Species (<https://www.iplant.cn/ias/>, accessed on 18 October 2025). According to the relevant classification, *I. purpurea* is classified as Level I (malicious invasion), *I. nil* as Level II (serious invasion), and *I. quamoclit*, *I. lacunosa*, and *I. alba* as Level III (localized invasion) in China.

Occurrence records of the five invasive *Ipomoea* species were then obtained from the GBIF (Global Biodiversity Information Facility) (<https://www.gbif.org/>, accessed on 20 October 2025), Plant Intelligence (<https://www.iplant.cn/ias/>, accessed on 20 October 2025), and CVH (Chinese Virtual Herbarium) (<https://www.cvh.ac.cn/>, accessed on 22 October 2025). To maintain a constant sampling density and lessen sampling bias, the occurrence points were spatially thinned through the “SpThin” package in R (version 4.4.2; R Foundation for Statistical Computing, Vienna, Austria), making sure that each point was at least 7.5 km apart. Following this step, the dataset included 430 valid records for *I. nil*, 340 for *I. purpurea*, 173 for *I. quamoclit*, 28 for *I. lacunosa*, and 56 for *I. alba* (Figure 1 and Table 1).

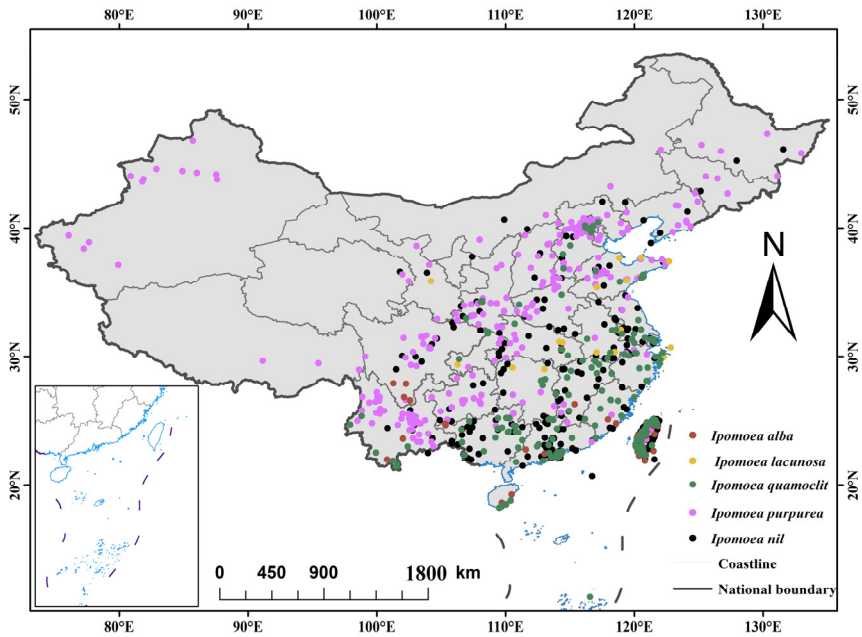


Figure 1. Five species of *Ipomoea* are distributed across China.

Table 1. Lifeforms and origin of five invasive plants in the *Ipomoea*.

Plants	Life Form	Origin	Intrusion Level	Number of Distribution Records
<i>I. nil</i>	Annual herb	Tropical America	Serious invasion	430
<i>I. purpurea</i>	Annual twining herb	Tropical America	Malicious intrusion	340
<i>I. quamoclit</i>	Annual, slender twining herb	Tropical America	Localized invasion	173
<i>I. lacunosa</i>	Annual twining herb	Eastern and central America	Localized invasion	28
<i>I. alba</i>	Annual or perennial large twining herb	Tropical America	Localized invasion	56

2.2. Selection of Variables

A total of 34 predictor variables, including climate, soil, terrain, and UV-B radiation, as modeling factors (Table 2). Climatic data were derived from the CHELSA database (Climatologies at high resolution for the earth's land-surface areas) (<https://chelsa-climate.org>, accessed on 27 October 2025) and include 19 bioclimatic variables (Bio1–Bio19) and SCD (snow cover days), representing key climatic characteristics of the study area. All variables were processed at a 30-arcsecond (approximately 1 km) spatial resolution. Meanwhile, we used the CMIP6 (Coupled Model Intercomparison Project Phase 6) Shared Socioeconomic Pathways (SSPs) as future climate projections. Three representative scenarios were selected in this study, including SSP126, SSP370, and SSP585, representing different levels of future climate change intensity. Specifically, SSP126 is generally considered a sustainable development pathway characterized by strong international cooperation, low-carbon development, and increased reliance on renewable energy, with global warming estimated at around 1.8 °C. SSP370 reflects a regional rivalry pathway, with relatively high emissions and an estimated global warming of approximately 3.6 °C. In contrast, SSP585 describes a high-emission pathway driven by continued fossil fuel dependence and limited climate mitigation efforts, with global temperatures projected to rise by approximately 4.4 °C by 2100. The data for these three scenarios are based on the ensemble mean of five CMIP6 Global Climate Models (GCMs) (GFDL-ESM4, UKESM1-0-LL, MPI-ESM1-2-HR, IPSL-CM6A-LR, and MRI-ESM2-0) to reduce the systematic bias of individual models and improve the reliability and representativeness of future climate projections. Elevation data were derived from the 30-m DEM available through the Geospatial Data Cloud (<https://www.gscloud.cn/>, accessed on 28 October 2025). On this basis, we used the ArcGIS 10.8.1 tool (Esri, Redlands, CA, USA) to extract slope, aspect, and TWI information to reflect the geomorphic features of the study area, as these variables are closely related to local topography, solar radiation, and moisture conditions, which may influence the distribution of invasive *Ipomoea* species. Previous studies have shown that UV-B radiation (Ultraviolet-B radiation) can affect seed germination, morphological development, and photosynthetic performance in *Ipomoea* species, whose growth and interspecific competition are also closely associated with light conditions [40]. Therefore, UV-B radiation was included as an environmental factor in this study. The relevant variables were obtained from the global UV-B radiation database (<http://www.ufz.de/gluv/>, accessed on 28 October 2025), including UV-B1 to UV-B6. The soil information, including soil organic carbon (OC), total nitrogen (TN), pH, and bulk density (BD) at depths of 0–5 cm and 5–15 cm, was obtained from the SoilGrids database (<https://soilgrids.org/>, accessed on 29 October 2025) and averaged across the two layers to better represent surface soil properties and to reflect the effects of soil fertility, nutrient availability, and physicochemical conditions on the distribution of the five invasive *Ipomoea* species.

To reduce redundancy among predictors, we conducted a Pearson correlation analysis across the 34 environmental variables. Variable pairs with correlations above 0.8 were deemed highly collinear, and only those with clear ecological relevance and high contribution and permutation importance in preliminary modeling were kept (Figure 2 and Table S1). In addition, to ensure spatial consistency among all environmental rasters, the original 30-m DEM was resampled to a target resolution of 1 km × 1 km using bilinear interpolation in ArcGIS, and all environmental layers were projected to the WGS-1984 coordinate system.

2.3. Model Settings and Model Construction

To predict the potential ranges of five invasive *Ipomoea* species in China, species-specific MaxEnt model settings were selected using ENMeval in R [41–43]. Specifically, model-

ing for *I. nil* was conducted using feature classes (FC) = LQH (Linear + Quadratic + Hinge) and regularization multiplier (RM) = 1, while *I. purpurea* was modeled with FC = LQH (Linear + Quadratic + Hinge) and RM = 1. For *I. quamoclit*, modeling employed FC = LQHT (Linear + Quadratic + Hinge + Threshold) and RM = 2 (Figure S1). Given their limited occurrence records (fewer than 80 spatial points), default MaxEnt feature-class and regularization settings were directly adopted for *I. lacunosa* and *I. alba* [41,44,45].

Table 2. 34 types of environmental variables.

Type	Variable	Variable Description	Unit
Climate	Bio1	Average Annual Temperature	°C
	Bio2	Mean Diurnal Range	—
	Bio3	Isothermality	°C
	Bio4	Temperature Seasonality	°C
	Bio5	Highest Temperature of Hottest Month	°C
	Bio6	Min Temperature of Coldest Month	°C
	Bio7	Temperature Annual Range	°C
	Bio8	Mean Temperature of Wettest Quarter	°C
	Bio9	Mean Temperature over the Driest Quarter	°C
	Bio10	Mean Temperature of Warmest Quarter	°C
	Bio11	Mean Temperature of the Coldest Quarter	°C
	Bio12	Annual Precipitation	mm
	Bio13	Precipitation of the Wettest Month	mm
	Bio14	Precipitation of the Driest Month	mm
	Bio15	Precipitation Seasonality	mm
	Bio16	Precipitation of the Wettest Quarter	mm
	Bio17	Precipitation of the Driest Quarter	mm
	Bio18	Precipitation of the Warmest Quarter	mm
	Bio19	Precipitation of the Coldest Quarter	mm
	SCD	Snow Cover Days	d
Altitude	Aspect	Aspect	°
	Elevation	Elevation	m
	Slope	Slope	°
	TWI	Topographic Wetness Index	—
Soil Variables	BD	Bulk Density	g/cm ³
	OC	Soil Organic Carbon	g/cm ³
	pH	Soil pH	—
	TN	Total Nitrogen	g/cm ³
UV-B	UVB1	Annual Mean UV-B Radiation	kJ m ^{−2} day ^{−1}
	UVB2	UV-B Radiation Seasonality	kJ·m ^{−2} ·day ^{−1}
	UVB3	Mean UV-B of Highest Month	kJ m ^{−2} day ^{−1}
	UVB4	Mean UV-B radiation of the wettest quarter	kJ·m ^{−2} ·day ^{−1}
	UVB5	Sum of Monthly Mean UV-B during Highest Quarter	kJ m ^{−2} day ^{−1}
	UVB6	UV-B Radiation of the Driest Quarter	kJ·m ^{−2} ·day ^{−1}

Note: “—” represents unselected variables in the model.

In this study, MaxEnt was set to randomly select 25% of each species’ occurrence data as the model test dataset, with the remaining 75% used as the model training dataset [46]. Model replicates were implemented using bootstrap resampling with a total of 10 replicates. For each replicate, a maximum of 10,000 background points were randomly sampled across mainland China, which was defined as the unified accessible modeling area for all five *Ipomoea* species. To comprehensively evaluate model performance, we used area under the Curve (AUC), true skill statistic (TSS), omission rate, and the continuous Boyce index

(CBI) to assess model discrimination, prediction error, and calibration (Table 3), with final results averaged across 10 replicates to reduce random variation [47,48]. AUC, TSS, and CBI values closer to 1 indicate better model performance, with stronger discrimination and greater consistency between predicted suitability and observed occurrences [49–51], whereas lower omission rates indicate fewer missed occurrences and better predictive performance [52]. The Jackknife test was used to figure out how important each variable was, and the logistic outputs showed the chances of each event happening, while the other settings stayed the same. Based on the continuous logistic suitability outputs, the potential distribution was further classified into three habitat suitability categories using unified thresholds across current and future climate scenarios: unsuitable ($p < 0.4$), moderately suitable ($0.4 \leq p < 0.6$), and highly suitable ($0.6 \leq p \leq 1.0$) [53]. To reduce random error, the final results were averaged over 10 copies. Combined with ArcGIS, species presence was quantified on a scale of 0 to 1, where higher values reflect a better probability of existence. Meanwhile, a threshold of 50% probability of occurrence was adopted to distinguish predicted presence from absence [54–56].

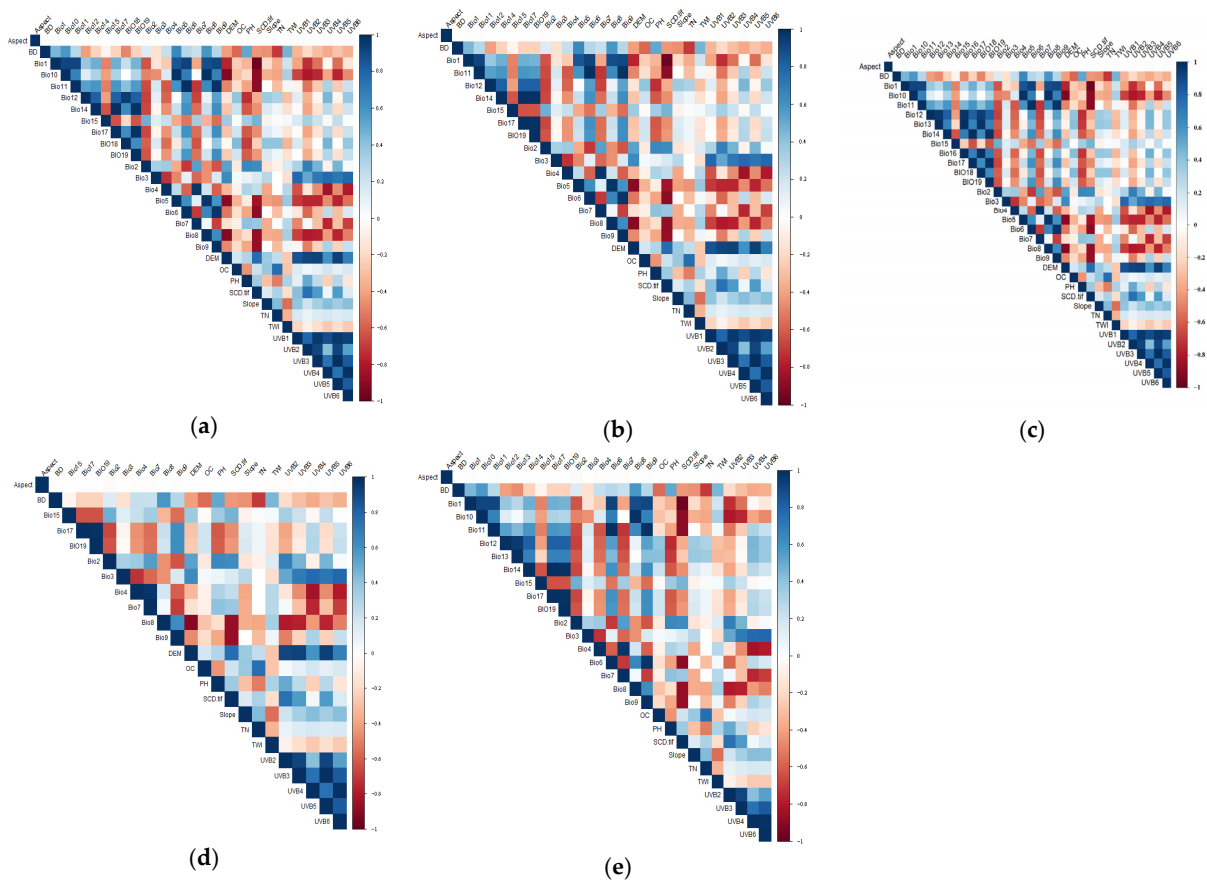


Figure 2. Correlation matrices of 5 *Ipomoea* species: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit*, (d) *I. lacunosa*, (e) *I. alba*.

Table 3. Model evaluation metrics of five *Ipomoea* species from ten runs under the current climate.

Plants	Metric Type	1	2	3	4	5	6	7	8	9	10	Avg.
<i>I. nil</i>	Training AUC	0.9218	0.9377	0.9330	0.9203	0.9269	0.9190	0.9231	0.9321	0.9196	0.9225	0.9256
	Test AUC	0.9065	0.9245	0.9131	0.9175	0.9127	0.8923	0.9023	0.9077	0.9250	0.9110	0.9113
	TSS	0.8143	0.8309	0.8425	0.8493	0.8493	0.8543	0.8587	0.8644	0.8669	0.8661	0.8492
	Training Omission	0.1289	0.0383	0.0941	0.0627	0.101	0.0801	0.1254	0.1498	0.0662	0.0871	0.0934
	Test Omission	0.1579	0.0737	0.1789	0.1158	0.1263	0.1053	0.2105	0.2632	0.0526	0.1263	0.1411
	CBI	0.995	0.99	0.964	0.992	0.984	0.985	0.999	0.992	0.995	0.995	0.9891

Table 3. Cont.

Plants	Metric Type	1	2	3	4	5	6	7	8	9	10	Avg.
<i>I. purpurea</i>	Training AUC	0.9007	0.9096	0.9050	0.9119	0.9120	0.9173	0.9051	0.9056	0.9223	0.9171	0.9107
	Test AUC	0.9039	0.9154	0.8879	0.8815	0.8885	0.8946	0.8871	0.8958	0.8762	0.8922	0.8923
	TSS	0.8111	0.8243	0.8391	0.851	0.8602	0.8723	0.8785	0.8845	0.8914	0.8942	0.8606
	Training Omission	0.0724	0.0618	0.0837	0.0946	0.0753	0.0871	0.0685	0.0912	0.0776	0.0889	0.08011
	Test Omission	0.0736	0.0589	0.0817	0.0943	0.0875	0.0768	0.0642	0.0916	0.0695	0.0824	0.0781
	CBI	0.991	0.986	0.989	0.989	0.994	0.992	0.975	0.993	0.992	0.993	0.9894
<i>I. quamoclit</i>	Training AUC	0.9481	0.9530	0.9491	0.9422	0.9388	0.9428	0.9444	0.9452	0.9524	0.9572	0.9473
	Test AUC	0.9178	0.9367	0.9239	0.9161	0.9289	0.9153	0.9299	0.9385	0.9606	0.9398	0.9308
	TSS	0.8327	0.8329	0.8421	0.8539	0.8671	0.8759	0.8867	0.8889	0.8949	0.8821	0.8655
	Training Omission	0.0088	0.0619	0.0885	0	0.0442	0.0265	0.0265	0.1239	0.0708	0.0354	0.0487
	Test Omission	0.0541	0.027	0.1622	0	0.0541	0.1081	0.1351	0.1622	0.0541	0.1351	0.0892
	CBI	0.89	0.921	0.973	0.98	0.952	0.97	0.929	0.96	0.98	0.978	0.9533
<i>I. lacunosa</i>	Training AUC	0.9803	0.9796	0.9698	0.9794	0.9900	0.9801	0.9730	0.9849	0.9894	0.9707	0.9797
	Test AUC	0.9807	0.9796	0.9565	0.9554	0.9261	0.9874	0.9273	0.9599	0.9817	0.9817	0.9636
	TSS	0.7581	0.7851	0.7889	0.7983	0.8071	0.8162	0.8253	0.8303	0.8409	0.8529	0.8103
	Training Omission	0.0625	0.0625	0	0.0625	0	0	0.125	0.0625	0	0	0.0375
	Test Omission	0	0.2	0	0.2	0.6	0	0.6	0.2	0	0	0.18
	CBI	0.889	0.872	0.886	0.841	0.756	0.94	0.829	0.742	0.808	0.716	0.8279
<i>I. alba</i>	Training AUC	0.9862	0.9926	0.9945	0.9898	0.9931	0.9889	0.9892	0.9856	0.9895	0.9872	0.9897
	Test AUC	0.9818	0.9875	0.9901	0.9897	0.9868	0.9661	0.9608	0.9852	0.9947	0.9815	0.9824
	TSS	0.847	0.8606	0.8453	0.8214	0.8355	0.8525	0.8198	0.8131	0.8661	0.8039	0.8365
	Training Omission	0.0303	0.0303	0	0.0606	0.0303	0.0303	0.0606	0.1212	0.0303	0.0606	0.0454
	Test Omission	0	0.1	0	0.2	0.2	0.2	0.3	0.1	0	0.1	0.13
	CBI	0.866	0.925	0.808	0.918	0.869	0.874	0.958	0.78	0.834	0.84	0.8672

3. Results

3.1. Performance and Validation of the Model

The average AUC from ten replicates demonstrates high predictive accuracy and strong model discrimination. The mean AUC values for *I. nil*, *I. purpurea*, and *I. quamoclit* were 0.926, 0.911, and 0.947, respectively. Although *I. lacunosa* and *I. alba* were modeled using the default settings, they still reached high AUC levels at 0.980 and 0.990, respectively (Figure 3 and Table 3).

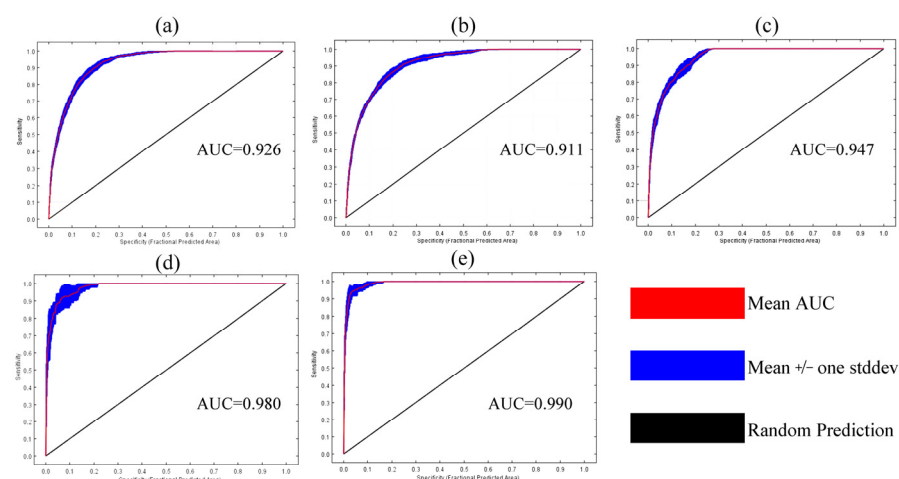


Figure 3. ROC (Receiver Operating Characteristic) curve and AUC results of five *Ipomoea* species under current climate conditions (1981–2010) based on ten runs: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit*, (d) *I. lacunosa*, (e) *I. alba*.

3.2. Key Environmental Factors Influencing the *Ipomoea* Invasion

Table 4 shows the impact of various environmental variables on the potential habitats of five invasive plants in *Ipomoea*. Meanwhile, the jackknife test (Figure 4) shows the relative importance of individual environmental factors, residual variables after removing factors,

and a complete model that includes all variables. Based on this, the study identified the most influential variables as the key factors determining the likely ranges of the five invasive *Ipomoea* species and analyzed the response curves for each species. In these response curves, the red and gray shaded areas represent the mean and standard deviation across ten model runs, respectively (Figure S2).

Table 4. Percentage contribution of environmental variables.

Type	Variable	Variable Description	Unit	Percent Contribution (%)				
				<i>I. nil</i>	<i>I. purpurea</i>	<i>I. quamoclit</i>	<i>I. lacunosa</i>	<i>I. alba</i>
Climate	Bio2	Mean Diurnal Range	°C	3.9	0.1	3.9	3.6	0.4
	Bio3	Isothermality	Unitless	0.6	4.2	0.6	5.3	0.2
	Bio4	Temperature Seasonality	Unitless	—	—	—	5.3	—
	Bio7	Temperature Annual Range	°C	12.9	2.6	0.7	—	2.8
	Bio8	Mean Temperature of Wettest Quarter	°C	—	—	6.2	—	0.8
	Bio9	Mean Temperature over the Driest Quarter	°C	—	—	57.0	—	—
	Bio11	Mean Temperature of Coldest Month	°C	—	—	—	—	65.6
	Bio12	Annual Precipitation	mm	3.7	13.9	11.6	—	—
	Bio13	Precipitation of the Wettest Month	mm	—	—	—	—	0.8
	Bio15	Precipitation Seasonality	Unitless	1.2	1.1	1.7	0.6	2.2
	Bio19	Precipitation of the Coldest Quarter	mm	—	—	—	15.5	2.0
	SCD	Snow Cover Days	d	53.3	41.1	—	—	—
Soil	BD	Bulk Density	g/cm ³	3.7	0.7	2.5	1.5	—
	TN	Soil Nitrogen	g/cm ³	1.6	0.5	0.1	2.9	0.6
	pH	Soil pH	Dimensionless	6.1	14.4	1.2	2.3	1.1
	OC	Soil Organic Carbon	g/cm ³	0.3	4.2	1.7	2.2	13.9
Altitude	Aspect	Aspect	(°)	0.7	1.0	0.2	2.5	0.4
	Elevation	Elevation	m	—	—	—	41.5	—
	Slope	Slope	(°)	1.8	2.0	2.4	11.0	1.6
	TWI	Topographic Wetness Index	unitless	3.2	1.0	0.9	1.3	2.5
UV-B	UVB2	UV-B Radiation Seasonality	kJ·m ⁻² ·day ⁻¹	5.6	5.8	9.0	—	1.2
	UVB4	Mean UV-B radiation of the wettest quarter	kJ·m ⁻² ·day ⁻¹	1.4	7.5	0.2	—	2.3
	UVB6	UV-B Radiation of the Driest Quarter	kJ·m ⁻² ·day ⁻¹	—	—	—	4.5	—

Note: “—” represents unselected variables in the model.

The distribution of *I. nil* was primarily associated with SCD, Bio7 (Temperature annual range), and pH. Its occurrence probability showed a continuous decline with increasing SCD and Bio7, suggesting a preference for areas with fewer snow-covered days and a relatively narrower annual temperature range. The optimal pH range was 5.6–7.8, with the highest occurrence probability (approximately 0.78) at around pH 7.0.

For *I. purpurea*, SCD, pH, and Bio12 (Annual precipitation) were the main environmental predictors. Occurrence probability declined with increasing SCD, whereas its response to pH was highest within the range of 6.4–8.2, reaching a maximum of approximately 0.85 at pH 7.5. The occurrence probability remained above 0.5 across a broad range of Bio12 (500–7000 mm), with the highest probability (approximately 0.77) occurring at around 800 mm.

The distribution of *I. quamoclit* was primarily associated with Bio9 (Mean temperature of the driest quarter), Bio12, and UV-B2 (UV-B Radiation Seasonality). Its occurrence probability increased with Bio9 and reached approximately 0.98 at around 29 °C.

The response of *I. quamoclit* to Bio12 was relatively broad, with occurrence probabilities above 0.5 between 1200 and 6200 mm and a peak of approximately 0.95 at around 3500 mm. In contrast, occurrence probability showed a generally negative response to UV-B2 and declined markedly at relatively high UV-B2 levels, suggesting that strong UV-B radiation seasonality may constrain the habitat suitability of *I. quamoclit*.

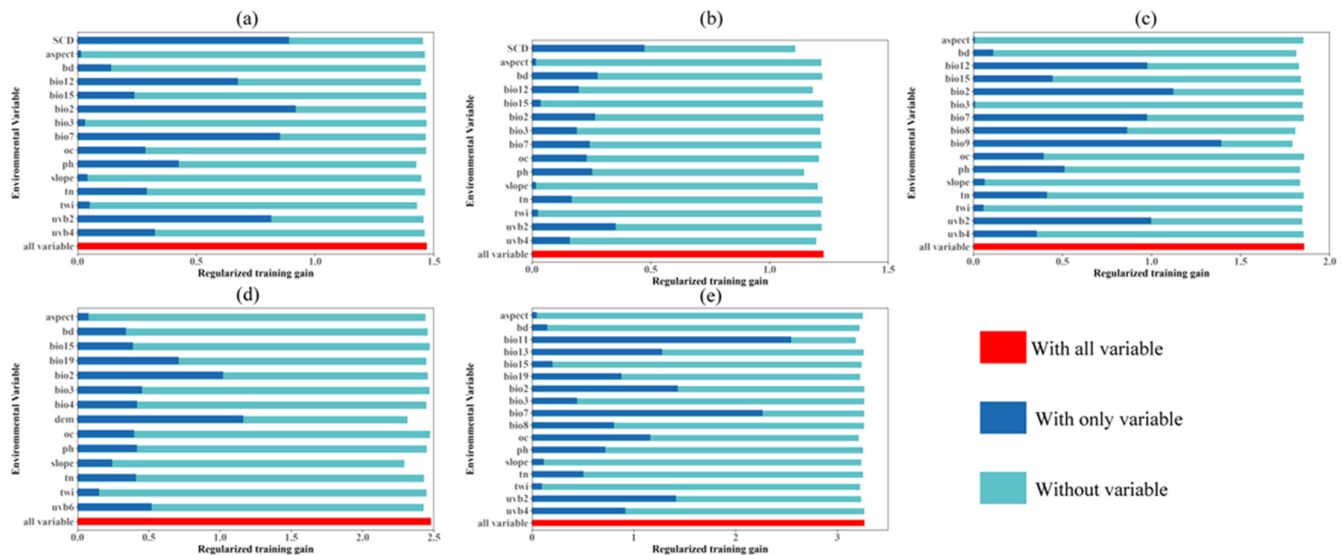


Figure 4. Jackknife test results: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit*, (d) *I. lacunosa*, (e) *I. alba*.

For *I. lacunosa*, elevation, Bio19 (Precipitation of coldest quarter), and slope were the primary predictors. Its occurrence probability decreased with increasing elevation. The response to Bio19 was highest within 50–700 mm, reaching a peak probability of approximately 0.85 at 150 mm. The suitable slope range was 0–5°, with the highest occurrence probability (approximately 0.70) at 0°.

The distribution of *I. alba* was primarily associated with Bio11 (Mean Temperature of Coldest Quarter), OC (soil organic carbon), and Bio7. Its occurrence probability increased with Bio11 and OC, whereas a decreasing trend was observed with increasing Bio7.

3.3. Potential Distribution Under Current Climatic Circumstances

Using the results from MaxEnt predictions, potentially suitable habitat patterns for five invasive *Ipomoea* species in the current period were obtained (Figure 5).

I. nil was mainly distributed in southern and southwestern China, particularly across Chongqing, Guangxi, and Guangdong, with 37.19×10^4 km² of highly suitable habitat extending toward the southeastern coast. *I. purpurea* exhibited the broadest potential distribution, with highly suitable habitats (57.55×10^4 km²) concentrated in Guangxi, Guangdong, Fujian, Taiwan, and southeastern Chongqing, while moderately suitable areas extended toward the middle and lower reaches of the Yangtze River and the Yunnan–Guizhou Plateau. *I. quamoclit* showed a similar southern distribution pattern, with 26.48×10^4 km² of highly suitable habitat mainly occurring in southern China and the southeastern coastal region, and moderately suitable areas extending into central-southern and eastern southwestern China. In contrast, *I. lacunosa* displayed a more localized distribution, with 10.56×10^4 km² of highly suitable habitat concentrated in the middle and lower reaches of the Yangtze River, particularly around eastern Chongqing, northeastern Guizhou, and northern Fujian. *I. alba* had the most restricted potential distribution, with 3.70×10^4 km² of highly suitable habitat primarily located in Hainan and Taiwan, while moderately suitable areas occurred mainly in central Yunnan and southeastern Tibet. Overall, the five species shared a predom-

inantly southern distribution pattern but differed substantially in the extent and spatial configuration of their potential habitats.

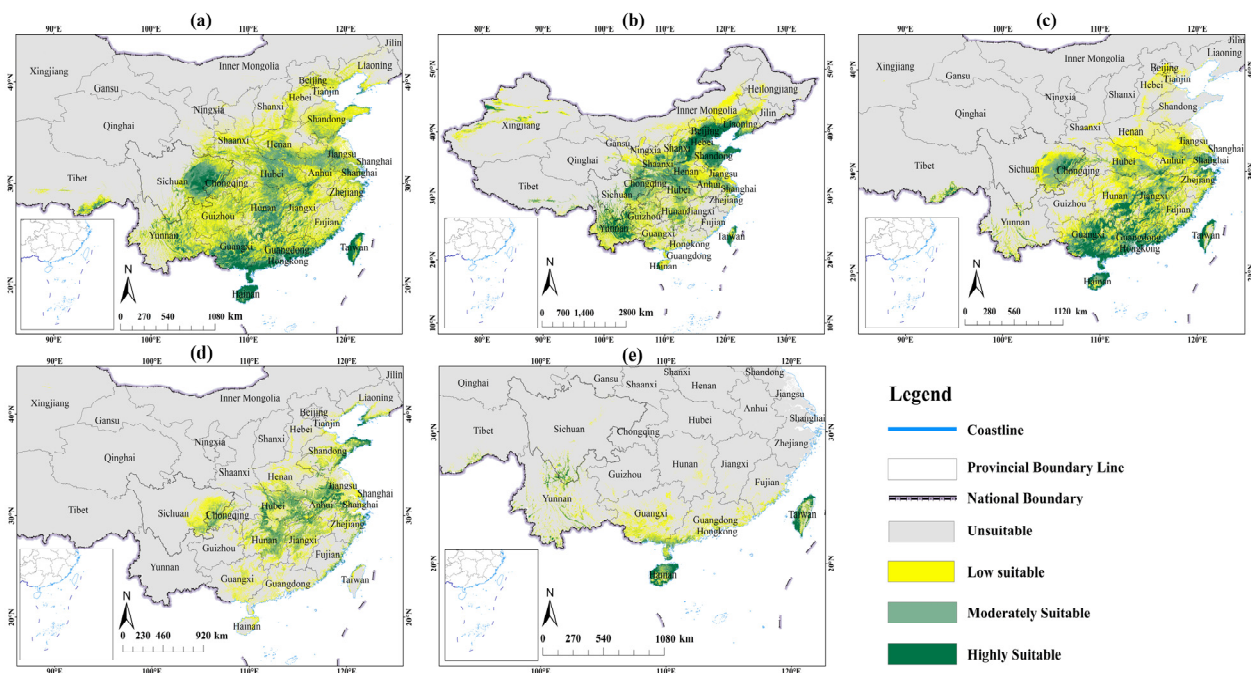


Figure 5. Distribution status of *Ipomoea* species in China: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit*, (d) *I. lacunosa*, (e) *I. alba*.

3.3.1. Potential Habitat of *I. nil* Under Projected Climate Scenarios

Figure 6 and Table 5 show that the potentially suitable area for *I. nil* exhibits different change responses under different climate scenarios in the future. Compared with the current total suitable area (suitability value ≥ 0.4 ; $105.27 \times 10^4 \text{ km}^2$), the total suitable area of *I. nil* was projected to expand under all three future climate scenarios, with the magnitude of expansion increasing over time. Under SSP126, the highly suitable area showed the most pronounced expansion during 2041–2070, reaching $86.48 \times 10^4 \text{ km}^2$, an increase of 132.45% relative to the current period. Under SSP370, the moderately and highly suitable areas continued to expand, resulting in a total suitable area of $181.57 \times 10^4 \text{ km}^2$ by the end of the 21st century, representing a 72.48% increase relative to the current period. Under SSP585, areas with low suitability decreased progressively, with a corresponding shift toward moderate and high suitability levels. Spatially, highly suitable areas were projected to expand primarily toward northern China, the Huai River Basin, and southwestern China, while moderately suitable areas extended toward northeastern and northwestern China.

3.3.2. Potential Habitat of *I. purpurea* Under Projected Climate Scenarios

The MaxEnt projections indicated that the total suitable area of *I. purpurea* generally increased under the three future climate scenarios (Figure 7 and Table 6). The current total suitable area was $140.10 \times 10^4 \text{ km}^2$. It increased progressively under SSP126 and SSP370, whereas SSP585 showed a slight decline during 2011–2040 followed by a marked expansion to $255.84 \times 10^4 \text{ km}^2$ during 2071–2100, representing an 82.61% increase relative to the current period. The highly suitable area reached its greatest increase under SSP370, at $138.71 \times 10^4 \text{ km}^2$ (141.02%), while the moderately suitable area generally expanded over time. The potential range of *I. purpurea* was projected to shift toward northern and western China. Moderately suitable habitats reached the margins of the Qinghai–Tibet Plateau and Inner Mongolia, whereas highly suitable habitats became more extensive across Northeast

China, Northwest China, and inland North China, indicating an increasing potential invasion risk in these regions under future climate scenarios.

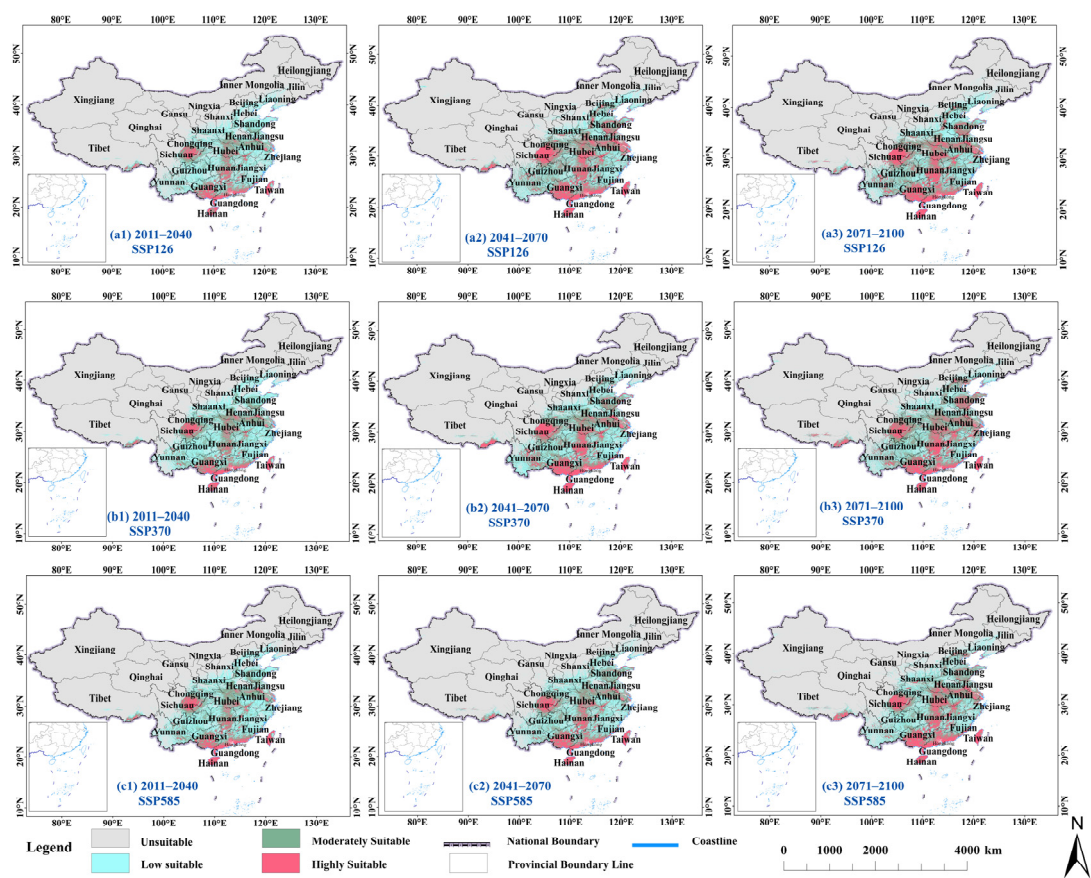


Figure 6. Potentially suitable habitats for *I. nil* across China under projected climate scenarios.

Table 5. Appropriate area of *I. nil* in different periods ($\times 10^4$ km²).

Scenario and Year		Low Suit-ability	Change (%)	Middle Suitability	Change (%)	High Suitability	Change (%)	Total Suit	Change (%)
Reference period	2011–2040	114.61	-	68.08	-	37.19	-	105.27	-
	2041–2070	113.77	−0.73	68.53	0.66	41.66	12.01	110.19	4.67
	2071–2100	100.48	−12.3	91.78	34.81	86.45	132.45 ↑	178.23	69.30
	2071–2100	101.64	−11.31	91.68	34.67	85.50	129.90	177.18	68.31
SSP126	2011–2040	118.52	3.41	81.96	20.39	44.54	19.76	126.50	20.16
	2041–2070	107.21	−6.46	88.15	29.48	77.01	107.07	165.16	56.89
	2071–2100	97.18	−15.21 ↓	97.66	43.45	83.92	125.65	181.57	72.48
SSP370	2011–2040	118.07	3.02	79.84	17.27	44.30	19.12	124.14	17.92
	2041–2070	107.76	−5.98	82.94	21.83	59.15	59.05	142.09	34.97
	2071–2100	106.11	−7.42	86.59	27.19	78.17	110.19	164.76	56.51

Note: “Change (%)” shows the percentage change in the appropriate region relative to the current time. ‘↑’ indicates the greatest growth, whereas ‘↓’ indicates the maximum reduction.

3.3.3. Potential Habitat of *I. quamoclit* Under Projected Climate Scenarios

I. quamoclit suitable areas consistently expanded under all three future climate scenarios (Figure 8 and Table 7). The highly suitable area of *I. quamoclit* increased markedly under SSP126 and SSP370, particularly under SSP370, reaching 65.40×10^4 km² during 2041–2070, an increase of 146.97%, with moderately suitable areas simultaneously expanding over time. By contrast, SSP585 showed an initial decline in total suitable area, with the largest reduction occurring in the moderately suitable area during 2011–2040 (31.70×10^4 km²;

–25.05%), followed by a gradual recovery and increase in total suitable area over the subsequent periods. The potential distribution was projected to shift toward northern and western China, with highly suitable habitats extending into North China, the Huang Huai region, and southwestern China, and moderately suitable habitats reaching further northwest and northeast.

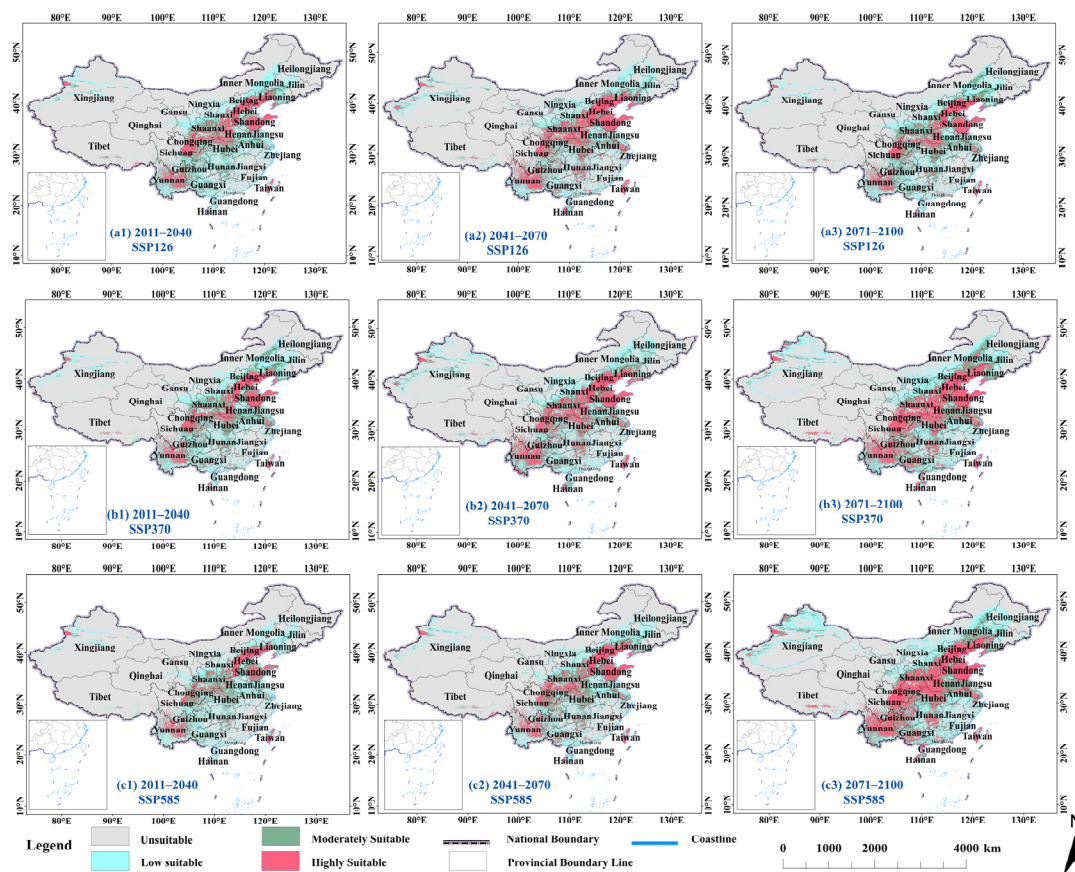


Figure 7. Potentially suitable habitats for *I. purpurea* across China under projected climate scenarios.

Table 6. Appropriate area of *I. purpurea* in different periods ($\times 10^4$ km²).

Period	Low Suitability	Change (%)	Middle Suitability	Change (%)	High Suitability	Change (%)	Total Suitability	Change (%)
Reference period	126.73	-	82.55	-	57.55	-	140.10	-
SSP126	2011–2040	4.82	83.32	0.93	76.99	33.78	160.31	12.60
	2041–2070	4.31	82.53	−0.03	113.23	96.75	195.76	39.72
	2071–2100	−3.79	92.23	11.72	77.64	34.90	169.87	21.24
SSP370	2011–2040	−1.02	83.15	0.72	77.29	34.31	160.44	14.51
	2041–2070	9.89	89.48	8.39	111.72	94.13	201.20	43.61
	2071–2100	13.95	98.37	19.16	138.71	141.02	237.07	69.21
SSP585	2011–2040	−9.04	74.57	−9.67 ↓	57.82	0.47	132.39	−5.50
	2041–2070	−6.76	80.05	−3.03	83.80	45.61	163.85	16.95
	2071–2100	25.33	104.48	26.55	151.36	163.01 ↑	255.84	82.61

Note: “Change (%)” shows the percentage change in the appropriate region relative to the current time. ‘↑’ indicates the greatest growth, whereas ‘↓’ indicates the maximum reduction.

3.3.4. Potential Habitat of *I. lacunosa* Under Projected Climate Scenarios

Compared with the current total suitable area (31.16×10^4 km²), *I. lacunosa* is projected to initially decline before expanding rapidly under future climate scenarios (Figure 9 and Table 8). During 2011–2040, all suitability classes declined across the three scenarios, with

the largest reduction in moderately suitable area under SSP585 ($12.03 \times 10^4 \text{ km}^2$; -40.02%). The suitable areas subsequently recovered and expanded, with the most pronounced increase in highly suitable habitat under SSP370 during 2071–2100, reaching $69.41 \times 10^4 \text{ km}^2$, an increase of 557.21%. Future warming is projected to improve habitat suitability for *I. lacunosa*, expanding its potential distribution and increasing its invasion potential. Geographically, highly suitable habitats were projected to shift mainly northward, while moderately suitable habitats extended toward northwestern and southwestern China and low-suitability areas reached farther into northern and northwestern regions.

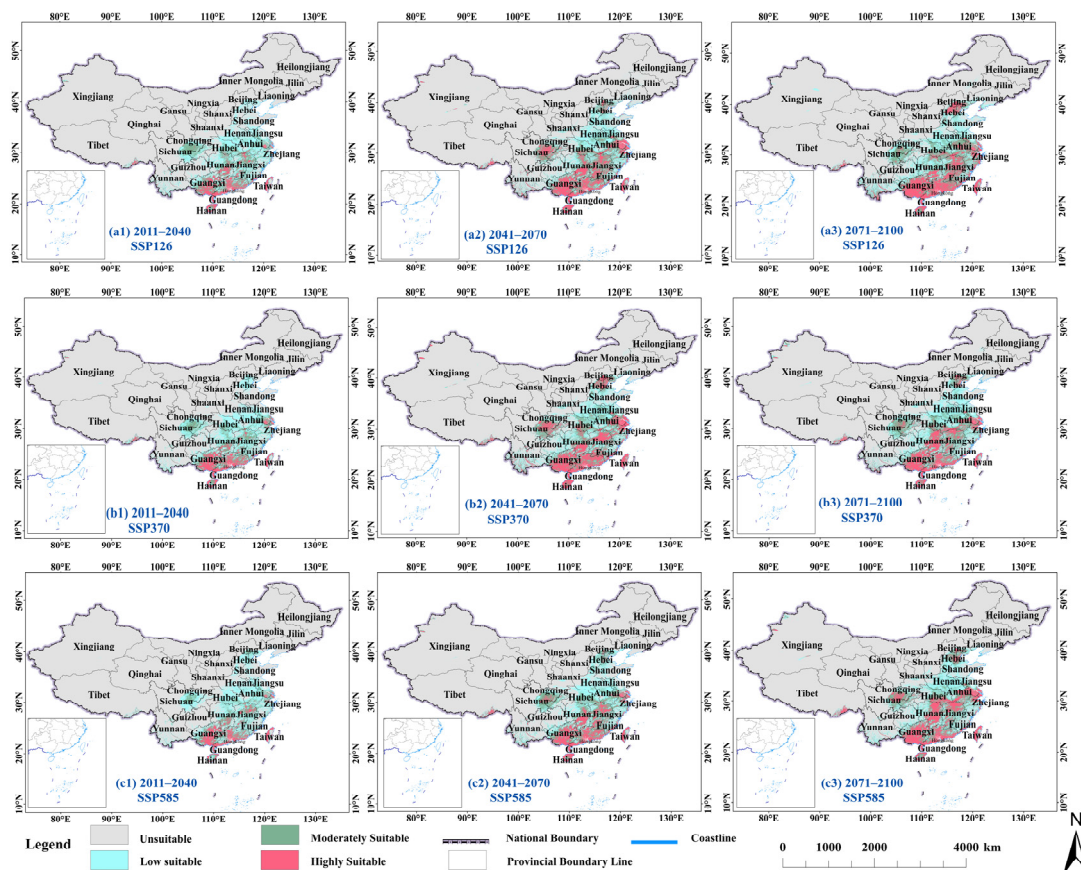


Figure 8. Potentially suitable habitats for *I. quamoclit* across China under projected climate scenarios.

Table 7. Appropriate area of *I. quamoclit* in different periods ($\times 10^4 \text{ km}^2$).

Period	Low Suitability	Change (%)	Middle Suitability	Change (%)	High Suitability	Change (%)	Total Suitability	Change (%)
Reference period	71.44	-	42.29	-	26.48	-	68.77	-
SSP126	2011–2040	80.85	13.17	43.41	2.64	25.78	69.19	0.61
	2041–2070	76.60	7.22	55.18	30.47	58.28	113.46	64.98
	2071–2100	76.07	6.47	60.79	43.74	63.11	123.90	80.16
SSP370	2011–2040	74.81	4.72	37.66	-10.96	26.29	63.95	-7.00
	2041–2070	75.10	5.12	56.69	34.04	65.40	122.09	77.53
	2071–2100	80.14	12.17	54.60	29.1	52.73	107.32	56.05
SSP585	2011–2040	77.52	8.5	31.70	$-25.05 \downarrow$	21.77	53.47	-22.24
	2041–2070	75.41	5.56	52.25	23.55	40.74	93.00	24.23
	2071–2100	77.11	7.94	52.57	24.31	58.67	111.24	61.75

Note: “Change (%)” shows the percentage change in the appropriate region relative to the current time. ‘↑’ indicates the greatest growth, whereas ‘↓’ indicates the maximum reduction.

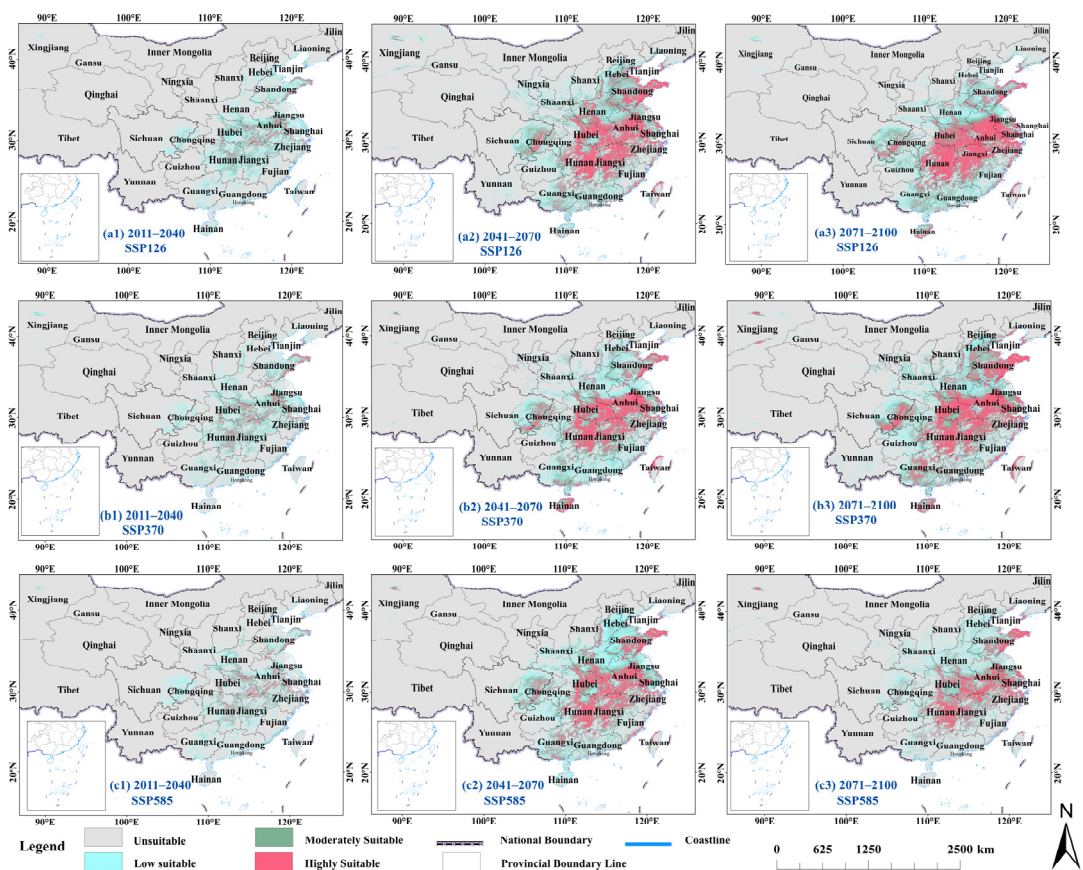


Figure 9. Potentially suitable habitats for *I. lacunosa* across China under projected climate scenarios.

Table 8. Appropriate area of *I. lacunosa* in different periods ($\times 10^4$ km²).

Period	Low Suit-ability	Change (%)	Middle Suitability	Change (%)	High Suitability	Change (%)	Total Suit-ability	Change (%)	
Reference period	47.46	-	20.06	-	10.56	-	30.62	-	
SSP126	2011–2040	44.72	−5.79	15.88	−20.84	6.55	−37.99	22.43	−28.01
	2041–2070	69.11	45.62	42.31	110.91	60.39	471.79	102.70	229.58
	2071–2100	59.31	24.95	37.85	88.68	59.77	465.99	97.62	213.28
SSP370	2011–2040	41.50	−12.56	16.51	−17.69	9.20	−12.87	25.71	−17.49
	2041–2070	64.07	34.99	35.72	78.06	50.58	378.98	86.30	176.95
	2071–2100	68.42	44.16	47.11	134.83	69.41	557.21 ↑	116.52	273.94
SSP585	2011–2040	36.65	−22.78	12.03	−40.02 ↓	8.83	−16.37	20.87	−33.02
	2041–2070	66.18	39.44	38.20	90.41	47.57	350.42	85.77	175.25
	2071–2100	53.74	13.22	27.53	37.23	37.51	255.14	65.03	108.69

Note: “Change (%)” shows the percentage change in the appropriate region relative to the current time. ‘↑’ indicates the greatest growth, whereas ‘↓’ indicates the maximum reduction.

3.3.5. Potential Habitat of *I. alba* Under Projected Climate Scenarios

Compared with the current total suitable area (7.92×10^4 km²), *I. alba* was projected to expand rapidly after an initial fluctuation under future climate scenarios (Figure 10 and Table 9). From 2011 to 2040, low suitability areas increased markedly, while moderately suitable areas expanded to varying degrees. In contrast, highly suitable areas declined slightly under SSP126 and SSP370 and more substantially under SSP585 (2.88×10^4 km²; −22.39%). From 2041 onward, all suitability classes increased rapidly, with the most pronounced growth in highly suitable areas under SSP585, reaching 20.44×10^4 km² (451.79%). The total suitable area also increased substantially during the later periods, particularly under SSP585, reaching 38.75×10^4 km² (389.26%). Highly suitable areas

expanded toward inland South China and southwestern China, while moderately and low suitability areas extended northward toward the Yangtze River Basin, indicating a progressive expansion of the suitable range under future climate scenarios.

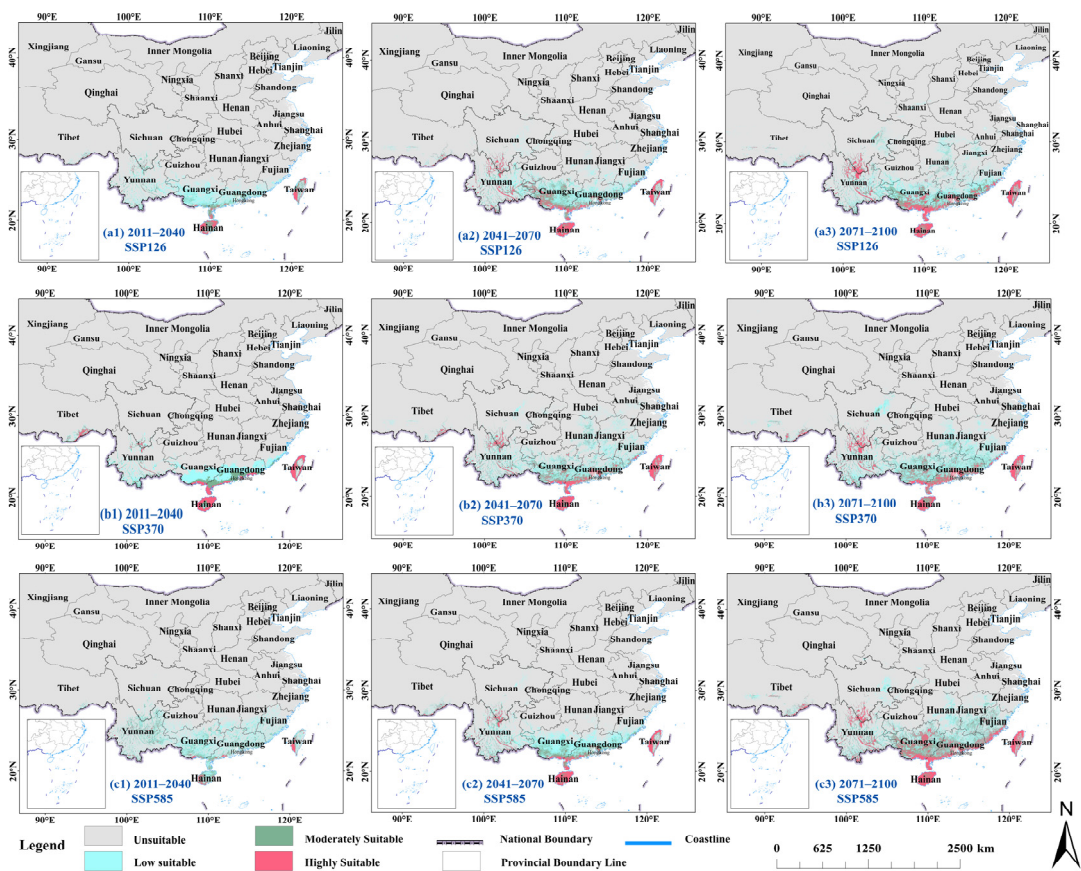


Figure 10. Potentially suitable habitats for *I. alba* across China under projected climate scenarios.

Table 9. Appropriate area of *I. alba* in different periods ($\times 10^4$ km²).

Period	Low Suit-ability	Change (%)	Middle Suitability	Change (%)	High Suitability	Change (%)	Total Suit-ability	Change (%)	
Reference period	12.80	-	4.22	-	3.70	-	7.92	-	
SSP126	2011–2040	19.52	52.52	5.93	40.43	3.43	−7.32	9.06	14.39
	2041–2070	26.78	109.22	12.52	196.41	12.02	224.46	24.54	209.84
	2071–2100	33.02	158.00	13.96	230.41	15.86	328.03	29.82	276.51
SSP370	2011–2040	19.30	50.82	7.28	72.26	8.03	116.63	15.31	93.30
	2041–2070	31.64	147.24	12.15	187.53	13.30	259.07	25.45	221.33
	2071–2100	35.17	174.78	14.90	252.60	14.99	304.71	29.89	277.39
SSP585	2011–2040	27.98	118.64	9.47	124.13	2.88	−22.39 ↓	12.35	55.93
	2041–2070	26.01	103.22	10.17	140.67	8.45	128.19	18.62	135.10
	2071–2100	30.90	141.46	18.31	333.29	20.44	451.79 ↑	38.75	389.26

Note: “Change (%)” shows the percentage change in the appropriate region relative to the current time. ‘↑’ indicates the greatest growth, whereas ‘↓’ indicates the maximum reduction.

3.4. Changes in Centroid Direction and Distance of 5 Plants in Ipomoea

As the climate changes, plant distribution centers adjust according to shifts in suitable habitat areas. Therefore, we plotted the migration patterns of the centroids of five potential distributions in *Ipomoea* (Figures 11–15 and Table S2).

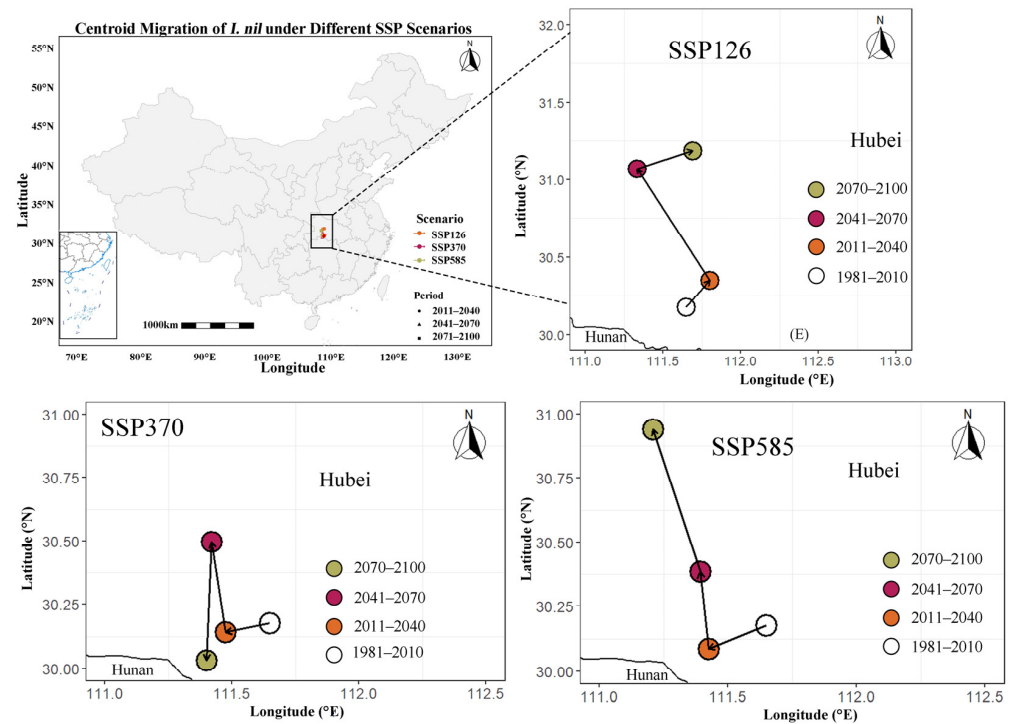


Figure 11. Changes in the distribution of *I. nil*'s total appropriate habitat centroids under various warming scenarios.

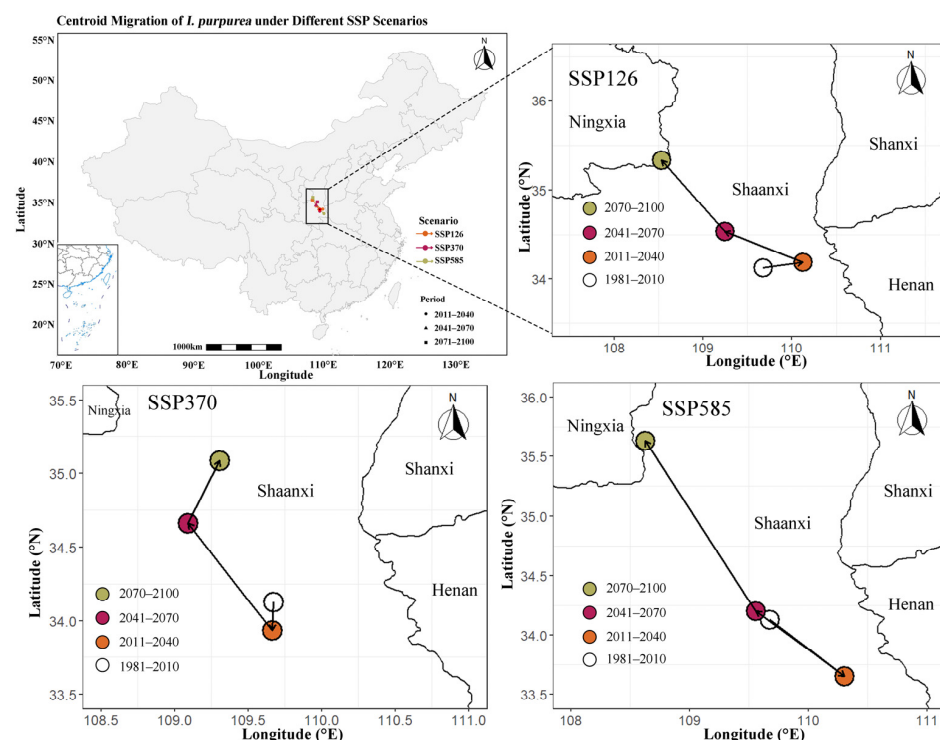


Figure 12. Changes in the distribution of *I. purpurea*'s total appropriate habitat centroids under various warming scenarios.

For *I. nil* (Figure 11), the current centroid was located in Yuan'an County, Hubei Province ($111^{\circ}38'56.4''$ E, $30^{\circ}10'33.6''$ N). Under SSP126, it shifted northeastward by 24.25 km during 2011–2040, northwestward by 91.71 km during 2041–2070, and northeastward by 36.42 km thereafter, remaining within Yuan'an and Nanzhang counties ($111^{\circ}41'27.6''$ E, $31^{\circ}11'16.8''$ N). Under SSP370, the centroid moved southwestward by

17.15 km, northwestward by 39.86 km, and southwestward by 51.55 km across the three periods, with the final position in Zhijiang City ($111^{\circ}24'3.6''$ E, $30^{\circ}1'55.2''$ N). Under SSP585, it shifted southwestward by 23.79 km, northwestward by 33.16 km, and northwestward by 64.97 km, ultimately reaching Nanzhang County ($111^{\circ}12'32.4''$ E, $30^{\circ}56'24''$ N). The largest displacement occurred under SSP585.

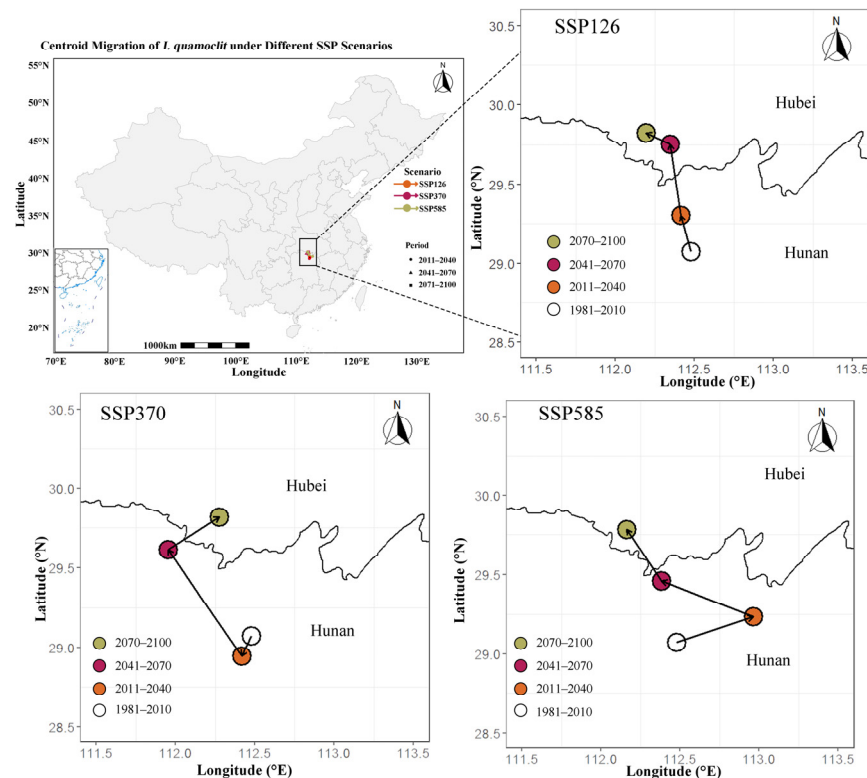


Figure 13. Changes in the distribution of *I. quamoclit*'s total appropriate habitat centroids under various warming scenarios.

The centroid of *I. purpurea* (Figure 12) was initially located in northeastern Yijun County, Shaanxi Province ($109^{\circ}40'26.4''$ E, $34^{\circ}7'48''$ N), but its subsequent trajectory differed substantially among scenarios. Under SSP126, it moved northeastward by 42.27 km before shifting northwestward by 89.83 and 110.53 km during the subsequent periods, ultimately reaching Haiyuan County, Ningxia Hui Autonomous Region ($108^{\circ}32'9.6''$ E, $35^{\circ}19'55.2''$ N). The SSP370 trajectory consisted of a southward shift of 21.68 km, followed by northwestward and northeastward movements of 96.35 and 50.86 km, respectively, ending in Fuxian County, Shaanxi Province ($109^{\circ}39'54''$ E, $33^{\circ}56'2.4''$ N). Under SSP585, the centroid first shifted southeastward by 78.95 km and then northwestward by 92.32 and 179.82 km, with its final position near the Ningxia–Shaanxi border ($108^{\circ}37'26.4''$ E, $35^{\circ}37'48''$ N).

Figure 13 shows the centroid shifts of the potential distribution of *I. quamoclit* under different climate scenarios, with the present centroid located in Yiyang County, Hunan Province ($112^{\circ}28'44.4''$ E, $29^{\circ}4'26.4''$ N). A predominantly northwestward trajectory was observed across all three scenarios. Under SSP126, the centroid moved northwestward by 26.16, 50.49, and 16.76 km over the three periods, respectively, ultimately reaching Songzi City, Hubei Province ($112^{\circ}11'42''$ E, $29^{\circ}49'37.2''$ N). The SSP370 pathway began with a southwestward shift of 15.31 km, followed by northwestward movements of 86.64 and 38.75 km, ending in Gong'an County, Hubei Province ($112^{\circ}16'33.6''$ E, $29^{\circ}49'8.4''$ N). In the SSP585 scenario, an initial northeastward displacement of 50.46 km was followed by northwestward shifts of 61.41 and 41.85 km, also resulting in a final position in Gong'an County ($112^{\circ}9'43.2''$ E, $29^{\circ}46'58.8''$ N).

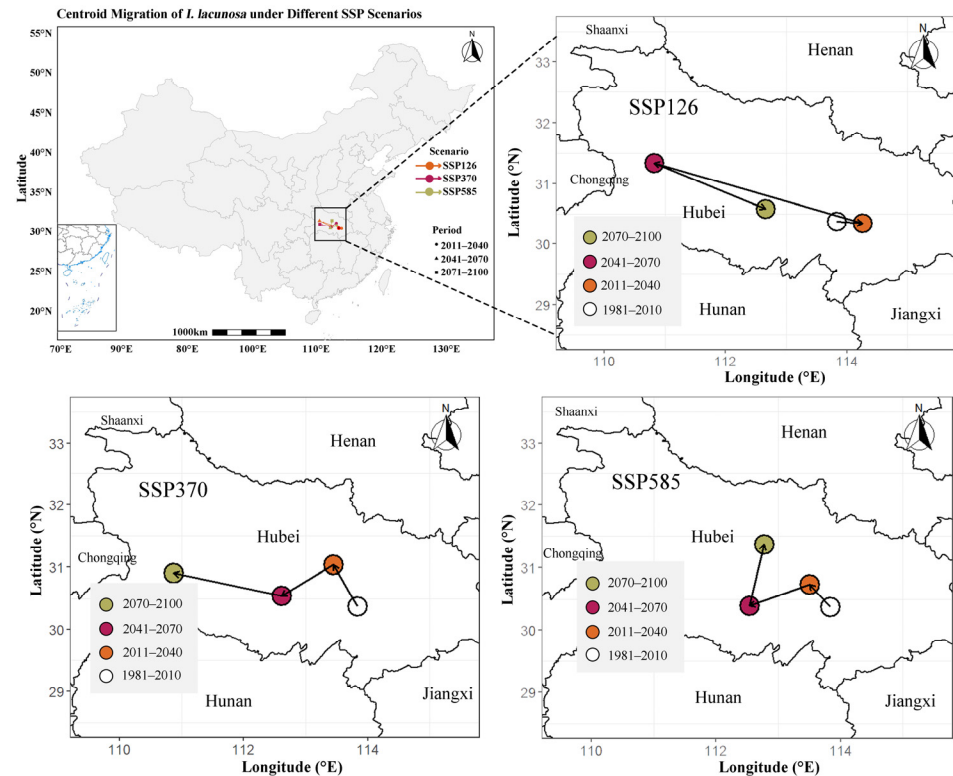


Figure 14. Changes in the distribution of *I. lacunosa*'s total appropriate habitat centroids under various warming scenarios.

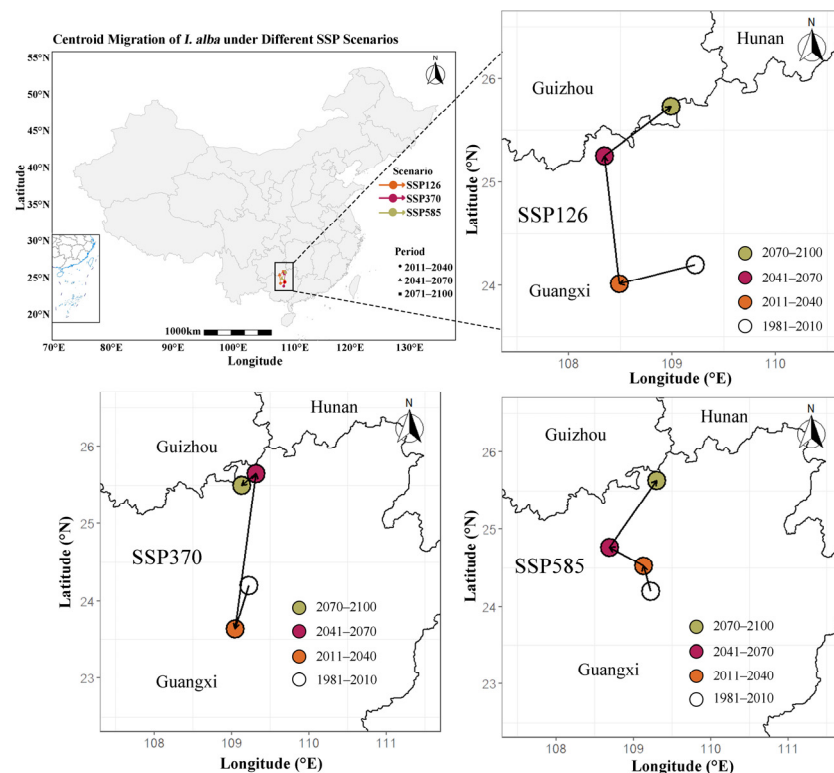


Figure 15. Changes in the distribution of *I. alba*'s total appropriate habitat centroids under various warming scenarios.

For *I. lacunosa* (Figure 14), the centroid during the baseline period was located in Huangpi District, Hubei Province (113°50'0" E, 30°22'8.4" N). Under SSP126, the centroid shifted eastward by 41.61 km, followed by a northwestward displacement of 347.11 km

and a subsequent southeastward shift of 196.40 km, ultimately reaching Xiangzhou District ($112^{\circ}39'39.6''$ E, $30^{\circ}35'2.4''$ N). Under SSP370, it moved northwestward by 82.59 km, southwestward by 97.24 km, and northwestward by 171.03 km, with the final position near Zigui County ($110^{\circ}52'16.6''$ E, $30^{\circ}54'7.2''$ N). Under SSP585, the centroid first shifted northeastward by 51.54 km, then southwestward by 99.83 km, and finally northeastward by 110.97 km, ending in Suizhou City ($112^{\circ}46'30''$ E, $31^{\circ}22'4.8''$ N).

Figure 15 indicates that the centroid of the potential distribution of *I. alba* is currently located in Liujiang District, Guangxi ($109^{\circ}13'15.6''$ E, $24^{\circ}12'7.2''$ N). Its migration pathway varied in both direction and magnitude among the future scenarios. The centroid under SSP126 moved southwestward by 77.98 km, northwestward by 137.95 km, and northeastward by 83.74 km, ultimately reaching Qianxinan Buyi and Miao Autonomous Prefecture, Guizhou ($108^{\circ}59'16.8''$ E, $25^{\circ}43'55.2''$ N). Under SSP370, the trajectory comprised southwestward, northeastward, and southwestward movements of 65.25, 224.51, and 25.06 km, respectively, with the final position in Luzhai County, Guangxi ($109^{\circ}7'44.4''$ E, $25^{\circ}29'49.2''$ N). Under SSP585, the centroid shifted northwestward by 37.06 and 51.67 km during the first two periods, followed by a northeastward displacement of 113.55 km and a final position in Rongshui Miao Autonomous County ($109^{\circ}17'56.4''$ E, $25^{\circ}38'6''$ N).

4. Discussion

4.1. Key Factors Analysis

Overall, the potential distributions of the five invasive *Ipomoea* species were primarily associated with temperature and precipitation, with additional effects of snow cover, soil properties, and topographic conditions. Temperature-related variables, including Bio7, Bio9, and Bio11, were important predictors for several species. These variables can influence thermal tolerance, metabolic activity, and the length of the growing season, thereby affecting the establishment and persistence of *Ipomoea* species along temperature gradients [57,58]. The species-specific responses further suggest that thermal conditions may impose different constraints among species. For example, the positive response of *I. quamoclit* to Bio9 indicates that warmer conditions during the driest quarter may favor its occurrence, whereas the positive response of *I. alba* to Bio11 suggests that warmer conditions during the coldest quarter may alleviate low-temperature constraints on this species. Precipitation was another important factor shaping the potential distributions of *Ipomoea* species. Bio12 (annual precipitation) and Bio19 (precipitation of the coldest quarter) influence water availability and habitat suitability at broad spatial scales [59]. Notably, Bio12 made relatively high contributions to the distributions of *I. purpurea* and *I. quamoclit*, although both species showed broad response ranges to annual precipitation. This broad response may be related to their tropical origins, strong environmental adaptability, and ecological plasticity, which enable them to establish across diverse habitats and tolerate substantial variation in precipitation. Thus, annual precipitation may not impose a narrow ecological limit on these species. However, spatial variation in precipitation can still influence regional water availability and interact with temperature, soil moisture, and topographic conditions to shape habitat suitability [60]. Therefore, the broad precipitation response of *I. purpurea* and *I. quamoclit* does not preclude the contribution of Bio12 to their potential distributions. Snow cover can alter soil temperature, moisture, and the timing of seasonal warming, thereby affecting plant phenology, germination, growth, and overwinter survival [61,62]. For tropical and subtropical invasive *Ipomoea* species that are generally sensitive to low temperatures, prolonged snow cover may delay the growing season, restrict germination and early growth, and increase cold stress, thereby limiting their establishment and persistence in colder regions. Soil properties, particularly organic carbon and pH, may

further influence habitat suitability by affecting microbial activity, nutrient availability, and soil conditions, thereby contributing to plant growth and establishment [63]. Topographic factors such as elevation and slope may also indirectly shape *Ipomoea* distributions by modifying local temperature, moisture, and other environmental conditions [64].

4.2. Range Expansion in Five Invasive *Ipomoea* Species

Compared with the baseline period (1981–2010), the projected expansion of suitable habitats under future climate scenarios suggests that climate change may progressively reduce the climatic constraints on the establishment of invasive *Ipomoea* species in regions that are currently less suitable. The overall increase in suitable areas, particularly under higher-emission scenarios and later periods, indicates that warming may provide broader opportunities for these species to establish beyond their current distribution ranges. The tendency for suitable habitats and distribution centroids to extend toward higher latitudes further suggests a potential northward shift in invasion risk. However, the magnitude and direction of these changes varied among species and climate scenarios, indicating that the effects of future climate change are unlikely to be uniform across the five *Ipomoea* species.

The future expansion of suitable habitats for *Ipomoea* species may result from the combined effects of climate warming and their ecological characteristics. As temperatures increase and precipitation patterns change, areas previously constrained by low temperatures or unfavorable climatic conditions may gradually become more suitable for the establishment and persistence of these species. This shift may be particularly pronounced for *Ipomoea* species originating from tropical and subtropical regions, where relatively warm climatic conditions prevail. Their preference for warm environments, together with their strong growth and reproductive capacities, may further facilitate population establishment and spread as climatic conditions become increasingly favorable, thereby promoting the expansion of their potential distribution ranges [65]. However, the continued expansion of suitable habitats for *Ipomoea* species may increase their opportunities to establish and spread in agricultural areas. Owing to their rapid growth and climbing characteristics, these species can quickly occupy the growing space of crops and compete with crops for light, water, and soil nutrients, thereby potentially impairing crop growth and reducing crop yields [66,67]. Meanwhile, the expansion of their populations may increase the difficulty of removal and routine management in agricultural fields, consequently increasing the labor and economic inputs required for invasive species control [68]. Beyond agricultural production, the establishment of *Ipomoea* species in new ecological areas may also alter the spatial structure of existing vegetation and patterns of resource use, thereby disrupting energy flow and nutrient cycling within ecosystems. According to Bajahmoum's study, the growth may also change the microhabitat conditions and soil nutrient cycling, which would threaten the stability of the ecosystem [69]. As their suitable habitats continue to extend toward higher latitudes and elevations, ecologically fragile areas such as mountainous regions and ecological transition zones may face increasing invasion pressure, potentially making ecosystem maintenance and recovery more difficult [70,71]. Overall, climate change may not only expand the potential distribution ranges of *Ipomoea* species but also extend their potential impacts on agricultural production and ecosystems.

The differences in future range expansion among the five *Ipomoea* species may reflect interspecific differences in climatic niche breadth and environmental tolerance. Species with broader ecological niches can generally tolerate a wider range of climatic conditions and are less constrained by individual environmental factors, thereby having greater potential for spatial expansion as climatic conditions change [72]. In contrast, species that are more dependent on specific temperature, precipitation, or other environmental conditions may experience stronger environmental constraints on their suitable habitats and consequently

show more limited responses to future climate change [73]. In this study, the relatively broad potential distributions of *I. purpurea* and *I. nil* may be associated with their wider environmental tolerance, allowing them to occupy a larger potential suitable area. In comparison, the relatively limited suitable ranges of *I. lacunosa* and *I. alba* suggest that their future distributional changes may be more strongly constrained by specific environmental conditions. These findings indicate that the effects of climate change on invasive *Ipomoea* species are not uniform, and that species-specific niche characteristics may be an important factor contributing to differences in their future range expansion.

Existing distribution records of *Ipomoea* species were mainly concentrated in parts of eastern, central-southern, and southwestern China [74,75]. These areas showed a high degree of spatial overlap with the potential suitable habitats predicted by the current model, indicating that the model could effectively identify areas with concentrated existing invasion records. Under future climate scenarios, the potential suitable habitats of the five *Ipomoea* species are expected to remain mainly concentrated in warm and humid regions, including the middle and lower reaches of the Yangtze River, southern China, southwestern China, and the southeastern coastal region, while gradually expanding toward northwestern and northern China, northeastern China, and inland areas. Therefore, future management should strengthen population removal and source control in core suitable areas such as the middle and lower reaches of the Yangtze River, southern China, and southwestern China, while enhancing monitoring and early warning in newly suitable areas in northern, central, and inland regions. In addition, species-specific management strategies should be implemented.

4.3. Research Limitations

This study used the MaxEnt model to predict the potential distributions of five invasive *Ipomoea* species under different climate scenarios. However, MaxEnt mainly considers environmental factors and cannot fully account for biotic interactions. For example, changes in pollinator populations and distributions may affect the reproduction and spread of *I. purpurea*, *I. nil*, and *I. quamoclit*. In addition, differences in sampling times, changes in temperature and species distributions, and the spatial resolution of environmental data may affect prediction accuracy. The relatively limited occurrence records for *I. lacunosa* and *I. alba* may also introduce some uncertainty. Future studies should incorporate more biotic factors, long-term distribution data, and higher-resolution environmental data to improve prediction reliability.

5. Conclusions

The results showed that bioclimatic variables (SCD, Bio9, and Bio11) were the main influencing factors for the expansion of the potential suitable areas of the five invasive *Ipomoea* species in China. Under future climate change scenarios, the potential suitable areas of the five invasive *Ipomoea* species are projected to expand to varying degrees, with the extent of expansion generally increasing under higher-emission scenarios and longer projection periods. The potential suitable areas are mainly concentrated in the middle and lower reaches of the Yangtze River, southern China, southwestern China, and the southeastern coastal regions, while gradually expanding toward eastern, northern, central, and northwestern China. Meanwhile, with climate warming, the potential distribution centroids of the five species are generally projected to shift northward or toward higher elevations. These findings can provide a spatial basis for monitoring and early control in key agricultural areas, quarantine and risk management of invasive species, and regional management, while helping to reduce potential impacts on native plant diversity and community structure and maintain ecosystem resilience.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agronomy16181763/s1>, Figure S1: Overview of the study workflow. Figure S2: Optimized Maxent model parameters: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit* (Note: If the sample size of *I. lacunosa* and *I. alba* is less than 80, the default mode will be used). Figure S3: Response curves of major environmental factors for each species: (a) *I. nil*, (b) *I. purpurea*, (c) *I. quamoclit*, (d) *I. lacunosa*, (e) *I. alba*. Table S1: Correlation Matrix of 34 Environmental Variables (When the correlation between two factors is greater than 0.8, only the factor with higher importance is taken). Table S2: Distribution centroids and centroid migration distances of 5 *Ipomoea* plants under.

Author Contributions: Z.W. (Zhengxuan Wei): Method research; Learning software; Data visualization; Article writing. Y.W.: Supervision; Review and edit; Data collection. W.C.: Supervision; Data interpretation; J.R.: Data collection; Data management. Z.W. (Zhijia Wang): Data collection; R language learning; Data management. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The processed results presented in this study are included in the article and its Supplementary Materials. The occurrence records for the five invasive *Ipomoea* species were obtained from the Global Biodiversity Information Facility (GBIF; <https://www.gbif.org/>, accessed on 20 October 2025), the Chinese Information System on Invasive Alien Species (<https://www.iplant.cn/ias/>, accessed on 18 October 2025), and the Chinese Virtual Herbarium (CVH; <https://www.cvh.ac.cn/>, accessed on 22 October 2025). The environmental input data were obtained from the CHELSA database (<https://chelsa-climate.org/>, accessed on 5 September 2026), the SoilGrids database (<https://soilgrids.org/>, accessed on 29 October 2025), the Geospatial Data Cloud (<https://www.gscloud.cn/>, accessed on 28 October 2025), and the Global UV-B Radiation Database (<http://www.ufz.de/gluw/>, accessed on 28 October 2025). Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Fachinello, M.C.; Romero, J.H.C.; de Castro, W.A.C. Defining invasive species and demonstrating impacts of Biological invasions: A scientometric analysis of studies on invasive alien plants in Brazil over the past 20 years. *NeoBiota* **2022**, *76*, 13–24. [CrossRef]
2. Haubrock, P.J.; Soto, I.; Ahmed, D.A.; Ansari, A.R.; Tarkan, A.S.; Kurtul, I.; Macêdo, R.L.; Lázaro-Lobo, A.; Toutain, M.; Parker, B.; et al. Biological invasions are a population-level rather than a species-level Phenomenon. *Glob. Change Biol.* **2024**, *30*, e17312. [CrossRef] [PubMed]
3. Manzoor, S.A.; Griffiths, G.; Lukac, M. Land use and climate change interaction triggers contrasting trajectories of biological invasion. *Ecol. Indic.* **2021**, *120*, 106936. [CrossRef]
4. Turbelin, A.J.; Cuthbert, R.N.; Essl, F.; Haubrock, P.J.; Ricciardi, A.; Courchamp, F. Biological invasions are as costly as natural hazards. *Perspect. Ecol. Conserv.* **2023**, *21*, 143–150. [CrossRef]
5. Hudgins, E.J.; Cuthbert, R.N.; Haubrock, P.J.; Taylor, N.G.; Kourantidou, M.; Nguyen, D.; Bang, A.; Turbelin, A.J.; Moodley, D.; Briski, E.; et al. Unevenly distributed biological invasion costs among origin and recipient regions. *Nat. Sustain.* **2023**, *6*, 1113–1124. [CrossRef]
6. Mungi, N.A.; Jhala, Y.V.; Svenning, J.C.; Qureshi, Q. Socioecological risks amplified by rising plant invasions in India. *Nat. Sustain.* **2026**, *9*, 130–141. [CrossRef]
7. Jiao, X.; Xie, W.; Wang, S.; Wu, Q.; Zhou, L.; Pan, H.; Liu, B.; Zhang, Y. Host preference and nymph performance of B and Q putative species of *Bemisia tabaci* on three host plants. *J. Pest Sci.* **2012**, *85*, 423–430. [CrossRef]
8. Li, Z.; Tao, J.; Zong, S. Cold tolerance in pinewood nematode *Bursaphelenchus xylophilus* promoted multiple invasion events in mid-temperate zone of China. *Forests* **2022**, *13*, 1100. [CrossRef]
9. Xie, X.; Ma, T.; Chen, Y.; Zhuo, J.; Chen, S.; Kang, T.; Hao, M.; Ding, F.; Jiang, D. Modeling the potential invasion risk of *Ageratina adenophora* in China from an ecological suitability perspective. *Ecol. Evol.* **2025**, *15*, e72392. [CrossRef] [PubMed]
10. Xu, H.; Ding, H.; Li, M.; Qiang, S.; Guo, J.; Han, Z.; Huang, Z.; Sun, H.; He, S.; Wu, H.; et al. The distribution and economic losses of alien species invasion to China. *Biol. Invasions* **2006**, *8*, 1495–1500. [CrossRef]
11. Diagne, C.; Leroy, B.; Vaissière, A.C.; Gozlan, R.E.; Roiz, D.; Jarić, I.; Salles, J.-M.; Bradshaw, C.J.A.; Courchamp, F. High and rising economic costs of biological invasions worldwide. *Nature* **2021**, *592*, 571–576. [CrossRef] [PubMed]

12. Fantle-Lepczyk, J.E.; Haubrock, P.J.; Kramer, A.M.; Cuthbert, R.N.; Turbelin, A.J.; Crystal-Ornelas, R.; Diagne, C.; Courchamp, F. Economic costs of biological invasions in the United States. *Sci. Total Environ.* **2022**, *806*, 151318. [[CrossRef](#)] [[PubMed](#)]
13. Li, Y.; Zhang, J.; Zhang, J.; Du, J.; Yang, R.; Niu, M.; Li, Y. The high economic cost of biological invasions in China. *J. Environ. Manag.* **2025**, *389*, 126224. [[CrossRef](#)] [[PubMed](#)]
14. Dai, Z.C.; Zhu, B.; Wan, J.S.; Rutherford, S. Global changes and plant invasions. *Front. Ecol. Evol.* **2022**, *10*, 845816. [[CrossRef](#)]
15. Hartl, T.; Srivastava, V.; Prager, S.; Wist, T. Evaluating climate change scenarios on global pea aphid habitat suitability using species distribution models. *Clim. Change Ecol.* **2024**, *7*, 100084. [[CrossRef](#)]
16. Hoshino, A.; Jayakumar, V.; Nitasaka, E.; Toyoda, A.; Noguchi, H.; Itoh, T.; Shin-I, T.; Minakuchi, Y.; Koda, Y.; Nagano, A.J.; et al. Genome sequence and analysis of the Japanese morning glory *Ipomoea nil*. *Nat. Commun.* **2016**, *7*, 13295. [[CrossRef](#)] [[PubMed](#)]
17. Sudmoon, R.; Kaewdaungdee, S.; Ho, H.X.; Lee, S.Y.; Tanee, T.; Chaveerach, A. The chloroplast genome sequences of *Ipomoea alba* and *I. obscura* (Convolvulaceae): Genome comparison and phylogenetic analysis. *Sci. Rep.* **2024**, *14*, 14078. [[CrossRef](#)] [[PubMed](#)]
18. Hao, Q.; Ma, J.S. Invasive alien plants in China: An update. *Plant Divers.* **2023**, *45*, 117–121. [[CrossRef](#)] [[PubMed](#)]
19. Chen, M.; Cai, M.; Xiang, P.; Qin, Z.; Peng, C.; Li, S. Thermal adaptation of photosynthetic physiology of the invasive vine *Ipomoea cairica* (L.) enhances its advantage over native *Paederia scandens* (Lour.) Merr. in South China. *Tree Physiol.* **2023**, *43*, 575–586. [[CrossRef](#)] [[PubMed](#)]
20. Ihara, N.; Kobayashi, H. Populations of *Ipomoea hederacea* var. *integriuscula* in field margins are maintained by seed production of individuals from a specific cohort. *Agronomy* **2022**, *12*, 2392. [[CrossRef](#)]
21. Webster, T.M. Weed survey-southern states: Broadleaf crops subsection. *Proc. South. Weed Sci. Soc.* **2001**, *54*, 244–259.
22. Sohrabi, S.; Yazlık, A.; Bazos, I.; Gherekhloo, J.; Kati, V.; Kitiş, Y.E.; Arianoutsou, M.; Kortz, A.; Pyšek, P. Alien species of *Ipomoea* in Greece, Türkiye and Iran: Distribution, impacts and management. *NeoBiota* **2025**, *97*, 135–160. [[CrossRef](#)]
23. Mircea, D.M.; Li, R.; Blasco Giménez, L.; Vicente, O.; Sestras, A.F.; Sestras, R.E.; Boscaiu, M.; Mir, R. Salt and water stress tolerance in *Ipomoea purpurea* and *Ipomoea tricolor*, two ornamentals with invasive potential. *Agronomy* **2023**, *13*, 2198. [[CrossRef](#)]
24. Oduor, A.M.O.; Long, H.; Fandohan, A.B.; Liu, J.; Yu, X. An invasive plant provides refuge to native plant species in an intensely grazed ecosystem. *Biol. Invasions* **2018**, *20*, 2745–2751. [[CrossRef](#)]
25. El-Barougy, R.F.; Dakhil, M.A.; Halmy, M.W.; Gray, S.M.; Abdelaal, M.; Khedr, A.H.A.; Bersier, L.F. Invasion risk assessment using trait-environment and species distribution modelling techniques in an arid protected area: Towards conservation prioritization. *Ecol. Indic.* **2021**, *129*, 107951. [[CrossRef](#)]
26. Mousikos, A.; Manolaki, P.; Knez, N.; Vogiatzakis, I.N. Can distribution modeling inform rare and endangered species monitoring in Mediterranean islands? *Ecol. Inform.* **2021**, *66*, 101434. [[CrossRef](#)]
27. Baker, D.J.; Maclean, I.M.; Goodall, M.; Gaston, K.J. Species distribution modelling is needed to support ecological impact assessments. *J. Appl. Ecol.* **2021**, *58*, 21–26. [[CrossRef](#)]
28. Cushman, S.A.; Kilshaw, K.; Campbell, R.D.; Kaszta, Z.; Gaywood, M.; Macdonald, D.W. Comparing the performance of global, geographically weighted and ecologically weighted species distribution models for Scottish wildcats using GLM and Random Forest predictive modeling. *Ecol. Model.* **2024**, *492*, 110691. [[CrossRef](#)]
29. Safdar, S.; Younes, I.; Ahmad, A.; Sastry, S. A comprehensive review of spatial distribution modeling of plant species in mountainous environments: Implications for biodiversity conservation and climate change assessment. *Kuwait J. Sci.* **2025**, *52*, 100337. [[CrossRef](#)]
30. Wani, Z.A.; Dar, J.A.; Lone, A.N.; Pant, S.; Siddiqui, S. Habitat suitability modelling and range change dynamics of *Bergenian stracheyi* under projected climate. *Front. Ecol. Evol.* **2025**, *13*, 1561640. [[CrossRef](#)]
31. Sun, X.; Long, Z.; Jia, J. A multi-scale Maxent approach to model habitat suitability for the giant pandas in the Qionglai mountain, China. *Glob. Ecol. Conserv.* **2021**, *30*, e01766. [[CrossRef](#)]
32. Li, Z.; Liu, Y.; Zeng, H. Application of the MaxEnt model in improving the accuracy of ecological red line identification: A case study of Zhanjiang, China. *Ecol. Indic.* **2022**, *137*, 108767. [[CrossRef](#)]
33. Zhao, Z.; Xiao, N.; Shen, M.; Li, J. Comparison between optimized MaxEnt and random forest modeling in predicting potential distribution: A case study with *Quasipaa boulengeri* in China. *Sci. Total Environ.* **2022**, *842*, 156867. [[CrossRef](#)] [[PubMed](#)]
34. Yan, H.; Feng, L.; Zhao, Y.; Feng, L.; Wu, D.; Zhu, C. Prediction of the spatial distribution of *Alternanthera philoxeroides* in China based on ArcGIS and MaxEnt. *Glob. Ecol. Conserv.* **2020**, *21*, e00856. [[CrossRef](#)]
35. Yudaputra, A.N.G.G.A. Modelling potential current distribution and future dispersal of an invasive species *Calliandra calothyrsus* in Bali Island, Indonesia. *Biodiversitas* **2020**, *21*, 674–682. [[CrossRef](#)]
36. Cao, J.; Xu, J.; Pan, X.; Monaco, T.A.; Zhao, K.; Wang, D.; Rong, Y. Potential impact of climate change on the global geographical distribution of the invasive species, *Cenchrus spinifex* (Field sandbur, Gramineae). *Ecol. Indic.* **2021**, *131*, 108204. [[CrossRef](#)]
37. Wu, K.; Wang, Y.; Liu, Z.; Huo, W.; Cao, J.; Zhao, G.; Zhang, F.G. Prediction of potential invasion of two weeds of the genus *Avena* in Asia under climate change based on Maxent. *Sci. Total Environ.* **2024**, *950*, 175192. [[CrossRef](#)] [[PubMed](#)]
38. Yang, W.; Sun, S.; Wang, N.; Fan, P.; You, C.; Wang, R.; Zheng, P.; Wang, H. Dynamics of the distribution of invasive alien plants (Asteraceae) in China under climate change. *Sci. Total Environ.* **2023**, *903*, 166260. [[CrossRef](#)] [[PubMed](#)]

39. Xiao, H.; Liao, D.; Zhang, S.; Zhang, Y.; Rehab, O.E.; Zeng, J.; Yan, X.; Su, Q.; Zhou, B. Differences in responses of invasive and native plants to climate change: A case study of *Bidens* (Asteracea) from China. *Front. Plant Sci.* **2025**, *16*, 1583552. [[CrossRef](#)] [[PubMed](#)]
40. Mousavi, S.S.; Karami, A.; Haghighi, T.M.; Maggi, F. Two Iranian *Scrophularia striata* Boiss. Ecotypes under UV-B radiation: Germination and initial growth perspective. *South Afr. J. Bot.* **2022**, *148*, 460–468. [[CrossRef](#)]
41. Muscarella, R.; Galante, P.J.; Soley-Guardia, M.; Boria, R.A.; Kass, J.M.; Uriarte, M.; Anderson, R.P. ENMeval: An R package for conducting spatially independent evaluations and estimating optimal model complexity for Maxent ecological niche models. *Methods Ecol. Evol.* **2014**, *5*, 1198–1205. [[CrossRef](#)]
42. Zhao, G.; Cui, X.; Sun, J.; Li, T.; Wang, Q.I.; Ye, X.; Fan, B. Analysis of the distribution pattern of Chinese *Ziziphus jujuba* under climate change based on optimized biomod2 and MaxEnt models. *Ecol. Indic.* **2021**, *132*, 108256. [[CrossRef](#)]
43. Giulian, J.; Jones, T.C.; Moore, D. Assessing the potential invasive range of *Trichonephila clavata* using species distribution models. *J. Asia-Pac. Biodivers.* **2024**, *17*, 490–496. [[CrossRef](#)]
44. Phillips, S.J.; Dudík, M. Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. *Ecography* **2008**, *31*, 161–175. [[CrossRef](#)]
45. Valavi, R.; Elith, J.; Lahoz-Monfort, J.J.; Guillera-Arroita, G. Flexible species distribution modelling methods perform well on spatially separated testing data. *Glob. Ecol. Biogeogr.* **2023**, *32*, 369–383. [[CrossRef](#)]
46. Elbahi, A.; Dugon, M.; Oubrou, W.; El Bekkay, M.; Hermas, J.; Lawton, C. Modelling the ecological niches of reptiles in highly biodiverse protected areas. *Geol. Ecol. Landsc.* **2025**, *9*, 1441–1462. [[CrossRef](#)]
47. Lobo, J.M.; Jiménez-Valverde, A.; Real, R. AUC: A misleading measure of the performance of predictive distribution models. *Glob. Ecol. Biogeogr.* **2008**, *17*, 145–151. [[CrossRef](#)]
48. Hao, T.; Elith, J.; Guillera-Arroita, G.; Lahoz-Monfort, J.J. A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. *Divers. Distrib.* **2019**, *25*, 839–852. [[CrossRef](#)]
49. Ahmed, N.; Atzberger, C.; Zewdie, W. Species Distribution Modelling performance and its implication for Sentinel-2-based prediction of invasive *Prosopis juliflora* in lower Awash River basin, Ethiopia. *Ecol. Process.* **2021**, *10*, 18. [[CrossRef](#)]
50. Allouche, O.; Tsoar, A.; Kadmon, R. Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.* **2006**, *43*, 1223–1232. [[CrossRef](#)]
51. Hirzel, A.H.; Le Lay, G.; Helfer, V.; Randin, C.; Guisan, A. Evaluating the ability of habitat suitability models to predict species presences. *Ecol. Model.* **2006**, *199*, 142–152. [[CrossRef](#)]
52. Merow, C.; Smith, M.J.; Silander, J.A., Jr. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. *Ecography* **2013**, *36*, 1058–1069. [[CrossRef](#)]
53. Li, F.; Lv, L.; Bao, S.; Cai, Z.; Fu, S.; Shi, J. Evaluation and Application of the MaxEnt Model to Quantify *L. nanum* Habitat Distribution Under Current and Future Climate Conditions. *Agronomy* **2025**, *15*, 1869. [[CrossRef](#)]
54. Taucare-Ríos, A.; Bizama, G.; Bustamante, R.O. Using global and regional species distribution models (SDM) to infer the invasive stage of *Latrodectus geometricus* (Araneae: Theridiidae) in the Americas. *Environ. Entomol.* **2016**, *45*, 1379–1385. [[CrossRef](#)] [[PubMed](#)]
55. Chi, Y.; Wang, G.G.; Zhu, M.; Jin, P.; Hu, Y.; Shu, P.; Wang, Z.; Fan, A.; Qian, P.; Han, Y.; et al. Potentially suitable habitat prediction of *Pinus massoniana* Lamb. in China under climate change using Maxent model. *Front. For. Glob. Change* **2023**, *6*, 1144401. [[CrossRef](#)]
56. Huang, Y.; Zhang, G.; Fu, W.; Zhang, Y.; Zhao, Z.; Li, Z.; Qin, Y. Impacts of climate change on climatically suitable regions of two invasive *Erigeron* weeds in China. *Front. Plant Sci.* **2023**, *14*, 1238656. [[CrossRef](#)] [[PubMed](#)]
57. Shan, Y.; Shen, H.; Huang, L.; Hamezah, H.S.; Han, R.; Ren, X.; Zhang, C.; Tong, X. Optimized MaxEnt analysis revealing the change of potential distribution area of *Lygodium japonicum* in China driven by global warming. *Front. Plant Sci.* **2025**, *16*, 1601956. [[CrossRef](#)] [[PubMed](#)]
58. Ren, W.; Peng, J.; Shrestha, N.; Bian, Z.; Yang, Y.; Liu, J.; Liu, X.; Huang, P.; Wu, J. Potential distribution and future shifts of invasive alien plants in China under climate change. *Glob. Ecol. Conserv.* **2025**, *60*, e03601. [[CrossRef](#)]
59. Wan, J.Z.; Wang, C.J.; Tan, J.F.; Yu, F.H. Climatic niche divergence and habitat suitability of eight alien invasive weeds in China under climate change. *Ecol. Evol.* **2017**, *7*, 1541–1552. [[CrossRef](#)] [[PubMed](#)]
60. Tu, W.; Xiong, Q.; Qiu, X.; Zhang, Y. Dynamics of invasive alien plant species in China under climate change scenarios. *Ecol. Indic.* **2021**, *129*, 107919. [[CrossRef](#)]
61. Qi, Y.; Wang, H.; Ma, X.; Zhang, J.; Yang, R. Relationship between vegetation phenology and snow cover changes during 2001–2018 in the Qilian Mountains. *Ecol. Indic.* **2021**, *133*, 108351. [[CrossRef](#)]
62. Li, W.; Lu, H.; Chen, J.M.; Piao, S.; Keenan, T.F.; Miao, G.; Liu, Q.; Zang, Z.; Xu, N.; Liu, J.; et al. Enhanced effect of warming on the leaf-onset date of boreal deciduous broadleaf forest. *Nat. Clim. Change* **2026**, *16*, 200–206. [[CrossRef](#)]

63. Spohn, M.; Bagchi, S.; Biederman, L.A.; Borer, E.T.; Bråthen, K.A.; Bugalho, M.N.; Caldeira, M.C.; Catford, J.A.; Collins, S.L.; Eisenhauer, N.; et al. The positive effect of plant diversity on soil carbon depends on climate. *Nat. Commun.* **2023**, *14*, 6624. [[CrossRef](#)] [[PubMed](#)]
64. Lu, Y.; Chen, W.; Chen, X.; Li, Z. Effects of microclimate on soil moisture distribution in complex topography at the small watershed scale in the Anning River Region, Southwest China. *J. Hydrol. Reg. Stud.* **2025**, *59*, 102381. [[CrossRef](#)]
65. Wang, J.; Zhao, M.; Zhang, J.; Zhao, B.; Lu, X.; Wei, H. Characterization and utilization of biochars derived from five invasive plant species *Bidens pilosa* L., *Praxelis clematidea*, *Ipomoea cairica*, *Mikania micrantha* and *Lantana camara* L. for Cd²⁺ and Cu²⁺ removal. *J. Environ. Manag.* **2021**, *280*, 111746. [[CrossRef](#)] [[PubMed](#)]
66. Arana, J.; Meyers, S.L.; Guan, W.; Johnson, W.G. Interference of morningglories (*Ipomoea* spp.) with ‘Fascination’ triploid watermelon. *Weed Sci.* **2022**, *70*, 488–494. [[CrossRef](#)]
67. Westbrook, A.S.; Han, R.; Zhu, J.; Cordeau, S.; DiTommaso, A. Drought and Competition With Ivyleaf Morningglory (*Ipomoea hederacea*) Inhibit Corn and Soybean Growth. *Front. Agron.* **2021**, *3*, 720287. [[CrossRef](#)]
68. Xiao, C.; Ye, J.; Zhang, H.; Qin, Y.; Yan, R.; Xu, G.; Zhou, H. Assessment of Habitat Suitability for the Invasive Vine *Sicyos angulatus* Under Current and Future Climate Change Scenarios. *Plants* **2025**, *14*, 2745. [[CrossRef](#)] [[PubMed](#)]
69. Bajahmoum, E.A.; Almaghami, A. Physicochemical degradation of *Avicennia marina* mangrove soils in the Red Sea: Implications for coastal ecosystem services. *Front. Soil Sci.* **2025**, *5*, 1621591. [[CrossRef](#)]
70. Zhang, Z.; Yang, Q.; Fristoe, T.S.; Dawson, W.; Essl, F.; Kreft, H.; Lenzner, B.; Pergl, J.; Pyšek, P.; Weigelt, P.; et al. The poleward naturalization of intracontinental alien plants. *Sci. Adv.* **2023**, *9*, eadi1897. [[CrossRef](#)] [[PubMed](#)]
71. Fuentes-Lillo, E.; Lembrechts, J.J.; Barros, A.; Aschero, V.; Bustamante, R.O.; Cavieres, L.A.; Clavel, J.; Herrera, I.; Jiménez, A.; Tecco, P.; et al. Going up the Andes: Patterns and drivers of non-native plant invasions across latitudinal and elevational gradients. *Biodivers. Conserv.* **2023**, *32*, 4199–4219. [[CrossRef](#)]
72. Slatyer, R.A.; Hirst, M.; Sexton, J.P. Niche breadth predicts geographical range size: A general ecological pattern. *Ecol. Lett.* **2013**, *16*, 1104–1114. [[CrossRef](#)] [[PubMed](#)]
73. Sheth, S.N.; Morueta-Holme, N.; Angert, A.L. Determinants of geographic range size in plants. *New Phytol.* **2020**, *226*, 650–665. [[CrossRef](#)] [[PubMed](#)]
74. Muñoz-Rodríguez, P.; Carruthers, T.; Wood, J.R.; Williams, B.R.; Weitemier, K.; Kronmiller, B.; Goodwin, Z.; Sumadijaya, A.; Anglin, N.L.; Filer, D.; et al. A taxonomic monograph of *Ipomoea* integrated across phylogenetic scales. *Nat. Plants* **2019**, *5*, 1136–1144. [[CrossRef](#)] [[PubMed](#)]
75. Weber, E.; Sun, S.G.; Li, B. Invasive alien plants in China: Diversity and ecological insights. *Biol. Invasions* **2008**, *10*, 1411–1429. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.