

Article

Spatiotemporal Shifts in Habitat Suitability of *Malus sieversii* and *Prunus cerasifera* in the Ili Valley Under Climate Change

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Abstract

Globally, Central Asian wild fruit forests are critical repositories of wild fruit germplasm resources and provide essential ecosystem services. However, their habitats are facing escalating degradation risks driven by climate warming, shifting precipitation regimes, and intensifying anthropogenic disturbances. Accurately quantifying climate-driven spatiotemporal variations in habitat suitability for keystone wild fruit tree species is therefore an essential prerequisite for formulating targeted conservation and management strategies in arid and semi-arid landscapes. In this study, we applied the maximum entropy (*MaxEnt*) model to simulate the current (2000–2020 baseline) and future (2030s, 2050s, 2070s) potential suitable habitats of two dominant wild fruit tree species, *Malus sieversii* (Ledeb.) M. Roem. and *Prunus cerasifera* Ehrh., in the Ili Valley, a core distribution area of Central Asian wild fruit forests in northwestern China. We integrated rigorously screened species occurrence records with key environmental predictors and characterized future climate conditions using three Shared Socioeconomic Pathways (SSPs; SSP126, SSP245, and SSP585) spanning low to high radiative forcing levels. The model exhibited excellent predictive performance ($AUC > 0.85$), confirming the robustness and reliability of our habitat suitability simulations. *Elevation* and *annual precipitation* were identified as the dominant environmental variables governing habitat suitability for both species, highlighting the critical role of terrain–hydroclimate interactions in maintaining viable dryland refugia for wild fruit forests. Under the baseline climate scenario, the total area of suitable habitats reached $24.014 \times 10^3 \text{ km}^2$ for *Malus sieversii* and $18.990 \times 10^3 \text{ km}^2$ for *Prunus cerasifera*. Future climate projections revealed a consistent and significant contraction trend in suitable habitats for both species, with the magnitude of habitat loss escalating with increasing radiative forcing and longer projection time horizons. Specifically, under the high-emission SSP585 scenario by the 2070s, the suitable habitat area is projected to decline by $7.579 \times 10^3 \text{ km}^2$ for *Malus sieversii* and $9.883 \times 10^3 \text{ km}^2$ for *Prunus cerasifera* relative to the baseline. Our findings delineate climate-vulnerable hotspots of wild fruit forests and provide a robust spatial scientific basis for prioritizing in situ conservation, targeted habitat restoration, and anthropogenic disturbance regulation to support the long-term persistence of these irreplaceable wild fruit germplasm resources under accelerating global climate change.

Keywords: habitat suitability modeling; arid landscape; semi-arid landscape; environmental variable; habitat distribution



Academic Editor: Andrew M. Barton

Received: 25 February 2026

Revised: 21 March 2026

Accepted: 30 March 2026

Published: 10 April 2026

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1. Introduction

Climate change has been widely recognized as a major threat to biodiversity, with profound consequences for the structure and functioning of terrestrial ecosystems [1–4]. The Intergovernmental Panel on Climate Change (IPCC) reported that global mean temperature increased by 0.85 °C during the 20th century, and it is projected to rise further in the 21st century [5,6]. Such changes are expected to reshape species' geographic ranges and habitat availability over the coming decades [1,7–9], thereby altering spatial biodiversity patterns and increasing extinction risks [10,11]. Climate-driven impacts have been documented across multiple biological dimensions, including distributional shifts [4,12,13], phenological changes [14,15], physiological responses [16,17] and reductions in forest productivity [18]. For endangered plants, anticipating future habitat suitability is therefore critical for identifying exposure hotspots and supporting proactive conservation planning [8,19].

Various species distribution models (SDMs) [20], such as genetic algorithms for ruleset production (GARP) [21], machine learning (LSTM), CLIMEX, and maximum entropy (MaxEnt) models, have been applied to evaluate the distribution regions, ecological responses, and ecological requirements of key species as a consequence of climate change [22,23]. Many intercomparison studies of models report that the MaxEnt model [24], based on the principle of maximum entropy, generally outperforms other SDMs in terms of high tolerance and high predictive accuracy, especially for small sample sizes [25]. It can visually provide the magnitude of species distribution area in different periods, and the comparison can lead to models of the response of the same species to different climate changes [26]. For example, Zhang [27] used the MaxEnt model to predict China's potential geographic distribution of peony species under climate change. Valdeir [28] used MaxEnt to indicate Brazilian species' current and potential future habitats. Two different climate change scenarios (SSP245 and SSP585) were used to quantify the potential changes in the bioclimatic area of the habitats of 135 potential agroforestry-native species in Brazil. By providing the spatial range of loss or acquisition of species, this model helps to predict the impact of climate change on species' habitats by providing the spatial extent of species loss or gain, enabling appropriate conservation strategies [29].

The Ili Valley, known as a “wet island” in the arid interior of Central Asia, is characterized by relatively abundant precipitation and well-preserved semi-arid forest landscapes, serving as the core distribution area of Central Asian wild fruit forests. However, this fragile dryland ecosystem has suffered severe disturbances in recent decades; rapid regional warming has disrupted the local hydrothermal balance [30,31]. Remote sensing monitoring has detected widespread vegetation degradation since the 1990s [32,33], and ongoing climate change is expected to further exacerbate degradation and threaten regional ecological sustainability [34]. *Malussieversii* (Ledeb.) Roem. is a dominant tree species of wild fruit forests, mainly distributed on shady and semi-shady slopes at elevations of 900–1930 m [35]. *Prunus cerasifera* Ehrh. is a typical deciduous small tree or shrub, inhabiting valley bottoms and stony slopes at 1000–1600 m [36]. Both species are national Class II protected plants in China, carrying precious and endangered wild fruit germplasm resources with core ecological and economic values. Unfortunately, prolonged climate stress, intensive human activities, and pest–disease pressures have contributed to habitat contraction and population decline in these two species, sharply elevating their extinction risk and highlighting the urgent need for targeted wild fruit forest conservation to maintain ecosystem stability, soil and water conservation functions, and regional biodiversity [37].

In recent years, SDMs have been increasingly used to predict species habitat suitability under current and future climate scenarios [27,38–41], but most existing studies adopt the 1970–2000 climate period as the baseline, which fails to reflect the latest climate warming characteristics of the 21st century. Additionally, many studies rely on single climate

scenarios, ignoring the uncertainty of future socioeconomic development and radiative forcing levels [42–46]. This methodological limitation leads to biased habitat projection results, which cannot provide accurate decision support for the conservation of wild fruit forests in arid and semi-arid regions. Against this background, we put forward the core scientific hypothesis. *Malus sieversii* and *Prunus cerasifera* continuous climate warming and altered precipitation patterns in the Ili Valley will significantly reduce the suitable habitat area, and the degree of habitat degradation will be positively correlated with emission intensity and time span. To test this hypothesis and address the above research gaps, we collected 414 standardized occurrence records of the two target species, selected 2000–2020 as the updated baseline climate period, and projected habitat suitability dynamics under three SSP scenarios (SSP126, SSP245, SSP585) across three future time slices (2030s, 2050s, 2070s). The specific research objectives of this study are (1) to identify the dominant environmental factors driving the habitat suitability distribution of *Malus sieversii* and *Prunus cerasifera*; (2) to quantify the spatial extent and structural characteristics of suitable habitats under the baseline and future climate scenarios; and (3) to reveal the spatiotemporal patterns of habitat gain and loss under divergent scenarios, and propose targeted conservation and management countermeasures for wild fruit forests in the Ili Valley and similar arid and semi-arid regions.

2. Materials and Methods

2.1. Study Area

The Ili Basin, the core distribution region of Central Asian wild fruit forests, is situated in the interior of Eurasia between the northern and southern branches of the Tianshan Mountains ($42^{\circ}15'–44^{\circ}51' \text{ N}$, $80^{\circ}10'–85^{\circ}00' \text{ E}$), covering a total area of approximately $58,191.2 \text{ km}^2$. The basin is relatively flat, bounded by high mountains on three sides, and is characterized by a west–east narrowing geomorphology (Figure 1). The research area has a temperate continental climate with rapid warming of 0.4°C per decade and increasing precipitation of 11.2 mm over the last two decades [47,48]. Strong environmental gradients and pronounced spatial heterogeneity make the Ili Basin an important refuge for semi-arid ecosystems.

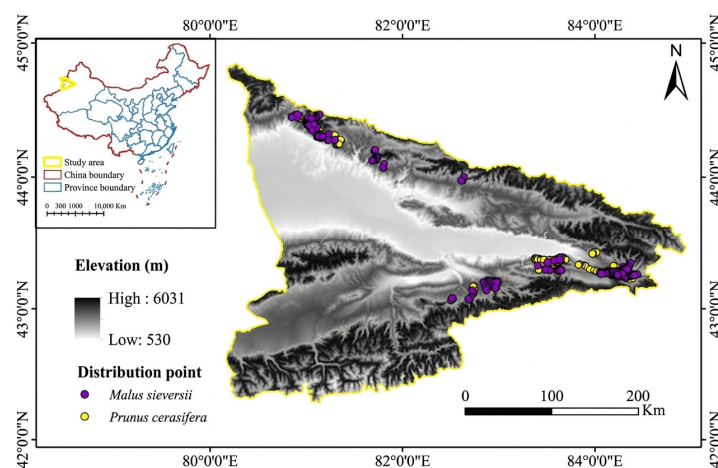


Figure 1. Map showing the location of the Ili Basin in northwest China, along with its topography and grayscale elevation. Occurrence points of *Malus sieversii* and *Prunus cerasifera* are overlaid on the elevation gradient. Data sources: National and provincial boundaries of China are derived from the standard base map of the National Administration of Surveying, Mapping and Geoinformation of China; elevation data are sourced from the SRTM 90 m Digital Elevation Model (DEM); the Ili Basin boundary is extracted and delineated via hydrological analysis of the DEM. Coordinate reference system: WGS84 (EPSG:4326).

2.2. Maxent Prediction

Species Occurrence Data and Spatial Distribution Mapping

This study focused on two dominant and nationally protected wild fruit tree species in the Ili Basin. *Malus sieversii* and *Prunus cerasifera* are both listed in the National List of Key Protected Wild Plants (1999 First Edition) as representative endangered endemic species of the region. To obtain reliable species presence data, we collected geo-referenced occurrence records (including geographic coordinates and detailed sampling locations) primarily from the Chinese Virtual Herbarium (<http://www.cvh.ac.cn>), a standardized national plant specimen database. The coordinate accuracy of raw records was verified and calibrated using the Baidu Map geocoding tool (<http://api.map.baidu.com/lbsapi/getpoint/index.html> (accessed on 17 December 2025)) to eliminate positional deviations. To reduce sampling bias and spatial autocorrelation that may interfere with model accuracy, we conducted strict data preprocessing, duplicate occurrence records were removed, and spatial filtering was performed using a 1 km × 1 km grid (matching the resolution of environmental predictors), retaining only one presence point per grid. The final filtered dataset contained 230 valid occurrence records for *Malus sieversii* and 184 records for *Prunus cerasifera*, totaling 414 high-quality presence-only points. The spatial distribution map of the two target species was generated and visualized using ArcGIS 10.8 software, with the study area boundary as the clipping mask (Figure 1).

3. Environmental Predictors

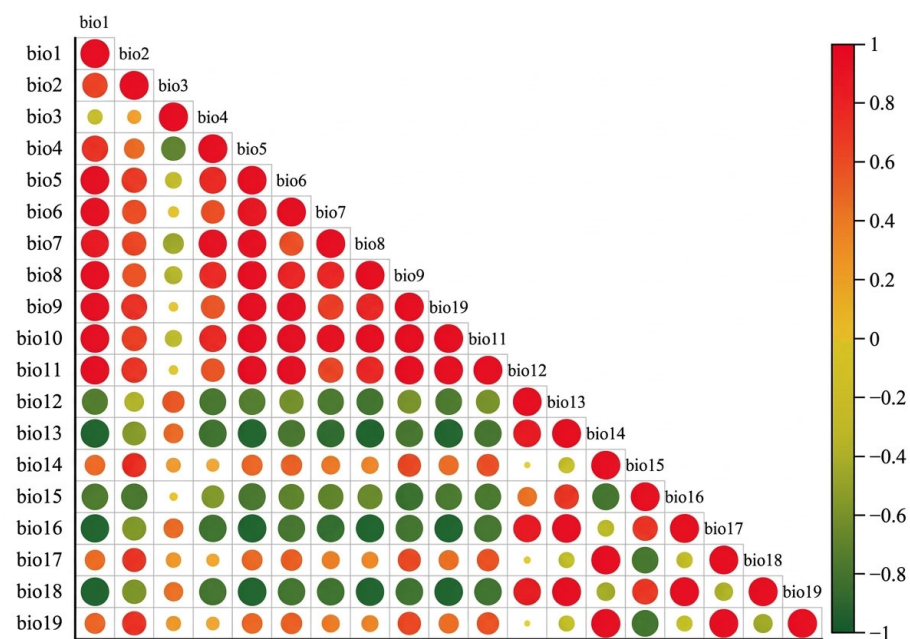
3.1. Baseline Environmental Variables

To represent the current (2000–2020) environmental background of the study area, we adopted the CN05.1 gridded observational climate dataset, which is derived from monthly observation records of more than 2400 national meteorological stations in China and has high reliability for regional climate simulation. The original dataset has a spatial resolution of (0.25° × 0.25°); we converted the NetCDF format data to GeoTIFF format, resampled it to a 1 km resolution consistent with species occurrence data, and performed cropping, projection conversion, and other preprocessing operations using ArcGIS 10.8 software.

Based on the baseline climate dataset, 19 bioclimatic variables (Table 1) were calculated using the R 4.2.1 package “BioVars” to reflect long-term climate characteristics [49], with a final spatial resolution of 30 arc seconds (~1 km). To reduce the interference of multi-collinearity among variables, we used SPSS 21.0 software to calculate Pearson correlation coefficients and excluded variables with $|r| > 0.8$ (Figure 2), retaining the most ecologically relevant factors. Finally, we retained ten bioclimatic variables, one specific soil variable (soil sand content, mass percentage), one vegetation index (NDVI), and three topographic variables from the initial 19 environmental predictors [27] (Table 2). The selection of soil sand content was based on three key rationales: (1) Ecological relevance to target species: *Malus sieversii* and *Prunus cerasifera* are typical dryland wild fruit trees, and soil sand content directly regulates soil water-holding capacity, aeration, and root penetration, critical factors for their growth and establishment in arid and semi-arid regions. (2) Regional adaptability: The Ili Valley has heterogeneous soil types (e.g., Chernozems, Kastanozems) with significant variations in sand content, which effectively captures soil spatial heterogeneity complementary to climatic and topographic predictors. (3) Data reliability: The FAO soil dataset provides standardized sand content data for Central Asia, consistent with the 1 km spatial resolution of other environmental variables, avoiding scaling biases in modeling.

Table 1. Description of the 19 selected bioclimatic factor variables in this study.

Code	Variables	Unit
bio1	Annual mean temperature	°C
bio2	Mean diurnal range (mean of monthly max. and min. temp.)	°C
bio3	Isothermality ((Bio2/Bio7) × 100)	
bio4	Temperature seasonality (standard deviation × 100)	C of V
bio5	Max temperature of warmest month	°C
bio6	Min temperature of coldest month	°C
bio7	Annual temperature range	°C
bio8	Mean temperature of wettest quarter	°C
bio9	Mean temperature of driest quarter	°C
bio10	Mean temperature of warmest quarter	°C
bio11	Mean temperature of coldest quarter	°C
bio12	Annual precipitation	mm
bio13	Precipitation of wettest month	mm
bio14	Precipitation of driest month	mm
bio15	Precipitation seasonality (CV)	C of V
bio16	Precipitation of wettest quarter	mm
bio17	Precipitation of driest quarter	mm
bio18	Precipitation of warmest quarter	mm
bio19	Precipitation of coldest quarter	mm

**Figure 2.** Correlation analysis of environmental variables.**Table 2.** Environment variables used in the study.

Variables	Indicators	Data Sources	Data Processing
Meteorological factors	bio 1, bio 2, bio 3, bio 4, bio 12, bio 13, bio 14, bio 15, bio 17, bio19	WorldClim (http://worldclim.org/version2 (accessed on 17 December 2025))	Random value points were extracted and then interpolated to 90 m resolution; calibrated using a Calibration Factor

Table 2. *Cont.*

Variables	Indicators	Data Sources	Data Processing
Topographical factors	Altitude, Slope, Aspect	Geospatial Data Cloud (GDC) (http://www.gscloud.cn/) (accessed on 17 December 2025))	Clipped and coordinate-projected correspondingly after being downloaded from GDC layer (selected data was processed by GDC using the data of ASTER GDEM version 1); kept at their native resolution of 90 m.
Soil factors	Soil	FAO SOILS PORTAL (https://www.fao.org/soils-portal/resources/en/) (accessed on 17 December 2025))	
Vegetation factors	Normalized Difference Vegetation Index (NDVI)	United States Geological Survey (USGS) (https://www.usgs.gov) (accessed on 17 December 2025))	Calculated from red and near-infrared (NIR) values as $(rNIR - rRed)/(rNIR + rRed)$; combined with LULC database

3.2. Future Climate Scenario Data

To predict the spatiotemporal dynamics of habitat suitability under future climate change, we selected global circulation model (GCM) outputs under shared socioeconomic pathways (SSPs) from the IPCC Sixth Assessment Report. Four representative SSP scenarios (SSP126, SSP245, SSP370, SSP585) depict distinct future greenhouse gas emission trajectories and climate change trends, corresponding to different levels of radiative forcing [50,51]. In this study, we adopted the BCC-CSM2-MR model (second-generation Moderate Resolution Climate System Model developed by the National Climate Center of China), which has been proven to perform excellently in simulating temperature and precipitation patterns in northwest China and arid Central Asia. We selected three typical scenarios (SSP126: sustainable low-emission; SSP245: intermediate development; SSP585: fossil-fueled high-emission) and three future time slices (2030s, 2050s, 2070s) to quantify future habitat shifts, ensuring the comprehensiveness of climate change uncertainty analysis.

3.3. Model Settings and Validation

The MaxEnt model (Version 3.4.4, Phillips et al., USA) was constructed and run with standardized parameter settings to ensure the reliability and repeatability of simulation results, with specific configurations as follows:

1. In total, 75% of the filtered species occurrence records were randomly selected as the training dataset for model fitting, and the remaining 25% were used as the test dataset for independent validation.
2. The Regularization Multiplier (RM) was set to 1.1 and optimized via preliminary gradient tuning (0.5, 1.0, 1.1, 1.5, 2.0) to balance model fitting accuracy and avoid overfitting, which achieved the highest AUC for our dataset. We adopted 10-fold cross-validation, and the average output of 10 replicate runs was used for subsequent analysis to reduce random errors.
3. We enabled linear, quadratic, product, and hinge features to capture complex species–environment relationships.

The Jackknife test was used to assess the importance of environmental variables [52,53]. Model predictive performance was evaluated using two complementary metrics for presence-only data: (1) the area under the curve (AUC) of receiver operating characteristic (ROC) analysis [54,55], with $0.75 < \text{AUC} < 0.85$ and $0.85 < \text{AUC} < 1$ interpreted as relative acceptable and highly accurate predictive ability for presence-only data, respectively; (2) the Continuous Boyce Index (CBI) [56–58], a validated metric for presence-only SDMs, where $\text{CBI} > 0.5$ was considered indicative of robust model predictive performance.

For transforming habitat suitability probabilities (0–1) into binary classifications, the optimal logistic threshold was determined using the CBI [59], replacing the previously used maximum specificity and sensitivity threshold (inappropriate for presence-only data). In subsequent analysis, the distribution of endangered species was reclassified using the 10% training presence threshold method (i.e., the value excluding the lowest 10% of predicted locations was set as a threshold) [56], and suitability was divided into four levels using the mean logical value (I: <20%; II: 20%–40%; III: 40%–60%; IV: 60%–100%), indicating non-suitable, low-suitable, moderately suitable, and highly suitable areas, respectively [57]. To quantify the spatial shift in suitable habitats, the central mass (weighted centroid) of suitable habitats was calculated. The specific method was as follows: (1) we first screened grid cells with suitability > 20% (i.e., lowly to highly suitable areas) as the target habitat range; (2) the central mass was determined using the weighted centroid formula, where the suitability value of each grid cell was used as the weight to account for the contribution of habitat quality to the centroid position:

$$X_c = \frac{\sum_{i=1}^n (x_i \times s_i)}{\sum_{i=1}^n s_i} \quad Y_c = \frac{\sum_{i=1}^n (y_i \times s_i)}{\sum_{i=1}^n s_i} \quad (1)$$

where (x_i, y_i) represent the longitude and latitude of the i_{th} suitable grid cell, s_i is the suitability value (0–1) of the i_{th} grid cell, and n is the total number of suitable grid cells. This method integrates both the spatial distribution and quality of suitable habitats, ensuring a robust characterization of the core habitat center.

4. Results

4.1. Model Performance and Predictor Importance

MaxEnt was applied to model the potential distributions of *Malus sieversii* and *Prunus cerasifera* in the Ili Valley. Model performance was jointly validated by the AUC (for relative discriminatory ability) and Continuous Boyce Index (CBI, for presence-only data robustness). The results indicated strong predictive performance: AUC values were 0.893 for *Malus sieversii* and 0.986 for *Prunus cerasifera* (both >0.85, indicating highly accurate relative discriminatory ability), and CBI values were 0.78 for Ms and 0.85 for Pc (both >0.5, confirming robust model predictions for presence-only data). Based on the CBI, the optimal logistic thresholds for transforming suitability probabilities (0–1) into binary classifications were determined as 0.23 for *Malus sieversii* and 0.27 for *Prunus cerasifera*, providing a rigorous basis for subsequent habitat suitability grading (Figure 3).

Variable contributions were averaged across 10 replicate model runs to ensure stability. Jackknife tests of regularized training gain revealed interspecific differences in dominant environmental constraints, with core controlling factors showing partial consistency (Table 3). Under the 2000–2020 baseline climate, elevation (DEM: 32.7%) was the most influential predictor for *Malus sieversii*, followed by annual precipitation (bio12: 26.4%), soil type (12.2%), and temperature seasonality (bio4: 4.6%); these four variables collectively contributed 75.9% of the total explanatory power for habitat suitability. For *Prunus cerasifera*, elevation (24.7%) and annual precipitation (bio12: 24.7%) were equally dominant as the top two predictors, succeeded by mean diurnal temperature range (bio2: 11.3%) and slope (10.5%),

with a cumulative contribution of 71.2% to the model (Figure 4). The consistent dominance of topographic and hydroclimatic variables highlights the critical role of water–heat–terrain coupling in shaping the habitat suitability of these two wild fruit tree species in arid and semi-arid landscapes.

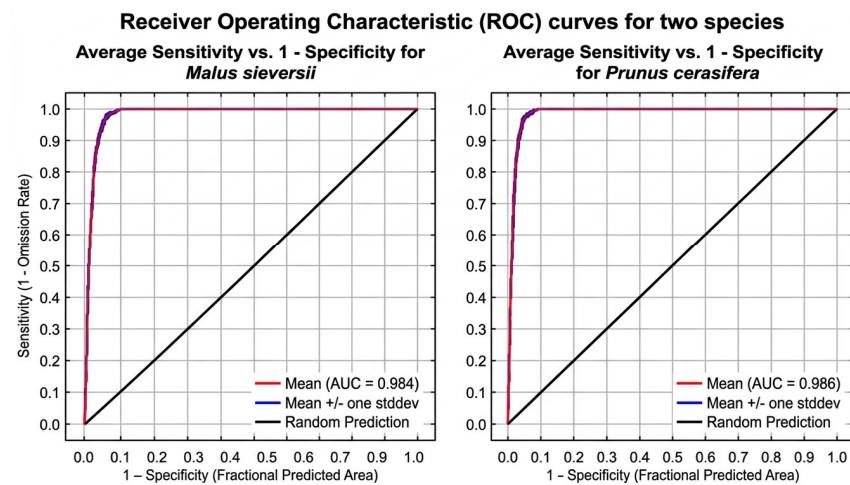


Figure 3. ROC curve verification of species prediction results by the model.

Table 3. Distribution contribution of each environmental factor to *Malus sieversii* and *Prunus cerasifera*.

Abbreviation	Ms Contribution (%)	Pc Contribution (%)
Dem	32.7	24.7
bio12	26.4	24.7
Soil	12.2	7.5
bio4	4.6	1.4
NDVI	4	9.7
bio2	3.9	11.3
bio3	3.8	0.9
Slope	3.5	10.5
bio14	2.9	1.4
Aspect	1.9	3.2
bio13	1.5	0.7
bio17	1.3	0.2
bio1	0.6	0.4
bio15	0.4	2.2
bio19	0.1	1.4

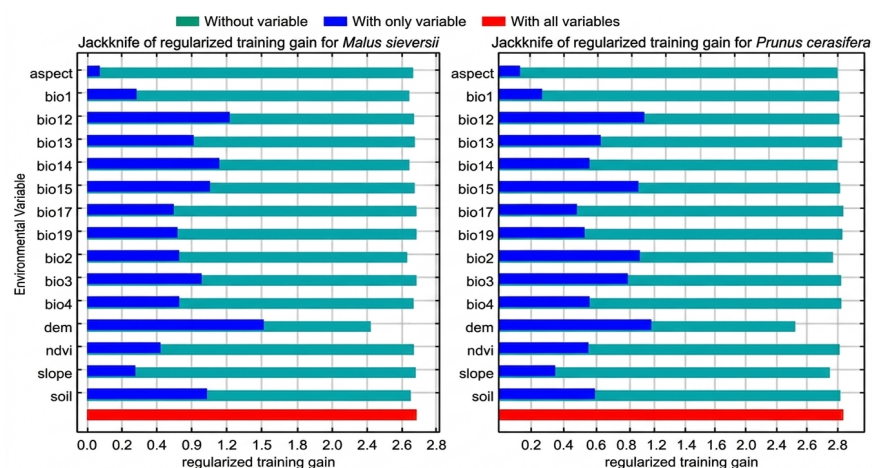


Figure 4. Jackknife test of model importance for environmental variables.

4.2. Response Curves and Climatic Optima

Species response curves (Figure 5) clearly delineated distinct climatic and topographic optima for the two species, reflecting their divergent ecological niches. *Malus sieversii* exhibited peak habitat suitability at approximately 1200 m elevation, with optimal annual precipitation (bio12) ranging from 150 to 250 mm and mean diurnal temperature range (bio2) near 10.5 °C. In contrast, *Prunus cerasifera* showed maximum suitability at a higher elevation of ~1500 m elevation, with bio12 around 330 mm and bio2 near 11.2 °C. This divergence indicates that *Prunus cerasifera* prefers relatively wetter and higher-elevation microhabitats compared to *Malus sieversii*, reinforcing the interspecific niche differentiation in the study area.

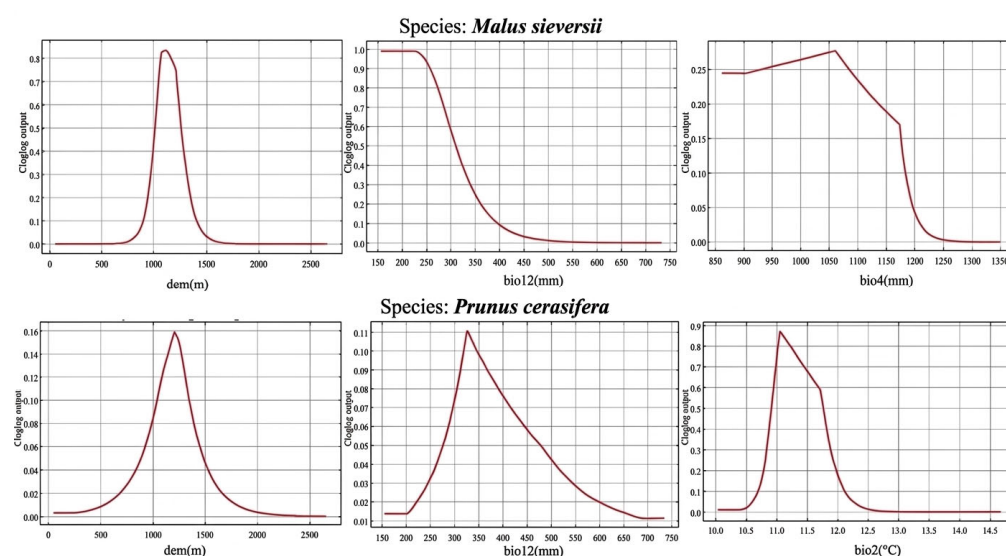


Figure 5. Response curves of the three dominant environmental variables driving habitat suitability for *Malus sieversii* (top) and *Prunus cerasifera* (bottom) under current climate conditions.

4.3. Soil Associations

Soil conditions in the Ili Valley exhibit strong heterogeneity along geomorphic and altitudinal gradients, ranging from deep loess deposits in foothills and alluvial fans to distinct mountain soil belts at higher elevations. Habitat suitability patterns uncovered significant species-specific soil affinities (Figure 6), which serve as a key driver of habitat partitioning between the two taxa. Highly suitable areas for *Malus sieversii* were predominantly associated with Leptosols and Chernozems, characterized by moderate soil depth and good water retention capacity. In comparison, *Prunus cerasifera* suitability was strongly linked to Chernozems and Kastanozems, which feature better drainage and higher organic matter content in mid-elevation zones. These soil preference differences further amplify the habitat differentiation and spatial segregation of the two wild fruit tree species in the region.

4.4. Current Potential Habitat Distribution

Under the current baseline climate (2000–2020), the predicted total suitable habitats covered 23.03% of the Ili Valley for *Malus sieversii* and 20.57% for *Prunus cerasifera* (Figure 7). Habitat hotspots were concentrated in the southeastern and northwestern parts of the study area, with core distributions centered in Xinyuan, Huocheng, and Gongliu counties. Notably, highly suitable habitats only accounted for 2.55% of the total study area for *Malus sieversii* and 1.97% for *Prunus cerasifera*, revealing that high-quality core habitats are spatially limited, fragmented, and highly clustered in the landscape.

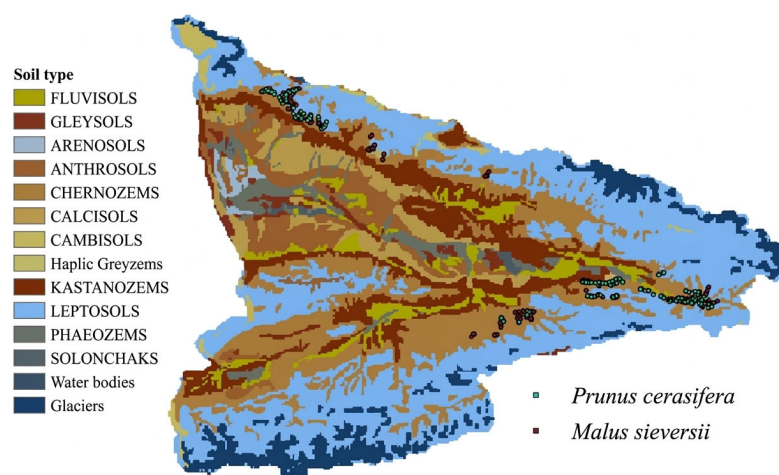


Figure 6. Distribution of *Malus sieversii* and *Prunus cerasifera* in relation to categorical soil types in the Ili Valley. Soil classes follow the FAO classification system; high-contrast colors for species points ensure distinguishability from soil background tones.

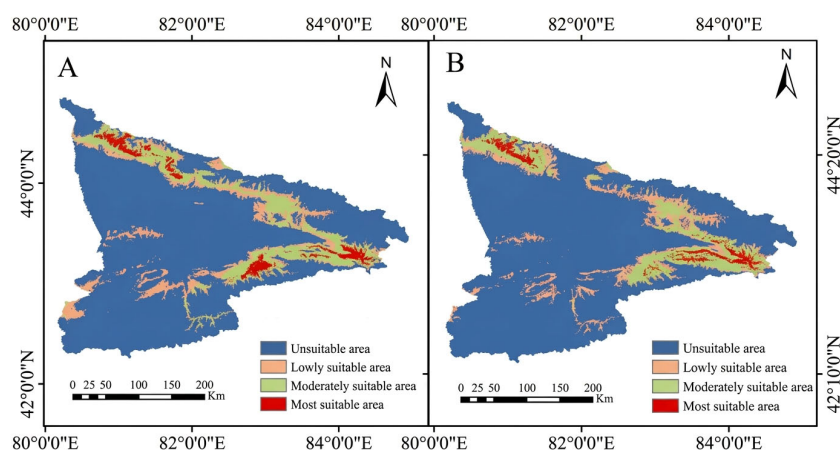


Figure 7. Current potential suitable habitat distributions of *Malus sieversii* (A) and *Prunus cerasifera* (B) in the Ili Valley.

4.5. Projected Changes Under Future Climate Scenarios

Future projections revealed a consistent scenario- and time-dependent pattern of habitat change (Figure 8): (1) short-term (2030s) slight expansion of suitable habitats for both species occurred under all three SSP scenarios, with *Prunus cerasifera* showing a more pronounced increase; (2) long-term (2050s onward) contraction became universal, with the magnitude of habitat loss escalating with higher radiative forcing and longer time horizons. The most severe declines were observed under the high-emission SSP585 scenario by the 2070s: suitable habitat area decreased by $7.579 \times 10^3 \text{ km}^2$ for *Malus sieversii* and $9.883 \times 10^3 \text{ km}^2$ for *Prunus cerasifera* (relative to the baseline). Notably, high-suitability habitats (suitability > 60%) suffered the sharpest reductions, dropping from 2.55% to 0.91% for *Malus sieversii* and from 2.00% to 0.784% for *Prunus cerasifera* under SSP585 (2070s), highlighting the vulnerability of core habitats to extreme climate change.

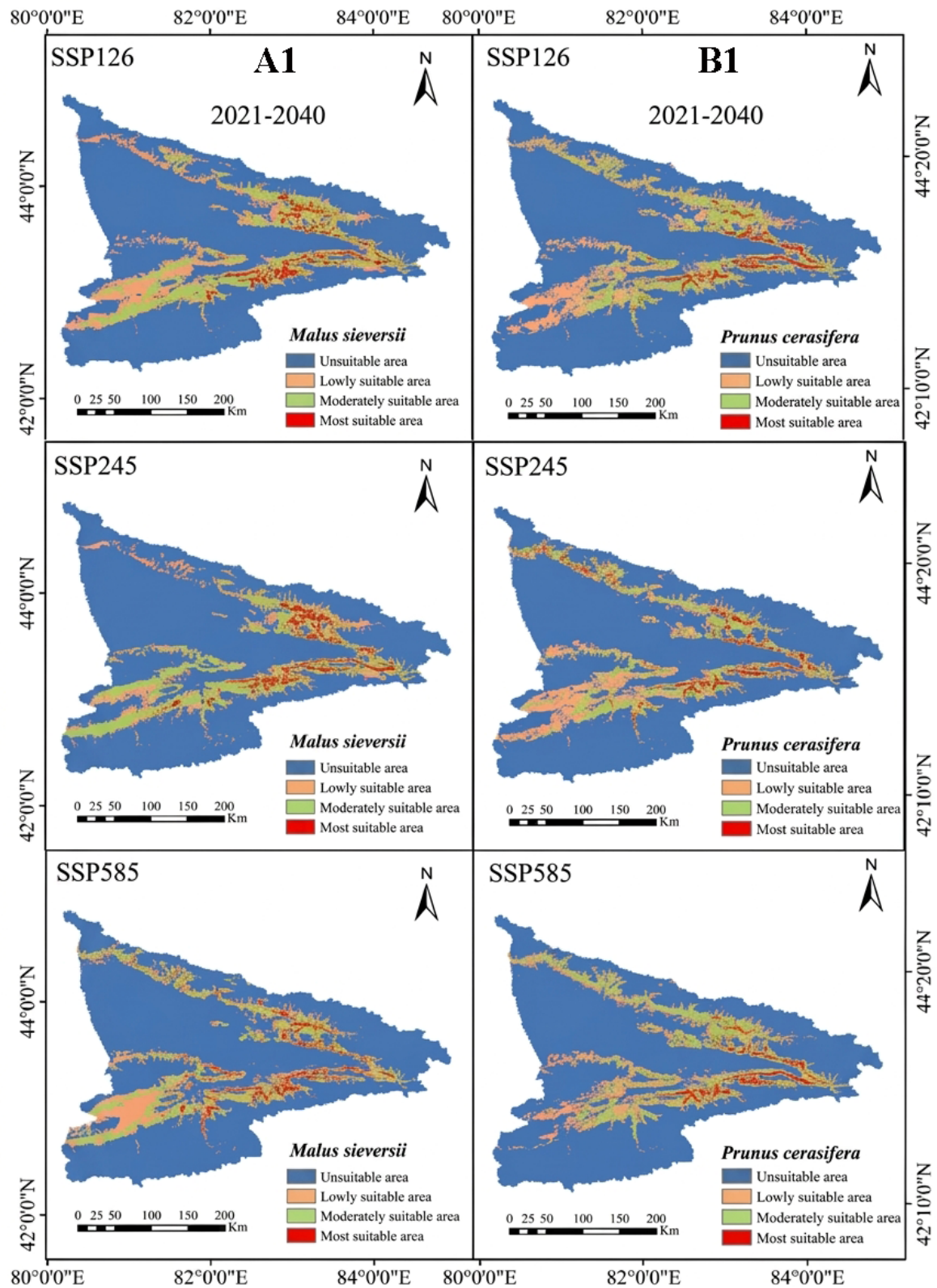


Figure 8. Cont.

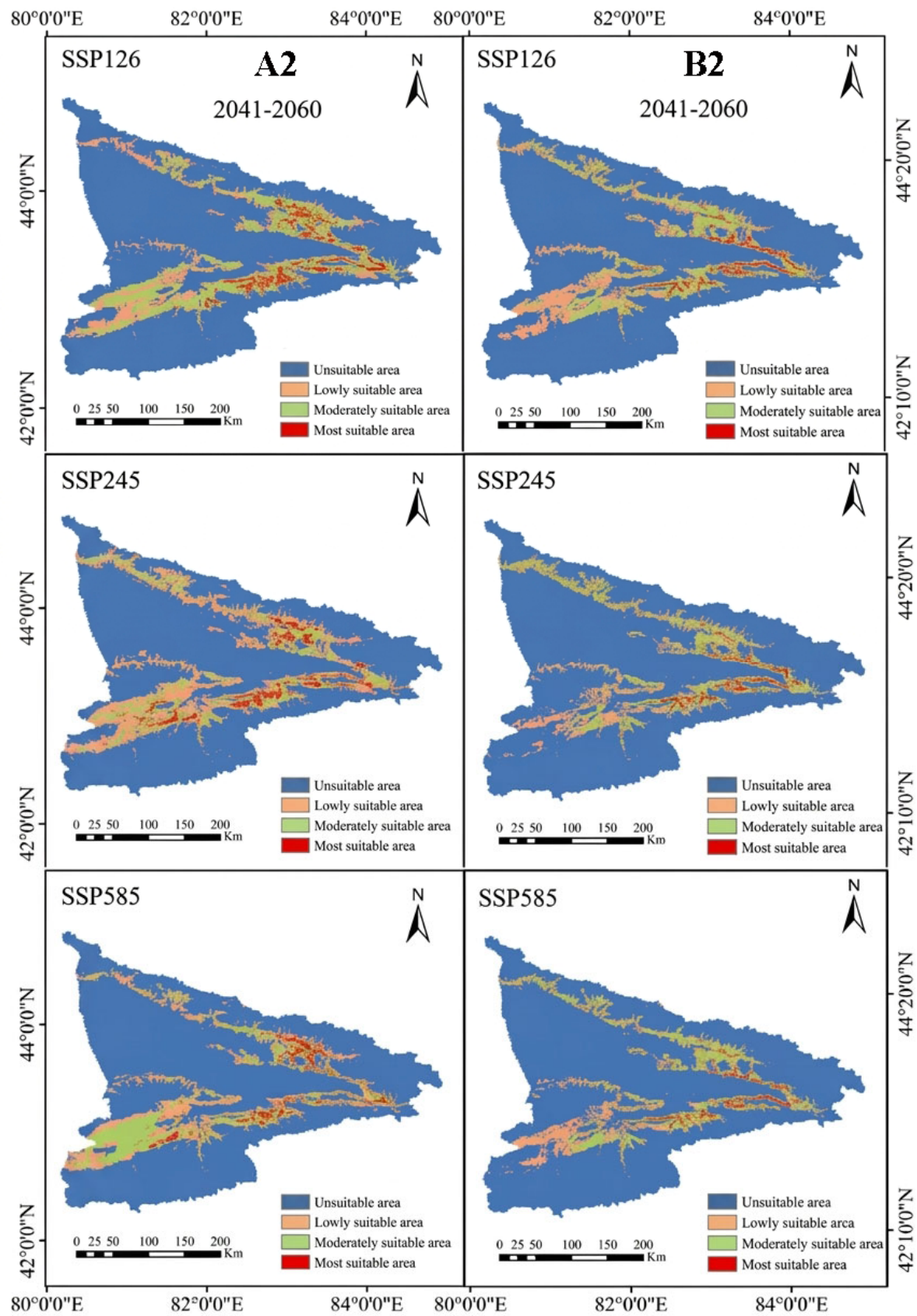


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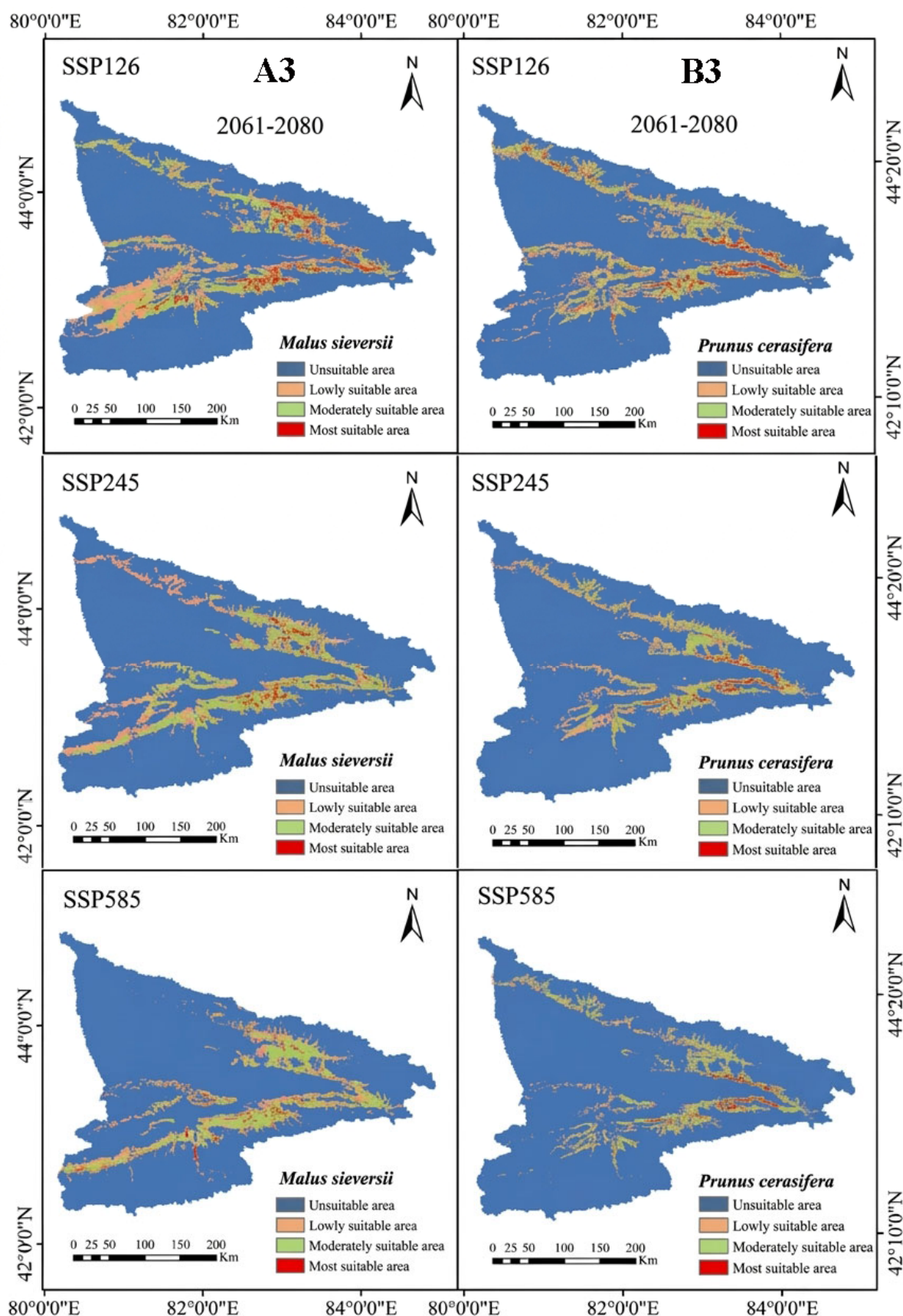


Figure 8. Predicted potential suitable habitats of *Malus sieversii* (A) and *Prunus cerasifera* (B) under three SSP climate scenarios (SSP126, SSP245, SSP585) for the 2030s, 2050s, and 2070s. SSPs: Shared Socioeconomic Pathways; SSP126: sustainable development; SSP245: moderate development; SSP585: fossil-fueled development.

As shown in Figure 9, habitat area declined progressively over time under each fixed scenario, with maximum reductions of $8.244 \times 10^3 \text{ km}^2$ for *Malus sieversii* and $12.894 \times 10^3 \text{ km}^2$ for *Prunus cerasifera* under SSP585 by the 2070s. Across all scenarios, habitat area increased marginally for both species in the 2030s (3.09%, 0.52%, and 0.64% for *Malus sieversii*; 5.00%, 3.27%, and 2.89% for *Prunus cerasifera* under SSP126, SSP245, and SSP585, respectively). By the 2050s, only SSP126 and SSP245 showed slight gains for *Malus sieversii* (1.44%, 0.54%), while all scenarios except SSP126 showed habitat loss for *Prunus cerasifera*. By the 2070s, significant habitat loss was observed across all scenarios, with reductions of 1.25%, 4.29%, and 7.27% for *Malus sieversii* and 2.08%, 7.03%, and 9.48% for *Prunus cerasifera* under SSP126, SSP245, and SSP585, respectively. The exacerbated drought and heat stress under high-emission scenarios disproportionately intensified habitat degradation for both species, with *Prunus cerasifera* exhibiting greater vulnerability to climate change due to its narrower climatic and soil niche.

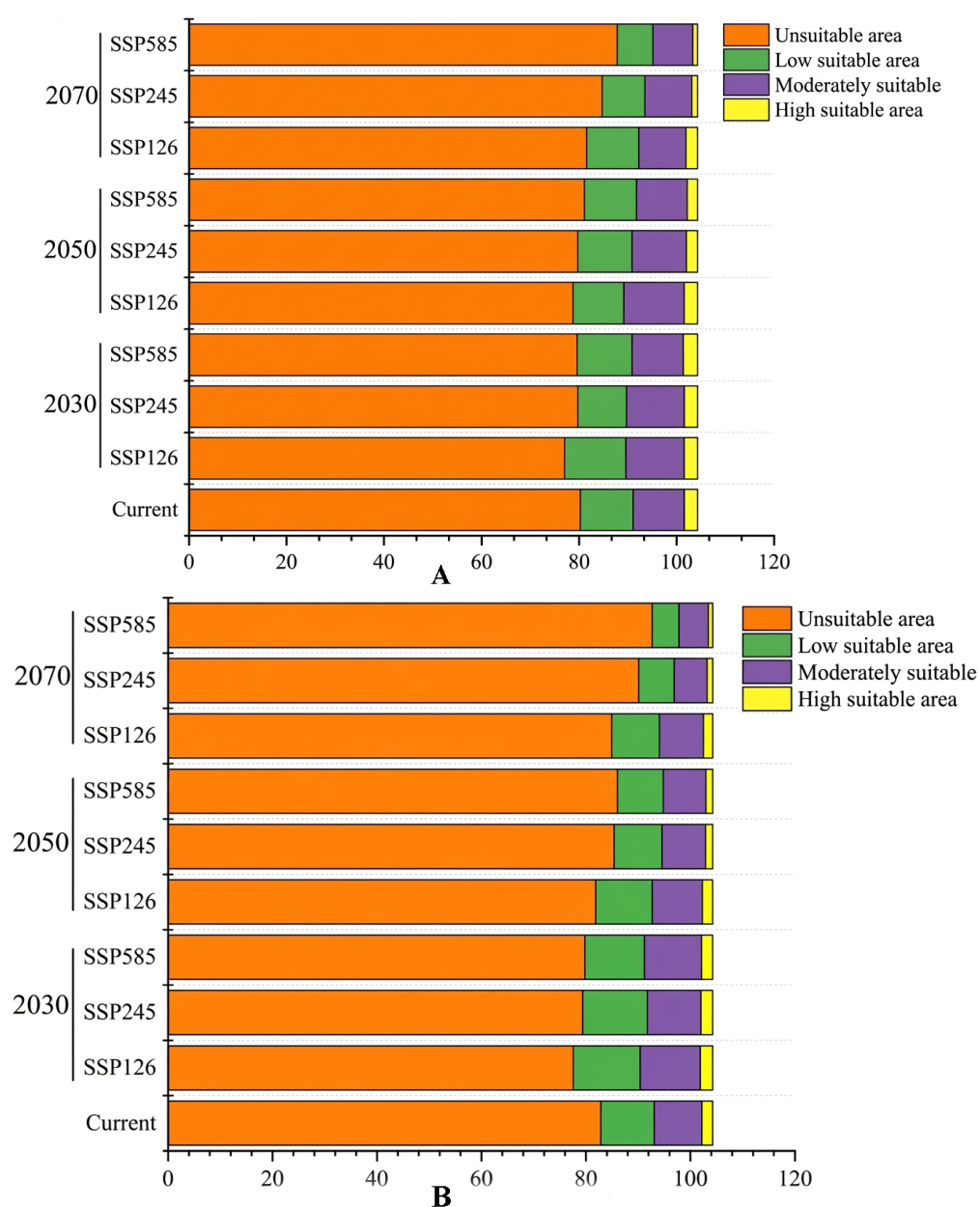


Figure 9. Changes in the area of suitable habitat for *Malus sieversii* (A) and *Prunus cerasifera* (B) under current and future climate scenarios (units: $\times 10^3 \text{ km}^2$).

5. Discussion

Malus sieversii and *Prunus cerasifera* are Class II protected wild plant species in China and play important ecological roles in wind protection, soil and water conservation, and ecosystem stabilization. At present, many wild plant species are seriously threatened by over-exploitation, destructive logging, deforestation, and habitat degradation [39,40,60]. Plant performance and persistence are jointly shaped by intrinsic biological traits and external environmental conditions. Therefore, species-specific geospatial information is fundamental for biodiversity conservation, especially under climate change. Such information helps identify potential refugia, vulnerable habitats, and priority areas for conservation and restoration. Changes in temperature and precipitation patterns caused by climate change affect individual species and the way they interact with their habitats, leading to changes in ecosystem structure and function and ultimately changes in biodiversity and ecosystem services [60–64]. Diverse biomes and well-functioning ecosystems are essential for maintaining ecosystem services for human well-being [65] (Figure 10).

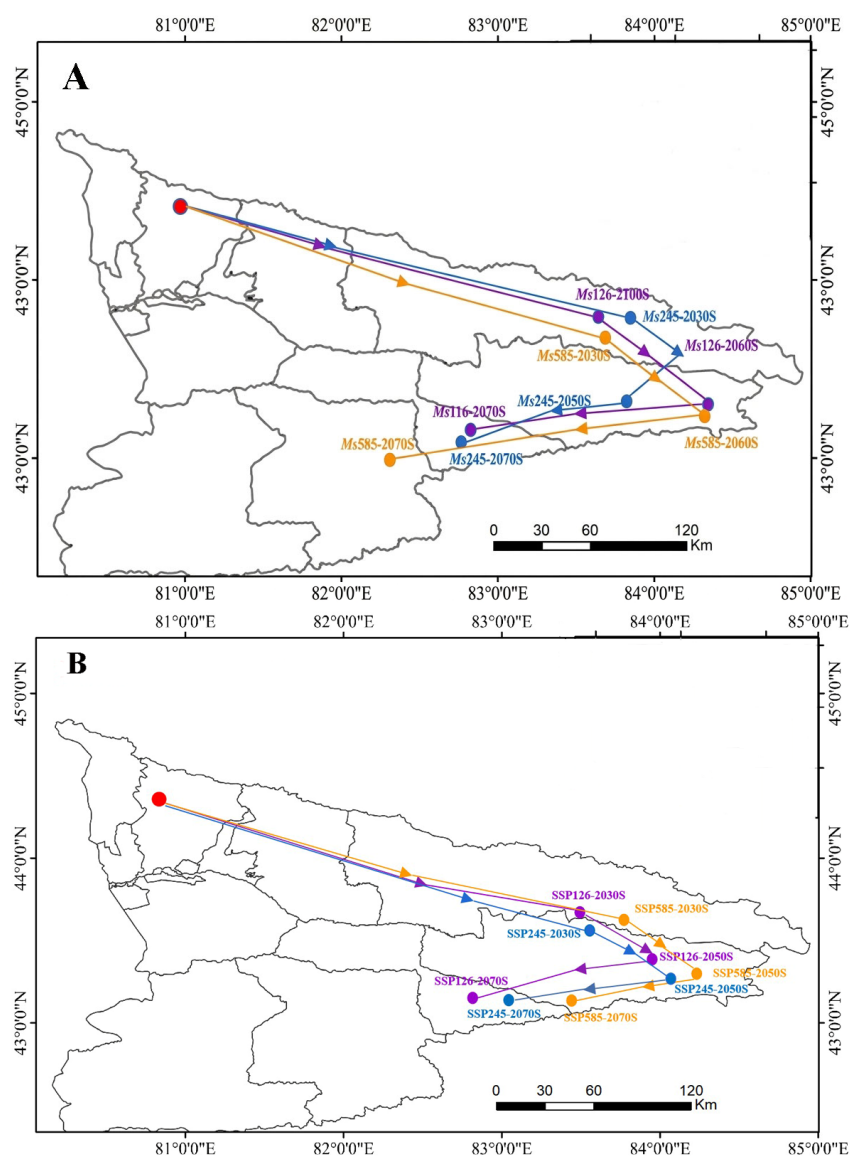


Figure 10. Shifts in the centroids of suitable habitats for *Malus sieversii* (A) and *Prunus cerasifera* (B) under current and future climate scenarios. The red dot denotes the current centroid, while colored points and arrows show projected centroid positions under SSP126, SSP245, and SSP585 scenarios for the 2030s, 2050s, and 2070s.

5.1. Influence of Environmental Variables on Habitat Suitability

Environmental factors play a crucial role in species habitat suitability and the biological processes that drive species growth, which is a crucial aspect of modeling [66,67]. Our results indicate that elevation, annual precipitation, and soil type were the most important predictors for *Malus sieversii*, whereas elevation, annual precipitation, and mean diurnal temperature range (bio2) were the dominant variables for *Prunus cerasifera*. The results showed that altitude and annual precipitation were common predictors for both vegetation simulations. This suggests that both species are strongly constrained by topography-related climatic gradients, although the magnitude of these effects differs between taxa.

Comparing the suitable habitat distribution maps and response curves of the two plants, it is clear that there are significant differences in elevation between the two species. The stronger contribution of elevation in the model for *Malus sieversii* indicates that this species may be more sensitive to topographic and climatic filtering than *Prunus cerasifera*. Because elevation is closely associated with temperature, moisture availability, radiation, and snow conditions, differences in elevational preference likely reflect differences in the realized ecological niches of the two species. Hosseini and Kappas [68] also reported that altitude was one of the essential factors driving habitat differentiation of related species in arid and semi-arid rangelands.

Also, precipitation is one of the critical constraints for species distribution. The response curves suggested that the optimum annual precipitation was approximately 150–250 mm for *Malus sieversii* and around 330 mm for *Prunus cerasifera*, indicating that the latter may prefer relatively wetter habitat conditions. Many previous studies have highlighted the role of precipitation as a critical variable influencing species establishment and survival [69,70]. Changes in precipitation affect plant physiological and ecological processes at different scales [71,72], and the relationship between water effectiveness and species distribution depends on local site conditions, hydrological profiles, and species-specific ecological requirements [73]. In addition, plant growth is directly affected by water availability; for example, the height, branch number, leaf area, and photosynthetic capacity of *Malus sieversii* decrease significantly under water limitation [27,74]. These findings support our interpretation that precipitation is a major determinant of habitat suitability for both species in the Ili Valley. Soil type is another important variable in determining plant distribution. Soils are the product of a combination of soil-forming parent material, climate, biology, topography, and time, with climate and biology being the more active factors [75]. In our model, soil acted as a non-climatic environmental filter that may help explain the habitat differentiation between the two species. Each species undergoes its own specific biogeochemical cycle, resulting in soil properties that are most conducive to its growth and establishment [76]. Changes in temperature and precipitation may lead to changes in biogeochemical soil cycles, which alter soil types due to interactions between environmental variables and organisms [76]. Studies have shown that plants are sensitive to climate-induced changes in soil conditions [77]. Therefore, the combined effects of climate and soil heterogeneity are likely to increase the vulnerability of *Malus sieversii* and *Prunus cerasifera* under future climate change.

5.2. Projected Changes in Climate on Species Distribution

Under the current climatic conditions, the suitable habitat area of *Malus sieversii* is larger than that of *Prunus cerasifera*. At present, highly suitable habitats for *Malus sieversii* are mainly distributed in Huocheng, Xinyuan, and Gongliu counties, whereas suitable habitats for *Prunus cerasifera* are mainly concentrated in Huocheng and Xinyuan. Under future climate change scenarios, the potentially suitable habitats of both species are projected to become smaller than under the current climate. For *Malus sieversii*, future

suitable habitat is expected to persist mainly in the southern part of the study area and central Nilek County, whereas future suitable habitat for *Prunus cerasifera* is projected to be concentrated in the southern part of the study area. However, the overlap between the suitable habitats of the two species should be interpreted cautiously. Although habitat overlap may imply potential co-occurrence, interspecific competition was not explicitly modeled in MaxEnt, and therefore realized distributional constraints cannot be inferred directly from overlap patterns alone. Furthermore, the projected reduction in suitable habitat and the concentration of remaining suitable areas indicate that both species may become more vulnerable to future climate change.

To better contextualize our results, we now note that similar patterns of habitat contraction and spatial redistribution under warming scenarios have also been reported by studies using other species distribution modeling approaches, including ensemble SDMs and machine learning or regression-based algorithms such as Random Forest, GLM, and BRT. At the same time, recent studies have shown that future suitability projections can vary substantially depending on predictor selection, model calibration, and model transferability. Therefore, our MaxEnt-based projections should be interpreted as a plausible estimate of future climatic suitability rather than a deterministic forecast of realized distribution. In addition, coarse-resolution macroclimatic projections may overestimate the magnitude of actual range shifts because local topography and microrefugia can buffer species against regional warming [78].

Similar declines in suitable habitats have been observed for species worldwide under future climate change scenarios [79–82]. Consistent with our findings, an assessment of the potential distribution of fir in northern Pakistan under the influence of climate change also predicts a significant loss of suitable habitat [83]. By modeling the effects of climate change on the distribution of Qinghai spruce in the Qilian Mountains in China, Rong et al. [84] observed not only a decrease in potentially suitable habitat under a warming climate but also a shift from areas of high suitability classification to areas of low suitability classification, which is also consistent with our results. Taken together, these findings suggest that climate warming may reduce the extent and quality of suitable habitats for both species, with potential consequences for vegetation productivity and ecosystem services. Nevertheless, uncertainties associated with future climate scenarios, model structure, and species adaptation capacity should be acknowledged when interpreting these projections.

5.3. Impacts of Climate Change on Species Migration

In the face of climate change, vegetation can respond through a combination of phenotypic adjustment, demographic change, local persistence in refugial habitats, and range shifts toward newly suitable areas [85,86]. However, rapid climate change may not allow many species to evolve or disperse fast enough to track shifting climatic niches [85,87], and migration is often constrained by dispersal limitation, establishment failure, habitat fragmentation, and ecological time lags [87]. Thus, changes in climatically suitable habitat predicted by our MaxEnt model should not be equated directly with realized migration in the field.

Our results suggest that the potential habitat of *Malus sieversii* and *Prunus cerasifera* vegetation likely shifted to the northeast in response to a warmer climate in the 21st century. This pattern is broadly consistent with the expectation that many terrestrial species track cooler conditions through elevational or latitudinal redistribution, although recent empirical syntheses indicate that such responses are neither universal nor spatially uniform. Even though the MaxEnt model helps to identify future changes in potential climatic suitability, it does not estimate dispersal capacity, migration lag, demographic processes, or biotic interactions [88]. Accordingly, our projections should be interpreted as

potential shifts in suitable climatic space rather than direct evidence of actual migration rates. Díaz-Alba et al. [89] estimated that *Salix purpurea* would need to move more than 1 km per year to keep pace with climate change. Similarly, the persistence of *Malus sieversii* and *Prunus cerasifera* in future suitable areas will depend not only on climatic suitability, but also on dispersal ability, recruitment success, habitat connectivity, and the availability of local microhabitats.

From a conservation perspective, these results support several management priorities: protecting current high-suitability refugia, maintaining or restoring habitat connectivity between current and future suitable areas, reducing overgrazing and other anthropogenic disturbances, and considering assisted regeneration or ex situ conservation where natural tracking of climate change is unlikely. Such actions would improve the capacity of both species to persist under future climate change, even if realized migration falls behind the pace of climatic change.

6. Conclusions

In this study, the potential distribution of the two species was successfully modeled for key environmental variables including climatic, soil, and topographic factors. Precipitation and elevation were the critical environmental variables influencing the habitat suitability of the species selected, and the predicted results showed that the potential habitat area of Ms species decreased by 1.25%, 4.29%, and 7.27% and Pc by 2.08%, 7.03%, and 9.48%, respectively. It is predicted that future climate change will adversely affect the distribution of Ms and Pc. Areas that currently exhibit high suitability for the species are expected to exhibit moderate-to-low suitability in future climate scenarios.

With future gradual warming, the potential habitat of this species will shift to the northeast, and most of the habitat will be lost with climate warming in the SSP585 climate scenario. The temporal match between climate and distribution data, and the uncertainty of future climate change, provides decision-makers with potential habitats for Ms and Pc to develop more specific conservation strategies based on our findings.

Author Contributions: S.L.: Conceptualization, methodology, writing—original draft, writing—review and editing. C.W.: Conceptualization, writing—review and editing. M.Y.: Formal analysis, validation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 32460279). Yili Normal University Research Start-up Grant Project (2025RCYJ27).

Data Availability Statement: The datasets supporting the conclusions of this article are fully presented in the manuscript and figures. The original raw occurrence records and customized environmental layers are not publicly available due to relevant biodiversity protection regulations; reasonable data requests can be sent to the corresponding author.

Acknowledgments: The authors sincerely appreciate the support provided by the 2025 Xinjiang Uygur Autonomous Region Government Sponsored Overseas Study Group Project: Research on Managed Aquifer Recharge (MAR) Technology in Arid Regions.

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

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