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# Assessing the impacts of climate changes and human activities on cotton distribution in Xinjiang

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Both climate change and human activities play critical roles in shaping the spatial distribution of cotton cultivation, particularly in arid and semi-arid environments. However, existing studies have not sufficiently quantified their synergistic effects, and regional-scale applications remain limited. This study selected key variables from 31 environmental factors—including climate, soil, topography, and human footprint—and employed an optimized MaxEnt model to project cotton distribution across three Shared Socioeconomic Pathways (SSP126, SSP245, and SSP585). We developed models based on (i) current climate conditions, (ii) an integrated model incorporating both current climate conditions and human footprint, and (iii) future climate projections for the 2030s, 2050s, and 2070s. The results indicate that human footprint, mean diurnal temperature range (bio2), mean temperature of the coldest quarter (bio11), precipitation of the coldest quarter (bio19), and solar radiation intensity are the primary factors influencing cotton distribution. Under prevailing climate conditions, suitable cotton habitats are mainly located in Aksu, Kashgar, Tacheng, Bayingolin Mongol Autonomous Prefecture, and Changji, where human activities have significantly expanded the cultivation range. Future climate projections indicate a decrease in the extent of suitable cotton habitats, with its distribution center shifting toward lower-altitude areas. This study offers key empirical evidence and conceptual understanding to address climate-induced risks to cotton farming, forming a basis for informed strategies in sustainable cultivation and habitat conservation.

## KEYWORDS

human footprint, climate change, suitable habitat for cotton, MaxEnt model, Xinjiang

## 1 Introduction

Climate change and human activities are the principal forces driving the evolution of global agricultural ecosystems, profoundly shaping agricultural production patterns through their impacts on crop phenology, yield stability, and the boundaries of cultivation zones (Yue et al., 2019; Onuegbu et al., 2024; Zafar et al., 2024). Climate factors such as solar radiation, temperature, and precipitation have a significant impact on crop growth (Sun et al., 2017; Jiang et al., 2021). Solar radiation is fundamental to photosynthesis, while moderate diurnal temperature fluctuations enhance cotton growth. As a tropical crop, cotton is highly sensitive to low temperatures, with frost potentially causing damage that disrupts the interaction between cotton roots, soil, and microbial communities, thus inhibiting seed germination (Li et al., 2023b; Li et al., 2024). Particularly in arid and semi-arid regions, the synergistic effects

of climate change and human activities have significantly increased the vulnerability of agricultural ecosystems, leading to more complex environmental changes (Zain-ul-Hudda et al., 2024; Nazarova et al., 2025). Studies from South Asia and Africa show that the increased frequency of droughts and the reduction of water resources caused by climate change have directly impacted the distribution of cotton cultivation areas (Gérardeaux et al., 2018; Ullah et al., 2022). Furthermore, human activities such as land-use changes and infrastructure development further influence the spatial distribution of cotton cultivation (Chen et al., 2022). Soil properties, such as organic carbon content and soil texture, provide the necessary environmental conditions for cotton growth, while natural factors like topography play a crucial role in regulating water and nutrient supply (Malode et al., 2021; Wu et al., 2024). Therefore, the distribution of cotton is influenced not only by climate change but also by the combined effects of human activities, soil properties, and topographical features.

Xinjiang is one of the largest cotton-producing regions in China (Kuang et al., 2024; Zahra et al., 2025). However, as climate change intensifies, challenges such as water scarcity, temperature fluctuations, and precipitation uncertainty are significantly altering the cotton-growing environment, profoundly impacting the boundaries of suitable cultivation areas (Li et al., 2023a). Similar trends have been observed in major cotton-growing regions, including the United States, India, and Australia (Hebbbar et al., 2013; Williams et al., 2015; Nouri et al., 2021). The effects of climate change on cotton production manifest in different patterns across these regions, with some variations influenced by local water management strategies. Nevertheless, many of these regional studies often overlook the combined impact of human activities and climate change.

Globally, considerable research has been conducted on crop distribution modeling (Benito Garzón et al., 2019). Existing studies have demonstrated that ecological niche models (ENMs) and species distribution models (SDMs) are effective tools for assessing the potential impacts of climate change on agricultural ecosystems (Roy et al., 2022). The MaxEnt (Maximum Entropy) approach has gained recognition for its superior predictive accuracy, owing to its computational efficiency, resilience to missing data, and capacity to deliver accurate predictions from limited occurrence records (Elith et al., 2011; Merow et al., 2013). Consequently, the MaxEnt model has been extensively utilized in agricultural and ecological studies (Xu et al., 2019; He et al., 2023).

Recent studies on cotton have widely adopted MaxEnt to examine how climate variability influences its geographic distribution (Shi et al., 2021; Li et al., 2023a; Mai and Liu, 2023). These studies investigate how shifts in climate conditions may alter suitable cultivation zones by analyzing differences between current and projected cotton distributions, thereby supporting adaptation strategies in cotton farming. While the influence of climate change on cotton distribution has been widely acknowledged, it is equally important to recognize that cotton growth and distribution are substantially influenced by anthropogenic activities, particularly through water resource management, land-use changes, and genetic advancements (Wu et al., 2022; Lang et al., 2023; Shi et al., 2023). Although previous studies have delineated climate suitability zones for cotton across various provinces and regions, there remains a significant gap in research integrating both climate change and anthropogenic activities in the evaluation of cotton's climate suitability (Li et al., 2020b). Most existing studies have primarily concentrated on evaluating climatic

influences on cotton suitability, largely overlooking the roles of human activities. Nonetheless, the synergistic impacts of climate change and anthropogenic activities on cotton distribution patterns constitute a critical yet underexplored research domain.

To assess the combined influence of climate dynamics and anthropogenic factors (as indicated by the human footprint), this study examines their interactive effects on cotton distribution patterns. Accordingly, key variables influencing cotton growth in Xinjiang—including bioclimatic conditions, soil characteristics, topography, and human activities—were selected and analyzed using the MaxEnt model. The objectives of this study are: (1) to compare cotton habitat distributions in Xinjiang under scenarios with and without human intervention; (2) to evaluate changes in cotton habitat distribution patterns under multiple future climate scenarios; and (3) to examine the spatial dynamics and development trends of cotton cultivation in Xinjiang. The results enhance the understanding of how climate variability and human activities jointly influence cotton distribution in Xinjiang, thereby informing more effective cultivation strategies, rational resource use, and long-term agricultural sustainability in the region.

## 2 Materials and methods

### 2.1 Study area

Located in the northwestern part of China, Xinjiang (73°40'–96°18'E, 34°25'–48°10'N) represents the country's most extensive provincial-level region and experiences a typical temperate continental climate. As China's primary cotton production base, Xinjiang plays a critical role in national cotton yield and quality, owing to its extensive land resources and favorable thermal and solar conditions (Li et al., 2020b). However, situated within an arid and semi-arid region, Xinjiang experiences scarce natural precipitation, rendering cotton growth highly dependent on artificial irrigation. Therefore, Xinjiang serves as an ideal region for studying the suitability distribution of economic crops in arid and semi-arid environments.

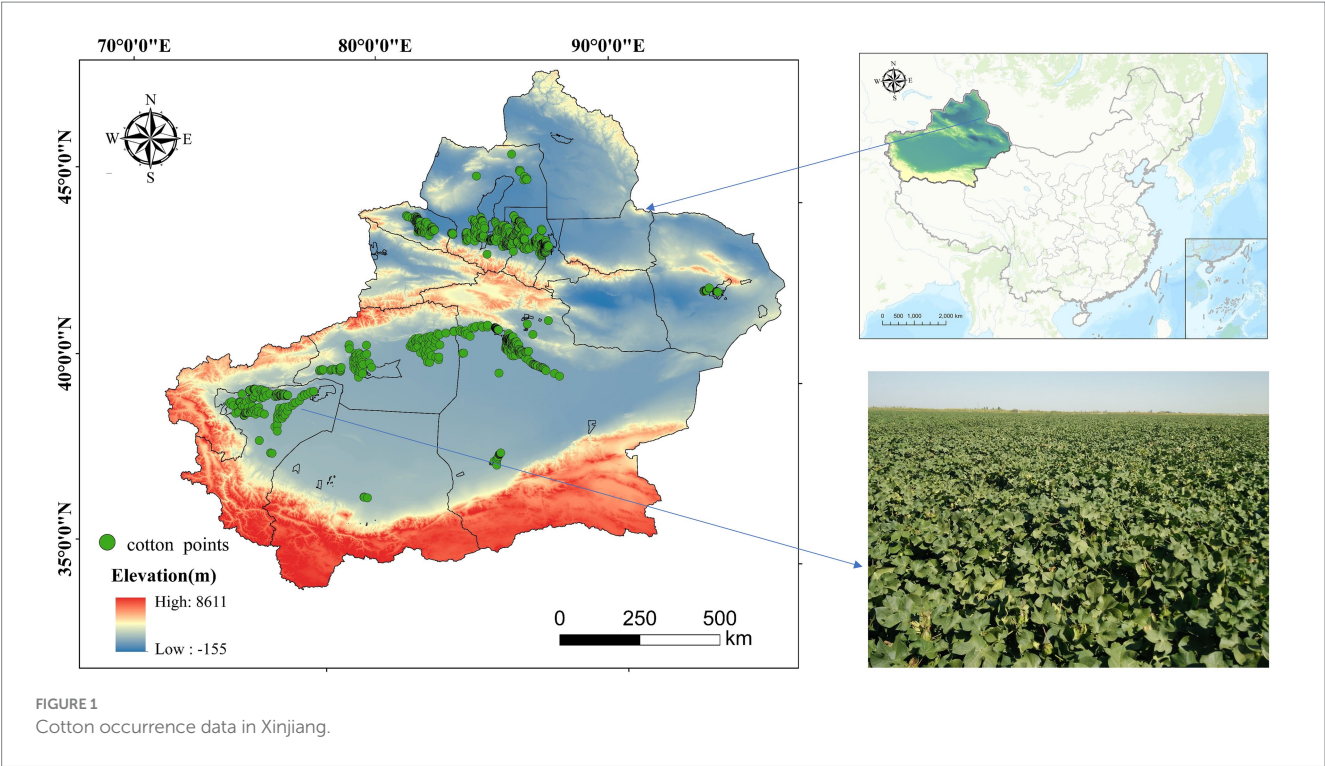
### 2.2 Data sources

#### 2.2.1 Species occurrence data

This study utilized field survey data collected from agricultural regions of Xinjiang between 2015 and 2020. GPS was used to record the latitude, longitude, and elevation of cotton planting sites, thereby generating occurrence data for cotton distribution across Xinjiang. To reduce redundancy and avoid overfitting, ENMTools.pl. was applied to preprocess the dataset, allowing a single valid record per spatial grid. After this refinement, 1,195 unique cotton presence points remained and were used in the modeling phase (Figure 1).

#### 2.2.2 Environmental variables

In order to estimate how cotton may be distributed across Xinjiang in projected climate conditions, this study adopted the BCC-CMS2-MR global climate model (GCM), as recommended in the IPCC's Sixth Assessment Report. This model, optimized from earlier versions, demonstrates strong predictive capabilities for future climate scenarios. The analysis incorporated three Shared Socioeconomic Pathways (SSPs)—SSP126, SSP245, and SSP585—to



develop predictive models of cotton suitability distribution in Xinjiang under future climate scenarios.

Additionally, 31 environmental variables potentially affecting cotton distribution were collected, encompassing soil, topography, solar radiation, bioclimatic characteristics, and human activities to build an integrated analytical framework. Specifically, soil data were sourced from the HWSD database to assess soil characteristics. Topographic data were acquired from the Geographic Space Data Cloud Platform and processed with ArcGIS 10.8 to derive slope and aspect features. Solar radiation data, representing both current and future scenarios, were sourced from WorldClim and the NASA NEX-GDDP-CMIP6 high-resolution datasets (Table 1).

Research has shown a close relationship between the severity, extent, and spread of the human footprint and the suitability of land

for agriculture. Human footprint data were retrieved from the Global Human Impact Dataset (Venter et al., 2016), which integrates information on land use, population density, and infrastructure to quantify the intensity of human activities. These components serve as indirect proxies for agricultural activities, such as infrastructure development and land conversion, especially in arid regions where direct irrigation data is often lacking. Previous studies have demonstrated significant correlations between the human footprint index and changes in hydrological systems, agricultural expansion, and ecological pressure (Jaramillo and Destouni, 2015; Grill et al., 2019; Lines et al., 2021; Grill et al., 2019; Jaramillo and Destouni, 2015). Therefore, in this study, we incorporate the human footprint index as a continuous variable into the MaxEnt model to represent the combined effects of human activity on the suitability distribution of cotton. The relationship between human footprint intensity and agricultural suitability highlights the critical role of human-induced land use and infrastructure development in shaping crop growth potential, particularly in areas with limited natural climate resources.

These data reflect both natural and human-driven factors influencing cotton distribution in Xinjiang. Future scenario predictions for the 2030s, 2050s, and 2070s were generated under the assumption that topography and soil characteristics would remain constant, offering a robust basis for assessing potential suitable regions for cotton cultivation in Xinjiang (Egli et al., 2018). These analyses lay the groundwork for investigating how climate variability and human interventions affect cotton distribution and for optimizing planting strategies. This study integrates multiple climate scenarios for the 2030s, 2050s, and 2070s, resulting in nine distinct future scenarios: SSP126-30s, SSP126-50s, SSP126-70s, SSP245-30s, SSP245-50s, SSP245-70s, SSP585-30s, SSP585-50s, and SSP585-70s. To reduce multicollinearity among variables, a correlation analysis module in ENMTTools.pl. was employed to remove those with a correlation coefficient greater than 0.8

TABLE 1 Data sources and descriptions.

Data type	Resolution	Data source
Soil	30 arcsec	<a href="http://www.iiasa.ac.at/">http://www.iiasa.ac.at/</a>
DEM	1 km	<a href="https://www.gscloud.cn/">https://www.gscloud.cn/</a>
Human Footprint	1 km	<a href="http://www.ciesin.columbia.edu/wild_areas">http://www.ciesin.columbia.edu/wild_areas</a>
Current Bioclimatic	30 arcsec	<a href="https://worldclim.org/">https://worldclim.org/</a>
Future Bioclimatic	30 arcsec	<a href="https://worldclim.org/">https://worldclim.org/</a>
Current solar radiation	30 arcsec	<a href="https://worldclim.org/">https://worldclim.org/</a>
Future solar radiation	0.25°	<a href="https://nex-gddp-cmip6.s3.us-west-2.amazonaws.com/index.html#NEX-GDDP-CMIP6/">https://nex-gddp-cmip6.s3.us-west-2.amazonaws.com/index.html#NEX-GDDP-CMIP6/</a>
Administrative boundary data of Xinjiang	-	<a href="https://www.resdc.cn/">https://www.resdc.cn/</a>



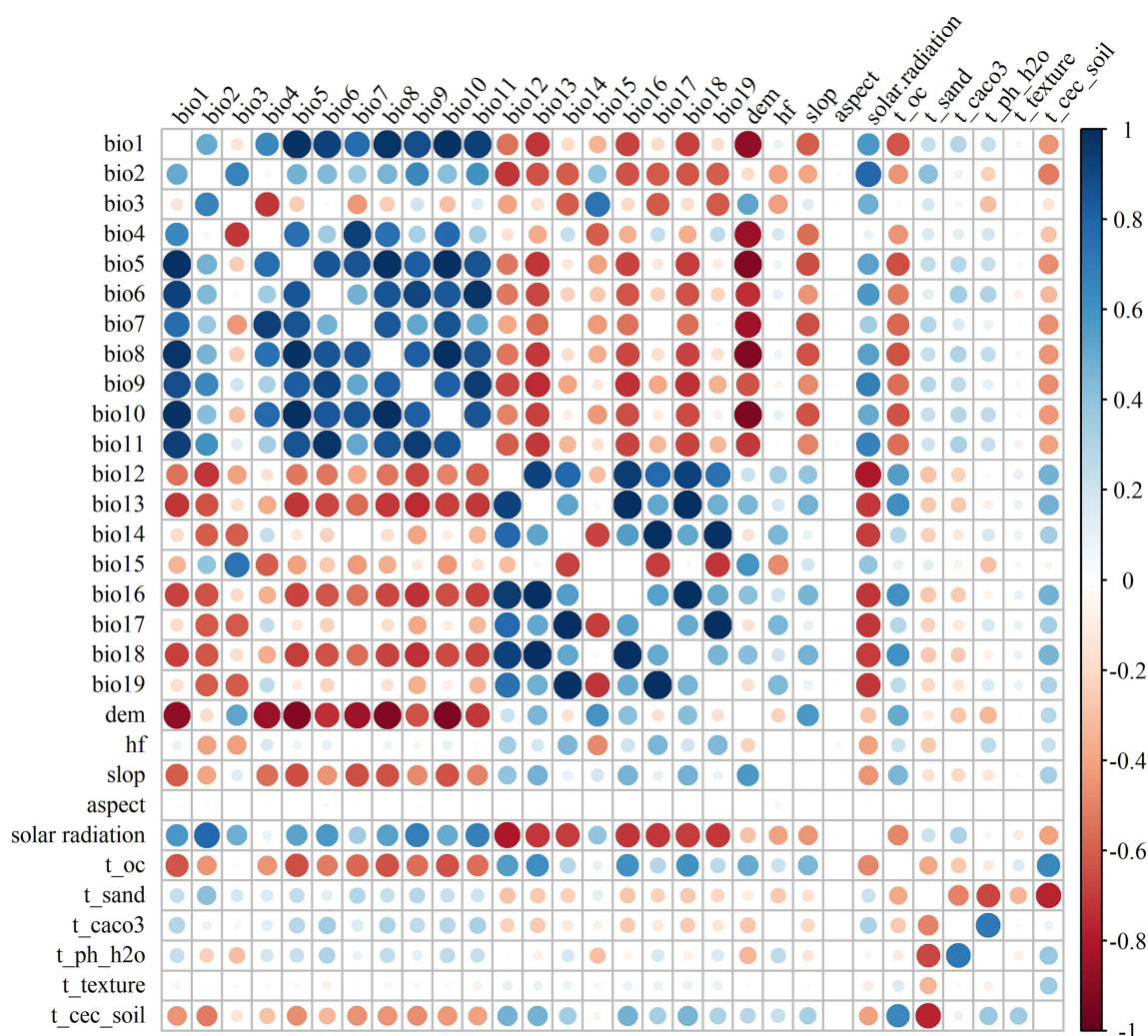


FIGURE 2  
Correlation of 31 environmental variables.

(Warren et al., 2021) (Figure 2). Through a stepwise backward selection process, 17 environmental variables were ultimately selected for model analysis (Rodríguez-Caballero et al., 2018) (Table 2).

## 2.3 Principle of the MaxEnt Model

The MaxEnt model is a machine learning technique grounded in the principle of maximum entropy, widely used for species distribution modeling (SDM) (Elith et al., 2011). The fundamental concept is to identify a probability distribution that maximizes entropy, meaning it is the least biased and most uniform given partial environmental data. According to the principle of maximum entropy, when no additional information is available, the most uniform distribution should be chosen (Guíasu and Shenitzer, 1985; Brummer and Newman, 2019). In the MaxEnt framework, a species' potential habitat distribution is represented by a probability distribution, where various environmental variables are introduced as feature functions (e.g., linear, quadratic, hinge features) to capture the relationship between

environmental conditions and species distribution. The objective of the MaxEnt model is to find the optimal predictive model by maximizing the entropy of this distribution. The model's optimization goal is expressed as follows:

$$P(x) = \frac{\exp\left(\sum_i \lambda_i f_i(x)\right)}{\sum_{x'} \exp\left(\sum_i \lambda_i f_i(x')\right)}$$

Where  $p(x)$  is the probability of the species occurring at location  $x$ .  $f_i(x)$  is the feature function for the environmental variable at location  $x$ , which describes the relationship between environmental factors and species distribution.  $\lambda_i$  is the weight associated with each feature function, representing the impact of various environmental variables on species distribution.

Through adjusting these weights  $\lambda_i$ , the MaxEnt model maximizes the entropy of the species distribution to predict the most suitable habitats for the species under different environmental conditions.



TABLE 2 Modeling variables.

Variables	Description	Unit
Bio2	Mean Diurnal Range	°C
Bio3	Isothermality	unitless
Bio11	Mean temperature of coldest quarter	°C
Bio15	Precipitation seasonality	unitless
Bio18	Precipitation of warmest quarter	mm
Bio19	Precipitation of coldest quarter	mm
Dem	DEM	m
Aspect	Aspect	°
Slope	Slope	°
t_ph_h2o	Topsoil PH(H <sub>2</sub> O)	unitless
t_oc	Topsoil organic carbon	% weight
t_texture	Topsoil texture	code
t_sand	Topsoil sand fraction	% wt
t_caco <sub>3</sub>	Topsoil calcium carbonate	% weight
t_cec_soil	Topsoil CEC (soil)	cmol(+)kg
Solar radiation	Solar radiation	kJ/m <sup>2</sup> /day
HF	Human footprint	unitless

## 2.4 Model analysis

The environmental dataset was processed through bilinear-based interpolation and harmonized to a consistent 250 × 250-meter grid resolution (Xu et al., 2024). To evaluate the combined effects of environmental changes and human activities on the cotton cultivation potential in Xinjiang, three predictive models were developed: Model A: Simulates the potential distribution of cotton under natural conditions using environmental variables representing the current climate, including bioclimatic, soil, topographic, and solar radiation data. Model B: Expands upon Model A by incorporating human footprint data to evaluate the role of human activities in shaping cotton habitat suitability. Model C: Evaluates how climate change may affect cotton distribution by utilizing environmental variables under future climate scenarios, including bioclimatic, soil, topographic, and solar radiation data.

To optimize model parameters and mitigate overfitting, 75% of the data were used for training and 25% for testing. The ENMeval package was employed to optimize the regularization multiplier (RM, ranging from 0.5 to 4 in increments of 0.5) and feature combinations (FC, consisting of six types: L, LQ, H, LQH, LQHP, and LQHPT) in the MaxEnt model. A total of 48 parameter combinations (8 regularization multipliers × 6 feature combinations) were systematically evaluated, and model complexity was assessed (Kass et al., 2021; Huang et al., 2024). The final selection of parameter combinations, based on a balance between model complexity and predictive performance, prioritized lower complexity and stronger ecological interpretability, thus ensuring a balance between predictive accuracy and the risk of overfitting.

The influence of each environmental factor on model predictions was evaluated through the jackknife method, with response curves visualized to demonstrate their impact on cotton suitability. The suitability threshold was determined based on expert knowledge and the Maximum Training Sensitivity plus Specificity (MTSS) criterion within the MaxEnt model. Suitability levels were classified into four categories: unsuitable (<MTSS), low suitability (MTSS–0.3), moderate suitability (0.3–0.4), and high suitability (0.4–0.8) (Shabani et al., 2018; Wang et al., 2019). To ensure comparability across different models and climate scenarios, all predictions were based on the same threshold classification. Comparing Model A and Model B reveals the impact of human activities on cotton suitability, whereas comparing Model A and Model C highlights the potential effects of climate change on cotton distribution and agricultural potential, thus guiding the development of adaptive agricultural management strategies.

## 2.5 Model evaluation and validation

This study utilized ROC curves and the Area Under the Curve (AUC) metric to evaluate model performance, where AUC values range from 0 to 1. AUC values closer to 1 indicate higher predictive accuracy. According to AUC grading standards, model performance ranges from poor (0 < AUC ≤ 0.6) to excellent (0.9 < AUC ≤ 1) (Zhao et al., 2021). The True Skill Statistic (TSS) was introduced as a supplementary evaluation metric. TSS is calculated by summing sensitivity and specificity and subtracting 1, with values ranging from –1 to 1 (Allouche et al., 2006). Based on evaluation standards, TSS scores are categorized as poor (–1 to –0.4), fair (0.4–0.7), very good (0.7–0.85), and perfect (0.9–1) (Préau et al., 2018). By integrating AUC and TSS, the models' performance in predicting suitable cotton habitats in Xinjiang was assessed comprehensively. AUC emphasizes overall predictive capacity, whereas TSS refines the accuracy in distinguishing species presence and absence. Together, these two metrics offer a more comprehensive framework for model evaluation (Kabir et al., 2017).

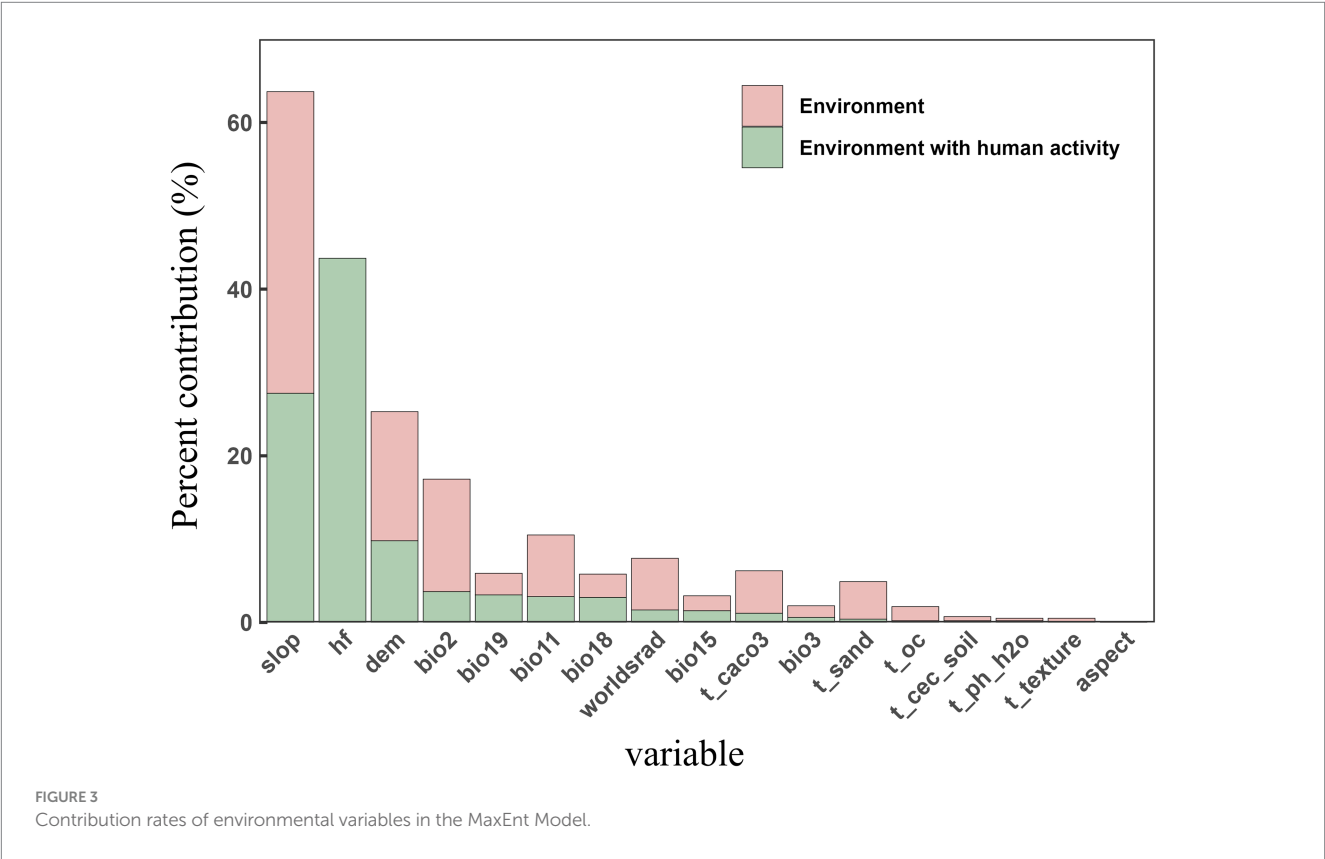
## 3 Results

### 3.1 Model parameter optimization results

In this study, simulation prediction results were evaluated using a combination of AUC and TSS metrics. Under the MaxEnt model, the average training AUC was 0.947, the average testing AUC was 0.941, and the average TSS was 0.840, indicating a high level of predictive accuracy and model reliability (Table 3). When the regularization multiplier (RM) was set to 1 and the feature combination (FC) to LQHPT, the MaxEnt model achieved optimal performance. In this configuration, the training AUC reached 0.946, the testing AUC reached 0.943, and the TSS was 0.837 (Table 3). Under environmental conditions (Model A), the variables influencing cotton distribution were: slope (36.2%), DEM (15.5%), bio2 (13.5%), bio11 (7.4%), solar radiation (6.2%), t\_CaCO<sub>3</sub> (5.1%), and t\_sand (4.5%), with a cumulative contribution rate of 88.4%. Under human activity influences (Model B), the variables influencing cotton distribution were: HF (43.7%), slope (27.5%), DEM (9.8%), bio2 (3.7%), and bio19 (3.3%), with a cumulative contribution rate of 88%. As the human footprint increased, environmental variables such as slope, DEM, and bio2, each initially

TABLE 3 Model accuracy evaluation.

Scenario	AUC <sub>train</sub>	AUC <sub>test</sub>	TSS
Current	0.946	0.943	0.837
Current_HF	0.947	0.938	0.843
SSP126 ~ 2030	0.948	0.940	0.844
SSP126 ~ 2050	0.948	0.934	0.839
SSP126 ~ 2070	0.947	0.943	0.840
SSP245 ~ 2030	0.947	0.945	0.839
SSP245 ~ 2050	0.946	0.943	0.841
SSP245 ~ 2070	0.947	0.943	0.840
SSP585 ~ 2030	0.945	0.938	0.833
SSP585 ~ 2050	0.946	0.943	0.842
SSP585 ~ 2070	0.946	0.944	0.837



contributing more than 6%, exhibited decreases compared to Model A (with reductions of 8.7, 5.7, 9.8, and 4.7%, respectively). Conversely, in Model B, the contribution rate of bio19 increased by 0.7% (Figure 3).

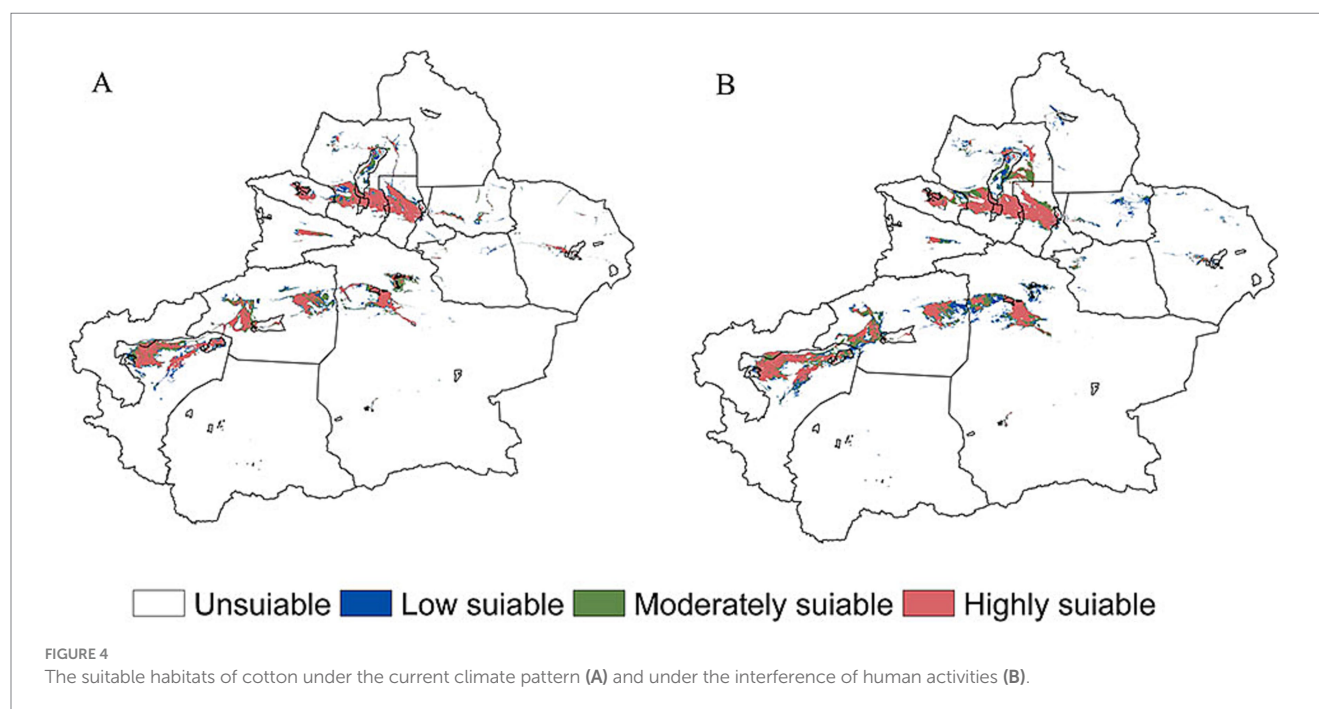
### 3.2 Distribution of cotton planting areas under current climate and human interference

The MaxEnt model was used to simulate cotton suitability habitats under scenarios both with and without human activity interference, followed by classification analysis and area calculations for each suitability

level (Table 4). Under the current climate model, when only environmental variables were considered, the total suitable habitat area for cotton in Xinjiang was  $7.97 \times 10^4 \text{ km}^2$ . Of this,  $4.56 \times 10^4 \text{ km}^2$  was classified as highly suitable,  $1.84 \times 10^4 \text{ km}^2$  as moderately suitable, and  $1.57 \times 10^4 \text{ km}^2$  as poorly suitable. The suitable habitats were primarily distributed in regions such as Aksu, Kashgar, Tacheng, Bayingolin Mongol Autonomous Prefecture, and Changji (Figure 4A). When human activity interference was considered, the total suitable habitat area expanded to  $9.50 \times 10^4 \text{ km}^2$ , representing a 19% increase compared to the scenario based solely on environmental variables. The area corresponding to each suitability category also increased (Figure 4B). Specifically, the highly suitable habitat area expanded by  $0.26 \times 10^4 \text{ km}^2$ , with new regions primarily located in

TABLE 4 The area of suitable habitat of a cotton with and without human activity interference ( $\times 10^4 \text{ km}^2$ ).

Human activity	High suitability zone	Moderate suitability zone	Low suitability zone	Unsuitable zone
With human activity (HF)	4.82	2.48	2.20	146.94
Without human activity (History)	4.56	1.84	1.57	148.47



northern Kashgar, northern Bayingolin Mongol Autonomous Prefecture, southern Tacheng, and eastern and western Aksu. The moderately suitable habitat area increased by  $0.64 \times 10^4 \text{ km}^2$ , with new regions mainly in southern Tacheng, eastern and western Aksu, northern Kashgar, and northern Bayingolin Mongol Autonomous Prefecture. The poorly suitable habitat area increased by  $0.63 \times 10^4 \text{ km}^2$ , primarily concentrated in northern Bayingolin Mongol Autonomous Prefecture, with scattered patches in Changji.

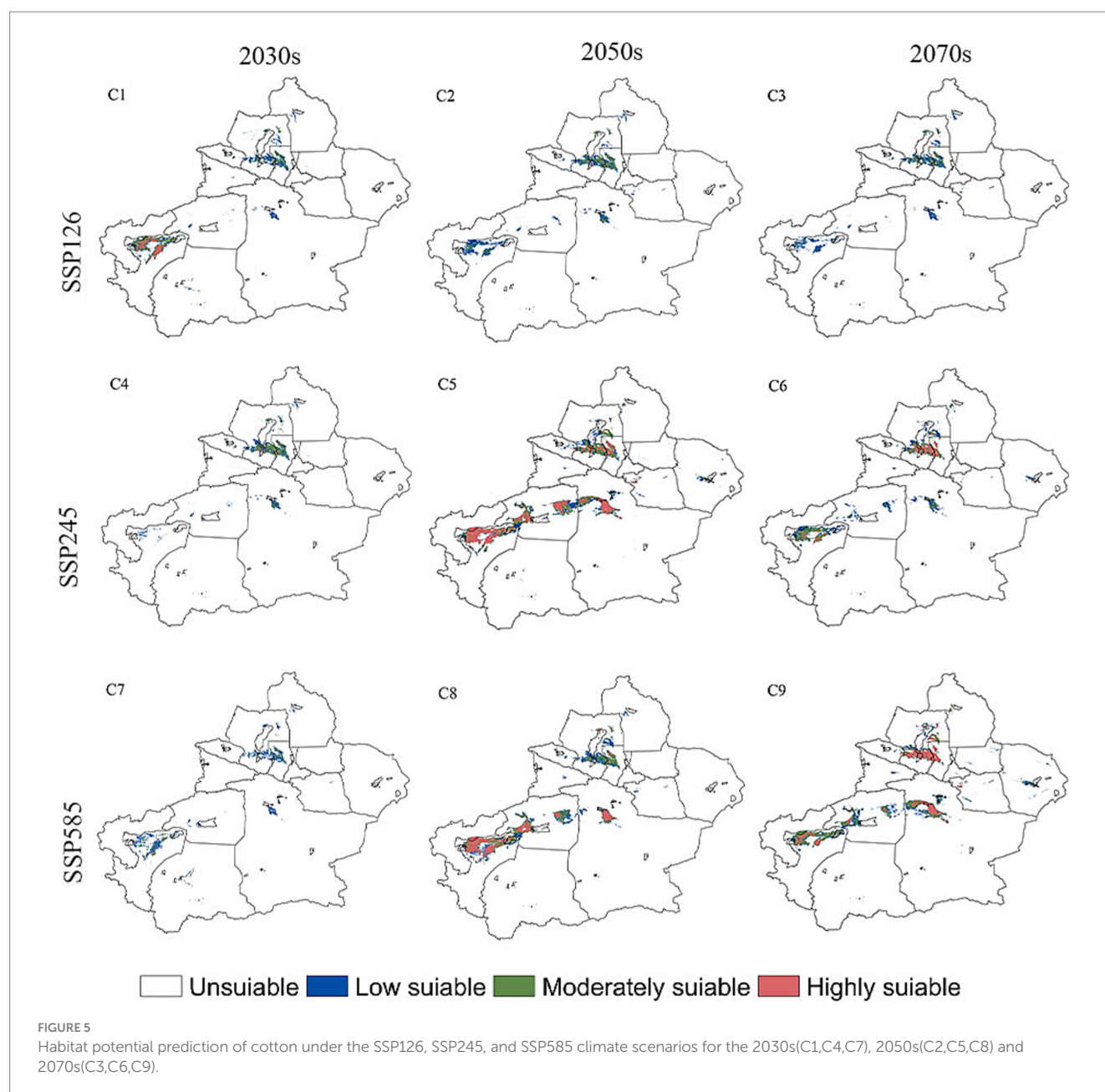
### 3.3 Changes in cotton spatial distribution under different climate change scenarios

Predicted suitable habitat ranges for cotton show significant variation across different future climate scenarios (Figure 5). Under the SSP126 scenario, suitable cotton habitats are predominantly concentrated in the southern part of Tacheng, northern Kashgar, central and western Shihezi, Kuitun, and northern Bayingolin Mongol Autonomous Prefecture. Cotton habitats are projected to contract primarily in Bayingolin Mongol Autonomous Prefecture and Aksu (Figure 6). Under the SSP245 scenario, the contraction trend is most pronounced during the 2030s. Suitable habitats are concentrated in the southern part of Tacheng, central and western Shihezi, Kuitun, and northern Bayingolin Mongol Autonomous Prefecture. By the 2050s, the cotton distribution pattern remains largely stable, with suitable habitats primarily located in the northern part of Kashgar, southern Tacheng, northern Bayingolin Mongol Autonomous Prefecture,

western Shihezi, and Kuitun, with minor contraction observed. Under the SSP585 scenario, distribution patterns in the 2050s and 2070s remain similar to current patterns, whereas the 2030s exhibit a notably greater contraction trend. Suitable habitats are projected to be predominantly located in northern Kashgar, central and western Shihezi, northern Bayingolin Mongol Autonomous Prefecture, southern Tacheng, and Kuitun.

The predicted suitable habitat area for cotton shows substantial differences compared to the current climate scenario (Figure 7). Under the current climate scenario, the total suitable habitat area for cotton is  $7.97 \times 10^4 \text{ km}^2$ , accounting for 5.1% of Xinjiang's total area. Under the SSP126 scenario, the suitable habitat area is projected to range between  $2.37 \times 10^4 \text{ km}^2$  and  $3.37 \times 10^4 \text{ km}^2$ , representing 1.52 to 2.15% of Xinjiang's area, with the highly suitable habitat area peaking at  $0.57 \times 10^4 \text{ km}^2$  in the 2030s, accounting for 17% of the total suitable area. In the SSP245 scenario, the suitable habitat area is projected to range between  $2.06 \times 10^4 \text{ km}^2$  and  $8.09 \times 10^4 \text{ km}^2$ , corresponding to 1.32 to 5.17% of the total area. By the 2050s, the suitable habitat area is expected to exceed the current extent, with highly suitable habitats reaching a maximum of  $3.35 \times 10^4 \text{ km}^2$ , representing 41% of the total. Under the SSP585 scenario, suitable habitat areas are expected to range between  $2.12 \times 10^4 \text{ km}^2$  and  $6.96 \times 10^4 \text{ km}^2$ , accounting for 1.36 to 4.45% of Xinjiang's total area, with the highly suitable habitat area peaking at  $2.23 \times 10^4 \text{ km}^2$ , or 32% of the total, in the 2070s. Area percentage analysis indicates that under the SSP126 scenario, cotton's suitable habitat continuously contracts over time





(Figure 8), while under the SSP245 scenario, the habitat follows a contraction–expansion–contraction pattern. In contrast, under the SSP585 scenario, an initial contraction is followed by expansion. Overall, changes are most pronounced under the SSP245 scenario, followed by SSP585, with relatively stable conditions observed under SSP126.

### 3.4 Potential shift of cotton distribution center in Xinjiang

The “Centroid Shift (Line)” tool in SDMToolbox was employed to analyze the changes in the centroid of suitable cotton habitats under three Shared Socioeconomic Pathways (SSP126, SSP245, and SSP585) for the 2030s, 2050s, and 2070s, relative to the current centroid. These changes include shifts in latitude, longitude, and elevation (Figure 9).

The current centroid of suitable cotton habitats in Xinjiang is situated in the northwest of Bayingolin Mongol Autonomous Prefecture (42.57°N, 83.86°E), at an elevation of 4,082 m. In the SSP126 scenario, the centroid of cotton distribution shifts northeastward along a horizontal gradient. In the SSP245 and SSP585 scenarios, the centroid shifts southwestward along a horizontal gradient, with a vertical shift toward lower altitudes.

The centroid shifts under different climate scenarios are summarized as follows: Under the SSP126 scenario, the centroid in the 2030s is located at 41.69°N latitude, 81.26°E longitude, and 1,518 meters elevation; by the 2050s, it shifts to 42.58°N latitude, 82.75°E longitude, and 3,087 meters elevation; and by the 2070s, it moves to 43.05°N latitude, 83.48°E longitude, and 3,451 meters elevation. Under the SSP245 scenario, the centroid in the 2030s is located at 43.89°N latitude, 84.89°E longitude, and 3,060 meters elevation; by the 2050s, it shifts to 41.84°N latitude, 82.60°E longitude, and 1,520

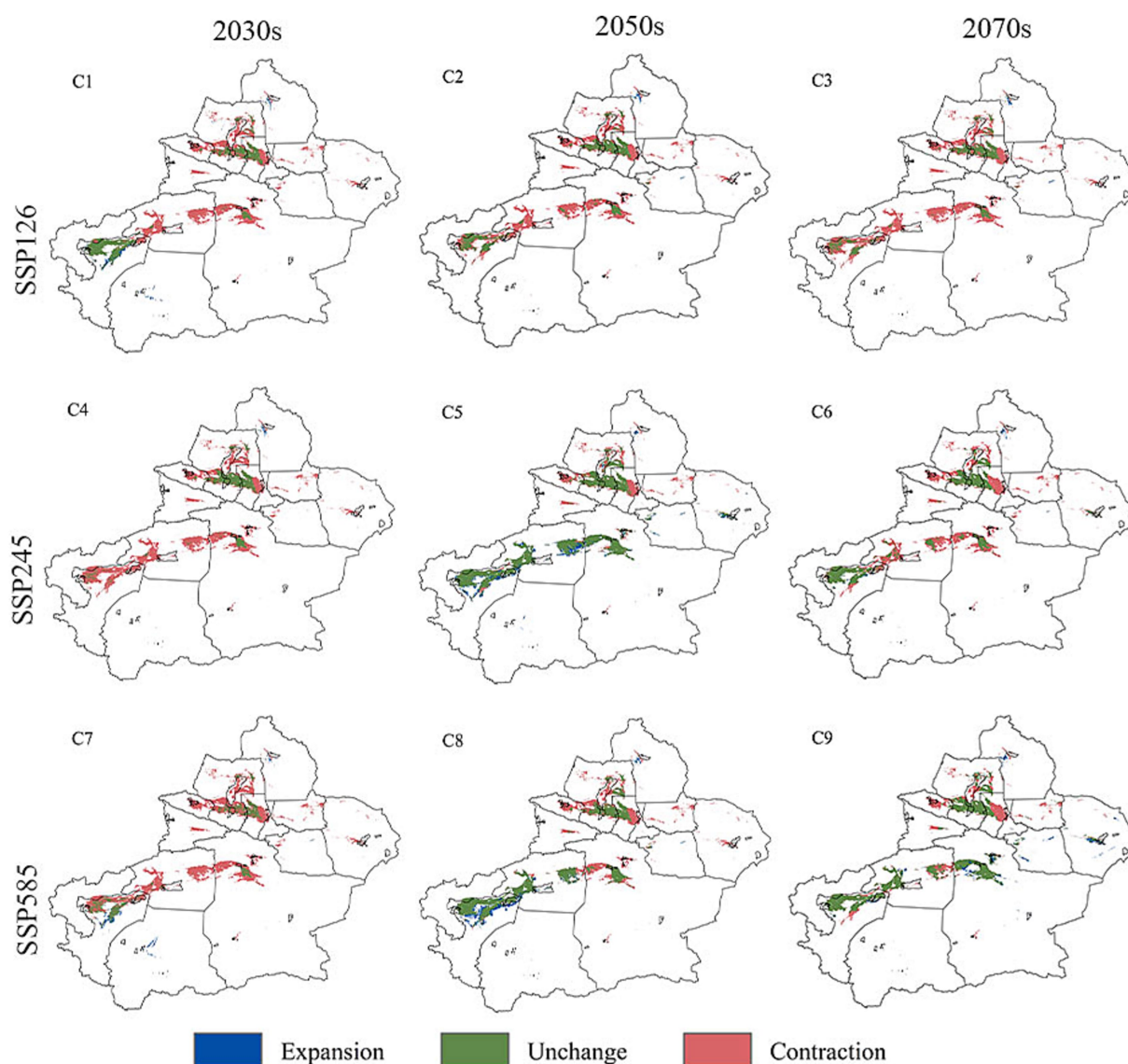


FIGURE 6

Changes in the potential cotton habitats under the SSP126, SSP245, and SSP585 climate scenarios for the 2030s(C1,C4,C7), 2050s(C2,C5,C8) and 2070s(C3,C6,C9).

meters elevation; and by the 2070s, it moves to 42.29°N latitude, 82.40°E longitude, and 2,306 meters elevation. Under the SSP585 scenario, the centroid in the 2030s is located at 41.79°N latitude, 81.98°E longitude, and 1,231 meters elevation; by the 2050s, it moves to 41.51°N latitude, 81.53°E longitude, and 1,379 meters elevation; and by the 2070s, the centroid is located at 42.10°N latitude, 83.13°E longitude, and 1,620 meters elevation.

## 4 Discussion

### 4.1 Analysis of major impact factors

Optimal MaxEnt model predictions reveal that, under the combined influences of climate change and human activities, the primary factors influencing cotton growth in Xinjiang are the Human

Footprint (HF), solar radiation, the mean diurnal range (bio2), the mean temperature of the coldest quarter (bio11), and the precipitation of the coldest quarter (bio19). The response curves for each environmental variable demonstrate the range of cotton's adaptability to these factors. At the Maximum Training Sensitivity Specificity (MTSS) threshold, the probability response curves reveal the relationship between cotton occurrence probability and the environmental variables. Specifically, the suitable range for human footprint is between 5.82 and 41.80, solar radiation ranges from 14,866.70 to 16,138.84 KJ, the optimal range for bio2 is from 8.68 to 11.99°C and 12.77 to 15.29°C, for bio11, it is from −13.59 to −9.66°C and −5.46 to 0.45°C, and for bio19, it is from 2.41 to 23.98 mm (Figure 10).

Cotton cultivation in Xinjiang is predominantly concentrated in oasis plain regions, characterized by flat terrain and controllable water resources, making them typical artificial agricultural ecosystems. The

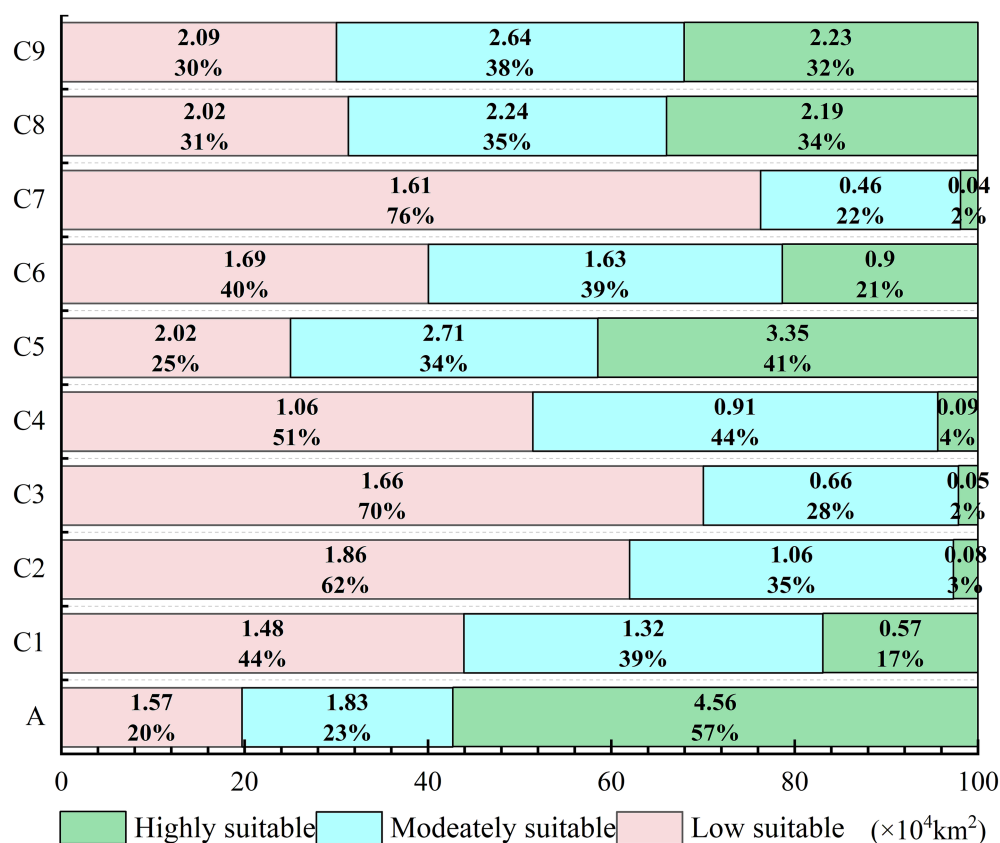


FIGURE 7  
Percentage and area of each suitable habitat for cotton under different climate change scenarios.

simulation results of this study indicate that the inclusion of the human footprint (HF) variable significantly increased the area of suitable cotton habitat, with an approximate 19% expansion compared to the no-disturbance scenario. This finding quantitatively highlights the positive influence of human activities on shaping the spatial distribution of cotton, particularly in regions where natural climatic resources are limited. Through the construction of irrigation systems, improvements in farmland infrastructure, soil preparation, and fertilizer management, human interventions have effectively enhanced the ecological suitability for cotton cultivation (Duan et al., 2021; Onuegbu et al., 2024; Zhang et al., 2024). For example, certain areas in the lower reaches of the Tarim River were not suitable for cotton cultivation under natural climatic conditions; however, following the establishment of canal irrigation systems, habitat suitability for cotton significantly improved. These findings align with previous research highlighting the reliance of agricultural expansion in arid regions on artificial irrigation (Abou Zaki et al., 2022; Ahmed et al., 2023).

Previous studies have highlighted the crucial role of solar radiation in the growth and development of cotton (Pinnamaneni et al., 2022). While various experimental methods have explored its relationship with cotton growth, a systematic quantitative analysis of the role of solar radiation in regional suitability assessments remains lacking (Lin et al., 2023). This study utilizes the MaxEnt model to quantitatively characterize the impact of solar radiation on the distribution of suitable areas for cotton. Furthermore, adequate precipitation contributes to increased soil moisture, thereby providing a favorable growth environment for cotton. However, excessive precipitation may impair cotton's photosynthetic capacity, hinder

growth, and ultimately affect its final yield (Jans et al., 2021). In this study, we found that the suitable range for cotton in relation to bio2 is between 8.68°C and 15.29°C, effectively supporting its growth. Additionally, cotton is particularly sensitive to low temperatures, and the suitable range for bio11 is from −13.59°C to −9.66°C and from −5.46°C to 0.45°C, which helps prevent frost damage and supports regenerative growth. Similarly, bio19, with a range of 2.41 mm to 23.98 mm, ensures the accumulation of soil moisture, satisfying cotton's drought tolerance requirements. These findings are consistent with previous research, where temperature and precipitation are key drivers of cotton growth, with similar trends in suitable ranges and influence mechanisms observed across different regions (Chen et al., 2019; Sun et al., 2024; Khan et al., 2025).

## 4.2 Geographical distribution of suitable habitats for cotton in Xinjiang under future climate scenarios

Future climate change scenarios suggest substantial uncertainty regarding the trends in suitable habitats for cotton cultivation in Xinjiang. Compared to the current distribution, the total area of suitable habitats is projected to decline under both the SSP126 and SSP585 scenarios. Rising temperatures, changes in precipitation patterns, and an increased frequency of drought events are expected to reduce suitable planting areas under both low-emission (SSP126) and high-emission (SSP585) scenarios, consistent with previous studies on the negative impacts of



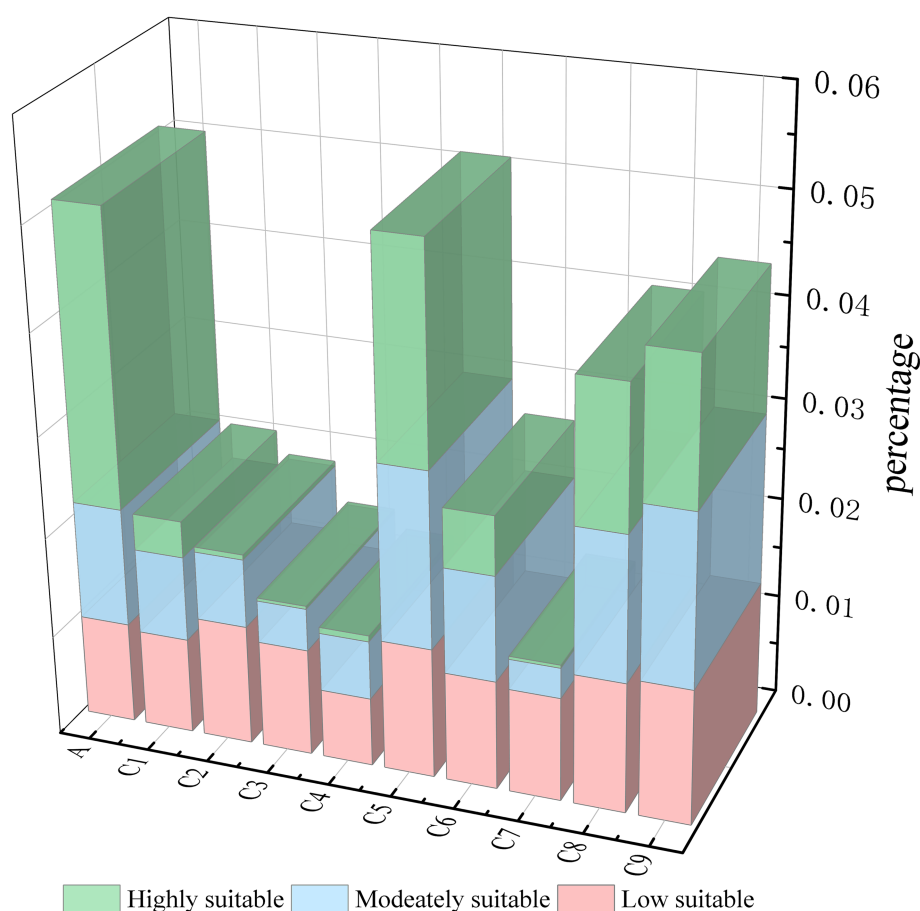


FIGURE 8  
3D histogram of the percentage of suitable habitat for cotton under different climate scenarios.

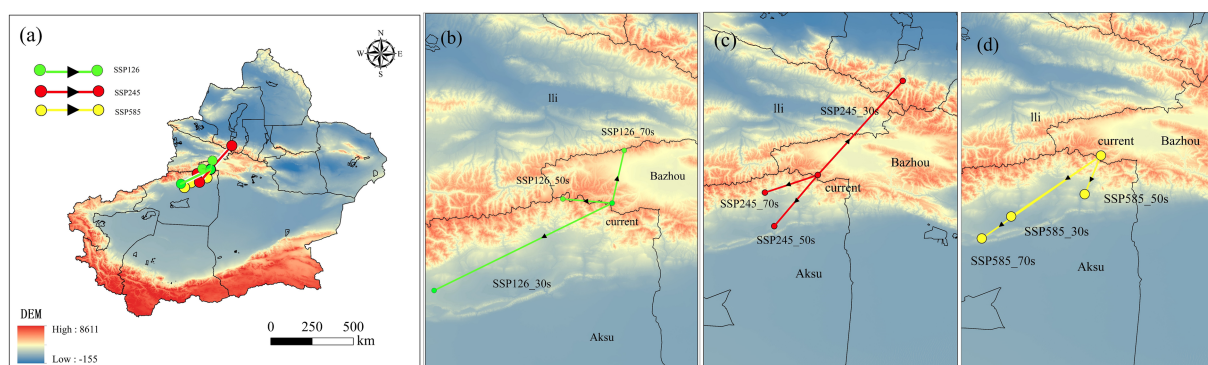


FIGURE 9  
Shift of the center point between the current climate scenario and the 2030s, 2050s and 2070s climate scenarios. (a) Cotton Distribution Center Migration in Xinjiang. (b) Shift of the centre point in SSP126 scenario. (c) Shift of the centre point in SSP245 scenario. (d) Shift of the centre point in SSP585 scenario.

climate change on crop production in arid regions (Feng et al., 2024; Nazarova et al., 2025). Temperature plays a crucial role in cotton growth, and yields decline significantly when temperatures exceed 32°C. If global temperatures rise by 1.5–2.0°C, cotton yields could decrease by up to 40% by 2,100 (Schlenker and Roberts, 2009). Historical evidence also indicates that cotton

yields in the southwestern United States have declined by approximately 26% due to heat stress (Elias et al., 2018). In the low desert region of Arizona, cotton seed yields are projected to decrease by 40% by mid-century (2036–2065) and by 51% by the end of the century (2066–2095), compared to the baseline period of 1980–2005 (Ayankojo et al., 2020). These findings are broadly

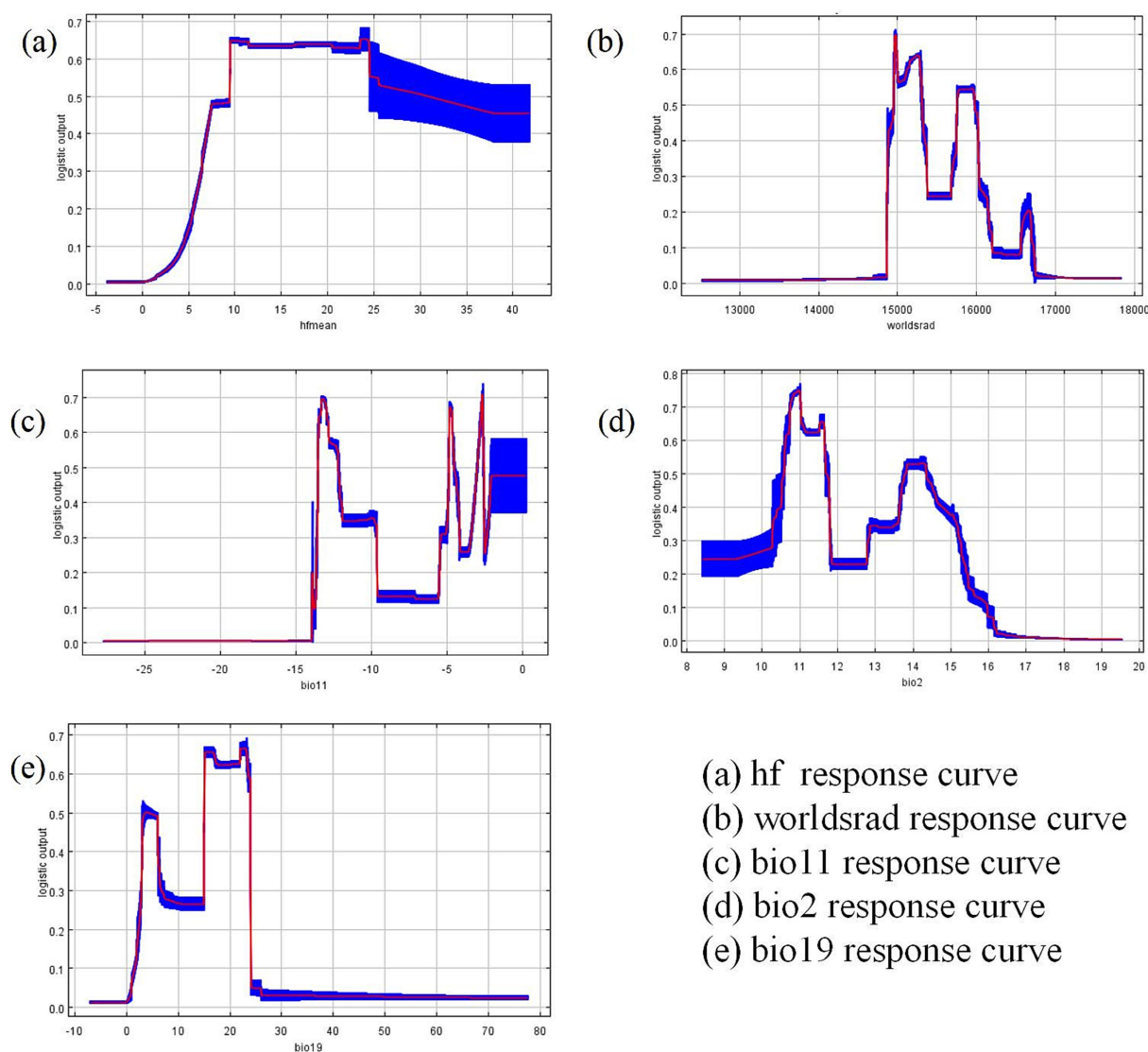


FIGURE 10  
Response curves for dominant environmental variables.

consistent with the trends of habitat suitability changes for cotton cultivation identified in this study.

In contrast, under the SSP245 scenario, predictions for the 2050s indicate an expansion trend, whereas the 2030s and 2070s are projected to experience continued contraction. Under the moderate emission scenario (SSP245), moderate warming, combined with improved precipitation patterns and optimized irrigation systems, is likely to provide relatively favorable growing conditions for cotton. This result further emphasizes the key role of human activity management in shaping cotton suitability. Additionally, advancements in cotton adaptive breeding technologies, such as the promotion of drought-resistant varieties, could further facilitate the expansion of suitable habitats (Wang et al., 2023). Relevant studies suggest that with appropriate climate adaptation strategies, crops like cotton can adjust to environmental changes induced by climate change, expanding their suitable habitats even under rising temperatures and shifting precipitation patterns (Li et al., 2021).

### 4.3 Migration of the cotton centroid in Xinjiang

This study shows that under the SSP126, SSP245, and SSP585 climate scenarios, the center of suitable cotton habitats in Xinjiang generally migrates from higher to lower altitudes. This shift is mainly driven by a combination of rising temperatures, changing precipitation patterns, and human water resource management (Wang et al., 2021; Zhou et al., 2022). As temperatures rise and precipitation patterns shift, droughts intensify, and water shortages become more severe in high-altitude regions, thus restricting cotton growth. In contrast, low-altitude areas, with richer water resources and well-developed irrigation infrastructure, are becoming increasingly suitable for cotton cultivation (Li et al., 2020a). Recently, Xinjiang has strengthened water security for agriculture in low-altitude regions by promoting efficient water-saving irrigation technologies and implementing integrated regional water resource management strategies (Liang et al., 2019). Therefore, future efforts to address the spatial reorganization of cotton cultivation areas under climate change should

integrate water resource management with agricultural adaptation strategies.

## 4.4 Limitations and future research

This study utilized the MaxEnt model to assess the impacts of climate change and human activities on the suitability of cotton habitats in Xinjiang. However, several limitations should be acknowledged. First, the temporal and spatial scales considered in this study were relatively limited; future research should consider incorporating longer temporal spans and a broader range of climate scenarios to enhance the robustness and comprehensiveness of projections. Second, although the Human Footprint (HF) index was used to represent human activities, it primarily reflects pressures such as population density and infrastructure development and does not directly account for agricultural irrigation systems or water resource availability. Given the significant reliance of cotton cultivation in Xinjiang on irrigation, future studies should consider integrating irrigation-related datasets or conducting sensitivity analyses to more accurately assess potential impacts. Furthermore, this study did not fully consider factors such as pest and disease outbreaks, genetic modification, and policy interventions. Future research should aim to include a broader set of driving forces, thus enabling the development of more targeted adaptation and management strategies to support the sustainable development of the cotton industry in Xinjiang (Khan et al., 2023; Farooq et al., 2024; Zafar et al., 2024).

## 5 Conclusion

This study employed the ecological niche model (MaxEnt) to establish a comprehensive analytical framework integrating multi-source data—including bioclimatic variables, soil properties, topographic conditions, solar radiation, and human activity footprints—to systematically assess the impacts of climate change and human activities on the spatiotemporal distribution of cotton in Xinjiang. The findings indicate that the human footprint, bio2, bio11, bio19, and solar radiation intensity are key factors influencing cotton distribution. Human activities have considerably expanded the suitable habitat for cotton, especially in northern Bayingolin Mongol Autonomous Prefecture, underscoring their positive role in optimizing cotton cultivation areas. However, climate change has led to an overall decline in suitable habitats, especially in eastern and western Aksu, northern Kashgar, and northern Bayingolin Mongol Autonomous Prefecture, which should be prioritized as vulnerable regions. Future increases in temperature and shifts in precipitation are projected to drive the migration of the centroid of suitable cotton habitats toward lower-altitude areas, resulting in substantial changes in its distribution dynamics. Therefore, future efforts should focus on improving mechanization, irrigation infrastructure, and agricultural coverage in low-altitude areas, as well as strengthening agricultural technology training for farmers. This study deepens the understanding of the dynamic

nature of cotton's suitable habitats in Xinjiang and provides scientific guidance for climate adaptation strategies and regional cultivation optimization.

## Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: data classified as confidential. Requests to access these datasets should be directed to Shanshan Wang, 320223639@xjau.edu.cn.

## Author contributions

SW: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Writing – original draft, Writing – review & editing. MS: Supervision, Writing – review & editing. YF: Data curation, Funding acquisition, Resources, Supervision, Writing – review & editing. PJ: Conceptualization, Project administration, Supervision, Writing – review & editing. SC: Writing – review & editing. YL: Supervision, Writing – review & editing. LH: Validation, Writing – review & editing. JZ: Supervision, Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

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