The wild tending framework of medicinal plants constructed based on Biomod2 and PLUS model: A case study of Thesium chinense Turcz. in China

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Abstract

Wild medicinal plants dominate the market of Traditonal Chinese Medicine (TCM). However, the intensification of human activities and ecological deterioration have caused a gradual depletion or extinction of wild medicinal plant resources in China. Scientific planning of wild tending areas is a priority to realize the sustainable utilization of wild medicinal plant resources. Thesium chinense, a known "plant antibiotic", has been overharvested in recent years, resulting in a sharp reduction in its wild resources. In this study, we combined three atmospheric circulation models and four common socio-economic approaches (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) to explore the main environmental factors affecting the distribution of T. chinense and the changes in the suitable area under the complete niche based on the Biomod2 package. The PLUS model was used to predict and analyze the land use change trend in the climate-stable areas of T. chinense in the future. And the wild tending areas of T. chinense were planned using ZONATION software. In the next hundred years, the climate-stable areas of T. chinense in China will mainly be distributed in humid and subhumid area, and the natural habitat areas of T. chinense in this region will decrease year by year. Hot spot analysis showed that Qiqihar, Chifeng, Zunyi, and other counties were the most suitable for the wild tending of T. chinense. These results can provide a comprehensive research framework for wild tending planning of T. chinense and other medicinal plants.

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Abstract

Wild medicinal plants dominate the market of Traditonal Chinese Medicine (TCM). However, the intensification of human activities and ecological deterioration have caused a gradual depletion or extinction of wild medicinal plant resources in China. Scientific planning of wild tending areas is a priority to realize the sustainable utilization of wild medicinal plant resources. *Thesium chinense* , a known "plant antibiotic", has been overharvested in recent years, resulting in a sharp reduction in its wild resources. In this study, we combined three atmospheric circulation models and four common socio-economic approaches (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) to explore the main environmental factors affecting the distribution of *T. chinense*and the changes in the suitable area under the complete niche based on the Biomod2 package. The PLUS model was used to predict and analyze the land use change trend in the climate-stable areas of *T. chinense*in the future. And the wild tending areas of *T. chinense* were planned using ZONATION software. In the next hundred years, the climate-stable areas of *T. chinense* in China will mainly be distributed in humid and subhumid area, and the natural habitat areas of*T. chinense* in this region will decrease year by year. Hot spot analysis showed that Qiqihar, Chifeng, Zunyi, and other counties were the most suitable for the wild tending of *T. chinense* . These results can provide a comprehensive research framework for wild tending planning of *T. chinense* and other medicinal plants.

Keywords: *Thesium chinense* ; climate change; land use change; species distribution model; wild tending

1. Introduction

Climate is one of the most important factors in determining the distribution of species. The response of vegetation to climate change and the regional changes of plant distribution under the influence of climate are hot topics in biogeography, macroecology, and other disciplines (Y. Chen, Le, et al., 2022; O'Connor et al., 2020). With the continuous intensification of global warming, the global average surface temperature will rise by 1.1 to 6.4 by the end of the 21st century (P. Gao et al., 2023). Global warming is likely to significantly alter the structure and function of terrestrial ecosystems and increase the risk of species extinction (Thomas et al., 2004). To adapt to these changing conditions, plants can modify their ecological niche and distribution areas to match the new environment (Tang et al., 2021; Moran & Alexander, 2014). Climate change will pose significant uncertainty for future rational cultivation of medicinal plants (Higa et al., 2013). Blind introduction and expansion of medicinal plants without scientific guidance not only jeopardizes their quality but also misallocates resources (He et al., 2021). Long-term field introduction trials have traditionally been the most reliable way to identify suitable areas for herbal plant cultivation. However, it requires substantial resources and observation of several growth cycles (F. Li et al., 2019). Therefore, it is crucial to predict the potential suitable areas of medicinal plants under future climate change, which facilitates a better understanding of the cultivation potential of medicinal plants in new habitats.

Habitat loss caused by land use change will exacerbate the impact of climate change on species and ecological dynamics globally (Pant et al., 2021). Most studies that explore changes in plant species distribution and their future distribution only consider climate factors, with little attention paid to the synergistic effects of habitat and climate change (Sirami et al., 2017). However, in exploring changes in plant distribution, climate change-driven range expansion occurs in a spatial context. Yet each species' habitat is unique. Thus, although many regions are suitable for survival, they may not be suitable as natural population habitats due to land use limitations. With increasing human activity, it is expected that 10% to 20% of natural grasslands and forests will be replaced by agriculture and urban infrastructure by 2050, leading to substantial habitat loss for most wild species (Y. Chen, Li, et al., 2022; X. Li et al., 2016). In this sense, it is necessary to explore the impact of land use change on species' habitat. Integrating both climate and land use changes is essential for gaining a more accurate understanding of species' distribution range under future climate and land use change.

Thesium chinense Turcz. is a semi-parasitic perennial herb of the genus Thesium in the Santalaceae. Its wild population is distributed in China, Japan, Korea, and other places (Chinese botanical society, 1988). As an important medicinal plant in China, dried whole grass of *T. chinense* has significant anti-inflammatory and analgesic effects. It is often used to prevent and treat all kinds of acute inflammation, so it has the reputation of a "plant antibiotic" (Luo & Guo, 2011). In recent years, due to the deterioration of the ecological environment caused by excessive harvesting and the intensification of human activities, the population of *T. chinense* has sharply decreased throughout China and even disappeared in some ecological areas, seriously reducing the production of *T. chinense* (J. Gao et al., 2023). The supply-demand contradiction has become more prominent with the increasing demand from medicinal herb manufacturers (Luo et al., 2012). But at present, the system of artificial breeding of *T. chinense*is not fully mature, which can not meet the rapid development of the *T. chinense* industry (J. Gao et al., 2023). Wild tending is a way to artificially or naturally increase the population in its native or similar environment according to the growth characteristics of the target species and its requirements for ecological environmental conditions. The significance of this method is to make the amount of resources available for people to collect and use, and to maintain the balance of the community (S. Chen et al., 2004, 2016). Therefore, planning a wild tending area for *T. chinense* is very important.

In this study, Biomod2 based ensemble species distribution model was used to investigate the relationship between population distribution and environmental factors in the complete ecological niche, and to predict and analyze the changes of population distribution under climate warming conditions in the century and the changes of natural habitat areas in the climate stable areas of China. In addition, we planned the wild tending areas of *T. chinense* in China based on ZONATION software (integrating future climate and land use change results). Furthermore, the synergistic effects of climate and land use change were considered, aiming to provide a more effective reference for the sustainable use of *T. chinense* in China under the land use and climate change. The purpose of this study is: (1) To determine the main environmental factors limiting the distribution of *T. chinense* ; (2) To investigate the effects of climate change on the population distribution of *T. chinense* ; (3) To identify habitat changes within the climate-stable areas of *T. chinense* in China; (4) To plan wild tending areas for *T. chinense* in China and put forward management strategies.

2 Materials and Methods

2.1 Source and processing of species occurrence data

The geographical occurrence data of *T. chinense* were obtained by three methods: (1) Field investigation. An extensive survey was conducted from May 2018 to July 2022. (2) Network database. The Global Biodiversity Information Facility (GBIF, https://www.gbif.org), the Chinese Virtual Herbarium (CVH, http://www.cvh.ac.cn), and the National Specimen Information Infrastructure (NSII, http://www.nsii.org.cn) and the Teaching Specimen Resource sharing platform (http://mnh.scu.edu.cn) have collected geographic location information with precise latitude and longitude and time range from 2000 to the present. (3) Literature search. Through the above methods, a total of 271 geographic occurrence data were obtained. Used Google earth pro software (Google Earth USA) to reject geographical occurrence data of *T. chinense* in construction land, cultivated land, and waters. To further eliminate the spatial autocorrelation of occurrence data, the "spThin" package was used to remove the occurrence data gathered within 10 km (Aiello-Lammens et al., 2015). Finally, 174 occurrence data were retained for modeling (Figure 1).

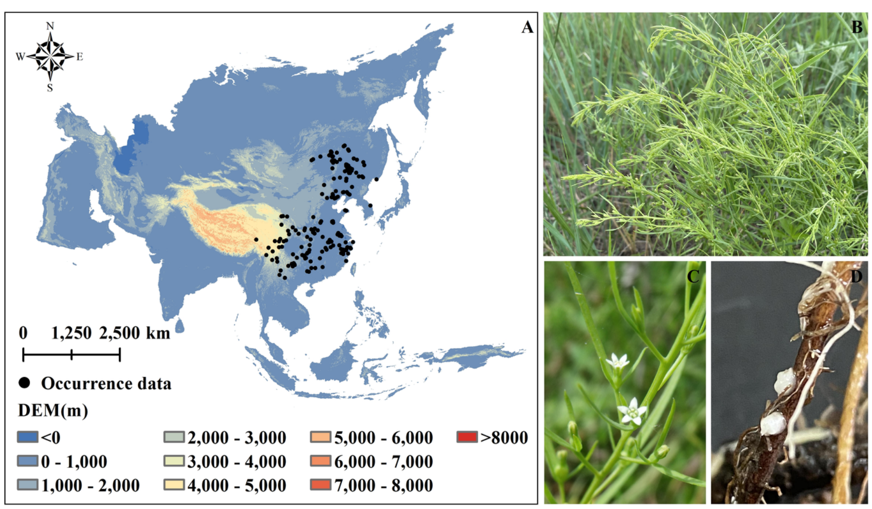


FIGURE 1 Morphological characteristics and occurrence data of *T. chinense* . (A): Occurrence data; (B):

Plants of *T. chinense* ; (C): Flowers of *T. chinense* ; (D): Haustoriums of*T chinense* .

2.2 Environmental data sources and processing

2.2.1 Environmental factors

Using 22 environmental factors (including climate, soil and biology) to study the changes in the distribution of *T. chinense* (Table S1). In order to match the environmental factors with the current climate scenario, based on the monthly temperature and precipitation data provided by the Worldclimate database (v2.1), we calculated 19 climate data in the time range of 2000-2018 through the "biovar" package. The two soil factors (T_OC and T_pH_H2O) were downloaded from Harmonized World Soil Database (HWSD, http://www.fao.org). As a semi-parasitic plant, vegetation (host) is the prerequisite for the growth of *T. chinense* . Therefore, we included NDVI factors that can reflect vegetation growth in the ensemble species modeling. NDVI data was downloaded in MODIS (https://www.earthdata.nasa.gov). We averaged the NDVI data from 2000 to 2020 according to the month of the growth period (May to July) of *T. chinense* , and finally obtained layer was required for the species distribution model modeling.

The high correlation between environmental factors may lead to the species distribution model overfitting. Therefore, we first built the initial model (10 repeated modeling) with MAXENT 3.4.4 software without adjusting the parameters, and removed the environmental factors that contributed less than 1%. The correlation function in ENMTools software was then used to analyze the remaining environmental factors' correlation (Warren et al., 2010). The two environmental factors with | r | [?] 0.8 were screened, and the one with relatively small contribution rate was removed. After the above steps, we reserved 11 environmental factors for the final modeling.

To estimate the distribution changes of *T. chinense* in different periods in the future (2050s: 2041-2060, 2070s: 2061-2080, 2090s: 2081-2100), we selected three widely used atmospheric circulation models (MIROC-ES2L, CNRM-CM6-1, MRI-ESM2-0) to build species distribution model in the future. Each atmospheric circulation model includes four shared socio-economic pathways: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, with 12 climate scenario combinations. Among the four selected shared socio-economic pathways, the low to high radiative forcing scenarios range from SSP1-2.6 to SSP5-8.5 (Jiang et al., 2020). ArcMap10.5 software was used to average the data of three climate models in the same carbon emission scenario and year. The spatial resolution of environmental data was 2.5 min.

2.2.2 Land use and driver data

In the simulation of future land use in China, the land use data were downloaded from the Resource and Environment Science and Data Center (RESDC), including 2010 and 2015. Referring to the classification system of China's National Land Use and Cover Change (CNLUCC) (Table S2), the land use data in 2015 were reclassified by ArcMap10.5 software, including cultivated land, forest, grassland, waters, construction land, and unused land. The region expressed by the classified grassland (all kinds of grasslands with herbaceous plants and coverage of more than 5%, including shrub grassland dominated by grazing and sparse forest grassland with canopy density of less than 10%) is consistent with the habitat previously recorded by *T. chinense* , so we regarded the grassland as the natural habitat of *T. chinense* . The driving factors were divided into physical geography, human disturbance, and bioclimate (Figure S1). Physical geographic factors included elevation (WorldClim Database v2.1), soil erosion (RESDC), and distance from water. Distance from the water was calculated based on water system data (RESDC) using the EuclideanDistance tool in ArcMap10.5. Human disturbance factors included the population data and GDP data of 2015 were downloaded from the RESDC and the distance from road and railway (DRA) calculated by EuclideanDistance tool based on the road data and railway data of RESDC. Bioclimatic factors included annual precipitation and mean temperature data from WorldClim Database v2.1 in 2015. All the above data layers used the Resample tool in ArcMap10.5 to unify the data resolution to 2.5 min.

2.3 Construction of species distribution model

Ten modeling (GLM, GBM, CTA, RF, GAM, ANN, SRE, FDA, MARS and MAXENT) algorithms provided by "Biomod2" package were used to predict the potential distribution of *T. chinense* . All models use default parameters except the MAXENT model.

The prediction accuracy of MAXENT model is affected by parameter settings. We tested the complexity and performance of the MAXENT model under different settings of regularization multiplier (RM) and feature class (FC) used the kuenm package in R 3.6.3 (Cobos et al., 2019). Candidate models were created by combining 17 RM values and all 31 possible combinations of five FC (L: linear feature, Q: secondary feature, H: fragmentation feature, P: product feature and T: threshold feature). According to Akaike information criterion (AICc) model of the delta on the choice of the optimal model, when the minimum value AICc (deltaAICc = 0), it is considered to be the optimal model (Cobos et al., 2019). The optimized MAXENT software parameters were RM=3 and FC=LQPT.

In species distribution modeling using the Biomod2 package, 70% of occurrence data was selected as training data, and the rest was used as testing data. The above process has been carried out five times. In order to reduce spatial bias and better simulate the actual distribution of species, we created 5,000 pseudo-absence points, repeated 3 times and modeled. In the end, 150 layers were generated. We evaluated each model using the true skill statistic (TSS) and the area under the receiver operating characteristic curve (AUC) (Bucklin et al., 2015; X. Zhang et al., 2020). The closer the TSS value and AUC value are to 1, the more reliable the prediction will be (Zhao et al., 2021; Freitas et al., 2019). We used the model with large average TSS ([?] 0.8) and AUC ([?] 0.9) values to calculate the final species distribution layer.

2.4 Division of suitable areas and climatic characteristics

When converting a continuous prediction result into the Boolean form of "suitable habitat" and "unsuitable habitat", it is important to select the appropriate threshold (Chen et al., 2022). We used the maximum training sensitivity plus specificity threshold, which maximizes the TSS value to create binary maps (de Andrade et al., 2020; Jiménez-Valverde & Lobo, 2007). The threshold value (P) of the suitable areas of *T. chinense* was 0.275. In addition, the suitable areas of *T. chinense* also included three levels of suitable areas, which were low suitable areas (0.275 [?] $P < 0.5$), medium suitable areas (0.5 [?] $P < 0.7$), and high suitable areas (P [?] 0.7). We used SDMtools to compare the spatial changes of the suitable areas of *T. chinense* under different climate scenarios.

To analyze the change of environmental characteristics in the suitable areas of *T. chinense* , we randomly selected 5000 points in the current suitable areas of *T. chinense* . We extracted the corresponding values from the 5000 points in the layers of different climatic conditions corresponding to the dominant environmental factors. R 4.2.0 software was used to calculate the 95% quantile and average value of the extracted values, and what kind of environmental pressure will be faced by *T. chinense* in the future was intuitively verified (Tagliari et al., 2021).

2.5 Future land use simulation

PLUS model is a new land use simulation model based on cellular automata, which has advantages in studying the causes of land use change and dynamically simulating the changes of various land uses, especially forest and grassland patches (Sun et al., 2023; J. Wang et al., 2022). By extracting the samples of the mutual transformation of various types of land use between the two time periods of land use data for training, the future land use is simulated based on the transformation probability. The random forest algorithm calculated the expansion and driving factors of various land use types to obtain the development probability and the contribution of driving factors to the expansion of various land use types in this period. And we combined with the generation of random patches and the transition matrix, determined future land use (Sun et al., 2023; Qiao et al., 2013). The PLUS Model mainly includes Land Expansion Analysis Strategy (LEAS) and Cellular Automata Model Based on Muiti-type Random Patch Seeds (CARS). The module calculation formula can be found in relevant literature (Ji et al., 2023; J. Wu & Wang, 2022; Liang et al., 2021).

2.6 Planning of wild tending area

To serve the wild tending action of *T. chinense* under climate change and land use change, the grassland types in 2015, 2050, 2070, and 2090 were superimposed to obtain grass stability region this century. Considering the prohibition of the development of nature reserves, the existing protection areas in China were removed from the current high suitable areas. By using the core area zonation algorithm in ZONATION4.0 software (https://www.helsinki.fi/), the layers of the high suitable areas in different climate scenarios in the grass stability region were superimposed. The weight of each layer was set to 1, and other parameters were the default values (B. Chen et al., 2023; B. Zhang et al., 2023). The natural discontinuity method was used to classify the output layers from 0 to 1, and the wild tending areas with low, medium, and high suitability of *T. chinense* were obtained.

3.Result

3.1 Accuracy of ensemble species distribution model

The ensemble species distribution model results showed differences in the prediction accuracy of the 10 models (Figure 2). Among them, RF, GBM, and MARS models have the highest prediction accuracy, and the repeated modeling is stable which the TSS and ROC met the standards of establishing the ensemble models. MAXENT and GLM also had high prediction precision, and only part of repeats did not reach the standard. In addition, the performance of ANN and SRE models was the worst. All replicates of the SRE model failed to meet the specified TSS and ROC value standards, and only a few replicates of ANN reached the standard. Therefore, these two models were not involved in ensemble models.

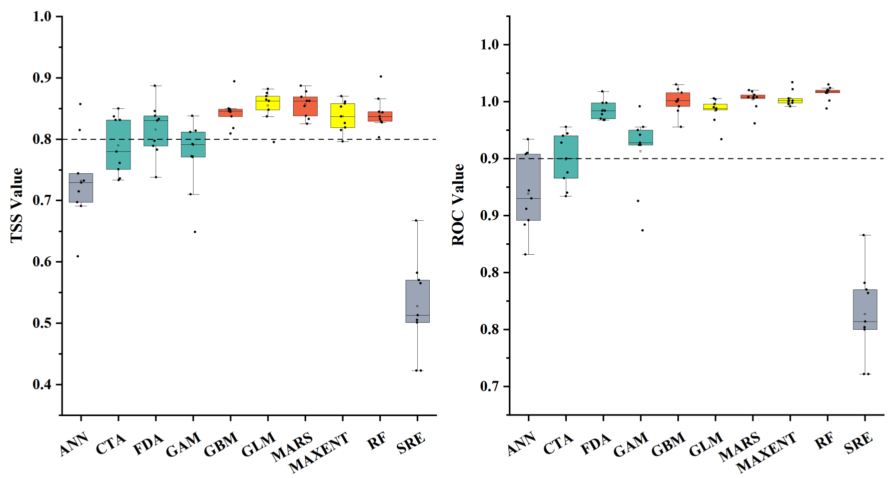
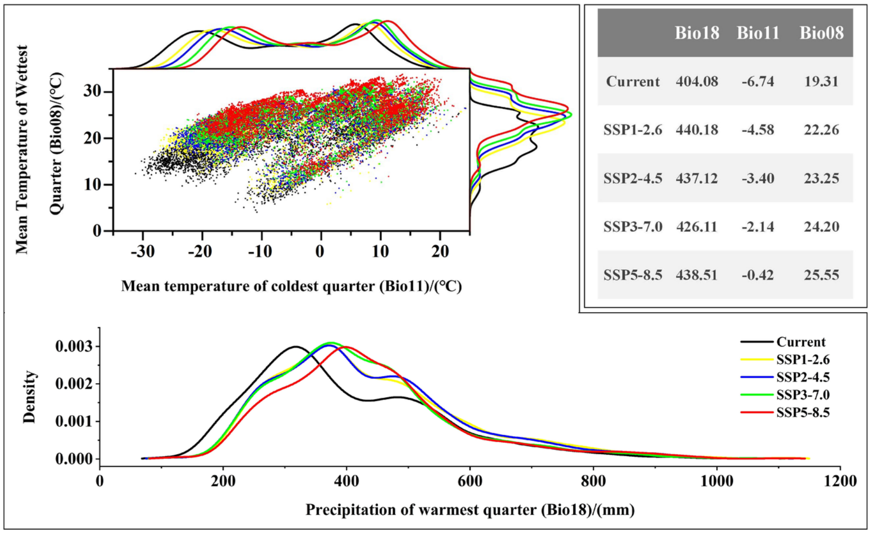


FIGURE 2 Prediction accuracy evaluation of different models.

3.2 Environmental factors affecting the distribution of *T. chinense*

After screening, the 11 environmental factors were used to establish the model and their importance were shown in Table S5. Among them, Bio18 (precipitation of warmest quarter) is the most important environmental factor, followed by Bio11 (mean temperature of coldest quarter) and Bio08 (mean temperature of wettest quarter). These three factors are the main environmental factors that affect the distribution of *T. chinense* . The suitable range of main environmental factors in the current suitable area of *T. chinense* was shown in Table S6. Specifically, the suitable range of Bio18 is 188.98 mm ˜ 763.52 mm. The suitable value distribution of Bio11 was -26.47 to 13.22. The lowest suitable value for Bio08 was 9.08, and the highest value was 26.38. In the future climate scenario, the value ranges of Bio18, Bio11, and Bio08 show an increasing trend in the current suitable area. With the increase of carbon emission concentration, the increase rate will increase year by year (Table S6). It is expected that under the climate scenario combination of 2090s-SSP5-8.5, Bio11 and Bio08 will rise to the highest level, with an increase of 6.32 and 6.24 compared with the current climate scenario. The highest value of Bio18 appears in the 2090s-SSP1-2.6 climate scenario combination, increasing by approximately 36.10 mm (Figure 3).



	Bio18	Bio11	Bio08
Current	404.08	-6.74	19.31
SSP1-2.6	440.18	-4.58	22.26
SSP2-4.5	437.12	-3.40	23.25
SSP3-7.0	426.11	-2.14	24.20
SSP5-8.5	438.51	-0.42	25.55

FIGURE 3 Changes of the dominant environmental factors in the current suitable area of *T. chinense* under different carbon emission scenarios in the 2090s.

3.3 Distribution range of the suitable areas of *T. chinense* under current climate conditions

Under the current climate conditions, the suitable area of the complete ecological niche of *T. chinense* is mainly distributed in three vegetation areas (Boreal forest, Temperate seasonal forest, and Shrubland) in the eastern of Asia (Figure 4A). The total area of suitable areas is about 734.53 * 104 km2, among which the high, medium, and low suitable areas are about 280.89 * 104 km2, 174.02 * 104 km2, and 279.62 * 104 km2, respectively. In China, the total area of the suitable areas of *T. chinense* is 509.26 * 104 km2, mainly distributed in the humid and semi-humid areas, with a small amount of distribution in the semi-arid area of northeast China (Figure 4B). The high suitable areas of *T. chinense* in China is approximately 273.72 * 104 km2, mainly distributed in the subtropical evergreen broad-leaved forest region, the warm temperate deciduous broad-leaved forest region, the temperate grassland region and the temperate coniferous and deciduous broad-leaved mixed forest region, accounting for 99.82% of the total area of high suitable areas, and a small amount of the tropical monsoon forests, rainforest region and the cold temperate coniferous forest region; The medium suitable areas are distributed around the high suitable areas, from the south to the subtropical evergreen broad-leaved forest region from the north to the cold temperate coniferous forest region were distributed in large numbers, with an area of about 131.00 * 104 km2; The low suitable areas is about 104.54 * 104 km2, which is mainly distributed in the subtropical evergreen broad-leaved forest region, the temperate grassland region and the high cold vegetation region on the Qinghai Tibet Plateau, accounting for about 36.82%, 27.99% and 13.17%, respectively (Figure 4C).

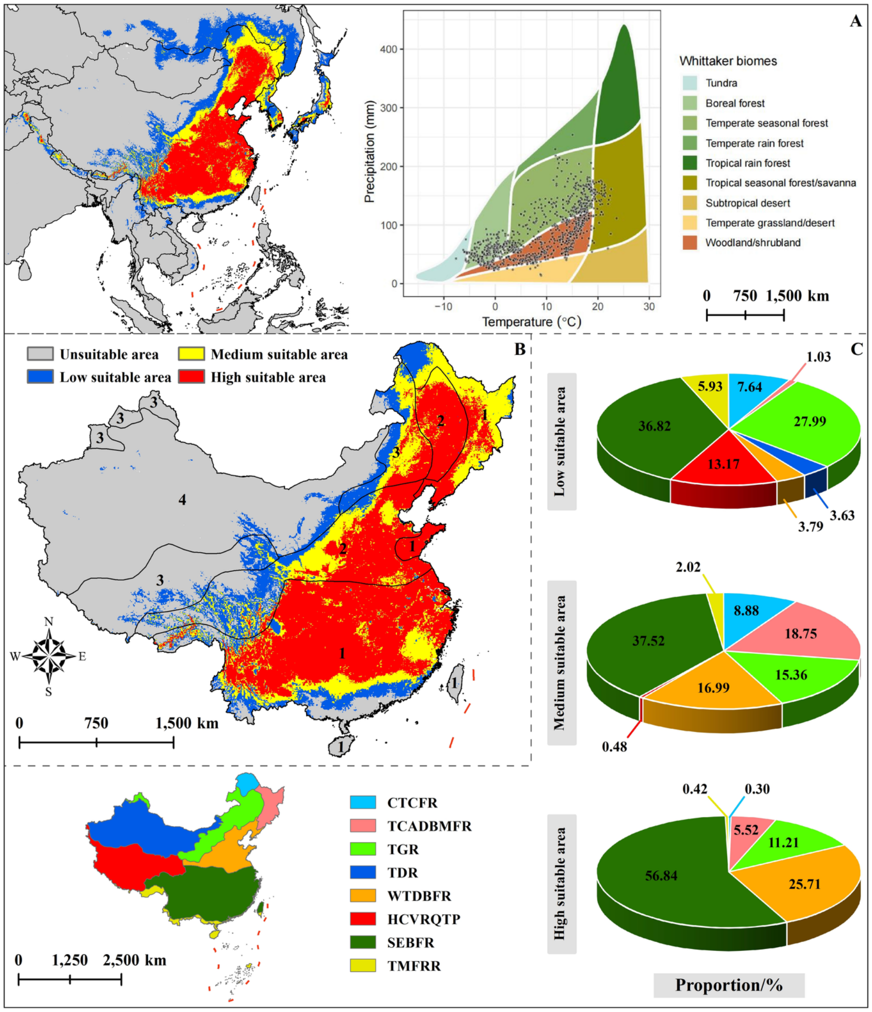


FIGURE 4 Distribution of potential suitable areas of *T. chinense* . (A): Current distribution range ; (B): The distribution range and dry and wet areas of *T. chinense* in China, among which 1-4 represent: 1: humid area, 2: sub-humid area, 3: semi-arid area, 4: arid area; (C): The proportion of suitable areas of different grades of *T. chinense* in each vegetation areas in China, where the abbreviations represent: CTCFR: Cold temperate coniferous forest region, TCADBMFR: Temperate coniferous and deciduous broad-leaved mixed forest region, TGR: Temperate grassland region, TDR: Temperate desert region, WTDBFR: Warm temperate deciduous broad-leaved forest region, HCVRQTP: High cold vegetation region on the Qinghai Tibet Plateau, SEBFR: Subtropical evergreen broad-leaved forest region, TMFRR: Tropical monsoon forests, rainforest region.

3.4 Changes in the suitable areas of *T. chinense* under future climatic conditions

Figure S2 and S3 showed the spatial distribution pattern and area change of suitable areas at each level of the complete ecological niche of *T. chinense* under future climate conditions. In China, the suitable areas will still be mainly distributed in the eastern and southern of China under future climatic conditions. As climate warming intensifies (increase of year and carbon emissions), the suitable areas will gradually expand to the northern part of the current suitable range and Tibet, and only slightly decrease in the southern part of the suitable areas (Figure 5A). Under future climate change, it is expected that *T. chinense* will move towards higher altitude and higher latitude areas in China (Figure 5B). Compared with the current distribution of suitable areas, the total area of suitable areas of *T. chinense* in China will increase year by year with the increase of carbon emissions, and the total area of *T. chinense* will expand to the maximum (557.82 * 104 km2) under the climate scenario of 2050s-SSP3-7.0 (Figure 6). In all levels of suitable areas, the areas of high suitable areas show a decreasing trend, while the areas of low suitable areas and medium suitable areas show an increasing trend. Moreover, the degree of change is gradually obvious with the increase of year and carbon emissions. In the 2090s-SSP5-8.5, the area of high suitable areas is reduced to the smallest, which decreases by 36.76% compared with the current situation. Under the 2090s-SSP5-8.5 scenario, the area of low suitable areas expands to the largest, about 159.95 * 104 km2.

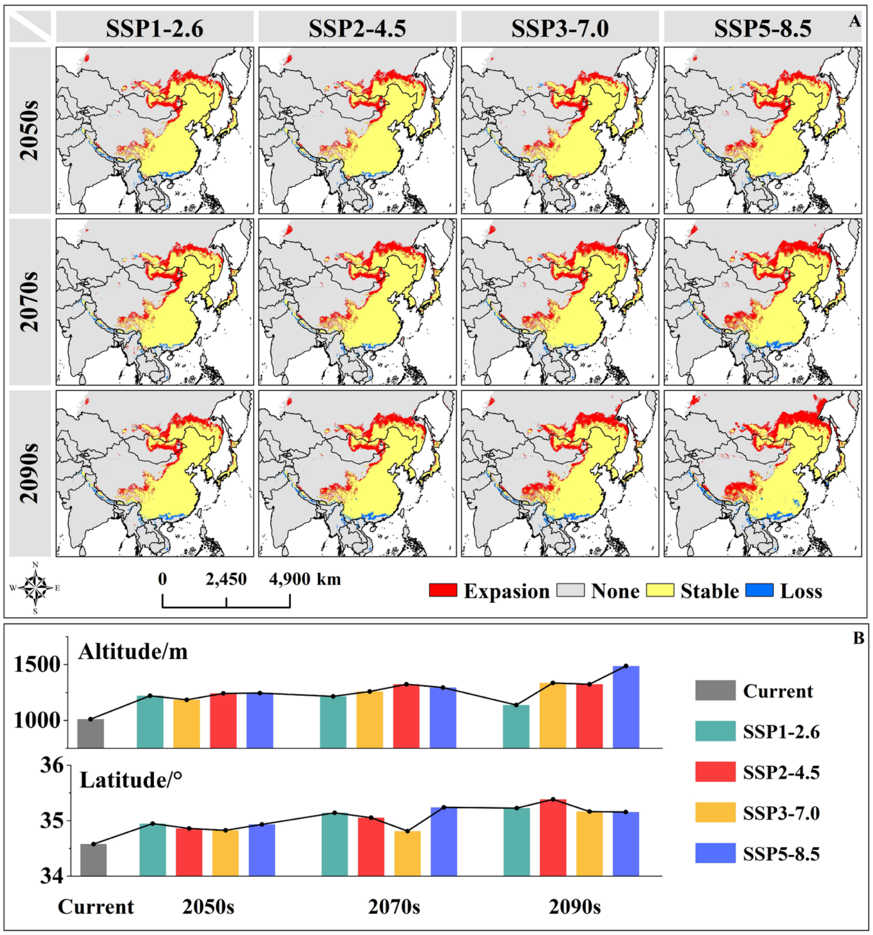


FIGURE 5 Spatial pattern, altitude, and latitude variations of *T. chinense* in China under different climatic scenarios. (A): Spatial pattern changes; (B): Changes in altitude and latitude of the suitable area for *T. chinense* .

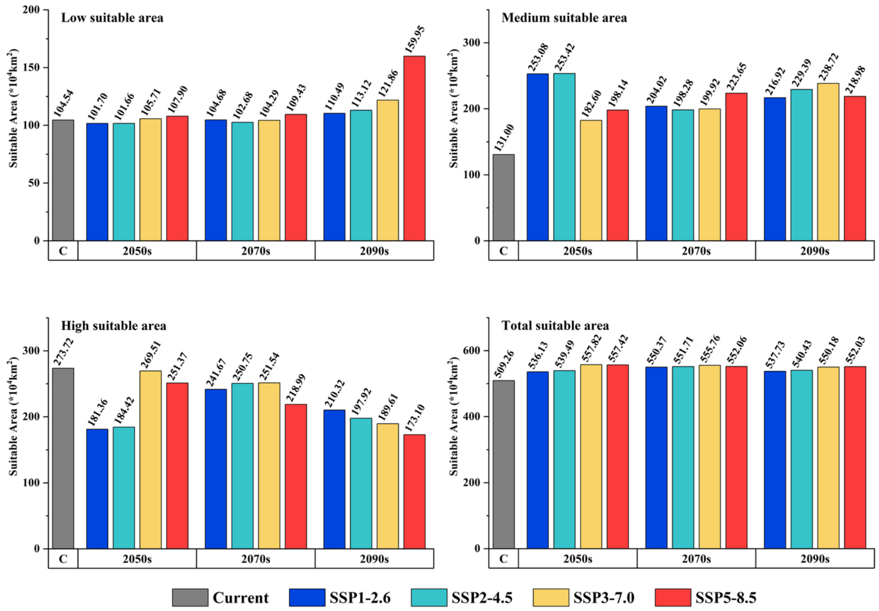


FIGURE 6 Changes in the areas of suitable areas of different grades of *T. chinense* under different climatic scenarios.

3.5 Distribution and change of land use pattern in climate-stable areas of *T. chinense* in China

Kappa coefficient was used to verify the simulation accuracy between the simulation results in 2015 and the actual land use data in 2015. The results showed that the overall accuracy of the simulation results of land use change in 2015 was 0.992 and Kappa=0.990, indicating that the PLUS model was reliable and could predict future land use distribution. The contribution degree of driving factors of each land use type change was shown in Table S7. The largest contribution of driving factor of grassland areas change was distance from water, followed by annual precipitation (Figure. 7B).

Under different climate scenarios, the total area of climate-stable areas of *T. chinense* in China is about 480.01 * 104 km2 (Figure 7A). According to the expansion and contraction trends of land use in 2010 and 2015, the distribution pattern of land use in 2050, 2070 and 2090 within the climate-stable areas is predicted (Figure S4). Among them, the cultivated land, grassland, and unused land in the climate-stable areas show a downward trend. And by 2090, they will decrease by 1.63%, 13.84%, and 10.67%, respectively, compared with 2015 (Figure 7C). In the future, the land use types transferred to grassland types mainly are forest, unused land, and construction land. From 2050 to 2070, the areas will transfer from forest, unused land, and construction land to grassland is about 1.83 * 104 km2, 0.90 * 104 km2, and 0.70 * 104 km2. With the increase of the years, the transferred areas gradually increase, and it is estimated that the transferred areas from 2070 to 2090 are about 3.00 * 104 km2, 0.97 * 104 km2, and 1.08 * 104 km2. In the future, grassland will mainly transfer to forest and construction land, and the transferred areas will increase from 4.65 * 104 km2 and 1.98 * 104 km2 in 2050 and 2070 to 5.80 * 104 km2 and 2.26 * 104 km2 in 2070 to 2090 (Figure 7C and Table S8). In the future, the area of forest, waters, and construction land in this region will show an increasing trend, especially the construction land. By 2090, the area of forest and water will increase by 5.51% and 1.49%, respectively. Construction land will increase to 25.71 * 104 km2, expanded by about 46.94%.

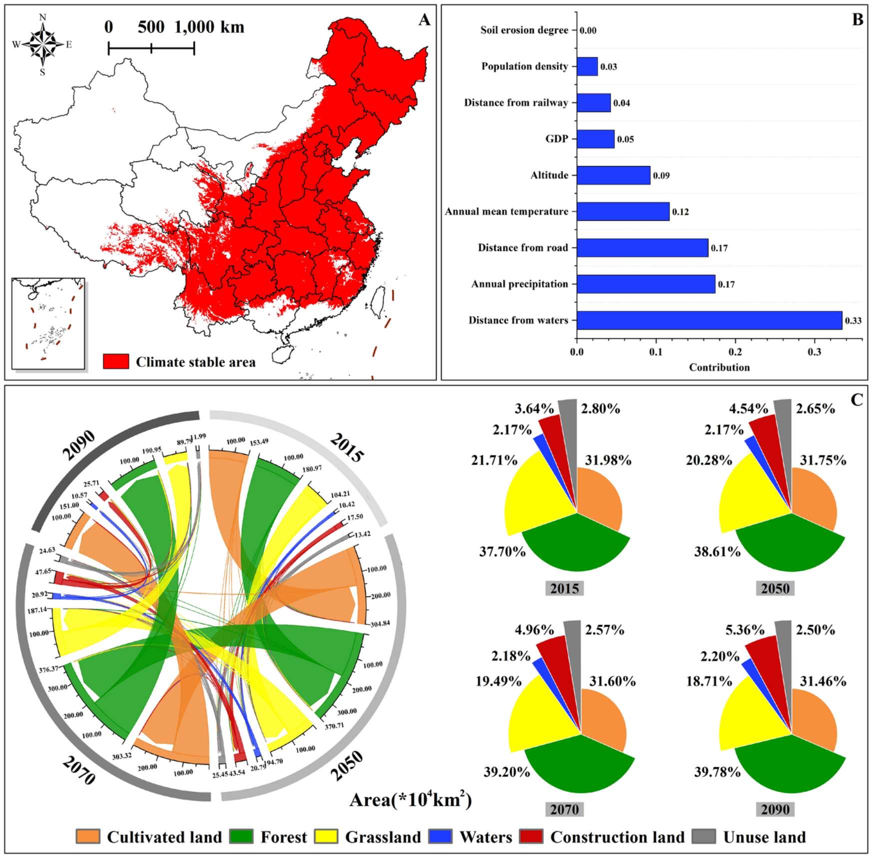


FIGURE 7 Map of the climate-stable areas and land use change of *T. chinense* in China. (A): Climate-stable areas of *T. chinense* under different climate scenarios in China; (B): Contribution of driving factors to the change of grassland; (C): Conversion and change of land use type area in 2015, 2050, 2070, and 2090 within the climate-stable areas of China.

3.6 Wild tending areas of *T. chinense*

Under the current climate situation, the habitat of about 17.69 * 104 km2 in the high suitable areas will not be affected by future land use change, which will be the stable habitat areas of the *T. chinense*in hundred years (Figure 8A). High, medium, and low suitable wild tending areas were obtained by superposing the suitable layers of *T. chinense* under current and future climate scenarios in the region. Guizhou Province has the largest area of high suitable wild tending area, followed by Inner Mongolia Autonomous Region, Hebei and Heilongjiang (Figure 8B). Based on the hot spot analysis of the area of the high suitable wild tending areas (administrative units), the results showed that there are 23 cities that are most suitable for planning the wild tending areas of *T. chinense* , such as Qiqihar City, Chifeng City, Zunyi City (Figure 8B, S5).

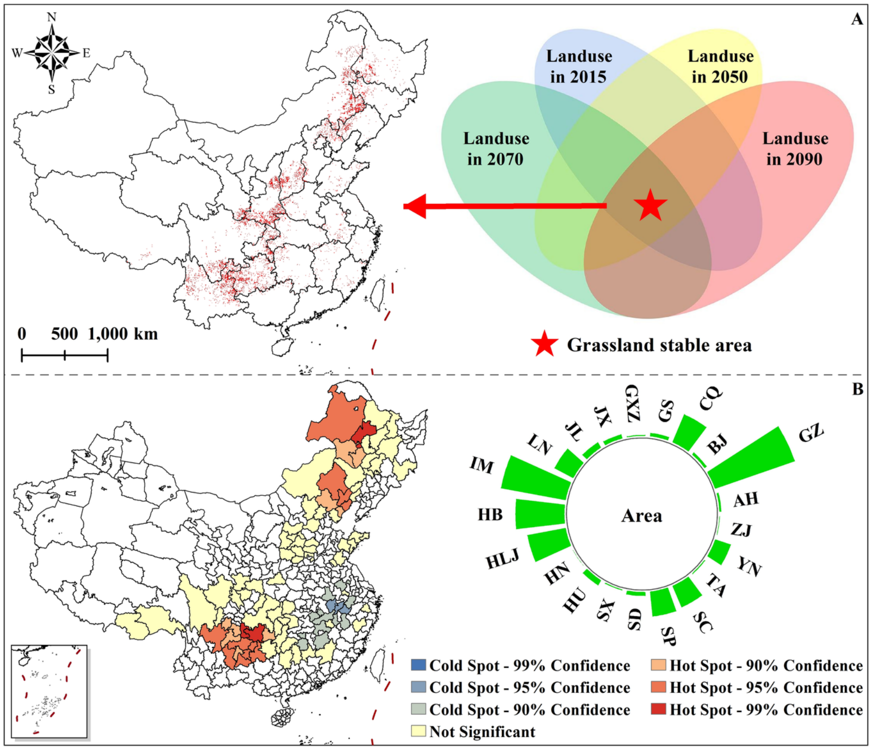


FIGURE 8 The distribution of grassland-stable areas and wild tending areas in the current high suitable areas of *T. chinense*in China. (A): The grassland-stable areas within the potential high suitable areas of *T. chinense* under the current climate scenario in China; (B): Analysis on the provincial area and hot spots at city level of high suitable wild tending area, where the abbreviations represent: GXZ: Guangxi Zhuang Autonomous Region, GS: Gansu Province, CQ: Chongqing City, BJ: Beijing, GZ: Guizhou Province, AH: Anhui Province, ZJ: Zhejiang Province, YN: Yunnan Province, TA: Tibet Autonomous Region, SC: Sichuan Province, SP: Shanxi Province, SD: Shandong Province, SX: Shaanxi Province, HU: Hunan Province, HN: Henan Province, HLJ: Heilongjiang Province, HB: Hebei Province, IM: Inner Mongolia Autonomous Region, LN: Liaoning Province, JL: Jilin Province, JX: Jiangxi Province.

4. Discussion

4.1 The influence of environmental factors on *T. chinense*'s distribution

Among the many environmental factors that affect the growth and development of *T. chinense* , only a few major environmental factors affect its distribution. Under the current climate conditions, water-related environmental factors (Bio18) have the highest impact on the distribution of *T. chinense* , which is basically consistent with the research of Gao et al. (P. Gao et al., 2023). *T. chinense* is mostly found in shaded or humid areas, and has poor drought resistance. If there is insufficient rainfall, its growth and development will be inhibited (Tang et al., 2021; Chinese botanical society, 1988). In the summer, excessive moisture in the soil or water on the surface can lead to root rot and hinder its growth (Tang et al., 2021; Yanar et al., 1997). In addition to precipitation, temperature also has an important impact on the distribution of *T. chinense* . Among them, Bio11 and Bio08 play an important role in the distribution of *T. chinense* . The suitable value range of Bio11 is wide (-26.47˜ 13.22), and it could be seen that *T. chinense* has high cold resistance. In cold winter, in the process of overwintering and dormancy of *T. chinense* , starch may be degraded into soluble sugar mainly through starch phosphorylation to ensure that there are sufficient carbohydrates to maintain its growth and improve its stress resistance in low-temperature environment during dormancy, so that it can overwinter smoothly (Song et al., 2015). At the same time, the soluble sugar forms small molecular solutes under low-temperature stress, which further improves its ability to resist severe cold (Blasing et al., 2005). Bio08 represents the mean temperature of wettest quarter. The spatial and temporal distribution of precipitation in Asia is extremely uneven. There is more precipitation in summer, and the wettest quarter is mainly concentrated in summer (Zhan, 2013). When the summer temperature is greater than 30, seedling collapse occurs in the*T. chinense* . And the mortality rate of annual individual seedling collapse is relatively high, which is basically unable to survive (Song et al., 2015). This seriously affects the renewal of the *T. chinense* population and the continuation of its species. The range of Bio08 (9.08 ~ 26.38) well reflects this phenomenon (Luo & Guo, 2012).

By the 2090s, the Bio11 and Bio08 within the suitable area of *T. chinense* have risen by 6.32°C and 6.42°C, respectively. For high-latitude areas within the suitable area, the increased winter temperature may prevent *T. chinense* from entering its hibernation period, leading to continuous nutrient consumption and potentially adverse effects on the growth and reproductive capacity of the following year. For low-latitude areas in the suitable area, high temperatures may not only exacerbate the lodging of *T. chinense* , but also accelerate leaf senescence, reduce the reuptake rate of N and P, and weaken its ability to adapt to the environment (X. Li et al., 2023; Vergutz et al., 2012). Therefore, in a century of climate change, temperature increasing may be detrimental to the growth of *T. chinense* , reducing its ability to adapt to the environment and further threatening the population. By the end of this century, the Bio18 may increase to 438.51 mm. It is speculated that, with increasing summer precipitation, the negative effect of the single temperature factor (the increase in soil evaporation) on *T. chinense* may be counterbalanced by the increase in precipitation (the increase in soil moisture) to reach an equilibrium state. However, supposing there is further increase in precipitation or temperature, the balance may be disrupted, creating water or temperature stress. In that case, it may limit the growth of *T. chinense* .

4.2 Spatial transformation characteristics of *T. chinense*under climate change scenarios

In this study, Biomod2 was used to predict the distribution of *T. chinense* in Asia, and the results were not completely consistent with the regional niche results predicted by Tang et al. and Gao et al. using the MAXENT model (P. Gao et al., 2023; Tang et al., 2021). It is speculated that there are four reasons for this result. The first point is the choice of modeling scope. In the existing studies, the methods of constructing species distribution models are divided into complete and regional niche models. Complete niche models are more reliable models for describing the climatic niche of species because they can calibrate the presence and capture a wider range of occupied environmental conditions (Pearson et al., 2004). However, if unoccupied but environmentally suitable areas for the species are considered for model training, then the capacity to predict the species' potential distribution will be reduced (Acevedo et al., 2012). Barve et al. argued that the appropriate geographical background for model training, validation, and comparison should comprise the set of localities that a species has over its history (Barve et al., 2011). In this study, the geographical distribution of *T. chinense* was reviewed, and the region with the highest accessibility (Asia) was selected as the study area. In addition, the use of ensemble species distribution model can reduce the instability of a single model (Goldsmit et al., 2020; Araújo & New, 2007), and can more accurately predict the range of suitable areas of *T. chinense* . Secondly, there is a serious bias in the geographical distribution of the occurrence data used by Tang and Gao et al. in constructing the model (P. Gao et al., 2023; Tang et al., 2021). Through our field investigation, we found *T. chinense* populations also distribute in the high-latitude areas in the northern of China. However, in the studies of Tang et al and Gao et al., there are few or even no occurrence data of *T. chinense* in high latitude areas, relatively concentrated data in low latitude in the southern of China, which is biased from the real occurrence data of *T. chinense* . This biased regional data cannot objectively identify the niche of species (El-Gabbas & Dormann, 2018). In addition to the above factors, we speculate that the choice of factors is also one of the reasons for the different results. As a semi-parasitic plant, vegetation (host) is the premise for the good growth of *T. chinense* , so biological factors play a certain role in the distribution modeling of the species. At present, the inclusion of interspecific interactions is considered to be the main challenge for species distribution modeling (Y. Wang et al., 2022). Considering that there are many host species of *T. chinense* , mainly Asteraceae, Fabaceae, and Poaceae, and the host distribution is extensive (Guo & Luo, 2011), we included NDVI data reflecting vegetation growth in the species distribution model. Although NDVI data can not describe the specific conditions of vegetation classification groups in the land acquisition table, we believe that the inclusion of NDVI data may make the modeling results closer to its real niche for *T. chinense* .

Compared with the current, the suitable areas of *T. chinense* show an increasing trend under the combination of future climate scenarios. Spatially, consistently with the migration direction of most plant species (B. Chen, Zou, et al., 2022; W. Li et al., 2019; Yin et al., 2022; L. Zhang et al., 2022), the overall distribution areas gradually move to the northwest of the current suitable areas (high latitude and high altitude areas). In the future, the suitable areas of *T. chinense* in China will mainly expand to Tibet. The expansion area is currently located in the semi-arid area, and its soil moisture content can meet the needs of the growth of *T. chinense* . However, due to the high altitude, its temperature is lower than other semi-arid areas suitable for the growth of *T. chinense* . Therefore, this area is not suitable for the growth of *T. chinense* in the current climate. In the future, the plateau temperate zone in the southern of China will expand northward, gradually replacing the plateau sub-cold zone in western China, and gradually increasing the temperature in this region (S. Wu et al., 2010). Therefore, the climate conditions in this area may be similar to those in the current suitable areas of *T. chinense* in the future, which may be one of the reasons for the expansion of the suitable areas in this area. In the future, the disappearing areas of suitable areas of *T. chinense* are mainly located in the southern of China, which will change from the subtropical zone to the tropical zone with climate warming in the future (S. Wu et al., 2010). At the same time, the increasing temperature will reduce the moisture of the surface soil, increase evaporation, reduce the Climate Moisture Index, and is not conducive to the absorption of soil fertility (Michaelian et al., 2011; Peng et al., 2011). This will make the areas no longer suitable for the growth of *T. chinense* .

4.3 Land use conversion characteristics and wild tending areas planning in the climate-stable areas of *T. chinense*

Human activities are a major factor leading to global change, which overwhelm the natural changes brought about by climate change in the past few thousand years (Houghton et al., 1990). Human activities such as agriculture, forestry, and other land management have changed the entire landscape, thus affecting the flora and fauna communities of many ecosystems worldwide (Ojima et al., 1994). In China, the climate-stable areas of *T. chinense* are mainly distributed in humid and semi-humid areas, and the major changes of land use types in this area in the future are mainly construction land and grassland. It is predicted that the construction land in the region will expand rapidly in the next hundred years, an increase of about 46.94% compared with 2015. The distribution of construction land is mainly related to population density. Future population projections indicate that although the proportion of the population in the southeast of China will decrease over the next 20 years, the change will only be between 0.1% and 0.3% (L. Wang et al., 2014). Although the overall pattern of spatial population distribution in China will not change fundamentally, with the southeast being densely populated and the northwest being sparsely populated, the scale and degree of population agglomeration in urban agglomerations are gradually increasing, and the trend of population agglomeration is more obvious (L. Wang et al., 2014) Therefore, this study predicted that the rapid growth of the construction land of*T. chinense* in the future climate-stable areas in China is in line with the actual situation.

In addition to the rapidly expanding construction land, the grassland areas in the climate-stable areas have also changed significantly, and their areas have decreased by 15.18% compared with 2015. Grassland ecosystem is the largest ecosystem in land surface types and occupies an extremely important role in the terrestrial ecosystem. The impact of human activities on the grassland ecological system in recent years growing (X. Zhang et al., 2022). Since the 21st century, the Chinese government has invested vigorously in ecological restoration projects and carried out ecological restoration work, such as returning farmland to grassland, which significantly affects the restoration of grassland soil nutrients (carbon) (C. Chen et al., 2019). In the climate-stable areas of *T. chinense* in the next hundred years, there will be no such transfer from 2050 to 2090, except that a small amount of cultivated land will be transferred to grassland from 2015 to 2050. Therefore, the soil nutrients restored by returning cultivated land to grassland in the next hundred years will be very low. In the future, the areas of construction land transferred to grassland in the region will increase yearly. It is estimated that by 2090, the areas of construction land transferred from 2070 will account for about 1.22% of the grassland areas in 2090. Large scale construction projects have not only seriously damaged grassland vegetation and topsoil, resulting in a sharp decline in grassland carbon storage, which will take many years to recover, but also exacerbated climate change and indirectly affected grassland ecosystem, causing a certain impact (X. Chen & Shang, 2011). Therefore, in the context of future climate change and land use change, the natural habitat suitable for the growth of *T. chinense* will face a huge threat.

Under land use and climate change, although climate change increases the total suitable areas of *T. chinense* , it will seriously threaten the high suitable areas. In the climate-stable area of *T. chinense* under different climate scenarios, the habitat areas suitable for the growth of *T. chinense* will gradually reduce due to the change in land use. These future changes may limit the expansion of wild populations. Furthermore, combined with excessive harvesting, wild resources are increasingly depleted, making it difficult for the species to continue. At present, wild resources can not meet the needs of medicine, but its artificial breeding technology is not mature. And according to the Non-grain Production policy in China, cultivated land is forbidden to grow economic crops. Therefore, it is necessary to carry out wild tending of *T. chinense* , which can promote the recovery and sustainable utilization of *T. chinense* population. Wild tending is an available approach to solve the contradiction between the shortage of wild resources of medicinal plants and the large market demand. It is a production mode of artificially or naturally increasing the population of target medicinal materials, which can not only greatly increase the available resources, but also maintain the community balance after over-collecting, and continuously supply genuine-quality medicinal materials (S. Chen et al., 2004). The wild tending area has the characteristics of primitive environment, less human intervention and far away from pollution sources. It is very important to predict the change range of the suitable habitat of *T. chinense* for formulating agricultural policies and planting planning (Shen et al., 2021). Based on the current high suitable areas of *T. chinense* in China, combined with the future climate and land use change, this study planned the wild tending areas of *T. chinense* for hundred years. This can effectively avoid the huge economic losses caused by blind planting. According to the results of the wild tending area, we made the following recommendations: (1) The wild tending areas of *T. chinense* in China are mainly distributed in the north, northeast, and southwest of China. In the future, most of the areas will be high suitable area, and only a few areas will be transformed into medium or low suitable areas. It is suggested that germplasm collection and diversity evaluation of wild plants should be carried out in the climate transformation areas, which is conducive to the conservation and domestication of the core germplasm of *T. chinense* . (2) The local government should take more actions to protect the natural ecology, enhance the awareness of the protection and restoration of local natural land types, and avoid irreversible damage to them. (3) The planned wild tending area of *T. chinense* should be combined with local policies, integrate ecological, economic, and social benefits, and strengthen the establishment of wild tending medicinal material bases. This will effectively solve the contradiction between *T. chinense*ecological protection and biodiversity, resources and supply demand. (4) The precondition of artificial breeding and wild tending is to master the basic characteristics of growth and development of TCM. Therefore, we should strengthen the research on population ecology and developmental biology, especially on the influence of different hosts on the composition and the mixed cultivation mode with other crops. This can not only maintain the stability of *T. chinense* population, but also improve the quality and yield of *T. chinense* . At the same time, the mixed cultivation mode can effectively make full use of land resources and make up for the shortage of grassland resources in some areas due to the dense population.

5 Conclusions

High-quality TCM should be planted in specific natural conditions and ecological environments. Therefore, the prediction and suitability evaluation of potential distribution areas of TCM have important guiding significance for scientific planning of wild tending areas. This study analyzed the change in the distribution range of *T. chinense* in China under future climate and land use changes. Although the stable areas suitable for the growth of *T. chinense* under climate change are still large, the grassland in this area is decreasing year by year, which may pose a threat to the population of *T. chinense* in China. To solve the contradiction between the supply and demand of*T. chinense* , we used ZONATION software and hot spot analysis to determine the counties in China that are suitable for the wild tending of *T. chinense* . This will provide a scientific and effective reference for the relevant government departments at all levels when planning the wild tending area of *T. chinense* , and also provide an important reference for the diversity protection, restoration and sustainable development of other wild medicinal species. From the macro-view, the distribution of *T. chinense* under the future climate and land use change was explored. In future, we will continue to explore other factors that affect the change of the wild population structure of *T. chinense* , and find the reasons for the change of distribution pattern from a microscopic perspective. We should strengthen the research on the correlation between the content of effective components of *T. chinense* and environmental factors and hosts, and construct the spatial distribution layer of effective components of *T. chinense* , to provide a more accurate and scientific theoretical basis for more proper planning of the wild tending areas of *T. chinense* population.

AUTHOR CONTRIBUTIONS

Boyan Zhang: Methodology (lead); software (lead); formal analysis (lead); data curation (equal); writing—original draft preparation (lead); writing—review and editing (lead). Bingrui Chen: Methodology (equal); formal analysis (equal); writing—review and editing (lead). Xinyu Zhou: Validation (lead); investigation (equal). Hui Zou: Validation (equal); writing—review and editing (equal). Detai Duan: Investigation (equal). Xiyuan Zhang: Validation (equal). Xinxin Zhang: Conceptualization (lead); methodology (equal); writing—review and editing (equal); supervision (lead).

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DATA AVAILABILITY STATEMENT

The original contributions presented in this study are included in the article/Supplementary material, further inquiries can bedirected to the corresponding author.

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