J Arid Land (2024) 16(9): 1255–1269
doi: 10.1007/s40333-024-0061-8; CSTR: 32276.14.JAL.02400618

Science Press Springer-Verlag

Potential distribution of *Haloxylon ammodendron* in Central Asia under climate change

CHEN Zhuo[1,2], SHAO Minghao[2,3], HU Zihao[4], GAO Xin[1,2*], LEI Jiaqiang[1,2]

[1] Key Laboratory of Ecological Safety and Sustainable Development in Arid Lands, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China;
[2] University of Chinese Academy of Sciences, Beijing 100049, China;
[3] National Engineering Technology Research Center for Desert-Oasis Ecological Construction, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China;
[4] University of Emergency Management, Beijing 101601, China

Abstract: Understanding the spatial distribution of plant species and their dynamic changes in arid areas is crucial for addressing the challenges posed by climate change. *Haloxylon ammodendron* shelterbelts are essential for the protection of plant resources and the control of desertification in Central Asia. Thus far, the potential suitable habitats of *H. ammodendron* in Central Asia are still uncertain in the future under global climate change conditions. This study utilised the maximum entropy (MaxEnt) model to combine the current distribution data of *H. ammodendron* with its growth-related data to analyze the potential distribution pattern of *H. ammodendron* across Central Asia. The results show that there are suitable habitats of *H. ammodendron* in the Aralkum Desert, northern slopes of the Tianshan Mountains, and the upstream of the Tarim River and western edge of the Taklimakan Desert in the Tarim Basin under the current climate conditions. The period from 2021 to 2040 is projected to undergo significant changes in the suitable habitat area of *H. ammodendron* in Central Asia, with a projected 15.0% decrease in the unsuitable habitat area. Inland areas farther from the ocean, such as the Caspian Sea and Aralkum Desert, will continue to experience a decrease in the suitable habitats of *H. ammodendron*. Regions exhibiting frequent fluctuations in the habitat suitability levels are primarily found along the axis stretching from Astana to Kazakhskiy Melkosopochnik in Kazakhstan. These regions can transition into suitable habitats under varying climate conditions, requiring the implementation of appropriate human intervention measures to prevent desertification. Future climate conditions are expected to cause an eastward shift in the geometric centre of the potential suitable habitats of *H. ammodendron*, with the extent of this shift amplifying alongside more greenhouse gas emissions. This study can provide theoretical support for the spatial configuration of *H. ammodendron* shelterbelts and desertification control in Central Asia, emphasising the importance of proactive measures to adapt to climate change in the future.

Keywords: *Haloxylon ammodendron*; potential suitable habitats; climate change; desertification; maximum entropy (MaxEnt) model; Central Asia; Aralkum Desert

Citation: CHEN Zhuo, SHAO Minghao, HU Zihao, GAO Xin, LEI Jiaqiang. 2024. Potential distribution of *Haloxylon ammodendron* in Central Asia under climate change. Journal of Arid Land, 16(9): 1255–1269. https://doi.org/10.1007/s40333-024-0061-8; https://cstr.cn/32276.14.JAL.02400618

1 Introduction

Desertification involves rapid alterations in soil characteristics, vegetation patterns, and hydrological conditions. It profoundly impacts inland regions and presents a significant challenge

*Corresponding author: GAO Xin (E-mail: gaoxin@ms.xjb.ac.cn)
Received 2024-04-01; revised 2024-06-26; accepted 2024-06-28

for human societies (Rengasamy, 2006; Tarhouni et al., 2010; Paolo et al., 2013). Desertification in Central Asia is an environmental issue garnering scrutiny. Biodiversity and ecological stability in this region are vulnerable to climate change (Bohovic, 2016). The temperature in Central Asia has been rising rapidly, which can accelerate desertification in the region (Hu et al., 2014; Davi et al., 2015; Jiang et al., 2017; Zhang et al., 2020). Currently, an effective measure to combat desertification is to select suitable tree species to establish a comprehensive shelterbelt system (Fang et al., 2024). However, our knowledge of shelterbelt construction based on Central Asian climate conditions remains insufficient (Wang et al., 2009; Shao et al., 2022; Fang et al., 2024; Xiao et al., 2024). Therefore, a detailed analysis of the suitable distribution areas for the selected plant species is a timely contribution to combating desertification in arid areas.

Vegetation in arid areas provides ecological benefits by sustaining the survival of livestock and wildlife and offering crucial ecological functions such as preventing soil desertification (Lioubimtseva, 2015; Jiang et al., 2017; Tao et al., 2017). Therefore, the response of vegetation to climate change in arid areas has become a focal point of global research. *Haloxylon ammodendron* has various ecological benefits, including increasing vegetation coverage, enhancing soil moisture retention, suppressing soil erosion, and improving carbon sequestration, and this species is widely distributed in arid areas (Abdi et al., 2019; Li et al., 2019). Its root system can tap deep into groundwater, making it resilient to drought (Shao et al., 2022). The roots act as rebars that strengthen the soil in desert regions, protect against the encroachment of dunes, and help maintain soil fertility (Shao, 2008). Its parasitised roots contain medicinal components that play a role in inhibiting the activity of disease-related enzymes (Trampetti et al., 2019; Song et al., 2021). Additionally, *H. ammodendron* forests in arid areas can create an environment conducive to diverse flora and fauna, providing suitable habitats for various species to survive (Wang et al., 2009). Assessing and predicting the impact of climate change on the suitable habitats of *H. ammodendron* is of significant importance for promoting sustainable development in Central Asia.

Much of our current understanding on the distribution prediction and identification of suitable habitats of *H. ammodendron* depends on model simulations. Several species distribution models have been developed and applied to explore the habitat suitability and potential distribution of species, including the Mahalanobis distance (MD) model (Etherington, 2019), generalised linear model (GLM) (Guisan et al., 2002), sector-vector machine (SVM) (Betancourt, 2005), random forest (RF) (Mi et al., 2017), and maximum entropy (MaxEnt) model (Phillips et al., 2006). The potential of using ensemble models to improve prediction accuracy has also been tested (Pecchi et al., 2020). Among these species distribution models, the MaxEnt is a machine-learning method that determines the ecological requirements of a species based on species distribution records and environmental factors (Kang et al., 2023). It uses a probability distribution function known as the MaxEnt principle to predict the probability of species occurrence across geographical spaces (Phillips et al., 2006). Compared with correlative and mechanistic models, the MaxEnt model can achieve higher distribution accuracy with fewer sample points and is widely used in data-limited regions such as Central Asia (Gherghe et al., 2018; Sun et al., 2020).

Intergovernmental organisations have recognised the urgent need to combat desertification in Central Asia (Zhang et al., 2020). Drought stress can influence the expression of drought-resistant genes of *H. ammodendron*, thereby altering its spatial distribution pattern (Xiao et al., 2006). Large areas of *H. ammodendron* shelterbelts have been planted in Central Asia, particularly in dry lake basins (Chen et al., 2022; Shao et al., 2022). Some shelterbelts are unsustainable in fragile ecological environments (Jiang et al., 2017). This kind of cultivation not only leads to the wastage of resources but also may cause damage to the existing ecology of arid areas. Climate change has been considered one of the most significant threats to global biodiversity since the beginning of the 21st century (Dawson et al., 2011). From 2011 to 2020, the global surface temperature increased by 1.1°C compared with the period from 1850 to 1900 (Intergovernmental Panel on Climate Change (IPCC), 2023). Against the backdrop of global climate change, the future of existing *H. ammodendron* shelterbelts in Central Asia remains uncertain (Xiao et al., 2024), and it is essential to investigate the distribution of *H. ammodendron* in Central Asia. Therefore, we aimed to explore and predict the potential habitats of *H. ammodendron* in Central Asia. Based on the historical climate data (1970–2000) and the current distribution of *H. ammodendron*, we systematically mapped the suitable habitats of *H. ammodendron* and identified the key factors influencing its distribution. Utilising climate data under four different shared socioeconomic pathway (SSP) scenarios with varying greenhouse gas emission intensities for three future periods (2021–2040, 2041–2060, and 2061–2080), we projected the future potential distribution pattern of *H. ammodendron* in Central Asia. This study may improve our understanding of the scientific construction of *H. ammodendron* shelterbelts in Central Asia, which is a timely contribution to the formulation of local government environmental protection policies.

2 Materials and methods

2.1 Study area

Central Asia, the central region of Asia, serves as a vital transportation link between Asia and Europe. The study area extends from the Caspian Sea in the west to the border of western China in the east, encompassing Kazakhstan, Uzbekistan, Turkmenistan, Tajikistan, Kyrgyzstan, and Xinjiang Uygur Autonomous Region of China (34°19′59″–55°27′15″N, 46°29′30″–96°23′15″E; Fig. 1), situated between. Geographically, the altitude gradually decreases from the mountain ranges of the Altay Mountains, Tianshan Mountains, and Pamirs in eastern Kazakhstan and Uzbekistan, traversing Kyrgyzstan and Tajikistan, until reaching the shores of the Caspian Sea in western Kazakhstan and Turkmenistan. Characterised by a typical continental climate, the spatial variation in precipitation and temperature in this region follows gradients from mountainous areas to plains and from north to south (de Beurs et al., 2015). Apart from mountainous and hilly regions, the average annual temperature ranges from 2.0°C in northern Kazakhstan to over 18.0°C in southern Turkmenistan (Mohammat et al., 2013). Against the backdrop of global temperature rise, this region is more sensitive to extreme climate (Jiang et al., 2017; IPCC, 2023). The majority of deserts in Turkmenistan, Uzbekistan, southern Kazakhstan, and Xinjiang of China, including the Kyzylkum, Aralkum, Muyunkum, and Taklimakan (in the Tarim Basin) deserts, are characterised by sparse vegetation. The arid climate of these flatlands poses a challenge for plant growth. According to statistical data since 1977, *H. ammodendron*s is mainly distributed in Xinjiang of China, with some communities found in Kazakhstan and Uzbekistan (Fig. 1).

2.2 Data preparation

2.2.1 Distribution data

Distribution data for *H. ammodendron* were obtained from the Global Biodiversity Information Fund (GBIF; http://www.gbif.org) and field observations at the Aralkum Desert. The field observation data were collected during the scientific expedition in the Aralkum Desert conducted during 20–29 December 2019. In total, 202 distribution records for *H. ammodendron*, including 195 GBIF and 7 field observation records, were collected for this study (Fig. 1). Accurate longitude and latitude information was extracted as inputs for the MaxEnt model. Although data from the same source usually exhibit relatively stable and uniform data resolution, considering the requirement of sufficient data volume for the construction of the MaxEnt model and the accuracy of model distribution prediction, mixing species distribution information from different sources is crucial for the model construction (Shao et al., 2022). To avoid the sampling bias and overfitting caused by densely clustered points, we screened the obtained coordinate data and removed redundant entries. An "ENMeval" package in R software was used to perform the aforementioned tasks to ensure that the spatial resolution of the recorded events matched that of the environmental variables (Muscarella et al., 2015). "ENMeval" was designed for the automated tuning and evaluation of ecological niche models, also known as a species distribution model. This model can estimate species distribution ranges and niche characteristics utilising data on species distributions and environmental variables. In total, 167 valid records were retained in this study.

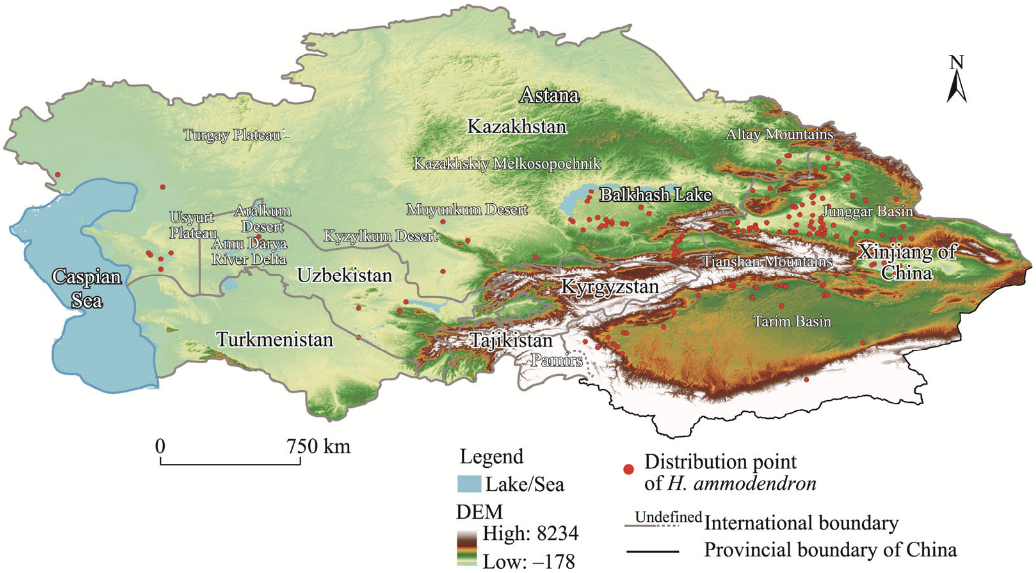

Fig. 1 Overview of the study area based on the digital elevation model (DEM) and spatial distribution points of *Haloxylon ammodendron* obtained from the Global Biodiversity Information Fund (GBIF; http://www.gbif.org) and field observations. Note that the figure is based on the standard map (GS(2016)1665) from the Standard Map Service System (http://bzdt.ch.mnr.gov.cn/index.html) marked by the Ministry of Natural Resources of the People's Republic of China, and the standard map has not been modified.

2.2.2 Predictor variables

We opted for 23 predictor variables to model the main factors affecting the distribution pattern of *H. ammodendron* in Central Asia under the current climate conditions (1970–2000) and future shared climate change scenarios (2021–2080) (Table 1). Bioclimatic variables with 19 categories (BIO1–BIO19; Table 1) were obtained from the WorldClim database (https://www.worldclim.org/). Elevation data were derived from the WorldClim historical climate dataset (https://worldclim.org/data/worldclim21.html). It is a high-resolution global weather and climate database that involves key parameters of vegetation growth and is widely used to drive species distribution models (Yang et al., 2023; Fang et al., 2024). Soil is a key limiting factor for vegetation growth, affecting the distribution of plant species (Shao et al., 2022). Topsoil sand content was obtained from the OpenLandMap dataset as the soil parameter driven the MaxEnt model, which is the outcome of machine-learning predictions derived from the comprehensive aggregation of soil profiles and samples worldwide (Tomislav, 2018). Topsoil water content was downloaded from the OpenLandMap soil water content dataset, which was predicted at six standard depths (0, 10, 30, 60, 100, and 200 cm) at a resolution of 250 m for 33 and 1500 kPa suctions (Tomislav and Surya, 2019). Human activities are believed to have influenced the distribution of *H. ammodendron* in arid areas, especially in the northwestern region of China (Abdi et al., 2019). The population distribution in Central Asia with a resolution of 100 m used in this study was from the WorldPop global project population data (Sorichetta et al., 2015). The annual population distribution in 2020 was selected to quantify the impact of human activities on the growth and distribution of *H. ammodendron*.

The topsoil sand content, topsoil water content, and population distribution were resampled using the Google Earth Engine (GEE). Owing to the abundance of field survey data records conducted by our research team, the distribution data of *H. ammodendron* are relatively precise. Simultaneously, utilising environmental variables with spatial resolutions matching the accuracy of the distribution data in the model distribution can greatly enhance the precision of the model and the accuracy of species distribution predictions (Sillero et al., 2014; Sofaer et al., 2019).

Future climate data utilised SSPs sourced from the Coupled Model Intercomparison Project

(CMIP6) of the IPCC. To avoid the uncertainty caused by using a single climate model, we derived future climate data that were employed to predict the potential distribution of *H. ammodendron* by averaging the results from three General Circulation Models (GCMs): INM-CM5-0, MIROC6, and MRI-ESM2-0. Each GCM was assessed for three periods (2021–2040, 2041–2060, and 2061–2080) under four shared climate change scenarios: SSP126, SSP245, SSP370, and SSP585.

Elevation, soil variables, and population distribution were considered constants. Highly correlated environmental variables can severely impact model performance, resulting in overfitting and thus affecting the acquisition of more realistic variable response curves (De Marco Júnior et al., 2018). Therefore, using traditional correlation methods is often a compromise. Principal component analysis (PCA) can generate orthogonal variables that capture entire suites of response curves, transforming all variables into ecologically meaningful orthogonal components (Hirzel et al., 2002). In this study, PCA was employed for variable reconstitution and selection to eliminate the potential overfitting of the model stemming from autocorrelation among the variables. It can convert all environmental variables into distinct orthogonal components while preserving their ecological significances. The initial set of 23 environmental variables was transformed into eight restructured variables labelled PC1–PC8 (where PC is the principal component). These variables encapsulated over 95.0% of the pertinent information that is considered essential for model construction. The top six variables contributing to each category in the PCA are listed in Table 1.

Table 1 Predictor variables and their abbreviations and classifications after downscaling

Predictor variable	Abbreviation	Classification of action
Annual mean temperature	BIO1	PC1
Mean diurnal range	BIO2	PC4, –PC5, PC6*, and –PC7
Isothermality	BIO3	–PC2, PC4, PC6, and –PC7
Temperature seasonality	BIO4	PC2, PC3, and PC8
Max temperature of warmest month	BIO5	PC1 and PC2
Min temperature of coldest month	BIO6	–PC3
Temperature annual range	BIO7	PC3, PC6, and PC8
Mean temperature of wettest quarter	BIO8	PC4* and –PC6
Mean temperature of driest quarter	BIO9	–PC3 and –PC4
Mean temperature of warmest quarter	BIO10	PC1 and PC2
Mean temperature of coldest quarter	BIO11	PC1 and –PC3
Annual precipitation	BIO12	–PC1
Precipitation of wettest month	BIO13	PC4 and PC8
Precipitation of driest month	BIO14	–PC5 and –PC8*
Precipitation seasonality	BIO15	–PC2 and PC8
Precipitation of wettest quarter	BIO16	PC4
Precipitation of driest quarter	BIO17	–PC5, PC6, and –PC8
Precipitation of warmest quarter	BIO18	–PC1* and PC7
Precipitation of coldest quarter	BIO19	–PC3* and PC6
Population distribution	PD	–PC2*
Elevation	Elev	PC5* and PC7*
Topsoil sand content	TSC	–PC5 and PC7
Topsoil water content	TWC	PC5 and –PC7

Note: PC, principal component. *, the factor that contributes most to each classification; –, negative correlation between this factor and the PC category.

2.3 Model framework

The MaxEnt model combines many highly regarded algorithms and is well used to identify the areas for plant protection (Guillera-Arroita et al., 2014). Especially in the background weighting and random processes, the MaxEnt model is recognized for the highly comparable results and predictive performance in identifying test data and is considered a practical approach for handling imbalanced biased data in species distribution models (Ahmadi et al., 2023). The use of ensemble methods is considered to reduce the uncertainty of models and increase their robustness in accurately simulating species distribution (Marmion et al., 2009). There are two basic steps in MaxEnt modelling: (1) using all the occurrence records of *H. ammodendron* in the study area, processing variables (PC1–PC8) to construct the MaxEnt model, and generating the distribution of *H. ammodendron*; and (2) training the MaxEnt model using the distribution of *H. ammodendron* records to generate predicted distributions under different climate change scenarios in the future. The traditional areas under the curve have been widely used (Yang et al., 2023; Fang et al., 2024). However, previous studies have indicated that the areas under the curve may not be entirely applicable for assessing the performance of presence-only or presence-background ecological niche models (Leroy et al., 2018; Velasco and González-Salazar, 2019). Therefore, this study was motivated by the foregoing reasons for selecting the continuous Boyce index to evaluate model performance (Hirzel et al., 2002). Boyce index ranges from –1 to 1, where a positive value signifies an alignment between the predicted and observed distributions, while a negative value implies poor predicted habitat quality.

During the running of the model, 10,000 background points were randomly selected as pseudo-absences. Further, 75.0% of the distribution records were used for training, and the remaining 25.0% of the distribution records were used for testing. Moreover, cross-validation is essential to verify the accuracy of the model. Therefore, we chose the hierarchical checkerboard2 method based on the size of the study area and the distribution of *H. ammodendron*. As the distribution of *H. ammodendron* at the regional scale is derived from limited data, it is necessary to assess the uncertainty associated with extrapolation after predictive training (Mannocci et al., 2017, 2018). In this phase, we utilised the "dsmExtra" package in R software to create two metrics: the extrapolation detection metric, which can evaluate extrapolation in environmental space and model transferability; and the percentage of data nearby, which can assess extrapolation reliability in a multivariate environmental space (Bouchet et al., 2020). Generally, a low extrapolation detection or a high percentage of data nearby represents higher extrapolation reliability, whereas the opposite suggests lower extrapolation reliability (Miller et al., 2013).

The measuring geographic distribution function of spatial statistical tools was used in ArcGIS 10.8 to estimate the geometric centre of *H. ammodendron* distribution. Before conducting this processing, a reclassification procedure was applied to predict the spatial distribution of *H. ammodendron* under different climate change scenarios to derive spatial distribution polygons for further calculation.

3 Results

3.1 Potential suitable habitats of *H. ammodendron* under current climate conditions

Figure 2 depicts the potential distribution of *H. ammodendron* in Central Asia under the current climate conditions. Regions with highly suitable habitats (habitat class>0.60) of *H. ammodendron* in Central Asia cover an area of approximately 0.322×10^6 km^2, which are primarily located on the northern slopes of the Tianshan Mountains, and the upstream of the Tarim River and the western edge of the Taklimakan Desert in the Tarim Basin. Meanwhile, there are scattered highly suitable habitats of *H. ammodendron* within Uzbekistan and Kazakhstan, including the central Caspian coastal plain, Amu Darya River Delta, Aralkum Desert, western Kazakhstan, and southern coast of the Balkhash Lake. The medium suitable habitats (0.30<habitat class≤0.60) of *H. ammodendron*, with an area of approximately 0.602×10^6 km^2, are mainly distributed around highly suitable

habitats. Unsuitable habitats (habitat classes≤0.15) of *H. ammodendron* are widely distributed in the central and southern parts of the study area (approximately 3.620×10^6 km^2), which are mainly located in the south of 50°N. These regions, including the Taklimakan Desert, Karakum Desert, and Uzbekistan, cannot support the natural growth of *H. ammodendron* owing to the arid climate.

The combined influence of multiple factors results in potential pattern variations in the suitable habitats of *H. ammodendron*. Most areas around the Caspian Sea, Aralkum Desert, Balkhash Lake, Ili River, and Tarim River are highly suitable for the natural growth of *H. ammodendron*. The presence of inland lakes and rivers can impact the local climate, consequently affecting plant growth. The distribution pattern of *H. ammodendron* shifts depending on the distance from inland water bodies. Furthermore, the potential distribution pattern of *H. ammodendron* in Xinjiang of China reflects the distance dependence of the mountains. PCA results show that elevation and precipitation can dominate the factors (PC3, PC5, PC7, and PC8; Table 1) that affect the distribution of *H. ammodendron* (data not shown). This may explain the decrease in suitable habitat areas with increasing distance from the Tianshan Mountains. Additionally, scattered suitable habitats of *H. ammodendron* are distributed within the oases on the edge of the Taklimakan Desert. Favourable soil and water conditions in the oasis areas can sustain the natural growth of *H. ammodendron*.

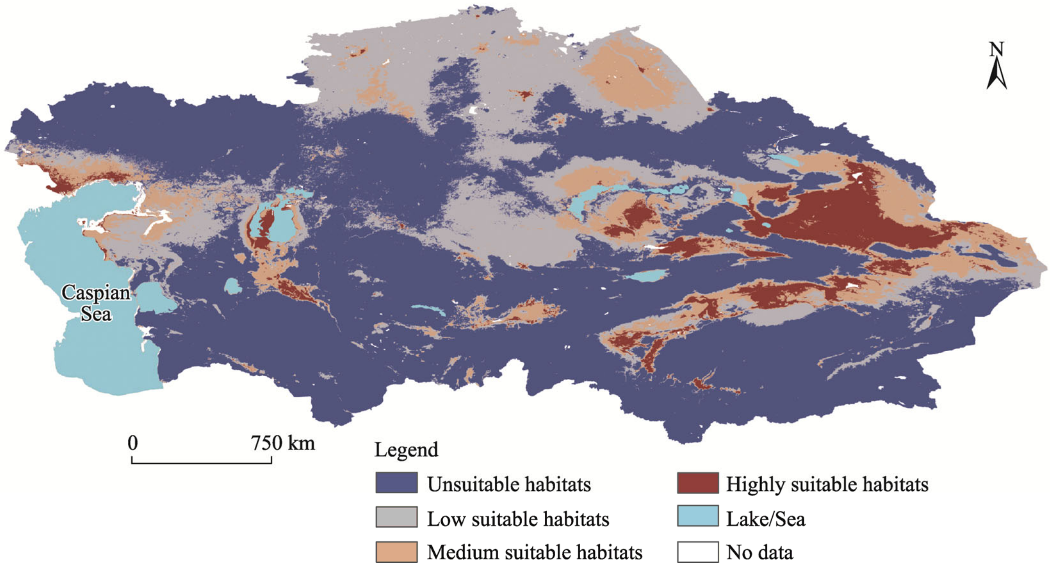

Fig. 2 Potential distribution pattern of *H. ammodendron* under current climate conditions based on the habitat classes. Highly suitable habitats: habitat class>0.60; medium suitable habitats: 0.30<habitat class≤0.60; low suitable habitats: 0.15<habitat class≤0.30; unsuitable habitats: habitat classes≤0.15. Note that the figure is based on the standard map (GS(2016)1665) from the Standard Map Service System (http://bzdt.ch.mnr.gov.cn/index.html) marked by the Ministry of Natural Resources of the People's Republic of China, and the standard map has not been modified.

3.2 Potential suitable habitats of *H. ammodendron* in Central Asia under future climate change scenarios

The potential suitable habitats of *H. ammodendron* under 12 different future climate conditions (three periods (2021–2040, 2041–2060, and 2061–2080) with four shared climate change scenarios (SSP126, SSP245, SSP370, and SSP585)) are shown in Figure 3. Under different future climate conditions, the distribution of the suitable habitats of *H. ammodendron* remains similar, with consistently shifting trends. Overall, the suitable habitat areas in northern Central Asia, notably Kazakhstan, will increase under future climate change scenarios. The period from 2021 to 2040 shows significant changes in the suitable habitats of *H. ammodendron* in Central Asia. For example, unsuitable habitat areas are expected to decrease by approximately 15.0% during

2021–2040 and stabilise during 2041–2060 The total area of medium and highly suitable habitats is projected to increase to 1.550×10^6 km^2 during 2021–2040 before stabilising thereafter. The increased area of highly suitable habitats, such as the Junggar Basin, is mainly distributed in northern Xinjiang of China. Compared with the current distribution pattern, the highly suitable habitat area in the eastern part of the Junggar Basin will increase by approximately 0.105×10^6 km^2. Inland areas further from the ocean will continue to experience a decrease in the suitable habitats of *H. ammodendron*. Meanwhile, the highly suitable habitat area of *H. ammodendron* in the Aralkum Desert will significantly decrease from 2021 to 2080, indicating that ecological issues in the Aralkum Desert may become even more severe in the future (Micklin, 2007).

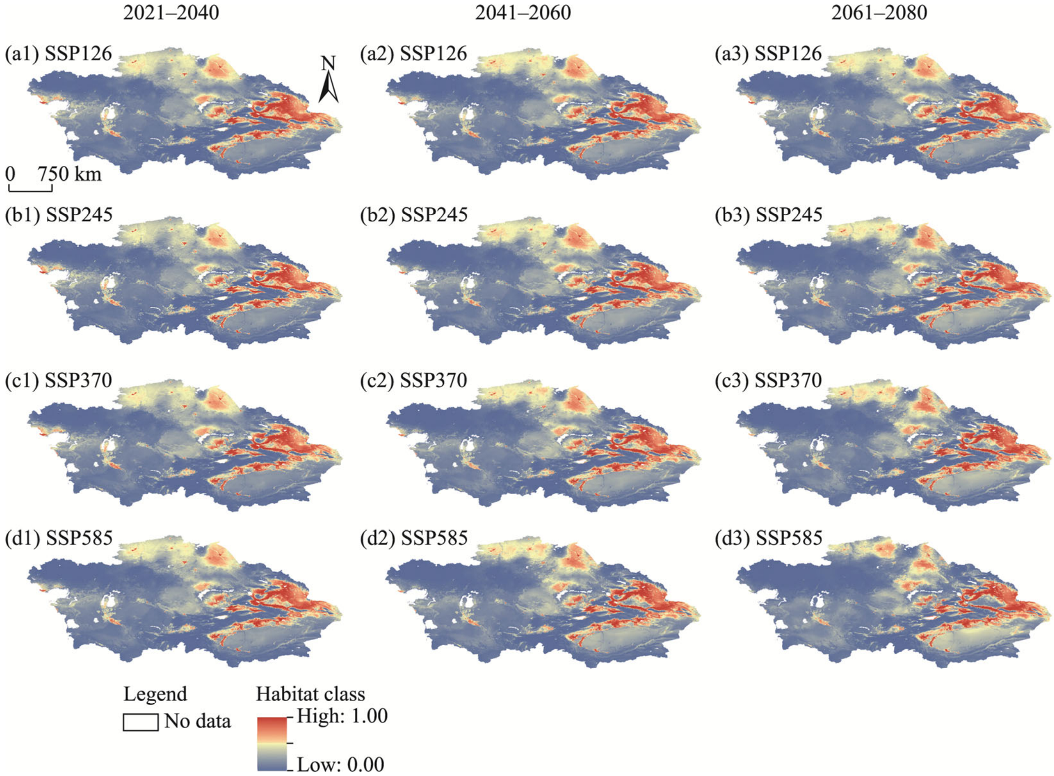

Fig. 3 Potential suitable habitats of *H. ammodendron* under future climate change scenarios: SSP126 (a1–a3), SSP245 (b1–b3), SSP370 (c1–c3), and SSP585 (d1–d3) during 2021–2040, 2041–2060, and 2061–2080. SSP, shared socioeconomic pathway. Note that the Caspian Sea is not involved in this analysis; the figures are based on the standard map (GS(2016)1665) from the Standard Map Service System (http://bzdt.ch.mnr.gov.cn/index.html) marked by the Ministry of Natural Resources of the People's Republic of China, and the standard map has not been modified.

3.3 Distribution shifts in the suitable habitats of *H. ammodendron*

The transfer of the suitable habitats of *H. ammodendron* with different habitat classes during 2021–2040, 2041–2060, and 2061–2080 is shown in Figure 4. The unsuitable habitat area of *H. ammodendron* in Central Asia will decrease in the future. Climate change will affect desertification in Central Asia. The species *H. ammodendron* has the characteristics of wide geographical distribution range, strong climate tolerance, high fecundity, and short maturation time. It can quickly respond to climate change and shift its spatial distribution pattern. Therefore, *H. ammodendron* is more adaptable to climate change and will expand its distribution range in the future. During 2021–2040, habitats that are highly and moderately suitable for the natural growth of *H. ammodendron* are projected to increase by 64.4% and 58.8%, respectively. However, low ($0.15<$habitat class≤0.30) and unsuitable habitat areas will decrease by 4.3% and 15.2%, respectively. From 2041–2060 to 2061–2080, the area of the suitable habitats of *H. ammodendron* will tend to stabilise, and conversion only occurs between the adjacent classes of suitable habitats. Compared with the current distribution condition, the unsuitable habitat area of *H. ammodendron* will decrease by 15.7% by 2080.

To clarify the evolutionary pattern of the suitable habitats of *H. ammodendron* in Central Asia, we identified regions with different variation characteristics based on the temporal sequence of transfer (Fig. 5). In the northern part of Kazakhstan, Taklimakan Desert, Junggar Basin, and eastern region of Turkmenistan, the suitable habitat level is increasing steadily. The simulation results for the period of 2021–2080 in these regions do not indicate a decline, with only differences observed in the magnitude of the increase across locations. For instance, the suitability of habitats for *H. ammodendron* in the Taklimakan Desert under the future climate conditions will increase compared with that under the current climate conditions; however, it still falls within the low suitable habitat zone.

Regions with frequent fluctuations in habitat suitability level during 2021–2080 are mainly distributed along the Astana to Kazakhskiy Melkosopochnik in Kazakhstan. These regions have better soil and water conditions than the core areas of Central Asia. Under different future climate change scenarios, the habitat suitability level for *H. ammodendron* may change in various ways.

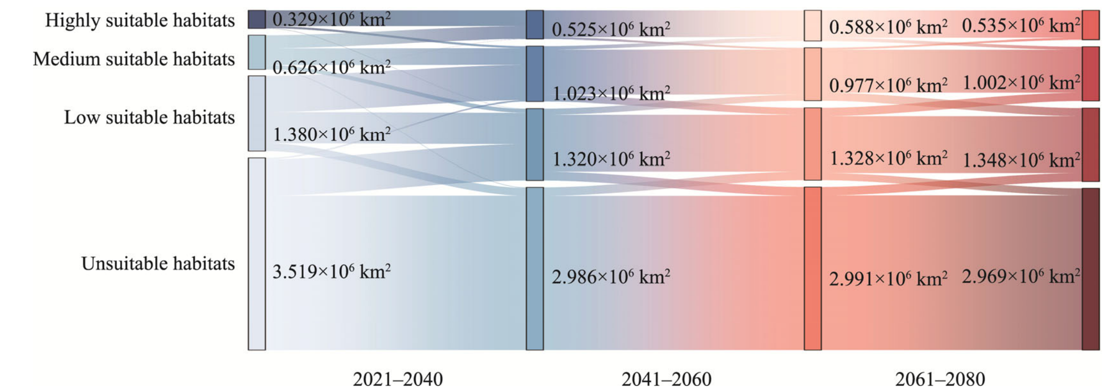

Fig. 4 Transfer of the suitable habitats of *H. ammodendron* with different habitat classes during 2021–2040, 2041–2060, and 2061–2080

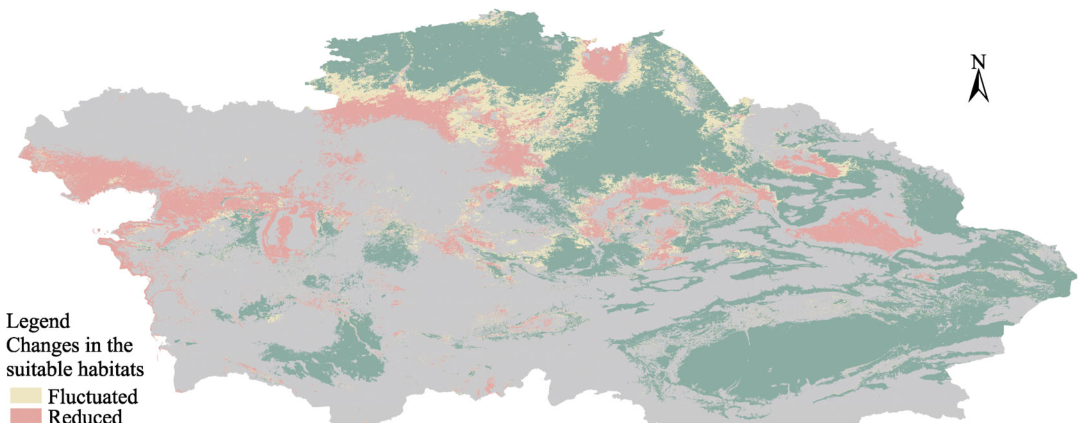

Fig. 5 Spatial distribution of changes in the suitable habitats of *H. ammodendron* from the current to future climate conditions. Note that the Caspian Sea is not involved in this analysis; the figure is based on the standard map (GS(2016)1665) from the Standard Map Service System (http://bzdt.ch.mnr.gov.cn/index.html) marked by the Ministry of Natural Resources of the People's Republic of China, and the standard map has not been modified.

The regions where suitable habitat levels continue to decline are primarily along the northern coast of the Caspian Sea, the Aralkum Desert, southern part of the Kazakhskiy Melkosopochnik, and northern foothills of the Tianshan Mountains. Geographically, the regions between 45°N and 55°N with an area of approximately 0.503×10^6 km^2 are anticipated to experience a greater reduction in suitable habitats under future climate change scenarios. This could be due to climate change, which causes a decrease in the climate adaptability and competitiveness of *H. ammodendron*, leading to a contraction in its distribution range.

3.4 Spatial pattern changes in the potential suitable habitats of *H. ammodendron* under future climate change scenarios

The geometric centre of the potential suitable habitat regions of *H. ammodendron* tends to migrate eastward under future climate change scenarios (Fig. 6). Under the SSP126 scenario, the geometric centre will migrate 147 km to the southeast during 2021–2040, followed by an eastward displacement of 80 km in the 2050s, and finally a westward shift of 45 km in the 2070s. The geometric centres under the SSP245, SSP370, and SSP585 scenarios exhibit a gradual eastward movement trend. The movement distance of the geometric centre increases with the increase of greenhouse gas emissions of the meteorological predictions. For instance, the movement distance of the geometric centre under the SSP126 scenario is only 176 km, whereas it can reach 405 km under the SSP585 scenario. Climate change could intensify desertification in the core regions of Central Asia, gradually shifting the geometric centre of the potential suitable habitats of *H. ammodendron* towards areas closer to the ocean. An alternative explanation for this phenomenon is the influence of precipitation. Larger precipitation values of SSP scenarios typically imply higher carbon emissions and temperatures, leading to increased aridity in Central Asia. Nevertheless, under future climate conditions, the MaxEnt model predicts a gradual decrease in the potential suitable habitats of *H. ammodendron* in the hinterland of Central Asia, leading to a westward shift in its geometric centre.

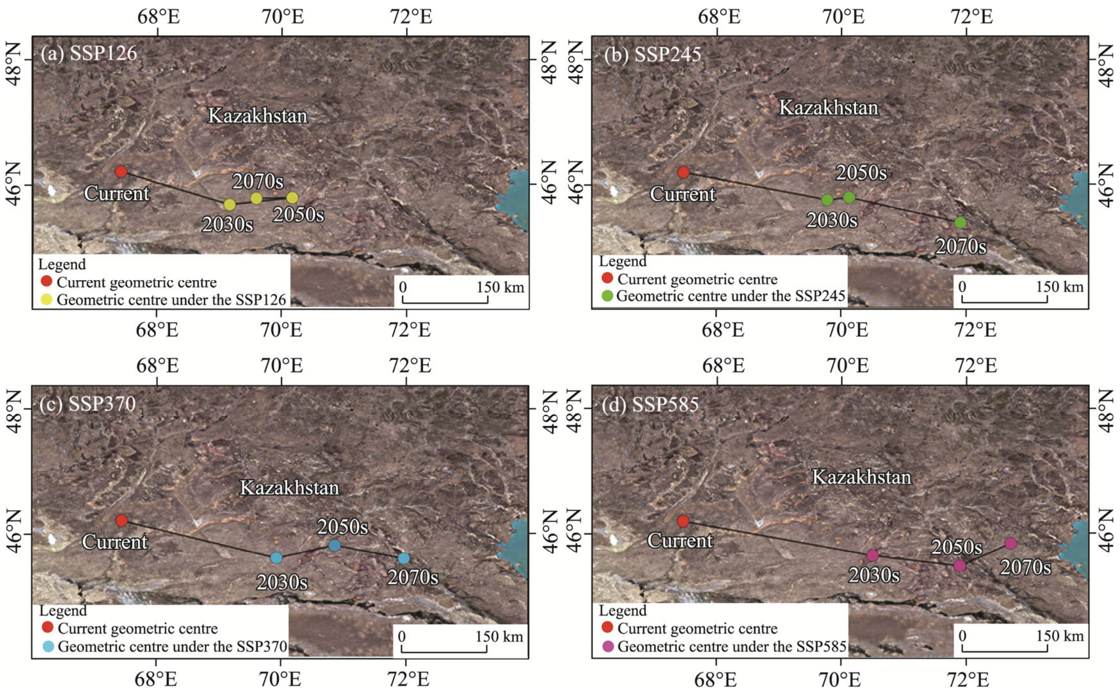

Fig. 6 Transformation of the geometric centre of the potential suitable habitats of *H. ammodendron* from the current to future climate conditions under the SSP126 (a), SSP245 (b), SSP370 (c), and SSP585 (d) scenarios. The true colour image of the base map was obtained from the Google Maps.

4 Discussion

4.1 Effects of environmental factors on the spatial distribution of *H. ammodendron* in Central Asia

Plant species distribution is primarily influenced by climate, and hydrothermal conditions also play a crucial role in this process (Dillon et al., 2010). PCA can generate all possible model parameter settings by considering cross-validation and appropriate features and select the optimal model based on the maximum Boyce index, thereby elucidating the key environmental factors influencing the spatial distribution (Shao et al., 2022). In this study, the precipitation-related climate conditions dominate PC1, PC3, and PC8 (Table 1). The variance explanation rates for PC1, PC3, and PC8 are 37.63%, 17.84%, and 2.39%, respectively. For example, in the Junggar Basin north of the Tianshan Mountains, the terrain is not completely enclosed, so prevailing westerly winds from the Atlantic Ocean and airflow from the Arctic Ocean can be lifted onto the northern slopes of the Tianshan Mountains to form orographic precipitation. As a result, the moisture conditions on the northern slopes of the Tianshan Mountains are better than those on the southern slopes, creating suitable habitats for the growth of *H. ammodendron*. The contribution of the temperature-dominated influencing factor (PC4) to the spatial distribution of *H. ammodendron* is approximately 5.83%. Therefore, factors related to hydrothermal conditions account for a cumulative contribution of 63.69% of the total variance in the spatial distribution of *H. ammodendron*. The temperature-related factors such as annual mean temperature (BIO1), temperature seasonality (BIO4), and temperature annual range (BIO7) can also have impacts on the spatial distribution of *H. ammodendron* through other PCA categories.

Elevation influences the spatial distribution of *H. ammodendron* through PC5 and PC7, accounting for a cumulative contribution of 7.10%. Notably, the factor (PC2) dominated by population density contributes approximately 22.42% of the factors between PC1 and PC8. This phenomenon may be related to the utilisation of *H. ammodendron* roots to produce *Cistanche deserticola* in Xinjiang of China (Shao et al., 2022). This discrepancy may be attributed to the multifaceted nature of plant survival, which is influenced by several environmental factors.

4.2 Layout of *H. ammodendron* shelterbelts in Central Asia under future climate conditions

H. ammodendron is an important plant species for desertification control (Li et al., 2022). Its root system can stabilise sandy soils and reduce wind erosion (Shao, 2008). It may be necessary to adjust the coverage and density of *H. ammodendron* shelterbelts to cope with more frequent extreme climate events such as drought, high temperatures, and wind erosion. The fluctuated zone of the suitable habitats of *H. ammodendron* is expected to become susceptible to desertification under future climate conditions. Maintaining ecological stability in these regions will be a priority for desertification control in Central Asia in the future, which can reduce the spread of desertification, safeguard local ecological environments, and support sustainable human livelihoods. Transitional zones composed of drought-resistant plants should also be established at the edges of the aforementioned regions to provide a stable transitional environment for local ecosystems.

Considering that hydrothermal conditions may dominate the spatial distribution of *H. ammodendron*, desertification control in Central Asia should also be based on terrain characteristics and hydrothermal distribution (Jiang et al., 2017). It is advisable to strategically lay the *H. ammodendron* shelterbelts in regions such as river valleys and foothills, by utilising surface water and groundwater resources to provide the necessary moisture for the growth of *H. ammodendron* and enhance its soil retention capacity. Additionally, when constructing the *H. ammodendron* shelterbelts, it is essential to consider the connectivity of ecosystems by establishing ecological corridors that connect shelterbelts. This facilitates the migration and genetic exchange of flora and fauna, thereby enhancing the stability and resilience of ecosystems.

4.3 Sustainable recommendations for the establishment of *H. ammodendron* shelterbelts in response to future climate change

Human activities can significantly affect the habitats of *H. ammodendron* and contribute to desertification processes in Central Asia (Shao et al., 2022). Unsustainable utilization of water resources, such as excessive water diversion for irrigation, can further reduce the available water in the downstream areas (Chen et al., 2022). Changes in hydrological regimes can alter soil moisture levels, further influencing the growth and survival of plants (Micklin, 2007). Considering that the Uzbekistan government is currently implementing afforestation measures in the Aralkum Desert to mitigate salt-dust disasters, the sustainability of these measures requires further consideration under future climate conditions. Therefore, more efforts should be focused on these areas, by strengthening the management of *H. ammodendron* shelterbelts, and minimising the impact of climate change on afforestation. Moreover, the suitable habitat area of *H. ammodendron* in the western part of the Junggar Basin will decrease under future climate conditions. To mitigate the impact of human activities on the suitable habitats of *H. ammodendron*, integrated land management approaches are essential (Qi et al., 2023). *In-situ* conservation efforts should be focused on preserving and restoring natural habitats conducive to the growth of *H. ammodendron*. This involves protecting the existing stands of *H. ammodendron* and their associated ecosystems, as well as restoring degraded habitats through sustainable land management practices such as reforestation, soil conservation, and water management (Abdi et al., 2019). Furthermore, community engagement and stakeholder participation are vital components for the protection of *H. ammodendron* shelterbelts. *H. ammodendron* can also provide important ecosystem services and economic values in arid and semi-arid areas. It can absorb and store atmospheric carbon dioxide. Local governments can facilitate carbon sequestration in desert areas by systematically planting *H. ammodendron*, thereby supporting international efforts towards sustainable land management practices. The parasitic roots of *H. ammodendron* are widely used in traditional Chinese medicine to treat various ailments, owing to their antimicrobial, anti-inflammatory, and antioxidant properties (Trampetti et al., 2019; Song et al., 2021). Appropriate planning for cultivating *H. ammodendron* and increasing the yield of their parasitic roots can bring economic benefits, thereby increasing residents' income in desertified areas. In summary, by implementing a comprehensive approach that integrates *in-situ* and *ex-situ* conservation measures and engages local communities and stakeholders, we can effectively conserve *H. ammodendron* and ensure its continued survival in the face of climate change in the future. Climate change will inevitably lead to global warming and increased droughts (Yang et al., 2023). This requires the implementation of appropriate artificial interventions to prevent desertification in the affected regions.

5 Conclusions

This study applied the growth-related data of *H. ammodendron* to the MaxEnt model and analysed the spatial distribution of the potential suitable habitats of *H. ammodendron* in Central Asia under the current and future climate conditions. The highly suitable habitat area of *H. ammodendron* in Central Asia is approximately 0.322×10^6 km^2 under the current climate conditions, primarily distributed in the Aralkum Desert, northern slopes of the Tianshan Mountains, upstream of the Tarim River, and western edge of the Taklimakan Desert. The unsuitable habitat area, covering approximately 3.620×10^6 km^2, is widely distributed in the south of 50°N. Under the future climate change scenarios, the suitable habitat area of *H. ammodendron* will decrease in regions far from the ocean. The highly suitable area of *H. ammodendron* in the Aralkum Desert is expected to decrease significantly. The geometric centre of the potential suitable habitat area of *H. ammodendron* shows a tendency to shift eastward in the future, with the distance of geometric centre movement increasing with more greenhouse gas emissions. By 2080, the movement of the geometric centre can reach up to 405 km, leading to a gradual shift of the suitable habitats of *H.*

ammodendron towards regions closer to the ocean. The current study only analysed the potential spatial distribution of *H. ammodendron* in Central Asia in the future, however, for the construction of *H. ammodendron* shelterbelts, it is still necessary to reasonably incorporate other plant species to achieve better ecological service functions of the shelterbelts.

Conflict of interest

LEI Jiaqiang is an editorial board member of Journal of Arid Land and was not involved in the editorial review or the decision to publish this article. All authors declare that there are no competing interests.

Acknowledgements

This study was supported by the the Basic Frontier Project of Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences (E3500201), the Xinjiang Tianshan Talent Program (2022TSYCLJ0002), and the Fundamental Research Funds for the Central Universities (ZY20240223).

Author contributions

Conceptualization: CHEN Zhuo, SHAO Minghao; Methodology: CHEN Zhuo, SHAO Minghao, HU Zihao; Investigation: CHEN Zhuo; Writing - original draft preparation: CHEN Zhuo, SHAO Minghao; writing - review & editing: GAO Xin, LEI Jiaqiang; Supervision: GAO Xin, LEI Jiaqiang; Funding acquisition and resources: GAO Xin, LEI Jiaqiang. All authors approved the manuscript.

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