PREDICTING THE CURRENT AND FUTURE DISTRIBUTION OF THE BAMBOO LEAF ROLLER (*ALGEDONIA COCLESALIS*) IN CHINA USING THE MAXENT MODEL: IMPLICATIONS OF CLIMATE CHANGE FOR HABITAT SUITABILITY AND DISTRIBUTION SHIFTS

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Abstract. Climate change has significantly altered the geographical distribution of numerous pest species, raising concerns about their potential impacts on ecosystems and economies. The bamboo leaf roller (*Algedonia coclesalis*), a major pest of bamboo forests in China, poses severe threats to the ecological balance and commercial bamboo production. This study employs the Maximum Entropy (MaxEnt) model to predict the current and future distributions of *A. coclesalis* in China under Shared Socioeconomic Pathway 126, 370, and 585 (SSP126, SSP370, SSP585) for 2041–2070 and 2071–2100. Key environmental variables, including precipitation of the driest month (bio14), mean temperature of the wettest quarter (bio8), and surface solar radiation, were identified as dominant factors influencing the distribution of *A. coclesalis*. Results reveal significant northward, westward, and southward expansion of high suitability area, with northern provinces such as Hubei, Henan, and Shanxi emerging as new high-risk zones for bamboo forests. The study provides critical insights into pest management strategies, emphasizing the importance of early detection, integrated pest management, and cross-regional collaboration to mitigate ecological and economic risks.
Keywords: *Algedonia coclesalis, climate change impact, distribution forecasting, species distribution models, pest management*

Introduction

Algedonia coclesalis (Lepidoptera: Crambidae), commonly known as the bamboo leaf roller, is a significant pest of bamboo forests. This pest is particularly notorious for its detrimental impact on bamboo forests (specifically, *Phyllostachys edulis*, *Phyllostachys glauca*, *Phyllostachys viridis*, *Bambusa oldhamii*, and *Pleioblastus amarus*, among others.). The life cycle of *A. coclesalis* consists of four stages: egg, larva, pupa, and adult. The larvae are the most destructive stage, feeding voraciously on bamboo leaves, which leads to significant defoliation. This damage not only affects the aesthetic value of bamboo forests but also impairs the growth and overall health of bamboo plants, thereby reducing their commercial value and ecological function (Zhang and Li, 2011). The larvae roll the bamboo leaves to form protective shelters, hence the name "leaf roller." Inside these rolled leaves, larvae feed and develop until pupation. Adult moths are nocturnal and are attracted to light sources. They lay eggs on the bamboo leaves, and the life cycle

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repeats (Chen et al., 2014). The damage caused by *A. coclesalis* includes reduced photosynthetic capacity of bamboo due to leaf loss, which can lead to stunted growth and increased susceptibility to other pests and diseases. In severe infestations, the economic losses can be substantial, affecting industries reliant on bamboo for products and materials (Wang and Lin, 2012).

Understanding the current and potential future distribution of this pest is critical for effective management and mitigation strategies. Recent advances in ecological modeling, such as the Maximum Entropy (MaxEnt) model, have enabled more accurate predictions of species distributions by integrating various environmental and climatic variables (Phillips et al., 2006). This study aims to utilize the MaxEnt model to map the current and potential future distribution of *A. coclesalis* in China. The objectives are as follows: (1) to identify the current potential distribution of *A. coclesalis*, (2) to determine the key environmental variables influencing its distribution, (3) to assess the impact of future climate change scenarios on its distribution, (4) to analyze the potential shifts in the geographical center of its distribution under changing climate conditions. By achieving these objectives, this research will provide valuable insights into the ecology and management of *A. coclesalis*, thereby supporting the development of targeted pest control measures and conservation strategies for bamboo forests in China. The distribution of species is influenced by various environmental factors, and understanding these influences is essential for predicting future distributions, particularly under climate change scenarios (Elith et al., 2010).

The MaxEnt model is a machine learning method used for predicting species distributions from presence-only data (Phillips et al., 2006). This method has been widely applied in ecological niche modeling due to its robustness and effectiveness in handling small sample sizes (Elith et al., 2010). MaxEnt estimates the probability distribution for a species' occurrence that is closest to uniform (maximum entropy), subject to the constraint that the expected value of each environmental variable matches its empirical average (Phillips et al., 2006). Previous studies have demonstrated the effectiveness of MaxEnt in predicting the distribution of various species based on environmental variables (Hijmans and Graham, 2006; Pearson et al., 2007; Kumar and Stohlgren, 2009). Determining the key environmental variables that influence the distribution of *A. coclesalis* is essential for understanding its ecological niche. Variables such as mean annual temperature, annual precipitation, and vegetation type were considered. The relative importance of each variable was assessed using permutation importance and jackknife tests provided by the MaxEnt model (Phillips et al., 2006). Identifying these key variables helps in understanding the habitat preferences and ecological requirements of *A. coclesalis* (Merow et al., 2013).

Climate change is expected to have significant impacts on species distributions (Andrew et al., 2012; Khadioli et al., 2014; Campbell-Staton et al., 2017; Ntiri et al., 2019). Climate change has a significant impact on the development and distribution of insects. It not only affects their population size, number of generations, and host selection but also influences their global distribution range and the evolution of suitable habitats (Sporleder et al., 2004; Hodkinson et al., 2005; Damos et al., 2012). To assess these impacts, future climate data from global climate models (GCMs) were used to predict the distribution of *A. coclesalis* under different climate change scenarios. The Representative Concentration Pathways (RCPs) provided a range of possible future climates, and these scenarios were integrated into the MaxEnt model (Phillips et al., 2006; Warren et al., 2013; Zhang et al., 2018). Shared Socioeconomic Pathway 126 (SSP126, low emissions

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scenario), 370 (SSP370, intermediate emissions scenario), and 585 (SSP585, high emissions scenario) are climate change scenarios from the Shared Socioeconomic Pathways (SSPs) framework, which is used for projecting future global climate and socioeconomic changes (O'Neill et al., 2017; Riahi et al., 2017; Gidden et al., 2019; Tebaldi et al., 2021; Chen et al., 2021). SSPs are paired with RCPs to model how different levels of greenhouse gas emissions and societal changes will influence future climate outcomes. These scenarios are widely used in climate research, including biodiversity, agriculture, and environmental studies.

This approach allows us to project potential shifts in the distribution of *A. coclesalis* and identify areas that may become more or less suitable for the species in the future. Analyzing shifts in the geographical center of the distribution of *A. coclesalis* under changing climate conditions is crucial for understanding the broader ecological implications of climate change. The centroid of the predicted distribution was calculated for current and future scenarios. Shifts in the centroid indicate changes in the overall distribution pattern of the species, which can have significant implications for pest management strategies (Thuiller et al., 2005; Warren et al., 2010). Additionally, understanding the key environmental variables influencing the distribution of *A. coclesalis* can inform conservation efforts to maintain the ecological balance of bamboo forests (Hijmans and Graham, 2006; Franklin, 2009).

In conclusion, this study aims to provide a comprehensive understanding of the current and potential future distribution of *A. coclesalis* in China using the MaxEnt model. By integrating environmental variables and future climate scenarios, we identify key factors influencing the distribution and predict shifts in the geographical center of the species' range. These insights will be crucial for developing effective pest management and conservation strategies for bamboo forests in China.

Materials and methods

Collection of A. coclesalis distribution data

In this study, the distribution of *A. coclesalis* was systematically investigated by integrating data from reports submitted by provincial and prefecture-level Forestry Bureaus across China, supplemented by field observations conducted by dedicated research teams to observe behavior and biological habits of *A. coclesalis*. The observation time is 2023, and the place is in the northern region of Zhejiang Province, mainly including Huzhou City, Hangzhou City and Jiaxing city. The specific location is the hazard location in the data of the Forestry Bureau, and the way to obtain the insect source is lamp lure. Initially, this approach yielded 240 distribution sites for *A. coclesalis*. Subsequently, these data underwent a rigorous review and refinement process utilizing a buffer zone analytical approach within ArcMap software (Gorshkov and Novikova, 2018; Feng et al., 2019). Following this screening procedure, a refined dataset comprising 127 distribution sites was selected for further analysis. The sites were strategically spaced more than 10 km apart to ensure data robustness. For each site, the species name, longitude, and latitude were meticulously recorded in CSV format for subsequent analysis using MaxEnt software. This comprehensive dataset formed the foundation for predictive modeling of the potential distribution of *A. coclesalis* under varying climatic conditions.

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Environmental variables

For the MaxEnt model to best simulate the prediction of the potential future distribution area of *A. coclesalis*, 27 environmental variables were used (*Table 1*). 19 climatic variables (from bio01 to bio19) downloaded from CHELSA Version1.2 database (Downloads – Chelsa Climate (chelsa-climate.org) (accessed on 18 March 2024)). The human activity impact index data were obtained from the Socioeconomic Data and Applications Center (SEDAC) (http://sedac.ciesin.columbia.edu/wildareas/(accessed on 18 March 2024)). Land cover type and percentage of vegetation cover data were acquired from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (https://www.resdc.cn(accessed on 18 March 2024)). Slope, aspect and elevation data were extracted from a 100m resolution DEM (Digital Elevation Model) dataset, which was sourced from the Computer Network Information Center, Chinese Academy of Sciences, and the Global Science Data website (http://www.gscloud.cn/(accessed on 18 March 2024)). Surface solar radiation data were obtained from the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/home(accessed on 18 March 2024)). Distance to river data: http://swww.diva-gis.org/(accessed on 18 March 2024).

Table 1. *Twenty-seven environmental variables considered in the A. coclesalis MaxEnt model*

Environmental Variables	Abbreviation
Annual mean temp (°C)	bio01
Mean diurnal range (°C)	bio02
Isothermality	bio03
Temperature seasonality	bio04
Maximum temp of warmest month (°C)	bio05
Minimum temp of coldest month (°C)	bio06
Temperature annual range (°C)	bio07
Mean temp of wettest quarter (°C)	bio08
Mean temp of driest quarter (°C)	bio09
Mean temp of warmest quarter (°C)	bio10
Mean temp of coldest quarter (°C)	bio11
Annual precipitation (mm)	bio12
Precipitation of wettest month (mm)	bio13
Precipitation of driest month (mm)	bio14
Precipitation seasonality (mm)	bio15
Precipitation of wettest quarter (mm)	bio16
Precipitation of driest quarter (mm)	bio17
Precipitation of warmest quarter (mm)	bio18
Precipitation of coldest quarter (mm)	bio19
Elevation (m)	elev
Slope (°)	Slope
Aspect	aspect
Distance to River (m)	dis.river
Surface Solar Radiation (W/㎡)	Rs
Land Cover Type	gm_lc
Percentage of Vegetation Cover	gm_ve
Human Activity Impact Index	hf

A correlation analysis of the variables was performed using SPSS. Identify highly correlated variable factors with an absolute correlation coefficient greater than 0.75 ($|R| > 0.75$). Highly correlated variables underwent further screening to assess their significance

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and potential redundancy. Additionally, when highly correlated variables are identified, consider evaluating their impact on the model's performance and interpretability. This screening can help in simplifying the model by removing redundant variables, thus improving efficiency and reducing multicollinearity.

Species distribution modeling

MaxEnt 3.4.4 (http://biodiversityinformatics.amnh.org/open_source/MaxEnt/ (accessed on 18 March 2024)) was utilized to predict the current and future potential distributions of *A. coclesalis*. Due to the diversity of observers and collectors for the distribution sites, a 10% training presence logistic threshold was implemented to mitigate sampling bias (Bean et al., 2012). All environmental layers were converted to ASC format using the Arc Tools feature in ArcGIS. The resulting ASC format layers, along with the distribution data, were input into the MaxEnt model. Subsequently, 75% of the distribution data was randomly selected for model training, while the remaining 25% was used for model validation (Phillips et al., 2006). The output layer was configured to Logistic, with all other parameters set to the model's default values (Phillips and Dudík, 2008). To further evaluate the modeling results, the R package Presence Absence was used to calculate the True Skill Statistic (TSS) and Kappa values (FREEMAN and MOISEN, 2008). The evaluation criteria for TSS and Kappa are as follows: 0.85–1, excellent; 0.7–0.85, good; 0.55–0.7, fair; 0.4–0.55, poor; <0.4, fail. The default parameter settings in MaxEnt often lead to significant discrepancies in the actual distribution of species; therefore, parameter optimization is crucial for enhancing prediction accuracy and the reliability of the results (Tamura et al., 2011). The ENMeval tool (https://github.com/marlonecobos/kuenm (accessed on 5 October 2022); https://www.r-project.org/ (accessed on 5 October 2022)) was employed for parameter optimization (Kass et al., 2021). The fit and complexity of different parameters were evaluated using the Akaike Information Criterion correction (AICc) (Warren and Seifert, 2011). The suitability of each parameter setting was assessed by comparing the training and test Area Under the Curve (AUC), the 10% training omission rate, and the minimum training presence omission rate. Through these methods, the most suitable combination of parameters was determined.

In this study, the final model's TSS training sensitivity threshold, MTSPS threshold, and TPT balance threshold were used as breakpoints (Aidoo et al., 2022). Combining the distribution data with the fit of the suitability areas, the model results were reclassified into four categories: unsuitable areas (0–0.0211), low suitability areas (0.0211–0.0813), moderate suitability (0.0813–0.2457), and high suitability areas (0.2457–1). By multiplying the number of grid units with different suitability levels on the distribution map by the spatial resolution, the areas and percentages of different suitability levels for *A. coclesalis* under current and future climate scenarios were calculated.

Centroid distribution changes of A. coclesalis

To analyze the shifts in the suitable habitat distribution center, the Species Distribution Model (SDM) toolbox (http://www.sdmtoolbox.org/downloads) and the GIS toolkit (http://gistoolkit.sourceforge.net), both Python-based (https://www.python.org/downloads/), were utilized. Present and future SDMs were generated using MaxEnt, and the SDM toolbox was employed to reduce the distributions to single centroid points representing the geographic center of suitable habitat areas. The geographic centroids were calculated based on raster layers for each climate scenario

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(SSP126, SSP370, and SSP585) and each time period (2041–2070 and 2071–2100). The GIS toolkit was then used to estimate the magnitude and direction of centroid shifts over time, using vector-based calculations to track movements between current and future periods. This enabled the identification of time-dependent variations in centroid positions. Comparative analysis of centroid shifts under different climate scenarios revealed patterns of movement, such as northward or westward expansions, and their correlation with environmental changes, providing quantitative insights into the dynamics of habitat distribution for *A. coclesalis*.

Results

Current distribution sites of A. coclesalis

A. coclesalis is primarily located in the southern regions of China at relatively low elevations (*Fig. 1*). These regions mainly include the middle and lower Yangtze River plains (Jiangsu, Zhejiang, and Anhui provinces), the Sichuan Basin (Sichuan province), as well as Guangdong and Fujian provinces. It is only sporadically distributed in provinces such as Shandong, Henan, Hubei, Jiangxi, Taiwan and so on.

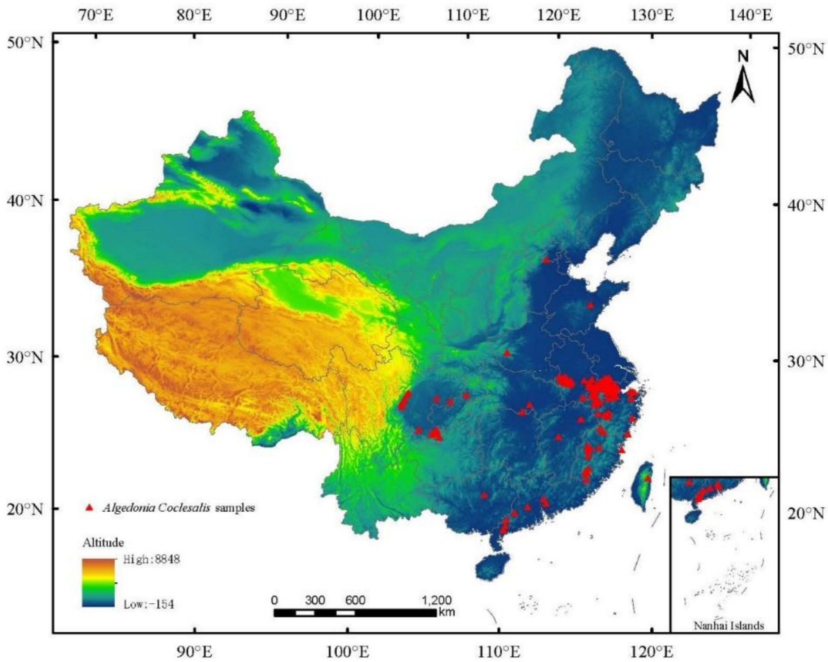

***Figure 1.** Occurrence records of Algedonia coclesalis in China*

Performance and variable selection of the MaxEnt model

To further evaluate the modeling results, the R package PresenceAbsence was used to calculate the TSS and Kappa values. The evaluation criteria for TSS and Kappa are as follows: 0.85–1, excellent; 0.7–0.85, good; 0.55–0.7, fair; 0.4–0.55, poor; <0.4, failing. Evaluation results: TSS=0.89, Kappa=0.87, indicating a very satisfactory prediction with a high level of trustworthiness. Through Pearson correlation analysis and the percentage contribution (*Table 2*), thirteen environmental variables were selected for use in the MaxEnt model.

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Table 2. *Thirteen environmental variables were selected for use in the MaxEnt model and their percent contribution*

Variables	Percent contribution
bio14	69.2
bio8	10
rs	4.9
gm_ve	3.9
bio7	3.4
bio12	2.4
bio15	2.4
bio10	1.7
bio2	1
slope	0.8
aspect	0.3
gm_lc	0.2
dis.river	0.1

Present potential distribution area of A. coclesalis

Based on the modeling of present potential distribution area of *A. coclesalis* in China (*Fig. 2*), *A. coclesalis* is mainly distributed in southeastern China. The high suitability areas are mainly located in the provinces of Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, Fujian and so on. The moderate and low suitability areas are primarily surrounding the high suitability regions, and include the provinces of Shandong, Henan, Shaanxi, Guizhou, Yunnan, Hainan and Taiwan.

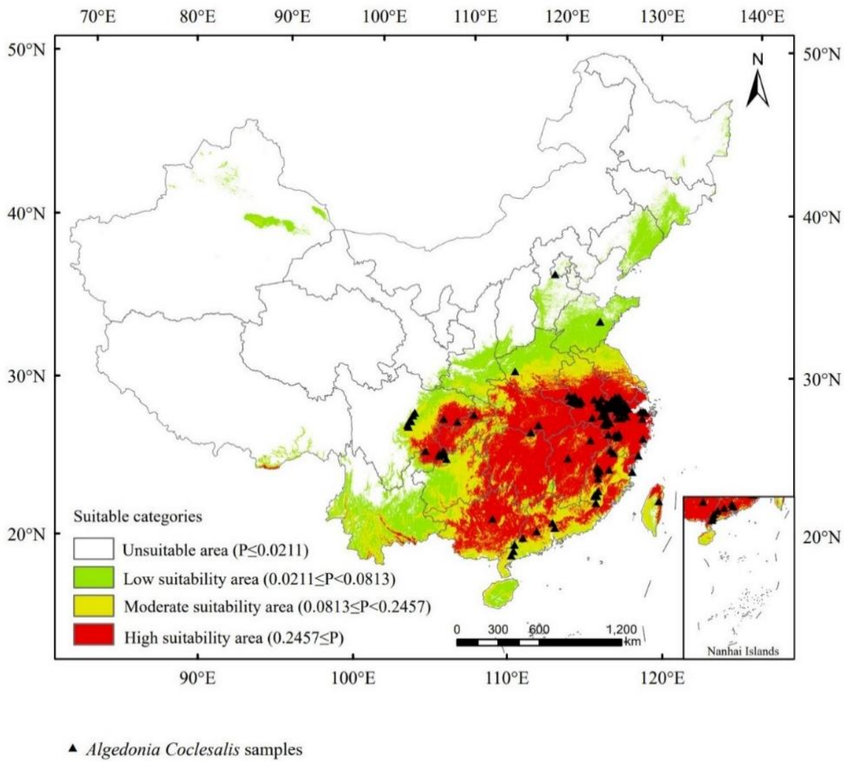

Figure 2. *Present potential distribution area of A. coclesalis in China*

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Future potential distribution area of A. coclesalis

The potential future distribution of *A. coclesalis* was predicted for the 2041–2070 and 2071–2100 under SSP126, SSP370, and SSP585 (*Fig. 3*). The high suitability areas are mainly located in the Jiangsu, Zhejiang, Fujian, Guangdong, Guangxi, Anhui, Jiangxi, Hubei, Chongqing, Guizhou and Hunan provinces under all scenarios. Under SSP126 in the 2041–2070, the high, moderate, low, and total suitable areas occupying the land in China are 138.51 × 10^4 km^2, 71.50 × 10^4 km^2, 102.70 × 10^4 km^2, and 312.71 × 10^4 km^2, respectively (*Fig. 3*).

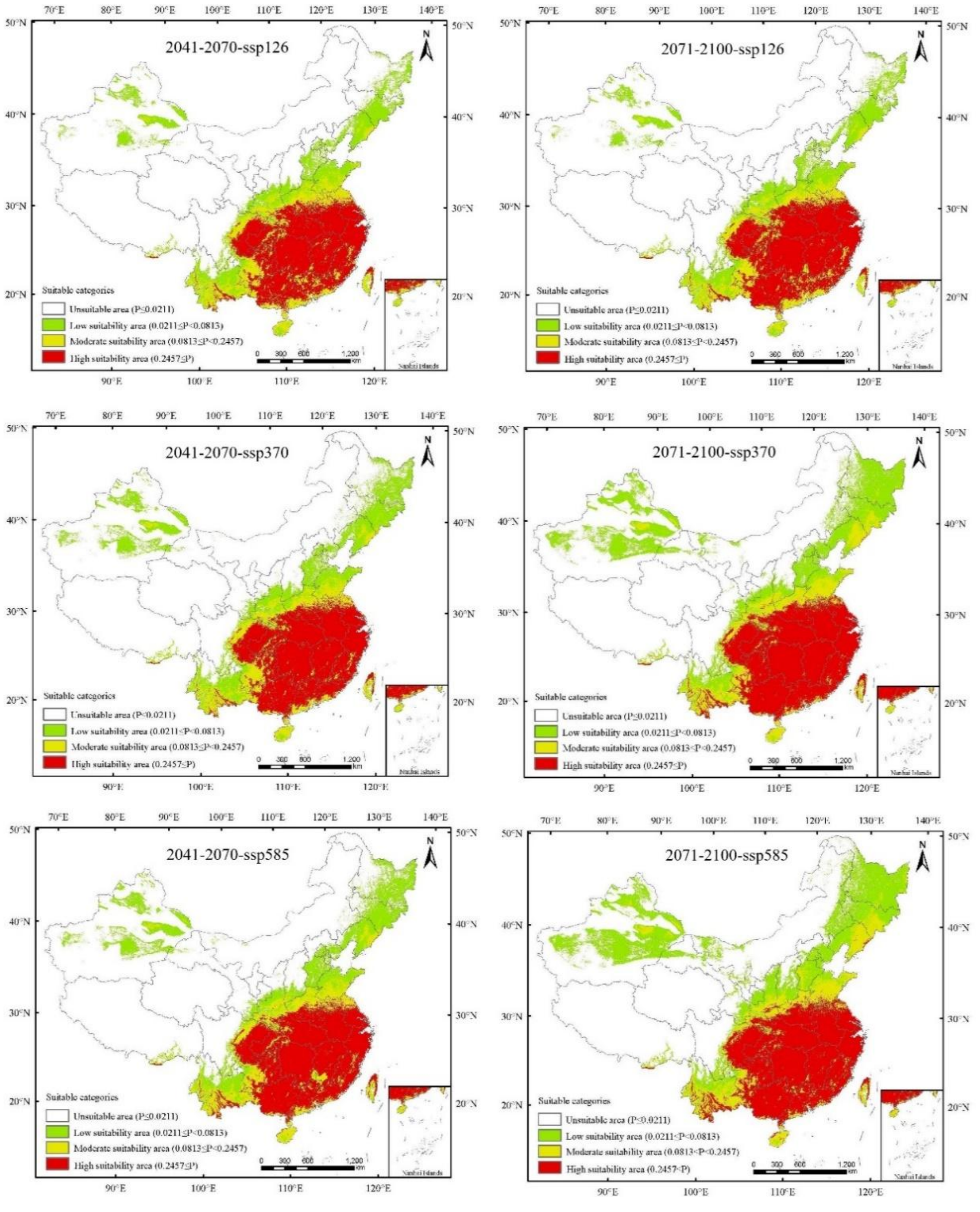

***Figure 3.** Future potential distribution area of A. coclesalis under SSP126, SSP370, and SSP585 during the 2041–2070 and 2071–2100 in China*

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Under SSP126 in the 2071–2100, the high, moderate, low, and total suitable areas occupying the land in China are 142.50 × 10^4 km^2, 66.65 × 10^4 km^2, 104.83 × 10^4 km^2, and 313.98 × 10^4 km^2, respectively (*Fig. 3*). Under SSP370 in the 2041–2070, the high, moderate, low, and total suitable areas occupying the land in China are 149.64 × 10^4 km^2, 65.00 × 10^4 km^2, 130.57 × 10^4 km^2, and 345.21 × 10^4 km^2, respectively (*Fig. 3*). Under SSP370 in the 2071–2100, the high, moderate, low, and total suitable areas occupying the land in China are 171.06 × 10^4 km^2, 71.29 × 10^4 km^2, 165.85 × 10^4 km^2, and 408.2 × 10^4 km^2, respectively (*Fig. 3*). Under SSP585 in the 2041–2070, the high, moderate, low, and total suitable areas occupying the land in China are 155.44 × 10^4 km^2, 68.21 × 10^4 km^2, 130.94 × 10^4 km^2, and 354.59 × 10^4 km^2, respectively (*Fig. 3*). Under SSP585 in the 2071–2100, the high, moderate, low, and total suitable areas occupying the land in China are 176.70 × 10^4 km^2, 84.02 × 10^4 km^2, 196.19 × 10^4 km^2, and 456.91 × 10^4 km^2, respectively (*Fig. 3*).

Change of suitable A. coclesalis distributions and area proportion (%)

From current to 2041–2070–SSP126, the area of the stable suitable habitat is 274.39 × 10^4 km^2, the suitable habitat has expanded by 51.46 × 10^4 km^2, and the area of the contracted suitable habitat is 0.39 × 10^4 km^2 (*Fig. 4*). From 2041–2070–SSP126 to 2071–2100–SSP126, the area of the stable suitable habitat is 321.26 × 10^4 km^2, the suitable habitat has expanded by 5.72 × 10^4 km^2, and the area of the contracted suitable habitat is 4.59 × 10^4 km^2 (*Fig. 4*). From current to 2041–2070–SSP370, the area of the stable suitable habitat is 274.52 × 10^4 km^2, the suitable habitat has expanded by 80.82 × 10^4 km^2, and the area of the contracted suitable habitat is 0.27 × 10^4 km^2 (*Fig. 4*). From 2041–2070–SSP370 to 2071–2100–SSP370, the area of the stable suitable habitat is 351.45 × 10^4 km^2, the suitable habitat has expanded by 61.10 × 10^4 km^2, and the area of the contracted suitable habitat is 3.89 × 10^4 km^2 (*Fig. 4*). From current to 2041–2070–SSP585, the area of the stable suitable habitat is 274.57 × 10^4 km^2, the suitable habitat has expanded by 89.53 × 10^4 km^2, and the area of the contracted suitable habitat is 0.21 × 10^4 km^2 (*Fig. 4*). From 2041–2070–SSP585 to 2071–2100–SSP585, the area of the stable suitable habitat is 361.10 × 10^4 km^2, the suitable habitat has expanded by 96.35 × 10^4 km^2, and the area of the contracted suitable habitat is 3.00 × 10^4 km^2 (*Fig. 4*).

Under SSP126, the high suitable areas increased from the present day to 2041–2070 (increased by 29.07%) and increased from 2041–2070 to 2071–2100 (increased by 2.84%); the moderate suitable areas decreased from the present day to 2041–2070 (decreased by 2.61%) and decreased from 2041–2070 to 2071–2100 (decreased by 6.85%); the low suitable areas increased from present to 2041–2070 (increased by 32.75%) and increased from 2041–2070 to 2071–2100 (increased by 2.06%); the total suitable areas increased from present to 2041–2070 (increased by 21.16%) and increased from 2041–2070 to 2071–2100 (increased by 0.37%) (*Fig. 5A*). Under SSP370, the high suitable areas increased from the present day to 2041–2070 (increased by 39.45%) and increased from 2041–2070 to 2071–2100 (increased by 14.30%); the moderate suitable areas decreased from the present day to 2041–2070 (decreased by 11.50%) and increased from 2041–2070 to 2071–2100 (increased by 9.75%); the low suitable areas increased from present to 2041–2070 (increased by 68.73%) and increased from 2041–2070 to 2071–2100 (increased by 27.06%); the total suitable areas increased from present to 2041–2070 (increased by 33.73%) and increased from 2041–2070 to 2071–2100 (increased by 18.27%) (*Fig. 5B*). Under SSP585, the high suitable areas increased from the present day to 2041–2070 (increased by 44.81%) and increased from 2041–2070 to

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2071–2100 (increased by 13.71%); the moderate suitable areas decreased from the present day to 2041–2070 (decreased by 7.06%) and increased from 2041–2070 to 2071–2100 (increased by 23.07%); the low suitable areas increased from present to 2041–2070 (increased by 69.23%) and increased from 2041–2070 to 2071–2100 (increased by 49.85%); the total suitable areas increased from present to 2041–2070 (increased by 37.37%) and increased from 2041–2070 to 2071–2100 (increased by 28.86%) (*Fig. 5C*).

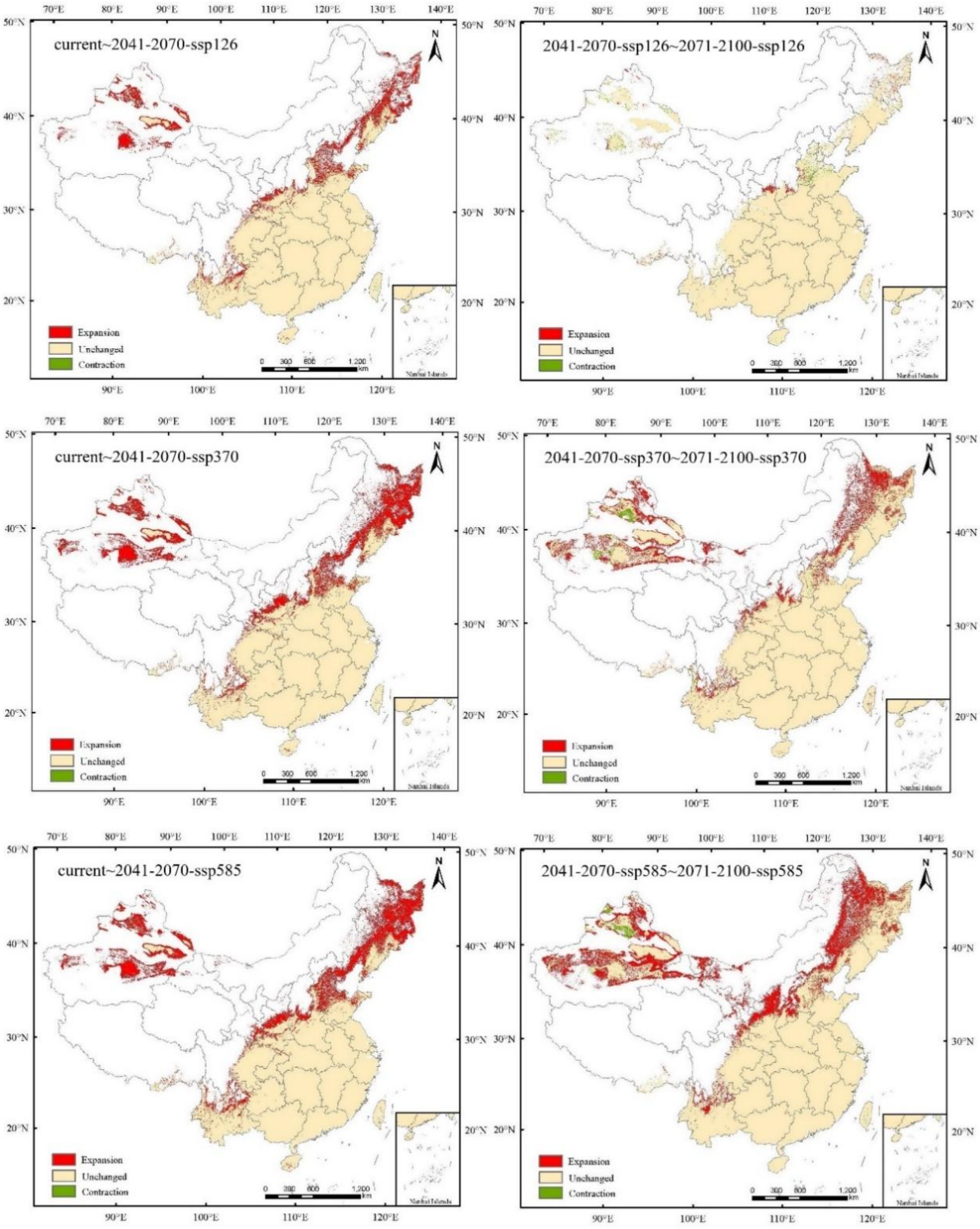

Figure 4. *Change of suitable A. coclesalis distributions from present day to 2071–2100 using MaxEnt under climate models SSP126, SSP370 and SSP585. Red represents expansion zones, pale yellow indicates areas with no change, and green denotes contraction zones*

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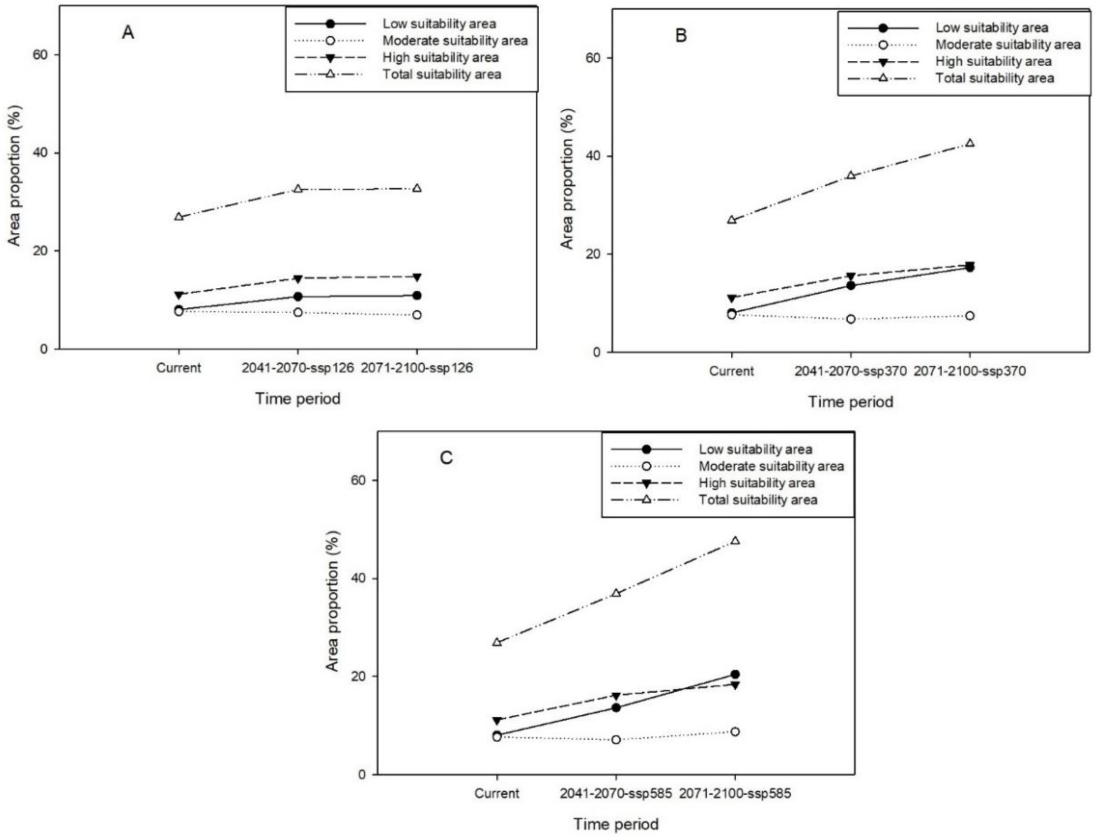

Figure 5. *Change in area proportion (%) from present day to 2071–2100 under SSP126 (A), under SSP370 (B), and under SSP585 (C)*

Changes in the centroid distributional shifts

The shift in the distribution center of *A. coclesalis* in China under current and future climate change scenarios is shown in *Figure 6*. The current distribution center of *A. coclesalis* in China is located in the northern part of Hunan Province. However, under different climate scenarios and timeframes, the distribution centers of *A. coclesalis* have shown a trend of northward shift. Under SSP126 in the 2041–2070, the distribution center has gradually shifted northward, reaching Yichang City in central Hubei Province and the movement distance of the central site is 199.38 km. Subsequently, by the 2071–2100 under SSP126, a shift in the northeast direction occurs, reaching Jingmen City in Hubei Province and the movement distance of the central site is 30.42 km. For SSP370, in the 2041–2070, the distribution center shifts northward, reaching Xiangyang City in northern Hubei Province and the movement distance of the central site is 320.67 km. By the 2071–2100 under SSP370, the distribution center continues to shift northward, reaching the southwest region of Henan Province and the movement distance of the central site is 168.18 km. Under SSP585, in the 2041–2070, the distribution center has shifted northward, reaching Xiangyang in the northern part of Hubei Province and the movement distance of the central site is 333.42 km. By the 2071–2100 under SSP585, the distribution center continues to shift northwest, crossing Henan Province and reaching the southern part of Shanxi Province and the movement distance of the central site is 267.01 km.

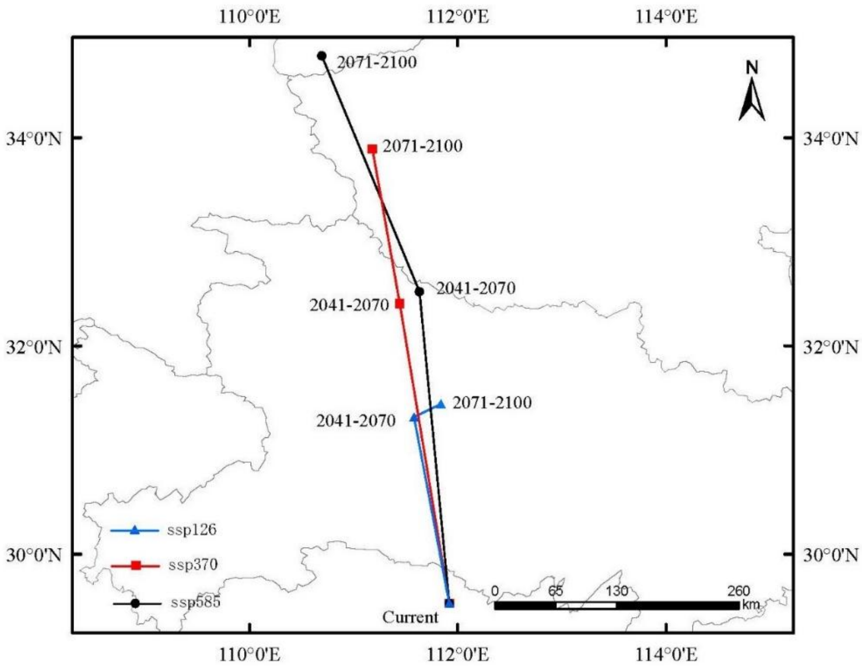

Figure 6. *Changes in the centroid distributional shifts of A. coclesalis under climate change*

Discussion

Based on the current distribution records of *A. coclesalis*, we can conclude that it is primarily concentrated in the middle and lower Yangtze River plains, followed by the southeastern coastal areas and the Sichuan Basin. The primary host of *A. coclesalis*, moso bamboo, is a dominant economic bamboo species in China, widely distributed in the southern regions of the country (Zhao et al., 2023). The narrow distribution range of *A. coclesalis* (*Fig. 1*) compared to the distribution range of its host suggests that host distribution is not the main factor. When studying the distribution of target species, many researchers have found that the host's effect is not very obvious, and it may not be a significant influencing factor (Hanspach et al., 2014; Wang et al., 2020). Current reports indicate that *P. edulis*, *P. viridis*, and other bamboo species have been introduced to regions such as Xinjiang and Northeast China. Under future climate change scenarios, southern bamboo species may establish more extensive suitable habitats in these areas. As shown in *Figure 4*, the projected expansion zones of *A. coclesalis* are primarily concentrated in Xinjiang and Northeast China. However, due to the diversity of *A. coclesalis* host species and the uncertainties surrounding future bamboo introductions, predictive models face excessive variables. If these potential host distribution zones were excluded from the pest's suitability analysis, the accuracy of predictions could be significantly compromised. Therefore, future projections of *A. coclesalis* distribution in Northeast China and Xinjiang must dynamically integrate both climatic suitability forecasts and real-time host species distribution data to achieve more reliable results.

Further, according to the combined results of 27 environmental variables (*Tables 1, 2*), bio14 (Precipitation of driest month (mm)) occupies the largest percent contribution, at 69.2%.

Moreover, bio8 (Mean temp of wettest quarter (°C)) accounts for 10% and Surface Solar Radiation (W/m^2) accounts for 4.9%. From the above analysis, it can be concluded

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that the Precipitation of the driest month (mm) is the dominant factor influencing the distribution of *A. coclesalis*. The prioritization of bio14 as the dominant variable influencing *A. coclesalis*' distribution reflects the vulnerability of the species to changes in precipitation patterns. Such insights enable targeted interventions, such as improving water management practices in bamboo forests to mitigate the pest's proliferation. Additionally, integrating these findings into national pest control frameworks ensures that local actions align with broader ecological and economic goals.

Based on the results of the present potential distribution area of *A. coclesalis* in China (*Fig. 2*), the high suitability areas are primarily concentrated in the Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, Fujian and Sichuan provinces. However, the current distribution of *A. coclesalis* is mainly located in the provinces of Jiangsu, Zhejiang, Anhui, Hubei, Guangdong, Fujian, and Sichuan provinces (*Fig. 1*). Given the large areas of high suitability for *A. coclesalis* in Guangxi, Hunan, and Jiangxi provinces, despite the current low distribution of the pest in these regions, proactive prevention strategies are crucial to mitigate future risks.

By comparing the current potential distribution with future potential distributions under different scenarios (*Figs. 2, 3*), it was found that the overall area of high suitability area has significantly increased, with expansion trends observed toward the north, west, and south. The affected areas are primarily concentrated in southeastern China. The significant expansion of high suitability area for *A. coclesalis* toward the north, west, and south under future climate change scenarios can be attributed to several key factors: (1) One of the primary drivers of the expansion is the increase in average temperatures due to global warming. As temperatures rise, regions previously unsuitable for *A. coclesalis* due to colder climates are becoming more conducive to its survival and reproduction. This is particularly evident in the northward expansion, as warmer climates allow the pest to colonize areas that were previously too cold. (2) Precipitation is a critical environmental factor influencing the distribution of *A. coclesalis*. The identified dominance of bio14 (precipitation of the driest month) as a key variable indicates that alterations in precipitation levels are creating favorable conditions in previously unsuitable areas. Regions in the west and north, which are generally drier, may now experience conditions more suitable for the pest's establishment due to shifting rainfall patterns. (3) The expansion trends may also correlate with the availability of bamboo forests, which serve as the primary host for *A. coclesalis*. As climate change impacts vegetation distribution, host plants may extend their range into new areas, providing the pest with the necessary resources to thrive in previously unoccupied regions. (4) Low and moderate suitability areas, particularly in the west and north, are becoming more hospitable for *A. coclesalis* due to the combined effects of temperature and precipitation changes. These areas are gradually transitioning into higher suitability zones, thus contributing to the pest's geographical expansion. (5) The ability of *A. coclesalis* to adapt to varying environmental conditions, coupled with its potential to exploit new niches, facilitates its spread into regions with changing climates. The pest's ecological flexibility allows it to respond effectively to altered environmental parameters. These factors collectively suggest that climate change is reshaping the ecological landscape, enabling the northward, westward, and southward expansion of high suitability area for *A. coclesalis*. This highlights the need for proactive monitoring and adaptive management strategies to mitigate the potential risks posed by its expanding range.

The relationship between population density and suitability values indicates that low population densities can be found in areas with both low and high suitability values, while

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high population densities are typically concentrated in areas with better suitability (Tôrres et al., 2012; Oliver et al., 2012). From our analysis of the significant expansion of high suitability area for *A. coclesalis* in southern China, combined with the characteristic of high suitability area being capable of supporting high population densities, southern provinces—particularly Guangxi, Hunan, and Jiangxi—are expected to face increasingly severe challenges in the future. First, these provinces should implement early warning and surveillance systems to monitor any potential spread of the pest. Regular surveys and trapping should be conducted in both high-risk areas and new areas showing increased suitability due to climate change. Second, public awareness campaigns should be strengthened to educate local farmers, forestry workers, and the general public about the pest, its damage, and early detection methods. Timely reporting of suspected infestations can significantly reduce the pest's establishment. Additionally, the provinces should consider integrated pest management (IPM) strategies, including biological control measures, the use of resistant plant varieties, and selective pesticide applications, ensuring that any intervention is both effective and environmentally sustainable. Lastly, collaboration with neighboring provinces and national pest control agencies is essential for sharing data and coordinating control efforts, particularly as *A. coclesalis* may spread across provincial borders as its suitable habitat expands. By adopting these preventive measures, Guangxi, Hunan, and Jiangxi can better manage the potential threat of *A. coclesalis* and reduce the risk of future outbreaks.

At the same time, by analyzing the expansion of suitable areas as shown in the change of suitable *A. coclesalis* distributions from present day to 2071–2100 using MaxEnt under climate models SSP126, SSP370, and SSP585 (*Fig. 4*), and comparing it with the Future potential distribution area of *A. coclesalis* under SSP126, SSP370, and SSP585 during the 2041–2070 and 2071–2100 in China (*Fig. 3*), it was found that the areas of outward expansion are primarily moderate and low suitability areas. The expansion locations are mainly concentrated in Heilongjiang, Jilin, Liaoning, Xinjiang, Hebei and Shaanxi Provinces. From the above analysis, we can conclude that under future climate change scenarios, *A. coclesalis* exhibits a tendency to expand northward.

In the context of climate change, the potential habitat areas of other insects also tend to shift northward, for example, those of *Anoplophora chinensis* and *Apocheima cinerarius* (Zhou et al., 2022; Ding et al., 2022), while the potential habitat area of some insects is shrinking in the south (Chen et al., 2017; Wei et al., 2022). In several studies, climate models have been used to investigate the distribution of *Ostrinia nubilalis*. The results indicate that *O. nubilalis* is gradually shifting to northern regions and higher altitudes, accompanied by an increase in the number of generations (Porter et al., 1991; Trnka et al., 2007; Diffenbaugh et al., 2008; Kocmánková et al., 2008, 2010; Eitzinger et al., 2013; Dubrovsky et al., 2015). From the comparison of the above studies, we can conclude that the northward shift of *A. coclesalis* is consistent with the findings of most current research.

To address the potential threat posed by *A. coclesalis* in provinces like Heilongjiang, Jilin, Liaoning, Xinjiang, Hebei, and Shaanxi, which are projected to experience an expansion of suitable habitat under future climate change scenarios, the following measures should be implemented: (1) Establish comprehensive pest monitoring networks in these provinces to track the spread and population dynamics of *A. coclesalis*. Utilize pheromone traps, remote sensing technology, and predictive modeling to identify high-risk areas. Develop real-time reporting systems to ensure timely detection and response. (2) Conduct educational campaigns to inform local farmers, forestry workers, and the

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public about the risks of *A. coclesalis*, its life cycle, and the signs of infestation. Train personnel in pest identification, reporting protocols, and integrated pest management (IPM) strategies. (3) Implement IPM approaches that combine biological control (e.g., introducing natural predators or parasites of *A. coclesalis*), cultural practices (e.g., removing infested bamboo debris), and selective use of environmentally friendly pesticides. Develop pest-resistant bamboo varieties through research and genetic engineering to reduce susceptibility in high-risk areas. (4) Establish collaboration among affected and neighboring provinces to share data, resources, and best practices for pest management. Coordinate with national and local forestry and agricultural agencies to align pest control measures with broader ecological and economic objectives. (5) Adjust forestry practices to account for changing climatic conditions, such as altering planting schedules and diversifying bamboo species to enhance ecosystem resilience. Prioritize afforestation and reforestation efforts in northern provinces with pest-resistant bamboo and other tree species. (6) Secure government funding to support research on pest dynamics under climate change and to develop advanced pest control technologies. Formulate region-specific pest management policies that address the unique ecological and economic challenges of each province. (7) Enhance the use of predictive modeling tools, such as MaxEnt, to regularly update forecasts of potential distribution areas. Investigate the ecological interactions between *A. coclesalis* and its environment in newly affected regions to refine management strategies. By adopting these proactive measures, the provinces at risk of *A. coclesalis* infestation can effectively mitigate its impact, safeguard their ecological and economic resources, and ensure sustainable forest management in the face of climate change.

Climate change has had a significant impact on scale insects, expanding their range of suitable areas, increasing the number of pest generations, and raising the risk of alien pest invasion (Skendžić et al., 2021). From the above results, it can be observed that climate change has a significant impact on the future distribution of *A. coclesalis* in China, as supported by a considerable amount of evidence for other species (Maclean and Wilson, 2011; Ziter et al., 2012), and the strength of this influence has a strong correlation with the location of the species (Stoeckli et al., 2020).

The northward shift in the centroid distribution of *A. coclesalis* under all climate scenarios highlights the significant impact of climate change on the species' geographical distribution. This trend is observed consistently across SSP126, SSP370, and SSP585 scenarios, with varying degrees of movement depending on the severity of the climate model. The movement of the centroid from Hunan Province to areas such as Hubei, Henan, and Shanxi suggests that northern regions, previously less affected, will face increased pressure from *A. coclesalis*. This could lead to substantial ecological changes, particularly in bamboo-dominated ecosystems. The shift implies that *A. coclesalis* is likely to expand into previously unsuitable habitats, potentially disrupting local ecosystems and increasing competition with other species. Regions like northern Hubei and southern Shanxi, which currently have limited bamboo pest infestations, may need to adapt to this new challenge. While the species is adapting to new climatic conditions, its host plant availability and quality in the newly affected areas will play a critical role in determining the pest's ability to establish and proliferate. Provinces such as Hubei, Henan, and Shanxi should implement enhanced monitoring systems to detect early signs of *A. coclesalis* infestation. Pheromone traps and remote sensing technologies should be deployed to track the northward movement of the species. Preemptive pest control strategies, including biological controls and habitat management, should be introduced in

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regions predicted to experience increased suitability for *A. coclesalis*. Collaboration between southern and northern provinces is essential to share data, expertise, and resources for effective pest management. The observed northward movement aligns with trends seen in other pest species, such as *A. chinensis* and *A. cinerarius*, which also show northward shifts due to climate change. This indicates a broader pattern of climate-driven ecological changes that necessitate a unified response. The varying distances of centroid shifts across SSP scenarios underline the role of temperature and precipitation as critical drivers. Future research should further investigate how these specific variables influence the pest's behavior and survival. Predictive modeling tools like MaxEnt should continue to be refined to improve accuracy in forecasting distribution shifts. These insights will be invaluable for developing adaptive strategies that address both ecological and economic impacts.

Different SDMs showed variations in the species' distribution forecasts (Elith et al., 2006; Marmion et al., 2009). Some factors other than climatic conditions, such as human activities, geography, and natural enemies, are challenging to incorporate into the analysis (Iannella et al., 2019; Niemczyk et al., 2021; Terry et al., 2021). Therefore, in this study, in addition to the 19 conventional environmental variables, eight additional variables were introduced: Elevation (m), Slope (°), Aspect, Distance to River (m), Surface Solar Radiation (W/m^2), Land Cover Type, Percentage of Vegetation Cover, and Human Activity Impact Index. This was done to enhance the accuracy of the model predictions. However, the MaxEnt model used in this study is faster and more reliable than other conventional models (Yang et al., 2021), and it offers advantages in processing small sample sizes of data (Wisz et al., 2008). Some of this study's limitations were: (1) despite MaxEnt's advantages in handling small datasets, the small size may still impact result accuracy; (2) while the ENMeval tool is used to optimize MaxEnt's default parameter settings, the predicted outcomes may vary when using alternative SDMs.

Conclusions

This study underscores the profound impact of climate change on the future distribution of *A. coclesalis* in China, revealing significant northward, westward, and southward expansion trends under different climate scenarios. Regions such as Hubei, Henan, Shanxi, Heilongjiang, Jilin, Liaoning, and Xinjiang are projected to face an increase in suitable habitats, while southern provinces like Guangxi, Hunan, and Jiangxi are expected to encounter more severe challenges due to their high suitability area supporting dense populations of the pest. The analysis identifies bio14 (precipitation of the driest month) as the most influential factor shaping the distribution of *A. coclesalis*, highlighting the species' sensitivity to changes in precipitation patterns. Additionally, the northward centroid shift across all SSP scenarios underscores the dynamic influence of rising temperatures and altered precipitation on the pest's range. Moderate and low suitability areas in northern and western China, previously unsuitable for *A. coclesalis*, are becoming potential new habitats due to changing environmental conditions. The study recommends implementing early detection systems, strengthening pest management strategies, increasing public awareness, and fostering cross-regional collaboration to mitigate these risks. While the use of MaxEnt and the inclusion of additional environmental variables, such as human activity impact and vegetation cover, have enhanced prediction accuracy, limitations such as small dataset sizes and the exclusion of natural enemies and human interventions point to the need for further research. Future studies should focus on incorporating larger datasets, validating predictions using alternative SDMs, and exploring ecological interactions in newly affected regions. These findings provide critical insights into the potential future distribution of *A. coclesalis*, emphasizing the need for sustainable pest control and forest management strategies to mitigate the ecological and economic risks posed by climate change.

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