*Bulletin of Entomological Research*

**cambridge.org/ber**

# Potential distribution prediction of two destructive rice weevils in China based on an ensemble model

Xueping Shi, Mingli Yu, Yongli Fu, Jinyang Wang, Faliang Qin and Xingya Wang

College of Plant Protection, Shenyang Agricultural University, Shenyang, P. R. China

**Review Article**

**Cite this article:** Shi X, Yu M, Fu Y, Wang J, Qin F, Wang X (2026) Potential distribution prediction of two destructive rice weevils in China based on an ensemble model. *Bulletin of Entomological Research* **116**, 121–132. https://doi.org/10.1017/S0007485325100515

Received: 6 February 2025
Revised: 3 September 2025
Accepted: 19 September 2025
First published online: 7 October 2025

**Keywords:**
*Echinocnemus squameus*; ensemble model; invasive alien species; *Lissorhoptrus oryzophilus*; potential distribution area

**Corresponding author:** Xingya Wang; Email: wangxingya20081@163.com

## Abstract

Rice water weevils (RWWs) (*Lissorhoptrus oryzophilus*) and rice weevils (RW) (*Echinocnemus squameus*) (both Coleoptera: Curculionidae) are major rice pests that cause significant economic losses in China. Understanding their potential distribution areas is crucial for effective management. This study used the Biomod2 package in R to simulate and predict the current and future potential distributions, changes in suitable areas, shifts in distribution centres, and overlaps under climate change for both pests under three greenhouse gas emission scenarios. By 2023, the suitable areas for RWWs and RWs were 538.52 × 104 km$^2$ and 376.05 × 104 km$^2$, respectively. The suitable area for the former pest expanded southwestward and northeastward across China, whereas the latter spread mainly into Northeast China. The suitable area for RWWs is projected to remain stable, whereas that for RWs is expected to decline. The distribution centroid of RWWs is anticipated to shift toward southeastern or southwestern Shaanxi, whereas RWs are likely to migrate toward central-eastern or northeastern Shaanxi. The niche overlap between the two pests is high (Schoener's $D = 0.658$, $I = 0.816$), with overlap concentrated in central, eastern, and southern China. The key factors influencing their distributions include precipitation of the wettest month (Bio13), mean temperature of the warmest quarter (Bio10), and precipitation of the driest month (Bio14). This study provides a theoretical basis for the prediction of the potential distribution of both pests, which offers valuable insights for the development of effective pest control strategies in China.

## Introduction

Economic globalisation, enhanced connectivity through international trade, and the frequent movement of agricultural commodities have collectively facilitated the rapid global spread of invasive alien species (IASs) (Vilà *et al.,* 2011). Moreover, the effects of climate change are projected to exacerbate the frequency, severity, and extent of damage caused by IASs, as well as increase their volatility and geographic distribution, thereby profoundly affecting agricultural production (Ramasamy *et al.,* 2022). The rapid spread of IASs poses a notable threat to agriculture, causing substantial crop damage (Zhang *et al.,* 2024). The resulting crop damage underscores the urgency of understanding invasion pathways, predicting habitat suitability under climate shifts, and deciphering interactions between environmental and human factors, all of which are key to effective monitoring and management.

Rice water weevils (RWWs), *Lissorhoptrus oryzophilus* Kuschel, and rice weevils (RWs), *Echinocnemus squameus* Billberg (both Coleoptera: Curculionidae) are two major pests that cause significant economic losses in major rice-producing regions of China. RWW is considered the most significant pest affecting rice worldwide, with its parthenogenesis capability enabling rapid population expansion and invasion (Aghaee and Godfrey, 2014; Wan and Yang, 2016). Native to North America, it has spread and established in southern China since 1959 (Stout *et al.,* 2002; Saito *et al.,* 2005). Since its initial detection in Tanghai County, Hebei Province, China, in 1988, the species has expanded rapidly across the country. It is now established in 25 provinces (autonomous regions and municipalities), including coastal regions such as Liaoning, Tianjin, Shandong, Zhejiang, Fujian, and Taiwan, as well as inland areas such as Hunan, Anhui, Shanxi, Shaanxi, Yunnan, Xinjiang, Guizhou, and Sichuan, affecting 492 counties (cities or regions) as of 2025 (Shang *et al.,* 2003; Li *et al.,* 2025). In contrast, the RW is native to China and is widely distributed across the country, ranging from Heilongjiang in the north to Guangdong and Hainan in the south and from western regions such as Shaanxi, Gansu, Sichuan, and Yunnan to eastern coastal areas and Taiwan. Both species can be found in the same areas and have overlapping ecological niches, which cause severe damage to rice plants. Adult RWW feed on leaves, and their larvae consume roots, leading to impaired root development, seed dislodgement, and yield reduction (Zou *et al.,* 2004; Tindall *et al.,* 2013). Similarly, adult RWs feed on young stems and leaves, whereas larvae target tender roots, resulting in symptoms such as yellowing leaf tips,

© The Author(s), 2025. Published by Cambridge University Press.

stunted growth, incomplete panicle formation, blighted grains, and, in severe cases, patchy plant death.

Species distribution models (SDMs) are valuable tools for assessing the impact of climate change on IASs (Lake *et al.,* 2020; Liu *et al.,* 2020). Recently, SDMs have been increasingly used to predict the potential geographical distributions of IASs by integrating environmental and species occurrence data, as well as ecophysiological information, under various climate change scenarios (Runquist *et al.,* 2019, 2021). Previous studies have focused primarily on the potential impacts of climate change on the distributions of various species at the regional level, including plants (Garcia *et al.,* 2013), mammals (Alamgir *et al.,* 2002), birds (Tingley *et al.,* 2009), reptiles (Araújo *et al.,* 2006), amphibians (Thomas *et al.,* 2004), and insects (Hongoh *et al.,* 2012). Commonly used SDMs for predicting the potential geographical distributions of weeds, biocontrol agents, disease vectors, and pathogens include the maximum entropy model (Maxent), CLIMEX, the generalised linear model (GLM), and the genetic algorithm for rule-set prediction (GARP) (Rathore and Sharma, 2023). Numerous SDMs are available, each differing in principles, algorithms, and predictive performance (Luo *et al.,* 2017). Integrating results from multiple models into a consolidated output can increase the accuracy of predictions. Accordingly, the R-based modelling platform Biomod was developed in 2003 and has since been widely used for predicting species' potential geographic distributions (Thuiller, 2003).The R package Biomod2 supports integrated modelling via multiple algorithms, including the Maxent, GLM, GARP, multiple adaptive regression spline (MARS), surface distance envelope (SRE), flexible discriminant analysis (FDA), categorical regression tree analysis (CTA), gradient boosting model (GBM), random forest (RF), and artificial neural network (ANN) (Lantschner *et al.,* 2019). Users can freely customise model combinations and adjust initial conditions, model types, parameters, and boundary conditions to achieve optimal predictive performance. Compared with single-model approaches, ensemble models (EMs) integrate predictions from multiple techniques to improve accuracy, reduce bias, and enhance reliability, making them tools for predicting the potential geographical distributions of species (Araújo and New 2007; Dormann *et al.,* 2018; Lázaro-Lobo *et al.,* 2021).

The objectives of this study were to (1) predict the potential geographical distribution areas of RWW and RW in China under current and three future 2050s climate change scenarios; (2) assess shifts in their distribution centres under three sustainable paths (SSP126, SSP245, and SSP585); (3) evaluate niche overlap between the two species; and (4) identify the key environmental factors influencing their distributions. These findings provide a critical foundation for predicting the potential distributions of RWW and RW in China, thereby supporting the development of effective prevention and control strategies.

## Materials and methods

### *Species geographical distribution data*

Data on the occurrence of RWW and RW in China were collected from the Global Biodiversity Information Facility (GBIF) database (https://www.gbif.org/), relevant literature and papers published in China, and government documents and reports. The distribution data were matched with the Geographic Names Database to obtain the corresponding latitude and longitude for each location. The distribution data were organised by region, longitude, and latitude and saved in .csv format for future use. To ensure compatibility with the resolution of the environmental variables, we refined the occurrence data via ENMTools by retaining only one record per 2.5 × 2.5 km grid, thereby reducing spatial autocorrelation and minimising potential bias from clustered data points (Warren *et al.,* 2010; Wang *et al.,* 2017). To elucidate the spatiotemporal dynamics of the suitable habitats of the two weevil species across China in response to climate change, agricultural landscape transformations, and anthropogenic control measures since their first records, occurrence data have been partitioned into discrete temporal windows for analysis (RW: 1954–2003, 1954–2013, and 1954–2023; RWW: 1988–2003, 1988–2013, and 1988–2023). Both future projections of suitable habitats and the niche equivalence and similarity tests conducted with the ecospat package were based on complete, undivided occurrence datasets (RW: 1954–2023; RWW: 1988–2023), thereby fully encompassing the climatic and environmental space occupied by the two weevil species to date.

### *Data acquisition and screening of environmental factors*

The near-current climate data (1970–2000) and future climate data (2041–2060), including 19 bioclimatic variables with a spatial resolution of 2.5 arcmin (table S1), were downloaded from WorldClim v. 2.1 (www.worldclim.org) (Fick and Hijmans, 2017). The BCC-CSM2-MR model has been shown to accurately simulate long-term temperature and precipitation trends in China (Wu *et al.,* 2019; Xin *et al.,* 2019).

Future climate projections for the 2050s were obtained from three Shared Socioeconomic Pathways (SSPs) within the CMIP6 framework: SSP126, SSP245, and SSP585. These scenarios represent varying levels of radiative forcing by the year 2100: 2.6 W/m$^2$ under a sustainability-oriented pathway (SSP126), 4.5 W/m$^2$ under an intermediate development trajectory (SSP245), and 8.5 W/m$^2$ under a fossil-fuelled development scenario with high emissions (SSP585) (Albuquerque *et al.,* 2018; Zhang *et al.,* 2019). The projections are based on the BCC-CSM2-MR model, which integrates SSP narratives with Representative Concentration Pathways to simulate future climate conditions (Zhang *et al.,* 2022). Climate variable screening is crucial for evaluating species habitat suitability (Sillero, 2011). Pearson correlation analyses were conducted on the 19 environmental variables to reduce collinearity; whenever 2 variables were highly correlated ($|r| > 0.8$), the more meaningful one was retained. (fig. S1; tables S2 and S3)

### *Model construction and accuracy evaluation*

We used the Biomod2 package in RStudio to model the current and future distributions of RWW and RW based on their distribution points and bioclimatic variable data. Biomod2 integrates ten modelling algorithms (GLM, GBM, GAM, MARS, CTA, ANN, SRE, FDA, RF, Maxent) and is freely available (Cola *et al.,* 2017). For each model, 75% of the data were used for training, and 25% were used for testing (Zhao *et al.,* 2021). The dataset was partitioned into training and testing via five repetitions. Additionally, 1000 pseudoabsence points were randomly generated, and this process was repeated three times. Ultimately, 480 models were developed for each insect species. Models with average TSS $> 0.75$ and AUC $> 0.8$ were selected for the EM to analyse the distribution in China. Model accuracy was evaluated via the TSS and AUC, with higher values indicating greater accuracy (Allouche *et al.,* 2006; Peterson *et al.,* 2008).

Based on the EM results, we performed a binary transformation of the potential distributions of each species via the

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

'BIOMOD_Ensemble modeling' function in Biomod2. This generated an ASCII grid with values from 0 to 1, representing the species occurrence probability ($p$). According to the IPCC-CMIP5 classification, suitability areas were categorised as highly suitable ($0.5 \leq p \leq 1.0$), moderately suitable ($0.05 \leq p < 0.5$), lowly suitable ($0.01 \leq p < 0.05$), or unsuitable ($0 \leq p < 0.01$). We then used ArcGIS spatial tools to map the suitable areas of RWW and RW, including their overlapping areas.

### Shift in the potential geographic distribution centre and measurement of the ecological niche

The SDM tool (http://www.sdmtoolbox.org) was used to analyse the migration of RWW and RW distribution centres between current and future climate conditions. This tool was integrated with ArcGIS (version 10.2) for these calculations (Brown, 2014). Niche similarity tests were conducted via the ecospat package in R to measure the overlap of ecological niches between the origin and invasion sites of RWW and RW (Broennimann *et al.*, 2012). If the observed $D$ value exceeds the 95% confidence interval of the randomly generated $D$ value, niche similarity is rejected, indicating significant differences (Warren *et al.*, 2008). We also generated predicted niche occupancy profiles for key environmental variables using the 'var.import' function in the Biomod2.

## Results

### Occurrence information and selection of environmental variables

We collected data on 638 occurrences of RWW and 388 occurrences of RW. After filtering with ENMTools software, we retained 583 occurrences of RWW and 347 occurrences of RW (fig. S2). Following the screening process, we selected 7 (RWW: Bio02, Bio03, Bio08, Bio10, Bio13, Bio14, and Bio15; RW: Bio03, Bio04, Bio08, Bio10, Bio13, Bio14, and Bio15) environmental variables that were strongly correlated with the occurrence of both RWW and RW. These bioclimatic variables effectively encapsulate key ecological factors, including annual trends, seasonality, and extreme or limiting environmental conditions (table S3).

### Model accuracy evaluation

The performance of ten individual model algorithms was assessed, and three models were selected for ensemble modelling for RWW (CTA, GBM, RF) (fig. 1A–F) and RW (GAM, GBM, RF) (fig. 1G–L). These models effectively predict the impacts of climate change on the spread of both rice species. The TSS and AUC values for all 12 EMs exceeded 0.85, indicating high accuracy. This high accuracy reduces uncertainty and enhances the reliability of the predicted geographic distributions of RWW and RW.

### Prediction of the potential distributions of RWW and RW under current climatic conditions

Model simulations indicate that suitable areas for RWW in China are located primarily in South, North, Central, Northeast, and Northwest China. High-suitability areas are concentrated in Liaoning, central Jilin, southeastern Hebei, Beijing, Tianjin, Shandong, Jiangsu, Anhui, Zhejiang, northwestern Jiangxi, Guizhou, Sichuan, Fujian, and Chongqing (fig. 2A–C). Over time, the area suitable for RWW has continued to expand from $423.30 \times 10^4$ km$^2$ during 1988–2003 to $477.40 \times 10^4$ km$^2$ in 1988–2013, and further extended to $538.53 \times 10^4$ km$^2$ by 1988–2023. This represents a cumulative gain of $115.22 \times 10^4$ km$^2$, accounting for 11.98% of China's total land area (table S4). This trend reflects spatial diffusion from core suitable areas to peripheral regions, with notable improvements in suitability observed, particularly in parts of Northwest China and Northeast China.

Suitable areas for RW are located primarily in South, East, Central, Southwest, and Northeast China. High-suitability regions are concentrated in southern Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Guangdong, Guangxi Zhuang Autonomous Region, Hainan, southeastern Guizhou, Chongqing, and eastern Hubei and Hunan (fig. 2D–F). Over time, the total suitable area for RW has shown a consistent decline, from $495.55 \times 10^4$ km$^2$ during 1954–2003, to $440.10 \times 10^4$ km$^2$ in 1954–2013, and further decreased to $376.06 \times 10^4$ km$^2$ by 1954–2023. This corresponds to a net reduction of $119.49 \times 10^4$ km$^2$, accounting for approximately 12.42% of China's total land area (table S4). Spatially, the contraction occurred not only within core high-suitability zones but also within peripheral and ecologically marginal areas, particularly in parts of the southwest and northeast.

### Prediction of suitable areas for RWW and RW under future climatic conditions

For RWW, by 2041–2060, the total suitable areas for RWW under the three climate change scenarios (SSP126, SSP245, and SSP585) were $526.16 \times 10^4$ km$^2$, $481.37 \times 10^4$ km$^2$, and $509.37 \times 10^4$ km$^2$, respectively. The optimal areas for the RWW under the three climate change scenarios in China were $209.77 \times 10^4$ km$^2$, $198.41 \times 10^4$ km$^2$ and $215.48 \times 10^4$ km$^2$. The areas with low suitability were $183.16 \times 10^4$ km$^2$, $158.97 \times 10^4$ km$^2$ and $169.16 \times 10^4$ km$^2$, respectively (table S5). In contrast, the areas of low suitability and optimal suitability were the highest in the SSP126 scenario and the lowest in the SSP245 scenario. Overall, no significant increase in the total area of suitable areas in China under the three scenarios was observed, which was similar to that in 2023 (fig. 3A–C).

For RW, by 2041–2060, the total areas suitable for SBPH under the three climate change scenarios (SSP126, SSP245, and SSP585) were $508.06 \times 10^4$ km$^2$, $425.51 \times 10^4$ km$^2$, and $349.79 \times 10^4$ km$^2$, respectively. The optimal areas were 209.47 km$^2$, $130.01 \times 10^4$ km$^2$ and $160.13 \times 10^4$ km$^2$, respectively (table S5). The areas with low suitability were $177.82 \times 10^4$ km$^2$, $157.08 \times 10^4$ km$^2$, and $110.21 \times 10^4$ km$^2$, respectively. The areas of low suitability and optimal suitability were the highest in the SSP126 scenario. Overall, the total area of suitable areas for RW decreases gradually, as do carbon emissions, across these three future climate scenarios (fig. 3D–F).

### Niche overlap analyses

According to the EMs, the overlapping distribution of RWW and RW is mainly in the central, eastern, southern, northern, and northeastern parts of China. The overlapping area was $376.59 \times 10^2$ km$^2$ from 1954–2003, accounting for 88.9% of the total area of RWW and 76.0% of the total area of RW. By 2013, it had increased to $384.14 \times 10^2$ km$^2$, with the RWW proportion decreasing to 80.4% and the RW proportion increasing to 87.3%. By 2023, the overlapping area decreased to $364.64 \times 10^2$ km$^2$, with the RWW proportion further decreasing to 67.7% and the RW proportion increasing to 97.0%. Future climate projections for the 2050s suggest that the overlapping area of RWW and RW will be $454.25 \times 10^2$ km$^2$ under the SSP126 scenario, representing 89.4% of the total

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

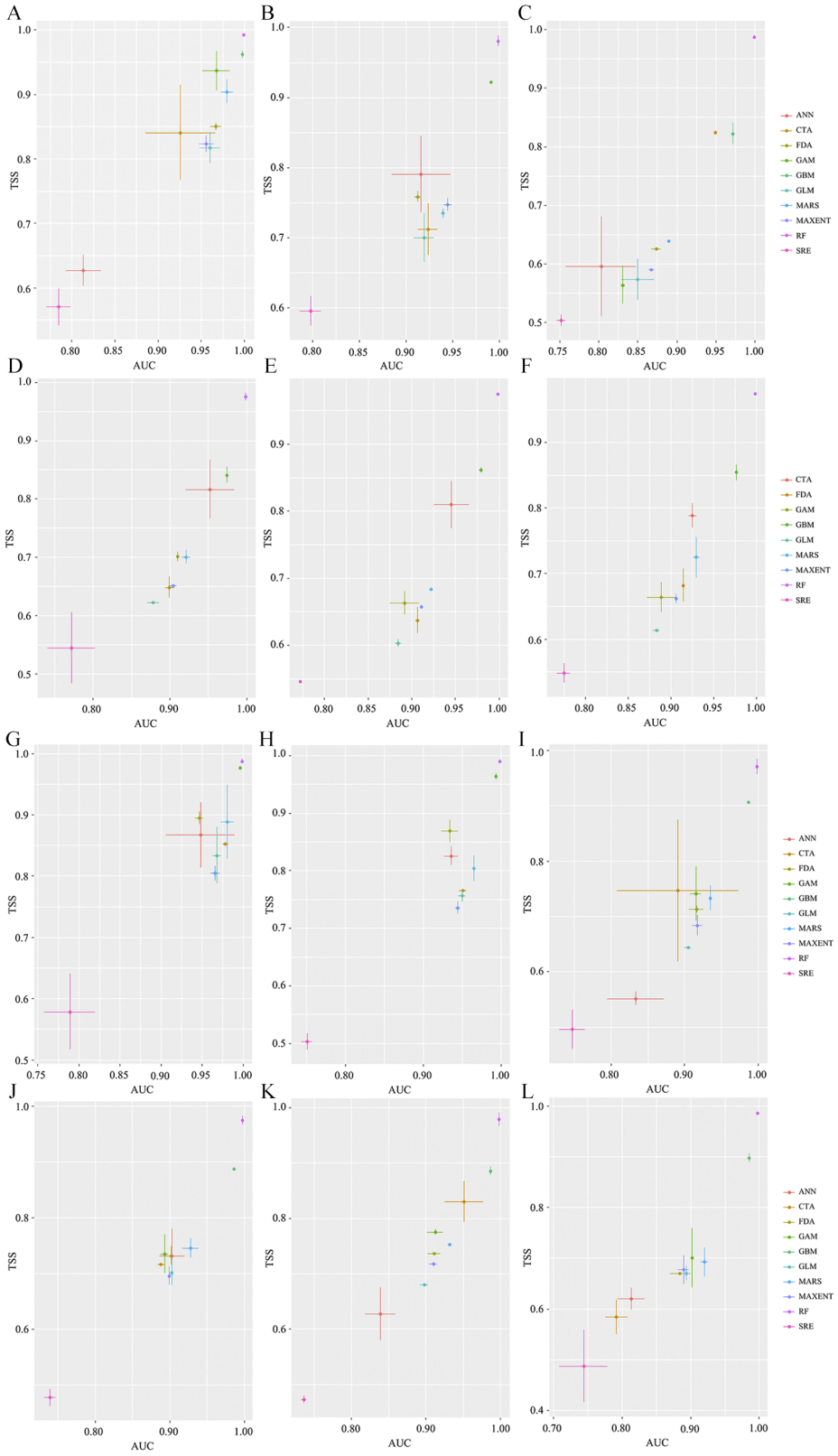



**Figure 1.** Evaluation indices of individual prediction models for *Lissorhoptrus oryzophilus* and *Echinocnemus squameus* in China during different occurrence periods and future climate scenarios. (A: 1988–2003, B: 1988–2013, C: 1988–2023, D: SSP126, E: SSP245, F: SSP585, G: 1954–2003, H: 1954–2013, I: 1954–2023, J: SSP126, K: SSP245, l: SSP585). *Notes*: AUC, area under the receiver operating characteristic curve; TSS, true skill statistic.

area of RWW and 86.3% of the total area of RW. This indicates a relatively stable habitat. However, under the SSP245 scenario, the overlapping area is expected to decrease to 378.28 × $10^2$ $km^2$ and further decline to 333.30 × $10^2$ $km^2$ under the SSP585 scenario.

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

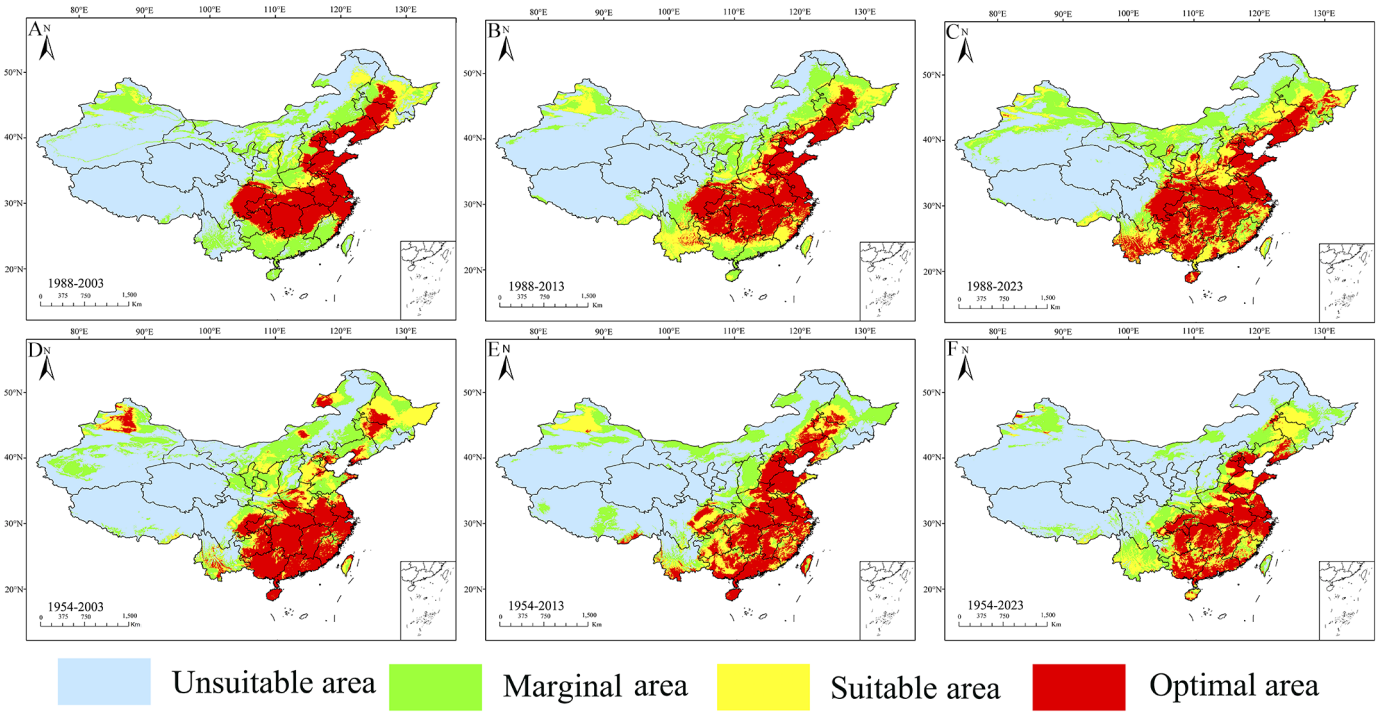



**Figure 2.** Current geographical distributions of *Lissorhoptrus oryzophilus* and *Echinocnemus squameus* in China, as predicted via ensemble models (EMs). (A–C: *Lissorhoptrus oryzophilus*; D–F: *Echinocnemus squameus*).
*Notes*: TA, total suitable area; MA, marginal area; SA, suitable area; OA, optimal suitable area.

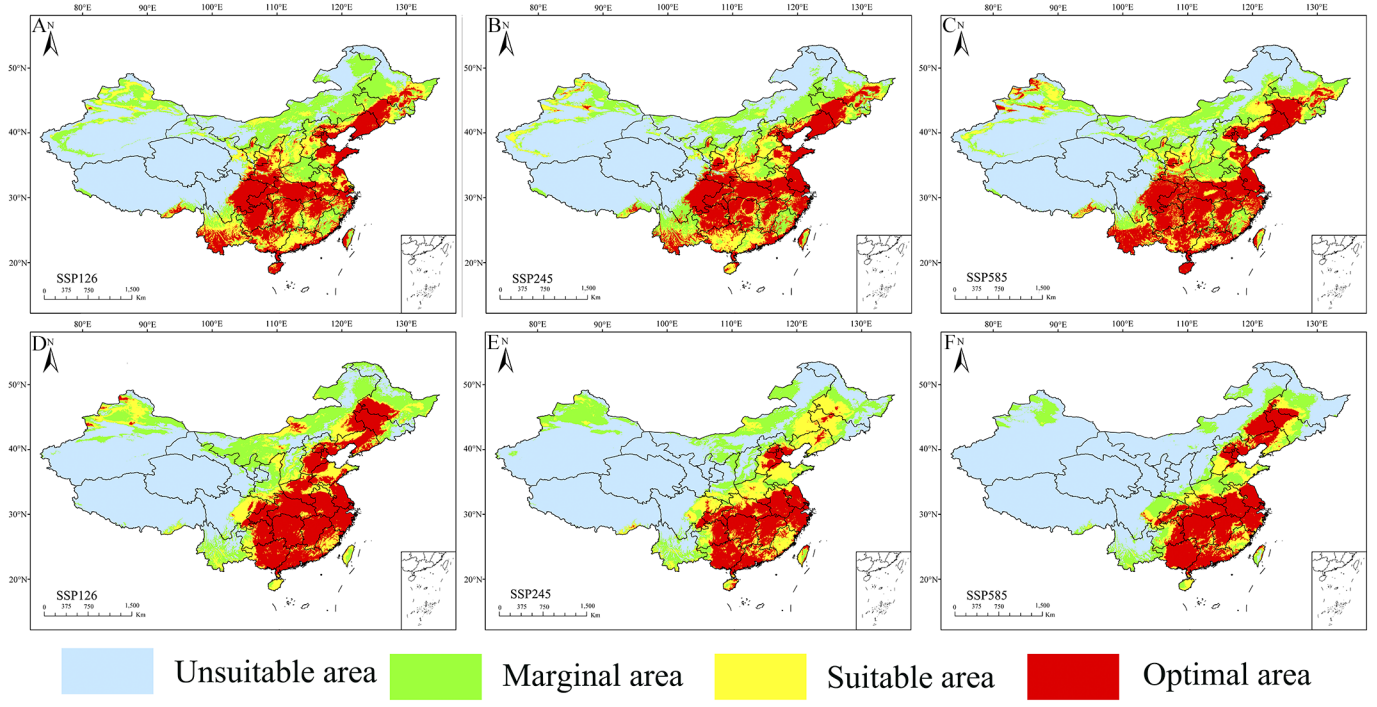



**Figure 3.** Potential geographical distributions of *Lissorhoptrus oryzophilus* and *Echinocnemus squameus* in China in the 2050s, as predicted via ensemble models (EMs). (A–C: *Lissorhoptrus oryzophilus*; D–F: *Echinocnemus squameus*).
*Notes*: TA, total suitable area; MA, marginal area; SA, suitable area; OA, optimal suitable area.

Overall, the overlapping area is projected to shrink gradually due to global warming, with suitable habitats shifting southwards toward Henan Province and eastwards toward Chongqing and southeastern Sichuan (fig. 4 and table 1). In conclusion, climate change notably affects the distributions of both species, with the overlapping area remaining stable only under SSP126 but facing challenges under the other scenarios.

We calculated the degree of ecological niche overlap between RWW and RW, with values ranging from 0 (no overlap) to 1 (complete overlap) (Bachiller *et al.*, 2021). High ecological niche

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

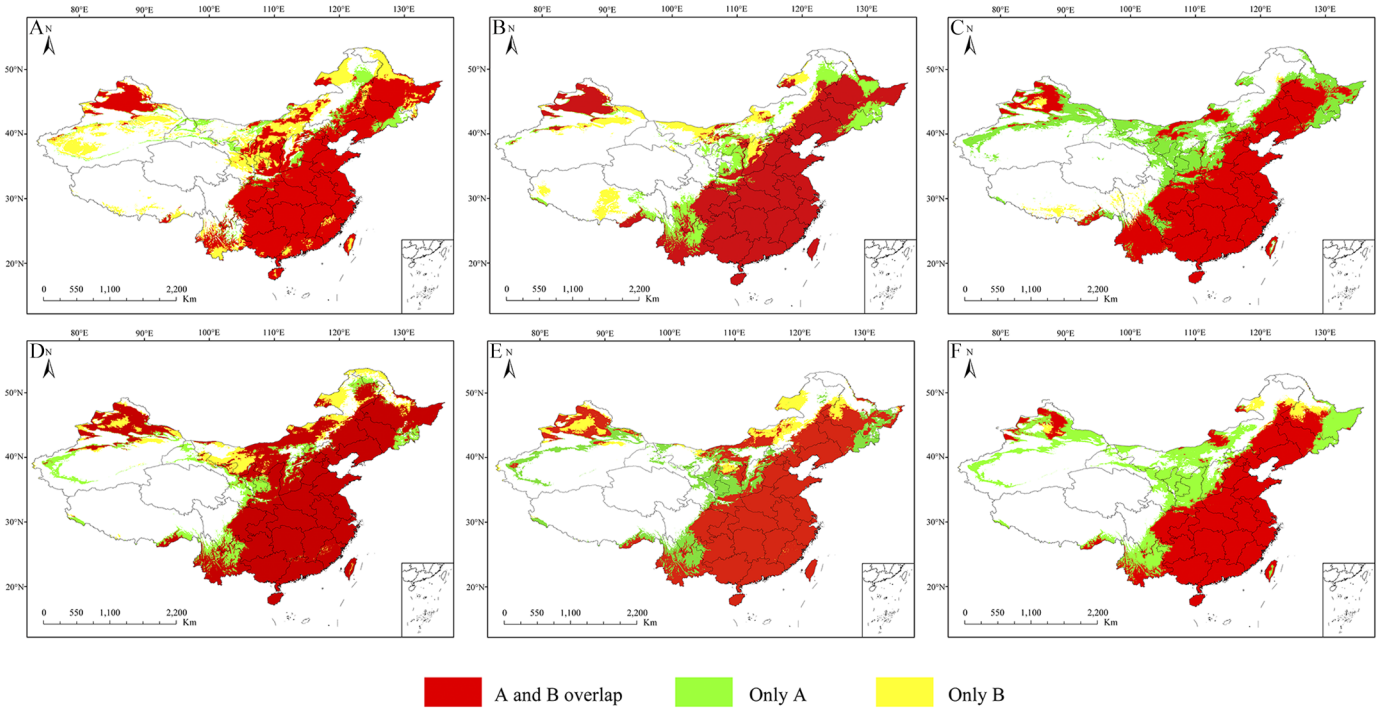



**Figure 4.** Overlapping areas between *Lissorhoptrus oryzophilus* (A) and *Echinocnemus squameus* (B) in China under current and future climates (2050s). (A: 1954–2003; B: 1954–2013; C: 1954–2023; D: SSP126; E: SSP245; F: SSP585).

**Table 1.** Overlapping area (OA) of potential geographical distribution of the *Lissorhoptrus oryzophilus* (A) and *Echinocnemus squameus* (B) under the current and future (2050s) climate conditions (unit: × $10^4$ $km^2$)

| | 1954 (1988)–2003 | 1954 (1988)–2013 | 1954 (1988)–2023 | SSP126 | SSP245 | SSP585 |
|---|---|---|---|---|---|---|
| A and B overlapping area (×$10^4$ $km^2$) | 376.59 | 384.14 | 364.64 | 454.25 | 378.28 | 333.30 |
| $OA/TA_{RWW}$ (%) | 88.9 | 80.4 | 67.7 | 89.4 | 78.5 | 65.4 |
| $OA/TA_{RW}$ (%) | 76.0 | 87.3 | 97.0 | 86.3 | 88.8 | 95.3 |

*Notes*: OA, overlapping are; TA, total suitable area.

overlap was observed between RWW and RW, with *D* and I values of 0.658 and 0.816, respectively. The null hypotheses of RWW and RW, which are based on bioclimatic variables of native and invasive areas, were rejected ($p = 0.09$). Compared with RW, RWW has a slightly expanded niche. PC1 accounted for 54.37% of the environmental variation, whereas PC2 explained 20.01% (fig. 5).

### *Shift in potential geographic distribution centres and significant environmental variables*

Under the current climate conditions, the distribution centre of the suitable area for RWW shifted from central Shaanxi (1988–2003) to southeastern Shanxi (1988–2013) and then moved slightly southwestward by 2023. Under the future climate scenario, the distribution centre is expected to shift southeastward under SSP126 but migrate toward southwestern Shaanxi under SSP245 and SSP585 (fig. 6A). For RW, the distribution centre moved from southwestern Shaanxi (1954–2003) to northeastern Chongqing (1954–2013) and then northeastward to northwestern Hubei by 2023. Under future scenarios, the distribution centre is projected to continue eastwards to central-eastern Shaanxi under SSP126 but to shift northeastward under SSP245 and SSP585 (fig. 6B).

For RWW, we used CTA, GBM, and RF to estimate the contribution of each environmental variable and analysed those that significantly influence the potential distribution. Across the current and future climate scenarios, the precipitation of the wettest month (Bio13) consistently had the greatest impact, with contributions of 0.286 (1988–2003), 0.209 (1988–2013), 0.165 (1988–2023), 0.246 (SSP126), 0.251 (SSP245), and 0.310 (SSP585). The mean temperature of the warmest quarter (Bio10) also plays a significant role (fig. 7 A, B). For RW, in the current and SSP126 climate scenarios, Bio10 was the most influential variable. In the SSP245 and SSP585 climate scenarios, Bio14 (precipitation of the driest month) had the greatest impact (fig. 7 C, D).

## Discussion

This research aimed to predict habitat suitability and ecological niche shifts for both invasive and native species of RWs in China. Using an EM, we explored habitat suitability changes and niche overlaps between both species. Compared with the current climate, the suitable area for RWW showed less fluctuation across the three future climate scenarios, with a trend toward stabilisation and expansion mainly toward the northeast and southwest. In contrast, the suitable area for RW expanded primarily toward the northeast, whereas the total suitable area generally decreased. This study revealed the greatest ecological niche overlap between RWW and RW, although the environmental variables influencing their

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

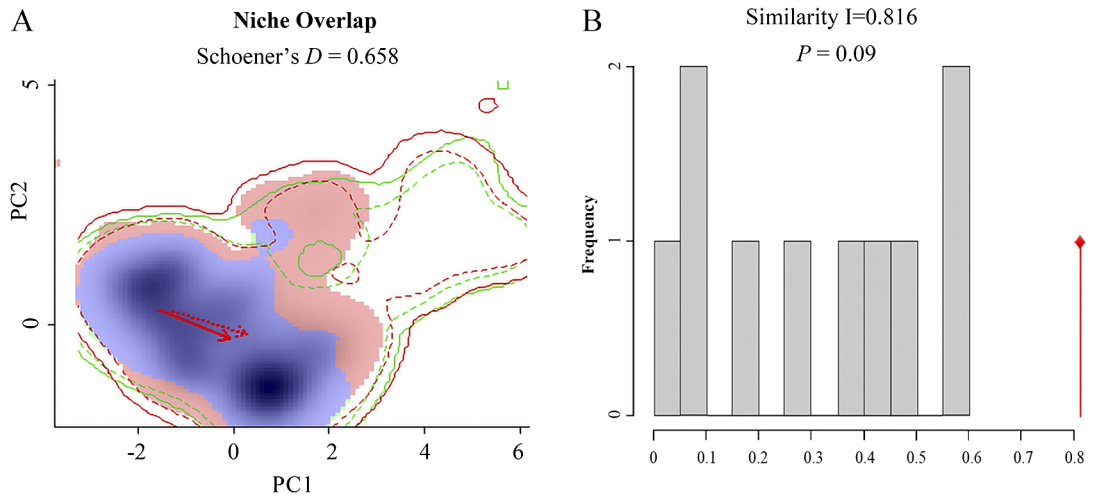



**Figure 5.** Migration of the centre of the potential geographical distribution of *Lissorhoptrus oryzophilus* (A) and *Echinocnemus squameus* (B). Color coding for distribution centres: Green circle: Current climate scenario (1954/1988–2003); Yellow circle: Current climate scenario (1954/1988–2013); Red circle: Current climate scenario (1954/1988–2023); Blue circle: Future climate scenario (2050s SSP126); Purple circle: Future climate scenario (2050s SSP245); Pink circle: Future climate scenario (2050s SSP585).

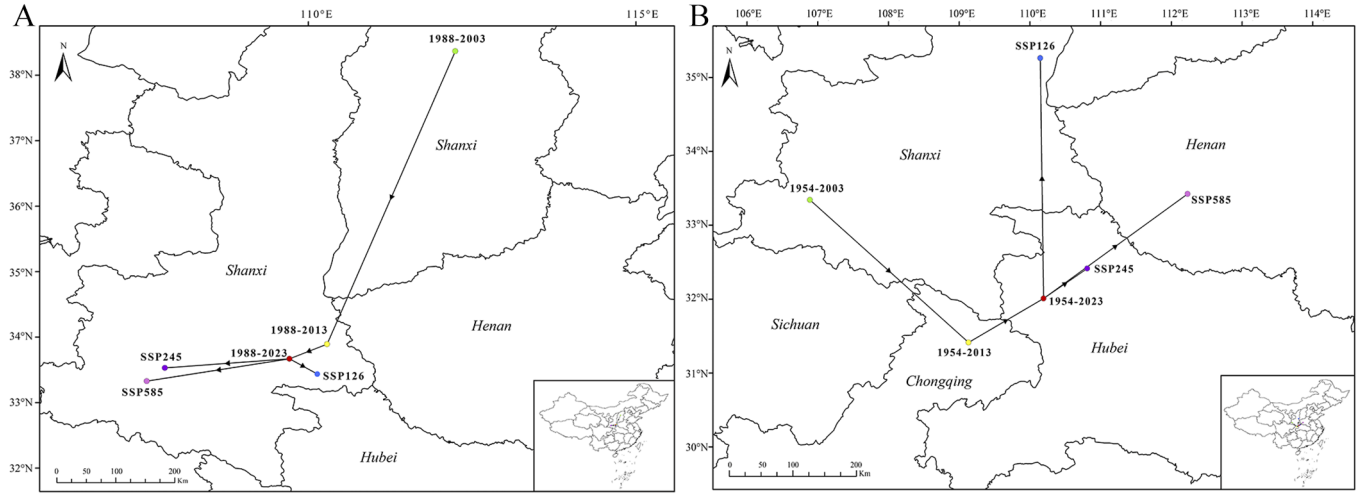



**Figure 6.** Ecological niches and niche similarity of *Lissorhoptrus oryzophilus* and *Echinocnemus squameus*. (A) Ecological niches under current climatic conditions. (B) Ecological niche similarity between *L. Oryzophilus* and *E. Squameus*. Color coding: red: climatic niche of *L. Oryzophilus*; green: climatic niche of *E. Squameus*; blue: niche overlap; red arrows: centroids of the realised ecological niches of each species.

distributions differed. This study offers valuable insights into how climate change may affect the distribution and ecological interactions of RWs in China and highlights the potential ecological and agricultural implications of niche overlap between native and invasive species.

### *Model accuracy evaluation*

SDMs integrate species occurrence data with biotic and abiotic variables to predict the potential distributions of invasive plant species (Elith and Leathwick, 2009). Although widely used, individual SDMs are susceptible to underfitting or overfitting (Peterson *et al.,* 2007). EMs, which combine multiple modelling algorithms, can improve predictive accuracy and reduce bias (Araújo and New, 2007; Naimi and Araújo, 2016). Commonly used EM platforms include Biomod (Thuiller *et al.,* 2009), ModEco (Guo and Liu, 2010), OpenModel (De Souza Muñoz *et al.,* 2011), mopa (Iturbide *et al.,* 2015), and SDM (Naimi and Araújo, 2016), each with specific strengths and limitations that depend on user expertise and objectives (Mugo and Saitoh, 2020). In this study, we developed EMs based on high-performance SDMs for each species. The resulting models showed high predictive performance, with average AUC values above 0.9 and TSS values exceeding 0.8 for both RWW and RW, indicating that the EMs provide more reliable predictions of potential species distributions compared to single-model approaches.

Despite their advantages, SDMs and EMs have several limitations that should be considered. First, model uncertainty remains a fundamental challenge, as different algorithms can yield divergent predictions even when trained on identical data (Araújo and New, 2007). Second, the accuracy of predictions heavily depends on the quality and representativeness of species occurrence data. Biased or incomplete distribution records may lead to erroneous projections (Guisan *et al.,* 2017). Third, the selection of environmental variables is critical; inappropriate variables may cause models to deviate from biological reality (Elith and Leathwick, 2009).

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

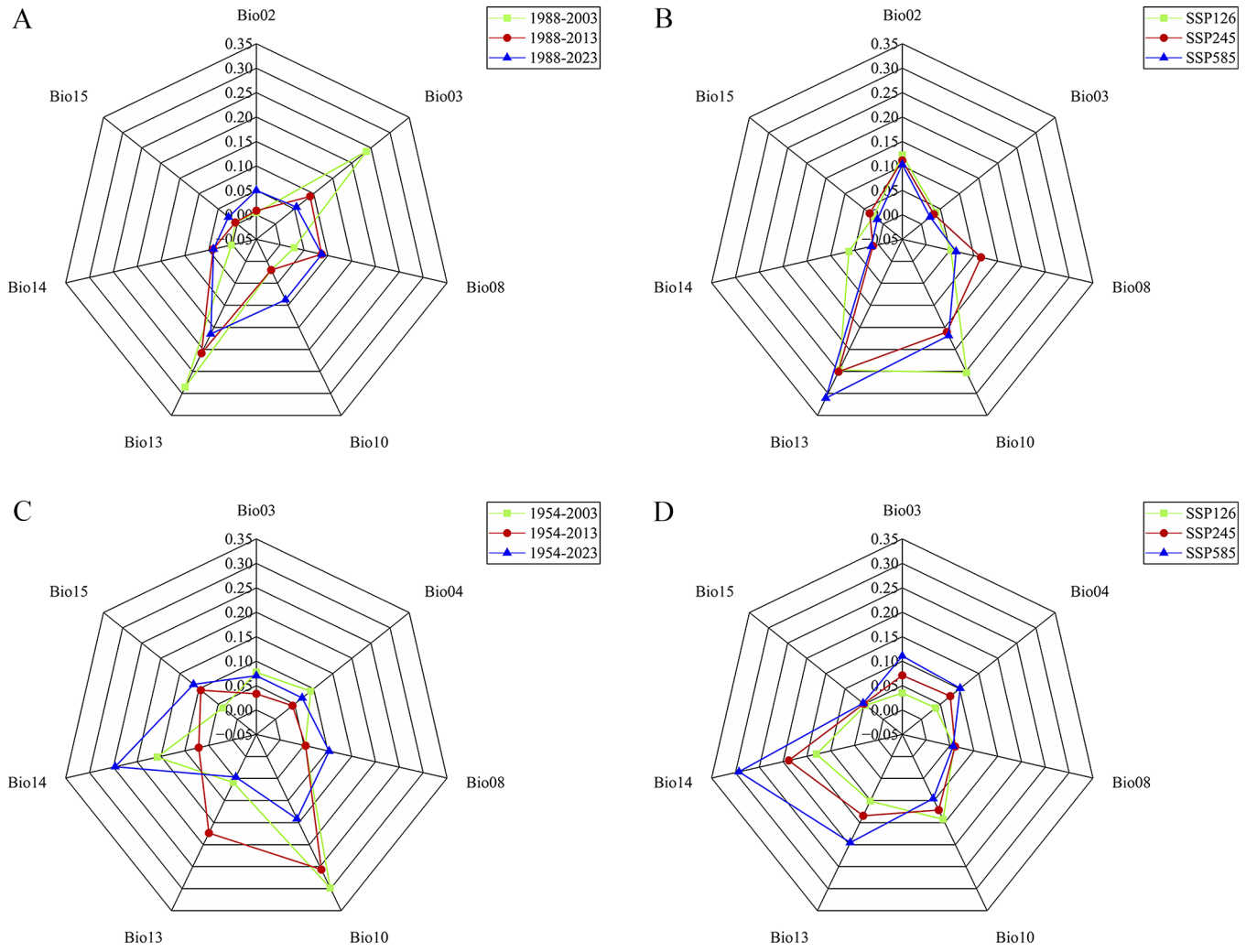



**Figure 7.** Contribution of each environmental variable to *Lissorhoptrus oryzophilus* in the current (A) and future (B) scenarios and to *Echinocnemus squameus* in the current (C) and future (D) scenarios.

Fourth, model complexity must be carefully managed to avoid overfitting, particularly when sample sizes are small, as excessively complex models may perform poorly when generalised to new areas (Hastie *et al.*, 2009). Furthermore, key drivers such as terrain heterogeneity and anthropogenic factors are not always sufficiently incorporated; however, they can significantly influence species distributions (González-Moreno *et al.*, 2014; Abdulwahab *et al.*, 2022). Finally, EMs often overlook species interactions, such as competition and predation, relying solely on environmental factors and potentially introducing bias into the results (Wisz *et al.*, 2013). In this study, the limited occurrence point data and influencing factors were unable to capture the species' full fundamental niche. To address these issues in future research, we recommend that future studies incorporate distribution data from the species' native range in North America to further refine the model. In addition, we integrate multisource data (e.g. remote sensing, soil properties, land use, and dispersal constraints) with ecological mechanism-based modelling. Approaches that account for biotic interactions and dynamic processes such as climate change and invasion pathways could further enhance model realism.

### *Prediction of the potential distributions of RWW and RW in the present and future*

As global temperatures rise, the structure and function of terrestrial ecosystems may undergo substantial alterations, leading to pronounced shifts in the extent and distribution of biological areas (Lawler, 2009). Numerous studies have demonstrated that ecological niche models (ENMs) are effective tools for evaluating the effects of climate change on insect populations (Faleiro *et al.*, 2018; Müller *et al.*, 2019; Tepa-Yotto *et al.*, 2021; Azrag *et al.*, 2022; Jin *et al.*, 2022). Therefore, based on the current distributions of RWW and RW, we predicted their potential redistribution in response to climate change under three twenty-first-century scenarios (SSP126, SSP245, and SSP585). The results revealed that the distribution range of suitable areas for RWW was relatively stable across all three future climate scenarios, with the total extent peaking under SSP126 and being lowest under SSP245. For RW, the total adaptive area is projected to decrease with increasing carbon emissions, being largest under SSP585 and smallest under SSP245. Compared with those under the current distribution, the areas suitable for RW are expected to decrease under SSP126 and SSP245 but expand under SSP585.

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

The present study predicts that RWW and RW have extensive potentially suitable areas in China, covering more than 90% of the rice cultivation regions. The highly suitable areas are mainly concentrated in central and southern China, with limited distributions around the Bohai Bay region. These findings align closely with the research of Qi *et al.* (2012), who reported that the distribution of RWW had expanded to 20 provinces, autonomous regions, and municipalities, showing no signs of slowing down. It has spread to Yunnan, Jiangxi, Heilongjiang, Hubei, Guizhou, and Xinjiang, with a noticeably accelerating trend. Although regions such as Guangdong, Guangxi, and Hainan in southern China, Sichuan and Chongqing in southwestern China, Jiangsu and Shanghai in eastern China, and Henan in central China have not yet recorded invasions, their adjacent areas have already been affected, indicating a high risk of introduction (Qi *et al.,* 2012). The suitability distribution projected by our ENM further supports earlier observations regarding the ongoing expansion and high risk of spread of RWW. This study highlights the continued threat of invasion in southern, central, and parts of eastern China, underscoring the urgent need for enhanced monitoring and preventive measures to curb further spread and establishment of this pest.

### *Shift in the potential geographic distribution centre*

RWW has multiple modes of transmission. It can spread to nearby areas through its own activities, such as crawling and flying, as well as through natural dispersal mechanisms such as wind, rain, and water flow (Zhang *et al.*, 1994), enabling short-distance spread. However, long-distance transmission primarily occurs through human activities, with transportation vehicles and the movement of straw and rice being the main means of long-distance spread (Zhai *et al.,* 1999; Wang *et al.,* 2005). In this study, based on migration trend analysis, under current climate conditions, the distribution centre of the suitable area for RWW shifts from central Shanxi to southeastern Shaanxi, whereas the distribution centre for RW moves from western Chongqing to northwestern Hubei. Under future climate scenarios, the distribution centre of the suitable area for RWW within Shanxi is projected to move southeastward and southwestward, whereas the distribution centre for RW is expected to migrate northwards and northeastwards to the central-eastern part of Shanxi and the central-western part of Henan. Overall, these shifts reflect significant changes in the geographic distribution centres of both species under different climate scenarios. Two significant peak periods in the expansion of RWW in China were identified. The first peak occurred between 1988 and 1993, during which RWW rapidly spread from coastal rice areas in North China, migrating southwards into southern rice-growing regions. The second peak occurred between 2001 and 2003, with notable westwards expansion into the southwestern and central-southern regions, thereby further increasing its range of influence. These two peak periods not only highlight the adaptability of RWW to different climatic conditions but also reflect the close relationship between its spread and factors such as climate and changes in agricultural production patterns (Jiang, 2009). This study revealed that the expansion of RWW has accelerated in recent decades, particularly in North China, East China, and Southwest China. These areas have experienced the expansion of suitable areas and the migration of RWW. Against the backdrop of current climate change, the distribution centre for RWW is undergoing dynamic shifts, showing a trend of moving toward regions with more favourable climatic conditions.

The northwards and upwards shifts in the distribution centres of these pests suggest that they are expanding into regions previously unaffected, where local ecosystems – such as wetland and aquatic communities – may lack evolved resistance mechanisms, posing a substantial threat to biodiversity (Bellard *et al.,* 2012; Pecl *et al.,* 2017). Moreover, the coexistence and niche overlap of the two species, particularly under future climate conditions, indicate that rice fields may experience concurrent infestations by both pests. While larvae of RWW feed on roots, both adults and larvae of RW damage leaves and stems; such combined attacks are likely to produce synergistic effects, leading to significantly greater crop damage than that caused by either species alone. In newly developed rice-growing areas, farmers' lack of experience in pest identification and control may lead to missed optimal intervention windows, resulting in overreliance on chemical pesticides and consequently increased risks of pollution to local soil and water environments. Therefore, monitoring the spread and biological characteristics of RWW, especially in newly emerging expansion areas, is critical and cannot be overlooked in future pest control efforts.

### *The role of key environmental factors in driving distributions*

ENMs are employed to explore the relationships between species distributions and their corresponding environmental variables. These models are based on the assumption that the species—environment relationship can elucidate and forecast both current and future spatiotemporal distributions of species (Mulieri and Patitucci, 2019). By analysing the contribution of each variable, we identified the key factors influencing the distributions of RWW and RW. Under both current and future climate scenarios, the wettest monthly rainfall (Bio13) had the greatest impact on the distribution of RWW, whereas the warmest quarterly average temperature (Bio10) and driest monthly rainfall (Bio14) had the greatest influence on RW. Variable rainfall significantly affects insect populations. For example, increased summer rainfall and drought conditions impact soil-dwelling wireworms (Agriotes lineatus), which are significant pests of crops such as potatoes and corn (Staley *et al.,* 2007). Climate change may exacerbate this issue, potentially intensifying the challenges posed by wireworms (Johnson *et al.,* 2008). Additionally, climate change markedly alters the geographical distribution of pests, with low temperatures generally playing a more critical role than high temperatures in shaping pest distribution patterns (Hill, 1988). The spread of RWW is constrained by cold winter temperatures in Heilongjiang and Jilin Provinces, as well as by high altitudes in Sichuan and Yunnan Provinces, according to CLIMEX software analysis (Chen *et al.,* 2005). It is hypothesised that the combination of summer dryness and cold winter temperatures inhibits the spread of the weevil in northwestern regions, including Inner Mongolia and Gansu. As an invasive species, the distribution of RWW is shaped primarily by its sensitivity to water requirements (Bio13). In contrast, the native RW species shows broader adaptability to local heat conditions (Bio10) and drought stress (Bio14). This finding not only explains the current distribution patterns but also provides valuable insights into how future climate change – such as increased precipitation variability and warming winters – may affect the population dynamics of both species. For example, drier summers (decreased Bio14) in certain regions may limit the spread of RW, while simultaneously intensifying expansion or contraction pressures on RWW, which is more dependent on water availability.

Climate change also alters the geographic ranges of numerous pest species, with the global fruit trade, transportation of

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

plant seedlings, and packaging materials acting as key conduits for the inadvertent transmission of IAS to new regions (Yan *et al.,* 2017). This dispersal can significantly impact agricultural production, particularly for crop pests (Meynard *et al.,* 2013). Invasive insect pest species are likely to experience increased geographic ranges, elevated population densities, and enhanced voltinism due to anticipated climate change scenarios (Hill *et al.,* 2016), posing significant challenges to sustainable agricultural production (Ziska *et al.,* 2011). Compared with native insects, invasive species often possess broader bioclimatic ranges, allowing them to locate a wider array of suitable areas (Walther *et al.,* 2009). Consequently, it remains crucial to comprehend and forecast insect responses to climate change across various scenarios.

### *Pest management implications*

RWW and rice water (RW) are highly destructive pests of rice, necessitating the development of effective and sustainable control strategies. In this study, for the first time, an EM was employed to analyse changes in suitable regions for RWW and RW at different stages and to identify potential distribution areas under current and future climate change scenarios. We highlight both the expansion of suitable areas and potential new invasion zones and provide a critical spatial framework for implementing proactive and targeted pest management strategies. Specifically, these findings can be directly integrated into Integrated Pest Management (IPM) programs. For example, in areas identified as newly suitable or high risk, monitoring efforts should be prioritised and enhanced. Biological control, a cornerstone of IPM, is a particularly promising strategy for managing these invasive pests (Nair and Peterson, 2023). Our model outputs can guide the deliberate introduction or conservation of natural enemies by pinpointing regions where they are most likely to establish and be effective. Further research into the ecological relationships between RWWs and key natural enemies, informed by our distribution predictions, will be invaluable for advancing these methods.

Rising temperatures associated with climate change are expected to accelerate population growth and metabolic rates in insect pests, leading to significant crop losses and increased reliance on chemical insecticides (Porter *et al.,* 1991; Deutsch *et al.,* 2018; Skendžić *et al.,* 2021). Therefore, our findings on future distribution shifts underscore the urgency of developing and adopting sustainable alternatives to chemical control. However, research has also shown that agricultural productivity can increase if effective pest management strategies are implemented in response to climate change (Müller, 2013). The EM developed here provides a decision-support tool for such strategic implementation. Enhancing resilience and adaptation through improved agricultural practices and a better understanding of the future distribution of agricultural pests are essential for informed decision-making aimed at mitigating the impacts of climate change (Vermeulen *et al.,* 2012). Our study contributes to this understanding by offering a predictive outlook that can inform long-term agricultural planning and policy.

In practical terms, for preemptive exclusion, our maps are essential for biosecurity planning. In areas that are potentially suitable but not yet infested, establishing official quarantine zones is vital to prevent further spread. It is also critical to implement stringent quarantine measures for the importation of seedlings, straw, and soil from infested to noninfested regions and to avoid the use of quarantined straw as packaging material (Mulcahy *et al.,* 2022).

### *Conclusions*

This study used an EM to examine changes in habitat suitability, shifts in suitable area centres, and niche overlap for RWW and RW. The results show that the potential distributions of both pests are primarily concentrated in central, eastern, southern, northern, and northeastern China, with high niche overlap in the central, eastern, and southern regions. The precipitation of the wettest month (Bio13) is a key factor influencing the RWW distribution, whereas the mean temperature of the warmest quarter (Bio10) and the precipitation of the driest month (Bio14) significantly influence the RW distribution. Overall, the ensemble model effectively identifies optimal regions for RWW and RW spread, offering a solid theoretical basis for pest control strategies.

**Supplementary material.** The supplementary material for this article can be found at https://doi.org/10.1017/S0007485325100515.

**Acknowledgements.** We are grateful to Dr. Bin Lv, at the Chengdu Institute of Biology, Chinese Academy of Sciences, Chengdu, China, for providing valuable comments and suggestions. This research was supported by the Science & Technology Fundamental Resources Investigation Program (Grant No. 2023FY100500) and the Natural Science Foundation of Liaoning Province of China (No. 2023-MS-209).

**Author contributions.** XPS and XYW conceived the research. XPS and MLY conducted the experiments. XYW contributed material. XPS, JYW and YLF analysed the data and conducted the statistical analyses. XPS and FLQ wrote the manuscript. XYW secured funding. All the authors have read and approved the manuscript, and they participated sufficiently in the work to take public responsibility for appropriate portions of the content.

**Competing interests.** The authors declare that they have no conflicts of interest.

**Data availability statement.** The data will be made available on request.

## References

**Abdulwahab UA, Hammill E and Hawkins CP** (2022) Choice of climate data affects the performance and interpretation of species distribution models. *Ecological Modelling* **471**, 110042.

**Aghaee MA and Godfrey LD** (2014) A century of rice water weevil (Coleoptera: Curculionidae): A history of research and management with an emphasis on the United States. *Journal of Integrated Pest Management* **5**, 1–14.

**Alamgir M, Mukul SA and Turton SM** (2002) Modelling spatial distribution of critically endangered Asian elephant and Hoolock gibbon in Bangladesh forest ecosystems under a changing climate. *Applied Geography* **60**, 10–19.

**Albuquerque F, Benito B, Macı´as-rodrı´guez MA and Gray C** (2018) Potential changes in the distribution of Carnegiea gigantea under future scenarios. *PeerJ* **6**, e5623.

**Allouche O, Tsoar A and Kadmon R** (2006) Assessing the accuracy of species distribution models: Prevalence, kappa, and the true skill statistic (TSS). *Journal of Applied Ecology* **43**, 1223–1232.

**Araújo MB and New M** (2007) Ensemble forecasting of species distributions. *Trends in Ecology and Evolution* **22**, 42–47.

**Araújo MB, Thuiller W and Pearson RG** (2006) Climate warming and the decline of amphibians and reptiles in Europe. *Journal of Biogeography* **33**, 1712–1728.

**Azrag AG, Mohamed SA, Ndlela S and Ekesi S** (2022) Predicting the area suitability of the invasive white Mango scale, *Aulacaspis tubercularis* (Newstead, 1906) (Hemiptera: Diaspididae) using bioclimatic variables. *Pest Management Science* **78**, 4114–4126.

**Bachiller E, Gim´enez J, Albo-Puigserver M, Pennino MG, Marí-Mena N, Esteban A, Lloret-Lloret E, Bellido JM and Coll M** (2021) Trophic niche overlap between round sardinella (*Sardinella aurita*) and sympatric pelagic

fish species in the Western Mediterranean. *Ecology and Evolution* **11**, 16126–16142.

**Bellard C, Bertelsmeier C, Leadley P, Thuiller W and Courchamp F** (2012) Impacts of climate change on the future of biodiversity. *Ecology Letters* **15**, 365–377.

**Broennimann O, Fitzpatrick M, Pearman P, Petitpierre B, Pellissier L, Yoccoz N, Thuiller W, Fortin M-J, Randin C, Zimmermann N, Graham C and Guisan A** (2012) Measuring ecological niche overlap from occurrence and spatial environmental data. *Global Ecology and Biogeography* **21**, 481–497.

**Brown JL** (2014) Sdmtoolbox: A python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *Methods in Ecology and Evolution* **5**, 694–700.

**Chen H, Chen Z and Zhou Y** (2005) Rice water weevil (Coleoptera: Curculionidae) in mainland China: Invasion, spread and control. *Crop Protection* **24**, 695–702.

**Cola V, Broennimann O, Petitpierre B, Breiner FT, DAmen M, Randin C, Engler R, Pottier J, Pio D, Dubuis A, Pellissier L, Mateo RG, Hordijk W, Salamin N and Guisan A** (2017) ecospat: An R package to support spatial analyses and modelling of species niches and distributions. *Ecography* **40**, 774–787.

**De Souza Muñoz ME, De Giovanni R, De Siqueira MF, Sutton T, Brewer P, Pereira RS, Canhos DAL and Canhos VP** (2011) openModeller: A generic approach to species' potential distribution modelling. *GeoInformatica* **15**, 111–135.

**Deutsch CA, Tewksbury JJ, Tigchelaar M, Battisti DS, Merrill SC, Huey RB and Naylor RL** (2018) Increase in crop losses to insect pests in a warming climate. *Science* **61**, 916–919.

**Dormann CF, Calabrese JM, Guillera-Arroita G, Matechou E, Bahn V, Bartoń K and Hartig F** (2018) Model averaging in ecology: A review of Bayesian, information-theoretic, and tactical approaches for predictive inference. *Ecological Monographs* **88**, 485–504.

**Elith J and Leathwick JR** (2009) Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* **40**, 677–697.

**Faleiro FV, Nemésio A and Loyola R** (2018) Climate change likely to reduce orchid bee abundance even in climatic suitable sites. *Global Change Biology* **24**, 2272–2283.

**Fick SE and Hijmans RJ** (2017) WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* **37**, 4302–4315.

**Garcia K, Lasco R, Ines A, Lyon B and Pulhin F** (2013) Predicting geographic distribution and area suitability due to climate change of selected threatened forest tree species in the Philippines. *Applied Geography* **44**, 12–22.

**González-Moreno P, Diez JM, Ibáñez I, Font X and Vilà M** (2014) Plant invasions are context dependent: Multiscale effects of climate, human activity and area. *Diversity and Distributions* **20**, 720–731.

**Guisan A, Thuiller W and Zimmermann NE** (2017) *Habitat Suitability and Distribution Models: With Applications in R*. Cambridge: Cambridge University Press.

**Guo QH and Liu Y** (2010) ModEco: An integrated software package for ecological niche modelling. *Ecography* **33**, 637–642.

**Hastie T, Tibshirani R and Friedman J** (2009) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York, NY: Springer Science & Business Media.

**Hill MP** (1988) The role of temperature in the distribution of insect pests. *Environmental Entomology* **17**, 617–622.

**Hill MP, Bertelsmeier C, Clusella-Trullas S, Garnas J, Robertson MP and Terblanche JS** (2016) Predicted decrease in global climate suitability masks regional complexity of invasive fruit fly species response to climate change. *Biological Invasions* **18**, 1105–1119.

**Hongoh V, Berrang-Ford L, Scott ME and Lindsay LR** (2012) Expanding geographical distribution of the mosquito, Culex pipiens, in Canada under climate change. *Applied Geography* **33**, 53–62.

**Iturbide M, Bedia J, Herrera S, Del Hierro O, Pinto M and Manuel Gutierrez J** (2015) A framework for species distribution modelling with improved pseudoabsence generation. *Ecological Modelling* **312**, 166–174.

**Jiang MX** (2009) Distribution and expansion of the rice water weevil in China. In Hao WF, Guo JY, Zhang F, *et al*. (eds), *Studies on Biological Invasions in China*. Beijing: Science Press, pp. 96–97.

**Jin Z, Yu WT, Zhao HY, Xian XQ, Jing KT, Yang N, Lu XM and Liu WX** (2022) Potential global distribution of invasive alien species, *Anthonomus grandis* Boheman, under current and future climate using optimal Maxent model. *Agriculture* **12**, 1759.

**Johnson SN, Anderson EA, Dawson G and Griffiths DW** (2008) Varietal susceptibility of potatoes to wireworm herbivory. *Agricultural and Forest Entomology* **10**, 167–174.

**Lake TA, Briscoe Runquist RD and Moeller DA** (2020) Predicting range expansion of invasive species: Pitfalls and best practices for obtaining biologically realistic projections. *Diversity and Distributions* **26**, 1767–1779.

**Lantschner MV, de la Vega G and Corley JC** (2019) Predicting the distribution of harmful species and their natural enemies in agricultural, livestock and forestry systems: An overview. *International Journal of Pest Management* **65**, 190–206.

**Lawler JJ** (2009) Climate change adaptation strategies for resource management and conservation planning. *Annals of the New York Academy of Sciences* **1162**, 79–98.

**Lázaro-Lobo A, Ramirez-Reyes C, Lucardi RD and Ervin GN** (2021) Multivariate analysis of invasive plant species distributions in southern US forests. *Landscape Ecology* **36**, 3539–3555.

**Li ZZ, Du W, Duan XN, Hou ZZ, Sheng YB, Wu P, Shi YY, Lu ZJ, Zhou XL, Sun YP and Cao SJ** (2025) Preliminary study on occurrence and field control effects of invasive pest *Lissorhoptrus oryzophilus* in Ningxia. *Journal of Agriculture* **15**, 36–40.

**Liu CL, Wolter C, Xian WW and Jeschke JM** (2020) Species distribution models have limited spatial transferability for invasive species. *Ecology Letters* **23**, 1682–1692.

**Luo M, Wang H and Lyv Z** (2017) Evaluating the performance of species distribution models Biomod2 and MaxEnt using the giant panda distribution data. *The Journal of Applied Ecology* **28**, 4001–4006.

**Meynard CN, Migeon A and Navajas M** (2013) Uncertainties in predicting species distributions under climate change: A case study using *Tetranychus evansi* (Acari: Tetranychidae), a widespread agricultural pest. *PLoS ONE* **8**, 1–10.

**Mugo R and Saitoh SI** (2020) Ensemble modelling of skipjack tuna (*Katsuwonus pelamis*) areas in the Western North Pacific using satellite remotely sensed data: A comparative analysis using machine-learning models. *Remote Sensing* **12**, 2591.

**Mulcahy M, Wilson B and Reagan T** (2022) Spatial distribution of *Lissorhoptrus oryzophilus* (Coleoptera: Curculionidae) in rice. *Environmental Entomology* **51**, 108–117.

**Mulieri PR and Patitucci LD** (2019) Using ecological niche models to describe the geographical distribution of the myiasis-causing *Cochliomyia hominivorax* (Diptera: Calliphoridae) in Southern South America. *Parasitology Research* **118**, 1077–1086.

**Müller C** (2013) African lessons on climate change risks for agriculture. *Annual Review of Nutrition* **33**, 395–411.

**Müller FA, Dias NP, Gottschalk MS, Garcia FRM and Nava DE** (2019) Potential distribution of *Bactrocera oleae* and the parasitoids *Fopius arisanus* and *Psyttalia concolor*, aiming at classical biological control. *Biological Control* **132**, 144–151.

**Naimi B and Araújo MB** (2016) SDM: A reproducible and extensible R platform for species distribution modelling. *Ecography* **39**, 368–375.

**Nair RR and Peterson AT** (2023) Mapping the global distribution of invasive pest *Drosophila suzukii* and parasitoid *Leptopilina japonica*: Implications for biological control. *PeerJ* **11**, e15222.

**Pecl GT, Araújo MB, Bell JD, Blanchard J, Bonebrake TC, Chen IC, Clark TD, Colwell RK, Danielsen F, Evengard B, Falconi L, Ferrier S, Frusher S, Garcia RA, Griffis RB, Hobday AJ, Janion-Scheepers C, Jarzyna MA, Jennings S and Williams SE** (2017) Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science* **355**, 1–9.

**Peterson A, Papeş M and Eaton M** (2007) Transferability and model evaluation in ecological niche modelling: A comparison of GARP and Maxent. *Ecography* **30**, 550–560.

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press

**Peterson AT, Papeş M and Soberón J** (2008) Rethinking receiver operating characteristic analysis applications in ecological niche modelling. *Ecological Modelling* **213**, 63–72.

**Porter JH, Parry ML and Carter TR** (1991) The potential effects of climatic change on agricultural insect pests. *Agricultural and Forest Meteorology* **57**, 221–240.

**Qi GJ, Gao Y, Huang DC and Lyu LH** (2012) Invasion dynamics and suitability analysis of *Lissorhoptrus oryzophilus* (Coleoptera: Curculionidae) in China based on MAXENT. *Journal of Plant Protection* **39**, 129–136.

**Ramasamy M, Das B and Ramesh R** (2022) Predicting climate change impacts on potential worldwide distribution of fall armyworm based on CMIP6 projections. *Journal of Pest Science* **95**, 841–854.

**Rathore MK and Sharma LK** (2023) Efficacy of species distribution models (SDMs) for ecological realms to ascertain biological conservation and practices. *Biodiversity and Conservation* **32**, 3053–3087.

**Runquist BRD, Lake TA, Tiffin P and Moeller DA** (2019) Species distribution models throughout the invasion history of Palmer amaranth predict regions at risk of future invasion and reveal challenges with modelling rapidly shifting geographic ranges. *Scientific Reports* **9**, 2426.

**Runquist RDB, Lake TA and Moeller DA** (2021) Improving predictions of range expansion for invasive species using joint species distribution models and surrogate co-occurring species. *Journal of Biogeography* **48**, 1693–1705.

**Saito T, Hirai K and Way MO** (2005) The rice water weevil, *Lissorhoptrus oryzophilus* Kuschel (Coleoptera: Curculionidae). *Applied Entomology and Zoology* **40**, 31–39.

**Shang HW, Cheng JA, Jiang MX, Tang QY and Gu YQ** (2003) Survival of the rice water weevil, Lissorhoptrus oryzophilus, in early rice grain in Zhejiang Province. *Acta Entomologica Sinica* **46**, 190–195.

**Sillero N** (2011) What does ecological modelling model? A proposed classification of ecological niche models based on their underlying methods. *Ecological Modelling* **222**, 1343–1346.

**Skendžić S, Zovko M, Živković IP, Lešić V and Lemić D** (2021) The impact of climate change on agricultural insect pests. *Insects* **12**, 440.

**Staley JT, Hodgson CJ, Mortimer SR, Morecroft MD, Masters GJ, Brown VK and Taylor ME** (2007) Effects of summer rainfall manipulations on the abundance and vertical distribution of herbivorous soil macroinvertebrates. *European Journal of Soil Biology* **43**, 189–198.

**Stout MJ, Riggio MR, Li Z and Roberts R** (2002) Flooding influences ovipositional and feeding behavior of the rice water weevil (Coleoptera: Curculionidae). *Journal of Economic Entomology* **95**, 715–721.

**Tepa-Yotto GT, Gouwakinnou GN, Fagbohoun JR, Tamò M and Sæthre MG** (2021) Horizon scanning to assess the bioclimatic potential for the alien species *Spodoptera eridania* and its parasitoids after pest detection in West and Central Africa. *Pest Management Science* **77**, 4437–4446.

**Thomas CD, Cameron A, Green RE, Bakkenes M, Beaumont LJ, Collingham YC, Erasmus BF, De Siqueira MF, Grainger A, Hannah L, Hughes L, Huntley B, Van Jaarsveld AS, Midgley GF, Miles L, Ortega-Huerta MA, Peterson AT, Phillips OL and Williams SE** (2004) Extinction risk from climate change. *Nature* **427**, 145–148.

**Thuiller W** (2003) Biomod: Optimizing predictions of species distributions and projecting potential future shifts under global change. *Global Change Biology* **9**, 1353–1362.

**Thuiller W, Lafourcade B, Engler R and Miguel B** (2009) BIOMOD—a platform for ensemble forecasting of species distributions. *Ecography* **32**, 369–373.

**Tindall KV, Bernhardt JL, Stout MJ and Beighley DH** (2013) Effect of depth of flooding on the rice water weevil, *Lissorhoptrus oryzophilus*, and yield of rice. *Journal of Insect Science (Online)* **13**, 62.

**Tingley MW, Monahan WB, Beissinger SR and Moritz C** (2009) Birds track their Grinnellian niche through a century of climate change. *Proceedings of the National Academy of Sciences* **106**, 19637–19643.

**Vermeulen SJ, Aggarwal PK, Ainslie A, Angelone C, Campbell BM, Challinor AJ, Hansen J, Ingram J, Jarvis A, Kristjanson P, Lau C, Nelson G, Thornton P and Wollenberg E** (2012) Options for support to agriculture and food security under climate change. *Environmental Science & Policy* **15**, 136–144.

**Vilà M, Espinar JL, Hejda M, Hulme PE, Jarošík V, Maron JL, Pergl J, Schaffner U, Sun Y and Pyšek P** (2011) Ecological impacts of invasive alien plants: A meta-analysis of their effects on species, communities, and ecosystems. *Ecology Letters* **14**, 702–708.

**Walther GR, Roques A, Hulme PE, Sykes MT, Pyšek P, Kühn I, Zobel M, Bacher S, Botta-Dukát Z, Bugmann H, Czúcz B, Dauber J, Hickler T, Jarošík V, Kenis M, Klotz S, Minchin D, Moora M, Nentwig W, Ott J, Panov VE, Reineking B, Robinet C, Semenchenko V, Solarz W, Thuiller W, Vilà M, Vohland K and Settele J** (2009) Alien species in a warmer world: Risks and opportunities. *Trends in Ecology and Evolution* **24**, 686–693.

**Wan FH and Yang NW** (2016) Invasion and management of agricultural alien insects in China. *Annual Review of Entomology* **61**, 77–98.

**Wang RL, Li Q, Feng CH and Shi ZP** (2017) Predicting potential ecological distribution of *Locusta migratoria* tibetensis in China using MaxEnt ecological niche modeling. *Acta Ecologica Sinica* **37**, 8556–8566.

**Wang ZJ, Shang HW, Li DM and Cheng JA** (2005) Spatial pattern analysis of spread for the rice water weevil in Zhejiang and Fujian provinces, East China. *Journal of Biomathematics* **20**, 257–263.

**Warren DL, Glor RE and Turelli M** (2008) Environmental niche equivalency versus conservatism: Quantitative approaches to niche evolution. *Evolution* **62**, 2868–2883.

**Warren DL, Glor RE and Turelli M** (2010) ENMTools: A toolbox for comparative studies of environmental niche models. *Ecography* **33**, 607–611.

**Wisz MS, Pottier J, Kissling WD, Pellissier L, Lenoir J, Damgaard CF, Dormann CF, Forchhammer MC, Grytnes JA, Guisan A, Heikkinen RK, Høye TT, Kühn I, Luoto M, Maiorano L, Nilsson MC, Normand S, Öckinger E, Schmidt NM and Svenning JC** (2013) The role of biotic interactions in shaping distributions and realised assemblages of species: Implications for species distribution modelling. *Biological Reviews* **88**, 15–30.

**Wu T, Lu Y, Fang Y, Xiaoge X, Li L, Li W, Jie W, Zhang J, Liu Y, Zhang L, Zhang F, Zhang Y, Wu F, Li J, Chu M, Wang Z, Shi X, Liu X, Wei M and Liu X** (2019) The Beijing Climate Center Climate System Model (BCC-CSM): The main progress from CMIP5 to CMIP6. *Geoscientific Model Development* **12**, 1573–1600.

**Xin XG, Wu TW, Zhang J, Zhang F, Li WP, Zhang YW, Lu YX, Fang YJ, Jie WH and Zhang L** (2019) Introduction of BCC models and its participation in CMIP6. *Climate Change Research* **15**, 533–539.

**Yan YW, Wang YC, Feng CC, Wan PH and Chang K** (2017) Potential distributional changes of invasive crop pest species associated with global climate change. *Applied Geography* **82**, 83–92.

**Zhai BP, Zheng XH, Shang HW and Cheng JA** (1999) Effect of wind on the flight of rice water weevil. *Chinese Agricultural Meteorology* **20**, 24–27.

**Zhang L, Chen X and Xin X** (2019) Overview and review of CMIP6 scenario model comparison program (ScenarioMIP). *Progress in Climate Change Research* **15**, 519–525.

**Zhang L, Yu HY and Xu ZX** (1994) Rice water weevil and plant quarantine (I). *Plant Quarantin* **8**, 215–219.

**Zhang XY, Zhao J, W M, Li ZP, L S and C H** (2022) Potential distribution prediction of Amaranthus palmeri S. Watson in China under current and future climate scenarios. *Ecology and Evolutio* **12**, e9505.

**Zhang YJ, Hu J, Wang CB, Wang YQ, Ji ML, Fang-Zhou M and Lu YQ** (2024) Estimating global geographical distribution and ecological niche dynamics of *Ammannia coccinea* under climate change based on Biomod2. *Scientific Reports* **14**, 30579.

**Zhao GH, Cui XY, Sun JJ, Li TT, Wang Q, Ye XZ and Fan BG** (2021) Analysis of the distribution pattern of Chinese *Ziziphus jujuba* under climate change based on optimized biomod2 and Maxent models. *Ecological Indicators* **132**, 108256.

**Ziska LH, Blumenthal DM, Runion GB, Hunt ER and Diaz-Soltero H** (2011) Invasive species and climate change: An agronomic perspective. *Climatic Change* **105**, 13–42.

**Zou L, Stout MJ and Dundand RT** (2004) The effects of feeding by the rice water weevil, *Lissorhoptrus oryzophilus* Kuschel, on the growth and yield components of rice, *Oryza sativa*. *Agricultural and Forest Entomology* **6**, 47–53.

https://doi.org/10.1017/S0007485325100515 Published online by Cambridge University Press