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Assessing the invasion risk of *Chelydra serpentina* in China under current and future climate change scenarios

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Chelydra serpentina, a species introduced to China for aquaculture purposes, is commonly found in its natural habitats within the country. The invasion of *C. serpentina* poses potential threats to both the biodiversity of China and human health. The potential distribution of *C. serpentina* has been simulated using the species distribution model – MaxEnt, incorporating global distribution data, climate, and land cover variables. Our simulations encompasses both current conditions and four future climate change scenarios. Currently, the potential distribution is concentrated in central, eastern, and southeastern regions of China, with the central and eastern regions facing the highest risk of invasion. Under future climate change scenarios, the distribution area may expand by 30–90%, and multiple provinces will face a more severe threat of invasion. This study presents the inaugural simulation of the potential invasion range of *C. serpentina* under current climatic conditions. Moreover, it reveals that climate change is likely to contribute to the expansion of its invasive range, thus furnishing a reference foundation for scientific prevention and control measures. We propose integrating citizen science and eDNA technologies into species monitoring to enhance the efficiency of detecting invasive species. This research has filled the gap in the research on the invasive distribution range of *C. serpentina* in China and globally, while also providing novel perspectives on the invasion control of this species.

KEYWORDS

***Chelydra serpentina*, invasive alien species, species distribution models, climate change, potential distribution, management**

1 Introduction

Globally, non-native freshwater turtles have been intentionally or unintentionally introduced into various habitats (Sung et al., 2021), causing damage to local biodiversity and ecosystems through competition (Díaz-Paniagua et al., 2011), hybridization (Ueno et al., 2021), and the spread of parasites (Mendoza-Roldan et al., 2020) and diseases (Bosch et al., 2015). To prevent the further spread of invasive alien species (IAS), employing species distribution models (SDMs) to analyze the current and future ranges of IAS can provide a scientific basis for decision-making (Bertolino et al., 2020).

It is expected that the global surface temperature will continue to increase at least until the middle of the century (Masson-Delmotte et al., 2021). Climate change and biological invasions occur simultaneously in both space and time, and there is a potential for synergistic effects in the future (Stephens et al., 2019). The persistent climate change poses an escalating threat to biodiversity and ecosystems (Watson et al., 2019). Forecasts suggest that global warming will alter the geographical ranges of various species (Duan et al., 2016). The survival of species in response to climate change will likely depend on their dispersal capabilities (Capinha et al., 2013). Species with narrow ecological niches and limited dispersal abilities, including many endangered species, are significantly more vulnerable to environmental changes (Malcolm et al., 2006) compared to species with extensive dispersal abilities (Slatyer et al., 2013) like IAS. IAS are often better adapted to local conditions, outcompeting slower-spreading species and potentially leading to their extinction (Urban et al., 2012).

China's complex terrain and climatic diversity contribute to its abundant biodiversity compared to other countries at similar latitudes (SEP A (State Environmental Protection Administration), 1998). China has identified over 660 IAS (Xian et al., 2018), including four species from the Testudines order: pond slider turtle (*Trachemys scripta*), Florida softshell turtle (*Apalone ferox*), alligator snapping turtle (*Macrochelys temminckii*), and common snapping turtle (*Chelydra serpentina*) (Ji, 2023). The original natural range of *C. serpentina* extends from the southeastern region of Alberta, Canada, eastward in the United States to the east of the 105th meridian, and southwards to the Gulf Coast (Ernst and Lovich, 2009). *C. serpentina* has been introduced in various countries across Asia (including China, Japan, Singapore), Europe (Germany, the Netherlands, France, Spain), and South America (Mexico, Honduras, Costa Rica, Panama, Ecuador) primarily through the pet and food trade (Koo and Sung, 2020). Around 1997, China began introducing *C. serpentina* due to its rapid growth, high egg production, substantial meat yield, simple feeding requirements, and low susceptibility to disease. This led to rapid development in aquaculture, and in 2005, the Ministry of Agriculture of the People's Republic of China endorsed this species for aquaculture promotion (Liu et al., 2007). *C. serpentina* is frequently discovered in the natural habitats of China and has been featured in various online news outlets (Liu et al., 2021). In the region of Hong Kong, *C. serpentin*a has also been witnessed on no less than 10 occasions (Sung et al., 2021). Therefore, we hold the belief that China is currently confronted with a significant risk of *C. serpentina* invasion. As apex predators, these formidable creatures exert a significant cascading effect on freshwater ecosystems (Wilbur, 1997; Lovich et al., 2018; Garig et al., 2020). Even their brief visits can induce substantial changes in freshwater communities (Garig et al., 2020).

SDMs are statistical models that utilize observed distribution data to infer species ecological requirements and map their potential distribution (Austin, 2002). They are widely used to quantify species responses to climate change (Araújo et al., 2011; Newbold et al., 2020). This study aims to simulate the potential global and China-specific distributions of *C. serpentina* by utilizing existing records of its occurrence and high-resolution data on climate warming and water bodies. The study sets forth three distinct research objectives: (1) Assessing the potential distribution of *C. serpentina* in both current and future climatic conditions; (2) Spatially delineating the contraction and expansion patterns within the distribution range of *C. serpentina*; (3) Identifying the principal environmental variables that strongly correlate with the distribution of *C. serpentina*. This study presents the inaugural simulation of the potential invasion range of *C. serpentina* under current climatic conditions. Additionally, it reveals the impact of climate change on the invasive range of *C. serpentina*, thus furnishing a reference foundation for scientific prevention and control measures. Moreover, based on the biological characteristics of *C. serpentina*, suggestions for conducting field investigations have been proposed to enhance monitoring efficiency. This study has filled the gap in the research on the invasive distribution range of *C. serpentina* in China and globally, while also providing novel perspectives on the invasion control of this species.

2 Materials and methods

2.1 Occurrence and environmental data

We obtained the global occurrence records for *C. serpentina* from the Global Biodiversity Information Facility (GBIF), accessed on 23 May 2023 (GBIF, 2023). Any records that fell outside the range of bioclimatic variables were excluded. In order to reduce the impact of sampling bias, we performed spatial thinning using the spThin R package (R Version 4.3.0), with a minimum distance of 10km between pairs of sites (Aiello-Lammens et al., 2015). In the end, we obtained 7,897 occurrence records of *C. serpentina* for our study, of which 97.34% were within the original range (Figure 1). We utilized global occurrence data for model calibration because relying solely on occurrence data from native habitats may lead to an underestimation of potential distribution areas. This is primarily because it overlooks the essential survival strategies species employ to mitigate the effects of environmental changes. These mechanisms include exploiting microclimates, regulating body temperature, adjusting life history traits, and exhibiting evolutionary adaptations (Bonebrake et al., 2014; Faye et al., 2014; Bush et al., 2016). This is particularly relevant for IAS, which often exhibit heightened adaptability (Kolar and Lodge, 2001).

Nineteen global bioclimatic and elevation variables were sourced from the WorldClim databas (Hijmans et al., 2005), derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5). The current climatic variables are based on the long-term average data for 1960–1990. As turtles are aquatic organisms, land cover data of Chen et al. (2022) were utilized to generate data on water bodies and distance from water bodies. The current land cover variables use 2015 data. Water bodies were represented using binary data (1 for water, 0 for non-water) (Gábor et al., 2022), while the distances from water bodies were represented using continuous

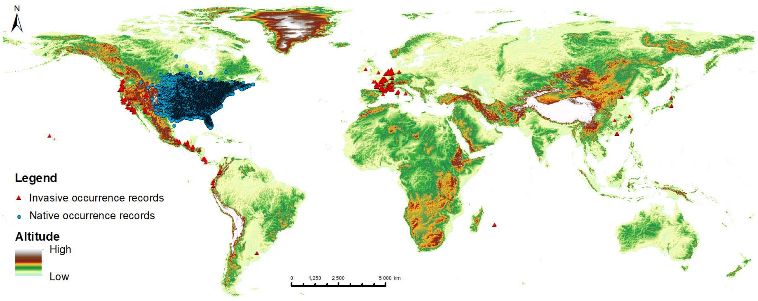

FIGURE 1
Map of global distribution of *C. serpentina*.

data. For future predictions, the Beijing Climate Center Climate System Model (BCC-CSM1-1) was employed, as it is widely utilized in the Asian region, and our primary focus is on species invasion issues in China (Dakhil et al., 2021). We selected climate and land cover variables for four "Representative Concentration Pathways" (RCPs: 2.6, 4.5, 6.0, and 8.5) for 2050 and 2070. The four RCPs represent hypothetical future greenhouse gas concentrations, ranging from low to high (van Vuuren et al., 2011). All environmental data were obtained at a high resolution of 2.5 arcminutes (equivalent to 5 km × 5 km). To avoid collinearity in our statistical models, we used Pearson's rank correlation coefficient to identify and remove highly correlated climate variables ($|r| > 0.70$) (Dormann et al., 2013). The final environmental variables incorporated into the model and subsequent analysis were Annual Mean Temperature, Mean Diurnal Range, Mean Temperature of Wettest Quarter, Annual Precipitation, Precipitation Seasonality, Precipitation of Warmest Quarter, Elevation, Water Bodies and Distance from Water Bodies.

2.2 MaxEnt model

Maximum Entropy Modeling (MaxEnt) is a useful method to simulate the potential habitat redistribution under climate change, due to high predictive accuracy and strong stability (Phillips et al., 2006; Wisz et al., 2008; West et al., 2016). Parameter optimization is critical for rigorously developing the model, as its purpose is to determine the optimal parameter combination that best represents the phenomenon of interest through finding the best fit to the data (Steele and Werndl, 2013; Jayasinghe and Kumar, 2019). We utilized the R 4.3.0 program and the kuenm package (Cobos et al., 2019) to evaluate candidate solutions on a global scale, encompassing all 31 possible combinations of the feature types (linear = l, quadratic = q, product = p, threshold = t, and hinge = h), and 10 regularization multiplier settings (0.1, 0.3, 0.6, 0.9, 1, 2, 3, 4, 5, and 6). The selection of optimal parameters for modeling hinged on three criteria: statistical significance, predictive power, and model complexity. The Partial ROC method was employed to gauge statistical significance (Peterson et al., 2008). Model performance was appraised via the omission rate (Anderson et al., 2003), whereas model complexity was ascertained by the AICc value (Warren et al., 2010). Previous research has shown that the model with the lowest AICc value (delta AICc = 0) is considered the best (Cobos et al., 2019). The final MaxEnt model's feature and regularization multiplier were selected based on the optimization process outcomes. The maximum number of background points was set to 10,000. For calibration, 70% of the occurrence records were utilized, with the remaining 30% used for model prediction evaluation. Extrapolation with clamping settings was applied, treating environmental conditions not encountered during model training as if they were at the limits of the training range. This approach holds fitted species responses at constant probabilities outside of training conditions, thereby limiting model extrapolations when projecting into novel environments (Elith et al., 2011). To ensure stable model predictions, the analysis included 10 replicate runs with cross-validation. Logistic regression was chosen as the output format, while all other parameters were set to the MaxEnt model defaults.

The predictive efficacy of the models was evaluated using the True Skill Statistic (TSS). Within the framework of species distribution models (SDMs), TSS is a threshold-dependent measure derived from sensitivity and specificity, or the probability that the model correctly predicts true presences and true absences, respectively (Allouche et al., 2006; Liu et al., 2009). TSS is extensively applied in assessing the predictions of SDMs. Interpretation of TSS values can be categorized as follows: values < 0.4 were poor, 0.4–0.8 useful, and > 0.8 good to excellent (Allouche et al., 2006). The impact of environmental variables on species distribution was assessed through percentage contribution (PC) analysis. PC is an intuitive and continuous measure of variable importance, was the most frequently reported metric (Bradie and Leung, 2017).

2.3 Classification of suitable habitats

We incorporated the results produced by MaxEnt software 3.3.4 (AMNH, New York, NY, USA) into ArcGIS 10.5 (ESRI, Redlands, CA, USA). The conversion tool was used to convert the data into raster data, and then the classification of suitable *C. serpentina* habitat was carried out using the reclassify tool. The comprehensive probability of suitable distribution regions was classified into four classes: unsuitable area ($0 \le p \le 0.1$), low-suitability area ($0.1 < p \le 0.3$), medium-suitability area ($0.3 < p \le 0.5$), and high-suitability area ($0.5 < p \le 1$) (Yan et al., 2021).

2.4 Changes in suitable habitat area

We reclassified the MaxEnt output to a binary grid using the 10th training presence logistic threshold values (1 = above the threshold; 0 = below). The 10th training presence logistic threshold categorizes fewer than 10% of the training presence locations as unsuitable area (Capinha et al., 2013). To quantify the extent of changes in *C. serpentina* habitat distributions under future climate scenarios, we utilized the binary map and Python 2.7-based geographic information system (GIS) toolkits SDMtoolbox 2.5 (Brown et al., 2017). We calculated the change in suitable habitat for *C. serpentina* in China from the present to the future. The focus is on the central, eastern and southeastern regions, as well as 19 provincial administrative regions that currently have or will have suitable habitats in the future.

3 Results

3.1 Parameter selection and model evaluation

From an initial pool of 310 candidate models, only one set of model parameters met our selection criteria. In this candidate model (regularization multiplier = 1, feature class combination = lq), the mean AUC ratio was 1.686, the partial ROC was 0, the omission rate was 0.047, and the AICc was 149045.283. The average TSS value for 10 repeated runs is 0.76 (SD = 0.002), indicating that the MaxEnt model output based on model parameters can accurately simulate the potential distribution of *C. serpentina*.

3.2 Predicted habitat area of *C. serpentina* in the current climate

On a global scale, our results showed that optimal habitats for *C. serpentina*, apart from their indigenous regions, are predominantly located in western North America, southeastern and southern South America, southern Europe, a small range of northern central and southern Africa, eastern Asia and southern of Australia and New Zealand in Oceania. (Figure 2A). In China, high and middle suitable habitats are mainly distributed in the central and eastern regions, and there are scattered low suitable habitats in the southeast region (Figure 2B). Currently, the suitable habitat for *C. serpentina* in China only accounts for 4.34% of the total area (Figure 3). However, in the specific regions we are focusing on, the proportion of suitable habitat reaches 15.05% (Figure 4). Shanghai (91.74%), Anhui (58.69%), Hubei (56.73%), Henan (47.90%) and Jiangsu (42.72%) provinces face the highest risk of *C. serpentina* invasion, then followed by Jiangxi (23.35%), Zhejiang (18.09%) and Fujian (14.77%) provinces (Table 1). The most important environmental factors affecting the distribution of *C. serpentina* were Annual Precipitation (31.5%) and Annual Mean Temperature (27.5%), then followed by Precipitation Seasonality (17.6%) and Mean Diurnal Range (11.0%). The other five environmental factors had little effect on *C. serpentina* distribution (Table 2).

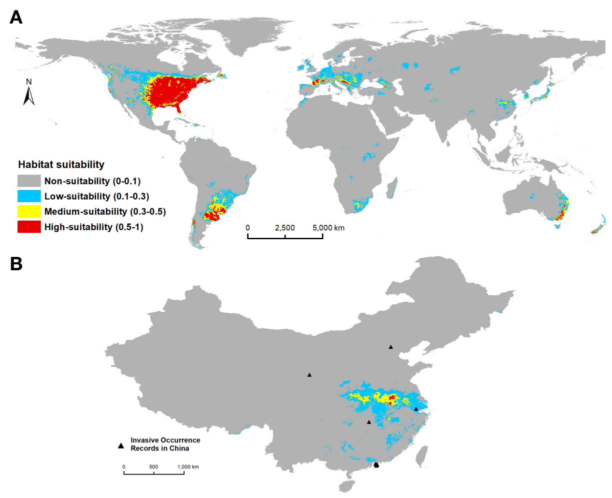

FIGURE 2
Under current climate conditions, the potential distribution area of *C. serpentina* in the world **(A)** and China **(B)**.

3.3 Effects of climate change on the habitat area of *C. serpentina* in China

Under various future climatic conditions, the potential geographic distribution range for the four climate change scenarios demonstrates a significant outward expansion. Within China, the future suitable habitat of *C. serpentina* is projected to expand by 30% to 90%, with new suitable habitat emerging in northeast China (Supplementary Figure 1). In the central, eastern, and southeastern regions of China that are the focus of our study, the changes in the area of suitable habitat align with the national scale changes. The suitable habitats in the central and eastern regions exhibit varying degrees of expansion, while there is some contraction in the southeast. In the RCPs2.6 and 4.5 scenarios, the suitable habitat in 2070 is expected to decrease to some extent compared to 2050, whereas the RCPs6.0 and 8.5 scenarios show an increase (Figure 4). Among the eight provinces with more than 10% suitable habitat, only Fujian Province is projected to experience a downward trend in the future, while the remaining seven provinces

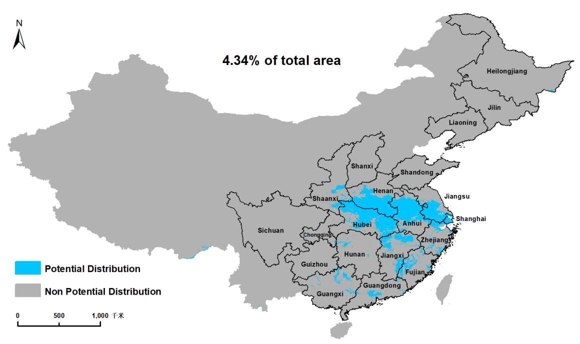

FIGURE 3
Under current climatic conditions, the binary map of potential distribution area of *C. serpentina* in China.

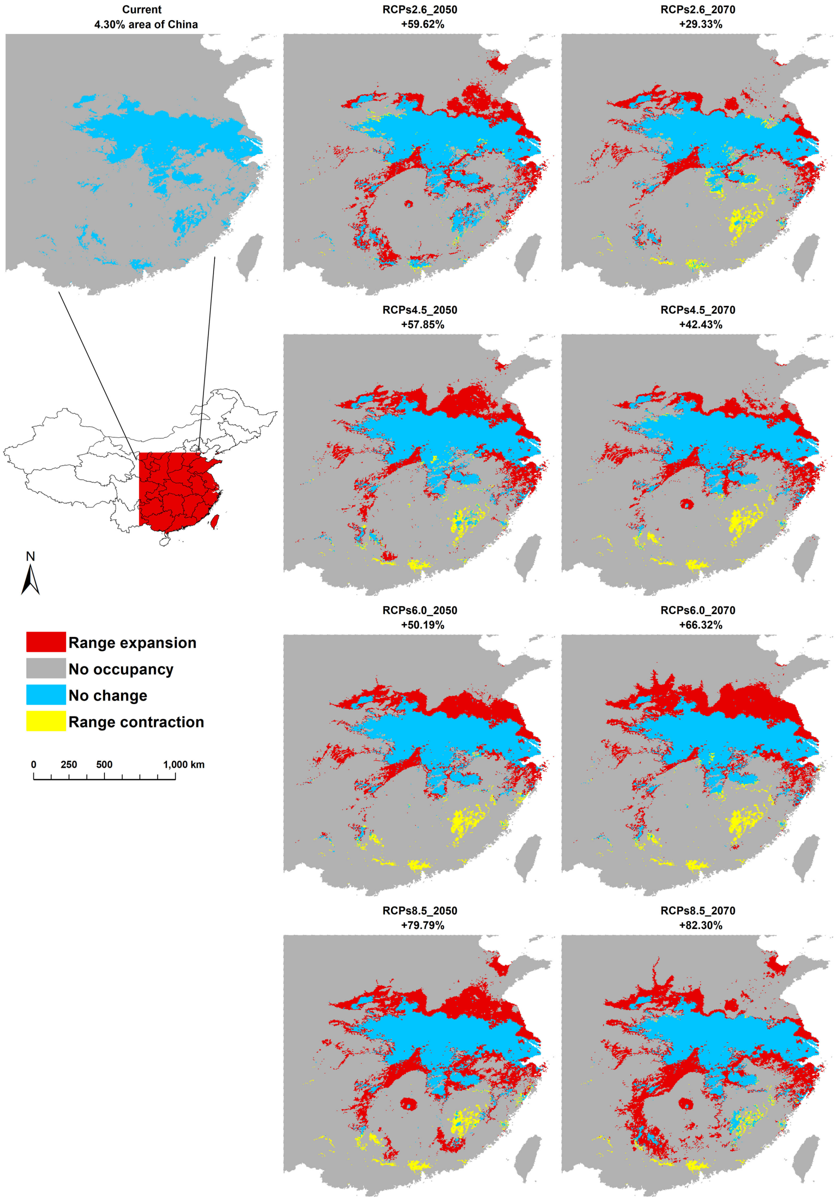

FIGURE 4
The changes in the potential distribution of *C. serpentina* in central, eastern, and southeastern China from the current conditions to 2070 under the climate scenarios of RCP2.6, RCP4.5, RCP6.0, and RCP8.5.

are expected to see an upward trend, particularly Jiangsu and Zhejiang Province, which may experience two to three times growth. Among the twelve provinces where the current proportion of suitable habitats is less than 10%, Guangdong and Guangxi will show a downward trend in some scenarios, while the remaining ten provinces will show an upward trend, especially Shaanxi and Hunan provinces, where the proportion of suitable habitats may exceed 20% in the future (Tables 1, 3).

4 Discussion

Risk maps play a crucial role in the strategic management of IAS by visually displaying potential settlement areas. The research findings indicate that, given current climate conditions, the potential invasion range of *C. serpentina* in China is relatively low. But the central, eastern, and southeastern regions of China that we are focusing on have a high risk of invasion currently and in the future. Presently, Shanghai, Anhui, Hubei, Henan, and Jiangsu provinces face a high risk of invasion, while Jiangxi, Zhejiang, and Fujian provinces have a relatively low risk. Existing research reports indicate that only the Hong Kong region in China has recorded dense wild sightings of *C. serpentina* (Sung et al., 2021). However, Hong Kong does not fall within the suitable habitat range according to our findings. Therefore, we believe that the individuals found in the region were more likely released into the wild during the captive breeding period, though this requires further field investigation. Through online information retrieval, we

TABLE 1 Share of current and 2050 C. *serpentina* habitat areas in 20 provincial administrative regions.

Province	Total area (km^2)	Current	RCPs2.6	RCPs4.5	RCPs6.0	RCPs8.5
Shanghai	6,300	91.74%	99.17% ↑	100% ↑	97.52% ↑	98.35% ↑
Anhui	139,700	58.69%	70.05% ↑	76.68% ↑	76.17% ↑	86.24% ↑
Hubei	185,900	56.73%	68.83% ↑	67.27% ↑	70.46% ↑	75.71% ↑
Henan	167,000	47.90%	60.81% ↑	77.53% ↑	75.09% ↑	77.55% ↑
Jiangsu	102,600	42.72%	87.36% ↑	85.75% ↑	95.79% ↑	94.74% ↑
Jiangxi	167,000	23.35%	35.35% ↑	21.98% ↓	23.16% ↓	36.15% ↑
Zhejiang	102,000	18.09%	48.05% ↑	60.64% ↑	44.14% ↑	54.15% ↑
Fujian	121,300	14.77%	21.09% ↑	7.56% ↓	0.57% ↓	8.68% ↓
Shaanxi	205,600	7.04%	9.00% ↑	15.07% ↑	16.95% ↑	19.80% ↑
Guangdong	180,000	5.75%	9.78% ↑	1.24% ↓	0% ↓	5.92% ↑
Guangxi	236,000	5.37%	15.83% ↑	6.76% ↑	2.71% ↓	3.95% ↓
Hunan	211,800	2.35%	13.66% ↑	12.00% ↑	11.00% ↑	21.96% ↑
Chongqing	82,300	0.88%	5.77% ↑	11.96% ↑	14.8% ↑	7.18% ↑
Guizhou	176,000	0.34%	2.63% ↑	2.63% ↑	1.82% ↑	3.77% ↑
Heilongjiang	473,000	0.24%	1.51% ↑	3.38% ↑	2.36% ↑	2.62% ↑
Shanxi	156,300	0.14%	1.45% ↑	4.02% ↑	5.60% ↑	5.90% ↑
Shandong	153,800	0.12%	15.94% ↑	17.25% ↑	6.11% ↑	20.94% ↑
Jilin	184,700	0.04%	10.46% ↑	0.12% ↑	0.17% ↑	3.45% ↑
Liaoning	145,900	0.02%	5.49% ↑	0.01% ↓	0.21% ↑	0.57% ↑
Sichan	481,400	0.02%	0.34% ↑	0.96% ↑	1.44% ↑	0.71% ↑

"↑" indicates an increase in *Chelydra serpentina* habitat share, while "↓" indicates a decrease.

discovered news reports indicating the presence of *C. serpentina* in the wild environment across all eight provinces that face a high risk of invasion. *C. serpentina* has been discovered in China for over a decade (Liu et al., 2021), but the status of its invasion in the country remains entirely unknown. It is imperative that China conducts an urgent investigation into the status of *C. serpentina* invasion.

TABLE 2 Average percentage contribution (PC) of environmental variables in MaxEnt for *C. serpentina*.

Environmental variable	PC (%)
Annual Precipitation	31.5
Annual Mean Temperature	27.5
Precipitation Seasonality	17.6
Mean Diurnal Range	11.0
Precipitation of Warmest Quarter	5.2
Distance from Water Bodies	4.2
Elevation	2.1
Mean Temperature of Wettest Quarter	0.8
Water Bodies	0

Annual precipitation and annual mean temperature are the most significant variables limiting the suitable habitat of the *C. serpentina*. Established populations of *C. serpentina* are most frequently occur in ponds, marshes, swamps, peat bogs, shallow bays, river and lake edges, and slow-moving streams (Harding and Mifsud, 1997; Ernst and Lovich, 2009; Paterson et al., 2012). The dependence on water bodies makes annual precipitation the most important factor in predicting the distribution of *C. serpentina*. Although *C. serpentina* can hibernate in soil (Brown and Brooks, 1994), or raise their body temperature by sunning their backs (Obbard and Brooks, 1979), their eggs require a hatching temperature of above 20°C to survive, and the appropriate hatching temperature can increase the survival rate of *C. serpentina* hatchlings (McKnight and Gutzke, 1993; O'Steen, 1998; Rollinson et al., 2012). Consequently, the average annual temperature is also important for the distribution of *C. serpentina*. The lack of effect of water bodies and distance from water bodies on the distribution of *C. serpentina* may be due to their extensive nesting and terrestrial migration in wetlands within their range to cope with extreme conditions such as drought (Steen et al., 2010), leading to a lower dependency on water bodies. Another explanation lies in the fact that climate variables can directly provide mechanisms and physiological explanations for species distribution, but land cover are supposed to have little direct

TABLE 3 Share of current and 2070 *C. serpentina* habitat areas in 20 provincial administrative regions.

Province	Total area (km^2)	Current	RCPs2.6	RCPs4.5	RCPs6.0	RCPs8.5
Shanghai	6,300	91.74%	100% ↑	99.72% ↑	97.80% ↑	100% ↑
Anhui	139,700	58.69%	64.79% ↑	77.18% ↑	80.57% ↑	77.73% ↑
Hubei	185,900	56.73%	68.83% ↑	71.98% ↑	68.25% ↑	76.55% ↑
Henan	167,000	47.9%	65.48% ↑	66.15% ↑	85.32% ↑	71.04% ↑
Jiangsu	102,600	42.72%	58.12% ↑	77.45% ↑	99.16% ↑	60.50% ↑
Jiangxi	167,000	23.35%	15.35% ↓	23.75% ↑	17.61% ↓	35.87% ↑
Zhejiang	102,000	18.09%	44.87% ↑	56.49% ↑	49.25% ↑	63.33% ↑
Fujian	121,300	14.77%	3.07% ↓	1.94% ↓	1.71% ↓	6.31% ↓
Shaanxi	205,600	7.04%	16.89% ↑	11.62% ↑	26.37% ↑	24.05% ↑
Guangdong	180,000	5.75%	0.95% ↓	0% ↓	0.74% ↓	4.88% ↓
Guangxi	236,000	5.37%	6.50% ↑	1.35% ↓	2.98% ↓	16.91% ↑
Hunan	211,800	2.35%	8.16% ↑	12.25% ↑	8.32% ↑	28.91% ↑
Chongqing	82,300	0.88%	10.36% ↑	15.77% ↑	10.63% ↑	14.68% ↑
Guizhou	176,000	0.34%	1.13% ↑	1.82% ↑	2.65% ↑	10.08% ↑
Heilongjiang	473,000	0.24%	1.55% ↑	4.74% ↑	6.57% ↑	2.49% ↑
Shanxi	156,300	0.14%	3.61% ↑	2.99% ↑	13.81% ↑	9.93% ↑
Shandong	153,800	0.12%	2.95% ↑	2.58% ↑	22.62% ↑	10.04% ↑
Jilin	184,700	0.04%	0.29% ↑	5.79% ↑	4.08% ↑	5.09% ↑
Liaoning	145,900	0.02%	0.08% ↑	0.57% ↑	0.19% ↑	9.98% ↑
Sichan	481,400	0.02%	1.23% ↑	1.44% ↑	0.99% ↑	1.08% ↑

"↑" indicates an increase in *Chelydra serpentina* habitat share, while "↓" indicates a decrease.

physiological relevance for species (Guisan and Zimmermann, 2000; Pearson and Dawson, 2003). Because land cover can only be applied within limited geographical ranges without significant errors, as the same land cover type can correspond to different climate combinations in different regions or time periods (Guisan and Zimmermann, 2000). Hence, the distribution of a species at the continental scale primarily depends on its climate tolerance rather than the type of land cover (Pearson and Dawson, 2003; Thuiller et al., 2004).

Climate change is expected to cause the expansion of suitable habitats in all scenarios. The suitable habitat shows a pattern of significant initial increase with the intensity of climate change, followed by a slight decrease, and ultimately increasing again. The central and eastern regions' suitable habitats will significantly expand toward the north and south. Among the eight provinces currently facing higher risk, except for Fujian Province, the other seven provinces will indeed face even more severe invasion risks in the future. The suitable habitats in Shaanxi and Hunan provinces may account for more than 20% in the future. We strongly recommend the establishment of long-term monitoring plans for *C. serpentina* in Shaanxi, Hunan, and the eight provinces currently facing higher risk.

Turtles, symbolizing luck and longevity in Chinese culture, are popular as pets and extensively used for food and traditional medicine (Cheung and Dudgeon, 2006; Zhou and Jiang, 2008). The turtle farming industry in China has seen rapid expansion since the 1990s to meet this significant demand (Wu et al., 2020). Freshwater turtles, especially favored in the pet trade, are frequently abandoned by their owners or intentionally released into the wild during religious events, potentially leading to their establishment in new habitats (Perry et al., 2007; Masin et al., 2014). Despite being a relatively species-poor order, turtles have been introduced more frequently than any other reptiles (Kraus, 2009). The worldwide pet trade has documented at least 61 species of chelonians (Gong et al., 2009). In the Chinese turtle trade market, alien species constitute approximately 67.05% (Hong et al., 2022). As per 2023 data, 43 species of the order Testudines inhabit China, including 39 native and 4 invasive alien species (Ji, 2023). China's rapidly developing e-commerce industry is facilitating the purchase and release of potential invasive turtle species within the country (Liu et al., 2021). Among the eight provinces currently facing higher risk of invasion, except for Jiangxi Province, the Gross Domestic Product (GDP) of the other seven provinces ranks within the top ten in China, and their developed economy will further promote the establishment of IAS (Gallardo, 2014). Moreover, turtle farms are heavily concentrated in the provinces of Zhejiang, Jiangsu, and Guangdong within these regions (Zhou and Huang, 2007), which heightens the risk of species escaping. The existence of irrigation channels could further aid the dispersal of this specie to more remote areas (Alles et al., 2022). In conclusion, human activities are likely to increase the chances of *C. serpentina* establishing stable populations in their suitable habitats.

According to the Convention on Biological Diversity, which establishes a "three-stage hierarchical approach," priority should be given to prevention in high-suitability areas where the species has not yet been recorded (UNEP Mittermeier, 2002). Given the limited knowledge we currently have about the extent of *C. serpentina* invasion in China, it is essential to prioritize monitoring efforts in the areas indicated by our risk map. Citizen science, which involves public participation in data collection and analysis, has proven to be an effective approach for monitoring biological invasions and detecting IAS at an early stage (Kalaentzis et al., 2023). Although the unique shape traits of *C. serpentina* make it easier to identify in the wild (Ernst and Lovich, 2009), underwater observation can still be challenging. A solution to this challenge is the use of environmental DNA (eDNA) technology, which detects genetic material from the organisms' surroundings (Kelly et al., 2014). By combining citizen science engagement with a simple eDNA sampling toolkit, public awareness of invasive organisms such as *C. serpentina* can be increased, and the efficiency of scientific monitoring can be greatly improved (Zhang et al., 2023). Using trained dogs to detect *C. serpentina* through olfaction would be an efficient investigation method (Kapfer et al., 2012). During May-August of the year and in the morning and afternoon of the day, *C. serpentina* is the most active period and the best time to investigate (Obbard and Brooks, 1981). The primary area of investigation is the surrounding vicinity of a permanent body of water (Graves and Anderson, 1987).

For government agencies, effectively managing invasive species from a legal and enforcement perspective is crucial. In America, *C. serpentina* lacks endangered species classification yet faces significant threat from unprecedented harvesting meeting international market demands. In response to the over-commercial harvest and the resulting decline in *C. serpentina* populations, certain states in the United States have already taken steps to ban this practice (Colteaux and Johnson, 2017). *C. serpentina* was listed in the Appendix II of the Washington Convention (CITES, Convention on International Trade in Endangered Species) in 2023. The illegal possession and trafficking of these animals will be punished under the Chinese Wildlife Protection Law. However, the specific implementation of the law is still being explored, especially given the challenges posed by China's large market for this species.

The reliability of extrapolating SDMs to new ranges and future climates has been extensively debated (Sequeira et al., 2018). One important factor influencing the model's ability to extrapolate is the number of occurrences used in model calibration. In our study, we utilized 7,897 occurrence data for model calibration. This abundance of occurrence data helps mitigate the influence of outliers during model calibration (Guisan and Thuiller, 2005). We studied a species that has a very wide distribution in North America, and the wide range and many native occurrence data mean that *C. serpentina* live in a wider range of climates, resulting in a relatively large native niche and a more conservative niche than specialist species (Li et al., 2014; Liu et al., 2020). The conservatism of the climate niche in *C. serpentina* enhances the reliability of our results when extrapolating the calibrated model to new ranges (Liu et al., 2020). Despite the limitations of SDMs (Pearson and Dawson, 2003; Record et al., 2018), this method remains one of the most promising tools for predicting the potential distribution of invasive species (Bellard et al., 2013; Hill et al., 2017), which is a fundamental objective of conservation biology (Jeschke and Strayer, 2008).

In addition to the controversy over model extrapolation, there are some limitations to our simulation results. We did not consider source populations, biotic interactions, and the dispersal capacity and pathway of *C. serpentina*. The species has multiple geographic lineages within its native rang (Iverson et al., 1997; Ewert et al., 2005), and if the environmental tolerances of these geographic lineages differ, the introduced population may only occupy a portion of the entire niche (Jeschke and Strayer, 2008; Tingley et al., 2016). As we do not know which geographic lineages were introduced to China, we may have overestimated the suitable habitat for *C. serpentina* in China. Biotic interactions, such as competition and predation, directly influence the distribution of species at a local scale (Jeschke and Strayer, 2008; Yates et al., 2018). Our results can only be interpreted as suitable habitats under abiotic environmental factors. The dispersal capacity and pathway of invasive species significantly affect the scope and speed of invasion (Hulme, 2009). As *C. serpentina* has weak dispersal abilities (Obbard and Brooks, 1981), releasing them into the wild is likely the primary way they spread in China (Liu et al., 2021; Sung et al., 2021). Therefore, it is crucial to consider local customs and habits when investigating their distribution. The occurrence data we used on a global scale comes from the GBIF database, which has spatial bias that is challenging to eliminate, even when carrying out spatial sparsity processing (Beck et al., 2014). Furthermore, there are several inherent limitations to using presence-only data (Yackulic et al., 2013).

5 Conclusion

Our modeling indicates that suitable habitats for *C. serpentina* are currently concentrated in central, eastern, and southeastern China, with Shanghai, Anhui, Hubei, Henan and Jiangsu provinces facing the highest risk of invasion. Climate change may substantially expand future suitable areas, and multiple provinces will face a more severe threat of invasion. To prevent the establishment and spread of *C. serpentina*, we urgently recommend implementing monitoring programs that leverage the integration of citizen science, eDNA technology, and other methods, particularly in high-risk regions. Moreover, the government should address legal and enforcement challenges associated with the trade of this species. While our modeling has some inherent limitations, it nonetheless offers valuable scientific support for managing *C. serpentina* invasion in China. Further research incorporating source populations, biotic interactions and dispersal abilities would provide greater insight into the invasion dynamics of this generalist turtle species. Actively preventing and early detecting *C. serpentina* is of paramount importance for the conservation of China's freshwater ecosystems.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://doi.org/10.15468/dl.rvmyvk.

Ethics statement

Ethical approval was not required for the study involving animals in accordance with the local legislation and institutional requirements because, although we conducted research on vertebrates, we only obtained occurrence data and analyzed it through databases. We did not conduct animal experiments nor had direct contact with animals.

Author contributions

CM: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. PL: Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

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Conflict of interest

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

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2023.1277058/full#supplementary-material

SUPPLEMENTARY FIGURE 1
Changes in the potential distribution of *C. serpentina* in China from the current conditions to the 2070 under the climate scenarios of RCP2.6, RCP4.5, RCP6.0, and RCP8.5.

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