



## Global invasion risk assessment of *Lantana camara*, a highly invasive weed, under future environmental change

Pradeep Adhikari<sup>a,1</sup>, Yong Ho Lee<sup>a,b,1</sup>, Prabhat Adhikari<sup>c</sup>, Anil Poudel<sup>c</sup>,  
Sue Hyuen Choi<sup>c</sup>, Ji Yeon Yun<sup>c</sup>, Do-Hun Lee<sup>d</sup>, Yong-Soon Park<sup>e,f,\*</sup>,  
Sun Hee Hong<sup>c,\*\*</sup>

<sup>a</sup> Institute of Humanities and Ecology Consensus Resilience Lab, Hankyong National University, Anseong 17579, Republic of Korea

<sup>b</sup> OJeong Resilience Institute, Korea University, Seoul 02841, Republic of Korea

<sup>c</sup> School of Plant Science and Landscape Architecture, College of Agriculture and Life Sciences, Hankyong National University, Anseong 17579, Republic of Korea

<sup>d</sup> National Institute of Ecology, Seocheon-gun 33657, Republic of Korea

<sup>e</sup> Department of Plant Resources, College of Industrial Sciences, Kongju National University, Yesan 32439, Republic of Korea

<sup>f</sup> Agricultural and Fisheries Life Science Research Institute, College of Industrial Sciences, Kongju National University, Yesan 32439, Republic of Korea

### ARTICLE INFO

#### Keywords:

Climate change  
Random forest model  
Invasion  
*Lantana camara*  
Species distribution model  
Suitable habitat

### ABSTRACT

Invasion risk assessments are essential for making informed decisions, allocating resources, and implementing targeted strategies to prevent or minimize the harmful effects of invasive species on native biodiversity, agricultural productivity, and natural ecosystems. In this study, the random forest algorithm was used to assess the spatial invasion risk of *Lantana camara*, one of the world's top 100 worst invasive weeds, across all continents under current and future environmental conditions. The current invasion risk was relatively high on four continents (i.e., Africa, Australia, Oceania, and South America) within approximately 35°N and 35°S latitude, estimated to cover at least 68.98 % of the total land surface. Furthermore, projections for future environmental changes suggested a substantial increase in invasion risk across all continents, with the most significant changes (251.52 %) observed in Europe compared with current invasion levels. Additionally, invasion risk was predicted to extend beyond 35°N latitude. Categorizing 200 countries and territories into distinct risk levels, 27 countries had current invasion potential, and introduction and establishment was predicted in 114 countries. Moreover, at least 45 countries, including Canada, India, Italy, and United States, were projected to transition from no or low invasion risk to high invasion risk and 28 countries had a risk increase of over 50 %. Current study provides valuable insights into the global invasion risk posed by *L. camara*. These results are expected to be of great utility for invasive weed management, facilitating the development of control and sustainable management strategies for this notorious weed at both global and local scales.

\* Corresponding author at: Department of Plant Resources, College of Industrial Sciences, Kongju National University, Yesan 32439, Republic of Korea.

\*\* Corresponding author.

E-mail addresses: [yspark2005@kongju.ac.kr](mailto:yspark2005@kongju.ac.kr) (Y.-S. Park), [shhong@hknu.ac.kr](mailto:shhong@hknu.ac.kr) (S.H. Hong).

<sup>1</sup> These authors contributed equally to this work.

<https://doi.org/10.1016/j.gecco.2024.e03212>

Received 28 May 2024; Received in revised form 12 September 2024; Accepted 22 September 2024

Available online 24 September 2024

2351-9894/© 2024 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

## 1. Introduction

Invasive weeds are non-native plant species that are introduced into novel ecosystems, either intentionally or inadvertently. They pose a significant threat to natural ecosystems, agricultural productivity, and ecosystem services, leading to trophic imbalances and resulting in substantial economic losses worldwide (Diez et al., 2012; IPBES, 2023). Global annual costs of biological invasions are estimated to exceed USD 423 billion per year (IPBES, 2023).

A global assessment reported the introduction of more than 37,000 alien species in various regions and biomes up to 2023, including the globally-recognized list of the 100 worst invasive species (IPBES, 2023; van der Weijden et al., 2007). Of note among these species, *Lantana camara* belongs to the family *Verbenaceae* and a perennial and notorious weed native to tropical Central and Southern America (Lowe et al., 2000; Thomas, 2022).

*L. camara* is an aggressive and fast-growing plant that can thrive in a wide range of soil types, including saline to acidic and fertile or infertile soils (Sharma et al., 2005; Thomas, 2022). In Australia, India, and South Africa, the weed covers millions of hectares of land (Bhagwat et al., 2012). Global climate change can exacerbate the threats of invasive weeds by creating more favorable conditions for their growth and reproduction. Invasive weeds often have traits that enable survival under extreme climatic conditions, including prolonged heat waves, heavy rainfall, and excessive drought (Diez et al., 2012; Weiskopf et al., 2020). These traits can confer a competitive advantage over native plants, allowing invasive weeds to spread rapidly (Adhikari et al., 2019). Similarly, modern advances in trade, transportation, and landscape connectivity accelerate human movement, facilitating the introduction and invasion of alien weeds into new geographical regions (Adhikari et al., 2019; Weiskopf et al., 2020). Therefore, the introduction, establishment, and spread of invasive weeds as a result of climate change and anthropogenic land cover changes are important issues (IUCN, 2021; Williams et al., 2015).

*L. camara* populations are expected to spread in response to future climate change. The species is projected to expand by up to 65 % in South Africa, China, India, and Zimbabwe by 2070 (Ncube et al., 2020; Taylor et al., 2012; Tiwari et al., 2022). To effectively manage the risks associated with this proliferation (i.e., to implement robust quarantine measures and establish plans for early detection and eradication), information about the distribution and abundance of the species under current and future climate scenarios is needed (Adhikari et al., 2023b). In this context, species distribution models (SDMs) serve as valuable tools to predict the spatial and quantitative distribution of invasive weeds with spatially explicit data for climate and anthropogenic disturbance (Elith and Leathwick, 2009; Peterson et al., 2011; Tiwari et al., 2022).

Among various algorithms employed in SDMs, the random forest (RF) algorithm has high classification accuracy and robustness; it creates multiple decision tree models and combines their predictions to yield a reliable outcome (Cutler et al., 2007). The RF excels in handling complex interactions between species occurrences and environmental variables, such as temperature, precipitation, land cover, and topography, making it suitable for modeling the potential distribution of invasive weeds in new geographical areas (Adhikari et al., 2023b; Cutler et al., 2007; Zhang et al., 2020).

We previously assessed the prediction accuracy of five SDMs using a multi-species approach, revealing that the RF model provided the most accurate predictions for assessing spatial risk of ecosystem-disturbing alien plants in South Korea (Adhikari et al., 2022c). Subsequently, applying the RF model, we found that future climate change is likely to increase the invasion risk of *Parthenium hysterophorus*, one of the world's 100 worst invasive weeds, across South Korea (Adhikari et al., 2023a). Many other studies have performed SDM-based invasion risk assessment and predicted biological invasion in South Korea (Adhikari et al., 2019; Adhikari et al., 2022a; Adhikari et al., 2021; Lee et al., 2022; Hong et al., 2021). Collectively, these studies suggest that the risk of invasion by various alien species in South Korea is high under future climate change (Adhikari et al., 2019; Adhikari et al., 2022a; Adhikari et al., 2021; Lee et al., 2022; Hong et al., 2021). Furthermore, a global assessment of the invasion risk posed by *Chromolaena odorata*, another highly invasive weed, revealed a substantial expansion in new habitats, with potential new introductions in 15 countries, including Gambia, Guinea-Bissau, and Lesotho, between 2061 and 2080 (Adhikari et al., 2023b).

Integrating of bioclimatic variables with other environmental factors, such as land use change, latitude, and biome shifts, enhances the precision, relevance, and practicality of SDMs (Andersen et al., 2022; Tang and Zhao, 2022). However, a prior research has often focused on a single factor, predominantly centered around climate change, while overlooking significant variables, such as biomes (Titeux et al., 2016). Biomes delineate unique ecological regions defined by specific combinations of climate, vegetation, and geography (Franklin, 1995). They play a pivotal role in identifying suitable habitats for invasive species and informing invasion pathways within models. Therefore, this study aimed to combine biome information with bioclimatic variables for SDMs of *L. camara*, with the following key objectives: (1) assessing model performance through a comparison of SDMs with and without biome variables using RF modeling, (2) projecting current and future potential habitats of *L. camara* worldwide, and (3) evaluating invasion risk by categorizing countries into distinct risk levels.

Furthermore, based on our current understanding, this is the first study to introduce various risk categories using the SDM approach for the classification of countries based on the *L. camara* invasion risk. This research provides valuable insights for the control and management of one of the world's most notorious invasive weeds, underscoring the significance of collaborative efforts on a global scale.

## 2. Materials and methods

### 2.1. Global species occurrence data

The open access data source GBIF ([www.gbif.org](http://www.gbif.org), accessed on July 01, 2023) was utilized to download global occurrence records

for *L. camara*, a total of 67,264 data points. GBIF may include species occurrence records from non-systematic observations, such as museum collections, administrative records, and citizen science initiatives (Moudry and Devillers, 2020). Information from these sources can be subject to various errors related to observation, collection, processing, and recording (Moudry and Devillers, 2020; Zarzo-Arias et al., 2022). To address these potential issues, we conducted manual checks of the data. We removed data points recorded prior to 1970, along with improper data sources, points lacking reporting dates, and points in unlikely geographical locations, such as the sea, desert, and polar regions, resulting in the removal of 3427 points. The final validation of the data points was performed by an expert with extensive knowledge on *L. camara*, having worked with this species for long time.

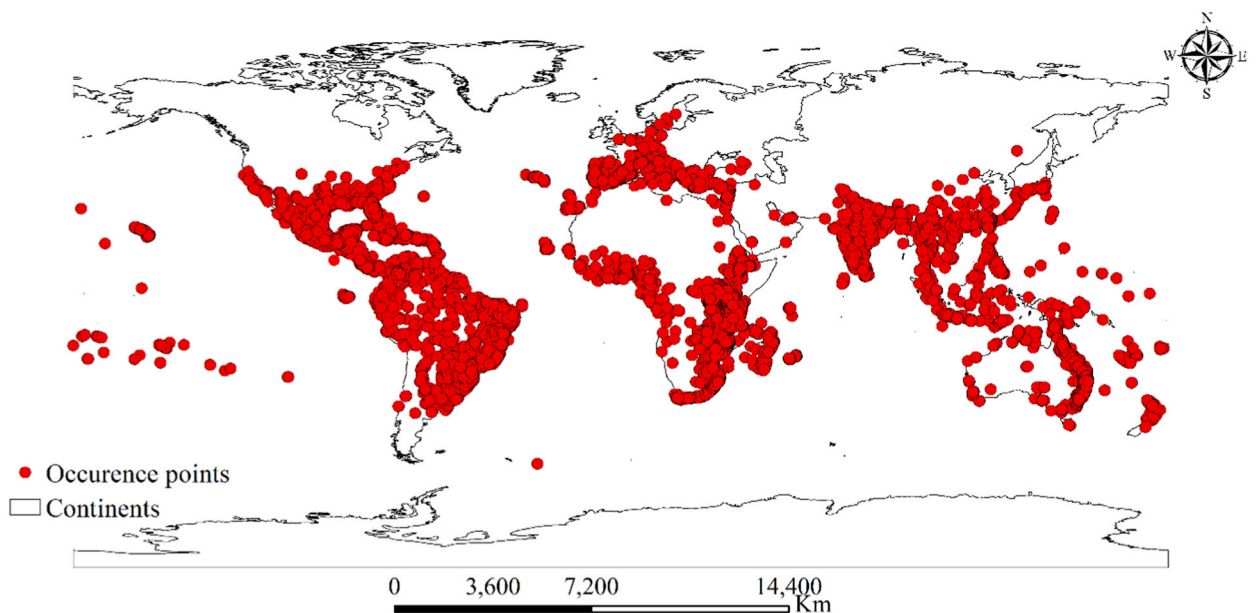
The remaining species occurrence points underwent a process of rarefaction at various resolutions (e.g., 1, 5, 10, 20, and 50 km). This rarefaction aimed to eliminate multiple occurrences of the same species within a given grid. The spatial rarefaction procedure was conducted using the ArcGIS SDM toolbox version 2.4 (Brown et al., 2017) to prevent issues like overfitting and inaccurate inflation of model outcomes arising from spatial autocorrelation (Boria et al., 2014). Ultimately, five distinct sets of rarified species occurrence points were obtained, with 27,501 points for a distance of 1 km, 14,005 points for 5 km, 9347 points for 10 km, 5905 points for 20 km (Fig. 1), and 2,952 points for 50 km (Table 1). These rarified datasets, alongside the initial species occurrence records downloaded from GBIF, were employed in the RF modeling of *L. camara*.

## 2.2. Environmental data

Environmental variables, including bioclimatic and biome variables, play a crucial role in the invasion of weeds. For instance, the 19 bioclimatic variables derived from temperature and precipitation data in the WorldClim dataset have a direct impact on the establishment and growth of invasive weeds (Allen et al., 2014). These variables determine the suitability of new regions for invasive species. Therefore, the 19 bioclimatic variables were downloaded based on historical data from 1970 to 2000 sourced from WorldClim v2.1, with a spatial resolution of 2.5 minutes, roughly equivalent to 4.5 km at the equator (Fick and Hijmans, 2017). Likewise, future bioclimatic variables were obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) through the WorldClim data portal, also at a 2.5-minute resolution (Eyring et al., 2016). Two shared socioeconomic pathway (SSP) scenarios, namely SSP2–4.5 and SSP5–8.5, were used to depict the future bioclimatic variables under climatic conditions for 2061–2080. The SSP scenarios represent a range of plausible future conditions based on GHG emissions and different combinations of socioeconomic factors, including population growth, economic development, technological advancements, and governance structures (Riahi et al., 2017). SSP2–4.5 is intermediate and SSP5–8.5 represents very high GHG emissions, estimated to raise the global temperature by 2.1–4.3°C and 3.8–7.4°C, respectively, relative to estimates for 1880–1900 by 2090–2100 (Eyring et al., 2016).

The bioclimatic variables were developed under the global circulation model MPI-ESM1–2-HR (Max Planck Institute Earth System Model version 1.2 - High Resolution), a cutting-edge global climate model developed by the Max Planck Institute for Meteorology in Germany (Müller et al., 2018). As a part of the Earth System Model family, it offers a comprehensive simulation of Earth's interconnected climate components, including the atmosphere, oceans, land surfaces, and sea ice, with high-resolution predictions of the seasonal climate over decades (Reick et al., 2013). The bioclimatic variables are predictors of future distributions of species.

A global biome is a major terrestrial ecosystem or ecoregion; it refers to a large-scale biological community characterized by



**Fig. 1.** Global occurrence records of *Lantana camara* ( $n = 5905$ ). Red points indicate occurrence points of *L. camara*. The map was generated using ArcGIS Desktop 10.8 (<https://desktop.arcgis.com>).

**Table 1**

Average predictive performance of random forest models of *Lantana camara* with and without biome variables under the current and future climate change scenarios.

Resolution to rarify (km)	Presence Points	Without biome				With biome			
		AUC	TSS	Kappa	TAI <sup>a</sup>	AUC	TSS	Kappa	TAI <sup>a</sup>
No rarifying	63,837	0.662	0.512	0.301	0.492	0.667	0.553	0.345	0.522
1 km	27,501	0.734	0.512	0.404	0.550	0.701	0.561	0.425	0.562
5 km	14,005	0.711	0.682	0.461	0.618	0.726	0.701	0.524	0.650
10 km	9347	0.88	0.646	0.511	0.679	0.812	0.704	0.563	0.693
<b>20 km</b>	<b>5905</b>	<b>0.881</b>	<b>0.705</b>	<b>0.561</b>	<b>0.716</b>	<b>0.935</b>	<b>0.802</b>	<b>0.679</b>	<b>0.805</b>
50 km	2952	0.859	0.646	0.571	0.692	0.852	0.731	0.612	0.732

<sup>a</sup> Total accuracy index (TAI) was estimated by averaging AUC, TSS, and Kappa values. The AUC, TSS, and Kappa values shown in Table 1 are average values of model performance under the current and future climate change (SSP2–4.5 and SSP5–8.5) by 2061–2080.

distinct climatic conditions, vegetation types, and ecological features (Conradi et al., 2020). Examples of global biomes include tropical rainforests, deserts, grasslands, temperate forests, and tundra regions. Biomes directly influence the success and spread of invasive weeds, allowing predictions of their establishment and spread (van Wilgen et al., 2008). Therefore, biomes are essential variables for species distribution modeling of weeds. In this study, we integrated biomes and bioclimatic variables for modeling *L. camara* distributions.

Pearson's correlation coefficients were used to evaluate relationships between 19 bioclimatic WorldClim variables and biome (Table S1) using the PROC CORR function of SAS 9.4 (SAS Institute, Inc., Cary, NC, USA), as described previously (Adhikari et al., 2022b; Shin et al., 2018). Six of the 19 bioclimatic variables, annual mean temperature (Bio1), mean diurnal temperature range (Bio2), isothermality (Bio3), annual precipitation (Bio12), precipitation in the wettest month (Bio13), precipitation in the driest month (Bio14), and biome (Table 2), were chosen for further analyses based on low correlations with one another ( $r \leq 0.75$ ; Table S1).

### 2.3. Model development

Twelve sets of RF models were established using six sets of species occurrence points (e.g., no rarefaction and rarefaction at 1, 5, 10, 20, and 50 km resolutions) and two sets of input variables, including bioclimatic variables with or without biome. Species distribution modeling of *L. camara* with RF was performed using the Biomod2 package, version 4.2–4 (Thuiller et al., 2023). The species occurrence records and selected bioclimatic variables and biome were imported into the R environment. Identifying species absence points for invasive weeds is difficult because habitats are likely expanding and species distributions may be in an equilibrium state (Jiménez-Valverde et al., 2011). Therefore, use of background points (pseudo-absence points) within the study area can provide reliable distribution models (Barbet-Massin et al., 2012). There were various approaches for selecting background points including random selection, environmentally stratified sampling, geographic filtering, Bias-adjusted random sampling, Spatial weighting, Minimum convex polygon, and Ensemble approach (Barbet-Massin et al., 2012; Steen et al., 2024; Whitford et al., 2024). In this study, we randomly selected background points and the model fitted with a large number of pseudo-absences but equally weighted to the presence points as suggested by (Barbet-Massin et al., 2012), and employed in several earlier studies (Adhikari et al., 2023b; Jeon et al., 2020). All the background points within the study area were selected using ArcGIS 10.8.

The species occurrence data for *L. camara* were split into two random subsets: 75 % for model calibration and 25 % for model validation (Araujo and Guisan, 2006; Kim et al., 2021). Alternative model configurations were executed using default settings, and the model was replicated 10 times, following previously described methods (Adhikari et al., 2020; Adhikari et al., 2022a).

### 2.4. Model evaluation and validation

Model performance under the current and future climate change (SSP2–4.5 and SSP5–8.5) was evaluated using three statistical parameters: the area under the receiver operating characteristic curve (AUC) (Pearson, 2010), true skill statistic (TSS) (Allouche et al., 2006), and Kappa coefficient. The AUC can be used to distinguish between presence and absence points independently of predefined thresholds; the score ranges between 0 and 1 (Thuiller et al., 2005). Although the AUC is independent of the dataset size, it treats errors

**Table 2**

Bioclimatic variables selected for modeling *Lantana camara* distributions.

Code	Description	Unit	Model contribution (%)
Bio1	Annual mean temperature	°C	21.53
Bio2	Mean diurnal temperature range	°C	0.71
Bio3	Isothermality (BIO2/BIO7) ( $\times 100$ )	%	11.01
Bio12	Annual precipitation	mm	30.86
Bio13	Precipitation in the wettest month	mm	3.10
Bio14	Precipitation in the driest month	mm	0.63
Biome	Biome	-	32.16

of commission and omission with equal importance and may not consistently assess prediction accuracy (Lobo et al., 2008). Notably, when the habitat extends beyond the species occurrence range, the AUC score can be high, potentially leading to overfitting (Adhikari et al., 2018; Lobo et al., 2008).

The TSS accounts for specificity and sensitivity and takes values from  $-1$  to  $+1$  (Allouche et al., 2006). It is a valuable tool for evaluating model accuracy, as it considers both omission and commission errors. Similarly, the Kappa coefficient assesses the ratio of correctly predicted observations to erroneous ones. It also ranges from  $-1$  (indicating poor agreement) to  $+1$  (representing perfect prediction) (Allouche et al., 2006; Monserud and Leemans, 1992). Higher scores for these parameters indicate a better model performance. The use of these complementary metrics improves our understanding of the reliability and effectiveness of models.

### 2.5. Estimation of the total accuracy index for model selection

The average values of AUC, TSS, and Kappa under the current climate and future climate change scenarios SSP2–4.5 and SSP5–8.5 were estimated. Similarly, the total accuracy index (TAI) of each RF model was estimated based on the average of three evaluation parameters: AUC, TSS, and Kappa. The TAI was used to select the best model among the 12 sets of RF models built from different input variables and occurrence points. The selected model was then used to predict the global spatial distribution of *L. camara* and for a risk assessment.

### 2.6. Global invasion risk assessment of *L. camara*

RF modeling results were used to generate binary distribution maps of *L. camara*, applying the TSS threshold defined in the Bio-mod2 package (Thuiller et al., 2023). This analysis considered both current and future climate change scenarios (SSP2–4.5 and SSP5–8.5) for the period between 2061 and 2080. The resulting global binary distribution maps identify habitats as either suitable or unsuitable for *L. camara*. The number of suitable habitat cells, representing areas of potential *L. camara* invasion, was estimated for each continent and country worldwide using zonal statistics tools in ArcGIS Desktop 10.8 (Esri, Redlands, CA, USA). Subsequently, the changes in the extent of the spatial invasion risk from 2061 to 2080 compared with the current potential invasion risk were evaluated under SSP2–4.5 and SSP5–8.5.

The current and future invasion risk of *L. camara* was assessed for 200 countries and territories based on average habitat suitability, categorized into five groups: no invasion risk, potential invasion risk, stable invasion risk, invasion risk change I, and invasion risk change II. Countries within *L. camara*'s native range (South and Central Americas and the Caribbean regions) and areas predicted to be climatically unsuitable were classified as having no invasion risk. Countries lacking current occurrence records but predicted to be climatically suitable for *L. camara* invasion under the current climate were assigned to the potential invasion risk category. Countries where the mean habitat suitability remained unchanged between 1970–2000 and 2061–2080 were classified as having stable invasion risk. "Invasion risk change I" denotes a transition from no risk to low risk (up to 50 % invasion), while "Invasion risk change II" indicates a shift from low risk to high risk (invasion exceeding 50 %).

## 3. Results

### 3.1. High relative importance of biome, annual mean temperature, and annual precipitation in RF models of *L. camara*

Based on Pearson's correlation coefficients ( $r \leq 0.75$ ), we selected three temperature-related variables (Bio01, Bio2, and Bio03), three precipitation-related variables (Bio12, Bio13, and Bio14), and biome for the modeling of *L. camara* distributions using the RF algorithm (Table 2). In a comparison of these seven variables for the current (1970–2000) and future time periods (2061–2080), biome, Bio12, and Bio1 had the highest relative contributions to the model fit, explaining 32.16 %, 30.86 %, and 21.53 % of the total variance, respectively (Table 2). Accordingly, these three parameters (biome, Bio1, and Bio12) have distinct effects and are important determinants of the distribution of *L. camara* under the current and future climate change.

### 3.2. Species occurrence records at 20 km resolution with bioclimatic variables and biome provided the best predictive performance for *L. camara*

The performance of 12 sets of RF models built using various rarified species occurrence data and input variables for *L. camara* was evaluated based on the TAI. The model utilizing species occurrence records rarified at a 20 km resolution with both biome and bioclimatic variables as inputs exhibited the highest TAI (i.e., 0.805) (Table 1). This model had the highest predictive performance among the RF models for the global spatial distribution of *L. camara*. Using the test dataset, the AUC, TSS, and Kappa values for this RF model were 0.935, 0.802, and 0.679, respectively (Table 1), indicating an excellent model performance and strong agreement between the observations and predictions.

### 3.3. High current risk of invasion in Africa, Australia, Oceania, and South America

The global invasion risk of *L. camara* between 1970 and 2000 considering the current climate is presented in Fig. 2. Under current conditions, areas with a high invasion risk of *L. camara* were primarily concentrated in the Southern Hemisphere and at approximately 35° north and 35° south latitudes. However, an invasion risk was also predicted for areas in Europe beyond this range. The current

invasion risk of *L. camara* was estimated to cover 2709,165 cells, encompassing 22.19 % of the global land surface (Table S2). Four continents, namely Africa, Australia, Oceania, and South America, had a high risk of invasion by *L. camara*, estimated to cover 79.83 %, 68.98 %, 78.27 %, and 88.26 % of their respective land areas. Other continents, such as Asia (E.g., India, Indonesia, Malaysia, Thailand, Sri Lanka, and Nepal), Europe (e.g., France, Greece, Italy, Portugal, and Spain), North America (e.g., Mexico and United States), and Antarctica, had lower risks of invasion, covering only up to 10.41 % (Table S2).

### 3.4. Future spatial invasion risk of *L. camara* increases on all continents, particularly in Europe

The global invasion risk of *L. camara* between 2061 and 2080 was estimated under the climate change scenarios SSP2–4.5 and SSP5–8.5 and is presented in Fig. 2. Under global climate change, by 2061 and 2080, the potential distribution of *L. camara* will expand on each continent. Future climate change increased the proportion of areas with an invasion risk on all continents. The rate of estimated invasion risk by 2061–2080 was highest for Europe (SSP2–4.5, 140.70 % and SSP5–8.5, 251.52 %), followed by North America (SSP2–4.5, 31.65 % and SSP5–8.5, 53.94 %) and Asia (SSP2–4.5, 27.39 % and SSP5–8.5, 39.62 %) (Fig. 3). Global climate change was predicted to make a small portion of Antarctica favorable for *L. camara*, with an invasion risk covering 0.017 % and 0.018 % of the total area by 2061–2080. *L. camara* is a tropical weed; therefore, the hot and humid climate expected in the future would provide a

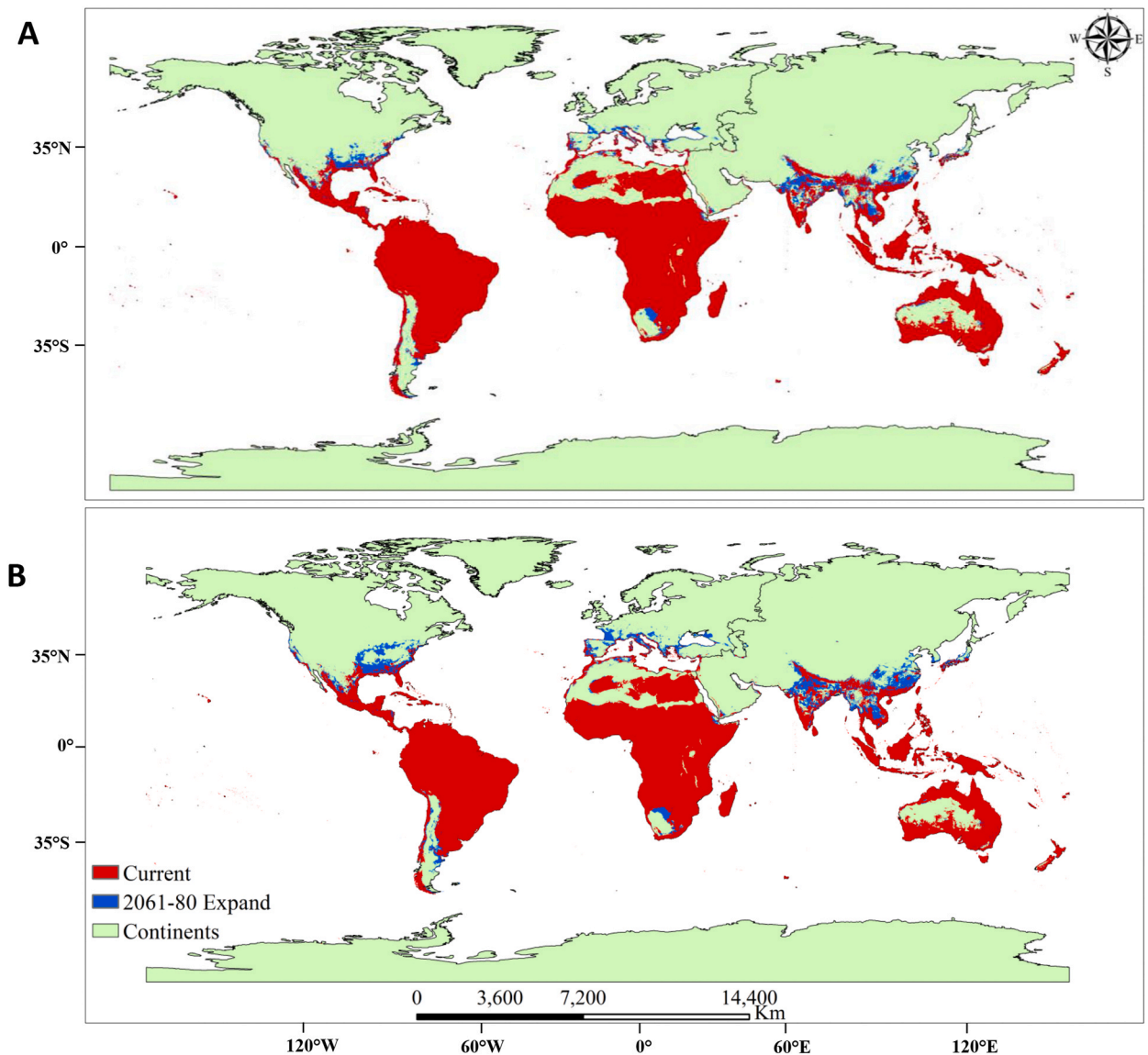


Fig. 2. Global spatial invasion risk of *Lantana camara* under the current climate and future climate change scenarios SSP2–4.5 (A) and SSP5–8.5 (B) in 2061–2080. Red and blue indicate the current potential invasion risk and expansion of the invasion risk in 2061–2080. The map was generated using ArcGIS Desktop 10.8 (<https://desktop.arcgis.com>).

suitable environment for its invasion.

### 3.5. Invasion risk categorization revealed 27 countries with current potential invasion risk and 45 countries during 2061 and 2080

An invasion risk assessment of *L. camara* was conducted by classifying 200 countries and territories into five invasion risk categories under current and future climate change scenarios (SSP2–4.5 and SSP5–8.5), as presented in Fig. 4. The invasion risk categories were as follows: 1) no invasion risk, 2) current potential invasion risk, 3) stable invasion risk, 4) change of invasion risk from no risk to low risk, and 5) change of invasion risk from low risk to high risk. Under current conditions, there was no invasion risk for 59 countries, including 37 with climatically unsuitable conditions and 22 in the native range (i.e., in Central and South America and the Caribbean regions) (Fig. 4 and Fig. 5).

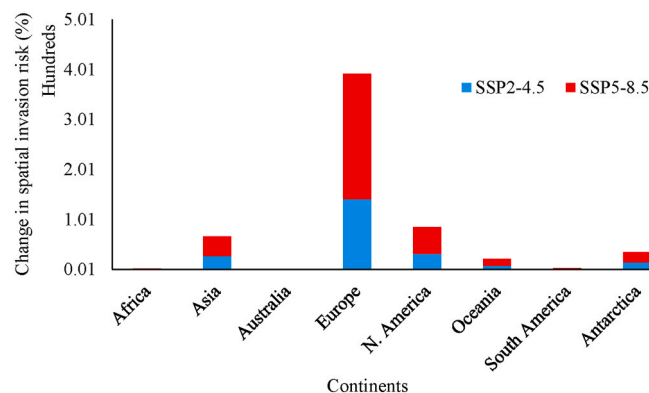
Additionally, 27 countries, including Norway, Russia, Somalia, South Korea, and the United Kingdom, were assigned to the current invasion risk category (Figs. 4A and 4B). Despite no species occurrence records, the RF model revealed a risk of invasion in these countries (Table 3). Global climate change and anthropogenic activities have facilitated the introduction, establishment, and spread of *L. camara*. Under current conditions, its introduction and establishment were predicted in 114 countries in Africa, Asia, Australia, and Oceania (Fig. 5). In total, 57 countries (such as Antigua and Barbuda, Congo, and Sri Lanka) under SSP2–4.5 and 54 countries (such as Australia, Nigeria, and Indonesia) under SSP5–8.5 were projected to have a stable invasion risk from 2061–2080.

The model predicted the expansion of *L. camara* habitats under global climate change, with changes in the invasion risk from low to high in 43 countries (i.e., China, India, and the United States) under SSP2–4.5 and 45 countries (i.e., France, Nepal, and Switzerland) under SSP5–8.5 (Fig. 4). Furthermore, for 25 countries under SSP2–4.5 and 28 countries under SSP5–8.5, areas at risk of invasion were projected to expand by over 50 % across different continents (Table 3). Future climate change between 2061 and 2080 is expected to create climatically suitable habitats in the Northern hemisphere, leading to a potential increase in areas at risk of invasion in Europe and North America. Therefore, 10 countries under SSP 2–4.5 (i.e., Afghanistan, Bulgaria, and Canada) and 13 countries under SSP5–8.5 (i.e., Turkmenistan, Ukraine, and Macedonia) are expected to undergo a transition from no risk to low risk, covering up to 50 % of the land surface in these countries (Table 3). These modeling results and risk categorizations on a global scale are consistent with the highly invasive nature of *L. camara* and indicate that global climate change is amplifying the rate of invasion worldwide.

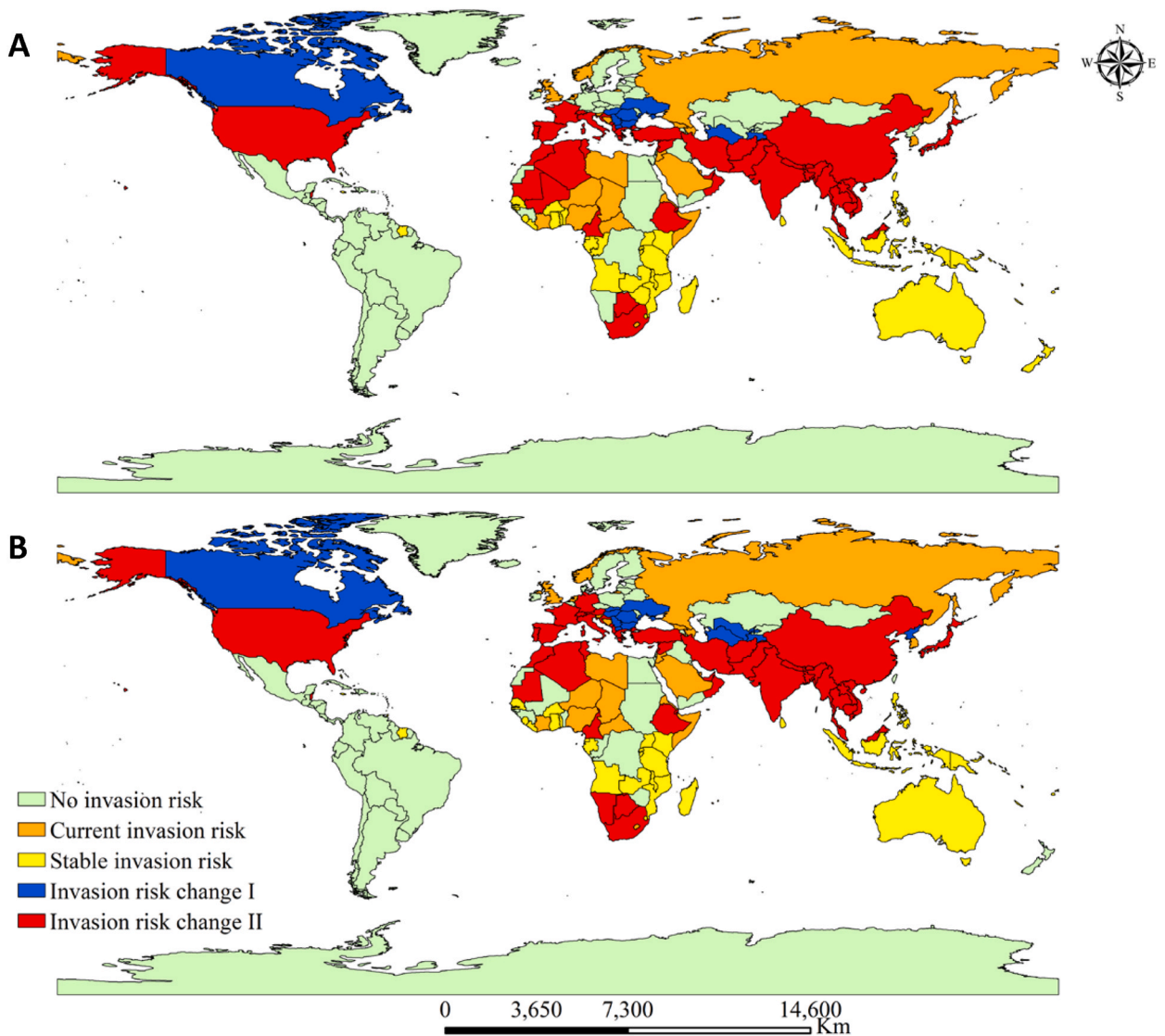
## 4. Discussion

The study yielded several major findings on the invasive potential of *L. camara*. First, an RF model based on global occurrence records analyzed at a 20 km resolution combined with bioclimatic and biome variables exhibited the highest predictive performance (Table 1). Second, the current spatial invasion risk was high in Africa, Australia, and Oceania, affecting approximately 68.98–79.83 % of the total land surface of each continent (Fig. 3). In the future, the spatial invasion risk is projected to increase on all continents, with the highest increase in Europe (251.52 %) (Fig. 3). Third, a current potential invasion risk has been detected in 27 countries, while 114 countries have already been invaded and established by *L. camara* (Table 3 and Fig. 4). Finally, future risk assessment suggested that *L. camara* is likely to be introduced into new countries, with at least 10 countries transitioning from no risk to low risk and 45 countries moving from low risk to high invasion risk categories (Fig. 5). Countries with notable shifts in risk level included Bulgaria, Canada, Russia, Croatia, Italy, India, and San Marino.

Invasion risk assessments are essential to identify potential threats, prioritize resources, and implement effective prevention and control measures for invasive weeds (Poudel et al., 2023). A proactive strategy based on profiling invasive weeds and identifying areas at risk of invasion can effectively mitigate negative impacts (Santamarina et al., 2019; USDA, 2019). Moreover, this approach minimizes ecological disruption, economic losses, and the need for expensive and challenging control measures. Therefore, risk assessment provides a basis for avoiding the intentional introduction of invasive species and for prioritizing management (Matthews et al., 2017).

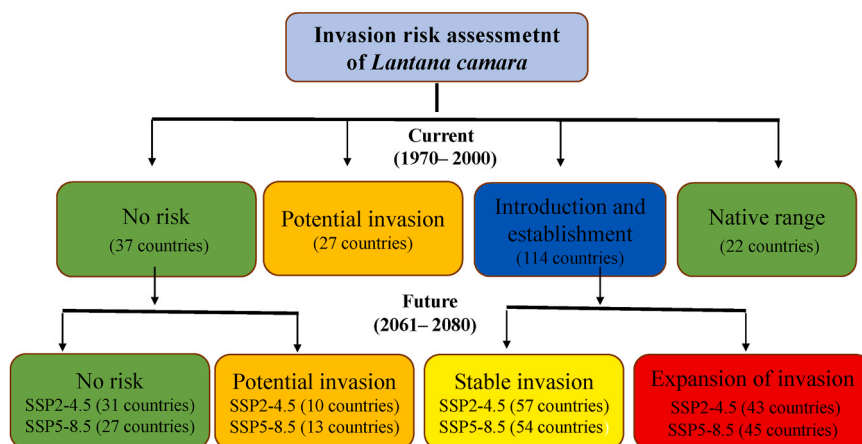


**Fig. 3.** Change in the proportions of areas with a risk of invasion compared with the current potential habitats of *Lantana camara* under the climate change scenarios SSP2–4.5 and SSP5–8.5 for 2061–2080. The potential habitat of *L. camara* was estimated based on the cell number and each cell had a resolution of 2.5 minutes (4.5 km<sup>2</sup> at the equator). The number corresponding to y-axis are expressed in percentage.



**Fig. 4.** Categorization of the invasion risk in different countries and territories under current and future climate change scenarios, specifically SSP2-4.5 (A) and SSP5-8.5 (B) during the period 2061–2080. "No invasion risk" indicates countries that are climatically unsuitable, native to *Lantana camara*, and are expected to have decreasing suitable habitats in the future. "Current invasion risk" denotes countries without current species occurrence records but climatically suitable habitats in the model prediction. "Stable invasion risk" refers to countries where there is no change in the invasion area under both current and future climate change. "Invasion risk change I" and "Invasion risk change II" signify the transition from no risk to low risk (up to 50 % invasion) and the transition from low risk to high risk (invasion exceeding 50 %), respectively. The map was generated using ArcGIS Desktop 10.8 (<https://desktop.arcgis.com>).

Over the past few decades, the importance of risk assessment techniques in predicting the invasion risk of alien species has become widely recognized (Roy et al., 2018). However, there is no single, consistently used risk assessment technique. It is estimated that 70 unique risk assessment techniques have been developed for screening or identifying ecological hazards (Roy et al., 2018). One of the earliest approaches to weed risk assessment (WRA) was developed as a biosecurity tool to evaluate introduced weeds, focusing on the use of questionnaires and scoring systems to determine the risk level associated with the biological status, distribution, and climate and environmental preferences of invasive plants (Verbrugge et al., 2010). The WRA approach was initiated by the Australian Government Department of Agriculture, Fisheries, and Forestry in 1999, specifically for introduced plants in Australia and New Zealand (Gordon et al., 2010). Subsequently, this tool was modified into WRA-derived electronic toolkits and applied in Hawaii and Florida in the United States as well as in the Pacific Islands, Czech Republic Central Europe, islands of Japan, and Central Italy (Hill and Lawson, 2015; USDA, 2019). However, the WRA technique is limited in addressing climatic and other environmental conditions that support the unintentional introduction and expansion of invasive weeds, making it difficult to develop management policies, including control, eradication, and quarantine measures (Hulme, 2012).



**Fig. 5.** Diagrammatic representation of different categories of invasion risk and corresponding number of countries in each category under the current and future climate change scenarios SSP2–4.5 and SSP5–8.5 during 2061–2080. Mapping of each invasion risk category is presented in Fig. 4.

**Table 3**

Current and future potential invasion risk of *Lantana camara* in different countries.

Current invasion risk <sup>a</sup>	Future potential invasion risk			
	New invasion risk <sup>b</sup>		Expanded invasion risk (>50 %) <sup>c</sup>	
Azerbaijan	SSP2–4.5	SSP5–8.5	SSP2–4.5	SSP5–8.5
Bosnia and Herzegovina	Bulgaria	Bulgaria	Afghanistan	Afghanistan
Cape Verde	Canada	Canada	Albania	Albania
Central African Republic	Hungary	Hungary	Bangladesh	Austria
Chad	Macedonia	Macedonia	Bhutan	Bangladesh
Eritrea	Romania	North Korea	Cambodia	Bhutan
Micronesia	Russia	Romania	China	Cambodia
Gaza Strip	Serbia	Russia	Croatia	China
Georgia	Tajikistan	Serbia	Djibouti	Croatia
Ivory Coast	Turkmenistan	Slovakia	France	Djibouti
Jordan	Ukraine	Tajikistan	Greece	France
Lesotho		Turkmenistan	India	Germany
Libya		Ukraine	Italy	Greece
Marshall Islands		Uzbekistan	Japan	India
Netherlands			Laos	Iran
Niger			Lebanon	Italy
Norway			Morocco	Japan
Qatar			Myanmar	Laos
Russia			Pakistan	Lebanon
Saudi Arabia			Portugal	Montenegro
Slovenia			Russia	Morocco
Somalia			Spain	Myanmar
South Korea			Switzerland	Pakistan
St. Kitts and Nevis			Turkey	Portugal
St. Lucia			United Arab Emirates	Russia
St. Vincent and the Grenadines			United States	Spain
United Kingdom				Switzerland
				Turkey
				United States

<sup>a</sup>, no occurrence records of *L. camara* during 1970–2000 but a climatically suitable habitat predicted by the model under the current climate (27 countries). <sup>b</sup>, Potential invasion risk in new countries by 2061–2080. <sup>c</sup>, Expansion of the invasion risk by over 50 % compared with the current invasion risk area by 2061–2080.

Therefore, we introduced an SDM-based invasion risk assessment approach to assess the risk of biological invasions (Adhikari et al., 2021). SDMs account for current occurrence records and incorporate various environmental factors, including climatic variables and anthropogenic disturbances, such as land use and land cover changes (El-Barougy et al., 2021; Santamarina et al., 2019). SDMs predict potential habitats under climate change. In our previous studies, we employed similar approaches to evaluate the invasion risk of various noxious weeds on a global scale and in South Korea (Adhikari et al., 2019; Adhikari et al., 2022c; Adhikari et al., 2021; Adhikari et al., 2023b). SDM-based risk assessments offer invaluable insights for facilitating cost-effective decision-making and the

proactive management of invasive species (Vicente et al., 2013).

Selection of modeling variables identifies potential predictor variables demonstrating linear relationships with the response variables, and assists in minimizing multicollinearity (Dormann et al., 2013). Here, we used Pearson's correlation coefficients to select important variables among the 19 bioclimatic variables and biome. Ultimately, the RF model exhibited outstanding performance with rarefaction at 20 km, utilizing bioclimatic variables and biome. At the same resolution, model performance was relatively low using only bioclimatic variables (Table 1). Moreover, the biome had highest contribution to model fit among the variables. These results suggest that in addition to bioclimatic variables, other environmental variables such as biome should be incorporated into the model for accurate predictions.

*Lantana camara*, a highly noxious weed, has been introduced outside its native range since the early 1800s as an ornamental plant, hedge plant, and for use in folk medicine, and has unintentionally spread through various biotic and abiotic dispersal mechanisms (Corlett, 1998; Vardien et al., 2012). The seeds of *L. camara* are dispersed by means of birds (i.e., Indian myna, *Acridotheres tristis*), lizards, and mammals (i.e., goats and sheep), natural disasters (i.e., floods and cyclones), and accidental introduction via contaminated seeds of food crops (Heleno et al., 2013). It has spread rapidly to more than 60 regions of the world and is well-established in seven major terrestrial biomes such as tropical forest, temperate forest, boreal forest, and temperate grassland (Thomas, 2022).

The first record of *L. camara* in Asia is believed to be in India at the first decade of 18th century, primarily as an ornamental plant (Burkill, 1966). Over time, it spread widely across the country and later to other parts of Asia, becoming an invasive species in many regions. Similarly, it is introduced in Australia in 1841 (AGDAFF, 2024), South Africa in 1858 (Ruwanza, 2020), and Europe at the end of the 17th century (William, 2001).

Under current conditions, its predicted distribution was mainly in the tropics and subtropics, approximately between 35°N and 35°S. In the Southern Hemisphere, four continents (Africa, Australia, Oceania, and South America) had a risk of invasion covering more than 68.98 % of the total land surface, while the other continents had a relatively narrow potential distribution (up to 10 %). These results suggest that *L. camara* thrives in tropical and subtropical climates with relatively warm temperatures (25–28°C, on average), supported by a previous research on its ecological and physiological characteristics (Zhang et al., 2014).

Under future climate change scenarios, the invasion risk of *L. camara* may expand into areas (i.e., the Mediterranean region, East Asia, and southeastern North America) that are currently unfavorable (Fig. 2). These results are consistent with earlier findings, indicating that a 1°C increase in mean annual temperature could result an approximately 200 km poleward shift in the world's vegetation (Walther et al., 2002). In the CMIP6 model, the global temperature is estimated to increase by 3.8–7.4°C (SSP5–8.5) by 2081–2100 (Eyring et al., 2016). This suggests that the Northern margin of *L. camara* may exceed 35°N latitude with a poleward shift in warm climate zones and altered precipitation patterns (Trenberth et al., 2007). Therefore, the change in areas at risk of invasion in the future compared with the current potential distribution was highest in Europe and relatively high in North America and Asia (Fig. 3). In the Southern Hemisphere, the *L. camara* distribution already reached saturation, with adaptation to heat, dry, and wet stresses, as suggested previously (Taylor et al., 2012). However, in North and Central Asia, continental Europe, and a major portion of North America, there is no risk of invasion, indicating that the growth and survival of *L. camara* is limited by cold stress over several months (Zhang et al., 2014).

The SSP5–8.5 scenario presents a higher invasion risk for *L. camara* compared to SSP2–4.5 by 2061–2080 in several countries, including Argentina, Bangladesh, Croatia, Greece, and Italy. New invasion risks emerge in North Korea, Slovakia, and Uzbekistan, while Austria, Germany, and Montenegro show expansion of invasion risk exceeding 50 % under SSP5–8.5. These findings suggest that the high-emissions scenario projects more extreme climate changes, leading to expanded suitable habitats for invasive plants, particularly at higher latitudes and elevations (Adhikari et al., 2023b; Yang et al., 2023). The intense climate changes under SSP5–8.5 may increase stress on native plant communities, making them more vulnerable to invasion and potentially allowing invasive species to outcompete native ones (Diez et al., 2012). Additionally, the synergistic effects of climate change and anthropogenic factors, such as land use changes, can create conditions that further promote invasion under the SSP5–8.5 scenario (Adhikari et al., 2019; Yang et al., 2023). These combined factors contribute to higher predicted invasion risks for alien weeds under SSP5–8.5 compared to the more moderate SSP2–4.5 scenario across many regions globally.

Countries were classified into four categories based on invasion risk. Twenty-seven countries, including Georgia, South Korea, and the Netherlands, have no records of *L. camara* to date (Table 3). However, global climate change and human-induced activities place several of these countries at risk of invasion (Adhikari et al., 2021; Adhikari et al., 2023b; Zhang et al., 2014). Many countries with extreme cold in the winter (i.e., Norway) and extreme hot in the summer (i.e., Saudi Arabia and Qatar) are predicted to become high-risk countries. Interestingly, some parts of Antarctica are predicted to be at risk for *L. camara* invasion. Antarctica, with an annual mean temperature consistently below freezing, is climatically unsuitable for *L. camara*. Nonetheless, over the past 200 years, anthropogenic activities, such as research, exploration, exploitation, and tourism, in this region have increased significantly (Chwedorzewska et al., 2020). As a result, the area could potentially become a suitable habitat for *L. camara*. These findings provide insight into countries with a potential invasion risk, providing a basis for the establishment of quarantine measures to prevent the introduction of *L. camara*.

Globally, the management of *L. camara* presents several challenges owing to its unique characteristics, including its rapid colonization of diverse habitats, adaptive traits, resilience to various control methods (i.e., chemical resistance), and the presence of a long-lived seed bank (Priyanka et al., 2013; Thomas, 2022). Therefore, *L. camara* is recognized as one of the 100 most notorious weeds worldwide (Lowe et al., 2000; Thomas, 2022). Our model predicted *L. camara* invasion in 114 countries, among which this weed is established in 78 countries, accounting for more than 50 % of the total land area in those countries. These results highlight that the invasion of *L. camara* is a global issue, necessitating international collaboration and coordination for its effective management (Priyanka et al., 2013).

Future climate change is expected to increase the invasion risk in at least 45 countries across Asia, Africa, and Europe. This could lead to transitions from no or low risk of invasion to a high risk in various countries by 2061–2080. In countries like India, China, Japan, South Africa, and the United States, invasive species may expand inland, as demonstrated previously (Taylor et al., 2012). These countries may require more detailed risk assessments for *L. camara*. The response of invasive weeds to environmental changes should be a fundamental aspect of this assessment, especially for countries that are currently at risk and will continue to be at risk in the future (Crossman et al., 2011), as identified in this study. These areas are of particular importance for agricultural productivity and biodiversity conservation, including the southwest of Australia, many countries in South America, the Caribbean Islands, Southeast China, Central India, and South Africa.

Warming climate and increased precipitation have positive effects on seed germination (Chen et al., 2017). Moreover, species-specific traits, such as the reproduction rate, growth rate, and seed biomass, are correlated with invasion potential (Carboni et al., 2016). Physiological traits, including the photosynthesis rate, competitive ability, and resource utilization, may play crucial roles in invasion success (Ni et al., 2021). As the several natural and biological phenomenon e.g., runoff, wind, tides, and animal vectors, can facilitate the invasion of various weeds, including *L. camara* (Adhikari et al., 2023a). Hence, in addition to bioclimatic and biome variables, other biological and physiological traits need to be incorporated into the model for more accurate predictions. These represent the limitations of this study, and we anticipate addressing these points in future research.

## 5. Conclusions

We conducted a global spatial invasion risk assessment of *L. camara* using the RF modeling approach within the changing environmental context. The assessment revealed a high risk of invasion on four continents (Africa, Australia, Oceania, and South America) within the approximate latitudes of 35°N and 35°S under the current and projected future environmental conditions. Notably, the rate of invasion is increasing substantially in Asia, Europe, and North America, with a maximum increase of 251.52 % compared with the current invasion levels, and invasion risk is expected to expand beyond 35°N. Furthermore, our study predicted a current potential invasion risk in 27 countries and the introduction and establishment of *L. camara* in 114 countries. We identified countries with low, moderate, and high invasion risks, along with new invasion risks and expansions of areas with an invasion risk between 2061 and 2080. Similarly, our future risk assessment suggested that *L. camara* is likely to be introduced into new countries, with at least 10 countries transitioning from no risk to low risk and 45 countries moving from low risk to high invasion risk categories. These findings provide valuable insights into the invasion status of *L. camara* and can serve as a valuable resource for designing control and management strategies at global and local scales. It is important to recognize that the successful management of *L. camara* cannot be achieved by the efforts of a single country. Therefore, a global network, coordination, and collaboration are imperative for the sustainable management of this notorious invasive weed.

## Declaration of generative AI in scientific writing

The authors declare that they have not use AI assisted tools for the writing of this paper.

## CRediT authorship contribution statement

**Pradeep Adhikari:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing—original draft preparation, Writing—review and editing. **Yong Ho Lee:** Conceptualization, Investigation, Validation, **Prabhat Adhikari:** Formal analysis, Data curation. **Anil Poudel:** Data curation. **Sue Hyuen Choi:** Data curation. **Ji Yeon Yun:** Data curation. **Do-Hun Lee:** Data curation **Yong-Soon Park:** Writing—review and editing and supervision. **Sun Hee Hong:** Conceptualization, Project administration, Supervision, Funding acquisition.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data Availability

The data that has been used is confidential.

## Acknowledgements

This work is supported by National Research Foundation (NRF) of Korea (Project number RS-2023-00247840) and by the research grant of Kongju National University in 2023 (Project for Yong-Soon Park). Therefore, authors are grateful to the NRF Korea and Kongju National University for providing research funds.

## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.gecco.2024.e03212](https://doi.org/10.1016/j.gecco.2024.e03212).

## References

- Adhikari, P., Jeon, J.-Y., Kim, H.W., Oh, H.-S., Adhikari, P., Seo, C., 2020. Northward range expansion of southern butterflies according to climate change in South Korea. *J. Clim. Chang. Res.* 11, 643–656. <https://doi.org/10.15531/KSCCR.2020.11.6.643>.
- Adhikari, P., Jeon, J.-Y., Kim, H.W., Shin, M.-S., Adhikari, P., Seo, C., 2019. Potential impact of climate change on plant invasion in the Republic of Korea. *J. Ecol. Environ.* 43, 36. <https://doi.org/10.1186/s41610-019-0134-3>.
- Adhikari, P., Kim, B.-J., Hong, S.-H., Lee, D.-H., 2022a. Climate change induced habitat expansion of nutria (*Myocastor coypus*) in South Korea. *Sci. Rep.* 12, 1–12. <https://doi.org/10.1038/s41598-022-07347-5>.
- Adhikari, P., Kim, H.W., Shin, M.S., Hong, S.H., Cho, Y., 2022b. Potential distribution of the silver striped skipper (*Leptalina unicolor*) and maiden silvergrass (*Miscanthus sinensis*) under climate change in South Korea. *Entomol. Res.* <https://doi.org/10.1111/1748-5967.12622>.
- Adhikari, P., Lee, Y.-H., Poudel, A., Lee, G., Hong, S.-H., Park, Y.-S., 2023a. Predicting the impact of climate change on the habitat distribution of *Parthenium hysterophorus* around the world and in South Korea. *Biology* 12, 84. <https://doi.org/10.3390/biology12010084>.
- Adhikari, P., Lee, Y.H., Adhikari, P., Hong, S.H., Park, Y.-S., 2022c. Climate change-induced invasion risk of ecosystem disturbing alien plant species: an evaluation using species distribution modeling. *Front. Ecol. Evol.* 681. <https://doi.org/10.3389/fevo.2022.880987>.
- Adhikari, P., Lee, Y.H., Park, Y.-S., Hong, S.H., 2021. Assessment of the spatial invasion risk of intentionally introduced alien plant species (IIAPS) under environmental change in South Korea. *Biology* 10, 1169. <https://doi.org/10.3390/biology10111169>.
- Adhikari, P., Lee, Y.H., Poudel, A., Hong, S.H., Park, Y.-S., 2023b. Global spatial distribution of *Chromolaena odorata* habitat under climate change: random forest modeling of one of the 100 worst invasive alien species. *Sci. Rep.* 13, 9745. <https://doi.org/10.1038/s41598-023-36358-z>.
- Adhikari, P., Shin, M.-S., Jeon, J.-Y., Kim, H.W., Hong, S., Seo, C., 2018. Potential impact of climate change on the species richness of subalpine plant species in the mountain national parks of South Korea. *J. Ecol. Environ.* 42, 36. <https://doi.org/10.1186/s41610-018-0095-y>.
- AGDAFF, 2024. *Lantana camara* Common Lantana, Pink Flowered Lantana. Weeds of Australia. Australian Government Department of Agriculture, Fisheries and Forestry. <https://weeds.org.au/profiles/lantana-common-kamara/> (accessed 29 September 2024).
- Allen, S.K., Plattner, G.-K., Nauels, A., Xia, Y., Stocker, T.F., 2014. Climate change 2013: the physical science basis. An overview of the working group I contribution to the fifth assessment report of the intergovernmental panel on climate change (IPCC). *EGU Gen. Assem. Conf. Abstr.* 3544.
- Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.* 43, 1223–1232. <https://doi.org/10.1111/j.1365-2664.2006.01214.x>.
- Andersen, D., Litvinchuk, S.N., Jang, H.J., Jiang, J., Koo, K.S., Maslova, I., Kim, D., Jang, Y., Borzée, A., 2022. Incorporation of latitude-adjusted bioclimatic variables increases accuracy in species distribution models. *Ecol. Model.* 469, 109986. <https://doi.org/10.1016/j.ecolmodel.2022.109986>.
- Araujo, M.B., Guisan, A., 2006. Five (or so) challenges for species distribution modelling. *J. Biogeogr.* 33, 1677–1688. <https://doi.org/10.1111/j.1365-2699.2006.01584.x>.
- Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012. Selecting pseudo-absences for species distribution models: how, where and how many? *Methods Ecol. Evol.* 3, 327–338. <https://doi.org/10.1111/j.2041-210X.2011.00172.x>.
- Bhagwat, S.A., Breman, E., Thekaekara, T., Thornton, T.F., Willis, K.J., 2012. A battle lost? Report on two centuries of invasion and management of *Lantana camara* L. in Australia, India and South Africa. *PLoS One* 7, e32407. <https://doi.org/10.1371/journal.pone.0032407>.
- Boria, R.A., Olson, L.E., Goodman, S.M., Anderson, R.P., 2014. Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecol. Model.* 275, 73–77. <https://doi.org/10.1016/j.ecolmodel.2013.12.012>.
- Brown, J.L., Bennett, J.R., French, C.M., 2017. SDMtoolbox 2.0: the next generation Python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *PeerJ* 5, e4095. <https://doi.org/10.7717/peerj.4095>.
- Burkill, I.H., 1966. *A dictionary of the economic products of the Malay Peninsula*, Second ed. Kuala Lumpur.
- Carboni, M., Munkemüller, T., Lavergne, S., Choler, P., Borge, B., Violle, C., Essl, F., Roquet, C., Munoz, F., Consortium, D., 2016. What it takes to invade grassland ecosystems: traits, introduction history and filtering processes. *Ecol. Lett.* 19, 219–229. <https://doi.org/10.1111/ele.12556>.
- Chen, B.-M., Gao, Y., Liao, H.-X., Peng, S.-L., 2017. Differential responses of invasive and native plants to warming with simulated changes in diurnal temperature ranges. *AoB Plants* 9. <https://doi.org/10.1093/aobpla/plx028>.
- Chwedorzewska, K.J., Korczak-Abshire, M., Znoj, A., 2020. Is Antarctica under threat of alien species invasion? *Glob. Chang. Biol.* 26, 1942–1943. <https://doi.org/10.1111/gcb.15013>.
- Conradi, T., Slingsby, J.A., Midgley, G.F., Nottebrock, H., Schweiger, A.H., Higgins, S.I., 2020. An operational definition of the biome for global change research. *N. Phytol.* 227, 1294–1306. <https://doi.org/10.1111/nph.16580>.
- Corlett, R.T., 1998. Frugivory and seed dispersal by vertebrates in the Oriental (Indomalayan) Region. *Biol. Rev.* 73, 413–448. <https://doi.org/10.1017/S0006323198005234>.
- Crossman, N., Bryan, B., Cooke, D., 2011. An invasive plant and climate change threat index for weed risk management: Integrating habitat distribution pattern and dispersal process. *Ecol. Indic.* 11, 183–198. <https://doi.org/10.1016/j.ecolind.2008.10.011>.
- Cutler, D.R., Edwards Jr, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. *Ecology* 88, 2783–2792. <https://doi.org/10.1890/07-0539.1>.
- Diez, J.M., D'Antonio, C.M., Dukes, J.S., Grosholz, E.D., Olden, J.D., Sorte, C.J., Blumenthal, D.M., Bradley, B.A., Early, R., Ibáñez, I., 2012. Will extreme climatic events facilitate biological invasions? *Front. Ecol. Environ.* 10, 249–257. <https://doi.org/10.2307/41811809>.
- Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36, 27–46. <https://doi.org/10.1111/j.1600-0587.2012.07348.x>.
- El-Barougy, R.F., Dakhlil, M.A., Halmy, M.W., Gray, S.M., Abdelaal, M., Khedr, A.-H.A., Bersier, L.-F., 2021. Invasion risk assessment using trait-environment and species distribution modelling techniques in an arid protected area: towards conservation prioritization. *Ecol. Indic.* 129, 107951. <https://doi.org/10.1016/j.ecolind.2021.107951>.
- Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. *Annu. Rev. Ecol. Evol. Syst.* 40, 677–697. <https://doi.org/10.1146/annurev.ecolsys.110308.120159>.
- Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.* 9, 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>.
- Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.* 37, 4302–4315. <https://doi.org/10.1002/joc.5086>.
- Franklin, J., 1995. Predictive vegetation mapping: geographic modelling of biospacial patterns in relation to environmental gradients. *Prog. Phys. Geogr.* 19, 474–499. <https://doi.org/10.1177/0309133395019004>.
- Lee, G., Taeyang, C., Adhikari, P., Lee, Y.-H., Lee, I.Y., Hong, S.-H., 2022. Prediction of Habitat Expansion and Invasion Risk Assessment of *Spartina anglica* and *Spartina alterniflora* in Korea. *Weed Turf. Sci.* 11, 215–228. <https://doi.org/10.5660/WTS.2022.11.2.215>.

- Gordon, D.R., Mitterdorfer, B., Pheloung, P.C., Ansari, S., Buddenhagen, C., Chimera, C., Daehler, C.C., Dawson, W., Denslow, J.S., LaRosa, A., 2010. Guidance for addressing the Australian weed risk assessment questions. *Plant Prot. Q.* 25, 56–74.
- Heleno, R.H., Olesen, J.M., Nogales, M., Vargas, P., Traveset, A., 2013. Seed dispersal networks in the Galápagos and the consequences of alien plant invasions. *Proc. R. Soc. B* 280, 20122112. <https://doi.org/10.1098/rspb.2012.2112>.
- Hill, J.E., Lawson, K.M., 2015. Risk screening of Arapaima, a new species proposed for aquaculture in Florida. *North Am. J. Fish. Manag.* 35, 885–894. <https://doi.org/10.1080/02755947.2015.1064835>.
- Hong, S.H., Lee, Y.H., Lee, G., Lee, D.-H., Adhikari, P., 2021. Predicting impacts of climate change on northward range expansion of invasive weeds in South Korea. *Plants* 10, 1604. <https://doi.org/10.3390/plants10081604>.
- Hulme, P.E., 2012. Weed risk assessment: a way forward or a waste of time? *J. Appl. Ecol.* 49, 10–19. <https://doi.org/10.1111/j.1365-2664.2011.02069.x>.
- IPBES, 2023. Summary for Policymakers of the Thematic Assessment Report on Invasive Alien Species and Their Control of the Intergovernmental Science-policy Platform on Biodiversity and Ecosystem Services. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Bonn, Germany.
- IUCN, 2021. Invasive alien species and climate change. ([https://iucn.org/sites/default/files/202204/ias\\_and\\_climate\\_change\\_issues\\_brief\\_2021](https://iucn.org/sites/default/files/202204/ias_and_climate_change_issues_brief_2021)) (Assessed on September 11 2024).
- Jeon, J.-Y., Adhikari, P., Seo, C., 2020. Impact of climate change on potential dispersal of *Paeonia obovata* (Paeoniaceae), a critically endangered medicinal plant of South Korea. *Eco Env. Cons.* 26, S145–S155.
- Jiménez-Valverde, A., Peterson, A.T., Soberón, J., Overton, J.M., Aragón, P., Lobo, J.M., 2011. Use of niche models in invasive species risk assessments. *Biol. Invasions* 13, 2785–2797. <https://doi.org/10.1007/s10530-011-9963-4>.
- Kim, H.W., Adhikari, P., Chang, M.H., Seo, C., 2021. Potential distribution of amphibians with different habitat characteristics in response to climate change in South Korea. *Animals* 11, 2185. <https://doi.org/10.3390/ani11082185>.
- Lobo, J.M., Jiménez-Valverde, A., Real, R., 2008. AUC: a misleading measure of the performance of predictive distribution models. *Glob. Ecol. Biogeogr.* 17, 145–151. <https://doi.org/10.1111/j.1466-8238.2007.00358.x>.
- Lowe, S., Browne, M., Boudjelas, S., De Poorter, M., 2000. 100 of the World's Worst Invasive Alien Species: A Selection from the Global Invasive Species Database. Invasive Species Specialist Group Auckland.
- Matthews, J., Beringen, R., Creemers, R., Hollander, H., van Kessel, N., van Kleef, H., van de Koppel, S., Lemaire, A., Odé, B., Verbrugge, L., 2017. A new approach to horizon-scanning: identifying potentially invasive alien species and their introduction pathways. *Manag. Biol. Invasions* 8, 37–52. <https://doi.org/10.3391/mbi.2017.8.1.04>.
- Monserud, R.A., Leemans, R., 1992. Comparing global vegetation maps with the Kappa statistic. *Ecol. Model.* 62, 275–293. [https://doi.org/10.1016/0304-3800\(92\)90003-W](https://doi.org/10.1016/0304-3800(92)90003-W).
- Moudry, V., Devillers, R., 2020. Quality and usability challenges of global marine biodiversity databases: an example for marine mammal data. *Ecol. Inform.* 56, 101051. <https://doi.org/10.1016/j.ecoinf.2020.101051>.
- Müller, W.A., Jungclaus, J.H., Mauritsen, T., Baehr, J., Bittner, M., Budich, R., Bunzel, F., Esch, M., Ghosh, R., Haak, H., 2018. A higher-resolution version of the max plank institute earth system model (MPI-ESM1. 2-HR). *J. Adv. Model. Earth Syst.* 10, 1383–1413. <https://doi.org/10.1029/2017MS001217>.
- Ncube, B., Shekede, M.D., Gwitira, I., Dube, T., 2020. Spatial modelling the effects of climate change on the distribution of *Lantana camara* in Southern Zimbabwe. *Appl. Geogr.* 117, 102172. <https://doi.org/10.1016/j.apgeog.2020.102172>.
- Ni, M., Deane, D.C., Li, S., Wu, Y., Sui, X., Xu, H., Chu, C., He, F., Fang, S., 2021. Invasion success and impacts depend on different characteristics in non-native plants. *Divers. Distrib.* 1194–1207. <https://doi.org/10.1111/ddi.13267>.
- Pearson, R.G., 2010. Species' distribution modeling for conservation educators and practitioners. *Lessons Conserv* 3, 54–89.
- Peterson, A., Soberón, J., Pearson, R., Anderson, R., Martínez-Meyer, E., Nakamura, M., Araújo, M., 2011. Ecological Niches and Geographic Distributions. Princeton University Press, Princeton, NJ. <https://doi.org/10.1515/9781400840670>.
- Poudel, A., Adhikari, P., Na, C.S., Wee, J., Lee, D.-H., Lee, Y.H., Hong, S.H., 2023. Assessing the potential distribution of *Oxalis latifolia*, a rapidly Spreading Weed, in East Asia under global climate change. *Plants* 12, 3254. <https://doi.org/10.3390/plants12183254>.
- Priyanka, N., Shiju, M.V., Joshi, P.K., 2013. A framework for management of *Lantana camara* in India. *Proc. Int. Acad. Ecol. Environ. Sci.* 3, 306 <http://www.iaees.org/publications/journals/piaees/online-version.asp>.
- Reick, C., Raddatz, T., Brovkin, V., Gayler, V., 2013. Representation of natural and anthropogenic land cover change in MPI-ESM. *J. Adv. Model. Earth Syst.* 5, 459–482. <https://doi.org/10.1002/jame.20022>.
- Riahi, K., Van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., 2017. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob. Environ. Change* 42, 153–168. <https://doi.org/10.1016/j.gloenvcha.2016.05.009>.
- Roy, H.E., Rabitsch, W., Scalera, R., Stewart, A., Gallardo, B., Genovesi, P., Essl, F., Adriaens, T., Bacher, S., Booy, O., 2018. Developing a framework of minimum standards for the risk assessment of alien species. *J. Appl. Ecol.* 55, 526–538. <https://doi.org/10.1111/1365-2664.13025>.
- Ruwanza, S., 2020. Effects of *Lantana camara* invasion on vegetation diversity and composition in the Vhembe Biosphere Reserve, Limpopo Province of South Africa. *Scientific African* 10, e00610. <https://doi.org/10.1016/j.sciaf.2020.e00610>.
- Santamarina, S., Alfaro-Saiz, E., Llamas, F., Acedo, C., 2019. Different approaches to assess the local invasion risk on a threatened species: opportunities of using high-resolution species distribution models by selecting the optimal model complexity. *Glob. Ecol. Conserv.* 20, e00767. <https://doi.org/10.1016/j.gecco.2019.e00767>.
- Sharma, G.P., Raghubanshi, A.S., Singh, J.S., 2005. *Lantana* invasion: an overview. *Weed Biol. Manag.* 5, 157–165. <https://doi.org/10.1111/j.1445-6664.2005.00178.x>.
- Shin, M.-S., Seo, C., Lee, M., Kim, J.-Y., Jeon, J.-Y., Adhikari, P., Hong, S.-B., 2018. Prediction of potential species richness of plants adaptable to climate change in the Korean Peninsula. *J. Environ. Impact Assess.* 27, 562–581. <https://doi.org/10.14249/eia.2018.27.6.562>.
- Steen, B., Broennimann, O., Maiorano, L., Guisan, A., 2024. How sensitive are species distribution models to different background point selection strategies? A test with species at various equilibrium levels. *Ecol. Model.* 493, 110754. <https://doi.org/10.1016/j.ecolmodel.2024.110754>.
- Tang, J., Zhao, X., 2022. Forecasting the combined effects of future climate and land use change on the suitable habitat of *Davidia involucreata* Baill. *Ecol. Evol.* 12, e9023. <https://doi.org/10.1002/ece3.9023>.
- Taylor, S., Kumar, L., Reid, N., Kriticos, D.J., 2012. Climate change and the potential distribution of an invasive shrub, *Lantana camara* L. *PLoS One* 7, e35565. <https://doi.org/10.1371/journal.pone.0035565>.
- Thomas, S., 2022. *Lantana camara* (lantana). CABI International. <https://doi.org/10.1079/cabicompendium.29771>. Accessed 03 March 2024.
- Thuiller, W., Georges, D., Gueguen, M., Engler, R., Breiner, F., Lafourcade, B., Patin, R., 2023. Package 'biomod2': ensemble platform for species distribution modeling. Version 4, 1–2. (<https://biomodhub.github.io/biomod2/>).
- Thuiller, W., Lavorel, S., Araújo, M.B., 2005. Niche properties and geographical extent as predictors of species sensitivity to climate change. *Glob. Ecol. Biogeogr.* 14, 347–357. <https://doi.org/10.1111/j.1466-822X.2005.00162.x>.
- Titeux, N., Henle, K., Mihoub, J.B., Regos, A., Geijzendorffer, I.R., Cramer, W., Verburg, P.H., Brotons, L., 2016. Biodiversity scenarios neglect future land-use changes. *Glob. Change Biol.* 22, 2505–2515. <https://doi.org/10.1111/gcb.13272>.
- Tiwari, S., Mishra, S., Kumar, D., Kumar, B., Vaidya, S., Ghosh, B.G., Rahaman, S.M., Khatun, M., Garai, S., Kumar, A., 2022. Modelling the potential risk zone of *Lantana camara* invasion and response to climate change in eastern India. *Ecol. Process.* 11, 1–13. <https://doi.org/10.1186/s13717-021-00354-w>.
- Trenberth, K.E., Jones, P.D., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., Parker, D., Rahimzadeh, F., Renwick, J.A., Rusticucci, M., 2007. Observations. Surface and atmospheric climate change. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L. (Eds.), *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

- USDA, 2019. Guidelines for the USDA-APHISPPQ Weed Risk Assessment Process. Animal and Plant Health Inspection Service United States Department of Agriculture North Carolina, United States, p. 125.
- van der Weijden, W., Leewis, R., Bol, P., 2007. 100 of the world's worst invasive alien species. Biological globalization. KNNV Publishing, pp. 206–208. [https://doi.org/10.1163/9789004278110\\_019](https://doi.org/10.1163/9789004278110_019).
- van Wilgen, B.W., Reyers, B., Le Maitre, D., Richardson, D., Schonegevel, L., 2008. A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. *J. Environ. Manag.* 89, 336–349. <https://doi.org/10.1016/j.jenvman.2007.06.015>.
- Verbrugge, L., Leuven, R.S., Velde, G., 2010. Evaluation of international risk assessment protocols for exotic species. (<http://hdl.handle.net/2066/83709>) (Accessed 11 September 2024).
- Vardien, W., Richardson, D.M., Foxcroft, L.C., Thompson, G.D., Wilson, J.R.U., Le Roux, J.J., 2012. Invasion dynamics of *Lantana camara* L.(sensu lato) in South Africa. *S. Afr. J. Bot.* 81, 81–94. <https://doi.org/10.1016/j.sajb.2012.06.002>.
- Vicente, J., Fernandes, R., Randin, C., Broennimann, O., Gonçalves, J., Marcos, B., Pôças, I., Alves, P., Guisan, A., Honrado, J., 2013. Will climate change drive alien invasive plants into areas of high protection value? An improved model-based regional assessment to prioritise the management of invasions. *J. Environ. Manag.* 131, 185–195. <https://doi.org/10.1016/j.jenvman.2013.09.032>.
- Walther, G.-R., Post, E., Convey, P., Menzel, A., Parmesan, C., Beebee, T.J., Fromentin, J.-M., Hoegh-Guldberg, O., Bairlein, F., 2002. Ecological responses to recent climate change. *Nature* 416, 389–395. <https://doi.org/10.1038/416389a>.
- Weiskopf, S.R., Rubenstein, M.A., Crozier, L.G., Gaichas, S., Griffis, R., Halofsky, J.E., Hyde, K.J., Morelli, T.L., Morissette, J.T., Muñoz, R.C., 2020. Climate change effects on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States. *Sci. Total Environ.* 733, 137782. <https://doi.org/10.1016/j.scitotenv.2020.137782>.
- Whitford, A.M., Shipley, B.R., McGuire, J.L., 2024. The influence of the number and distribution of background points in presence-background species distribution models. *Ecol. Model.* 488, 110604. <https://doi.org/10.1016/j.ecolmodel.2023.110604>.
- William, G.L., 2001. Introduced plants, negative effects of. In: Simon, A.L. (Ed.), *Encyclopedia of Biodiversity*. Academic Press, New Zealand.
- Williams, M., Zalasiewicz, J., Haff, P., Schwägerl, C., Barnosky, A.D., Ellis, E.C., 2015. The anthropocene biosphere. *Anthr. Rev.* 2, 196–219. <https://doi.org/10.1177/2053019615591020>.
- Yang, M., Zhao, H., Xian, X., Wang, R., Yang, N., Chen, L., Liu, W.-x., 2023. Assessing risk from invasive alien plants in China: Reconstructing invasion history and estimating distribution patterns of *Lolium temulentum* and *Aegilops tauschii*. *Front. Plant Sci.* 14, 1113567. <https://doi.org/10.3389/fpls.2023.1113567>.
- Zarzo-Arias, A., Penteriani, V., Gábor, L., Šimová, P., Grattarola, F., Moudrý, V., 2022. Importance of data selection and filtering in species distribution models: A case study on the Cantabrian brown bear. *Ecosphere* 13, e4284. <https://doi.org/10.1002/ecs2.4284>.
- Zhang, Q., Zhang, Y., Peng, S., Zobel, K., 2014. Climate warming may facilitate invasion of the exotic shrub *Lantana camara*. *PLoS One* 9, e105500. <https://doi.org/10.1371/journal.pone.0105500>.
- Zhang, X., Wei, H., Zhao, Z., Liu, J., Zhang, Q., Zhang, X., Gu, W., 2020. The global potential distribution of invasive plants: *Anredera cordifolia* under climate change and human activity based on random forest models. *Sustainability* 12, 1491. <https://doi.org/10.3390/su12041491>.