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Modelling potential habitat suitability of three invasive alien plant species under the projected climate scenarios and land use/land cover change in the Lake Zone of Tanzania

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Abstract

Invasive alien plant species pose significant ecological and socio-economic risks across East Africa, yet invasion risk assessments in Tanzania have largely relied on single-species and climate-only projections. Such approaches may overestimate invasion potential by neglecting land-use constraints and inter-model uncertainty. This study evaluates current and future habitat suitability of three invasive species, *Chromolaena odorata* and *Lantana camara* (terrestrial), and *Eichhornia crassipes* (aquatic) in the Mara–Simiyu region of northern Tanzania. Habitat suitability was modelled using MaxEnt and spatial block cross-validation. Projections were generated under three CMIP6 climate models (ACCESS-CM2, MIROC6, MRI-ESM2-0) and three emission pathways (SSP1–2.6, SSP3–7.0, SSP5–8.5). The suitable area was quantified using the 10th percentile training presence (P10) threshold, and ensemble predictions were derived by averaging across climate models. Climate-only projections indicate that terrestrial species retain moderate suitability under low-emission scenarios but experience increasing fragmentation and contraction of highly suitable areas under higher-emission pathways. Niche overlap between *L. camara* and *C. odorata* was moderate to high across scenarios (Schoener's D = 0.45–0.81), suggesting substantial climatic similarity and potential spatial convergence under future warming. In contrast, *E. crassipes* maintained broad climatic suitability across scenarios. When land-use projections were incorporated, suitable habitat estimates were substantially reduced and exhibited greater spatial uncertainty. For *C. odorata*, suitable habitat covered approximately 55–65% of the region under SSP1–2.6, but this uncertainty increased under high-emission scenarios (coefficient of variation ≈ 65–75% by 2090). *L. camara* showed even stronger contractions, with uncertainty exceeding 85–90% under SSP5–8.5. These findings suggest that climate-only models may overestimate potential niche space by ignoring

land-use constraints. Therefore, integrating multiple environmental drivers provides a more realistic assessment of invasion risk and supports climate-adaptive management strategies.

Keywords

MaxEnt, invasive species, species distribution modelling, climate change, land use, Tanzania

Introduction

Climate change and land-use dynamics are the primary forces driving significant changes in ecosystems and species distributions (Tylianakis et al. 2008, Bellard et al. 2016, Crowl et al. 2008). The frequency of extreme events, temperature regimes, and precipitation patterns is altered by climate change, which also affects habitat appropriateness (Sirami et al. 2017, Bellard et al. 2018, Soifer et al. 2025). For instance, rising temperatures and fluctuating rainfall allow invasive species to spread into previously unsuitable areas, particularly in ecologically sensitive regions such as East Africa (Hawinkel et al. 2016, Bellard et al. 2018, González-Orenga et al. 2022).

The establishment and spread of invasive alien species (IAS) are further aided by the simultaneous transformation of habitat structure and resource availability brought about by land-use and land-cover change (LUCC), which is fuelled by infrastructure development, urbanisation, deforestation, and agriculture (Jarnagin 2004, Vila and Ibáñez 2011). Predicting and controlling biological invasions is becoming increasingly challenging due to interactions between LUCC and climate change (Pyšek et al. 2020). Therefore, a comprehensive understanding of these drivers is necessary for effective conservation efforts in areas that are undergoing rapid change, such as the Lake Zone in Tanzania (Odada et al. 2009).

Climatic forecasts indicate that Tanzania will experience significant warming and increased rainfall variability, potentially leading to agricultural failure, disease outbreaks, and elevated risks of biological invasion (Luhunga et al. 2018). These climatic changes, when combined with extensive land-use transformation, intensify the impacts of invasive alien species (IAS) and threaten agriculture, biodiversity, and human well-being (Bukombe et al. 2021). The country's expanding agricultural activities, ongoing deforestation, and increasing climate variability create favourable conditions for the establishment and proliferation of invasive species (World Bank 2019, Ojija et al. 2017, Bukombe et al. 2021, Busungu 2025). Primary human-mediated pathways, such as crop trade, movement of contaminated agricultural equipment, and road expansion, are accelerating the spread of IAS into new regions. IAS already exerts substantial negative effects on biodiversity, ecosystem services, and human livelihoods. In particular, infestations of *Lantana camara*, *Chromolaena odorata*, and *Eichhornia crassipes* are especially severe in the Lake Zone, where they disrupt agricultural production, degrade native ecosystems, and compromise water resources. Addressing these challenges requires integrated, interdisciplinary management strategies that utilise geospatial technologies for effective monitoring and mapping (Rai and Singh 2020). Such approaches include species distribution models (SDMs), such as MaxEnt, which offer a robust framework for predicting potential species ranges under diverse land-use and climatic scenarios (Peterson 2003, Guisan and Thuiller 2005).

Most previous studies in Tanzania have examined a single invasive species and have primarily relied on climate variables to predict future distributions (Kija et al. 2013, Nyarobi et al. 2022, Meshili and Yang 2025). Few studies have integrated land-use change with climate scenarios, and even fewer have modelled multiple invasive species concurrently. This limited scope fails to account for the interactive effects of climate and land-use/land-cover change (LUCC), which together influence invasion dynamics and the effectiveness of management interventions. Additionally, there is a notable absence of subnational-level projections to inform decision-making in biodiversity hotspots such as the Lake Zone.

To address these gaps, this study integrates climate projections and land-use/land-cover dynamics to model the potential distribution of three ecologically and socioeconomically significant invasive species (*L. camara*, *C. odorata*, and *E. crassipes*) in the Lake Zone of Tanzania. Using MaxEnt, high-resolution bioclimatic and LUCC data are combined to assess current and future habitat suitability across various Shared Socioeconomic Pathways (SSPs-RCP) and time periods. This approach enables a more comprehensive assessment of invasion risks by (i) evaluating multiple species simultaneously, (ii) explicitly incorporating LUCC alongside climate drivers, and (iii) generating fine-scale regional projections for the Mara and Simiyu regions. Consequently, the study advances the methodological application of species distribution models (SDMs) in East Africa. It provides actionable insights for ecological risk assessment, land-use planning, and the development of proactive management strategies to safeguard biodiversity and local livelihoods.

Material and methods

Study area and target species

This research focuses on the Mara and Simiyu regions of Tanzania, located within the Lake Victoria Basin. The study area roughly extends from 1°29′44.88″ S, 33°48′18″ E to 3°08′17.88″ S, 34°17′16.08″ E. These regions exhibit diverse climatic conditions and land-use patterns, including agriculture, forestry, wetlands, and expanding urban areas, making them well-suited for examining the dynamics of invasive alien plant species. The study area was defined using official administrative boundaries and verified with land-cover datasets to ensure spatial accuracy and ecological relevance (Fig. 1).

In this study, we selected three species based on field observations of abundance and diversity, as well as a literature review of their impacts on biodiversity and human livelihoods. The species *are Chromolaena odorata, Eichhornia crassipes, and Lantana* camara. *C. odorata, also known as siam weed, is* a perennial shrub belonging to the Asteraceae family, native to the tropical and subtropical regions of Central and South America, including Mexico, Brazil, and the Caribbean (Tiamiyu and Okunlade 2020)**.** As it transitions from herbaceous to woody, this plant can reach up to 2 meters in height. Its propagation occurs via both vegetative and sexual means, with high fecundity and rapid germination (Muniappan et al. 2005). It is a fast-growing shrub that invades grasslands, forests, and agricultural lands, suppressing native plants and reducing crop yields (Shackleton et al. 2017). *Lantana amara is a woody shrub species native to the American tropics and has been* introduced to Africa, India, and Asia since the early 19th century as an ornamental garden plant (Day et al. 2003). The weed can reach 1-3 meters in height and 2.5 meters in width. The species invades a wide range of habitats, but grows best in open, disturbed ecosystems, along forest edges, and roadsides (Sharma et al. 2005). *Eichhornia crassipes* is commonly known as water hyacinth. It infests Tanzania's freshwater bodies, particularly in the lake zone regions surrounding Lakes Victoria, Tanganyika, and Nyasa. It creates dense, impenetrable mats that obstruct waterways and hydroelectric intakes, disrupting transportation, fisheries, and other water-related activities (Ndunguru et al. 2001, Jafari 2010, Omondi and Merceline 2023). The plant also reduces oxygen levels in the water, negatively impacting aquatic biodiversity (Coetzee et al. 2014). Due to its rapid growth rate and noxious effects, both species have been listed among the world's 100 worst alien invasive species by the IUCN.

Data resources

Species occurrence records

Species occurrence records for *L. camara, C. odorata*, and *E. crassipes* were compiled from field observations, global biodiversity databases (GBIF and iNaturalist), and contributions from a collaborating researcher (Rudolf). Data preprocessing in R (versions 2024 and 2025) included filtering to valid geographic bounds, converting coordinate fields to numeric format, removing missing or erroneous records, and projecting all data to WGS 84 (EPSG:4326). Cleaned occurrences were cropped to the study extent covering the Mara and Simiyu regions of northern Tanzania (33.0°E–36.0°E; −3.0° to 0.0° latitude).

To reduce spatial sampling bias, we used a three-step correction process. First, we applied spatial thinning by setting a minimum distance between records to lower local spatial autocorrelation. After this step, 272 of 503 *L. camara*, 117 of 604 *C. odorata*, and 22 of 76 *E. crassipes* records remained.

Next, we matched the occurrence data to the 1-km-resolution environmental layers using grid-based filtering, keeping only one record per 1-km² cell. This left 234, 104, and 21 records for the three species, ensuring no grid cell was over-represented and that environmental variation was covered (Table 1).

In the third step, we corrected for spatial sampling bias in presence-only data by weighting background points with a bias raster, following the target-group method from Phillips et al. 2009). We created a kernel density surface from GBIF vascular plant records and used it as a bias file in MaxEnt, so background points were sampled more in areas with higher sampling effort. This approach helps background points align with the spatial bias of the presence data, reducing the likelihood that the model reflects observer effort rather than real species–environment patterns. Using spatial thinning, grid-based filtering, and bias-weighted background sampling together gives a strong correction for spatial bias at both local and regional level.

Environmental predictors

To model the potential distribution of invasive species, we selected a matching set of environmental predictors that represent climate and land-use factors. These predictors were chosen based on their ecological relevance and availability at appropriate spatial resolutions.

Bioclimatic Variables

Nineteen bioclimatic variables (BIO1–BIO19) were derived from the WorldClim v2.1 (https://worldclim.org/) dataset at a spatial resolution of 30 arc-seconds (~1 km²) (Fick and Hijmans 2017). Future climate projections for the 2030s, 2050s, 2070s, and 2090s were sourced from MIP6-Downscaled climate projections, which include three General Circulation Models: ACCESS-CM2, MIROC6, and MRI-ESM2, under four Shared Socioeconomic Pathway scenarios: SSP1, SSP2, SSP3, and SSP5. These variables represent meaningful temperature and precipitation metrics that influence species distributions, including annual mean temperature (BIO1), temperature seasonality (BIO4), and precipitation in the wettest quarter (BIO16). All layers were projected to WGS84 (EPSG:4326) and retained their native extent (global coverage) to ensure consistent analysis across all study areas and scenarios.

Multicollinearity Assessment

To reduce predictor redundancy and avoid multicollinearity, we conducted a Pearson correlation analysis on a random sample of 10,000 grid cells extracted from the bioclimatic raster stack. Variables with pairwise correlation coefficients $|r| > 0.7$ were considered highly correlated (Dormann et al. 2013). To further refine variable selection, we used the Variance Inflation Factor (VIF) with the vifcor() function from the usdm R package, setting the threshold at 10 (Zainodin et al. 2015). This procedure followed established recommendations for reducing predictor redundancy in species distribution modelling and retained only variables with low multicollinearity for model calibration (Dormann et al. 2013). Based on ecological relevance and statistical independence, a final set of seven bioclimatic variables was retained (Table 2).

Multicollinearity assessment was restricted to bioclimatic predictors because these represent continuous environmental gradients that are commonly highly correlated. Fractional land-cover predictors were treated separately, as they represent anthropogenic land-use proportions rather than climatic gradients, and were retained based on ecological relevance and thematic independence.

Land use and land cover data

In addition to climatic predictors, we incorporated land use and land cover (LUCC) data from the current land use download available from ESSA version 2, 2020, provided by the European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover dataset, which has a 10-meter resolution (Zanaga et al. 2021). The six tiles were cropped to the study area, leaving two tiles. To ensure consistency with the 30-second (~1 km) resolution of the bioclimatic variables, the land-use rasters were resampled using the nearest-neighbour method, which preserves categorical integrity (Fitzpatrick and Hargrove 2009). They were then aggregated to match the modelling scale (Huang and Wu 2004) and reclassified into seven major land-cover categories (forest, grassland, agriculture, urban, water, wetland, and barren land) to harmonise the datasets and reduce class complexity (Pontius and Malanson 2005).

Future land-use projections were obtained from the harmonised global land use and land cover (LULC) dataset developed by Woodman et al. (2025), available via Zenodo (Version 1, https://doi.org/10.1016/j.oneear.2025.101525). This dataset provides globally consistent, downscaled LULC projections at 1-km resolution spanning 1960–2100 and aligned with SSP–RCP scenarios. The projections were generated using a harmonised allocation framework designed to produce high-resolution representations of land-use transitions consistent with integrated assessment model outputs (Woodman et al. 2025). Raster layers corresponding to the selected SSP–RCP scenarios and time periods (2030, 2050, 2070, 2090) were extracted and reclassified into seven aggregated land-cover categories to ensure compatibility with the species distribution modelling framework.

Modelling approach, settings, and validation

We modelled the current and future potential distributions of *Lantana camara*, *Chromolaena odorata*, and *Eichhornia crassipes* using MaxEnt v3.4.3 (Phillips et al. 2006), implemented through the ENMeval v2.0.5.2 framework (Muscarella et al. 2014, Kass et al. 2021). Each species was modelled independently using its own occurrence dataset and tuning procedure. Models were fitted using presence-only occurrence data and environmentally heterogeneous predictors.

For all species, predictor sets initially included seven bioclimatic variables selected after filtering for multicollinearity. For the two terrestrial invaders (*L. camara* and *C. odorata*), land-use information was additionally incorporated using ESA land-cover data for the Mara–Simiyu region. To retain landscape heterogeneity, categorical land-cover layers were aggregated to derive continuous fractional-cover predictors representing the proportion of each land-use class within each 1-km cell. This approach reduces information loss associated with categorical resampling and aligns with best practice for incorporating land-use data into species distribution models (Franklin 2010, Guisan et al. 2017). All predictors were resampled to a standard 30-arc-second grid and converted to the Terra SpatRaster format prior to analysis.

Due to the limited number of spatially filtered occurrences available for *Eichhornia crassipes* (21 records after 1-km filtering), model complexity was deliberately constrained to reduce the risk of overfitting. Overfitting is particularly problematic in species distribution models with small sample sizes and high predictor dimensionality (Breiner et al. 2015). Previous studies have demonstrated that reliable MaxEnt models can be developed with limited occurrence records when model complexity is appropriately controlled (Hernandez et al. 2006, Galante et al. 2018). Accordingly, we restricted predictors for *E. crassipes* to four ecologically interpretable, weakly correlated climate variables and limited feature classes to linear and quadratic forms.

Model complexity was optimised using ENMeval by evaluating combinations of feature classes (L, Q, H, LQ, LQH) and regularisation multipliers ranging from 0.5 to 3.0. For each species–predictor set (climate-only and climate plus land use), the optimal model was selected using the minimum Akaike Information Criterion corrected for small sample sizes (AICc), thereby balancing goodness-of-fit and model parsimony (Warren and Seifert 2011, Kass et al. 2021).

Model performance evaluation

Model performance was evaluated using spatially explicit block cross-validation implemented in ENMeval. Occurrence records were partitioned into four geographically structured blocks using the latitude–longitude (“block”) strategy (Roberts et al. 2017), resulting in a four-fold cross-validation scheme in which each block was used once as an independent test dataset, and the remaining three blocks were used for model calibration. This spatial partitioning reduces spatial autocorrelation between the training and test data, providing a more conservative, realistic assessment of model transferability than random data splitting (Roberts et al. 2017, Valavi et al. 2022).

MaxEnt continuous suitability outputs (cloglog transformation) were retained for interpretation and for projecting habitat suitability under current and future climate scenarios(Phillips et al. 2006, Elith et al. 2011). For map-based interpretation, suitable–unsuitable maps were derived using three widely applied threshold criteria: the 10th percentile training presence (P10), equal sensitivity and specificity (ESS), and maximum sensitivity plus specificity (maxSSS) (Liu et al. 2005, Liu et al. 2016, Hellegers et al. 2025). Thresholds were calculated using presence records and background points within the MaxEnt modelling framework. Employing multiple threshold criteria enabled comparison among species while explicitly acknowledging uncertainty associated with threshold selection.

Model discrimination was evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC) calculated from spatially independent validation folds generated during block cross-validation. Mean validation AUC (auc.val.avg) was used as the primary performance metric because it provides a threshold-independent measure of discrimination and reduces over-optimistic inflation associated with training AUC. Training AUC values were reported for reference only. Following common practice in species distribution modelling, AUC values ≥ 0.80 were interpreted as indicating good discriminatory performance, whereas values between 0.60 and 0.80 were considered moderate.

Future projections, ensemble modelling, and suitability classification

We projected future habitat suitability using four CMIP6 Shared Socioeconomic Pathways (SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5), which represent a range of greenhouse gas forcing levels (Mölg and Pickler 2022). Projections were based on three CMIP6 General Circulation Models (GCMs): ACCESS-CM2, MIROC6, and MRI-ESM2-0. These models were selected for their availability across all SSPs and time periods (2030, 2050, 2070, 2090), structural diversity, and provision of bias-corrected, downscaled bioclimatic layers at approximately 1-km resolution. While CMIP6 models have demonstrated general capability for East African climate modelling (Ayugi et al. 2021, Mölg and Pickler 2022, Makula and Zhou 2022), our specific model selection prioritized data availability and consistency across scenarios.

We calibrated MaxEnt models with current data and projected them using the cloglog output, which provides a continuous, interpretable index of relative occurrence probability suitable for scenario and time-period comparisons (Phillips et al. 2009). We combined climate projections with land-use layers corresponding to each SSP for 2030, 2050, 2070, and 2090, and matched them to the relevant bioclimatic periods (2021–2040, 2041–2060, 2061–2080, and 2081–2100). All predictors were resampled and aligned to a common 1-km grid before projection.

For each species, SSP, and time period, we projected suitability separately for each GCM. We then generated ensemble predictions by averaging across the GCMs with equal weights. To assess model uncertainty, the projected suitable area was quantified across global climate models (ACCESS-CM2, MIROC6, and MRI-ESM2-0). For each species, year, and SSP, suitable habitat was defined as grid cells with predicted suitability ≥ the 10th percentile training presence threshold. The total suitable area (km^2) was calculated separately for each GCM within the AOI, and inter-model uncertainty was summarized using the mean, standard deviation, and coefficient of variation of suitable area. For each species, year, and SSP, suitable habitat was defined as grid cells with predicted suitability at or above the 10th percentile training presence threshold. Total suitable area (km^2) was calculated separately for each GCM within the AOI, and inter-model uncertainty was summarized using the mean, standard deviation, and coefficient of variation of suitable area. We produced ensemble suitability maps, uncertainty layers, and area-based summaries.

We retained continuous cloglog predictions for all modelling, evaluation, and uncertainty analyses.

For visualization and area-based summaries, continuous MaxEnt cloglog outputs were converted into discrete suitability classes using statistically derived thresholds rather than arbitrary value ranges. Specifically, the 10th percentile training presence (P10) threshold was used to distinguish between unsuitable and suitable conditions. The P10 threshold is widely used in presence-only species distribution modelling because it accommodates potential geolocation error and environmental uncertainty by allowing a small proportion (10%) of training occurrence records to fall below the suitability threshold (Liu et al. 2005, Pearson et al. 2007, Radosavljevic and Anderson 2014). The methodological steps used in the modelling process are illustrated in Fig. 2

Results

Variable importance and model performance evaluation

Model performance remained high for both climate-scenario and combined climate-and-land-use scenario models, and they were selected based on AICc. For climate-only models, the area under the curve (AUC) values were 0.983 for *Lantana camara*, 0.978 for *Chromolaena odorata*, and 0.776 for *Eichhornia crassipes*. When climate and land-use predictors were combined for terrestrial species, predictive performance remained high, with *L. camara* achieving 0.980 and *C. odorata* 0.989. These results show that the models are reliable for assessing habitat suitability in Tanzania's Lake Zone.

In the climate-only models, temperature and precipitation variability were the primary drivers, but their influence varied across species. Annual temperature range (Bio7) was the most important *L. camara* (47.29%) and *C. odorata* (47.29%). Temperature seasonality (Bio4) was also important, especially for E. *crassipes* (34.6%), *L. camara* (21.34%), and *C. odorata* (17.28%). Precipitation seasonality (Bio15) had a strong effect on *C. odorata* (39.92%) and *L. camara* (15.19%), while precipitation of the warmest quarter (Bio18) and mean temperature of the wettest quarter (Bio8) were key factors for *E. crassipes* (34.8%) and (30.6%), respectively Table 3.

In the combined climate–land-use models, Bio7 and Bio4 remained the dominant predictors for both *L. camara* (33.71% and 23.04%, respectively) and *C. odorata* (29.52% and 20.12%). Precipitation seasonality (Bio15) also contributed substantially, and land-use/land-cover under the water category emerged as an important predictor for *C. odorata* (14.84%) and *L. camara* (14.14%). Precipitation in the wettest quarter (Bio16) had a moderate relative contribution. However, its higher permutation importance indicates a strong influence on model predictions, despite a lower fitted contribution Suppl. material 1.

Jackknife analysis based on regularized training gain revealed that a subset of bioclimatic variables contributed disproportionately to the model structure across species (Fig. 3). For all three species, variables related to precipitation seasonality and temperature variability yielded relatively high gains when used in isolation, whereas omitting them led to notable reductions in model gain. Response curves (Fig. 4) further illustrate how predicted habitat suitability varies along individual environmental gradients while holding other predictors constant.

Current habitat suitability patterns

Across the Mara–Simiyu landscape, current habitat suitability was spatially heterogeneous, with suitable areas concentrated in the central–western and northern portions of the study area, particularly along riparian corridors and adjacent floodplain systems (Suppl. material 2, Fig. 5). Under climate-only models*,* *C. odorata* and *L. camara* exhibited broadly similar patterns, with approximately 13–17% of the region classified as marginal to highly suitable, while *E. Crassipes* showed slightly lower overall suitability (≈13%). Highly suitable areas for terrestrial species were largely restricted to zones with higher moisture availability and productive land cover, whereas the eastern and southern parts of the landscape were dominated by unsuitable conditions. Incorporating land-use information resulted in modest reductions in suitable habitat for *C. odorata* and *L. camara* , primarily through contraction of moderately and highly suitable areas in fragmented agricultural and urbanised zones, while suitability along riparian corridors remained comparatively stable. For *C. odorata*, the proportion of highly suitable area declined from 4.58% under climate-only conditions to 4.26% under the combined model, and for *L. camara* from 5.61% to 5.46%, without substantial shifts in the overall spatial pattern.

Future habitat suitability projections

Climate-only model

Future climate projections indicated substantial changes in habitat suitability across species, scenarios, and time periods (Fig. 6).

Spatial patterns of future suitability

Spatial patterns of projected habitat suitability varied markedly among species across Shared Socioeconomic Pathways (SSPs) and General Circulation Models (GCMs) (Fig. 6). For *C. odorata* and *L. camara*, areas exceeding the P10 suitability threshold were largely concentrated in the eastern portion of the study area during the early projection period (2030), with smaller patches extending toward central regions. Under SSP1–2.6, these spatial configurations remained relatively stable through mid-century, with only gradual contraction along peripheral margins.

In contrast, under higher-emission scenarios (SSP3–7.0 and SSP5–8.5), both terrestrial species exhibited progressive spatial restriction of suitable areas, particularly after 2050. By the late century, suitability became increasingly confined to small, fragmented patches in the eastern sector or disappeared entirely in some GCM projections, resulting in extensive expansion of areas classified as unsuitable (<P10). Divergence among GCMs was most pronounced under these higher-emission pathways, with some models projecting a near-complete loss of suitable conditions, while others retained only limited residual patches.

E. crassipes displayed a contrasting spatial response. Suitable conditions (≥P10) were widespread across much of the study area even under moderate scenarios, and under SSP3–7.0 and SSP5–8.5, suitability expanded and became increasingly spatially homogeneous by mid- to late century. In several projections, unsuitable areas were confined to narrow peripheral zones or were nearly absent in ensemble means. This broad expansion reflects projected climatic suitability rather than realised habitat occupancy, as the species remains ecologically restricted to aquatic systems**.**

Species-Specific Trends

Area-based summaries were consistent with the spatial patterns depicted in the maps (Table 4). For *C. odorata* and *L. camara*, highly suitable areas declined under higher-emission scenarios, particularly toward the end of the century, while marginal and unsuitable areas expanded. These results indicate a gradual reduction in optimal climate conditions rather than a complete loss of suitability.

In contrast, *E. crassipes* generally exhibited stable or expanding areas of suitable habitat over time. In certain late-century SSP3-7.0 and SSP5-8.5 scenarios, unsuitable areas were minimal or absent. However, the proportions of marginal, moderate, and highly suitable areas differed among scenarios and general circulation models (GCMs).

No species experienced a complete loss of climatically suitable habitat in any scenario. However, specific suitability classes were absent in some scenarios and time periods. More details for the area suitability are in (Suppl. material 3).

Ensemble Agreement and Uncertainty

Ensemble uncertainty, quantified using the coefficient of variation (CV) among GCM projections (Suppl. material 4), showed clear temporal divergence among species. These patterns are consistent with changes in the total suitable area illustrated in the figure.7

For the terrestrial species *Chromolaena odorata* and *Lantana camara*, relative uncertainty increased from 2030 to 2090, particularly under higher-emission pathways. As the suitable area declined (Fig. 7), variability among GCMs increased, indicating greater disagreement regarding the spatial extent of climatically suitable habitat under intensified warming. This divergence was most pronounced in late-century projections under SSP3–7.0 and SSP5–8.5.

In contrast, *Eichhornia crassipes* displayed mixed uncertainty patterns. Under scenarios where suitability became spatially dominant and approached saturation (Fig. 7), relative uncertainty declined, reflecting stronger agreement among GCMs. Higher variability was primarily observed during intermediate periods, when suitability transitioned between marginal and moderate classes.

Overall, the climate-only projections with fixed-threshold classification revealed species-specific responses to projected climate change. The two terrestrial invasive species exhibited progressively contracting and increasingly uncertain suitable habitats under higher-emission scenarios. By contrast, *E. crassipes* maintained broad climatic suitability across most projections, with future change characterized more by redistribution among suitability classes than by expansion of unsuitable areas.

Combined Climate and Land-Use Projection

Spatial future Suitability and ensemble mean

Across scenarios, both species exhibit a persistent north–central concentration of suitable habitat, with unsuitable conditions expanding toward the south and western margins, a pattern that intensifies with increasing emissions and time. For *Chromolaena odorata*, moderate-to-high suitability generally dominates under SSP1–2.6 and SSP2–4.5, covering roughly 55–65% of the area, with relatively low inter-model uncertainty (CV mostly <15%). Under higher forcing (SSP3–7.0 and SSP5–8.5), suitable areas become more fragmented and restricted by mid- to late century, accompanied by increasing model divergence, with CVs for high suitability rising to ~65–75% by 2090. In contrast, *Lantana camara* shows earlier and stronger spatial contraction, with suitable habitat increasingly confined to limited north–central patches and extensive expansion of unsuitable conditions. This spatial decline is coupled with substantially higher uncertainty: CVs for high suitability frequently exceed 60% by mid-century and reach ~85–90% under SSP3–7.0 and SSP5–8.5 by 2090, indicating highly model-dependent outcomes. Overall, combined land-use and climate projections suggest progressively constrained and increasingly uncertain habitat suitability under stronger warming, with *L. camara* exhibiting both greater spatial loss and higher uncertainty than *C. odorata* (Fig. 8 ;Suppl. material 5).

LUCC-driver uncertainty

Inter-model uncertainty in the effective suitable habitat is strongly land-use-dependent. For both species, cropland contributes the largest effective suitable area and is relatively stable for *Chromolaena* (cropland CV typically ~1–19%), but becomes much more uncertain for *Lantana* under higher forcing, rising from ~6–12% (2030–2050) to ~33–74% by 2070–2090 in SSP3–7.0/SSP5–8.5. In contrast, the water class shows the highest variability across all scenarios, with very large CVs (Chromolaena water CV often ~33–93%; Lantana water CV commonly ~78–159%), indicating that model disagreement is concentrated in water-associated areas. Forest shows intermediate variability but increases under high emissions toward the late century (up to ~31% for *Chromolaena* and ~43% for *Lantana*). Shrubland and urban areas contribute small absolute areas and can display inflated CV when means are low. Selection ratios indicate non-random land-use association, with both species generally selecting forest/shrubland (SR > 1) and avoiding water (SR < 1) consistently across scenarios (Suppl. material 6).

Spatial overlap and invasion hotspots

Niche overlap between *Lantana camara* and *Chromolaena odorata* remained moderate to high across all climate scenarios (Schoener's D = 0.45–0.81; Hellinger's I = 0.78–0.97). Under low-emission conditions (SSP126), overlap remained stable over time, reflecting persistent climatic niche similarity. In contrast, intermediate- and high-emission scenarios showed greater variability among general circulation models. Some projections indicated increased climatic convergence by the end of the century (e.g., SSP585–2090; D = 0.81), while others suggested partial niche divergence (e.g., SSP370–2090; D = 0.45). These findings demonstrate that although the two terrestrial invaders currently share broadly similar environmental requirements, the extent of future climatic overlap will depend strongly on both the emission trajectory and the climate model structure (Suppl. material 7).

Spatial overlap in projected suitable areas, measured using Jaccard similarity of binary P10-thresholded maps, exhibited similar patterns but with greater variability among models. Under SSP126 in 2030, approximately 47–49% of the suitable habitat was shared between the two species. In subsequent periods, spatial overlap varied widely among general circulation models, ranging from a complete absence of co-suitable area (0%) in scenarios where one species lost suitability, to values exceeding 50% in projections with broad co-suitability. When both species retained suitable habitat, 70–80% of the smaller species' suitable range overlapped with that of the other species, indicating substantial geographic convergence. Comprehensive spatial overlap metrics, including co-suitable area (km²) and Jaccard percentages, for all scenarios are presented in Suppl. material 8.

Discussion

Current distribution patterns

This study provides a subnational, spatially explicit assessment of the current and future distribution of three invasive plant species across contrasting ecosystems in the Mara–Simiyu region using a threshold-based MaxEnt modelling framework (Suárez-Mota et al. 2016, Shilky Kishore et al. 2023). Two terrestrial species, *Chromolaena odorata* and *Lantana camara*, and one aquatic species, *Eichhornia crassipes*, were modelled under climate-only and combined climate–land-use scenarios using cloglog outputs and a fixed 10th-percentile training presence threshold (Pearson et al. 2007).

Under current climatic and land-use conditions, the model identified distinct invasion hotspots for the terrestrial species in the central, western, and northern parts of the region. These areas correspond to disturbed rangelands, agricultural mosaics, and transport corridors, consistent with previous studies in Tanzania and East Africa (Mgumia and Oba 2003, Mwangi and Swallow 2008). In contrast, suitability for *E. crassipes* was largely associated with riparian systems and aquatic corridors, aligning with well-documented patterns in the Lake Victoria basin and connected river systems (Albright et al. 2004, Njiru et al. 2012).

Environmental drivers and ecological interpretation

Analysis of variable contributions indicates that temperature variability and seasonal precipitation are key determinants of species distributions, although their relative importance differs among species (Phillips et al. 2006, Elith et al. 2011).

For *Lantana camara* and *Chromolaena odorata*, temperature seasonality (Bio4) and annual temperature range (Bio7) were the dominant predictors, suggesting sensitivity to thermal variability. In tropical savanna systems, temperature fluctuations influence physiological stress tolerance, growth rates, and competitive interactions, thereby shaping invasion success (Bradll et al. 2010). Climate projections for Tanzania indicate increasing mean temperatures and greater temperature variability during the 21st century (Luhunga et al. 2018, Luhunga and Songoro 2020, Magesa 2024). Such changes may alter seasonal temperature regimes, potentially expanding suitable conditions in some regions while increasing climatic stress in others.

For *Eichhornia crassipes*, temperature seasonality (Bio4) and precipitation during the warmest quarter (Bio18) were more influential, reflecting its dependence on warm, moist conditions that support rapid vegetative growth (Villamagna and Murphy 2010). Regional projections indicate increasing temperatures, changes in rainfall seasonality, and more frequent extreme precipitation events (Luhunga and Songoro 2020, Magesa 2024). These hydroclimatic changes may enhance environmental conditions favourable to *E. crassipes*, particularly in lowland and lacustrine systems, helping explain the broad climatic suitability projected under higher-emission scenarios.

Precipitation of the wettest quarter (Bio16) showed moderate contribution but high permutation importance, indicating that model performance declined when this variable was randomized. This suggests that Bio16 captures seasonal water availability not fully represented by other rainfall variables. Seasonal rainfall patterns strongly influence plant establishment and survival in tropical ecosystems (Baltzer and Davies 2012), while water availability regulates biomass production across wet–dry gradients (Muller-Landau et al. 2021). Disturbance events interacting with seasonal moisture conditions may further enhance invasion success (Setterfield et al. 2005).

When land-use variables were incorporated, the relative contribution of climatic predictors decreased but remained dominant. Temperature-related variables declined by approximately 30–40% in relative importance compared with climate-only models, although they continued to represent the primary drivers of suitability. This indicates that invasion risk is shaped by both broad-scale climatic constraints and local habitat availability. Consequently, these findings support the view that invasion dynamics result from interactions between environmental conditions and anthropogenic landscape modification rather than climate alone (Roura-Pascual et al. 2011, Early et al. 2016, Ren et al. 2025).

Climate-only projections

When considering only climate projections, the two invasive species maintained mostly stable core areas under low-emission scenarios (SSP1–2.6). In contrast, under higher-emission scenarios (SSP3–7.0 and SSP5–8.5), especially later in the century, the most suitable areas became more fragmented and shrank. This matches predictions of rising average temperatures and greater temperature swings across Tanzania under high-emission scenarios (Luhunga et al. 2018, Luhunga and Songoro 2020). Since annual temperature range (Bio7) and temperature seasonality (Bio4) were the main factors in our models, the drop in suitability likely means the climate is moving outside the species' preferred temperature range, not just shifting locations. Too much warming and more variable temperatures can stress these species, make them less competitive, and limit their ability to establish in already warm tropical areas.

So, if warming is strong, some parts of the study area could move beyond the climate limits needed for *L. camara* and *C. odorata* to grow well, causing their range to shrink rather than expand. This fits with other research showing that tropical invasive plants may lose suitable habitat when temperatures exceed their tolerance thresholds or when the climate becomes too unpredictable (Kriticos et al. 2005, Bellard et al. 2018).

Unlike other species, *E. crassipes* showed broad climatic suitability in most scenarios. Late-century projections often showed greater uniformity in suitability, with few areas marked as unsuitable. This pattern reflects that the climate is generally permissive, not that the species is expanding its habitat, since it is still limited to aquatic environments. The continued widespread suitability matches evidence that floating aquatic plants can keep or even expand their suitable climate ranges as tropical regions warm (Villamagna and Murphy 2010, Kriticos et al. 2015).

Continued climatic suitability will likely continue to put pressure on freshwater ecosystems by causing surface mats, blocking light, reducing oxygen, and altering nutrient cycles. This can reduce native biodiversity and alter how these ecosystems function. For people, ongoing suitability increases long-term risks to fisheries, irrigation systems, hydropower, and local communities that rely on open water. These results suggest that climate change could make management harder, even if the species does not move into new climate zones.

For terrestrial species, divergence among general circulation models (GCMs) increased under high-emission scenarios, leading to greater variability in projected high-suitability areas. This trend indicates increasing uncertainty in temperature and rainfall projections over time (Araújo and Peterson 2012, Buisson et al. 2010). Ecologically, this divergence implies more heterogeneous invasion outcomes across the landscape. From a management perspective, it underscores the need for adaptive strategies that account for multiple plausible climate futures. These results emphasize the importance of ensemble approaches for invasion risk assessment in East Africa.

Combined climate-land-use projections

Incorporating land-use change substantially altered the patterns of climate-driven suitability. For *C. odorata* and *L. camara*, suitable habitat was further reduced under high-emission scenarios, and model uncertainty increased over time. These findings underscore the need to include land-use dynamics in invasion modelling (Franklin 2010, Mainali et al. 2015, Thuiller et al. 2019). As uncertainty increases with greater warming, late-century projections should be interpreted as risk estimates rather than precise predictions. Regions where models converge are more reliable for forecasting invasion risk, whereas areas with high variability require close monitoring and adaptive management.

Both species were often found to prefer cropland, showing they are linked to disturbed and human-changed habitats. However, confidence in these predictions decreased under high-emission scenarios, indicating greater uncertainty in agricultural areas. Water classes showed the most variation in the models, possibly because they are sensitive to climate assumptions or to how land cover is represented (Václavík and Meentemeyer 2009). Forest areas had moderate variability that increased with stronger warming, suggesting that climate change could change habitat suitability there.

Selection ratios (SR > 1 for forest and shrubland; SR < 1 for water) indicate that land-use associations are not random, highlighting the importance of habitat context for invasion risk (González-Moreno et al. 2014). Climate determines the overall suitability, but land-use patterns can either increase or limit invasion at the local level.

Spatial overlap and potential co-occurrence

Moderate to high environmental niche overlap between *L. camara* and *C. odorata*, quantified using Schoener's D and Hellinger's I (Broennimann et al. 2012), indicates substantial similarity in climatic tolerances. However, spatial overlap in projected suitable areas provides a more direct estimate of potential co-occurrence. Under low-emission scenarios in 2030, approximately 47–49% of climatically suitable area was shared between the two species, indicating considerable potential for co-invasion.

Under mid- and late-century projections, spatial overlap became increasingly variable among GCMs. In some projections, Jaccard overlap exceeded 50%, suggesting strong spatial convergence, whereas in others overlap declined sharply or approached zero due to the contraction of suitable habitat for one species. This divergence indicates that while climatic niches remain broadly similar, geographic co-suitability is highly sensitive to model-specific climate trajectories.

Such variability implies that future co-invasion risk may intensify in some climate futures but diminish in others, reinforcing the need to interpret projected species interactions within an ensemble framework (Alexander et al. 2016).

Methodological considerations and limitations

Using the P10 threshold enabled consistent comparisons of suitability patterns across species and scenarios (Jiménez-Valverde and Lobo 2007, Elith et al. 2011). However, other threshold criteria were not systematically tested in the final projections. Choosing different thresholds could change the size of the predicted suitable areas.

There are several limitations to note. First, while MaxEnt performs better than other modelling methods with small sample sizes (Breiner et al. 2015, Moudrý et al. 2024), the limited number of occurrence records filtered for *E. crassipes* may still increase uncertainty and make it harder to apply the results to future climate scenarios. The model was kept simple to avoid overfitting, so predictions for this species should be viewed with caution.

Second, using a presence-only modelling approach makes it hard to distinguish between truly unsuitable environments and areas that have not been sampled but could be suitable. This is a common issue in correlative species distribution models because results depend on the type and quality of the available occurrence data (Brotons et al. 2004, Yackulic et al. 2013, Jarnevich et al. 2015). Even with spatial bias correction and background weighting, predicting into new climate conditions can still involve extrapolation and uncertainty.

Third, model performance was mainly measured using spatially structured test AUC. While AUC is commonly used and does not depend on thresholds, it does not fully reflect model calibration or ecological realism (Lobo et al. 2008). For this reason, AUC was considered along with omission rates, response curves, and jackknife diagnostics.

Fourth, the chosen general circulation models (GCMs) provided consistent data across all Shared Socioeconomic Pathways (SSPs) and time periods, but they were not the best-performing CMIP6 models for predicting East African rainfall. This trade-off between having complete data and getting the best regional results may lower the accuracy of predicted suitability patterns, especially for species sensitive to rainfall.

Finally, future land-use predictions remain uncertain because they depend on the socio-economic assumptions underlying the Shared Socioeconomic Pathway (SSP) narratives. Even though land-use and cover change (LUCC) layers matched the climate scenarios, uncertainty about future land use adds another source of variation in the predicted invasion risk.

Implications for management and future research

From a management perspective, projected contraction and fragmentation of highly suitable habitats for terrestrial invaders suggest prioritizing monitoring and early detection in stable core areas and agricultural mosaics identified as high-risk zones. For aquatic systems, the persistence of broad climatic suitability indicates continued vulnerability of riverine and lacustrine networks under warming scenarios.

Future research should incorporate hydrological predictors for aquatic species, evaluate dispersal constraints, and validate projections through long-term field monitoring. Improved representation of land-use transitions and socio-economic drivers would further enhance the realism of invasion modelling scenarios.

Conclusions

Combining land-use change and climate projections allows us to evaluate how these factors jointly influence the potential distribution of invasive species. In the Mara–Simiyu region, invasion risk varies by location and species. Aquatic habitats are likely to remain suitable for *Eichhornia crassipes*, while terrestrial invaders may encounter greater challenges as climate and land use evolve, particularly under high-emission scenarios. Identifying suitable and vulnerable agricultural areas supports prioritization of monitoring and adaptive management across climate scenarios.

While uncertainties persist in climate projections, land-use scenarios, and modelling methods, the ensemble approach clarifies areas of agreement and disagreement among models. These results provide risk estimates to inform planning rather than precise predictions. Future research could enhance projections by incorporating hydrological data on aquatic species, accounting for species dispersal, and validating hotspots through long-term fieldwork. By explicitly integrating climate and land-use factors and addressing uncertainty, this study delivers clear, location-specific insights into invasion risk in tropical landscapes under global change.

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Author contributions

NM: Conceptualization, Methodology, Data curation, formal analysis, Writing – original draft, Visualization, review, and editing. NK: Methodology, formal analysis, Visualization, Writing – review and editing, Validation. JL: Methodology, Writing– review and editing, Visualization, Validation. TB: Conceptualization, Methodology, Writing–review and editing, Supervision, Validation, Funding acquisition.

Conflicts of interest

The authors have declared that no competing interests exist.

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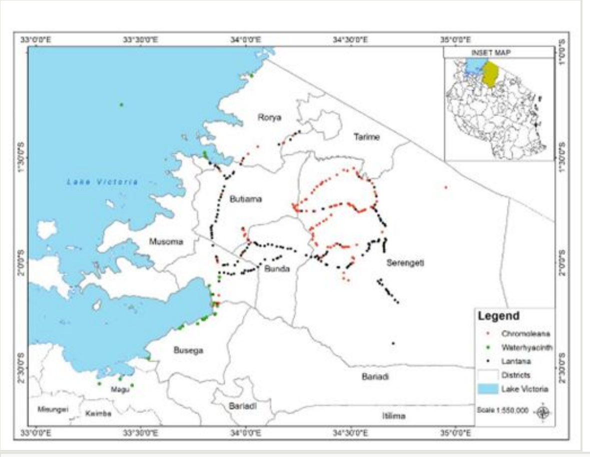

Figure 1.

Location of the study area

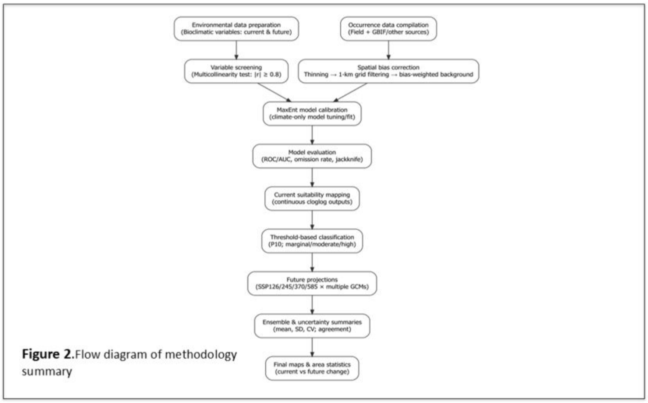

Figure 2.

Flow diagram of the methodology summary.

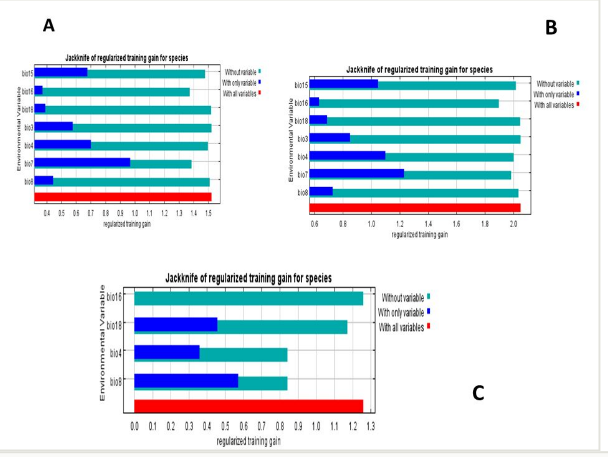

Figure 3.

Jackknife analysis of regularized training for the MaxEnt models. **A** *Lantana camara*, **B** *Chromolaena odorata*, and **C** *Eichhornia crassipes* under climatic conditions.

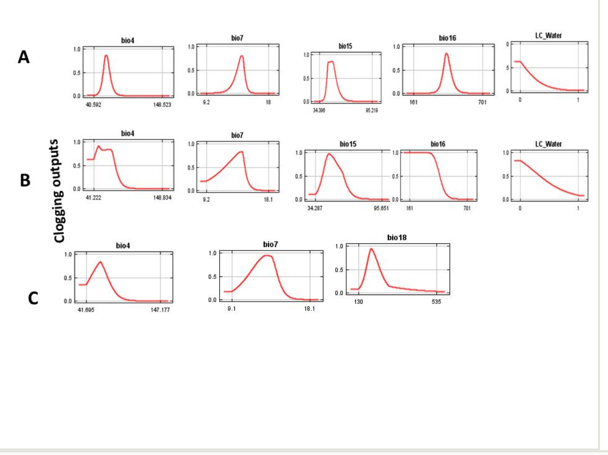

Figure 4.

Major parameters response curve for model: **A** *Chromolaena*, **B** *Lantana*, **C** Water hyacinth.

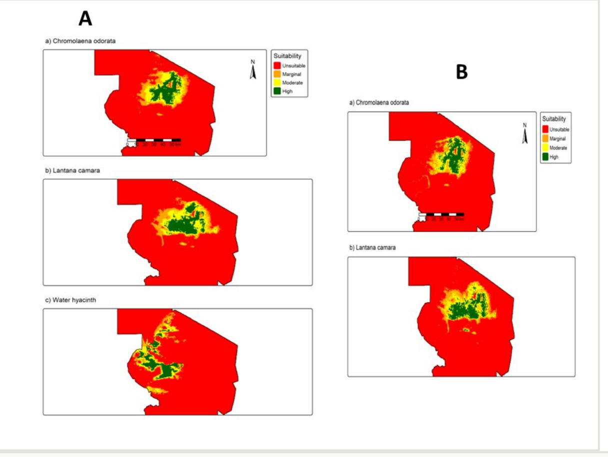

Figure 5.

Potential distribution map of the three species *Chromolaena odorata, Lantana camara*, and *Eichhornia crassipes* under current climate conditions (A), and (B) for the combined model. High suitability (dark green) represents areas with the highest likelihood of species establishment, while red areas indicate unsuitable habitat.

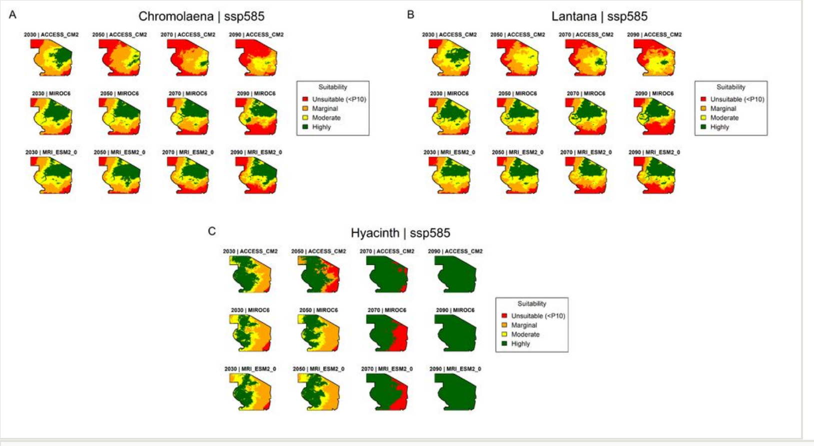

Figure 6.

Present potential distribution maps for three species: the terrestrial *Chromolaena* and *Lantana* (A and B) projected for 2090 under SSP5 (RCP 8.5), and the aquatic Water hyacinth (C) under three general circulation models (GCMs).

https://doi.org/10.3897/arphapreprints.e192024

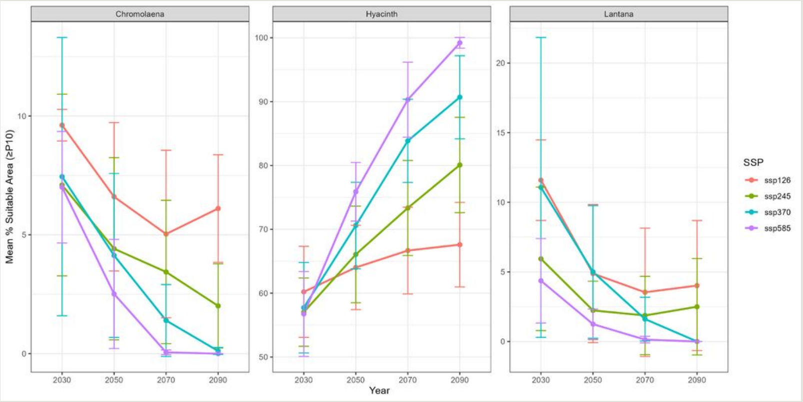

Figure 7.

Projected changes in total climatically suitable area (≥P10) under low- and high-emission scenarios from 2030 to 2090. While *C. odorata* and *L. camara* show contraction and increasing variability under higher SSPs, *E. crassipes* exhibits widespread expansion and reduced inter-model variability by the late century.

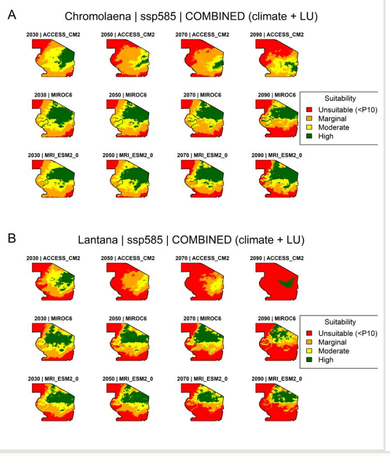

Figure 8.

Projected distribution maps for *Chromolaena* (A) and *Lantana* (B) in 2090 under the SSP5 (RCP 8.5) climate and land-use scenario, based on three general circulation models.

Table 1.

Occurrence data used for model training and testing.

Common name	Scientific name	Available occurrence data	Used occurrence data
Siam Weed	*Chromolaena odorata* (L.)	604	104
Lantana	*Lantana camara L*	503	234
Water hyacinth	*Eichhornia crassipes* (Mart.)	76	21

https://doi.org/10.3897/arphapreprints.e192024

Table 2.

Bioclimatic variables considered in model development and their selection status after variance inflation factor (VIF) filtering.

label	**Predictor variable**
bio3	Isothermality
bio4	Temperature Seasonality
bio7	Temperature Annual Range
bio8	Mean Temperature of Wettest Quarter
bio15	Precipitation Seasonality
bio16	Precipitation of the Wettest Quarter
bio16	Precipitation of Warmest Quarter

https://doi.org/10.3897/arphapreprints.e192024

Table 3.

Percentage contribution of each parameter used in the MaxEnt climate model on the three species.

Variable Label	**Descriptions**	***C.* (%)**
bio16	Precipitation of the wettest quarter	7.8
bio15	Precipitation Seasonality	3**0.**
bio18	Precipitation of the warmest quarter	0.9
bio3	Isothemality	0.2
bio4	Temperature Seasonality	17.
bio7	Annual temperature range	**41.**
bio8	Mean Temperature of the Wettest Quarter	1.5

Table 4.

Species-specific summary of spatial habitat suitability responses under future climate scenarios (climate-only; 10p threshold).

Species	**SSP1–2.6**	**SSP3–7.0**	**SSP5–8.5**	**Overall**
C. odorata	Stable eastern high-suitability core	Fragmentation and redistribution after mid-century	Strong late-century contraction of high suitability	Contraction
L. camara	Broadly stable suitability	Increasing restriction and fragmentation	Late-century retreat to eastern refugia	Gradual contraction
E. rassipes	Widespread suitability	Expansion of suitable classes	Dominance of suitable habitat	Expansion

Supplementary materials

Suppl. material 1: Variable percentage contribution and permutation importance

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table
Brief description: Table S1. Percentage contribution and permutation importance of bioclimatic variables used in the MaxEnt models for *Chromolaena odorata*, *Lantana camara*, and *Eichhornia crassipes*. Percentage contribution reflects the relative influence of each predictor during model training, while permutation importance indicates the decrease in model performance when variable values are randomly permuted, providing an independent measure of variable importance.
Download file (23.13 kb)

Suppl. material 2: Area habitat suitability classes under future climatic scenarios

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table (Excel)
Brief description: Table S2. Projected area (km^2) of habitat suitability classes for the invasive species *Chromolaena odorata*, *Lantana camara*, and *Eichhornia crassipes* under future climate scenarios. Suitability was classified into four categories (Unsuitable, Marginal, Moderate, and High) based on model thresholds. The table summarizes the area of each suitability class across projection years and Shared Socioeconomic Pathway (SSP) scenarios, derived from ensemble outputs of multiple General Circulation Models (GCMs). These results support the spatial patterns shown in the maps and highlight scenario-dependent changes in suitable habitat, including declines in highly suitable areas for *C. odorata* and *L. camara* under higher-emission scenarios and relatively stable or expanding suitability for *E. crassipes*.
Download file (29.44 kb)

Suppl. material 3: Uncertainty metrics of the three species under future climatic scenarios

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table
Brief description: Table S3. Projected mean habitat suitability and associated uncertainty metrics for three invasive plant species (Chromolaena, Hyacinth, and Lantana) under future climate scenarios. Values represent ensemble predictions derived from three General Circulation Models (nGCM = 3) for the years 2030 and 2090 across four Shared Socioeconomic Pathway (SSP) scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The table reports mean suitability (meanSuitability), standard deviation among GCM projections (meanSD), and the coefficient of variation (meanCV), indicating the relative uncertainty of model projections.
Download file (29.44 kb)

Suppl. material 4: Spatial future suitability under Combined Climate and Land-Use projections

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table
Brief description: Table S4. Projected area (km²) of habitat suitability classes for *Chromolaena odorata* and *Lantana camara* under combined future climate and land-use scenarios. Suitability was classified into four categories: Unsuitable (<P10), Marginal, Moderate, and High. Values represent the ensemble mean area (Area_mean_km²) derived from three General Circulation Models (nGCM = 3) for each Shared Socioeconomic Pathway scenario (SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP5–8.5) and projection year (2030, 2050, 2070, and 2090). The table also reports the standard deviation among GCM projections (Area_sd_km²) and the coefficient of variation (Area_cv_pct), indicating the level of inter-model uncertainty in projected suitable areas.
Download file (55.09 kb)

Suppl. material 5: Land-use drivers and uncertainty metrics for the projected suitable habitat of *Chromolaena* and *Lantana*

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table (Excel)
Brief description: Table S5 (Excel file). Land-use–specific effective suitable habitat area and associated uncertainty metrics for *Chromolaena odorata* and *Lantana camara* under combined future climate and land-use scenarios. The spreadsheet reports ensemble mean effective suitable area (km²), standard deviation, coefficient of variation (CV), proportional use and availability of land-use classes, and selection ratios across projection years and Shared Socioeconomic Pathway (SSP) scenarios.
Download file (31.86 kb)

Suppl. material 6: Spatial species niche overlap.

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table
Brief description: Table S6. Spatial overlap metrics among future habitat suitability projections derived from different General Circulation Models (GCMs) across projection years (2030, 2050, 2070, 2090) and Shared Socioeconomic Pathway (SSP) scenarios. The table reports Schoener's D and Hellinger's I indices, which quantify the similarity between predicted suitability distributions, with values closer to 1 indicating higher spatial agreement among model projections.
Download file (32.53 kb)

Suppl. material 7: Spatial overlap between projected suitable habitats of *Lantana* and *Chromolaena* across climate model scenarios.

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table (Excel)
Brief description: Table S7 (Excel file). Spatial overlap between projected suitable habitats of *Lantana camara* and *Chromolaena odorata* under future climate scenarios. The spreadsheet reports species-specific suitable area (km²), intersection and union of predicted suitable areas, and overlap metrics including Jaccard index, percentage Jaccard overlap, and overlap relative to the minimum species range across projection years (2030, 2050, 2070, 2090), Shared

Socioeconomic Pathway (SSP) scenarios, and General Circulation Models (GCMs). These metrics quantify the degree of spatial co-occurrence between the two invasive species under future conditions.
Download file (16.08 kb)

Suppl. material 8: Area (km²) and percentage of the study area in each suitability class (current conditions).

Authors: Neema C. Mtenga, Ng'winamila D. Kasongi, Jan R. K. Lehmann., Tillmann K. Buttschardt
Data type: Table
Brief description: Table S8. Area (km^2) and percentage distribution of the study area across different habitat suitability classes under current conditions, for the three invasive plant species.
Download file (28.23 kb)