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Modeling the Distribution of the Invasive Water Hyacinth (*Eichhornia crassipes*) in the Wetlands of Côte d'Ivoire

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ABSTRACT: *Eichhornia crassipes* (water hyacinth) is one of the world's most invasive aquatic plants, causing severe ecological and socio-economic impacts in freshwater ecosystems, including those of Côte d'Ivoire. This study aimed to assess the current and future distribution of *E. crassipes* in the wetlands of Côte d'Ivoire. Species occurrence data were compiled, and future distribution projections were generated under two Shared Socioeconomic Pathways (SSPs): SSP2-4.5 (intermediate stabilization scenario) and SSP5-8.5 (high greenhouse gas emission scenario) for the 2050 and 2070 time horizons. The results indicate that climate change is expected to substantially promote the expansion of *E. crassipes* across Côte d'Ivoire. Rising minimum temperatures (Bio6), identified as the primary determinant of the species' distribution, together with changes in precipitation patterns, are projected to create highly suitable environmental conditions over most of the country by 2070. Depending on the climate scenario, the species' potential suitable habitat could increase by a factor of 11 to 21, with no projected loss of currently suitable habitats. These findings highlight the urgent need to implement proactive prevention, monitoring, and management strategies, particularly in the central and northern regions of the country, which are currently free from invasion.

KEYWORDS: *Eichhornia crassipes*, species distribution, wetlands, climate change, Côte d'Ivoire.

1. INTRODUCTION

An Invasive Alien Species (IAS) is an alien species whose intentional or accidental introduction by humans results in its establishment and spread. This process threatens ecosystems, habitats, and native species, leading to adverse ecological, economic, and/or public health consequences (Soubeyran, 2008). Climate change has become a major driver exacerbating this phenomenon (Bellard et al., 2013). By altering the availability of suitable climatic niches, it facilitates the expansion of many alien species into regions that were previously climatically unsuitable. The water hyacinth, *Eichhornia crassipes* (C. Mart.) Solms, is a representative example. This free-floating perennial aquatic plant belongs to the family Pontederiaceae. Native to South America, *Eichhornia crassipes* was introduced, either intentionally or accidentally, through human activities and has subsequently spread throughout the world.

In Africa, *Eichhornia crassipes* was first reported in the early twentieth century in the Nile Delta and was subsequently recorded in Zimbabwe in 1937 (Holm *et al*., 1977). Its spread accelerated from the 1950s onward, extending to the Congo River Basin and Gabon. The species subsequently invaded several West African countries, including Nigeria, Benin, Burkina Faso, Niger, and Togo (Akinyeiji, 1987; Harley, 1994; Yao et al., 2025). It is a highly invasive aquatic plant that colonizes freshwater bodies and has been the subject of numerous studies across different regions of the world. Most of these studies have documented the wide range of adverse impacts of *E. crassipes* on the economy, ecosystems, and public health (Sucharit et al., 1981; Dagno et al., 2007; Yao et al., 2025). According to Lowe et al. (2000), *E. crassipes* is among the world's most harmful invasive alien plant species.

In Côte d'Ivoire, *Eichhornia crassipes* is believed to have been introduced in 1968 as an ornamental plant (Neuba et al., 2014; GBIF). Since then, it has spread rapidly throughout the country and has become an integral component of the wetlands of Côte d'Ivoire (Nicole et al., 1987; Egnankou, 1995, 2015; Neuba et al., 2014; Adou et al., 2016; Noba et al., 2017; Ouattara et al., 2017). The species proliferates through rapid vegetative reproduction, exceptional tolerance to polluted environments, and the absence of

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effective natural enemies in its introduced range (Almoustapha et al., 2008). It spreads primarily through stolons (daughter plants), enabling a single individual to produce thousands of new plants within a few weeks, thereby covering lagoons, rivers, and irrigated water bodies (Villamagna & Murphy, 2010). *Eichhornia crassipes* causes numerous environmental and socio-economic impacts in Côte d'Ivoire. Dense infestations reduce light penetration into aquatic ecosystems, including rivers and lagoons, thereby disrupting aquatic ecological processes. They also interfere with fishing activities and inland water transportation and severely limit the recreational and tourism use of water bodies (Nicole et al., 1987; Egnankou, 2015; Adou et al., 2016). In response to these impacts, mechanical, chemical, and biological control measures have been implemented at several infestation sites in Côte d'Ivoire (Nicole et al., 1987; Egnankou ; 1995, ;2015; Adou et al., 2016). However, these management strategies have not been supported by predictive assessments of the species' potential spatial expansion.

In Côte d'Ivoire, research on *Eichhornia crassipes* has primarily focused on inventories of aquatic macrophytes (Guiral & Etien, 1991; Etien & Arfi, 1996; Adou et al., 2016), phytoremediation (Kouamé et al., 2016; Nongbe et al., 2026), and its role as a microhabitat for macroinvertebrates (Kouamé, 2011). Other studies have investigated the ecological (Etien & Arfi, 1996; Egnankou, 1995, 2015; Traore et al., 2019) and economic (Etien & Arfi, 1996; Egnankou, 1995; 2015) impacts of the species. However, studies aimed at predicting the distribution of this invasive alien species remain scarce. This knowledge gap is particularly concerning given that climate change is expected to substantially reshape the geographic distribution of invasive alien species worldwide (Bellard et al., 2013). Kriticos & Brunel (2016) highlighted this issue through the first global assessment of the future invasion risk of E. crassipes. In Côte d'Ivoire, predictive studies integrating future climate scenarios remain limited.

The overall objective of this study was to improve current knowledge of the present and future distribution of suitable habitats for Eichhornia crassipes in the wetlands of Côte d'Ivoire under climate change. Specifically, the study aimed (i) to identify the main environmental drivers, particularly bioclimatic and edaphic variables, determining the current distribution of the species in Ivorian wetlands, and (ii) to project future changes in the spatial distribution of suitable habitats for *E. crassipes* by the 2050 and 2070 time horizons under two contrasting climate scenarios, SSP2-4.5 and SSP5-8.5.

2. MATERIAL AND METHODS

2.1. Study area

Côte d'Ivoire (Figure 1) is located in West Africa between 4°30′ and 10°30′ N latitude and 2°30′ and 8°30′ W longitude. The country covers an area of approximately 322,462 km² (RGPH, 2014). It is characterized by four major climatic zones: subequatorial, humid tropical, tropical, and montane climates (Eldin, 1971; Peel et al., 2007). The soils of Côte d'Ivoire are classified into four main groups: Ferralsols, tropical ferruginous soils, soils developed on basic rocks with lateritic crusts, and hydromorphic (coastal) soils (Perraud, 1971; FAO, 2006). The country's wetlands comprise swamp forests, lagoons and estuaries together with their associated vegetation (mangroves and marsh grasslands), lakes, and permanently or seasonally flooded savannas (Nicole et al., 1987).

2.2. Methods

2.2.1. Occurrence Data

Occurrence data for *Eichhornia crassipes* were obtained from the Global Biodiversity Information Facility (GBIF) database (https://www.gbif.org), as well as from master's theses, doctoral dissertations, scientific articles, and technical reports addressing the floristic diversity of wetlands in Côte d'Ivoire. These sources notably included studies by Nicole et al. (1987) ; Egnankou (1995 ; 2015) ; Neuba et al. (2014) ; Adou et al. (2016) ; Ouattara et al. (2017). Occurrence data were cleaned using the R package CoordinateCleaner (Zizka et al., 2019) to remove erroneous records, including invalid coordinates (zero coordinates) and exact duplicates. To reduce spatial sampling bias and spatial autocorrelation, spatial thinning was performed using the spThin package (Aiello-Lammens et al., 2015), retaining only one occurrence per grid cell corresponding to the resolution of the environmental variables (approximately 1 km). Since reliable absence data were unavailable, pseudo-absence data (background points) were randomly generated within the study area following the recommendations of Barbet-Massin et al. (2012), with the number of pseudo-absences adjusted according to the modelling algorithm: 10,000 background points for MaxEnt, and a number equal to the presence records for regression methods (Generalized Additive Models, GAM) and classification methods (Random Forest, RF; Boosted Regression Trees, BRT).

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2.2.2. Environmental variables

2.2.2.1 Bioclimatic variables

Six bioclimatic variables were extracted from the WorldClim v2.1 database (Fick & Hijmans, 2017) at a spatial resolution of 30 arc-seconds (approximately 1 km): bio4 (temperature seasonality), bio6 (minimum temperature of the coldest month), bio8 (mean temperature of the wettest quarter), bio9 (mean temperature of the driest quarter), bio14 (precipitation of the driest month), and bio15 (precipitation seasonality). These variables were selected because they represent key physiological and phenological constraints that may influence the distribution of tropical aquatic macrophytes (O'Donnell & Ignizio, 2012; Hijmans et al., 2005).

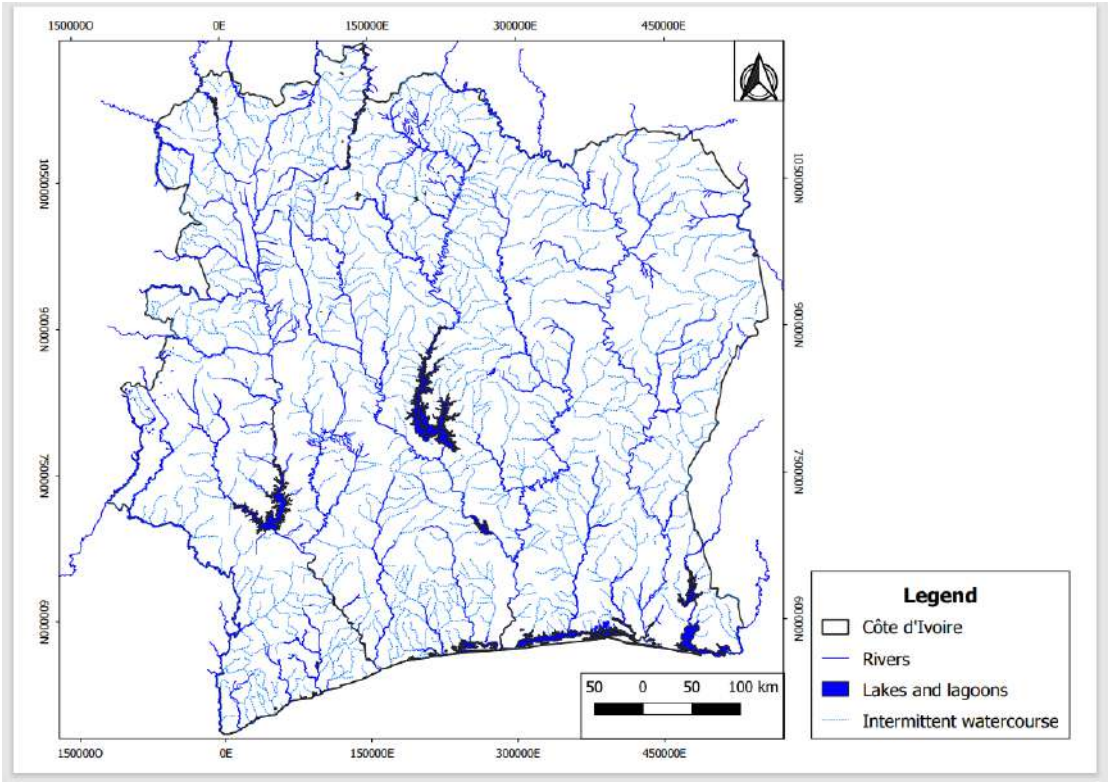


Figure 1: Location of wetlands in Côte d'Ivoire

2.2.2.2. Edaphic variables

Four edaphic variables were extracted from the SoilGrids 2.0 database (Poggio et al., 2021) at a spatial resolution of 250 m and subsequently resampled to 1 km to ensure consistency with the climatic variables: soil pH (ph), sand content (sand), soil organic carbon content (soc), and bulk density (bdod). These variables were obtained for the 0–30 cm soil depth interval, which is relevant for riparian and wetland habitats colonized by *Eichhornia crassipes*.

2.2.3. Variable selection

Multicollinearity among predictors was assessed by calculating Pearson's correlation coefficient (Figure 2) and the variance inflation factor (VIF) using the usdm R package (Naimi et al., 2014). A threshold of $|r| > 0.9$ was used to identify highly correlated variable pairs. However, all ten variables were retained in the analysis to preserve complementary ecological information, following the approach of Dormann et al. (2013), who highlighted that machine-learning methods (RF, BRT, and MaxEnt) are relatively robust to predictor collinearity.

2.2.4. Future climate scenarios

Future projections were performed under two Shared Socioeconomic Pathways (SSPs) from the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (CMIP6; Eyring et al., 2016): SSP2-4.5 (intermediate stabilization scenario) and SSP5-8.5 (high greenhouse gas emission scenario) (Riahi et al., 2017; O'Neill et al., 2016), for the 2050 time horizon (2041–2060 average) and the 2070 time horizon (2061–2080 average). To reduce uncertainty associated with the choice of climate model, an ensemble average of several General Circulation Models (GCMs) was used, following the recommendations of Thuiller et al. (2019).

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2.2.5. Ecological niche modeling

2.2.5.1. Ensemble modeling approach

Four species distribution modeling (SDM) algorithms were implemented, representing the main families of predictive biogeographic modelling approaches:

• MaxEnt (Maximum Entropy): a maximum entropy-based approach relying on presence-only data (Phillips et al., 2006; Phillips & Dudík, 2008), particularly suitable for datasets containing only species occurrence records.

• Random Forest (RF): an ensemble learning method based on the aggregation of decision trees (Breiman, 2001), implemented using the randomForest package (Liaw & Wiener, 2002).

• Boosted Regression Trees (BRT): an additive modelling approach based on boosting regression trees (Elith et al., 2008), implemented using the gbm package (Ridgeway, 2007).

• Generalized Additive Model (GAM): a generalized additive modelling framework allowing the characterization of nonlinear relationships between predictors and species occurrence (Hastie & Tibshirani, 1990; Wood, 2017), implemented using the mgcv package.

The entire modelling workflow was conducted using the biomod2 platform (Thuiller et al., 2009; Thuiller et al., 2023), which natively integrates these algorithms, as well as cross-validation and ensemble modelling procedures. An ensemble modelling approach was adopted to reduce the uncertainty associated with the selection of a single algorithm (Araújo & New, 2007; Hao et al., 2019). The ensemble prediction was calculated as a weighted average of individual models according to their Area Under the Curve (AUC) values, retaining only models with AUC > 0.7 (Marmion et al., 2009). It should be noted that this correlative approach relies on the assumption of equilibrium between the species and its environment, and that future projections involve extrapolation towards novel climatic conditions (no-analog climates) that may not be represented under current training conditions (Thuiller et al., 2019).

2.2.5.2. Model parameterization and validation

For each algorithm, ten replicates were performed using a random split-sample cross-validation procedure (70/30), with 70% of the data used for model calibration and 30% for model evaluation. Model performance was assessed using the Area Under the Receiver Operating Characteristic Curve (AUC; Swets, 1988; Fielding & Bell, 1997) and the True Skill Statistic (TSS; Allouche et al., 2006). According to Swets (1988), an AUC value ranging from 0.7 to 0.8 indicates acceptable model performance, values between 0.8 and 0.9 indicate very good performance, and values above 0.9 indicate excellent performance. The relative contribution of environmental variables was assessed using random permutation procedures (Thuiller et al., 2009), and response curves were generated following the methodology proposed by Elith et al. (2005).

2.2.5.3. Binarization of prediction maps

Continuous probability maps were converted into binary maps (suitable/unsuitable habitat) by applying the threshold that maximizes the sum of sensitivity and specificity (maximum sensitivity plus specificity threshold, maxSSS; Liu et al., 2013), which is recognized as one of the most effective thresholding approaches for presence-only datasets.

2.2.6. Future projection and change analysis

Models calibrated under current environmental conditions were projected onto future climate scenarios (SSP2-4.5 and SSP5-8.5, for the 2050 and 2070 times horizons), while edaphic variables were assumed to remain temporally constant. For each scenario, the extent of suitable habitat was calculated (in km²), along with indicators of change relative to the current scenario, including the rate of change (Rc, %), habitat gain, and habitat loss. A trend classification (stable, expansion, or contraction) was established following the approach proposed by Bellard et al. (2013).

2.2.7. Software and analytical tools

All statistical and geospatial analyses were performed using the R packages biomod2 (Thuiller et al., 2023), terra (Hijmans, 2024), sf (Pebesma, 2018), dismo (Hijmans et al., 2023), and ggplot2 (Wickham, 2016) for data visualization.

3. RESULTS

3.1. Model performance

The predictive performance of the four algorithms was evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC). Three out of the four modelling approaches achieved a performance level classified as “very good” (AUC > 0.7). The MaxEnt model showed the highest mean AUC value (≈ 0.85), closely followed by Random Forest (RF, ≈ 0.85) and Boosted

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Regression Trees (BRT, ≈ 0.82). The Generalized Additive Model (GAM) exhibited lower predictive performance, with a mean AUC of approximately 0.65, corresponding to an "acceptable" performance level. Error bars indicated moderate variability among model replicates, with GAM showing the greatest dispersion. All models, except GAM, clearly exceeded the threshold of 0.7 (Figure 2), confirming the reliability of the selected consensus ensemble model for subsequent projections.

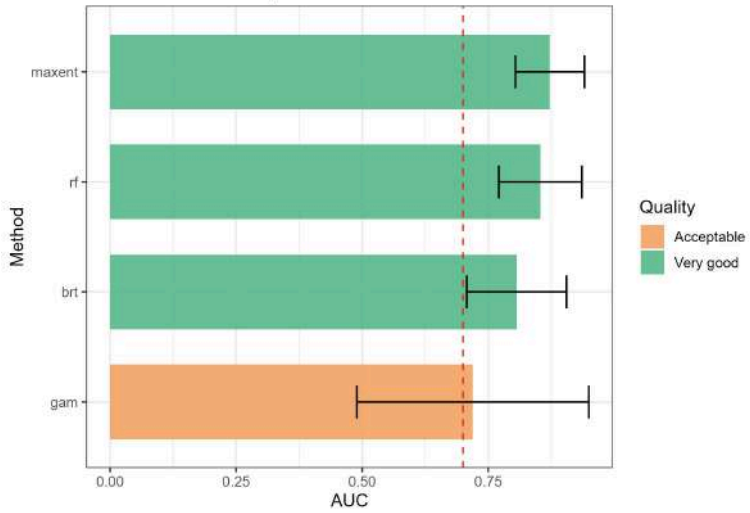


Figure 2: AUC values of the four modelling algorithms for *Eichhornia crassipes*.

3.2. Selection and correlation of environmental variables

Ten environmental variables were retained for the modelling process, including six bioclimatic variables (bio4, bio6, bio8, bio9, bio14, and bio15), three edaphic variables (soil pH, sand proportion, and soil organic carbon content [soc]), and soil bulk density (bdod). The Pearson correlation matrix (Fig. 3) revealed several strong correlations among these predictors. The most notable negative correlations were observed between soil pH and bio6 (r = −0.93), soil pH and bio14 (r = −0.83), bdod and soc (r = −0.81), and soil pH and sand proportion (r = −0.80). Significant positive correlations were also observed between bio6 and bio14 (r = 0.78), as well as between bio6 and sand proportion (r = 0.71). Despite these correlations, all variables were retained in the analysis to capture the diversity of environmental factors influencing the distribution of the species.

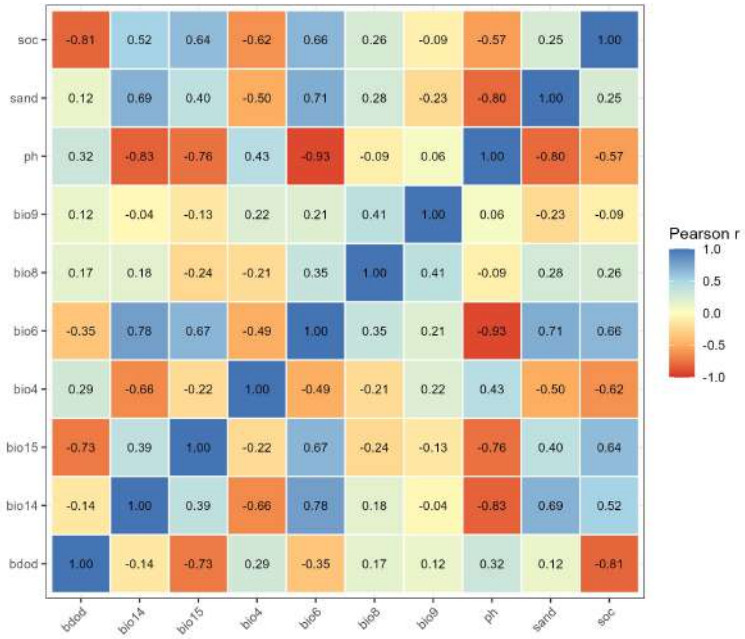


Figure 3: Pearson correlation matrix among the selected environmental variables.

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3.3. Variable importance and response curves

The analysis of the relative importance of environmental variables (Figure 4) showed that bio6 (minimum temperature of the coldest month) was the dominant predictor, accounting for 27.4% of the model contribution. It was followed by bio14 (precipitation of the driest month, 13.3%), bio9 (mean temperature of the driest quarter, 10.8%), and bio4 (temperature seasonality, 10.4%). The variables bio8 (9.1%), soil pH (8.3%), bio15 (8.1%), and sand content (8.1%) showed relatively similar contributions, whereas bdod (2.9%) and soc (1.6%) had a minor influence on model predictions.

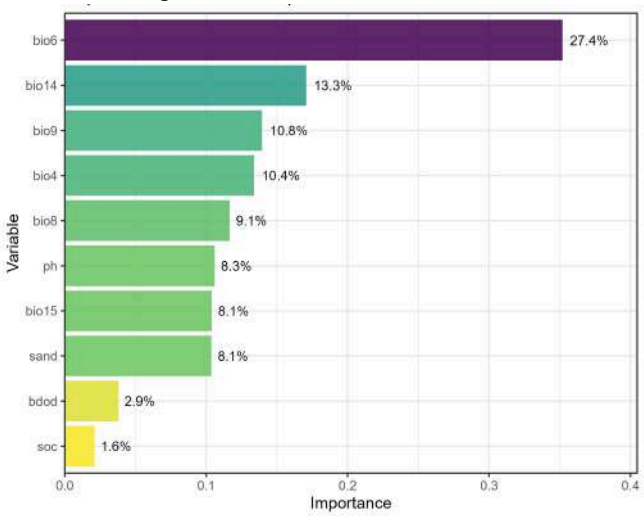


Figure 4: Relative importance of environmental variables in the modelling of *Eichhornia crassipes.*

The mean response curves (Figure 5) confirmed these relationships. For bio6, the probability of occurrence increased markedly with minimum temperature, rising from approximately 0.15 at 19°C to nearly 0.50 at 22°C, reflecting the thermophilic preference of *E. crassipes*. Bio14 exhibited a positive relationship, with occurrence probability increasing with precipitation of the driest month and reaching a plateau of around 0.40 at precipitation values above 20 mm. The bdod variable showed an opposite trend, with the highest probability of occurrence (≈0.50) observed at low bulk density values and decreasing probabilities beyond 1.2. The response to soil pH was positive, with occurrence probability gradually increasing from 0.29 to 0.47 between pH 5.3 and pH 6.3. Bio8 (mean temperature of the wettest quarter) displayed a probability peak around 25.5°C, followed by a decline, suggesting an optimal thermal range for the species during the wet season.

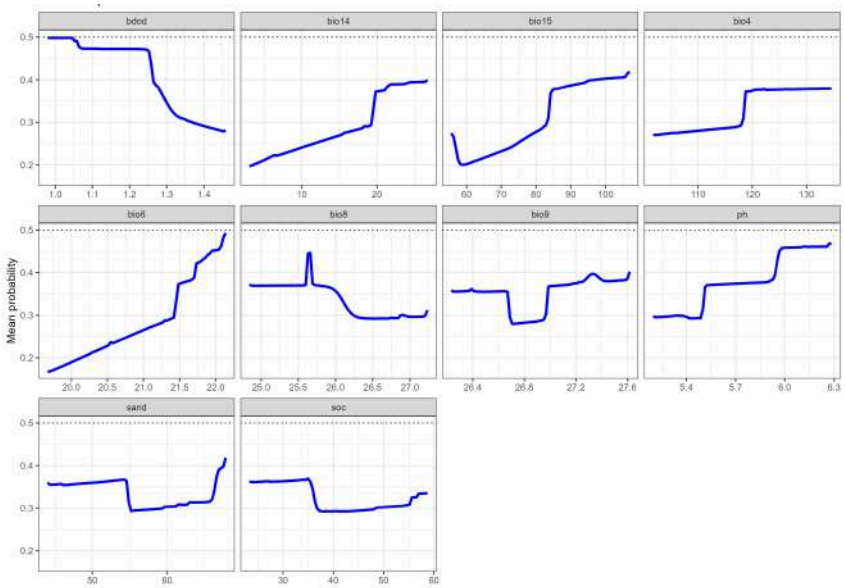


Figure 5: Mean response curves of *Eichhornia crassipes* to environmental variables.

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3.4. Current distribution and future projection

Under current climatic conditions, suitable habitat for *Eichhornia crassipes* in Côte d'Ivoire is highly restricted, covering approximately 9,913 km². It is mainly confined to the southwestern coastal regions and a few isolated areas in the southern part of the country. Future projections reveal a substantial expansion of climatically suitable areas under all considered scenarios (Table 1).

Table 1: Suitable habitat area and rate of change under each scenario.

Scenario	Area (km²)	Rate of change (%)	Gain (km²)	Tendency
Current	9 913	—	—	Stable
SSP2-4.5 / 2050	116 470	+1 075	106 557	Expansion
SSP2-4.5 / 2070	133 932	+1 251	124 019	Expansion
SSP5-8.5 / 2050	156 353	+1 477	146 439	Expansion
SSP5-8.5 / 2070	211 978	+2 038	202 064	Expansion

Under the SSP2-4.5 scenario (intermediate stabilization scenario), the extent of suitable habitat increased from 9,913 km² under current conditions to 116,470 km² by 2050 (+1,075%), and further to 133,932 km² by 2070 (+1,251%). Under the SSP5-8.5 scenario (high greenhouse gas emission scenario), habitat expansion was even more pronounced, reaching 156,353 km² by 2050 (+1,477%) and 211,978 km² by 2070 (+2,038%). Relative to the total land area of Côte d'Ivoire (322,462 km²), suitable habitat currently represents only 3.1% of the national territory, compared with 36.1% under SSP2-4.5 in 2050, 41.5% under SSP2-4.5 in 2070, 48.5% under SSP5-8.5 in 2050, and as much as 65.7% under SSP5-8.5 in 2070. Under the most pessimistic scenario, nearly two-thirds of the country are projected to become climatically suitable for *Eichhornia crassipes* by 2070. Notably, no habitat loss was projected under any of the climate scenarios. All areas currently identified as suitable remained suitable in future projections, while extensive new areas became climatically suitable for the species.

Spatially, the projection maps (Fig. 6) indicate a progressive expansion of *E. crassipes* across Côte d'Ivoire. By 2050, under the SSP2-4.5 scenario, suitable habitat expands throughout most of the southern half of the country and begins to extend into the central regions. By 2070, under the SSP5-8.5 scenario, almost the entire national territory is projected to become climatically suitable for the species, including the northern regions that have so far remained free from invasion.

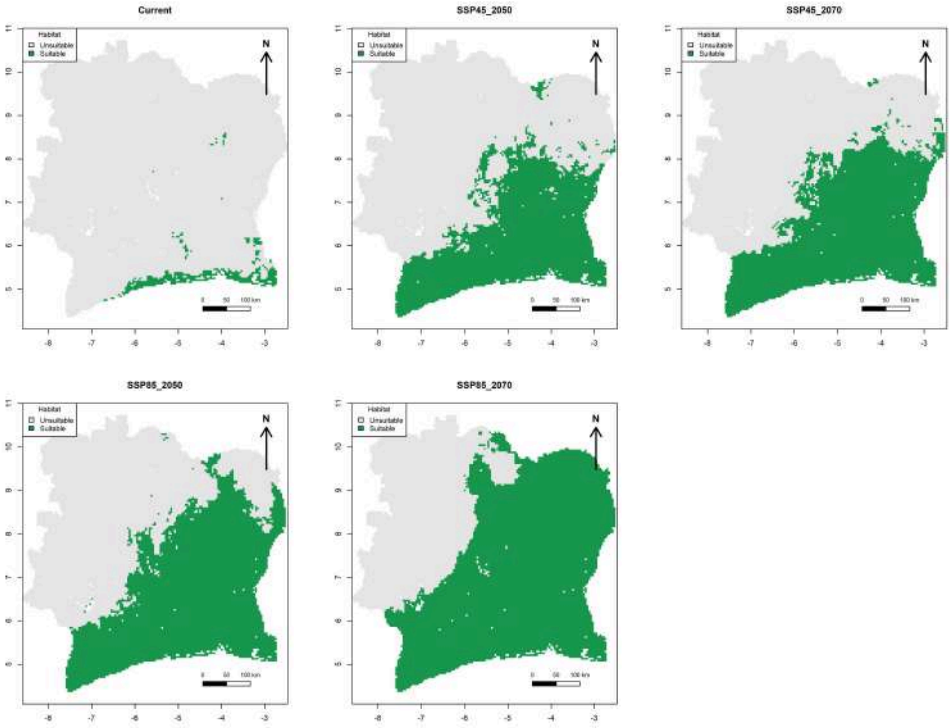


Figure 6: Distribution maps of suitable habitat for *Eichhornia crassipes* under current and future climate conditions.

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3.5. Habitat velocity

The habitat velocity map (Fig. 7) illustrates the rate at which climatically suitable conditions shift spatially over time. A large proportion of Côte d'Ivoire exhibits moderate habitat velocity (1–5 km yr^{-1}), particularly across the northern and central regions. Areas with high velocity (5–10 km yr^{-1}) to extreme velocity (>10 km yr^{-1}) are concentrated in the central-western and southwestern parts of the country, corresponding to transition zones between currently suitable habitats and future colonization areas. The southeastern coastal regions and some northern areas show low habitat velocity (<1 km yr^{-1}), indicating either the persistence of stable suitable habitats or the absence of suitable habitat during both periods. These results suggest that *E. crassipes* may not require particularly high dispersal capacities to track the spatial displacement of suitable habitats, especially given its efficient vegetative and hydrochorous propagation mechanisms.

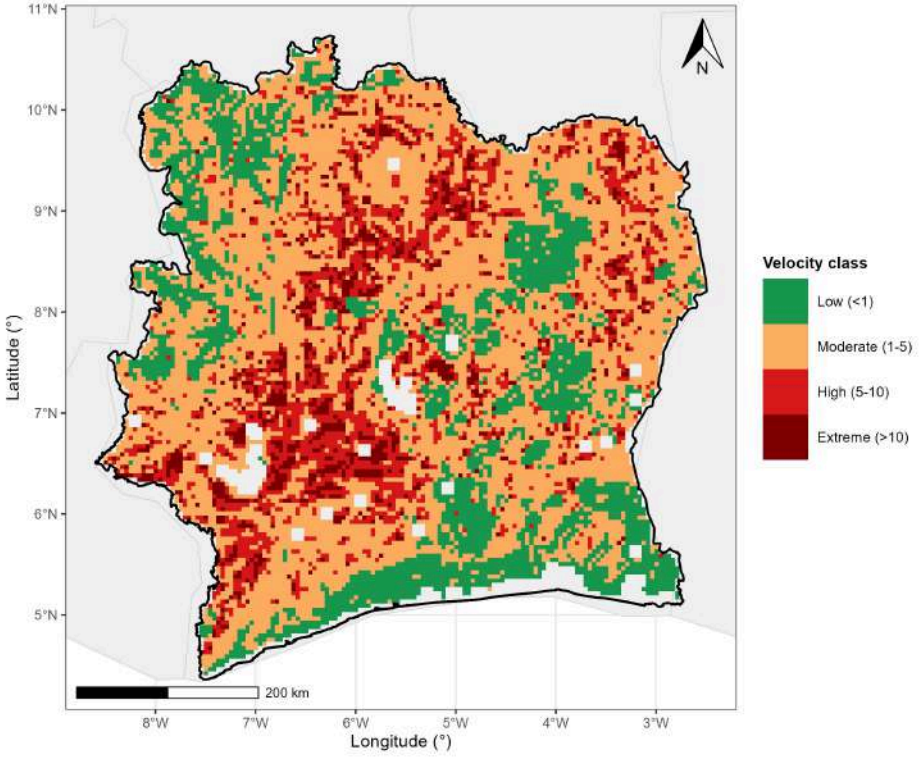


Figure 7: Habitat velocity classes for *Eichhornia crassipes* in Côte d'Ivoire.

4. DISCUSSION

4.1. Environmental factors determining the current distribution of *Eichhornia crassipes* in Ivorian wetlands

The overall performance of the models confirms the relevance of the ensemble approach adopted in this study. The convergence of three out of the four algorithms used (MaxEnt, RF, and BRT) towards AUC values above 0.8, despite their different statistical architectures, strengthens the robustness of the resulting predictions. These findings are consistent with the recommendations of Hao et al. (2019) and Marmion et al. (2009), who emphasized the value of multi-model approaches for reducing uncertainty associated with the selection of a single algorithm. The relatively lower performance of the GAM, likely due to its sensitivity to highly nonlinear relationships and threshold effects, explains its reduced contribution to the final consensus model. The analysis of environmental predictors revealed a strong influence of climatic factors on the current distribution of *E. crassipes*. The predominance of bio6 (minimum temperature of the coldest month) indicates that thermal constraints play a major role in limiting the species' expansion. As a species native to tropical and subtropical regions of South America, water hyacinth exhibits limited tolerance to low temperatures, which may reduce vegetative growth and constrain its clonal reproduction potential (Villamagna & Murphy, 2010). Therefore, temperature variations currently represent an important ecological filter controlling the establishment of the species in Côte d'Ivoire.

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Conversely, the low contribution of edaphic variables, such as soil pH, sandy texture, soil bulk density (bdod), and soil organic carbon (soc), confirms that terrestrial environmental factors have limited influence on the distribution of a strictly aquatic free-floating plant. This pattern is consistent with the broad ecological amplitude of *Eichhornia crassipes* and its ability to colonize highly disturbed environments, nutrient-enriched habitats, and ecosystems subjected to various forms of pollution (Almoustapha et al., 2008). These findings indicate that, in Ivorian wetlands, climate currently represents the main factor regulating the potential distribution of the species, rather than the physicochemical characteristics of the substrate. The dominance of climatic factors also highlights the indirect role of human activities in shaping the species' dynamics. Indeed, anthropogenic disturbances, such as eutrophication, urban and agricultural discharges, and alterations in hydrological regimes, may locally improve habitat suitability for *E. crassipes*. Therefore, although climatic variables determine the species' overall potential distribution range, local environmental conditions within aquatic ecosystems may accelerate its establishment and proliferation.

4.2. Projection of spatial changes in suitable habitats under future climate scenarios

The projections performed for the 2050 and 2070 time horizons indicate a substantial increase in climatically suitable habitats for *Eichhornia crassipes* in Côte d'Ivoire. Depending on the climate scenario considered, the suitable area could increase by a factor ranging from 11 to 21, reflecting a major shift in the species' potential climatic niche. This projected expansion is consistent with trends reported by Bellard et al. (2013), who demonstrated that climate change can facilitate the spread of invasive alien species by reducing environmental barriers, particularly thermal constraints. The absence of suitable habitat loss under all projected scenarios represents a particularly concerning finding. It suggests that currently established populations are unlikely to experience climate-induced natural declines under future climatic conditions. Instead, increasing temperatures may alleviate some ecological limitations and enable the species to colonize new areas, particularly in the central and northern regions of Côte d'Ivoire. These results are consistent with global projections conducted by Kriticos & Brunel (2016). Using a CLIMEX-based approach, these authors also predicted a substantial expansion of suitable areas for E. crassipes under climate warming, particularly towards regions currently constrained by low temperatures. The agreement between these findings obtained through different modelling approaches (CLIMEX and ensemble modelling using biomod2) strengthens the reliability of the projected climatic expansion signal identified for Côte d'Ivoire. The habitat velocity map provides an important complementary assessment by evaluating the spatial feasibility of this expansion. The estimated rates of displacement of suitable climatic conditions in central and central-western Côte d'Ivoire remain considerably lower than the dispersal capacity of *E. crassipes*. This species exhibits high vegetative propagation capacity and efficient dispersal through hydrochory (water-mediated dispersal) (Villamagna & Murphy, 2010). These observations are consistent with the findings of Loarie et al. (2009) and Hamann et al. (2015) on climate velocity, which indicate that species capable of dispersing faster than the movement of their climatic niche can effectively track newly suitable environmental conditions.

In the Ivorian context, these results indicate that natural dispersal is unlikely to represent a major limitation to the future expansion of *Eichhornia crassipes*. The combination of increasing suitable habitat availability and high propagation capacity could therefore accelerate the colonization of new wetland areas. These findings highlight the need for proactive rather than reactive management strategies for this species. Areas that are currently poorly or not yet colonized but identified as future suitable habitats should become priority zones for ecological monitoring. The implementation of early detection systems, combining scientific monitoring with local community involvement, would help limit the establishment of new invasion foci. These actions should complement the mechanical, biological, and chemical control methods already tested in invaded areas (Nicole et al., 1987; Egnankou, 1995 ; 2015; Adou et al., 2016). Finally, strengthening regulations regarding the introduction and circulation of the species for ornamental purposes appears necessary. Since this pathway contributed to the introduction of the species into Côte d'Ivoire in 1968 (Neuba et al., 2014), its control represents an essential management lever for preventing the emergence of new invasion foci, particularly in regions that remain only weakly affected.

5. CONCLUSION

The overall findings converge towards a concerning conclusion: climate change is expected to substantially promote the expansion of *Eichhornia crassipes* in Côte d'Ivoire. The increase in minimum temperatures (bio6), identified as the main driver of species distribution, combined with changes in precipitation patterns, will create favourable conditions across most of the national territory by 2070. The potential suitable habitat area could increase by a factor of 11 to 21, depending on the scenario considered, with no loss of currently suitable habitats projected under future climate conditions. These projections call for the urgent implementation of

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proactive prevention and management strategies, particularly in central and northern regions that are currently not colonized. An early detection and monitoring system, combined with an adaptive management plan and primarily deployed in these currently unaffected areas, represents the most appropriate response to the magnitude and rapidity of the projected expansion.

CONFLICT OF INTEREST

All authors have approved the final version of the manuscript. No conflict of interest is declared.

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