

Prediction of the Potential Distribution of *Ximenia americana* L. in Benin (West Africa) Under the Effect of Climate Change

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Abstract

Original Research Article

Ximenia americana L. is a multifunctional indigenous woody species of West Africa, exploited for its food, medicinal and energy uses, but whose distribution could be affected by climate change. This study aimed to model the current and future potential distribution of the species in Benin and to identify the main environmental factors that determine it. The modeling mobilized 902 occurrences (field data and GBIF) and four algorithms (Random Forest [RF], MaxEnt, generalized linear model [GLM] and generalized additive model [GAM]) under the biomod2 package, integrating bioclimatic, topographic and edaphic variables. Future projections were made from the MIROC6 climate model under scenarios SSP2-4.5 and SSP5-8.5, at 2050 and 2070 horizons. The four models showed satisfactory predictive capacity (AUC: 0.888-0.949; TSS: 0.660-0.788), with the RF showing the best performance. Seasonal rainfall, soil type and altitude emerged as the main determinants of the species' distribution. Under current conditions, the favorable habitat is estimated between 70599 and 89068 km² according to the algorithm. Projections indicate a gradual contraction of this habitat, particularly marked under SSP5-8.5 by 2070, where GLM and MaxEnt predict a near disappearance of the favorable habitat, unlike GAM and RF which maintain a substantial area. These results, despite significant inter-algorithm uncertainty, indicate a potential vulnerability of *X. americana* to climate change and call for prioritizing its conservation in areas of climate stability and its integration into Beninese agroforestry systems.

Keywords: *Ximenia americana*; modeling the distribution of species; climate change; Benin; MaxEnt.

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INTRODUCTION

Wild plant species are essential resources for local communities, particularly in terms of food, health and livelihoods (Fonta and Ayuk, 2013; Rendón-Sandoval *et al.*, 2020). Wild fruit trees and shrubs contribute particularly to the supply of non-timber forest products, and thus play an important role in food security and Dauksta, 2013). However, these resources are increasingly subject to the combined effects of anthropogenic pressures and climate change, which promote the degradation, fragmentation, and reduction of natural habitats (Blades, rural economies (Ritter *et al.*, 2016; Ellison and Gilliam, 2019; Pokhriyal *et al.*, 2020). Global warming thus constitutes a major threat to biodiversity, which could modify the abundance, distribution, and persistence of plant species (Pecl *et al.*, 2017; Andreasson *et al.*, 2023; Wang *et al.*, 2024).

Among the plant species of socioecological interest is *Ximenia americana* L., a native and multifunctional species widely distributed in tropical Africa and particularly used in West Africa. It is exploited by local populations for various uses, including food, medicine and energy. Its drugs (roots, leaves and bark) are notably used in traditional pharmacopoeia to treat various conditions (Gronhaug *et al.*, 2008). A recent review on the medicinal uses of the species in Africa confirms the importance of *X. americana* in traditional medicine and nevertheless highlights the pressures it faces, notably due to its use as fuelwood (Ngeiywa *et al.*, 2024). This socioeconomic importance therefore reinforces the need for a better understanding of the factors that may affect its availability and distribution in the context of environmental changes.

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Climate change can indeed lead to changes in the species' range by transforming the thermal and rainfall conditions necessary for their maintenance. These changes may cause contractions, displacements or fragmentations of favorable habitats and ultimately increase the risks to plant populations (Foden and Young 2016; Rubenstein *et al.*, 2023; Wudu *et al.*, 2023). The identification of areas likely to remain favorable for species under future climate conditions is thus an important prerequisite for planning conservation and sustainable management actions (Mkala *et al.*, 2023; Amindin *et al.*, 2024). For *X. americana*, Lompo *et al.*, (2021) showed, from MaxEnt modeling, that annual rainfall and certain thermal variables strongly determine its distribution in Burkina Faso and that the favorable areas could decrease by 15% under RCP4.5 and 25% under RCP8.5 by 2070.

In this context, species distribution models (SDM) are relevant tools to analyze the relationships between species occurrences and environmental factors and to estimate the current and future suitability of habitats (Guisan *et al.*, 2017; Guo *et al.*, 2021). Statistical and machine learning approaches, including generalized linear models (GLM), generalized additive models (GAM), random forests (RF) and MaxEnt, allow us to characterize the environmental factors determining species distribution and to project their response in different climate scenarios (Pearson, 2010; Thapa *et al.*, 2018; Charney *et al.*, 2021). Ensemble models can also reduce the uncertainty associated with choosing an algorithm and improve the robustness of predictions (Thuiller *et al.*, 2009; Hao *et al.*, 2019; Dang *et al.*, 2020).

Thus, given the ecological and socioeconomic importance of *Ximenia americana* L. and the threats likely to affect its habitats, it appears necessary to better understand its distribution and its potential evolution in the face of climate change. The present study therefore aims to assess the current suitability of *X. americana* L. habitats., identify the main environmental factors that determine its distribution and predict the evolution of favorable areas in future climate scenarios, in order to contribute to the conservation, sustainable management and enhancement of this species.

2. MATERIALS AND METHODS

2.1. Study environment

This study was conducted at the national level, taking into account the three main biogeographical zones of Benin: the Guinean-Congolese zone, the Sudano-Guinean zone and the Sudanian zone. This subdivision is

mainly based on ecological factors such as climate, edaphic and geological characteristics and land use (Adomou *et al.*, 2006). It makes it possible to take into account the environmental and climatic gradient that structures the distribution of plant species at the national scale.

In terms of climate, Benin has a marked gradient between the South and the North. The South is subject to a sub-equatorial climate type characterized by two rainy seasons, from April to July and from September to November, alternating with two seasons Karimama and Malanville. The annual temperature range remains relatively low in the south, ranging from 5-10°C, but gradually increases northward to about 11-13°C from 8th latitude north (Adam and Boko 1993). dry, from August and December to March. Conversely, the North is subject to a tropical climate characterized by a single rainy season, generally from May to October, followed by a long dry season from November to April (Adam and Boko 1993). Average annual rainfall thus varies from about 1000 to 1300 mm in the South, 900 to 1100 mm in the transition zone and 750 to 900 mm in the North. Average annual temperatures are between 26 and 28 °C, with peaks reaching 35 to 40 °C in some northern localities, notably in Kandi,

In the Guinean-Congolese zone, mainly corresponding to southern Benin, the climatic conditions are characterized by an average annual temperature of between 25 and 29 °C, a relative humidity ranging from 69 to 97% and a bimodal annual rainfall of about 1200 mm. (Assogba *et al.*, 2022). This area, which is subject to strong anthropogenic pressure linked in particular to population density and agricultural activities, presents a land cover largely dominated by cultivated lands and fallow areas (Idohou *et al.*, 2016). The Sudano-Guinean zone constitutes a transition zone characterized by a bimodal rainfall regime tending towards a unimodal regime, with an average annual rainfall of between 900 and 1110 mm. a relative humidity ranging from 31 to 98% and average annual temperatures between 25 and 29 °C (Assogba *et al.*, 2022). Its vegetation consists notably of riparian and dry forests, wooded savannas, shrubs and herbaceous as well as wooded savannas (Idohou *et al.*, 2016). Finally, the Sudanian zone, which covers the northern part of the country, is characterized by mainly unimodal rainfall, which can be less than 1000 mm per year, a relative humidity between 18 and 99% and average annual temperatures ranging from 24 to 31 °C (Assogba *et al.*, 2022).

The location of the study environment is presented in Figure 1.

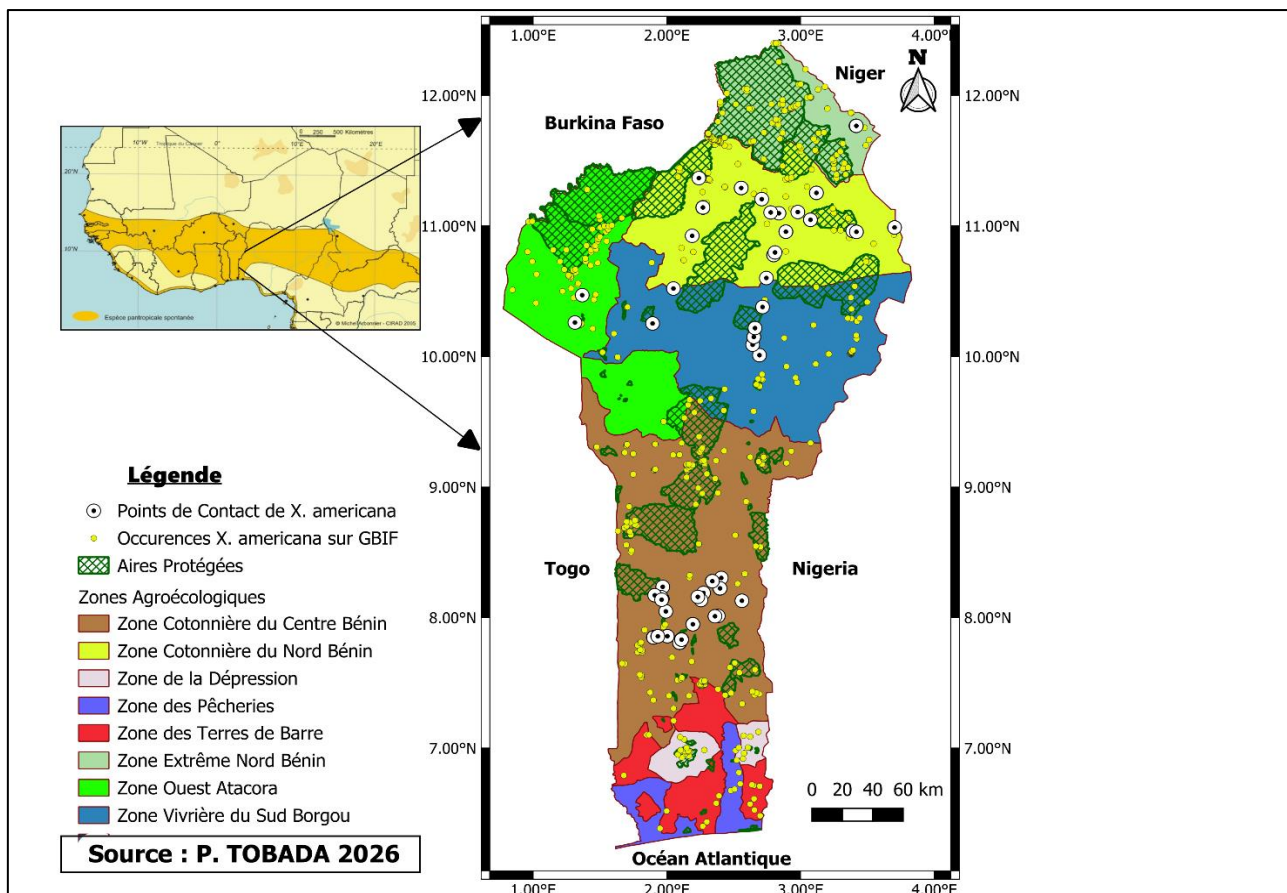


Figure 1: Map of the study environment

2.2. Occurrence data of *Ximenia americana*

The occurrence data of *Ximenia americana* L. were formed from 170 geographical coordinates (latitude and longitude) recorded in the field between 2023 and 2026, to which additional occurrences from the Global Biodiversity Information Facility (GBIF) have been added. The GBIF request, carried out on July 26, 2026 at 16:08:42, provided 732 records from 42 scientific publications (GBIF, 2026; DOI: 10.15468/dl.tun4tk). The combination of field data and secondary data allowed to build an initial base of 902 occurrences.

2.3. Environmental data

Environmental predictors used to model the distribution of *X. americana* included bioclimatic, topographic and edaphic variables considered likely to influence the species' distribution. Bioclimatic variables and altitude were obtained from the WorldClim database, at a spatial resolution of 30 arc seconds, corresponding to approximately 1 km at the equator (Fick and Hijmans, 2017). Soil data were extracted from FAO's Harmonized World Soil Database (HWSD). The different environmental layers were harmonized, projected and divided according to the extent of the study area before their integration into the modeling. The use of a common spatial resolution ensures correspondence between occurrence data and the environmental conditions associated with each location (Fick and Hijmans, 2017).

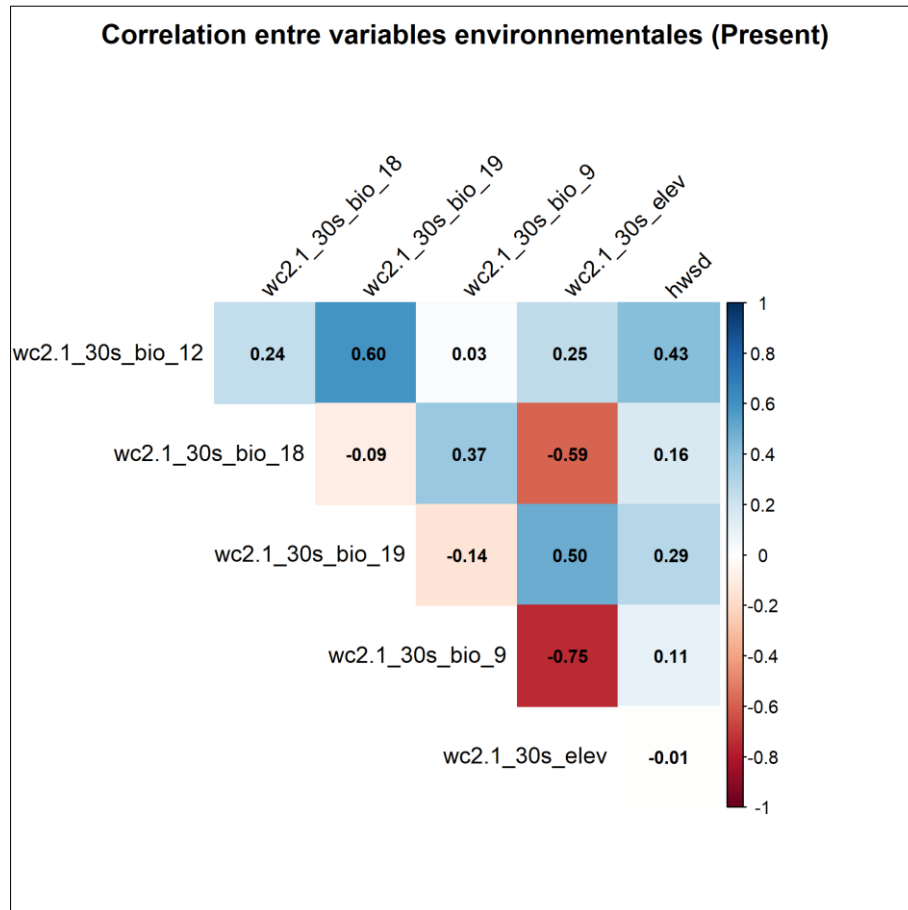
For the assessment of the potential response of *X. americana* to climate change, future climate projections were obtained from the global climate model MIROC6, integrated into the CMIP6 framework, according to two shared socio-economic scenarios: SSP2-4.5 and SSP5-8.5. The projections were considered for two-time horizons, 2050 (2041-2060) and 2070 (2061-2080). Scenario SSP2-4.5 corresponds to an intermediate trajectory of radiative forcing, while SSP5-8.5 represents a trajectory of higher emissions and greater warming. These scenarios thus make it possible to examine the potential sensitivity of the species' distribution according to different future climate trajectories (Fick and Hijmans, 2017).

2.3.1. Selection of environmental variables

Before modeling, environmental variables were subjected to a multicollinearity analysis in order to limit the redundancy between predictors and improve model stability and interpretation. Two complementary approaches were used: (i) a Pearson correlation matrix to identify linear relationships between variables (Table 1 and Figure 2) and (ii) the variance inflation factor (VIF) calculation to quantify multicollinearity between selected variables.

Table 1: Pearson correlation matrix between the selected environmental variables ($|r| \geq 0.70$: high correlation; $0.50 \leq |r| < 0.70$: moderate correlation; $|r| < 0.50$: low correlation)

	bio_12	bio_18	bio_19	bio_9	elev	hwsd
bio_12	1.00	0.24	0.60	0.03	0.25	0.43
bio_18	0.24	1.00	-0.09	0.37	-0.59	0.17
bio_19	0.60	-0.09	1.00	-0.14	0.50	0.29
bio_9	0.03	0.37	-0.14	1.00	-0.74	0.11
elev	0.25	-0.59	0.50	-0.74	1.00	-0.01
hwsd	0.43	0.17	0.29	0.11	-0.01	1.00

**Figure 2: Correlation matrix of environmental variables (heatmap)**

Highly correlated variables were examined and redundant variables were eliminated based on their ecological relevance and potential contribution to the species distribution. The selection criterion chosen was a $VIF > 10$, a threshold commonly used to limit multicollinearity problems in statistical models. A similar procedure combining correlation and VIF was employed in recent species distribution modeling work to select a set of predictors sufficiently independent for modeling.

2.4. Modeling of the potential distribution

The current and future potential distribution of *Ximenia americana* L. was modeled using four complementary algorithms: Random Forest (RF), Maximum Entropy (MaxEnt), Generalized Linear Model (GLM) and Generalized Additive Model (GAM). These approaches combine statistical and machine learning

methods with different structures and capabilities for representing the relationships between occurrences and environmental variables. Their joint use makes it possible to limit the dependence of the results on a particular algorithm, as predictive performance may vary depending on the methods used (Buisson *et al.*, 2010; Thuiller *et al.*, 2019; Norberg *et al.*, 2019; Valavi *et al.*, 2022). Recent work has notably mobilized this combination of GLM, GAM, RF and MaxEnt in the context of modeling current and future distributions of plant species.

The analyses were carried out under R using the biomod2 package, which allows to calibrate and evaluate several algorithms in a homogeneous methodological framework (Thuiller *et al.*, 2009). The use of several algorithms is a particularly relevant overall approach to reduce the uncertainty associated with the choice of a

single Thuiller model and improve the robustness of predictions (*et al.*, 2009; Hao *et al.*, 2019; Hao *et al.*, 2020).

The occurrences were randomly distributed into two subsets: 80% for model calibration and 20% for independent validation. The default settings for biomod2 have been maintained, unless otherwise noted. For algorithms requiring contrast data with presences, 1000 background/pseudo-absence points were generated by biomod2. This procedure is comparable to that used in recent work using the same four algorithms, with automated background point generation in biomod2.

2.5. Performance evaluation and mapping

The predictive performance of each model was evaluated using two complementary metrics: the area under the ROC curve (AUC) and the True Skill Statistic (TSS). The AUC measures the model's ability to discriminate between sites favorable and sites unfavorable to the presence of the species, while the TSS simultaneously evaluates its ability to discriminate between attendance and absence. The joint use of these two indicators provides a more robust assessment of the predictive performance of models (Thuiller *et al.*, 2009).

The continuous predictions produced by the different algorithms were then converted into presence/absence binary maps from the threshold corresponding to the maximum TSS value (MaxTSS). This approach makes it possible to identify the pixels for which the environmental conditions are considered favorable to the species. The MaxTSS threshold was chosen because it allows to maximize simultaneously the sensitivity and specificity of the model.

Finally, the distribution maps obtained for current conditions and different future climate scenarios were exported and processed in ArcGIS 10.8 for their cartographic representation and spatial analysis. The final maps made it possible to visualize areas potentially favorable to *X. americana* dans current climatic conditions as well as potential changes in their distribution under SSP2-4.5 and SSP5-8.5 at the 2050 and 2070 horizons.

3. RESULTS

3.1. Model performance and validation

The validation results show that all four models have a generally satisfactory predictive capacity to model the potential distribution of *Ximenia americana*. The AUC values range from 0.888 to 0.949, while the TSS values are between 0.660 and 0.788, indicating a good general ability of models to distinguish favorable and unfavorable conditions for the presence of the species. Random Forest (RF) has the best validation performance, with a TSS of 0.788 and an AUC of 0.949.

It is followed by MAXENT, with a TSS of 0.782 and an AUC of 0.933, then by GAM, with a TSS of 0.774 and an AUC of 0.933. These results reflect a good predictive capacity of these three models. The GLM has the lowest validation performance, with a TSS of 0.660 and an AUC of 0.888, although these remain acceptable. Thus, on the basis of validation results only, the RF appears as the most efficient model, followed by the MAXENT and the GAM, while the GLM shows the lowest predictive performance.

3.2. Importance of environmental variables

The analysis of the importance of variables shows that rainfall factors are the main determinants of the potential distribution of *Ximenia americana*. The precipitation of the coldest quarter (bio19) is particularly important for GAM, with a contribution of 38.29%, while the precipitation of the hottest quarter (bio18) shows the highest contributions for GLM (28.59%) and MAXENT (22.88%). These results highlight the importance of seasonal rainfall conditions in the species' distribution. Soil type is also an important factor, with contributions ranging from 14.35% to 17.35% depending on the models. Altitude contributes between 9.32% and 17.40%, while the average temperature of the driest quarter shows contributions ranging from 11.34% to 14.49%. These results show that the distribution of *Ximenia americana* résulte due to the combined action of several environmental factors, even if rainfall variables play a predominant role. The RF model is distinguished by a relatively balanced contribution of variables, none of them exceeding 19% in importance. The correlation matrix between the selected variables is presented in Table 1 and Figure 2.

3.3. Distribution dynamics of *Ximenia americana*

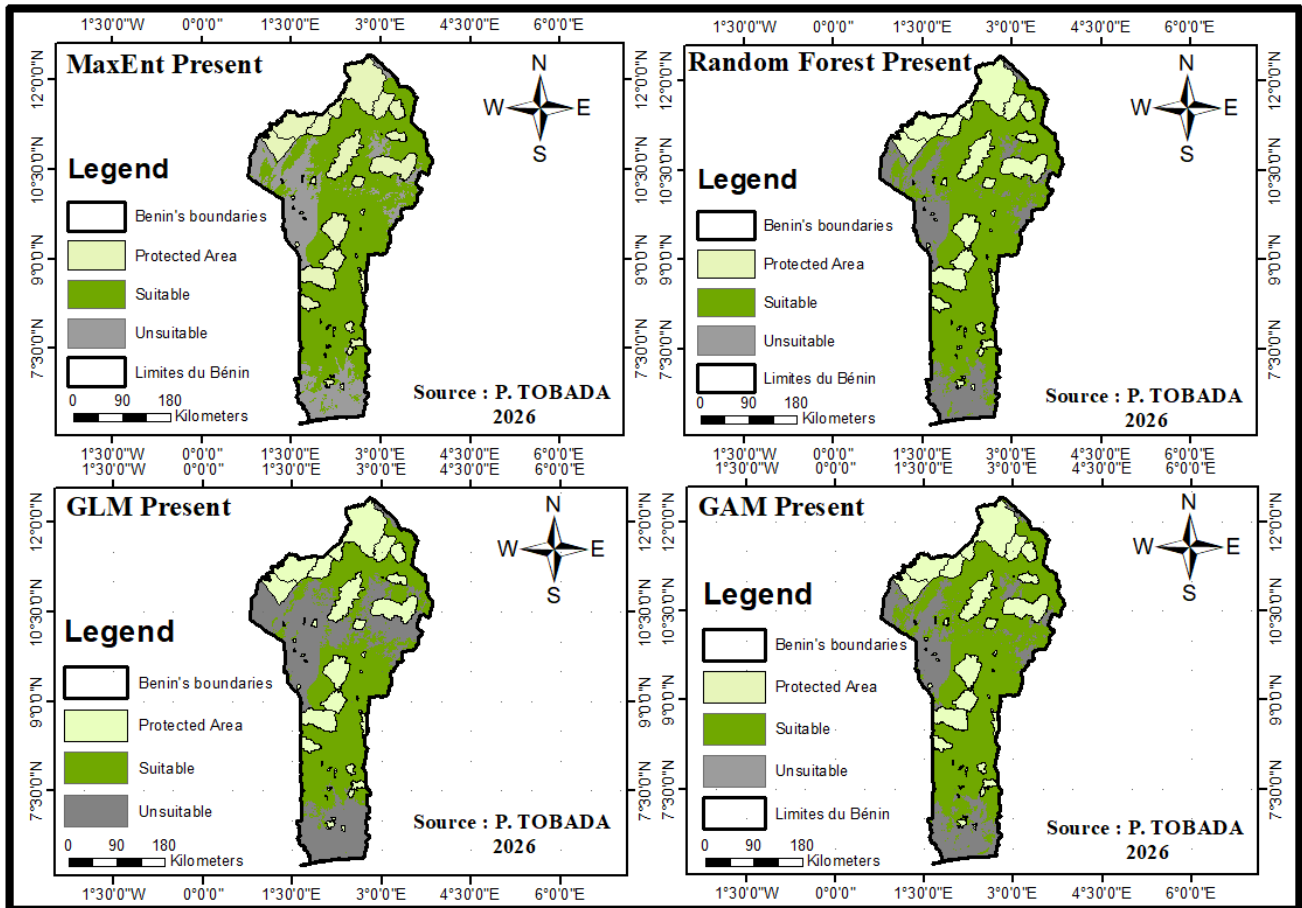
3.3.1. Current distribution of *Ximenia americana*

Under current climatic conditions, models predict a relatively large area of suitable habitat for *Ximenia americana*. The GAM estimates this area at 87,576.50 km², the RF at 89,068.04 km², GLM at 70,599.26 km² and MAXENT at 87,142.68 km² (Table 2, Figure 3). Despite some differences between the algorithms, three models, namely GAM, RF and MAXENT, produce relatively close estimates. This convergence is an important element in the interpretation of the current distribution of the species.

The difference observed with the GLM, however, shows that the estimate of the favorable area depends partly on the algorithm used. The GLM identifies a smaller favorable area than the other three models. This variability between models must therefore be taken into account in the interpretation of results. Nevertheless, all models indicate that a large area of the studied area currently presents conditions considered favorable to the potential distribution of *Ximenia americana*.

Table 2: Areas of favorable and unfavorable habitats for *Ximenia americana* under current climate conditions

Algorithm	Not favourable (km 2)	Favourable (km 2)
GAM	28 954,07	87 576,50
RF	27 462,53	89 068,04
GLM	45 931,30	70 599,26
MAXENT	29 387,89	87 142,68

**Figure 3: Current potential distribution of *Ximenia americana* according to different ecological niche models**

3.3.2. Evolution of the distribution under scenario SSP2-4.5

The projections under SSP2-4.5 show a decrease in the area of suitable habitats compared to the current situation. By 2050, the GAM estimates the favorable area at 71,961.66 km² against 87,576.50 km² currently. The FR also projects a decrease from 89,068.04 km² to 82,031.95 km² (Table 3, Figure 4). This evolution indicates that, even in the intermediate climate scenario, future environmental conditions could become less favorable to *Ximenia americana* sur in part

of the study area. The decrease is however much more pronounced according to GLM and MAXENT. In 2050, these two models foresee respectively 30,470.90 km² and 27,400.71 km² of favorable habitat. These values represent a significant reduction compared to the current area estimated by these same models. The divergence between the algorithms thus shows that the extent of the future response of the species remains uncertain, even if the general trend towards a reduction in favorable habitat appears in the projections.

Table 3: Areas of favorable and unfavorable habitats for *Ximenia americana* under the SSP2-4.5 scenario by 2050

Algorithm	Not favourable (km 2)	Favourable (km 2)
GAM	44 568,90	71 961,66
RF	34 498,62	82 031,95
GLM	86 059,67	30 470,90
MAXENT	89 129,85	27 400,71

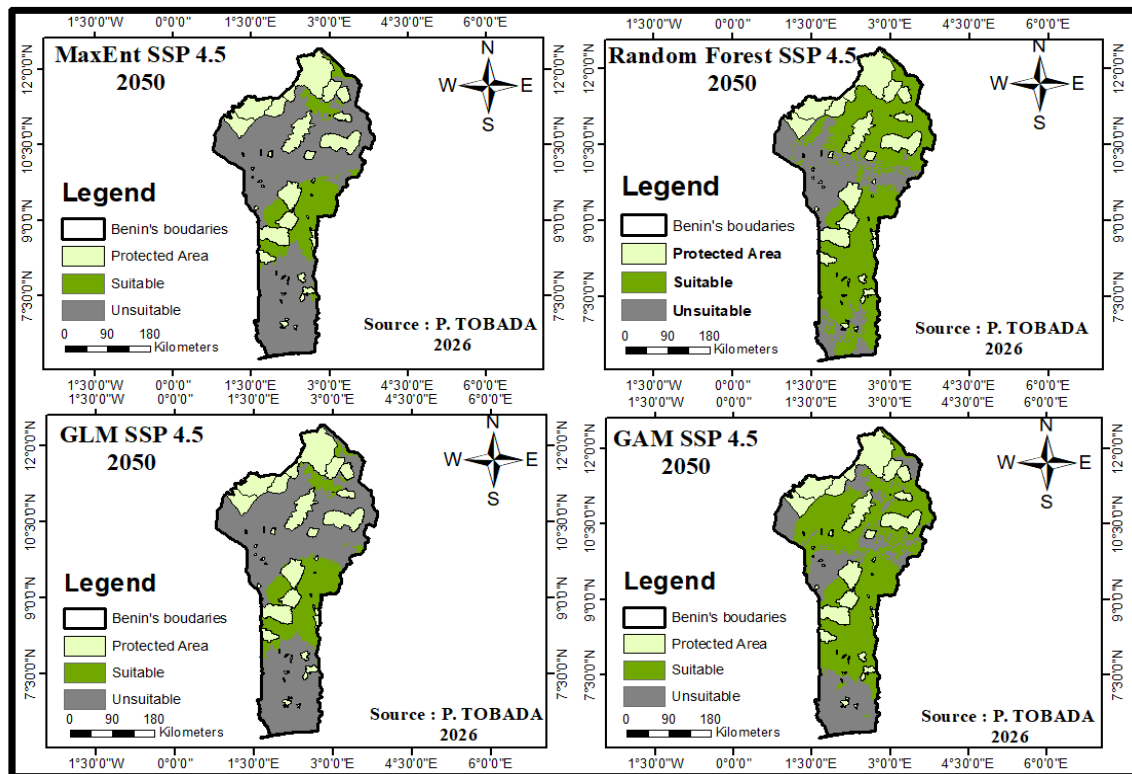


Figure 4: Potential future distribution of *Ximenia americana* under the SSP2-4.5 scenario by 2050

By 2070, this contraction trend continues under SSP2-4.5. The GAM forecasts 71,652.81 km² of favorable habitat and the RF 74016.42 km². GLM and MAXENT yield 37,504.70 km² and 28,334.27 km² respectively (Table 4, Figure 5). Thus, the favorable area

remains substantial according to GAM and RF, while it becomes significantly smaller according to GLM and MAXENT. This evolution shows that the effect of climate change could increase over time, but that its intensity depends heavily on the algorithm used.

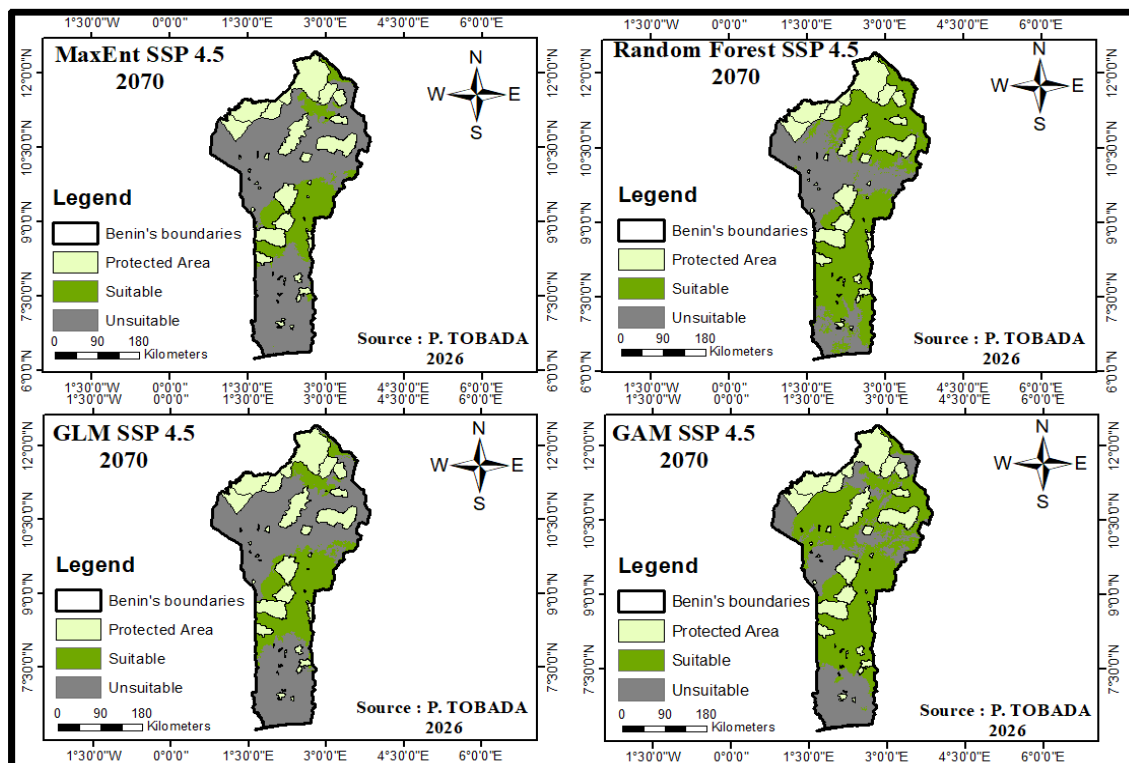


Figure 5: Potential future distribution of *Ximenia americana* under the SSP2-4.5 scenario by 2070

Table 4: Areas of favorable and unfavorable habitats for *Ximenia americana* under the SSP2-4.5 scenario by 2070

Algorithm	Not favourable (km 2)	Favourable (km 2)
GAM	44 877,76	71 652,81
RF	42 514,14	74 016,42
GLM	79 025,87	37 504,70
MAXENT	88 196,29	28 334,27

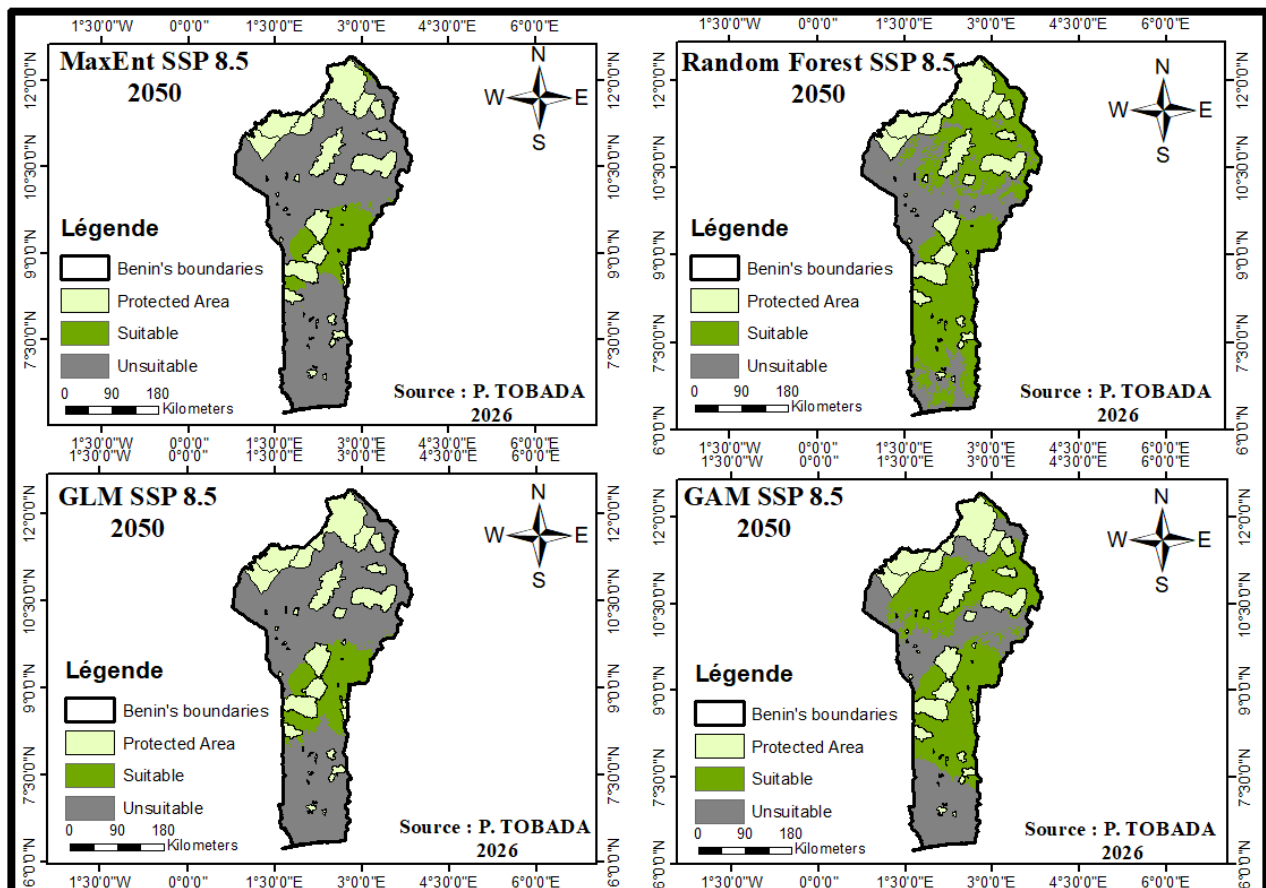
3.3.3. Evolution of the distribution under scenario SSP5-8.5

Projections become more concerning under the SSP5-8.5 scenario, which leads to the largest reductions in suitable habitat area. In 2050, the GAM forecasts 63,335.99 km² of favorable habitat, while the RF

forecasts 76,147.41 km². These two values are lower than the current area estimated by the same models. The decrease is much greater according to GLM and MAXENT, which forecast only 21,216.82 km² and 19,472.43 km² of suitable habitat respectively (Table 5, Figure 6).

Table 5: Areas of favorable and unfavorable habitats for *Ximenia americana* under the SSP5-8.5 scenario by 2050

Algorithm	Not favourable (km 2)	Favourable (km 2)
GAM	53 194,57	63 335,99
RF	40 383,15	76 147,41
GLM	95 313,75	21 216,82
MAXENT	97 058,13	19 472,43

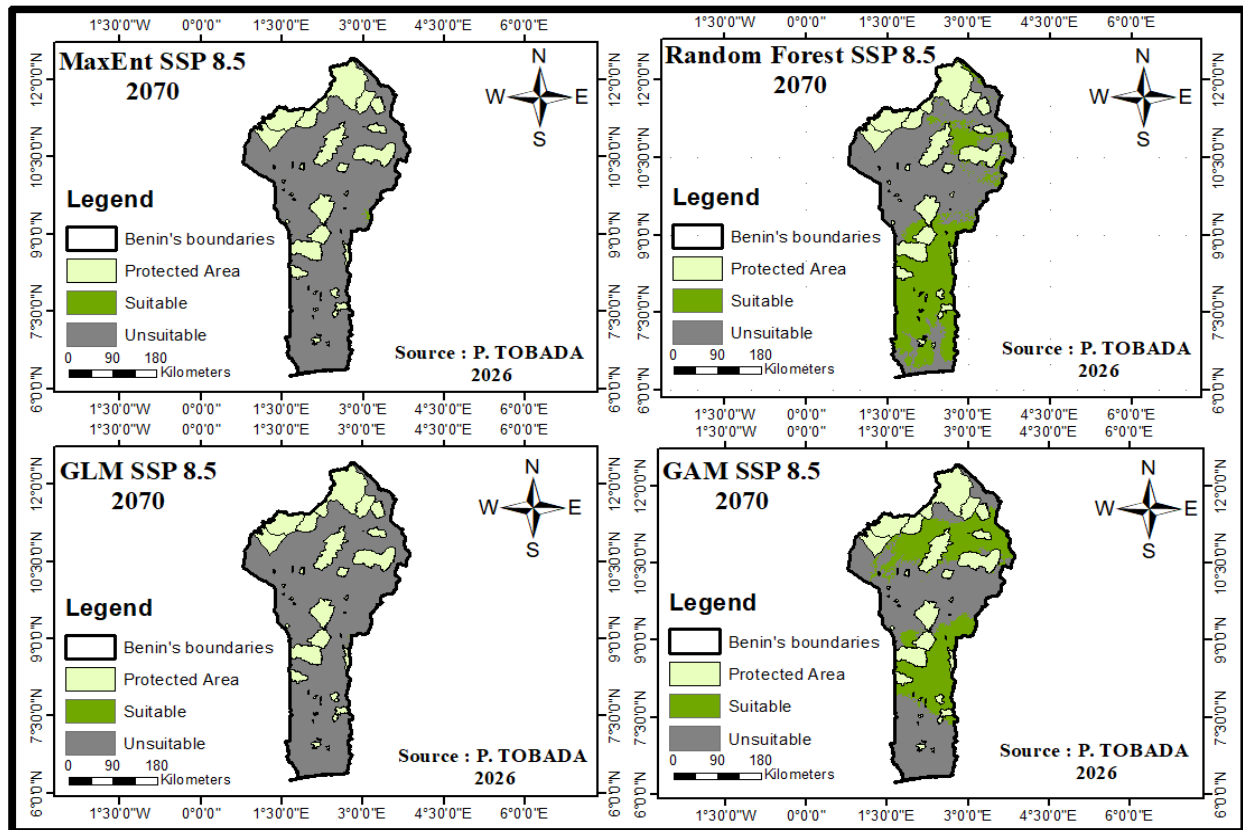
**Figure 6: Potential future distribution of *Ximenia americana* under the SSP5-8.5 scenario by 2050**

The situation becomes particularly marked in 2070. The GAM then forecasts 42,875.50 km² of favorable habitat and the RF 46062.00 km². On the other hand, GLM is now only 16.05 km² and MAXENT 208.18 km² (Table 6, Figure 7). These results correspond, for the last two models, to a near

disappearance of the area considered favorable to *Ximenia americana*. GLM and MAXENT thus project a virtual disappearance of the favorable habitat under SSP5-8.5 by 2070, unlike GAM and RF which maintain a significant favorable area.

Table 6: Areas of favorable and unfavorable habitats for *Ximenia americana* under scenario SSP5-8.5 by 2070

Algorithm	Not favourable (km 2)	Favourable (km 2)
GAM	73 655,07	42 875,50
RF	70 468,56	46 062,00
GLM	116 514,51	16,05
MAXENT	116 322,39	208,18

**Figure 7: Potential future distribution of *Ximenia americana* under the SSP5-8.5 scenario by 2070**

3.3.4. Comparison between climate scenarios

Comparing the two scenarios clearly shows that increasing the severity of climate change is accompanied by a larger decrease in suitable habitat. The SSP2-4.5 scenario already leads to a contraction of potential habitat, but this contraction becomes much more significant in SSP5-8.5, particularly by 2070. This trend is consistent with the important role played by climate variables, particularly seasonal rainfall, in distribution patterns.

The temporal evolution also shows that the projected effects are more important in the long term. For the GAM and RF models, the favorable area gradually decreases between the current situations, 2050 and 2070, with a particularly significant reduction under SSP5-8.5. For GLM and MAXENT, this decrease becomes extremely sharp, until reaching almost zero areas in 2070 under the SSP5-8.5 scenario. The results therefore suggest a potential worsening of habitat loss with the intensification of climate change and the lengthening of the time horizon.

3.3.5 Uncertainty of projections and interpretation of results

A key consideration is the high divergence observed between models, especially for long-term projections under SSP5-8.5. Indeed, while GLM and MAXENT forecast a near complete disappearance of favorable habitats in 2070, GAM and RF still forecast 42,875.50 km² and 46,062.00 km² respectively. This considerable difference shows that the projections should not be interpreted as a single, certain prediction of the species' future distribution.

The most robust conclusion to be drawn from these results is therefore related more to the direction of change than to its exact magnitude. The different models converge globally towards a reduction of favorable habitat when future climatic conditions become more restrictive, but they diverge strongly on the importance of this reduction. It is thus more prudent to state that *Ximenia americana* presents a potential vulnerability to climate change, rather than asserting with certainty a future disappearance of the species or its habitat.

4. DISCUSSION

4.1. Performance and robustness of the models

The validation results obtained in this study confirm the ability of the four algorithms to satisfactorily model the potential distribution of *Ximenia americana*, with AUC values between 0.888 and 0.949 and TSS values between 0.660 and 0.788. These performances are in line with the thresholds commonly accepted in the literature to consider a model as reliable, namely an AUC greater than 0.70 (Hill *et al.*, 2017) and a value of TSS close to 1 (Watling *et al.*, 2015). The Random Forest (RF) stood out as the most efficient model, followed by the MaxEnt and then the GAM, with the GLM showing the lowest performance although still acceptable. This superiority of the RF corroborates findings made in other modeling studies in West Africa, where the RF has also proved to be the most robust algorithm for predicting areas favorable to woody species. (case of *Uvaria chamae* au Benin, where the RF also surpassed the GLM, the GAM and the MaxEnt). This convergence also meets the more general conclusions of the literature on machine learning applied to niche modeling, which highlights the particular robustness of the RF when faced with datasets with significant variability or correlated predictors (Lorena *et al.*, 2011; Natras *et al.*, 2022). The use of several algorithms rather than a single one, as has been done here, makes it possible to limit the biases specific to each approach and to obtain more stable projections, as shown by overall modeling studies conducted in a mountain context (Araujo and New, 2007; Breiner *et al.*, 2015).

4.2. Contribution of environmental variables

The analysis of the importance of variables highlighted the preponderance of rainfall factors (precipitation from the coldest quarter and the warmest quarter) in the potential distribution of *X. americana*, followed by soil type, the altitude and average temperature of the driest quarter. This result is consistent with several studies conducted in West Africa on ecologically similar woody species: Dimobe *et al.*, in Burkina Faso, have thus shown that rainfall and temperature constitute the main bioclimatic determinants of the distribution of shea (Vitellaria paradoxa), while Assogba *et al.*, highlighted the joint influence of edaphic and climatic factors on the distribution of baobab in Benin, a pattern that directly matches our results regarding the significant contribution of soil type (14.35% to 17.35%). This importance of seasonal rainfall in the distribution of tropical woody species contrasts with the results observed in mountain contexts (Himalayas, Pyrenees, Ethiopian highlands), where temperature and altitude generally dominate models due to the steep thermal gradients specific to high-altitude environments (Chandra *et al.*, 2021; Kemppinen *et al.*, 2024). The relatively modest but significant contribution of altitude in our models (9.32% to 17.40%) reflects more the moderate topographic heterogeneity of the Beninese territory than the marked altitudinal gradient effects observed in mountain areas.

4.3. Current, future distributions and vulnerability of *X. americanato* climate change

Under current climatic conditions, the models globally agree on a favorable area (between 70599 and 89068 km² according to the algorithm), with a notable convergence between GAM, RF and MaxEnt. However, future projections indicate a gradual reduction of this favorable area, the extent of which depends strongly on the climate scenario, the time horizon and, above all, the algorithm considered. This result is directly comparable to that obtained by Lompo *et al.*, (2021) on the same species, *Ximenia americana*, in Burkina Faso, where climate change also led to a favorable range reduction by 2070, especially according to the MaxEnt model. Our results therefore confirm, in a different geographical context (Benin), the trend already observed for this species in the West Sudanese zone African, thus strengthening the robustness of the hypothesis of a global vulnerability of *X. americana* to projected climate changes at the regional scale. This concordance is also consistent with the more general observation that climate change can substantially alter the range of plant species (Pearson *et al.*, 2007), particularly for multi-use species highly sought after by rural populations.

The particularly marked magnitude of the contraction projected under the SSP5-8.5 scenario by 2070 for the GLM and MaxEnt models (near disappearance of suitable habitat, with only 16.05 km² and 208.18 km² respectively) deserves to be put into perspective with similar trends observed elsewhere: in the Pyrenees, the most pessimistic scenarios (SP370, SP585) after 2041-2060 also produce the most alarming reductions in favorable bioclimatic areas (up to -95.21% for some endemic species). Similarly, for the endemic Ethiopian bird *C. xantholaema*, overall projections predict highly favorable habitat losses of 80.8% and 73.2%, respectively, in 2050 and 2070. This parallel confirms a widely shared trend in the niche modeling literature: the more severe the emission scenario and the longer the time horizon, the greater the contraction of the favorable habitat is marked, regardless of the taxonomy or region considered.

4.4. Uncertainty in projections and model divergence

The strong divergence observed between the algorithms, in particular between the GAM/RF pair, which maintains a substantial favorable surface area at all horizons, and the GLM/MaxEnt pair, which projects a much more radical reduction, is an outcome that must be interpreted with caution, in accordance with the methodological recommendations made in several studies. This inter-algorithm variability is in line with warnings issued about species distribution models in general, which emphasize that long-term projections under severe climate scenarios (SSP370, SSP585) remain particularly uncertain due to the growing divergence between climate models and statistical algorithms. From this perspective, following what has

been recommended for the endemic flora of the Pyrenees, it appears more prudent, for *X. americana*, to retain the direction of change (a generalized reduction in habitat favorable to the intensification of climate change) rather than its exact amplitude, which remains dependent on the methodological choice. This approach is also consistent with the conclusions concerning *Uvaria chamae* au Benin, where variations in prediction depending on future climate conditions had already been noted, and with the general recommendations in favor of multi-species ensemble approaches algorithms to limit the biases specific to each model (Araujo and New, 2007; Thuiller *et al.*, 2009).

4.5. Implications for the management and conservation of *X. americana* au Benin

Ximenia americana being a species of high socio-economic and medicinal value for rural communities, like *Uvaria chamae* and other West African utilitarian ligneux, the anticipated reduction of its favorable habitat, even in the most conservative hypothesis carried by the GAM and RF models, calls for particular vigilance. The divergence between models should not be a hindrance to action: as highlighted by studies on endemic flora in the Pyrenees and endemic birds in Ethiopia, the identification of areas of climate stability (areas where several models converge towards maintaining favorable conditions) should be prioritized in the conservation and domestication strategies of the species. It would also be relevant, in the continuity of work carried out on other Beninese woody species (Assogba *et al.*, 2022; work on *Uvaria chamae*), to cross these projections with the location of protected areas in order to determine whether the climatically stable zones for *X. americana* are beneficiary of sufficient protection, and to consider, if necessary, its integration into agroforestry systems to ensure their sustainable conservation in the face of the combined pressure of overexploitation and climate change.

CONCLUSION

This study allowed us to model the current and future distribution of *Ximenia americana* L. in Benin from four algorithms, with generally satisfactory validation performance. Seasonal rainfall, particularly in the coldest and warmest quarters, appears to be the main determinant of species distribution. The projections show a gradual reduction of favorable habitats under the effect of climate change, particularly under the SSP5-8.5 scenario and by 2070. Despite a significant discrepancy between models regarding the magnitude of this reduction, the overall trend indicates a potential vulnerability of *X. americana* face to future climate changes. Given the socio-economic and medicinal importance of this species and the pressures already exerted on its populations, these results highlight the need to strengthen its conservation in Benin. It appears particularly important to prioritize areas where models converge towards the maintenance of favorable habitats, to assess their level of protection, to promote the

integration of *X. americana* dans into agroforestry systems, and to strengthen field monitoring. This study thus constitutes a scientific basis to guide the strategies of conservation, sustainable management and domestication of the species, while highlighting the value of further work to reduce the uncertainty of future projections.

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