Intermediary report I

"Improvement of the conservation status of *Afzelia africana* in Benin" Project (ID: 41122-1)

Agbatan Marc KOUTCHORO, MSc

Laboratory of Ecology, Botany and plant Biology, University of Parakou (Benin)

Doctoral School of Agricultural and Water Sciences, University of Parakou

Email: marckoutchoro@gmail.com

Phone: +229 64306702/97526325

1. Introduction

Climate change is one of the main ecological factors influencing the geographical distribution of species (Agbo *et al*., 2019; Zhang *et al.,* 2019). It inevitably impacts ecosystem structure and function, affecting species richness and composition (Thapa *et al.*, 2018), as well as tree phenology and physiology (Thuiller *et al.*, 2005). Among the most affected species is *Afzelia africana* (Saliou *et al.*, 2015; Adjahossou *et al.*, 2016), an endangered species that deserves special conservation attention. However, conservation efforts need to be multiplied in order to save it from extinction. Intensifying conservation efforts requires a good understanding of the habitats favorable to the conservation of the species. This will make it possible to know the locations suitable for its silviculture (Fandohan *et al.*, 2013) and also to make decisions on where conservation efforts should be concentrated for optimal impact, and this in a context of limited financial resources (Adjahossou *et al.*, 2016). The aim of our work is to assess habitats favorable to the conservation of *A. africana* in Benin. It is a component of the "*Improvement of the conservation status of Afzelia africana in Benin*" project funded by Rufford Foundation.

2. Methodology

2.1. Data collection

Two types of data were used to model the spatial distribution of *A. africana*. These are occurrence and environmental data.

Occurrence data

Presence points for *A. africana* were obtained from fieldwork using GPS (Global Positioning System). In addition to field points, points over the last ten years were extracted from the Global Biodiversity Information Facility (GBIF: www.gbif.org). In order to achieve excellent accuracy in the modelling results, it is necessary to extend the collection of presence points outside the study area (Fitzpatrick & Hargrove, 2009). However, we have completed occurrences from countries in the region based on the distribution observed on GBIF (accessed on 18th February 2024; Fig. 1). In total, 466 occurrences of *A. africana* were used to run the distribution model.

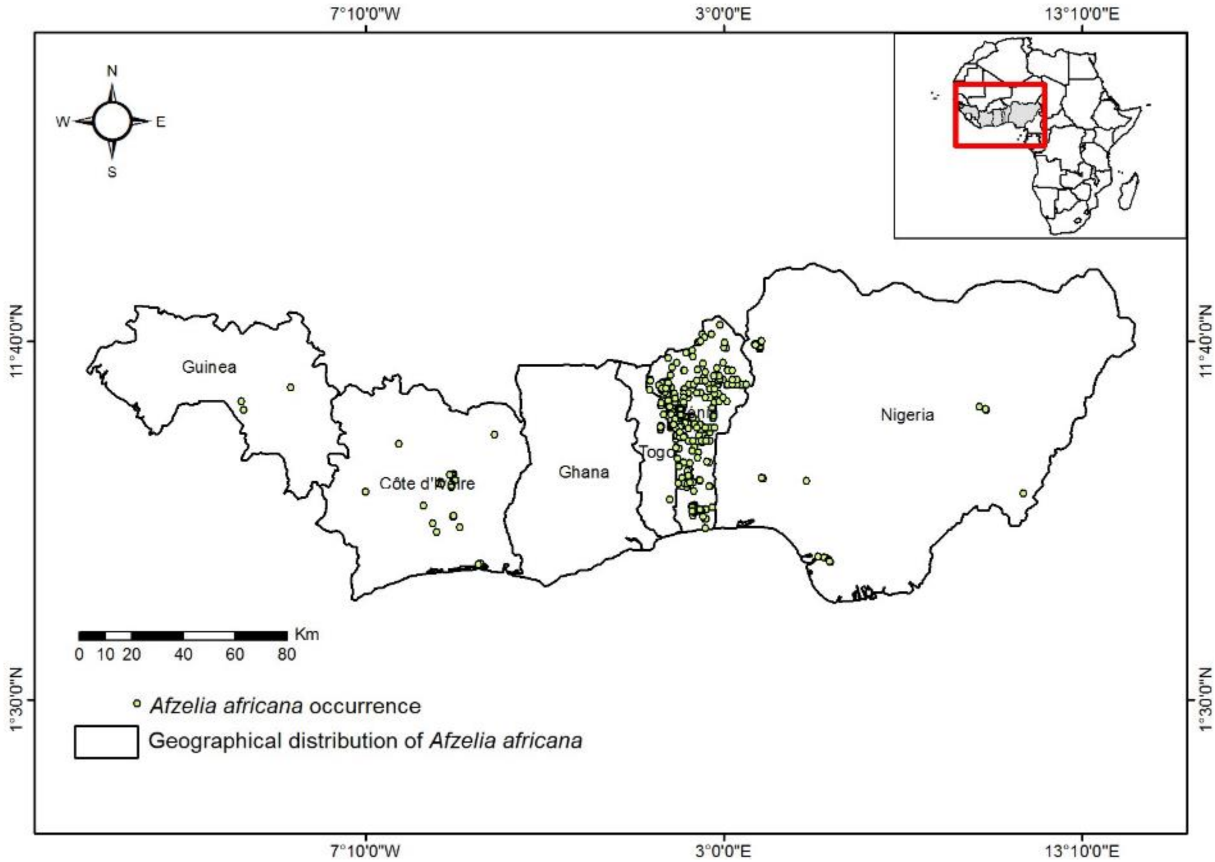

Fig. 1. Map of the study area showing the geographical distribution of *A. africana* in Benin and the sub-region.

Environmental data

Bioclimatic variables, soil variable and elevation (altitude) are the environmental data used. Bioclimatic and elevation variables were extracted from the WorldClim platform (https://www.worldclim.org/data/index.html, accessed on 30th May 2024). There are 19 variables relating to humidity and temperature (Table 1). The soil variable comes from the World Soil Database platform (https://iiasa.ac.at/models-tools-data/hwsd, accessed on 30 May 2024). These variables have a resolution of 30 seconds (~1km^2). Bioclimatic variables are recognized for their ecological impact on species distribution. They provide information on mean annual and seasonal conditions, as well as extreme and intra-annual values (Booth *et al.*, 2014). However, some of the 19 bioclimatic variables show discontinuities in America and sub-Saharan Africa (Escobar *et al*., 2014; Booth, 2022; Biaou *et al*., 2023). This concerns mean temperature of wettest quarter (bio 8), mean temperature of driest quarter (bio 9), precipitation of warmest quarter (bio 18) and precipitation of coldest quarter (bio 19). These variables were removed from our models to limit bias.

For the projections, the HadGEM3-GC3.1 global circulation model from the Met Office Centre's family of climate prediction models for the 2041-2060 horizon was used with two climate scenarios: the optimistic scenario (SSP2-4.5: https://geodata.ucdavis.edu/cmip6/30s/HadGEM3-GC31-LL/ssp245/wc2.1_30s_bioc_HadGEM3-GC31-LL_ssp245_2041-2060.tif) and the pessimistic scenario (SSP5-8.5: https://geodata.ucdavis.edu/cmip6/30s/HadGEM3-GC31 LL/ssp585/wc2.1_30s_bioc_HadGEM3-GC31-LL_ssp585_2041-2060.tif). This is the third version of the HadGEM configuration, integrating components of the NEMO ocean model and the CICE sea ice model, with a climate sensitivity of 5.4°C per CO2 doubling. This configuration also includes a land system with dynamic vegetation, ocean biology and atmospheric chemistry (Ridley *et al.*, 2018). In addition, SSPs (Shared Socioeconomic Pathways) are based on five narratives describing alternative socioeconomic pathways, including sustainable development, regional rivalry, inequality, fossil-fueled development and intermediate development (Nazarenko *et al*., 2022).

Table 1. Environmental variables used

Code	Variable description	Units
Bio 01	Annual mean temperature	°C
Bio 02	Mean diurnal range	°C
Bio 03	Isothermality	-
Bio 04	Temperature seasonality	°C
Bio 05	Maximum temperature of warmest month	°C
Bio 06	Minimum temperature of coldest month	°C
Bio 07	Temperature annual range	°C
Bio 08	Mean temperature of wettest quarter	°C
Bio 09	Mean temperature of driest quarter	°C
Bio 10	Mean temperature of warmest quarter	°C
Bio 11	Mean temperature of coldest quarter	°C
Bio 12	Annual precipitation	mm
Bio 13	Precipitation of wettest month	mm
Bio 14	Precipitation of driest month	mm
Bio 15	Precipitation seasonality	-
Bio 16	Precipitation of wettest quarter	mm
Bio 17	Precipitation of driest quarter	mm
Bio 18	Precipitation of warmest quarter	mm
Bio 19	Precipitation of coldest quarter	mm
Elev	Elevation	m
Soil	Soil	-

2.2. Data analysis

Occurrence data

Thanks to ArcGIS 10.7 mapping software, the Wallace reproductive modeling interphase (#WallaceEcoMod), and the Geocat tool (http://geocat.kew.org/editor), occurrence data have been cleaned at temporal, spatial or geographical scale and at taxonomic scale. Only occurrence data from the GBIF database with the essential attributes of an occurrence are retained. These are data with the specific epithet well precise (taxonomic analysis) and informed, the date of collection well informed (temporal analysis), the method of collection informed (only points resulting from human observation are considered). Also, only occurrences with geographic references (decimal longitude and latitude coordinates) are considered (spatial analysis). Outliers and duplicates were removed from the database. Field data and GBIF platform data were cleaned and combined in semi-colon separator format (csv.). Thanks to the "*sp Thin*" function in the "*shinny*" package, the density of points of presence in the Wallace interphase was regulated to a minimum distance of 1km.

Environmental data

The environmental variables obtained in the WorldClim platform were sliced according to the mask (geographical space in which the species is currently observed). These variables were then aligned and converted into ASCII (.ascii) format, ready for use in the Maxent algorithm.

Model conception

The *A. africana* distribution model was run in the Maxent algorithm, which is par excellence designed to elaborate distribution models based on observations of species presence only (Merow *et al.*, 2013; Phillips *et al.*, 2017; Alsamadisi *et al.*, 2020). In addition, these authors point out the following advantages of MaxEnt (Maximum Entropy): the possibility of using qualitative data, the ability to eliminate sampling bias and avoid overestimation of results, and the use of even small quantities of data.

The converted bioclimatic variables were integrated into the model, where a cross-validation was carried out according to AUC (Area Under the Curve) metric values, in order to select the variables that best fit the species distribution. The Jackknife test was used to assess the individual contribution of each environmental variable to the model on the one hand, and to provide indications of how the model works when each variable is excluded from the model on the other (Phillips *et al*., 2006). On the basis of these variables, potential present distribution maps were obtained and projected into the future according to two scenarios, SSP2-4.5 and SSP5-8.5, for the horizon 2041-2060.

The model was run five (05) times using the "*logistic*" approach as output format. The value *"10 percentile training presence logistic threshold"* was used as the probability threshold to define levels of habitat suitability for the species (Liu *et al*., 2013). The probability of occurrence below the threshold is considered unfavorable habitat for the species, and that above the threshold corresponds to more favorable habitat for the species. Model exactitude was assessed using True Skill Statistics (TSS; Allouche *et al.*, 2006). The cross-validate method was used to calculate AUCs (Hao *et al*., 2020). Twenty-five (25%) of the species observation points were used to test the model and seventy-five (75%) of the points to calibrate the model. AUC values of 0.5-0.7 correspond to low accuracy, those of 0.7-0.89 to good accuracy and those above 0.9 to high accuracy (Hao *et al*., 2019).

Three classes (Unfavorable, Relatively favorable and Highly favorable) were selected for the classification of the species' habitats based on the threshold value of 10% (Peterson, 2011; Liu *et al*., 2013; Adjahossou *et al*., 2016). For the quantification of *A. africana* habitats, the outputs of the model designed via the Maxent algorithm were submitted and classified in ArcGIS 10.7. mapping software through the *"Reclassify"* function of the *"spatial analysis tools"* extension. For this purpose, only the "Highly Favorable" class is considered as favorable habitat and consequently the "Unfavorable" and "Relatively Favorable" classes are merged and considered as unfavorable habitats for this species.

3. Results

3.1. Importance of environmental variables and model validation

Five environmental variables were selected according to the importance of their permutation and their contribution to model development. These are bio7 (temperature annual range), bio12 (annual precipitation), bio4 (temperature seasonality), bio15 (precipitation seasonality), bio14 (precipitation of driest month). The variables that contributed most to model development when used in isolation in the model are bio12, bio4, bio7, bio15 and bio14 respectively (Fig. 2).

Model performance was assessed by the area under the curve (AUC) value, the TSS value and the partial ROC statistical test. The AUC value resulting from the Maxent model run is 0.87. This threshold suggests a very good performance of the Maxent algorithm in capturing variations in environmental data (Fig. 3). Similarly, the TSS value obtained was 0.49, allowing us to conclude that the model performed better than a random model. In addition, the result of the partial ROC test indicates that the model worked significantly with a normal distribution of partial AUC (Fig. 4).

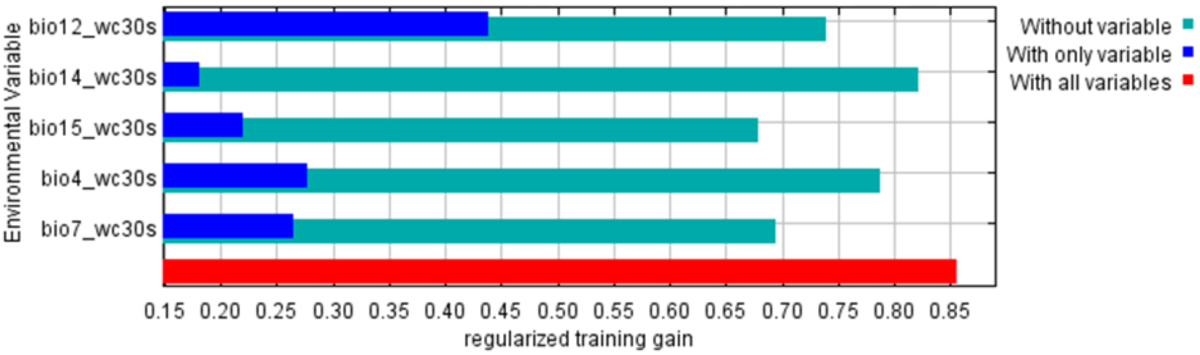

Fig. 2. Result of the Jackknife test on the contribution of variables to the model.

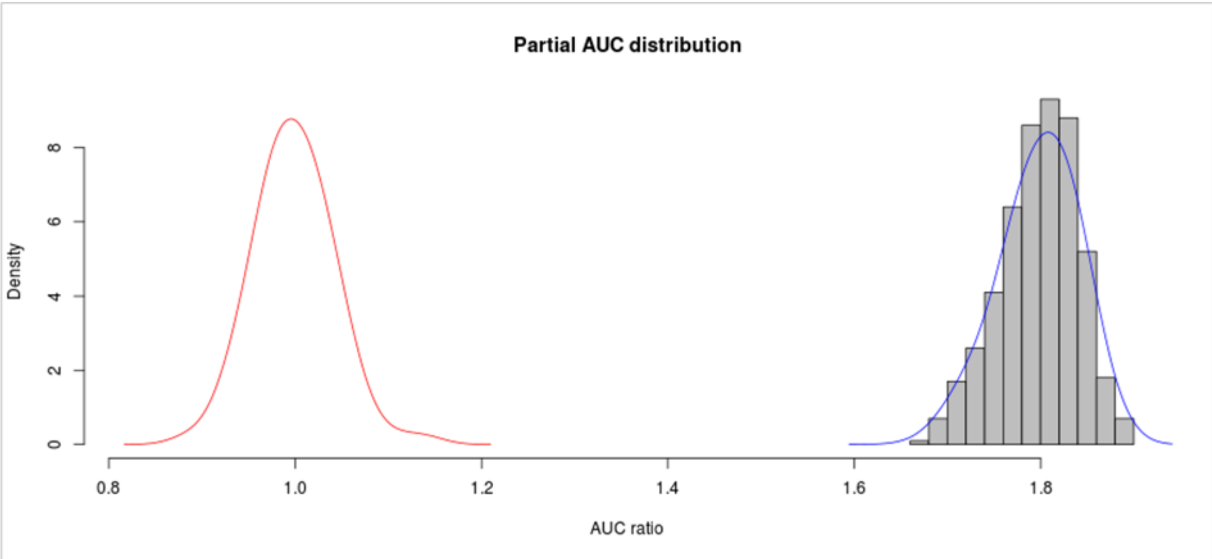

Fig. 3. Mean area under the curve (AUC) for *A. africana*.

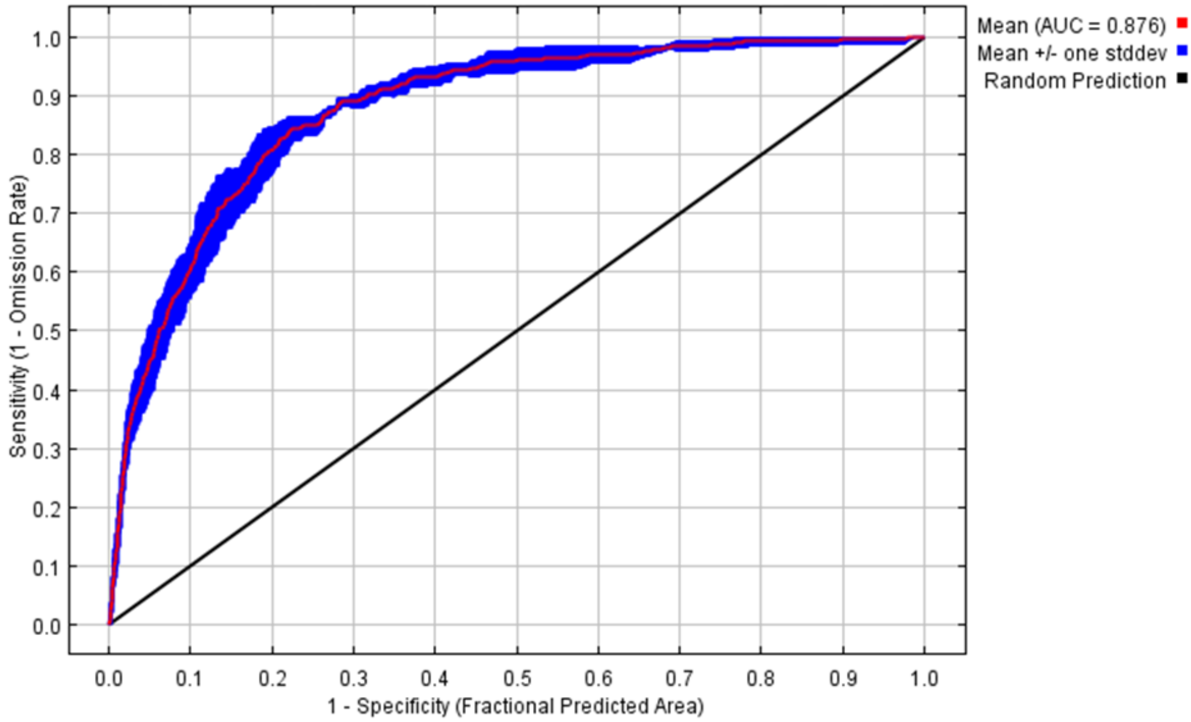

Fig. 4. Result of the Partial AUC distribution obtained from the Partial ROC test.

3.2. Current distribution of habitats favorable to the conservation of *A. africana*

The areas that are currently most favorable for the conservation of *A. africana* in Benin represent 56.97% of the country's national area (Table 2). These favorable habitats are distributed over the country's three climatic zones, with a high concentration observed in the Sudano-Guinean transition Zone (SGZ; 7°30' - 9°45'N) and the Sudanian Zone (SZ; 9°45' - 12°25'N) (Fig. 5). Thus, in the SGZ, the most favorable protected areas for the conservation of *A. africana* are: Gazetted Forest (GF) of Wari-Maro, Ouémé Supérieur, Béléfoungou, Sérou, Pénessoulou, Bassila, Dogo, Kétou, Atchérigbé, Dan and the Périmètre de Reboisement des Tanékas. As for the SZ, we have: GF of Goungoun, Guéné, the Sota, Ouénou Bénou, Alibori Supérieur, Mékrou, Kouandé and Birni. Some portions of Benin's two National Parks (Pendjari and W) are also more favorable to the species' conservation.

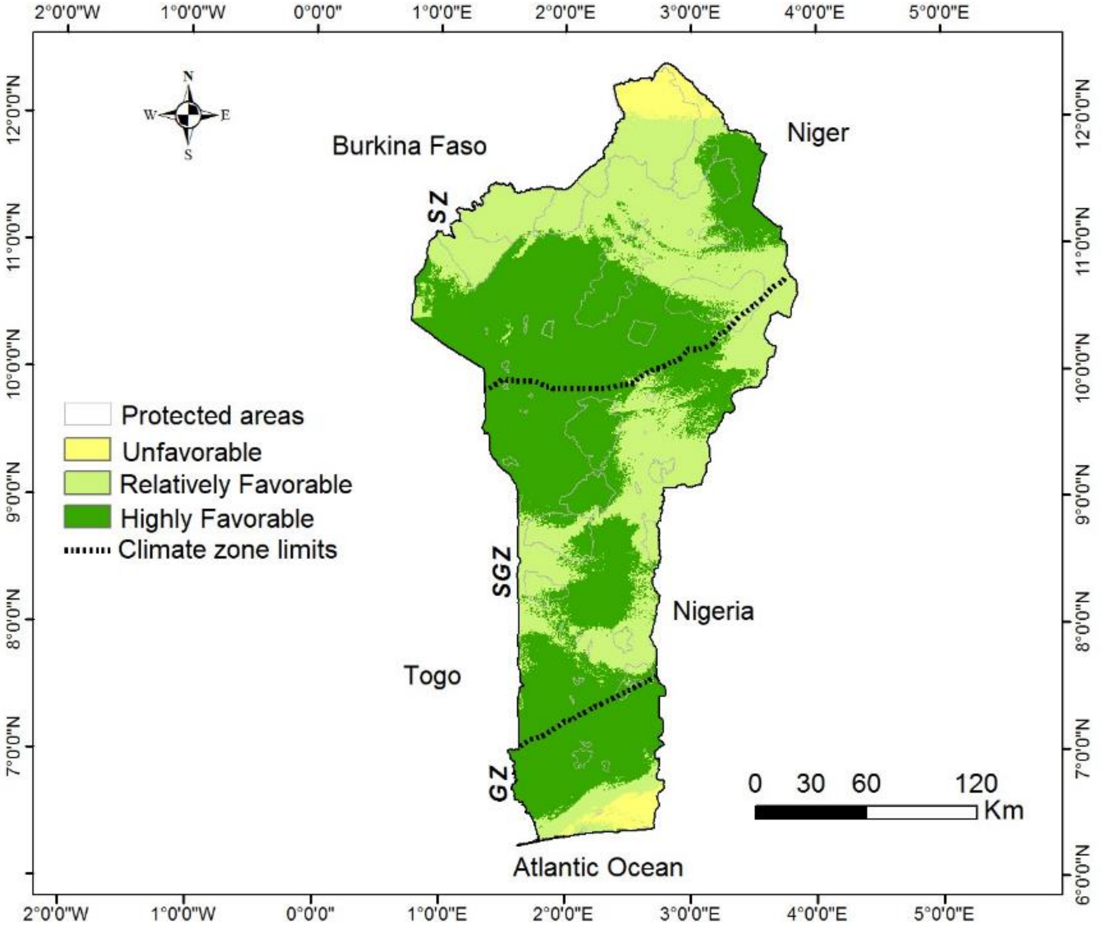

Fig. 5. Current spatial distribution of *A. africana* habitas in Benin. On the figure, GZ = Guinean Zone, SGZ = Sudano-Guinean Zone, SZ= Sudanian Zone.

3.3. Potential future distribution of habitats favorable to the conservation of *A. africana*

The model predicts a significant reduction in areas currently favorable for *A. africana* conservation, with an estimated loss of 16.22% under the optimistic scenario (SSP2-4.5) and 16.32% under the pessimistic scenario (SSP5-8.5; Table 2). This reduction by 2041-2060 horizon is more pronounced with the pessimistic scenario (-22.29%), characterized by an expansion of relatively favorable areas and a reduction of highly favorable areas in the SZ and SGZ (Fig. 6). Whatever the scenario, the GFs of Wari-Maro, Ouémé Supérieur and N'dali remain the most favorable for future *A. africana* conservation in the SGZ, while those of Mékrou, Kouandé and Birni, and some portions of Alibori Supérieur and W Park, are the most favorable in the SGZ.

Table 2. Impact of climate change on habitats favorable to the conservation of *A. africana*.

	Favorable areas		Unfavorable areas		Total area
	Surface (Km²)	Trend (%)	Surface (Km²)	Trend (%)	Trend (Km²)
Présent	65384,54 (56,97 %)	- -	49378,46 (43,03 %)	- -	114763
SSP2-4.5	54711,86	-16,32	60051,13	+21,61	114763
SSP5-8.5	50807,46	-22,29	63955,53	+ 29,52	114763

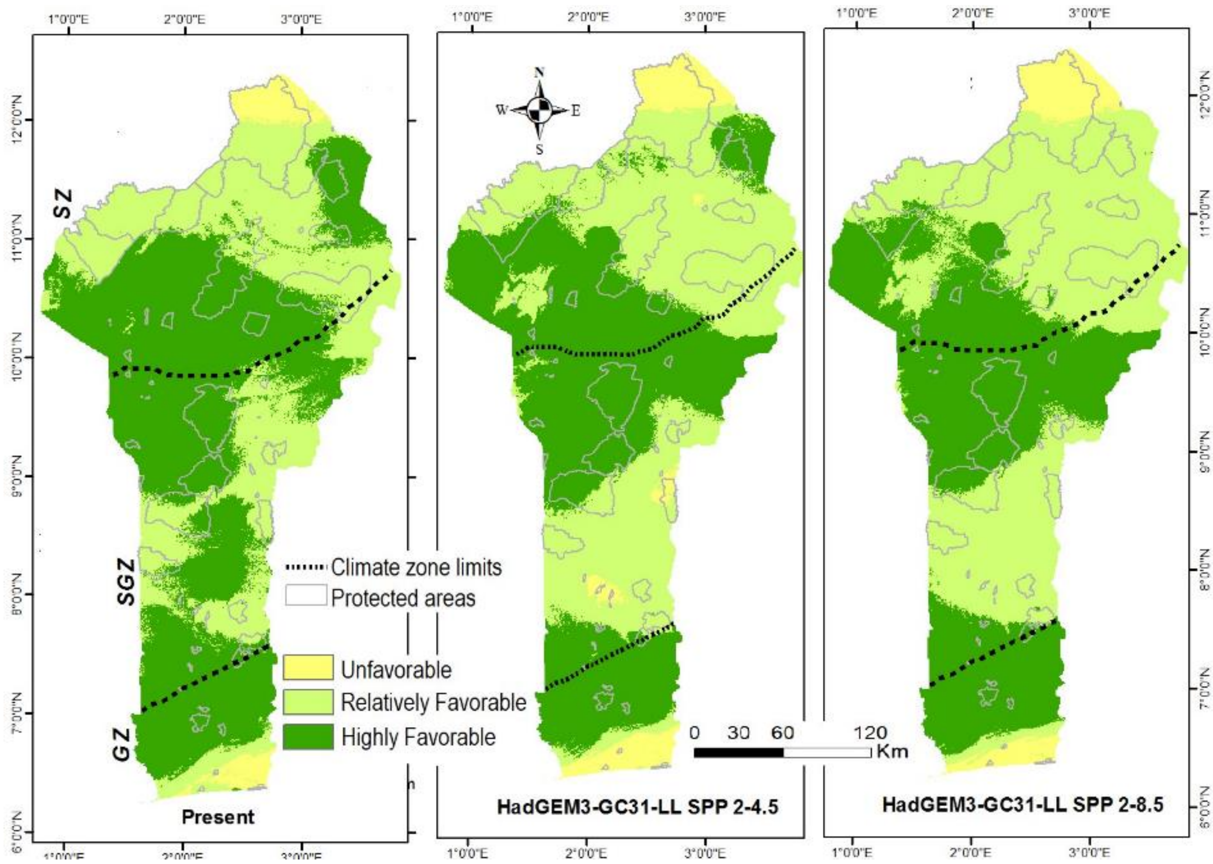

Fig. 6. Prediction of the future distribution of habitats favorable to the conservation of *A. africana* according to the SSP2-4.5 and SSP5-8.5 scenarios. On the figure, GZ = Guinean Zone, SGZ = Sudano-Guinean Zone, SZ= Sudanian Zone

4. Conclusion

The aim of this first intermediary report is to assess the habitats favorable to the conservation of *A. africana* in Benin. The areas that are currently most favorable for the conservation of *A. africana* in Benin represent 56.97% of the country's national area. The model predicts a significant reduction in these areas currently favorable for *A. africana* conservation, with an estimated loss of 16.22% under the optimistic scenario (SSP2-4.5) and 16.32% under the pessimistic scenario (SSP5-8.5). The second intermediary report presents the impact of pastoral livestock on the demographic structure of *A. africana* populations in the most favorable habitats.

5. Références

Adjahossou, S.G.C., Gouwakinnou, G.N., Houehanou, D.T., Sode, A.I., Yaoitcha, A.S., Houinato, M.R.B., Sinsin, B., 2016. Efficacité des aires protégées dans la conservation d'habitats favorables prioritaires de ligneux de valeur au Bénin. *Bois & Forêts des Tropiques* 328, 67–76.

Agbo, R.I., Idohou, R., Vihotogbè, R., Missihoun, A.A., Dagba, R.A., Assogbadjo, A.E., Agbangla, C., 2019. Spatio-temporal dynamics of suitable habitats for *Detarium microcarpum* Guill. & Perr. (Caesalpiniaceae), a priority food tree species in Benin (West Africa). *Model. Earth Syst. Environ.* 5, 595–604. https://doi.org/10.1007/s40808-018-0550-x.

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol. 43, 1223–1232*.

Alsamadisi, A.G., Tran, L.T., Papes¸, M., 2020. Employing inferences across scales: integrating spatial data with different resolutions to enhance Maxent models. *Ecol. Model*. 415, 108857.

Biaou, S., Gouwakinnou, G.N., Noulèkoun, F., Salako, K.V., Houndjo Kpoviwanou, J.M.R., Houehanou, T.D., Biaou, H.S.S., 2023. Incorporating intraspecific variation into species distribution models improves climate change analyses of a widespread West African tree species (Pterocarpus erinaceus Poir, Fabaceae). *Glob. Ecol. Conserv.* 45, e02538. https://doi.org/10.1016/j.gecco.2023.e02538.

Booth, T.H., 2022. Checking bioclimatic variables that combine temperature and precipitation data before their use in species distribution models. *Austral Ecol.* 47, 1506–1514. https://doi.org/10.1111/aec.13234.

Booth, T.H., Nix, H.A., Busby, J.R., Hutchinson, M.F., 2014. bioclim: the first species distribution modelling package, its early applications and relevance to most current MaxEnt studies. *Divers. Distrib*. 20, 1–9. https://doi.org/10.1111/ddi.12144.

Escobar, L.E., Lira-Noriega, A., Medina-Vogel, G., Peterson, A.T., 2014. Potential for spread of the white-nose fungus (Pseudogymnoascus destructans) in the Americas: use of Maxent and NicheA to assure strict model transference. *Geospatial Health* 9, 221–229.

Fandohan, A.B., Gouwakinnou, N.G., Fonton, H.N., Sinsin, B. Liu J., 2013. Impact des changements climatiques sur la répartition géographique des aires favorables à la culture et à la conservation des fruitiers sous-utilisés : cas du tamarinier au Bénin. *Biotechnol. Agron. Soc. Environ.*, 17(3): 450-462. https://popups.uliege.be/1780-4507/index.php?id=10186

Fitzpatrick M. C., Hargrove W. W., 2009. The projection of species distribution models and the problem of non-analog climate. *Biodiversity Conservation*, 18: 2255-2261.

Hao, T., Elith, J., Guillera-Arroita, G., Lahoz-Monfort, J.J., 2019. A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. *Diversity and Distributions* 25, 839–852. https://doi.org/10.1111/ddi.12892

Hao, T., Elith, J., Lahoz-Monfort, J.J., Guillera-Arroita, G., 2020. Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography* 43, 549–558. https://doi.org/10.1111/ecog.04890

Liu C., White M., Newell G., 2013. Selecting thresholds for the prediction of species occurrence with presence-only data. *Journal of Biogeography*, 40: 778-789.

Merow, C., Smith, M.J., Silander Jr, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography* 36, 1058–1069.

Peterson, A.T., 2011. Ecological niche conservatism: a time-structured review of evidence. *J. Biogeogr.* 38, 817–827. https://doi.org/10.1111/j.1365-2699.2010.02456.x.

Phillips, S.J., Anderson, R.P., Dudík, M., Schapire, R.E., Blair, M.E., 2017. Opening the black box: an open-source release of Maxent. *Ecography* 40, 887–893. https://doi.org/10.1111/ecog.03049.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. *Ecol. Model*. 190, 231–259.

Ridley, J. K., Blockley, E. W., Keen, A. B., Rae, J. G. L., West, A. E., and Schroeder, D., 2018. The sea ice model component of HadGEM3-GC3.1. *Geosci. Model Dev.*, 11, 713–723, https://doi.org/10.5194/gmd-11-713-2018.

Saliou, A.R.A., Oumorou, M., Sinsin, B.A., 2015. Modélisation des niches écologiques des ligneux fourragers en condition de variabilité bioclimatique dans le Moyen-Bénin (Afrique de l'Ouest). *Revue d'Écologie* 70(4) : 342-353.

Thapa, R., Mirsky, S.B., Tully, K.L., 2018. Cover crops reduce nitrate leaching in agroecosystems:a global meta-analysis. *J. Environ. Qual.* 47, 1400–1411. https://doi.org/10.2134/jeq2018.03.0107.

Zhang, Z., Xu, S., Capinha, C., Weterings, R., Gao, T., 2019. Using species distribution model to predict the impact of climate change on the potential distribution of Japanese whiting Sillago japonica. *Ecol. Indic.* 104, 333–340. https://doi.org/10.1016/j.ecolind.2019.05.023.