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Research Article

Climate change and *Pentaclethra macrophylla* Benth: Forecasting alterations in native distributional range across West and Central Africa

Akwaji Patrick Ishoro[1]*, Onah Dough Owojoku[1], Ajikah Linus Bashie[1,2], Oden Glory Nicholas[1], Okon Ekeng Ita[3], Nkang Nkoyo Ani[4], Amaraizu Mary Nneoma[5], Ugbogu Omokafe Alaba[6]

[1]Department of Plant and Ecological Studies, Faculty of Biological Sciences, University of Calabar, P.M.B. 1115, Calabar, Cross River State, Nigeria
[2]Evolutionary Studies Institute (ESI), East Campus, Cnr. Jorrissen & Yale Rds. University of the Witwatersrand, Johannesburg, South Africa
[3]Department of Plant Sciences and Biotechnology, Faculty of Biological Sciences, University of Cross River State (Unicross), Calabar, Cross River State, Nigeria
[4]Department of Science Laboratory Technology, Faculty of Biological Sciences, University of Calabar, P.M.B 1115, Calabar, Cross River State, Nigeria
[5]Faculty of Law, University of Calabar, P.M.B. 1115, Calabar, Cross River State, Nigeria
[6]Department of Forest Conservation and Protection, Forestry Research Institute of Nigeria (FRIN), Jericho Hills, Ibadan, Oyo State, Nigeria
*Email: akwajipatrick@unical.edu.ng

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Abstract

The tree species known as the African oil bean (*Pentaclethra macrophylla* Benth) retains numerous applications. For rural residents, almost all of its traded elements represent a significant source of income. Numerous terrestrial habitats have reportedly experienced negative biological, temporal, and spatial effects concerning climate change lately. Understanding the out-turn of changing climate towards the geographic distribution of species could help predict their growth or decline and, if necessary, provide appropriate conservation measures. We examined whether climate change will affect the geographical distribution of this species throughout its native distributional area across West and Central Africa in light of the strong interest that this species holds for rural African residents. Under AfriClim RCP 8.5 scenario 2070 conditions, the inquiry was carried out by applying the MaxEnt model.

According to the MaxEnt results, climate change shall hold a major footprint toward species' native spread. About 5% (5889 km2) of the nations across West and Central Africa are predicted to have stable species populations. These are mostly the regions located along the southern coasts of Guinea Bissau, Sierra Leone, Liberia, Cote d'Ivoire, Nigeria, Cameroon, and Gabon. The model threshold indicated a huge 95.29% (119135.9 km2) reduction in the species' appropriate habitat. The southern coasts of Senegal, Ghana, Togo, and the Benin Republic, along with the Democratic Republic of the Congo, are predicted to be unsuitable, as are the topmost northern portions associated with the Sahel regions of West and Central African countries. Additionally, it is expected that the entire Burkina Faso, Central African Republic, Democratic Republic of the Congo, and south-eastern Angola will no longer be appropriate for the species. It is necessary to build up the preservation of the species by raising and establishing it in the anticipated suitable areas/agroforestry plan to ensure its sustainable usage and practicable conservation.

Keywords: Forecast, Tree species, MaxEnt model

Introduction

A growing number of articles have been written on the subject over current times because of the fear and uneasy feelings that global climate change has sparked in a variety of media technologies and academia (Nabout et al., 2011). At a global level and from one region to another, large, destructive fires, a prolonged period of abnormally hot weather, low rainfall causing a water shortage, outflow of water, and powerful spinning storms are all examples of the heating trend or temperature change that is occurring (IPCC, 2013). The effects mentioned above possibly will culminate in the deficit of path to adequate supplies of low-cost, nutrient-rich food, the downswing or extinction of biological diversity, along with a loss to do with economic benefits (deliverable) supplied to people via ecosystems' ecological functions (Bentz et al., 2010).

An imminence concerning climate change may cause different species to respond differently. For instance, species may relocate to new locations with better ecological conditions, persist to inhabit or subsist near the fringe or extremity of their territorial radius, or perhaps cease to exist altogether (IPCC, 2014; Abrahms et al., 2017). We must increase our understanding of species' spatial distributions and the factors that influence their geographic patterns to mitigate or manage climate change's menace to biological diversity. The regional distributions of species in different sites or areas may be influenced by climatic and physical factors (Soberon & Peterson, 2005). When determining a species' global distribution at sizeable geographic gradation, weather patterns or conditions are thought to be more appropriate than biotic interactions (Pearson & Dawson, 2003). According to those above, the ecological niche model (ENM) offers the relationship between species occurrence locality as well as associated ecological parameters that one may depict an ecological niche (climate preference) along with prospective latitudinal dispersal as to species (Peterson et al., 2011). These ecological niche and species distribution models arise universally applied within conservation biology along with ecology, branches of biology that deal with the geographic dispersal of flora together with fauna species (Pearson et al., 2007; Elith et al., 2011).

The importance of predicting species distribution is increasing because of the outcome of global change towards local ecosystems. Considering guesstimating elimination possibility and calculating potential time ahead dangers deriving from situations like climate change, facts or information on a species' spatial and temporal distribution are essential (Pacifici et al., 2015). According to Peterson et al. (2011), Ganglo et al. (2017), Altamiranda-Saavedra et al. (2017), and Djotan et al. (2018), ENMs are acclimated to deduce the environmental needs of species, forecast topographical dispersal, determine locality for conservation, and predict consequences of global heating. MaxEnt is one of the most popular or widely used programs for ENMs and suitability predicting of habitat when compared to this type of data utilized per this inquiry, species presence-only data. According to Phillips et al. (2006), such modeling devices employing presence-only data have solely to do with this foremost operating rote amid such applying climatic modeling processes or approaches. It is also vigorous for minuscule or constrained populations (Pearson et al., 2007). By carefully analyzing this dispersal likelihood concerning upper limit unpredictability and adhering toward that restriction in that this predicated valuations concerning any factor below such evaluated dispersal ought to equal that factual midpoint, MaxEnt is an apparatus learning procedure that calculates species distribution over that survey quarter (Phillips et al., 2006).

The African oil bean tree (*Pentaclethra macrophylla* Benth) can reach heights of 21 to 30 m and a width of more than 60 cm. It is primarily found in the Guinea savanna, tropical rain forests, and other shoreline (coastline) regions of West and Central Africa in the tropics (Keay, 1989). There are no recognized differences in the taxonomic classification of the plant, which is related to the family Fabaceae and the subfamily Mimosoideae (Oboh, 2007). According to Orwa et al. (2009), *P. macrophylla* is said to fix nitrogen and have spiritual qualities. Its application against bad spirits was described by Kone et al. in 2008. Mandeng (2009) provided details on the laxative properties of roots and how to cure dysentery. Up to 30–36% of the oil in the seed is oil. Candle and soap production has occurred in this location (Ehiagbonare & Onyibe, 2008). Oboh (2007) noted the use of mature fruits of the tree as a cure for either anthropoid fauna infections or a decoction from the bark as an abortifacient in Nigeria and Cameroon. He also noted the consumption of boiled and roasted seeds in several households in a muggy forest belt as in Africa. To treat gonorrhea, lactogenicity, infertility, diarrhea, wounds, itching, and convulsions, distillates about leaves, barks, pods, and seeds, together with seed pulp, have been reported to have anti-inflammatory and pain-reliever properties (ICRAF, 2004, Zapfack et al., 1999; NFT, 1995; Abbiw, 1990). Its common name, "oil bean tree," comes from Gill (1992), who described vegetable oil production from its seed. When dried, the empty fruit pods are utilized as cooking fuel. In Ghana and Nigeria, the wood is ideally suited for making bowls, charcoal, and other household products (Abbiw, 1990). A colorful substance called the dye is created in Ghana using the ashes left over from burning pods (Abbiw, 1990). According to Enujiugha and Agbede (2000), it contains the twenty essential proteins (organic compounds or amino acids), which account for over 10% of the oil's carboxylic acids. According to Enujiugha and Akanbi (2005), the seeds have a carbohydrate content of 19.16 0.76% dry weight and an oil content of 53.98 0.99%. Its seeds are cooked, refined, as well as effervesce to ugba in the south-eastern areas of Nigeria, where they are used to make soups, regional salads, and sausages that may be consumed with a variety of conventional diets (Enujiugha, 2003). It is in high demand for both domestic consumption and international trade due to its excellent vitamin and mineral content. It is milled into flour and used to increase the concentration of a crucial micronutrient in food and confections due to its mildly acidic composition. Cooking, making candles, and making soap all use the edible oil from its seed (Okafor & Fernandez, 1987). In addition to making chaplets and beads worn around the neck, seed carapaces are sometimes used to decorate (ICRAF, 2004; NFT, 1995).

P. macrophylla is categorized as Least Concern on the IUCN Red List (IUCN, 2020). The species' assets are still protected or obtained from the wild despite the species' considerable usefulness and socioeconomic characteristics. Several agroforestry and conservation initiatives have not considered the species in Africa. Overuse, deforestation, various anthropological activities, and climate change threaten the species. Our inquiry projected the likely outcome concerning climate change on the natural distributional range for *P. macrophylla* under present-day along with time ahead circumstances employing the results as to the MaxEnt model projected under RCP 8.5 2070 framework. This was done in light of the colossal consumption and the commercial worth of the tree species to the populations in Africa, which are in a state of unmanageable usage, along with circumstances of changing climate. Our inquiry shall aid with regulating and preserving this earth's natural resources for present-day and future generations throughout its natural range in West and Central Africa.

Material and methods

Study data on species and occurrence

From Senegal in West Africa to Angola in Central Africa and down to Sao Tome & Principe, *Pentaclethra macrophylla* Benth can be found throughout Sub-Saharan Africa. This multipurpose tree can only be found in West and Central Africa's humid or wet regions and some of their dry or semi-hazy regions. Although it is primarily found in rainforests, individuals can be found elsewhere in high forest environments. It is frequently seen as a little tree with an untidy habit and a broad crown on farms and roadsides, and it can also be found at the edges of mildly wet slopes and adjacent to streams. Due to its deciduous wood, it has typically been conserved in these places and is now an heirloom. It is uncommon in uplands and mountainous areas, and it thrives in climates with appropriate precipitation of 1000–2000 mm and a yearly periodic temperature of at least 18°C (Ladipo et al., 1993). Naturally, the distribution of *P. macrophylla* suggests that these acidic medium soils are where it is most common (Okafor & Fernandez, 1987). The species is resistant to soil saturation with water, as in southern Nigeria's coastal regions, Cameroon and Togo. Our study reserved a definitive detail of 1059 geographic coordinates to execute MaxEnt (Phillips et al., 2006). This data was cleaned with QGIS (2.18.1) to remove data without geographic coordinates and records outside our study area (Phillips et al., 2006). Figure 1 shows the location of the species that occurred in the area of inquiry. It is worth noting that certain of our study locations in the study area had more *P. macrophylla* occurrence points than other locations. Sample bias occurs when some regions of the area under research are surveyed more widely than others, which is a common example of a basic limitation on the distribution of a representative sample alone (Philips et al., 2009). With the aim of this, we envisaged that the species may not have been sampled to the same extent in our study area, where it thrives. As a result, we adopted the method of Elith et al. (2011) and Ganglo et al. (2017) by scoring deviation points to depict sampling efforts in the study area. Those above made available bias occurrence points for "MaxEnt model" (Ganglo et al., 2017).

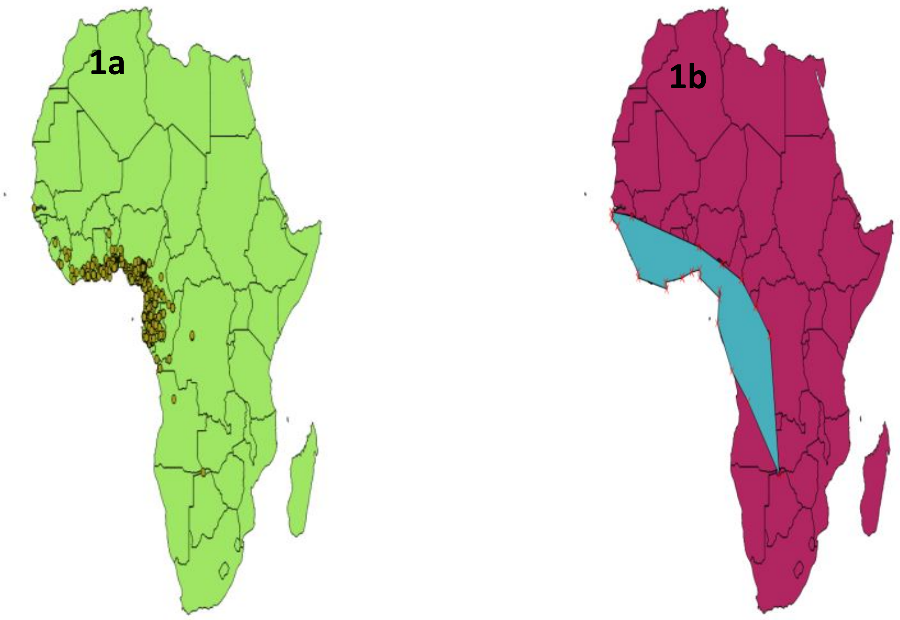

Figure 1. *Pentaclethra macrophylla* Benth occurrence sites across West and Central Africa (GBIF Occurrence download https://doi.org/10.15468/dl.kahrZs (GBIF.org 9th October, 2020); and b) *P. macrophylla* are used for modeling.

Fitting/calibration of MaxEnt

To execute our model’s current distribution, we downloaded fifteen essential bio-climatic variables (BIO 1 to BIO 7 and BIO 10 to 17) which are relevant to tree natural environment within Africa out of: https://www.world clim.org/bioclim (Hijmans et al., 2005). These traits were derived from once-a-month "temperature and precipitation" records for a portion in connection with 1950–2000; because they occur tangentially related to the growth, maturity, and dispersal of species, the variables continue to be widely utilized over the evaluation concerning species dispersal or geographical spread (Elith et al., 2006; Warren et al., 2013).

To determine the chance of this species occurring within the inquiry area, the MaxEnt model uses stochastically acquired background data (Phillips et al., 2006). The objective of the background data selection arises that one may distinguish that habitat features impacting spatial dispersion have to do with occurrence inputs (Philips et al., 2009). A metric like this crops up essential toward presence-only records as it lessens sample predilection together and elevates the accuracy of model predictions (Philips et al., 2009). The MaxEnt model's approach is somewhat constrained because true-absence data are necessary to determine with accuracy that these species are distinctly possible to exist within a particular quarter of focus (Pearce & Boyce, 2006; Soberon & Nakamura, 2009). Other algorithmic programs that have been recognized to have less than desirable forecasting capabilities are the Genetic Algorithm for

Rule-Set Prediction (GARP), Generalized Linear Models (GLM), and Boosted Regression Tree (BRT) (Pearson et al., 2007). As a result, MaxEnt is also applicable in survey purpose designed to find new locality where species are dispersing (Pearson et al., 2007; Elith & Graham, 2009). MaxEnt consistently emerges as having forecasted a significant section of species presence, predicting the relatedness of species to habitat plot prediction and extrapolating predictions beyond the training data. Running the MaxEnt model requires adjusting the climatic variables from the World Climate database to the locality of interest because they are global in scope. Such calibration will offer pinpoint climatic data for the investigated locality (Philips et al., 2006). To do this, we used QGIS to calibrate environmental layers to Africa before processing the environmental data for modeling (Philips et al., 2006). The climatic variables (BIO1 - 7; 10 - 17) were translated as Raster files, and afterward, the occurrence data was clipped employing predesignated number 1 as regularization multiplier or beta value; they were polygonized, categorized, and converted into ASCII setup applying QGIS. Following this, appropriate climatic parameters were chosen based on the variables' percentage contributions and jackknife testing. We monitored the ambient factors that had a notable impact on the MaxEnt model while it was being trained. The system assigns the increase exponentially in gain on the climatic factor after that the species depends, modifying or restoring such accompanied by percentage flanking conclusion concerning the training performance or functioning (Philips et al., 2006).

All footmarks for the MaxEnt program increase the model's gain alongside substituting the multiplier concerning a unique feature. Phillips and Dudik's (2008) suggested framework that became proven to lay out robust or wholesome results was applied during this inquiry to evaluate this specificity. The numeral of synchronizations was adjusted to 10, while the maximum number of iterations was set at 1000. Each residual replacements are set to default. The perspectives of alteration or adaptation during that measure concerning fluctuation in energy within the atmosphere caused via anthropoid interference in connection with climate change, measured over watts/meter2, are the foundation for the models simulating climate change (IPCC, 2013). The 'Representative Concentration Pathways' (RCPs), this novel sequence about horizons exploited within the IPCC's Fifth Assessment Report (ARS), was applied to the cutting-edge climate programs (models) created via a 'World Climate Research Program's Coupled Model Inter Comparison Project Phase 5' (CMIP5). This choice concerning emission horizons significantly impacts the intensity of the expected climate changes (IPCC, 2013). Within CMIP5, four RCP time-frames are utilized. The highest measure or stasis concerning contemporary era (21st century) radiative forcing (RF) obtained by this feed-in model is used to identify and define them (IPCC, 2013). This RCPS consists of a lower limit RCP scope, which in 2100 is equivalent to a "RF of 2.6 W/m^2," two intermediate RCP horizons, which are comparable to a "RF of 4.5" and a "RF of 6 W/m^2," respectively, and the highest RCP horizon, which in 2100 is parallel to a "RF of 8.5 W/m^2." Discharges may need to drop significantly or decline across all of these horizons, focusing on arriving at a status of "2.5 W/m^2" towards that edge in connection with the twenty-first century. As attested by van Vuuren et al. (2011), the progressive or cumulative emissions consumption needed to reach this goal will be almost 70% more than the baseline drift this century. This will require significant efforts and collaboration from every country to increase energy productivity and switch from the unstoppable use of petroleum to the sustainable or inexhaustible energy source known as nuclear energy (van Vuuren et al., 2011). Little has been done to reach this aim nationally and worldwide, and nations that emit significant amounts of greenhouse gases disagree on the trajectory or policies that should be followed to reduce emissions. As a result, it is unclear or debatable if the RCP 2.6 horizon will achieve its objective. Additionally, "RCP 4.5" is a middle ground where certain international and governmental efforts to lower its levels are predicted to lower "RF in 4.5 W/m2" by 2100, which is also less plausible.

From those above, we selected an "RCP 8.5" scenario; the aforementioned is the mass uttermost scenario in which extenuation endeavors by administrative bureaucrats and the general public are hypothesized to be low to anticipate the distribution of *P. macrophylla*. The model was run 50 times via bootstrap, albeit with a corresponding run categorization, using all data points—including test data—to identify the most significant variables. The training data is selected randomly by adding up or interchanging using the occurrence points in the "bootstrapping" synchronization technique, where the absolute numeral of presence points and the integer of samples match (Phillips, 2010). This option would make up for the sampling bias in the study area.

Model assessment

This model comes about appraised in this study utilizing an "area under the receiver operating characteristic (ROC) curve" (Peterson et al., 2008) along with an "area under curve (AUC)" (Elith et al., 2006), percentage contributing variable table, as well as Regularized training gain (Jackknife plot), was learned thoroughly to confirm the greatest noteworthy devoted feature to this model (Phillips & Dudik, 2008). The regularized training gain guides model fitting. Each proportion, integer, or gradation of the interlude either of any dyad if not extra randomly features which evince tally inequality over arbitrarily chosen framework plots and concurrent scattering of predictor higher than studied species plots is known as the regularized training gain (Elith et al., 2011). Therefore, in a second training gain (RTG 1) suggests a specified habitat insufficiency, whilst an expansive regularization training gain (RTG 1) shows the attraction considering a narrow capacity concerning ecological circumstances contrary to sizeable territory. Therefore, a considerable rise in 1 for a certain factor or parameter indicates a certain factor has a noteworthy forecasting value. The main benefit is the above mentioned factors are connected to life processes and are desired indicators of where species may develop (Elith et al., 2006). According to Elith et al. (2006), AUC represents the credibility of a given species' variable chosen existence location, which will turn out to be deemed to be extra suited relative to its unpredictable preferred nonappearance location.

When AUC is within reach of 1 (AUC 0.75), a model exists thought toward having exceptional performance (Elith et al., 2006). True skills statistics (TSS) were also utilized to evaluate the accomplishment of this model (Allouche et al., 2006; Elith et al., 2006). That adeptness of a model toward accurately or impeccably recognizing that error-free existence along with nonappearance is known as TSS. In contrast, a model with a TSS of about 1 (TSS 0.5) has great atypical and calculable robustness (Allouche et al., 2006). A model with a TSS of 0 specifies an arbitrary forecast. Exploiting the TSS Excel worksheet, we used the MaxEnt model for the species to get a TSS value considering ten harmonization runs.

Model's projection

Considering projection, we used Future_2070_rcp85 to estimate the MaxEnt model for *P. macrophylla* in the climate framework instead of the year 2070 (Phillips et al., 2006). For Future_2070_rcp85_bis prediction, we selected suitable climate variables from the Paired Model Inter Comparison database found at (https://webfiles.york.ac.uk/KITE/AfriClim/Geo TIFF_150s/ - Available from the Project Phase 5 (CMIP5) of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) for the years 2070; middle of the 2061–2080 cycle (Platts et al., 2014). Within that process of quadrivium greenhouse gas congregation surroundings or environment known as “Representative Concentration Pathway’s” (RCP’s), 15 General Concentration Models (GCM) predicted these results. RCP remains a posterity arrangement that has been preferred by the Special Report on Emissions Scenarios (SRES) because the group permits higher conformism together with lower costs/expenditures throughout the modeling process by van Vuuren et al. (2011). Additionally, RCP calls for cordial collaborations in climate and unified evaluation modeling and collision, adaptation, and vulnerability studies (van Vuuren & Carter, 2014). According to Moss et al. (2010), this RCP framework was developed to examine various scenarios involving demography, the economy and society, human use of land, and technology. Because only 15 projection environmental layers (BIO 1 - BIO 7 and BIO 10 - BIO 17) are available in the AfriClim database, we depended upon the World Climate database (WorldClim) to pick specific related environmental factors for this species' existing distribution. Because theirs, to a greater extent, firmly matched with the biome reality in Africa relative to the overall tally of unanimity resolutions in the finite image of extensive training models, the AfriClim variations turned out to be given preference considering forecast over the WorldClim alternative (Platts et al., 2014). In addition, mass rotation models do not replicate rainfall at the regional level due to the unpredictability of estimates (IPCC, 2013), which is accomplished via this AfriClim component resulting from two regional rotation models. Mass rotation models have a restricted guarantee of replicating external climate on a regional scale instead of the broad-gauged. The model was constrained to a resolution that could depict regional environmental variations or fluctuations and was useful or practicable for regional ecological applications using various observational criteria (Platts et al., 2014).

Model threshold

Reclassification, transformation, and polygonization of raster to vector connected output layer were executed using QGIS 2.18.1 to threshold the MaxEnt model. We also estimated the species span corresponding alongside resolution thresholds for the present and subsequent (future) weather conditions in the 2070 framework wherein locality/dimensions regarding dispersal modifications. However, "minimum training presence" was the only choice threshold we employed. Since *P. macrophylla* has habitual or traditional occurrence areas that remain constant and fixed, together with overall an environmentally safe logical substitute, the orbit constitutes locations wherein biological parameters are the same way favorable or preferable to those of those sites (Pearson et al., 2007). Maximum training presence in comperes is to a lesser degree reliable and almost all distinctly possible substitute existence. We categorized the MaxEnt ASCII file output into three categories based on the minimum training presence threshold: suitable (0.92-1), (0.77-0.8), and (0.48-0.69), as well as unsuitable (0-0.3.8) of species presence.

Results

Model validation for MaxEnt

With ten bootstrapping synchronizations, the findings for MaxEnt model evaluations of *P. macrophylla* indicate/define validity along with AUC = 0.907/TSS = 0.85 (Figures 2 and 3), respectively. Because of this, this model outperformed arbitrary ones in terms of performance, efficiency, and positive predictive ability.

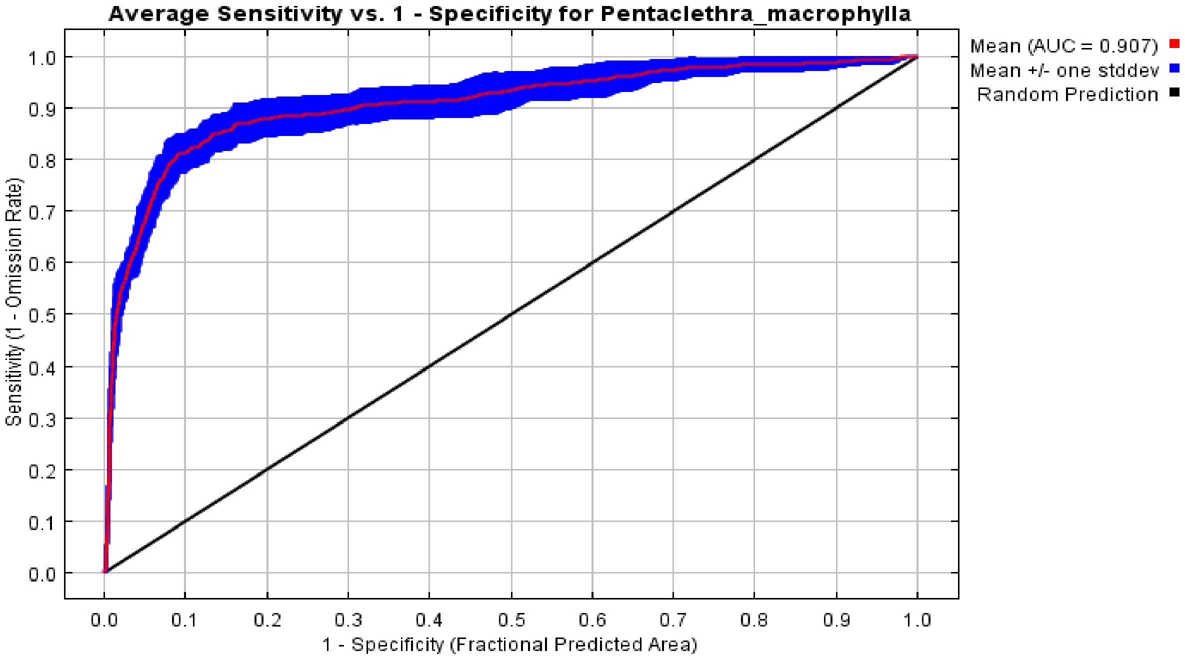

Figure 2. MaxEnt model AUC evaluation for *P. macrophylla*

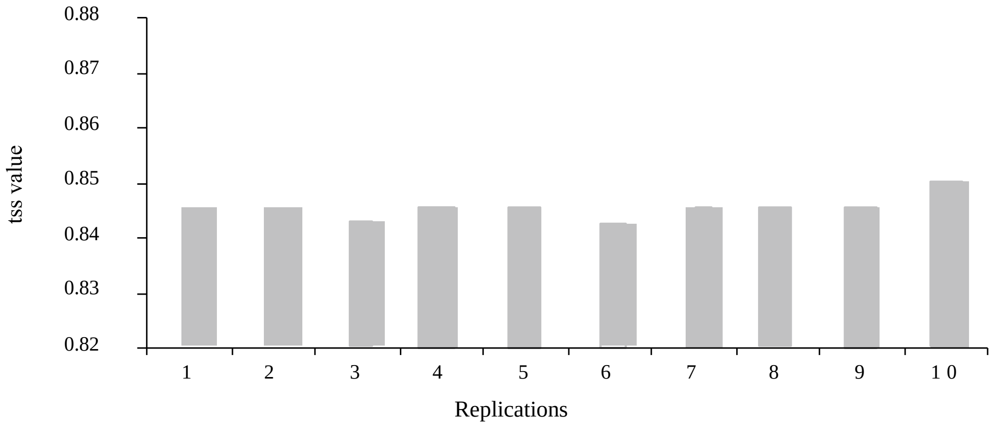

Figure 3. True skill statistics (TSS) of the MaxEnt model for *P. macrophylla*

P. macrophylla's geographic range in West and Central Africa is influenced by climate factors

In this study, the tables of variable ratio input along with an order of significance (Table 1) and Jackknife plot (Fig. 4). This action or standard entirely depends on the MaxEnt model's final series, regardless of how it was accomplished. By arbitrarily rearranging the values concerning that individual climatic variable within that training point's "presence and background," that variable's role is modified. The decline within training AUC is then calculated. The significant reduction designates how heavily the model depends on a weather factor. Weather factors are interposed to acquire a percent input ratio) singled out five weather factors concerning holding that substantial footprint regarding the native distribution area of *P. macrophylla* in West and Central Africa: "BIO 6 - "minimum temperature of coldest month," "BIO 12 - annual precipitation," "BIO 13 - precipitation of the wettest month," BIO 16 - Precipitation of wettest quarter along with "BIO 17 - precipitation of driest quarter." The variable input ratio for *P. macrophylla* (Table 1) confirmed the variable influence chart (Figure 4), asserting BIO 16 as the maximum symbolic explicate otherwise determining weather factor between the five weather factors extracted inside this model. When eliminated, BIO 17 significantly lessens gain and was a most insightful variable in the model.

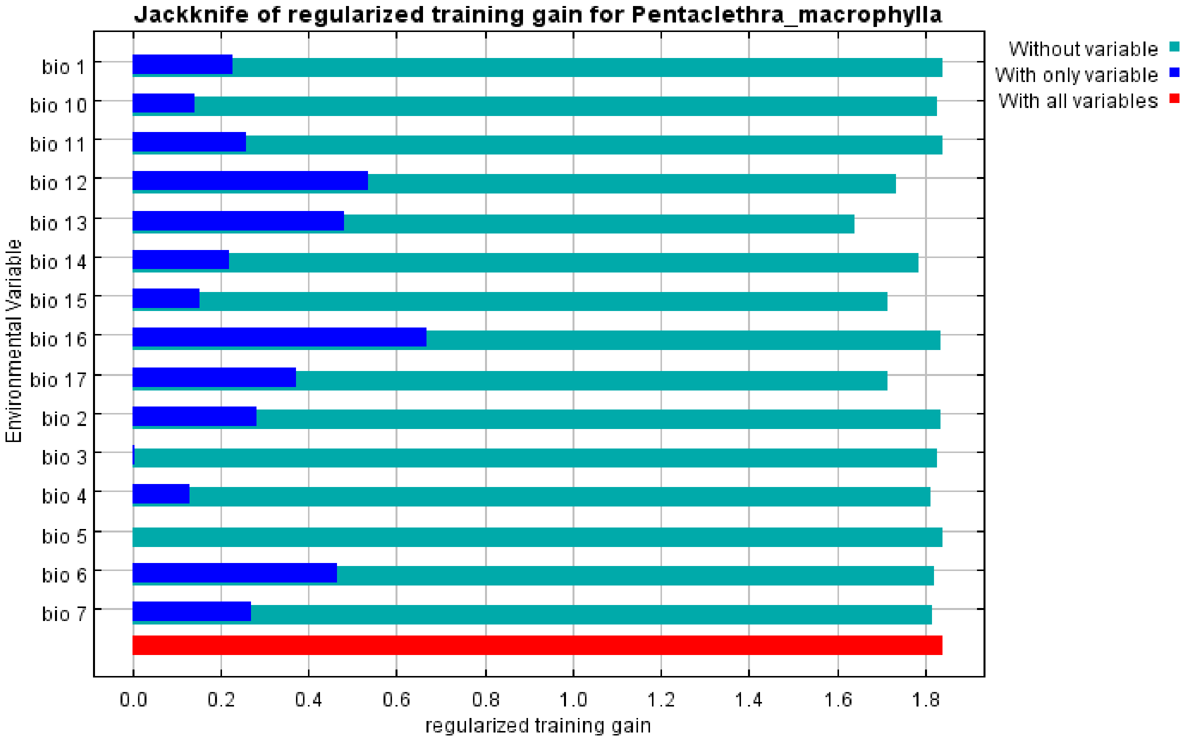

Figure 4. Maximum symbolic determining weather factors to *P. macrophylla* distribution

Table 1. Weather factors average input/sequence of significance

Weather factors	Average input (%)	Sequence of significance
BIO 16	33.8	32.5
BIO 12	28.2	10.8
BIO 13	26.5	16.2
BIO 6	20.3	12.8
BIO 17	17.4	43.6

Figures 5i, ii, iii, iv, and v, respectively, show the reaction charts of the weather mentioned above factors toward predicting fitness or credibility prediction regarding *P. macrophylla*. The apparent array in BIO 6 (Figure 5i) shows how sensitive a species is to variations in the minimum temperature during the coldest months of the year. Logistic forecasts reveal a minor gain in response output arising out of the minimal temperature from 0°C toward 18°C, following this, the rapid upsurge and optimization at 24°C is congruous for this species ecosphere or life assemblage. This low-point temperature toleration borderline about the species occurs, therefore allying 18 and 24°C inside these coldest months, according to the reaction curve of BIO 6. How different species respond to BIO 12 (Figure 5ii) also reflects how they interact with their ecological communities. For example, 1000 mm and above of precipitation are considered to be optimal or effectual levels towards the forecast peculiar to a species' high-point fitness if not productiveness, regardless of how, in really rainy seasons (rainfall of more than 3000 mm annually), the reaction's yield drops dramatically (Figure 5ii). The species' reaction to BIO 13 (Fig. 5) demonstrates outstanding response production with rising precipitation from 0 to 800 mm, followed by a dramatic reduction after the suitability threshold of about 800 mm. Figures 5v and 5v, representing the species' reaction curve for BIO 16 and 17, demonstrate exceptional reaction output originating at 0 toward 1000 mm and 0 toward 250 mm, followed by a rapid decline after the trapping threshold, respectively. The *outcome of the P. macrophylla reaction curves* demonstrates that the species, as mentioned above, is susceptible to wet and dry spells in its natural or developed habitat in West and Central Africa.

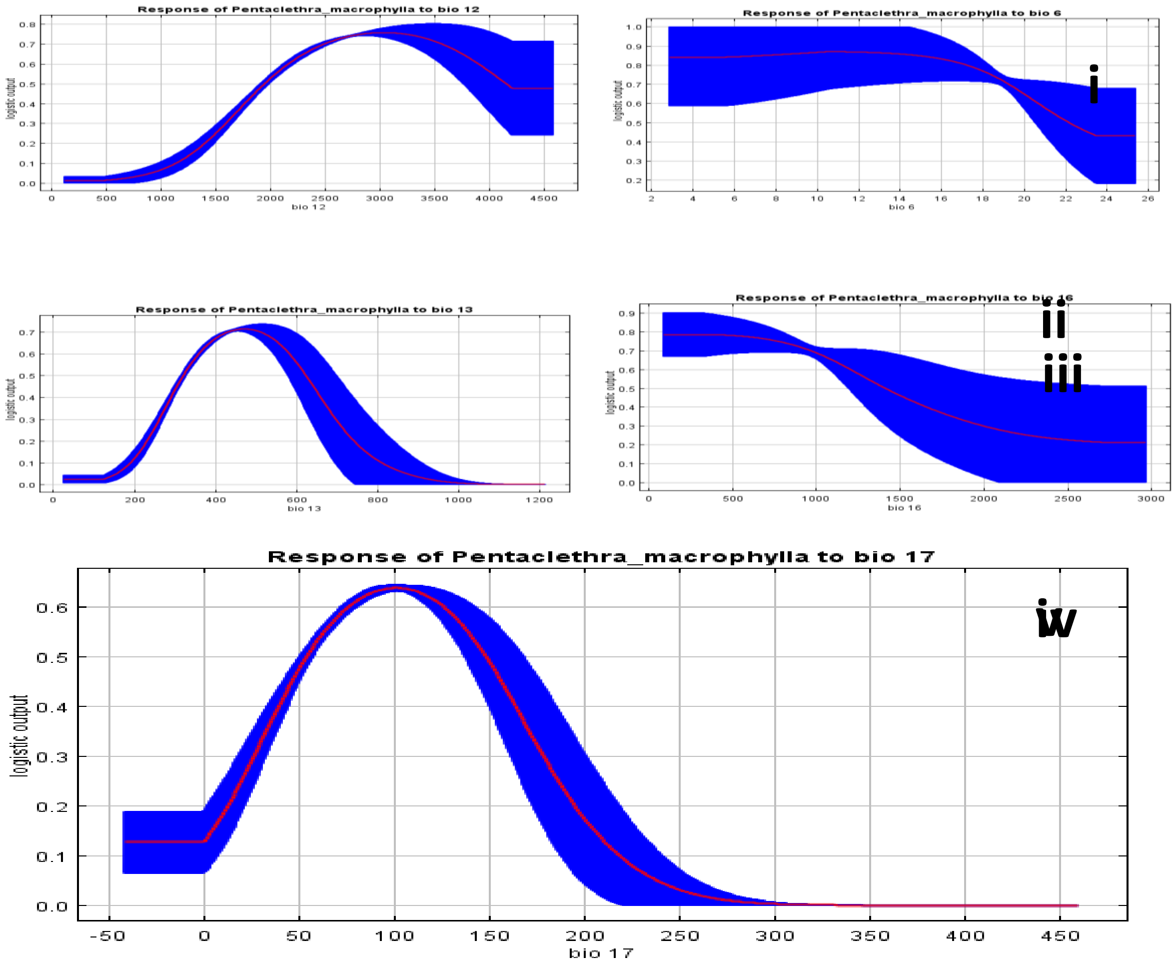

Figure 5. Responses chart of each weather factor specifically impacting growth of *P. macrophylla*

Geographic spread of *P. macrophylla* at present and the future

Figure 6a shows the present-day geographic spread of *P. macrophylla* within the study belt of West along with Central Africa. The outcome regarding this model indicated that the suitability forecast is more accurate in southern geographic regions, mainly in coastal regions of West and Central African nations. However, it was anticipated that there would be suitability gaps (locations with low suitability) along the whole coastline. The northern regions of West and Central Africa raise the subject of adverse predictions, which may arise due to this region's primarily dry Sahel environment, which is inconsistent with the species' geographic range or ecological needs. Figure 6b, using AfriClim RCP 8.5, shows the predicted (future) geographic distributions of *P. macrophylla* for 2070 within our study area. We noticed that most of the nations in West and Central Africa had a steadily declining suitability projection compared to the existing distribution (Figure 6a). Nevertheless, despite the species' projected decline in geographic distribution, the southern zones along the seashore of nations within West and

Central Africa persist and are predicted to continue to be suitable for *P. macrophylla* distribution. This is consistent with the suitability forecast across our study area.

Impact of climate change on *P. macrophylla's* regional distribution

We found that the predicted stable region of P. *macrophylla* distribution under AfriClim RCP 2070 will be roughly 5% (5889 km2) of West and Central African countries at the 'minimum training presence' threshold. Most predicted favorable locations for the species' distribution are restricted to the southern coasts of Guinea-Bissau, Sierra Leone, Liberia, Cote d'Ivoire, Nigeria, Cameroon, and Gabon. The model threshold indicated a huge 95.29% (119135.9 km2) reduction in the species' appropriate habitat. The southern coasts of Senegal, Ghana, Togo, the Benin Republic, and the Democratic Republic of the Congo are predicted to be unfavorable for *P. macrophylla*, also the uppermost northern regions linking with the Sahel parts of West and Central African countries. Additionally, it is predicted that the entire Central African Republic, Democratic Republic of the Congo, and south-eastern Angola will not be appropriate for the species.

Table 2. Climate change impact on the geographic spread of *P. macrophylla* at the minimum training presence threshold

Suitability prediction	**AfriClim (RCP 8.5) scenario**	
	Range (km^2)	**Ratio (%)**
Suitable (0.92-1), (0.77-0.89) and (0.48-0.69)	5889	4.71
Unsuitable (0-0.3.8)	119135.9	95.29
Total	125024.9	100

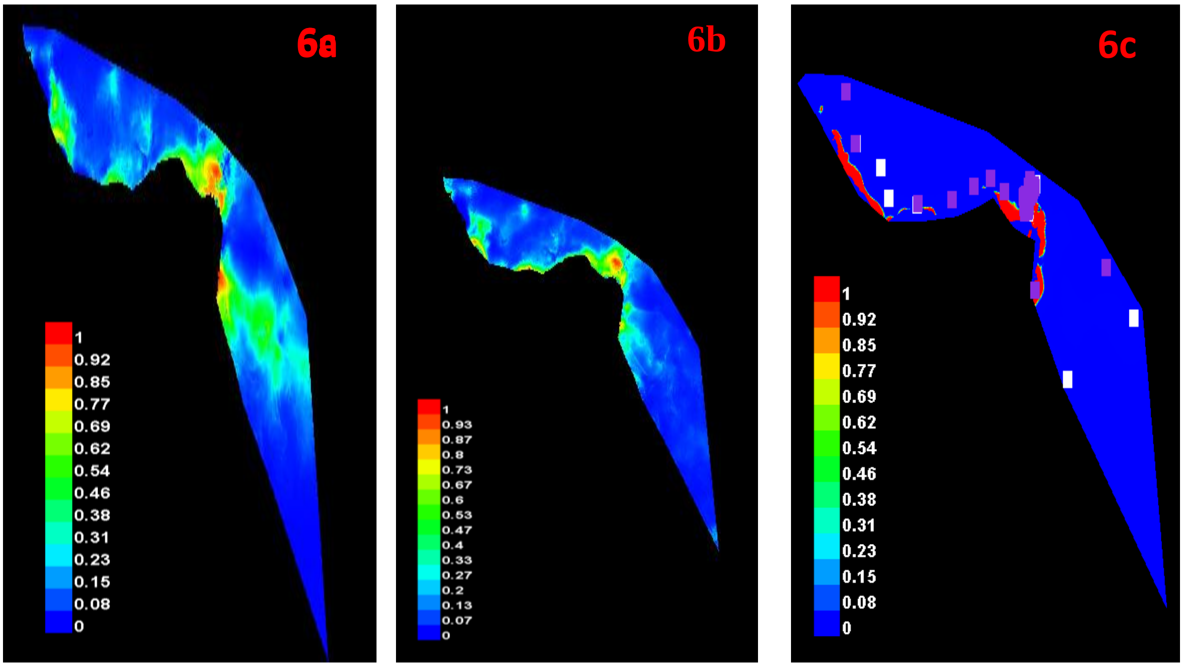

Figure 6. (a) *Pentaclethra macrophylla's* current geographic distribution in West and Central Africa, (b) the projected distribution under an AfriClim RCP 8.5 2070 framework and (c) the impact pertaining to climate change at the minimum training presence threshold are shown

Discussion

Model validation for MaxEnt

Recognizing species with a high likelihood of having no live members and identifying specific determinant elements to reverse the decline in biodiversity is extremely important or necessary, taking into account changes in the global climate (Darrah et al., 2017). For determining each species' terrestrial radius and its realized niche, facts or data operating change in the direction of a particular species' ecological niche are paramount (Breiner et al., 2017). According to our investigation's AUC and TSS values, the MaxEnt model's application demonstrated great performance and strong predictive power. The wide region examined in our study may have contributed to the models' robustness or strong ability to predict. Similar results of the MaxEnt model's robust, exceptional, and predictive ability have been reported for *Milicia excelsa* in Benin, West Africa (Kakpo et al., 2019), *Juniperus excelsa* in Central/Eastern Alborz Mountains, Iran (Fatemi et al., 2018), *Lonchocarpus sericeus* together with *Anogeissus leiocarpa* in Benin, West Africa (Gbetoho et al., 2017), and Additionally, environmental factors including temperature and precipitation were taken into account in the current study. When modeling is conducted across vast areas, temperature, and precipitation, direct input data are additionally well organized, according to Guisan and Zimmermann (2000). Contrarily, incidental input-data that are not only poorly organized but also more likely to cause model errors should be avoided.

Geographic spread of *P. macrophylla* within West along with Central Africa is influenced by climatic factors.

Multiplex web of biologic along with azoic variables or situations governs the dispersal or spread of a plant species in the physical features of a region. These variables include local weather patterns, soil characteristics, competition between species, artificial interruptions, and restrictions on dispersal (Blach-Overgaad et al., 2010). Dispersal constraints and social interactions may also change the distribution of the species, but weather factors arise as one preeminent indication of their way of life (Soberón & Peterson, 2005). A thorough grasp of each species' biological circumstances is essential for assessing the broad geographic range in which it may cling to life together with inherent prospective reaction toward change in climate on account of conservancy and management plans (Bowe & Haq, 2010). Originating at Senegal eastward towards South-eastern Sudan, southward to Angola, along with the island or islet of Sao Tome and Principe, *P. macrophylla* can be found in the forests about West along with Central Africa (Oboh, 2007). According to Orwa et al. (2009), this species is found within primary and secondary forests as well as coastal savannas, typically close to streams and rivers. Even though growth is possible near greater levitations where there is sufficient rainfall and temperatures at no time drop below 18 °C, it is most abundant at elevations up to 500 m. According to Emebiri et al. (2012), it requires 1000–1500/2000-2700 millimeters of annual rainfall and an annual average temperature of roughly 25°C. Our research identified five weather factors as being particularly important to the attitudinal distribution regarding *P. macrophylla* in West and Central Africa: BIO 6, 12, 13, 16, and 17; minimum temperature of coldest month, annual precipitation, precipitation of wettest month, precipitation of wettest quarter together with Precipitation of driest quarter), respectively. Therefore, in terms of species status, our findings are trustworthy. Encompassed by characteristics that hold the biggest influence operating the model toward forecasting the attitudinal dispersal regarding this species were BIO 12 along with the variations above, BIO 13, 14, 16, and 17. A species' ability to expand or disperse depends largely on the weather (Vayreda et al., 2013), especially concerning water-related factors (Svenning & Skov, 2006). The year-round variation in rainfall is measured by BIO 12 (O'Donnell & Ignizio, 2012). The model determined that a yearly rainfall range characterized by 1000–2700 mm is appropriate for P. macrophylla's spatial distribution regarding the study area and also compatible with this life assemblage regarding this plant. When compared to global scales, water has several uses in plants and is known to positively impact species distribution patterns (Willis & Whittaker, 2002). In addition to serving like the temperature thermostat in the course of that activity about moisture exhalation by a hydathode together with acting like a grist in the activity of photosynthesis, that is one indispensable procedure foundational for total growth or existence, it has the ability toward dissolving more material to macro-nutrients including a web of plant food synthesize within that plant (Ferguson, 1959). A lack of moisture and an abundance of moisture can cause problems for plants (Haferkamp, 1987). The presence of moisture within the surroundings in regard to plants is unquestionably of the essence when taking into account those significant tasks. Because the species is widespread in primary and secondary forests as well as guinea savanna, its reaction to annual fluctuations during precipitation (BI 13, BIO 14, 16 and 17) within the area studied additionally implies this species lives susceptible tolerant with dry as well as wet periods inside this customary habitat. Although a fluctuation within the lowest temperature as to the coldest month (BIO 6) was shown to exert an influence on the regional dispersal regarding this species significantly, the every year mean temperature (BIO 1) arose by no means among this mostly significant supporters toward this distribution model of *P. macrophylla*. It is important to emphasize that any plant owns a distinctly fixed temperature scale with a minimal, high, and ideal temperature range that is overseen by the terrain temperature (O'Donnell & Ignizio, 2012; Hatfield & Prueger, 2015). That minimum temperature of the coldest month (BIO 6) defines the coldest month as having a low average temperature of 21.7°C. According to the logistic prediction of the response curve, *P. macrophylla's* minimum temperature increased from 0°C to 18–25°C. According to the response curve for the coldest month's minimum temperature (BIO 6), the minimum temperature appropriate for the species' geographic distribution is 25°C, which is also in line with the ecology of the species. Hatfield and Prueger (2015) claim that while temperature advances toward each species-ideal volume, vegetative growth expands and multiplies, along with a substantial aggregate concerning plant species; vegetative development typically holds a higher optimum estimate than reproductive growth. In consonance with the findings as to their inquiry, this arises credible significant temperature dissimilarity, such as a sublime rate about BIO 6, may affect this P. macrophylla's ideal temperature as a consequence later on the impact this dispersal and growth of *P. macrophylla* occurrence during vegetative together with reproductive phases. Thus, it could be concluded that the greatest estimate of BIO 6 transcends the temperature at which *P. macrophylla* regional distribution may be negatively impacted, to be specific., 25°C. In this investigation, this factor BIO 6 determined the species' light/heat accessibility and changeability, while BIO 12, 13, 16 and 17 determined *P. macrophylla's* water availability and variability, respectively. This models might perhaps continue generalized towards locations outside the regions under investigation and can outline directed toward goal pertaining to species regulation within related localities because the factors which govern this geographical distribution concerning this species arise fundamental primary set of conditions (Elith et al., 2011).

Effect of climate change on *P. macrophylla's* geographic range in West and Central Africa

Only environmental influences during the construction of our MaxEnt model were studied in this study. Therefore, the prediction of species distribution is somewhat constrained and ambiguous (Abrahams, 2017). Without a doubt, niche models predict a habitat compatible with the species' prospective site (Soberon & Peterson, 2005). Inconstant certainties or inconstant uncertainties within a species' appearance in that predicted geographic area may result (Thuiller et al., 2005). Inconstant uncertainties develop while factors apart from weather affect a species' dispersal and prevent it from developing consistently inside that appropriate locality, belt, or zone undergoing study (Thuiller et al., 2005; Blach-Overgaard, 2010). Inconstant uncertainties, contrariwise, appear when insufficient information about a habitat representative or poor representative selection techniques averts error-free forecast or precise species existence. The ability of species to disseminate as well as interconnect among one another apropos of geographic localities where a model weather is creating its essential niche may be connected to supplementary influences that arise neither connected nor equated to weather (Soberon & Peterson, 2005). These additional factors may also affect the dissemination of this species.

That all-inclusive indispensable criterion for forecasting a dispersal of species at local, national, intercontinental, and global scales is climate, which is largely indisputable or unquestionable (Wills & Whittaker, 2002; Thuiller et al., 2005; Blach-Overgaard et al., 2010). To project modifications within species dispersion ascribed to global changes, adopting climate models alongside a specific algorithmic (MaxEnt) has cropped up expansively demonstrated (Svenning & Skov, 2006). The critical core space is modeled when climate circumstances or factors are present, with each projected result in geographical regions fitted towards the likelihood dispersion (Pearson et al., 2007). Hutchison (1957) defined a fundamental niche as a full range of biological circumstances where a species can coexist and procreate without migrating. The model used in our study showed that the species' present geographic distribution is the southern and coastal regions of the countries in the West along with Central Africa (Figure 6a). According to our study, the species' current dispersion may be due to little to no variation in climatic factors like rainfall and temperature, which are significant environmental factors influencing natural environments and geographical dispersion of species (Anderson et al., 2006).

Among-st related inquiry utilizing MaxEnt, Gbetoho et al. (2017) as well as Kakpo et al. (2019) assert 83 along with 98.9% of Benin were current natural environments for *Lonchocarpus sericeus* together with *Anogeissus leiocarpa*, respectively, and that 47.1% of Benin was currently suitable for *Milicia excelsa*. To assess the danger attributed to elimination along with forecast perspective over time threats arising out of situations like climate change, it's pivotal to fathom the geography together with existing dispersal as to a species (Pacifici et al., 2015). Conversely, towards this species' present-day geographical dispersion, the futurity forecast (Figure 6b) revealed that, within this RCP 8.5 2070 framework, this species' appropriate natural environment would outstandingly decrease across the southern coastline countries of West and Central Africa. Additionally, there occurred a considerable decline within the habitat that was fitting concerning the species at the "threshold of minimum training presence" of 96.29% (figure 6c). Only about 5% of the territories under investigation will remain a natural habitat instead of the spatial distribution of this species. Solely, 'minimum training presence' (a paramount fixed and ecologically possible choice) instead of a 'maximum training presence' (a lesser fixed and more hypothetically existence choice) was chosen based on thresholds decision. We understand that specialized modeling that one may assay an impact of modification in weather forecast regarding species dispersions depends interminably on the atmospheric or ecological circumstances contemplated during model construction along with the lowest levels utilized towards explaining that outputs, as indicated by Pearson et al. (2007). Therefore, it is important to choose thresholds carefully. The largest stable alternative, however, stems from the idea that those above (minimum training presence threshold) is preferable for the reason that it embody a straightforward ecological clarification toward generating quarters that are at least as appropriate as those within where the species have existed or inhabited (Pearson et al., 2007). On the other hand, the maximal training presence threshold is a more expansive approach that is theoretically direct but less reliable. For instance, *Dialium guineense* Willd's ecological niche was modeled by Ganglo et al. in 2017. Minimum training presence (70% habitat suitability was observed) and maximum training presence (a decline in habitat suitability to 17% was recorded) were both used in West Africa at 2055 scenario under RCP 8.5. However, they showed that this last criterion was less factual or exploratory and hence less able to categorize most of the potential places of the species' range. They calculated that at the minimal threshold, their investigations revealed the highest prospective towards their species' geographic dispersion over time (future) because MaxEnt is known to have enhanced predicting power (Pearson et al., 2007).

As we thought about the effects of changing climate on other species, we noticed a certain Lantana camara was predicted by Fandohan et al. (2015) to cover 65% attributed to the nature preserve (Pendjari) along with about 6% of W Regional Park of Benin, consecutively. This forecast held over time (future) within RCP 8.5 at the adjustable training presence maximal threshold. Out of the first, this persists that this minimal threshold arises moreover dependable including actual besides the maximal threshold. Changes in these values of climate parameters can be used to account for the discrepancy between current forecasts and projections for the future. According to AfriClim's Representative Concentration Pathway (Platts et al., 2015), the climate tends to start en route towards getting warmer and less humid (drier) in West and Central Africa, which will result in increased muggy climatic modifications and a potential dispersion of this species by the middle of the twenty-first century. Additionally, the decline in suitable habitats may result from historical and urgent changes expected for bioclimatic variables, primarily precipitation and temperature. For instance, *P. macrophylla* has evolved to tolerate temperatures in the middle of 25 along with 30°C, precipitation in the middle of 1500, and 2700 mm annually (Orwa et al., 2009). The change from the current state of these relevant climate variables will unquestionably modify or impact that dispersion concerning species.

As Busby et al. (2010) indicated, shifting climatic components like temperature and precipitation may well retain an effect on biodiversity along with the geographic distribution of suitable natural environments. According to projections for the future, our study discovered that protected areas will be important for maintaining *P. macrophylla* in countries throughout West and Central Africa. Forecasts for the species' habitat suggested that protected sites, including the Takamanda Forest Reserve in Cameroon, Koroup National Park, and Cross River National Park in Nigeria, were suitable. Our findings support Doxa et al.'s (2017) observation that protected or guarded territories are a key strategy considering on-site biodiversity management.

Conclusion

Within West and Central Africa, where *P. macrophylla* has its natural distribution range, our study predicted some consequences or outcomes concerning climate change. The geographic dispersion of this species occurs controlled by five environmental variables (BIO 6, 12, 15, 16, and 17): a minimum temperature of the coldest month, annual precipitation, precipitation of the wettest month, precipitation of wettest quarter together with precipitation of driest quarter), which is congruous alongside that bioecology concerning this species in it’s natural distributional range. According to the habitat suitability forecasts, this species is currently primarily restricted to the southern coastal regions, with minor gaps of occurrence throughout its natural geographical range. Given that the suitability estimates will be greatly reduced or eliminated in most nations in West and Central Africa under the RCP 8.5 2070 scenario, climate change is bound to retain a footprint on the geographical range of this species. Our research results provide a scientifically sound rationale for effective strategies and implementing this species' conservation intentions, which are anticipated in the next quarters.

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