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Research Article

Occurrence and ecological niche modelling of *Irvingia gabonensis* at cross river state, Nigeria

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Abstract

The African bush mango, *Irvingia gabonensis* Baill, 1884 (Aubry-lecomte ex o'rorke) is a diverse species whose edible seeds are commonly used as a delicacy in soups and as a main source of income throughout Cross River State, Nigeria. Given its enormous economic value for the rural population, we investigated current and future occurrence, geographic distribution, and suitable and unsuitable habitats in the face of unsustainable use and changing climate scenarios. Our study assessed and marked the occurrence of *I. gabonensis* using Global Positioning System (GPS) software in 36 forested areas encompassing northern, central and southern geographical zones of Cross River State, Nigeria. Maximum Entropy (MaxEnt) was applied to forecast the ecological niche of *I. gabonensis* currently and in the future under the AfriClim (RCP 8.5) 2070 scenario. The performance of the MaxEnt model was gauged by the 'area under the receiver operating characteristic curve' (ROC) and the complementary 'area under the curve' (AUC), 'variable contribution rate, 'jackknife tests' and true skill statistics (TSS). MaxEnt results set quadruple BioClim variables ('BIO 6 - minimum temperature of coldest month', 'BIO 12 - annual precipitation', 'BIO 13 - precipitation of coldest month', and 'BIO 14 - precipitation of driest month' as most important decisive variables playing a role in the geographic distribution of the species. Currently, 94.79% of Cross River State is suitable habitat for *I. gabonensis*, with future projections showing a significant 79.59% reduction in suitable habitat at the 'minimum training presence' threshold. Only a few secure areas (20.41%); Afi Mountain Wildlife Sanctuary (central zone), Cross River National Park, Okwangwo Division (central zone) and Oban Division (southern zone) will continue to exist as suitable habitats for the species. The results achieved call attention to the need to protect, cultivate or breed and initiate the species in the preferred areas.
Keywords: Biodiversity, climate change, conservation

Introduction

Biodiversity is the heterogeneity of the distinct manifestations of life on earth, including the diverse types of plants, animals, and microorganisms, the basic physical and functional unit of hereditary they carry within, and the ecosystems they configure. Biodiversity is essential in many ways including supporting the aesthetic value of the natural environment and playing a role in our material well-being through practical values by distributing food, feed, fuel, timber and medicine (MEA, 2005). Despite the utmost importance of biodiversity for the stability of humanity, Nigeria, as the highest populated nation in Africa, exerts the greatest and increasing pressure on biodiversity and forest resources of national and universal importance (Aju and Ezeibekwe, 2010). The major threats to biodiversity and rainforests in Nigeria incorporate direct and indirect circumstances related to poverty, population expansion, habitat degradation, unsustainable use of natural resources, and organizational, coordination and administrative issues (USAID, 2008). Many natural resources are overused, and the environment is facing increasing degradation due to uncontrolled agricultural applications, water and air pollution, and a wide range of circumstances. Desertification, habitat loss and climate change exacerbate the pressure (USAID, 2008).

Habitat is the place or space in which an organism lives and interacts with the biotic and abiotic ecological factors in its habitat. Measurable or quantifiable habitat attributes and standards have an indirect marked effect on species dispersion and the number of different species represented in the environment. Habitat depletion alters the arrangement of individual species of the remaining habitat and leads to climatic change and habitat being broken into fragments (Purves and Dushoff, 2005). For this reason, habitat depletion has detrimental consequences for the number of different species that can be long-lasting and of extreme magnitude (Kruess and Tscharntke, 1994; Anadon *et al.,* 2014). Habitat depletion is the principal cause of species threat, extirpation and biodiversity disappearance (Tilman *et al.,* 2001; Fischer and Lindenmayer, 2007). Some causes, such as long term shifts in temperatures and weather patterns and conversion or transformation of land's use by humans, can reduce, disrupt or wipe out plant and animal habitats (Grimm *et al.,* 2008, Yang *et al.*, 2015).

Currently, heating direction or temperature variation and climate-related types such as prolonged unusually hot weather, low rainfall leading to water shortage, water outflow in many places, strong rotational storms and clouds large, destructive fires are being observed at worldwide scale and from region to region (IPCC, 2013, 2014). These consequences could result in lack of reliable access to sufficient and affordable nutritious food, decline or disappearance of biological diversity, and economic benefits derived from the ecological functions of ecosystems for people (Bentz *et al.,* 2010, IPCC, 2014). In addition to the threat of long term shifts in temperatures and weather patterns, species may react in divergent ways. For-instance, species may continue to live or exist at the edge or border of their regional range, travel or migrate to novel spheres in which ecological factors or circumstances are to a greater extent suitable, or may surprisingly have no living members (IPCC, 2014; Abrahms *et al.,* 2017). To organize or manage the dangers of long term shifts in temperature and weather conditions to biodiversity; it is necessary to understand more about the geographic distribution of species and the circumstances that give rise to their spatial patterns.

The dispersion of a plant species in a set of ordered locations is controlled by the different but interrelated interaction of living and non-living conditions. Some circumstances comprise climate, soil attributes or features, competition between members of the same species and competition between members of different species, anthropogenic disturbance and dispersion restriction (Blach-Overgaad *et al.,* 2010). Nevertheless, environmental conditions are the principal indicators of species' life states, while dispersion restrictions and biotic reciprocal action can additionally make partial changes to distribution (Soberón and Peterson, 2005). An exceptional understanding of a species' environmental needs is for that reason essential to appraise the huge geographical extent at which place it might exist and associated possible response to long term shifts in temperature and weather conditions for preservation or protection and supervision goals (Bowe and Haq, 2010). Developed upon this slant, ecological niche modelling uses the connection amid or around species' locations of existence and the individual associated environmental factors to give a description or details of the ecological niche and likely geographical dispersion of species (Peterson *et al.,* 2011). Such ecological niche modelling techniques are now extensively employed in the detailed investigation and analysis of species dispersion in geographic space, protection and restoration of biodiversity and ecology (Stockwell and Peterson, 2001; Seguardo and Arajuo, 2004; Pearson *et al.,* 2007; Elith *et al.,* 2011).

Irvingia gabonensis is a species of tree belonging to the family Irvingiaceae and grows to a mid-height of 30-50 m. It is native to the muggy forest region of the northernmost part of the tropical Atlantic Ocean from Western Nigeria to the Central African Republic south to Angola and further into western DR Congo. Also present in São Tomé and Príncipe (Orwa *et al.,* 2009). Its preferred habitat is a slightly wet lowland tropical forest extending underneath 1000 m elevation and with a yearly rainfall of 1500–3000 mm and an average yearly temperature of 25–32 °C (Tchoundjeu and Atangana, 2007; Orwa *et al.,* 2009). Fruits are consumed as an excellent source of vitamins in addition to their economic value as a main source of income (FAO, 2007). The fruits are also refined into jelly, jam, juice and sometimes even wine (FAO, 2007). The paste is used to produce a black dye for colouring fabrics; the seeds are smoothed to make edible oil used for cooking (Iponga *et al.,* 2018). The oil is additionally refined into soap and cosmetics (Tchoundjeu and Atangana, 2007). The hardwood is used for heavy construction and branches as fuel (Tchoundjeu and Atangana, 2007). Food additives from species are used for weight control (Egras *et al.,* 2011). The doubled population and high levels of poverty lead to further dependence on this forest resource (*I. gabonensis*) in Cross River State. This has culminated in the unsustainable use of the species in the wild. The conservation status of this species is currently near threatened (IUCN, 2020). Given the enormous economic value of the species to the public, in the face of unsustainable uses and in the context of climate change, we have assessed emerging, suitable and unsuitable habitats (current and future) of the species. Our findings will lead to effective management, sustainable use and conservation of the species in Cross River State, Nigeria.

Materials and methods

Study area

The study was carried out in Cross River State, a coastline state located in southern Nigeria and christened after the Cross River, which flows across the state. The area of the state is about 20, 156 km^2. Cross River State borders Benue to the north, Enugu and Abia to the west, Republic of Cameroon to the east and Akwa Ibom and the Atlantic Ocean to the south (Fig. 1a). The State is located between, latitude 5° 45′N and 6˚ 10ˈN and longitude 8° 30′E and 8˚ 39ˈE (Aju and Ezeibekwe, 2010). The study was conducted in thirty-six (36) communities, selected on the basis of their forest areas, located in the Northern, Central and Southern zones of Cross River State, Nigeria (Fig. 1b). An eighteen (18) month study was conducted between April 2019 and October 2020 to generate field data. The height of the study area is between 140 m and 400 m above sea level. The state has a tropical climate with a mean yearly rainfall of 1250 mm - 2800 mm or more (NIMET, 2015). The rainy season lasts about seven months. The area usually experiences a rainy climate, and daily temperature variations are noticeable throughout the year. Two periods appear in the year; the dry period which occurs around November to March, and the rainy period which begins in March, reach its highest levels in July and September (FME, 2006). The temperature is intense throughout the year with only slight or minor differences. The proximity of the Atlantic Ocean has a reasonable impact on temperature with an average daily maximum of 35°C and an observed mean real temperature of 26°C. The measure of the water vapour content of the air is about 80-90% (NIMET, 2015). The terrain is highly undulating and has soils that usually extend downward away from the upper or surface, and permeable, poorly organized and completely dry soils with small to medium conditions (NIMET, 2015). The flora of the area is a mixture or assortment of mangroves, rainforests and savannahs. Rainforests are also subdivided into lowland rainforests and freshwater swamp forests (Edet *et al.*, 2012).

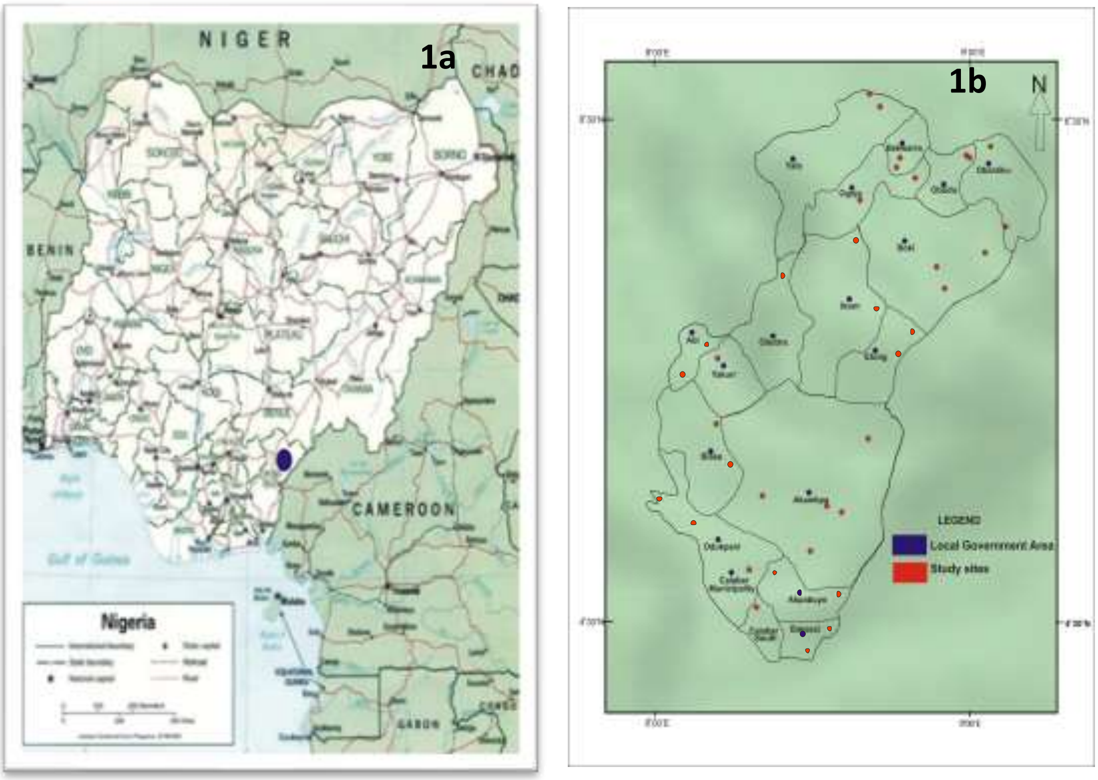


Figure 1. a) Location of Cross River State on the geographic map of Nigeria, **b**) Cross River situation map showing study areas (from data generated during fieldwork)

Occurrence data

Occurrence data that we used in our study are primary data obtained from our forest study. Two forest areas were sampled in each local government area of Cross River State (Fig. 1b). A total of 190 geo-referenced records across the northern, central and southern zones of Cross River State were obtained and used to run the model. Species encounter points obtained in our study area are presented in Fig. 2. It is pertinent to state that some of our study sites or zones had more occurrence points of *I. gabonensis* than other sites or zones. It is a well-known fact that a rudimentary or primitive constraint on sampling data only is sample bias, in which certain areas in the area under study are sampled more extensively or strongly than the rest (Philips *et al.*, 2009). As a means to this end, we anticipated that in our study area, where the species thrives, we may not have sampled to the same magnitude, therefore we scored deviation points on a scale of 1 (less attempt at sampling scale) to 4 (largest sampling scale attempt) to represent sampling attempts in our study area (Elith *et al.*, 2011). The above allowed us to make available bias occurrence points to run our 'MaxEnt model'. The coordinates of species recorded in our sampled forests were marked with Global Positioning System (GPS) software (GARMIN GPS MAP 78 sc). Moreover, we validated each coordinates and transformed it to acquire the decimal latitude and decimal longitude using the site www.gps-coordinates.net. Species name, decimal latitude, and decimal longitude for species were computed on a Microsoft Excel spreadsheet and saved as a .csv (comma-separated value) file, then used to run MaxEnt model (Philips *et al.*, 2006) as the niche model recognizes only a .CSV file. The terminal dataset of geo-referenced species records was exported into Quantum Geographic Information System (QGIS) software ver. 2.18.1 to check if any coordinates fell outside our study area.

Figure 2. *Irvingia gabonensis* occurrences in Cross River State forests

Ecological niche modelling for the geographic distribution of the species

The likely geographic distribution of *I. gabonensis* suitable and unsuitable habitats in the current and future was predicted using; BioClim and AfriClim variables, Quantum Geographic Information System (QGIS) software ver. QGIS-OSGeo4W-2.18.1and Maximum Entropy species distribution model ver. Jre-8u191-windows.

BIOCLIM variables used to forecast the current distribution of *I. gabonensis*

Our study, utilized fifteen downloads of basic bioclimatic variables (BIO 1 – BIO 7 as well as BIO 10 – 17) for forest tree habitats in Africa and Nigeria from the WorldClim site (https://www.world clim.org/ bioclim – Hijmans *et al.,* 2005) to drive our model (current distribution). These characteristics were obtained via monthly ‘temperature and precipitation’ input data covering part of 1950-2000 and are loosely affiliated with the enlargement, maturation and spread of species, therefore they remain broadly or extensively used in the species distribution evaluation (Elith *et al.,* 2006, Graham *et al.,* 2008, Warren *et al.,* 2013).

MaxEnt model calibration and fitting

MaxEnt model employs stochastically collected background data in the area of interest to compute the likelihood of the species' occurrence (Phillips *et al..,* 2006). To separate the environmental variables influencing the spatial dispersion of occurrence records is the goal behind the background data selection (Philips *et al.,* 2009). Such a measure is crucial for presence-only data considering it reduces sample bias and refine the way that models do predictions (Philips *et al.,* 2009). The approach used by the MaxEnt model is in some ways restrictive because true-absence data are required to obtain a reliable estimate of the likelihood of a species' presence in a given area of interest (Soberon and Peterson, 2005; Pearce and Boyce, 2006; Soberon and Nakamura, 2009). The Genetic Algorithm for Rule-Set Prediction (GARP), Generalized Linear Models (GLM), and Boosted Regression Tree (BRT) are among other algorithmic programs that have been acknowledged to have less acceptable forecasting abilities (Pearson *et al.,* 2007). MaxEnt typically appears to have predicted a sizable portion of species presence, forecasting the connections of species to environment mapping forecasts, deducing or inferring forecasts past the training data, and is therefore also applicable in analysis objectives devised to detect novel dispersion areas of species (Pearson *et al.,* 2007; Elith and Graham, 2009). The environmental layers from the WorldClim database must be adjusted to our research area in order to run the MaxEnt model because they cover the entire world. The precise environmental information for the area under consideration will be provided by such calibration (Philips *et al.,* 2006). To achieve this objective, we processed the environmental data for modelling by calibrating environmental layers to Africa and Nigeria using QGIS (Philips *et al.*, 2006). After clipping the occurrence data on the variables using the setting or predesigned value 1 as regularization multiplier (beta value), the BioClim variables BIO1 - 7 and 10 - 17 downloaded as Raster files were polygonized, categorized, and translated to ascii format using QGIS. After that, suitable environmental characteristics were selected using the percentage contribution of variables and jackknife tests. While training the MaxEnt model, we kept track of the environmental features that have a salient effect on the model. Each trace of the MaxEnt encryption or program elevates the gain of the model by changing the multiplier for a single variable; the algorithm allocates or allots the multiply in gain to the bioclim variable on which the species relies, changing or replacing them with per-centum at the termination of the training operation or procedure (Philips *et al.,* 2006). In this study, to test this detail, we used the recommended settings or indications that have been shown to provide vigorous or healthy outcomes as reported by Phillips and Dudik (2008). The maximum iteration was set-to 1000, and the number of synchronizations was set-to 10. The remaining substitutes are placed in default. The models replicating climate change build upon the horizons (scenarios) of modification or adjustment in the rate of movement of energy in the aerosphere triggered by human activities of climate change, calculated in watts/meter^2 (IPCC, 2013). In the scheme of the IPCC's Fifth Assessment Report (ARS), a novel number of horizons, the ‘Representative Concentration Pathways’ (RCPs), were employed for the novel climate programs or models developed by the ‘World Climate Research Program's Coupled Model Inter Comparison Project Phase 5’ (CMIP5). The intensity of predicted modifications in climate is significantly influenced by the option of emission horizons (IPCC, 2013). Foursome RCP horizons are employed within CMIP5. They are denoted and described by the maximum level or equilibrium of 21st century radiative forcing (RF) procured via the input model (IPCC, 2013). The RCPS is; the minimum RCP horizon equivalent to an ‘RF of 2.6 W/m^{2}’ in 2100, two middle RCP horizons equivalent to an ‘RF of 4.5’ of 6 W/m^{2}’ in 2100, respectively, and the maximum or peaked RCP horizon that it is equivalent to an ‘RF of 8.5 W m^{2}’ in 2100. Amongst all these horizons, discharges may be required to decrease or reduce significantly to get to a measure or extent of ‘2.5 W/m^{2}’ by the termination of the 21st centenary. To achieve this goal, the progressive or cumulative emissions consumption will be around 70% compared to baseline drift this century (van Vuuren *et al.,* 2011). This will require considerable attempts and participation or action by every nation to boost or amplify energy productivity, replacing the inexorable utilization of petroleum with inexhaustible or sustainable energy, thermonuclear energy (van Vuuren *et al.*, 2011). At the moment, both at the country level and globally, not much has been done to achieve this goal, and indeed, countries among the countries that emit massive greenhouse gases do not agree on the steps or measures to be taken with regard to reducing emissions. Thus, accomplishing the goal of the RCP 2.6 horizon is unclear or questionable. Also, 'RCP 4.5' is the middle way where some government and international people's attempts to reduce its levels are predicting to reduce 'RF in 4.5 W/m^{2}' by 2100 which is also less likely. From the foregoing, in predicting the distribution of *I. gabonensis*, we chose the 'RCP 8.5' scenario which is the most extreme scenario and where mitigation efforts by governments and international people are hypothesized to be minimal. When selecting the largest significant variables for the model, the model was run using all data points, i.e. test data included and run 50 times with bootstrap as a duplicate run category. In the 'bootstrapping' synchronization procedure the training data is chosen at random with the addition or substitution via the occurrence points. Where the quantity of samples matches the total number of presence points (Phillips, 2010). This alternative would recompense for the smaller number of sites present in the study area.

MaxEnt model evaluation

In this study, the model was appraised by utilizing the 'area under the receiver operating characteristic (ROC) curve' (Peterson *et al.*, 2008) and its associated 'area under curve (AUC)' (Elith *et al.*, 2006), percentage contributing variable table and jackknife plots; 'Regularized training gain', 'Test gain', and 'AUC' were mastered to set the largest significant dedicated variable to the model (Phillips and Dudik 2008). The regularized training gain is used as a guide for model fitting. Regularized training gain is the size, number, or degree of interval in the middle of two or more distribution variables of any two or more random variables that exhibit correlated variation over randomly selected background plots and coincident distribution of covariates over known species plots (Elith *et al.*, 2011). As a result, an enormous regularization training gain (RTG $\geq$ 1) indicates an attractiveness for a limited scope of environmental conditions compared to large or large terrain, while a one-minute training gain (RTG $\leq$ 1) indicates a specific habitat deficiency (Merow *et al.*, 2013). The test gain is, in general, an indication of how much better the model is than the random fit. A large increase $\geq$ 1 for a particular variable therefore means that the variable has significant prognostic value. The major advantage is that these variables are desirable predictors of where species may develop and are related to life processes (Elith *et al.*, 2006). AUC typifies the likelihood that a stochastically selected presence position of a species will-be classified as farther suitable relative to stochastically selected absence position (Elith *et al.,* 2006). A model is contemplated to have an excellent or unique performance whenever AUC is approximately 1 (AUC ≥ 0.75) (Elith *et al.,* 2006). In addition, model performance was assessed using true skills statistics (TSS) (Allouche *et al.,* 2006; Elith *et al.,* 2006). TSS is the ability consanguineous to model to correctly or flawlessly identify the precise presence and precise absence. A model with TSS ≤ 0 specifies an arbitrary forecast; whilst one with a TSS approximately 1 (TSS > 0.5) has excellent diagnostic and numerical strength (Allouche *et al.,* 2006). We obtained the TSS value for ten synchronization runs from the MaxEnt model for the species using the TSS Excel spreadsheet.

MaxEnt model projection

To predict the MaxEnt model for *I. gabonensis* we created another niche model that was projected into the climate scenario for the year 2070 (Phillips *et al.,* 2006) called the Africlimate Ensemble Model under the 'Representative Concentration Pathway RCP 8.5' Future_2070_rcp85 was created. We used compatible climate variables for prediction of Future_2070_rcp85_bis from the Paired Model Inter Comparison available on AfriClim database (https://webfiles.york.ac.uk/KITE/AfriClim/GeoTIFF_150s/ - Platts *et al.,* 2014), Available from the 'Project Phase 5 (CMIP5)' of the 'Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment' for the years 2070; intermediate of 2061-2080 interval. These data are forecasted by 15 General Concentration Models (GCM) under four greenhouse gas concentration settings recognized as RCPs. According to van Vuuren *et al.,* (2011) RCPs are next-generation configurations and are favoured by the Special Report on Emissions Scenarios (SRES) since they permit greater docility and reduce charges or expenditure in the modelling procedure. In addition, RCPs require friendly relationships in collision, adaptation and vulnerability studies, as well as climate and unified evaluation modelling (van Vuuren and Carter, 2014). The RCP setting was devised to investigate different mergers of scenarios such as demographics, economic and social, human use of land and technology (Moss *et al.,* 2010). Solely 15 projection environmental layers (BIO 1 – BIO 7 as well as BIO 10 – BIO 17) are obtainable on AfriClim database, in addition to that asserts the motive we depended upon WorldClim to select specific connected environmental variables for the current distribution of the species. The AfriClim variants have been considered for prediction over the WorldClim variants for the reason that they are more closely aligned with the realities of the biome in Africa than the total number of census decisions in the numerical picture of large-scale training models (Platts *et al.*, 2014). As another matter, mass rotation models possess limited assurance of simulating exterior temperatures at the regional scale compared to the broad scale and do not simulate precipitation at the regional scale as a result of the unpredictability in estimations (IPCC, 2013), is done in the AfriClim unit arising out-of two regional rotation models. An array of observation criteria was applied to limit the model to a resolution capable of showing local environmental fluctuations or differences and is functional or practical for local ecological applications (Platts *et al.,* 2014).

MaxEnt model threshold

To threshold the MaxEnt model, we used QGIS 2.18.1 to reclassify, transform, and polygonize raster to vector connected output layer as well as estimate the species space associated with decision thresholds for current and future climates in 2070 Scenarios where the area or size of the distribution changes. However, the only decision threshold we used was "minimum training presence". The reason is that this range represents areas where environmental characteristics are as favourable or superior as the occurrence of *I. gabonensis* established occurrence sites that are permanent, stable, and all an ecologically rational alternative (Pearson *et al.*, 2007). In comperes, maximum training presence is less consistent and most likely alternate presence. Based on the threshold of the minimum training presence, we classified MaxEnt ASCII file output as suitable and unsuitable (Kakpo *et al.*, 2019).

Results

Species presence records

A total of 190 occurrence points (species presence records) for *I. gabonensis* (plate 1) were recorded across forests in the study area and used in this study. The coordinates (decimal latitude (˚N) and longitude (˚E) of the species recorded across Cross River State forests are listed in Appendix 1.

Plate 1. *Irvingia gabonensis* (O'Rorke) Baill. (i) tree (ii) flowers (iii) fruits (iv) seeds

MaxEnt model validation

The results with respect to niche model assessments pertaining *I. gabonensis* denote or specify its robustness with ten bootstrapping synchronizations AUC = 0.944 (Fig. 2) and TSS = 0.85 (Fig. 3). For this reason, the model performed well and had positive predictive ability and performed efficiently compared to arbitrary ones.

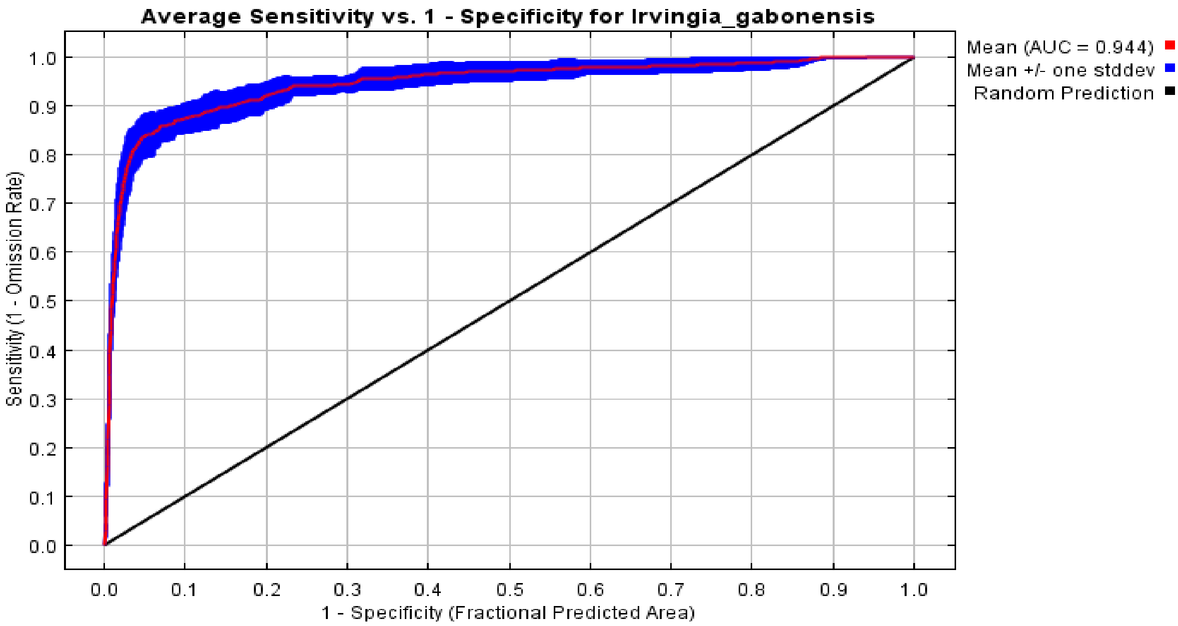


Figure 2. Ten bootstrapping synchronization runs AUC using the MaxEnt model

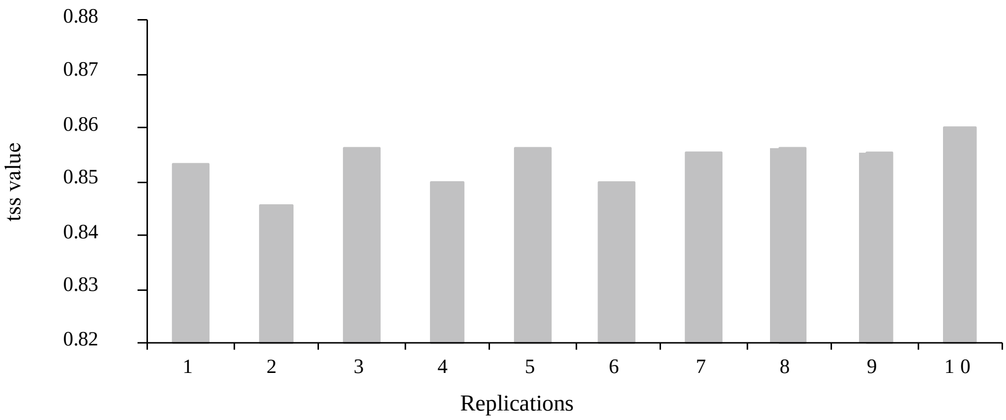
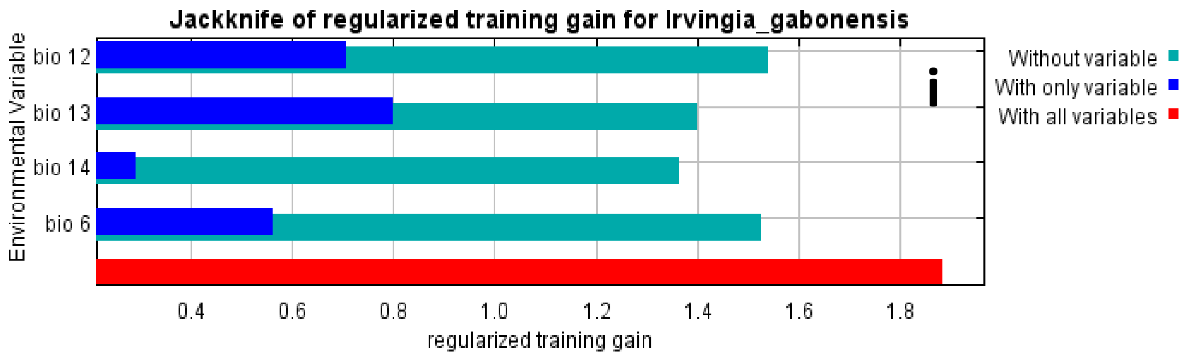
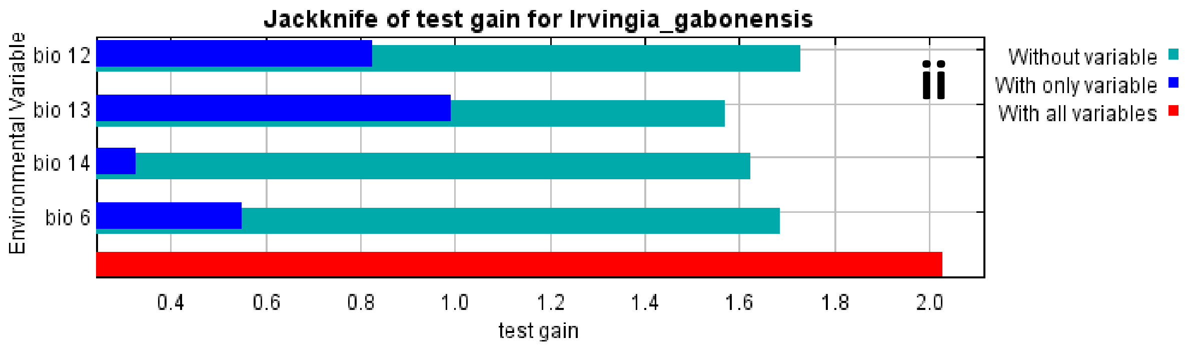


Figure 3. True skill statistics (TSS) for MaxEnt model

Climate variables influencing the geographic distribution of *Irvingia gabonensis*

In this study, the charts of variable importance (Fig. 4 i, ii and iii) and the table of variable ratio input and order of significance (Table 1): this action or standard depends entirely on the final series of the MaxEnt model, not the route or pathway used to achieve this. The role played by the individual climate variable is adjusted by arbitrarily changing the placement order of that variable's values amidst the training points; 'presence and background' and calculating or computing the resultant reduction in training AUC. A high reduction specifies intensely the model is strongly dependent on this variable; Variables are interpolated to obtain per cent input ratio) identified quadruple climatic variables ('BIO 6 - minimum temperature of coldest month', 'BIO 12 - annual precipitation', 'BIO 13 -precipitation of the wettest month', as well as 'BIO 14 - precipitation of the driest month') as playing the greatest part of the range or distribution area of *I. gabonensis* throughout Cross River State. Variable importance charts supported that removing any of these four variables did not allow for optimization compared to using the entire variable set (regularization training gain, AUC, and test gain). Consistent with the variable influence charts, the variable input ratio table for *I. gabonensis* (Table 1) shows that BIO 12 was the most significant defining or influencing variable among the quadruple variables reserved within the model. BIO 14 reduced gain the highest when excluded and was the greatest revealing variable of the model.





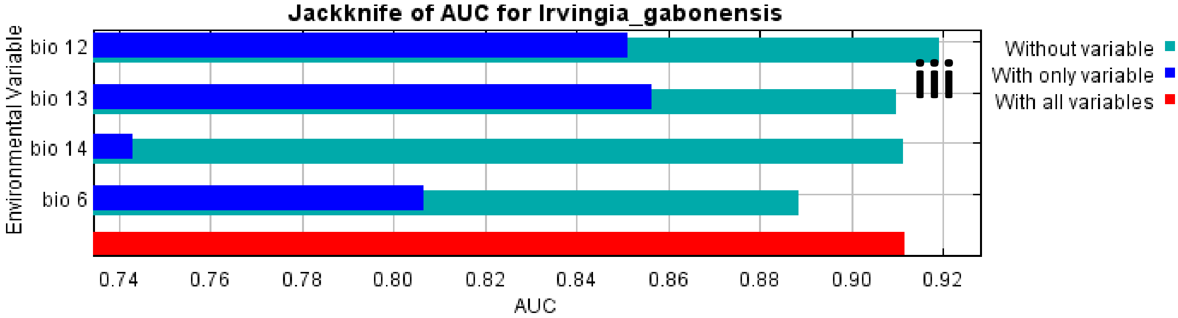


Figure 4. Most influencing climatic variables to *I. gabonensis* distribution

Table 1. Variable ratio input and order of significance

Climatic features	Ratio input (%)	Order of significance
BIO 12	33.5	23.6
BIO 14	27.8	44.2
BIO 13	25.3	5.9
BIO 6	19.6	34.7

The reaction curves of these variables to the forecasts fitness or validity of *I. gabonensis* are presented in Fig. 5 i, ii, iii and iv, respectively. BIO 6 (Fig. 5i) clearly represents the receptivity or tolerance of the species to the minimum temperature of the coldest month versus year variance. Consistent with the species' biosphere or ecological community; logistic predictions show a slight increase in response output from a minimum temperature of 0°C to 12°C, followed by a steep rise and optimization at 25°C. Therefore, the reaction curve of BIO 6 shows that the low-temperature tolerance limit of this species is between 12 - 25˚C in the coldest months. Species’ reaction to BIO 12 (Fig. 5ii) is additionally in accordance with its ecological communities, such as precipitation values of 1000 mm and above as optimized or effective values for the prediction of species high fitness or effectiveness. However, the yield of the reaction decreases significantly in very wet seasons (rainfall greater than 3000 mm per year) (Fig. 5ii). Species response to BIO 13 (Fig. 5iii) shows an excellent response with increasing rainfall from 0 to 600 mm and then a sharp decline after the suitability threshold of about 600 mm. The reaction curve of the species on BIO 14 (Fig. 5iv) shows a good response output from 0 to 60 mm and then a sharp drop after the trapping threshold after 60 mm. The result of the *I. gabonensis* response curves further shows that the species is vulnerable to periods of non-humidity (dry) and humid (wet) in its native or established habitat

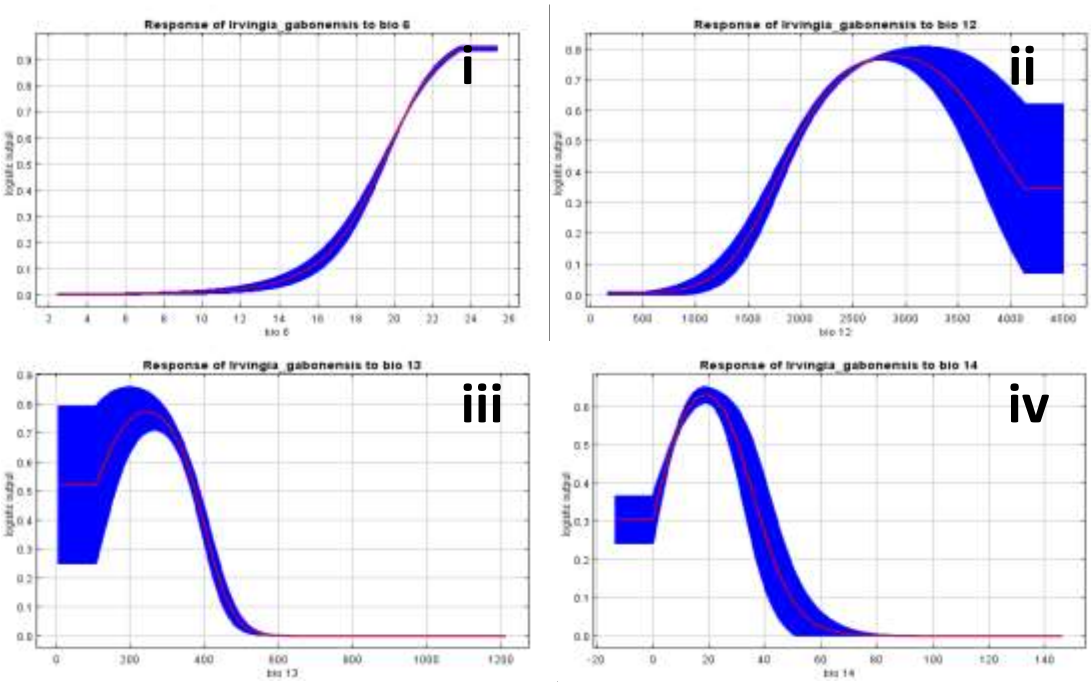


Figure 5. Reaction curves of the climatic variables that most affect the growth of *I. gabonensis*

Current and projected geographical distribution of *I. gabonensis*

We validated that the current projected optimal habitat for the species' geographic distribution was 94.79%, equivalent to 19,106 sq. km of the study area (20,156 km^2) (Fig. 6a and Table 2) Currently, the species is geographically distributed in Guinea Savannah and forested areas of the Northern, Central and Southern geographical regions in Cross River State. However, few areas in Ogoja and Yala local government areas (Northern region) are areas of unfavourable forecasts that might be linked to the region's drier climate which is incompatible with species stature. In contrast, the projected future suitable habitats under the AfriClim RCP 8.5 scenario show a significant 79.59% decrease in suitable habitat area in 2070, equivalent to 16,042 km2 for the species in the various regions in Cross River State (Fig. 6b and Table 2) at the “minimum training presence threshold”. The suitable areas fall within a few secure areas (Afi Mountain Wildlife Sanctuary (central zone) and Cross River National Park, Okwangwo Division (central zone) and Oban Division (Southern zone) and are the only areas that will continue to be suitable habitats for *I. gabonensis*. The entire northern region will no longer be a suitable habitat in the future scenario for the species.

Table 2. Current and projected geographical distribution of *Irvingia gabonensis* across Cross River State

Suitability	**Current**		**AfriClim (RCP 8.5) scenario**	
	Range (km^2)	**Ratio** (%)	**Range (km^2)**	**Ratio (%)**
Suitable	19, 106	94.79	4, 114	20.41

Unsuitable	1, 050	5.21	16, 042	79.59
Total	20, 156		20, 156	

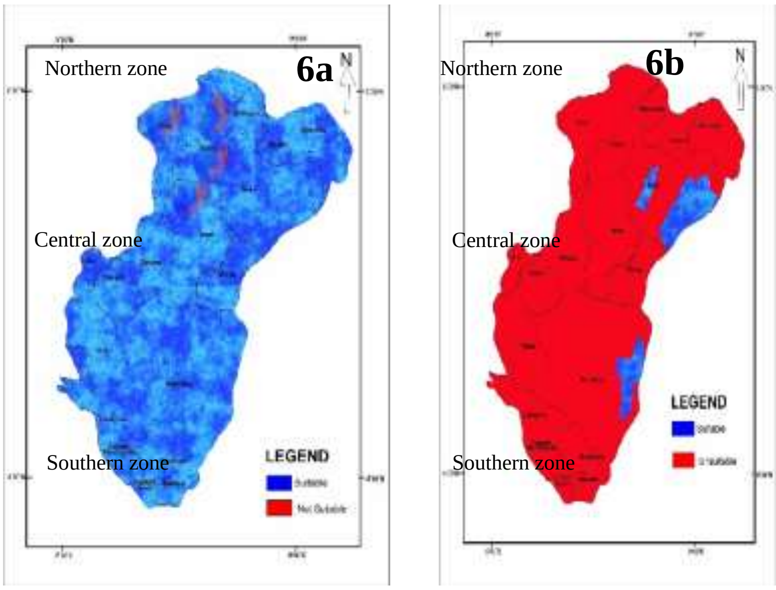


Figure 6a. Current predicted geographic distribution of *Irvingia gabonensis* in Cross River State and 6b) Projected distribution under AfriClim RCP 8.5 2070 scenario at the minimum training presence threshold

Discussion

Species presence

The presence records of *I. gabonensis* show the spatial distribution of the species spread throughout the study area (Fig. 2). However, the total number of 190 occurrence points of the species in 36 forest areas sampled in our study is quite low (Appendix 1). This observation is in congruent or concurrence with other reports of tropical forest ecosystems in Cross River State which reported a low number of individuals of the species in forest ecosystems (Edet *et al.*, 2012; Adeyemi *et al.*, 2013; Aigbe *et al.*, 2014; Adeyemi *et al.*, 2015; Aigbe and Omokhua, 2015; Akwaji and Edu, 2017). The low distribution points of the species in our study area is not unexpected given that the tree is overused, as it plays an extremely crucial function in the cultural, medical and socio-economic life of people in the study areas. Egbe *et al.*, (2012) reported a lower number of species due to pressure from human use affecting the growth and production of the species in Korup National Park, Cameroon. The very low incidence could also be attributed to the scarcity of availability of viable seeds for regeneration in forests, since they are mainly collected from the wild. Olajide (2004) reported that patterns of seed use in forests can lead to a severe shortage of regenerated seeds, as a large number of mother trees must have bare viable seeds. It is true that there is a positive association among the poor populations of some trees and the exploitation of their mature mother plants (Aigbe and Omokhua 2015). Another factor for the low occurrence of this species may be forest disturbance and fragmentation due to illegal logging and rural agricultural land conversion. This is in line with the report by Kumar *et al.,* (2002) that several tropical forests are under immense anthropogenic pressure and require intermediation to maintain comprehensive biodiversity, productivity and sustainability. According to FAO (2005), actions such as logging and construction can lead to or contribute to a sustained decline in the area, health, stocks and flows of forest resources. In addition, the proximity of some of the forests to urban settlement (urbanization) may also account for the low occurrence of species in the area. Johnson and Mercellinus (2013) reports that areas that are generally obstructed or impeded by human use have measurable elements of the forest, such as trees, disturbed and the balance disrupted. The consequences of disturbance vary in precision according to how much of the natural environment is still protected in the process of resource use and development. Varshney and Anis (2014) reported that globally the survival of tree species of wood value is threatened by human actions and other factors such as geographical changes, sudden and significant increase in population and urbanization. In most cases, urbanization and agricultural activities are associated with some development activities, the land is cleared, and trees are felled, rather than considering their importance. It is perhaps unsurprising that endangered trees have been removed along the path of these developments (Wakawa *et al.,* 2017). Finally, the low species presence could be due to modifications in climate factors like temperature and rainfall throughout the study area that may not be favourable for their distribution. Climate has been widely described as the main factor affecting the distribution of tree species on a local or broad range (Darrah *et al.,* 2017; Breiner *et al.,* 2017).

Environmental factors controlling the spatial distribution of *Irvingia gabonensis* in Cross River State

Irvingia gabonensis is native to the muggy forest region of the northernmost part of the tropical Atlantic Ocean from West Nigeria through the Central African Republic and south to Angola and the western region of DR Congo (Tchoundjeu and Atangana, 2007; Orwa *et al.,* 2009). In Cross River State the species is distinguished by abundant and regular rainfall in the Guinea savannah and forest areas in the northern, central and southern regions. In the natural environment, the preferred habitat is low-lying tropical forests at elevations below 1000 m and a yearly rainfall of 1,500 - 3000 mm and an average yearly temperature of 25 - 32˚C (Tchoundjeu and Atangana, 2007; Iponga *et al.,* 2018). Our study, established quadruple environment variables; 'BIO 6 - minimum temperature of the coldest month', 'BIO 12 - annual rainfall', 'BIO 13 - rainfall of wettest month' and 'BIO 14 - rainfall of driest month' for contributing the most to spatial distribution of *I. gabonensis* across Cross River State. Therefore, our findings are reliable in terms of species status. In fact, BIO 12 and its variants, BIO 13 and BIO 14, are among the features that had the greatest impact on our model for predicting the geographic distribution of the species. On a broad range, the spread or dispersion of a species relies mostly on climate (Vayreda *et al.,* 2013), exceptionally on variables connected to water (Svenning and Skov, 2006). BIO 12 is a measure of changes in rainfall throughout the year (O'Donnell and Ignizio, 2012). According to the model, an annual rainfall of 1000 - 2700 mm was found to be suitable for the spatial distribution of *I. gabonensis* in our study area, which is also consistent with the ecological community of the species. Water has several purposes in the plants and is established to influence the distribution designs of species at excellent scales (Willis and Whittaker, 2002) as compared to worldwide scales. It is able to dissolve other substances for mineral nutrients and the network of organic matters manufactured inside the plant; in addition function as a temperature adjuster throughout the course of plant exhalation of water vapour through the stomata and acts as raw material in the procedure of photosynthesis which is the essential process fundamental to all life (Ferguson, 1959). Plants can be troubled by absence of moisture in addition to an excess of moisture (Haferkamp, 1987). Considering those significant tasks, the existence of water in the environment of plants is absolutely of high-priority. The response of the species to the annual variations in precipitation BIO 13 and BIO 14 in our study area also suggests that the species is sensitive to dry and wet period in its habitual range as the species is common in primary and secondary forest and guinea savannah (Orwa *et al.*, 2009). Even though yearly mean temperature (BIO 1) was not one of the most significant backers to the distribution model of *I. gabonensis* its variation in terms of 'minimum temperature of coldest month (BIO 6)' demonstrated to notably influence the geographic distribution of the species. It is imperative to accentuate here that the speed of plant growth and development is superintend by its terrain temperature and each plant has a clearly defined temperature range distinguished by a minimal, high and optimal (Hatfield and Prueger, 2015). BIO 6 estimates the coldest month with the lowest mean minimum temperature of 21.7˚C (O'Donnell and Ignizio, 2012). The logistic prediction of the response curve showed a minimal increase in temperature from 0˚C up to 12˚C and was stable at 25˚C for *I. gabonensis*. The response curve for Bio 6 therefore confirms that the 'minimum temperature of coldest month' appropriate for the spatial distribution of the species is 25 °C, again is agreeable with the ecological environment of the species. According to Hatfield and Prueger (2015), vegetative growth enlarge and multiply as temperature climbs to the species optimal level and for a greater number of plant species vegetative growth normally has a superior optimal rate than for the reproductive growth. According to the results of their study, it is conceivable that immense differences in temperature like elevated value of BIO 6 can influence the optimal temperature of *I. gabonensis* and subsequently affect the distribution and growth of *I. gabonensis* development in both vegetative and reproductive stages. Therefore, it can be inferred that the highest value of BIO 6 exceeds that which the dispersion of *I. gabonensis* can be adversely affected, i.e. 25 ˚C. In our study, the variables BIO 6 calculated light and heat availability and variability for the species, whereas BIO 12, 13 and 14 calculated water availableness and variableness for *I. gabonensis*, respectively. Since these variables that control the geographic distribution of the species are basic principal circumstances, the models can be generalizable to areas beyond our study area and set out the motive of species management in such areas (Elith *et al.*, 2011).

Current and future geographical distribution of *I. gabonensis*

In our study, we only examine environmental factors during our MaxEnt model building. As a result there is some restriction and ambiguity in the prediction of species distribution (Abrahams, 2017). Undoubtedly, niche models forecast habitat that is consistent with the species' potential location (Soberon and Peterson, 2005). It could give way to 'false positives' or 'false negatives' in the occurrence of a species in a forecasted geographical area (Thuiller *et al.,* 2005). 'False positives' arise if additional circumstances or conditions other than climate affect the dispersion of such species and avert the species from thriving naturally across the likely district, zone or region under investigation (Thuiller *et al.,* 2005; Blach-Overgaard, 2010), while on the contrary 'False Negatives' manifest when the dearth of details amidst the environment sample or flawed sampling attempts avert accurate prediction or exact species presence. Evidently, those additional factors that are not linked or matched to climate may be connected to species' ability to disperse and interact with each other as far as geographical areas creating a perfect climate its basic niche (Soberon and Peterson, 2005) and in this way influence the dispersal or spread of the species. Even so, it is to a large extent inarguable or incontestable that at local, national, intercontinental and worldwide scales, climate is the overall key variable for predicting the dispersion of species (Wills and Whittaker, 2002; Thuiller *et al.*, 2005; Blach-Overgaard *et al.*, 2010), Projecting changes in species spread due to worldwide change, using climate models with the particular algorithm is MaxEnt, which has been proven extensively (Svenning and Skov, 2006). When climate conditions or factors are used, the critical core space is modelled and the predicted outcome in geographic space is fit to a probability distribution (Pearson *et al.,* 2007). The fundamental niche is defined by Hutchison (1957) as the total scale of environmental factors where a species can exist and reproduce without migration. In our study, the model exhibited that the current geographic distribution of the species is 94.79% in the Guinean savannah and forest areas of Cross River State (Fig. 6a). The present dispersion of the species as discovered in our study may be the result of little or no variability in climatic factors such as rainfall and temperature (Anderson *et al.,* 2006), which are important environmental variables contributing to suitable habitats and the geographic distribution of species (Darrah *et al.,* 2017). In a similar study using MaxEnt; Kakpo *et al.*, (2019) recounted that 47.1% are currently suitable habitats for *Milicia excelsa* in Benin; also, 83 and 98.9% of Benin are currently suitable habitats for *Lonchocarpus sericeus* and *Anogeissus leiocarpa* (Gbetoho *et al.,* 2017). Understanding the geography and current spread of a species is of vital importance for assessing the risk of extinction and predicting potential future risks from circumstances such as climate change (Pacifici *et al.,* associates, 2015). In contrast to the current geographic distribution of the species, future projections (Fig. 6b) show a significant reduction of 79.59% in suitable habitat at the 'threshold of minimum training presence' for the species in Cross River State under the RCP 8.5 2070 scenario. Based on thresholds decision, only the 'minimum training presence' (the most stable and environmentally feasible alternative) was used versus the maximum training presence (the less stable and most likely presence alternative). As confirmed or suggested by Pearson *et al.*, (2007), we fathom that specialized modelling to approximate the effect of change in climate conditions on species distributions relies on both the environmental conditions considered in model assembly and the bottom limits used to explain the outputs. Thresholds should therefore be chosen with caution. Nevertheless, our alternative is based on the premise that the minimum training presence threshold (largest stable alternative) is favourable because it embraces a forthright ecological explanation for creating areas no less than as applicable as that in which a species has been listed (Pearson *et al.,* 2007). On the contrary, the maximum training presence threshold is a broader alternative, although less stable but hypothetically direct. For example, Ganglo *et al.,* (2017) modelled the ecological niche of *Dialium guineense* Willd in West Africa in the future under RCP 8.5 using both thresholds; minimum training presence and maximum training presence. They revealed that this last threshold was less factual or exploratory and thus not so much as adept to classify the maximum of the likely sites of distribution of the species. Because MaxEnt is acknowledged to encompass heightened forecasting power (Pearson *et al.,* 2007), they estimated that at the minimum training presence threshold (the wide-ranging stable alternative) their results showed the greatest potential for the species spatial distribution in the future. We also noticed that Fandohan *et al.,* (2015) predicted *Lantana camara* to spread over 65% of a biosphere reserve (Pendjari) and around 6% of W Regional Park in Benin, respectively and their prediction remains so in the future under RCP 8.5 and under the flexible maximum training presence threshold. From the former, it is clear that the minimum training presence threshold is the more effective and reliable threshold than the maximum training presence. The difference between current forecasts and future projections can be explained by changes in the values of climate parameters. The climate has been predicted to begin to become warmer and less humid (dryer) in West Africa under AfriClim's Representative Concentration Path (RCP) (Platts *et al.,* 2015), and will lead to a more humid climate changes in the possible spread of the species mid-21st century. Also, the reduction of suitable habitats may be due to the imperative and historical changes predicted for bioclimatic variables, mainly precipitation and temperature. For example, *I. gabonensis* is currently adapted to temperatures ranging from 25 to 30°C and precipitation from 1500 to 2700 mm per year (Orwa *et al.,* 2009). Therefore, a shift in these appropriate climate variables from what they currently are will definitely affect or impact species distribution. As indicated by Busby *et al.,* (2010), changing climatic characteristics such as precipitation and temperature will affect biodiversity and the spatial distribution of suitable habitats. From future forecasts our study found that only a few protected areas remain suitable habitats and conserved *I. gabonensis* in Cross River State. Our finding confirms that of Doxa *et al.,* (2017) that preserved or secured areas are a major tool for in situ conservation of biodiversity.

Conclusion

We surveyed the presence and geographic distribution of *I gabonensis* in Cross River State, Nigeria, to learn with certainty the species' geographic distribution currently and under future scenario (AfriClim RCP 8.5 2070) using the MaxEnt model. Our study identified four bioclim variables that control the geographic distribution of the species. These are 'BIO 6 - minimum temperature of coldest month', 'BIO 12 - annual precipitation', 'BIO 13 - precipitation of wettest month' and 'BIO 14 - precipitation of driest month'. The species is currently suitable and geographically distributed in the northern, central and southern zones of our study area. According to future projections, suitable habitats will decrease significantly in the different zones under the AfriClim RCP 8.5 2070 scenario. Only a small set of protected areas in both scenarios; the Afi Mountain and Wildlife Sanctuary (Central Area), Cross River National Park, Okwangwo Division (Central Area) and Oban Division (South Area) will play an indispensable role in conserving the species in Cross River State. Therefore, it is essential to take measures or steps to effectively conserve the species in the protected areas. For the sound management of the species, forest controllers or administrators ought-to fortify the defence of these protected areas, in particular by organizing periodic surveillance or monitoring. Additionally, this species could be exploited in agroforestry and afforestation programmes in Cross River State, Nigeria.

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Appendix 1: Species presence records of *Irvingia gabonensis* (Aubry-LeComte ex O'Rorke) Baill. in Cross River State

S/N	Tree specie	Decimal Latitude (˚N)	Decimal Longitude (˚E)
1.	*Irvingia gabonensis* (O'Rorke) Baill.	5.275	8.691111
2.	*Irvingia gabonensis* (O'Rorke) Baill.	5.220277	8.695833
3.	*Irvingia gabonensis* (O'Rorke) Baill.	5.2175	8.701111
4.	*Irvingia gabonensis* (O'Rorke) Baill.	5.259444	8.931666
5.	*Irvingia gabonensis* (O'Rorke) Baill.	5.243611	8.941666
6.	*Irvingia gabonensis* (O'Rorke) Baill.	5.078888	8.689444
7.	*Irvingia gabonensis* (O'Rorke) Baill.	5.285	8.886111
8.	*Irvingia gabonensis* (O'Rorke) Baill.	5.311666	8.850833
9.	*Irvingia gabonensis* (O'Rorke) Baill.	5.3441667	8.838333
10.	*Irvingia gabonensis* (O'Rorke) Baill.	5.21	8.980555
11.	*Irvingia gabonensis* (O'Rorke) Baill.	5.343055	8.708333
12.	*Irvingia gabonensis* (O'Rorke) Baill.	5.341944	8.706111
13.	*Irvingia gabonensis* (O'Rorke) Baill.	5.340555	8.702222
14.	*Irvingia gabonensis* (O'Rorke) Baill.	5.342222	8.658611
15.	*Irvingia gabonensis* (O'Rorke) Baill.	5.426111	8.600277
16.	*Irvingia gabonensis* (O'Rorke) Baill.	5.4225	8.596944
17.	*Irvingia gabonensis* (O'Rorke) Baill.	5.416666	8.601666
18.	*Irvingia gabonensis* (O'Rorke) Baill.	5.380555	8.630277
19.	*Irvingia gabonensis* (O'Rorke) Baill.	5.588611	8.566388
20.	*Irvingia gabonensis* (O'Rorke) Baill.	5.588611	8.566111
21.	*Irvingia gabonensis* (O'Rorke) Baill.	5.550277	8.578338
22.	*Irvingia gabonensis* (O'Rorke) Baill.	5.445277	8.504444
23.	*Irvingia gabonensis* (O'Rorke) Baill.	5.369444	8.513611
24.	*Irvingia gabonensis* (O'Rorke) Baill.	5.410555	8.480833
25.	*Irvingia gabonensis* (O'Rorke) Baill.	5.573888	8.516388
26.	*Irvingia gabonensis* (O'Rorke) Baill.	5.573888	8.518611
27.	*Irvingia gabonensis* (O'Rorke) Baill.	5.5875	8.566666
28.	*Irvingia gabonensis* (O'Rorke) Baill.	5.443333	8.476944

29.	*Irvingia gabonensis* (O'Rorke) Baill.	5.417777	8.529166
30.	*Irvingia gabonensis* (O'Rorke) Baill.	6.405555	9.440555
31.	*Irvingia gabonensis* (O'Rorke) Baill.	6.411944	9.199166
32.	*Irvingia gabonensis* (O'Rorke) Baill.	6.492777	9.443333
33.	*Irvingia gabonensis* (O'Rorke) Baill.	6.627222	9.421388
34.	*Irvingia gabonensis* (O'Rorke) Baill.	6.46944	9.220833
35.	*Irvingia gabonensis* (O'Rorke) Baill.	6.583888	9.266388
36.	*Irvingia gabonensis* (O'Rorke) Baill.	6.513888	9.265
37.	*Irvingia gabonensis* (O'Rorke) Baill.	5.865833	8.398888
38.	*Irvingia gabonensis* (O'Rorke) Baill.	5.843888	8.400833
39.	*Irvingia gabonensis* (O'Rorke) Baill.	5.868333	8.399444
40.	*Irvingia gabonensis* (O'Rorke) Baill.	5.849444	8.388888
41.	*Irvingia gabonensis* (O'Rorke) Baill.	5.834722	8.396111
42.	*Irvingia gabonensis* (O'Rorke) Baill.	5.946388	8.252222
43.	*Irvingia gabonensis* (O'Rorke) Baill.	5.746944	8.108611
44.	*Irvingia gabonensis* (O'Rorke) Baill.	5.871944	8.298055
45.	*Irvingia gabonensis* (O'Rorke) Baill.	5.943055	8.250555
46.	*Irvingia gabonensis* (O'Rorke) Baill.	5.748611	8.118333
47.	*Irvingia gabonensis* (O'Rorke) Baill.	5.727777	8.296666
48.	*Irvingia gabonensis* (O'Rorke) Baill.	5.017777	8.418888
49.	*Irvingia gabonensis* (O'Rorke) Baill.	5.013611	8.418888
50.	*Irvingia gabonensis* (O'Rorke) Baill.	4.998055	8.420833
51.	*Irvingia gabonensis* (O'Rorke) Baill.	4.989444	8.427222
52.	*Irvingia gabonensis* (O'Rorke) Baill.	4.988333	8.428333
53.	*Irvingia gabonensis* (O'Rorke) Baill.	4.983333	8.433333
54.	*Irvingia gabonensis* (O'Rorke) Baill.	4.981388	8.436388
55.	*Irvingia gabonensis* (O'Rorke) Baill.	4.973611	8.444444
56.	*Irvingia gabonensis* (O'Rorke) Baill.	4.953333	8.472222
57.	*Irvingia gabonensis* (O'Rorke) Baill.	4.960277	8.508055
58.	*Irvingia gabonensis* (O'Rorke) Baill.	4.937222	8.539166
59.	*Irvingia gabonensis* (O'Rorke) Baill.	4.983055	8.416388
60.	*Irvingia gabonensis* (O'Rorke) Baill.	6.313055	9.112222
61.	*Irvingia gabonensis* (O'Rorke) Baill.	6.333055	9.102777
62.	*Irvingia gabonensis* (O'Rorke) Baill.	6.325833	9.356111
63.	*Irvingia gabonensis* (O'Rorke) Baill.	6.31	9.207777
64.	*Irvingia gabonensis* (O'Rorke) Baill.	6.469444	9.255555
65.	*Irvingia gabonensis* (O'Rorke) Baill.	6.477777	9.263888
66.	*Irvingia gabonensis* (O'Rorke) Baill.	6.328611	9.354444
67.	*Irvingia gabonensis* (O'Rorke) Baill.	6.254444	9.100555
68.	*Irvingia gabonensis* (O'Rorke) Baill.	5.258888	8.655833
69.	*Irvingia gabonensis* (O'Rorke) Baill.	5.260277	8.657222
70.	*Irvingia gabonensis* (O'Rorke) Baill.	5.266666	8.659722
71.	*Irvingia gabonensis* (O'Rorke) Baill.	5.266666	8.66
72.	*Irvingia gabonensis* (O'Rorke) Baill.	5.266666	8.658611
73.	*Irvingia gabonensis* (O'Rorke) Baill.	5.266944	8.666388

74.	*Irvingia gabonensis* (O'Rorke) Baill.	5.271666	8.638888
75.	*Irvingia gabonensis* (O'Rorke) Baill.	6.34	9.108888
76.	*Irvingia gabonensis* (O'Rorke) Baill.	6.503888	9.13
77.	*Irvingia gabonensis* (O'Rorke) Baill.	6.463888	9.111388
78.	*Irvingia gabonensis* (O'Rorke) Baill.	6.347777	9.0825
79.	*Irvingia gabonensis* (O'Rorke) Baill.	6.498611	9.028888
80.	*Irvingia gabonensis* (O'Rorke) Baill.	6.500277	9.0225
81.	*Irvingia gabonensis* (O'Rorke) Baill.	6.496666	9.221944
82.	*Irvingia gabonensis* (O'Rorke) Baill.	6.532777	9.120277
83.	*Irvingia gabonensis* (O'Rorke) Baill.	6.533055	9.122222
84.	*Irvingia gabonensis* (O'Rorke) Baill.	6.390277	9.081111
85.	*Irvingia gabonensis* (O'Rorke) Baill.	6.476666	9.258888
86.	*Irvingia gabonensis* (O'Rorke) Baill.	5.371190	8.604686
87.	*Irvingia gabonensis* (O'Rorke) Baill.	5.562418	8.634485
88.	*Irvingia gabonensis* (O'Rorke) Baill.	5.551190	8.596314
89.	*Irvingia gabonensis* (O'Rorke) Baill.	5.562878	8.530740
90.	*Irvingia gabonensis* (O'Rorke) Baill.	5.562878	8.566448
91.	*Irvingia gabonensis* (O'Rorke) Baill.	5.554934	8.580350
92.	*Irvingia gabonensis* (O'Rorke) Baill.	5.566552	8.596143
93.	*Irvingia gabonensis* (O'Rorke) Baill.	5.581587	8.568677
94.	*Irvingia gabonensis* (O'Rorke) Baill.	5.564502	8.633908
95.	*Irvingia gabonensis* (O'Rorke) Baill.	5.557924	8.612622
96.	*Irvingia gabonensis* (O'Rorke) Baill.	5.569713	8.601292
97.	*Irvingia gabonensis* (O'Rorke) Baill.	6.028468	8.875751
98.	*Irvingia gabonensis* (O'Rorke) Baill.	6.026957	8.881245
99.	*Irvingia gabonensis* (O'Rorke) Baill.	6.029817	8.884335
100.	*Irvingia gabonensis* (O'Rorke) Baill.	6.028750	8.861150
101.	*Irvingia gabonensis* (O'Rorke) Baill.	6.007752	8.862877
102.	*Irvingia gabonensis* (O'Rorke) Baill.	6.008691	8.868241
103.	*Irvingia gabonensis* (O'Rorke) Baill.	6.008734	8.888665
104.	*Irvingia gabonensis* (O'Rorke) Baill.	6.030504	8.877262
105.	*Irvingia gabonensis* (O'Rorke) Baill.	6.031417	8.859557
106.	*Irvingia gabonensis* (O'Rorke) Baill.	6.048546	8.889918
107.	*Irvingia gabonensis* (O'Rorke) Baill.	6.037685	8.906046
108.	*Irvingia gabonensis* (O'Rorke) Baill.	6.047988	8.934115
109.	*Irvingia gabonensis* (O'Rorke) Baill.	6.004949	8.939014
110.	*Irvingia gabonensis* (O'Rorke) Baill.	5.994392	8.821837
111.	*Irvingia gabonensis* (O'Rorke) Baill.	5.996422	8.832861
112.	*Irvingia gabonensis* (O'Rorke) Baill.	6.105029	8.712010
113.	*Irvingia gabonensis* (O'Rorke) Baill.	5.966521	8.610105
114.	*Irvingia gabonensis* (O'Rorke) Baill.	5.951145	8.636842
115.	*Irvingia gabonensis* (O'Rorke) Baill.	5.940773	8.647313
116.	*Irvingia gabonensis* (O'Rorke) Baill.	5.935608	8.622551
117.	*Irvingia gabonensis* (O'Rorke) Baill.	5.972722	8.591051
118.	*Irvingia gabonensis* (O'Rorke) Baill.	5.984331	8.574572

119.	*Irvingia gabonensis* (O'Rorke) Baill.	5.974429	8.601007
120.	*Irvingia gabonensis* (O'Rorke) Baill.	5.965551	8.602724
121.	*Irvingia gabonensis* (O'Rorke) Baill.	5.963102	8.581781
122.	*Irvingia gabonensis* (O'Rorke) Baill.	5.976360	8.406858
123.	*Irvingia gabonensis* (O'Rorke) Baill.	5.983872	8.393125
124.	*Irvingia gabonensis* (O'Rorke) Baill.	5.965775	8.390036
125.	*Irvingia gabonensis* (O'Rorke) Baill.	5.977043	8.370466
126.	*Irvingia gabonensis* (O'Rorke) Baill.	5.883169	8.067977
127.	*Irvingia gabonensis* (O'Rorke) Baill.	5.888804	8.072612
128.	*Irvingia gabonensis* (O'Rorke) Baill.	5.902123	8.084285
129.	*Irvingia gabonensis* (O'Rorke) Baill.	5.887097	8.010299
130.	*Irvingia gabonensis* (O'Rorke) Baill.	5.931235	8.167369
131.	*Irvingia gabonensis* (O'Rorke) Baill.	5.928504	8.144367
132.	*Irvingia gabonensis* (O'Rorke) Baill.	5.809654	7.992618
133.	*Irvingia gabonensis* (O'Rorke) Baill.	6.854725	8.857388
134.	*Irvingia gabonensis* (O'Rorke) Baill.	6.854939	8.841552
135.	*Irvingia gabonensis* (O'Rorke) Baill.	6.841517	8.834256
136.	*Irvingia gabonensis* (O'Rorke) Baill.	6.870621	8.747166
137.	*Irvingia gabonensis* (O'Rorke) Baill.	6.863122	8.797978
138.	*Irvingia gabonensis* (O'Rorke) Baill.	6.432685	8.577067
139.	*Irvingia gabonensis* (O'Rorke) Baill.	6.431864	8.578322
140.	*Irvingia gabonensis* (O'Rorke) Baill.	6.569702	8.948769
141.	*Irvingia gabonensis* (O'Rorke) Baill.	6.570043	8.952417
142.	*Irvingia gabonensis* (O'Rorke) Baill.	6.624184	8.929903
143.	*Irvingia gabonensis* (O'Rorke) Baill.	6.625293	8.932650
144.	*Irvingia gabonensis* (O'Rorke) Baill.	6.626188	8.931749
145.	*Irvingia gabonensis* (O'Rorke) Baill.	6.624099	8.931963
146.	*Irvingia gabonensis* (O'Rorke) Baill.	6.610796	8.876538
147.	*Irvingia gabonensis* (O'Rorke) Baill.	6.607599	8.878598
148.	*Irvingia gabonensis* (O'Rorke) Baill.	6.609602	8.875508
149.	*Irvingia gabonensis* (O'Rorke) Baill.	6.608323	8.875508
150.	*Irvingia gabonensis* (O'Rorke) Baill.	6.595221	9.014303
151.	*Irvingia gabonensis* (O'Rorke) Baill.	6.594326	9.010655
152.	*Irvingia gabonensis* (O'Rorke) Baill.	6.594795	9.014217
153.	*Irvingia gabonensis* (O'Rorke) Baill.	6.591981	9.015419
154.	*Irvingia gabonensis* (O'Rorke) Baill.	6.628435	9.117769
155.	*Irvingia gabonensis* (O'Rorke) Baill.	6.626602	9.121760
156.	*Irvingia gabonensis* (O'Rorke) Baill.	6.538982	9.154057
157	*Irvingia gabonensis* (O'Rorke) Baill.	6.529432	9.270443
158.	*Irvingia gabonensis* (O'Rorke) Baill.	6.509648	9.290356
159.	*Irvingia gabonensis* (O'Rorke) Baill.	6.611629	9.212422
160.	*Irvingia gabonensis* (O'Rorke) Baill.	6.513400	9.272160
161	*Irvingia gabonensis* (O'Rorke) Baill.	6.527385	9.219975
162	*Irvingia gabonensis* (O'Rorke) Baill.	6.519540	9.190793
163.	*Irvingia gabonensis* (O'Rorke) Baill.	6.524315	9.276280

164.	*Irvingia gabonensis* (O'Rorke) Baill.	6.508624	9.291230
165.	*Irvingia gabonensis* (O'Rorke) Baill.	6.520563	9.277653
166.	*Irvingia gabonensis* (O'Rorke) Baill.	6.510671	9.290013
167.	*Irvingia gabonensis* (O'Rorke) Baill.	6.510330	9.270787
168.	*Irvingia gabonensis* (O'Rorke) Baill.	6.539664	9.222035
169.	*Irvingia gabonensis* (O'Rorke) Baill.	6.554672	9.231991
170.	*Irvingia gabonensis* (O'Rorke) Baill.	6.557401	9.195599
171.	*Irvingia gabonensis* (O'Rorke) Baill.	6.519625	9.278340
172.	*Irvingia gabonensis* (O'Rorke) Baill.	6.508710	9.291043
173.	*Irvingia gabonensis* (O'Rorke) Baill.	6.531826	9.272847
174.	*Irvingia gabonensis* (O'Rorke) Baill.	6.527811	9.268384
175.	*Irvingia gabonensis* (O'Rorke) Baill.	6.510756	9.289326
176.	*Irvingia gabonensis* (O'Rorke) Baill.	6.347936	9.320569
177.	*Irvingia gabonensis* (O'Rorke) Baill.	6.352713	9.330546
178.	*Irvingia gabonensis* (O'Rorke) Baill.	6.376256	9.311986
179.	*Irvingia gabonensis* (O'Rorke) Baill.	6.360220	9.326748
180.	*Irvingia gabonensis* (O'Rorke) Baill.	6.379327	9.314389
181.	*Irvingia gabonensis* (O'Rorke) Baill.	6.382739	9.322972
182.	*Irvingia gabonensis* (O'Rorke) Baill.	6.364314	9.328122
183.	*Irvingia gabonensis* (O'Rorke) Baill.	6.383933	9.315075
184.	*Irvingia gabonensis* (O'Rorke) Baill.	6.386322	9.334817
185.	*Irvingia gabonensis* (O'Rorke) Baill.	6.384957	9.315934
186.	*Irvingia gabonensis* (O'Rorke) Baill.	6.396045	9.316964
187.	*Irvingia gabonensis* (O'Rorke) Baill.	6.391781	9.332928
188.	*Irvingia gabonensis* (O'Rorke) Baill.	6.384274	9.328637
189.	*Irvingia gabonensis* (O'Rorke) Baill.	6.385298	9.316964
190.	*Irvingia gabonensis* (O'Rorke) Baill.	6.401846	9.322800