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RESEARCH ARTICLE

SPATIALLY EXPLICIT ASSESSMENT OF THE SUITABLE AREAS FOR THE THREATENED IROKO'S (*MILICIA EXCELSA* [WELW.] C.C. BERG) CONSERVATION IN BENIN: A COMBINATION OF GEOSTATISTICS AND ECOLOGICAL NICHE MODELING

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Abstract

Although Iroko (*Milicia excelsa*) is listed endangered and has a great socioeconomic and cultural importance in Benin, there have been few attempts to definition of sustainable conservation strategies for the species. This study explored the spatial patterns of the species and tested if the species distribution may be affected under future climates forecasts. Moran index was used to measure the spatial autocorrelation of the abundance of Iroko. For the niche modeling, records of the species were added to bioclimatic variables (current and future conditions) and soil layers in the maximum entropy algorithm. Results showed overall a spatial dependency between Iroko population according to the density ($P < 0.001$). The population density seems similar between 0 and 3 km but differ from 3 to 150 km. A slight increase was noted from the present-day distribution to the future forecasts (4.71 % and 6.95 % respectively following the scenarios RCP4.5 and RCP8.5). Urgent conservation actions are needed to safeguard the remnant populations of Iroko in Benin.

Introduction:-

The climate trend revealed by prediction models around the world indicates increasesof temperatures, decreasesof precipitations, as well as random distribution patterns of these two main climatic parameters, across years. This situation is leading to unexpected long-lasting and severe droughts and / orflooding in any geographic area (Appiah 2013). Several studies suggest that climate changes cause great threats, impacting survival of economic and socio-culturally important tree species in many regions (Sala et al. 2000; Thomas et al. 2004), especially in sub-Saharan Africa (Connolly-Boutin and Smit 2016).

Milicia excelsa (Welw.) C.C Berg (Moraceae), commonly known as Iroko tree, is a native species with several ecological, economic, and socio-cultural values (Daïnou et al. 2010; Ouinsavi et al. 2005). Irokotrees, which rank

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first among valuable woody species, are intensively logged in forest reserves (Ouinsavi et al. 2009). From a prospection on wood markets and sawmills, timbers from Iroko were scarce (Sopkon and Ouinsavi 2004). Today, the species is classified as “Endangered” on the National Red List for Benin (Neuenschwander et al. 2011). Therefore, strategies for appropriate conservation and management of the species are vital for the survival of relic populations’country wide.

Efficient conservation and management strategies design for Iroko require information on locals’ endogenous knowledge, the species’ spatial ecology, and suitable geographical areas for ecological restoration. Several scholars investigated the ecology, genetic, morphology, utilization and traditional *in situ* conservation of *M. excels* in Benin (Sokpon and Agbo 1999; Sopkon and Ouinsavi 2004; Ouinsavi et al. 2005; Ouinsavi et al. 2009; Ouinsavi and Sokpon 2010). Nonetheless, spatial patterns of the species as well as suitable habitats for its conservation remain barely documented, while these aspects are crucial, since they will generate additional information on which depends the implementation of conservation strategies.

Several statistical and mechanistic techniques proved effective in quantifying niches and spatial distribution of native species (Idohou et al. 2017; Syfert et al. 2016) among which are Ecological niche modeling (ENM). ENM allows to predict species’ potential distribution, even in a situation of limited and biased samplings (Elith et al. 2006). This modeling approach links geographic locations with their corresponding climate layers to estimate the probability of a targeted species’ presence across a given geographical space (Elith et al. 2006; Soberon and Peterson 2005; Villar-Hernandez 2014). The geographic distribution of a plant species is determined by complex interactions among and between biotic and abiotic factors, including climate, soil properties, species physiology, dispersers’ availability, dispersal limitation, etc. (Soberón 2007). Accordingly, comparing the known distribution records to the potential ones for identifying priority areas for conservation, might be valuable for long – lasting conservation strategy design (Montes-Leyva et al. 2018).

Environmental data associated with the locations of species’ presence are not often independent (Carl and Kuhn 2008; Dormann et al. 2007; Dormann 2007), while handling with this spatial autocorrelation (Dale et al. 2002) represents a major challenge in SDM, even though it plays a significant role as source of information to study processes responsible for observed patterns (Schabenberger et al. 2017 ; Dormann et al. 2007). The interest in quantifying and including spatial autocorrelation in the understanding of natural phenomena is frequent nowadays (Dale et al. 2002, Liebhold and Gurevitch 2002).

This study aimed to explore the current spatial patterns and the potentially suitable areas for *M. excelsa* conservation in Benin. Therefore, it addressed the following research questions: (1) How is the density of Iroko population linked to altitudinal variation? (2) How far does the present-day suitable area for the Iroko trees’ conservation differ from the future ones?

Material And Methods:-

Study area

This study was carried out in the Republic of Benin (West Africa) which lies between 6°20’ to 12°25’N and 1° to 3°40’E. The country encompasses three climatic zones: the Guineo-Congolean zone, the Sudano-Guinean transition zone, and the Sudanian zone (White 1983; Fig.1). Annual rainfall varies between 900–1300 mm. The Guineo-Congolean zone is characterized by spatially scattered relics of semi-deciduous forests, savannah and plantations of various tree species. This is the zone of very high densities of human concentrations, with competitive land occupation for small-scale agriculture. The Sudano-Guinean transition zone is covered by a mosaic of forest woodlands, sometimes dry forests, and wooded savannah crossed by gallery forests, whereas vegetation in the Sudanian zone is composed of shrub savannah, ticklish pseudo-steppes, and gallery forests (Adjanohoun et al. 1989).

Study species

Milicia excelsa is a large dioecious and deciduous tree species. It is often found in deciduous / semi deciduous and evergreen forests, as well as in savannah woodlands (Ouinsavi et al. 2009). The specieshas a wide geographical range, occurring from Guinea to Mozambique and Tanzania (Daïnou et al. 2012). It can reach 30–50 m height, with a diameter of 1.70–2 m, with umbrella-like crown shape growing from a few thick branches (Ouinsavi et al. 2005). Iroko tree tolerate severe dry seasons up to 6 months in areas with mean annual rainfall as low as 700 mm, since the species has access to extra water from a perennial stream or underground source (Orwa et al. 2009). In Benin, the natural range of Iroko tree extends from the south up to 10°30’N (Ouinsavi and Sokpon 2010). Apart from natural forests reserves, Iroko tree grows spontaneously across various traditional agroforestry systems, with low densities for adults as well as for regeneration (Ouinsavi et al. 2005). *Milicia excelsa* has several economic and social values for Africans. The species is very useful in carpentry and joinery, in traditional medicine, and is of significant sociocultural values (Ouinsavi et al. 2005). The economic values of the Iroko tree are the main reasons for the species' overexploitation; thus reducing the population size, and leading to poor natural regenerations across it entire distribution range (Daïnou et al. 2010; Ofori and Cobbinah 2007).

Data collection

Assessing the spatial patterns of Iroko tree across land use types

Ouinsavi and Sokpon (2010) described the distribution of *M. exclesa* population across the entire national territory in Benin. Following that description, data were collected in randomly sampled districts, across phytochorogical zones (Fig. 1) across the country. Depending on the extent of each sampled district, three to four mega-transects of 10 km long line, were defined based on the presence of the species along. Along the mega-transects, inventory plots of 50 m x 30 m were installed when the species is present. Overall, fifty-three plots were installed (24 and 28 plots in forests and farmlands respectively). Using the Global Positioning System (GPS Garmin), the geographic coordinate of each plot was recorded at its center together with the following information: number of individuals of the species and threats to the species (i.e. bark removal, branch mutilation, pruning, etc.).

Assessing suitable habitat for Iroko conservation

Occurrence data

Records of *M. excelsa* were collected along the mega-transects. Complementary data were gathered from online databases especially the Global Biodiversity Information Facility (GBIF; www.gbif.org). The data was checked and used as an occurrence record, only if the identification was sufficiently trustworthy. Duplicate and doubtful records were discarded from the database, using ENMtools (www.ENMTools.com) and visual inspections (Idohou et al. 2017). In total, 117 records were gathered: 104 from fieldworks and 13 from GBIF database.

Environmental layers

Hamann and Wang (2006) demonstrated that climate plays crucial role in plant species distribution on earth, while soil factors give opportunity to visualize effects of ecological micro-variations, shaping tree species' occurrence and distribution at a fine scale across Tropical Africa (Pearson et al. 2003; Linder et al. 2005). Therefore, environmental data used in this research were twofold: climate and soil data. We downloaded current climate conditions (1950–2000) from the Africlim database (Platts et al. 2014). These data comprised the 19 bioclimatic variables at a resolution of 30 second grid cell (approximately 1 km x 1 km; Hijmans et al. 2005). Due to uncertainty in observational baselines (future anomalies) for Africa in four different main bioclimatic variables (mean temperature of wettest quarter, mean temperature of driest quarter, precipitation of warmest quarter, and precipitation of coldest quarter; Platts et al. 2014), we used the 15 most steady remaining climatic variables. We examined correlation patterns among these variables to select the totally independent ones. Therefore, only a set of environmental layers with a Pearson correlation coefficient below 0.80 (Elith et al. 2010) was considered. Here, we downloaded the soil data previously used by Idohou et al. (2017) and Sanchez et al. (2010), from ISRIC database (http://www.isric.org/; Nachtergaele et al. 2012). These data included: soil organic carbon (g/kg), pH, sand content (%), silt content (%), clay content (%), cation exchange capacity (cmol/kg), and bulk density (t/m^3) for six depth horizons (0–5, 5–15, 15-30, 30–60, 60–100, and 100–200 cm). Soil layers were also obtained at a spatial resolution of 30 arc second grid cell.

In order to assess potential impacts of climate change on the distribution of the species, we first gathered the regional climate models available for Africa (AFRICLIM; Platts et al. 2014). Two emission scenarios of the Representative Concentration Pathways (RCP) were considered: RCP4.5 and RCP8.5. RCPs are the third generation of scenarios and are preferred to Special Report on Emissions Scenarios (SRES) because they allow more flexibility (and reduced costs) in modeling processes (van Vuuren et al. 2011; Idohou et al. 2017). RCP4.5 includes relatively small changes with a temperature average increase of 2.4 °C, while RCP8.5 provides the most alarming trend with an average increase of 4.9 °C above preindustrial levels by 2100 (Rogelj et al. 2012), with atmospheric CO_2 equivalents of 650 and 1370 ppm by 2100 (Moss et al. 2010).

Data analysis

Density data description and autocorrelation verification

The density of *M. excelsa* was computed and described through the use of descriptive statistics. Parameters such as mean, minimum, maximum and standard deviation were calculated.

To test for probable spatial autocorrelation in the density of the species, Moran index was computed for each pair of sample plots, using the following formula:

$$I_{Moran} = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad \text{(Eq. 1)}$$

Where n is the number of plots, x is the variable of interest (density), and W_{ij} is an element of a matrix of spatial weights. The Moran statistic varies from -1 to +1, with 0 indicating absence of autocorrelation and thus, total independence between any random pair of plots. Values greater than 0 are indicative of positive spatial autocorrelation, while negative ones indicate negative spatial autocorrelation. Moran index values different from zero suggest dependence between plots (Goodchild 1986). The Moran index was computed using the Geostatistics for the Environmental Science (GS +) software.

Modeling the density spatial structure

Variogram function was used to build probabilistic model of the spatial structure of the density of Iroko trees. To perform the model, we assumed the: (1) the Iroko trees' regionalized density data were considered a gaussian random field, finite, and with first and the second order stationarities (Goovaerts 1997).These assumptions imply that the mean of the Iroko trees' density was constant all over our study area and that differences between densities at locations z_α and $z_{\alpha+h}$ existed and depended only on the lag-distance h. Thus, the semi variogram function of the Iroko tree density data was calculated as follow:

$$\gamma(\mathrm{h}) = \frac{1}{2\mathrm{N(h)}} \sum_{\alpha=1}^{\mathrm{N(h)}} [\mathrm{d}(\mathrm{z}_\alpha) - \mathrm{d}(\mathrm{z}_{\alpha+\mathrm{h}})]^2 \quad (2)$$

$\gamma(\mathrm{h}) =$ Semivariance, h = lag distances; $\mathrm{N(h)}$ is the number of data pairs within the class of distance, including direction effect; $[\mathrm{d}(\mathrm{z}_\alpha) - \mathrm{d}(\mathrm{z}_{\alpha+\mathrm{h}})]$ is an h-increment of the Iroko tree density. Omnidirectional experimental semi variogram was calculated and anisotropy was checked by computing directional semi variograms in four direction, with an angular tolerance of 22.5° for the experimental semi variograms of the density of Iroko trees was computed. Using the criterion of the coefficient of determination value, the isotropic model was fitted.

The Gaussian or hyperbolic isotropic model is similar to the exponential model but assumes a gradual rise for the y-intercept. The formula used for this model is:

$$\gamma(\mathrm{h}) = C_0 + \mathrm{C}\left[1 - e^{\left(-\frac{h}{A_0{}^2}\right)}\right] (3)$$

Where $\gamma(\mathrm{h}) =$ semivariance for interval distance class h, h = lag interval; $C_0 =$ nugget variance ≥ 0, $\mathrm{C} =$ structural variance $\geq C_0$, and $A_0 =$ range parameter. In the case of Gaussian model, the effective range $A = 3^{0.5}A_0$, which is the distance at which the sill $(C_0 + \mathrm{C})$ is within 5 % of the asymptote (the sill never meets the asymptote in the Gaussian or exponential models). The Experimental variogram was performed in the Geostatistics for the Environmental Science (GS +) software. Since, the coefficient of determination of the final model is low (R^2=0.338), kriging was not performed to estimate the density of Iroko trees at test locations (Alohou et al. 2017).

Modeling the distribution of the species

The maximum entropy algorithm (MaxEnt version 3.3.3k; Phillips et al. 2006) was used to model the ecological niche of the species, as this approach is considered to be robust and predictive (Elith and Graham 2009). MaxEntis a machine learning algorithm which applies the principle of maximum entropy to a species' presence-only data to estimate the species' potential geographic distribution (Phillips et al. 2006).

Maxent models were run using 10,000 background points, a maximum of 1000 iterations. Minimum training presence and five bootstrap replicates were used for training the models. Results of the model were evaluated using the partial ROC procedure (Peterson et al. 2008). For that, occurrence data were split into training (50 %) and testing (50 %) subsets at random and run with 500 iterations, to permit assessment of how the model is robust and predictive. The partial ROC test assesses whether the AUC ratios resulting were significantly higher than 1.0, which is the performance of a random classifier (Peterson et al. 2008). Suitable habitats for *M. excelsa* under current and future climatic conditions generated with MaxEnt were mapped using ArcGIS 10.1 software.

Results:-

Patterns of spatial autocorrelation

Descriptive statistics showed that *M. excelsa* density ranges from 6.6 stems/ha to 23.36 stems/ha with an average of 9.6 stems/ha (± 4.83). The highest values were recorded on farms, while the lowest values were recorded in forests. Test of Moran index clearly showed that there was a spatial autocorrelation inside the Iroko trees' density data across the landscape (p = 0.01; Fig. 2). Both positive and negative values of Moran index calculated, clearly indicated spatial dependence between *M. excelsa* populations according to the density (Fig. 2a). Moran index was constantly negative up to 100 km and decreased sharply (Fig. 2b). Beyond 100 km, the index increased in value. Population density of the species seemed to be different when they are two by two distant from 3 km to 150 km, but seemed similar between 0 and 3 km on one hand and beyond 150 km on the other hand (Fig. 2b).

Spatial structure of the density of *M. excelsa*

The calculation of the spatial structure of the density of Iroko trees reveals non-significant differences among and between directional and omnidirectional experimental variograms. Thus, the density of Iroko trees is a pure isotropic process (Fig. 3). A combination of a nugget plus gaussian models is adjusted to the omnidirectional variogram constructed for this study (solid line, Fig. 3). For this model, the nugget effect was evaluated to 8.2, the sill 57.4, and the range 3 km (Fig. 3). Semivariance of the density of Iroko trees can be predicted using the equation:

$$\gamma(\mathrm{h}) = 8.2 + 49.2\left[1 - e^{\left(-\frac{h}{1683.02^2}\right)}\right] (4)$$

Knowing the semivariance, the density of Iroko trees will be easily predict using the equation (2).

Variable selection and performance of the distribution models

Results from the correlation test revealed the six following variables as the most contributive to the models: annual precipitation, mean diurnal range, precipitation of driest period, and precipitation of driest quarter for bioclimatic variables; cation exchange capacity (cmol/kg) and sand content (%) for soil data variables. Precipitation of driest quarter, precipitation of driest period and cation exchange capacity were the best predictors (Table 1). The frequency histogram developed from the distribution of null values among 500 replicates showed that AUC ratio was above 1.0 (Fig. 4) for the model prediction. AUC ratio was between [1.10 – 1.99], with a mean partial AUC equal to 1.71, indicating a robust model, yielding predictions statistically significantly better than random (P □ 0.0001).

Geographically, the present-day distribution model indicated that the highest suitable areas for conservation were confined to the southern part of the study area and specifically located between 6°2' and 8°2' N. Highly suitable areas for *M. excelsa* fell within the Guineo-Congolean zone which is characterized by humid climate. Beyond latitude 8°2 N, the species habitat is less suitable and became unsuitable above latitude 10° North (Fig. 5). Results also demonstrated that distribution of *M. excelsa* will remain stable on the 2055-time horizon. A slight increase was noted across the highly suitable habitat for *M. excelsa*. According to future models with scenarios RCP4.5 and RCP8.5, respectively 4.71 and 6.95 % of present-day distribution suitable habitat of species will be converted in highly suitable habitat (Table 2). Moderately suitable habitat of *M. excels* was expected to expand toward the north part of country following scenario RCP8.5 (Fig. 6).

Discussion:-

Spatial variability of *Milicia excelsa* density

The stand density calculated for *M. excelsa* populations in this study was low but higher than the one previously reported by Ouinsavi and Sokpon (2010). These differences can be explained by the differences linked to the data collection protocol or to an awareness of the local populations and also restrictions of national conservation administrations on the species in recent years. The observations and data collected showed that *M excelsa* individuals are very rare in forest reserves, fields and fallow. However, the sacred groves were the last refuges of the species. Previous studies have revealed that sacred groves were key landscape features that can sustain higher levels of diversity; in southeastern Benin, they contribute to local conservation of native tree species of dense semi-deciduous forests (Ouinsavi and Sokpon 2010). Small forest fragments can be very relevant in maintaining plant species diversity provided that their habitat is of high quality and the management appropriate (Alohou et al. 2017). Forest reserves have shown weakness in conserving forest resources in the face of sacred groves (Alohou et al. 2017). The limited physical access to the sacred groves due to their religious character may have significant conservation implications. On-field isolated individuals of the species were mostly recorded. *Milicia excelsa* is found scattered in public places, farms, fallows and forests. Indeed, fragmentation of forest ecosystems can explain the isolation of *M. excelsa* individuals in the environment. The few individuals of *M. excelsa* isolated in nature are mostly preserved by traditional religions and beliefs (Alohou et al. 2016). Vihotogbé et al. (2019) and Salako et al. (2019) calculated higher range values for *Irvingia gabonensis* (Irvingiaceae) and *Borassus aethiopum* (Arecaceae), respectively. Because *I. gabonensis* is intensively cultivated in Benin, the variogram of this species presented the highest range. Therefore, this study confirms Iroko tree as the most threatened of these three species as classified in Benin.

Spatio-temporal dynamics of suitable areas for *Milicia excelsa*

Results indicated that, the most relevant factors explaining Iroko distribution were precipitation of driest quarter, precipitation of driest period and cation exchange capacity. This assumption suggests that rainfall during the dry season is a critical factor for the presence of *M. excelsa*, presumably because rainfall supports the persistence of the humidity of the soil. This might also explain why the range of *M. excelsa* has low expansion beyond 9° N, as the climate in this semi-arid zone with mean annual rainfall usually less than 1000 mm. The model also predicted that region above 11° latitude North provides no suitable habitat for *M. excelsa.* This may also be explained by climatic conditions, as this region has typically a more severe dry season. Among soil variables, cation exchange capacity (CEC) was most important factor which explained distribution of Iroko considering soil characteristics. A study realized by Ouinsavi et al. (2009) on morphological variation of iroko populations across different biogeographical zones in Benin, revealed that environmental variables and edaphic factors significantly affect morphological variation in iroko populations. They found most important variables which affect morphological variation in iroko populations were rainfall and CEC. These results seem to show that preference ecological conditions of Iroko were based on rainfall and soil factors (mostly, cation exchange capacity).

For species with limited information, predictive models are a useful tool to assist conservation planning (Wilting et al. 2010). Present model shows that distribution area for Iroko occurs in Guineo-congolean and Sudano-guinean zones. Both zones correspond to the area where the climate is humid and sub-humid. Results are consistent with the findings of Ouinsavi and Sopkon (2010) and Ouinsavi et al. (2005). According to the present and future conditions models, almost all high suitable area for Iroko distribution is confined to the Guineo-congolean zone of study area which provide actually a mean annual rainfall of 1200 mm (Sinsin et al. 2004). We note scanty increase of suitable areas of Iroko with future climates conditions under two Representative Concentrative Pathways (RCP4.5 and RCP 8.5), probably because according these futures scenario rainfall is projected to increase in western and eastern parts of the continent. According to our projection, climate change will not affect negatively the suitable habitat of *M. excelsa*. Our models have shown that SDMs can be helpful to indicate priority areas to study the sustainability of Iroko in Benin. Although SDMs play a key role in identifying areas with suitable abiotic conditions, it remains essential to realize that SDMs do not replace ground truthing (van Andel et al. 2015). Potential distribution ranges of Iroko does not necessarily mean that the species can easily survive at identified place. Species can be absent from areas with suitable abiotic conditions due to lack of biotic interactions (i.e. pollinator is missing), competitive exclusion by other species, inaccessibility due to geographical or (a)biotic barriers, or overharvesting by humans (Araújo and Peterson 2012). Accordingly, with its high distribution range confined in south of the country and its "Endangered" status on the Red List for Benin, *M. excelsa* needs an urgent conservation plan to ensure survival of remnants individuals of the species.

Implications for conservation

This overview of the potential distribution of *M. excelsa* population is a first step towards improving the conservation efforts of this threatened species in Benin. The current study provides evidence that the range of *M. excelsa* populations across the country has been severely depleted, possibly due to human activities (intensive logging and habitat destruction) combined with climate changes impacts. Fortunately, present-day distribution of the species which is highly suitable for *M. excelsa* is located in the Southern part and could contribute to protection of the existing remnants populations. For the future forecasts, a slight increase of the currently suitable habitat for the species is noted. Actually, most of existing Iroko remnants populations is located at the south western part of the country. In these regions, iroko trees are protected by traditional authorities as well as religious authorities, and anyone who contravenes the conservation are exposed to several severe consequences (Ouinsavi et al. 2005). This protection type adds to highly suitable areas of Iroko provides, good conditions for the species'conservation.

Conservation of sacred groves and reforestation activities using this species will be an advantage for protection and conservation of Iroko tree in Benin.

Table 1:- Contribution of predictor variables to the model.

Variables	Contribution %
Precipitation of driest quarter	39.5
precipitation of driestperiod	23.2
Cation exchange capacity	18.2
Sand	9.1
Annualprecipitation	8.6
Mean diurnal range	1.3

Table 2:- Potential habitat suitability for *M. excelsa* in Benin under current and future climates.

Species	Models	High suitability		Medium suitability		Low suitability	
		Area (km²)	Trends %	Area (km²)	Trends %	Area (km²)	Trends %
Milicia excelsa	Current	10515.94	--	12366.76	--	91791.30	--
	RCP4.5_2055	11011.52	+4.71	11098.26	-10.25	92564.22	+0.84
	RCP8.5_2055	11247.65	+6.95	12404.22	+0.3	91022.12	-0.83

(+): Positive percentage indicates gain; (-): Negative percentage indicates loss. Low suitability stands for probability □ 0.15, medium suitability stands for probability between 0.15 and 0.5; high suitability stands for probability is □ 0.5.

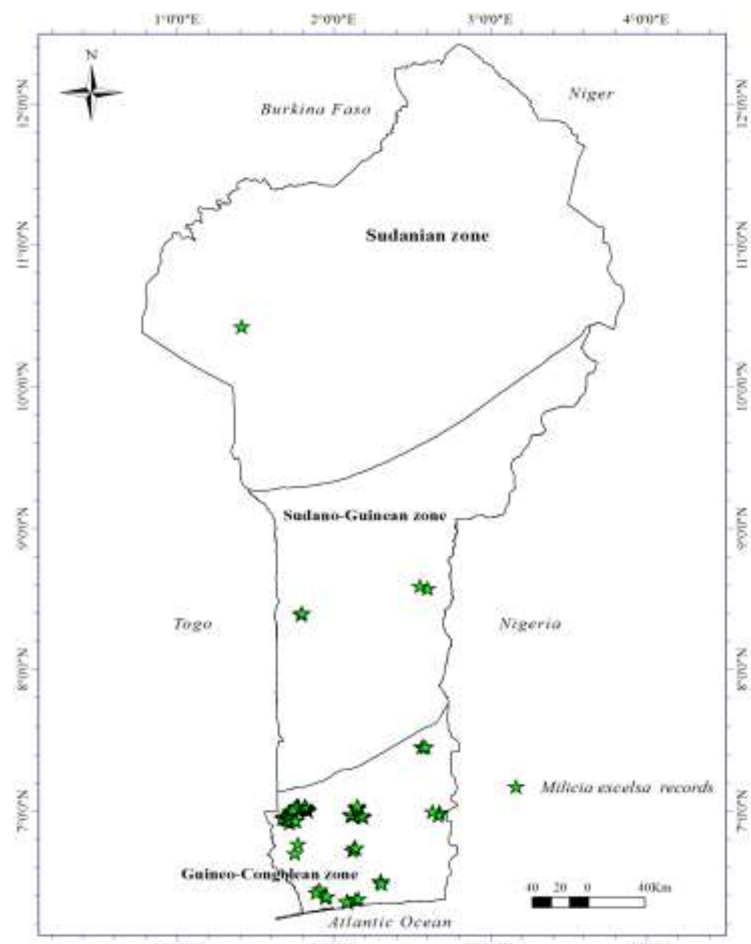
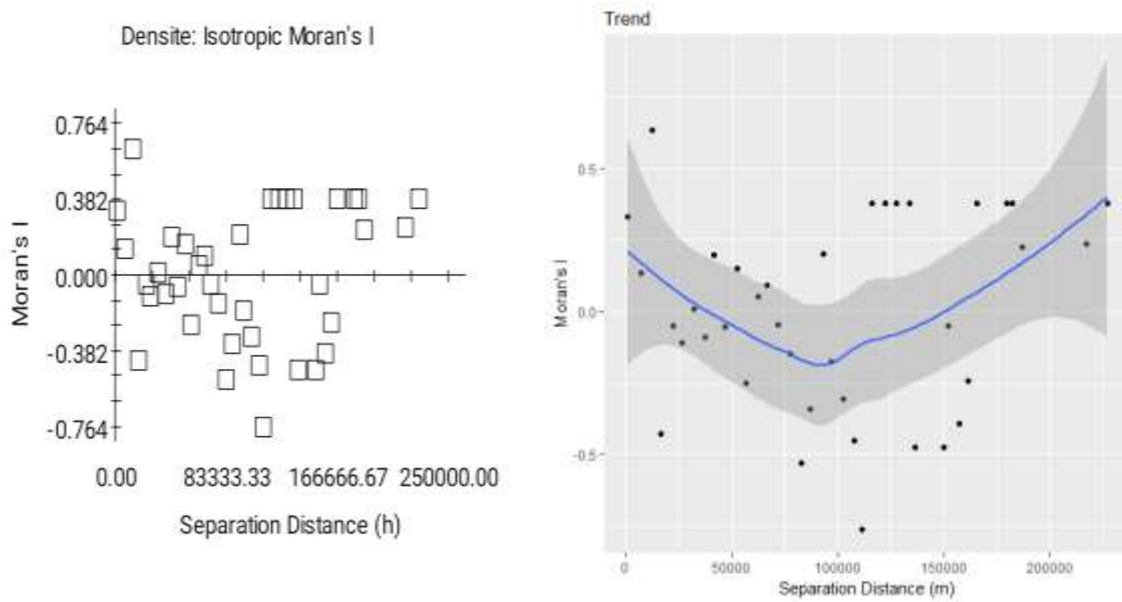
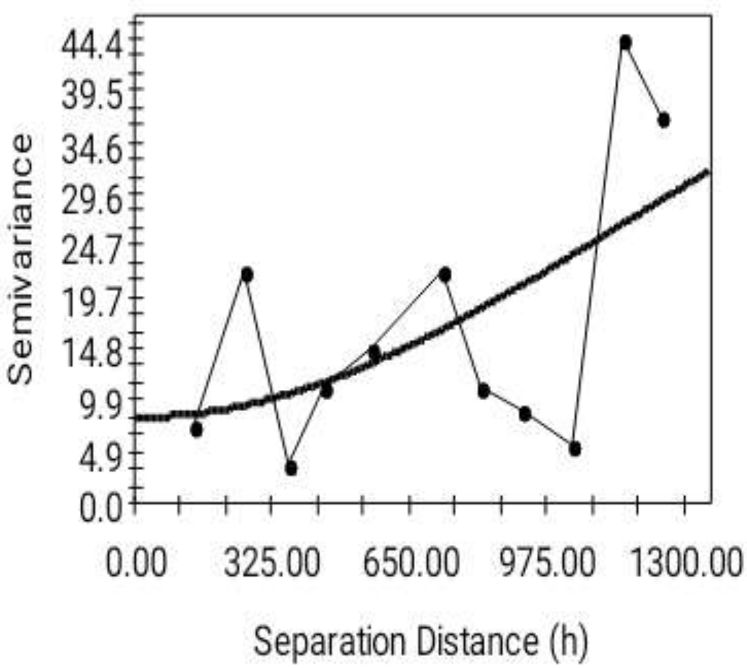


Fig. 1:- Map of study area showing occurrence records of *M. excelsa* across biogeographical zones of Benin.



a) b)

Fig. 2:- Spatial correlogram showing the patterns of spatial autocorrelation between plots.



Gaussian model (Co = 8.20000; Co + C = 57.40000; Ao = 1683.00; r2 = 0.338 RSS = 1159.)

Fig. 3:- Density of Iroko tress modeling: Isotropic Variogram.

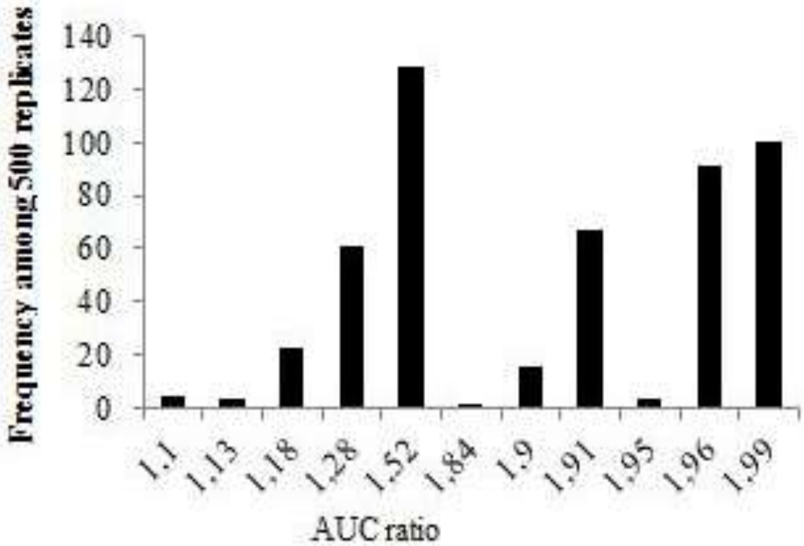


Fig. 4:- Maps showing variation of AUC ratio for 500 replicates using the Partial ROC procedure for *M. excels.*

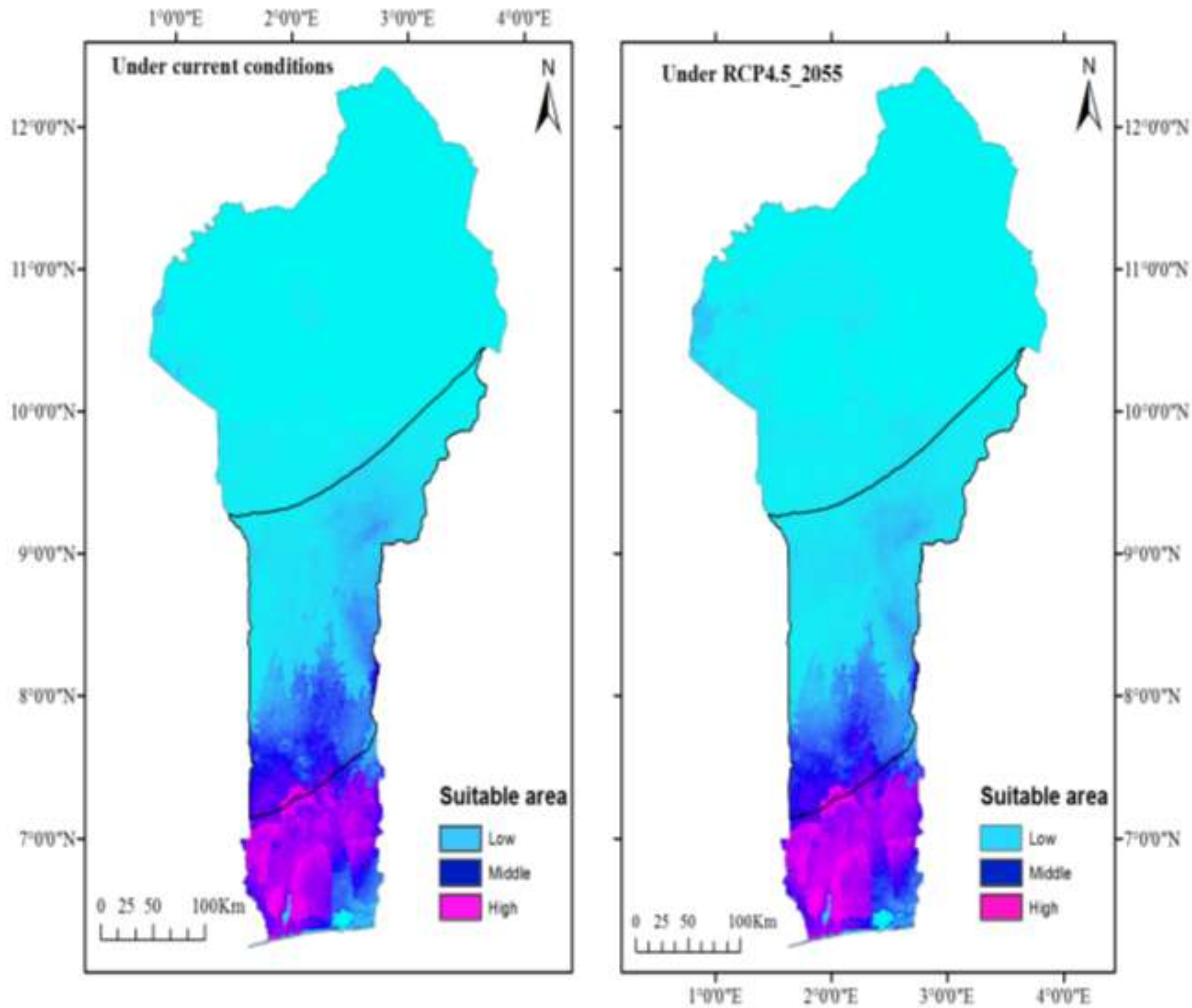


Fig. 5:- Suitable areas for conservation of *M. excelsa* under present and future climate (RCP4.5_2055).

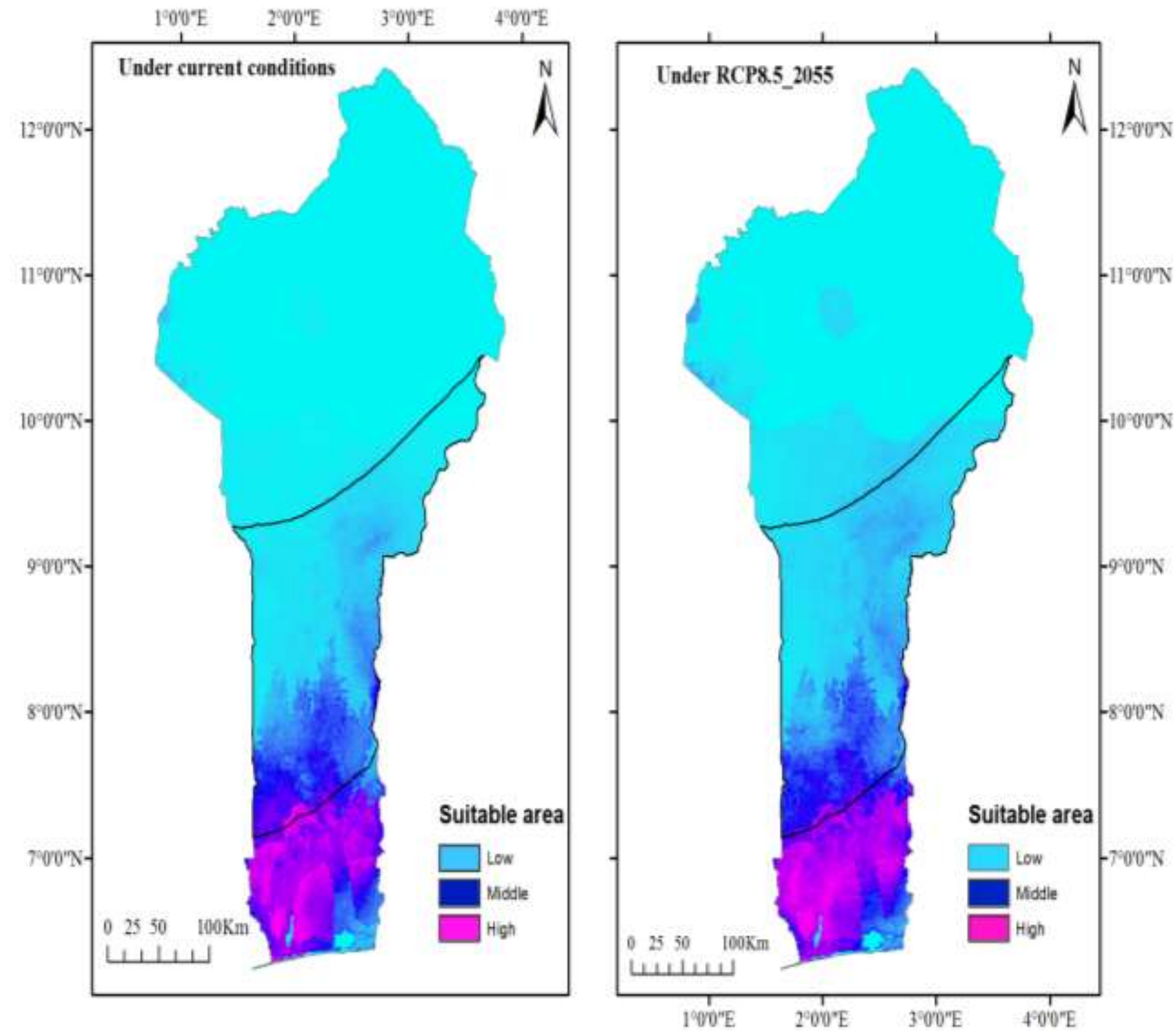


Fig. 6:- Suitable areas for conservation of *M. excelsa* under present and future climate (RCP8.5_2055).

Conclusion:-

This study assessed the spatial patterns and the suitable areas for Iroko conservation countrywide. Few expansions of the currently suitable areas to the species could be observed following future climate scenarios. These results imply that proper conservation measures should be taken to halt the fragmentation of the species habitat and reverse the tendency towards decline of populations of the species.

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Conflicts of interest :

The author declare that they have no conflict of interest

Availability of data and material :

Complementary data were gathered from online databases especially the Global Biodiversity Information Facility (GBIF; www.gbif.org). The data collected in the presented study after publication will also be available on the same site.

Code availability :
Not applicable

Ethics approval :
Not applicable

Consent to participate :
Not applicable

Consent for publication :
I affirm that the all authors have seen and agreed to the submitted version of the paper and their inclusion of name(s) as co-author(s).

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