Ecological Indicators 122 (2021) 107282



Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind





Impact of climate change on the spatial distribution of endemic legume species of the Guineo-Congolian forest, Africa

O.O. Oyebanji [a,b,*,1], G. Salako [c,1], L.M. Nneji [d,1], S.O. Oladipo [e], K.A. Bolarinwa [f], E. C. Chukwuma [g], A.O. Ayoola [d], T.E. Olagunju [h], D.J. Ighodalo [i], I.C. Nneji [j]

[a] Department of Botany, University of Lagos, Akoka, Yaba, Lagos State, Nigeria
[b] Kunming Institute of Botany, Chinese Academy of Sciences, Kunming, Yunnan Province, China
[c] Department of Environmental Management and Toxicology, Kwara State University, Malete, Kwara State, Nigeria
[d] Kunming Institute of Zoology, Chinese Academy of Sciences, Kunming, Yunnan Province, China
[e] Department of Biotechnology and Biosciences, Kwara State University, Malete, Kwara State, Nigeria
[f] Department of Science Education (Biology-unit), Distance Learning Institute, University of Lagos, Akoka, Lagos State, Nigeria
[g] Forest Herbarium Ibadan (FHI), Forestry Research Institute of Nigeria, Ibadan, Oyo State, Nigeria
[h] Department of Biology/Microbiology/Biotechnology, Alex Ekwueme Federal University, Ndufu-Alike Ikwo, Ebonyi State, Nigeria
[i] Department of Crop Protection and Environmental Biology, University of Ibadan, Oyo State, Nigeria
[j] Department of Biological Sciences, University of Abuja, Federal Capital Territory, Nigeria

ARTICLE INFO

Keywords:
Climate change
Leguminosae
SDM
Spatial distribution
Guineo-Congolian

ABSTRACT

Legumes (family Leguminosae) are an economically important and widely distributed species found in several regions of the world, including the Guineo-Congolian (GC) forest region. Recent studies have reported the impact of climate change on plant biodiversity. Thus, understanding the distribution pattern of the endemic legume species of the GC region under current and future climate scenarios are imperative for long-term conservation management plans. We used 762 occurrence data of the 237 endemic legume species to elucidate the habitat suitability and impact of climate change on the species. Analyses used an ecological niche modeling ensemble method to map the current and future (2050–2070) distribution patterns of the endemic legumes under the RCP 4.5 scenario. Further, we generated the ensemble of four different species distribution modeling methods to predict areas where climatically suitable regions is lost or gained under future climate change. The model predicted the current suitable areas for endemic legumes to be Southern Cameroon, Equatorial Guinea, Gabon, Republic of Congo (COG), and Democratic Republic of Congo (DRC). Our findings indicate precipitation of Warmest Quarter and seasonality as the significant climatic variables affecting the habitat suitability of endemic legumes in the GC regions. Results showed areas such as the coastal region of Cote d' Ivoire, southwest province of Cameroon, Central African Republic, COG (Ngounnie), central DRC, and southern Nigeria will experience >40% loss of climatically suitable areas by 2050. Also, species such as *Baphia maxima,* and *Psophocarpus scandens* were projected to experience a 70% reduction in their climatically suitable areas under future climate scenarios. Our study concludes that the projected distribution of the endemic legume species in the GC region will consequently decline in the future due to the gross effect of climate change. The anticipated changes in the distribution patterns of the endemic legumes could have significant ecological and socio-economic significance. Therefore, we recommend improved conservation to protect the endemic legume species and its associated habitats in GC forest.

1. Introduction

The Guineo-Congolian (GC) region – a biogeographic realm in Africa- is mostly covered by rain forest and swamp forest, with savanna and secondary forest (Myers et al., 2000). It divides into two regions- (Lower Guineo-Congolian (LGC) and Upper Guineo-Congolian (UGC) forests (Lebrun, 2001; White, 1983). The GC forest holds a striking pattern of species richness, endemism, and distribution pattern

* Corresponding author.
E-mail addresses: oyebanjioyetola@gmail.com, ooyebanji@unilag.edu.ng, oyetola@mail.kib.ac.cn (O.O. Oyebanji).
[1] These authors contributed equally to the work.

https://doi.org/10.1016/j.ecolind.2020.107282
Received 15 June 2020; Received in revised form 11 November 2020; Accepted 14 December 2020
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suggestive of a biodiversity hotspot (Beentje, 1996; Gomez et al., 2009; Lebrun, 2001; Mittermeier et al., 2004; White, 1983). However, previous studies have revealed an increased rate of plant diversity loss due to climate change (Dupont et al., 2001; Gentry, 1993; Lebrun, 2001; Richardson et al., 2001). The gradual loss of plant biodiversity has prompted studies on the habitat suitability and effect of climate change on the flora of the GC, especially the economically important plant families such as Leguminosae (de la Estrella et al., 2012; Demenou et al., 2016; Franklin, 2010).

The family Leguminosae (synonym: Fabaceae, see Turland et al., 2018), consisting of >19,000 species, is one of the most species-rich angiosperm families. It is globally distributed and occurs in diverse ecosystems, including arid, Mediterranean, temperate, tropical, and savanna (LPWG, 2013; Schrire et al., 2005). The Leguminosae remains one of the most dominant plant families in the GC forest, with many endemic species. The family presents diverse life-forms such as giant rain forest trees, woody lianas, shrubs, herbs, twining climbers, aquatics, and fire-adapted savanna species (Lewis and Schrire, 2003; LPWG, 2013).

Previous study on the legume distribution recorded >250 genera in Sub-Saharan Africa, with about 173 genera and 4481 species endemic to the region (Lewis, 2005). In GC forest, legumes provide many socio-economic services to humans, animals, and the environment (Lock, 1989; Sprent et al., 2010; Richardson et al., 2011). Despite the accrued socio-economic importance of legume, recent studies (Catarino et al., 2019) have reported increased threats to species survival and persistence in GC forest. Human activities, with its resultant effects on the climate pattern, present one of the most critical threats to plant biodiversity in the region. For example, plants such as *Albizia gummifera* (J.F. Gmel.) C.A. Sm., *Burkea africana* Hook., and *Pentaclethra macrophylla* Benth., are widely exploited for tannin production, human consumption, wood construction, and fodder (Catarino et al., 2019; Sprent et al., 2010). These activities represent a significant factor influencing the abundance and distribution pattern of legume species in GC forest. Besides, increased human actions could directly or indirectly affect environmental factors (e.g., temperature, humidity, and wind), which in turn predicts species distribution patterns. For instance, the temperature of the wettest quarter has been reported as an important environmental variable that predicts the distribution pattern of *Trifolium* Tourn. ex L. and *Adenocarpus* DC. (de la Estrella et al., 2012). The combined effects of climate change due to increased human activities may drive the endemic legume species of GC forest to local extinction (Ahmadi et al., 2019; Saltre et al., 2014). However, despite the importance of the legume species in the GC region, fewer study has addressed the impact of climate change on the current and future distribution of the endemic legume species. Thus, it is imperative to elucidate the habitat suitability and effects of climate change on the endemic legume species found in the GC forest region.

Several models have been developed to evaluate the influence of climate change on species distribution (Pearson and Dawson, 2003). An example of such a model is the Species Distribution Model (SDM). The SDM correlates occurrence data and environmental variables (e.g., climate, elevation, and vegetation) to predict species distribution over time (Ellis et al., 2014; Pearson and Dawson, 2003). It presents niche characteristics useful in influencing biodiversity management and conservation (Andriamparanya et al., 2015; Kremen et al., 2008; Monsarrat et al., 2019). The SDM approach is more reliable and accurate than the grid and expert-drawn methods (Graham and Hijmans, 2006). This model allows species delineation based on geographic and environmental niches through quantifying the relationships between their occurrences and associated biotic and abiotic variables. It also allows the prediction of species niches in unsampled regions. For instance, the SDM has been used to predict the distribution patterns and niche characteristics of several plants, such as *Dioscorea* L. spp. (Andriamparanya et al., 2015), *Chasmanthera dependens* Hochst. (Iloh et al., 2017), *Coffea canephora* Pierre ex A. Froehner (Gomez et al., 2009), *Distemonanthus benthamianus* Baill. (Demenou et al., 2016), legumes of West Central Africa (de la Estrella et al., 2012) and woody legumes in the Neotropics (Mogni et al., 2015).

However, as a result of the rapid evolution of SDM, more alternatives (e.g., Ensemble species distribution model [ESDM]) are becoming accessible because single algorithms can lead to uncertainty in species distributions. The ESDM allows a combination of several statistical algorithms, thus has been recommended to advance the species current range, species richness, and diversity (Marmion et al., 2009; Parviainen et al., 2001; Carvalho et al., 2010; Mateo et al., 2012). Different packages have been to conduct the ESDM. These models include stacked species distribution model (SSDM), raster, and rgdal. Currently, the SSDM has been used to predict biodiversity patterns along important ecological gradients and multiple species (Guisan and Rahbek, 2010). Typically, the SSDM uses a simple stacking of species responses to the environment and does not principally harmonize probable constraint on the peak number of species that can co-exist in a particular geographical area (Guisan and Rahbek, 2010; Carvalho et al., 2011). The efficiency of the SSDM to predict the biogeographic patterns for high species-rich clades has been reported in the past (Rahbek, 1995). Also, the SSDM approach has been used to predict species richness patterns for families such as Araceae and Bromeliaceae (Mateo et al., 2012). The SDM has also been applied to propose conservation planning for an economically important plant families (e.g. Sapindaceae) in West Africa (Adeyemi et al., 2012).

To date, there is limited information on the habitat suitability and impact of climate change on the endemic legume species in the GC forest. The effects of climate on the distribution of species, including endemic ones, are well established. But, the relative importance of different components of the environment varies with region and taxa. Identification of such specific climate elements that strongly affect species distribution is vital for understanding the impacts of climate change on their distribution. Given this, we used the SSDM approach to predict the spatial distribution under climate change and identify the conservation of endemic legume species in the GC region. Our objectives are as follows: (1) to predict the distribution patterns of the endemic legumes using the occurrence data; (2) to identify the climatic variables associated with the distribution of the endemic legume species in the GC forest; and (3) to predict where climatically suitable area is lost or gained under future climate change. Analyses used occurrence records of the legumes in the Global Biodiversity Information Facility (GBIF) database and environmental variables (bioclimatic variables and elevation) to generate the SDMs for the endemic legume species in the GC region. This study provides insights into the distribution patterns and impact of climate change on the endemic legume species in GC forest and critical areas of conservation priorities.

2. Materials and methods

2.1. Study area

The GC forest overlaps the global biodiversity hotspot Guinean Forest of West Africa and separated by the Dahomey Gap to form the two regions (LGC and UGC; White, 1983). The LGC forest spans the Congo Basin, Albertine Rift mountains in East Africa, and the West of the Atlantic Ocean, while the UGC extends from Sierra Leone to Ghana (Plana, 2004). Elevation in the GC forest varies accordingly. It ranges between 0 and 300 m along the West African coast and between 800 and >1000 m in Guinean highland and Eastern Democratic Republic of Congo (DRC). The GC forest is characterized by high total annual rainfall from 1500 mm to 2000 mm. The mean annual temperature is between 27 and 30 °C, with an extremely low-temperature range of 4 °C. Globally, the GC forest has been described as one of the richest biodiversity regions as it provides habitat for over 10,000 plant species (Gentry, 1993; Lebrun, 2001). To date, >8,000 plant species (see Gomez et al., 2009; Mittermeier et al., 2011) have been reported from the GC forest,

while ca. 1,800 are endemic to this region (Mittermeier et al., 2011). Our study area includes all the Guinean forest belt regions of West Africa except Mauritania, Mali, and Niger. The study covered 13 countries found across the GC forest: Benin, Burkina Faso, Cameroon, Central African Republic, Republic of Congo (COG), DRC, Cote d'Ivoire, Equatorial Guinea, Gabon, Ghana, Nigeria, Senegal, and Togo.

2.2. Data retrieval/ species occurrence data

To generate a comprehensive checklist of species of legumes endemic to the GC forest, we searched the Plant of the World online web database (http://www.plantsoftheworldonline.org; last access date-10.12.2019) and the International Legume Database and Information Service (www.ildis.org) to confirm the biogeography and endemic legume species of the GC. Therein, only the native range of a particular species (298) were retained for the study at the initial stage. For the occurrence data of each of the species, we consulted the GBIF (Marshall and Strine, 2019). We used the keyword "Leguminosae" to perform the initial search. Then, we strategically searched for the occurrence data of the endemic legume species in our focal countries (Fig. 1).

Further, the species occurrence list was reduced through systematic sampling reduction methods based on the years $\geq$ 1970 to date (Ranjitkar et al., 2014), species-level identification, inaccurate geographical location points, and incomplete records. After that, we performed data cleaning and quality control by checking the accuracy of the occurrence data by overlaying them on the administrative shapefile of our study areas (Scheldeman and van Zonneveld, 2010). Through this approach, we could filter out data that does not correspond to their point locations or found outside the study areas. To avoid over prediction and generalization, we query and used only species with occurrence records of a minimum of 3 and above. Finally, our model was run on 762 occurrence points (237 species) for the endemic legume species (Fig. 1; Appendix 1).

2.3. Environmental data and variable selection

The elevation data was downloaded from the USGS SRTM database (https://lta.cr.usgs.gov/SRTM1Arc) and was re-classified at 1000 m interval. The bioclimatic variables for the present and future projections were obtained from the WorldClim database (www.worldclim.org) at a spatial resolution of 30 arc-sec. To maintain spatial uniformity within the bioclimatic variables, we resampled the elevation data at 1 km^2 using the "vifstep" function in the USDM R package, R programming language. The Variation inflation factor (VIF) was used to optimize

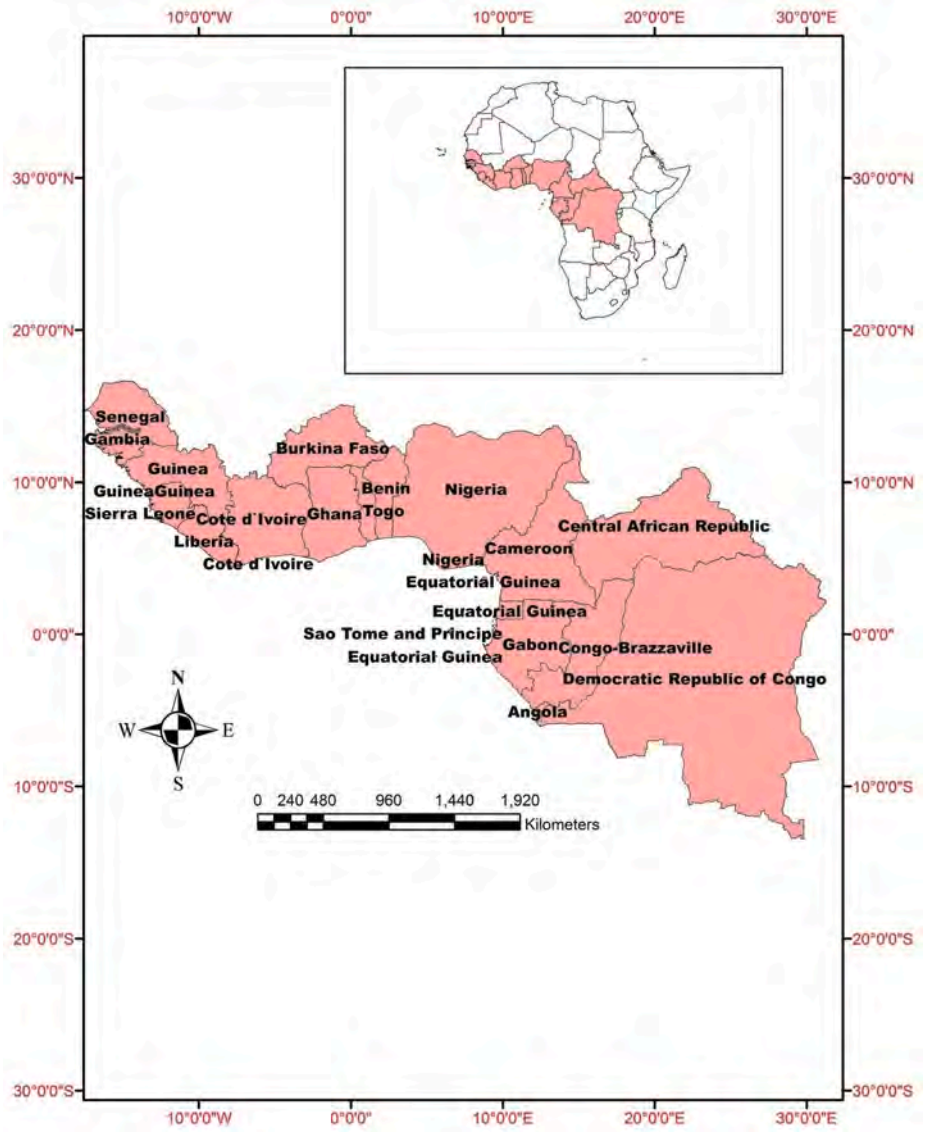


Fig. 1. Map of the study area showing the countries.

variables that best explain the distribution pattern of the endemic species (Ranjitkar et al., 2014). The rationale of the VIF has been previously reported (Quinn and Keough, 2002) with a VIF value > 10 indicating high collinearity; thus, such variable with VIF > 10 can negatively influence the SDM. Based on this, our initial analyses removed five highly correlated variables (BIO1, BIO7, BIO10, BIO16, and BIO17). We further performed repeated correlation computation with the maximum threshold set at 10 to reduce the variables. Given this, only variables ≤ 10 (Craney and Surles, 2002) were finally selected: BIO8, BIO13, BIO 14, BIO 15, and BIO18 with the most appropriate elevation (gc_alt2) (Table 1, Fig. S2). All the environmental variables were clipped to the study area boundary using mask command in Raster (Rgdal) package in R language.

The future climate projections of 2050 were retrieved from four databases: GCM, HadGEM2-AO, HadGEM2-ES, HadGEM-CC, and CCSM4. Thus, we used the RCP 4.5, which stands between optimistic RCP 2.6 and pessimistic RCP 8.5. Also, it is assumed that global greenhouse gas (GHG) emissions might begin to decline by 2040 in line with RCP 4.5 (Meinshausen et al., 2011), if the current concerted measures being taken globally are sustained.

2.4. Modeling approach and spatial analysis

We created the species distribution range map using ESDM at current (1950–2000) and future (2050). The mapping was performed by associating the 762 occurrence points data of the legume species, and pseudo absence data, which was randomly generated by the model (Barbet-Massin et al., 2012). All the six models were treated with unique SDM algorithms to determine the most suitable models for the ESDM (Ranjitkar et al., 2014). After that, we selected the four best models based on Area Under the Receiver Operator Curve (AUC) and Kappa values for ensemble modeling.

Analyses were performed using four models as follows: CTA (Classification Tree Analysis), MARS (Multivariate Adaptive Regression Spline Ensembles), GLM (Generalized Linear Model), and MAXENT: Maximum Entropy with suitability ranges from 0 (unsuitable) to 1 (highly suitable). We evaluated our model performance using AUC and Cohen's KAPPA values. We set the threshold to 0.8, indicating the exclusion of any species with AUC < 0.8 for the modeling. The closer the AUC values (0 ≤ 1) to 1, the more the accuracy of the model to predict the suitability of the occurrence of species (Salako et al., 2015). Finally, the maps of the species richness for the current and future projections were generated using stacked species distribution models (SSDM). This was estimated by finding the weighted means of all the four selected models in the ESDM of our aggregated multiple species. However, the species richness map was rescaled from 0 to 30 for more differentiated comparisons across the landscape. In our study, we evaluated the variable importance/contribution scores for the individual variable in the study area using Pearson's correlation coefficients (Nneji et al., 2019; Rana et al., 2018). The outcome of this analysis was used to determine to what extent does a variable contributes to the model. Two binary rasters, 0 and 1, indicating absence and presence respectively, were produced to model the current and future distributions of the endemic legume species in the GC.

Table 1
Variables and Modeling algorithms used for the legume species endemic to the GC forest.

Item	Name of variable	Description
Variable	Years	Current (1950–2000) as baseline and 2050 for future
	Scenarios	An ensemble of downscaled Models under RCP 4.5
	Location	GC region
	Spatial resolution	1 km (~30 arc-sec)
	Climate	BIO8 (Mean temperature of wettest quarter – °C), BIO13 (Precipitation of Wettest period – mm) BIO 14 (Precipitation of Driest Month – mm), BIO 15 (Precipitation seasonality [coefficient of variation] – %) BIO18 (Precipitation of warmest quarter – mm)
	Elevation	gc_alt2
Model	Method	Description
	CTA	A simple non-parametric regression approach, which recursively partitioned all area covered by the predictor variables into a set of rectangular areas
	MARS	A non-parametric regression technique that automatically models non-linearities and interactions between variables.
	GLM	GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of the predictor variable.
	MAXENT	It is a machine-learning method that estimates the species distribution probability by assessing the maximum entropy distribution, so that the most spread-out, or closest to the uniform.

To predict areas that will experience loss or gain of endemic legume species in the GC, we used the 2050 GCM projection. Herein, only the variables (VIF ≤ 10; BIO8, BIO13, BIO 14, BIO 15, and BIO18) with the most appropriate elevation (gc_alt2) that significantly contributed to the model prediction were used for the analysis (Fig. S2). Then, we estimated the potential impact of climate change on species distribution. To achieve this, we first identified six sub-regions for our analyses based on the elevational gradient: 1. Guinean highland, 2. West coast lowland (Sierra Leone, Liberia, Ghana, and Nigeria), 3. Cameroon highland (southern and central), 4. Congo basin lowland, 5. Equatorial Guinea, COG and DRC, and 6. DRC East highland. Then, we generated changes in species richness distributional ranges (biodiversity change) by performing image differences between the two images (current and future distributional range). This was calculated by finding the difference between each pixel in each image using map algebra of current and future species distribution range. The mathematical expression is

$$\mathrm{Img.d}(x, y) = \frac{Img2(x.y) - Img1(x, y)}{Img1(x, y)} * 100$$

where;

Img.d = image difference,
*Img*1= Images at the current time,
*Img*2 = Image at a future time
x and y = geographic coordinates of the images
*100 = multiply by 100

Note: A positive sign indicates an increase in class size, while a negative indicates a decrease (Karthik and Shivakumar, 2017).

Lastly, we subsequently masked out regions based on percentage biodiversity loss (<10%, 20%, 30% and > 30%) due to climate change. We performed both the current and future spatial analysis by countries using five suitability categories: Not suitable, Marginally suitable, Moderately suitable, Suitable, and Very suitable (Appendix S2). All the spatial analysis was performed in ArcMap 10.2.

3. Results

3.1. ESDM and SSDM analysis

The models generated for the training data set are reliable, as indicated by the Area Under Curve (AUC = 0.869) and Kappa (0.704) values. Our Ensemble SDM presents high species richness in five countries, namely: Cameroon (southern), Equatorial Guinea, Gabon, COG, and DRC (Fig. 2a). Further, *Afzelia bipindensis* Harms, *Albizia* Durazz. spp., *Amphimas pterocarpoides* Harms, *Baphia nitida* G.Lodd., and *Dialium angolense* Welw. ex Oliv. were the most dominant species in the GC forest. According to Pearson's correlation coefficient analysis, the

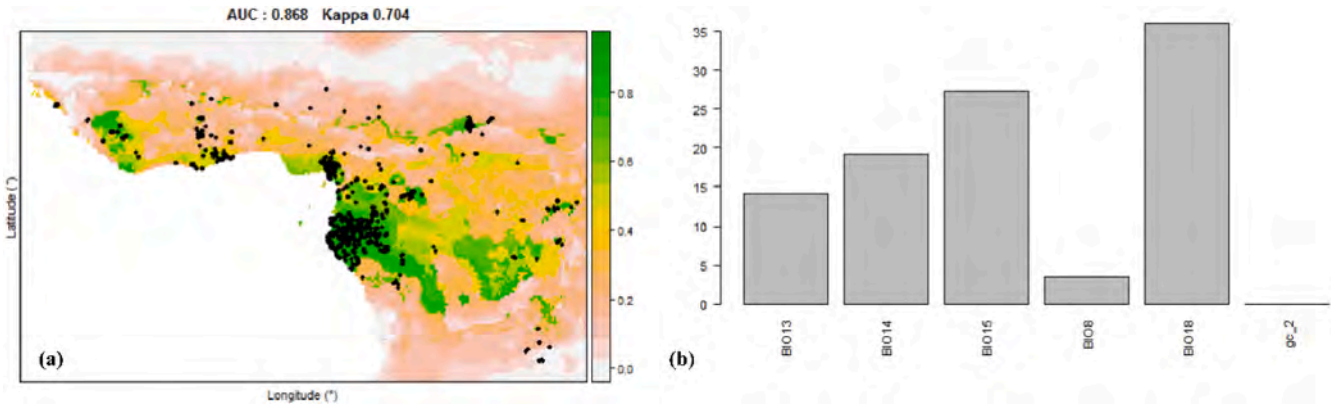


Fig. 2. Map of Ensemble SDMs in the GC forest (a) plant species at the current level and (b) and variable importance.

environmental variable BIO18 (Precipitation of Warmest Quarter) had the highest environmental importance as it contributed about 35% of the total variance. In comparison, the elevation had the least <2% (Fig. 2b).

3.2. Legume diversity pattern in the GC forest

The present SDMs of the endemic legumes were stacked to generate species distribution models of the current and future distribution for each country in the GC (Fig. 3; Appendix S2). The spatial distribution pattern of endemic legumes of GC forest in the ESDM map greatly corresponds with the species richness map at the current level (Fig. 3a and b). Currently, the endemic legume species richness hotspots occurred along the coastline of Guinea, Ghana, Nigeria, Cameroon, Gabon, Equatorial Guinea, and the central part of DRC. These areas are projected to lose up to 30% of their species suitability range. Our analysis

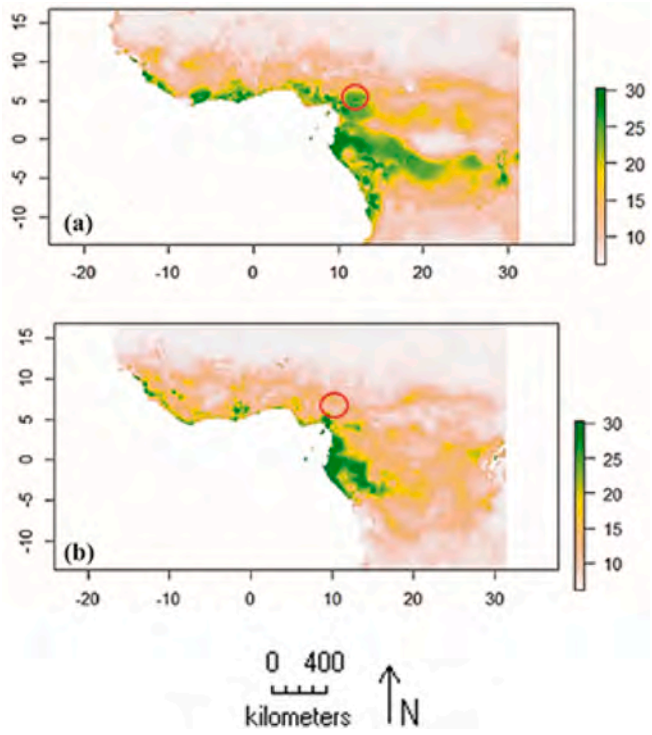


Fig. 3. Stacked Species Distribution Models (SSDM) of Plant species Richness at (a) current and (b) Future 2050. Biodiversity richness/loss in Cameroon is indicated red circle. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

predicted a decrease in species richness of endemic legumes, especially in Cote d'Ivoire, Nigeria, Cameroon, Central African Republic, COG, and DRC. Likewise, the analyses indicate species loss (>30%) of the endemic legume due to climate change (Fig. 4).

The result of image differences between current and future species distribution range shows that species reduction of ≥ 40% will occur in countries such as Cote d' Ivoire, Nigeria, Cameroon, Central African Republic, COG, and DRC (Fig. 4). Our model projected that ten species might lose their potential distributional range with >40% in these hotspots' areas by 2050 (Table 2). Specifically, our prediction revealed ten species that could lose >50% of climatically suitable areas due to climate change. Particularly, each species of *Baphia maxima* Baker and *Psophocarpus scandens* (Endl.) Verdc. might suffer a loss of up to 70% of their climatically suitable areas in DRC and COG (Table 2).

4. Discussion

The vast application of the SDM approach, particularly in areas where species occurrence is poorly known, has been reported in previous studies (Ranjitkar et al., 2016, 2014). To date, SDM remains one of the most suitable ecological approaches to understand relationships between species distribution and environmental variables. At the same time, it is useful in predicting the present and future occurrence of species (Andriamparanya et al., 2015; Demenou et al., 2016; Nneji et al., 2019; Pearson and Dawson, 2003; Rana et al., 2018). Our current study only used the SDM approach to investigate the influence of climate change on the climatic suitability for on the legume species endemic to the GC forest, while other aspects (e.g. productivity, dispersal, etc) that could be affected by climate change are unexplored. This study revealed high species richness of the endemic legume species along the coastline of Guinea, Ghana, Nigeria, Cameroon, Gabon, Equatorial Guinea, and central part of DRC. Our result on species richness in these countries corroborates with the previous study of Linder (2001). Plant species distribution patterns in these areas are driven by high rainfall and ecological variation (Plana, 2004; Sosef et al., 2006). Thus, it is likely that the observed high species richness and endemism may be due to suitable environmental factors (e.g., high rainfall, etc.) and climate stability over time (Linder, 2001; Moritz et al., 2000; Plana, 2004).

Our study found evidence that climate change can affect the distribution of legume species endemic to the GC forest. Climate change has a potential influence on plant distribution; thus, they predict the species population size (Nneji et al., 2019; Woodward, 1992). For instance, precipitation is the major climatic factors that determine the distribution of *Alnus* Mill. spp. in Nepal (Ranjitkar et al., 2016). Also, temperature and geology (>2000 m asl) account for the variability in the distribution of some legumes genera (e.g., *Adenocarpus* and *Trifolium*) found in the Afromontane regions of the Afro-tropics (Plana, 2004). These findings are congruent with our studies that reported

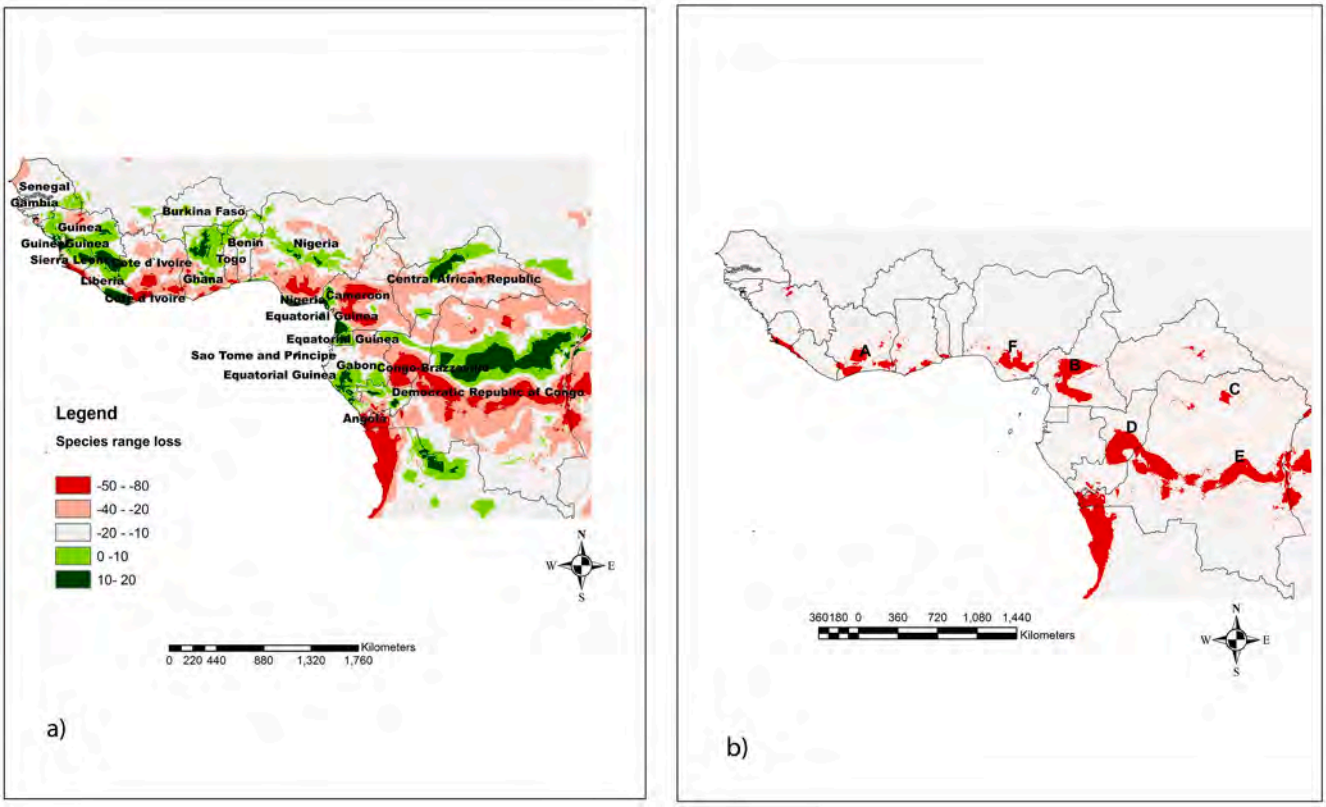


Fig. 4. Prediction of the loss of endemic legume species in the GC: (a) Biodiversity area loss by percentage and (b) Hotspots of biodiversity loss due to climate change. A = coastal region of Cote d' Ivoire B = Cameroon south west province, C = North western CAR, D = Upper Lacini reserve in the Plateau province, Congo and E = Mai Ndombe district in Congo Brazzaville F = Midwest and southeastern Nigeria around udi plateau and Oji rivers.

Table 2
Distributional range of legume species projected to reduce by ≤ 40% by the year 2050 in GC.

S/No	Species	Number of occurrence	Country/Region	% loss (−)
1	*Angylocalyx oligophyllus* Baker f.	10	Nigeria-Cameroon Border	−50
2	*Cynometra hankei Harms*	3	Cameroon	−50
3	*Pseudovigna sulaensis* R. Clark & Burgt	3	Siera Leone	−50
4	*Vigna comosa* Baker	7	Guinea-Cote d' Ivoire border	−50
5	*Adenocarpus mannii* Hook. f.	6	Cameroon	−60
6	*Berlinia grandiflora* (Vahl) Hutch. & Dalziel	6	Cote d' Ivoire	−60
7	*Cassia mannii* Oliv.	6	Gabon	−60
8	*Dialium tessmannii* Harms	3	Nigeria-Cameroon Border of COG and DRC	−60
9	*Baphia maxima* Baker	5	DRC	−70
10	*Psophocarpus scandens* (Endl.) Verdc.	4	COG; DRC	−70

precipitation of driest quarter and temperature ranges as the most significant variables that influence the distribution and climatically suitabe areas for *A. pterocarpoides* and *Albizia* spp. in the GC forest. Typically, temperature, water availability, humidity, rainfall, wind, and precipitation are critical environmental variables for delimiting vegetation types and species distribution in tropical Africa (Maharjan et al., 2011). Also, previous studies have reported seed dispersal and anthropogenic activities as an additional factor that may determine the species distribution range (e.g., Sexton et al., 2009). On the contrary, our modeling inferred that elevation did not significantly contribute to the distribution patterns of the endemic legumes in the GC. . For instance, the elevation contributed <2% of the total variables, thus has little impact on the focal group in this study (Fig. 2b). Although, previous studies reported that elevational changes might cause range expansion or contraction of plant species (Franklin, 2010; Rana et al., 2018; Ranjitkar et al., 2016; Salick et al., 2009). Therefore, we suggest future studies to critically evaluate the effects of elevation on the distribution pattern of the endemic legume species in the GC forest to achieve robust inferences.

Our SDM projection predicted an increase in the loss of the endemic legume species in the GC by 2050 due to climate change. Results showed a decrease (≥40%) in plant species richness in the coast line of Cote d' Ivoire, south east Nigeria border with Cameroon, south west province in Cameroon, Central African Republic, Ngounie region of COG, and central DRC. Although the data available precludes the evaluation of the contributions of the climate on species-specific occurrences, our model linked species range shifts and distributions within the GC forest in response to climate e.g., temperature and precipitation (Fig. 3b). However, we predicted endemic legume species that could loss (in percentages) their climatically suitable areas to climate change e.g., *Angylocalyx oligophyllus* Baker f., *Berlinia grandiflora* (Vahl) Hutch. & Dalziel, and *Baphia maxima* would loss 50, 60 and 70%, of their suitable habitats such as Nigeria-Cameroon border, Cameroon, and DRC, respectively (Table 2). According to a previous study, climate fluctuations during the Cenozoic and Pleistocene contribute to the loss of biodiversity in the African rainforests (Plana, 2004). Our findings are crucial to the future development of sustainable management of the endemic legume species in the GC forest. Interestingly, our model suggested the endemic legume species that may be given much conservation priorities in the GC (Table 2). Following this, we suggest further studies to evaluate the

integrative impacts of individual or multiple of these factors on the distribution pattern of endemic legumes in the GC forest. We further recommend an improved conservation policy to protect the endemic plant species from Gabon, Equatorial Guinea, and Central DRC.

Climate change may induce specific genetic diversity, gene flow, and coevolutionary patterns in plant community (Davis et al., 2005; Pauls et al., 2013; Szucs et al., 2017). Herein, our prediction revealed that that increase of temperature could lead to reduction of climatically suitable areas for specific endemic legume species. Thus, the genetic variability within the GC may perhaps be associated to the response of specific species to certain ecotypes. As a result, the same species adapted to hot environment could replace less adapted ecotypes, which could lead to a reduction of the species genetic variability, but not the extinction of the species. The genetic improvement of some of these species, especially, to cope under the varying temperature ranges may be necessary to intercept the genetic erosion envisaged. The loss/gain of species in a particular region over time is attributed to climate suitability and species adaptability. The adaptability features provide support to overcome barriers related to geographic patterns to thrive in a wide range of biotic and non-climatic environmental conditions (Bellard et al., 2013). Similar to most SDMs, the current study did not provide information on dispersal capacities and biotic interactions; instead, it focuses only on the impact of the future climate change on the distribution regions and predicted climatic suitability for the endemic legume species in the GC. This study confirms the extent of species-rich of the GC forest blocks; thus, it may be designated for conserving the endemic legumes species in tropical Africa (Dupont et al., 2001).

Moreover, previous studies have identified several other ecological factors that are also individually or combined with climate change to determine species distribution patterns. For instance, in Nigeria, the rapid expansion of human population has led to excessive logging, conversion of forest lands to farmland, urban development programs and over-exploitation. A total number of stems exploited for logs estimated to ca. 11,377 (volume of 295 089.67 m^3), which are typical hardwoods from tropical rainforests were over harvested from Ondo State forest reserves between 2003 and 2005 (Adekunle et al., 2010). Similar ecological disturbances have been reported in DRC as the majority derived their income from agricultural-based products and mining activities (e.g. in Katanga; Bart et al., 2012). Unfortunately, this trend extends across other hotspot regions regarded as the endemic legume species in the GC. These ecological factors, alongside climate change, maybe parsimonious to explain the distribution pattern of the endemic legume species in the GC forest. This agrees with the land use pattern, increase in population, expansion of tourist industries, infrastructural development, conversion of natural forest to monocropping vegetation, and species short generation times previously reported that can re-shape species diversity (Bradley et al., 2009; Paudel et al., 2016; Pyšek and Richardson, 2010; Shrestha et al., 2018).

Likewise, the study showed the relevance of species distribution occurrences data gathered over a longer time and archived in public databases. For this study, we recovered the occurrence data for the legume species endemic to the GC forest from the GBIF. Previous studies had recommended the leverage provided by the GBIF database through the availability of species occurrence data to address issues related to biogeography, conservation, and ecology (De Luca et al., 2019). Despite these huge advantages, we observed that incomplete information, inaccurate coordinate points, and inappropriate species identification might decrease the usability of these data. For instance, we could not use many location data for this study because of unknown status and incomplete information. Therefore, we suggest accurate data curation before submission to the GBIF archive. However, the occurrence distribution data in the GBIF was able to provide useful data, especially for extensive-scale studies on these economic species that are endemic to the GC forest.

5. Conclusion

Our study provides deep insights into the future effect of climate change on the distribution of endemic legumes in the GC forest. The conservation of the GC forest is highly essential because it contains endemic and economically important legume species. Thus, our study grossly recommends an improved conservation strategy and management plans for these areas, especially where the rate of loss of endemic legumes is high (>30%). Further, we recommend conservation awareness at regional, national, and local scales to reduce anthropogenic activities. In-situ and ex-situ method conservation and development of strict management conservation schemes are imperative to prevent the loss of endemic legume species as predicted in this study.

CRediT authorship contribution statement

O.O. Oyebanji: Conceptualization, Data curation, Writing - original draft, Writing - review & editing, Supervision, Methodology. **G. Salako:** Conceptualization, Data curation, Writing - original draft, Formal analysis, Methodology. **L.M. Nneji:** Conceptualization, Validation, Supervision, Methodology. **S.O. Oladipo:** Data curation, Project administration. **K.A. Bolarinwa:** Data curation, Writing - original draft. **E.C. Chukwuma:** Data curation, Writing - review & editing. **A.O. Ayoola:** Writing - original draft, Visualization. **T.E. Olagunju:** Data curation, Visualization. **D.J. Ighodalo:** Data curation, Project administration. **I.C. Nneji:** Investigation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.107282.

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