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The Impact of Changing Climate on Agroforestry Tree Distribution across Agroecological Zones of Nigeria: MaxEnt Modelling Perspective

Ibrahim Ndaginna Abdullahi

Department of Crop Science, Faculty of Agriculture, University of Abuja, Abuja, Nigeria
Email: ibrahim.abdullahi@uniabuja.edu.ng

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Abstract

The survival of agroforestry tree species in sub-Saharan Africa is essential for sustainable livelihoods, particularly in the semi-arid environment. Drought in the Agroecological zones (AEZ) of Nigeria is one of the environmental factors limiting parkland tree regeneration. Species distribution modelling offers the opportunity to predict future distributions of plant species based on current distribution data and bioclimatic variables. Maxent (maximum entropy) model was employed to predict the future tree distribution in AEZ parklands, under the four Representative Concentration Pathway (RCP) climate change prediction using current tree distribution (presence-only data) along a transect across three agroecological zones. The spatial data used were 19 bioclimatic variables and presence-only data for the two most important tree species—*Parkia biglobosa* and *Vitellaria paradoxa.* The result showed a drastic reduction (>45%) in the suitability of farmlands across predictions observed in the studied agroecological zones. The 2050 scenario in both species predicted areas had an increasing mid-range potential, over 44% lower suitability in sampled AEZ distribution predictions. The future prediction potential distribution maps for year 2070 of both species displayed large variations in suitability compared to 2050, showing a significant increase (up to 53%) in areas climatically suitable for both species to regenerate and thrive. This is attributed to over increased annual evapotranspiration, despite increasing seasonal precipitation. This study highlights the need for more climate-smart regeneration and improved restoration strategies to reduce land degradation as climate conditions change over time.

Keywords

Restoration, Species Distribution, Drought, Maximum Entropy

1. Introduction

Quantifying changes in the spatial pattern of tree distribution for parkland landscape species can assist farmers in appropriate species selection, enhancing trees outside forest contribution to sustainable livelihoods. The first stage in modelling parkland tree plant distribution is the evaluation of the relationship between current tree species occurrence and current environmental conditions. Next, future climate factors can be used to predict the tree growing conditions and these are used to determine the predictive distribution model. Output from such models is useful for landscape restoration (Chahouki & Sahragard, 2016). Predictive species distribution modelling (SDM) of trees has been applied in the study of invasive plant species trends and patterns (Thuiller et al., 2005), modelling species habitat niche and suitability (Deblauwe et al., 2016), deriving spatial information on species diversity and richness (Dubuis et al., 2011) as well as trying to predict the impact of changing climate effects on agrobiodiversity survival (Kotschi, 2006; Verheyen et al., 2016). There are species distribution models available for predicting the distribution of plant species and hydrology, each method having peculiar characteristics influencing the output factors (Moore et al., 2007; Onojeghuo et al., 2015; Oyerinde et al., 2016; Phillips et al., 1997; Prudhomme et al., 2014). Austin (2002) described the ecological model, the data model, and the statistical model as significant components contributing to fitting species distribution models. The best fitting models for species distribution include statistical modelling which is influenced by external factors, including the presence of data availability, environmental factors and different variables' effects on the model prediction (Chahouki & Sahragard, 2016; Phillips, Anderson, Dudík, Schapire, & Blair, 2017). Species distribution predictive models are classified into two categories based on the required type of input data (Guisan & Zimmermann, 2000). These are the presence-absence models and the presence-only models. However, the potential to maximise climate resource-use with a limited amount of data has generated different SDM methods for modelling presence-only data, particularly on the plant species distribution (Chahouki & Sahragard, 2016). The MaxEnt (Maximum Entropy) method is one presence-only model technique with better accuracy (and wider acceptance) in prediction than other methods. The model predicts plant species occurrence localities using the estimation of a set of environmental variables that explains a few factors influencing the suitability of a species niche in a given time (Phillips et al., 1997). The species' fundamental niche (forests, grasslands and parklands) is a combination of climate and ecological conditions that determine survivability in the long term. The real niche, a subset of the fundamental niche (e.g. parklands) that species occupy, can be predictable using the factors contributing to the overall agroecosystem (Case & Lawler, 2017). MaxEnt model is considered the best fitter because it is less sensitive to overfitting, especially when samples size, such as the real niche (parklands), is small, as it regularizes the input variables to help avoid the performance problems induced by overfitting. The model is being run using linear and quadratic terms in combination with other settings that are kept as default in MaxEnt software until modified. The training sample is focused on the input of environmental variables and species occurrences geographical information under tuned parameters and choice of feature classes.

Lyam et al. (2012) performed species distribution modelling for native *Chrysopyllium albidum* tree species in South-western Nigeria using MaxEnt and reported 55% of the niche distribution is associated with temperature (at the coldest quarter) and only about 18% for precipitation for all potential sites for regeneration. Other research findings in sub-Saharan Africa also showed that MaxEnt predicts geographical distributions of plant and animal species more accurately compared to other spatial methods (Bocksberger et al., 2016; Li et al., 2014; Onojeghuo et al., 2015; Phillips et al., 1997).

Bioclimatic variables from worldclim.org are considered as one of the most significant climate records for global species modelling. This is because of its influence on trees

2. Materials and Methods

1) Species Data

Field points spatial information of agroforestry trees were additional data collected across different farmland 774 locations corresponding to the local government areas in the agroecological zones of Nigeria (**Figure 1**).

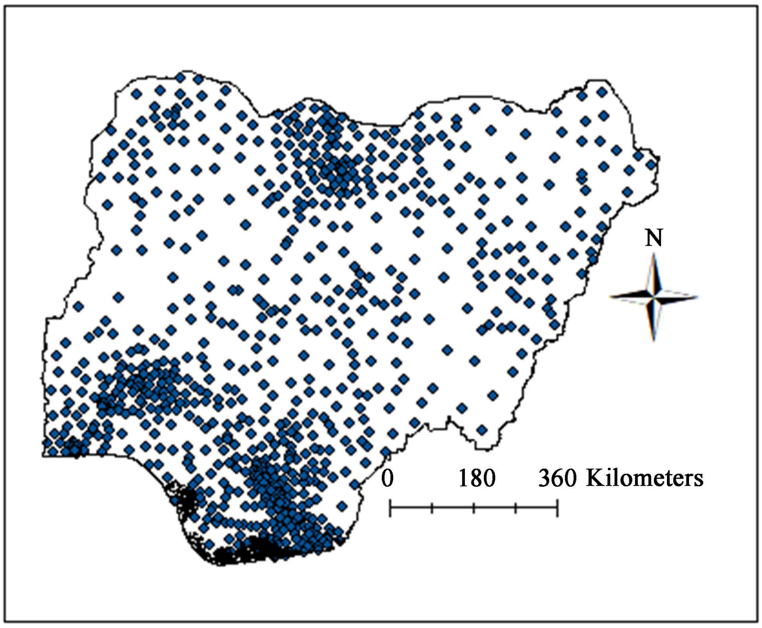

Figure 1. Map of Nigeria showing sampled 774 field points across the agroecological zones.

2) Environmental Data

Tree abundance and frequency were assessed and simulated with the climate data at the presence locations. Nineteen spatial bioclimatic datasets from the WorldClim database at 30' resolution or 1 square kilometre grids (Hijmans et al., 2005) were used. They are the 19 bioclimatic variables derived from global temperature and rainfall data of past and future (2050 and 2070) climates. The scenario is limited to the most extreme HadGEM3-ES model only with Representative Concentration Pathways (RCPs) 8.5 trajectory.

- Bio1 (annual mean temperature)
- Bio2 (mean diurnal range (mean of monthly (max temp-min temp.)
- Bio3 (isothermality (p2/p7) (100))
- Bio4 (temperature seasonality [standard deviation 100])
- Bio5 (max. temp. of warmest month)
- Bio6 (min. temp. of coldest month)
- Bio7 (temp. annual range (P5-P6)
- Bio8 (mean temp. of wettest quarter)
- Bio9 (mean temp. of driest quarter)
- Bio10 (mean temp. of warmest quarter)
- Bio11 (mean temp. of coldest quarter)
- Bio12 (annual precipitation)
- Bio13 (precipitation of wettest month)
- Bio14 (precipitation of driest month)
- Bio15 (precipitation seasonality [coefficient of variation])
- Bio16 (precipitation of wettest quarter)
- Bio17 (precipitation of driest quarter)
- Bio18 (precipitation of warmest quarter)
- Bio19 (precipitation of coldest quarter)

3) Species Distribution Modelling

Spatial interpolation is one of the most common geographic techniques for spatial data visualization in Geographic Information Systems (GIS). Kriging was applied as one of the numerous methods for spatial interpolation. Kriging is an estimator used to interpolate spatial data for better accuracy and interpretation. There are different types of kriging (Meng, Liu, & Borders, 2013). In this research, we managed to estimate the extracted 19 bioclimatic variables datapoints of 774 locations GPS coordinates using ordinary kriging; each location is the lowest administrative unit headquarters in Nigeria geopolitical zones. Ordinary kriging in ArcGIS 10.6 version was used because it minimises error variance in spatial estimation interpolation. The Kriging interpolation was in ArcGIS 10.6 geostatistical analysis and created the maps in layers. The interpolated maps were then subjected to modelling using the MaxEnt programming as done in Phillips and Dudik (2008). All layers of 19 bioclimatic variables were converted to ASCII raster grids and trees location coordinates remained in decimal degrees for accurate interpolation. The outputs produced, including the Jackknife test results and AUC values were in HTML format. Also, ASCII files reproduced by the output where taken into ArcMap for formating. The model classifications of years 2050 and 2070 climate data were altered and colours in stretched colour ramp of models of current climate data were modified for uniformity. This enabled the result predictions of all distribution maps to be visualised and edited in ArcMap. As explained in

(Phillips et al., 2006), we are using MaxEnt in predicting the potential distribution of *Parkia bilobosa* and *Vitellaria paradoxa* across agroecological zones within Nigeria by probability distribution estimation. However, this is subject to a set of constraints that represent a lack of absence data about the focused distribution. Currently, MaxEnt method is rated as the most popular and accurate approach to modelling presence-only data, even when the sample size is small (Guillera-Arroita et al., 2014; Phillips et al., 2017).

4) Model Validation and species presence mapping

In the study, model performance was assessed using several methods. First, we used the maximum entropy distribution free software 3.4.1 version of MaxEnt (Check: https://biodiversityinformatics.amnh.org/open_source/maxent/) to model the current and future distribution of parkland trees after preparation of the bioclimatic variable maps as well as species occurrence data entry in the maximum entropy software. To evaluate the predictive performance of the models, validation is necessary for accuracy and reliability. So, we did model validation by dividing the dataset into the training data used to build the model, comprising 70% of all data and the test data (independent dataset) used to test run the model, taking the remaining 30% of all data as seen in (De'ath & Fabricius 2000). The area under the receiver operating characteristic curve (AUC) represents a model performance measure focusing on sensitivity against specificity. The sensitivity for any threshold is a fraction of classified present positive instances while specificity is a fraction of classified negative instances that are not present. The AUC value typically is between **0.5** (random) and **1.0**. The AUC value that shifts closer to 1.0 indicates a better model performance. Furthermore, the success of the model was also evaluated on how the mapped probability values correspond to the presence records visually. This is because, in the continuous MaxEnt output (predicted maps), it is essential to regulate an optimal threshold for evaluating the presence/absence of target species in maps, as seen in Phillips et al. (2006) and Piri Sahragard and Ajorlo (2016). The geostatistical and modelling outputs between observed and predictive maps were determined in ArcGIS 10.6.1 release software. Monserud and Leemans (1992) defined the modelling accuracy in the following ranges of agreement:

No agreement—0.05;
Very poor—0.05 - 0.20;
Poor—0.20 - 0.40;
Fair—0.40 - 0.55;
Good—0.55 - 0.70;
Very good—0.70 - 0.85;
Excellent—0.85 - 0.99;
Perfect—0.99 - 1.00.

Positive values indicate extremely good agreement with matched records. A good model produces landscapes of high probability covering the closest zones of presence records while landscapes of low probability generate only a few or no presence points around the presence records.

3. Results

1) Variable contribution and Model performance

The model fitness using testing data (blue line) is the real test of the model predictive power. The receiver operating characteristic (ROC) curve graph indicates how significant the maxent model is at predicting the current scenario sampled tree data. The specificity against sensitivity Area under the curve (AUC) had >0.8 for current scenarios training data in both species sampled (Figure 2). The figure also indicated predicted areas. The AUC test data for *V. paradaoxa* is 0.2, which is less than the *P. biglobosa* specificity for the prediction of defined areas within the maps. The curves indicated probable predictability of presence changes for each varied environmental variable, keeping all other unwanted sample environmental variables at average value.

The jackknife test of variable importance in MaxEnt modelling showed that tree distribution across the agroecological zones landscapes was affected most by precipitation seasonality in the 19 bioclimatic variables, particularly drought regimes. For instance, when used individually the bio14w2 and bio17w2 were the leading important predictors across all the scenarios of the two sampled tree distribution in this study, except for *Vitellaria paradoxa* at year 2050 (Figure 2). Though bio06w2 identified the temperature seasonality of the coldest months as the most important variable predicting changes in 2050 for *V. paradoxa*, the drought indices on the biovariables tend to predict *P. biglobosa* distribution across the agroecological landscapes of Nigeria. Results also indicated that ecological distribution of *V. paradoxa* was not only meaningfully influenced by precipitation level in dry seasons but also by cold temperature regimes (Figure 3). In addition, parkland distribution of *P. biglobosa* and *V. paradoxa*, all the most important variables that were significant predictors with optimum variable range across the three scenarios are presented in Table 1.

2) Current and future distribution of *Parkia biglobosa* and *Vitellaria paradoxa* across dryland savannahs of Nigeria

The logistic map predicting *P. biglosa* and *V. paradoxa* distribution using current 19 bioclimatic climate data is shown in Figure 3 below. The zones with the highest parkland potential for each species (red) are seen as thus: *Parkia biglobosa* in Sudan savannah, Northern Guinea savannah and Southern Guinea savannah and *Vitellaria paradoxa* in Sahel savannah, Sudan savannah, Northern Guinea savannah and Southern Guinea savannah. Other agroecological zones with potential (light yellow) are seen extending from the drylands of the Sahel savannah in the northern region down to the forested edges of the Derived savannah AEZ.

Figure 3 also shows the 2050 and 2070 future parkland distribution maps for *Parkia biglobosa* and *Vitellaria paradoxa* across the AEZ of Nigeria. The zones with the highest suitability index (0.6 - 1.0) in future climates correspond to the current climate highest potential distribution areas but decreased in size in 2050 scenario, showing the extension of yellow colours in both species and increasing lower suitability index (0.4 - 0.6). The highly suitable areas in 2050 scenario tend

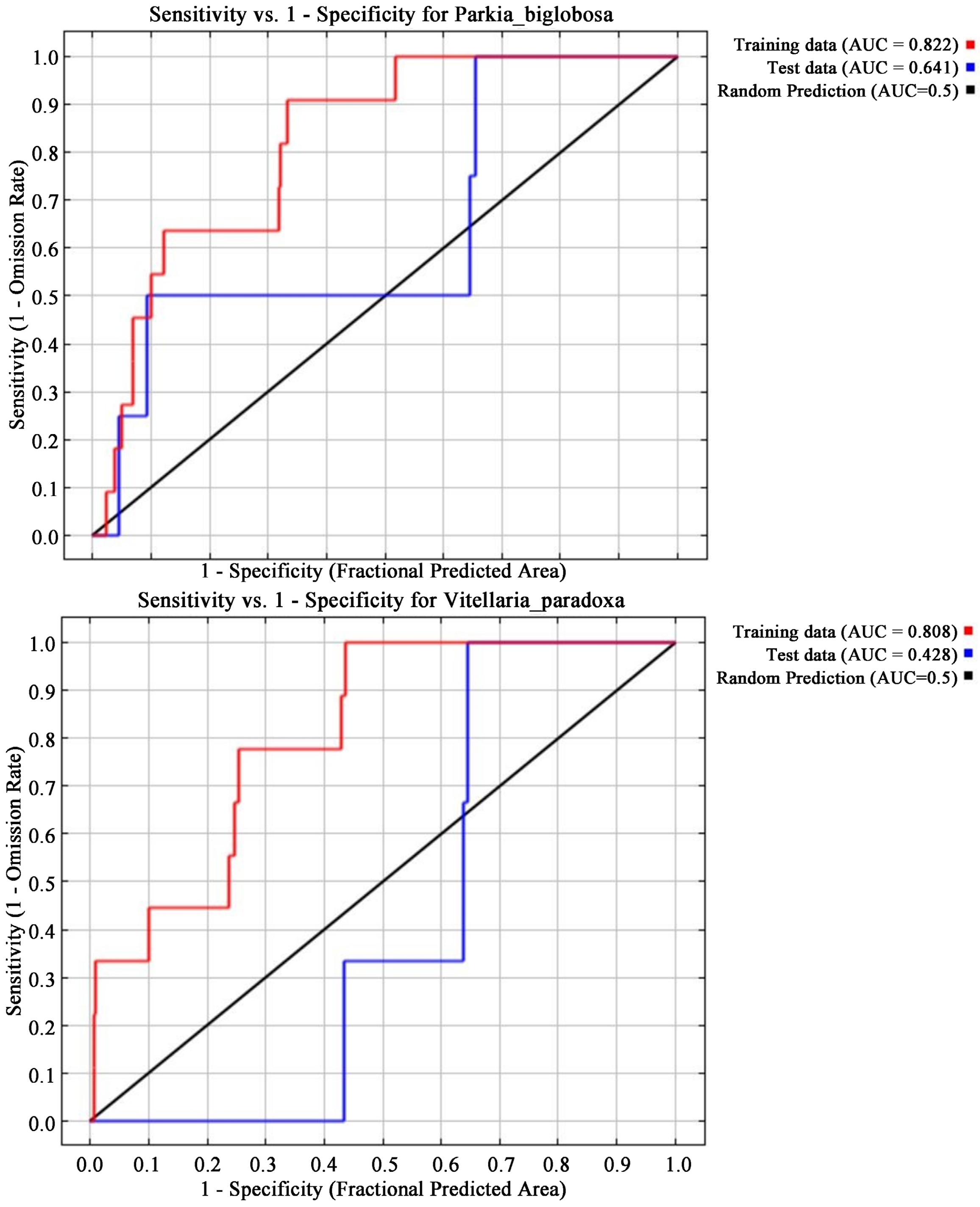

Figure 2. Specificity versus sensitivity of predicted maps of sample tree distribution across the AEZ.

to stretch towards north-eastern Sudan and Sahel savannah zones, with few patches found between NGS and SS zones in the central region. The 2050 scenario in both species predicted areas had an increasing mid-range potential (yellow), over 44% lower suitability (0.4 - 0.6) in sampled AEZ parkland distributions predictions. The 2070 future potential distribution maps for both *P. biglobosa* and *V. paradoxa* display large variations in parkland area suitability compared to

Table 1. The biovariables percent contribution and permutation importance of *Parkia biglobosa* and *Vitellaria paradoxa* MaxEnt model predictions.

Scenario	*Parkia biglobosa*	Percent contribution	Permutation importance	*Vitellaria paradoxa*	Percent contribution	Permutation importance
Current	bio14w2	66.7	45.8	bio11w2	43	19.2
	bio17w2	22.7	0	bio17w2	29	0
	bio12w2	5.1	12.3	bio14w2	28	75.9
	bio18w2	3.4	30	bio12w2	0	4.9
	bio13w2	2.1	11.9			
Year 2050	bio02w2	30.8	0	bio02w2	39	2
	bio16w2	23.2	23	bio09w2	15.2	0
	bio17w2	22.9	9.5	bio13w2	15	16.9
	bio13w2	13	17.3	bio14w2	12.5	69.3
	bio11w2	3	0	bio11w2	7	0
	bio12w2	2.2	26	bio06w2	6.5	11.8
	bio05w2	2.2	0	bio17w2	3.5	0
	bio06w2	1.1	0	bio04w2	1.3	0
	bio03w2	1	0			
	bio14w2	0.6	24.1			
Year 2070	bio14w2	47.1	65.7	bio09w2	26.4	0
	bio16w2	18.6	32.3	bio14w2	18.9	62.2
	bio6w2	12.4	0	bio13w2	12.3	0
	bio7w2	7.4	0	bio16w2	11.5	36.1
	bio13w2	7	0	bio6w2	10.9	0
	bio3w2	3.8	0	bio7w2	5.9	0
	bio1w2	1.9	2	bio4w2	5	0
	bio09w2	1.1	0	bio17w2	3.1	0
	bio11w2	0.4	0	bio10w2	2.5	0
	bio18w2	0.3	0	bio19w2	1.6	0
				bio11w2	1.2	0
				bio1w2	0.5	1.8
				bio3w2	0.1	0

2050, showing a significant reduction in climatically unsuitable areas for both species to regenerate and thrive. Areas that indicated the highest suitability index (0.6 - 1.0) significantly increased (53%) compared to similar areas in current conditions that exhibited high potential parkland tree distribution. Generally, all geopoints marked in **Figure 1** have reduced in suitability under future climate

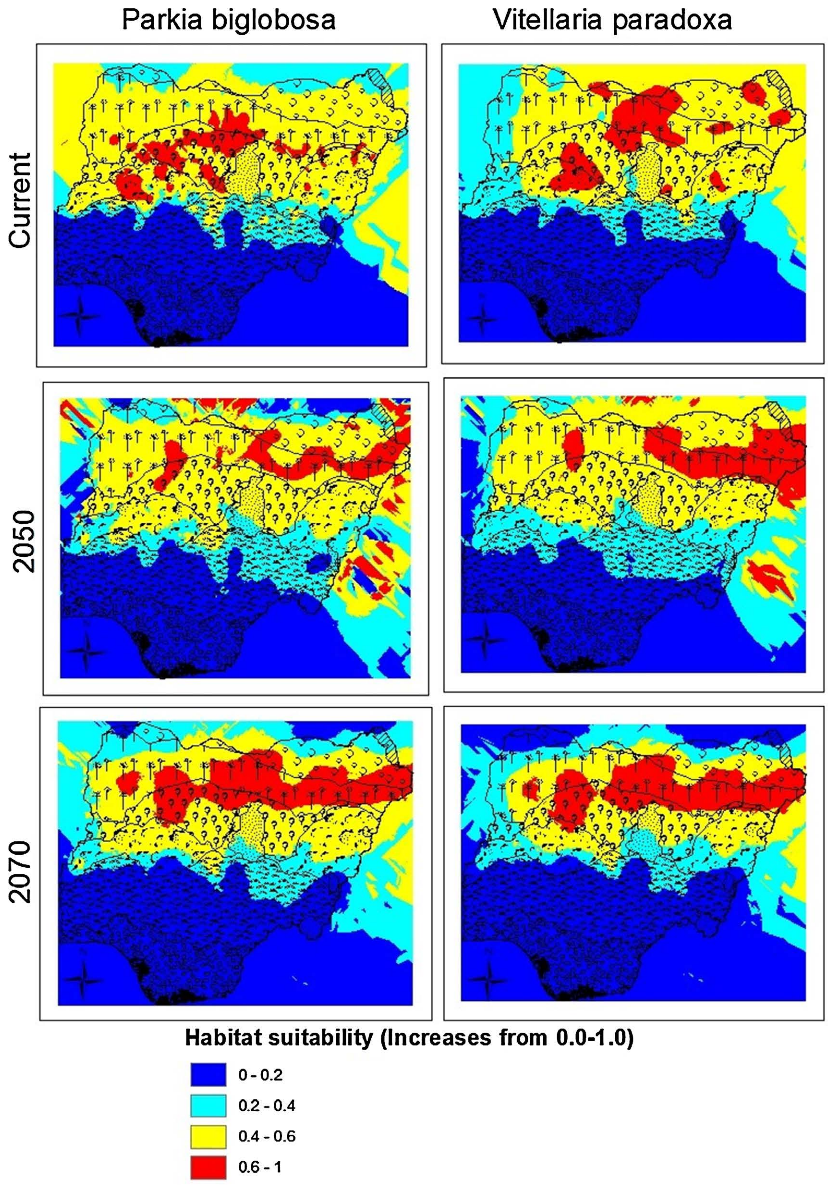

Figure 3. Modelled map showing suitability of habitat for agroforestry tree species for current and future climate scenarios.

predictions, as half of the geopoints are located in areas below high suitability index. There is a difference in suitability as seen in the maps, with shifts occurring from west to east or north-eastern ward species movement, but there is no significant reduction (45%) in area size. In other words, future distribution of the species with high regeneration and distribution potentials can be located in the Sudan and Northern Guinea savannahs of north-eastern region. The model also showed areas with similar environmental conditions for prediction outside the sampled area, in neighbouring countries of Niger and Cameroon.

4. Discussion

Based on the predictions through classification, communities in the central part of Nigeria are the most affected by climate change, with most localities experiencing drought-threatened conditions in future. The modelling of agroecological zone classification is to provide more insight into changing climate impacts on land-use change in Nigeria, with attention paid to livelihoods and farming systems. The local approach used in AEZ is more refined than the regional AEZ model as it offers more demonstration of how different AEZs will be affected at community levels, to allow policy makers and farmers to improve adaptation and mitigation to climate change impact (Seo, 2014). The projected local impacts of all the climate scenarios did not disagree with previous findings on the impacts magnitude of change in climate shifting agroecologies globally, up to 50% from the 2050s in sub-Saharan Africa (Bunn et al., 2015; Gaal et al., 2012; Kala et al., 2017; Seo, 2014). The zones that are suitable for cereals and tuber production now will in the future now have climates with higher temperatures and long dry seasons. These mean a total shift or possible disappearance of current AEZ characteristics in Northern Guinea savannah, Southern Guinea savannah and Mid-Altitude zones, as well as in most parts of the driest Sahel savannah. Furthermore, substantial landscapes across the northern region of Nigeria that currently lie within Sahel and Northern Guinea savannahs are to be replaced by Sudan savannahs in the future. Just as modelled in (Kala et al., 2017; Seo, 2012), these scenarios will offer great consequences for decision makers and landowners in sustainable livelihood strategies that involve forest management in semi-arid regions. On the one hand, parkland landscape areas productivity will struggle for sustainability while the forested parts of Nigeria may become more productive. Research to adapt agricultural productivity to mitigate climate change impact will thus have to make agroecosystems better adapted to heat and drought stress. Thus, there is a need for regions to change their agronomic and plantation practices to remain productive and sustainable, for example, by learning from Sudan savannah farmers what trees are planted and when they are planted in their locality. Other climate change-induced problems like the low yield in agricultural produce, and the disappearance of dryland resources, especially parkland trees, affect food security and livelihoods (Bayala et al., 2015; Ouedraogo et al., 2017). Across the agroecological zones, the high demand for land use to feed about 180 million human population with low input and technology is making parkland sustainability difficult (Abdullahi & Anyaegbu, 2017; Adesina & Chianu, 2002; Ehirim & Osuji, 2017; Okpoho, 2018). Currently, sub-Saharan Africa harbours savannah agroecological zones, which is home to over 700 million hectares of parklands sustaining livelihoods of about 230 million people (FSIN, 2018). One-third of the human population in the region are within rural Nigeria and depends on about 70 million low-fertile hectares of parkland landscapes for food security and livelihoods (IITA, 2000). The hectares cut across different savannahs within the predicted changing agroecological zone locations in Nigeria. On the other hand, classification of climate change induces AEZs shift was studied by (Kala et al., 2017) and (Seo, 2014) for sub-Saharan Africa. While the former used the generalised linear model for predicting farmers' decision impact on future AEZ shift using climate scenarios, the latter focused on how to evaluate the future behavioural decisions impact on land suitability. The results are useful but could not focus on the integration of ecological and climate sciences among regional states. Other studies used land cover datasets from Chinese GlobeLand30 land cover to predict the spatial land use change of cultivated landscapes between 2000-2010 (Arowolo & Deng, 2017). Although, seasonal length was relegated among the factors. The model estimated the current drivers of land-use change and the spatiotemporal intensity effect on agroecosystem distribution in Nigeria. Moreover, co-kriging interpolation was used to study the changing climate in Northern Nigeria after obtaining 1981 to 2010 temperature and rainfall variables from NIMET. The interpolated results showed a prediction map of high variability in Vegetation index (NDVI) and precipitation across the period. In Bunn et al. (2015), global multiclass classification of coffee plantation suitability for future climates in agroecological zones was projected using the Random Forest model. FAO-guided AEZ method approach was used to redefine future classification of the coffee plantation climate suitability migration, upwards of up to 500 m increase in elevation. Meanwhile, Nigeria's current AEZ is defined using overlay maps developed by the International Institute for Tropical Agriculture through multiple clustering analyses of local climate and other socio-ecological variables in Nigeria (IITA, 2000).

The use of machine learning techniques such as the Random Forest algorithm has been debated as weak in overfitting specific variables, depending on the scenarios (Bunn et al., 2015; Hand & Till, 2001). In order to meet the objectives, the variables chosen were those acceptable globally with low levels of error to produce high classification accuracy rated in the Out of Bag Error shown above. Lastly, the impact of the changing climate scenario projected is close to projected scenarios in similar studies by (Bunn et al., 2015; Gislason et al., 2006; Kala et al., 2017; Seo, 2014). However, climate change impacts on parklands are likely to be more severe, as was illustrated by the models under extreme emission scenarios, considering the shifts in agroecological zones.

5. Conclusion

The research study assesses the maximum entropy classification method to predict the impacts of climate change on agroecological zones (AEZs) of Nigeria with the observed and future bioclimatic variables. We concluded that the classification of AEZs is a major step for the parametrisation of agroecosystems in Nigeria, with a focus on parklands in the drylands of the Northern region. Consequently, the AEZ classification is limited to climate data for this research and predicted the gradual disappearance of three of the four current AEZs under different scenarios. We established a connection between climate data and agroeco-systems, under an extreme emission scenario. Hence, adaptation strategies should be induced by climate change drivers. The strategy of shifting agricultural and/or forest management if the future climate is altered, for instance, requires an explained model of the spatially simulated current of the AEZ classification. There is an urgent need for policy makers and researchers in agroecology to take climatic changes seriously when making decisions on ecological sustainability, such as woodland creation. There is a need for priority trials of agroforestry farming strategies across the AEZs with future conditions at the locations identified to change. Additional agroforestry research should expand the climatic variable limits to include environmental factors such as land cover (with land-use productivity index) when predicting the worst impacts of climate change on restoration schemes and land use change in the drylands of Nigeria.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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