



Research article

Impacts of climate change on the geographic distribution of African oak tree (*Afzelia africana* Sm.) in Burkina Faso, West Africa



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ARTICLE INFO

Keywords:
Threatened species
Climate change
Distribution modelling
Habitat suitability
West African Sahel

ABSTRACT

Afzelia africana Sm – a multipurpose leguminous tree species – is threatened in West Africa – a climate change hotspot region. Yet, although the impacts of land use on this species dynamics have been widely reported, there is a little literature on the impacts of climate change on its spatial distribution. This study aimed to predict the impacts of climate change on the geographic distribution of *A. africana* in Burkina Faso. A total of 4,066 records of *A. africana* was compiled from personal fieldwork and vegetation database. Current and future bioclimatic variables were obtained from WorldClim website. For future climatic projections, six global climate models (GCMs) were selected under two emission scenarios (RCP 4.5 & RCP 8.5) and two horizons (2050 & 2070). Presence data and bioclimatic variables were processed in ArcGIS software and used in the algorithm MaxEnt (maximum of entropy) to predict the species distribution. Findings showed that maximum temperature of warmest month and mean temperature of coldest quarter mostly affect the habitat suitability of *A. africana*. About 25.54% of Burkina Faso land surface was currently suitable for *A. africana* conservation. Under future climatic projections, all the climate models predict climate-driven habitat loss of the species with a southward range shift. Across the two emission scenarios, the spatial extent of suitable habitats was predicted to decline from 9.43 to 23.99% and from 12.29 to 25% by the horizons 2050 and 2070, respectively. Habitat loss and range shifts predicted in this study underline the high vulnerability of *A. africana* to future climate change. Reforestation actions and the protection of predicted suitable habitats are recommended to sustain the species conservation.

1. Introduction

Global climate change represents unprecedented challenges for biodiversity conservation worldwide. In most climate scenarios, extreme climatic events and high climate variability are expected to occur (IPCC, 2007; Busby et al., 2012; IPCC, 2014). Such changes will induce severe climatic stress to biodiversity with negative repercussions on all levels of biological organization. Several studies reported that ongoing climate variability is affecting tree phenology and physiology (Walther et al., 2002; Walther, 2003; Thuiller et al., 2005), plant diversity (Heubens et al., 2013) and ecosystem functions (Walther et al., 2002; Root et al., 2003; Thuiller, 2003). In many areas of the world, climate-driven range shifts and extinction risks are predicted for some woody plants (Thuiller, 2003; Walther, 2003; McClean et al., 2005; Thuiller et al., 2005; Sommer et al., 2010). These effects of climate change have drastically increased in

recent years a growing need for predicting the impacts of climate change on the geographic distribution of woody plants.

Understanding species distributional dynamics is important in ecology, evolution and conservation (Elith et al., 2006). The assessment of the effects of climate change on species distribution is based on the identification of bioclimatic envelopes through distribution modelling (Guisan and Zimmermann, 2000; Pearson and Dawson, 2003; Phillips et al., 2006). Species Distribution Models (SDMs) are effective tools for predicting species environmental suitability and potential changes in their geographic range. According to Thuiller et al. (2005) and Phillips et al. (2009), predictive models are efficient tools likely to guide conservation decisions. Indeed, SDMs allow the identification of bioclimatic envelopes of species which represent their potential climatic refuges or critical habitats (Thomas et al., 2004; Elith et al., 2006; Phillips et al., 2006). These models also enable to predict changes in the suitable

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habitats over time and to identify species which may be endangered, vulnerable or adapted to changing environmental conditions (Guisan et al., 2013).

West Africa represents a climate change hotspot region where increased probability of hazards, high vulnerability and severe exposure meet (Heubens et al., 2013; IPCC, 2014). In such a context, empirical data on species environmental suitability and distributional dynamics are essential for conservation planning. The lack of reliable data on the spatial distribution of plant biodiversity hampers the effectiveness of conservation actions (Schmidt et al., 2017). As West African plants constitute important providers of provisioning, supporting and cultural services that local people essentially and traditionally rely on (Schumann et al., 2011; Zizka et al., 2015), forecasting the impacts of climate change on the spatial distribution of tree species is essential for maintaining ecosystem services. In this perspective, a particular attention should be paid to the threatened plants with high socio-economic significance.

Previous studies reported severe impacts of anthropogenic pressures on the dynamics and stand diversity of some West African valuable plants (Nacoulma et al., 2011; Schumann et al., 2011). Similarly, other studies assessed the suitable habitats for the conservation of multipurpose trees such as *Parkia biglobosa* (Jacq.) R.Br. ex G.Don (Dotchamou et al., 2016), *Vitex doniana* Sweet (Hounkpevi et al., 2016), *Kigelia africana* (Lam.) Benth. (Guidigan et al., 2018) and *Vitellaria paradoxa* C.F. Gaertn. (Dimobe et al., 2020). Despite this growing literature, SDMs are lacking for threatened plants, hindering the development of effective conservation strategies for these species. Through this study, we aim to bridge knowledge gaps on distribution modelling of threatened plants in West Africa. The study is focused on *Afzelia africana* Sm, a threatened and multipurpose leguminous tree, endemic to Africa. The general objective of the study is to assess the geographic distribution of *Afzelia africana* in response to current and future climatic conditions.

We addressed the following research questions:

- (i) Which bioclimatic variables do control the distribution of *Afzelia africana*?
- (ii) What are the current spatial extents of suitable habitats for the species conservation?
- (iii) What are the dynamics of the suitable habitats of *A. africana*?
- (iv) Which factors affect the variations in species distribution models?

2. Material and methods

2.1. Study area

The study was conducted in Burkina Faso (Figure 1), a landlocked West African Sahelian country located between the latitudes 09°02'–15°05'N and the longitudes 02°02'E–05°03'W. Burkina Faso is situated at the centre of West Africa, covering the major bioclimatic gradient of the region. Biogeographically, the country extends from the Sudanian regional centre of endemism to the Sahelian transitional zone (White, 1983). Spanning the tropical sub-arid and sub-humid zones, Burkina Faso is subdivided into three climatic zones namely the Sahelian zone, the Sudano-sahelian zone and the Sudanian zone (Figure 1). The mean annual rainfall increases from the North to the South, varying from 300–600 mm. year⁻¹ in the Sahelian zone to 900–1200 mm. year⁻¹ in the Sudanian zone. The mean annual temperature decreases from 35 °C in the Sahelian zone to 20 °C in the Sudanian zone. The Sudano-sahelian zone represents an intermediate area between the Sahel and the Sudanian zone. This area has mean annual rainfall between 600–900 mm. year⁻¹ and mean annual temperature varying from 25 to 30 °C. The broader climatic gradient of the country imposes a similar gradient in plant diversity (Heubens et al., 2013) which increases from the Sahelian zone to the Sudanian zone (Schmidt et al., 2013, 2017). The vegetation is dominated by a mosaic of savannas (shrub savannas and tree savannas) with patches of forests (woodlands, dry forests and riparian forests).

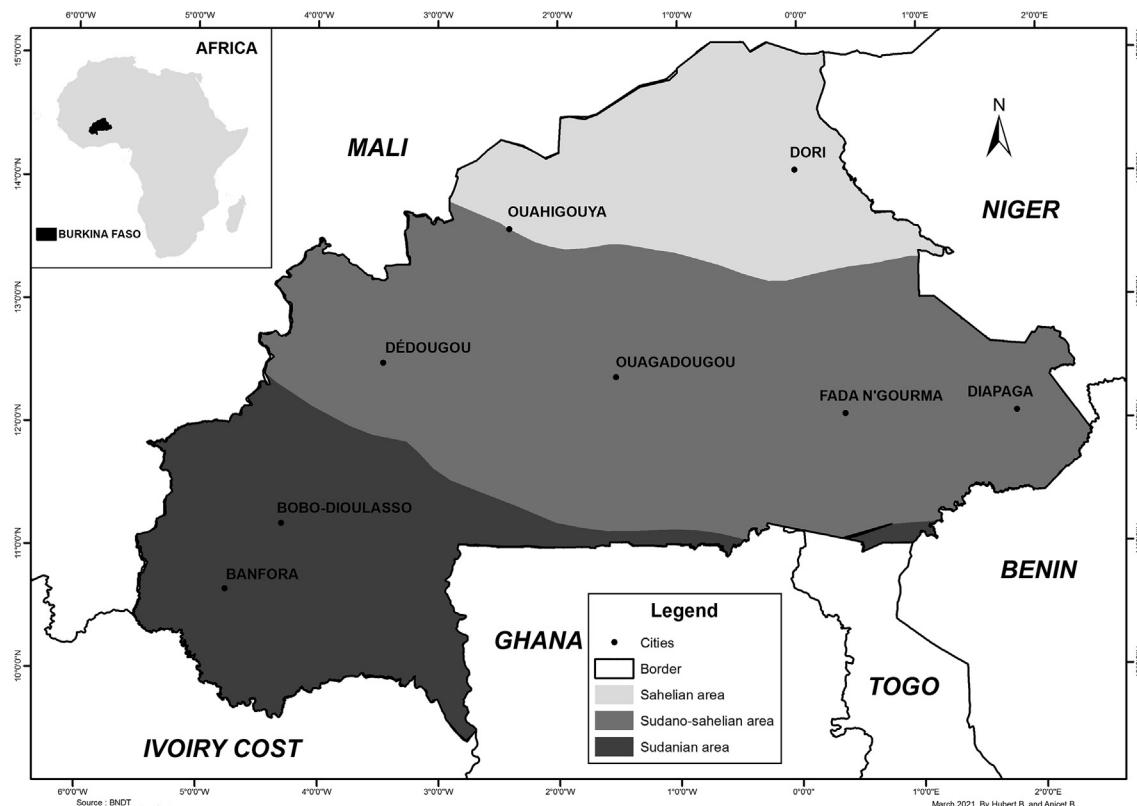


Figure 1. Location of the study area in Burkina Faso, West Africa.

2.2. Study species

Afzelia africana Sm. also called ‘African mahogany’ or ‘African oak’ is an African endemic leguminous timber species from the Fabaceae family. This species is the most widely distributed among the seven African *Afzelia* species. Its natural distribution range spans the Sudanian regional centre of endemism, the Guineo-Congolea/Sudanian regional transition zone and the Guineo-Congolean regional centre of endemism (Orwa et al., 2009), covering 19 African countries (Donkpegan et al., 2014). The natural geographic range of the species characterizes the transition zone between wooded savannas and dry forests (Orwa et al., 2009; Gérard and Louppe, 2011). In Burkina Faso, the distribution range of *A. africana* extends from the Sudano-sahelian zone to the Sudanian zone. The biophysical limits of this species are reported to range between 800–1800 mm for mean annual rainfall, 20–35 °C for mean annual temperature, and 200–1200 m for altitude (Orwa et al., 2009; Gérard and Louppe, 2011). *A. africana* is an agroforestry tree species with high socio-economic, industrial, cultural and ecological importance (Balima et al., 2018). Its wood called ‘doussié’ has a high economic value in the international timber market because of its excellent properties as termite resisting wood (Gérard and Louppe, 2011; Donkpegan et al., 2014). The leaves have high fodder value and are used as forage for livestock (Balima et al., 2018). The barks abound in various medicinal properties with potential interests in the traditional medicine (Orwa et al., 2009).

2.3. Input data

2.3.1. Species occurrence records

Presence data (or occurrence records) of *A. africana* (Figure 2) was compiled from two sources. A first phase extensive field survey was carried out throughout the species distribution area in Burkina Faso. The location of individual trees of the species was georeferenced using a GPS (Global Positioning System, Garmin 64). The collected occurrence records were supplemented by data from the vegetation database (VegDa)

of the University Joseph Ki-Zerbo (Ouagadougou, Burkina Faso). A total dataset of 4,066 occurrence records was obtained, of which 3,637 records (89.45%) were collected from field surveys and 429 records (10.55%) from the vegetation database (Supplementary information, Appendix 1).

2.3.2. Environmental data

Environmental variables were composed of both climatic and non-climatic data. Current (1950–2000) bioclimatic data were downloaded from WorldClim database version 1.4 (Hijmans et al., 2005, <http://www.worldclim.org>). This dataset includes 19 bioclimatic variables derived from interpolated averages of minimum and maximum temperature and rainfall (Hijmans et al., 2005). For future climate projections, six global climate models (GCMs) (ACCESS1-0, CCSM4, CNRM-CM5, HadGEM2-ES, MIROC5 and NorESM1-M) from the Coupled Model Inter-comparison Project phase 5 (CMIP5) were selected (Table 1). Among the set of selected GCMs, three models (HadGEM-ES, CNRM-CM5 and MIROC5) have been used in previous studies related to species distribution modelling in West Africa (Dotchamou et al., 2016; Hounkpevi et al., 2016; Guidigan et al., 2018; Dimobe et al., 2020). Climate models were downloaded at a spatial resolution of 30 s (1 km × 1 km) under the

Table 1. Global climate models used for running the species distribution model.

GCMs	Definition	Code
ACCESS1-0	Australian Community Climate and Earth-System Simulator	ac
CCSM4	Community Climate System Model	cc
CNRM-CM5	National Centre for Meteorological Coupled Model 5	cn
HadGEM2-ES	Hadley Global Environment Model 2 Met Office Climate Model	he
MIROC5	Model for Interdisciplinary Research on Climate	mc
NorESM1-M	Norwegian Climate's Center Earth System Model	no

GCMs: global climate model.

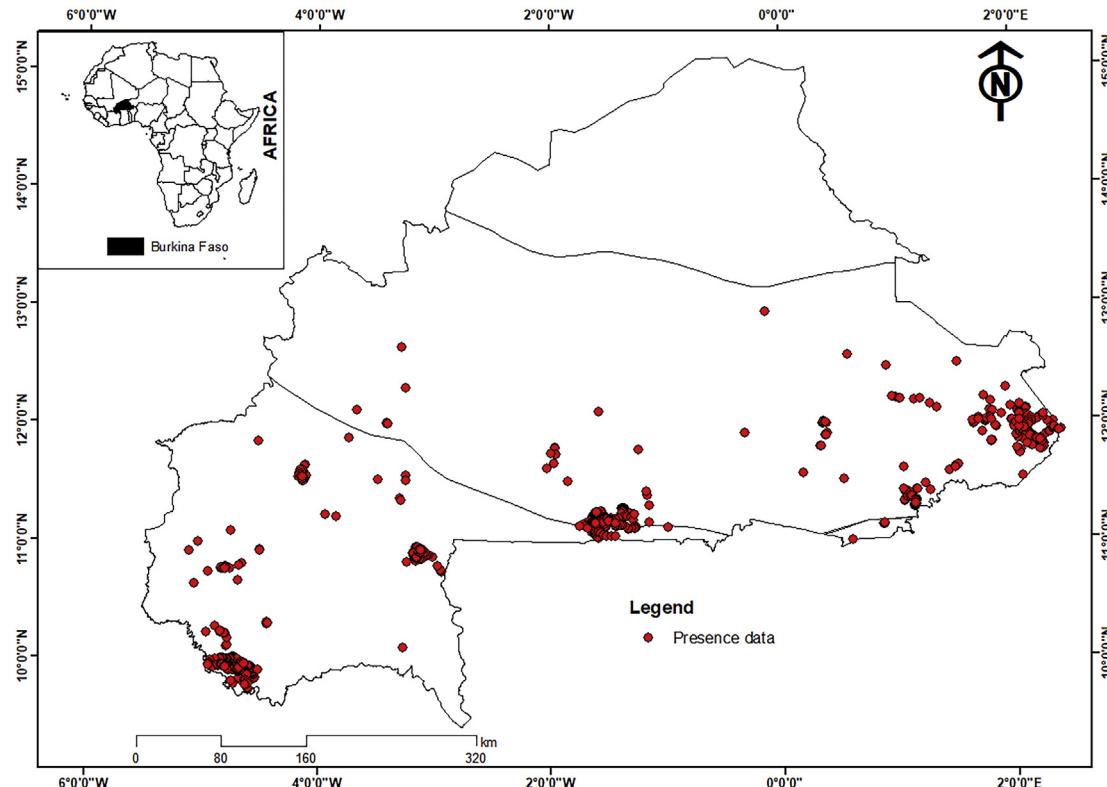


Figure 2. Geographic distribution of collected occurrence records of *A. africana* in Burkina Faso.

representative concentration pathways (RCP) 4.5 and 8.5 at the horizons 2050 and 2070. The two emission scenarios (RCP 4.5 and RCP 8.5) were considered to capture the range of emission uncertainties (Harris et al., 2014). Indeed, the RCP 4.5 describes the lowest emission scenario, whereas the RCP 8.5 describes the highest emission scenario. In addition to the bioclimatic layers, soil data composed of soil types were obtained from the national soil office of Burkina Faso.

2.4. Data processing and model calibration

The presence data and the bioclimatic variables were processed in ArcGIS 10.5 software using the package SDMtoolbox 2.0 (Brown, 2014; Brown et al., 2017). To reduce sampling bias, the occurrence records were spatially filtered using the function ‘spatially rarefy occurrence data’ in SDMtoolbox. This process enables to remove all duplicate records within each grid. A total of 590 presence records was kept after removing the duplicated records, and then compiled into a single CSV file format. The 19 bioclimatic variables were extracted for the study area (Burkina Faso) as GeoTIFF format and converted into ASCII format to be used in the algorithm. To determine how each predictor contributes to the distribution of the species, the environmental variables (20 variables in total) were submitted to autocorrelation tests using the function ‘remove highly correlated variables’ in SDMtoolbox (Brown, 2014; Brown et al., 2017). From the 19 bioclimatic variables and soil data, different sets of predictors were tested by accounting for different thresholds of the autocorrelation coefficient. Five least correlated predictors and ecologically meaningful for the studied species were selected at the pairwise correlation coefficient of 0.75. These variables were bio1 (annual mean temperature), bio3 (isothermality), bio5 (maximum temperature of warmest month), bio11 (mean temperature of coldest quarter) and bio14 (precipitation of driest month). The rarefied 590 presence records (CSV format) and the layers of the five bioclimatic variables (ASCII format) were used as input data to run the model (Supplementary information, Appendix 2).

2.5. Model fitting and evaluation

The model was run using MaxEnt v3.3.3k (Phillips et al., 2006), a machine learning algorithm that applies the principle of maximum entropy to predict the species potential distribution from a presence-only data and environmental predictors (Phillips et al., 2006). MaxEnt algorithm is one of the most powerful and widely used software programs for species distribution modelling (Elith et al., 2006; Pearson et al., 2007). This software has been used in several studies on species distribution modelling in West Africa (Fandohan et al., 2013; Gbesso et al., 2013; Gbètoho et al., 2017). Before running the model, the following regularization parameters were set: 25 for random test percentage, 10 replicates, subsample as replicated run type, and 5000 iterations. A Jackknife test was performed on the environmental variables to determine the contribution of each variable to the prediction of species distribution.

Regarding model evaluation, we used 25% of species occurrence records for model testing and 75% for model calibration. The predictive ability of the model was assessed using the Area Under the receiver operating characteristics Curve (AUC) (Phillips et al., 2006). The AUC is the probability that a randomly chosen presence cell have a higher predicted value than an absence cell (Araújo et al., 2005; Elith et al., 2006). This index measures the ability of a model to discriminate between sites where a species is present from sites where it is absent (Elith et al., 2006). The AUC values range from 0 to 1, where values close to one ($AUC \geq 0.75$) indicates a good fit, 0.5 implies a predictive discrimination that is no better than a random guess, and values less than 0.5 indicate performance worse than random (Elith et al., 2006). Due to the recent criticism about the limitations of AUC in assessing SDMs performance (Lobo et al., 2007; Jimenez-Valverde et al., 2012), threshold dependent test was used through the True Skill Statistics (TSS) for a better evaluation of the model (Allouche et al., 2006). The TSS is the capacity of the

model to accurately detect true presences (sensitivity) and true absences (specificity). Model with value of $TSS \leq 0$ indicates a random prediction (performance not better than random), while values close to 1 ($TSS > 0.5$) characterize a model with good predictive power (Allouche et al., 2006). The TSS values were averaged for the 10 run replicates using the background predictions and the sample predictions of the MaxEnt outputs. This index was computed using the following formula (Allouche et al., 2006):

$$TSS = \frac{ad - bc}{(a + c)(b + d)} = \text{Sensitivity} + \text{Specificity} - 1 \quad (1)$$

The model outputs were processed in the software ArcGIS 10.5. The averaged outputs of MaxEnt obtained for each climate model under each scenario at each horizon were converted from ASCII format to raster, and afterwards classified as ‘suitable habitats’ or ‘unsuitable habitats’ using the 10-percentile training presence logistic threshold. To calculate the current and future extents of suitable/unsuitable habitats, the raster files were polygonised. Maps of the species suitable areas were finally produced for current and future climatic conditions under the two scenarios at the two horizons.

3. Results

3.1. Model performance and variable contribution

Both the AUC and the TSS showed a good quality of the predicted model. The Area Under the receiver operating characteristic Curve (Figure 3) showed higher value of AUC ($AUC = 0.902 \pm 0.012$). This indicates a good predictive ability of the predicted model. The threshold dependent test also revealed high value of the True Skill Statistics ($TSS = 0.732$). Such value of TSS ($TSS > 0.5$) confirms that the model performs better than random with a good predictive ability.

The five least correlated variables were selected among the predictor variables to run the model. Among the selected predictors, the maximum temperature of warmest month (bio5) and mean temperature of coldest quarter (bio11) contributed the most to the model, while mean annual temperature (bio1) contributed the least (Table 2).

The results of the Jackknife tests (Figure 4) showed that bio5 (maximum temperature of warmest month) represents the environmental variable that decreases the gain the most when it is omitted. This variable also constitutes the environmental variable with highest gain when used in isolation. The maximum temperature of warmest month appears therefore to have both the most useful information by itself and the most information that is not present in the other predictors.

3.2. Distribution of *A. africana* under current and future climate change

The potential current suitable habitats for the species represent 25.542% of Burkina Faso land surface (Table 3). These habitats cover about 70,091.85 km² and span the Sudano-sahelian zone and the Sudanian zone of the country (Figure 5). About 74.46% of the national territory is unsuitable for *A. africana* conservation under current climatic conditions. At the horizon 2050, a decrease in the extents of the suitable habitats of the species was predicted by all the climate models under the two emission scenarios (Table 3, Figure 5). Under the RCP 4.5, the suitable habitats represented 4.32% (11,849.42 km²) to 13.48% (36,986.23 km²) of the total land surface of Burkina Faso, corresponding to habitat loss of 12.06% and 21.22% by 2050. Similarly, about 1.55% (4248.01 km²) to 16.12% (44,214.43 km²) of the country surface was predicted to be suitable by 2050, under the RCP 8.5, corresponding to about 9.43–23.99% loss in the suitable habitats of the species. At the horizon 2070, the projected suitable habitats range from 6,618.99 km² (2.41%) to 363,666.04 km² (13.25%) under the RCP 4.5. The RCP 8.5 predicted drastic changes in the species spatial patterns by 2070, with only 3.16% of suitable areas. Only predictions from the climate models

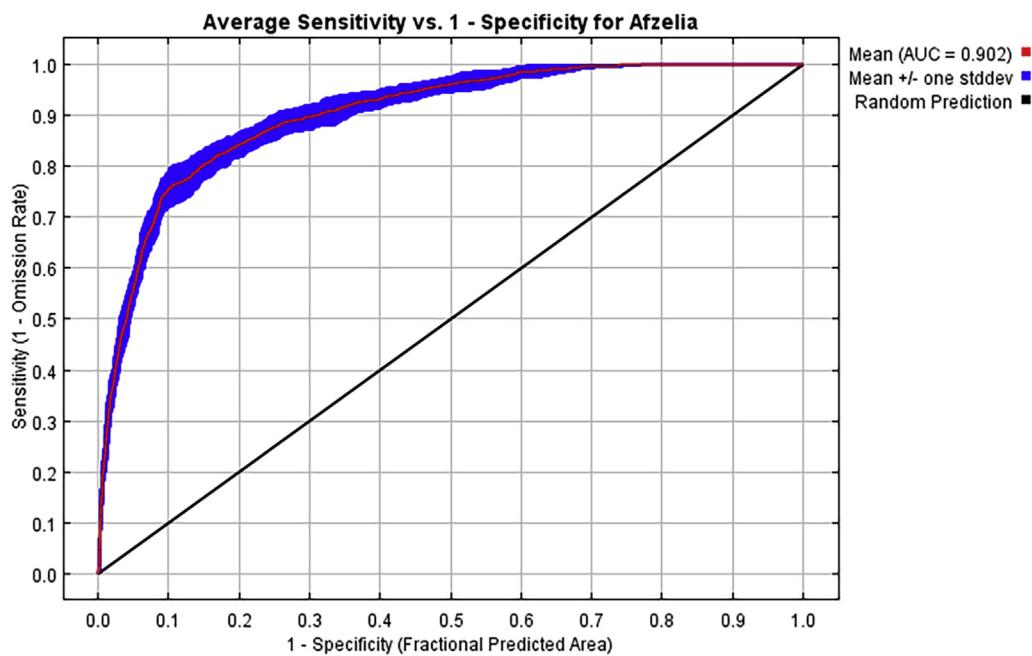


Figure 3. Average receiver operating characteristic curve and related AUC.

Table 2. Contribution of bioclimatic variables used for model running.

Variable	Variable definition	Percent contribution (%)	Permutation importance (%)
bio5	Max temperature of warmest month	46.1	56.8
bio11	Mean temperature of coldest quarter	25.2	21.2
bio3	Isothermality	16	10
bio14	Precipitation of driest month	9.3	7.2
bio1	Annual mean temperature	3.3	4.7

ACCESS1–0 and CCSM4 were presented (Figure 5). The results from the four other climate models (CNRM-CM5, HadGEM2-ES, MIROC5 and NorESM1-M) were provided as supplementary data (Supplementary information, Appendix 3 and Appendix 4).

Under current climatic conditions, the suitable habitats span the Sudano-sahelian and the Sudanian climatic zones (Figure 5). A southward shift in the current suitable habitats is predicted to occur under

future climatic conditions (Figure 5). Across all the climate models, only the Sudanian zone is predicted to be suitable for the species conservation at the horizons 2050 and 2070.

3.3. Factors affecting the variations of species distribution models

The range of habitats loss predicted for the species differs between the six climate models, the two emission scenarios and the two horizons. Under the RCP 4.5 and the horizon 2050, the model MIROC5 (mc4.5bi50) predicts the highest habitat loss (21.22%) of the species, while the model CNRM-CM5 (cn4.5bi50) predicts the lowest habitat loss (12.06%). The model CCSM4 (cc8.5bi50) and the model HadGEM2-ES (he8.5bi50) predict the highest habitat loss (23.98%) under the RCP 8.5 at the horizon 2050. The lowest habitat loss (9.43%) was predicted by the model CNRM-CM5 under the RCP 8.5 for the horizon 2050. At the horizon 2070 and under the RCP 8.5, all the climate models (except the model CNRM-CM5) predict a declining environmental suitability for the species with less than 1% of the suitable habitats. However, about 12.29% (CNRM-CM5) to 23.13% (CCSM4) of habitat loss was predicted for the horizon 2070 under the RCP 4.5. Across both horizons, habitat loss was more pronounced under the RCP 8.5 than the RCP 4.5. Similarly,

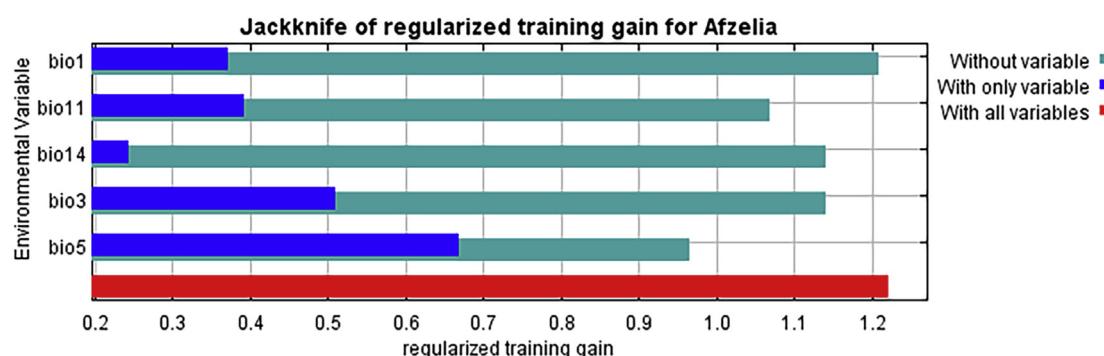


Figure 4. Jackknife tests for the regularized training gain for *A. africana*. For a given predictor variable, the corresponding green bar (without variable) shows how much the total gain is decreased if this specific variable is excluded from the model. The blue bar (with only variable) shows the obtained gain if the considered

Table 3. Current and future geographic distribution of *A. africana* in Burkina Faso.

GCM	Code	Unsuitable habitats		Suitable habitats		Trend (%)
		Extent (km ²)	%	Extent (km ²)	%	
Current						
		20,4312.752	74.458	70,087.248	25.542	
Horizon 2050						
ACCESS1-0	ac4.5b50	249,542.104	90.941	24,857.896	9.059	-16.483
ACCESS1-0	ac8.5b50	273,013.838	99.495	1386.162	0.505	-25.037
CCSM4	cc4.5b50	255,943.856	93.274	18,456.144	6.726	-18.816
CCSM4	cc8.5b50	270,124.848	98.442	4275.152	1.558	-23.984
CNRM-CM5	cn4.5b50	237,416.368	86.522	36,983.632	13.478	-12.064
CNRM-CM5	cn8.5b50	230,188.672	83.888	44,211.328	16.112	-9.429
HadGEM2-ES	he4.5b50	255,455.424	93.096	18,944.576	6.904	-18.638
HadGEM2-ES	he8.5b50	270,152.288	98.452	4247.712	1.548	-23.994
MIROC5	mc4.5b50	262,551.408	95.682	11,848.592	4.318	-21.224
MIROC5	mc8.5b50	258,232.352	94.108	16,167.648	5.892	-19.649
norESM1-M	no4.5b50	250,947.032	91.453	23,452.968	8.547	-16.995
norESM1-M	no8.5b50	261,012.024	95.121	13,387.976	4.879	-20.663
Horizon 2070						
ACCESS1-0	ac4.5b70	249,418.624	90.896	24,981.376	9.104	-16.438
ACCESS1-0	ac8.5b70	**	**	**	**	
CCSM4	cc4.5b70	267,781.472	97.558	6618.528	2.412	-23.129
CCSM4	cc8.5b70	**	**	**	**	
CNRM-CM5	cn4.5b70	238,036.512	86.748	36,363.488	13.252	-12.289
CNRM-CM5	cn8.5b70	265,739.936	96.844	8660.064	3.156	-22.386
HadGEM2-ES	he4.5b70	264,488.672	96.388	9,911.328	3.612	-21.929
HadGEM2-ES	he8.5b70	**	**	**	**	
MIROC5	mc4.5b70	258,836.032	94.328	15,563.968	5.672	-19.869
MIROC5	mc8.5b70	**	**	**	**	
norESM1-M	no4.5b70	257,041.456	93.674	17,358.544	6.326	-19.216
norESM1-M	no8.5b70	266,836.957	97.244	7563.043	2756	-22.786

The first two letters in column "code" (ac, cc, cn, he, mc and no) refer to global climate models; 4.5: RCP4.5; 8.5: RCP8.5; b: bioclimatic variables; 50: horizon 2050; 70: horizon 2070; *Unpredicted ($\leq 1\%$); negative sign (-) indicates habitat loss.

drastic habitat loss was expected at the horizon 2070 compared to the horizon 2050.

4. Discussion

4.1. Climatic variables controlling the distribution of *Afzelia africana*

Five less correlated predictors were used to predict the geographic distribution of the species. From the Jackknife tests and the table of variables' contribution, the findings showed that maximum temperature of warmest month (bio5) and mean temperature of coldest quarter (bio11) are the most important factors affecting the habitat suitability of *A. africana*. Higher value of the maximum temperature of warmest month decreases the habitat suitability, while lower value of the mean temperature of coldest quarter decreases the suitability. Our findings are in line with Guidigan et al. (2018) who reported the maximum temperature of warmest month among the significant climatic variables driving the distribution of *Kigelia africana* (Lam.) in Benin.

The findings highlight the ecology of *A. africana* which occurs in Africa humid forests and dry savannas (Orwa et al., 2009), demarcating the transition zone between wooded savannas and dense dry forests (Gérard and Louppe, 2011). The ecological optimum of *A. africana* regarding these climatic variables (bio5 and bio11) is within its tolerance limits for temperature in Burkina Faso, reported to range between 20–35 °C. Previous studies on species distribution modelling in West Africa reported the precipitation as the major factor influencing vegetation patterns and the distribution of woody plants (Sommer et al., 2010; Heubel et al., 2011; Ganglo et al., 2017). The mean annual rainfall was

not used as predictor in the modelling because of its high correlation with the other bioclimatic variables. The ecological tolerance of *A. africana* for rainfall in Africa ranges between 800–1200 mm of mean annual rainfall (Orwa et al., 2009; Gérard and Louppe, 2011). Due to this high ecological amplitude of the species, rainfall may not constitute a limiting factor for the species throughout the study area.

4.2. Distribution of *Afzelia africana* under current climatic conditions

The predicted current suitable habitats for *A. africana* conservation in Burkina Faso represent one fifth (25.54%) of the country total area. Habitats predicted suitable for the species conservation are located within the Sudanian regional centre of endemism which spans the Sudanian zone and the Sudano-sahelian zone. This finding is consistent with the distribution range of the studied species in West Africa. Indeed, the natural distribution range of *A. africana* extends from the Guineo-Congolean regional centre of endemism to the Sahel Southern limit. The current spatial extent of *A. africana* reported in this study is lower than those reported on other high socio-economic plants of West Africa. Indeed, a study by Hounkپevi et al. (2016) reported that about 85% of Benin area was suitable for the cultivation of *Vitex doniana* Sweet. Similarly, about 52% and 53% of Benin territory was reported to be very suitable for the conservation of *Kigelia africana* (Lam.) Benth. (Guidigan et al., 2018) and *Parkia biglobosa* (Jacq.) R.Br. ex G.Don (Dotchamou et al., 2016), respectively. The lower value of the current suitable habitats predicted for *A. africana* highlights the conservation status of this species in Burkina Faso. In fact, *A. africana* undergoes severe anthropogenic pressures across most West African countries where it is considered

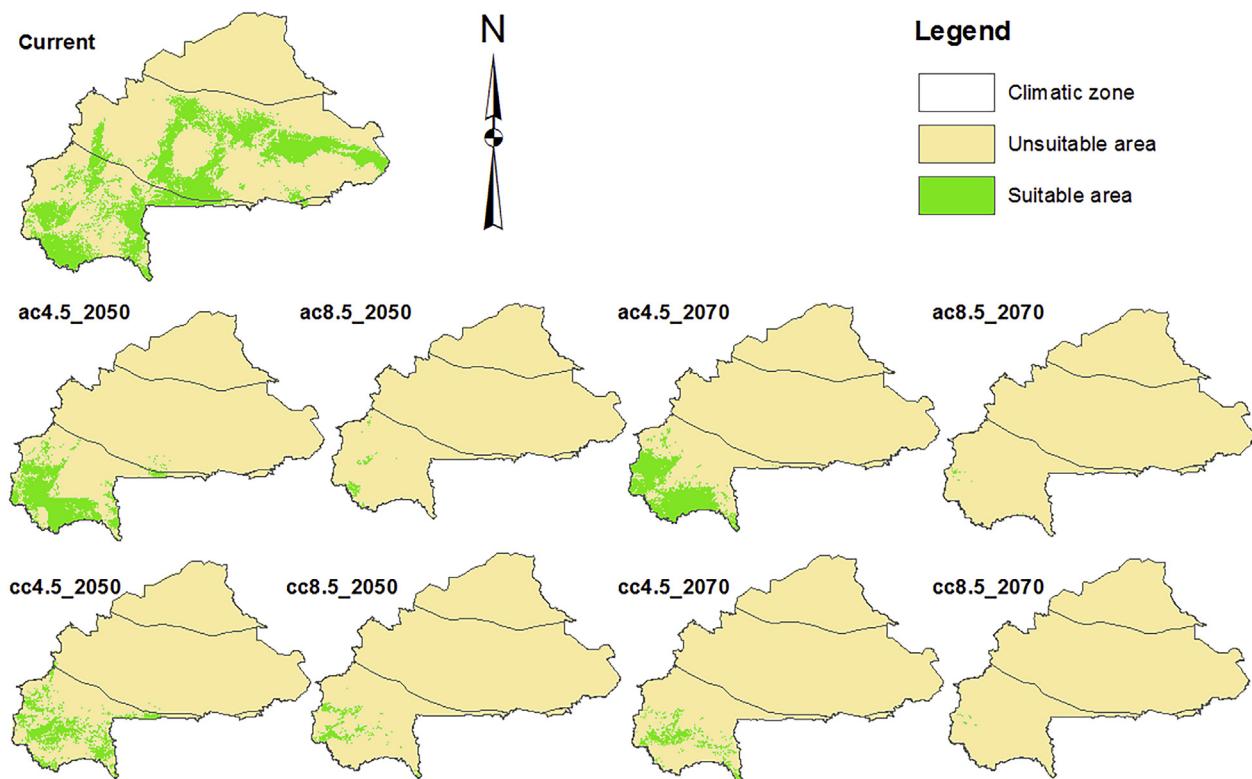


Figure 5. Geographic distribution of *A. africana* under the models ACCESS1–0 (ac) and CCSM4 (cc).

as a threatened (Nacoulma et al., 2011) or endangered species (Sinsin et al., 2004). These pressures reduce the occurrence and the geographic range of the species. *A. africana* is also classified as a vulnerable species in the IUCN Red List of threatened species.

4.3. Distribution of *A. africana* under future climatic projections

Afzelia africana has been reported to have a strong adaptation to various climatological conditions (Orwa et al., 2009; Gérard and Loupe, 2011). However, through this study, we found that future climate change will negatively affect the spatial patterns of this species in Burkina Faso. Across all climate models, a decline in the environmental suitability with a southward range shift trend was expected at both horizons. At the horizon 2050, *Afzelia africana* is predicted to lose between 12.06 and 21.22% of its current suitable habitats under the RCP 4.5. Under the RCP 8.5, between 9.43 to 23.99% of the suitable habitats will be lost. More drastic changes are expected at the horizon 2070, with 16.44–23.13% of habitat loss. Our results corroborate previous studies which predicted a climate-driven habitat loss for some valuable West African plants (Fandohan et al., 2013; Gbètoho et al., 2017). In fact, a growing body of empirical evidence supported that changing climatic conditions will cause range shifts and habitats loss for many species across the world (IPCC, 2007; Busby et al., 2012). Species range contraction and extinction risks have been also predicted in West Africa (Sommer et al., 2010) and elsewhere (Thomas et al., 2004; Thuiller et al., 2005). In Burkina Faso, climate change induced habitat loss was reported for *Vitellaria paradoxa* C.F. Gaertn. (Dimobe et al., 2020). Similarly, Heubès et al. (2013) reported that future climate change and land use change will significantly reduce plant diversity in Burkina Faso, with the impacts of climate change being more important than that of land use change. The predicted southward range shifts under future climate projections could be explained by significant changes in temperature. This may indicate that an increase in temperature will likely occur in the semi-arid areas of West Africa, thereby, reducing the environmental suitability of plant biodiversity and ecosystems. These findings imply high conservation

challenges for *A. africana* in Burkina Faso and call for reforestation actions within the Sudanian region to reduce species extinction risks.

In contrast to our findings, climate-induced range expansion was reported for some West African plants (Fandohan et al., 2013; Gbesso et al., 2013; Hounkپїvi et al., 2016; Kirchmair, 2017). Indeed, an average habitat increase of 70% was projected for 17 woody plants in Burkina Faso (Kirchmair, 2017), with higher projected increase for *Vitex chrysocarpa* Planch. ex Benth. (218%), *Anogeissus leiocarpa* (DC.) Guill. and Perr. (133%) and *Diospyros mespiliformis* Hochst. ex A. DC. (80%). Similarly, climate-induced habitat gain was predicted for *Tamarindus indica* L. (Fandohan et al., 2013), *Chrysophyllum albidum* G. Don (Gbesso et al., 2013), *Vitex doniana* Sweet (Hounkپїvi et al., 2016) and *Anogeissus leiocarpa* (DC.) Guill. and Perr. (Gbètoho et al., 2017) in Benin. A study by Heubès et al. (2011) reported a northward increase in species diversity across the Sahelian zone of Burkina Faso. Such predicted climate effects on the diversity and distribution of West African woody plants concur with the Sahel greening hypothesis which supports the replacement of savannas by deciduous and evergreen forest biomes (Heubès et al., 2011).

4.4. Factors affecting species distribution modelling

The study indicates that the geographic distribution of *A. africana* under future climate change varied within and between the six climate models (GCMs) across the two emission scenarios (RCP 4.5 and RCP 8.5) and the two horizons (2050 and 2070). This corroborates findings from previous studies (Thuiller et al., 2005; Fandohan et al., 2013; Heubès et al., 2013) and highlights the fact that distribution modelling outputs varied according to many factors. In fact, the model outputs firstly depend upon the environmental variables selected as predictors (Guisan and Zimmermann, 2000; Pearson et al., 2007). Significant variations in these predictors induce changes in the future potential distributions of the species. For instance, climate-induced range expansion as predicted for some plants in West Africa (Fandohan et al., 2013; Gbesso et al., 2013; Hounkپїvi et al., 2016; Kirchmair, 2017) may underscore the predicted

increase in mean annual rainfall in the region (Heubel et al., 2011, 2013; Platts et al., 2014). Although all models predicted a general trend in the geographic distribution of the species, some variations were observed regarding the range of habitat loss. Predicted habitat loss varied between climate models within each horizon and each emission scenario. These findings corroborate the fact that the choice of climate models in species distribution modelling influences the predicted models (Thuiller et al., 2005; Fandohan et al., 2013; Heubel et al., 2013). Across all climate models, the lowest impact of climate change was predicted by the model CNRM-CM5 under the two emission scenarios at both horizons. However, the models MIROC5, CCSM4 and HadGEM2-ES predicted the highest impacts of climate change. Such variations across climate models highlight the differences in the global climate models, and therefore introduce the issues of model uncertainties (Harris et al., 2014). Accordingly, a given species can be predicted extinct by a set of climate models, while under habitat loss or range expansion by other climate models. Therefore, the choice of climate models represents an important challenge in species distribution modelling (Heubel et al., 2013). The regional climate models (RCM) are reported to provide more statistically improved climate data which are suitable for ecological modelling in Africa (Platts et al., 2014). However, most studies related to species distribution modelling in Africa have relied on the use of global climate models (Fandohan et al., 2013; Gbesso et al., 2013; Dotchamou et al., 2016; Guidigan et al., 2018) rather than the use of regional climate models (Ganglo et al., 2017). Such inconsistent use of climate models may not enable to forecast the real impacts of climate change on woody plants. Accordingly, there is an urgent need to harmonize the use of climate models to reduce divergences of African climate forecasts (Heubel et al., 2011, 2013).

In accordance with our findings, the impact of future climate change on the geographic distribution of *A. africana* also varies between emission scenarios (Thuiller et al., 2005; Ganglo et al., 2017; Gbètoho et al., 2017). This result is consistent with Harris et al. (2014) who supported that emission scenarios represent the first source of model uncertainties. High spatial extent in the potential unsuitable areas was found under the highest emission scenario (RCP 8.5) compared to the lowest emission scenario (RCP 4.5). This suggests that in the absence of mitigation actions as assumed by the RCP 8.5, climate change will severely affect the distribution range of the species. Conversely, climate change impact could be reduced in the case of mitigation assumption under the RCP 4.5. The study further showed that modelling outputs also varied across periods with more drastic changes expected by 2070.

The predicted habitat loss (Sommer et al., 2010; Dimobe et al., 2020; Gbètoho et al., 2017) and range expansion (Gbesso et al., 2013; Hounkèvi et al., 2016; Kirchmair, 2017) as expected for woody plants in response to future climate change, highlight the uncertainties of future climate in West African region. Indeed, if warmer conditions (increase in temperature) are expected for West African Sahel under most climate projections (Sommer et al., 2010; Heubel et al., 2011; Fandohan et al., 2013), it is unclear whether precipitations will increase or decrease. Nevertheless, an increase in mean annual rainfall is projected in Western and Eastern parts of Africa (Platts et al., 2014). Similarly, increased rainfall is predicted across West African countries under most climate projections (Heubel et al., 2011, 2013; Platts et al., 2014). Conversely, a decrease in precipitations in West Africa has been also reported by some authors (Fandohan et al., 2013). The high variability of climate projections over West Africa (IPCC, 2007, 2014) constitutes an important challenge for regional ecological stimulations and compromises correct inference about the impact of future climate change on plant biodiversity and ecosystems. It is uncertain whether climate change will cause habitat loss or range expansion, species turnover, Sahel greening or drying out. Inversely, it is very obvious that some species will experience more impacts of climate change than some other species which may adapt, expand their spatial extent or shift their geographic range.

5. Conclusion

This study used six groups of global climate models to investigate the impacts of climate change on the geographic distribution of the African oak tree, a multipurpose and threatened woody plant in West Africa. We found that maximum temperature of warmest month and mean temperature of coldest quarter mostly influence the geographic distribution of *A. africana* in Burkina Faso. Climate change will negatively affect the spatial distribution of the species, resulting in a southward range shifts and a drastic loss in the suitable habitats by the horizons 2050 and 2070. The current suitable habitats of the species representing 25.5% of the country total area is predicted to drastically decline under future climatic conditions. The findings also showed that the spatial extents of the suitable habitats varied between climate models, emissions scenarios and horizons. To prevent biodiversity loss and ecological degradation in West African region, efficient and adapted management approaches are urgently needed. In this perspective, it is important to enforce forestry policies on the threatened plants with high socio-economic significance and to reinforce the conservation of protected areas which represent their last refuge. To prevent species habitat loss, studies on ecological niche modelling must be extended to the other valuable West African timber species. The use of different sets of climate models and the incorporation of the other environmental variables may contribute to generate more improved distribution models.

Declarations

Author contribution statement

Larba Hubert Balima: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Blandine Marie Ivette Nacoulma & Amadé Ouédraogo: Contributed reagents, materials, analysis tools or data.

Sié Sylvestre Da: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Dodiomon Soro: Conceived and designed the experiments.

Adjima Thiombiano: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Funding statement

This work was supported by German Federal Ministry of Education and Research (BMBF) (WASCAL_GRP/CCB2).

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at <https://doi.org/10.1016/j.heliyon.2021.e08688>.

Ethics approval

Not applicable.

Acknowledgements

The authors show their gratitude to the German Federal Ministry of Education and Research (BMBF) and the West African Science Service

Center on Climate Change and Adapted Land Use (WASCAL). The authors are also grateful to Dr. Dimobe Kangbéri for his help on the processing of bioclimatic layers. Special thanks to the two anonymous reviewers for their relevant comments which significantly improved the manuscript.

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