Impact of Climate Change on the Distribution of *Vachellia tortilis* subsp. *raddiana* (Savi) Kyal. and Boatwr. In Eastern Niger

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Abstract

The multipurpose species *Vachellia tortilis* (umbrella thorn) is a woody plant whose parts are extensively used for food, feed, traditional pharmacopoeia, energy, and handicrafts. The species also provides multiple ecological benefits. This study aims at assessing the impact of climate change on the geographical distribution of *V. tortilis* in Eastern Niger, by analyzing the climatic factors influencing its current distribution and predicting its future distribution areas under different climate scenarios. Species occurrence data were collected and combined with bioclimatic data derived from the WorldClim database and vegetation data. Two climate models were used for future projections (RCP 4.5 and RCP 8.5). Results from the Jackknife test showed that five variables contribute significantly to the models. *V. tortilis* has a wide distribution, being present in all agroecological zones, with a high concentration in the Sahelian zone. Future climate projections for 2055 indicate an increase in the current vegetational range of species of 19.8% to over 30%. However, the potential distribution of the species is not compromised by the 2055 climate projections or local disturbance factors. The species will remain highly suitable for the study area, continuing to provide all the ecosystem services it offers.

Keywords: *Vachellia tortilis*, Distribution, Climate change, Model, Niger

Introduction

The diversity of biological resources has been a central theme for several decades, bringing together multiple disciplines not only for its conservation but also for its sustainable use (Thiombiano et al., 2006). Plant diversity is vital for human survival and well-being. In addition to cultivated species, many wild plants continue to play an important role in meeting local needs for food, fuel, medicine, and building materials (Scheldeman and Van Zonneveld, 2012). However, with the increasing threats to biodiversity, some species are becoming increasingly rare in their natural habitats. In addition to anthropogenic threats, climate change has emerged as a major threat to the survival of species and the integrity of ecosystems worldwide (Heller and Zavaleta, 2009; Sala et al., 2001). Understanding the specific properties of these changes, which may impact species or their habitats, is central to adaptation strategies (Heller et al., 2009).

Climate change will have numerous complex repercussions on trees with the most visible consequences being modifications in species' distribution areas (Hughes, 2000; Gbesso et al., 2013). Species distribution is expected to be affected by climate change, which may act as a limiting factor for species location (Fournier et al., 2017). The risk of species extinction due to the unexpected impacts of climate change is high. Understanding how local species are distributed is an essential prerequisite for effective conservation strategies (Issoufou et al., 2022). Ecological niche modeling (ENM) has proven to be a useful tool for identifying habitats, predicting species presence, and assessing the effects of climate change on different taxonomic groups (Pecchi et al., 2019).

The ability to model the geographic distribution of a species based on occurrence data and environmental information relies on the assumption that abiotic factors directly or indirectly control species distribution (Austin, 2002). Generating and projecting species distribution patterns require environmental data layers that provide discriminatory power regarding species presence and absence. Correlative niche modeling approaches, which rely on statistical associations between species occurrences and environmental variables, are frequently used (Peterson et al., 2011; Alvarado-Serrano and Knowles, 2014). WorldClim bioclimatic variables (19 variables) are among the most widely used environmental data layers due to their high resolution, global coverage, and availability for both historical and future climate scenarios (Hijmans et al., 2005).

It is increasingly likely that fluctuations in climatic variables such as precipitation and temperature will affect biological diversity and the geographical distribution of favorable habitats for species (IPCC, 2007; Fandohan et al., 2013). In a changing environment, predicting variations in species distribution is crucial, particularly for species management and domestication (Elith and Leathwick, 2009). Ongoing and projected climate change has revitalized interest in spatiotemporal species distribution studies. Phytogeography, as a science, studies the distribution of species across the globe (Schnell, 1972). It relies on cartographic tools, with the distribution map being the primary instrument. This allows for precise knowledge of the geographical distribution of a species and the identification of the factors that control it (Lebrun, 2001).

The distribution of species in equilibrium with their environment can thus be considered the spatio-temporal dimension of the niche. However, one of the main causes of species distribution changes is habitat destruction. Understanding the reasons behind habitat modification and species responses is an important research challenge in the current climate and biodiversity crisis. Changes in geographic distributions of species in response to climate change have been studied first in higher animals (Root et al., 2003; Devictor et al., 2008) and plants (Penuelas and Boada, 2003; Lenoir et al., 2008), typically through retrospective approaches, comparing current and past distributions.

Recent advancements in statistical techniques and geographic information systems (GIS) allow for more reliable and accurate distribution models (Elith and Leathwick, 2009). These models help enhance understanding of species ecology and enable more accurate predictions. Among these models are Maximum Entropy models (Phillips et al., 2006), which relate species presence data with environmental variables to estimate a "bioclimatic envelope," within which the species is presumed to survive, develop, and reproduce (Cordier, 2012).

Research on plant spatial distribution has already been conducted in Africa using new technologies such as GIS. Notable studies include Thiombiano et al. (2006) on the influence of climatic gradients on the distribution of Combretaceae species in Burkina Faso; Koffi (2008) on the spatial structures of phytogeographical distribution of Acanthaceae in Central Africa; Ndayishimiye (2011) on the diversity, endemism, geography, and conservation of Fabaceae in Central Africa; Laouali et al. (2016) on the geographical distribution of *Prosopis africana* in Niger; and Gbesso et al. (2013) on the impact of climate change on the geographical distribution of *Chrysophyllum albidum* in Benin. However, studies on the impact of current and future climate change on the distribution of *V. tortilis* are still lacking.

Indeed, climatic degradation, coupled with other anthropogenic factors, has led to significant degradation of forest ecosystems, including protected areas (Boulain, 2004; Sambou, 2004; Ozer and Ozer, 2005; Vroh et al., 2010; González et al., 2012). The vegetation in the Diffa region consists of steppes dominated by *V. tortilis* (Issa et al., 2009; Bio et al., 2021). This vegetation faces numerous biotic and abiotic challenges and preserving its services for the well-being of local populations is a critical issue. Beyond its ecological benefits, all parts of this species are extensively used, including for human and animal food, the treatment of diseases, and trade (Timothy et al., 1999; Jaouadi et al., 2016).

The main objective of this study was to assess the impact of climate change on the geographical distribution of *V. tortilis* in Eastern Niger, by analyzing the climatic factors influencing its current distribution and predicting its future distribution areas under different climate scenarios.

Materials and Methods

Sampling and data collection

Data on the occurrence of Vachellia tortilis

The models cover all Eastern Niger, but the presence points were collected in two localities that are part of the Great Green Wall area. The presence of *V. tortilis* was recorded during vegetation data collection (Phytosociological surveys). In each survey, the Global Positioning System (GPS) coordinates of all the individuals of the species were recorded. A total of 374 occurrence points were recorded. The database created was supplemented with presence points available on the Global Biodiversity Information Facility (GBIF) website (http://www.gbif.org/occurrence/download/0001383-171219132708484).

Climate data

Ecological niche modeling requires environmental data and presence data (Djotan et al., 2018). Among the environmental factors considered, climate is undoubtedly one of the most important factors influencing the distribution and growth of species (Thiombiano et al., 2006). The environmental data considered were the bioclimatic variables, including rainfall, temperature, and their derivatives, which are available on several download sites, especially on a global scale (Platts et al., 2015). However, on a global scale, bioclimatic variables do not offer sufficient confidence for climate simulations when conducting ecological niche modeling studies in Africa (Platts et al., 2015). The variables used for modeling ecological niches include both current and future climate variables. The current climate variables, corresponding to the period 1950–2000, were downloaded from the following link: https://webfiles.york.ac.uk/KITE/AfriClim/GeoTIFF_150s/baseline_worldclim/ (Hijmans et al., 2005).

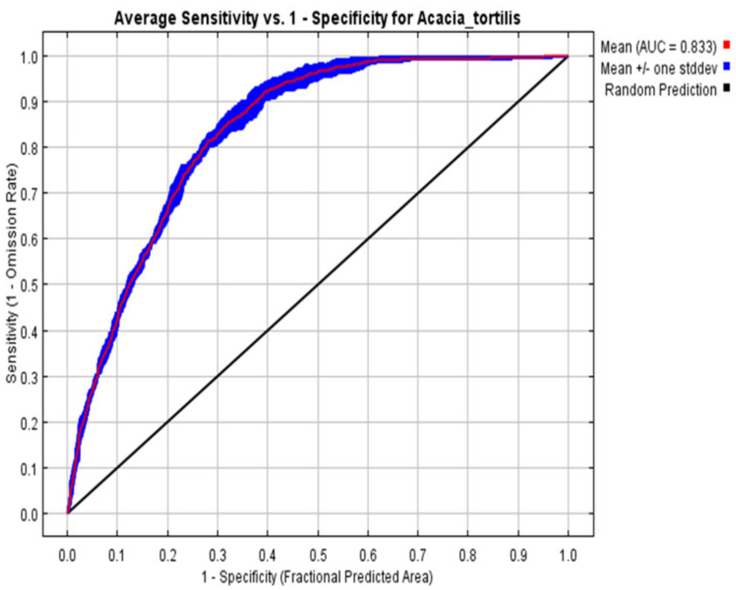

Figure 1 Receiver Curve (AUC)

TABLE 1
Africlim Climate Variables

Codes	Meanings
bio1	Annual average temperature
bio2	Mean diurnal difference (maximum temperature – minimum temperature; monthly mean)
bio3	Isothermality (BIO2/BIO7) * 100
bio4	Seasonality of temperature (Coefficient of variation)
bio5	Maximum temperature of the hottest period
bio6	Minimum temperature of the coldest period
bio7	Annual temperature difference (BIO5-BIO6)
bio8	Average temperature of the wettest quarter
bio9	Average temperature of the driest quarter
bio10	Average temperature of the warmest quarter
bio11	Average temperature of the coldest quarter
bio12	Annual precipitation
bio13	Precipitation of the wettest period
bio14	Precipitation of the driest period
bio15	Precipitation seasonality (Coefficient of variation)
bio16	Precipitation of the wettest quarter
bio17	Precipitation of the driest quarter
bio18	Warmest Quarter Precipitation
bio19	Precipitation of the coldest quarter

The future climate variables, corresponding to the 2055 horizon based on two scenarios, RCP 4.5 and RCP 8.5, were downloaded from the link: https://webfiles.york.ac.uk/KITE/AfriClim/GeoTIFF_150s/africlim_ensemble_v3_worldclim/ (Platts et al., 2015).

RCPs are climate models based on emissions and environmental protection policies, which provide insights into potential climate change (Stocker et al., 2013). According to Meinshausen et al. (2011), RCP 4.5 and RCP 8.5 are among the most realistic scenarios. Based on their respective forecasts, RCP 4.5 is optimistic, while RCP 8.5 is pessimistic (Meinshausen et al., 2011). RCP 4.5 predicts a stabilization of radiative forces after 2100 without exceeding the target value of 4.5 W.m² (Clarke et al., 2007; Wise et al., 2009), while RCP 8.5 predicts an ongoing increase in greenhouse gases over time, leading to the highest concentration of these gases in the atmosphere (Riahi et al., 2007; Djotan et al., 2018). For each of these scenarios, the ensemble mean model was used (Laouali et al., 2016; Djotan et al., 2018). The distribution of the species' presence points is shown in Figure 1. The climatic variables used to run the model are listed in Table 1.

Data processing

Modeling techniques

The niche models were constructed using the MaxEnt (Maximum Entropy) modeling algorithm (Phillips et al., 2006). The contribution table of biovariables and the Jackknife table, which evaluates the gain of training data, were used to select the five (5) variables most likely to explain the species' distribution (Djotan et al., 2018). These five (5) retained variables were then used to run the model in "cross-validation" mode with five (5) repetitions, and the mean values of the parameters were applied. These parameters include the species logistic distribution model, the decision threshold which excludes 10% of the presence points in the favorable areas ("10 percentile training presence"), the Area Under the Curve (AUC) validation criterion, and its standard deviation (Djotan et al., 2018). A decision threshold of 5% was retained. This threshold minimizes the omission error rate on the test of the model and the commission error rate on the species presence points, while providing a reasonable logistic probability of distribution value (Djotan et al., 2018).

Techniques for using MaxEnt results

For data preparation, the Africa data in TIF format was uploaded to the AfriClim website. The data were then cropped to the scale of Niger and converted to ASCII format (*.asc) using ArcGIS 10.6 software. ArcGIS 10.6 and QGIS 3.14 were used to process and present the results from MaxEnt. After generating maps of favorable areas for the species, a classification was performed based on the retained threshold value (5%). Areas where the logistic probability of distribution was below the threshold were defined as unfavorable, while areas with values above the threshold were classified as favorable (Djotan et al., 2018). The study area layer was then overlaid on the favorable areas for the species' distribution.

Stages of Ecological Niche Modeling

The stages of favorable ecological niche modeling are those described by Gbesso et al. (2013), namely:

Introduce the geographical coordinates of the species' presence into the MaxEnt processing algorithm in CSV format (the coordinates must be converted to decimal degrees).

Integrate the bioclimatic envelopes (precipitation and temperature data for a specified site, with a minimum surface area of 5m x 5m) into the same algorithm. These data include the 2000 climate scenarios and those predicted for climate change in 2050. According to the IPCC (2007), climate change scenarios are based on assumptions about the functioning of the Earth's climate and greenhouse gas emissions.

Evaluate the data integrated into the MaxEnt algorithm, which will generate a favorable ecological niche model. The prediction is based on interpolation of the bioclimatic characteristics of each species' presence point.

Add geographical boundaries and the outline of the study area to refine the interpretation of the model.

Mapping and spatial analysis

The modeling results produced by MaxEnt were imported into ArcGIS 10.6 software to map favorable habitats for *V. tortilis* under both current and future climate conditions, using the RCP 8.5 emission scenario. This scenario was preferentially used because it predicts a situation considered more likely for Africa by 2050 (Williams et al., 2007; Gbesso et al., 2013). Using the spatial analysis tool in QGIS 3.14, the extent of each habitat type under present and future climatic conditions was estimated by counting the number of pixels occupied by each habitat type. This allowed for the assessment of the gain or loss in the area favorable to the species at the scale of the study area, based on climate projections (Gbesso et al., 2013).

Results

MaxEnt Model Validation

Table 2 presents an estimate of the relative contributions of environmental variables to the MaxEnt model. The mean value of the

TABLE 2

Contribution of bioclimatic variables of the present

Variables	Percent contribution	Permutation importance
bio12	56.5	50.4
bio5	13.4	5
bio16	7.2	0
bio7	5.6	10.3
bio2	3.8	10
bio3	3.3	1.4

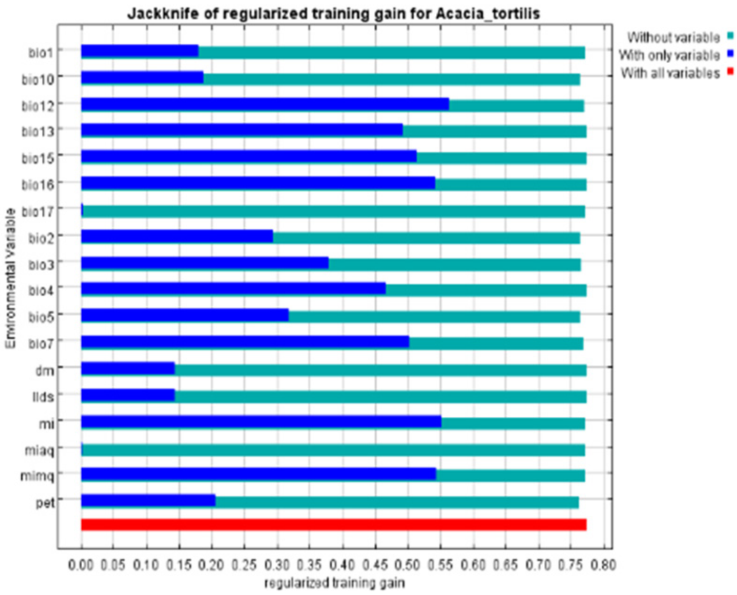

Figure 2 Gain jackknife regularized on calibration data

endpoint is 0.833 ± 0.009 (Figure 2). The five (5) retained variables are bio12, bio5, bio16, bio7, and bio2. The values shown are averages over repetitions. To determine the first estimate, at each iteration of the training algorithm, the increase in the regularized gain is added to the contribution of the corresponding variable or subtracted if the variation in the absolute value of lambda is negative. For the second estimate, the values of each environmental variable are permuted randomly with respect to the presence data and the baseline data. The model is re-evaluated using the permuted data, and the resulting drop in training AUC is shown in Table 2, normalized as percentages.

The Jackknife test of variable importance was also performed (Figure 3). The environmental variable that shows the highest gain when used in isolation is bio12, suggesting that this variable alone provides the most useful information.

Points of presence of Vachellia tortilis

Botanical records, including data from GBIF and phytosociological surveys, indicate that the species has a wide distribution. It is present in all climatic zones, with a particularly strong presence observed in the Sahelian and Sahelo-Saharan climatic zones of the country (Figure 4).

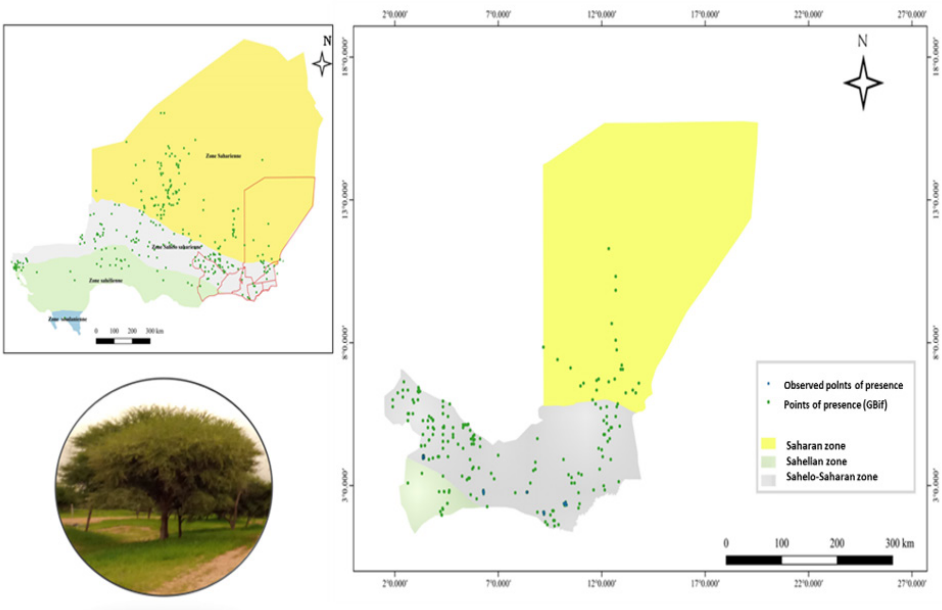

Figure 3 Current presence of *Vachellia tortilis*

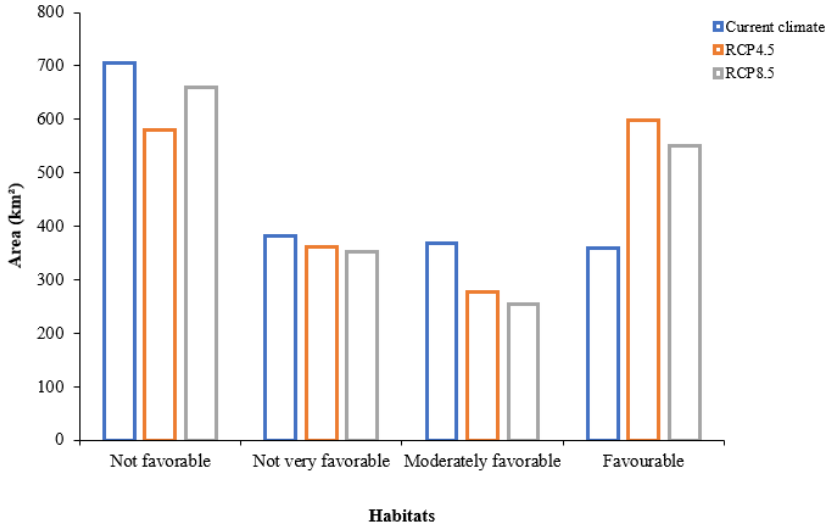

Figure 4 Habitats to *Vachellia tortilis* from the study area

Favorable areas for Vachellia tortilis according to current and future climates

The model based on current climate data identifies the areas favorable to the species, primarily covering the southern strip and extending slightly to the north of the study area. The extreme northern part of the zone (desert area) is not favorable for the species. The proportions of favorable habitats for *V. tortilis* in the study area are presented in Table 3. Under the current climate, the prediction shows that 19.8% of the total study area is favorable, while the RCP 4.5 and RCP 8.5 scenarios predict 32.85% and 30.33%, respectively, in the Sahelian and Sahelo-Saharan zones (Figure 5). The different scenarios indicate that the area of "unfavorable" zones for the species distribution is larger than that of favorable zones (Figure 6).

TABLE 3

Proportions of areas favorable to *Vachellia tortilis* from the study area

Scenarios	Not favorable (%)	Unfavorable (%)	Moderately favorable (%)	Favorable (%)
Current climate	36.86	21.05	20.29	19.8
RCP 4.5 (Horizon 2055)	31.94	19.92	15.29	32.85
RCP 8.5 (Horizon 2055)	36.26	19.37	14.04	30.33

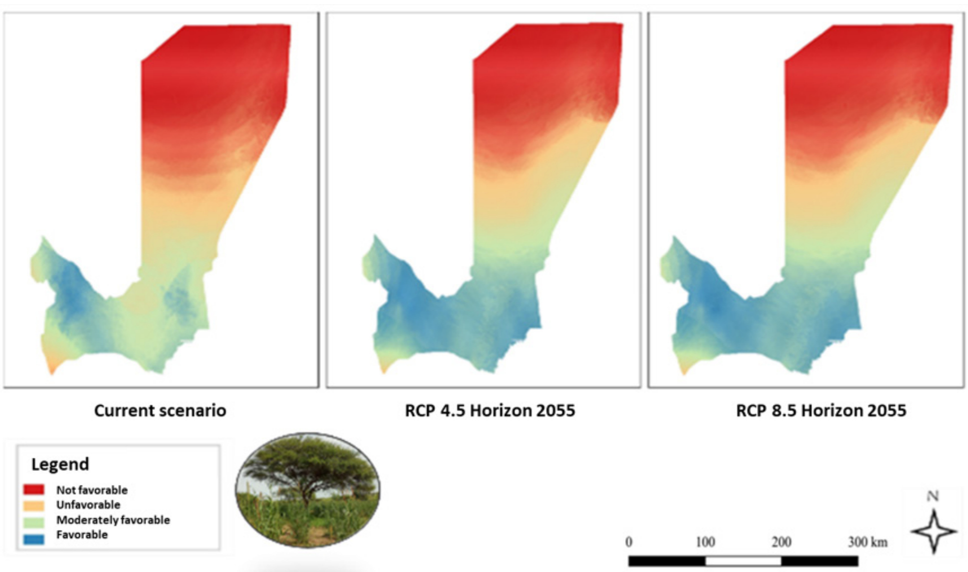

Figure 5 Distribution of areas predicted favorable to the species in the current climate and future climates, horizon 2055

Discussion

Ecological niche modeling is widely recognized as a powerful tool for mapping the current and future distribution of species, as well as predicting the impact of climate change on their distribution (Van Zonneveld et al., 2009; Nakao et al., 2010). According to Schmidt et al. (2008), models can be seen as a simplified representation of reality, providing critical bioclimatic data for decision-making and identifying potentially suitable new areas for the conservation of a given species (Schwartz, 2012).

The study highlighted the variables that most significantly contribute to the distribution of *V. tortilis*. A total of five (5) environmental variables were selected for the model, including bio12 (annual precipitation), bio5 (maximum temperature of the warmest period), bio16 (precipitation of the wettest quarter), bio7 (annual temperature deviation), and bio2 (diurnal temperature deviation). Of these, bio12 and bio5 were the most influential, reflecting the current climatic conditions of the area, particularly the precipitation difference between ecological zones, which corresponds to the species' high concentration in the Sahelian zone.

This study also demonstrates that the species has a broad distribution, present across all agro-ecological zones, with a high concentration in the Sahelian zone (Isohyets 300 to 350 mm/year). This wide distribution is likely due to the species' forage value and its ability to withstand drought. After the rainy season, *V. tortilis* forms a fodder bank for livestock. Through pastoral mobility, animals help disseminate the seeds of the species (zoochory). Bio et al. (2019) found that the passage of *V. tortilis* seeds through the digestive tracts of animals improves their germination. Given the role of herbivores in dispersing acacia seeds, grazing could be considered an environmental parameter of the species' ecological niche, though it may also disrupt the species' regeneration (Traoré et al., 2008).

Furthermore, the study found that climate variables alone do not predict the distribution of *V. tortilis*. The areas favorable for its distribution have changed from the current climate to future climate scenarios. These findings align with McClean et al. (2005), Alig (2011) and Djotan et al. (2018), who suggest that the favorable areas of plant species are constantly shifting and will continue to do so because of climate change. Pearson and Dawson (2003) argue that soil variables should be considered when estimating suitable habitats for species distribution at scales below 2000 km. However, Allen et al. (2011) claim that soil variables are unlikely to change in the future climate, and according to Wixon and Balser (2009), defining soil characteristics for future climates remains a significant challenge. Bio et al. (2020) reported that *V. tortilis* can withstand droughts lasting up to seven days, and the nature of the soil is not a limiting factor for its development. Therefore, climatic factors are likely the primary influences on the species' distribution in this area, supporting the findings of several authors (Guisan and Zimmermann, 2000; Gbesso et al., 2013; Fandohan et al., 2013; Laouali et al., 2016; Djotan et al., 2018), who have confirmed that temperature and precipitation are the most effective variables when modeling species distribution over large areas.

According to Fandohan et al. (2013), the current climate where a species is found represents its original ecological niche. It is possible that when the species first colonized these areas, the climate was significantly different (either wetter or drier). The current presence of the species is the result of millennia of adaptation to various climatic changes. Therefore, future climates by 2055 are expected to increase the favorable area for *V. tortilis* from 19.8% to more than 30%. This trend in expanding favorable habitats is attributed to increased rainfall predicted by the two climate models (RCP 4.5 and RCP 8.5). As a result, the species' potential distribution is not expected to be compromised by climate change by 2055, nor by local disturbances such as the ecological impact of refugees and displaced people.

Conclusion

In conclusion, this study highlights the significant impact of climate change on the distribution of *Vachellia tortilis* in Eastern Niger. The results demonstrate that climate change may drastically alter the habitat suitability for this species, with potential consequences for local pastoral practices and biodiversity. Our predictive models suggest that without adaptive measures, the species could face a reduction in suitable habitats, leading to challenges for livestock farming and forage availability in the region. To mitigate the negative effects of climate change on *V. tortilis* and local communities, it is crucial to develop and implement climate adaptation strategies. These may include the restoration of degraded land, the establishment of protected areas for the species, and the promotion of agroforestry systems that integrate climate-resilient species. Further research is needed to refine the species distribution models by incorporating more localized data and exploring the impacts of other environmental factors, such as land use and soil degradation. Monitoring the ongoing effects of climate change on *V. tortilis* will also be essential to ensure the sustainability of the species and the pastoral systems that depend on it.

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