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Response of Species to the Impact of Climate Change in the Gum Arabic Belt, Sudan: A Case Study in *Acacia senegal*

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Sustainable management strategies of trees are important for indigenous agroforestry plant species, such as *Acacia. Senegal (A. Senegal*), due to the impacts of rapid population growth, land use and climate change. The objective of this investigation was to predict the spatio-temporal distribution of *A.senegal* in the Gum Arabic belt in Sudan in current (1985–2000) and future climate scenarios (2021–2100). Bioclimatic data was used for modeling purposes utilizing Maxent, with the assessment of model precision conducted through the utilization of the Area Under the Curve (AUC) and shown a high goodness-of-it (AUC=0.905±0.003). Significant differences were shown in species distribution between current and future periods under selected Shared Socioeconomic Pathways (SSPs) of SSP2-4.5 and SSP5-8.5, climate scenario. Our findings indicated that the main predictors influence the distribution of the species were precipitation of wettest quarter and maximum temperature of warmest month. Under the current potential distribution (25.4%), it is projected that Acacia Senegal would expand 36.2%-87.7% (SSP2-4.5) and 38.9-42.5% (SSP5-8.5). It is expected that *A.cacia* Senegal will create new environments suitable for it due to expected climate changes. Hence, the research necessitates the formulation of a strategic plan aimed to rehabilitation plantations of *Acacia senegal* and cultivation these species within existing and prospective habitats conducive to their existence.

Keywords: Population growth; Acacia senegal; climate change; entropy.

1. INTRODUCTION

Population growth, expansion in agricultural areas, and CO_2 emissions are crucial threats that directly or indirectly affect biodiversity, especially within sub-Saharan Africa. Most regions in Africa are threatened by climate change [1,2]. Due to the social, environmental, and economic importance of this arid and semiarid region, its greatest threat is climate change, and land degradation is caused by unsustainable agriculture, overgrazing, desertification, and deforestation [3]. *Acacia senegal* is highly significant as a prevalent species within the sub-Saharan region [4]. *Acacia senegal* naturally occurs either as a common extensive pure stand or mixed with other species with good diversity, such as semidesert grassland, Anogeissus woodland and rocky hill slopes, and the species can grow on different soil textures (sandy-light loamy soils) [5]. It is a species of tree, and forest shrubs have multiple purposes for commercial use, food, medicine, and cosmetics. It also supports dry-land ecosystems [6–10].

Geographic shifts in species are caused by climate change, especially in Africa [11,12]. For instance, some studies are actively focusing on understanding how climate change affects the geographic shifts of various species by using predictive modeling (Maxent) [13-15]. Predictive modeling, which relies on environmental data sourced from documented occurrence sites, plays a pivotal role in analytical biology. It has applications in different fields, such as those related to the environment, such as sustainable management programs of reserves, ecology, evolution, and epidemiology. This approach enables the prediction of species geographic distributions and plays a significant role in understanding and addressing biological phenomena [16]. Maxent is a proper method for addressing insufficient or incomplete information to make predictions or extract inferences about species distributions in current potential areas or new suitable areas. It serves as a general-purpose tool for analyzing and estimating outcomes based on limited data availability. It estimates a target probability distribution through the identification of the probability distribution with maximum entropy. This corresponds to the distribution that is most common for species. This is achieved by considering a set of constraints that represent the limited information available regarding the target distribution [17]. Maxent has several advantages and drawbacks compared to other modeling methods. Some of these benefits include leveraging presence data and environmental information across the entire study area, eliminating the need for absence data, and the ability to handle both continuous and categorical data, allowing for the consideration of the relationships among various variables. The presence of effective deterministic algorithms ensures convergence to the optimal probability distribution with maximum entropy. The Maxent probability distribution is defined concisely, simplifying analysis and interpretation [16,17]. Maxent has been shown to provide model with acceptable predictive ability even when few prescience records are available, indicating that the model can predict well with small sampling presence points. Maxent can Handel small sample size, careful variable selections and model evaluation are critical when working with limited data [18]. The study also validate with excellent performance.

2. MATERIALS AND METHODS

2.1 Methodology

2.1.1 Site description

The Gum Arabic belt in the middle of Sudan extends from the western border of Sudan to the eastern border of Sudan and covers an area of approximately 520,000 km^2. The Gum Arabic belt in Sudan is located between 10°N and 14°N, covering 1/5 of the total area of Sudan [19]. Sandy soils are predominant in the western (Darfur stats) and central (Kordofan's stats) regions with pockets of clay soil (vertisol) in these areas, while clay soils are commonly found in the eastern (Al-Gadarif stat) and (Blue Nile stat) regions in the southern region [19,20]. The mean annual rainfall in this region ranges between 100 and 800 mm [21]. Specifically, the study area has diverse tree species dominated by many families, such as Fabaceae, Apocynaceae, Poaceae, and Balanitaceae [22–24]. The natural vegetation is woodland savannah dominated by various species, for instance, *Dichrosta. Cortolaria senegalensis* (Al-Safari Plant) *Acacia seyal*, Sorghum (Adar), *A. polyacantha Wild.*, and *Combretum* spp. [25]. Additionally, in this region, common vegetation cover can include poor rangeland and scattered woody plants dominated by Acacia species and *Leptadena pyrotechnica* [26]. Recently, in the areas to the north of west Darfur, Woodland Savanna forest, which forms vegetation cover, has been dominated by low rainfall. Herbal species include different species, such as *Chloris gayana*, *Cassia obtusifolia*, and *Tribulus terrestris*, in addition to Acacia being the dominant tree species, whereas formerly, Savanna woodland species predominated in the area [27]. The southern geographical area holds a diverse array of species, encompassing fruit-bearing trees such as *Adansonia digitata*, *Balanites aegyptiaca*, and *Diospyros mespiliformis*, as well as gum-producing species such as Acacia species and *Boswellia papyrifera*. Additionally, it features various other useful species, such as *Combretum aculeatum* and *Ficus sycomorus*, and is utilized locally for medicinal, fodder, and construction purposes, as well as for fuelwood production [28].

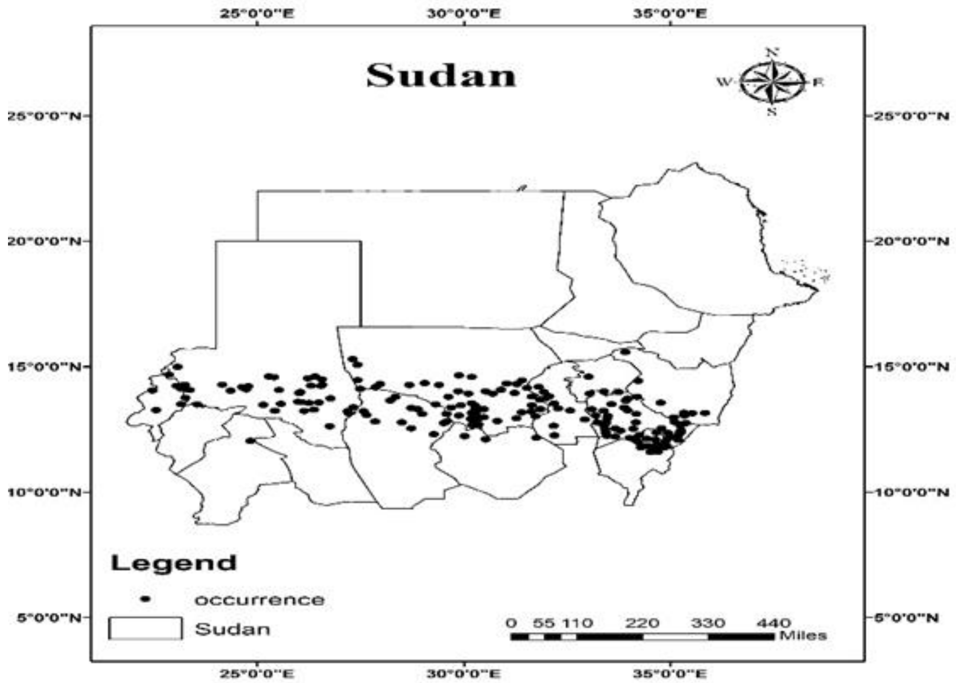


Fig. 1. Occurrence of *Acacia senegal* in Sudan

2.2 Data Collection

The input datasets were obtained from occurrence points with GIS for the ground data used GPS and satellite images collected in Sudan for WorldClim for climate data. A total of 164 geospatial coordinates (longitude and latitude) were obtained from fieldwork, the National Research Center, and previous research carried out in Sudan (Fig. 1). Bioclimate data were extracted for current data (1985-2000) and future data (2021-2100) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) WorldClim version 2.1. For future climate data for different periods, general distribution models (GCMs) were used, and a clustering approach was adopted to reduce model uncertainty. These datasets were also used to predict the distribution of *Acacia senegal* under current and projected climate conditions using the maximum entropy model. (Maxent 3.4)

This research utilized version 3.4.4 of the Maxent Model, an ecological niche modeling method, to predict the potential distribution of *Acacia senegal* under current and projected climatic conditions. Future climate data were obtained from three general circulation models (GCMs) covering the 2021-2040, 2041-2060, 2061-2080, 2081-20100 time periods. An ensemble of climate models was employed, including the Goddard Institute for Space Studies (GISS-EC-1G), Max Planck Institute Earth System Model 1-2-High Resolution (MPI-ESM1-2-HR), and Institute Pierre-Simon Laplace (IPSL) GCMs. These models were chosen for ensemble integration based on their demonstrated efficacy in previous research conducted in Sudan: GISS-EC-1G, MPI-ESM1-2-HR, and IPSL-CM6A-LR [29,30]. Like other East African countries, Sudan lacks its own calibrated general circulation model (GCM). Different models were applied.

This ensemble of three global climate models was used to process the limitations, unsureness, that are related to the use of one global climate model for strictly predicting future climate trends [31]. Several studies have reported that the remarkable development of utilizing the multi-model group technique has emerged as the foremost strategy for reducing model uncertainty [32]. To combine GCMs with equal weights, ArcGIS was used, and arithmetic mean arithmetic was commonly applied to combine multiple models. Regarding the arithmetic average, the arithmetic mean has been commonly applied to utilize multiple models, such as ArcGIS, which is an ensemble that incorporates general circulation models (GCMs) with uniform weighting [10].

The current climatic data were obtained from WorldClim version 2.1. This dataset comprises climate information spanning the temporal range from 1970 to 2000, while future projections extend from 2021 to 2100 [33]. The datasets for both the present and future climatic conditions were acquired with a spatial resolution of 30 seconds, equivalent to approximately (km)2, and were accessed from the WorldClim database. Future climate data were sourced from CMIP6, demonstrating both qualitative and quantitative advancements over prior phases such as CMIP5. These improvements encompass a more precise representation of physical phenomena, simulated variables, and enhanced spatial granularity [10]. Furthermore, comparative analyses with CMIP5 indicate superior performance in terms of resolution in CMIP6 [34]. The refined resolution in CMIP6 contributes to more substantial scientific insights [35].

Table 1. Variables contributing to prediction

Code	Bioclimatic variables	Code	Bioclimatic variables
Bio01	Annual Mean Temperature	Bio13	Precipitation of Wettest Month
Bio02	Mean Diurnal Range	Bio14	Precipitation of Driest Month
Bio03	Isothermality	Bio15	Precipitation Seasonality
Bio04	Temperature Seasonality	Bio16	Precipitation of Wettest Quarter
Bio05	Max Temperature of Warmest Month	Bio17	Precipitation of Driest Quarter
Bio06	Min Temperature of Coldest Month	Bio18	Precipitation of Warmest Quarter
Bio07	Temperature Annual Range	Bio19	Precipitation of Coldest Quarter
Bio09	Mean Temperature of Driest Quarter		
Bio10	Mean Temperature of Warmest Quarter		
Bio11	Mean Temperature of Coldest Quarter		
Bio12	Annual Precipitation		

The CMIP6 utilizes scenarios based on shared socioeconomic pathways (SSPs), which can be broadly classified into two categories: challenges to mitigation efforts and barriers to adaptation initiatives. SSP1 exhibits minimal impediments to both mitigation and adaptation, emphasizing policies focused on improving human welfare, promoting the advancement of clean energy technologies, and safeguarding natural ecosystems. Conversely, regional rivalry (SSP3) is marked by significant challenges to both mitigation and adaptation, prioritizing nationalist policies that address local and regional concerns over global priorities. Inequality (SSP4) is characterized by considerable challenges to adaptation but fewer hurdles to mitigation, whereas fossil fuel development (SSP5) faces substantial challenges in mitigation but fewer obstacles in adaptation efforts. [36].

In particular, SSP2 (middle of the road) delineates a situation characterized by moderate hurdles concerning both mitigation and adaptation efforts; for trend analysis, two SSPs were chosen for scrutiny: SSP2-4.5 and SSP5-8.5 [36,37]. These scenarios were chosen to simulate the distribution patterns of the three species under the expected future climate conditions. The choice of these SSPs was informed by their depiction of both moderate and extreme emission trajectories, along with a range of mitigation and adaptation approaches. This intentional selection enables the analysis of a "Middle of the Road" scenario and a "Fossil-fueled Development" scenario, covering a broad spectrum of extremes in contrast to existing adaptation and mitigation efforts [12].

2.3 Data Analysis

Previous studies stated that the decision to utilize the Maxent model for the analysis was driven by its strong ability to establish relationships between environmental variables and species presence records, as demonstrated previously [15]. Machine learning methods employ species presence data and environmental factors to estimate species distributions [38], which is particularly suited for presence-only records, particularly presence-only records [16] Maxent has shown superior predictive efficacy in comparison to alternative structured decision-making models such open moddeler, linear models, bioclim, GARP and others [13].

An important advantage of Maxent is its ability to mitigate collinearity issues during model training; highly correlated predictor variables are removed, which has negligible effects on its performance [39]. Maxent adeptly manages complexity by downplaying the significance of redundant variables, effectively addressing collinearity issues [15,16]. Maxent achieves an optimal balance between model fitting and complexity through regularization techniques [15].

2.3.1 Model Accuracy and species Suitability

In this study, model validation was conducted by splitting the occurrence points into two segments. The training phase utilized 80% of the observed species data, while the remaining 20% served as test data for validation. To evaluate model prediction performance, metrics such as the area under the Receiver Operating Characteristic (ROC) curve (AUC), True Skill Statistic (TSS), and Kappa statistic were employed, as outlined by Fu et al. [40].

The AUC metric is commonly employed to gauge model accuracy and selection criteria, as noted by Duan et al. [41] Model accuracy was assessed by establishing a threshold value for the AUC, ranging from 0.5 to 1.0. This threshold serves as an indicator of the model's accuracy level, as discussed by Braunisch [42,43] categorized AUC thresholds as follows: AUC ≥0.9 (very good), 0.8 < AUC <0.9 (good), 0.7 <AUC <0.8 (satisfactory), 0.6 <AUC <0.7 (unsatisfactory), and 0.5 <AUC <0.6 (invalid). These thresholds aid in determining the accuracy and reliability of the model predictions. The True Skill Statistic (TSS) is gaining recognition as a valuable metric for evaluating model performance, particularly in predicting presence-absence. It assesses both omission and commission errors, as well as chance success, on a scale from -1 to +1, where +1 signifies perfect agreement. TSS is often calculated by comparing model predictions with a validation dataset using a confusion matrix. The Kappa statistic is widely used to assess models predicting presence-absence, determining agreement based on an optimal threshold derived from the confusion matrix. Evaluation categories for Kappa range from excellent to fail, with specific thresholds. AUC, Kappa, and TSS are commonly employed metrics for model evaluation, derived from sensitivity and specificity calculations. This study utilized all three parameters, with AUC calculated by MaxEnt and Kappa and TSS manually computed.

The True Skill Statistic (TSS) is increasingly valued for evaluating models, according to Arau [44] Typically, models predicting presence-absence are assessed using a confusion matrix, comparing predictions with validation sites. TSS accounts for omission, commission errors, and random guessing, with a scale from -1 to +1 where +1 signifies perfect agreement. The Kappa statistic is another commonly used measure, evaluating agreement from an optimal threshold in the confusion matrix. Evaluation criteria for Kappa vary from excellent to fail. AUC, Kappa, and TSS, derived from sensitivity and specificity calculations, are widely employed metrics for model assessment, as highlighted by Konowalik and Nosol [45]. This study utilized all three parameters, with AUC computed by MaxEnt and Kappa and TSS manually calculated using specific equations (1-6).

$$x = a + b + c + d \tag{1}$$

$$Overall\ accuracy = \frac{a+d}{x} \tag{2}$$

$$Sensitivity = \frac{a}{(a+c)} \tag{3}$$

$$Specivity = \frac{d}{(b+d)} \tag{4}$$

$$TSS = Sensitivity + Specivity - -1 \tag{5}$$

$$Kappa\ statistic = \frac{(\frac{a+d}{2}) - \frac{(a+b)(a+c)(c+d)(d+b)}{x2}}{1 - \frac{(a+b)(a+c)(c+d)(d+b)}{x2}} \tag{6}$$

The Maxent method produces continuous raster outputs indicating habitat suitability on a scale from 0 to 1. This study utilized the 10th percentile value to categorize presence and absence maps. The model-generated maps were classified using Diva GIS 7.5 and ArcGIS 10.1 to identify high-impact, neutral, low-impact, and new suitable areas. This classification yielded four categories, shedding light on climate change's potential impact on species distribution.

The high-impact zone (Loss) comprises areas currently suitable but projected to become unsuitable in the future, indicating habitat loss. The zone outside the realized niche (Neutral) includes currently unsuitable areas projected to remain so. Conversely, the low-impact zone (Neutral) encompasses stable habitats currently and projected to remain suitable despite changing climates. Lastly, the new suitable zone (Gain) identifies currently unsuitable areas expected to become suitable in the future. These classifications, derived from binary rasters indicating presence (1) and absence (0), offer insights into climate change's implications for species distribution, informing targeted conservation and management strategies.

2.3.2 Data analysis

Statistical analysis was conducted to compare potential distributions depicted in current and future raster maps obtained from MaxEnt output. Point data were extracted using ArcGIS and converted to Excel format for compatibility with statistical analysis using SPSS version 20 software. The transition from present to future scenarios, based on SSP2-4.5 and SSP5-8.5 scenarios, was analyzed in temporal segments using a nonparametric statistical method. Additionally, the magnitude of suitability was compared using the same statistical approach.

3 RESULTS

3.1 Model Accuracy

The Maxent model exhibited excellent performance, and the outcome of the model was acceptable because the outcome reflected excellent performance in accurately delineating the distributional profile of *Acacia senegal*, with mean training and test AUC metrics of 0.905 (Fig. 4). Run for Aciaca senegal generated an AUC greater than 0.9, indicating great accuracy.

3.2 Thresholds and Suitability

The study established suitability thresholds for *Acacia senegal*, indicating that it is suitable when $0.36 < P < 0.54$, unsuitable when $0 < P < 0.18$, and extremely suitable when $0.72 < P < 1$. These thresholds demonstrated statistical significance for species distribution classification at a significance level of $P < 0.05$. By utilizing the tenth percentile of training presence, the study evaluated suitability percentages and their effects on habitat suitability throughout the entire research area, covering 520,000 km². Additionally, a notable discrepancy ($p < 0.05$) was noted in the suitability values between the present and future time frames under both SSP scenarios (Table 2). The average suitability value under SSP2-4.5 exhibited a reduced magnitude compared to the present value. In contrast, the average suitability value for SSP5-8.5 showed a significantly greater magnitude in the future, surpassing current suitability thresholds.

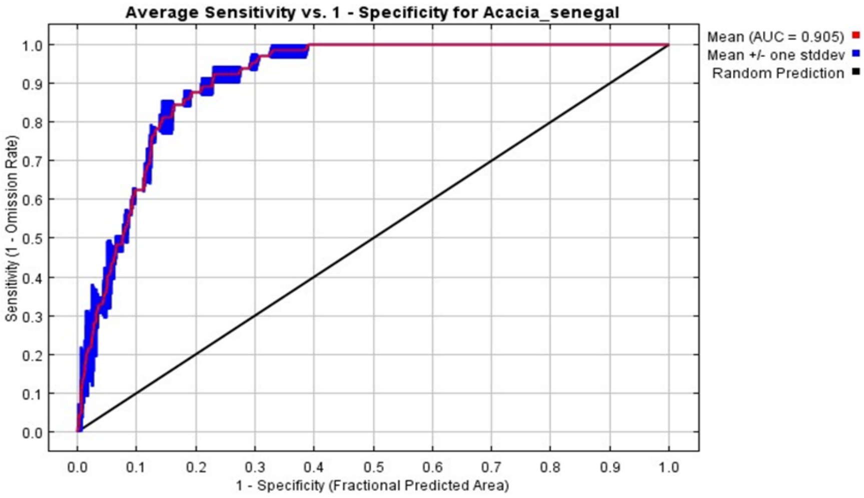


Fig. 2. Cross-validated AUC (area under the receiver operating characteristic curve)

Table 2. Distribution Threshold Magnitudes across Various Time Slices and SSPs

Period	Mean±SD	Maximum
Current	0.095 ± 0.164	0.903
2021-2040 SSP2-4.5	0.17 ± 0.25	0.988
2021-2040SSP5-8.5	0.22 ± 0.29	0.983
2041-2060SSP2-4.5	0.25 ± 0.33	0.997
2041-2060SSP5-8.5	0.29 ± 0.35	0.994
2061-2080SSP2-4.5	0.21 ± 0.30	0.993
2061-2080SSP5-8.5	0.27 ± 0.34	0.997
2081-2100SSP2-4.5	0.22 ± 0.30	0.995
2081-2100SSP5-8.5	0.26 ± 0.34	0.98

Table 3. Variable contributions and permutation importance

Variable	Definition	Percent contribution (%)	Permutation importance (%)
bio16	Precipitation of Wettest Quarter	56.3	3.4
Bio 5	Max Temperature of Warmest Month	10.5	3.2
Bio 7	Temperature Annual Range	9.5	1.5
Bio 19	Precipitation of Coldest Quarter	5.2	3.5
Bio 4	Temperature Seasonality	4.7	13.3
Bio13	Precipitation of Wettest Month	2.3	24.2
Bio 8	Mean Temperature of Wettest Quarter	2.2	12.2
Bio6	Min Temperature of Coldest Month	2.1	20.8
Bio15	Precipitation Seasonality	1.9	2.8
Bio1	Annual Mean Temperature	1.8	0.6
Bio3	Isothermality	1.2	0.6
Bio17	Precipitation of Driest Quarter	0.5	0.6
Bio18	Precipitation of Warmest Quarter	0.5	0.6
Bio10	Mean Temperature of Warmest Quarter	0.3	0
Bio12	Annual Precipitation	0.3	7.3
Bio11	Mean Temperature of Coldest Quarter	0.2	4.2
Bio 2	Mean Diurnal Range	0.2	1.3
Bio 9	Mean Temperature of Driest Quarter	0.2	0.1
Bio14	Precipitation of Driest Month	0	0

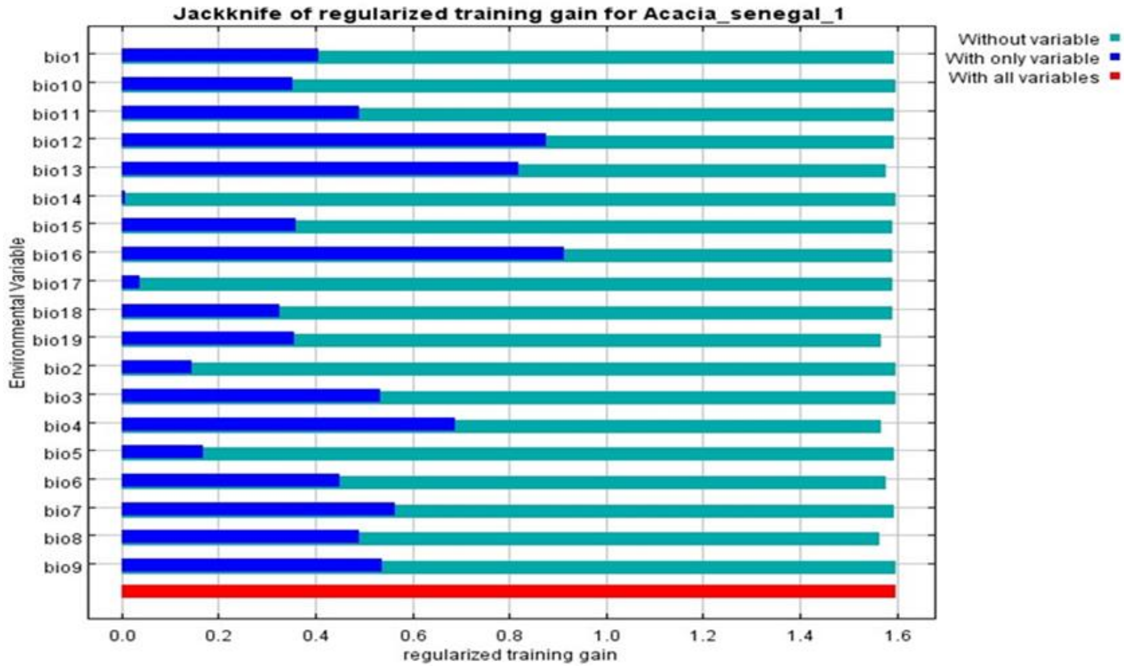
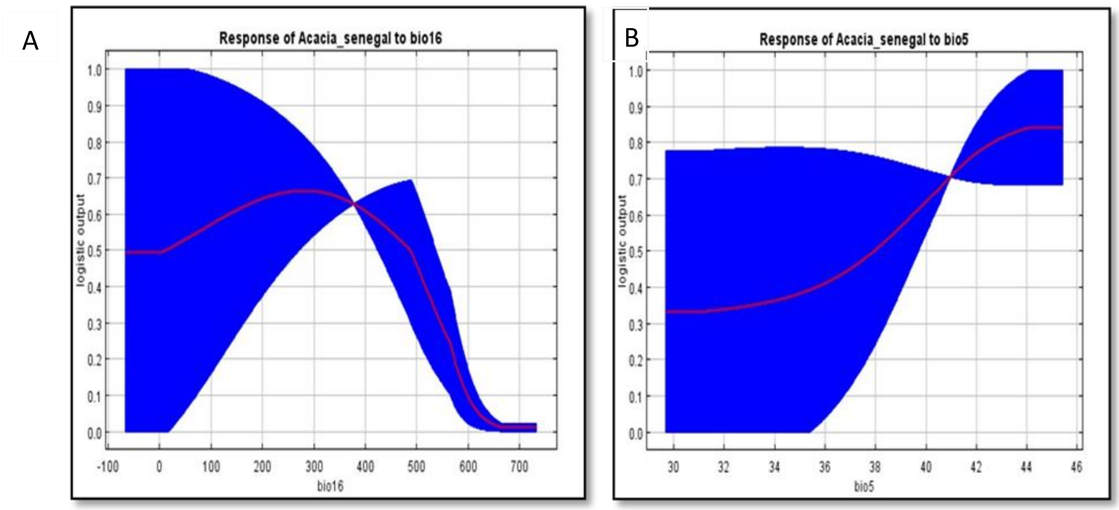


Fig. 3. Jackknife plot of the regularized training gain for *Acacia senegal*

Table 4. *Acacia senegal* distribution in SSP2-4.5 (% and km^2) as a proportion of the total study area (520000 km^2)

Period	Potential distribution SSP2-4.5		New suitable area SSP2-4.5	
	Area (Km^2)	Area (%)	Area (Km^2)	Area(%)
Current	132219.6	25.4	------	------
2020-2040	456001.6	87.7	323782	62.3
2041-2069	208998.0	40.2	76778.4	14.8
2061-2080	188166.6	36.2	55947	10.8
2081-2100	195271.6	37.6	63052	12.3



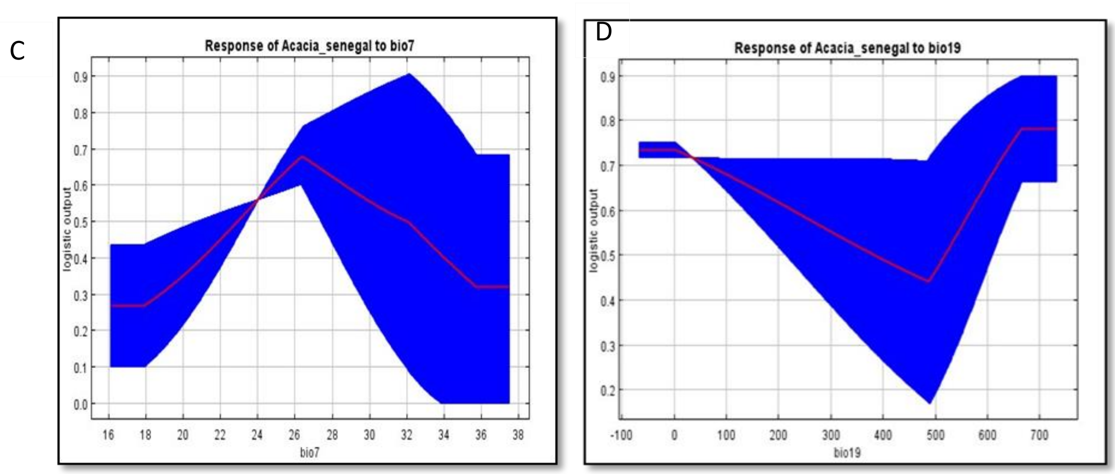


Fig. 4. Response curves of Acacia senegal to bioclimatic predictors in habitat suitability modeling

Logistic output. A- Precipitation of the wettest quarter (bio16, mm); B- Maximum temperature of the warmest month (bio5, °C); C- Annual temperature range (bio7, mm); D- Precipitation of the coldest quarter (bio19, mm).

3.3 Contribution of Variables

The major predictors that made excellent contributions to the species distribution were precipitation of wettest quarter (bio 16), with a percentage contribution of 56.3%; the second predictor was the maximum temperature of warmest month (bio5), with a percentage of 10.5%; and the following predictors, with a percentage less than 10%, were the temperature annual range (bio7), mean temperature of driest quarter (bio 9), precipitation of coldest quarter (bio 19), and temperature seasonality (bio 4) (Table 3). The environmental variable with the greatest increase when used in isolation was bio16, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is bio4, which therefore appears to have the most information that is not present in the other variables. The values shown are averages over replicate runs.

3.4 Response of *Acacia senegal* to Bioclimatic Predictors

The precipitation in *Acacia senegal* significantly differed from that in the Wettest Quarter boi16, with a peak in its occurrence probability in areas with precipitation between 200 and 300 mm (Fig. 4 A). According to Bioclimatic variable 5 (Bio5), the occurrence probability of the species was greatest at 44 °C (Fig. 4 B). Generally, the suitability of the species increased with the annual temperature range bio7 (Fig. 4 C). However, it decreased with the precipitation of the coldest quarter bio19 (Fig. 4 D).

3.5 Distribution of *A. Senegal* Species and Suitable Area Across Present and Future Conditions

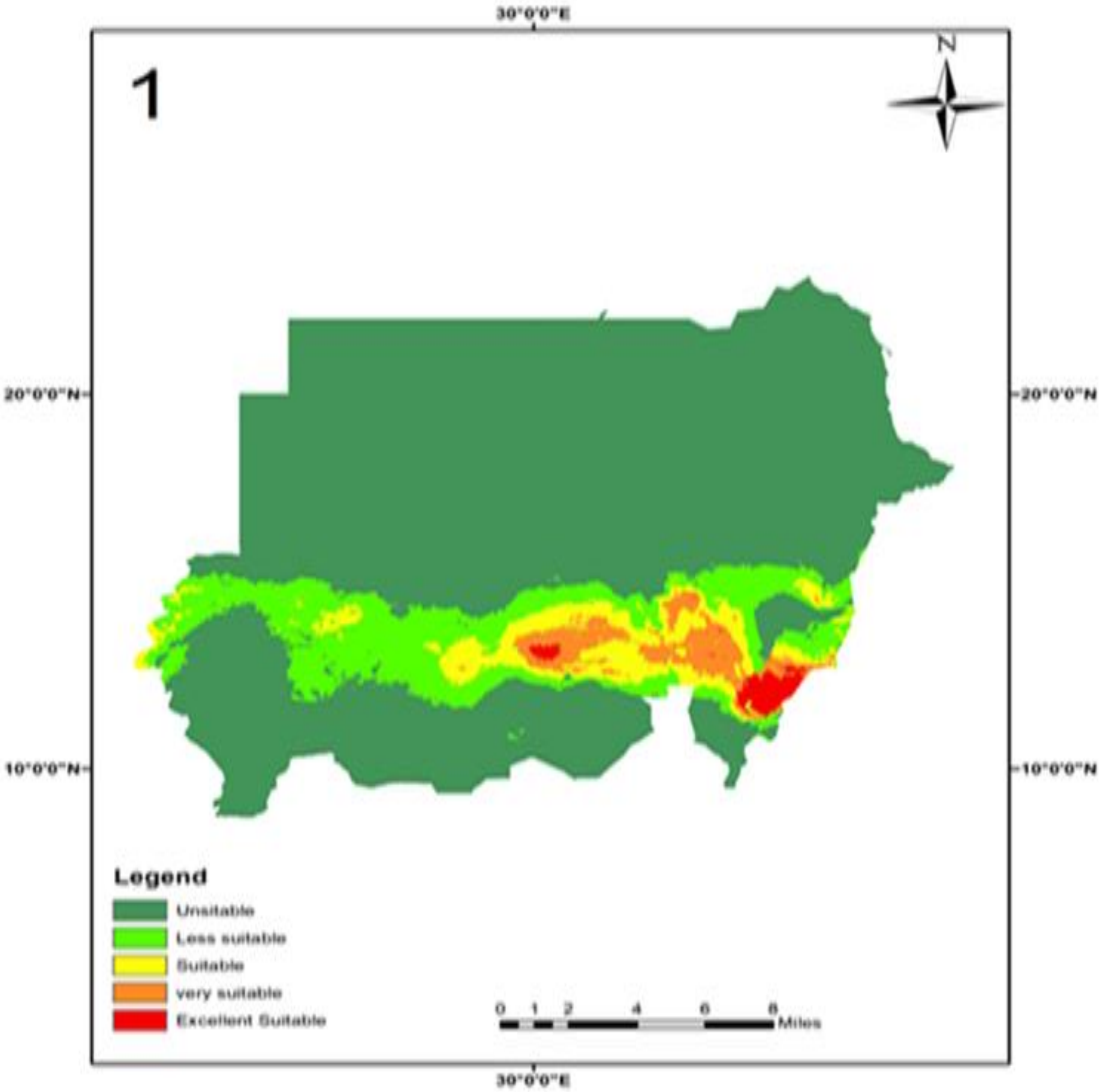
The Acacia Senegalese plant has been discovered across various regions in central Sudan within the Gum Arabic Belt, spanning from the most extreme west to the most extreme east, and has been identified in all the study areas. This presence accounts for approximately one-fifth of Sudan's total area, encompassing both ongoing and prospective projects. The observed expansion in geographic distribution is attributed to the plant's adaptation to a more favorable climate, characterized by increased rainfall during wetter quarters (bio 16). Notably, the impacts of climate change have played a significant role, with Acacia Senegalese exhibiting pronounced shifts in distribution due to these effects (bio 16).

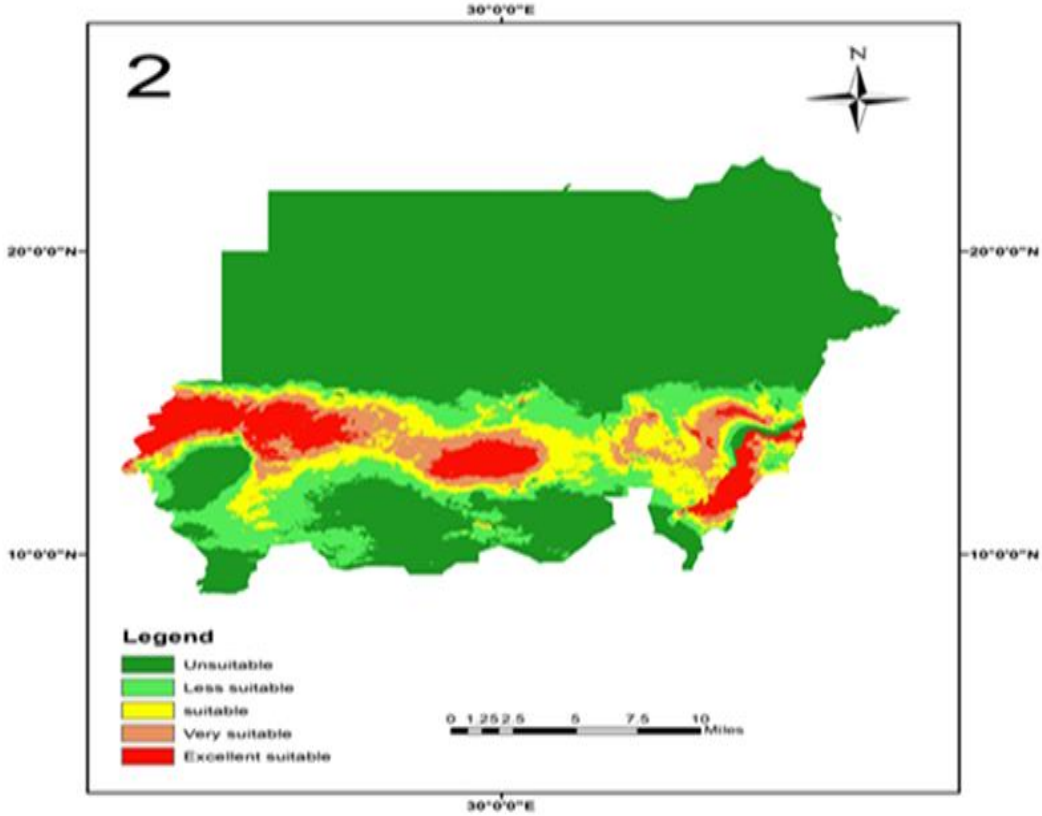
The current extent of the *Acacia senegal* distribution encompasses 132219.6 km2 within a total area of 520000 km2. Projections indicate an expansion of its range to 456001.6 km2, encompassing a span of 25.4% to 87.7% under SSP2-4.5 for the 2021–2100 period (Table 4). This expansion could result in a potential increase in the suitable area ranging from 46% to 62.3%. Conversely, under SSP5-8.5 conditions for the same period, the potential distribution may expand to a range of 25.4% - 42.5%, with prospective new suitable areas ranging between 13.5% - 17.1% (Table 5).

The model's predictive maps displayed significant shifts in the anticipated distribution of *Acacia sensgal* from the current distribution to the future. This study highlights a notable significant increase ($p<0.05$) in the distribution of *Acacia sengal* under projected future climatic conditions, which is particularly evident in the SSP2-4.5 scenario, in comparison to their current extent (Figs. 1 to 6).

Table 5. Distribution of *Acacia senegal* in SSP5-8.5 (% and km^2) as a proportion of the total study area (369 km^2)

Period	Potential distribution SSP5-8.5		New suitable area SSP5-8.5	
	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Current	132219.6	25.4	------	------
2020-2040	202098.8	38.9	69879.2	13.5
2041-2069	220322.4	42.4	88102.8	17
2061-2080	220921.6	42.5	88702	17.1
2081-2100	216306.74	41.6	84087.14	16.2

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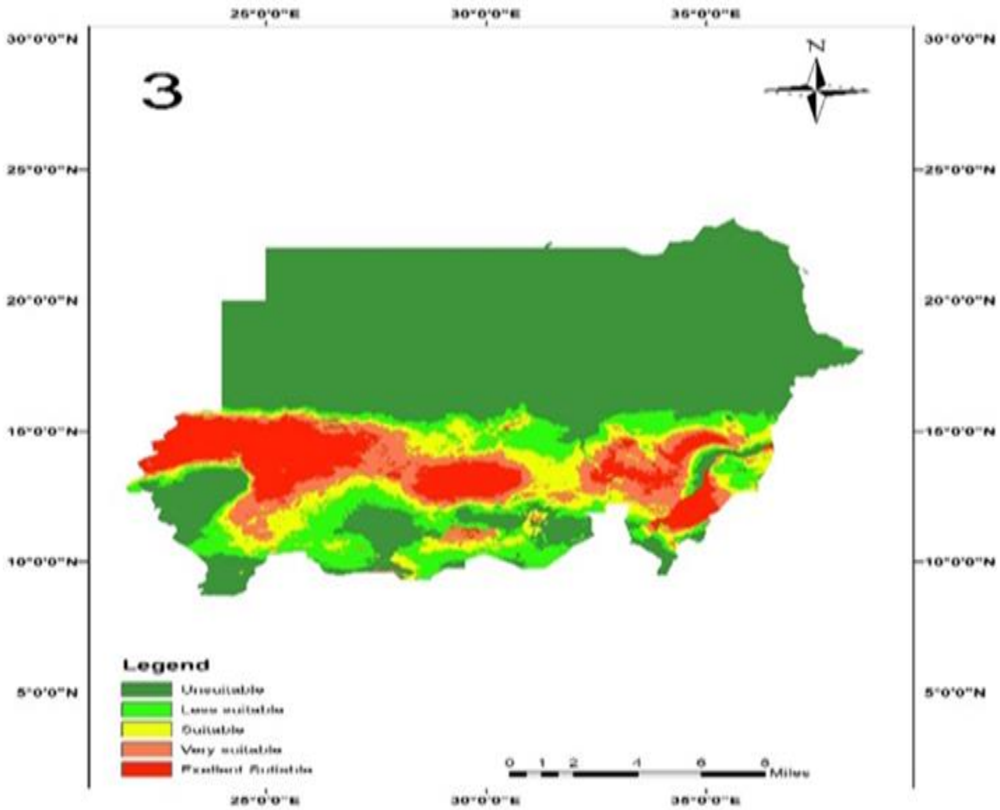
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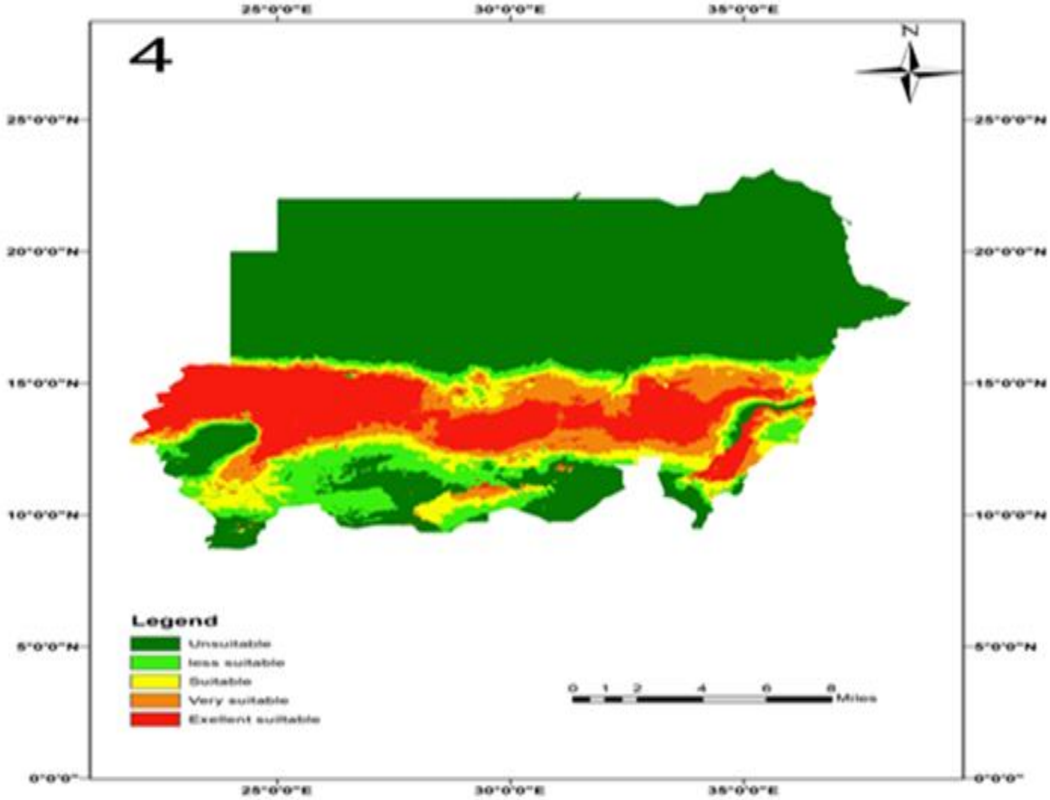
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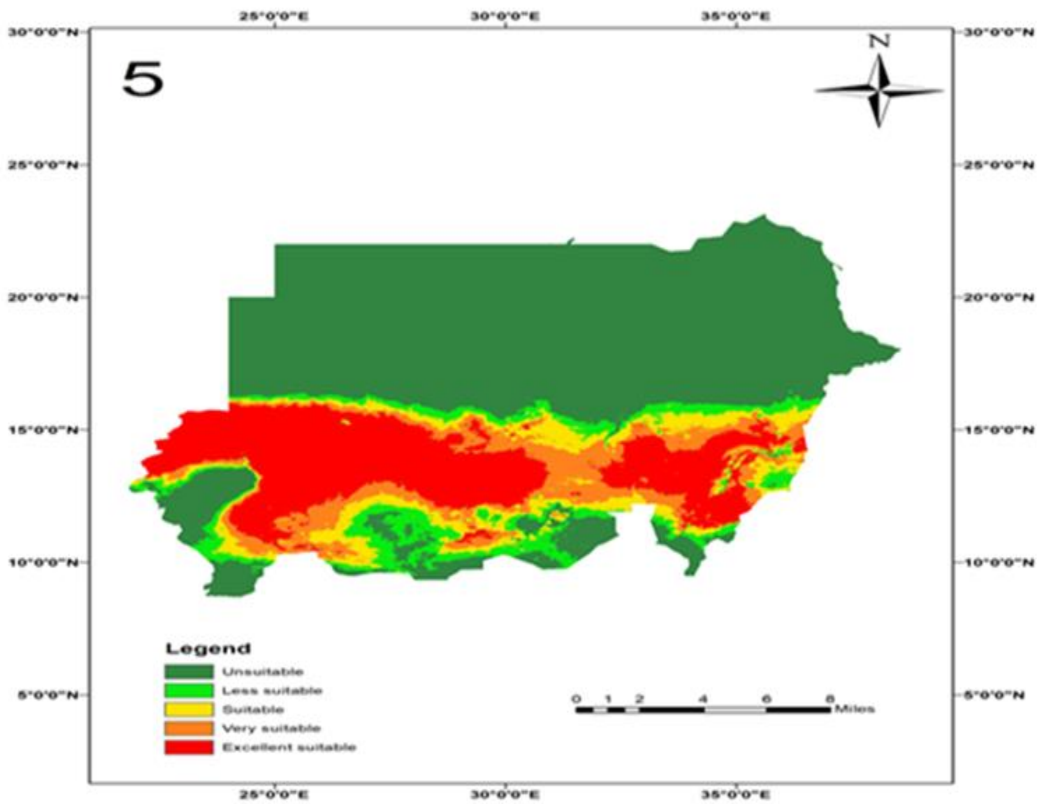
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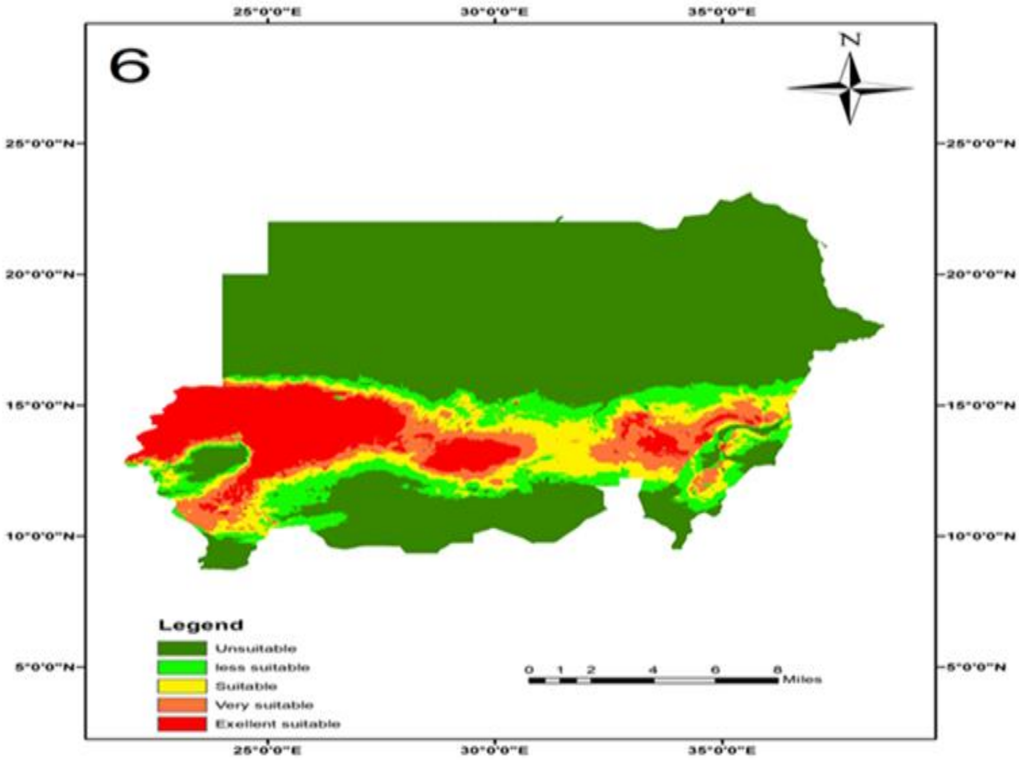
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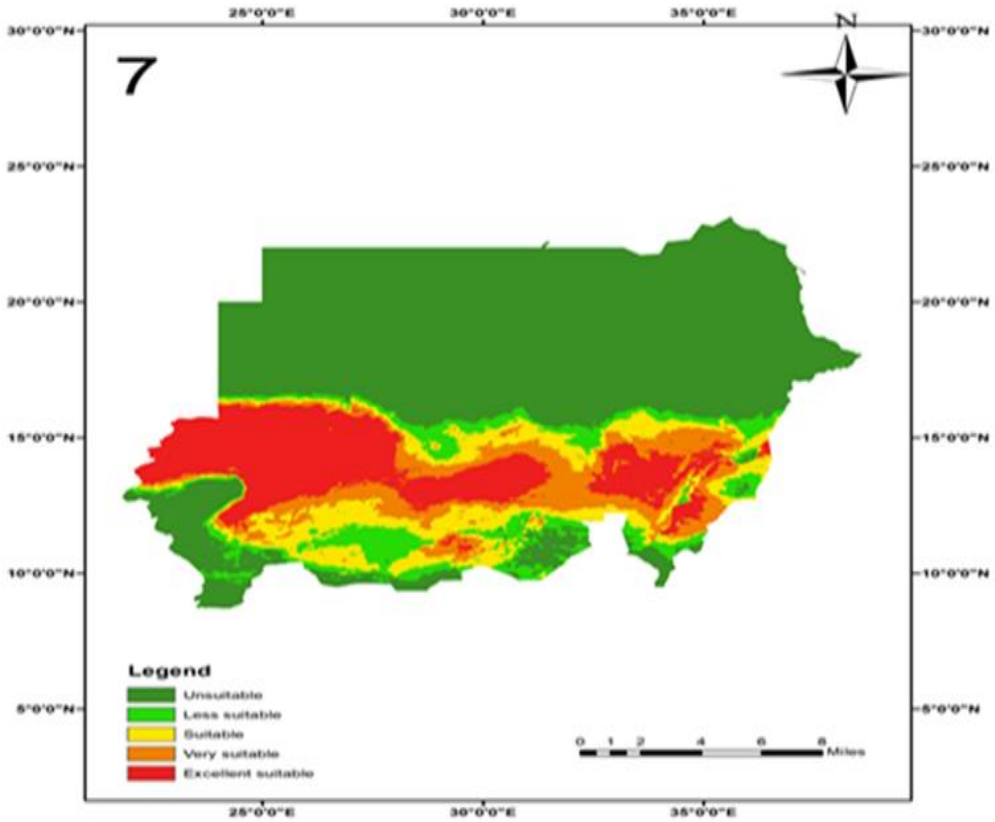
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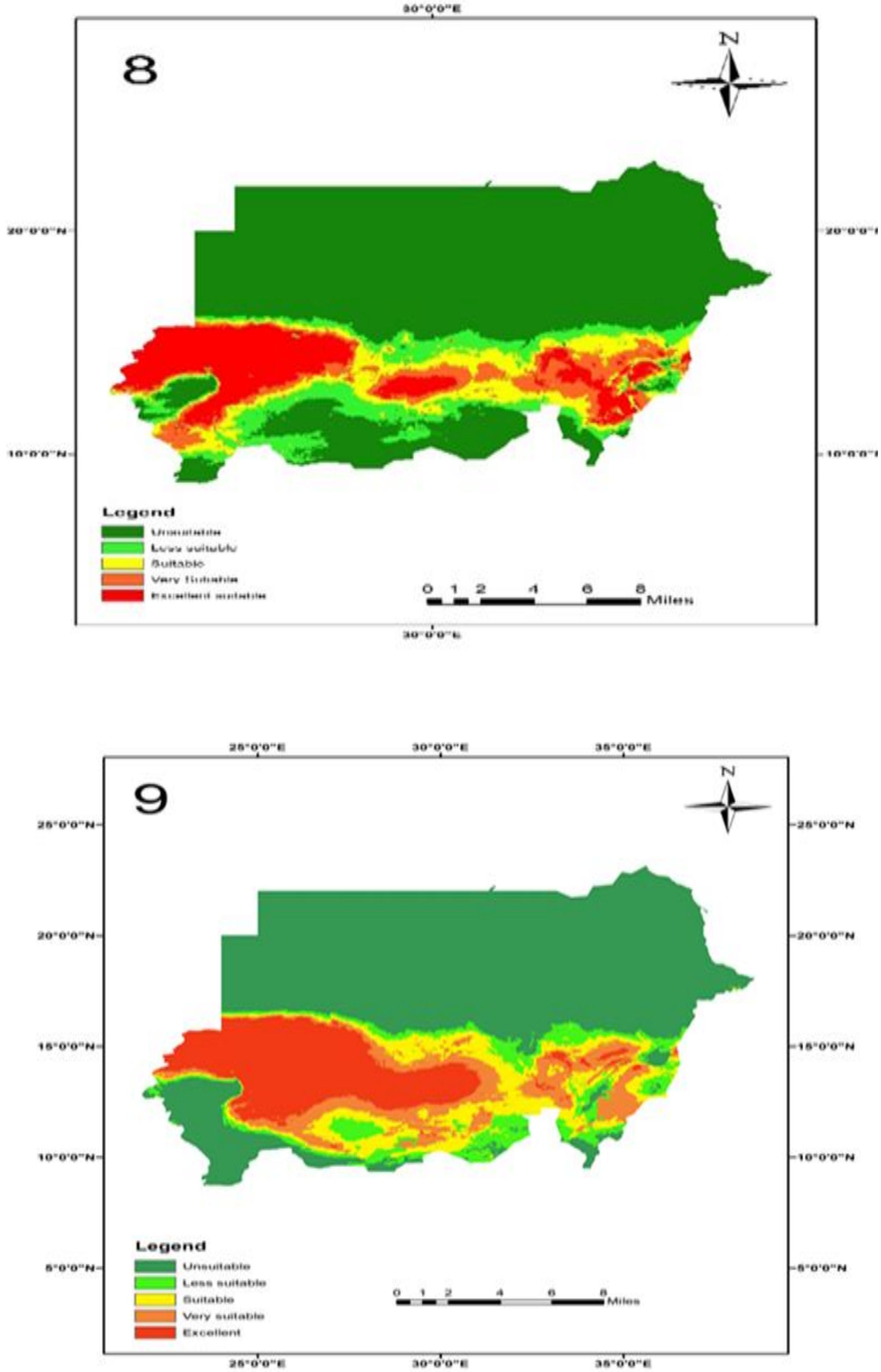

Fig. 5. Distribution of (1) current, (2) 2020-2040 SSP2-4.5, (3) 2020-2040 SSP5-8.5, (4) 2041-2060 SSP2-4.5, (5) 2041-2060 SSP5-8.5, (6) 2061-2080 SSP2-4.5, (7) 2061-2080 SSP5-8.5, (8) 2081-2100 SSP2-4.5, and (9) 2081-2100 SSP5-8.5 in *Acacia senegal*

4 DISCUSSION and CONCLUSION

4.1 Discussion

Previous studies have shown that biotic and abiotic factors have impacts on potential species distributions, and climate change plays a crucial role in determining these patterns [46]. There is ample evidence suggesting that climate change will significantly affect the distributions of numerous species [47]. Species distribution modeling (SDM) is extensively employed to assess habitat suitability patterns on a broad spatial scale. These models generate detailed maps that are invaluable for pinpointing areas where conservation efforts are particularly crucial or likely to be effective.

In general, species distribution modeling (SDM) techniques utilize data on habitat requirements obtained from known occurrence sites to forecast the potential habitat of species under existing or potential future conditions. While these models may not precisely indicate the realized niche, they do offer pertinent information on habitat suitability for a particular species. This information can be instrumental in guiding the development of sustainable management plans [16].

These data from the derived distribution map are valuable for pinpointing suitable areas for cultivation and assessing the conservation status of target species within reserved forests. It aids in identifying appropriate locations for cultivation while also evaluating the conservation needs of specific species within protected forest areas.

In this study, the maximum entropy algorithm (Maxent), a widely utilized species distribution modeling (SDM) technique, was employed to evaluate habitat suitability for both the cultivation and in situ conservation of *Acacia senegal* by different subpopulations under present and future (2100) climatic conditions. This study incorporated projections of future climate data obtained from three global climate models (GCMs), namely, GISS-EC-1G, MPI-ESM1-2-HR, and IPSL, under SSPs 2-4.5 and 5-8.5. These climate models indicated notable changes anticipated in the study area (Table 4 and Table 5).

The results revealed that bio 16 and bio 5 were the most significant predictors influencing the distribution of *Acacia senegal*, as shown in Table 3. [48,49]

According to our findings, approximately 25.4% of Sudan's Gum Arabic area is potentially suitable for *Acacia senegal*, and for the period of 2021–2100, approximately 46% to 62% of the area is potentially suitable for SSP2-4.5, whereas the new suitable area ranges from 13.5% to 17.1%. Significant increases were projected under future climatic 2100 scenarios, with several currently unsuitable areas becoming suitable under all the climatic models. These findings can be explained by the significant change projected for magnitude in the future, surpassing the existing suitability thresholds (Table 2). According to the climatic model used in this study, the precipitation of the wettest quarter with a peak in its occurrence probability in areas with precipitation between 200-300 mm and the maximum temperature of the warmest month and the occurrence probability of the species with the highest level at 44°C are projected to occur. The precipitation in *Acacia senegal* significantly differed from that in the Wettest Quarter, with a peak in its occurrence probability in areas with precipitation between 200 and 300 mm (Fig. 4 A). According to the maximum temperature of the warmest month, the occurrence probability of the species was greatest at 44 °C (Fig. 5). B)

In line with findings from previous research, it is crucial to recognize that, apart from climate, elevation exerts a significant influence on species distribution [48], while soil composition also contributes to shaping species distributions [49].

The impact of climate change is evident in various species, as they undergo alterations in cover, distribution, and genetic makeup within their respective climatic zones [50]. Research suggests that plants thrive predominantly in areas with suitable climatic conditions and subsequently adapt to changes in climate. This phenomenon implies that as climatic conditions continue to shift, species, including *Acacia senegal*, will likely experience more pronounced changes in distribution over time [51]. Global warming may magnify these changes, particularly in arid and semiarid regions, which are fragile ecosystems [52]. The study area, known as the GumArab belt, exhibits diverse climatic conditions conducive to plant species with high drought tolerance. Predominantly found in dry and semiarid regions, especially in sandy soils, *Acacia senegal* is a prime example of a species that is well adapted to such environments. In response to climatic changes, the distribution of this species may shift toward the western part of the Gum Arabic belt in search of suitable climatic conditions for adaptation. The current study of *Acacia senegal*, which is located mainly in the Gum Arabic belt, represents a significant area suitable for the future [54].

5.3 Conclusion

This study concluded that strategically planting and protecting these species is essential due to their significant environmental and economic contributions in both present and anticipated suitable areas. This study aimed to enhance ecosystem services and guarantee the continued survival of these species amidst changing climates. The study showed that under current climatic conditions, it is possible to grow the Acacia Senegalese plant and expand its cultivation in large areas of Sudan within the Gum Arabic Belt. In addition, suitable environmental conditions include a wide range of potentially favorable areas for this species in situ, and the future climate (2100) will increase the suitability of this habitat. With such a clear positive effect of climate on its suitable habitat, Acacia Senegal can be considered a good candidate for an ecosystem service and ecosystem-based adaptation approach to address climate change.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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