Response of Species to the impact of climate change in the Gum Arabic Beltbelt, Sudan: Case A case study in Acacia senegal

ABSTRACT

Sustainable management strategies are imperative for numerous indigenous agroforestry plant species, such as Acacia senegal, as they confront mounting challenges from rapid population growth, explanation in cultivated areas, and environmental threats like climate change. The goal of this study was to forecast the spatial distribution of Acacia senegal in the Gum Arabic belt in Sudan in current (1985-2000) and for future climate scenarios (2021-2100). Bioclimatic data was employed for modeling purposes utilizing Maxent, with the assessment of model precision conducted through the utilization of the Area Under the Curve (AUC) and showed a high goodness-of-it (AUC=0.905±0.003)--). Significant differences were shown were showed in species distribution between current and future periods under Shared Socioeconomic Pathways (SSPs) of SSP2-4.5 and SSP5-8.5 scenarios. Our findings indicated the main predictors was bio16 and bio5 with highest percent of contribution (56.3%3%) and 10.5%5%). Under 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%5 %((-SSP5-8.5). It is expected that Acacia 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 development. Whereas this plan seeks to enhance ecosystem functionalities and guarantee their sustained existence amidst shifting climatic conditions, owing to the economic, societal, and ecological advantage.

1. INTRODUCTION

Population growth, expanding in Agriculturalexpansion in agricultural areas, and CO2 emissionemissions are crucial threating which are affecting direct or indirect onthreats that directly or indirectly affect biodiversity, especially within sub-saharan Saharan Africa. Which is most region Most regions in Africa are threatened by climate change in Africa [1], [2]. Region of arid and semi-areaDue to the social, environmental, and economic importance of this region socially, environmentally, and economically, its biggestarid and semii-arid region, its greatest threat is climate change, and land degradation is caused by unsustainable agriculture, overgrazing, desertification, and deforestation [3]. Acacia senegal holds higher significance is highly significant as a prevalent species within the Subsub-Saharan region [4]. Acacia senegal naturally occurrence occurs either as a Common extensive pure stand or in-mixed with other species in awith good diversity, such as semi-desertsemidesert grassland, Anogeissus woodland and rocky hill slopes, and the species can grow on the different soil texturetextures (sandy-light loamy soils) [5]. It is a species of treestree, and forestsforest shrubs have multiple purposes for commercial usesuse, food-industries, medicine, and cosmetics. itlt also support the supports dry-land ecosystemecosystems[6]-[9][10].

Geographic shift forshifts in species is are caused to by climate change, especially in Africa[11], [12]. For instance-there is, some studies are actively focus to understand how the focusing on understanding how climate change effects on affects the geographic shiftshifts of various species by using predictive modeling (Maxent) [13], [14][15]. Predictive modeling, which relies on environmental data sourced from documented occurrence sites, plays a pivotal role in analytical biology. It findshas 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]. MaxentMaxentMaxEnt is a proper method when withfor addressing insufficient or incomplete information to make predictionpredictions or extract inferences forabout species distribution atdistributions in current potential area areas or new suitable area areas. It serves as a general-purpose tool for analyzing and estimating outcomes based on limited data availability. It's employ by estimating t estimates a target probability distribution through the identification of the probability distribution with maximum entropy. This corresponds forto the distribution that is most spreadcommon for species. It achieves this This is achieved by considering a set of constraints that represent the limited information available regarding the target distribution [17]. Maxent offers Maxent MaxEnt has several advantages and a few drawbacks, which will be 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, Abilityand 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 MaxentMaxentMaxEnt probability distribution is defined concisely, simplifying analysis and interpretation [16], [17].

2. MATERIAL MATERIALS AND METHODS

2 METHODOLOGY

2.1 Site Description

The location of Gum Arabic belt in the middle of Sudan , which is extended extends from the western border of Sudan to the eastern border of Sudan and covercovers an area about of approximately 520,000 Km2,km2. The Gum Arabic Beltbelt in Sudan find in the 10° N and 14° N, which is located between 10°N and 14°N, covering 1/5 from of the total area of Sudan (Eltohami, 2018). Sandy soils are predominant in the western (Darfur stats) and central (Kordofan's stats) regions with pockets of clay Seilsoil (vertisol) in these area areas, while clay soils are commonly found in the eastern (Al-Gadarif stat) and (Blue Nile stat) regions in the southern region [18], [19]. The mean annual rainfall in this region in rangeranges between 100- and 800 mm [20]. Specifically, the study area is diversified treeshas diverse tree species dominated by many family like Fabaceae afamilies, such as Fabaceae, Apocynaceae, Poaceae, and Balanitaceae[21]-[23]. The natural vegetation is woodland savannah dominated by various species, for instance-, Dichrosta. Cortolaria senegalensis (Al-Safari Plant) Acacia seyal, Sorghum happens (Adar), A. polyacantha Wild., and Combretum spp. spp., [24]. Additionally, in this region, the common vegetation cover can describes likeinclude poor rangeland and scatterscattered woody plants dominated by Acacia species, and Leptadena pyrotechnica [25]. Recently, in the areas to the north of west Darfur is dominated by the low rainfall, Woodland Savanna forest, which formforms vegetation cover. While the herbal, has been dominated by low rainfall. Herbal species include different species, such as Chloris gayana, Cassia obtusifolia, and Tribulus terrestris, beside wherein addition to Acacia being the dominant tree species are Acacia

whereas formerly. Savanna woodland species predominated in the area [26]. The southern geographical area holds a diverse array ofspecies, encompassing fruit-bearing trees such as Adansonia digitata, Balanites aegyptiaca, and Diospyros mespiliformis, alongsideas well as gum-producing species likesuch as Acacia specie'sspecies and Boswellia papyrifera. Additionally, it features various other useful species-like, such as Combretum aculeatum, and Ficus sycomorus, and it is utilized locally for medicinal, fodder, and construction purposes, as well as for fuelwood production [27].

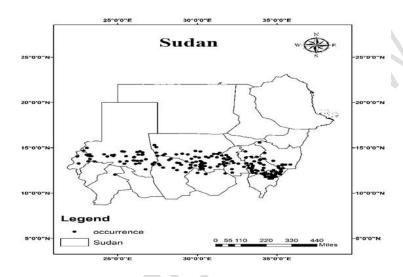


Fig. 1. Occurrence of Acacia senegal in Sudan

2.2 Data Collection collection

The input datasets <u>were obtained</u> from occurrence points and satellite <u>image carried outimages collected</u> in Sudan. A total of 164 geospatial coordinates (longitude and latitude) were obtained from fieldwork, <u>the National Research Center</u>, and previous research carried out in Sudan (Figure 5). Bioclimate data <u>was were</u> extracted for current data (1985-2000) and future data (2021-2100) from <u>the Coupled Model Inter comparison Intercomparison Project Phase 6 (CMIP6) worldClim WorldClim</u> version 2.1. For future climate data for different periods, <u>they were used by using general distribution models (GCMs), adopting were used, and a clustering approach <u>was adopted</u> 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)</u>

The This research utilized version 3.4.4 of the Maxent Maxent 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 time periods: the 2021-2040, 2041-2060, and 2061-2080 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

Comment [A1]: The selection of coordinate points is a crucial aspect of creating a distribution model, as it can significantly impact the outcome. Therefore, it's important to provide comprehensive information about the parameters utilized in the point selection process

(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, which, like other East Africa frican countries, such as Sudan, lacks especial lack a calibrated General Circulation Model (GCM). For that were applied different models in the studygeneral circulation model (GCM). Different models were applied in [28], [29].

Table 1. Variables contributing to prediction

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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			
Bio08	Mean Temperature of Wettest Quarter	Altitude	Elevation			
Bio09	Mean Temperature of Driest Quarter					
Bio10	Mean Temperature of Warmest					
	Quarter					
Bio11	Mean Temperature of Coldest Quarter					
Bio12	Annual Precipitation					

This ensemble of four global climate models was used to processing process the limitations, unsureness, that isare related byto the use of one global climate model infor strictly predicting for future climate trendtrends [30]. Several studies have reported that the remarkable development of utilizing the multi-modelmultimodel group technique emergeshas emerged as the foremost strategy for reducing model uncertainty [31]. To combine GCMs with equal weightweights, ArcGIS was used, and arithmetic mean arithmetic was commonly applied to combine multiple models. Regarding of the arithmetic average, Arithmeticthe arithmetic mean has been commonly applied to utilize multiple models, such as ArcGIS was, which is an ensemble, incorporating the General Circulation Models that incorporates general circulation models (GCMs) with uniform weighting [10].

The current climatic data <u>waswere</u> 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[32]. 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 <u>were</u> 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 [33]. The refined resolution in CMIP6 contributes to more substantial scientific insights [34].

The CMIP6 utilizes scenarios based on the Shared Socioeconomic Pathways (SSPs), theseshared 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, and promoting the advancement of clean energy

Comment [A2]: References are required or eplain the reason of choosing specific model

Comment [A3]: Using large number of variables may lead to multicollinearity which may results in biased model predictions (Dormann et al. 2013), therefore, all selected variables are required to be tested for variance inflation factor (VIF) analysis to minimize the multicollinearity effect. This can be done easily by using R package 'usdm' with (Naimi et al. 2014) in R programming language version 1.2.5033 (2019). Variables having VIF values < 3 are generally included in the models (Zuur et al. 2010).

The reason of inclusion of all variables need to be explained.

technologies, and safeguarding natural ecosystems. Conversely, Regional Rivalryregional 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 withby considerable challenges to adaptation but fewer hurdles to mitigation, whereas Fessil fueled Development (SSP5) faces substantial challenges in mitigation but fewer obstacles in adaptation efforts. [35].

ParticularlyIn particular, SSP2 (Middlemiddle of the Readroad) 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][36]. These scenarios were chosen to simulate the distribution patterns of the three species under the expected future climate circumstancesconditions. 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 [11].

2.3 Data analysis

Previous studies stated that the decision to utilize the MaxentMaxEnt model for the analysis was driven by its strong in establishingability to establish relationships between environmental variables and species presence records, as demonstrated previously[15]. The machineMachine learning method employsmethods employ species presence data and environmental factors to generate estimations of estimate species distribution species distributions [37], which is particularly suited for presence-only records [16]. MaxentMaxentMaxEnt has showedshown superior predictive efficacy in comparison to alternative structured decision-making models [13].

An important advantage of MaxentMaxentMaxent is its robustnessability to mitigate collinearity issues during model training: highly correlated predictor variables are removed having, which has negligible effects on its performance [38]. MaxentMaxentMaxent adeptly manages complexity by downplaying the significance of redundant variables, effectively addressing collinearity issues [15], [16]. MaxentMaxentMaxent achieves an optimal balance between model fitting and complexity through regularization techniques [15], indications proposeindicating that the extent of collinearity among predictors is unlikely to notably influence the outcomes of MaxentMaxentMaxentMaxent.

3 RESULTS

3.1 Model Accuracy accuracy

The MaxentMaxEnt model exhibited excellent performance, and the outcome of the model arewas acceptable, because the outcome reflectreflected excellent performance in faithfullyaccurately delineating the distributional profile of Acacia senegal, manifestingwith mean training and test AUC metrics of 0.905 (Figure 4-). Run for Aciaca senegal generated an AUC value moregreater than 0.9, showed performance greatlyindicating great accuracy.

Comment [A4]: Training data is used to formulate the model parameters, whereas testing data points is used to assess its prediction accuracy. Duplicate presence records are removed using basic settings along with random seed feature.

Nothing has been explained.

- Nothing has been explained
- How much data was used in training
 No information has been given regarding the duplicate presence data
- 3. No information provided regarding replicates were run for both models and logistic outputs.



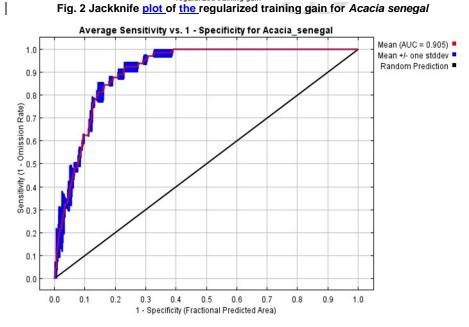


Fig.3 Cross-validated AUC (Areaarea under the receiver operating characteristic curve)

3.2 Thresholds and suitability

The study established suitability thresholds for *Acacia senegal*, indicating that it asis 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 < 0.05₇₂byBy utilizing the tenthstenth 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.

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

3.3 Contribution of variables

The majorpredictors makingthat made excellent contribution of contributions to the species distribution were Precipitation of Wettest Quarterprecipitation of wettest quarter (bio 16), by percentwith a percentage contribution of 56.3%; the second one predictor is Max Temperature of Warmest Month (bio5) by 10.5%; was the maximum temperature of warmest month (bio5), with a percentage of 10.5%; and the following predictors, it presented with a percentage less than 10%, are 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 highest gain when used in isolation iswere 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 isn'tis not present in the other variables. Values The values shown are averages over replicate runs figure.

Table .3 Variables contribution3 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

3.4 Response of Acacia senegal to bioclimatic predictors

The <u>precipitation in Acacia senegalsignificantly to Precipitation of differed from that in the Wettest Quarter, with a peak in its occurrence probability in <u>area areas</u> with precipitation between 200-<u>and</u> 300 mm (Fig.4 A). According to Bioclimatic variable 5 (Bio5), <u>the occurrence probability of the species was <u>highest level greatest</u> at 44 °C (Fig.4 B). Generally,</u></u>

the suitability of the species increased with Temperature Annual Range (Fig. 4 C). Butthe annual temperature range (Fig. 4 C). However, it decreased with the Precipitation of Coldest Quarter (Fig. precipitation of the coldest quarter (Fig. 4 D).

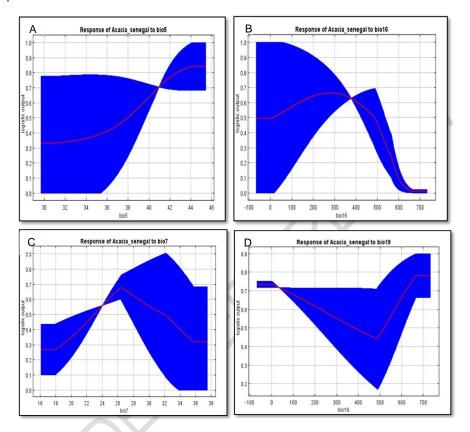


Fig 4. Response curves of Acacia senegal to bioclimatic predictors in the habitat suitability modeling

Logistic output.A- Precipitation of Wettest Quarterthe wettest quarter (bio16, mm);B- Max Temperature of Warmest Month Maximum temperature of the warmest month (bio5, °C);C-Temperature Annual Rangetemperature range (bio7, mm);D- Precipitation of Coldest Quarterthe coldest quarter (bio19,mm).

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 the wetter quarterguarters

Comment [A5]: Results of response curves are not satisfactory

(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).

Table .4 Acacia senegal Distribution in SSP2-4.5 (% and km²) as a proportion of the total Study Areastudy area (520000 km²)

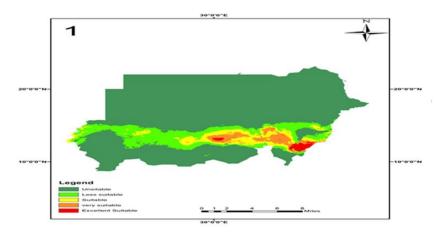
Potential distribution SSP2-4.5		New suitable area SSP2-4.5	
Area (Km²)	Area (%)	Area (Km²)	Area(%)
132219.6	25.4		
456001.6	87.7	323782	62.3
208998.0	40.2	76778.4	14.8
188166.6	36.2	55947	10.8
195271.6	37.6	63052	12.3
	Area (Km²) 132219.6 456001.6 208998.0 188166.6	Area (Km²) Area (%) 132219.6 25.4 456001.6 87.7 208998.0 40.2 188166.6 36.2	Area (Km²) Area (%) Area (Km²) 132219.6 25.4 456001.6 87.7 323782 208998.0 40.2 76778.4 188166.6 36.2 55947

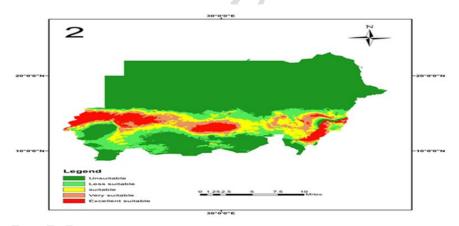
The current extent of the_Acacia senegal distribution encompasses 132219.6 km2 within a total area of 520000 km2. Projections indicate an expansion of its range to 456001.6 km2, encompassing a span of 25.4% to 87.7% under SSP2-4.5 for the period-2021-2100 period (Table -4). This expansion could result 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 area in-rangeareas ranging between 13.5% - 17.1% (Table -5).

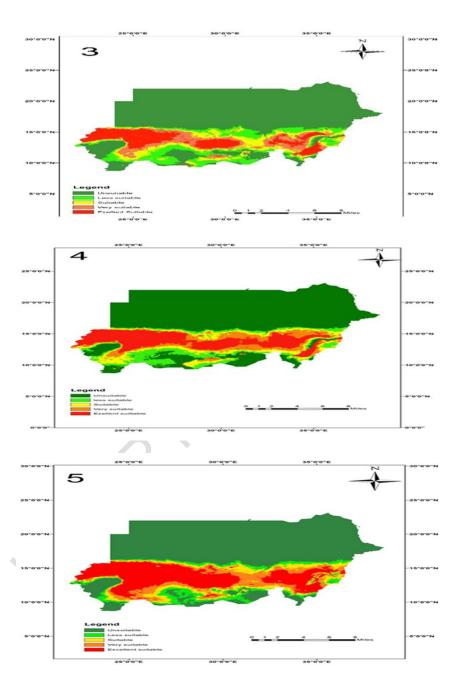
Table <u>-55 Distribution of Acacia senegal distribution</u> in SSP5-8.5 (% and km²) as a proportion of the total study area (369 km²)

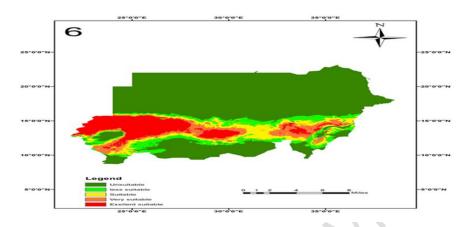
	Potential distribution SSP5-8.5		New suitable area SSP5-8.5	
Period	Area (Km²)	Area (%)	Area (Km²)	Area (%)
Current	132219.6	25.4		
2020-2040	202098.8	38.9	69879.2	13.5
2041-2069	220322.4	42.4	88102.8	17
2061-2080	220921.6	42.5	88702	17.1
2081-2100	216306.74	41.6	84087.14	16.2

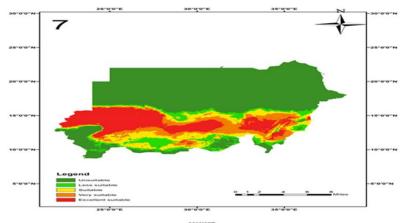
The model's predictive maps displayed significant shifts in the anticipated distribution of *Acacia sensgal*infrom the current distribution to future comparedthe future. This study highlights a notable significant riseincrease (p<0.05) in the distribution of *Acacia sengal* under projected future climatic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

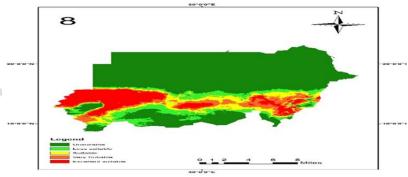












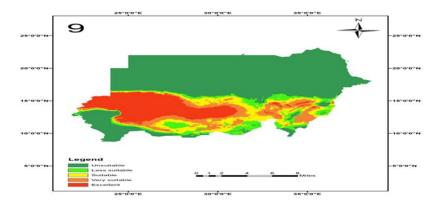


Fig.5—Acacia senegal distribution (1) Current; 5 Distribution of (1) current, (2) 2020-2040 SSP2-4.5; (3) 2020-2040 SSP5-8.5; (4) 2041-2060 SSP2-4.5; (5) 2041-2060 SSP5-8.5; (6) 2061-2080 SSP2-4.5; (7) 2061-2080 SSP5-8.5; (8) 2081-2100 SSP2-4.5; and (9) 2081-2100 SSP5-8.5 in Acacia senegal.

4 DISCUSSION and CONCLUSION 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 [39]. There is ample evidence suggesting that climate change will significantly effect on the distributionaffect the distributions of numerous species [40]. 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].

This These data from the derived distribution map isare 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 Entropymaximum entropy algorithm (MaxentMaxEnt), a widely utilized Species Distribution Modelingspecies 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. The This study incorporated projections of future climate data obtained from three Global Climate Models lobal 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 identified as the most significant predictors influencing the distribution of Acacia senegal, as shown in Table 3 (Pramani. 2021; Zhang et alet al. 2023).

Following According to our findings, approximately 25.44% of Sudan's Gum Arabic area is potentially suitable for Acacia senegal, and for the period of 2021-2100-about, approximately 46% to 62 % for potential suitable area with 62% of the area is potentially suitable for SSP2-4.5, whereas the new suitable area rangingranges from 13.55% to 17.4 %1%. Significant increases were projected under future climatic 2100 scenarios, with several currently unsuitable areas becoming suitable under all the climatic models. This These findings can explain be explained by the significant change projected for magnitude in the future, surpassing the existing suitability thresholds (Table 2). Indeed. rdingAccording to the climatic model used in this study, theprecipitation of the wettest quarter with a peak in its occurrence probability in area areas with precipitation between 200-300 mm and the maximum temperature of the warmest month, and the occurrence probability of the species was with the highest level at 44 °C are projected to be occur. The precipitation in Acacia senegal significantly to Precipitation of differed from that in the Wettest Quarter, with a peak in its occurrence probability in areaareas with precipitation between 200-and 300 mm (Figure 4 A). According to the Max Temperature of Warmest Month, maximum temperature of the warmest month, the occurrence probability of the species was highest level greatest at 44 °C (Figure 5). B)

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 [43]. Research suggests that plants predominantly thrive predominantly in areas with suitable climatic conditions and subsequently adapt their distribution in response to changes in the 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 [44]. Global warming may magnify these changes, particularly in arid and semi-aridsemiarid regions as, which are fragile ecosystems [45]. The study area, known as the Gum Arabic BeltGumArab belt, exhibits diverse climatic conditions conducive to plant species with high drought tolerance. Predominantly found in dry and semi-aridsemiarid regions, especially in sandy soils, Acacia senegal is a prime example of a species that is well-adapted to such environments, in react In response to climatic changes, species may shift their distribution rangethe distribution of this species may shift towardes the western part of the Gum Arabic Beltbelt in look forsearch of suitable climatic conditions tofor adaptation. The current study of Acacia senegal are mainly, which is located mainly in the Gum Arabic Beltbelt, represents a significant chance area suitable area infor the future.

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 action aimsstudy aimed to enhance ecosystem services and guarantee the continued survival of these species amidst changing climates, the. The study showed that, under the 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 areas potentially favorable areas for this species in situ, and that the future climate (2100) will increase the suitability of this habitat. With such a clear positive effect of climate on its suitable

Comment [A6]: The claim made in the study is very huge and may impact a huge area. Therefore the author need to strenthen its claim. As just saying that climate change will be the reason is not sufficent. The author is suggested to add a comprehensive explanation for the factors affecting the distribution of a species, the author should consider the following aspects and support their claims with relevant facts, figures, and citations:

- 1. Ecological factors:
- Habitat requirements (e.g., climate, vegetation, soil conditions)
- Biotic interactions (e.g., competition, predation, mutualism)
- Abiotic factors (e.g., temperature, humidity, precipitation)
- Availability of food resources
- Dispersal mechanisms and barriers

2. Physiological factors:

- Adaptations to specific environmental conditions
- Tolerance ranges for abiotic factors (e.g., temperature, humidity)
- Reproductive strategies and requirements
- Metabolic processes and energy requirements

3. Natural enemies:

- Predators, parasites, and pathogens
- Impacts on population dynamics and distribution
- Coevolutionary relationships and adaptations

To strengthen the claims made in the study, the author should:

- Conduct a thorough literature review and cite relevant scientific publications, including peerreviewed journal articles, books, and reports.
- Present quantitative data, such as population densities, geographic ranges, and environmental measurements, along with appropriate statistical
- Incorporate field observations, experimental data, or modeling results to support the proposed mechanisms and hypotheses.
- Discuss the potential interactions between different factors and their cumulative effects on the species
- Address any contradictory or conflicting evidence and provide explanations or alternative hypotheses. - Consider the limitations of the study and suggest future research directions to address knowledge

habitatshabitat, Acacia Senegal can be considered a good candidate for an ecosystem service and ecosystem-based adaptation approach to addressing address climate change.

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