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Modelling the Current and Future Spatial Distribution Area of *Adansonia digitata* L. in the Context of Climate Change in Malawi (Southern Africa)

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Abstract

Climate change is likely to affect the distribution of species worldwide. Understanding how these changes affect species distribution is important for planning conservation strategies and sustainable management methods. *Adansonia digitata* L. is of major ecological and socio-economic importance in Malawi, South Africa, but is highly threatened in its habitat. This work aims to investigate the effect of climate change on the ecological niche of Baobab and to find suitable habitats for its conservation and cultivation in Malawi. The distribution of this species was modeled using a maximum entropy algorithm (MaxEnt) based on 21 environmental variables and the occurrence of 480 species. Habitat prioritization was performed using Zonation software. Our results show that the variable contributing most significantly was the warmest month (47%), followed by isotherms (13.9%) and precipitation of the coldest quarter (8.6%). Under the current model, 1.17% of Malawi's territory is highly favorable for baobab development. A slight increase of 0.09% and 0.38% in highly favorable zones is predicted by 2055 under scenarios SSP370 and SSP 585, respectively. Southern Malawi and parts of the Central region should be prioritized in baobab reforestation policies to optimize conservation and value chain sustainability for baobab. Under the current model, 1.17% of Malawi will be highly favorable for baobab. A slight increase of 0.09 % and 0.38 % in highly favorable zones is predicted by 2055 under scenarios SSP 370 and SSP 585, respectively. Priority areas (98-100%) for conservation and cultivation of Baobab was a male located in the Southern region (34.51%) and central (7.62%), in contrast to the Northern region (0.21%). Our results suggest that climate change causes the reduction and shift of suitable habitats for species along a south-north gradient. These findings highlight the urgent need to incorporate climate change projections into conservation plans.

Identifying and prioritizing suitable habitats in the southern and central regions is crucial for effective conservation and sustainability.

Keywords: *A. digitata*, utility tree, climate change, MaxEnt, Malawi

1. Introduction

In Africa's semi-arid regions, the baobab tree (*Adansonia digitata* L., Malvaceae family) is seen as a promising crop for cultivation (Matig, Ndoye, Kengue, & Awono, 2006). The plant offers numerous benefits. It provides nutritious food (Nordeide et al., 1996), livestock fodder, materials for hunting and fishing, medicine, shade, and spiritual services to local communities (Sidibe & Williams, 2002). Baobab products are widely sold in markets, contributing significantly to local incomes (Diop et al., 2006). Rural populations in Africa particularly depend on the baobab for its nutritional and medicinal products (Buchmann et al., 2010). Additionally, the baobab fruit pulp is marketed in Europe and the United States (CEC, 2008; FDA, 2009) where the pulp is used in the different industrial sectors: cosmetics, food, and medicine (Sanchez, 2011; Wickens, 2008). The baobab is also vital for wildlife, providing food, water and shelter, and it enhances savannah site conditions (Amundson, Ali, & Belsky, 1995). This tree is known for its longevity, living up to 1200 years (Patrut et al., 2007), and it requires up to 23 years to begin fruiting (Wickens & Lowe, 2008). Animal dispersal, primarily by elephants and baboons, helps spread its seeds. When it comes to its ecology, it is more drought-tolerant than many annual crops. Furthermore, it doesn't need fertilizer or irrigation and is largely resistant to pests and diseases (Sidibe & Williams, 2002). This makes the plant to be a crucial savannah tree for conservation, domestication, and valorization in Africa (Eyog Matig, Gaoue, & Dossou, 2002).

However, it is being recorded a decline in baobab populations and species distribution due to a number of ecological factors, including climate change (CC) (Agbo et al., 2019; Salako et al., 2018; You et al., 2018) and over-exploitation. Climate change affects species diversity and composition, tree phenology and physiology, and the structure and functioning of ecosystems (Keshtkar & Voigt, 2016; Thapa, Mirsky, & Tully, 2018). The Intergovernmental Panel on Climate Change (IPCC) has projected that continuous increases in greenhouse gas emissions will cause the global surface temperature to rise by 1.5 to 3 °C by the end of the twenty-first century (Pörtner et al., 2022). According to Velásquez-Tibatá, Salaman, and Graham (2013), such climate shifts are likely to cause species redistributions through range movements or extinction events. According to Noulèkoun, Chude, Zenebe, and Birhane (2017), these territorial displacements may endanger species survival and interfere with the availability of ecological resources, which are essential for the stability of ecosystems. Furthermore, changes in the appropriateness of habitat may increase the danger of extinction for species, which is made worse by habitat degradation and fragmentation caused by humans (Krishnadas & Stump, 2021). The complex interactions between long-term ecological changes in the context of CC (Gaitán-Espitia & Hobday, 2021) and the unknowns surrounding species responses highlight important research areas in ecology, evolution, and conservation (Brodie et al., 2022; Elith et al., 2006), as well as biogeography (Hutchinson, 1959). Specifically, understanding species range shifts in CC scenarios and the underlying environmental factors is imperative for guiding species conservation efforts and management decisions (Hounkpèvi et al., 2020).

It becomes an impediment to elaborate baobab Species distribution models (SDMs) to assess the spatial distribution of species and the underlying environmental conditions. These models estimate species distribution patterns using digital environmental datasets and species occurrence records, which helps with planning for species conservation (Zhang, Xu, Capinha, Weterings, & Gao, 2019). Among the various SDMs available, the Maximum Entropy (MaxEnt) algorithm reigns supreme due to its superior predictive performance (Hijmans, Phillips, Leathwick, & Elith, 2017; Zeng, Low, & Yeo, 2016). Based on the 19 BIOCLIM variables from the WorldClim database, MaxEnt has been frequently used to simulate species distribution of numerous endangered species, including *Pterocarpus erinaeus* (Biaou et al., 2023), *Faidherbia albida (Delile) A. Chev.* (Noulèkoun et al., 2017), *Afzelia africana Sm.* (Balima et al., 2022), *Ziziphus spinosa (Bunge) H.H. Hu ex F.H.* Chen (Zhao et al., 2022), *Vitellaria paradoxa C.F. Gaertn* (Dimobe et al., 2020); and *Uapaca kirkiana* (Jinga, Liao, & Nobis, 2021).

Previous studies have looked at how *A. digitata* populations in Southern Africa are affected by changes in land use, CC, and human activity (Sanchez, 2011; Wan et al., 2021). Nonetheless, there is still much to learn about this subject, even though some research conducted in Malawi has indicated that CC affects species distribution (Sanchez, 2011). Understanding potential variations or preservations in climatic niches within populations of species may aid in directing future studies on genetic, phenotypic, and intraspecific variabilities.

This paper seeks answers to the subsequent queries: What habitats support species development? What pedoclimatic conditions dictate *A. digitata* distribution in Malawi? How does CC affect *A. digitata* habitats?

What are the potential habitat dynamics of the species in response to CC? Which areas should be prioritized for restoration and conservation efforts amid future CC challenges in Malawi?

Thus, the purpose of this study is to examine potential effects of CC on the distribution of *A. digitata*. The specific goals are to: Determine *A. digitata*'s probable habitats in Malawi currently and in the future (2055); Assess the effect of CC on *A. digitata*'s distribution in Malawi by 2055; Establish the locations where conservation and restoration efforts should be prioritized.

The findings from this study could aid in developing more effective conservation strategies for species facing Climate Changes. Additionally, beyond conservation and management objectives, comprehending CC's impact on the plant can assist in selecting suitable provenances for future introduction into new habitats (Jinga, Palagi, Chong, & Bobo, 2020). Hence, comprehending the pedoclimatic prerequisites that influence the development of baobab.

2. Method

2.1 Study Area

Malawi has a subtropical climate (meaning that the altitude, is the main factor influencing climate fluctuations). The country's Lower Shire Valley experiences semi-arid weather, transitioning to semi-arid to sub-humid conditions on plateaus, and sub-humid weather in the highlands. Ninety-five percent (95%) of the annual precipitation falls in the warm-wet season, which is followed by a cool dry season and a hot dry season (Sanchez, 2011). Malawi's vegetation reflects the country's varied climate and geography. Savannah predominates in the country's dry lowlands, while Miombo (Brachystegia) woodland stretches across the country's arid slopes and plateaus and grasslands and forests are common in the highlands. Although White (1983), places Malawi in the Zambezian zone, Hardcastle (1977) has distinguished several other silvicultural zones in Malawi. The bulk of Malawians, with one of the densest populations in southern Africa, depend mainly on agriculture; many of them do subsistence farming, typically making less than one USD per day (Devereux, 2009). The map (Figure 1) shows the distribution of Baobab in southern Africa and Malawi.

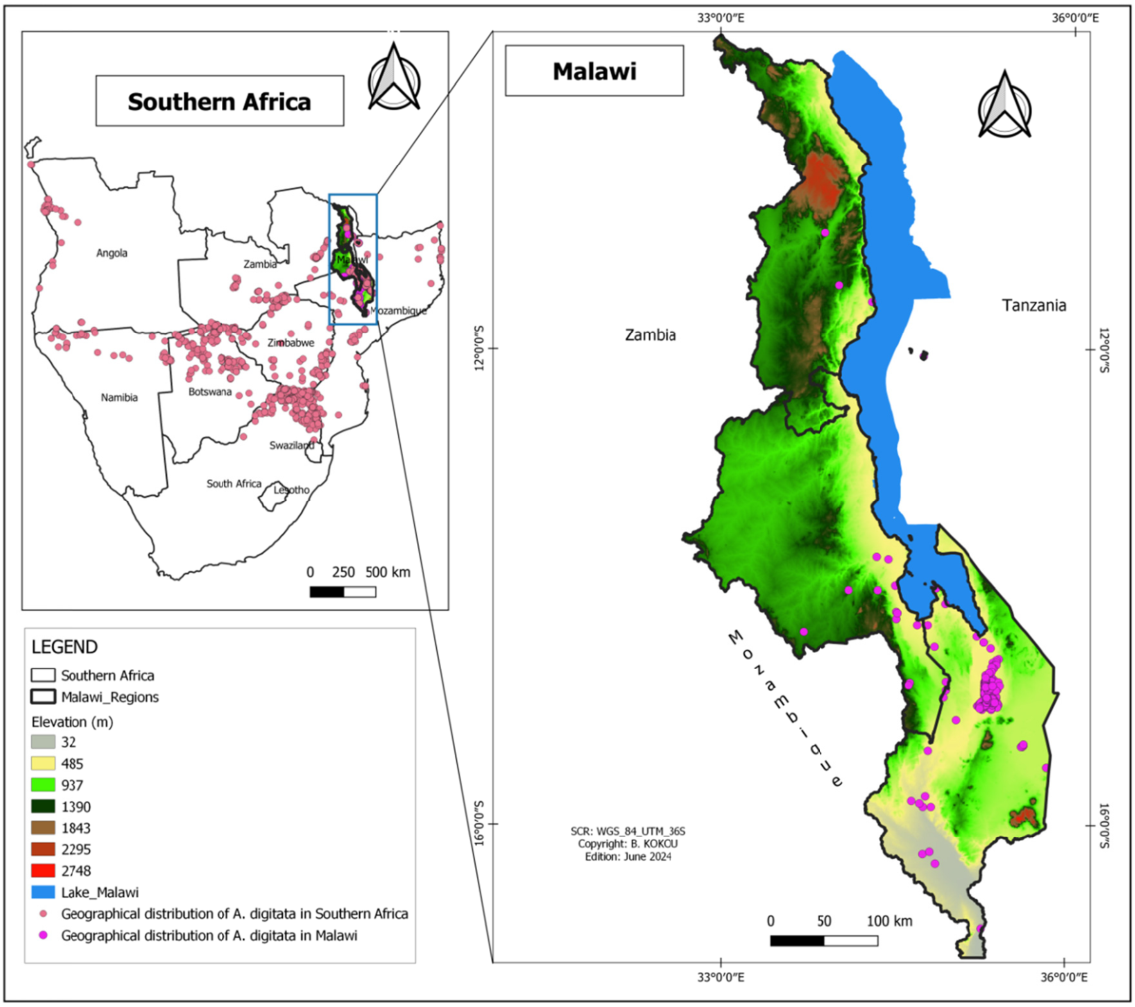

Figure 1. Map of the study area showing the geographical distribution of Baobab in Southern Africa and Malawi

2.2 Baobab Occurrence and Environmental Data

Occurrence data for the species were gathered from multiple databases spanning southern Africa. The data cleaning process initially involved eliminating duplicates, questionable, invalid, and incorrect occurrence coordinates through cross-referencing. Following this, a total of 480 occurrences of Baobab were included in the study. Of these, 80 % (795), were sourced from the Global Biodiversity Information Facility (GBIF) database (http://www.gbif.org), while 20 % (194) were obtained through extensive fieldwork conducted in Malawi.

The environmental data comprised 19 bioclimatic variables, elevation data from the Shuttle Radar Topography Mission (SRTM), and soil data (Assang et al., 2023). Elevation data were sourced from version 2.1 of the WorldClim database (https://www.worldclim.org/data/worldclim21.html) (Fick & Hijmans, 2017). Bioclimatic variables were obtained from the Chelsa Climate website (https://chelsa-climate.org). Soil type data were derived from version 1.2 of the Harmonized World Soil Database (http://www.fao.org/land-water/databases-and-software/hwsd/en) (FAO/IIASA/ISRIC/ISSCAS/JRC 2012). These datasets were processed and converted into ASCII format using ArcGIS 10.8, with southern Africa as the study area. A total of 21 environmental variables were included in the study, consisting of one categorical variable and 20 continuous variables (Table 1). All variables had a spatial resolution of 30 seconds, roughly equivalent to 1 km. The bioclimatic variables, which influence species distribution, encompass annual and seasonal averages, extremes, and intra-annual values (Booth et al., 2014). Evaluating various climate scenarios (*e.g.*, low, medium, and high) enables a more precise assessment of potential climate change impacts over a specific timescale (Harris et al., 2014). For this study, future climate scenarios based on the Shared Socio-economic Pathways (SSPs) were utilized (Riahi et al., 2017). The SSPs indicate that a future characterized by "resurgent nationalism" and international fragmentation could render the "well below 2°C" Paris target unattainable (Masson-Delmotte et al., 2021). The selected scenarios were SSP3-7.0 and SSP5-8.5, representing different development and concentration pathways. These scenarios correspond to a high challenge for mitigation and adaptation, and a high radiative forcing scenario with continued fossil fuel use in the future (Riahi et al., 2017). The future climate data from General Circulation Models (MPI-ESM1.2-HR) used in this study has a well-balanced radiation budget and a climate sensitivity tuned to 3 Kelvin. Despite modest reductions in long-term biases, improvements in atmospheric dynamics make this model suitable for forecasting and impact studies (Müller et al., 2018).

Table 1. Environmental variables to be used in modeling

Codes	Variables	Units
Elev	Elevation	M
Hwsd (Soil)	Soil types	
bio 01	Annual Mean Temperature	°C
bio 02	Mean Diurnal Range (Mean of monthly (Max temp-min temp)	°C
bio 03	Isothermality (BIO2/BIO7) (× 100)	%
bio 04	Temperature seasonality (standard deviation × 100)	°C
bio 05	Max Temperature of Warmest Month	°C
bio 06	Min Temperature of of Coldest Month	°C
bio 07	Temperature Annual Range (BIO5-BIO6)	°C
bio 08	Mean Temperature of the Wettest Quarter	°C
bio 09	Mean Temperature of the Warmest Quarter	°C
bio 10	Mean Temperature of the Driest Quarter	°C
bio 11	Mean Temperature of the Coldest Quarter	°C
bio 12	Annual Precipitation	mm
bio 13	Precipitation of Wettest Month	mm
bio 14	Precipitation of the Driest Month	mm
bio 15	Precipitation Seasonality (Coefficient of Variation)	mm
bio 16	Precipitation of Wettest Quarter	mm
bio 17	Precipitation of the Driest Quarter	mm
bio 18	Precipitation of the Warmest Quarter	mm
bio 19	Precipitation of the Coldest Quarter	mm

2.3 Model Development and Evaluation

The Maximum Entropy (MaxEnt) version 3.3.3k was used to design the current and future potential distribution of baobab in Malawi. MaxEnt used species occurrence records and environmental variables, to estimate the suitable area of species in other areas (Phillips, Anderson, & Schapire, 2006). We used ecological niche modeling to forecast regions in Malawi that are favorable to baobab development based on altitude and bioclimatic characteristics (Phillips et al., 2006) and simulate species' potential distribution by using the Maximum Entropy (MaxEnt) MaxEnt version 3.3 algorithm (Phillips et al., 2006). We chose MaxEnt because it has a higher predictive capacity than other modeling techniques like Genetic Algorithm for Rule Set Production (GARP). Additionally, prior research (Guisan & Zimmermann, 2000; Phillips et al., 2006) has demonstrated that MaxEnt is more adept at choosing ecologically significant factors for the presence-only data and using them to estimate environmental appropriateness for the species under study.

To set up the model, 70% of the data was randomly selected for training and the remaining 30% for testing. The model was processed with 10 replicates using a cross-validation procedure. The area under the receiver operating characteristic curve (AUC) statistic was used to evaluate model performance. AUC statistics range from 0.5 (indicating random prediction) to 1.0 (indicating perfect discrimination ability). AUC values range from 0.5 to 1.0, where AUC > 0.9 indicates excellent model performance; 0.80 < AUC < 0.90 show good; where 0.70 < AUC < 0.80 indicates acceptable model and if 0.60 < AUC < 0.70 the model is poor, but if AUC < 0.60 show an invalid model (de Souza Muñoz et al., 2011; Phillips et al., 2006; Yost, Petersen, Gregg, & Miller, 2008, McPherson & Jetz, 2007).

To predict suitable habitat in the year 2055, these models were projected using data from climate change scenarios. The modelling outcomes were imported into QGIS software. Two habitat categories were established based on the mean threshold value (T), known as the 10 percentile training presence: (i) Suitable habitats for values exceeding threshold T, and (ii) those unsuitable for values falling below the threshold (Moukrim et al. 2020). Suitable habitats were then further divided into three (3) subtypes: highly suitable ($p \geq T$), medium suitable ($T/2 \leq p < T$), and low suitable ($T/4 \leq p < T/2$) (Atakpama et al., 2023). Then the changes of the predicted potential habitats were calculated in ArcGIS. This allowed to quantify the range changes to illustrate the dynamic of the range extensions, contractions, persistence, and shifts.

2.4 Mapping Habitat and Determining Priority Areas

Potential habitat dynamics for Baobab by 2055 under each climate scenario were inferred by contrasting current areas with those of various habitat types under the two (2) climate scenarios. These data were employed to generate graphs using Microsoft Excel spreadsheets. Spatial priority area for conservation of Baobab were identified using systematic conservation planning (SCP) tools to avoid the adoption of an ad hoc approach (Margules & Pressey, 2000; Pressey & Bottrill, 2008) which is generally less effective (Delavenne et al., 2012; Honeck et al., 2020). These tools aim to maximize the representativeness of multiple biodiversity characteristics (Di Minin et al., 2019; Kujala et al., 2018). All spatial units of the study site (*i.e.*, pixels) were classified based on the concepts of irreplaceability and complementarity without the need to specify targets in conservation objectives (Lehtomäki & Moilanen, 2013). A conservation priority map was obtained by weighting the species by the respective biodiversity index. Zonation 5 v1.0 software, commonly used to optimize conservation planning (Moilanen et al., 2022) with input files comprising results from MaxEnt modelling: (i) current potential habitats, (ii) habitats projected for 2055 under SSP 3.7.0 scenario, and (iii) habitats projected for 2055 under SSP 8.5 scenario. Core Area Zonation 2 (CAZ2) was selected as the marginal pixel loss rule, which represents a good compromise between species richness and rarity (Moilanen et al., 2022).

3. Results

3.1 Variables Determining the Distribution of Baobab Trees and Quality of the Model

The analysis of the contributions of the different variables in the model reveals that the most significant variable, contributing to the Baobab distribution model, is the maximum temperature of the hottest month (Bio 5), with a value of 47%. Other important variables contributing to the model include the isothermality (Bio 3) and precipitations of the coldest quarter (Bio 19), with contributions of 13.9% and 8.6%, respectively.

The analysis of the Jackknife test results focused on the importance of environmental variables in the spatial modeling performance of the Baobab (Figure 2). The environmental variable "Bio 5" is the predictor with the highest gain when used individually in the modeling. The environmental variable that decreases the gain the most when omitted is hwsd (soil), indicating that it contains the unique information not present in the other variables.

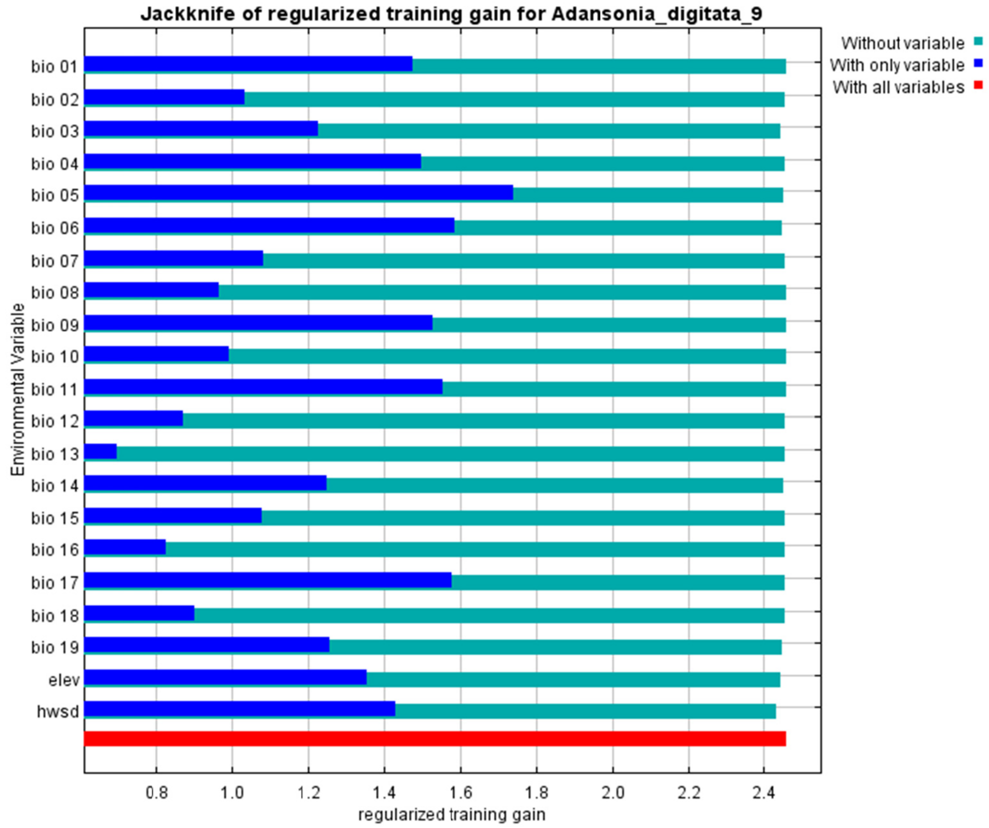

Figure 2. Contribution of bioclimatic variables (Jackknife test), legend (confers Table 1)

The average AUC values of the area under the ROC curve for running the MaxEnt model and testing it are 0.97 and 0.91, respectively (Figure 3). This reveals the excellent performance of the MaxEnt algorithm in predicting the area favorable to the species studied with a margin of error of (0.5%).

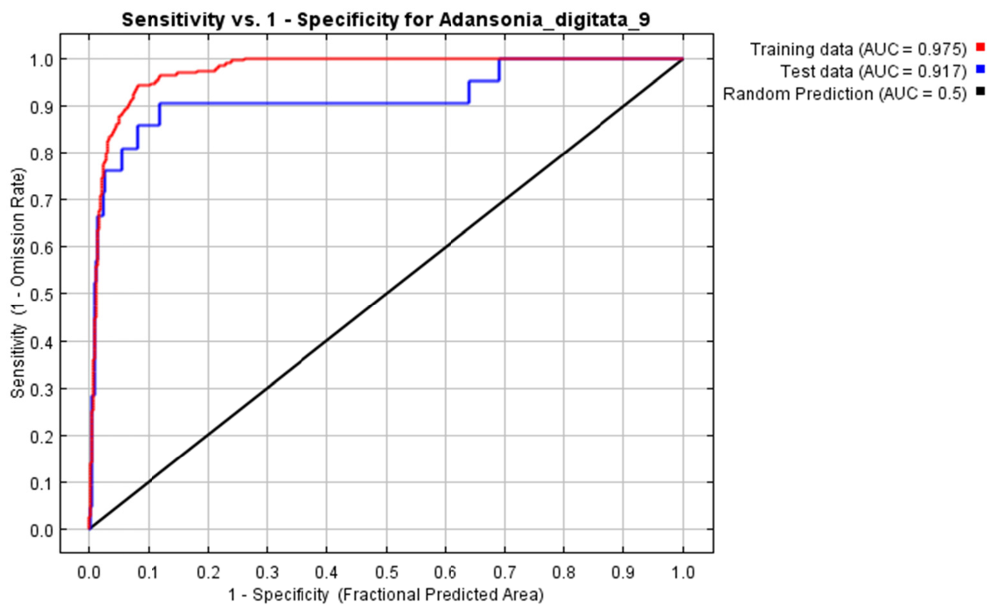

Figure 3. Value of the area under the curve (AUC, Area Under Curve)

3.2 Current and Future Potential Habitats

The distribution of land suitability under the current scenario, SSP370, and SSP585 are depicted (figure 4) categories are used to group the areas: highly, medium, low and unsuitable area. At the moment, about 1.19% of the land area is deemed to be highly suitable for conservation and cultivation; however, under the SSP 370 and SSP 585 scenarios, this percentage drops medium suitable, to approximately 1.13% and 1.10%, respectively. Currently, low-suitable lands make up roughly 13.61% of the land; under the SSP370 scenario, this percentage rises slightly to 14.84%, while in the SSP 585 scenario, it decreases to 13.20%. Under SSP 370, medium suitable areas stay stable at roughly 2.48%, while under SSP 585 they drop to 7.01%. Unsuitable areas, which currently make up around 83.24% of the land, marginally decline to about 81.42% and 78.22%, respectively, under the SSP370 and SSP585 scenarios.

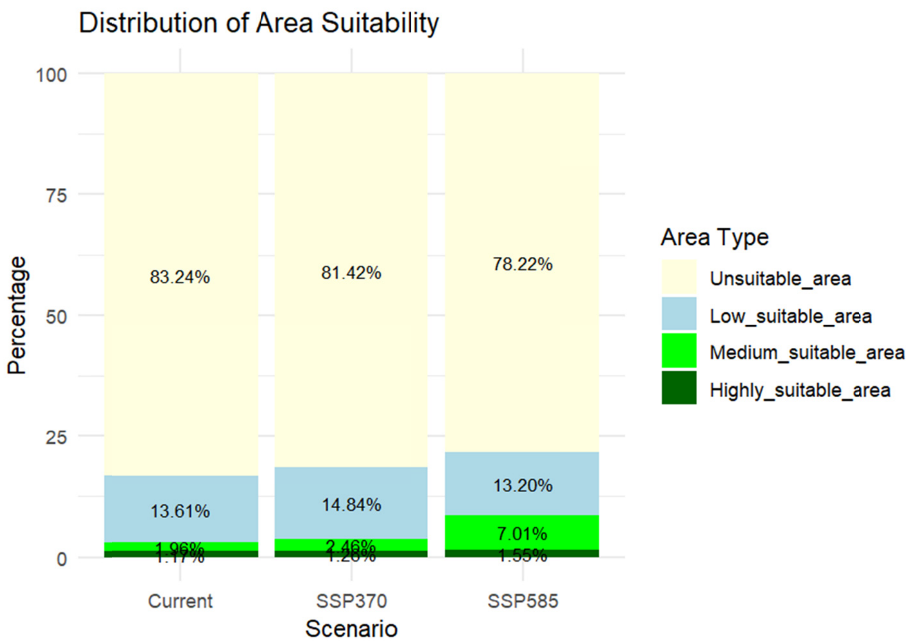

Figure 4. Quality of the current and future potential habitat in Malawi

The land suitability regions under the two scenarios (SSP 370 and SSP 585) are shown (figure 5) as a comparison to the current scenario. The unsuitable area drops by 1.8% in the SSP 370 scenario and more drastically by 5% in the SSP 585 scenario. In the SSP 370 scenario, the low suitable area rises by 1.2%, but in the SSP585 scenario, it falls by 0.4%. with SSP 370, the medium appropriate area shows a minor rise of 0.5%, but with SSP585, there is a significant increase of 5%. With a small increase of 0.1% under SSP 370 and a more notable increase of 0.4% under SSP 585, the highly suited area is still comparatively constant. All things considered, the SSP 585 scenario shows more dramatic changes, with a big decrease in inappropriate areas and a significant increase in medium and highly suitable areas, indicating a potential improvement in land suitability conditions under this scenario.

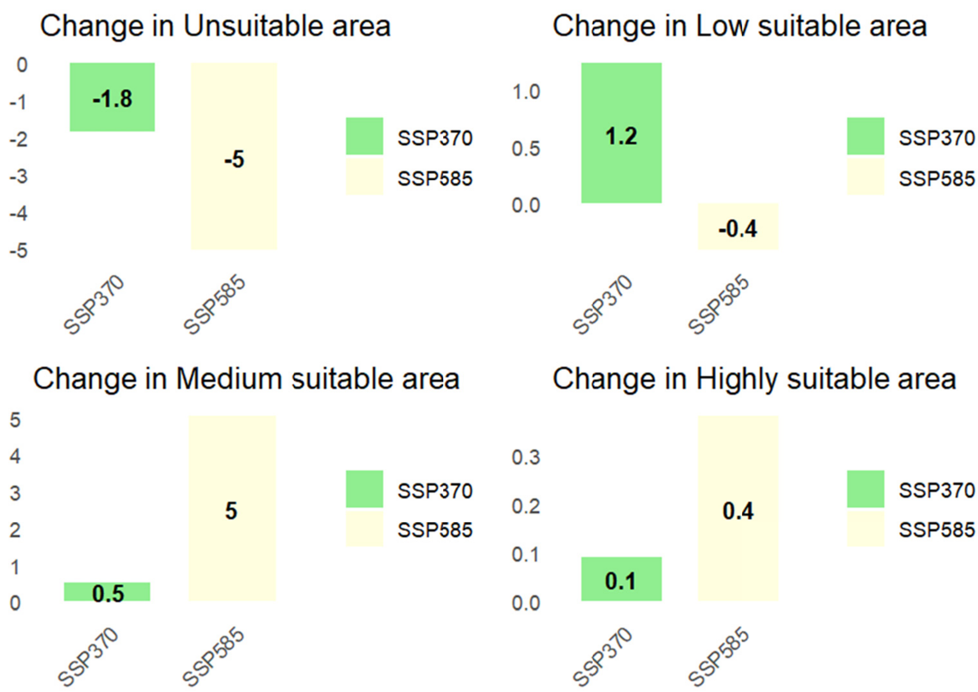

Figure 5. Potential habitat changes rates under SSP 3.7 and SSP 8.5

The maps show the distribution of habitat suitability in Malawi for three different scenarios: SSP370 for 2055, SSP585 for 2055, and the current state (Figure 6). The Central and Northern Regions are primarily unsuited in the current environment, whereas the Southern Region contains a combination of low, medium, and highly suitable locations. The Southern and Central Regions show a minor improvement under the SSP370 scenario, with more places becoming medium and very suited. But the Northern Region is still not very appropriate. With large tracts of medium- and highly-suitable land, especially in the Southern Region, enhanced suitability in the Central Region, and even some low-suitability patches in the Northern Region, the SSP585 scenario exhibits the greatest progress. SSP 585 scenario overall points to a greater.

The percentage of habitat suitable levels for Malawi's Northern, Central, and Southern regions in the two future scenarios SSP 370 and SSP 585 are displayed (Table 2). According to SSP 370 and SSP 585, respectively, 98.92% and 98.81% of the Northern Region's habitat area is deemed unfit in both scenarios. The Central Region exhibits modest improvements: medium suitable areas rise from 0.34% to 3.49%, while 89.77% of unsuitable areas under SSP 370 drop to 86.44% with SSP 585. The largest improvement (highly area) is seen in the Southern Region; as inappropriate areas drop from 57.93% under SSP 370 to 52.34% under SSP 585. Moreover, there is an increase in the proportion of extremely suitable places from 3.64% to 4.50% and medium suitable areas from 6.78% to 16.57%. All regions show improved habitats suitability according to the SSP 585 scenario.

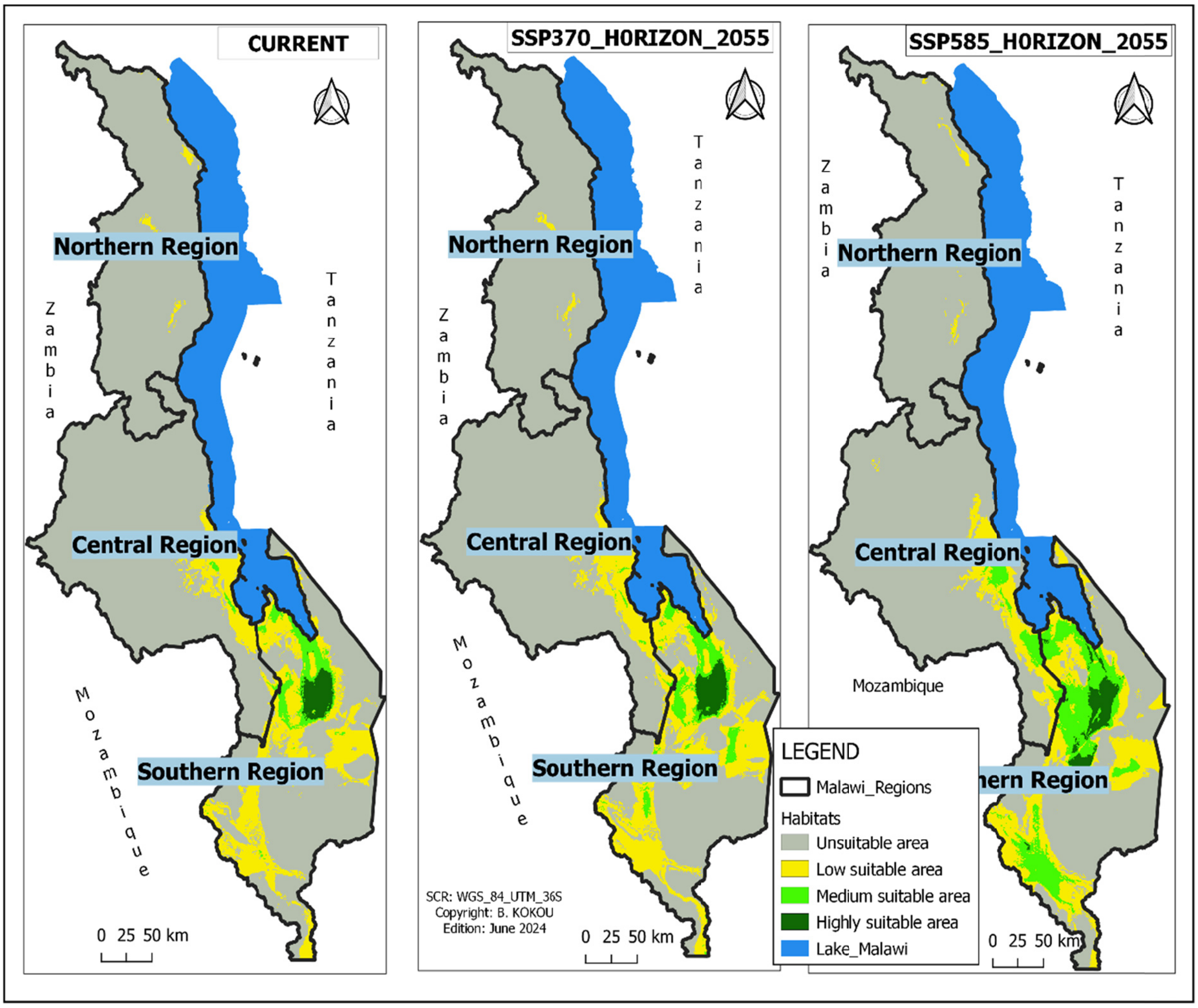

Figure 6. Predicted distribution of baobab under the current climate and the future climate scenarios (SSP 3-7.0 and SSP 4-8.5). Future projections have been made to 2055

Table 2. Potential rate of Baobab habitat dynamics across different Regions of Malawi

Scenarios	Levels	Regions		
		North	Central	South
SSP 370	Unsuitable area	98.92	89.77	57.93
	Low suitable area	0.97	9.88	31.65
	Medium suitable area	0.04	0.34	6.78
	Highly suitable area	**0.06**	**0.01**	**3.64**
SSP 585	Unsuitable area	98.81	86.44	52.34
	Low suitable area	1.10	10.07	26.59
	Medium suitable area	0.07	3.49	16.57
	Highly suitable area	**0.03**	**0.01**	**4.50**

3.3 Priority Conservation and Cultivation Area

The top 5% to 15% of the priority area for cultivation and sustainable conservation/management of baobab were located in the Southern Region and Central (Table 3). The predicted highly prioritized areas for the conservation and cultivation of baobab are mainly located in the Southern Region (34.51%). Southern Region emerges as the most crucial area for both conserving and cultivating baobab, whereas its presence was less anticipated in the Nouthern Region and Central respectively 0.21% and 7.62% (Table 3, Figure 7).

Table 3. Area of priority levels based on economic regions in Malawi

Priority level (%)		0-20	20-50	50-75	75-90	90-95	95-98	98-100
Regions	Northern	21.27	19.01	20.41	20.62	15.62	2.87	**0.21**
	Central	16.56	23.38	18.67	19.96	3.94	9.9	**7.62**
	Southern	4.45	0	3.95	3.54	24.82	28.74	**34.51**

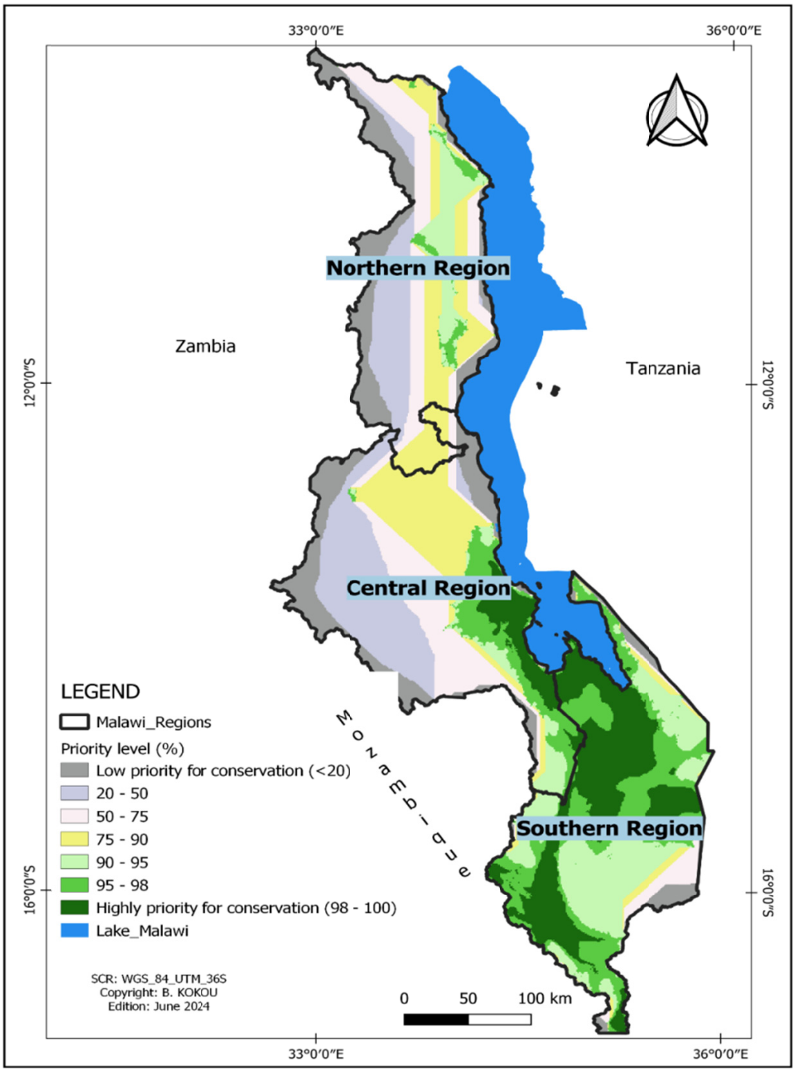

Figure 7. Priority conservation and promotion Baobab habitats in Malawi

4. Discussion

The model's performance was evaluated using the AUC (Area Under Curve) statistic, which exceeds 0.9. This indicates the model's outstanding capability to predict favorable Baobab habitats (Araujo, Pearson, Thuiller, & Erhard, 2005) in Malawi under different climate scenarios. This AUC value parallels findings from Atakpama et al. (2023), who modeled the ecological niche and climate change impacts on Baobab habitats in West Africa.

The study's findings suggest that the distribution of baobab trees in Malawi is primarily influenced by factors such as the highest monthly temperatures, temperature variability over seasons, altitude, and the coldest quarter's temperatures. Among these factors, the highest monthly temperatures play the most significant role in the model, accounting for 47% of the influence. Most baobabs (70%) are found at lower altitudes ranging from 350 to 850 meters. These results are consistent with Sanchez (2011) findings, which also noted a prevalence of baobabs at altitudes up to 800 meters in Malawi. Therefore, it can be concluded that the suitability of baobab habitats depends on altitude, the highest monthly temperatures, and temperatures during the coldest quarter.

The prominence of the highest monthly temperatures and coldest quarter temperatures in determining baobab distribution is unsurprising, given that baobab trees can withstand temperatures as high as 40-42 °C (Simpson, 1995). Our results align with those of Sanchez et al. (2010), who identified mean temperatures during the coldest quarter as significant predictors of baobab distribution. While Sanchez et al. (2010) also highlighted temperature seasonality, annual precipitation, and the wettest quarter's precipitation as important predictors, our study additionally found that precipitation during the coldest quarter, precipitation during the hottest quarter, and temperature seasonality also play crucial roles. Conversely, Moyo et al. (2019) in Zimbabwe suggested that mean temperatures during the driest quarter, along with altitude and mean temperatures during the coldest quarter, are better predictors of baobab distribution than precipitation and its variations.

Atakpama et al. (2022), emphasize that the quantity of dry months significantly influences the biological processes of *Vitellaria paradoxa* trees, especially their phenology. This environmental factor plays a crucial role in the plant's reproductive cycle, affecting both flowering and fruiting stages, thereby influencing productivity (Avaligbé et al., 2021; Boffa, 2000), germination, and seed dispersal. The authors further explain that annual moisture index and precipitation levels are closely linked and crucial for determining water availability, which directly impacts the plant's growth and phenological events through their effects on plant physiology. The results indicate that baobabs are broadly distributed in Southern Malawi, consistent with the findings of Avaligbé et al. (2021). Despite this extensive spread, only a few areas in southern Malawi have high baobab densities.

However, the model has limitations, such as not including demographic parameters (fertility, mortality, growth) and population dynamics. The ability of species to disperse, and their structural characteristics are crucial factors influencing how climate change could impact their habitats. Incorporating these parameters into modeling approaches is challenging, especially on a large scale. Furthermore, microclimatic variations and genetic diversity remain significant factors that could improve the accuracy of models.

Some habitats currently deemed suitable may not always coincide with where the species is actually found. Previous research indicates that a species' fundamental niche is typically broader than its actual realized niche (Atakpama et al., 2016; Pearson & Dawson, 2003), which is often constrained by the presence and interactions with other species (Van Dyke, 2008). The habitats favorable for growing baobab are predominantly located in the southern region of Malawi, where the climate conditions are optimal for this species (Nouvellet, Kassambara, & Besse, 2006). Conversely, the northern and central regions of the country, characterized by very cold temperatures and high precipitation, are less conducive to its growth.

The baobab's habitat is expected to change by 2055 based on projected climate scenarios. These projections suggest that the extent of currently suitable habitats for baobab cultivation will not remain constant in the future. These changes have been extensively documented in the literature (Atakpama et al., 2023; Biaou et al., 2023; Fandohan et al., 2015; Jinga et al., 2020). Generally, the current potential habitats for baobab are expected to expand at the expense of less favorable habitats, likely due to a shift towards a slightly drier climate. This finding mirrors observations in Niger (Boureima & Mahamane, 2020) and for tamarind trees in Togo by Samarou et al. (2023). However, reduced precipitation could extend the favorable conditions for baobab cultivation in Malawi, suggesting resilience of the baobab to future climate conditions in this region. Conversely, reductions and changes in *Vitellaria paradoxa* tree habitats in response to climate change have also been reported in Burkina Faso (Dimobe et al., 2020). Variations in the distribution of baobab and other species like *Uapaca kirkiana* have been noted by Atakpama et al. (2023) and Jinga et al. (2020). These differences may be explained by specific climatic conditions, the size of study areas, and the number of presence points used in modeling. It is established that model accuracy improves with the inclusion of more presence points (Benkendorf & Hawkins, 2020), though expanding the study area may diminish consideration of local constraints.

This study identifies the southern region of Malawi as crucial for conserving and cultivating baobab, while the northern and central regions are less favorable. This information is vital for evaluating the costs and benefits of species conservation and enhancement, aiding in the effective planning of strategies for the plant. Furthermore, it is underscored that areas predicted as highly favorable are generally more extensive than those identified as conservation or enhancement priorities, highlighting that a favorable area does not necessarily equate to conservation or enhancement priority (Atakpama et al., 2022). This distinction is influenced by habitat dynamics in response to future climate variability. The population in Malawi may be experiencing difficulties with natural regeneration, according to findings from recent research conducted there (Dao & Evelyne, 2015; Urbina-Cardona & Loyola, 2008). Several writers have observed that baobab trees in other regions of Africa encounter difficulties in generating naturally (Araujo et al., 2005; Atakpama et al., 2016; Atato et al., 2010), and they have linked this to changes in land use, overgrazing, and drought (Bup et al., 2014). One could argue that the long-term sustainability of baobab tree exploitation is questionable given the general "scattered" distribution of the tree throughout Malawi and the lack of spontaneous regeneration. Sowing the plant is one technique to address this issue.

4. Conclusion

This study on *Baobab* in Malawi provides new insights into the impact of climate change on species distribution. Results indicate that Baobab, tree species of cultural, economic and ecological importance in its natural range, will face significant range contractions by 2055 due to climate change. In a scenario of unlimited greenhouse gas emissions, the range of species is expected to shrink considerably, in the southern, northern and central regions of Malawi. Our results more reliably demonstrated that environmental factors and climate change will affect the distribution of *Adansonia digitata* in Malawi by 2055. The maximum temperature of the Warmest month (Bio 5), with a value of 47% and Other important variables contributing to the model include the isothermality (Bio 3) and precipitations of the coldest quarter (Bio 19), with contributions of 13.9% and 8.6%, respectively. The temperature and precipitation were identified as the most influential environmental variable. Currently, 1.17% of Malawi's predicted to be highly suitable for Baobab cultivation, predominantly concentrated in the southern region with some presence in the central area. By 2055, highly favorable habitats are expected to increase, with a more significant rise projected under SSP 8.5 compared to SSP 7.0 scenarios. This resilience of the plant to future climate change impacts is evident. Prioritization mapping results provide a valuable asset for optimizing investments in conservation, valorization, and cultivation of Baobab in Malawi, particularly recommending the southern administrative region for implementation. Several approaches to conserve the baobab tree could be implemented to safeguard its importance in local diets, medicine, and income generation in Africa, as well as its ecosystem. One strategy involves conserving baobab trees in situ within protected areas that are projected to maintain suitable habitats in the future. Another approach, particularly for regions where baobab populations face extinction risks, includes ex situ conservation through seed banks. Additionally, adopting a 'conservation through utilization' approach could prove effective in preserving the baobab tree's genetic diversity and ecological role.

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Authors Contributions

PhD Students. BKK, PS, IB, JN, GA, FPW, Dr. MU and Prof. JPR were responsible for study design and revising. PhD student. BKK was responsible for data collection. PhD student. BKK drafted the manuscript and PhD students. CTS, JN and Prof. MT, PM and JPR revised it. All authors read and approved the final manuscript.

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Competing Interests

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Obtained.

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The data supporting this study's findings are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data Sharing Statement

No additional data are available.