

Predicting Impacts of Climate Change on the Distribution of *Acacia mearnsii* (Black wattle) in the Southern Africa Region.

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Data Intelligence Malawi

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Abstract

Alien invasive species (IASs) are a threat to the ecological systems of southern Africa. *Acacia mearnsii*, a global top 100 invasive species has become a very invasive tree in the region, displacing native vegetation, altering fire regimes, and influencing water availability. In this study, Ecological Niche Modelling was used using the maximum entropy algorithm to predict the current and future distributions of *A. mearnsii* southern African under MIROC-6 climate models SSP2-4.5 and SSP5-8.5. Data used for modelling were collected from GBIF and 19 bioclimatic variables from Wordclim. The Model performance assessed with Area Under Cover-ROC metrics. The annual mean temperature, precipitation of the wettest month, and maximum temperature of the warmest month were the primary environmental drivers. Currently, highly suitable areas are concentrated in South Africa, Eswatini, and Lesotho. The projected future suitability suggests potential range expansion, particularly under SSP2-4.5, with highly suitable habitats increasing by 13.7%. However, under SSP5-8.5, extreme warming would lower habitat suitability in some regions with an increase (+ 646.21%). Climate change has a significant effect on *A. mearnsii*'s threat of invasion, emphasizing the importance of early detection, risk identification, and tailored management of susceptible ecosystems.

1.0. Introduction

Acacia mearnsii is a native species from Southeast Australia and poses challenges in southern African ecosystems [1]. Ranked among the top 100 invasive species, the species quickly outpaces native ecosystems due to multiple dispersal strategies and ability to quickly adapt to new environment [1][2]. *A. mearnsii* produces more seeds than native species higher seed production per unit seed mass in woody invasive plants [3][4]. The reproductive success of these plants is characterized by massive flowering, compensating for low fruit production. *A. mearnsii* rapidly grows 2–4 m per year in savannas, as reported in Tanzania, and it can begin producing seeds as early as 12 months of age [5]–[8]. When these traits are combined, the species has the ability to outcompete native vegetation for resources change has been reported as a major driver for biodiversity loss and range expansion of IAS [9][10][11][12].

Climate change is playing a significant role in shaping aquatic and terrestrial habitats and it is a leading cause of plant species distribution [13][14]. Apart from this, climate change is responsible for changes in population migration patterns pushing species with narrow climate range beyond their habitat requirements [15]. At the crux of this issue is shifts in temperatures and rainfall regimes that have contributed significantly by creating favourable habitat conditions for IAS expansion [16][17]. This has enabled IAS to easily expand and invade new areas putting native species at risk [18][19] [20][21][22]. These patterns highlight the need to consider the combined effects of IAS and climate change into biodiversity management and policy frameworks [23] [24][25]. Evidence from southern Africa suggests that, despite growing awareness of ecological impacts, existing management efforts remain insufficient and more effective control measures are still needed [26][27].

For decades, IAS have been a threat to global biodiversity and biosecurity. Either intentionally or non-intentionally introduced, IAS can be both beneficial and destructive to an ecosystem[13][12]. In particular, IAS are used for the control of soil erosion, timber, and energy consumption[11][28]. For example, countries such as South Africa, Tanzania, Mozambique and Malawi, jatropha was introduced intentionally for production of medicine, wood and bioenergy. Although IASs have offered economic and social benefits, they are a nuisance and disruptive to ecosystems. IASs such as water hyacinth have been linked to decreased water quality and reduced phytoplankton production [11]. These effects have severely impacted aquatic biodiversity sectors such as fisheries, irrigation, navigation, and tourism[29][30]. IAS disrupt critical ecosystems and have been recognized as contributing factors to poverty[31][32]. This problem has been further exacerbated by increasing anthropogenic activities, climate change, and land use/land change[33].

Southern Africa has unique and distinct ecological systems, such as miombo woodlands, savanna grasslands, rainforests, and desert ecosystems[34]. These ecosystems are vulnerable to the expansion of IAS, such as *A. mearnsii* in South Africa, Zimbabwe, Malawi, and Tanzania[2]. Some critically affected ecosystems affected by IAS invasions are fynbos and forest ecosystems[24][35]. Therefore, spatial assessment of IAS such as *A. mearnsii* is crucial for conservation of native species and management. Ecological niche modelling uses environmental predictors to assess the impact of climate change on species distributions[20]. It uses occurrence data and climatic factors to project future shifts in geographic ranges[22]. Predictive modelling has become an important and crucial objective in ecology[36]. This approach enables ecologists to understand the drivers affecting the growth of species within the dimensions of space and time[23][37];[25]. These models are particularly vital in the context of understanding biological invasions[38]. The assessment of potential spread is essential for informing early detection, risk assessment, and targeted management interventions[39][40]. Maximum entropy modelling has become one of the most widely used SDM techniques in ENMs[41]. Maxent estimates the probability distribution of a species' potential presence on the basis of occurrence data and environmental constraints[42][43].

Therefore, the objectives of this study were:

- To identify the key environmental variables influencing *A. mearnsii* distribution in southern Africa;
- To predict the potential habitat suitability of *A. mearnsii* under current and future scenarios
- To classify habitat suitability for guiding targeted management, restoration, and early detection efforts on the basis of countries in SADC.

2.0. Materials and Methods

2.1. Study Area Description

Figure show countries under the Southern Africa Development Community. The study was conducted in southern Africa (popularly known as SADC), which contains 16 countries, such as South Africa, Malawi,

Zambia, and Zimbabwe. The SADC is located at latitudes ranging from 15°S to 35°S and longitudes ranging from 10°E to 40°E. It is known for its savanna grassland, Miombo woodland and desert ecosystems. The regional climate ranges from arid, semiarid and subtropical climates with annual precipitation between 300 mm and 1200 mm. The regional elevations range from 3000 m to 4500 m above sea level, providing optimal growth for IAS. *A. mearnsii* is disturbing riparian zones, montane grasslands, and forest margins in South Africa, Eswatini, and Zimbabwe. Its aggressive spread poses serious ecological threats by reducing water availability, displacing native flora, and altering fire regimes.

2.2. Input data

2.2.1. Occurrence data

Occurrence records were collected from the Global Biodiversity Information Facility (www.gbif.org), which was accessed on 15 July 2025 via the pygbif library. The initial dataset contained 8350 occurrence points georeferenced with observations across southern Africa (1990–2024). Owing to nuances in the dataset, Open Refine was used for data cleaning. Open refine is one of the best software packages for cleaning messy data. Data points lacking georeferencing were removed via NumPy and Panda's library[44]. This process was repeated for data points that were outside the range of the study area. Spatial analysis was conducted to ensure data accuracy via geopandas and scikit-learn libraries. The aim of conducting spatial thinning was to reduce sampling bias. Therefore, a distance threshold of 5 kilometres is used as the minimum distance so that no more than two data points occur within the set distance minimum threshold [30].

The final dataset included species, decimal latitude and decimal longitude. This helps minimize the spatial autocorrelation of data collected in densely populated areas. The final curated dataset included 7361 high-confidence occurrence records that accurately represented the distribution of the species in key habitats, such as savannas, plantations, montane grasslands, and riparian zones. The final dataset was saved as a CSV and then exported to Python 3.13 for further data cleaning. In Python programming, the dataset was tested for a normal distribution via analysis of variance (ANOVA), and other exploratory analyses were also conducted[45][46].

2.2.2. Environmental data

Nineteen bioclimatic layers for current and future climate projections were obtained from www.worldclim.org/2.1 at a 30 second resolution, accessed and downloaded on 15 July 2025. MIROC6 climate dataset used for modelling of *A. mearnsii* was, which was developed by the Japanese Space Agency. The MIROC 6 experiments were designed to represent Earth's climate from 1850–2014 and 2014–2099, respectively[32]. The first experiment was modelled under the representative critical path (RCP), whereas the second experiment was modelled under the shared socioeconomic pathway by the Coupled Model Intercomparison Project phase 6, the latest climate predictor for current and future projections[41], [47]–[50].

Elevation, slope, aspect and topographic indices were also used in this study. Elevation is an important factor because it is used to assess temperature and rainfall changes across diverse ecosystems[51][52][53]. Slopes affect vegetation growth, water movement, soil stability, and water run-off; therefore, slope is an important variable for this study[34][54]. Aspect influences the position of the sun and therefore controls solar radiation[55]. Finally, the topographic index provides information on drainage conditions and soil moisture for plant survival and growth[35].

Table 1. shows environmental predictors used in this study used in the modelling of *A. mearnsii* in Southern Africa. From Bio 1 to bio-11, the unit measurement for each predictor degrees Celsius while from Bio 12-bio17 the unit value is mini-meters(mm).

Table 1
Environmental predictors downloaded from
www.worldclim.com/2.1.

Variable	Description
Bio1	Annual Mean Temperature
Bio2	Mean Diurnal Range
Bio3	Isothermality
Bio4	Temperature Seasonality
Bio5	Max Temperature of Warmest Month
Bio6	Min Temperature of Coldest Month
Bio7	Temperature Annual Range
Bio8	Mean Temperature of Wettest Quarter
Bio9	Mean Temperature of Driest Quarter
Bio10	Mean Temperature of Warmest Quarter
Variable	Description
Bio11	Mean Temperature of Coldest Quarter
Bio12	Annual Precipitation
Bio13	Precipitation of Wettest Month
Bio14	Precipitation of Driest Month
Bio15	Precipitation Seasonality
Bio16	Precipitation of Wettest Quarter
Bio17	Precipitation of Driest Quarter
Bio18	Precipitation of Warmest Quarter
Bio19	Precipitation of Coldest Quarter
Elevation	Digital Elevation Models
asp	Derived from DEM
Slope	Derived from DEM
TPI	Topographic index

2.2.3. Variable Selection and Multicollinearity Assessment

Figure 2. shows variable selection and multicollinearity assessment. To avoid multicollinearity, the variable inflation factor (VIF) was conducted via Python programming using the pandas, seaborn and statsmodels libraries. The aim was to reduce redundancy among environmental predictors and ensure that there are robust model results and interpretations. We conducted a VIF using pairwise Pearson correlation coefficients (PCCs) to identify environmental layers that had strongly correlated variables. The relationships among the environmental predictors were evaluated via the correlation coefficient of $|r^2| > 0.75$ [42][56]. Any predictor showing a strong linear relationship with other predictors is redundant (Guisan, et al., 2017). The results of the process revealed that Bio_2 (mean diurnal temperature), Bio_3 (isothermality), Bio_11 (mean temperature of the coldest quarter), Bio_1 (annual mean temperature) and Bio_1 (precipitation of the driest month) had lower correlations than the other environmental predictors. Therefore, these models were then used to construct a species distribution model for *Acacia mearnsii*.

2.5. Modelling Approach

Figure 3. shows methodology for species distribution modelling of *A. mearnsii*. Python programming language version 3.14 was used to perform ecological niche modelling of *A. mearnsii* in southern Africa [31]. The environmental layers were exported in Python programming 3.14 via the Jupyter notebook. Raster clipping to the southern Africa boundary was executed in Python programming 3.14 via the rasterio, geopandas, ecopy and xarray libraries [37]. All raster layers were aligned via WGS 84, EPSG 4326 for projection consistency. We utilized occurrence data in the CSV from the GBIF in CSV format alongside bioclimatic predictors in GeoTIFF. These inputs were used to produce habitat suitability maps and predict potential areas of invasion risk (Poudel, et al., 2024). Maximum entropy modelling, a machine learning algorithm, was integrated in Python via the Jupyter notebook. The occurrence dataset was randomly partitioned into model training and testing. Eighty percent of the occurrence records were portioned for testing, and 30% were portioned for model training (Brunialti, et al., 2021). Model performance was evaluated via the area under the receiver operating characteristic curve (AUC-ROC). According to Phillips (2012), values from 0.9–1 indicate excellent predictive accuracy. A net change analysis was also conducted to assess spatial and temporal changes in habitat suitability. Fifty replicate model runs, all executed and summarized within the Python environment.

3.0. Results

3.1. Analysis of variable contributions

Table 2. presents estimates of the relative contributions of the environmental variables to the Maxent model. The annual mean temperature emerged as the most dominant predictor, contributing 49% to the model's gain and registering the highest permutation importance of 40.7%. These findings indicate that the daily variability in temperature is a critical ecological factor influencing habitat suitability, potentially affecting species physiological responses and microhabitat stability. The precipitation of the driest

month had a strong influence on the model, with a percent contribution of 28% and a permutation importance of 13.4%. These findings underscore the relevance of seasonal thermal conditions, particularly extreme heat periods, in shaping species distributions.

Table 2
analysis of variable contributions

Variable	Percent Contribution	Permutation Importance
bio_1	49	40.7
bio_14	28.1	13.4
bio_5	14.2	24.5
bio_3	3.6	5
bio_12	2.5	7.3
elev	2.2	6.5
Slope	0.2	0
bio_13	0.2	2.3
TPI	0	0
Aspect	0	0

3.2. Jackknife results

Figure 4. shows the jackknife results for the study. The annual mean temperature was the most important variable influencing the distribution of *A. mearnsii*. When used in isolation, *Bio_1* achieved the highest training gain, indicating that it provided the greatest amount of useful information for predicting species occurrence. Moreover, its exclusion from the model led to a substantial reduction in training gain, further emphasizing its unique contribution. These findings suggest that the annual thermal regime plays a central role in determining habitat suitability for *A. mearnsii*, which aligns with the known sensitivity of this species to temperature and its preference for moderately warm climates.

3.3. Response curves

Figure 5. shows how each environmental variable affects the predicted probability of presence. They depict a threshold at which the species can survive, assessing its habitat preference. The response curve for the annual mean temperature shows that *A. mearnsii* responds positively to rising temperatures. The probability of presence at a peak temperature for *A. mearnsii* was between 15°C and 25°C. These findings indicate that *A. mearnsii* has an optimal thermal range for establishment and persistence(Shcheglovitova, et al., 2013). The temperatures above 22°C indicate that habitat suitability has declined. These findings suggest that warm climates may limit the growth and reproduction of this species.

The maximum temperature of the warmest month revealed that *A. mearnsii* performs best in regions where the maximum temperature ranges from 26°C to 32°C. The observed decline in habitat suitability above 35°C implies that extremely high temperatures may impact the physiological tolerance of *A. mearnsii*, affecting seed germination and water-use efficiency. While the Precipitation of the Driest Month showed a unimodal pattern, the probability of presence increased as the precipitation rose from 0 mm to 40 mm. After this point, habitat suitability declined. This finding indicates that *A. mearnsii* is tolerant of dry season conditions but may be disadvantaged in areas with high year-round precipitation.

3.4. Model performance

Figure 6. Shows the receiver operating characteristic (ROC) curve for this study. Note that the specificity is defined via the predicted area rather than the true commission. This implies that the maximum achievable AUC is less than 1.

3.5. Current habitat suitability model

Figure 7. shows Current distribution of *A. mearnsii* in southern Africa. The current habitat suitability model revealed that *A. mearnsii* was highly suitable in Northern region of Malawi, Lesotho, Zimbabwe, Tanzania and South Africa. Lesotho, Zimbabwe, and Eswatini presented more highly suitable and suitable classes. Madagascar, Mozambique, and the DRC Congo ranged from suitable to low suitable. Several areas in Tanzania were highly suitable, moderately suitable and poorly suitable. Madagascar and the DRC in the Congo have few areas that are in the low suitability to medium suitability classes. These findings indicate that these areas have climatic conditions that support the growth of *A. mearnsii*. Conversely, countries such as Zambia, Mauritius, Seychelles, and the Comoros Islands were largely classified as unsuitable for the establishment of *A. mearnsii*, likely because of ecological limitations or climatic unsuitability. Furthermore, the spatial predictive maps revealed that Namibia, Botswana, Angola, and Zambia did not have suitable classes.

The current habitat suitability map, derived from five classes not suitable, low suitability, medium suitability, suitable, and highly suitable indicated that *A. mearnsii* is presently most suited to the western and eastern Cape provinces of South Africa. These regions presented environmental conditions aligned with the most influential bioclimatic predictors, especially *Bio_1*, *Bio_14*, and *Bio_5*, which offer optimal conditions for species growth. Other countries, such as Lesotho, Zimbabwe, and Eswatini, also exhibited large areas of high and moderate suitability. Further north, Malawi, Mozambique, and the Democratic Republic of the Congo demonstrated varying degrees of suitability, ranging from high to low, depending on regional climatic variations. In contrast, countries such as Namibia, Botswana, Angola, and Zambia were predominantly categorized as not suitable for the species, likely because of their ecological limitations and unfavourable climatic conditions. Madagascar and the DRC displayed pockets of low to medium suitability, suggesting restricted but potentially viable conditions for future colonization.

3.6. Potential distribution of *A. mearnsii* under future scenario SSPRC4.5

Figure 9. Shows the future suitability map under SSP 45 and 85 climate scenarios. The map reveals an expected shift for *A. mearnsii* in the SADC region. The potential ranges expansion under suitability class in South Africa, Lesotho, Northern region of Malawi and Tanzania. Under the Medium suitable class SSP 45, the habitat potential suitability maps reveal that countries such as Mozambique and Zimbabwe showed a more shift of potential range increase under this class. The increase in expansion under medium suitability class suggest that these areas have the potential to support the growth of black wattle species. Across the same class, climate change will also create favourable conditions for *A. Meamsii* species in arid and semi-arid ecosystems such as Angola, Namibia, Lower shire in Malawi and Zambia. This suggest that Black wattle could spread to these areas and create conducive environmental optimal for growth in areas where there no current information.

Under the SSP2-4.5 climate change scenario, the results revealed a large expansion in the potential geographical range of the species. Under the highly suitable class, the potential areas increased from 3,841 km² to 28,659 km² representing a 646.21% increase in suitability. The potential areas increased significantly, by 14.69%, from 184,754 km² to 211,884 km². The lower suitability category showed notable losses under climate scenario SSP85 than SSP 45. As observed in Fig. 9., the area under the lower class increased by 24.57%, and under the medium suitable class, it decreased by 12.17%. These areas cannot support the growth of *A. mearnsii*. Notably, countries such as South Africa, Malawi, and Mozambique, which have few areas that are suitable under the current scenario, have now become suitable under this scenario. Furthermore, the shift under these scenarios suggests that changes in rainfall patterns, as shown by bio_14, could result in increased potential expansion of *A. mearnsii*. Similarly, in countries such as Zambia, Namibia, and Angola, few areas have achieved low suitability under this climate scenario. These findings indicate that *A. mearnsii* has the potential to colonize these areas. In Malawi, Zambia Tanzania and the DRC, it was also noted that there was a shift in classes from not suitable to the medium class. This suggests that northwards and altitudinal expansion of species niches has occurred in this country.

Table 2
habitat suitability analysis of *A. mearnsii* under five classes across the southern Africa Development Commission.

S.N	Countries	Unsuitable Habitat	Low Suitability	Moderate Suitability	Suitability	High Suitability
1	Angola	1,253,284.49	-	-	-	-
2	Botswana	629,051.83	-	-	-	-
3	Comoros	-	-	-	-	-
4	DR. Congo	2,254,100.58	12,585.77	666.94	-	-
5	Eswatini	12,263.06	2,172.93	4,625.54	-	-
6	Lesotho	11,036.75	20,997.80	2,517.15	-	-
7	Madagascar	501,085.74	49,525.54	9,552.28	-	-
8	Malawi	100,793.73	6,411.21	3,399.23	-	-
9	Mauritius	43.03	-	-	-	-
10	Mozambique	775,541.58	3,033.49	1,764.16	-	-
11	Namibia	868,719.30	-	-	-	-
12	Seychelles	-	-	-	-	-
13	South Africa	871,838.85	222,542.22	218,540.59	37,864.88	-
14	Tanzania	834,576.37	28,463.20	16,953.14	172.11	-
15	Zambia	776,595.77	43.03	-	-	-
16	Zimbabwe	375,486.22	29,323.77	9,294.11	-	-

3.7. Potential distribution of *A. mearnsii* under future scenario RCP 8.5

The results under the SSP-8.5 scenario reveal different trajectories than those under the current scenario and SSP-4.5 scenario. The highly suitable class increased from 3,841 km² to 27,060 km². Our results revealed a substantial decrease under this scenario under SSP-4.5. The suitability classes expanded by 28,659, whereas the low and medium classes expanded by 900,628 km² and 408,970 km² respectively. This reduction was observed in Mozambique, where more areas with low suitability changed to the unsuitable class, with similar observations in Malawi, DRC and Namibia.

The Potential areas previously recognized as highly suitable, for instance in Eswatini and Lesotho, transitioned into lower suitability classes, highlighting a threshold beyond which warming will become detrimental to optimal growth. South Africa experienced a net increase in potential range under this

scenario, with regions that were unsuitable now becoming suitable for invasion of the studied species. Mozambique exhibited a contraction in its medium suitability zones, implying that increased warming may hinder rather than facilitate the spread of *A. mearnsii* in certain areas. In Malawi, there was a loss of highly suitable zones, although these zones were partially offset by gains in medium suitability.

Climate change will facilitate the biological invasion of *Acacia mearnsii*, as the results suggest, across southern Africa. This is evidence of the changes in suitability classes, especially under highly suitable, suitable and moderately suitable classes. The strong expansion of highly suitable zones under both scenarios underscores the urgent need for proactive monitoring and management strategies, especially in regions newly projected to support the species.

Table 2
habitat suitability analysis of *A. mearnsii* under five classes across the southern Africa Development Commission.

S.N	Countries	Unsuitable Habitat	Low Suitability	Moderate Suitability	High Suitability	Very High Suitability
1	Angola	1,282,672.79	-	-	-	-
2	Botswana	629,503.62	-	-	-	-
3	Comoros	1,462.96	64.54	-	-	-
4	DR. Congo	2,347,127.71	2,495.64	-	-	-
5	Eswatini	12,177.00	2,194.44	4,690.08	-	-
6	Lesotho	10,606.47	15,253.52	8,691.71	-	-
7	Madagascar	568,984.36	39,327.84	24,052.80	-	-
8	Malawi	115,703.02	7,207.24	752.99	-	-
9	Mauritius	1,764.16	215.14	-	-	-
10	Mozambique	826,745.22	3,119.55	1,398.42	-	-
11	Namibia	894,407.18	-	-	-	-
12	Seychelles	193.63	0	-	-	-
13	South Africa	865,556.72	275,940.31	210,193.11	49,740.68	-
14	Tanzania	917,126.11	34,250.50	3,571.35	-	-
15	Zambia	778,811.73	-	-	-	-
16	Zimbabwe	380,886.27	28,011.41	5,206.42	-	-

3.8. Net gain and Loss analysis

Table 3
gain/loss risk analysis for distribution of *A. mearnsii* that was averaged by

Suitability Class	RCP4.5 (Gain/Loss)	RCP4.5 (%)	RCP8.5 (Gain/Loss)	RCP8.5 (%)
Highly suitable	+ 24,818	13.3%	+ 23,219	15.2%
Suitable	+ 27,130	14.5%	+ 24,005	15.7%
Medium suitable	-37,207	19.9%	-27,134	17.8%
Low suitable	-57,592	30.8%	-49,250	32.2%
Not suitable	+ 40,475	21.6%	+ 29,160	19.1%

The net gain and net loss analysis revealed an increase in highly suitability class increased by 28, 219 km² representing a 15.3% under RCP85. The suitability class expanded by 22,004 km² showing a partial intensification in the region. The range contraction and fragmentation under RCP85 where substantial losses between low suitability by -27,592 km² and medium suitable - 49,250 under RCP85 were observed. Under RCP45 scenario, highly suitable class expanded by + 24,818, representing (13.3%) while the suitability class contracted by + 27,130 representing (14.5%). Under the same scenario, larger losses were recorded under medium suitability class with - 37,207 km² while low suitability zones - 57,592 km². Notably, both scenarios show an increase in areas classified as not suitable, particularly under RCP4.5 (40,475), highlighting an overall trend toward habitat polarization. The findings suggest that climate change may reduce ecological shifts while concentrating suitability into fewer, more climatically favourable areas, with important implications for species persistence, dispersal, and management under future climate conditions.

4.0. Discussion

a. model inference

The maximum entropy model has excellent predictive power for species distribution modelling of *A. mearnsii* in southern Africa. The Maxent model uses the area under the curve (AUC) as a measure of model predictive performance. An AUC of 0.5 indicates random prediction, and an AUC of 0.9-1 represents excellent model performance(Phillips, et al., 2006). The model achieved high accuracy scores, with AUC-ROC values exceeding 0.932, indicating that the model made excellent predictions of 93.2%. This is attributed to the careful preprocessing of occurrence data and environmental variables. A minimum distance threshold of 5 kilometres between data points was applied spatially with the aim of reducing sampling bias and spatial autocorrelation(Stephan, et al., 2020)les.

The variable contributions revealed that three bioclimatic variables predominantly control *A. mearnsii* distribution in southern Africa. In this study, the annual mean temperature. Other variables that were important for the distribution of *A. mearnsii* were precipitation in the wettest month, which contributed

28.1%. This factor is important because it reveals how climatic factors, especially rainfall, contribute to the degree of water stress[41]. Furthermore, the other important factor, the maximum temperature of the warmest quarter. This finding suggests that increasing temperatures influence the distribution of *A. mearnsii* species in southern Africa [42]. The relatively low contributions from topographic variables such as elevation, slope, and aspect indicate that climatic factors are more influential than terrain variables in *A. mearnsii* distribution across the SADC region.

The geographical distribution displayed by the current distribution across southern Africa reveals various patterns. The suitability class showed more range expansion in South Africa than in other countries in southern Africa. The Mediterranean-type climate in South Africa resembles that of southern Australia, where *A. mearnsii* is a native species[57]. This climate provides an optimal climate where temperature and rainfall favour the growth of *A. mearnsii*[58]. Highly suitable classes were observed in Eswatini, northern Malawi, northern Tanzania, DRC, and Lesotho. Eswatini, Zimbabwe, and Lesotho have more savanna and montane grasslands and forest ecosystems. Montane and savanna grasslands provide optimal microclimates and water availability conditions for vegetation growth and reproduction[59]. The presence of probabilities under the suitability and medium suitability classes in Northern Malawi, Eswatini, and Tanzania suggests that *A. mearnsii* would expand its geographical range in watercourses[1]. Zambia, Botswana, Namibia, and Angola were largely classified as unsuitable, primarily because of their arid to semiarid climatic conditions and extreme temperature variations. The limited suitable habitat in these regions implies that climate acts as a natural barrier to *A. mearnsii* establishment and spread.

Future climatic scenarios show different patterns of range expansion and contraction. The moderate scenario (SSP-45) predicts geographical range expansion in areas previously under the unsuitable class. Range expansion is observed in Mozambique, Tanzania, Madagascar and Malawi, where transitional zones shift from unsuitable to low-suitability classes, as shown in Fig. 2. Southern African countries such as Namibia, Botswana, and Zambia have semiarid and arid climatic conditions. Under both scenarios, the shift from the not suitable class to the low suitable class suggests that these areas can support the growth of *A. mearnsii*.

The SSP5-8.5 scenario presents a different trajectory, revealing significant reductions in highly suitable areas. This was observed across Eswatini, Lesotho, and South Africa. This finding indicates that climate factors such as bio_1 may push optimal climatic conditions beyond the tolerance thresholds of a species. This will lead to habitat contraction in currently suitable areas while creating new areas in previously marginal habitats. The quantitative analysis revealed dramatic changes in habitat suitability classes. The highly suitable areas significantly increase under RCP4.5 and RCP8.5, expanding from 3,841 km² to over 27,000 km² under both scenarios. However, these gains are accompanied by substantial losses in the medium- and low-suitability classes, suggesting a polarization towards extreme suitability categories.

b. promoting Early detection and Rapid Response for adaptive IAS management.

From the management and conservation context, the projected shifts under both scenarios suggest an urgent need for adaptive strategies to slow the further expansion of *A. mearnsii* in this region. The study proposes Early Detection and Rapid Response (EDRR) especially in the newly transition zones such as Mozambique, DRC and Namibia where there are potential habitats that are at risk of invasion. This objective can be achieved through systematic survey using remote sensing, Ecological niche modelling and an investment in community-based monitoring through citizen science. For countries where biological control has been a success such as south Africa, there is a need for using integrated control approaches. Control mechanisms such as mechanical removal, application of herbicides and burning can reduced seed germination chances and also can prevent re-emergence of *A. mearnsii* in treated sites. In the treated sites, managers should consider restoring the lands with native vegetation limiting re-invasion of *A. mearnsii*. The region is under severe threat to IAS due to limited financial instruments to support biodiversity conservation programmes. There is a need for cross-sectorial corroboration between sectorial agencies, local and international actors. This could impact management of *A. mearnsii* by increasing funding for adaptive management strategies. Due to limited financial resources, member states should work with the academia to develop climate-informed risk maps essential hence it can easily be incorporated into invasive species management. Climate-informed maps could assist land managers to guide areas required for reafforestation, areas at risk of fire disturbances and improve land use land changes by predicting which classes are at risk of invasion. Hence reducing the risk of re-establishment and safeguarding ecosystems services while promoting and conserving native biodiversity.

c. Increasing data coverage among non-active member states to improve understanding of the distribution of *A. mearnsii* under changing climate.

Data is important because you can manage what you can't measure. The study was conducted using published occurrence records from five member states in the region. The rest of the member states particularly Zambia, Botswana, Namibia, and Angola have not published their data, although evidence suggest that *Acacia mearnsii* is present in these countries. The limited data availability reveals that to the need for better resourced and better coordinated field surveys among these member states. Although South Africa, Malawi, Tanzania, and Madagascar have made efforts to document *Acacia mearnsii* and publish their data, information remains uneven across the region, constraining effective regional planning and management. To improve and overcome this barrier, The member states with poor data representation such as Malawi, Mozambique and Angola should place much focus on more concrete solution such as community engagement. This can be integrated with research activities using citizen science and environmental education as means towards adaptive IAS management. Some of the strategies for community engagement including the use of local ecological knowledge in monitoring and awareness activities in the established plot where data is collected. In addition, the Southern African Development Community has a key role to play in supporting member states through targeted funding and technical assistance aimed at improving data coverage, consistency, and regional data sharing. Despite maxent predicting excellently (with 0.92 representing 92%), a representative data across the

region would enable a better understanding of how *Acacia mearnsii* would also impact protected areas in the countries with no data published.

All in all, the selected climate factors have performed excellently under Maximum Entropy model. However, we did not include other relevant drivers that could inform the management of *A. Mearnsii* in southern Africa. Future studies will need to include additional environmental layers in the analysis, and dispersal. Climate variables such as land use/land change, soils and other biotic interactions are crucial in understanding species distribution. The temporal scale of climate change projections provided a medium-term (2050) perspective of climatic change. However, longer temporal species environmental layers from 2061–2080 and 2100 for planning not only will require projections of climate but also projections of socio-economic dynamics to better understand the human footprint on future invasions in terms of enhancing or limiting impact. Similarly, in relation to the application of other machine learning and artificial intelligence models which will likely also clarify the past and present impacts of climate change on *A. mearnsii*.

5.0. Ethical Consideration

The Study used secondary data collected from GBIF that is a publicly available database. There was no involvement of animal nor plant specimen. The research study used No personal, sensitive data was used and we adhered to transparency towards the used of open-source data.

6.0. Conclusion

This study represents useful information on the current and future distributions of *A. mearnsii* in southern Africa under changing climates. The models performed well overall and identified strong, critical environmental drivers of climate change allowing us to be relatively confident when making targeted management decisions. The projected range

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Figures

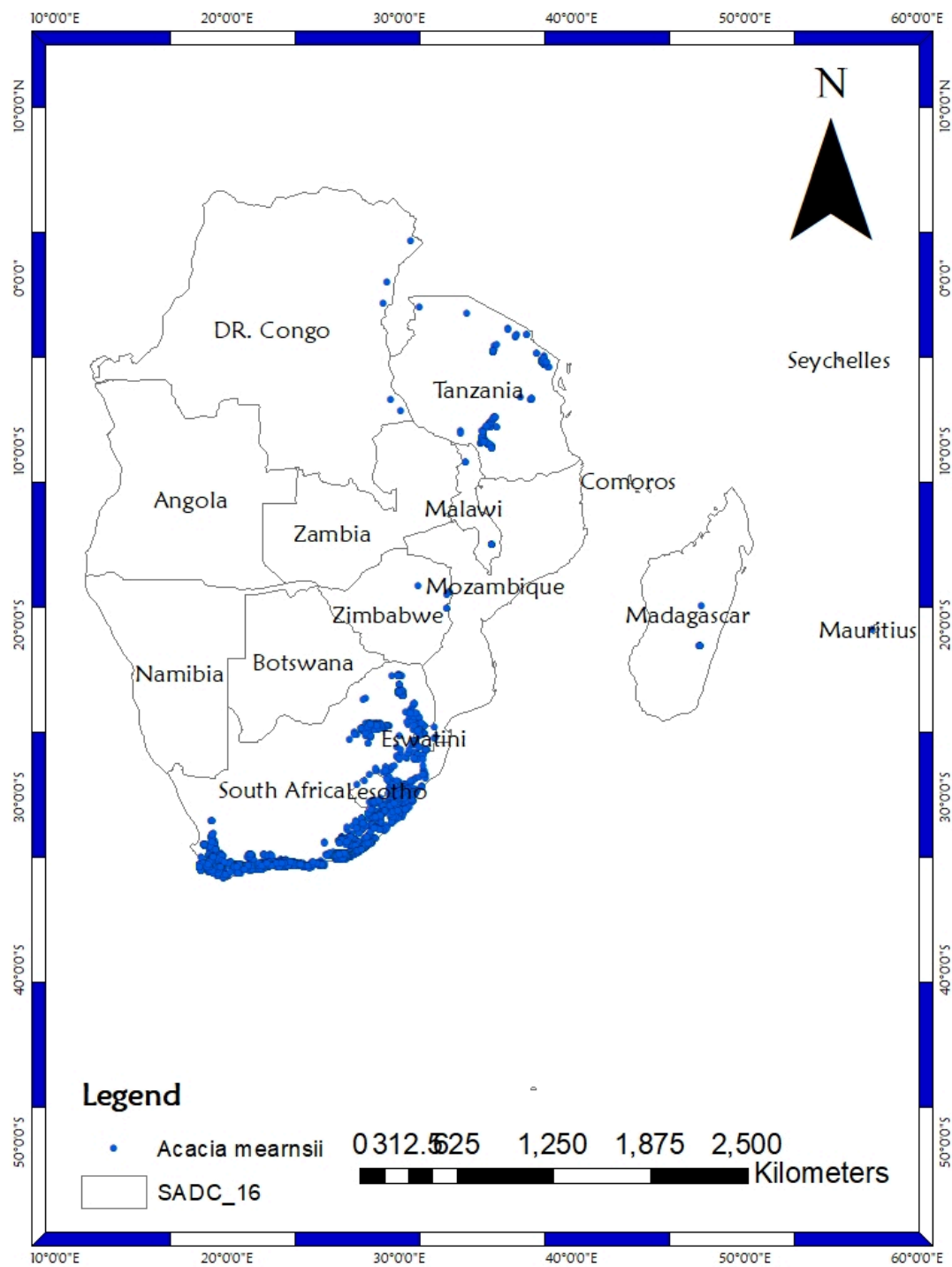


Figure 1

Occurrence data for A. mearnsii in southern Africa

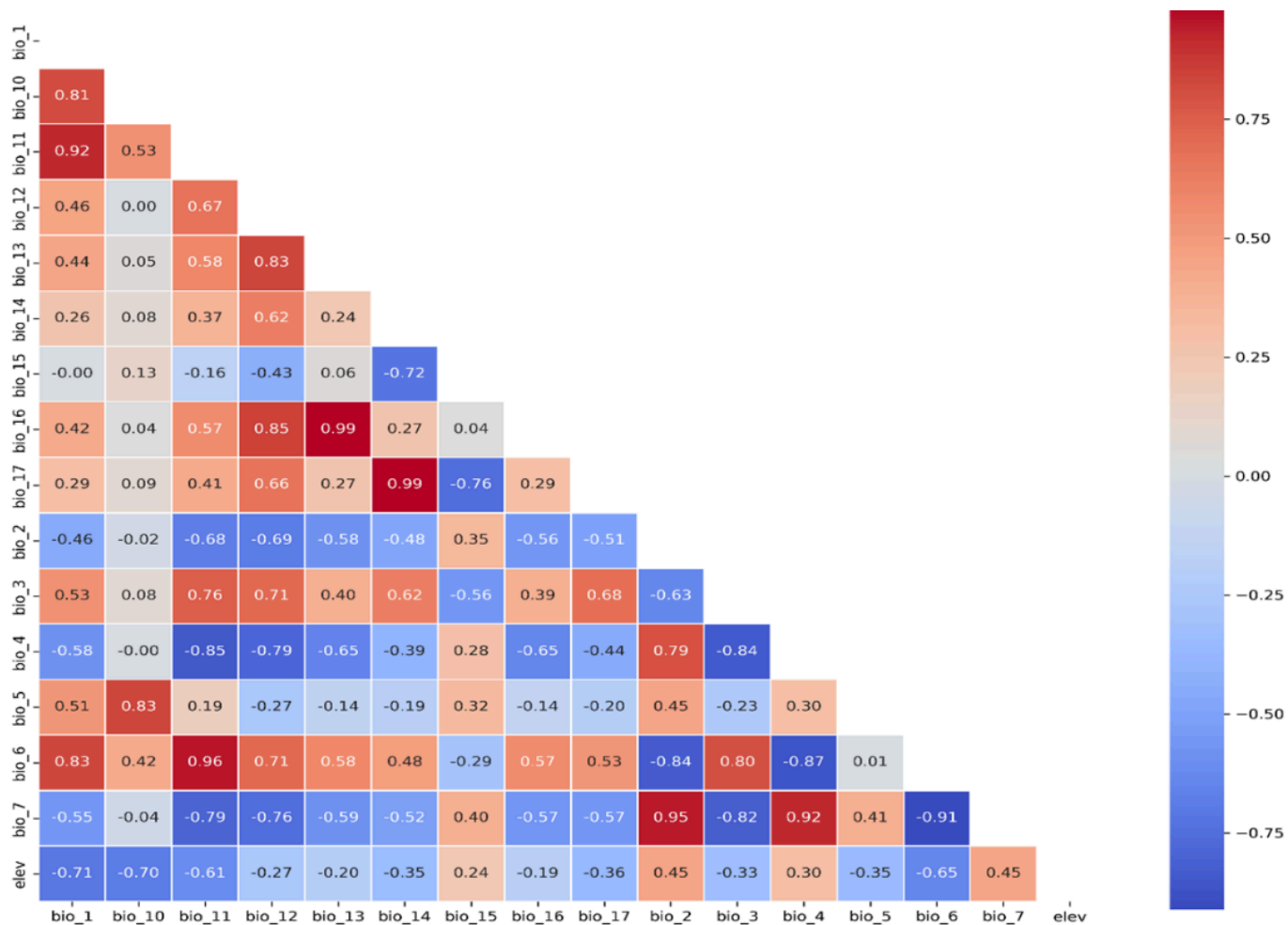


Figure 2

Results of the variable inflation factor for *Acacia meansii*

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Figure 3

Methodology for species distribution modelling of *A. mearnsii*.

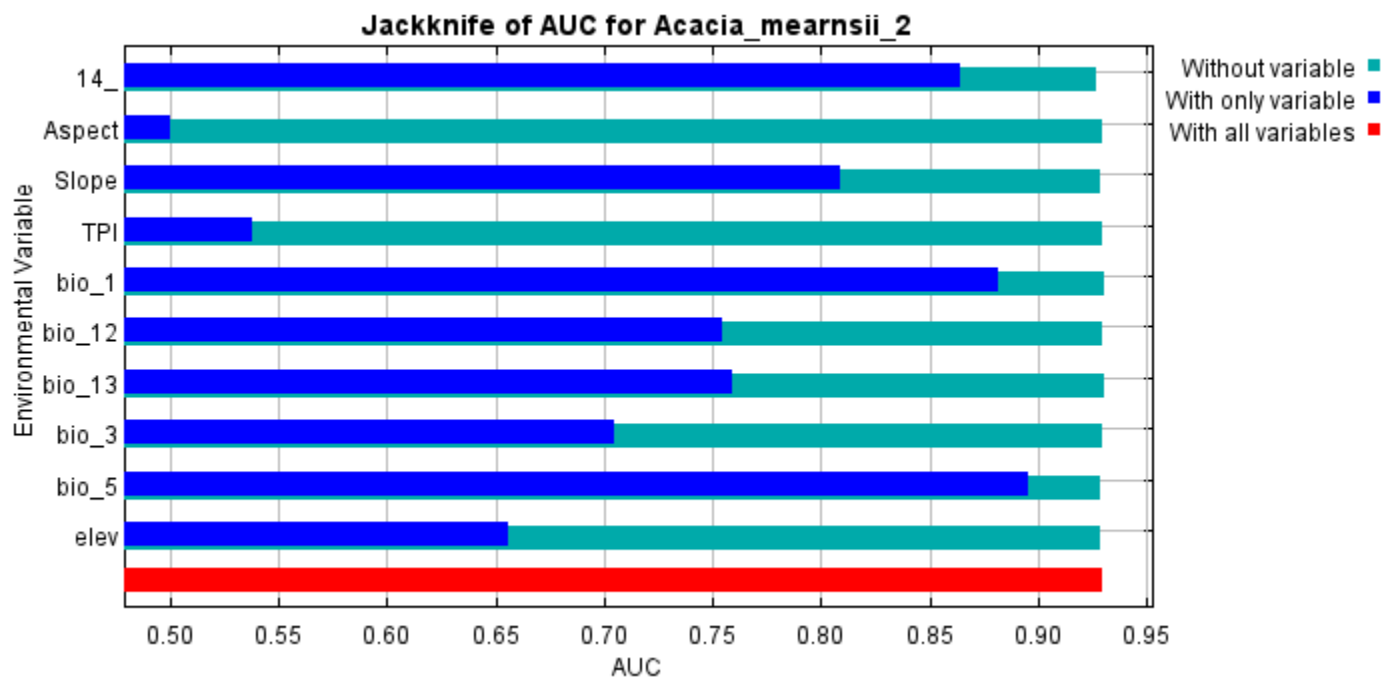


Figure 4

Jackknife model of area under curve for A. meansii

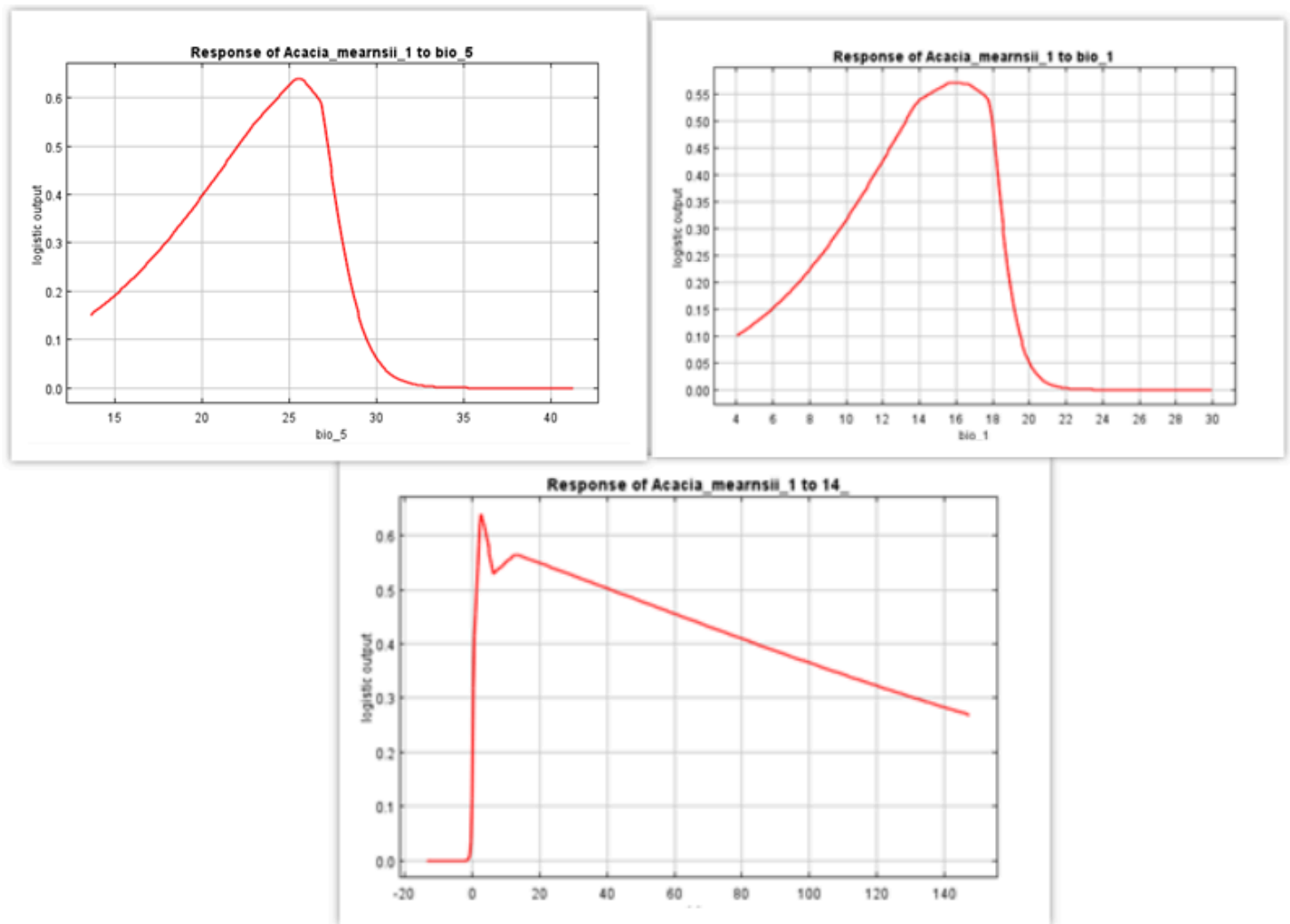


Figure 5

Response curves of *A. mearnsii*.

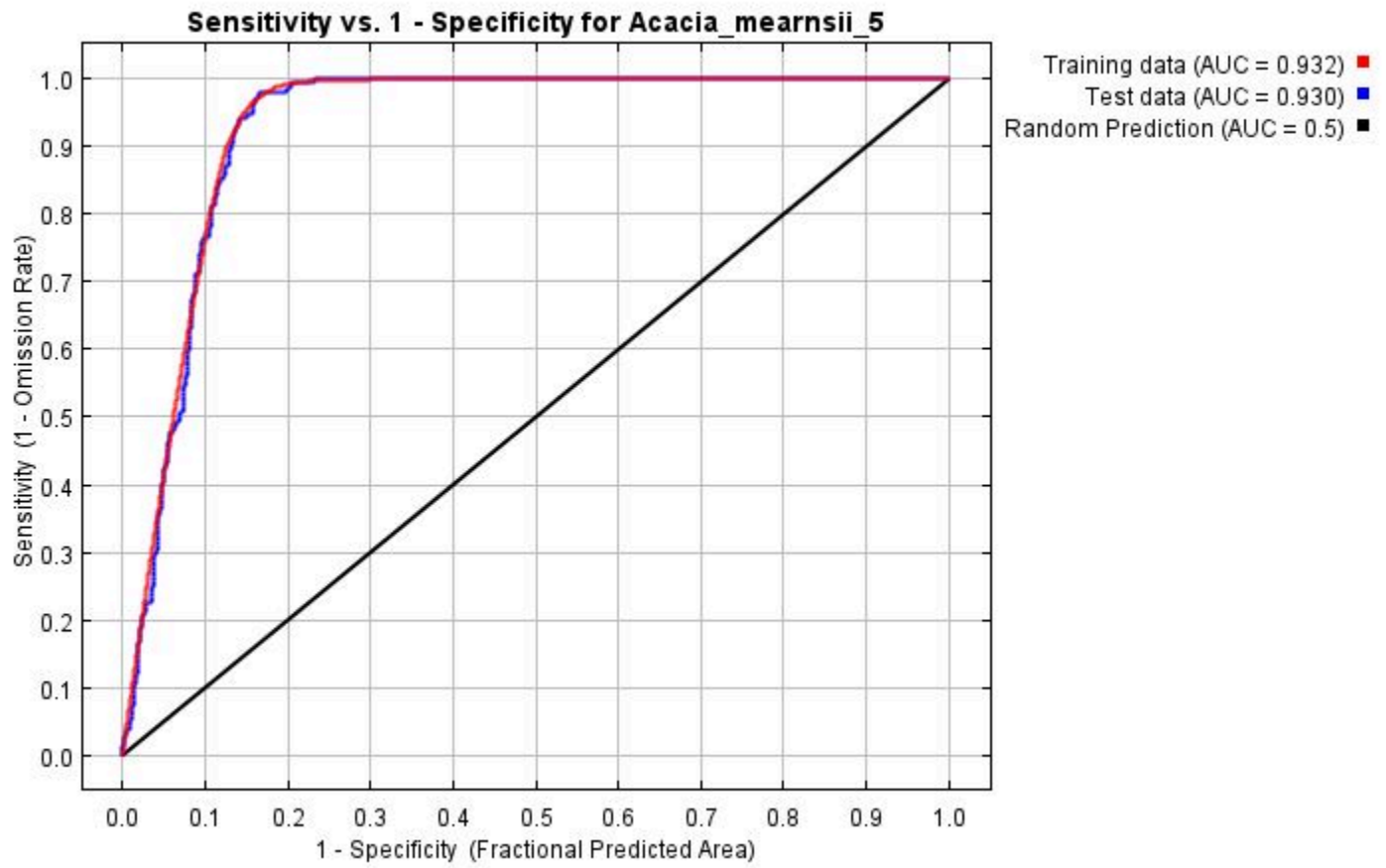


Figure 6

ROC AUC of *A. mearnsii*

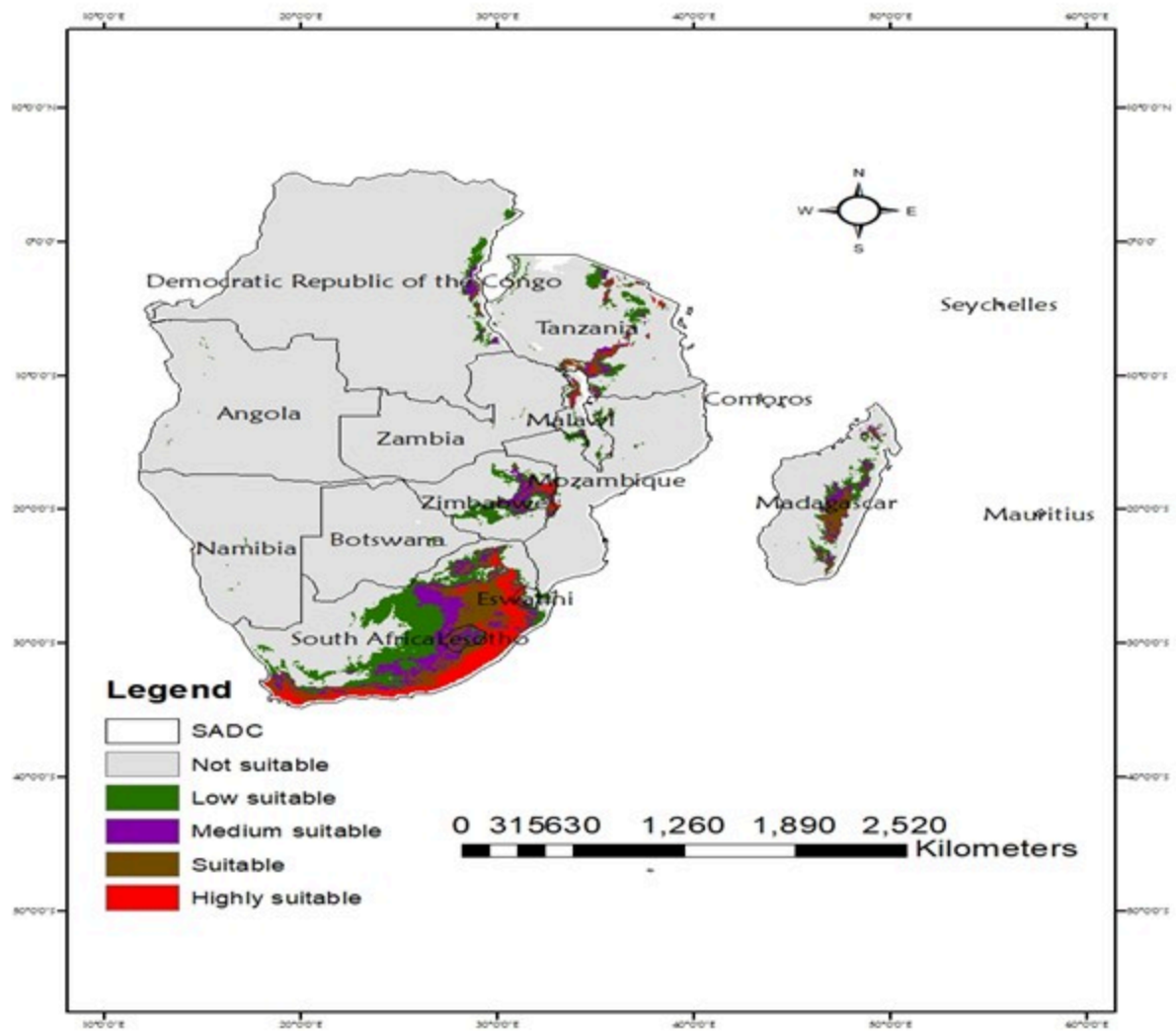


Figure 7

current distribution of *A. mearnsii* in southern Africa

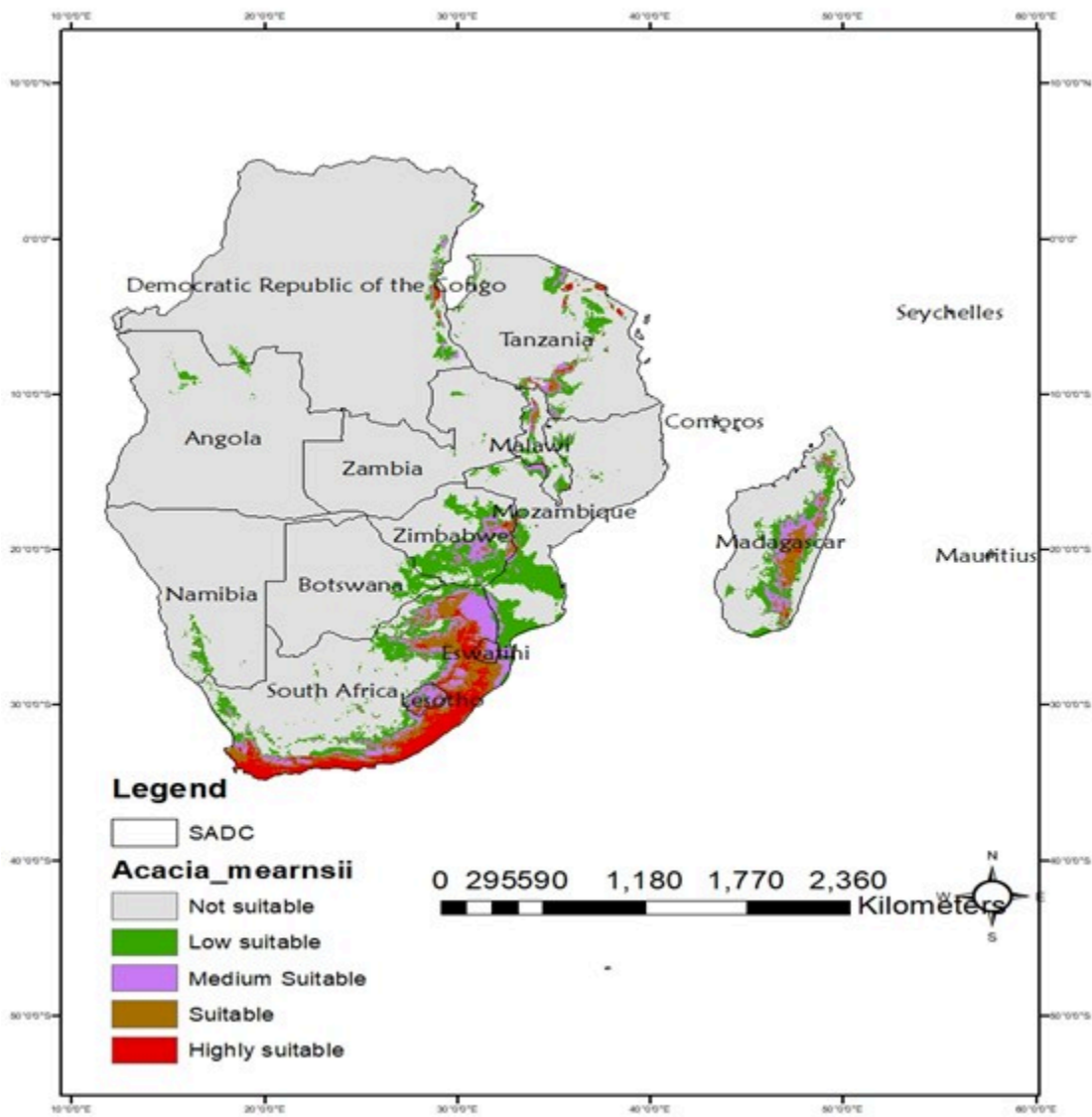


Figure 8

Figure 9. future distributions of *A. mearnsii* under SSP45 and SSP85 in Southern Africa.

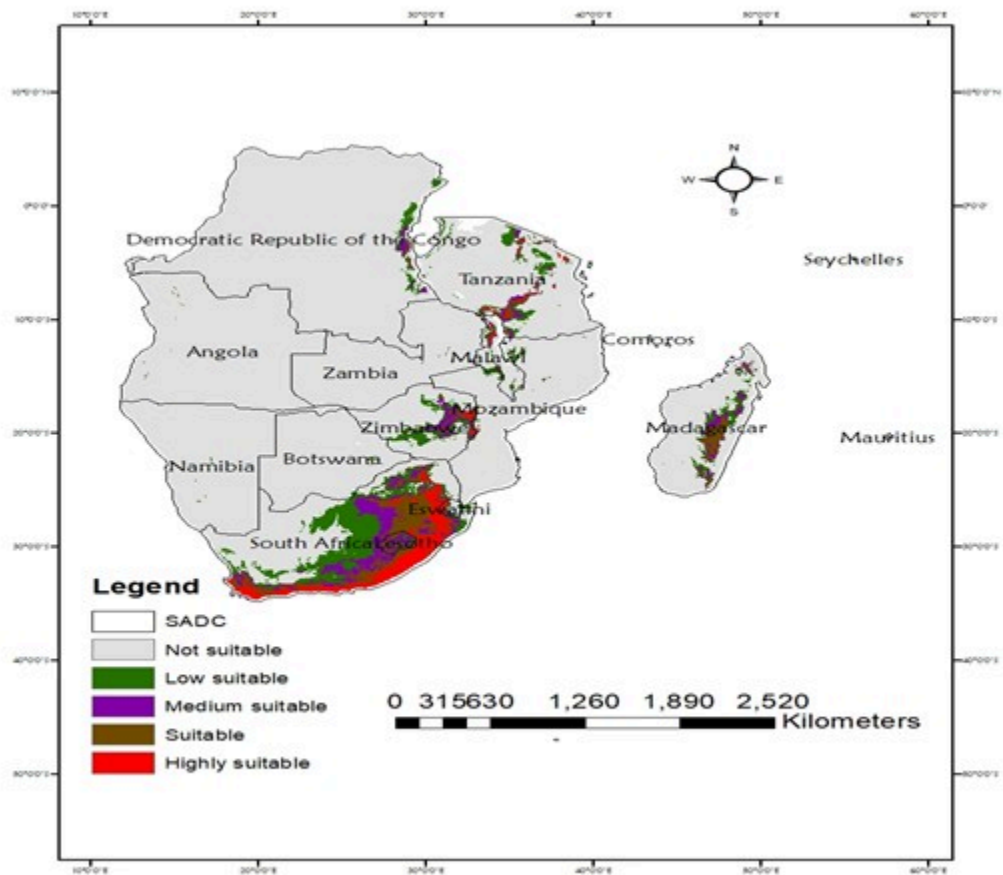


Figure 9

Unnumbered image in the Results section.