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Effects of Climate Change on Potential Geographical Distribution of *Prunus africana* (African cherry) in the Eastern Arc Mountain Forests of Tanzania

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Abstract

Determining distribution and status of species in the context of climate change allow conservationists to assess contemporary and/or future ranges for plant species in the protected areas. Climate change data are important predictor variables for determining species range, yet is rarely used in Tanzania when modelling future distribution of species. In this study, Maximum Entropy modelling was used to construct species distribution maps for *Prunus africana* to determine relative contribution and effects of climate change on the potential geographical distribution of *P. africana* based on climatic scenarios. Species presence data were used as a dependent variable, while climate, soil, and topographic data were used as predictor variables. The current distribution model was evaluated with the Area Under the Curve (AUC). The results indicate that the distribution of *P. africana* could be modelled with test AUC that is significantly better than random, with average test AUC values of 0.97. This indicates high performance of the model. Moreover, results for contribution of predictor variables revealed that the current distribution of *P. africana* was highly affected by climatic variables. Environmental variables found to have highest prediction contribution include; maximum temperature warmest month (27.2%), elevation (11.4%) and rainfall driest month (11.3%). Results for potential geographical distribution based on current climatic conditions revealed that suitable habitats for *P. africana* were predicted almost in all Eastern Arc Mount (EAM) forests. Moreover, current distribution maps depict areas with high elevations as having very high potential habitat suitability values. Furthermore, future distribution maps depict both gains and losses in range for *P. africana* under all climate scenarios in the EAM forests. Representative Concentration Pathways (RCP) 8.5 scenario records larger loss in range for *P. Africana* compared to RCP 4.5 in the Mid-century 2041-2070 (2055) and Late-century 2071-2100 (2085) in the EAM forests. Among the EAM forests Udzungwa, Rubeho, West Usambara, Ukagaru, Uluguru and Ukagaru forests will lose much more suitable habitats for *P. africana*. This implies that most of the areas currently predicted in EAM forests as suitable will not be suitable in the future. Therefore under changing climate, some species like *P. africana* might expand or contract their suitable habitats which will have implications on management and conservation of such species within the EAM forests.

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1.0 Introduction

1.1 Background Information

The Inter-governmental Panel on Climate Change (IPCC, 2001) identifies Africa as one of the least studied continents regarding ecosystem dynamics and climate variability, despite the potentially large impacts of climate change on community livelihoods and biodiversity conservation (IPCC, 2014). Increased droughts have affected rain-fed agriculture and hence the livelihood of poor farmers. Climatic change influences species distributions, often through species-specific physiological thresholds of temperature and precipitation tolerance (IPCC, 2014). Climate change is predicted to have large impacts on species and ecosystems in several different ways. Climate change differs from land use and land cover change, in the global extent and nature of its likely impacts on species and ecosystems (IPCC, 2014). In mountain and protected areas, like in the Eastern Arc Mountains (EAMs) forests, potential distribution of species is less influenced by land use and land cover change, whereas climate change affects such species more strongly at all elevations (Briner et al., 2013). Similarly, accelerating climate change will become the more important driver of changes to plant species distribution in mountain forests (Schirpke et al., 2017), such as EAM forests. It, however, remains unclear how plant species will be affected in the face of accelerating climate change.

With warming trends, plant species are expected to track the changing climate and shift their distributions to the extent that resource availability allows (Berry et al., 2002). Climate change influences on richness and species distributions as well as the composition of assemblages (Thuiller et al., 2008) may result in species either keeping their current range or respond to changing environmental conditions with range expansions, contractions or shifts (Sommer, 2010). Colonization of new suitable habitats or areas may result in poleward or upslope range expansions (Parmesan, 2006). However, retreat from unsuitable sites with unfavourable conditions may lead to local and even global extinction events (Thomas et al., 2004; Thuiller et al., 2005).

Pearson and Dawson (2003) revealed that species' range expansion and contraction are profoundly influenced by changing climate. Range loss for instance as the result of climate change may vary across species. Species most able to persist in the face of changing climate have larger geographical ranges, confirming that large ranges provide a buffer against environmental changes (Jetz et al., 2007) such as climate change. Range shifts are predicted to be more pronounced at higher latitudes, where temperatures are expected to rise more than near the equator (Langer et al., 2013). Species may disappear in certain areas at a faster rate than they can migrate or regrow in new areas (Parmesan, 2006). Estimation of range shifts among species has led to rapid advancements in the use of niche modelling to predict where species are likely to move (Araújo & Luoto, 2007), following expected climate change from established global and regional models (Meehl et al., 2007). Ecological niche modelling combines known occurrence records for the target species with environmental data to estimate potential geographic distribution patterns and species' ecological requirements (Khanum, 2013). Such estimates help to narrow down a matching set of possible occurrence sites for detailed field surveys (Menon et al., 2010).

The use of species distribution modelling (SDM) to map and monitor animal and plant distributions has become a favourite technique for mapping, identification of suitable habitats and evaluation of species' distribution for a wide variety of species (Porfirio et al., 2013). Species distribution models establish relationships between occurrences of species and environmental factors (Kumar & Stohlgren, 2009); and estimate species' environmental niches across geographical space within a particular period by substituting new variables that reflect expected environmental changes into spatial models (Botkin et al., 2007). There are varieties of species distribution modelling methods available for prediction of potential suitable habitats for a species (Elith et al., 2006). Generalized regressions, Bayesian approach, neural networks, classification techniques, and environmental envelopes are among the broad groups of methods developed over the years (Phillips et al., 2006). Some of these methods are based on presence only data while majority of them are based on presence absent data. Classification and regression tree analysis, artificial neural networks (ANN), generalized linear models (GLM), and generalized additive models (GAM) require presence/absence data (Elith et al., 2006). Presence only methods include bioclimatic envelope algorithm BIOCLIM, DOMAIN and MAXENT (Phillips et al., 2006). Presence only methods rely on the establishment of environmental envelopes around locations where species occur, which are then compared with to the environmental conditions of background areas (Brotons et al., 2004).

Maximum Entropy (MaxEnt) modelling (Phillips et al., 2006) in particular, has been widely used and shown promising results (Elith et al., 2006) and performs better than many different modelling methods in model comparisons when presence only data are used (Ortega-Huerta & Peterson, 2008).. MaxEnt combines species presence only data with environmental layers to create species distribution models using maximum entropy (Jaynes, 1990). Species environmental niche is estimated by finding probability distribution that is based on a distribution of maximum entropy and is in reference to a set of environmental variables (Philips et. al., 2006). In MaxEnt pixels of the study area make up the space on which MaxEnt probability distribution is defined, pixels with known species occurrence records constitute the sample points, and the features are climatic variables, soil and elevation (Austin, 2007).

MaxEnt is an innovative GIS-based method used to produce predictive maps of where species are likely to occur and likely not to occur. This makes it a suitable choice for species and environmental variables data to predict suitable environments for the likelihood of occurrence under climate scenarios. Some of the examples where MaxEnt models have performed well include predicting the current distribution of Humming-birds in the Andes (Tinoco et al., 2009), predicting the current global distribution of stony corals (Tittensor et al., 2009) and predicting the potential distribution of ants in New Zealand (Ward, 2007). Furthermore, MaxEnt models have successfully predicted the potential distribution of Nematodes in China (Wang et al., 2007), the current global distribution of seaweeds (Verbruggen et al., 2009), and the current distribution of birds in the Andes (Young et al., 2009). This study intends to use maximum entropy modelling to predict the potential distribution of *Prunus africana* based on climatic scenarios. *P. africana* is a wild tree listed as "vulnerable to extinction" (IUCN, 2018) due to over exploitation for pharmaceutical uses. It has been suspected that besides human exploitation, climate change is another serious threat to the current and future distribution of *P. africana*. The magnitude of climate change impacts on the distribution of this species, however, remains unclear in protected areas of Tanzania. If protected areas are to remain a key conservation tool for vulnerable species, climate change needs to be factored into conservation plans.

1.2 Problem Statement and Justification

In the era of changing climate, species are increasingly facing threats of range shits, decline in habitat and extinction both at local and global levels (Jetz et al., 2007; 2004; Thuiller et al., 2005). The adverse impacts of climate change are now evident in many land-based economic sectors in Tanzania. Some impacts of climate change include decline of income from farming for the rural poor. The response of poor farmers to the impact of changing climate has resulted in over-exploitation of forest resources, which is believed to compound the shortage of water and species habitat contraction (URT, 2016). Studies on the effects of climate change on distribution and status of species are therefore highly relevant given the predictions of changing temperature and precipitation patterns, as well as increases in extreme weather events that are occurring in many parts of the country (Kirtman et al., 2013).

Determining distribution and status of species in the context of climate change allow conservationists to determine declining trends of the ranges of species in the protected areas. Still, there has been no study that investigated the effects of climate change on the potential geographical distribution of *P. africana* in the EAM forests of Tanzania. (URT, 2016). This study, therefore, aims to investigate effects of climate change on the potential distribution of *P. africana* using GIS techniques and the maximum entropy distribution modelling approach. The findings of this study could help to comprehend potential geographical distributions of *P. africana* as a narrow ranged species in the face of changing climate. Furthermore, findings will provide useful indications of which forests will gain or lose suitable habitats for *P. africana* within EAM. This may provide an efficient starting point for biological surveys and consequently prioritizing conservation needs.

1.3 Research Goal, Objectives, and Research Questions

1.3.1 Research Goal

The goal of this study was to *assess effects of climate change on the potential geographical distribution of P. africana in the EAM forests of Tanzania.*

1.3.2 Research Objectives and Questions

To help achieve the above goal, the study is divided into three specific objectives. Each of these objectives is further divided into research questions.

Objective i: *To examine climatic variables important for predicting the potential geographical distribution of P. africana.*

i. Which of the selected climatic variables are important for predicting the potential geographical distribution of *P. africana* in the EAM forests
ii. What is relative contributions of the climatic variables to predict the potential geographical distribution of *P. africana* in the EAM forests

Objective ii: *To assess the potential geographical distribution of P. africana based on current climatic conditions and projected climatic scenarios*.

i. What is the current potential geographical distribution of *P. africana* in the EAM forests under current climatic conditions
ii. What is the potential geographic distribution of *P. africana* in the in the EAM forests under future climatic scenarios

Objective iii: *To estimate the geographical range shifts of P. africana under current climatic conditions, and following climate scenarios of different severity.*

i. How is the potential geographical distribution of *P. africana* in the EAM forests likely to change in the Mid-century (2055) and Late-century (2085) under RCP 4.5 and RCP 8.5 scenarios?
ii. Will *P. africana* gain or loss its suitable habitats EAM in the Late-century (2085) under RCP 4.5 and RCP 8.5 scenarios in the EAM forests?

2.0 Methods

2.1 Study Area Description

2.1.1 Location

The EAM are a chain of crystalline mountains near the Indian Ocean coast which run from the Taita Hills in South-East Kenya to the Udzungwa Mountains in South-Central Tanzania (Lovett, 1993; Burgess *et al*., 2007). They are located approximately between latitudes 3°2'S and 8°51'S and longitudes 34°49'E and 38°20'E. The EAM range from sea level up to 2,635m in altitude. There are 12 blocks in EAM of Tanzania, namely: North Pare, South Pare, West Usambara, East Usambara, Nguu, Nguru, Uluguru, Ukaguru, Rubeho, Malundwe, Udzungwa, and Mahenge (see Figure 1).

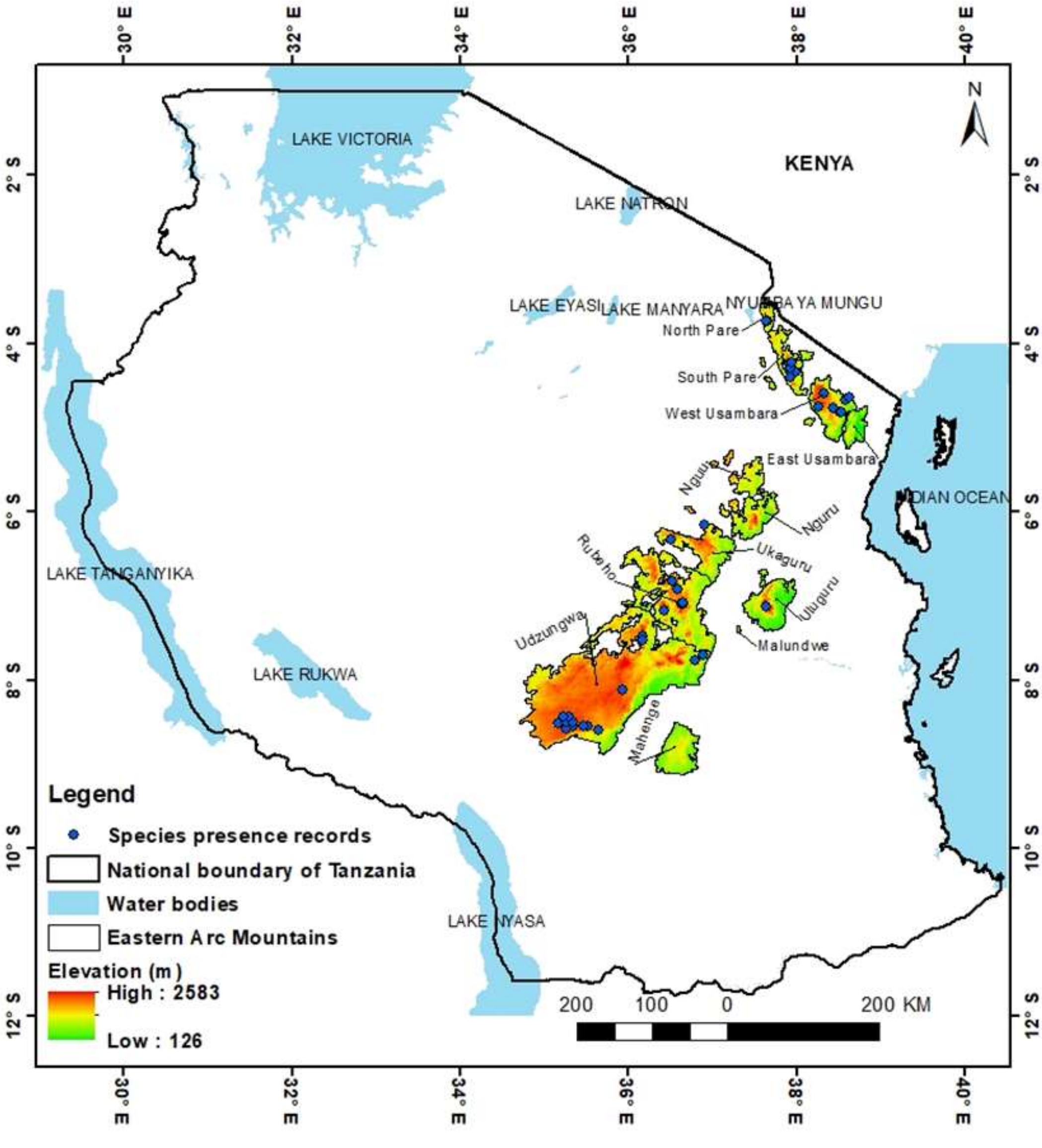

Figure 1: Study area map showing the location and elevation of the EAM, and presence records of *P.africana*

2.1.2 Climate

The EAM receive up to 500-2000 mm per year of rainfall, but in some mountain, blocks exceed 3000 mm per year (Mulligan, 2006). The area has wetter climate compared to surrounding lands. Windward slopes are wettest due to orographic rainfall and mist driven by Indian Ocean currents (Marchant et al., 2007) and support moist forests. Leeward slopes support open woodland rather than moist forest communities (Newmark, 1998). Uppermost montane plateaus are covered with grassland and heathland (Finch and Marchant, 2011). Mean annual temperatures in the study area range from 12.4-24.1 ˚C with a mean of 20.7 ˚C (Hijmans et al., 2005). The coolest months are June through August, when mean daily temperature drop below 5˚C at high altitudes while the warmest months are November through March, with mean daily maxima exceeding 34 ˚C on lower slopes (Platts, 2012).

2.1.3 Topography and Soils

The EAM are characterized by mountain blocks rising from the lowland topography and coastal plain of eastern Africa (Lovett & Wasser 1993). The highest elevation rises to 2,635 meters in Kimhandu peak in the Ulugurus. The forest can be divided into upper montane, montane and submontane forest with elevation ranges of 2635-1800 m, 1250-1800 m and 800-1250 m respectively (Pócs 1976). Upper montane forests are distinguished by large trees such as *Cassipourea malosana, Prunus africana and Olea capensis* and high rainfall. Submontane forests which overlap with montane forests are characterized by the presence of lowland species such as *Afrosersalisia cerasifera, Milicia excelsa*, and *Parkia filicoidea* (Lovett & Wasser 1993). The geology is composed of late Pre-Cambrian metamorphic rocks with two main highland soil types, namely, the humid ferrisols in the drier areas and humic ferralitic soils in the more humid and wet areas (Hall, 1980). The soils of EAM are less rich when compared to those of the volcanic mountains (Lovett & Wasser 1993). The soils are hihgly leached due to heavy precipitation and have high water holding capacity (Munishi, et al., 2007).

2.1.3 Biological importance

The forests are biodiversity hotspots home to hundreds of species found nowhere else on earth and store vast amounts of carbon (Burgess *et al*., 2007). The EAMs are nationally and internationally recognized as being of exceptional biodiversity value with high endemism in many taxa. The EAMs contain at least 800 endemic plant species accounting for more than 25 % of the plant species (Burgess *et al*., 2007). The EAM forests of Tanzania have recently been proposed to be UNESCO World Heritage site.

2.2 Study Species

P. africana is a medium to large evergreen tree with a height of more than 40 meters and a stem diameter of up to 1 meter (Gachie et al., 2012). *P. africana* long-lived (>100 years) monoecious tree species (Hall et al., 2000). It is a highland forest tree, and grows in the humid and semi-humid highlands and humid midlands (Orwa et al., 2009). It occurs in sub-Saharan Africa; in Tanzania, it naturally grows on the slopes of Eastern Arc Mountains. Its biophysical limits range from an altitude of 900-3400m, mean annual rainfall of 890-2600mm and mean annual temperature of 18-26 °C (Orwa et al. 2009). *P. africana* is found in association with tree species such as *Albizia gummifera*, *Cassipourea malosana*, *Celtis africana*, *Podocarpus falcatus* and *Hagenia abyssinica*.

Figure 2: Young trees of *Prunus africana*
Source: Author

It is a light demanding species, growing better in forest gaps (Orwa et al., 2009). For conservation purposes, *P. africana* is among threatened and vulnerable species (IUCN, 2018). According to Cunningham, (2005), the species is categorized as a species 'of urgent concerns' by CITES due to over-exploitation of the bark for treatment of benign prostatic hyperplasia. Since 1970, *P. africana* bark harvest has shifted from subsistence use to large-scale commercial use for international trade (Cunningham, 2005). Harvesting of bark is done locally by debarking using machette and sharp knives. This cause destruction of conduction tissue (phloem) that transport food from leaves to the roots.

2.2 Data collection

2.2.1 Species occurrence data

Species occurrence data (Longitudes and Latitudes) for *P. africana* was obtained from TROPICOS database (http://www.tropicos.org) and National Forest

Resources Monitoring and Assessment (NAFORMA) database (http://www.tfs.go.tz). Data were obtained in the form of presence records only. The oldest presence record for the study species dates back to 1972. This falls within the temporal resolution of the climate data being used (1950-2000). A total of 120 presence records in longitude and latitude coordinates were obtained for *P. africana*. The presence records were projected from WGS 84 lat/long into WGS, Africa Albers, in ArcGIS 10.5.

2.2.2 Environmental Variables

2.2.2.1 Current and Future Climate Data

Current and future climatic data were downloaded from KITE database (https://webfiles.york.ac.uk/KITE/AfriClim/ByCountry/Tanzania/). Current climate data were produced by spatial interpolation of monthly averages recorded at weather stations throughout the world for the 1950-2000 period (Hijmans, 2005). These data were interpolated using thin-plate smoothing splines due to its accurate spatial interpolation results (Hutchinson, 1995).

Future climate data used by this study were ensemble mean downscaled to the resolutions that suit ecological studies at local scales (up to 1 km) using 18 pairwise combinations of 5 RCMs driven by 10 GCMs (Platts et al., 2015). The ensemble were projected under two IPCC-AR5 representative concentration pathways, RCP4.5 and RCP8.5, which project global temperature anomalies of 2.4°C and 4.9°C above pre-industrial levels by 2100 (Rogelj et al., 2012), with atmospheric CO_2 equivalents of 650 and 1370 ppm by 2100, respectively (Moss et al., 2010). RCP8.5 depict a relatively conservative business as usual case with low income, high population and high energy demand due to only modest improvements in energy intensity (Riahi, et al., 2011). RCP4.5 scenario is comparable to a number of climate policy scenarios and several low-emissions reference scenarios (Van Vuuren et al., 2011). The emphasis is on clean and resource-efficient technologies, leading to a reduced warming trend (IPCC, 2007).

Both current and scenario climate data were downloaded with a spatial resolution of 30 arc-seconds (~1km). The dataset covers the period between 1950-2000 for current climate and Mid-century 2041-2070 (2055) and Late-century 2071-2100

(2085) time periods for future climate to represent two possible futures in terms of global emissions (RCP8.5) and mitigation (RCP4.5). Eleven (11) temperature and rainfall variables were derived by this study from these data set for both current and future conditions (Table 1). All data layers were projected from WGS 84 lat/long into WGS, Albers equal-area projection that defines each pixel (cell) to be a similar area for species contraction and expansion area calculations.

2.2.2.2 Topographical data

Digital Elevation Model (DEM) data was downloaded from Shuttle Radar Topography Mission (SRTM) database (http://srtm.csi.cgiar.org) in tiles. A total of 9 tiles were downloaded for Tanzania. The tiles were then combined into a mosaic layer in ArcGIS 10.5. Aspect and slope in degrees were calculated using spatial analyst tool in ArcGIS 10.5. Aspect was then converted into Northness and Eastness to produce two layers using equation 1 and 2 developed by Deng et al (2007).

Northness = cos (aspect)...eq (1)
Eastness = sin (aspect)...eq (2)

Cosine and sine transformation of aspect were used to obtain a continuous gradient, stressing the north-south or east-west gradient (northness or eastness). This conversion gives a value of -1 and 1 for northness and eastness respectively. These values represent the extent to which slope faces north (1), south (-1), east (1), or west (-1). Northness and eastness have been found to be more convenient for comparison with the topographic attributes (Deng et al., 2007) rather than circular linear correlation initially calculated as circular degrees clockwise from 0 to 360, which is difficult to compare because 0 and 360 imply the same aspect.

2.2.2.3 Soil data

Soil data was downloaded from the International Soil Reference and Information Centre (ISRIC) database (https://www.isric.online/). Africa Soil Grids dataset contains layers of soil properties for the whole African continent at 250 m spatial resolution at various soil depths produced by ISRIC - World Soil Information. The predictions are obtained using an automated mapping framework (3D regression-kriging based on random forests). Four (4) soil properties were derived from this dataset (Table 1). Soil layers were then projected into the working projection and masked to EAMs which is the study area. Layers were then resampled into a 1000m resolution to match the spatial resolution of the climate and topographical variables.

Table 1: Description of environmental variables used in modelling the potential distribution of *P. africana*

Category	**Original Resolution**	**Resample Resolution**	**Source**
Climatic			
[bio1] Mean annual temperature	925m	1000m	WorldClim data
[bio5] Max temp warmest month	925m	1000m	WorldClim data
[bio6] Max temp coolest month	925m	1000m	WorldClim data
[bio7] Annual temperature range	925m	1000m	WorldClim data
[bio10] Mean temp warmest quarter	925m	1000m	WorldClim data
[bio11] Mean temp coolest quarter	925m	1000m	WorldClim data
[bio12] Mean annual rainfall	925m	1000m	WorldClim data
[bio13] Rainfall of wettest month	925m	1000m	WorldClim data
[bio14] Rainfall driest month	925m	1000m	WorldClim data
[pet] Potential evapotranspiration	925m	1000m	WorldClim data
[mi] Annual moisture index	925m	1000m	WorldClim data
Topographic			
[el] Elevation	925m	1000m	SRTM
[sl] Slope	925m	1000m	SRTM
[nr] Aspect (Northness)	925m	1000m	SRTM
(es) Aspect (Eastness)	925m	1000m	SRTM
Soil			
[scec] Soil cation exchange capacity	250m	1000m	ISRIC
[sawc] Soil available water capacity	250m	1000m	ISRIC
[soc] Soil organic carbon	250m	1000m	ISRIC
[sph] Soil pH	250m	1000m	ISRIC

2.3 Modelling and Analysis

2.3.1 Modelling with Maximum Entropy (MaxEnt)

MaxEnt software version 3.3.3k was used to model the potential geographical distribution of *P. africana*. The software is available for download at https://biodiversityinformatics.amnh.org/open_source/maxent/. MaxEnt may be run both from a graphical user interface (GUI) and the command line. This study used GUI as it is relatively straight forward (Philips et al., 2006). MaxEnt is a general-purpose machine learning method with a precise mathematical formulation (Phillips et al., 2006). The idea of MaxEnt is "to estimate (approximate) unknown probability distribution of a species" based on maximum entropy (Phillips et al., 2006). Generally, the maximum entropy principle suggests that the best approach to approximating unknown probability distribution is to maximize entropy, subject to constraints (in this case, environmental data associated with species presences) representing incomplete information (Jaynes, 1957). The technique first constrains the modelled distribution to match certain features (environmental layers) of empirical data (training data) and choosing the probability condition that satisfies these constraints being as uniform as possible (Negga, 2007). Basically, if a pixel in the study has similar distribution as of the training data, then higher values are assigned and accordingly pixels with different distribution are assigned lower values. The result of Maxent shows a map where every grid has a value of 0-1 if the result output format is selected as logistic; this represents the estimate of probability distribution/habitat suitability for a species (Singh, 2013).

Maxent takes as input a set of layers or environmental variables (such as elevation, precipitation, etc.), as well as a set of geo-referenced occurrence locations (presence point locations/presence-only species records), and produces a model of the range of the given species. It is a powerful tool applicable in exploring ecological relationships with fine scale, raster (gridded) environmental data using spatial information on species occurrence in relation to environmental data to estimate potential (suitable) habitat for species. It is a promising method for modelling species potential distribution and has proven to perform well in comparison with alternative approaches (Elith et al., 2006). MaxEnt has been chosen for this study because it uses presence-only data and has the ability to project from current environmental conditions onto future or past conditions (Philips et al., 2006).

MaxEnt algorithm was run with default parameters (convergence threshold = 10^{-5}, regularization multiplier = 1, the maximum number of background points = 10000); these default settings have been shown to achieve good performance (Phillips & Dudík, 2008). Maximum iteration value was set to 5000 (to give the model adequate time for convergence). Replicates was set to 15 in MaxEnt to allow a model to run multiple times for the evaluation to have sufficient statistical power to give significant results, and then conveniently averages the results from all models created (Phillips et al., 2008). MaxEnt jackknife test was used to examine the importance of each variable (Phillips et al., 2006). The jackknife test shows which environmental variables have the highest gain when used in isolation. The one with the higher appears to have the most useful information by itself. Also jackknife test shows the environmental variables that decrease the gain most when it is omitted, such variables appears to have the most information that is not present in the other variables (Phillips et al., 2006).

MaxEnt offers many advantages and a few drawbacks. Taken from Phillips et al. (2006), the advantages include the following: 1) requires only presence data, not presence/absence data, 2) can use both continuous and categorical variables, 3) the optimization is efficient, 4) has a concise probabilistic definition, 5) it avoids over-fitting through l-regularization, 6) can address sampling bias formally, 7) output is continuous (not just yes/no), and 8) is generative rather than discriminative which makes it better for small sample sizes. Some drawbacks of the method are: 1) it has fewer methods for estimating the amount of error in prediction, 2) It uses a exponential model for probabilities which is not inherently bounded above and can give very large predicted values for environmental conditions outside the range present in the study area, and 3) it has possibility of over-fitting, limiting the capacity of the model to generalize well to independent data.

2.3.2 Autocorrelation Test

Before running, MaxEnt environmental data was tested for autocorrelations using SDM tool in ArcGIS 10.5 to find out which climatic variables to use. It is widely known that many climate variables are highly correlated variables (Brown, 2014) and may bias selection of variables to use (Cohen et al., 2003). Hence, among the two variables that have a high correlation coefficient ($|r|>0.7$), as proposed by Dormann et al., (2013), only one variable was selected for modelling due to its ecological importance for *P. africana* (Table 2). This is because a strong correlation between these variables would introduce a bias in the model (Dormann et al., 2013). The variables removed were mean diurnal range in temperature (bio2), isothermality (bio3), Temperature seasonality (bio4), rainfall seasonality (bio15), rainfall wettest quarter (bio16), and rainfall driest quarter (bio17) (Table 2).

Table 2: Correlation test results for variables used for the potential distribution of *P. africana*.

	bio1	bio5	bio6	Bio7	bio10	bio11	bio12	bio13	bio14	pet	mi	alt	slp	nor	es	sco	ph	sawc	scec	bio2	bio3	bio4	bio15	bio16	bio17
bio1	1																								
bio5	0.65	1																							
bio6	0.67	0.60	1																						
bio7	-0.26	-0.05	-0.47	1																					
bio10	0.66	0.66	0.67	-0.28	1																				
bio11	0.65	0.67	0.66	-0.23	0.69	1																			
bio12	0.19	-0.02	0.32	-0.68	0.21	0.15	1																		
bio13	0.17	-0.05	0.29	-0.67	0.18	0.13	0.68	1																	
bio14	0.20	0.19	0.30	-0.30	0.25	0.18	0.31	0.23	1																
pet	0.61	0.65	0.42	0.58	0.59	0.63	-0.48	-0.53	0.01	1															
mi	0.04	-0.17	0.19	-0.60	0.06	0.00	0.68	0.67	0.26	-0.63	1														
alt	-0.65	-0.61	-0.65	0.34	-0.66	-0.64	-0.26	-0.21	-0.35	-0.53	-0.12	1													
slp	0.05	0.05	0.08	-0.08	0.06	0.06	0.03	-0.01	0.17	0.05	0.02	-0.10	1												
nor	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.00	0.00	-0.01	-0.01	0.00	0.01	0.01	1											
es	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	-0.01	0.00	0.00	0.01	1										
sco	-0.29	-0.37	-0.22	-0.27	-0.28	-0.31	0.39	0.34	0.23	-0.39	0.43	0.21	0.35	0.00	0.00	1									
ph	0.40	0.51	0.28	0.41	0.38	0.41	-0.51	-0.50	-0.05	0.66	-0.58	-0.35	0.04	-0.01	0.00	-0.46	1								
sawc	-0.40	-0.42	-0.36	-0.03	-0.40	-0.40	0.08	0.07	-0.16	-0.33	0.15	0.36	0.27	0.00	0.00	0.48	-0.26	1							
scec	-0.02	-0.02	-0.01	-0.01	-0.01	-0.03	0.10	0.05	0.18	0.04	0.09	-0.02	0.35	0.00	0.00	0.54	0.05	0.21	1						
bio2	**-0.82**	**0.80**	**-0.72**	**0.97**	**-0.73**	**-0.77**	**-0.77**	**-0.79**	**-0.85**	**0.74**	**-0.81**	0.28	-0.02	0.00	0.01	-0.22	0.43	-0.03	0.05	1					
bio3	**-0.82**	**0.97**	**-0.86**	**0.88**	**-0.78**	**-0.73**	**-0.72**	**-0.76**	**-0.76**	**0.79**	**-0.78**	0.23	0.04	0.00	0.01	-0.14	0.41	-0.02	0.11	0.96	1				
bio4	**0.98**	**0.97**	**0.84**	**-0.80**	**0.85**	**0.72**	**0.72**	**0.85**	**0.97**	**0.80**	**0.77**	-0.39	0.07	0.00	0.00	0.13	-0.04	-0.11	0.15	-0.31	-0.30	1			
bio15	**0.74**	**-0.76**	**0.76**	**-0.72**	**0.74**	**0.82**	**0.89**	**0.93**	**-0.76**	**-0.81**	**0.91**	-0.04	-0.10	0.00	-0.01	0.26	-0.56	0.12	-0.06	-0.75	-0.76	0.11	1		
bio16	**0.79**	**-0.72**	**0.73**	**-0.77**	**0.80**	**0.86**	**0.95**	**0.98**	**0.87**	**-1.00**	**0.97**	-0.14	-0.06	0.00	-0.01	0.31	-0.56	0.08	-0.02	-0.80	-0.79	0.25	0.97	1	
bio17	**0.80**	**0.88**	**0.80**	**-0.73**	**0.75**	**0.88**	**0.84**	**0.76**	**0.99**	**-0.77**	**0.80**	-0.35	0.18	-0.01	0.00	0.26	-0.08	-0.14	0.20	-0.27	-0.17	0.58	-0.03	0.19	1

Note: The variables with bold correlation values are the ones removed before modelling

2.3.3 Current Distribution Modelling

To predict the current distribution of the *P. africana* with MaxEnt, all environmental layers are required to be in the same projection, extent and resolution and need to be converted into ASCII format (Phillips et al., 2006). Using boundary layer of the study area, in this case, EAM, the environmental layers were modified to be in the same extent (geographic bound and cell size) using ArcGIS 10.5. The occurrence records were prepared in Excel and saved as comma-separated value (.csv).

Species present records from TROPICOS database were randomly divided into training and test data. Then models were created using 75% of the presence records for training the model and 25% for model testing. Hence, for *P. africana,* with a total of 120 presence records, 89 presence records were set aside for training the model, while the remaining 29 were used for testing (Table 3). But, not all the training and test data had corresponding environmental variables in the study area. The presence records without ecological variables were afterwards removed before simulating. Model performance is known to rapidly decrease for sample sizes smaller than 20 (Stockwell and Peterson 2002) or 15 (Papeş and Gaubert 2007), and is dramatically poor for samples sizes smaller than 5 records (Pearson et al. 2007). So a sample size of 120 is sufficient because high model accuracy was observed when modelling distribution of *P. africana.*

Table 3: Training and test data used in the modelling for the potential distribution of *P. africana*

Species	Total presence records	Training records	Test records	Number of records removed
P. africana	120	89	29	2

2.3.4 Future Prediction Modelling

To investigate how future climate change may influence the potential distribution of the *P. africana*. Projected climate models for Mid-century 2041–2070 (2055) and Late-century 2071–2100 (2085) under RCP4.5 scenarios (a medium-low GHG emission pathway) and RCP8.5 scenarios (a high GHG emission pathway) were used. Changes in suitability conditions were then reclassified into 4 classes (Table 4). The 10 percentile training presence threshold of 0.27 (a minimum value for suitable habitat) was used as a cutoff value to define suitable habitat and unsuitable habitat for

P. africana. The 10 percentile training presence uses the suitability threshold associated with the presence record that occurs at the 10th percentile of presence records (i.e. the suitability of the presence record below which 10% of presence records' suitability fall (Pearson et al., 2004). The binary map for future prediction was given a value of 2 for suitable and 0 for unsuitable. The current conditions were reclassified into 1 and 0 values for suitable and unsuitable respectively. The current binary maps were then subtracted from the future maps to identify the effect of climate change in species range (contraction or expansion).

Table 4: Description for current and future classes for the change in species range

Class	Current suitability	Future suitability
-1	Suitable	Not suitable
0	Not suitable	Not suitable
1	Suitable	Suitable
2	Not suitable	Suitable

2.3.5 Model Calibration and Evaluation

From randomly partitioned data, the study selected 75% of presence records to train the model and 25% of presence records to test the model. For studies with few presence records like this Philips (2008) recommends to 75% by 25% partition to attain excellent prediction. This setting allows withholding a certain percentage of the presence data to be used to evaluate the model's performance at the same time avoiding bias due to inflated measure.

Statistical evaluation of the models was based on threshold-independent measure of Area Under the curve (AUC) of Receiver Operating Characteristic (ROC) parts of MaxEnt (Phillips et al., 2006). For presence-only modelling, the ROC curve is a plot of sensitivity (proportion of correctly predicted presences) against the fractional area predicted present. (Fielding & Bell, 1997). The resulting area under the ROC curve provides a single measure of overall model accuracy, which is independent on a particular threshold. The AUC metric (value ranges between 0 and 1.0) provides an assessment of how accurately the model predicts the suitable habitats for a species within a given area (Phillips et al. 2006; Phillips & Dudík 2008). Models with AUC values greater than 0.75 have good discrimination ability in accurately identifying the potential distribution of a species (Elith et al., 2011). In this study, an AUC approximating 1 would mean optimal discrimination of suitable versus unsuitable sites, whereas an AUC between 0 and 0.5 is indicative of predictions no better than random.

2.3.6 Jackknife Test of Variable Importance and Response curves

To measure which variables are most important in the model, a jackknife test part of MaxEnt was used to determine how each variable influences the presence of the modelled species. Jackknife test excludes one variable at a time when running the model to provide information on the performance of each variable in the model regarding how important each variable is at explaining the species distribution and how much unique information each variable provides (Yost, et al., 2008; Philips, 2012). Principal component analysis is another statistical approach that could have been used serve for the same purpose but a jackknife is a default test to MaxEnt. To show how each environmental variable affects the prediction the response curves part of MaxEnt was used. The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value (Philips, 2006)

2.3.7 Limitation of MaxEnt Modelling

MaxEnt Modelling has the possibility of overfitting (model begins to describe the random error in the data rather than the relationships between variables), limiting the capacity of the model to generalize well to independent data. To address this limitation, MaxEnt has the ‘regularization multiplier’ parameter which can limit the complexity of the model and generating a less localized prediction (Phillips and Dudík, 2008).

3.0 Results

3.1 Important Variables for Predicting Geographical Distribution of *P. africana*

3.1.1 Model Performance

Model for *P. africana* performed better than random, with average test AUC values greater than 0.5. The average training AUC values for *P. africana* were 0.97. An AUC value of >0.9 indicates high performance. Moreover, P-values calculated on both average Training AUC and average Test AUC for the model found to be significantly better than a random model ($p<0.05$). Hence, from the test statistics produced against a null model of 0.5, it can be concluded that it is possible to predict the potential geographical distribution of *P. africana* using environmental variables and achieve both test and training AUC that are significantly better than a random model.

Table 5: Results of threshold independent evaluation and p-values for the potential distribution of *P. africana* from average of 15 replicate runs

Species	Training AUC	Test AUC	AUC Standard Deviation	P-Values of average AUC
P. africana	0.97	0.95	0.025	0.00003

3.1.2 Analysis of Variable Contributions

The contribution of predictor variables to current distribution of *P. africana* in EAM forests shown in Table 6. The current species distribution was affected by maximum temperature warmest month, rainfall driest month and annual moisture index. This make up most important predictor climatic variables. Mean temperature warmest month had highest predictive contribution (27.2%) than other variables followed by elevation (11.4%), rainfall driest month (11.3), northness (7%) and soil organic carbon (6.5%) (Table 6). Variables recorded to have lowest predictive contribution include: soil cation exchange capacity (0.7), annual temperature range (0.5), Slope (0.4%), soil available water capacity (0.2%), minimum temperature coolest month (0.1%) and mean temperature warmest quarter (0.1%) (Table 6).

Table 6: Contributions variable in the potential distribution of *P. africcana* from average of 15 replicate runs

Variables	Abbreviation	Percent contribution (%)
Maximum temperature warmest month	bio5	27.2
Elevation	elv	11.4
Rainfall driest month	bio14	11.3
Annual moisture index	mi	10.1
Northness (north-south gradient)	nor	7.0
Soil organic carbon	soc	6.5
Soil pH	ph	5.6
Mean annual rainfall	bio12	4.1
Rainfall wettest month	bio13	4.1
Eastness (east-west gradient)	es	2.9
Mean temperature coolest quarter	bio11	2.8
Potential evapotranspiration	pet	2.8
Mean annual temperature	bio1	2.3
Soil cation exchange capacity	scec	0.7
Annual temperature range	bio7	0.5
Slope	slp	0.4
Soil available water capacity	sawc	0.2
Minimum temperature coolest month	bio6	0.1
Mean temperature warmest quarter	bio10	0.1

3.1.3 Jackknife Test of Variable Importance for *P. africana*

The environmental variable with the highest gain, when used in isolation, is maximum temperature coolest quarter (bio11) for *P. africana* (Figure 3). This appears to have the most useful information by itself. Other variables found to have a high gain when used in isolation are mean temperature warmest month (bio5), mean temperature warmest quarter (bio10), mean annual temperature (bio1) and elevation (elv). The high gain means that these variables are good predictors of where the *P. africana* can survive. Similarly, maximum temperature warmest month (bio5) and altitude (alt) contributed 27.2% and 11.4% respectively to the MaxEnt model for *P. africana*. Northness (nor) highly decreases the gain when it is omitted, and therefore appears to have the most information that is not present in the other variables. Other variables that highly decrease the gain when omitted are rainfall wettest month (bio13), rainfall driest month (bio14), eastness (es) and soil organic carbon (soc).

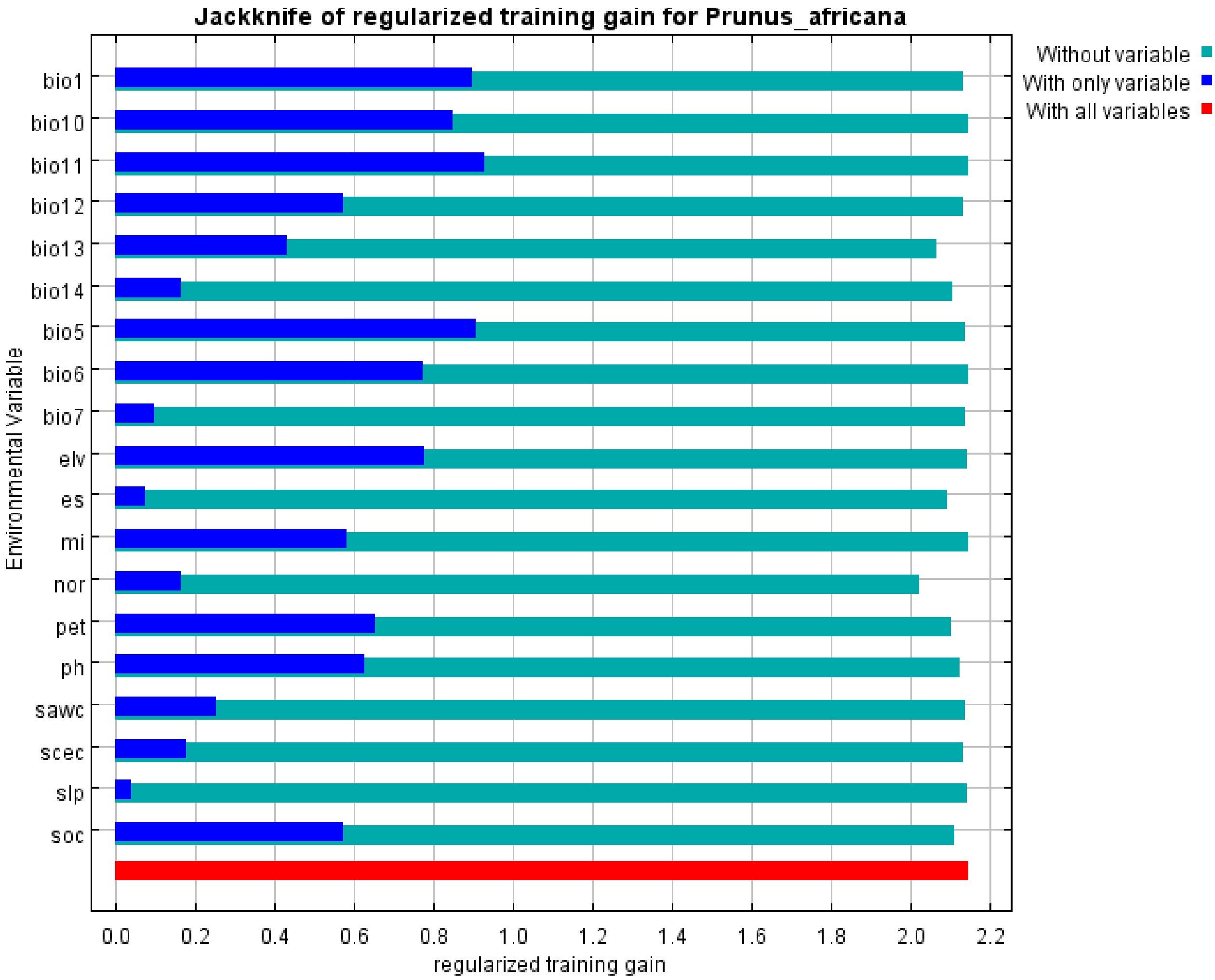

Figure 3: Jackknife test showing important variables for the potential distribution of *P. africcana* from average of 15 replicate runs

3.1.4 Response curves of *P. africana*

Figure 4 below show how the predictions depend on the variables. For *P. africana* as altitude (alt), soil cation exchange capacity (scec), soil organic carbon (soc), soil available water capacity (sawc) and slope (sl) increase the probability of its presence (habitat suitability) increases. While on the other hand, as mean annual temperature (bio1), maximum temperature warmest month (bio5), mean temperature warmest quarter (bio10), mean temperature coolest quarter (bio11), soil pH (ph) increases habitat suitability for *P. africana* decreases. However, there was a sharp decline in occurrence of *P. africana* with increasing rainfall wettest month (bio13), Mean annual rainfall (bio12) and annual moisture index (mi). Only potential evapotranspiration (pet) seem to decrease with habitat suitability of *P. africana* but at some points habitat suitability starts to increase again.

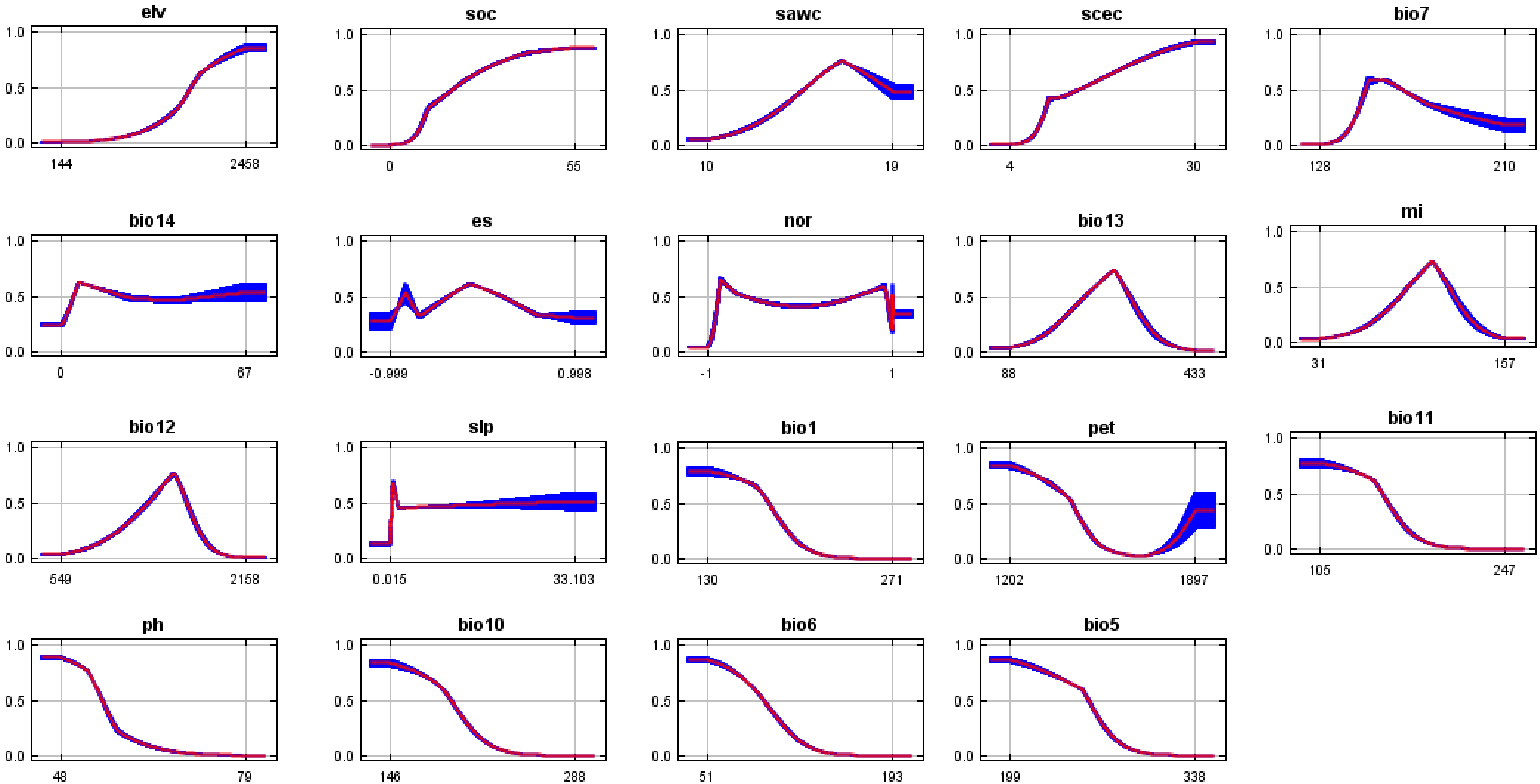

Figure 4: Response curves show how habitat suitability (y-axis) of *P. africana* changes as each environmental variable (x-axis) is varied. Red indicates the average response of the 15 replicate MaxEnt runs and blue the mean +/- one standard deviation

3.2. Current and Future Geographical Distribution

Figure 5 and 6 show map of the potential distribution of *P. africana*. Current suitable habitats for *P. africana* in EAM forests were predicted across all forests. Current distribution maps clearly depict areas with high elevations as having very high potential habitat suitability values. Also, areas with high mean annual rainfall, rainfall driest month, rainfall driest quarter, annual moisture index and soil organic carbon have potential habitat suitability values. Generally, *P. africana* seem to avoid lower altitudes and higher temperature with high suitability areas found in peaks of EAM forests. This implies that *P. africana* have a narrow range of potential suitable habitats in the study area.

Visual observation indicates that potential distribution of *P. africana* will change much in the future. There seems to be a decrease of potential suitability areas for *P. africana* for all future climate change scenarios. Future predictions were based on RCP 4.5 (focusing mainly on environmental sustainability and hence low-temperature predictions) and RCP 8.5 (more economic focus and thus high-temperature predictions).

Predicted current conditions **Predicted future conditions 2055 RCP 4.5** **Predicted future conditions 2055 RCP 8.5**

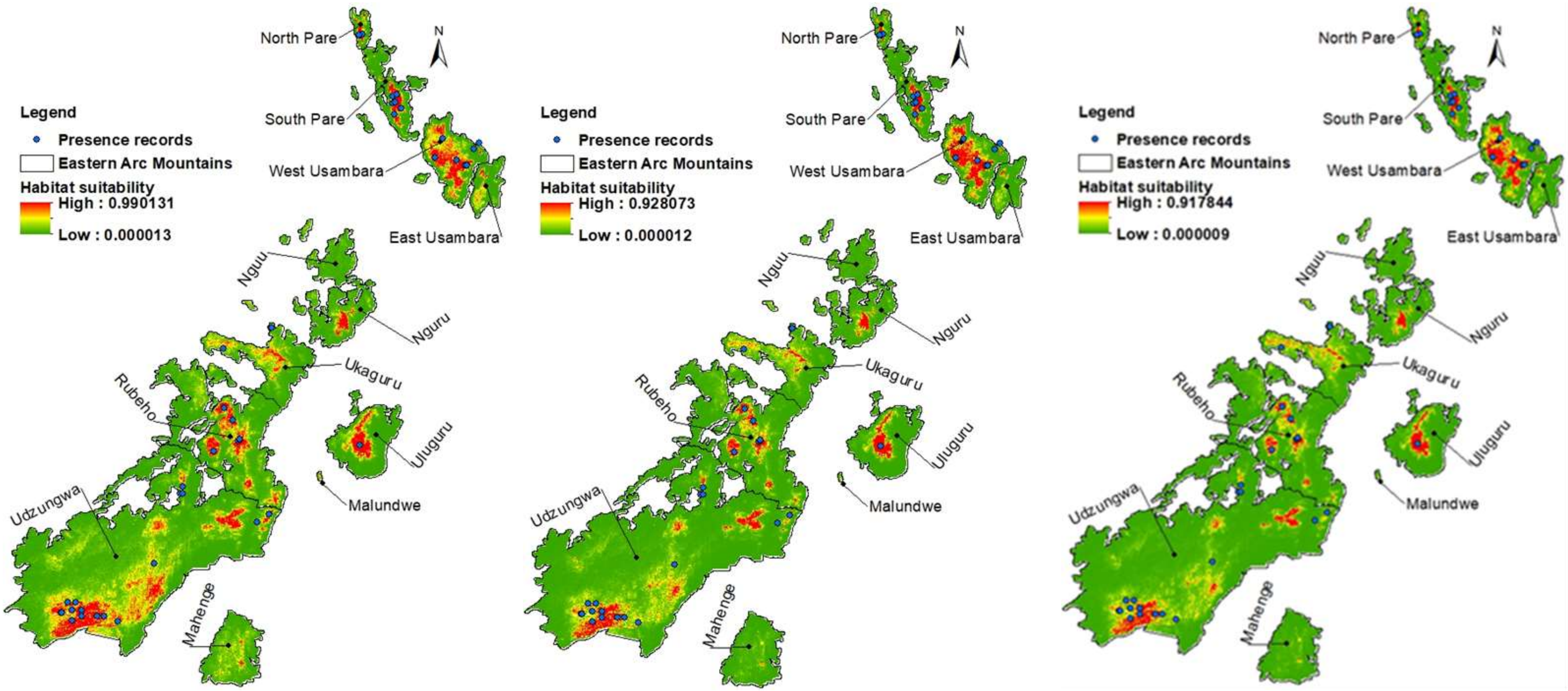

Figure 5: Current and future potential suitability maps showing distribution of *P. africana* in the EAM forests for Mid-century under RCP 4.5 and RCP 8.5 scenarios

Predicted current conditions **Predicted future conditions 2085 RCP 4.5** **Predicted future conditions 2085 RCP 8.5**

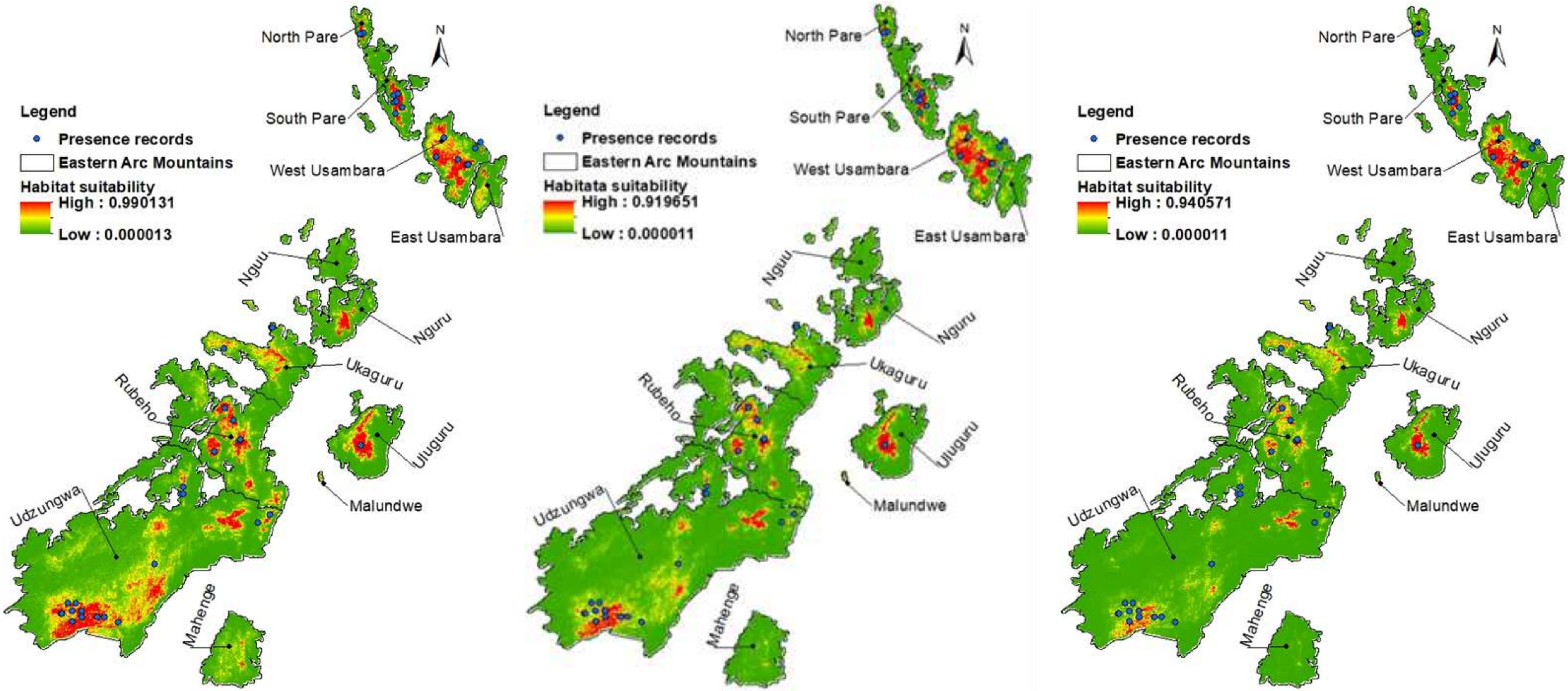

Figure 6: Current and future potential suitability maps showing distribution of *P. africana* in the EAM forests for Late-century under RCP 4.5 and RCP 8.5 scenarios

3.3 Potential Areas of Range Expansion or Contraction

Range expansion and contraction maps in Figure 7 and 8 clearly depict a gain and loss in range for *P. africana* under climate change scenarios. However, there is *a* substantial loss in range than actual gain in all climatic scenarios (Table 7 and 8). This shows that most of the areas currently predicted as suitable will not be suitable in the future in all EAM forests. RCP 8.5 scenario records larger loss in range for *P. Africana* compared to RCP 4.5 for both Mid-century 2041-2070 (2055) and Late-century 2071-2100 (2085). Among the EAM forests Udzungwa, Rubeho, West Usambara, Ukagaru, Uluguru, East Usambara, and South Pare forests will lose much more suitable habitats for *P. africana* compared to other forests under all climate change scenarios. Generally, a loss in range can be observed in the higher altitudes for *P. africana* while a gain in range is smaller to follow any clear pattern for all climatic scenarios.

On the other hand, future predictions showed that *P. africana* has high possibilities to gain new habitats only at Ukaguru for RCP 4.5 and 8.5 scenarios in the Mid-century (Table 6) while in the Late-century *P. africana* has high possibilities to gain new habitats in Ukaguru and Uluguru forests under the same climatic scenarios (Table 8). For instance, in Ukaguru a gain in range can be observed towards moderate elevation in areas with moderate temperature for both Mid-century and Late-century under RCP 4.5 and RCP 8.5 scenarios (Figure 9). In Uluguru forest a gain in range can be observed towards low elevation in the eastern areas with low temperature for Late-century under RCP 8.5 scenario only (Figure 9). Also a substantial loss in range for both Ukaguru and Uluguru can be observed towards higher elevation in the areas with low temperature for both Mid-century and Late-century under all climatic scenarios (Figure 9 and 10). Therefore, *P. africana* has significant possibilities to lose current habitats than to gaining new habitats in all climatic scenarios (Table 7 and 8).

Table 7: Potential areas (Km^2) of range expansion or contraction of *P. africana* in the EAMs for Mid-century under RCP 4.5 and RCP 8.5 scenarios

	Current 2018		2055 RCP4.5				2055 RCP8.5			
Name	**Unsuitable**	**Suitable**	**Unsuitable**	**Suitable**	**Gain**	**Loss**	**Unsuitable**	**Suitable**	**Gain**	**Loss**
North Pare	407	95	399	58	0	45	399	48	0	55
South Pare	1924	306	1932	167	0	131	1932	126	0	172
West Usambara	2085	1076	2079	697	18	367	2095	348	2	716
East Usambara	1021	169	1009	17	0	164	1009	8	0	173
Nguu	1458	0	1458	0	0	0	1458	0	0	0
Nguru	2365	121	2360	74	1	51	2355	57	6	68
Ukaguru	2938	455	2796	190	136	271	2744	162	188	299
Uluguru	2742	439	2740	272	0	169	2740	223	0	218
Malundwe	18	1	18	0	0	1	18	0	0	1
Rubeho	7504	906	7523	21	15	851	7526	1	12	871
Udzungwa	20569	4552	20631	1029	7	3454	20638	517	0	3966
Mahenge	2751	17	2751	0	0	17	2751	0	0	17
TOTAL	45782	8137	45696	2525	177	5521	45665	1490	208	6556

Table 8: Potential areas (Km^2) of range expansion or contraction of *P. africana* in the EAMs for Late-century under RCP 4.5 and RCP 8.5 scenarios

	Current 2018		2085 RCP4.5				2085 RCP8.5			
Name	**Unsuitable**	**Suitable**	**Unsuitable**	**Suitable**	**Gain**	**Loss**	**Unsuitable**	**Suitable**	**Gain**	**Loss**
North Pare	407	95	399	51	0	52	399	28	0	75
South Pare	1924	306	1932	150	0	148	1932	45	0	253
West Usambara	2085	1076	2090	636	7	428	2097	226	0	838
East Usambara	1021	169	1009	13	0	168	1009	1	0	180
Nguu	1458	0	1458	0	0	0	1457	0	1	0
Nguru	2365	121	2356	66	5	59	2331	40	30	85
Ukaguru	2938	455	2825	171	107	290	2799	84	133	377
Uluguru	2742	439	2740	258	0	183	2579	147	161	294
Malundwe	18	1	18	0	0	1	18	0	0	1
Rubeho	7504	906	7521	8	17	864	7531	0	7	872
Udzungwa	20569	4552	20636	719	2	3764	20638	25	0	4458
Mahenge	2751	17	2751	0	0	17	2751	0	0	17
TOTAL	45782	8137	45735	2072	138	5974	45541	596	332	7450

Expansion and contraction 2055 RCP 4.5 **Expansion and contraction 2055 RCP 8.5**

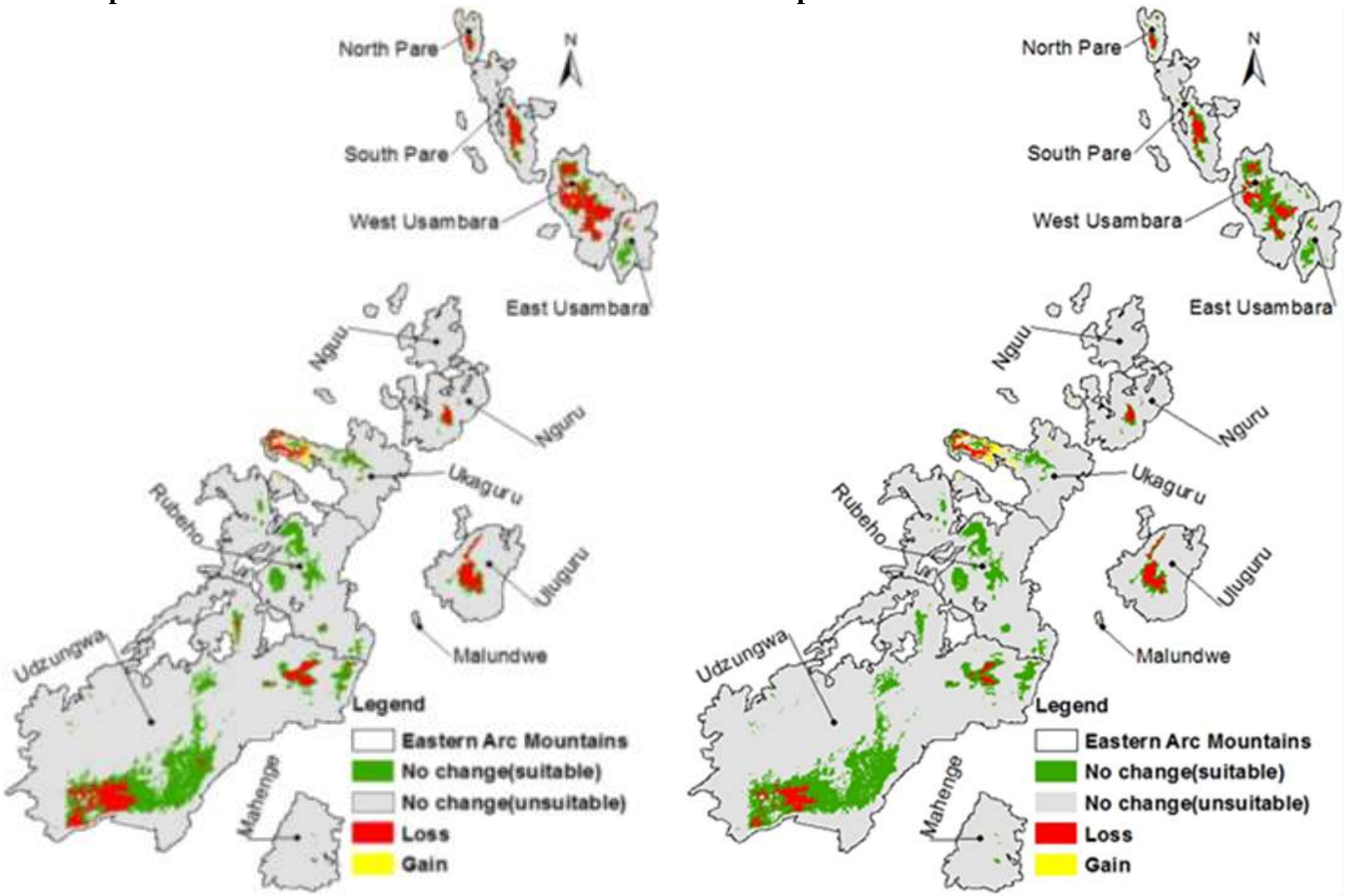

Figure 7: Maps showing change in potential distribution of *P. africana* EAM for Mid-century under RCP 4.5 and RCP 8.5 scenarios

Expansion and contraction 2085 RCP 4.5 **Expansion and contraction 2085 RCP 8.5**

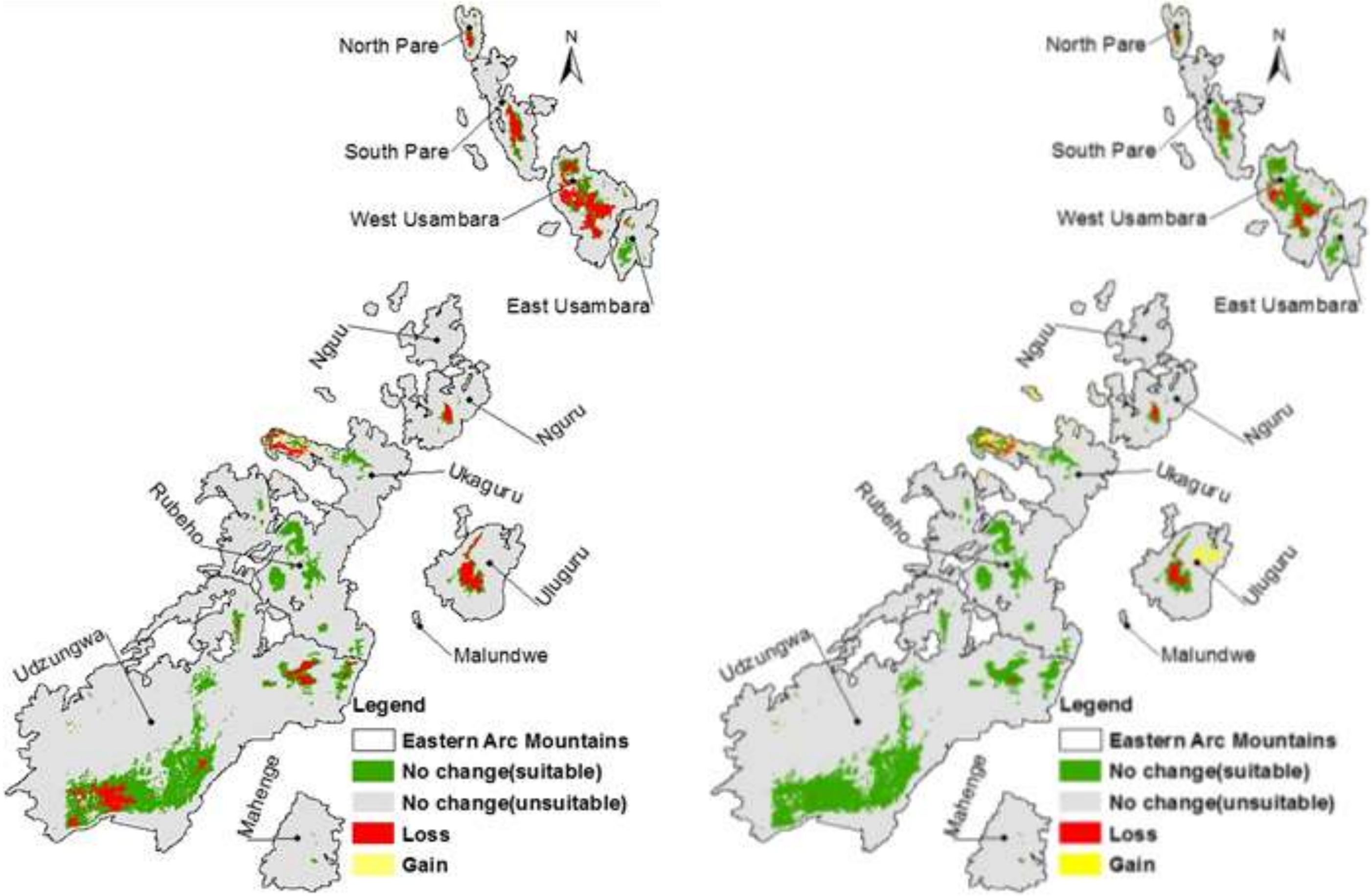

Figure 8: Maps showing change in potential distribution of *P. africana* EAM for Late-century under RCP 4.5 and RCP 8.5 scenarios

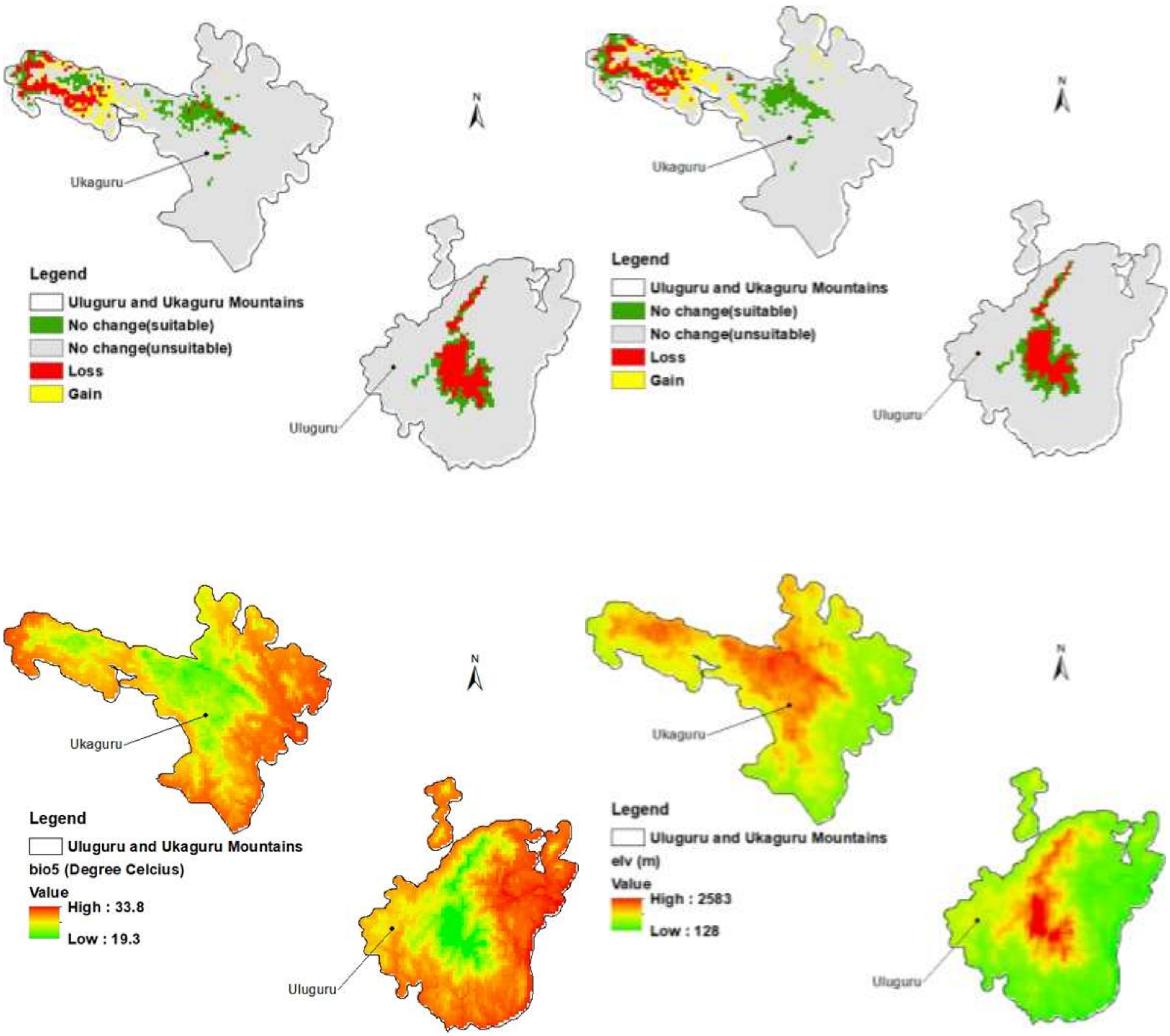

Figure 9: Maps showing zoom out of loss and gain to Uluguru and Ukaguru against the top predictor variables (maximum temperature warmest month and elevation) for Mid-century under RCP 4.5 and RCP 8.5 scenarios

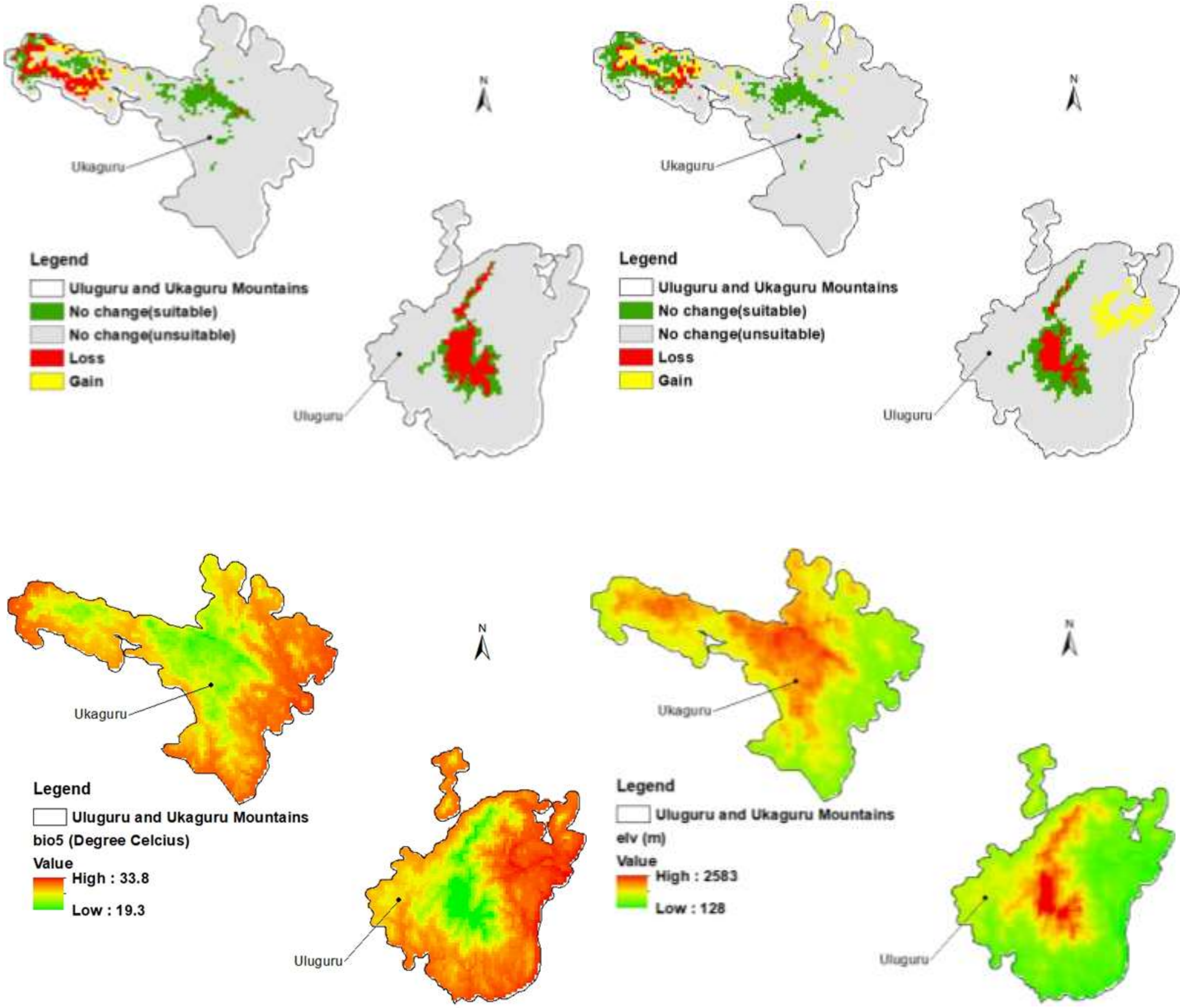

Figure 10: Maps showing zoom out of loss and gain to Uluguru and Ukaguru against the top predictor variables (maximum temperature warmest month and elevation) for Late-century under RCP 4.5 and RCP 8.5 scenarios

4.0 Discussion

4.1 Inference from Model Evaluation

Models for *P. africana* performed better than random, with average test AUC values of 0.97. This AUC values indicates that the models for *P. africana* performed optimal discrimination of suitable versus unsuitable habitats. AUC is a measure of model performance and varies from 0 to 1 (Fielding and Bell, 1997). An AUC value of 0.50 indicates that model did not perform better than random whereas a value of 1.0 indicates perfect discrimination (Swets, 1988). According to Philips et al. (2006), a perfect model should contain a set of environmental variables that sufficiently describes all parameters of the fundamental niche relevant to its distribution at the spatial scale of the model.

4.2 Potential distribution of *P. africana*

Distribution of plants is generally influenced by their physiological tolerance to climatic factors (Woodward, 1992). Modelling results indicate that climate-related variables have a significant contribution to the distribution of *P. africana*. From Jackknife test it can be observed that the climatic variables appear to have the most useful information to predict the potential distribution of *P. africana* followed by topographic and soil variables (Figure 3). The maximum temperature of warmest month showed highest predictive contribution and useful information to predict current and future potential distribution of *P. africana* in the EAM forests. Elsewhere, higher temperatures are reported to induce shifts in plant species towards altitudinal gradients and cause change in species composition (Telwala et al., 2013). Platts (2012) and Chitiki (2014) revealed that climatic variables mainly temperature has significant contribution to the distribution of tree species in the EAMs. Therefore, it can be concluded that in EAM forests climatic variables are important in defining current and future distribution of *P. africana* apart from topographical and soil variables only.

Climate is an important determinant of tree species distribution, but its effects are mediated through soils, and topographic features (Lo et al., 2010). Climate, topography and soils as environmental predictors can exert direct or indirect effects on species along a gradient. They can act as limiting factors, by controlling species eco-physiology (e.g. temperature, water, soil composition) (Boisvenue and Running, 2006). Temperature changes have a direct influence on the processes that determine local weather, chiefly precipitation, wind and the frequency and/or intensity of extreme weather events (IPCC, 2007). Moreover, at the continental scale, climate plays a major role in determining plant distribution, while at local and regional scales vegetation patterns are more strongly related to edaphic and topographic factors (Lafleur et al., 2010). Hence, single or combined results of climatic changes will drive changes in forest ecosystem resources, site conditions, disturbances, and individual trees (Williamson et al., 2009).

4.3 Climate Change Effects on *P. africana*

The study found that the projected distribution of *P. africana* under climate scenarios showed considerable effects. Results revealed that there could be some range expansion and contraction under different climate scenarios. In all scenarios there will be a larger range reduction than a range increase indicating decline of suitable habitats for *P. africana* (Table 7 and 8). A gain in range can be observed in the higher altitudes which suggest a shift toward higher altitudes for P. *africana* and thus, confirm findings from other studies which suggest an altitudinal movement of species under climate change (Araujo et al., 2006 and Girardello et al., 2009). Furthermore, it is known that species will move poleward with changes in climate (Araujo et al., 2006 and Girardello et al., 2009) but extent of change for study species does not follow northward movement of species under climate change suggesting that the study area is small to notice such movement. Elsewhere, northward shift of species' suitable habitats resulting from warming climates has also been observed for freshwater organisms (Hickling et al., 2005), as well as terrestrial organisms (Hickling et al., 2006; Chen et al., 2011).

Moreover, with warming trends, plant species are anticipated to track the changing climate and shift their distributions to the extent that resource availability and suitable conditions allow (Berry et al., 2002). Hence, warm-adapted and generalist species, which have a high dispersal ability (Hering et al., 2009), are forecasted to gradually replace cold-adapted species, which in turns are at risk of losing their suitable habitats (Jacobsen et al., 2012), and eventually suffer from a loss of regional genetic diversity (Pauls et al., 2013). Climate change is one of the most significant challenges to biodiversity and affects all organisms (Bellard et al., 2012). Changes have already been observed in different regions around the world, including geographical range reduction of the Namib Desert tree Aloe (Foden et al., 2007), habitat reduction of some trees of Eastern arc mountains (Philips, 2012) and Mediterranean habitat (e.g boreal tree species (Castro et al., 2004), and impacts to plant diversity in Europe (Thuiller et al., 2005).

4.4 Management implications

Results of this study revealed that climate change is expected to have a great impact on the distribution of *P. africana* around the EAM forests. *In-situ* long-term monitoring trends of the distribution, including recruitment and regeneration, should be sought. Institutions responsible for research in the country and public universities can take an interest in long-term monitoring of this species. In the future, it is likely suitable habitats for *P. africana* will be altered and lost enormously due to climate change. It is, therefore, crucial to supplement *in-situ* conservation actions with *ex-situ* interventions such as establish gene banks, botanical gardens and captive breeding to enhance the survival of *P. africana*. This raises a need to collect genetic materials especially in areas where there is threat of extinction. These can be stored in the gene banks for preservation, and future use as need be. In areas where species grow but occur outside protected areas; efforts should be elevated to promote tree retention on farms, or advocate further planting. The economic value of the tree should be promoted to encourage ex-situ conservation. Promotion of the tree planting and retention adjacent to protected areas will ensure conservation in the forest-farmland interface, to allow flow and exchange of genetic material (Dawson et al., 2017).

4.5 Limitations of the study

- The study relied only on observed presence records which are easy to acquire to predict the potential distribution of *P. africana,* recognizing that absence data are rarely available or reliable. However, absence data were replaced with background data, which are a random sample of the available environment in MaxEnt modelling.
- Selection of environmental or climatic variables to be included in the species distribution modelling can potentially introduce bias. To minimize such bias

only variables with low correlation and ecological importance for *P. africana* were only included in the model.

- Quality and resolution of the climate data as well as interpolation techniques from point data to raster grids can be sources of error when modelling of the spatial distribution of species. To minimize such error climate data with resolutions that fit ecological studies at local scales (up to 1 km) were acquired and used for this study. These climate data (ensemble mean), downscaled using 18 pairwise combinations of 5 RCMs driven by 10 GCMs.

5.0 Conclusion and Recommendations

5.1 Conclusion

When considering the results generated from species distribution modelling climatic, topographic and edaphic factors are important predictors in predicting species distribution. Climatic variables showed high effects on the potential geographical distribution of *P. africana* in the EAM followed by topographic derivatives and soils soil factors. Moreover, projected future distributions of *P. africana* show that there will be more contraction of suitable habitats than expansion under all climatic scenarios in the EAM. For instance, Udzungwa, West Usambara, Uluguru, Ukagaru and South Pare Forests will lose much more suitable habitats for *P. africana* than gaining. *P. africana* has high possibilities to gain new habitat within Uluguru, West Usambara, Ukaguru, Nguru and Rubeho Forests when compared to other forests Generally, plants from moderate altitude and climate (e.g. *P.africana*) will suffer more habitat loss from climate change compared to others (Khanum, et al., 2013). Conservation action is, therefore needed to conserve this species.

5.2 Recommendation

This study recommends the following:

- From the study findings, it is observed that the current and future potential distribution of *P. africana* in the EAMs to a large extent is influenced by climatic variables. Therefore it is advised that there should be on-going field monitoring of *P. africana*. This can be an effective tool in tree species restoration and conservation planning.
- Since different conservation strategies may be required for conservation of vulnerable species due to climate change within the ecosystem, this study recommends the use of produced current and future suitable habitat maps to help set priorities to restore natural habitats for the species observed with decreasing suitable habitats. This will as well enhance more effective conservation and management of the ecosystem.
- Despite the fact that climate change poses crucial challenges for forest biodiversity such as *P. africana*. Climate change issues have not been fully addressed in national forest policies in Tanzania. Therefore, it is advised to

integrate climate change strategies and plans relevant to forests into existing forest policy framework and other sectoral frameworks that influence forests.

- Because this study has generated valuable information for conservation management of *P. africana*. Findings from this study can be applied to identify new areas where *P. africana* is likely to spread for planting and conservation in those areas where current and future condition for *P. africana* is suitable.

6.0 References

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