INFLUENCE OF ENVIRONMENTAL VARIABLES ON THE DISTRIBUTION OF SELECTED TREE SPECIES IN LAKE MANYARA UPPER CATCHMENT, NORTHERN-TANZANIA

WANJALA JOHN MGAYWA

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN ECOSYSTEMS SCIENCE AND MANAGEMENT OF SOKOINE UNIVERSITY OF AGRICULTURE-MOROGORO, TANZANIA.

2018

ABSTRACT

This study was conducted to analyse the influence of environmental variables on the distribution of selected tree species in Chemchem River in the Manyara National Park under current conditions. The specific objectives were to assess the current distribution status, identify important environmental variables associated with the distribution and predict potential habitats of selected tree species in relation to environmental variables under current conditions. The area was stratified by elevation. Two transects in each elevation stratum were laid parallel to the river flow. Rectangular plots each of 0.02 ha were established. In each plot, trees were enumerated, identified by their scientific names and GPS points taken. Seven (7) environmental variables were used. Tree data was summarised into respective families, genera and species. Dominant tree species were selected based on index of dominance. All analysis were carried out in excel software. Prediction of the current habitats was done using Maximum Entropy Modelling (Maxent) software. Maxent models performed better than random, with average training and test AUC values of 0.8497 and 0.8577±0.0235 respectively. A total of forty five (45) tree species belonged to 36 genera and 21 families were found. Dominant species were *Acacia tortilis* (0.0415), *Ficus sycomorus* (0.0366), *Acacia robusta* (0.0135) and *Trichilia emetica* (0.0127). Species were distributed following the river flow with lower elevations inhabiting most species. The increase in elevation and temperature seasonality increased the probability of occurrences of most species. Significant predictive contribution of elevation was observed to particular species of *Albizia petersiana* (83.05%) and *Ficus thoningii* (75.72%). Furthermore, suitable habitats increased with increasing annual precipitation and temperature of the driest quarter and were predicted in the central and north eastern of the study area. These habitats were fragmented with some patches. Park management should help the communities conserve the upper areas of the river so as to

minimize illegal tree cut and farming in catchment areas. Furthermore, restoration and conservation efforts should be done targeting fragmented habitats, unsuitable habitats and species with small habitats.

DECLARATION

I, **Wanjala, J. Mgaywa**, do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted to any other institution.

_______________________ __________________

Wanjala J. Mgaywa Date

(MSc. EcoSM Candidate)

Above declaration is confirmed by:

_______________________ __________________

Dr. Alfred K. Chitiki Date

(Supervisor)

COPYRIGHT

ACKNOWLEDGEMENT

Many people have encouraged me throughout this process, from close friends and relatives to strangers at the University. Special thanks should go to the Tanzania Forest Service-Agency (TFS) for financing my studies, the Principal at Forestry Training Institute (FTI)-Olmotonyi for granting me permission for this valuable study and the Park-waden at the Lake Manyara National Park for his security support and approval to work within the park.

I would like to specifically thank my supervisor Dr. Alfred A. Chitiki for his close guidance, critics and constructive comments throughout the entire study period. His assistance and directives were highly valuable and appreciated. I wish to express my sincerely gratitude to Mr. Richard A. Giliba for his support on GIS. He was my mentor, editor and advisor. I am lucky to have such a positive advisor and a friend. I am also indebted to Mr. Canisius Kayombo, a Botanist at the Forestry Training Institute (FTI)-Olmotonyi for his field assistance and plant species identification during data collection. Your support and efforts are much acknowledged.

To my fellow classmates who always kept encouraging and reminding me that I can do it, thank you very much guys. God bless you all.

DEDICATION

This study is dedicated to my parents, the late Wanjala Masami and Chausiku Sindikwi, to my wife Evalyne Abraham and my children: Nicholaus, Alvin and Alice. I love you and thanking you in advance for your support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

ASCII	American Standard Code for Information Interchange
AUC	Area under the curve of Receiver operating characteristics (ROC)
EAM	Eastern Arc Mountains
EcoSM	Ecosystems Science and Management
FTI	Forestry Training Institute-Olmotonyi
GAM	Generalised Additive Models
GIS	Geographical Information System
GLM	Generalised Linear Models
GPS	Global Positioning System
Maxent	Maximum Entropy
RS	Remote Sensing
SD	Standard Deviation
SDM	Species Distribution Modelling
TFS	Tanzania Forest Service Agency

CHAPTER ONE

1.0 INTRODUCTION

The relationships between species and their overall environmental variables can cause different spatial patterns to be observed at different scales (Pearson *et al*., 2004). Gholinejad *et al*. (2012) reported that the appearance of plant groups in a given area is in response to changes in various factors such as climatic, topographic, edaphic and biotic parameters. Hence, vegetation groups are reported to be determined by the combined effects of a whole range of ecological factors. Changes in the soil, topography and grazing factors for example, can lead to different vegetation responses in each area of the landscape (Gholinejad *et al*., 2012). On the other hand, it is widely accepted that the distributions of plants are broadly constrained by their physiological tolerances to climatic factors (Thuiller, 2004) mainly temperature and rainfall (Gholinejad *et al*., 2012). However, there is a wide appreciation that the effects of climate to species are best expressed at large by spatial scales (Willis and Whittaker, 2002).

The fundamental range of tolerance of a species, which is a result of limiting variables of the environment, is a critical determinant of the resultant distribution pattern (Guisan and Thuiller, 2005). Limiting variables are typically related to climatic properties, such as temperature and water availability at a broad geographical scale (Feilhauer, 2012). At a finer scale, resource factors including nutrients, amount of light energy for plants and moisture level, driven by topographical variations and habitat types, are the main driving forces for shaping the patterns of species distribution. Additionally, natural and anthropogenic disturbances affect species distribution at various spatial scales (Feilhauer, 2012).

On the other hand, Pearson and Dawson (2003) indicated that changing climate has a profound influence on species' habitat range expansion and contraction. Habitat range loss for example as the result of the changing environment varies dramatically across species (Chitiki, 2014). Species that show minimal loss of habitat range are referred as wide-ranging species, confirming that wide ranges provide a buffer against environmental change (Jetz *et al.*, 2007). Habitat range shifts are predicted to be more pronounced at higher latitudes, where temperatures are also expected to rise more than near the equator (Chitiki, 2014). Consequently, forests may disappear in certain areas at a faster rate than they can migrate or regrow in new areas (Parmesan, 2006). There has been intense focus on estimation of range shifts among species which has led to rapid progress in the use of niche modelling to predict where species are likely to move (Peterson *et al.,* 2005; Araújo and Luoto, 2007 and Chitiki, 2014) given anticipated climate and land use changes from well-established global and regional models (Chitiki, 2014). Ecological niche modelling (ENM) merges known occurrence records for a species with environmental data to estimate species ecological requirements and potential geographic distribution patterns (Guisan and Thuiller, 2005). This estimation helps to narrow down sets of possible occurrence sites for more targeted field surveys (Menon *et al*., 2010).

A variety of species distribution modelling methods are available to predict potential suitable habitat for a species (Guisan and Thuiller, 2005; Elith *et al*., 2006). The maximum entropy (Maxent) modelling (Phillips *et al*., 2006) in particular, has shown promising results (Elith *et al*., 2006) and performs better compared to many different modelling methods (Ortega-Huerta and Peterson, 2008). Its applications range from estimation of species habitat ranges (Moreno *et al*., 2011), identification of suitable habitats, establishing conservation priorities and predicting range shifts under future climate change scenarios (Thomas *et al*., 2004). The model produces useful results and has been worldwide successful used for modelling the distribution of two critically endangered Dipterocarp trees in riparian forests of Borneo (Singh, 2013). In Tanzania, studies using Maxent have been done. Chitiki (2014) used Maxent to predict the current and future potential distribution of tree species in the Eastern Arc Mountains of Tanzania.

1.1 Problem Statement and Justification

Identifying the factors that affect species' distributions is an important unanswered issue in ecology (Araújo and Guisan, 2006). Distribution of dominant tree species for example, form the major structural and functional basis of tropical forest ecosystems and can serve as robust indicators of changes at the landscape scale (Kumar, 2006). However, there are no studies on the distribution of dominant tree species in Lake Manyara landscape, although several studies have reported on high degradation of species and their habitats in the study area (Sechambo, 2001; Thomson *et al*., 2004 and Kihwele *et al*., 2014). Understanding the factors influencing the distribution of dominant tree species in the study area may improve the knowledge on the drivers of species distribution and the extent to which these drivers are directly related to individual species. This information is essential in deciding proper management options for the studied species and their habitats within the study area.

Environmental change has a profound influence on species' habitat range expansion and contraction and varies dramatically across species (Pearson and Dawson, 2003 and Chitiki, 2014). The largest potential loss of habitat ranges occurs among species that have restricted ranges (Sillero *et al*., 2012). Therefore, species that already have small population sizes or range sizes or specialized habitat requirements, are exposed to high risks of extinction (Jetz *et al*., 2007). However, the effects of environmental change on species distribution particularly of plants, are poorly understood (Chitiki, 2014).

In addition, no studies have been done to understand the influence of environmental variables on the distribution of tree species in Lake Manyara. Understanding the influence of environmental variables on the distribution of tree species will be fundamentally important for planning integrated management strategies and conservation needs for tree species within the study site. Furthermore, information on suitable habitats of selected tree species will be useful indication of which areas (habitats) within the study site may be important for biodiversity conservation (Platts *et al*., 2010). In addition, information on modelling species distribution will provide useful means of commissioning future surveys in predicted species distribution area and hence prioritizing conservation efforts on the species under study. This information may be important and worthwhile to various ecologists within the study site, researchers and practitioners elsewhere.

1.2 Objectives

1.2.1 Overall objective

To assess the influence of environmental variables on the distribution of selected tree species in Lake Manyara upper catchment, Northern Tanzania

1.2.2 Specific objectives

i. To assess the current distribution status of selected tree species in lake Manyara upper catchment
ii. To identify important environmental variables associated with the distribution of selected tree species in lake Manyara upper catchment
iii. To predict suitable habitats for selected tree species under current conditions

1.3 Research Questions

- What is the current distribution of selected tree species in Lake Manyara Upper catchment?
- Which of the selected environment variables are important for predicting distribution of selected tree species in Lake Manyara upper catchment?
- What are the potential habitats for selected tree species under current conditions?

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Environmental Variables and Species Distribution

Knowledge on tree species distribution may help the understanding of the fundamental ecological processes that are important for management (Araújo and Guisan, 2006). It is reported by Parmesan (2006), that the distributions of many species are determined to a large extent by climatic variables and hence changes in climate will modify their distribution and abundance. For instance, a gradual distribution of species observed over a large extent and at coarse resolution is likely to be controlled by climatic regulators (Guisan and Thuiller, 2005). Furthermore, patchy distribution of species observed over a smaller area and at fine resolution is more likely to result from a patchy distribution of resources, driven by micro-topographic variation or habitat fragmentation (Guisan and Thuiller, 2005). Khanum *et al*. (2013) reported that climate change is a significant driver for biodiversity loss as it may affect species' natural distribution, cause temporal reproductive isolation and increase pest and disease outbreak frequencies. Some of the key climatic variables that stress forest ecosystems are changes in precipitation, temperature and evapotranspiration (Chitiki, 2014). These variables may lead to increased frequencies of fires and storms, a threat to forests and forest ecosystems (Ohlemüller *et al*., 2006). In addition, Tranquillini (1979) reported that temperature and droughts are the main factors limiting the growth of tree species at the upper limit of their habitat range. Berry *et al*. (2002) reported with continuous future changes in climate for example, plant species are expected either to adapt or shift their geographical distributions in order to avoid habitat loss and subsequent extinction. Furthermore, it is as well expected that, vegetation zones for instance, may move towards higher elevations in response to increasing average temperatures (Iverson and Prasad, 1998).

2.2 Species Prediction under the Influence of Current Cconditions

Predicting species ranges for different climates is commonly done with ‘climate envelope models’ (CEMs). These models use the current geographic distribution of a species to infer its environmental requirements (Hijmans *et al*., 2006). This is done based on species’ geographic distribution for the current, or for past or future climates. Recently, substantial efforts have been observed showing the response of biological systems to global change (Thuiller *et al*., 2005, McKenney, 2007). Compilation of such studies on the effect of projected climate change indicates that an alarming number of species may lose large part of their habitat range and become ‘committed to extinction’ (Thomas *et al*., 2004). For example, estimates of extinction risk following range shifts have largely been derived from modelled projections of ‘‘climatic envelopes’’ (Sala *et al*., 2005). Such models suggest that large number of species will potentially experience dramatic decrease in distribution area under predicted climate change scenarios (Williams *et al*., 2003 and Thomas *et al*., 2004). It is further reported that the projected losses due to land use change alone (native habitat loss), causing habitat reduction in tropical forests and woodland, savannah and warm mixed forest, account for 80% of the lost species (Chazal and Rounsevell, 2008). Between now and 2100, it is projected that approximately 25% of areas currently classified as natural will be transformed into another natural land cover category, 16% due to climate change and 9% due to land-use conversions (Jetz *et al*., 2007).

2.3 Species Distribution Models (SDMs)

The fascinating question of how plants and animals are distributed on Earth in space and time has a long history which has inspired many biogeographers and ecologists to seek explanations (Guisan and Thuiller, 2005). In the last two decades, interest in species distribution models (SDMs) of plants and animals has grown dramatically (Guisan and

Thuiller, 2005). The models have become a popular technique for calculating potential distribution of species for a wide variety of taxa (Jetz *et al*., 2007), evaluate the effects of climatic warming on species distribution (Araújo *et al*., 2006), and estimate suitable habitats of species in protected areas (Sillero *et al*., 2012). This is done by establishing relationships between occurrences of species and biophysical and environmental conditions in the study area (Kumar *et al*., 2009). Therefore, the models can estimate species' niches across geographical space within a particular period of time. Species' niches estimations is done by substituting new variables that reflect anticipated environmental changes into these spatial models (Botkin *et al*., 2007).

Species distribution models (SDMs) also called bioclimatic envelope or environmental niche models, have been increasingly as common method for describing the influence of current and future climate on the distribution of species (Schrag *et al*., 2007). These are empirical models relating field observations to environmental predictor variables, based on statistically or theoretically derived response surfaces (Guisan and Zimmermann, 2000). By 'training' a model on current species distributions and bioclimatic parameters, and assuming a static relationship between climate and vegetation in the future, predictions of future changes in distributions under various climatic regimes can be developed (Hannah *et al*., 2002). Species data can be presence, presence/absence or abundance observations based on random or stratified field sampling, or observations obtained opportunistically, such as those in natural history collections (Guisan and Thuiller, 2005). The most effective way to maximize the information content on species locality data is to apply species distribution models (SDMs) based on environmental characteristics (Cord *et al*., 2012).

A variety of ecological applications require data from broad spatial extents that cannot be collected using field-based methods (Kerr and Ostrovsky, 2013). Remote sensing data and techniques address these needs, which include identifying and detailing the biophysical characteristics of species' habitats, predicting the distribution of species and detect natural and human caused change at scales ranging from individual landscapes to the entire world (Kerr and Ostrovsky, 2013). The technique generates a remarkable array of ecologically valuable measurements, including the details of habitats (land cover classification) and their biophysical properties (Cord *et al*., 2013). Furthermore, it provides the only means of measuring the characteristics of habitats across broad areas and detecting environmental changes that occur as a result of human or natural processes (Elith and Leathwick, 2009). Remote sensing data are now commonly used in SDM(s) since they provide a low cost means to map environmental changes across multiple spatial-temporal scales (Kerr and Ostrovsky, 2013). Although the need for remote sensing is especially urgent for conservation related science, satellite-based earth observations are also being used for basic ecological research. These data are increasingly easy to find and use (Kerr and Ostrovsky, 2003). However, remote sensing is fundamental for ecological and conservation biological applications and will play an increasingly important role in the future (Cord *et al*., 2013).

2.4 Species Distribution Modelling using Maximum Entropy (Maxent)

Maximum Entropy (Maxent) is a general purpose machine learning method with a precise mathematical formulation (Phillips *et al*., 2006). It has been found to perform best among many different modelling methods (Elith *et al*., 2006; Ortega-Huerta and Peterson, 2008), and may remain effective despite small sample sizes (Hernandez *et al*., 2006; Pearson *et al*., 2007). It is more flexible than methods such as Generalised Linear Models (GLMs) and Generalised Additive Models (GAMs) and it can capture complex response curves to environmental gradients (Ashcroft *et al*., 2011). Due to its ability to produce useful results with a very small presence data (Singh, 2013), Tinoco *et al*. (2009) used Maxent to generate a species distribution model of the violet throated metal tail humming bird, a globally endangered bird species which is endemic to south-central Ecuador. The author modelled the distribution of the species using a limited species occurrence record (Singh (2013). In addition, Maxent has been also successful used in early studies. Other examples are such as predicting the potential distribution of ants in New Zealand (Ward, 2007), the distribution of bats in Madagascar (Lamb *et al*., 2008) and the distribution of birds in the Andes (Young *et al*., 2009).

Maxent is not strongly influenced by the number of environmental parameters used to build models because it ignores those that are non-informative, and uses regularization techniques to avoid over-parameterization (Phillips *et al*., 2006). It requires only species presence data and environmental variable (continuous or categorical) layers for the study area. However, Maxent software is in development and as a result, is sensitive to the number of regulations that can be placed. Despite its disadvantages, Maxent appears to have outperformed other presence-only data methods such as a genetic algorithm for rule production and envelope method (GARP) (Elith and Graham, 2009).

The basic idea of Maxent is “to estimate (approximate) unknown probability distribution of a species” (Phillips *et al*., 2006) and that the approximation should have maximum entropy. Entropy is defined by Shanon (1948) as how much ‘choice’ is involved in the selection of an event”. Thus, maximum entropy refers to maximum choice. Maximum choice is available when there are fewer constraints (environmental layers), i.e. unnecessary constraints should be avoided (Phillips *et al*., 2006). The environmental variable values at the presence localities impose constraints on the unknown distribution (Phillips *et al*., 2006). The maximum entropy approach then approximates an unknown distribution using the known occurrences and background points (all points/grid cell values in the study region) that maximizes entropy, subject to the constraints imposed by the known occurrences (Singh, 2013). 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 to 100 (if the result output format is set as cumulative) or 0-1 (if the result output format is selected as logistic); this represents the estimate of relative probability of species occurrence (Singh, 2013).

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Description of the Study Area

The study was conducted in the Lake Manyara basin which extends approximately 766,710 ha within Mbulu, Monduli, Ngorongoro and Babati districts (AWF, 2003). The Chemchem River flowing into the Lake Manyara and which is within the Chemchem village adjoining the Lake Manyara national park forest was the focus for the present study. The study covers about 8990 ha and is located between longitude $35^0$45'- $35^0$50' E and latitude $3^0$25'-$3^0$35' S (Faustine, 2008). The climate of the area is semiarid with two distinct rainy seasons, short rains in October to December and long rains (the long monsoon rains) in March to May (Rohde and Hilhorst, 2001). Additionally, the area receives an average rainfall of about 1000 mm per year and a mean annual temperature in the range of 18° C to 35° C (Faustine, 2008). Drought periods are also reported to be very common (Faustine, 2008). The soils vary from alkaline to non-saline-alkaline in reaction. In addition the soil textures of the area are clay, clay-loam, loam, loamy/sand-loam and sandy-loam/sandy-clay-loam (Cohen *et al*., 1993). Soils vary from fertile highly erodible volcanic material to a variety of moderate to low fertility sedimentary soil (Cohen *et al*., 1993). Crop cultivation is one of the main economic activities of the people living in adjacent villages of the study (Rohde and Hilhorst, 2001).

3.2 Study Design

3.2.1 Sampling design

In order to cover the whole study site and capture the variation within the area, stratified random sampling design was adopted. The area was stratified by elevation into two strata; the lower elevation (<1000m) and higher elevation between 1000m and 1800m.

Two transects were laid parallel to the river flow. Since, data was to be collected within a riparian buffer, the distance between transects were 20 m. In each stratum, a rectangular plot each of 0.02 ha (20 × 10 m) was established along transects (Munishi *et al*., 2007). According to Chitiki (2014), the size of the plot used should be small in order to keep environmental factors and forest structure homogeneous within the plots. Transects were laid in such a way that they covered as much variations as possible in both lower and upper elevation of the river. The starting point was subjectively chosen and the distance between plots was 100m. Plots were laid with their long axis perpendicular to the slope to minimize within-plot variations and maximize between-plot variations (Munishi *et al*., 2007).

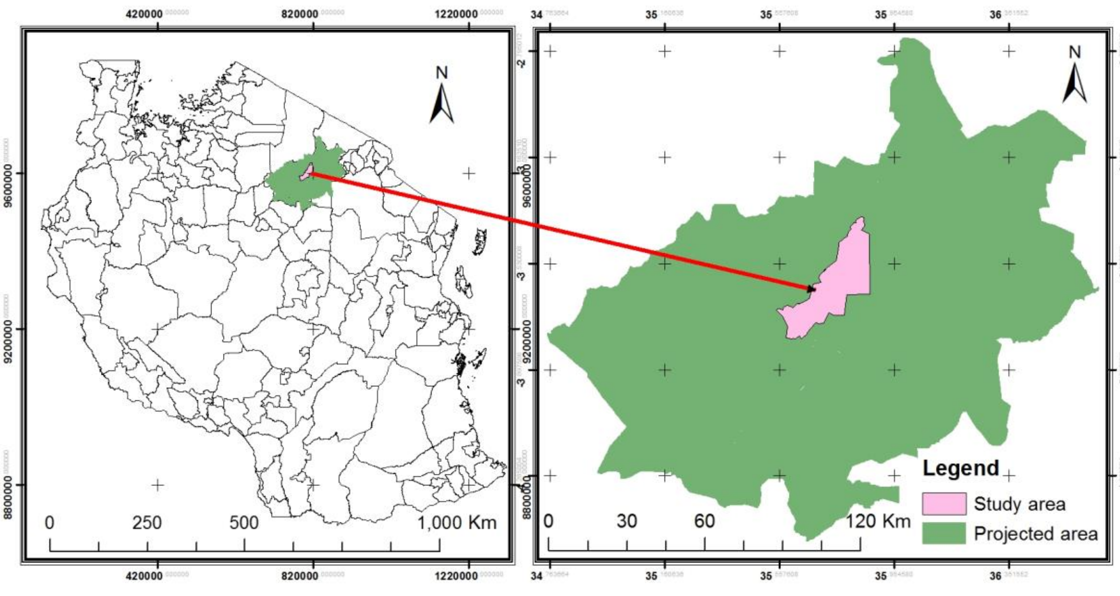


Figure 1: Study location of the Manyara National Park

3.3 Data Collection

3.3.1 Species occurrence data

In each plot, individual trees were enumerated and identified into their scientific names. Global Positioning System (GPS) coordinates for each individual tree was recorded corresponding to where the species was found. Other information collected on the study site included plot location, topographic position and elevation (m). Topographic position was identified into two classes of lower elevation (lower stream) and higher elevation (upper stream). Elevation and slope for each plot were obtained using GPS. Trees species were identified in the field by a qualified botanist from Forestry Training Institute (FTI) Herbarium-Arusha. Species not identified in the field, their specimens were collected for further identification in the herbaria.

3.3.2 Environmental layers (bioclimatic and topographical data)

Seven (7) environmental variables were considered as potential predictors of the distribution for the tree species (Table 1). These variables were chosen based on their biological relevance to plant species distributions and also considering other habitat modeling studies (Kumar *et al*., 2006; Guisan *et al*., 2007; Pearson *et al*., 2007; Murienne *et al*., 2009 and Chitiki, 2014). Furthermore, climatic variables (Table 1), biologically meaningful to define the distribution of species (Murienne *et al*., 2009), were obtained from WorldClim dataset (Hijmans *et al*., 2005; http://wwwworldclim.org/bioclim.htm) based on past and current records from the period 1960-2000 and were provided as grids at a spatial resolution of 30 arc seconds (1 km).

Four climatic gradients known to correlate well with plant distribution in the study area were derived from the monthly grids of bioclimatic data (Platts *et al*., 2013). These were mean annual temperature and temperature seasonality (annual range) and mean annual rainfall and dry season water stress (precipitation of the driest quarter). In addition, mean temperature of the driest quarter was also included as one of the limiting environmental factor to species distribution (Chitiki, 2014). Topographic variables were derived from Digital Elevation Model (DEM) (Kumar and Stohlgren, 2009) at 1km spatial resolution. As elevation is highly correlated with temperature and the latter is a more functional predictor of plant distribution, derived measures such as slope, aspect and topographical wetness index can be useful surrogates for soil mixture and micro-climate (Chitiki, 2014). Under this present study, only slope and elevation were computed and used as topographical predictor variables.

Table 1: List of Environmental Predictor Variables used in Maxent Modelling

Environmental Variables/Layers	Abbreviations	Description	Ranges
Climatic Variables	**mt**	Annual Mean Temperature	18.20 - 23.30 ^{0}C
	ts	Temperature Seasonality (Annual range/temperature CV	14.34 – 15.51^{0}C
	ap	Annual Precipitation	579 – 943 mm
	pq	Precipitation of the driest Quarter/Dry season water stress	5 – 15 mm
	tq	Mean Temperature of the Driest Quarter	16.4 – 20.5 ^{0}C
Topographic Variables	**sl**	Slope (degrees)	0 – 89 %
	el	Elevation (degrees)	942 – 1719 m

Note that: CV= Coefficient of Variation

3.4 Data Analysis

Spatially referenced inventory data (species occurrence records) combined with climate and topographic parameters (Table 1) were used to assess the distribution of selected dominant tree species using Remote sensing (RS), Geographical Information System (GIS) techniques and Maximum entropy distribution modelling approach (Phillips *et al.*, 2006).

3.4.1 Tree species occurrence data

Tree species data were summarised into their respective families, genera and species using Microsoft excel software. Dominant tree species was calculated based on index of dominance. Ten (10) trees were selected as dominant species (Appendix 13) from the entire list of encountered tree species in the study site. All analysis were carried out using excel software. Prediction of the suitable habitats under current conditions for ten (10) selected dominant tree species in the study area was done using Maxent software.

3.4.2 Maximum Entropy (Maxent) Modelling of Species Distribution

3.4.2.1 Data inputs preparation to run the model (Maxent)

All environmental variables were modified using GIS techniques into formats required by Maxent modelling (Phillips *et al*., 2006). In this study, model inputs comprised species occurrence data and environmental layers (Appendix 1). Since Maxent allows layers to be either continuous or categorical, the layers encompassed bioclimatic variables and topographical data which were continuous (Table 1). Species occurrence data (‘samples’ file trees) with longitude and latitude coordinates was converted to comma-separated value (csv) files in excel software for a particular modelled geographic extent. Moreover, all environmental layers (“grids”) in raster format were converted into ASCII format and modified using GIS tools (ArcGIS 9.2v software) into format required by Maxent (same cell size, extent or geographic bounds and projection system; e.g. geographic or UTM). Thus, all environmental layers were spatially projected to geographic coordinate system, ARC 1960 zone 37S.

Using Maxent, the samples (*y*-variables) for this particular case, the selected ten (10) dominant tree species were modelled with environmental variables (*x*-variables) based on the current conditions (Appendix 1). Maxent software version 3.3.3k was used to fit the models and the algorithm was run with default parameters (convergence threshold = 10^{-5}, regularization multiplier = 1, maximum number of background points = 10 000); these default settings have been shown to achieve good performance (Phillips and Dudík, 2008 and Chitiki, 2014). Maximum iteration value was set to 5000 (to give the model adequate time for convergence) and to avoid over prediction or under prediction of the relationships by the model (Phillips *et al*., 2006 and Chitiki, 2014).

3.4.2.2 Model calibration and validation

Testing or validation is required to assess the predictive performance of the model. Ideally an independent data set should be used for testing the model performance (Kumar and Stohlgren, 2009); but in many cases these data are missing. Therefore, an approach to manually partitioning the data randomly into ‘training’ and ‘test’ sets, was adopted, thus creating quasi-independent data for model testing (Guisan *et al*., 2003 and Kumar and Stohlgren, 2009). To support this approach, enough data were set aside for model validation and worked well.

From the manually partitioned data, the model was calibrated/trained using 75% of the dataset sample obtained at a given point in time and predictive accuracy of the model was evaluated using the 25% of the remaining data (test) for each modelled species (Araujo *et al*., 2005). This setting allowed 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 (overfitting) of model performance. The subdivision of data into separate calibration and evaluation datasets is a common practice, however, it is argued by Ashcroft (2011) that the practice does not result in a truly independent dataset and rather provides some protection against overfitting to the specific calibration data.

Statistical evaluation of the models were assessed based on the area under curve (AUC) (Cord *et al*., 2012) under the independent receiver operating characteristic (ROC) analysis (Phillips *et al*., 2006) involving 25% of the partitioned (test) data set. AUC is calculated by summing the area under the receiver operating characteristic (ROC) plot. The AUC is a non-parametric statistic that is independent of threshold values and demonstrates the likelihood that the model is able to rank a presence record higher than a record of background data (Turner, 2014). The ROC graph has its x-axis the fractional predicted area (the total habitat area) and as its y-axis the sensitivity or the proportion of occurrences the habitat captures. A model that predicts better than random will have training and test curves that lie above the random curve (Jobe and Zank, 2008). For the only species presence data modelling, the ROC curve is a plot of sensitivity (proportion of correctly predicted presences) against the fractional area predicted present (Chitiki, 2014).

The AUC values allow easy comparison of performance of one model with another, and are useful in evaluating multiple Maxent models (Phillips *et al*., 2006). A value of 0.80 for example signifies that 80% of the time, a value that is randomly selected from a presence site will have a higher rank than a random background site (Phillips *et al*., 2006). Values are given between 0 and 1, with 0.5 representing random predictions (Turner, 2014). The maximum achievable AUC for species presence-only models is less than one because the background data used consists of the range of habitat suitability scores within the study area, including those which may be predicted highly suitable (Phillips *et al*., 2006). The closer the output values from the model to 1, the stronger the models performance (Fielding and Bell, 1997 and Peterson *et al*., 2011). This also means that habitat generalists are predicted to have a large area of suitable habitat and usually will have a lower maximum achievable AUC compared to habitat specialists

(Ashcroft *et al.*, 2011). Therefore, an AUC value between 0 and 0.5 is an indication of predictions no better than random, while values closer to 1.0 indicate better model performance. High predictive power by the models with larger AUC values has also been strongly supported by Elith *et al.* (2006).

Tree species response to each variable was analysed by investigating the response curves, which represent the exponential changes that is predicted suitability, as each variable varies by maintaining all others at their average sample value (Phillips *et al.*, 2006). Maxent produces habitat suitability maps with presence-only data for all species that will be modelled. These maps do not predict the probability of presence, but provide relative index of suitability (Anderson *et al.*, 2003). They are usually produced by Maxent in binary classification (producing binary habitat maps) displaying suitable and unsuitable habitats. In producing habitat suitability maps by Maxent, a threshold value of "Ten (10) percentile training presence logistic thresholds" was used (Pearson *et al.*, 2004). Typically a 'threshold' chosen from Maxent converts continuous scale into a binary response of predicted suitable and unsuitable habitats. This was obtained from Maxent output and used as a minimum probability for habitat suitability (i.e. the minimum value for suitable habitat). Therefore, all predicted areas on produced maps having values greater than 0.5 are considered suitable habitats for persistence of the species (Stabach, 2009). On the other hand, estimates of the potential distribution for each species was done by relating the ratio of pixel counts in binary maps (i.e. number of pixels occupied by suitable versus unsuitable habitats). Results were then displayed for inference in a table in form of percentages.

3.4.2.3 Predictor variable importance

A jack-knifing procedure was used to examine the importance of each environmental predictor variable influencing the distribution of both tree species (Phillips *et al*., 2006). This method runs the model by excluding one environmental variable at a time, in order to see how effective the model is without a variable, and then runs a model using only a single variable each time (Turner, 2014). The Jack-knifing shows the training gain of each variable if the model was run in isolation, and compares it to the training gain with all the variables (Phillips *et al*., 2006). Simply, important variables will reduce the green bar and have a large blue bar (Jobe and Zank, 2008). Hence, variable that attained higher gain under this study was considered the most useful single variable for predicting the occurrence distribution of a particular species (Phillips *et al*., 2006). Furthermore, the higher the contribution, the more impact that particular variable had on predicting the occurrence of the corresponding species (Phillips *et al*., 2006).

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Model Performance

Maxent models of all tree species for the current conditions performed better than random, with average training and test AUC values of 0.8497 and 0.8577±0.0235 respectively (Table 2). Generally, an AUC value between 0 and 0.5 is an indication of predictions no better than random, while values closer to 1.0 indicate better model performance (Fielding and Bell, 1997 and Peterson *et al*., 2011). The models for this study may be considered robust and that, they provide reliable information on the distribution of suitable habitats of all species involved. However, there was a considerable variation in AUC scores among species. Elith *et al*. (2006) suggested that Maxent models that had an AUC values greater than 0.75 are considered to be useful. For this present study, AUC values for most species' model built by Maxent were greater than that suggested by Elith *et al*. (2006). These models have therefore shown high predictive power to suitable habitats for all species. Additionally, incidences of over estimations to AUC values up to one (~1) as the case reported by Chitiki (2014) was not observed to all models for all species modeled. Over prediction or under prediction by the model were avoided by setting maximum iteration value on Maxent to 5000 so as to give the model adequate time for convergence (Phillips *et al*., 2006). On the other hand, records of negative one (-1) to AUC standard deviation values as reported in a study by Chitiki (2014) were as well not observed. This proved that AUC standard deviation values for all species studied were calculated by the software due to available adequate presence records assigned as test data for model accuracy (Philips *et al*., 2006).

AUC values under (ROC) have been widely used in early studies to describe the extent and specialization in species' distribution (Ashcroft, 2011 and Cord *et al*., 2012). Under the present study, extent and specialization in species distribution using AUC values has been as well considered. It was found that all species models' built by Maxent varied. Few species showed higher AUC values than others. In general, and consistent with the findings reported from various literatures (Hernandez *et al*., 2006, Ashcroft, 2011 and Cord *et al*., 2012), it was observed that higher AUC values shown by few models were found from few species with small sample sizes. *Salvadora persica* is a good example under this category with fewer number of presence records. However, the species was found with the highest AUC scores among other species studied. According to Ashcroft (2011), this species can be good examples of habitat specialists. Usually, habitat specialist species have limited geographical ranges and are less distributed (Cord *et al.*, 2012). This is because they are restricted in habitats that only meet their ecological requirements (Cord *et al.*, 2012). Sillero *et al*. (2012) suggested that species with restricted range could be more accurately modelled than widely dispersed species. This may be the reason for *Salvadora persica* to attain higher AUC scores than others. Higher AUC values from species with fewer presence records have been as well reported by Sillero *et al*. (2012) and Ashcroft (2011) and confirmed clearly in early studies by Stockwell and Peterson (2002); Seoane *et al*., 2005 and VanDerWal *et al*., 2009. However, specialized habitat species reported in Ashcroft (2011), had additional ecological features of clustered distributions. It is assumed by the author that clustering in one area restricted these species in other habitats and that, upon habitat change, they are highly vulnerable to quickly losing their suitable habitats.

Species that occupy large habitats within an area are generally regarded as habitat generalist species. These species are predicted to have large area of suitable habitats and usually show a lower maximum achievable AUC value compared to habitat specialists (Ashcroft *et al*., 2011). *Acacia tortilis* and *Acacia robusta* are good examples under this category. These species had many presence records and showed wide range of distribution within the area. However, in some study areas species were a bit clustered in respect to the river flow. It is reported in Jetz *et al*. (2007), that wide ranging species show minimal loss of habitat range since large ranges are assumed to provide a buffer against environmental change.

Table 2: Average Training, Test and AUC STD values for the replicate runs in the Maxent Models

	Species Name		*Acacia_robusta*	*Acacia_tortilis*	*Albizia_petersiana*	*Celtis_africana*	*Euclea_divinorum*	*Ficus_sycomorus*	*Ficus_thonningii*	*Rauvolfia_caffra*	*Salvadora_persica*	*Trichilia_emetica*	**Average**
Current Conditions	**Training**	**AUC**	0.9562	0.9609	0.7107	0.694	0.7319	0.9731	0.7174	0.9644	0.9285	0.86	0.8497
	Test	**AUC**	0.9886*****	0.9895*****	0.6839	0.6668	0.7835	0.9768*****	0.7078	0.9817*****	0.9991*	0.7892	0.8577
	AUC	**STD**	0.002	0.003	0.0033	0.0355	0.0102	0.0018	0.0116	0.0012	0.0004	0.0235	±0.0235

***** Species with higher **'Test AUC'** values

4.2 The Current Distribution Status of Tree Species

A total of forty five (45) tree species were found, obtained from 325 occurrence records for all species surveyed, covering lower and higher elevation of the Manyara National Park along the Chemchem River (Appendix 12). These species were identified into their scientific names and belonged to 36 genera under 21 families. Dominant genera were *Fabaceae*, *Sapindaceae* and *Meliaceae* while dominant families were *Fabaceae* (16.3%), *Moraceae* (11.1%), *Sapindaceae* (9.9%) and *Meliaceae* (7.7%) (Table 3).

Table 3: Dominant families of selected tree species within the study area

Family	*Fabaceae*	*Moraceae*	*Sapindaceae*	*Meliaceae*
% Dominance	16.3	11.1	9.9	7.7

Note: % = Percentage

Additionally, the most dominant tree species based on index of dominance were *Acacia tortilis* dominated (0.0415), *Ficus sycomorus* (0.0366), *Acacia robusta* (0.0135) *Trichilia emetica* (0.0127), *Salvadora persica* (0.0043) and *Celtis africana* (0.0010) (Table 4; Appendix 13). The total number of species (45 species) documented in this study site is slightly lower than those reported by Faustine (2008). The author reported a total number of 47 tree species from the same study area. This difference in the total number of species may be due to differences in sampled area and procedures. Also, since it is a slight difference, it may be due to human errors during enumeration. Climate change and variability, edaphic variability and anthropogenic activities (Giliba, 2011) and natural phenomenon (Sarkar and Devi, 2014) have been as well reported as significant factors influencing species presence and distribution. These factors might have as well contributed to differences in the total number of species reported in this study.

Dominant species refers to species with considerable and prominent effects on their habitats in respect to size and frequency (Ardakani, 2009) and can utilize resources and have an extensive influence on the environmental conditions (Razavi, 2012). Although many tree species were encountered in lower elevation of the study site, *Acacia* species, and particularly *Acacia tortilis* and *Acacia robusta* were dominant in lower elevation. This area covered the lower slopes of the study site that extended adjacent to shores of Lake Manyara and mainly composed woodland vegetation. On the other hand, *Ficus sycomorus* and *Trichilia emetica* dominated in riverine and high ground water forest vegetation. Since, higher elevation had few species, it may be considered that presence of steeper slopes, illegal tree cut and other anthropogenic activities restricted the presence and distribution of most species. There were evidences of some farming activities and fresh cut trees in catchments areas of the river studied. Therefore, the suitability of most species decreased with increasing elevation.

Table 4: Selected dominant tree species in the study area

S/N	Species name	Abundance	Index of dominance	Relative abundance (%)
1	*Acacia tortilis*	65	0.0415	20.3762
2	*Ficus sycomorus*	61	0.0366	19.1223
3	*Acacia robusta*	37	0.0135	11.5987
4	*Trichilia emetica*	36	0.0127	11.2853
5	*Salvadora persica*	21	0.0043	6.5831
6	*Celtis africana*	10	0.0010	3.1348
7	*Cordia sinensis*	9	0.0008	2.8213
8	*Albizia petersiana*	8	0.0006	2.5078
9	*Ficus thonningii*	7	0.0005	2.1944
10	*Euclea divinorum*	6	0.0004	1.8809

4.2.1 Species responses to environmental variables

4.2.1.1 Contribution of predictor variables to current distribution of species

The contribution of each environmental predictor variables to the current distribution of ten (10) dominant tree species in the study area is shown in Table 5. For most species the current distribution was influenced by elevation, temperature seasonality and slope. Annual mean temperature, annual precipitation, precipitation of the driest quarter and temperature of the driest quarter showed non-contribution to some few species studied. Strong influence of environmental variables in determining the distribution of species was shown by elevation. The variable showed significant predictive contribution to particular species of *Albizia petersiana* (83.05%) and *Ficus thoningii* (75.72%). Therefore, elevation, slope and temperature seasonality may be regarded as three (3) strongest environmental predictor variables that influenced mostly the presence and distribution of species.

Environmental predictor variables can exert direct or indirect effects on species along a gradient. They can act as limiting factors (or regulators), by controlling species eco-physiology (e.g. temperature, water, soil composition); they can as well act as *disturbance*, defined as all perturbations affecting environmental systems and they can act as *resources*, defined as all compounds that can be assimilated by organisms (e.g. energy and water) (Chitiki, 2014). When closely investigating the variable contribution table results (Table 5), both topographical and bioclimatic variables appeared to play important influence in determining the presence and distribution of tree species. In contrary, a study by Singh (2013) showed that, the distribution of two critically riparian endangered tree species was only influenced by topographical variables in particular slope and elevation.

Table 5: **Percentage Variable Contributions in Maxent Models over 10 replicate runs**

Species										
Variables	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**	**(j)**
mt	0.00*	6.89	0.00	0.01	0.07	0.00*	0.00*	0.01	1.03	1.44
ts	47.68	46.19	11.59	22.11	10.95	35.24	17.44	44.53	31.38	1.23
ap	0.24	2.21	0.00*	0.14	0.96	2.53	0.00*	1.97	5.89	13.45
pq	1.65	0.89	0.00*	0.00*	0.42	0.91	0.01	4.74	0.07	3.10
tq	9.06	4.75	1.64	6.33	0.22	6.44	0.00*	10.54	14.81	0.00*
sl	27.84	25.48	3.72	4.10	30.08	36.90	6.83	22.55	35.12	20.88
el	13.53	13.59	83.05**	67.31	57.3	17.98	75.72**	15.66	11.70	59.90

Note: **= Values for the variables with strong contribution *= values for the variables with non-contribution. **Abbreviations**: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; el=elevation

Species: (a)*Acacia robusta* (b) *Acacia tortilis* (c) *Albizia petersiana* (d) *Celtis africana* (e) *Euclea divinorum* (f) *Ficus sycomorus* (g) *Ficus thonningii* (h) *Rauvolfia caffra* (i) *Salvadora persica* (j) *Trichilia emetica*

On the other hand, Chitiki (2014) reported a strong influence of bioclimatic variables in influencing the distribution of tree species in Eastern Usambara and Udzungwa mountains of the Eastern Arc Mountains (EAMs). Under this study, few bioclimatic variables and in particular temperature seasonality presented strong contribution in determining species distribution. It is reported by Gholinejad (2012) that, tree species distribution over a high geographical range is controlled by climatic factors, mainly temperature and rainfall. However, the distribution of tree species over a small range is related to other factors such as edaphic and topographical factors (Gholinejad, 2012 and Singh, 2013). A study by Singh (2013) reports further that, when small area size is studied by using environmental variables, the influence of some bioclimatic variables might not be significant. For this study and as stated earlier on, the influence of some bioclimatic variables in determining the presence and distribution of species was not significant. Singh (2013) reports that, when a study is conducted in a small area, climatic factors usually remain fairly constant throughout the study site while other factors such as land use, topography and vegetation for example keep varying significantly over the landscape. Therefore, it is assumed by this study that strong influence observed by slope and elevation to most species studied might be due to variation of topography within the area studied. Furthermore, since the area studied is relatively small, arguments presented in a study by Singh (2013) may have played a big role for the low contribution shown by few bioclimatic variables in influencing the presence and distribution of species.

Maxent modelling allows for performing an internal jack-knife test to quantify the importance of the variables in influencing the distribution of tree species (Singh, 2013 and Chitiki, 2014). Jobe and Zank, (2008), reported that, important variables will reduce the green bar and have a large blue bar (Figure 2). Results for jackknife test for variable importance revealed that both bioclimatic and topographical variables have influence in determining the distribution of most species (Figure 2 (a), (b) and (c)). It was observed that, elevation and temperature seasonality influenced the distribution of most species in the study area. These variables produced the highest gain when used in isolation.

According to Singh (2013), a variable with highest gain as shown by a Jack-knife test results in Maxent Modeling has the most useful information by itself for estimating the distribution of the species. Therefore, the increase of these variables increased the probability of occurrences of most species and determined their distribution. On the other hand, these variables decreased the gain the most when omitted and according to Singh (2013), the variables (elevation and temperature seasonality) appear to have the most information that is not present in other variables. Ashcroft *et al*. (2011), reports that the corresponding variables are likely to be important determinants of species distribution and local vegetation patterns in the area studied. However, other factors and especially for the present study (annual mean temperature, temperature of the driest quarter and precipitation of the driest quarter) were also important for other species, at different scales, or in different study areas (Ashcroft *et al*., 2011).

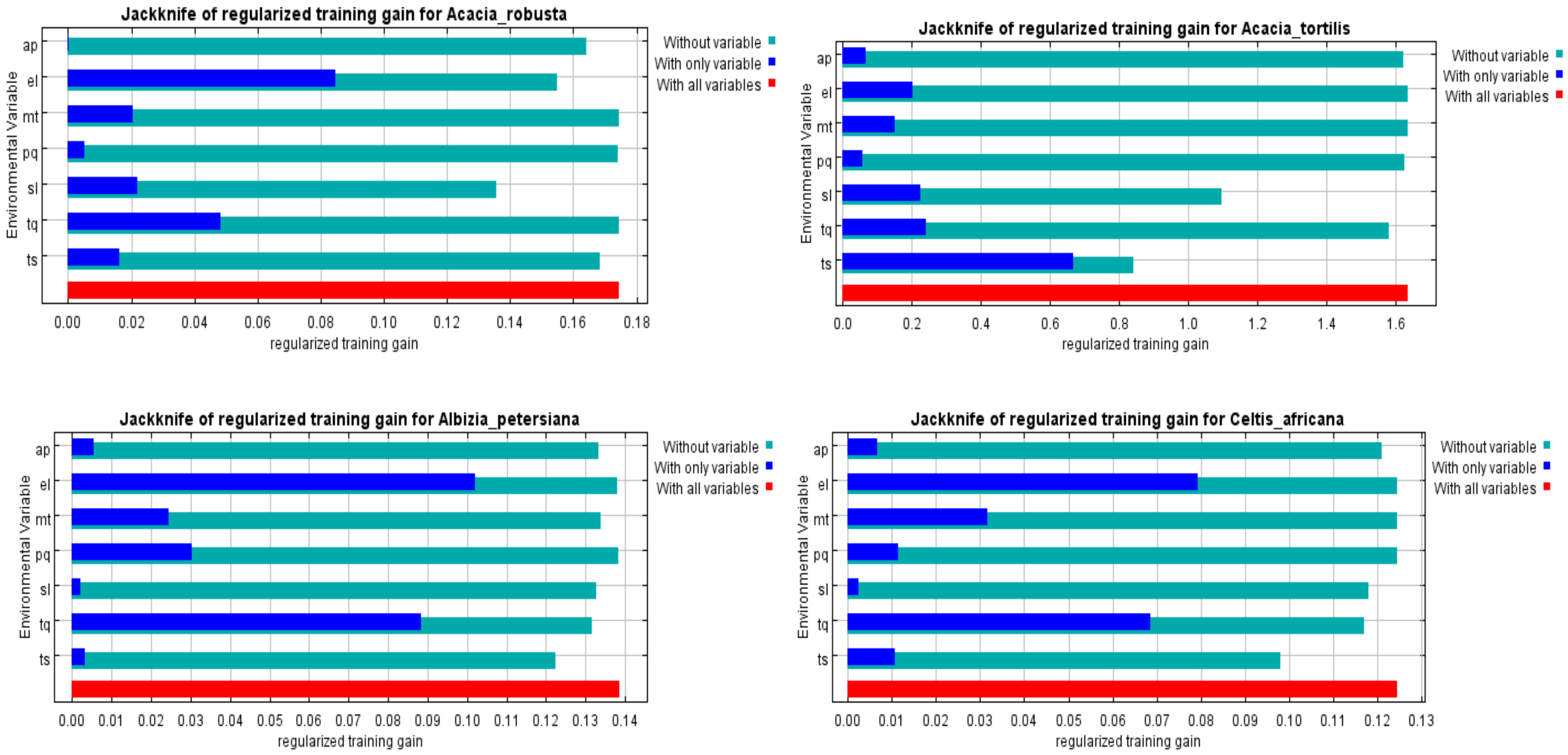


Figure 2 (a): Results of the jackknife test of variable importance for environmental variables for species of *A. robusta, A. tortilis, A. petersiana* and *C. africana*

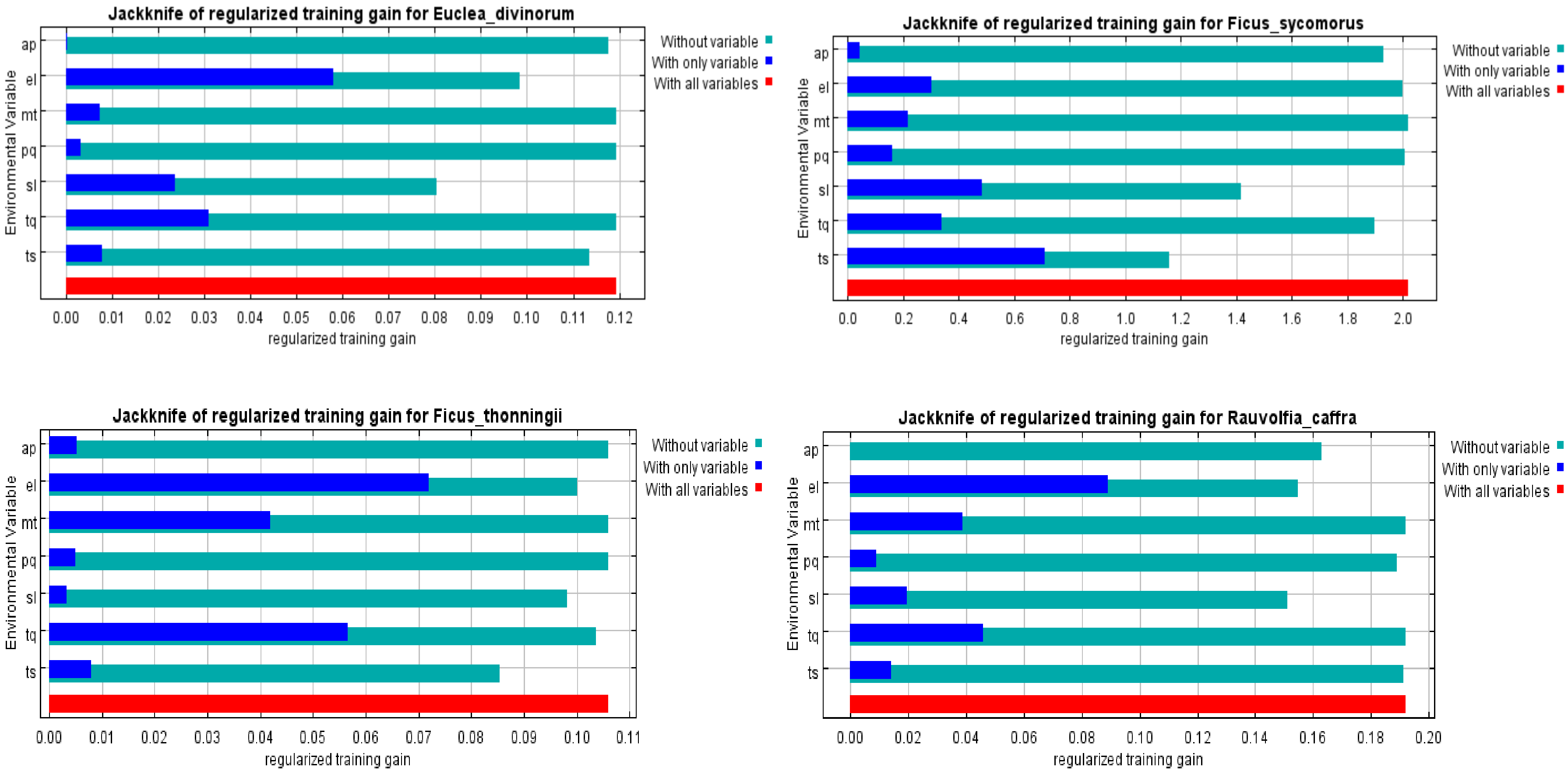


Figure 2 (b): Results of the jackknife test of variable importance for environmental variables for species of *E. divinorum, F. sycomorous, F. thoningii* and *R. caffra*

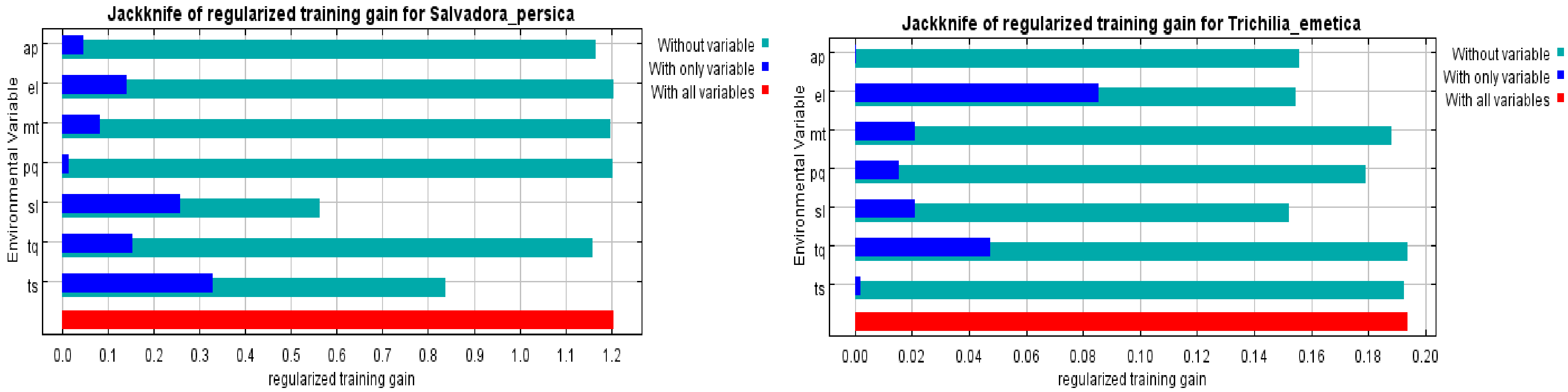


Figure 2 (c): Results of the jackknife test of variable importance for environmental variables for species of *S. persica* and *T. emetica*

4.2.1.2 Species probability of occurrence (Habitat Suitability)

The relationship between the response of the species and one top environmental predictor variable is shown in Figure 3. Elevation and temperature seasonality dominated the probability of occurrence for most species. Suitable habitats increased with increasing temperature seasonality for *Acacia robusta*. There was a decrease in suitable habitats for most species with increasing elevation. Most species occurred in lower elevation of the study area (Figure 3).

Tree species showed different response curves to various environmental predictor variables used for modelling. Response curves depicted the probability of occurrence (habitat suitability) of a species. Results showed that probability of occurrences for most species was affected with both bioclimatic and topographical variables. Suitable habitats for most species increased with the increasing in annual precipitation and temperature of the driest quarter (Appendix 2-11). A sharp increase in habitat suitability was observed for species of *Acacia tortilis* and *Ficus sycomorus* with increasing annual precipitation and mean temperature of the driest quarter. On the other hand, the increase in elevation decreased suitable habitats of most species of *Acacia robusta, Euclea divinorum, Rauvolfia cafra* and *Trichilia emetic*a. Therefore, for most species, lower elevation was mostly suitable for their growth and survival.

Topography affects species mostly indirectly through its correlation with temperature and precipitation, but also through landscape diversity and configuration, soil and water dynamics (Guisan *et al*., 2003). Through the analysis of various response curves temperature and rainfall have shown significant influence in determining suitable habitats for most species. The increase in rainfall increased probability of occurrence of most species. Since, most species encountered were river-line species and mostly found in lowland areas; the significance influence of rainfall and temperature in determining suitable habitats of most species was realized. These results are consistent in early studies by Chitiki (2014). The author reported on strong influence of rainfall and temperature in determining suitable habitats of most species studied. Although, species response curves have revealed a clear relationship of bioclimatic variables and species studied, elevation and slope on the other hand may be regarded as being indirectly affecting the species through temperature and rainfall (Guisan *et al*., 2013). Results show that, in higher elevation, suitable habitats decreased for most species. For, lowland species such as *Acacia robusta*, *Acacia tortilis* and *Salvadora persica* among others, the increase in elevation can be considered as the limiting factor for their survival and distribution.

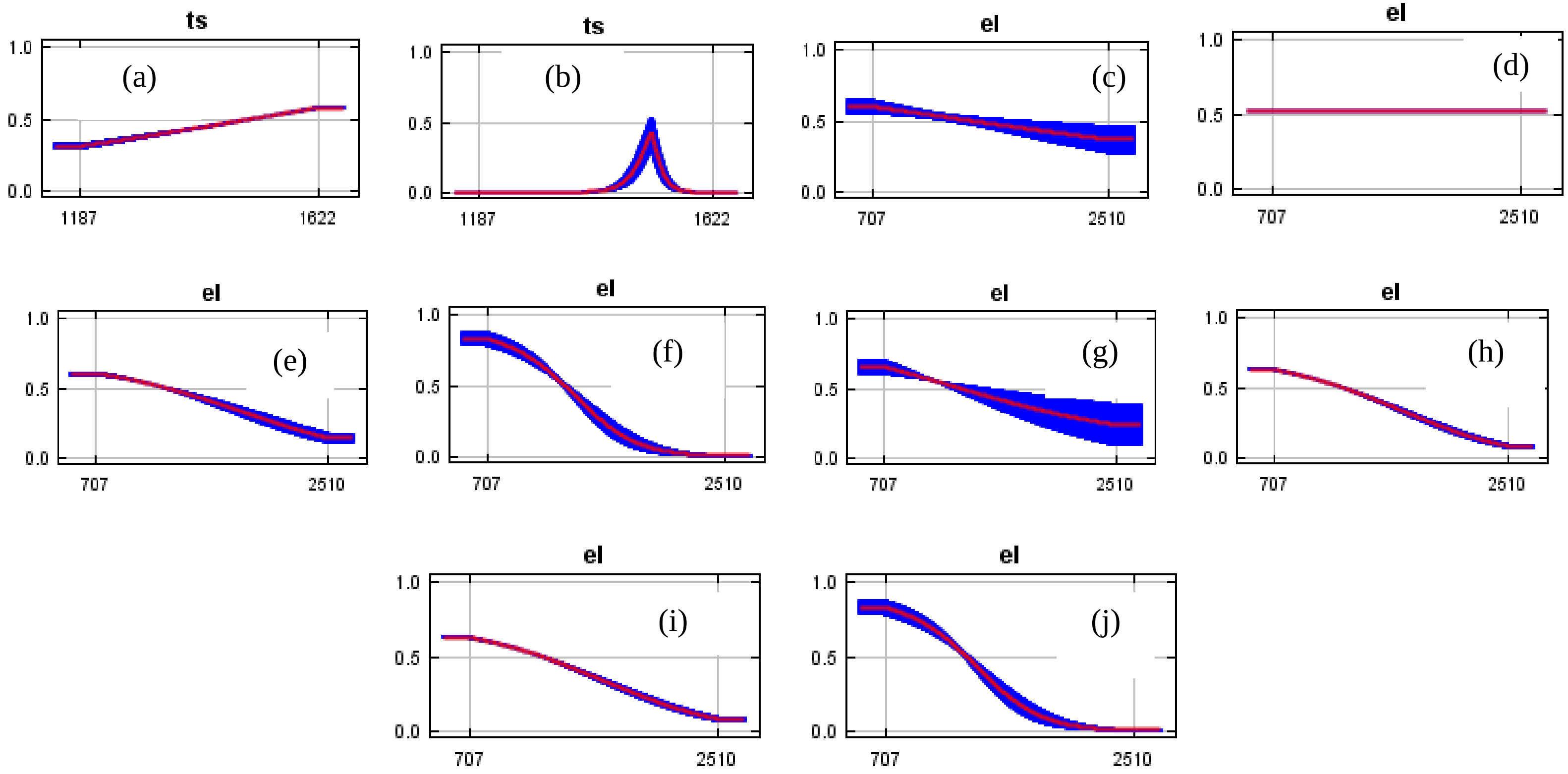


Figure 3: Response curves showing the relationships between the probability of presence of a species (y-axis) and one top environmental predictor variables (x-axis) under current conditions

Note: Values shown are averaged under 10 replicate run; dark margin shows +/- 1SD calculated over 10 replicates: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation: **Species:** (a) *Acacia robusta* (b) *Acacia tortilis* (c) *Albizia petersiana* (d) *Celtis africana* (e) *Euclea divinorum* (f) *Ficus sycomorus* (g) *Ficus thonningii* (h) *Rauvolfia caffra* (i) *Salvadora persica* (j) *Trichilia emetica*

4.2.1.3 Predicted current suitable habitats for selected dominant tree species

The current predicted suitable habitats for selected dominant tree species is shown in Figure 4 (a) and (b). For most species, suitable habitats were predicted in central, north eastern and some patches extending towards south eastern parts of the area. Lower elevation which covered most of the central parts of the study area had more suitable habitats for supporting growth and development of most species. Species with more range of suitable habitats were *Acacia robusta* (13.04%), *Acacia tortilis* (8.1%), *Trichilia emetica* (6.06%) and *Albizia pertesiana* (5.17%). Species that showed small range of their suitable habitats within the study area were *Celtis africana* (2.47%), *Ficus thoningii* (2.02%) *and Ficus sycomorus* (01.05%) (Figure 4(a) and (b) and Table 6). It is observed in this study that, species with restricted ranges had high AUC values and fewer presence records than widely dispersed species (see sect. 4.1).

Table 6: Percentage suitable and unsuitable habitats for selected dominant tree species within the study area

Species Name	*Acacia_robusta*	*Acacia_tortilis*	*Albizia_petersiana*	*Celtis_africana*	*Euclea_divinorum*	*Ficus_sycomorus*	*Ficus_thonningii*	*Rauvolfia_caffra*	*Salvadora-_persica*	*Trichilia_emetica*
Suitable Habitat	13.04*****	8.10*****	5.17	2.47	4.98	01.5	2.02	03.6	03.5	6.06
Unsuitable Habitat	86.96	91.90	94.83	97.53	95.02	98.5	97.98	96.4	96.5	93.94

Note: * Species with more habitat range of suitable habitats within the study area

Range loss being as the result of environmental change, varies dramatically across species (Chitiki, 2014). The largest potential loss of range size occurs among species that have restricted ranges. Under the present study species such as *Celtis africana*, *Ficus thoningii* and *Ficus sycomorus* may be considered to be in this category and that, for species that already have small population sizes or range size or specialized habitat requirements are exposed to a high risk of extinction (Jetz *et al*., 2007).

However, for many species encountered their suitable areas were fragmented and the distribution followed the pattern of river flow (Figure 4). Fragmentation of suitable habitats has been as well reported by Singh (2013) in modeling of *Shorea johorensis* species. Rainfall among other variables had significant contribution in determining suitable habitats of most species. This study argues that, presence of steeper slopes limited the distribution of most species and lowered suitable habitats in higher elevation. On the other hand, temperature and rainfall increased the suitability of habitats in lower elevation for most species. A visual examination of Figure 4 (habitat suitability maps) shows that, there were significant variations of suitable habitats for all species under current conditions. Species that showed wider range of suitable habitats in this study may generally be regarded as "generalists" species (Ashcroft *et al*., 2011). These species occupied large areas and may be considered lesser sensitive to risks of losing suitable habitats than specialists' species. Species in this group were *Acacia robusta*, *Acacia tortilis*, *Trichilia emetica* and *Albizia pertesiana*.

Environmental change and in particular climate change may affect the ability of nature reserves (Manyara National Park being among of them) to protect plant species or leading to physiological stress and damage to plants (Araujo *et al*., 2011). It has been reported that species highly at risks of damage are narrow ranged species. This is because when suitable habitats of plant species shift outside of their range to which these species are adapted, might face an increased risk of extinction (Thuiller *et al*., 2005). Since, similar situation might happen in Lake Manyara under the face of changing climate, prioritizing conservation needs targeting species at risks are therefore inevitable. Furthermore, results show that, areas sited at higher elevation were found to have least suitable habitats for supporting most of the species under this study. Since, Maxent software maps the fundamental niche (different from occupied niche) of the studied species using bioclimatic variables (Singh, 2013), this study agrees with several findings (Pearson 2007; Murienne *et al*., 2009 and Kumar, 2009) that in some areas, suitable habitats may have been over predicted.

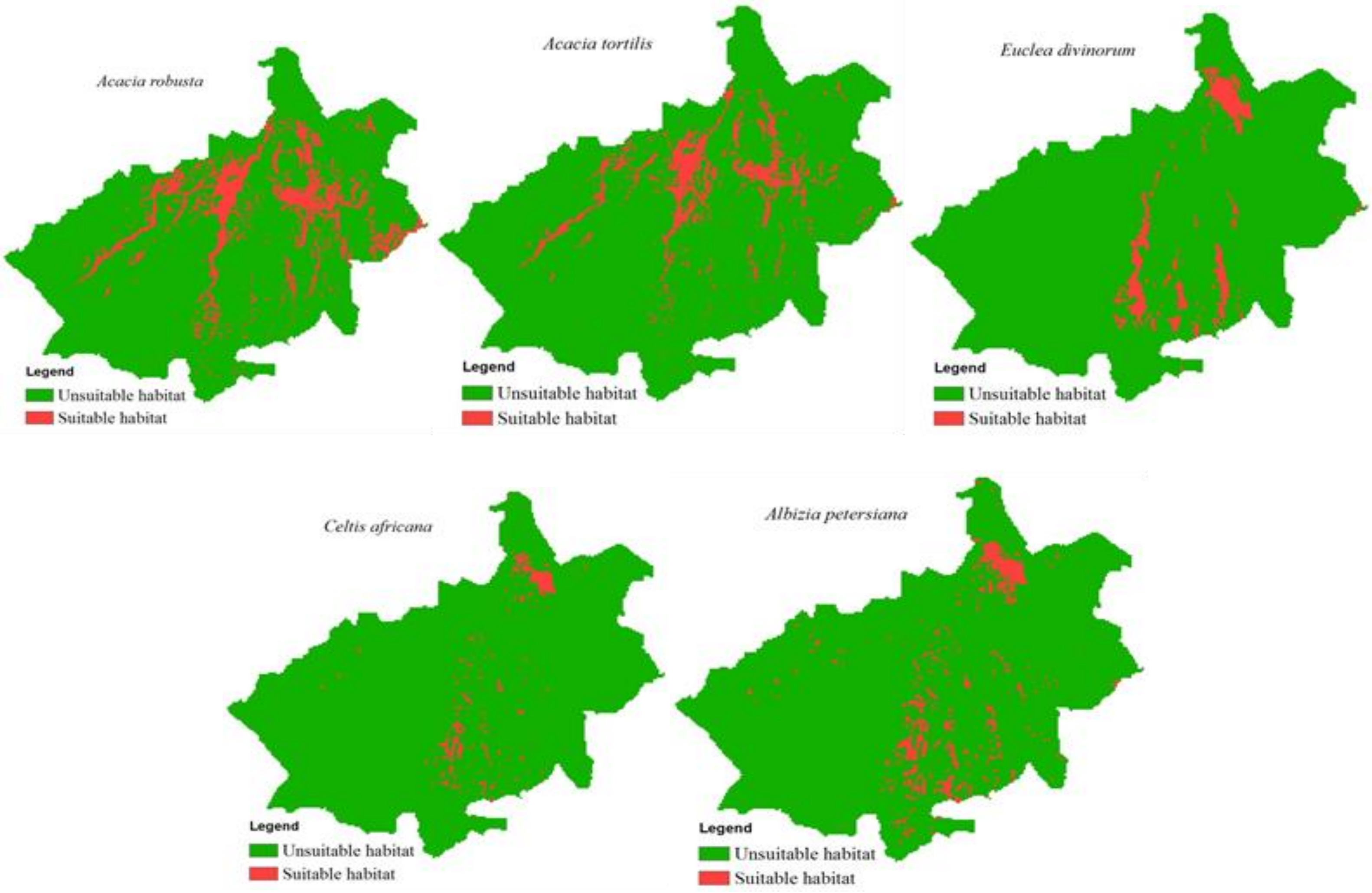


Figure 4 (a): Predicted current suitable habitats for *A. robusta, A. tortilis, E. divinorum, C. Africana and A. Petersiana*

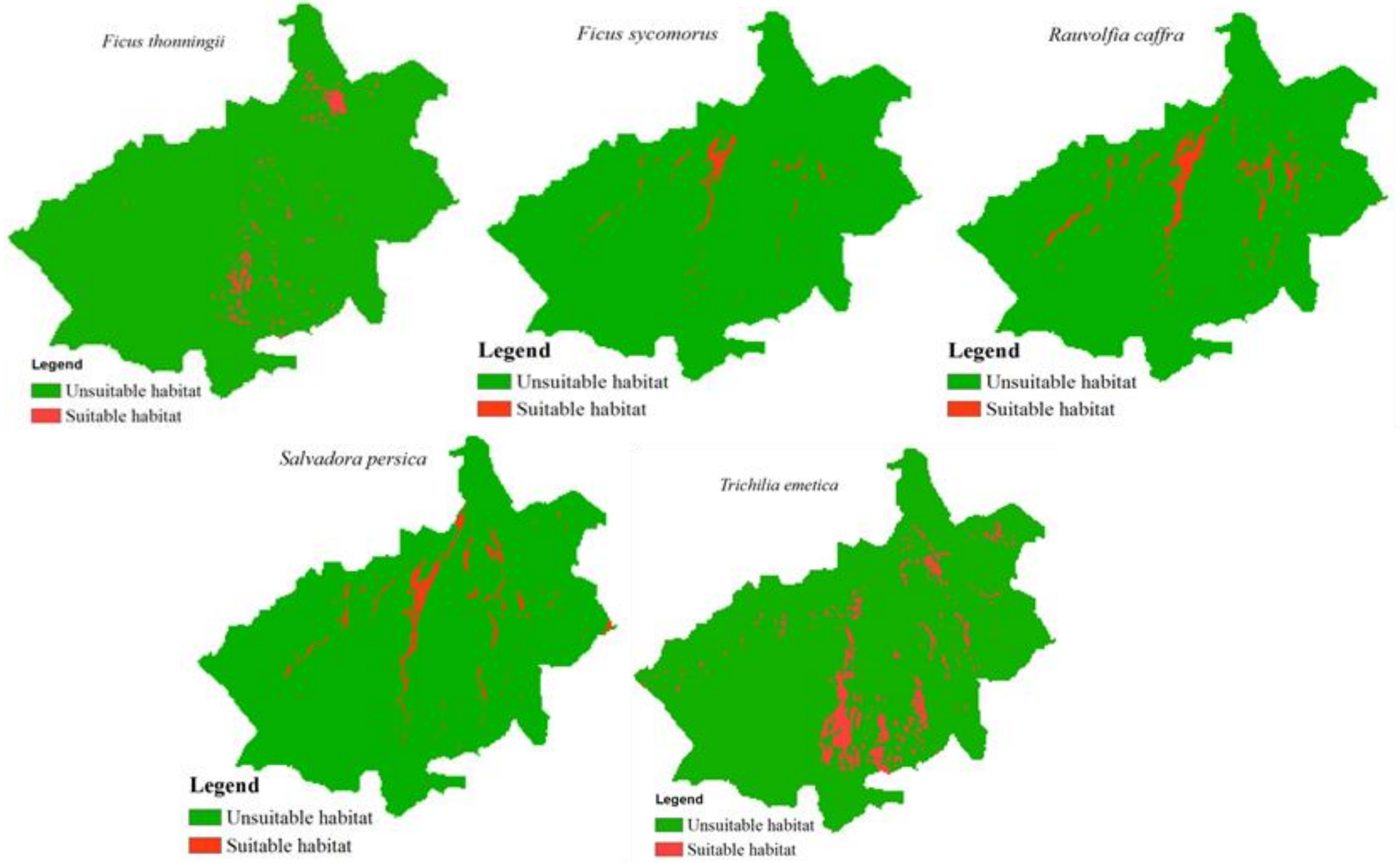


Figure 4 (b): Predicted current suitable habitats for *F. thoningii, F. sycomorous, R. caffra, S. persica* and *T. emetica*

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The influence of environmental variables on the distribution of selected tree species within the study area was realised. This study has been able to identify key environmental variables that influence the distribution of tree species in the study area. Further, the research has been able to successful predict suitable habitats for selected dominant tree species under current conditions. Maxent models of all tree species for the current scenarios performed better than random, with average training and test AUC values of 0.8497 and 0.8577±0.0235 respectively. Species with small sample sizes showed higher AUC values. A total of forty five (45) tree species were found, obtained from 325 occurrence records. The species belonged to 36 genera under 21 families. Dominant families were *Fabaceae* (16.3%), *Moraceae* (11.1%), *Sapindaceae* (9.9%) and *Meliaceae* (7.7%). Dominant species were *Acacia tortilis* (0.0415), *Ficus sycomorus* (0.0366), *Acacia robusta* (0.0135) and *Trichilia emetica* (0.0127). Species were distributed following the river flow while lower elevation was occupied by most species. For most species, the current distribution was influenced by elevation and temperature seasonality. Significant predictive contribution of elevation was observed to particular species of *Albizia petersiana* (83.05%) and *Ficus thoningii* (75.72%). Jack-knife test showed that both elevation and temperature seasonality had most useful information for estimating the distribution of the species. Their increase increased the probability of occurrences of most species.

Suitable habitats increased with increasing in annual precipitation and temperature of the driest quarter. There was a sharp increase in habitat suitability for species of *Acacia* *tortilis* and *Ficus sycomorus* with increasing mean temperature of the driest quarter. However, suitable habitats decreased with increasing elevation. For, lowland species such as *Acacia robusta, Acacia tortilis* and *Salvadora persica*, the increase in elevation may be considered as the limiting factor for their survival and distribution. There was a potential habitat variation for all species under current conditions. For most species, suitable habitats were predicted in central and north eastern of the study area. Habitats showed some patches extending towards south eastern parts of the area and were fragmented. Lower elevation had more suitable habitats for supporting growth and development of most species. Species with more range of suitable habitats were *Acacia robusta* (13.04%), *Acacia tortilis* (8.1%), *Trichilia emetica* (6.06%) and *Albizia pertesiana* (5.17%).

5.1 Recommendations

This study has achieved showing the current distribution of tree species and successful predicting their suitable habitats within the study area under current conditions. Important environmental variables and the responses of tree species against these variables have been clearly shown. However, the following are recommended;

i. Since, higher elevation showed poor habitats and inhabited few species; it is recommended that, park management should help the communities conserve the upper areas of the river through patrolling so as to minimize illegal tree cut and farming in catchment areas. These human activities were evident during data collection. The efforts may in future build up continuous stream flow which is important for the growth and development of lower and higher elevation plant species.

ii. The park management should think of identifying management priorities to restore natural habitats for the species observed with decreasing suitable habitats. Information on species with decreased habitats will provide the park management and other conservation practitioners with estimates of the spatial distributions of species requiring more attention. This may enhance more effective conservation targeting fragmented and unsuitable habitats and also in the management of the Manyara ecosystems at large.

iii. The present study predicted successful suitable habitats for the selected dominant species. Identification of suitability habitats may also be important to the management of the Manyara national park in aspects of resource management particularly in the face of inadequate funds and resources during biodiversity monitoring and survey within the study area.

REFERENCES

Anderson, R. P., Lew, D. and Peterson, A. T. (2003). Evaluating predictive models of species' distributions: criteria for selecting optimal models. *Ecological Modeling* 162: 211 – 232.

Araújo, M. B. and Guisan A. (2006). Five (or so) challenges for species distribution modelling. *Journal of Biogeography* 33: 1677 – 1688.

Araújo, M. B. and Luoto, M. (2007). The importance of biotic interactions for modelling species distributions under climate change. *Global Ecology and Biogeography* 16: 743 – 753.

Araujo, M. B., Pearson, R. G. and Thuiller, W. (2005). Validation of species–climate impact models under climate change. *Global Ecological Biogeography* 11: 1504 – 1513.

Ardakani, M. (2009). *Ecology.* Tehran University Press, Iran. 340pp.

Ashcroft, M. B., French, K. O. andChisholm, L. A. (2011). An evaluation of environmental factors affecting species distributions. *Ecological Modelling* 222(3): 524 – 531.

AWF (2013). *Lake Manyara Watershed Assessment: Progress Report Babati District, North-central Tanzania.* African Wildlife Foundation, Nairobi, Kenya. 27pp.

Berry, P. M., Dawson, T. P., Harrison, P. A. and Pearson, R. G. (2002). Modelling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. *Global Ecological Biogeography* 11: 453 – 462.

Botkin, D. B., Saxe, H., Araujo, M. B., Betts, R., Bradshaw, R. H. W. and Cedhagen, T. (2007). Forecasting effects of global warming on biodiversity. *Bioscience* 57: 227 – 236.

Chitiki, A. K. (2014). Implications of ecological gradients and climate change on tree species composition, diversity and distribution in two eastern arc mountains. Thesis for the Award of PhD at Sokoine University of Agriculture, Morogoro, Tanzania, 240pp.

Cohen, S. A., Halfpenny, J., Lockley, M. and Michael, E. (1993). Modern vertebrate tracks from Lake Manyara, Tanzania and their paleobiological implications. *Paleobiology* 19(4): 433 – 458.

Cord, F. A., Klein, D., Mora, F. and Dech, S. (2012). *Suitability of Land Cover and Remote Sensing Data for Modelling Species Distributions*. International Congress on Environmental Modelling and Software, Germany. 8pp.

Cord, F. A., Meentemeyer, R. K., Leitao, P. J. and Vaclavik, T. (2013). Modelling species distributions with remote sensing data: Bridging displinary perspectives. *Journal of Biogeography* 40: 2226 – 2227.

De Chazal, J. and Rounsevell, M. D. A. (2008). Land use and climate change within assessments of biodiversity change: *Global Environmental Change* 19(2009): 306 – 315.

Elith, J. and Leathwick, J. R. (2009). Species distribution models: ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* 40: 677 – 697.

Elith, J., Graham, C. H., Anderson, R. P., Dudik, M., Ferrier, S., Guisan, A., Hijmans, R. J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L. G., Loiselle, B. A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J. M., Peterson, A.T., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R. E., Soberon, J., Williams, S., Wisz, M. S. and Zimmermann, N. E. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29: 129 – 151.

Faustine, R. (2008). Impacts of farming systems on riparian vegetation of Lake Manyara upper catchment at Chemchem and Endabashi rivers in Karatu Districts, Tanzania. Dissertation for the Award of MSc Degree at Sokoine University of Agriculture, Morogoro, Tanzania, 70pp.

Feilhauer, H., He, K. S. and Rocchini, D. (2012). Modeling species distribution using niche-based proxies derived from composite bioclimatic variables and MODIS NDVI. *Remote Sensing* 4: 2057 – 2075.

Gholinejad, B., Farajollahi, A. and Pouzesh, H. (2012). Environmental factors affecting on distribution of plant communities in semiarid area: Kamyaran rangelands, Iran). *Annals of Biological Research* 3(8): 3990 – 399.

Guisan, A. and Thuiller, W. (2005). Predicting species distribution: Offering more than simple habitat models. *Ecology Letter* 8: 993 – 1009.

Guisan, A. and Zimmermann N. E. (2000). Predictive habitat distribution models in ecology. *Ecology Modelling* 135: 147 – 186.

Hannah, L., Midgley, G. F. and Lovejoy, T. (2002). Conservation of biodiversity in a changing climate. *Conservation Biology* 16: 264 – 268.

Hernandez, P. A., Graham, C. H., Master, L. L. and Albert, D. L. (2006). The effect of sample size and species characteristics on performance of different species distribution modeling methods. *Ecography* 29: 773 – 785.

Hijmans, R. J., Cameron, S. E., Parra J. L., Jones P. G. and Jarvis A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25: 1965 – 1978.

Hu, N., Fan, Y. L., Ding, S. Y. and Lu, X. L. (2008). Classification of plant functional types based on dominant tree species in the forest ecosystem at Funiu Mountain National Reserve, East China. *Chines Journal of Plant Ecology* 32: 1104 – 1115.

Iverson, L. R. and Prasad, A. M. (1998). Predicting abundance of 80 tree species following climate change in the eastern United States. *Ecological Monographs* 68: 465 – 485.

Jetz, W., Wilcove, D. S. and Dobson, A. P. (2007). Projected impacts of climate change and land-use change on the global diversity of birds. *PLOS Biology* 5: 1211 – N 1219.

Jobe, R. T. and Zank, B. (2008). *Modelling Species Distribution for the Great Smoky Mountains National Park Using Maxent*. University of Carolina, USA. 27pp.

Kerr, J. T. and Ostrovsky, M. (2003). From space to species: ecological applications for remote sensing. *Trends in Ecology and Evolution* 18: 299 – 305.

Khanum, R., Mumtaz, A. S. and Sunil, K. (2013). Predicting impacts of climate change on medicinal asclepiads of Pakistan using Maxent modeling: *Acta Oecologica* 49(2013): 23 – 31.

Kihwele, E. S., Lugomela, C. and Howell, K. M. (2014). Temporal changes in the lesser flamingos population (*Phoenicopterus minor*) in Relation to Phytoplankton Abundance in Lake Manyara, Tanzania. *Open Journal of Ecology* 4: 145 – 161.

Kumar, S., Spaulding, S. A. and Stohlgren, T. J. (2009). Potential habitat distribution for the freshwater diatom Didymospheniageminata in the continental US. *Frontiers in Ecology and the Environment* 7(8): 415 – 420.

Lamb, J. M., Ralph, T. M. C., Goodman, S. M., Bogdanowicz, W., Fahr, J., Gajewska, M., Bates, P. J. J., Eger, J., Benda, P. and Taylor, P. J. (2008). Phylogeography and predicted distribution of African-Arabian and Malagasy populations of giant mastiff bats, Otomops spp. (Chiroptera:Molossidae). *Acta Chiropterologica* 10: 21 – 40.

McKenney, D. W. (2007). Potential impacts of climate change on the distribution of North American. *Trees Bioscience* 57: 939 – 948.

Menon, S., Choudhury, B. I., Khan, M. L. and Peterson, A. T. (2010). Ecological niche modeling and local knowledge predict new populations of Gymnocladus assamicus a critically endangered tree species. *Endangered Species Research* 11: 175 – 181.

Moreno, R., Zamora, R., Molina, J. R., Vasquez, A. and Herrera, M. A. (2011). Predictive modelling of microhabitats for endemic birds in south chilean temperate forests using maximum entropy (MaxEnt). *Ecological Information* 6: 364 – 370.

Munishi, P. K. T., Shear, T. H., Wentworth, T. and Temu, R. P. C. (2007). Compositional gradients of plant communities in submontane rainforests of eastern Tanzania *Journal of Tropical Forest Science* 19: 35 – 45.

Negga, H. E. (2007). Predictive Modelling of Amphibian Distribution Using Ecological Survey Data: A case study of Central Portugal. Dissertation for Award of MSc Degree at International Institute for Geo-Information Science and Earth Observation, Enschede, The Netherlands, 88pp.

Ohlemüller, R., Gritti, E. S., Sykes, M. T. and Thomas, C. D. (2006). Quantifying components of risk for European woody species under climate change. *Global Change Biology* 12: 1788 – 1799.

Ortega-Huerta, M. A and Peterson, A. T. (2008). Modeling ecological niches and predicting geographic distributions: A test of six presence-only methods. *Revista Mexicana De Biodiversity* 79: 205 – 216.

Parmesan, C. (2006). Ecological and evolutionary responses to recent climate change. *Annual Review Ecology Evolution System* 37: 637 – 639.

Pearson, R. G. and Dawson T. P. (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful. *Global Ecological Biogeography* 12: 361 – 371.

Pearson, R. G., Dawson, T. E. and Liu, C. (2004). Modelling species distributions in Britain: A hierarchical integration of climate and land-cover data. *Ecography* 27: 285 – 298.

Pearson, R. G., Raxworthy, C. J, Nakamura, M. and Peterson, A. T. (2007). Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography* 34: 102 – 117.

Peterson, A. T., Soberón, J., Pearson, R. G., Anderson, R. P., Martínez-Meyer, E., Nakamura, M. and Araújo, M. B. (2011). *Ecological Niches and Geographic Distributions*. Princeton University Press, USA. 328pp.

Peterson, A. T., Tian, H., Martínez-Meyer, E., Soberón, J., Sánchez-Cordero, V. and Huntley, B. (2005). Modeling distributional shifts of individual species and biomes. In: *Climate Change and Biodiversity*. (Edited by Lovejoy, T. E. and Hannah, L.), Yale University Press, New Haven, USA. pp. 211 – 228.

Phillips, S. J. and Dudik, M. (2008). Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. *Ecography* 31: 161–175.

Phillips, S. J., Anderson, R. P. and Schapire, R. E. (2006). Maximum entropy modelling of species geographic distributions. *Ecological Model* 190: 231 – 259.

Phillips, S. J., Dudik, M. and Schapire, R. E. (2004). A maximum entropy approach to species distribution modeling. *Proceedings of the 21st International Conference on Machine Learning.* New York. pp. 655 – 662.

Platts, P. J., Ahrends, A., Gereau, R. E., McClean, C. J., Lovett, J. C., Marshall, A. R.,Pellikka, P. K. E., Mulligan, M., Fanning, E. and Marchant, R. (2010). Can distribution models help refine inventory-based estimates of conservation priority? A case study in the Eastern Arc forests of Tanzania and Kenya. *Diversity* and *Distributions* 16: 628 – 642.

Razavi, S. M., Mattaji. A., Rahmani. R. and Naghavi, F. (2012). The assessment of plant species importance value in beech (Fagus orientalis) Forests of Iran: A Case study of two (2) districts of Asalem, Guilan Province). *International Research Journal of Applied and Basic Sciences* 3(2): 433 – 439.

Rohde, R. and Hilhorst, T. (2001). *A Profile of Environmental Change in the Lake Manyara Basin, Tanzania. Drylands Programme*. Issue Paper No. 109. International Institute for Environmental Development, UK. 31pp.

Sala, O. E., Detlef van Vuuren, D., Pereira, H. M., Lodge, D., Alder, J., Cumming, G., Dobson, A., Wolters, V. and Xenopoulos, M. A. (2005). Biodiversity across scenarios. In: *Ecosystems and Human Well-being Scenarios*. Island Press, Washington DC. pp. 375 – 408.

Sarkar, M. and Devi, A. (2014). Assessment of diversity, population structure and regeneration status of tree species in Hollongapar Gibbon Wildlife Sanctuary, Assam, Northeast India. *Tropical Plant Research* 1(2): 26 – 36.

Schrag, A. M., Bunn, A. G. and Graumlich, L. J. (2007). Influence of bioclimatic variables on treeline conifer distribution in the Greater Yellowstone Ecosystem: Implications for species of conservation concern. *Journal of Biogeography* 35: 698 – 710.

Sechambo, F. (2001). Land Use by people living around protected areas: The case of Lake Manyara National Park. *UTAFITI* 4(1998): 105 – 116.

Seoane, J., Carrascal, L. M., Alonso, C. L. and Palomino, D. (2005): Species-specific traits associated to prediction errors in bird habitat suitability modelling. *Ecological Model* 185: 299 – 308.

Sillero, N., Brito C J., Martín-Alfageme, S., Meléndez, E., Toxopeus, A. G. and Skidmore, A. (2012). The significance of using satellite imagery data only in Ecological Niche Modelling of Iberian herps: *Acta Herpetologica* 7(2): 221 – 237.

Singh, M. (2013). Predictive modelling of the distribution of two critically endangered Dipterocarp trees: *Implication for Conservation of Riparian Forests in Borneo* 5(9): 254 – 259.

Stockwell, D. R. B. and Peterson, A. T. (2002). Effects of sample size on accuracy of species distribution models. *Ecological Model* 148: 1 – 13.

Thomas, C. D., Cameron, A., Green, R. E., Bakkenes, M., Beaumont, L. J. and Collingham, Y. C. (2004). Extinction risk from climate change. *Nature* 427: 145 –148.

Thuiller, W. (2004). Patterns and uncertainties of species' range shifts under climate change. *Global Change Biological* 10: 2020 – 2027.

Thuiller, W., Lavorel, S., Arau´jo, M. B., Sykes, M. T. and Prentice, I. C. (2005). Climate change threats to plant diversity in Europe. *Proceedings of the National Academy of Sciences* 102: 8245 – 8250.

Tinoco, B. A., Pedro, X., Latta, S. C. and Graham, C. G. (2009). Distribution, ecology and conservation of an endangered Andean humming bird violet throated metal tail bird. *Conservation International* 19: 63 – 76.

Tranquillini, W. (1979). Physiological ecology of the alpine timberline. Tree existence at high altitudes with special reference to the European Alps. *Ecological Studies* 1: 1 – 31.

Turner, C. (2014). Using habitat suitability modelling to assess the relationships between shrimp trawling and the distributions of deep sea corals. Dissertation for Award of MSc Degree at Imperial Collage, London, 57pp.

VanDerWal, J., Shoo, L. P., Graham, C. and Williams, S. E. (2009). Selecting pseudo-absence data for presence-only distribution modeling: How far should you stray from what you know? *Ecological Model* 220: 589 – 594.

Ward, D. (2007). Modelling the potential geographic distribution of invasive ant species in New Zealand. *Biological Invasions* 9: 723 – 735.

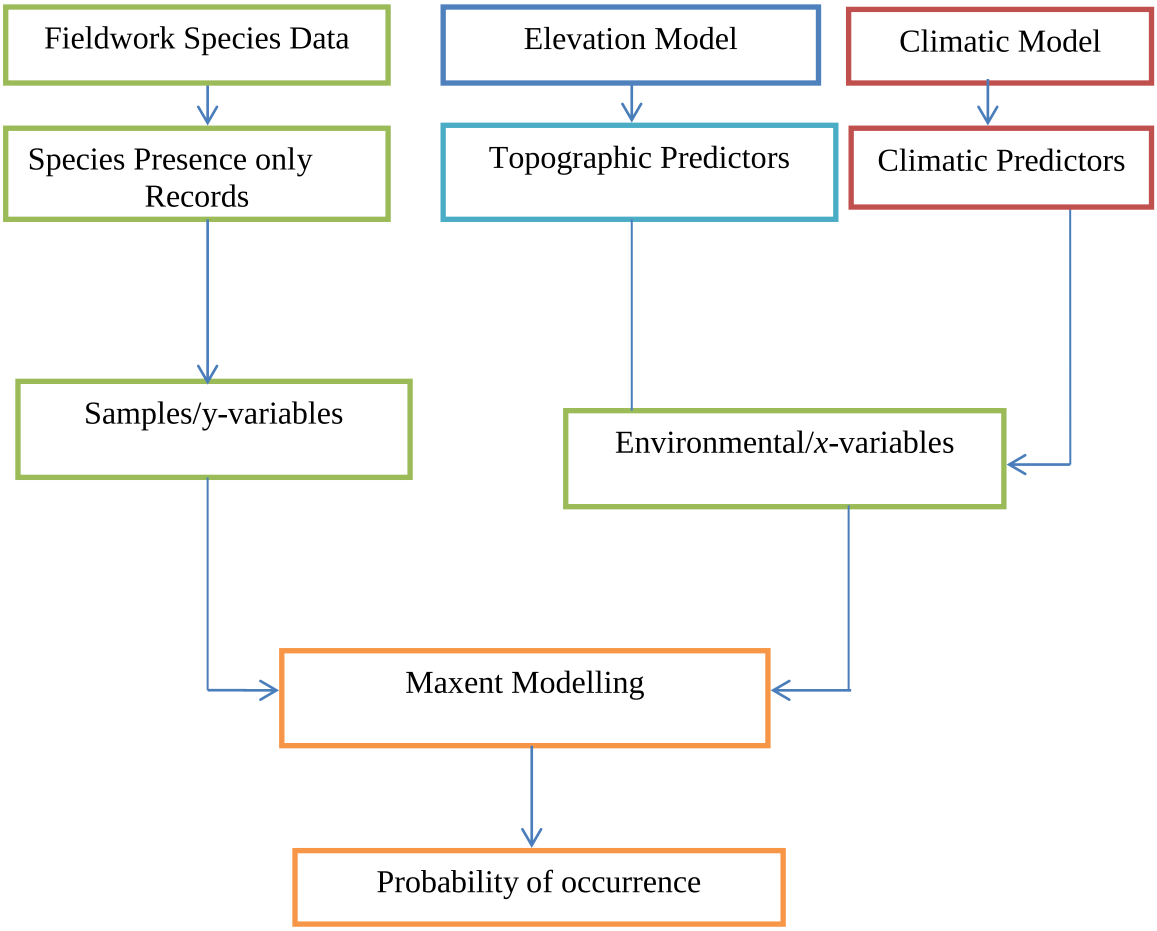
Williams, S. E., Bolitho E. E. and Fox, S. (2003). Climate change in Australian tropical rainforests: An impending environmental catastrophe. *Proceeding Research Society London* 270: 1887 – 1892.

Willis, K. J. and Whittaker, R. J. (2002). Species diversity-scale matters. *Science* 295: 1245 – 1248.

Young, B. F., Franke, I., Hernandez, P. A., Herzog, S. K., Paniagua, L., Tovar, C. and Valqui, T. (2009). Using spatial models to predict areas of endemism and gaps inthe protection of Andean slope birds. *Auk* 126: 554 – 565.

APPENDICES

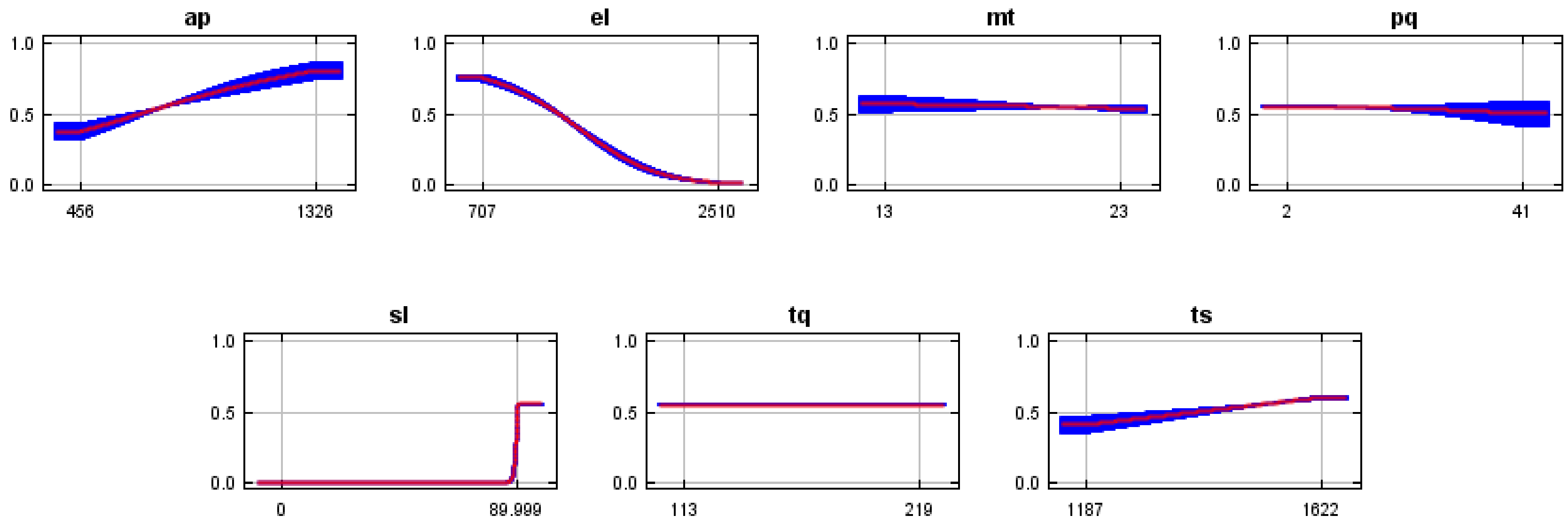
Appendix 1: Flow chart of the modelling procedure using Maximum Entropy (Maxent)



Modified from Chitiki (2014)

Appendix 2: Response Curves for a species of *Acacia robusta*

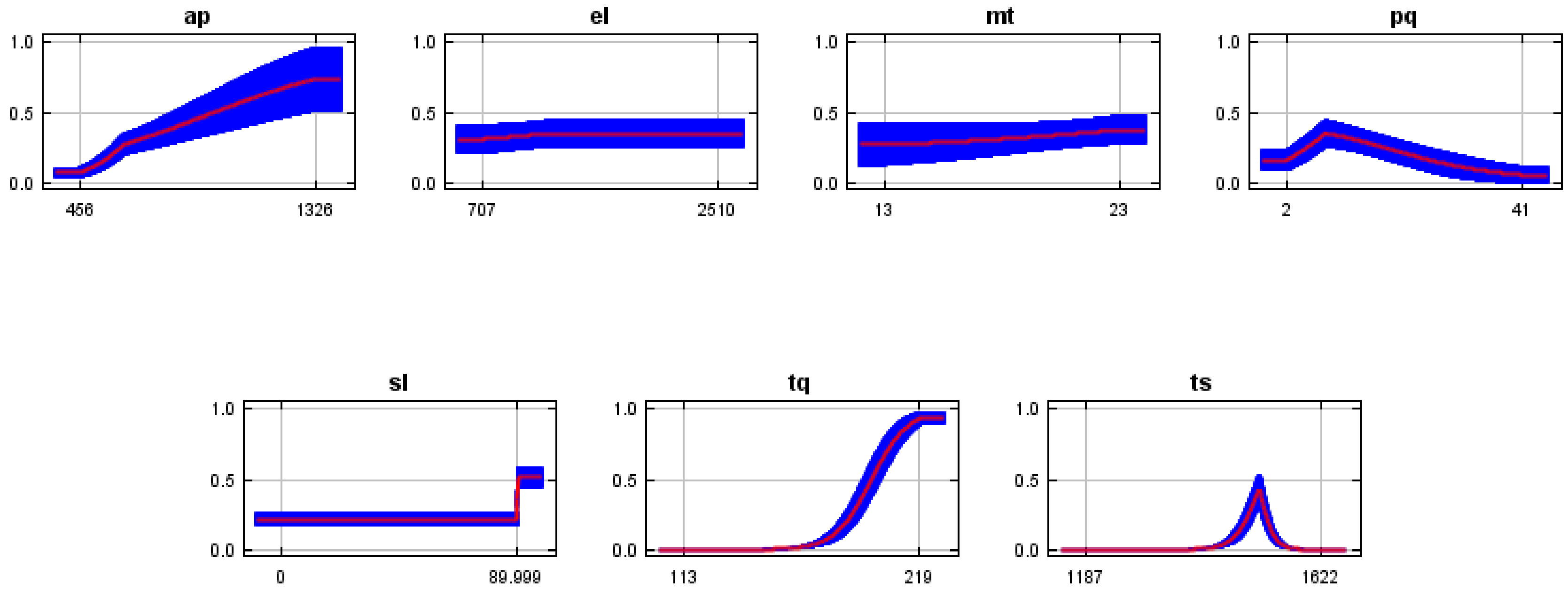
(a) *Acacia_robusta*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 3: Response Curves for a species of *Acacia tortilis*

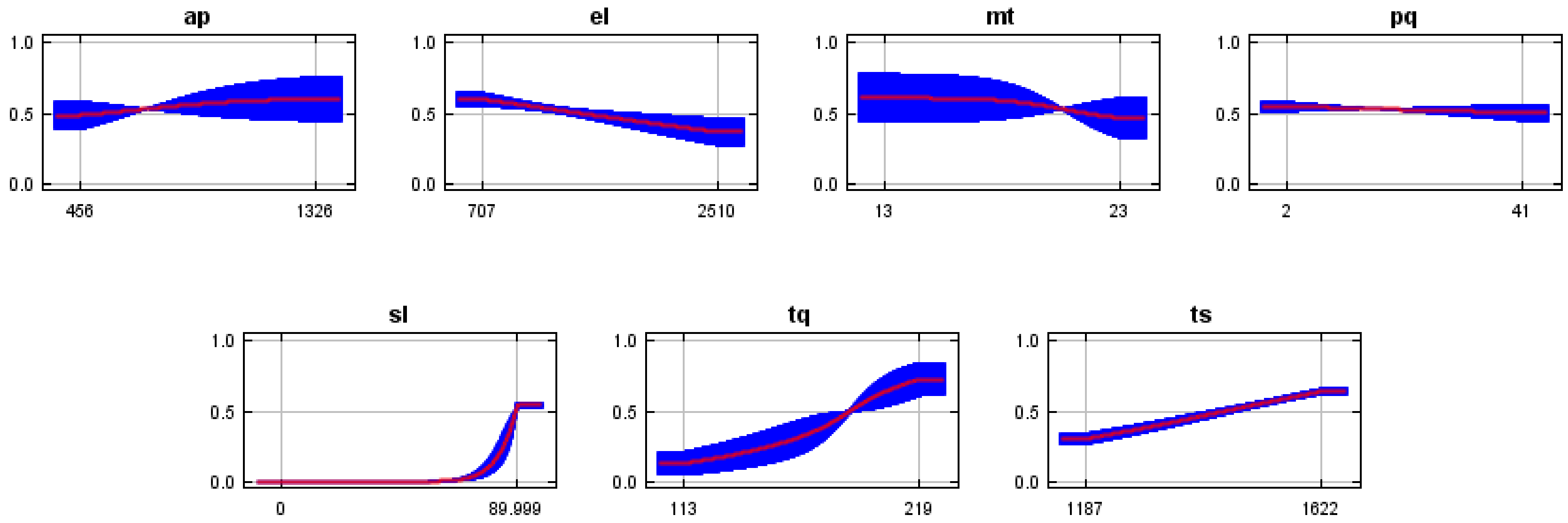
(b) *Acacia_tortilis*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 4: Response Curves for a species of *Albizia petersiana*

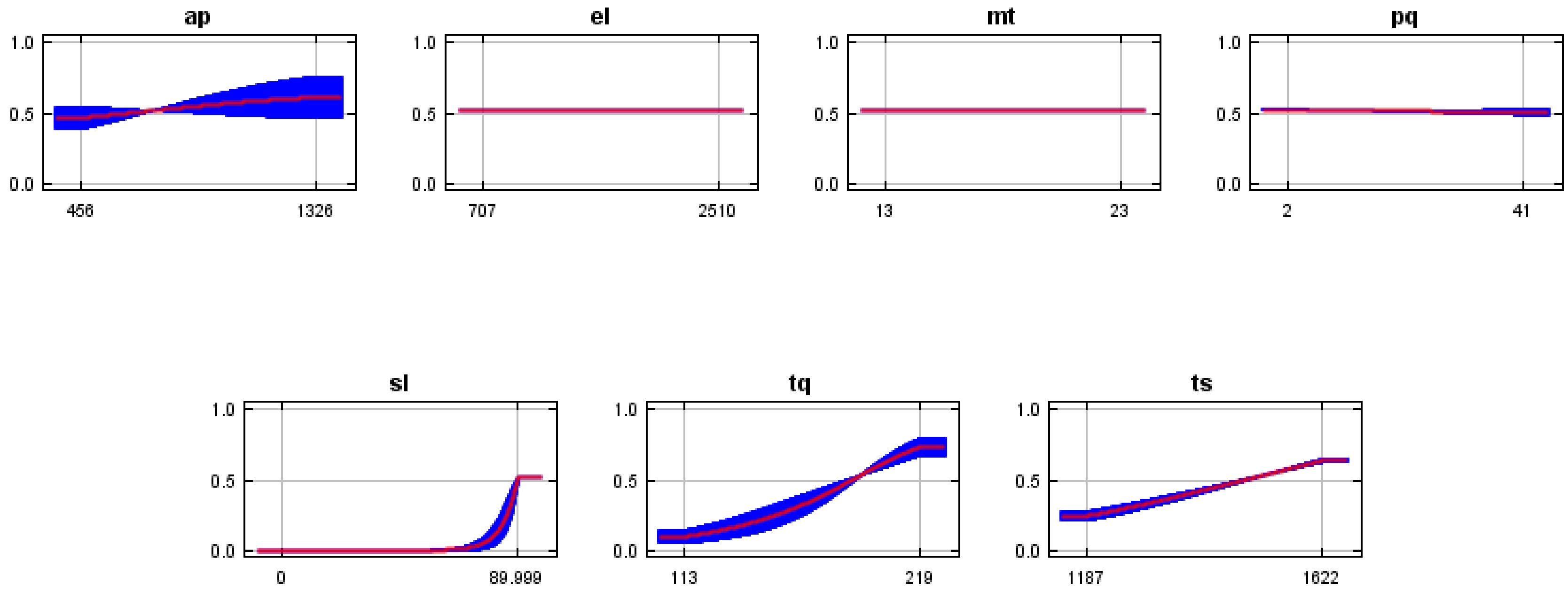
(c) *Albizia_petersiana*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 5: Response Curves for a species of *Celtis_africana*

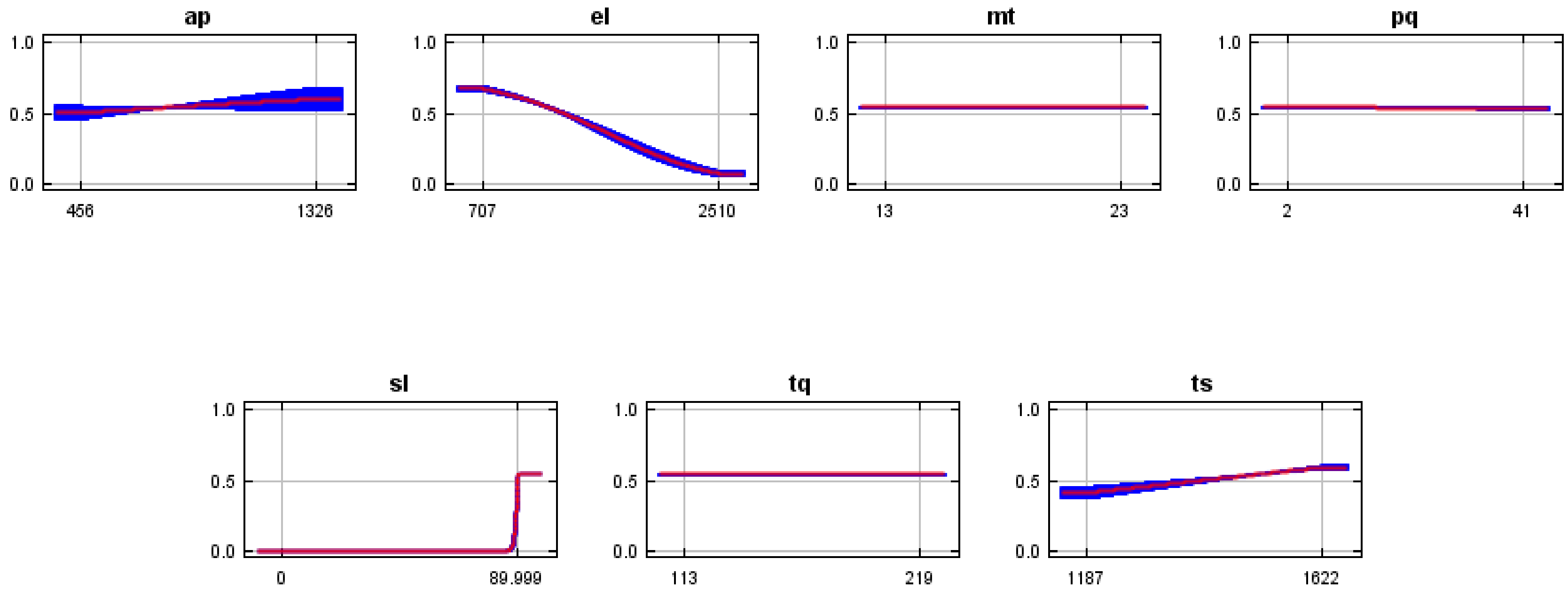
(d) *Celtis_africana*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 6: Response Curves for a species of *Euclea_divinorum*

(e) *Euclea_divinorum*

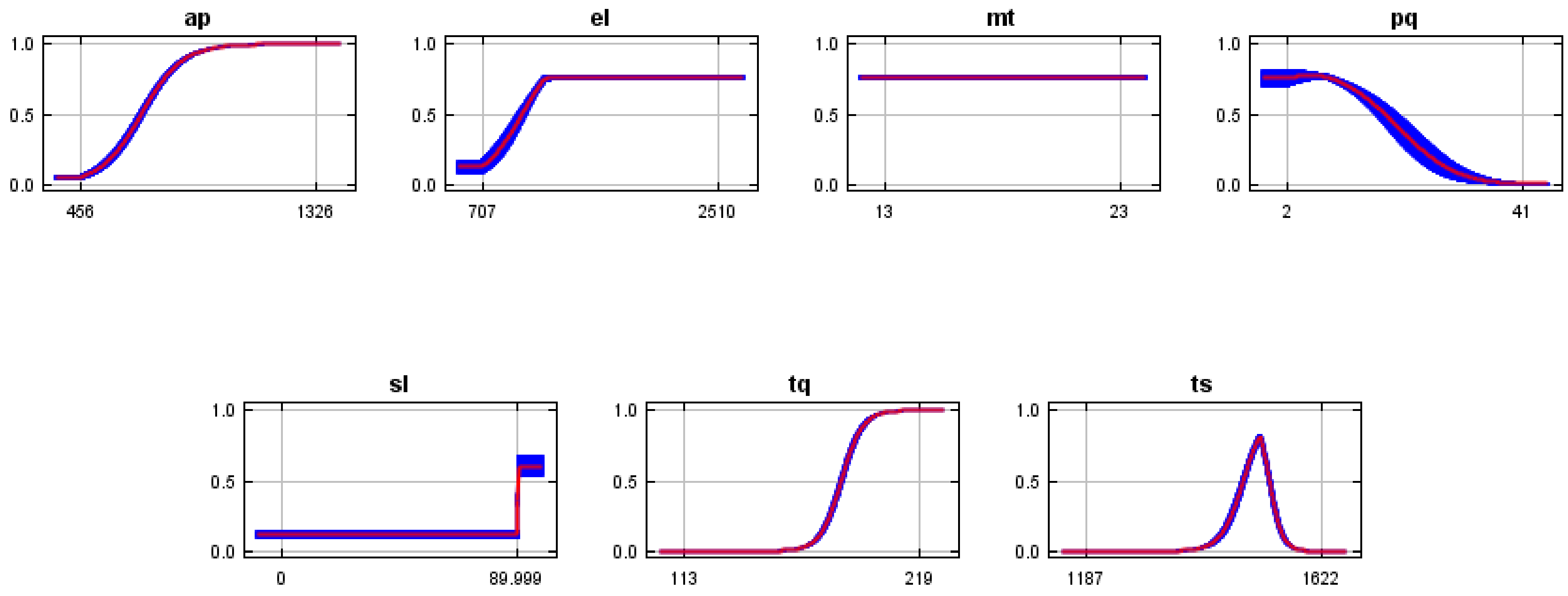


Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation;

pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 7: Response Curves for a species of *Ficus_sycomorus*

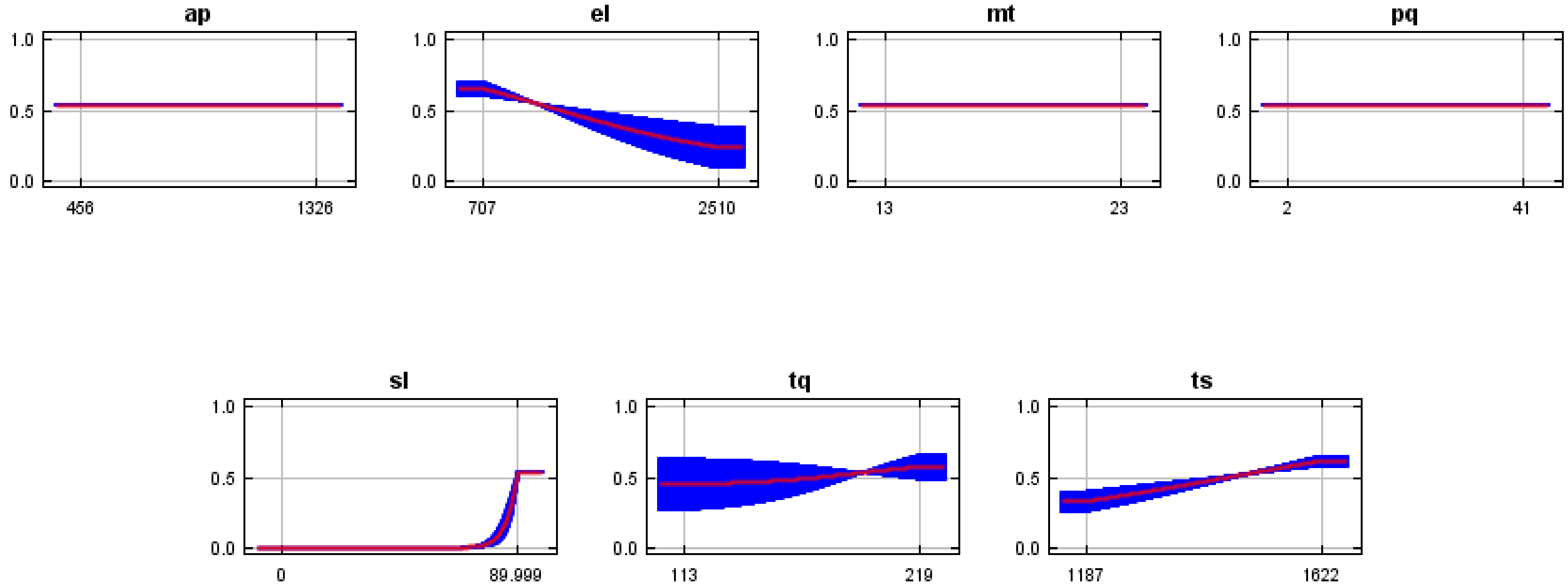
(f)*Ficus_sycomorus*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 8: Response Curves for a species of *Ficus_thonningii*

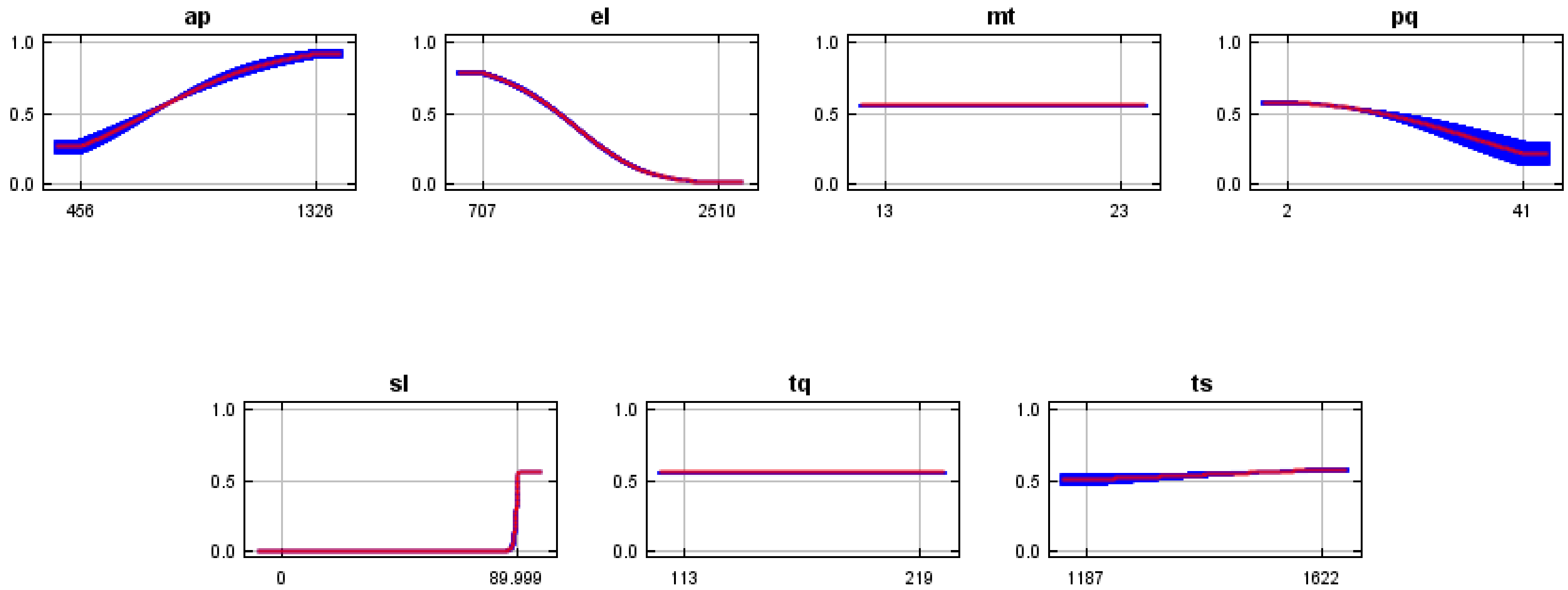
(g) *Ficus_thonningii*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 9: Response Curves for a species of *Rauvolfia_caffra*

(h) *Rauvolfia_caffra*

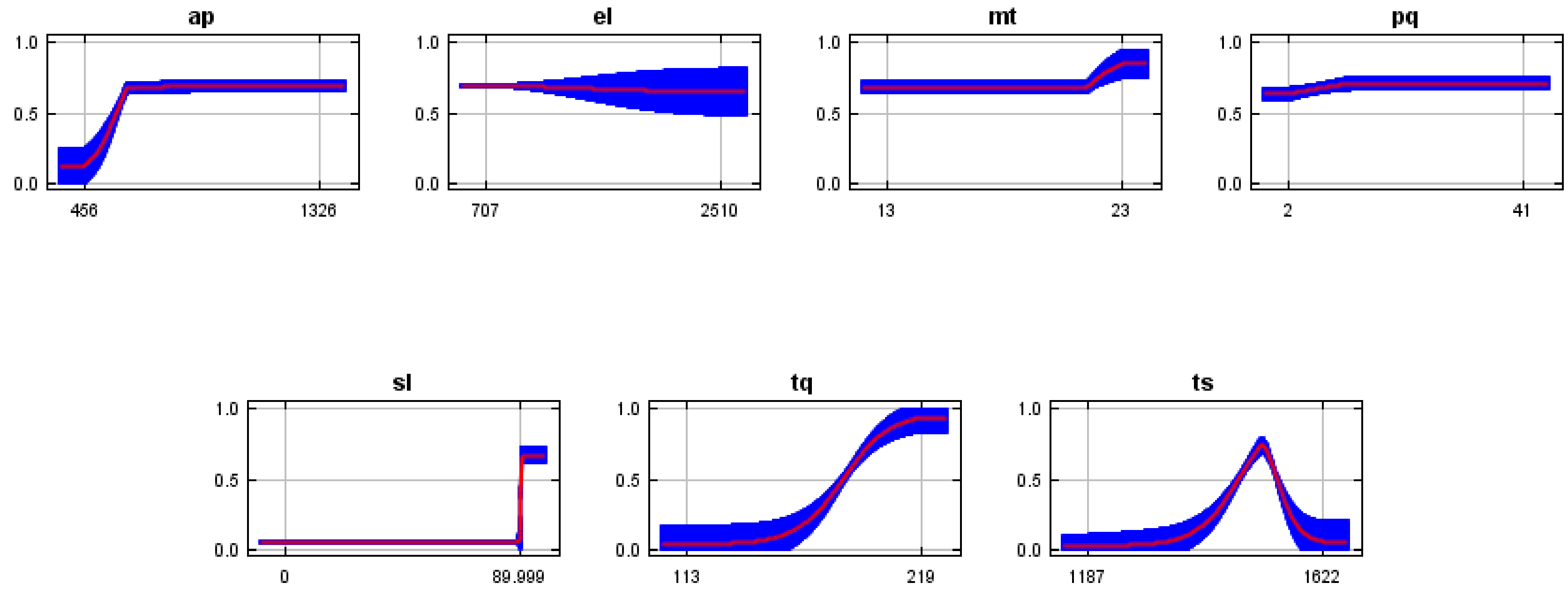


Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation;

pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 10: Response Curves for a species of *Salvadora_persica*

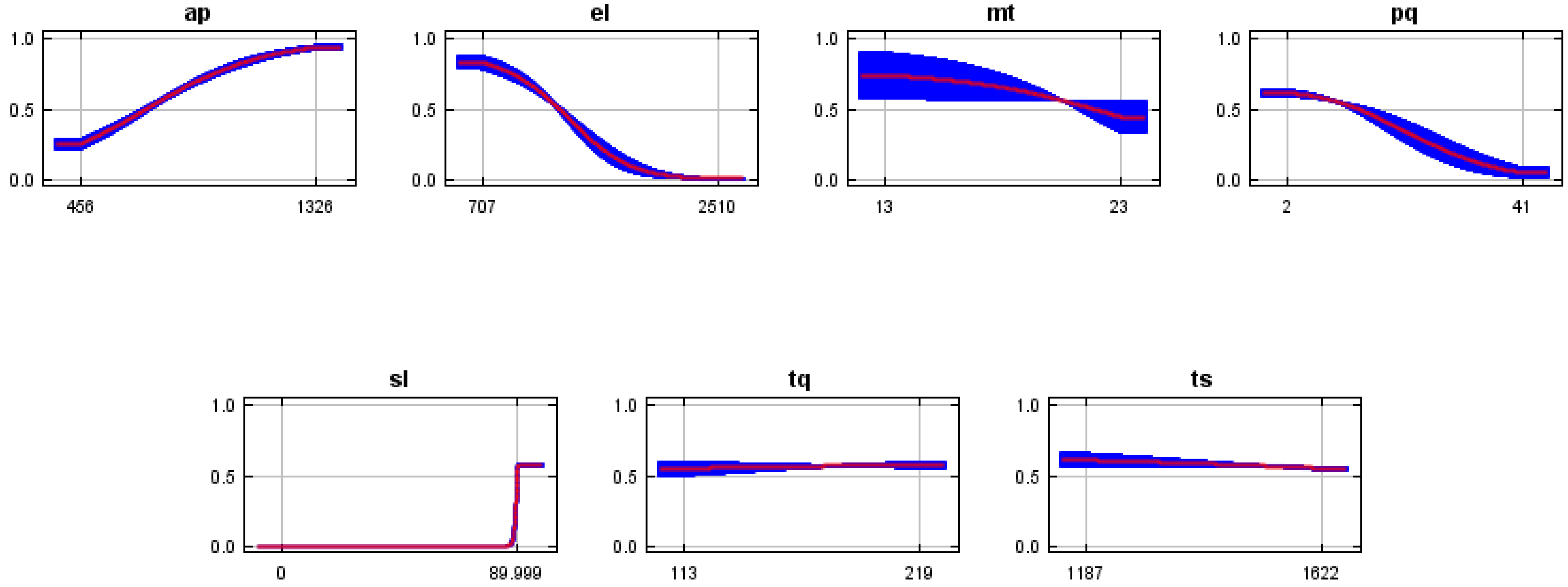
(i) *Salvadora_persica*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 11: Response Curves for a species of *Trichilia_emetica*

(j) *Trichilia_emetica*



Note: mt=Annual Mean Temperature; ts=Temperature Seasonality; tq=Mean Temperature of driest Quarter; ap= Annual Precipitation; pq= Precipitation of the driest Quarter; sl=slope; el=elevation

Appendix 12: **List of tree species identified at Chemchem River in the study area**

ID	Botanical name	Author	Family name	Locality
1.	*Acacia mellifera*	(Vahl.) Benth	Fabaceae	MNP
2.	*Acacia robusta*	Butch	Fabaceae	CCV
3.	*Acacia tortilis*	(Forssk.) Hyne	Fabaceae	MNP
4.	*Albiziapetersiana*	(Bole) Oliv.	Fabaceae	CCV
5.	*Allophyllusafricanus*	P. Beauv	Sapindaceae	CCV
6.	*Blighiaunijugata*	Bak	Sapindaceae	CCV
7.	*Brideliamicrantha*	(HOchst.) Baill	Euphorbiaceae	CCV
8.	*Calotropsisprocera*	(Ait) Ait.f.	Asclepiadaceae	MNP
9.	*Celtisafricana*	Burm.f.	Ulmaceae	CCV
10.	*Chaetac mearistata*	Planch	Ulmaceae	CCV
11.	*Commiphora africana*	(A.Rich.) Engl.	Burseraceae	CCV
12.	*Commiphora* sp.		Burseraceae	CCV
13.	*Cordia monoica*	Roxb	Boraginaceae	MNP
14.	*Cordia sinensis*	Lam	Boraginaceae	MNP
15.	*Croton megalocarpus*	Hutch	Euphorbiaceae	MNP
16.	*Deinbolia kilimandscharica*	Taub	Sapindaceae	CCV
17.	*Delonix elata*	(L.) Gambe	Fabaceae	CCV & MNP
18.	*Diospyros abyssinica*	(Hiern) F. White	Ebenaceae	CCV
19.	*Dovyalis abyssinica*	(Oliv.) Warb	Flacourtiaceae	CCV
20.	*Ekebergia capensis*	Sparrm	Meliaceae	CCV
21.	*Elaeis guineensis*	Jacq	Arecaceae	CCV
22.	*Elaeodendron buchananii*	(Loes.) Loes	Celasteraceae	CCV
23.	*Euclea divinorum*	Hiern	Ebenaceae	CCV
24.	*Ficus capreifolia*	Del	Moraceae	CCV
25.	*Ficus lutea*	Vahl	Moraceae	CCV
26.	*Ficus ingens*	Vahl	Moraceae	CCV
27.	*Ficus sycomorus*	L.	Moraceae	CCV
28.	*Ficus thonningii*	Bl.	Moraceae	CCV
29.	*Gardenia volkensii*	K. Schum	Rubiaceae	CCV & MNP
30.	*Kigelia africana*	(Lam.) Benth	Bignoniaceae	CCV&MNP
31.	*Lecaniodiscusfraxinifolius*	Bak	Sapindaceae	CCV
32.	*Maerua triphylla*	A. Rich	Capparaceae	MNP
33.	*Maytenus heterophylla*	(Eckl. &Zeyh.) Robson	Celasteraceae	MNP
34.	*Melia azedarach*	L.	Meliaceae	CCV
35.	*Rauvolfia caffra*	Sondd	Apocynaceae	CCV
36.	*Rhusnatalensis*	Krauss	Anacardiaceae	CCV
37.	*Salvadora persica*	L.	Salvadoraceae	MNP
38.	*Senna siamea*	(Lam.)Irwin &Barneby	Fabaceae	CCV
39.	*Sorindeia madagascariensis*	DC	Anacardiaceae	CCV
40.	*Syzygiumguineense*	(Willd.) DC.	Myrtaceae	CCV
41.	*Tabernaemontana ventricosa*	A.DC	Apocynaceae	CCV
42.	*Tamarindusindica*	L.	Fabaceae	CCV
43.	*Thylachium africanum*	Lour	Capparaceae	CCV
44.	*Trichilia emetica*	Vahl	Meliaceae	CCV
45.	*Ziziphus mauritiana*	Lam	Rhamnaceeae	CCV

Note that: ID = Identity; MNP= denotes Manyara National Park; CCV = Chemchem Village

Appendix 13: List of all tree species encountered with their Index of Dominance

Species name	Individuals	Index of dominance	Relative abundance (%)
Acacia tortilis	65	0.0415	20.3762
Ficus sycomorus	61	0.0366	19.1223
Acacia robusta	37	0.0135	11.5987
Trichilia emetica	36	0.0127	11.2853
Salvadora persica	21	0.0043	6.5831
Celtis africana	10	0.0010	3.1348
Cordia sinensis	9	0.0008	2.8213
Albizia petersiana	8	0.0006	2.5078
Ficus thonningii	7	0.0005	2.1944
Euclea divinorum	6	0.0004	1.8809
Dovyalis abyssinica	4	0.0002	1.2539
Maerua triphylla	4	0.0002	1.2539
Gardenia volkensii	4	0.0002	1.2539
Tamarindus indica	4	0.0002	1.2539
Rauvolfia caffra	4	0.0002	1.2539
Allophyllus africanus	4	0.0002	1.2539
Sorindeia madagascariensis	4	0.0002	1.2539
Commiphora sp.	3	0.0001	0.9404
Delonix elata	3	0.0001	0.9404
Tabernaemontana ventricosa	3	0.0001	0.9404
Ekebergia capensis	3	0.0001	0.9404
Ficus lutea	3	0.0001	0.9404
Blighia unijugata	2	0.0000	0.6270
Diospyros abyssinica	2	0.0000	0.6270
Calotropsis procera	2	0.0000	0.6270
Ficus ingens	2	0.0000	0.6270
Cordia monoica	2	0.0000	0.6270
Kigelia africana	2	0.0000	0.6270
Croton megalocarpus	1	0.0000	0.3135
Syzygium guineense	1	0.0000	0.3135
Senna siamea	1	0.0000	0.3135
Deinbolia kilimandscharica	1	0.0000	0.3135
Acacia mellifera	1	0.0000	0.3135
Lecaniodiscus fraxinifolius	1	0.0000	0.3135
Chaetacme aristata	1	0.0000	0.3135
Commiphora africana	1	0.0000	0.3135
Elaeis guineensis	1	0.0000	0.3135
Maytenus heterophylla	1	0.0000	0.3135
Elaeodendron buchananii	1	0.0000	0.3135
Melia azedarach	1	0.0000	0.3135
Thyllachium africanum	1	0.0000	0.3135
Ficus capreifolia	1	0.0000	0.3135
Ziziphus mauritiana	1	0.0000	0.3135
Rhus natalensis	1	0.0000	0.3135
Bridelia micrantha	1	0.0000	0.3135