MODELLING IMPACTS OF CLIMATE CHANGE ON TREE BIOMASS AND DISTRIBUTION IN ARABUKO SOKOKE FOREST RESERVE, KENYA

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UNIVERSITY OF NAIROBI

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DECLARATION AND APPROVAL

DECLARATION

I hereby declare that this dissertation is my original work and has not been presented for the award of degree in this university or any other university and that all the sources used herein have been acknowledged.

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ABSTRACT

The Arabuko Sokoke forest ecosystem is characterized by degradation from natural and anthropogenic drivers. Despite these challenges the forest has no study on how climate change will impact on forest biomass and species distribution. The main aim of this study was to project how climate change would impact on the tree biomass in the Arabuko Sokoke forest ecosystem. Experimental research design was used to determine the biomass accumulation rates of vegetation types as well as how climate change would impacts its distribution based on Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 using MaxEnt model. Tree data was collected through direct measurement of Diameter at Breast Height (DBH), while species were identified and recorded together with the plot centre coordinates. The total tree biomass was calculated using allometric equation and shoot: root ratios. The historical rainfall, mean maximum and minimum temperature were collected from meteorological station in Malindi Airport, while the future climate data were downloaded from Worldclim data and downscaled to Arabuko Sokoke forest using geographical information system. The analyzed results for the study indicated that tree biomass accumulated in brachystegia (335MgC-ha), Mixed forest (164.5Mg C-ha) and Cynometra (92.1Mg C-ha) in the last 25 years. Statistical analysis confirms that the accumulation was significant ($F_{1\ 68}$. =43.5, p=0.00). While the trend analysis for mean minimum temperature had significant trend (S = 338, p = 0.00). The results further show that the tree biomass related significantly with rainfall, maximum temperature and minimum temperatures ($F_{1\ 67}$. =9.78, p=0.00, R^2=0.55), ($F_{1\ 67}$. =32.00, p=0.00, R^2=0.55) and ($F_{2\ 68}$. =40.27, p=0.00, R^2=0.54) respectively. The MaxEnt model prediction based on RCP 4.5 and 8.5 indicated well the geographical distribution of brachystegia and mixed forest at 2050 and 2070 (AUC= 0.80-0.90), while cynometra forest had a poor model fit (AUC=0.60-0.70). Based on jackknife test and analysis of variable contribution the mean annual, anomalies and extremes of precipitations and temperature had an impact on the predictive power of three models for Arabuko Sokoke. In conclusion the study findings indicated that tree biomass in Arabuko Sokoke has significantly accumulated over time. Secondly, the evidence provided by this study indicated that there was significant temperature and rainfall variability between 1990 and 2014 in Arabuko Sokoke forest. Thirdly, the finding indicates that rainfall and temperature significantly related with biomass across the forest landscape. Fourthly, the results shows that the site suitability for mixed and brachystegia forests can be predicted using Maxent Model based on general climate model scenarios of RCP 4.5 and RCP 8. Lastly, species distribution predictive model for Arabuko Sokoke was strongly influenced by annual trends, seasonality and extremities of temperature and rainfall parameters. Based on the findings, the study recommended that the forest managers consider development of strategies to deal with possible shift species and fundamental niche reduction for key species in Arabuko Sokoke forest. Secondly, communities are advised to diversify their sources of livelihoods and reduce their dependency on forest. Thirdly, carbon accounting systems and greenhouse gases systems should take into consideration carbon accumulation and possible impacts of climate change on tree biomass in Arabuko Sokoke and finally further research is recommended on species distribution modeling with inclusion of non-climatic parameters such as forest use pressure and natural forest disturbances.

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LIST OF ABBREVIATIONS AND ACRONYMS AND DEFINITIONS

ANOVA ; Analysis of Variance

AUC : Area under Curve

BEF : Biomass Expansion Factor

CH_4 : Methane

CNRM-CM5 : Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique

CNRM-GAME : Centre National de Recherches Météorologiques

CO_2 : Carbon Dioxide

CSV : Comma-Separated Values

DBH : Diameter at Breast Height

DGVM : Dynamic global vegetation models

GAM : Generalized additive models

GHG : Green House gases

GIS : Geographical Information System

GLM : General Linear Model

GtC **:** Gigatonne carbon

IBA : Important Bird Areas

IPCC : Intergovernmental Panel on Climate Change

LULUCF : Land Use, Land Use Change and Forestry

MAXENT : Maximum entropy modeling

MK : Mann-Kendall

MRV : Monitoring Reporting and Verification

N_2O : Nitrous Oxide

PSP : Permanent Sample Plot

RCP : Representative Concentration Pathway

REDD+ **:**"Reducing emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries"

ROC : Receiver Operating Characteristics

RSR : Root Shoot Ratio

SDM : Species distribution model

SLEEK : System for Land based Emission Estimation in Kenya

UNFCCC : "United Nations Framework Convention on Climate Change"

UTM : Universal Transverse Mercator

DEFINITION OF TERMS

Biomass –This the sum of all organic matter that has been accumulated by a tree upper structure which is normally above the ground level and is expressed oven-dry tons per unit area

Diameter – This the girth of a growing tree as arrived at through measurement of over bark at a height of 1.3 m above the ground and is regularly called breast height (hence the expression diameter at breast height – dbh).

Climate change- It is changes in the climate system associated natural causes, directly or indirectly to anthropogenic activities, that brings about variation in the composition of the global atmosphere that can be detected within comparable durations

CHAPTER ONE: INTRODUCTION

1.1 Background

Forests provides a range of ecosystem goods and services, however they are facing pressures from increasing human population specifically the need for land for settlements and agriculture (Aye *et al.*, 2014). The net effect of land conversion from forests to other land uses includes loss of habitats, biodiversity and the increased greenhouse gases in form of CO_2 within the atmosphere leading to global warming and subsequently changes in climate system (Fujisaka *et al.*, 1998;Pielke *et al.*, 2002;Foley *et al.*, 2007;Pellikka *et al.*, 2009).

Deforestation and degradation within the tropics together with the interplay of global climate change have contributed towards the current studies which are mainly focusing on the of forests as carbon sinks (Glenday, 2006) and how it will be impacted by climate change (Desktop *et al.*, 2010).

Climate change has direct impact on the levels of temperature and precipitation being received at particular region in time such that any variability in temperature and rainfall has a direct impact on tree species distribution, growth process and respiration (Classen *et al.*, 2015;Álvarez-Dávila *et al.*, 2017). While species distribution strongly determines the amount of biomass stored by trees within a given forest ecosystem (Pan *et al.*, 2013) Kenya's forests are vulnerable to climate related effects and its likely to impacts on the species distribution, growth rates, regenerative capacity (Stiebert *et al.*, 2012) has not been precisely documented. The vulnerability is higher for forest ecosystems that borders the oceans and seas like Arabuko Sokoke (Field *et al.*, 2014). Arabuko-Sokoke Forest is one of the remnants of the larger coastal dry forest within the East African region (Glenday, 2006) and it plays a multiplicity of functions that includes provision of ecosystem goods and services to local livelihoods, store of genetic diversity, habitat to endemic fauna and climate amelioration (Glenday, 2008;Oyugi *et al.*, 2008;Musyoki *et al.*, 2016).

The need to predict species distribution and quantify the forest biomass have seen a suite of techniques ranging from those that utilize forest inventory data to those methodologies that combines field data with remote sensing technologies. Despite the array of approaches, the uncertainty of how climate affects species distribution and carbon stocks in tropical forest still exists largely due to conflicting and contrasting conclusion drawn from dynamic global vegetation models (Vieilledent *et al.*, 2016)

Recent studies (Glenday, 2006;Devaranavadgi *et al.*, 2013;Chave *et al.*, 2014;Poorter *et al.*, 2015) have pointed out the role of altitude, temperature and precipitation influencing species distribution as well as tree parameters such as heights and diameter of trees in tropical forests and thus influencing on level of forest biomass. Additionally the effect of anthropogenic tropical deforestation on greenhouse gas emissions and climate change has been investigated (Field *et al.*, 2014;Vieilledent *et al.*, 2016) and identified as a global issue although uncertainty exists as to how tropical forests will respond to increased anthropogenic carbon dioxide emissions and carbon-cycle feedback due to climate change (Vieilledent *et al.*, 2016)

Dynamic global vegetation models (DGVM) are generally in agreement that the net primary productivity and forest carbon sinks will increase due to higher rates of plant photosynthesis and efficient usage of water coupled with increased carbon dioxide in the atmosphere, however reduction in productivity is anticipated due to increased rates of plant respiration as a result of warmer temperatures (Moss *et al.*, 2010;Cox *et al.*, 2013;Huntingford *et al.*, 2013;Vieilledent *et al.*, 2016)

Despite these uncertainties associated with DGVMs (Field *et al.*, 2014) , its capacity to project the possible effects of climate change on forests cannot be underestimated. Possible climatic effects on forest could range from limiting internal growth process such as less growth in maximal diameter and heights of the trees to limiting environmental conditions therefore influencing the species range. However these same traits can influences species niche, tree biomass and forest growth (Cox *et al.*, 2013;Chave *et al.*, 2014;Vieilledent *et al.*, 2016) and thus it is most likely that a changes in climate could heavily constrain on tree species distribution and forest carbon sinks. The ability to predict how that will happen is therefore necessary and a simplified correlation method could offer quick and robust options in projecting how climate change will impact on tree species distribution and carbon storage in tropical forests (Vieilledent *et al.*, 2016). The study will focus on understanding how species distribution will respond to temperature and rainfall variability this will be useful in explaining how forest biomass will be impacted by climate change within Arabuko Sokoke forest

1.2 Statement of the Problem

The question of how tropical forests, especially those that borders the oceans and seas like Arabuko Sokoke will respond to changing climate still remains unanswered (Chave *et al.*, 2014;Vieilledent *et al.*, 2016). The Arabuko Sokoke forest ecosystem despite facing pressure from forest degrading activities supports a wide range of ecological and livelihood functions (Glenday, 2006;Oyugi *et al.*, 2008;Musyoki *et al.*, 2016). Very limited research (Mutangah, 1992;Glenday, 2008;Oyugi *et al.*, 2008;Matiku *et al.*, 2013;Musyoki *et al.*, 2016) has been undertaken on Arabuko Sokoke ecosystem and even much less focus has been given to how climate change will impact on tree biomass and species distribution (Pan *et al.*, 2013) and therefore the need for this study

1.3 Research questions

1) How has tree biomass accumulated in Arabuko Sokoke forest?
2) How is the trend in climate pattern of Arabuko Sokoke forest?
3) How does biomass accumulation vary across vegetation types in relation to temporal climate patterns in Arabuko Sokoke forest?
4) How will climate change impact on tree species distribution in Arabuko Sokoke forest?

1.4 Objectives of the Study

1.4.1 Broad objective

The broad objective of this study was contributing towards better understanding of the effects of climate change on tree biomass and species distribution through modeling for sustainable forest management in Arabuko Sokoke forest reserve

1.4.2 Specific objective

1) To estimate tree biomass accumulation in Arabuko Sokoke forest
2) To assess the temporal climate pattern of Arabuko Sokoke forest

3) To compare biomass accumulation between vegetation types based on temporal climate pattern in Arabuko Sokoke forest

4) To project the impacts of climate change on tree species distribution in Arabuko Sokoke forest

1.5 Hypotheses

1) There is no significant accumulation of tree biomass in Arabuko Sokoke

2) The temporal climate pattern of Arabuko Sokoke forest has not changed

3) There is no significant difference in biomass accumulation across vegetation types in Arabuko Sokoke forest

4) Climate change will not impact on tree distribution in Arabuko Sokoke forest

1.6 Justification of the Study

Predicted effects of climate change are anticipated to impact on temperature and rainfall regimes. This expected climatic variability will have an influence on vegetation distribution through influencing niche conditions and functions such as net primary productivity, reproduction and respiration. The net effect of such scenarios is dependent on the ecosystem ability to adapt to the changes and in the event of extreme conditions, then possible flip over of ecosystems are expected.

Theories have indicated species extinction may be part of the net effects of climate change. Though no species have been documented as lost within Arabuko Sokoke Forest ecosystem, its role as a reservoir of genetic diversity, habitat to endangered bird and mammal species increases the need for a better understanding of its dynamics especially in the face of climate change.

The forest is also a critical source of ecosystem good and services to the forest adjacent communities and therefore a drastic change within Arabuko Sokoke may curtail its productivity capacity and therefore jeopardizing the local community ability to meet their food security. The unique locality of the forest within the coastal strip of Indian ocean further create uncertainty of how the ecosystem will respond to climate change.

Therefore, a precise estimation of how the species distribution will respond to temperature and rainfall variability is vital in explaining how forest biomass would be impacted by climate change within Arabuko Sokoke. Additionally the forest model will provide vital answer the forest adjacent communities for their livelihood planning and adaptation. Country processes such as System for Land based Emission Estimation in Kenya (SLEEK), REDD+ will benefit from information generated by the finding of this study. The forest models to be generated by the study on species suitability sites and distribution will be useful in planning and decision making for sustainable forest management in Arabuko Sokoke forest ecosystem.

1.7 Scope of the Study

The study was done in Arabuko Sokoke Forest located in Kilifi County. Total tree biomass were derived using tropical forest allometric equations that uses diameter at breast height (DBH) data only and root: shoot formula. MaxEnt model was used to predict how climate change will affect the species distribution based on RCPs 4.5 and 8.5 climate projections for the region (Field *et al.*, 2014). RCP 4.5 postulates a situation in which the total radiative forcing is stabilized before 2100 by deployment of a raft of measures and interventions for diminishing greenhouse gas emissions. Whereas the RCP 8.5 is representative of the high range of policies that are not geared at climate change in fact, it predicts emissions of the order of 15 to 20 GtC by the end of the century.

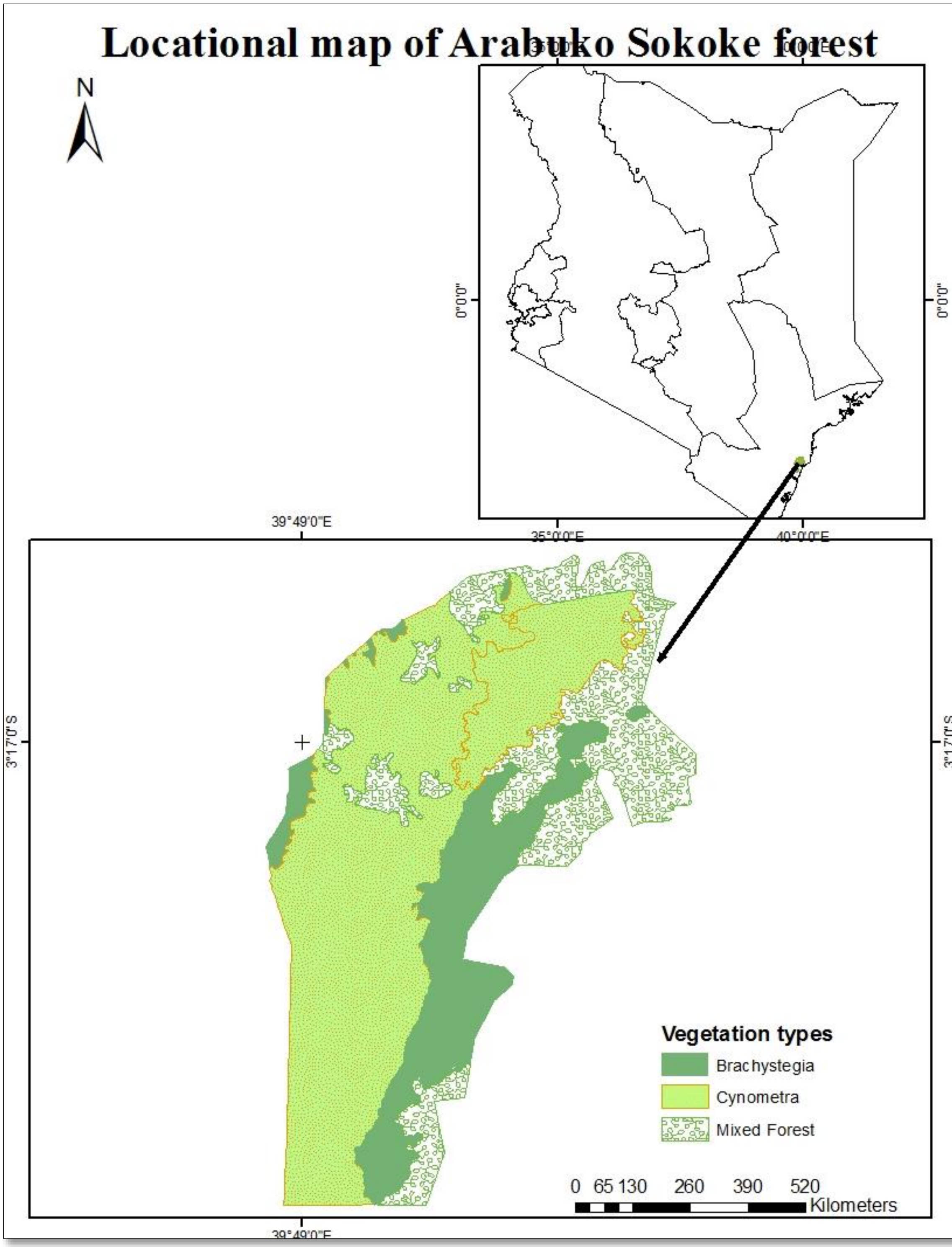

Figure 1: Location of the study site

CHAPTER TWO: LITERATURE REVIEW

This section focuses on the review of scientific literature on forest biomass, forest biomass accumulation and its importance to the current issue of climate change. The review looks at studies undertaken to understand how forest behave under the changing climate and how can climate change be model so as to capture how forest biomass will be impacted. The section has reviewed studies on climate change and climate extremes and forests of the world in order to answer whether climate change will influence how forests will be distributed.

2.1 Forests biomass and accumulation patterns

The international consensus based on studies (Law *et al.*, 2004;Lal, 2005;Robert Jandl *et al.*, 2007;Lüa *et al.*, 2010;Moss *et al.*, 2010;Pfeifer *et al.*, 2012;Willcock *et al.*, 2012 ;Field *et al.*, 2014) seems to endorse the important role forest ecosystems play in the climate change dynamics. Increasingly governments and global organization such as UNFCCC have placed considerable importance on the need to monitoring, reporting and verification (MRV) on a periodic basis the forest carbon stocks.

As countries work towards country specific values for national greenhouse gases inventories and other reporting. Intergovernmental Panel on Climate Change (IPCC) has availed default values for parameters such as biomass expansion factors (BEF) and root-to-shoot ratios (RSR) for boreal, temperate and tropical zones in the "Good Practice Guidance for Land Use, Land-Use Change and Forestry" (Penman *et al.*, 2003). The limitation with the using the default parameters is the great uncertainty associated with them at a local scale. And therefore the development of tree specific allometric values and carbon accounting values for national forest biomass assessment, monitoring and reporting has become of critical importance to many countries (Chave *et al.*, 2014;Feng *et al.*, 2014;Poorter *et al.*, 2015).

Comparison of periodic monitoring data, changes in tree DBH, height, and density can be utilized in estimating biomass in a forest ecosystem. However, this approach cannot identify the underlying dynamics of annual carbon accumulation nor explain the reasons for carbon pool variation (Poudel *et al.*, 2012;Zhao *et al.*, 2014).

Forest disturbances and global climate change is the genesis of scientific inquiry on how forests acts as carbon sinks and sources. The forest biomass stocks for Arabuko Sokoke vary across the three vegetation types; Brachystegia, Cynometra and Mixed forests (Glenday, 2006), the uncertainty remains on how the forest carbon has accumulated over a longer time frame for example the last 25 years.

2.2 Climate change

The link between increased GHGs and climate change globally moved from a concern to the scientific community to an international public policy in the last decade (Service, 1999).Warming trends of the Earth systems has been recorded over the last 150 years (Field *et al.*, 2014) and the associated climate variability have resulted in serious perturbations of its components systems. Studies (Bernstein *et al.*, 2008;Field *et al.*, 2014) have shown that the level of GHGs in the atmosphere are at a new scale.

The concentrations levels of methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2) have all shown exponential increase since 1750 (150%, 20% and 40% respectively). The increasing atmospheric GHGs is causing an increase earth's surface temperature, rise in sea level, melting of ice and glaciers (Bernstein *et al.*, 2008;Field *et al.*, 2014) . Many authors including (Bernstein *et al.*, 2008) have noted that changes in climate impacts on natural and human systems across continents and oceans. These impacts can be attributed to climate change in general. Such findings portray the fragibility of both natural and human systems to climate change.

For example increasing temperature has significant impact on natural systems; because it provides a longer growing season for the trees and favorable conditions for photosynthesis that stimulates Net Primary Production (NPP) especially in the boreal ecosystems (Bonan, 2008;Cox *et al.*, 2013). Further warming is expected from the continued emission of greenhouse gases and the possible long-lasting effects s on all the parts of the climate system, includes increased chances of extreme, pervasive and permanent impacts on human and natural ecosystems (Bernstein *et al.*, 2008;Field *et al.*, 2014). It's imperative therefore that some action is needed.

The global commitment to changing the trends has been indicated by the ratification of Paris Climate agreement by most countries (Clémençon, 2016). This strong global commitment is taking cognizant of recommendation from studies (Bernstein *et al.*, 2008;Field *et al.*, 2014) which indicated that mitigating on climate change call for concerted efforts and paradigm shift towards reductions in GHGs and when it is coupled with adaptation the results will be minimization of climate change risks. The business as usual scenario for the climate change indicates increasing GHGs leading to climate variability and climate extremes. A study (Rockstrom *et al.*, 2009) indicates that already three planetary boundaries has been crossed and climate change is one of them, the net effect is possible flip off of the earth systems.

2.3 Climate change and forests

Forest process will most likely be affected by instability in climate patterns as it has been portrayed by Northward displacement of forests in North America and Europe in the Holocene period (Gates, 1990;Johnson and Curtis, 2001;Bonan, 2008). Forest ecosystems are shaped by climate; thus changes in the climate are likely to strongly affect forest ecosystems through influencing tree physiology, growth, mortality and reproduction, the biotic relationship, and disturbance (winds, wildfires, insect attacks). In general the increased concentration of atmospheric CO_2 enhances plant growth, but this may be limited by dwindling soil water levels. The low soil water levels will limit plant growth by stomatal closure and starch accumulation leading to reduced photosynthesis processes (Gates, 1990).

These complex influences shows that climate change may results to non-linear reactions, tipping points and longevity of trees, implying that many individuals present today will experience substantial changes of associated with climate (Hlásny *et al.*, 2016) before being replaced by the next generation. Interestingly the climate related effects on carbon sequestration capacity in old-growth forest ecosystems remains uncertain (Zhou *et al.*, 2015). The climate changes and projected scenarios calls for paradigm shift in traditional forest management concepts practiced by forest managers which were based on historical niche ranges , natural range of variability, and ecological sustainability to determine the goals and objectives to be set and informing decision making for management (Millar *et* *al.*, 2007). The underlying principle in the traditional forest management approach involves maintenance of forest conditions within the presettlement ranges. The evolving challenge in forest management is how to sustainably maintain forests into the future. (Millar *et al.*, 2007) noted that despite the significant lessons to be learned from historical forest conditions, it cannot determine the present and future ecological and management conditions.

2.4 Modeling impacts of climate change on forests

The cornerstone for climate change assessments can be derived from climate model simulations (Desktop *et al.*, 2010;Field *et al.*, 2014) , but understanding of the future dynamics of the carbon cycle in the land based biosphere is complicated by the fact that forests, which account for 80% of terrestrial carbon (Dixon *et al.*, 1994) responds to climate change slowly. Despite the potential short coming, a lot of models have been developed with varying complexity and applications.

The suite of models ranges from those that model species niches, to those that predict it distributions. A model which is niche determined is a representation of species ecological niche based on observed environmental conditions. While a fundamental niche of a species' consists of all set of conditions that promote perpetual survival of species and its realized niche is that subcategory of the fundamental niche which is occupied by the species (Sillero, 2008). In retrospect species' realized niche could be minimal in comparison to its fundamental niche, due to anthropogenic disturbances, biotic interactions (for example; inter-specific competition, predation), or geographic limitation hindering dispersal and colonization; such factors may limit the ability of the species to inhabit (or even encounter) areas suitable for its optimal ecological capabilities.

While species distribution models (SDMs) examines the interaction between species occurrence and a biotic conditions and/or spatial extent of those sites (Schulp *et al.*, 2008;Vieilledent *et al.*, 2016). These models are used within natural resources disciples that includes; biogeography, conservation biology and ecology and as well as in climate change modeling (Elith *et al.*, 2009). Use of predictive models in determining the spatial scale of species based on the climatic conditions of sites plus their presence is critical in analytical biology (Dudı´K *et al.*, 2005;Elith *et al.*, 2009).

Some methods have tended to use presence only data in species distribution modeling because of its ability to predict species with less datasets. A few of these methods include; BIOCLIM (Busby, 1986;Nix, 1986) which has the ability to determine favorable variables in a "bioclimatic envelope", that consists of a rectilinear region in a spatial range (or some percentage thereof) of noted occurrence values in every environmental dimension. Whereas , DOMAIN (Carpenter *et al.*, 1993) utilizes a similarity matrices, where a projected suitability index is determined through computing the minimum distance in geographical locality to any presence record.

Maximum entropy modeling (MaxEnt) is a general-purpose machine learning method that has simplified and accurate mathematical function that can model species distributions from presence-only species records (Dudı´K *et al.*, 2005;Elith *et al.*, 2009). But when combined with together with environmental information it makes it more robust. MaxEnt has a functionalities that enables it perform modeling of species distribution. According to (Dudı´K *et al.*, 2005;Elith *et al.*, 2009) MaxEnt offers many advantages that includes; the model requires data that describe only presence and climatic data of the area under study. It also uses both continuous and categorical data as well as incorporation of interactions between different variables.

The model has robust and efficient deterministic algorithms developed to guarantee meeting at optimal probability distribution. Additionally the MaxEnt probability distribution has a concise mathematical definition, and therefore is amenable to analysis. To overcome errors associated with over-fitting, regularization capabilities have been develop. The other merit of the model is the continuous output, allowing fine distinctions to be made between the modeled suitability of sites and lastly the model can be applied to species presence/absence data by using a conditional model.

The MaxEnt model has some demerits that includes; the MaxEnt model has not statistical matured like GLM or GAM, which has lesser user guidelines and fewer techniques for estimating the number of error in a prediction. It requires a study to determine the amount of regularization and lastly it uses an exponential model for probabilities, which is not inherently bounded above and can provide more predicted values for climatic conditions beyond the range.

2.5 Previous studies

Arabuko Sokoke forest due to its important roles it plays within the coast of Kenya has seen a number of research works. (Oyugi *et al.*, 2008) studied on tree species diversity, density, dispersion patterns and size class distributions in Brachystegia in relations with disturbance where the study findings point out the species dynamics varied with human disturbance. While (Glenday, 2008) concluded that little empirical data existed regarding carbon storage in the forest. The livelihood context of the forest was studied by (Fitzgibbon *et al.*, 1995) in the study of mammal populations in Arabuko-Sokoke and concluded that the forest, provided an important source of protein and income for local communities. (Muriithi and Kenyon, 2002;Matiku *et al.*, 2013;Hoscilo *et al.*, 2014) studied the social and economic importance to the local community. It's therefore clear based on the studies conducted within the forest that no evidence exists on how climate change will impact on tree biomass and species distribution

2.6 Conceptual framework

The conceptual framework for this study will utilize tree information that includes species, diameter at breast height (Dbh) in determining tree biomass and occurrence data when they are coupled with bioclimatic variables based on RCP 4.5 and 8.5 will provide prediction for species distribution based on climate change scenarios. This process will yield biomass accumulation curves, models and species suitability maps as its final products or output.

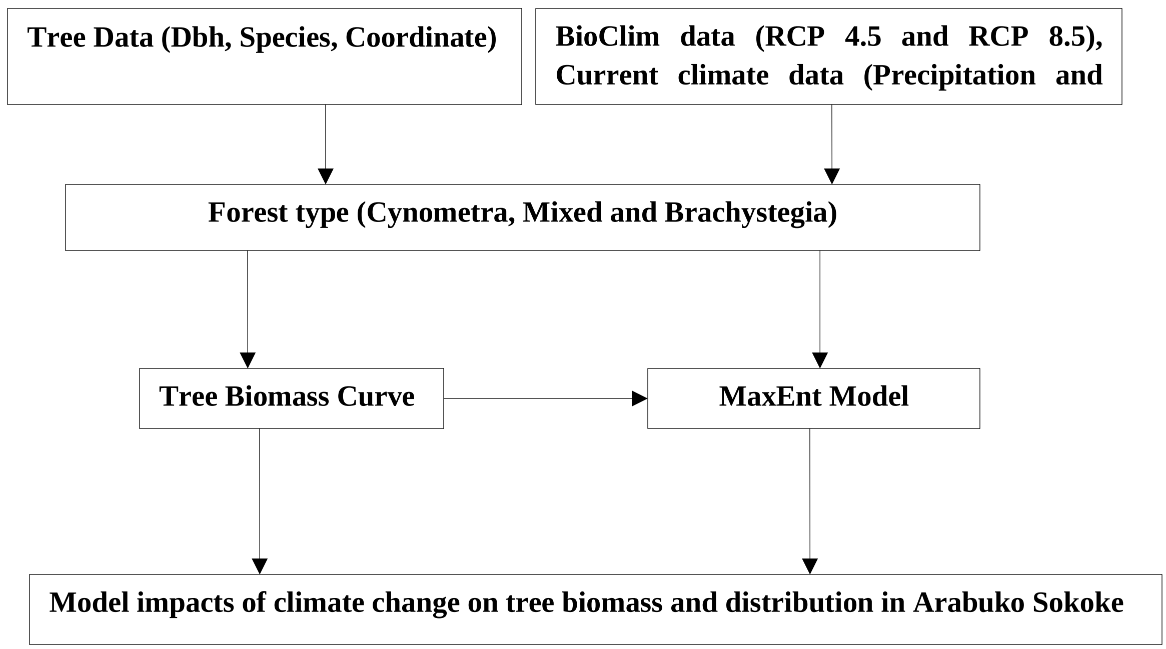

Figure 2: Conceptual framework for the study in Arabuko Sokoke forest reserve

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Study Area

The study was conducted in Arabuko-Sokoke forest located within Kenya's Coast strip of Kilifi County. The forest reserves lies within a geographical bounds of 3°20′ South and 39°50′East (Glenday, 2006). The Arabuko-Sokoke forest has an area of 41,600 ha with about 5,935 ha designated as nature reserve. The forest has three distinct and well described vegetation types (Mutangah, 1992;Muchiri and Kiriinya, 2001;Glenday, 2006;Musyoki *et al.*, 2016) as influenced by soil types, rainfall regimes and altitudinal variations. The vegetation types are briefly described below;

1. **Mixed forest** – This is a thick vegetation type that covers approximately 7,000 ha on the wetter coastal sands to eastern side of the forest. The section has high species diversity, which includes *Afzelia quanzensis*, *Hymenea verrucosum*, *Combretum schumanii*, *Manilkara sansibarensis* and *Encephalartos hilderbrandtii*
2. ***Brachystegia* forest** – This type of the forest covers an area of about 7,700 ha consisting majorly of *Brachystegia speciformis.*
3. **Cynometra forest –** It forms the largest type of vegetation type in Arabuko Sokoke covering about 23,500 ha and it is majorly occupied by *Cynometra webberi*, *Manilkara sulcata*, and *Euphorbia candelabrum* and less of Brachylaena huillensis

The forest is designated Important Bird Areas (IBA's) with endemic bird species numbering about 270 species including six which are globally threatened and three near threatened species.

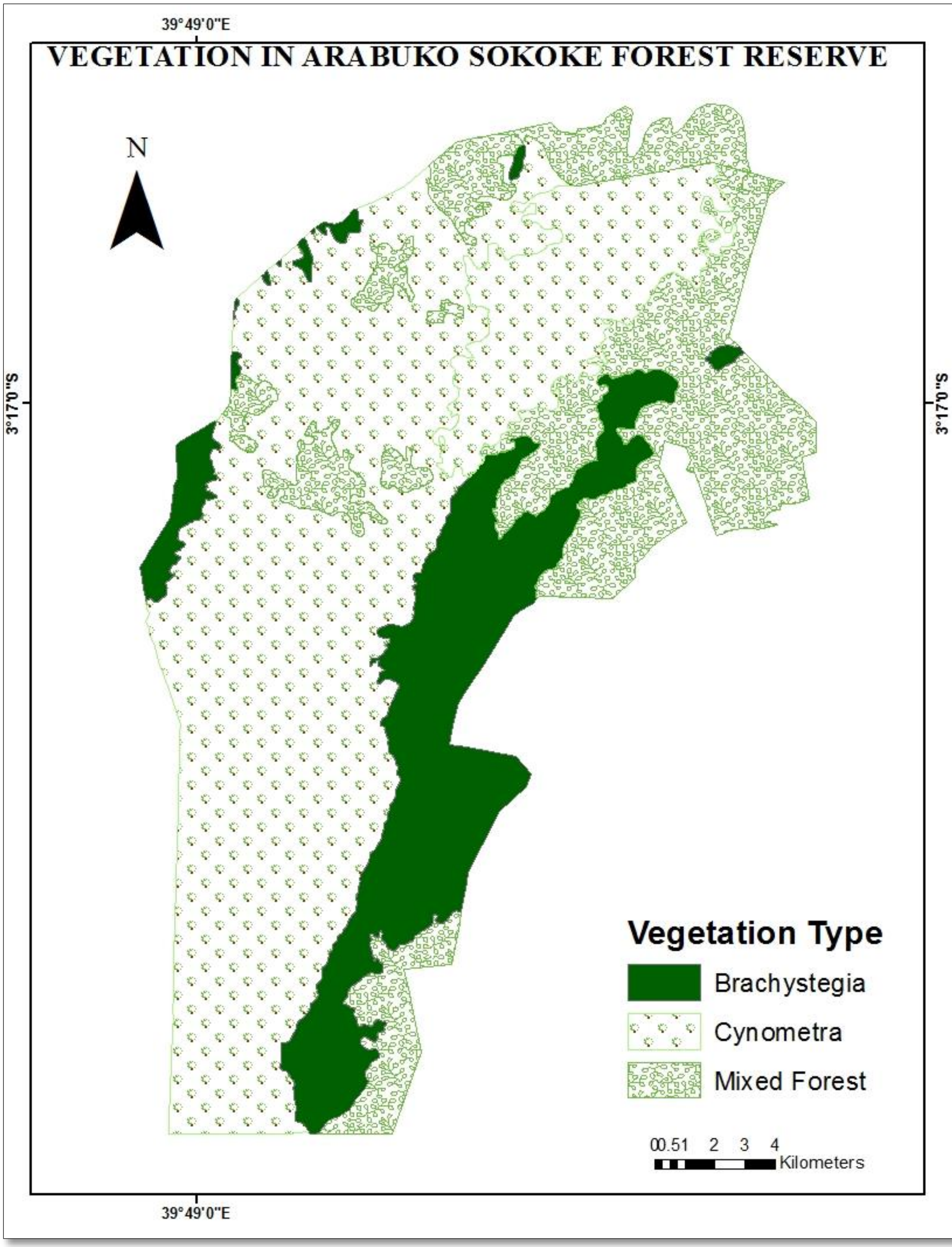

Figure 3: Map showing vegetation types in Arabuko Sokoke forest

3.1.1 Soils and topography

The local topography is fairly flat (Figure 4); the sandy coastal strip has influenced the soil types. The drier western ridge parts of the forest consist of leached red soils. The others parts has deep, band of white, infertile sandy soils. The grey colored pleistocene lagoonal sands and clays are mainly found in eastern coastal plain. While silt soils are found on the dry northwestern edges (Mutangah, 1992) (Figure 5).

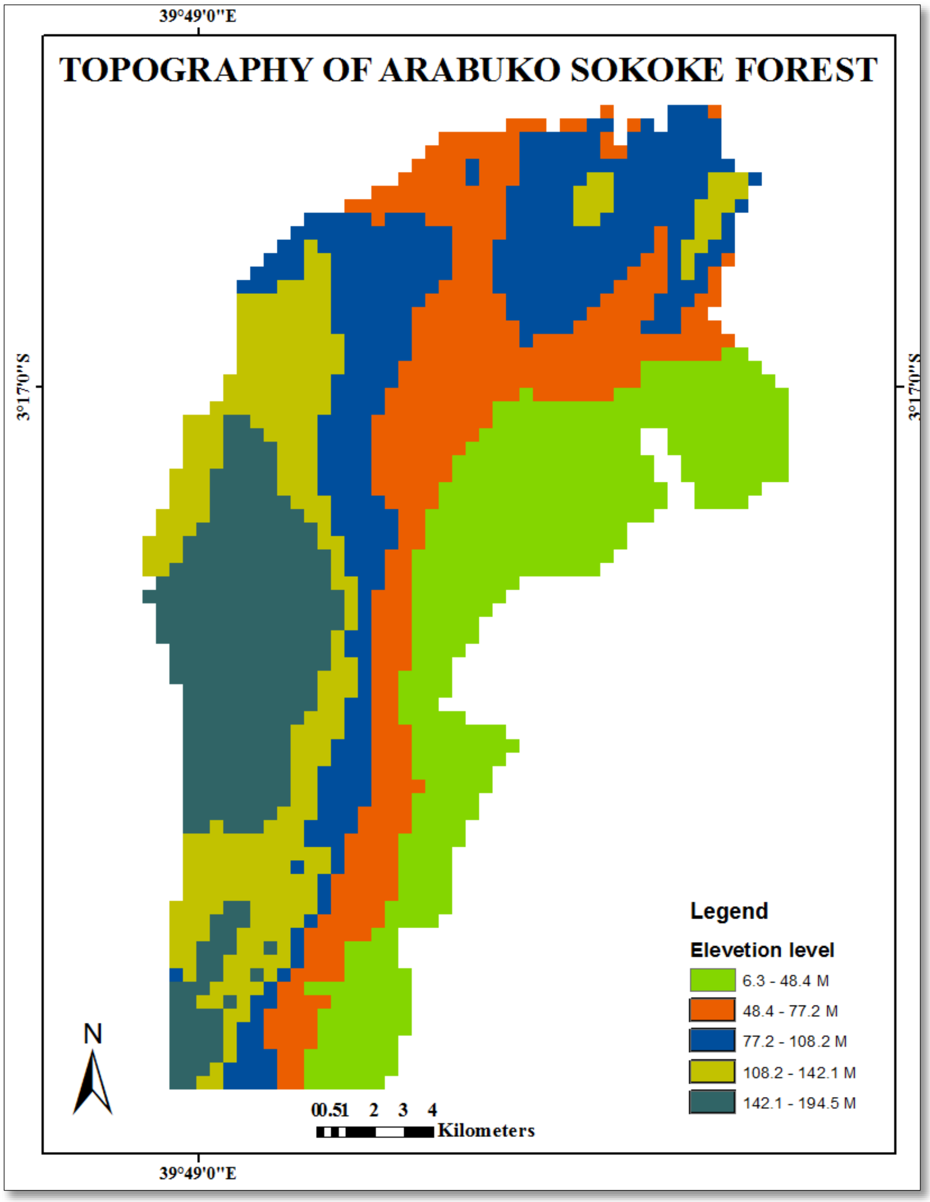

Figure 4: Map showing Elevation in Arabuko Sokoke forest

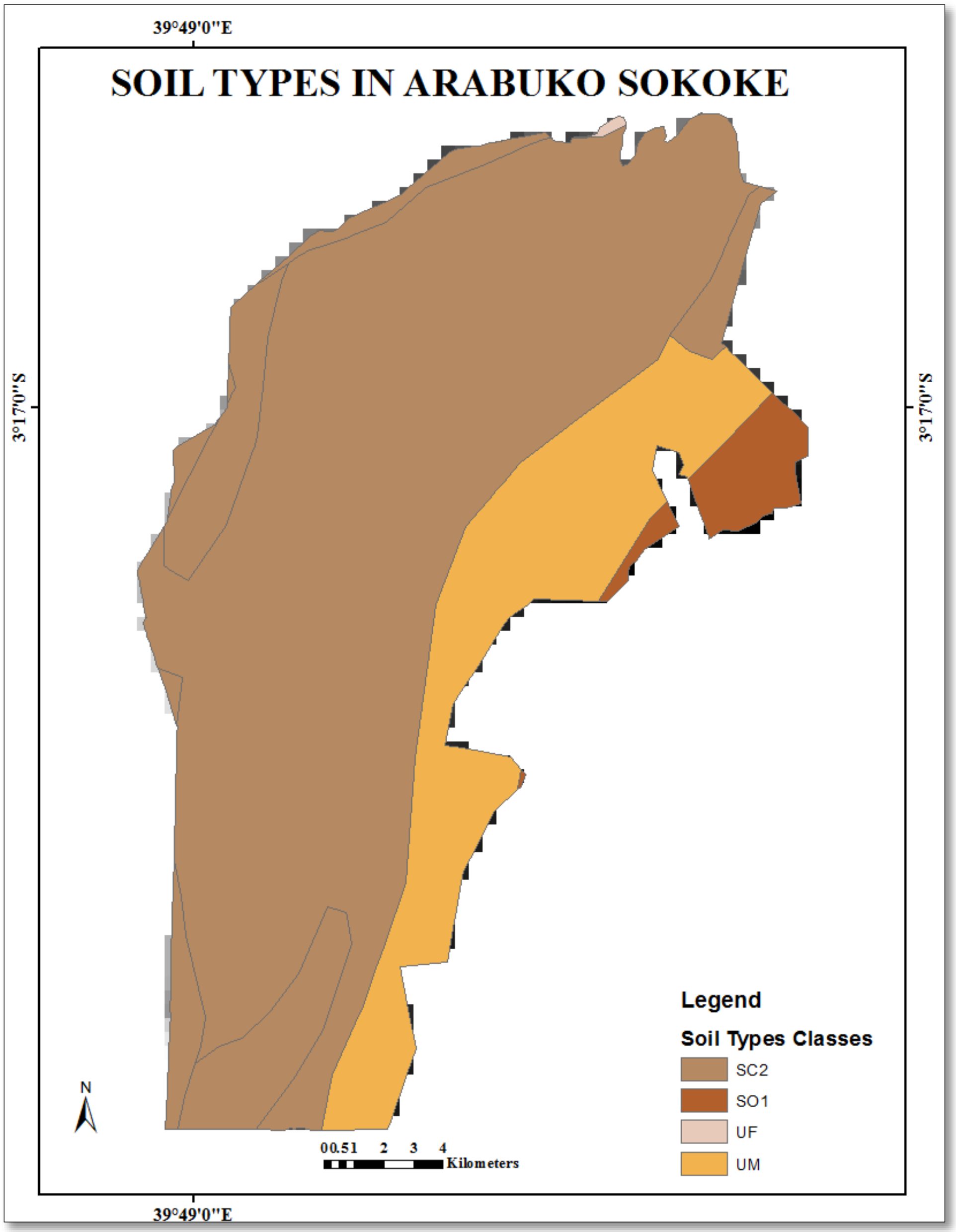

Figure 5: Map showing soil types in Arabuko Sokoke forest

3.1.2 Climate

The rainfall regime varies with altitudinal gradient with 1000–1100 mm/year being received in eastern side ridge and north western forest receives 600–900 mm/year. The mean annual temperature ranges from 21°C to 26°C with a mean daily temperature of 25°C. The humidity is generally high with little fluctuation throughout the year (Glenday, 2006).

3.1.3 Forest adjacent communities

The forest adjacent communities majorly comprised of small scale farmers are close to 104,000 inhabitants (Sinclair *et al.*, 2011). According to (Fitzgibbon *et al.*, 1995) 62.7% of forest adjacent of households and 33.3% of households living within 2 km of the forest depends on the forest for game meat. This indicates a community that has high forest dependency as a source of their nutritional and livelihood needs. While the eastern edges along the Gede-Malindi strip supports tourism industry.

3.2 Research and Sampling design

Experimental research design was used in determining the biomass accumulation rates of vegetation types as well as how climate change will impacts its distribution. A total of 21 Permanent Sample Plots (PSPs) distributed randomly within the three vegetation types namely; mixed forest (10 plots), brachystegia forest (6 plots) and cynometra forest (5 plots) were the source of tree data. These PSPs measuring 50 m x 50 m were established in 1988 and 1990 when the first tree measurement were done. The second and third tree assessments were done in 2004 and 2015 respectively. The information that was captured at the plot is the species type, tree Diameter at Breast Height (DBH) and plot coordinates.

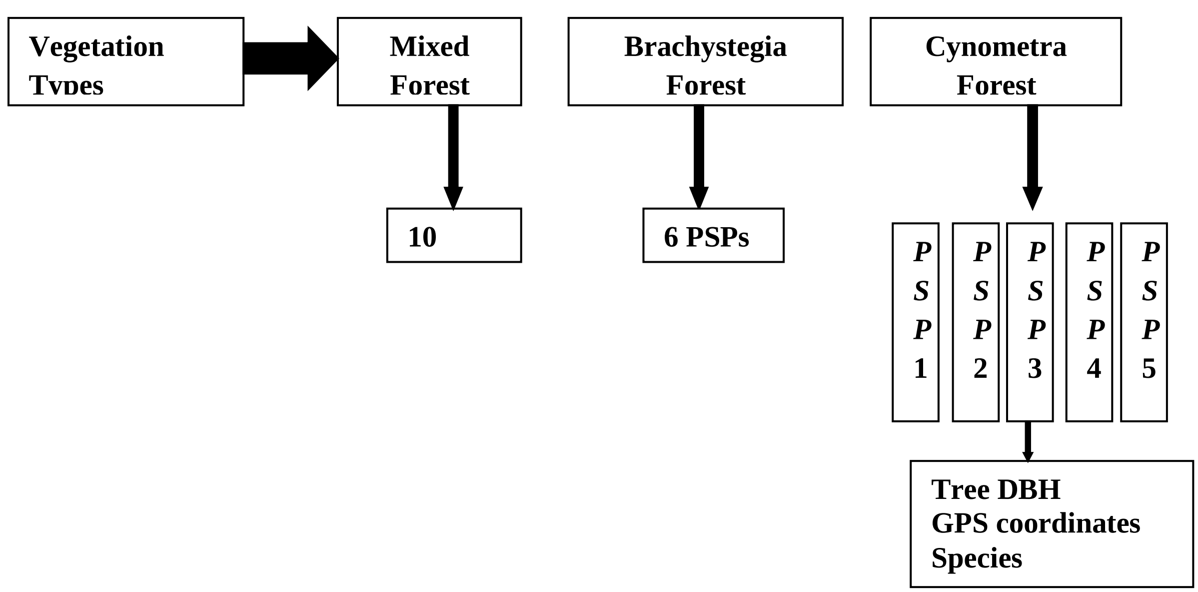

Figure 6: Research design of plot and tree data collection in Arabuko Sokoke

3.3 Data collection

3.3.1 Tree Biomass Estimation

The above ground biomass of individual trees were derived using allometric equation (Chave *et al.*, 2005) developed for moist tropical forests.

$B = \rho \times \exp(-1.499 + 2.148 \ln(dbh) + 0.207 \ln(dbh)^2 - 0.0281 \ln(dbh)^3)$ ----- *Equation 1*

Where *B*= Biomass,$\boldsymbol{\rho}$ =specific wood density (g cm^{-3}) and ***dbh*** is the diameter at breast height (cm).

While the below ground biomass of individual trees were derived using a root: shoot ratio approach (Cairns *et al.*, 1997). The total tree biomasses were derived by summing the above and below ground biomasses of every tree. The plot mean total biomasses were tabulated and clustered into vegetation types. The plot mean total biomass per vegetation type was then regressed against the time to in biomass accumulation curves.

3.3.2 Environmental Data

The mean maximum temperature, mean minimum temperature and total rainfall data for the study site were collected from Malindi Airport weather station which is approximately 20 km from Arabuko Sokoke. The data collected ranged from 1981 to 2014(35 years), the mean annual rainfall were tabulated and the trend and anomaly analysis done.

The future environmental data were obtained from Worldclim-Global climate data (Hijmans *et al.*, 2005;Climate, 2013;Climate, 2014) together with 19 derived bioclimatic variables (Table 1). The resolution of the data was 1 Km^2 and was based CMIP5 scenarios which were used in the development of the fifth IPCC report. The data for RCP 4.5 and RCP 8.5 at 2050 and 2070 were downloaded from CNRM-CM which was developed jointly by CNRM-GAME (Centre National de Recherches Me´te´orologiques—Groupe d'e´tudes de l'Atmosphe`re Me´te´orologique) and Cerfacs (Centre Europe´en de Recherche et de Formation Avance´e) in order to contribute to phase 5 of the Coupled Model Intercomparison Project (CMIP5). The choice of CNRM-CM was because data are provided freely for non-commercial uses. The RCP 4.5 represents the current directions of climate policy and technological interventions towards managing climate change, whereas RCP 8.5 presents the scenario based on no climate policy and other interventions in place with high population levels

Table 1: Table of bioclimatic Variables (Hijmans *et al.*,2005)

Code	Description	Code	Description
BIO1	Annual Mean Temperature	**BIO10**	Mean Temperature of Warmest
BIO2	Mean Diurnal Range (Mean of monthly (max –	**BIO11**	Mean Temperature of Coldest Quarter
BIO3	Isothermality(BIO2/BIO7)(* 100)	**BIO12**	Annual Precipitation
BIO4	Temperature Seasonality (standard deviation *100)	**BIO13**	Precipitation of Wettest Month
BIO5	Max Temperature of Warmest Month	**BIO14**	Precipitation of Driest Month
BIO6	Min Temperature of Coldest Month	**BIO15**	Precipitation Seasonality (Coefficient of Variation)
BIO7	Temperature Annual Range (BIO5- BIO6)	**BIO16**	Precipitation of Wettest Quarter
BIO8	Mean Temperature of Wettest Quarter	**BIO17**	Precipitation of Driest Quarter
BIO9	Mean Temperature of Driest	**BIO18**	Precipitation of Warmest Quarter
		BIO19	Precipitation of Coldest Quarter

3.3.3 Running MaxEnt Model to predict impact of climate change on tree species distribution

Tree Species occurrence data were derived from plot UTM coordinates. They were entered using excel and saved in "CSV" format. The BioClim layers from Worldclim-Global climate data were clipped into the spatial extent of Arabuko Sokoke Forest (Map).These layers represented the current and future environmental conditions based on climate model for 2050 and 2070. The first MaxEnt model run was trained using of 75 % of the data will the remaining 25% of data was used for model validation. Some output files (Figure 7) were manipulated using ArcGIS and displayed in form of maps to depict suitable and unsuitable sites for the three vegetation types in Arabuko Sokoke.

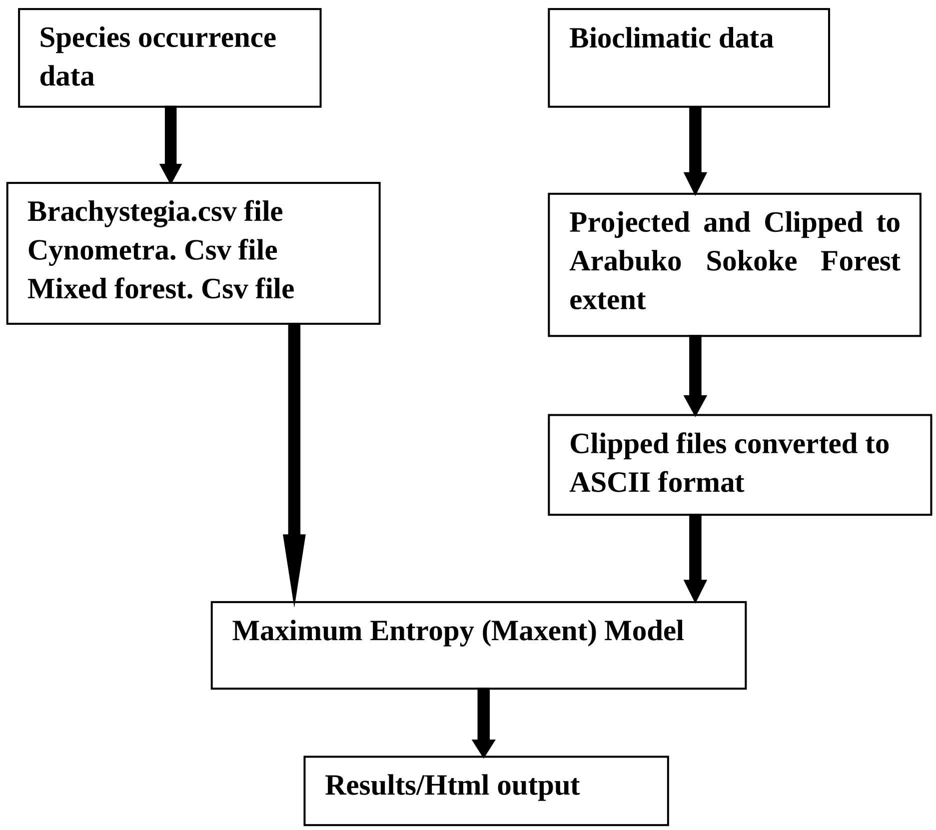

Figure 7: Schematic of MaxENT Model in modeling impacts of climate change

3.3.4 Data analysis methods

The collected data were subjected to data quality control through checking for entry mistakes, inaccurate data and outliers, then summarized and subjected to tests of normality and homogeneity of variance before being transformed to normal distribution where necessary. The quality controls showed that 95 % of data could be used in the study.

3.3.4.1 Estimation of tree biomass accumulation in Arabuko Sokoke forest

The allometric equation (equation 1) was used to derive the tree biomass, while regression analysis was used to develop biomass accumulation rates by regressing tree biomass with time as well as the vegetation types. The R coefficient value was used to assess the level of curve accuracy

3.3.4.2 Assessment of the temporal climate pattern of Arabuko Sokoke forest

The rainfall and temperature data was subjected to the Mann–Kendall (MK) test to detect trends in a time series. Mann-Kendall trend test is a nonparametric test used to identify a trend in a series and compares the relative magnitudes of sample data rather than the data values themselves.

3.3.4.3 Comparison of biomass accumulation between vegetation types based on temporal climate pattern in Arabuko Sokoke forest

The biomass content in the different vegetation types was compared using one way analysis of variance (ANOVA), Exponential Regression analysis was done to correlate biomass accumulation and temporal climate patterns because biological growth in nature follows exponential functions

3.3.3.4 Projection of the impacts of climate change on tree species distribution in Arabuko Sokoke forest

Performance of MaxEnt model was assessed by using Area under the Receiver Operating Characteristic (ROC). Where a value of 0 .5 indicates the results could be random and confidence increases the nearer to 1. Additionally visual comparison of the maps was done between actual and predicted species distribution. Analysis of variable of contribution was used to test of environmental variable contribution, while the Jackknife tests was used to identify the most important variables by running a test for each variable in isolation and comparing it to all of the variables (Joshi, 2015). Jackknife tests are used in statistical inference to estimate the bias and standard error (variance) of a statistic, when a random sample of observations is used to calculate it. The data analysis methods use in this study are summarized below in Table 2

Table 2: Summary of Data Analysis methods based on objectives

Hypothesis	**Variables**	**Data analysis**
There is no significant accumulation of tree biomass in Arabuko Sokoke forest	Tree Biomass Time(years	✓ Regression
The temporal climate pattern of Arabuko Sokoke forest	Rainfall, Temperature time series data	✓ Mann –Kendall test
There is no significant difference in biomass accumulation between forest types based on temporal climate pattern in Arabuko Sokoke forest	Tree biomass, Forest types, Climate pattern	✓ ANOVA ✓ Regression
Climate change will not impact on tree species distribution	Tree species distribution, Environmental Variables	✓ Area under the Receiver Operating Characteristic (ROC) ✓ Visual comparison of the maps ✓ Analysis of Variable of Contribution ✓ Jackknife tests

CHAPTER FOUR: RESULTS

This chapter presents and explained the results based on the objectives of the study. The results are presented in form of graphs, tables, maps and equations.

4.1 Tree biomass accumulation in Arabuko Sokoke forest

The results shows that a strong significant relationship between time and mean total tree biomass in Arabuko Sokoke ($F_{1\ 68}$. =43.5, p=0.00). In the observed relationship, 58.4 % of mean total tree biomass could be explained by time (Figure 8)

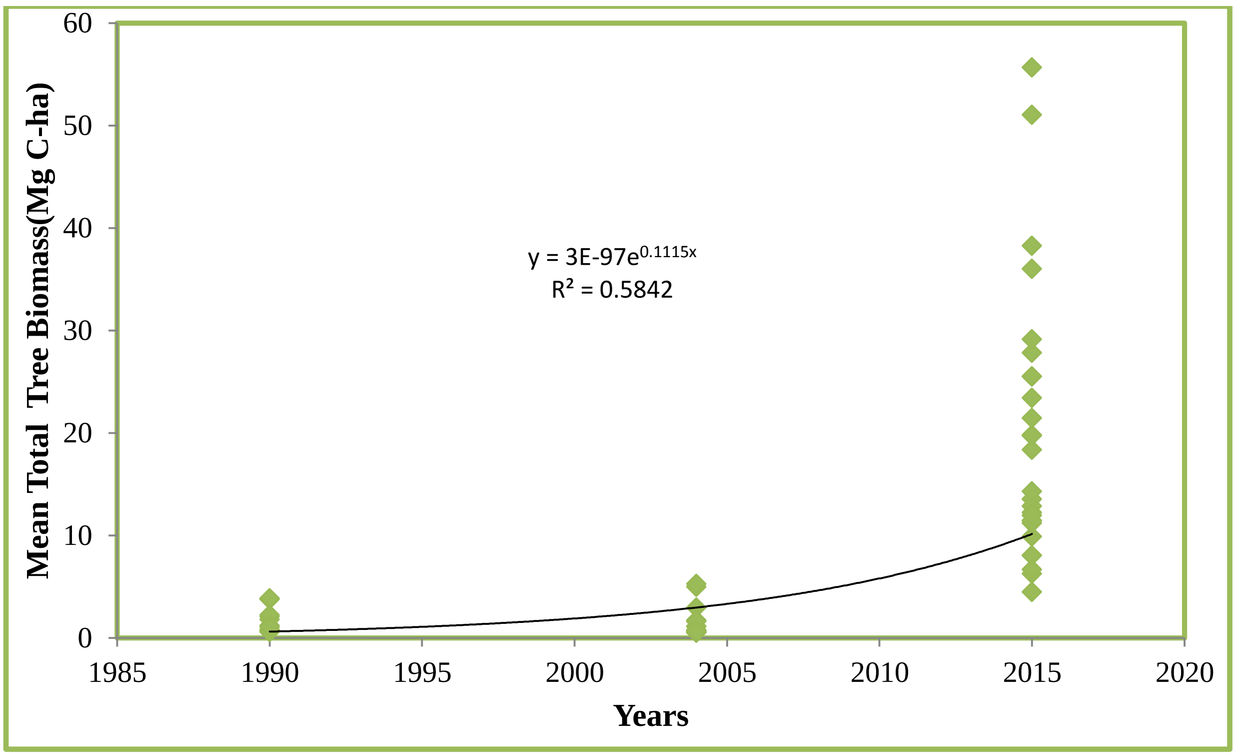

Figure 8: Regression of mean total tree biomass and time

The results showed that the forest had higher mean total tree biomass in 2015 followed by 2004 and least in 1990.The result shows; brachystegia forest recorded higher total tree biomass, followed by mixed forest and cynometra forest in 2015 and 1990. While mixed forest had higher total tree biomass in 2004, followed by brachystegia forest and cynometra forest (Figure 9)

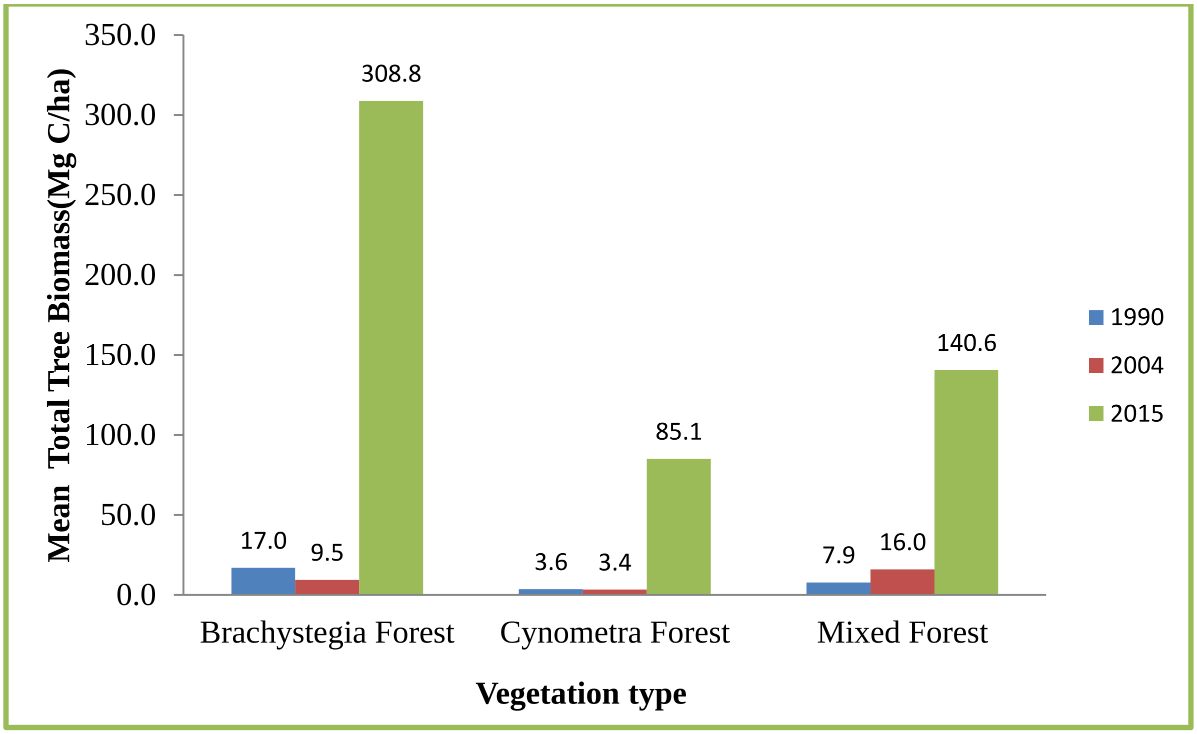

Figure 9: Mean total tree biomass of different vegetation in Arabuko Sokoke forest

A strong significant relationship between total tree biomass in Brachystegia forest and time was observed ($F_{1\ 17.}$ =25.5, p=0.00) with a good model fit (R^2=0.67) (Figure 10)

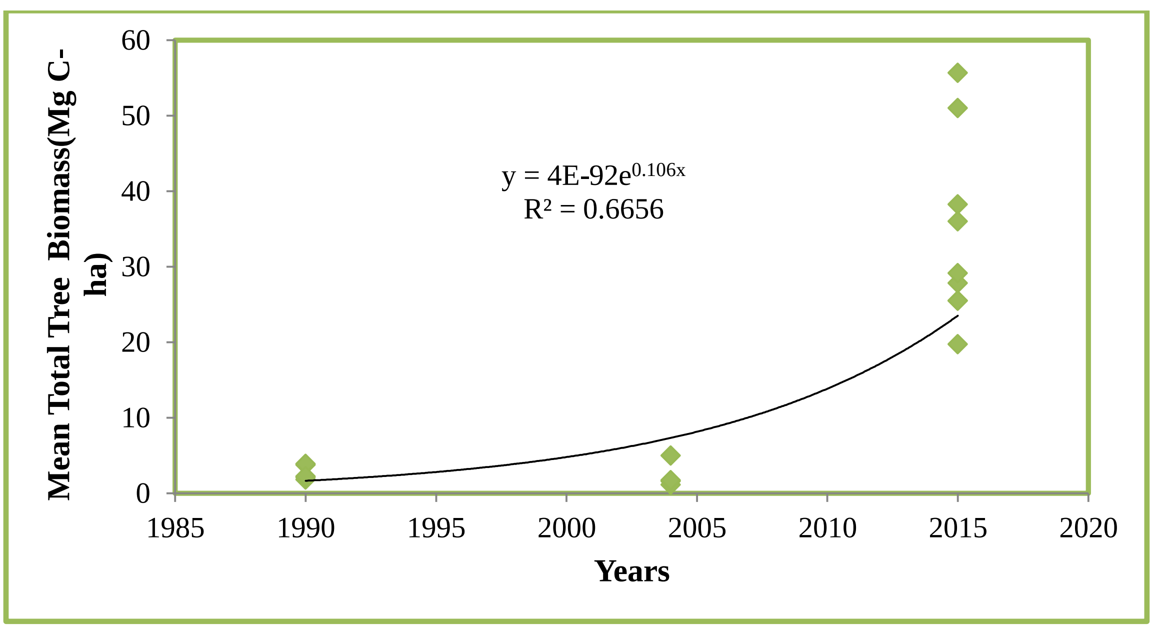

Figure 10: The mean total tree biomass of Brachystegia forest in different years

Total tree biomass in Cynometra forest showed a strong relationship with time ($F_{1\ 16}$. =14.4, p=0.00).Time could explain 69% of the observed mean total tree biomass in cynometra forest (Figure 11).

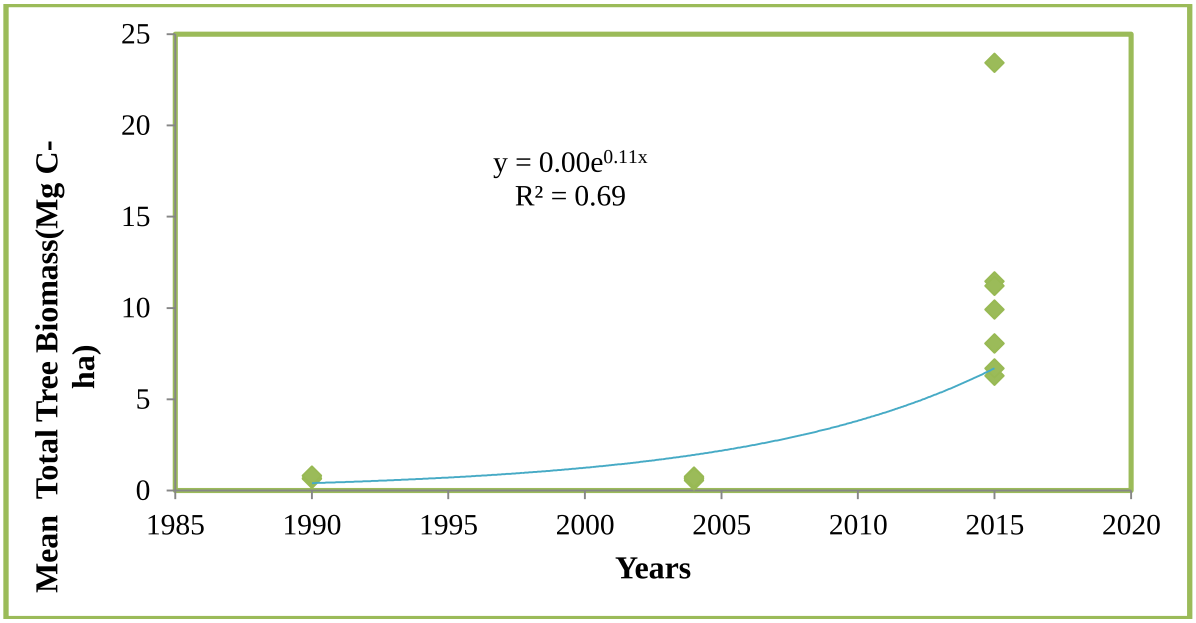

Figure 11: The mean total tree biomass of cynometra forest in different years

There were 61.6% explanation of mean total tree biomass by time in mixed forest; this relationship had a significant statistical difference ($F_{1\ 30}$. =39.14, p=0.00) (Figure 12)

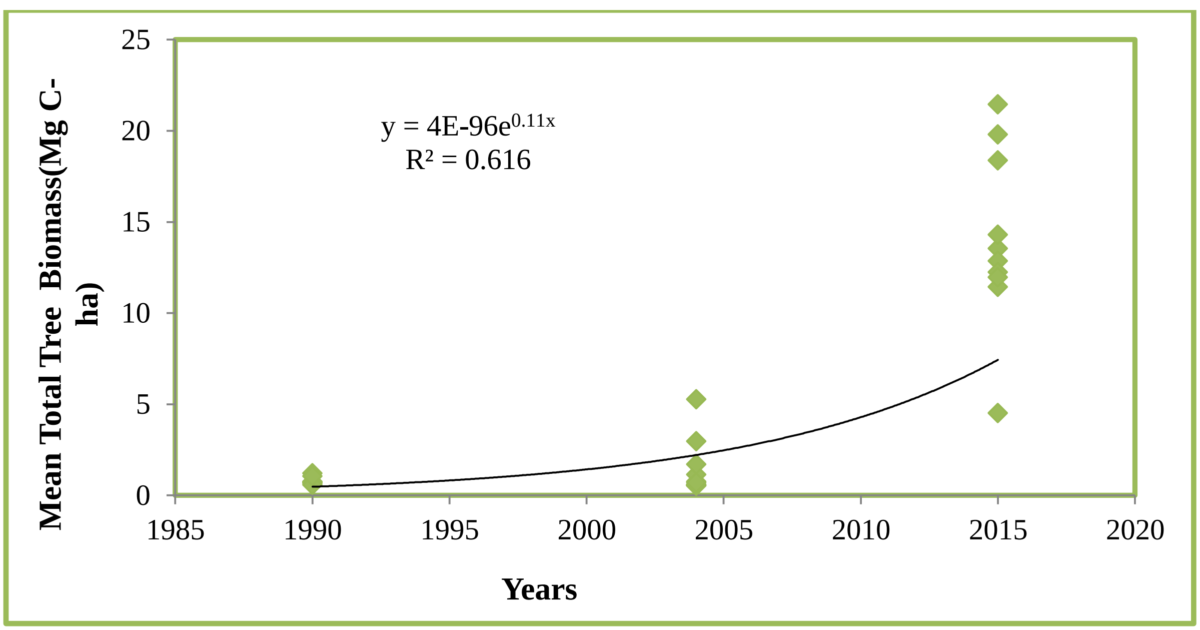

Figure 12: The mean total tree biomass of mixed forest at different years

4.2 Temporal climate pattern of Arabuko Sokoke forest

The section shows the results of how climate patterns have been within Arabuko Sokoke over the last 35 years. It documents trend and variability assessment for rainfall, maximum temperature and minimum temperature.

4.2.1 Mean annual rainfall trend in Arabuko Sokoke forest

The plotted mean annual rainfall for Arabuko Sokoke shows a trends (Figure 13) however according to the Mann-Kendall test the trend is not significant (S = -106, p = 0.10) and has a weak Kendall's tau (-0.21).The study shows a statistically significant decreasing trend of mean annual rainfall in Arabuko Sokoke forests (Sen's Slope= -0.50) and confidence intervals (-0.67 ,-0.37).

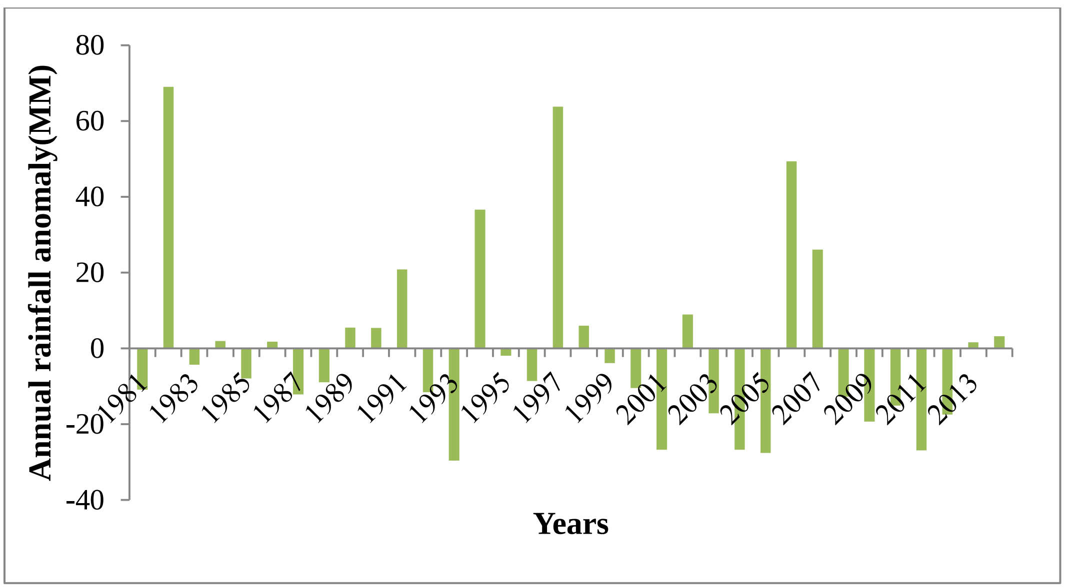

Figure 13: Annual rainfall (1987-2014) anomaly in Arabuko Sokoke

4.2.2 Trend of mean minimum temperature in the forest

The mean minimum temperature data in Arabuko Sokoke show a significant positive trend (S = 338, p = 0.00) according to the Mann-Kendall test and has a strong Kendall's tau (0.64). There is a statistically significant increasing trend of mean annual minimum temperature in Arabuko Sokoke forests (Sen's Slope= 0.03) and confidence intervals (0.03, 0.04). That upward trend is visible as indicated by Figure 14.

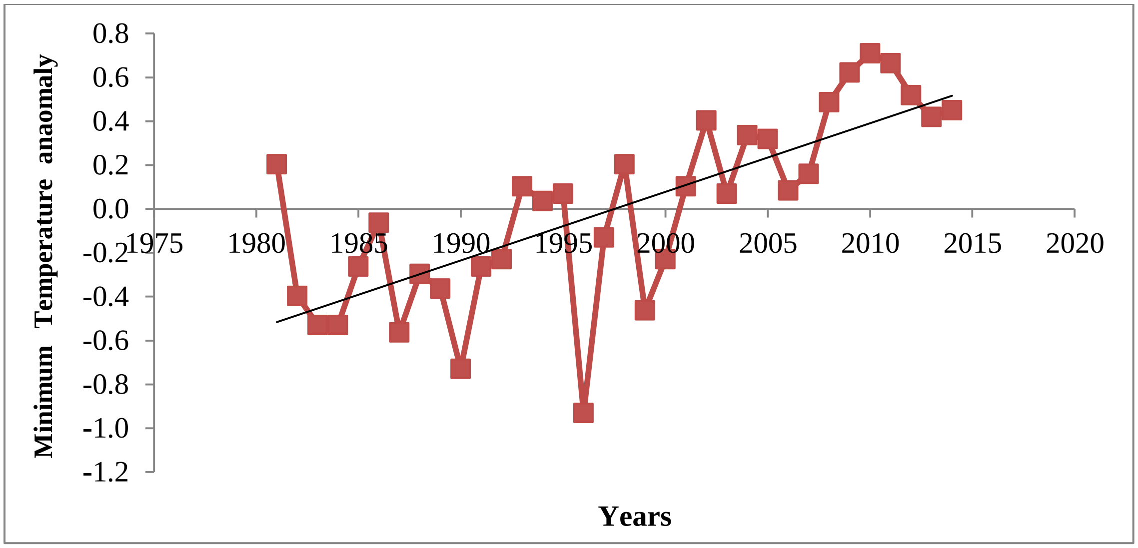

Figure 14: Minimum temperature (1987-2014) anomaly in Arabuko Sokoke

4.2.3 The mean maximum temperature trend in Arabuko Sokoke forest

The results show that the maximum temperature in Arabuko Sokoke has no significant trend (S=77, p=0.24) based on Mann-Kendall trend test and has a weak Kendall's tau (0.15). The plotted data (Figure 15) indicates a significant increasing trend of mean annual maximum temperature in Arabuko Sokoke forests as further confirmed by Sen's Slope (0.01) and confidence intervals (0.01 ,0.00).

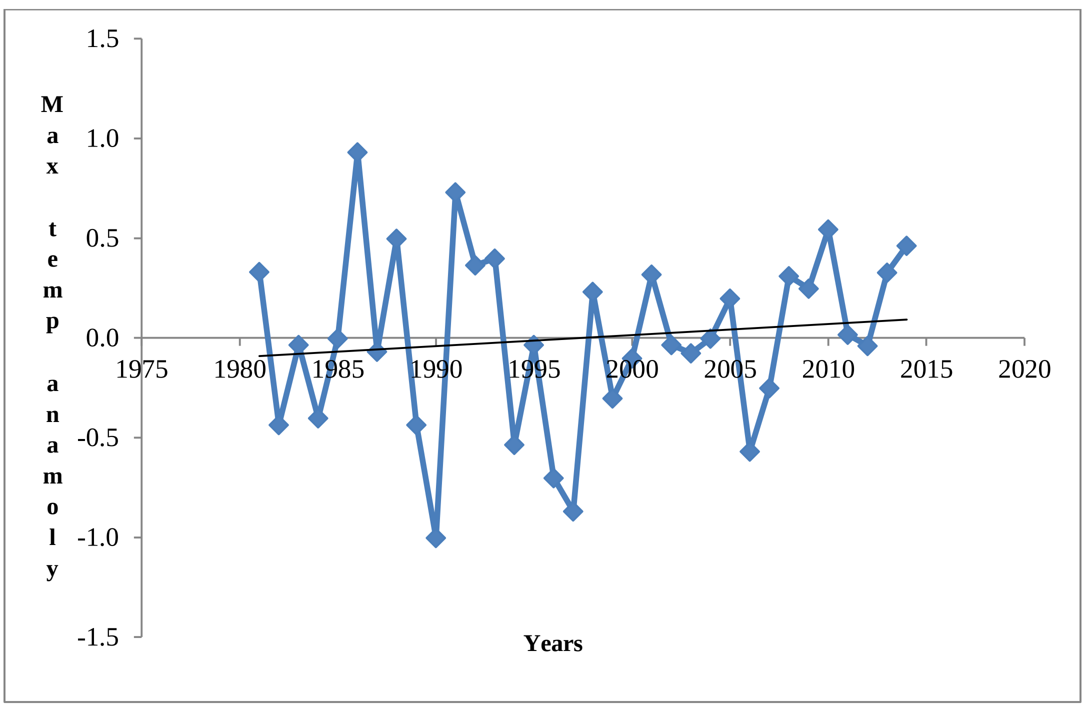

Figure 15: Maximum temperature (1987-2014) anomaly in Arabuko Sokoke

4.3 Comparison of total tree biomass based on temporal climate pattern in Arabuko Sokoke

A strong significant relationship between tree biomass, time and minimum temperature anomaly was observed ($F_{2\ 68.}$ =40.27, p=0.00) with a fair good (R^2=0.54). The regression equation for the relationship is as indicated below:

$$\boldsymbol{Mean\ total\ tree\ biomass}\left(\boldsymbol{Mg}\frac{\boldsymbol{C}}{\boldsymbol{ha}}\right) = -\mathbf{3220} + \mathbf{1.89} * \boldsymbol{time}(\boldsymbol{years}) - \mathbf{24.1} * \boldsymbol{Min\ temp} \text{...Equation 2}$$

Additionally annual rainfall anomaly has a significant relationship with mean total tree biomass ($F_{1\ 67.}$ =9.78, p=0.003).This relationship has a good regression equation ((R^2=0.55) as shown in figure 16

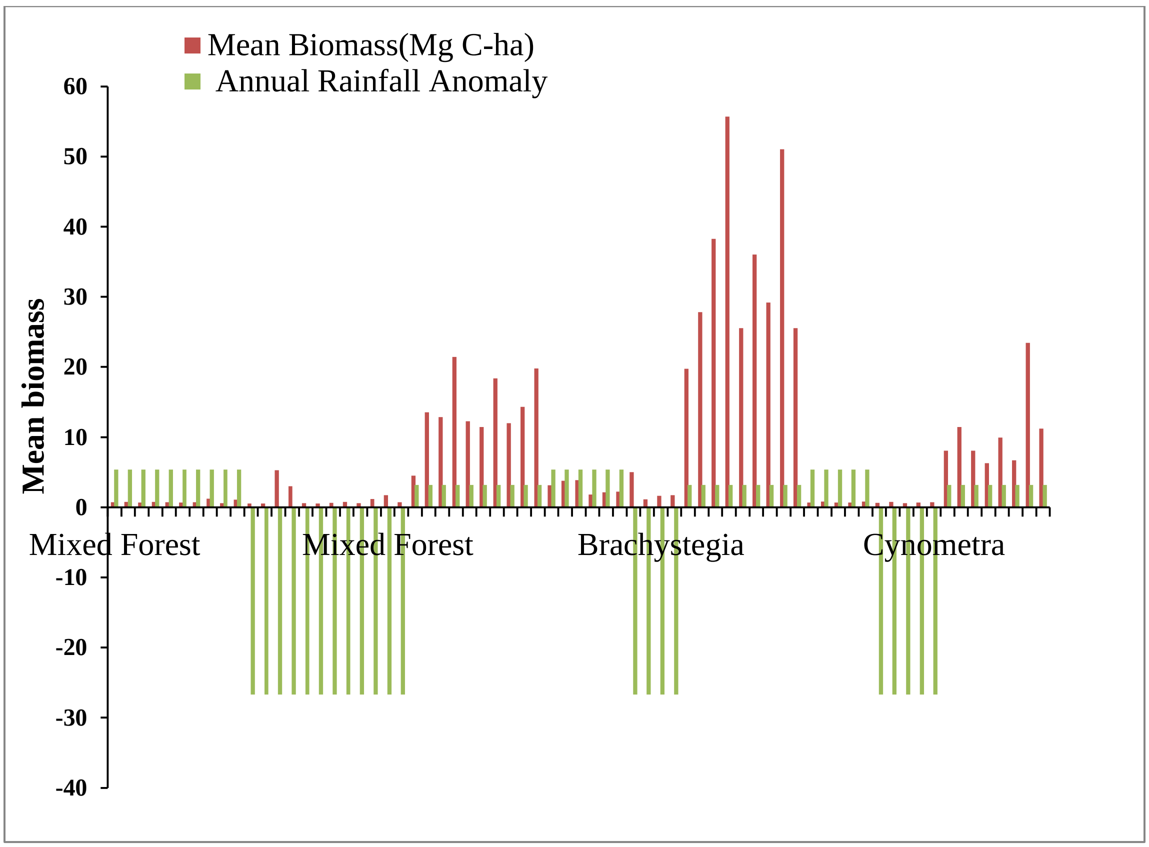

Figure 16: Relationship of mean total biomass and annual rainfalls anomaly

The result shows a strong significant relationship between mean maximum temperature anomaly and tree biomass ($F_{1\ 67.}$ =32.00, p=0.00). The regression of the relationships between mean maximum temperature anomaly and mean total tree biomass shows a fair fit (R^2=0.55) (Figure 17)

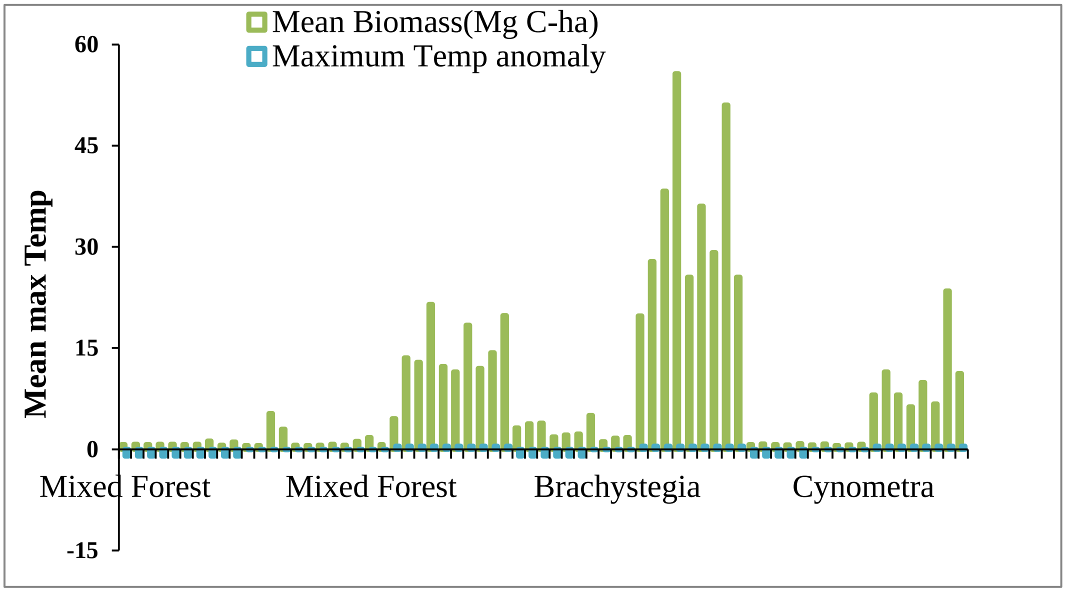

Figure 17: Relationship of mean total tree biomass and annual maximum temperature anomaly

The mean total tree biomass in Arabuko Sokoke forest showed a significant relationship with mean minimum temperatures anomaly ($F_{1\ 67}$. =16.47, p=0.00).The study indicates that 55% of total tree biomass could be explained by minimum temperatures (Figure 18).

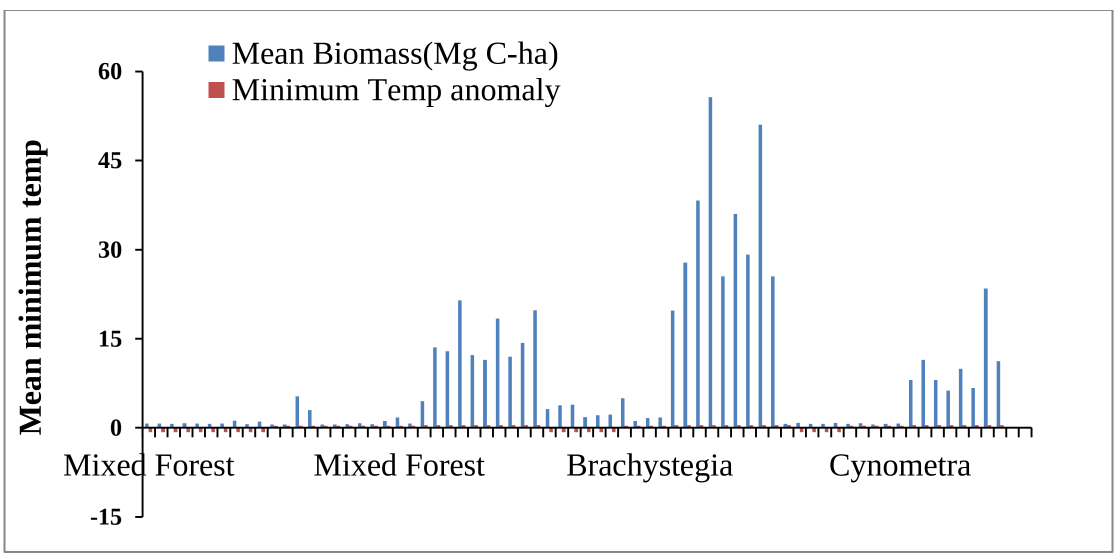

Figure 18: Relationship of mean total tree biomass and annual minimum temperature anomaly

4.3.1 Mixed forest tree biomass in relation to temporal climate pattern

Accumulation of tree biomass in mixed forest has a significant relationship with annual rainfall anomaly ($F_{1\ 30.}$ =6.46, p=0.01).The regression of the accumulation relationship has strong model fit (R^2=0.83) (Figure 19)

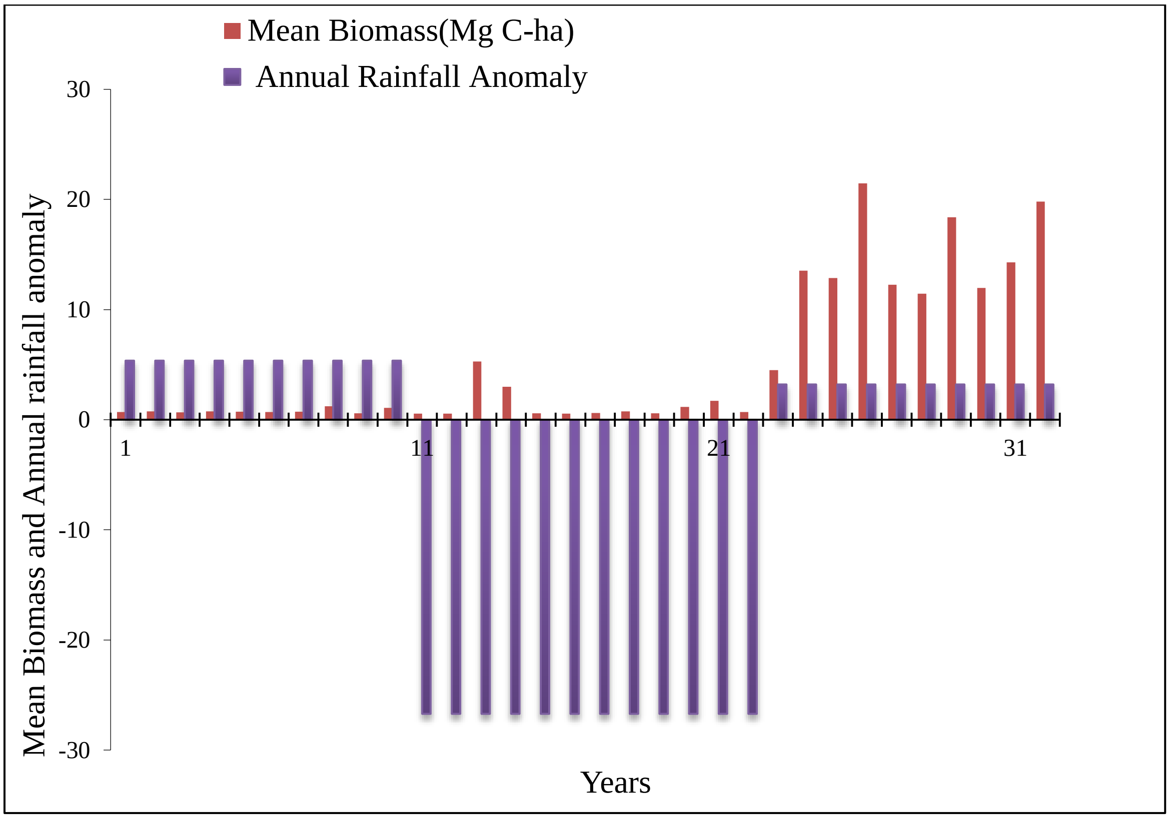

Figure 19: Relationship of mean total tree biomass and annual rainfall anomaly in mixed forest

Similarly the mean maximum temperature and mean minimum temperature anomalies had significant relationships with total tree biomass in mixed forest in Arabuko Sokoke ($F_{1\ 30.}$ =24.14, p=0.00) and ($F_{1\ 30.}$ =9.87, p=0.00). The regression relationship between the parameters had a poor model fit (R^2=0.45 and R^2=0.26) respectively (Figures 20 and Figures 21)

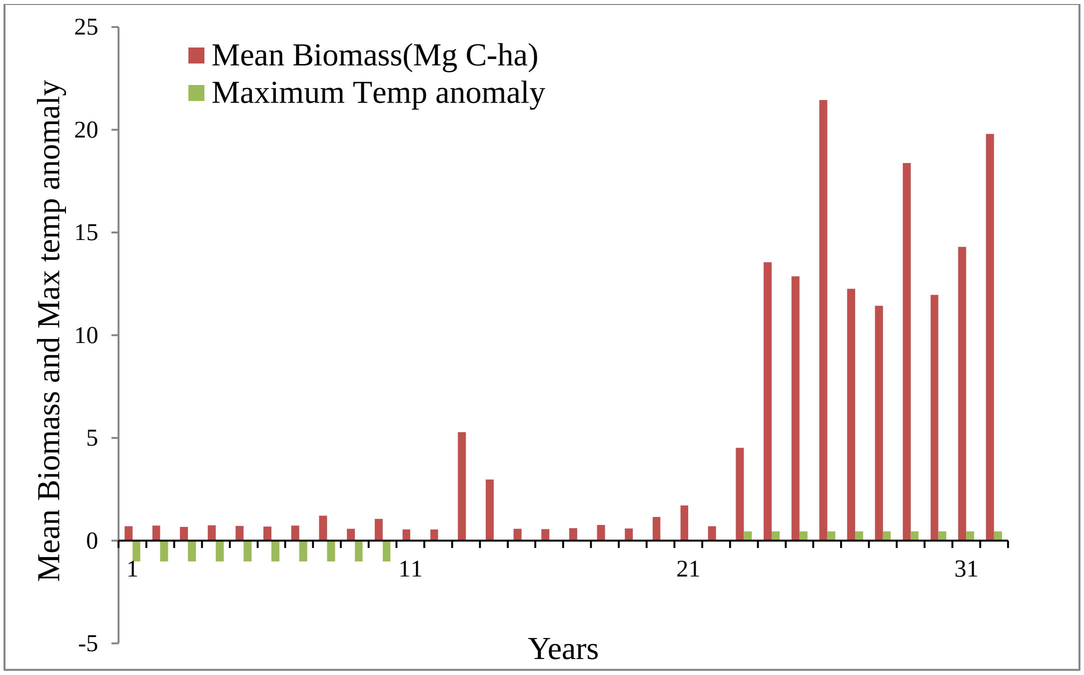

Figure 20: Relationship of mean total tree biomass and maximum temperature in mixed forest

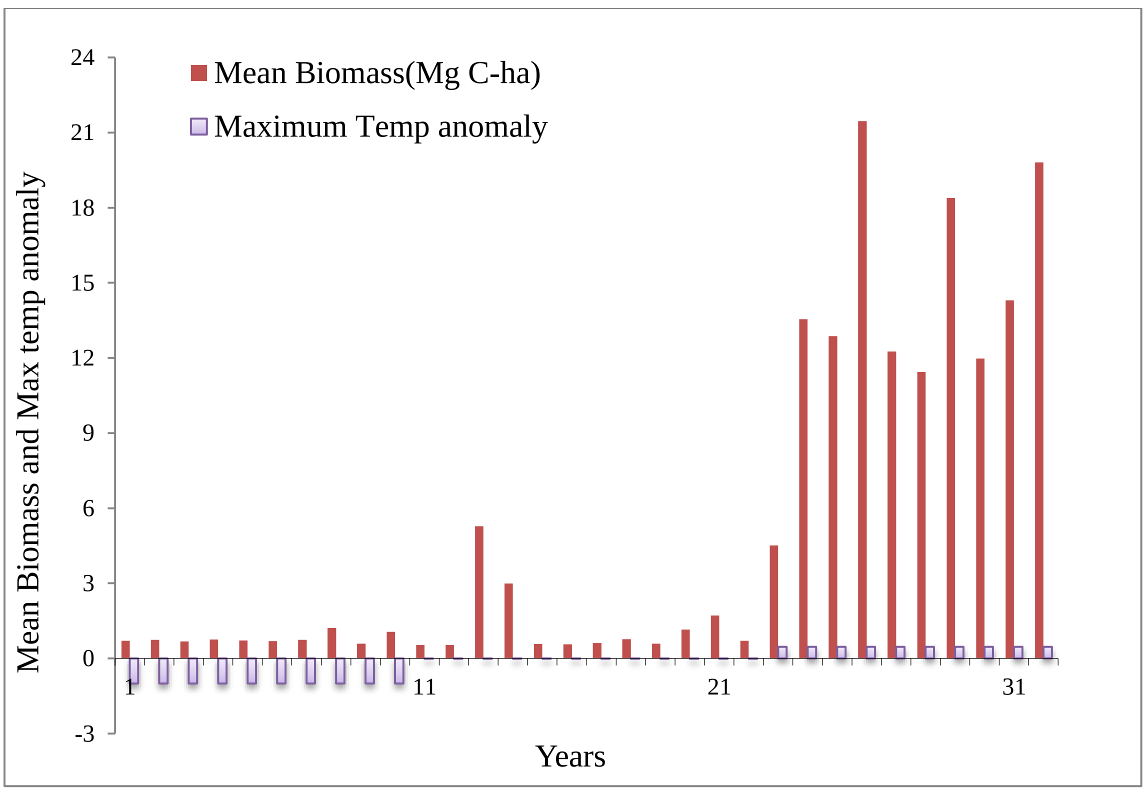

Figure 21: Relationship of mean total tree biomass and maximum temperature anomaly in mixed forest

4.3.2 Tree biomass in Cynometra forest in relation to temporal climate pattern

Tree biomass in Cynometra forest had no significant relationship with annual rainfall anomaly ($F_{1\ 16.}$ =3.99, p=0.06) (Figure 22), however the mean maximum temperature anomaly had a strong significant relationship while mean minimum temperature had weak significant relationships ($F_{1\ 16}$. =10.09, p=0.00) and ($F_{1\ 16}$. =4.73, p=0.05). The relationship between mean total tree biomass and mean maximum and mean minimum temperature anomalies had a poor model fit (R^2=0.24 and $R^{2=}$0.40) respectively (Figures 23 and Figures 24)

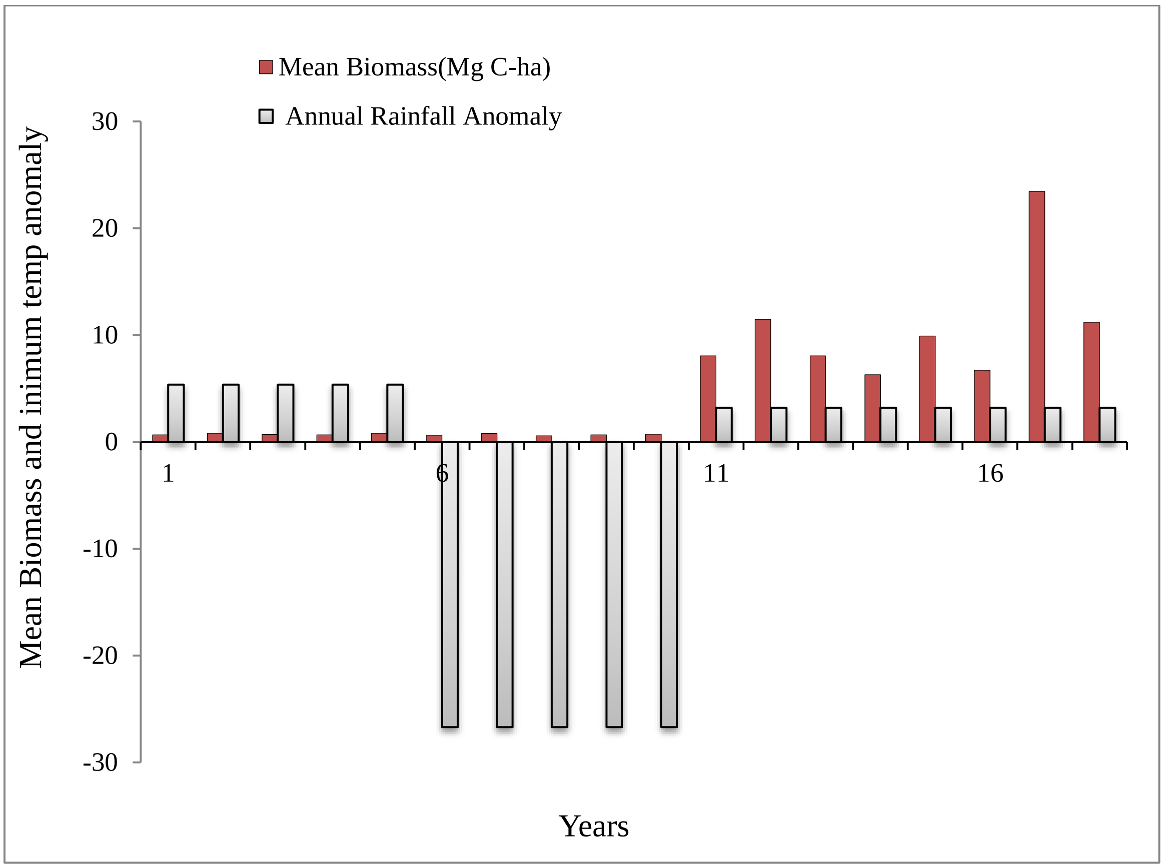

Figure 22: Relationship of mean total tree biomass and annual rainfall anomaly in cynometra forest

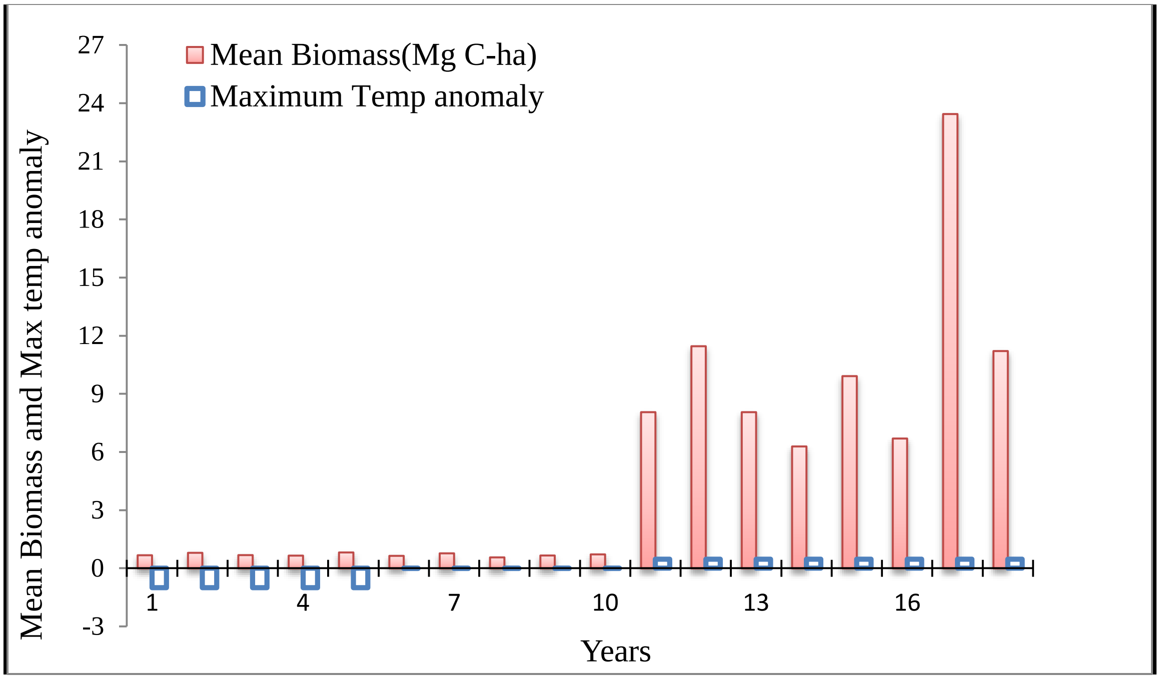

Figure 23: Relationship of mean total tree biomass and maximum temperature anomaly in cynometra forest

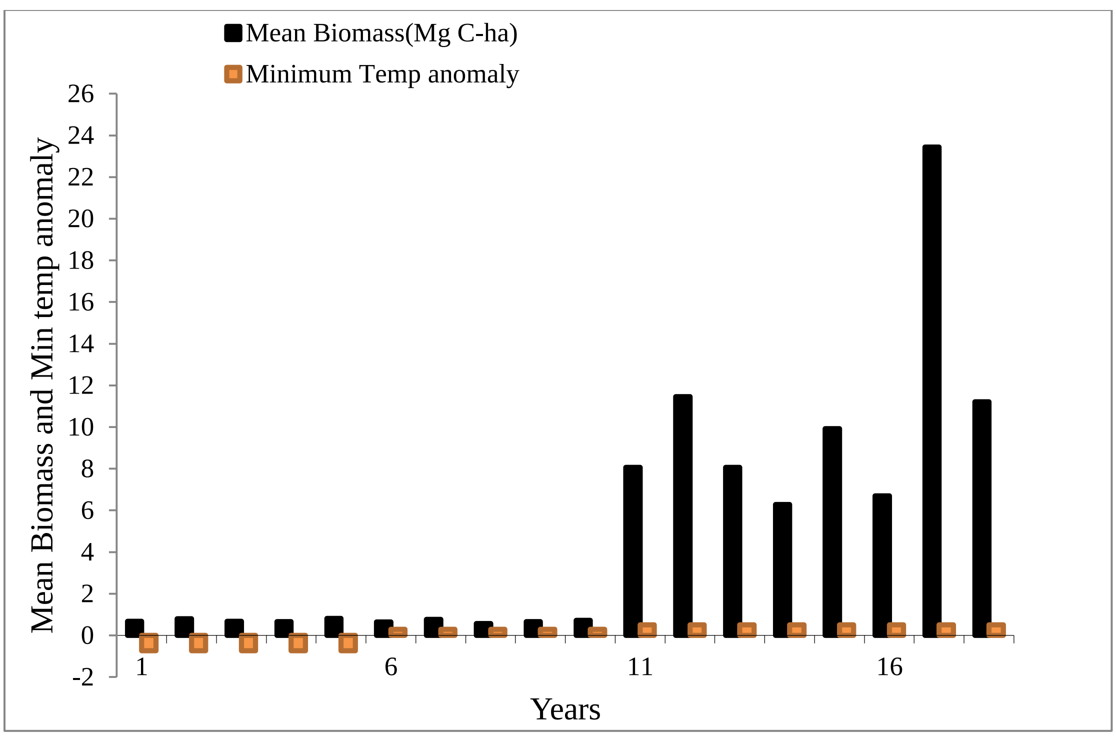

Figure 24: Relationship of mean total tree biomass and minimum temperature anomaly in cynometra forest

4.3.3 Tree biomass in Brachystegia forest in relation to temporal climate pattern

There was a significant relationship between tree biomass in brachystegia forest and annual maximum temperature anomaly ($F_{1\ 17.}$ =18.01, p=0.00), the regression model had a significant fit (R^2=0.52) (Figure 25) similarly minimum temperature anomaly had a significant relationships ($F_{1\ 17.}$ =9.19, p=0.01) and a poor model fit (R^2=0.37) (Figure 26)

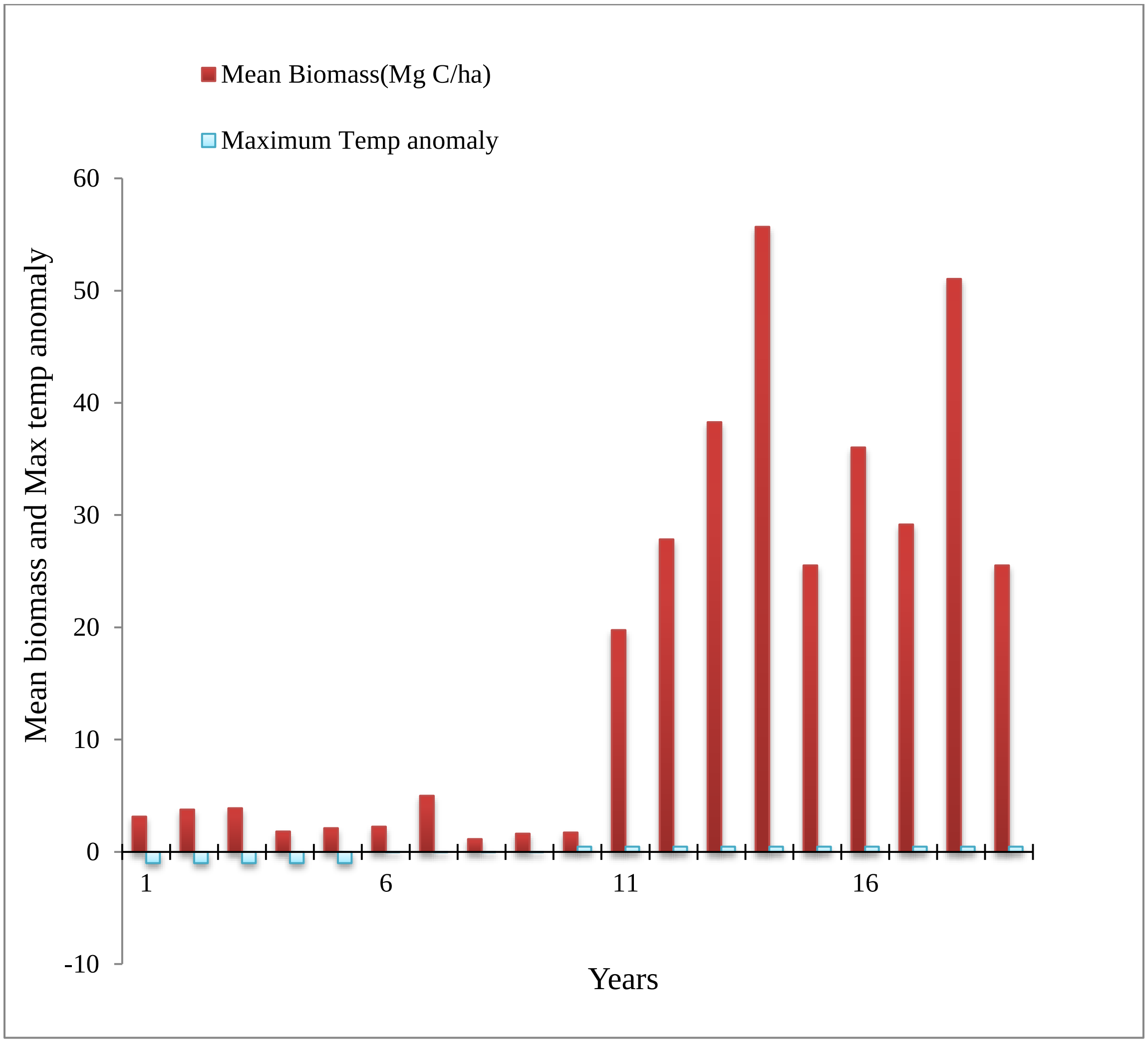

Figure 25: Relationship of mean total tree biomass and maximum temperature anomaly in brachystegia forest

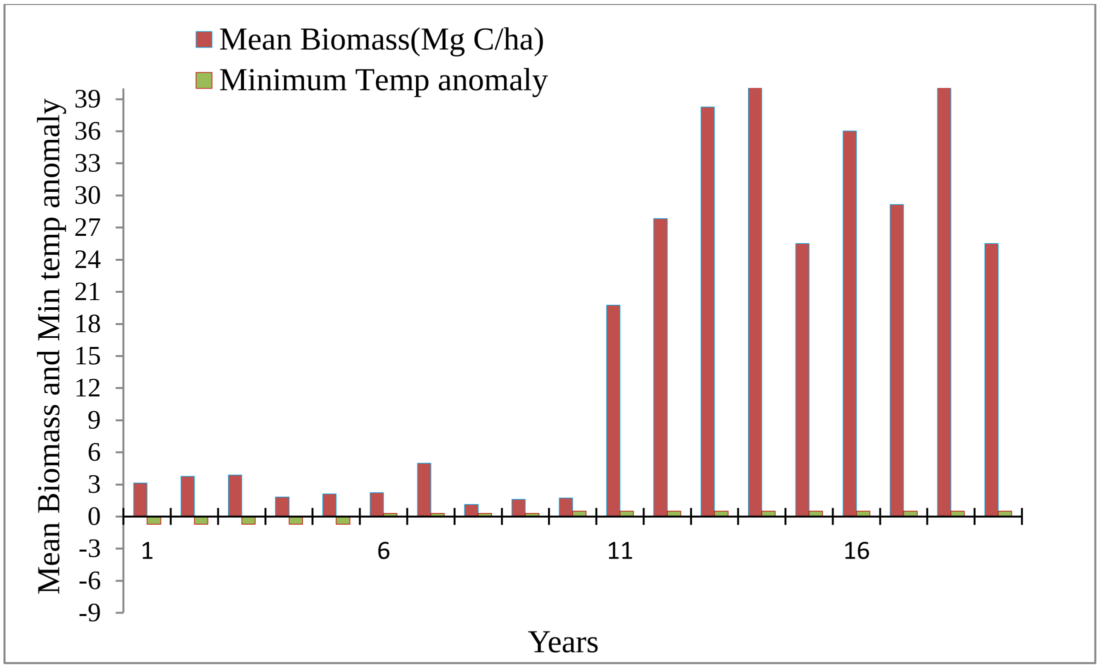

Figure 26: Relationship of mean total tree biomass and minimum temperature anomaly in brachystegia forest

However there was no significant relationship between mean total tree biomass and annual rainfall anomaly for brachystegia forest ($F_{1\ 17}$. =3.57, p=0.08) (Figure 27)

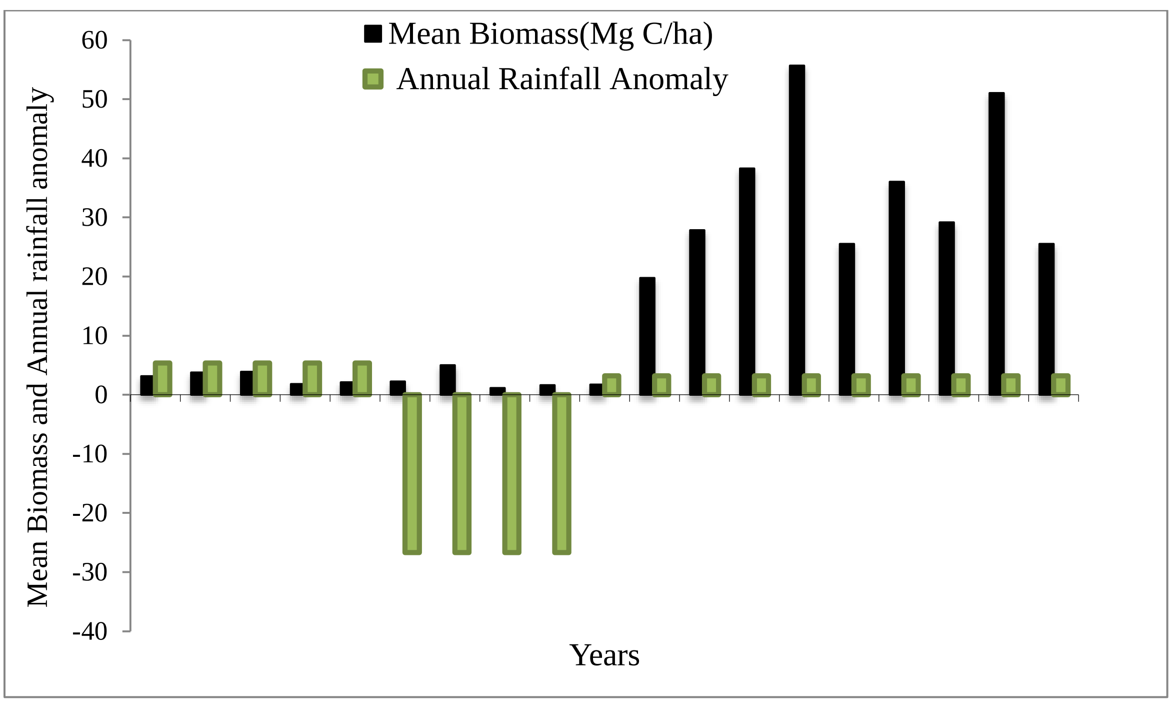

Figure 27: Relationship of mean total tree biomass and annual rainfall anomaly in brachystegia forest

4.4 Projection on impacts of climate change on tree species distribution

This section covers analysis of the impacts of future climate on tree biomass as modeled using MaxEnt model based on bioclimatic variables associated with RCP 4.5 and 8.5, which represent a state of deployment of policies and strategies to address the greenhouse gases emissions and business as usual scenarios respectively

4.4.1 Impacts of climate change based on RCP of 4.5 at 2050

This section covers results of MaxEnt model based on forest occurrence data and bioclimatic variables based on RCP 4.5 at 2050. RCP 4.5 postulates a future where a raft of proactive policies and strategies will be deployed to address the greenhouse gases by 2100.

4.4.1.1 Analysis of sensitivity and specificity based on RCP 4.5 at 2050

The significance of the (ROC) curve is determined by the area under curve (AUC) which has values that ranges from 0.5-1.0 and with levels of predictive accuracy (Swets, 1988): 0.50-0.60 (fail), 0.60-0.70 (poor), 0.70-0.80 (fair), 0.80-0.90 (good), and 0.90-1.0 (excellent).The AUC for brachystegia forest model based on RCP 4.5 at 2050 was 0.96 and 0.86, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had ‘good’ predictive level and thus can be used in site suitability projection for of brachystegia forest in Arabuko Sokoke forest reserve (Figure 28)

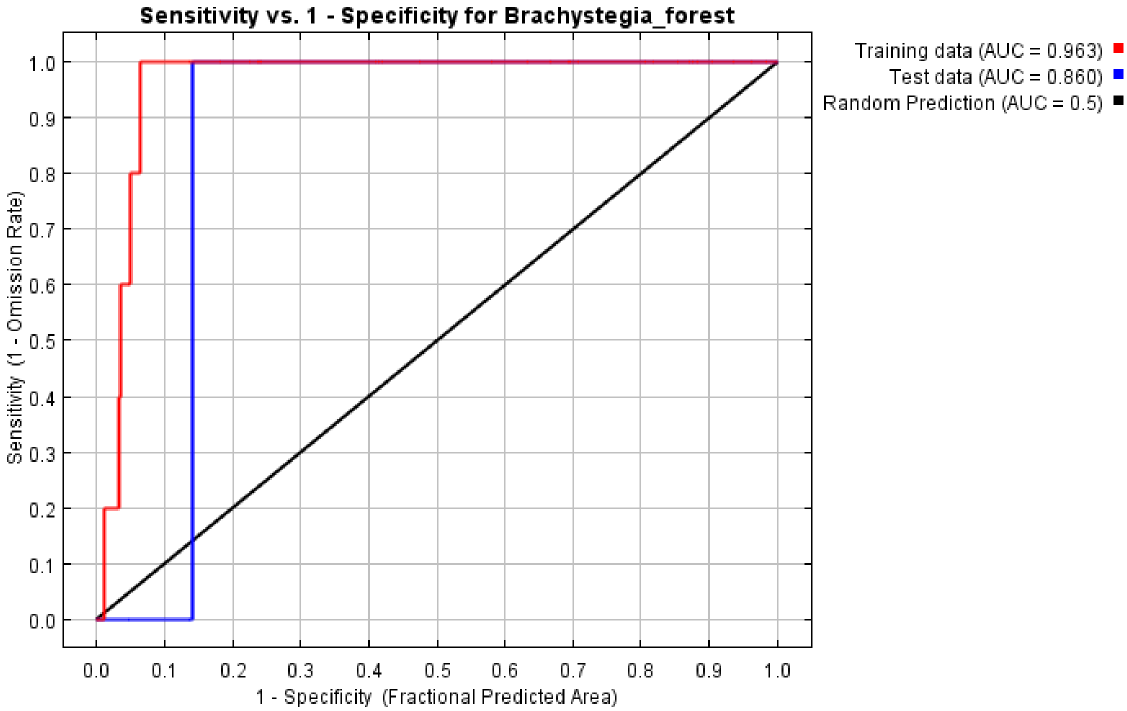

Figure 28: ROC curve of sensitivity versus specificity for brachystegia forest based on RCP 4.5 at 2050

The figure 29 indicates the area under curve (AUC) for cynometra forest model as determined by climatic factors associated with RCP 4.5 at 2050 was 0.87 and 0.50, for training and test data, respectively. This AUC value indicated that the constructed model is poor and had 'failed' predictive level and therefore it not suitable for predicting the geographic distribution of cynometra forest in Arabuko Sokoke forest reserve.

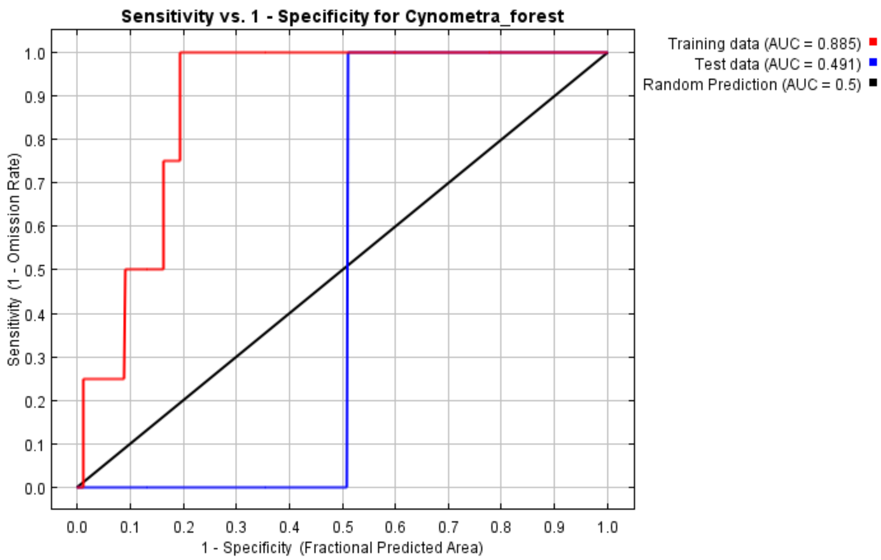

Figure 29: ROC curve of sensitivity versus specificity for cynometra forest based on RCP 4.5 at 2050

The study (Figure 30) indicates the area under curve (AUC) for mixed forest model as per climatic factors associated with RCP 4.5 at 2050 was 0.93 and 0.86, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had 'good' level of predictive accuracy and therefore it be used in projecting suitable spatial coverage for cynometra forest in Arabuko Sokoke.

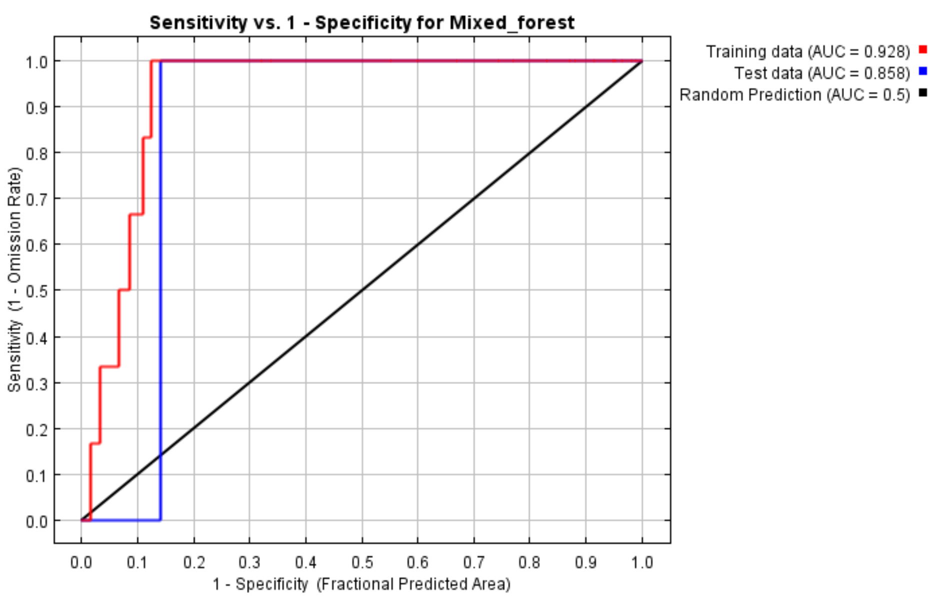

Figure 30: ROC curve of sensitivity versus specificity for mixed forest based on RCP 4.5 at 2050

4.4.1.2 Climate suitability maps generated from MaxEnt and Arc Gis based on RCP 4.5 at 2050

The future suitability zones were derived for RCP 4.5 at 2050, were determined through MaxEnt model. Geographical ranges of the certainly (0.6-1.0), likely (0.45-0.60), possibly (0.30.-0.45), unlikely (0.2-0.3) and rarely (0.00-0.17) are shown in the species suitability map using different colours (Figures 31, 32 and 33). The red colour indicates highly suitable areas while green colour depicts zones of unsuitability for brachystegia forest based on RCP 4.5 at 2050 and 2070. In the cynometra forest, the dark green colour shows areas of higher suitability while black colour indicates zones of unsuitability based on RCP 4.5 at 2050 and 2070.Similarly colour scheme for mixed forest based on RCP 4.5 at 2050 and 2070 are shades of green for suitable area and purple for unsuitable areas respectively

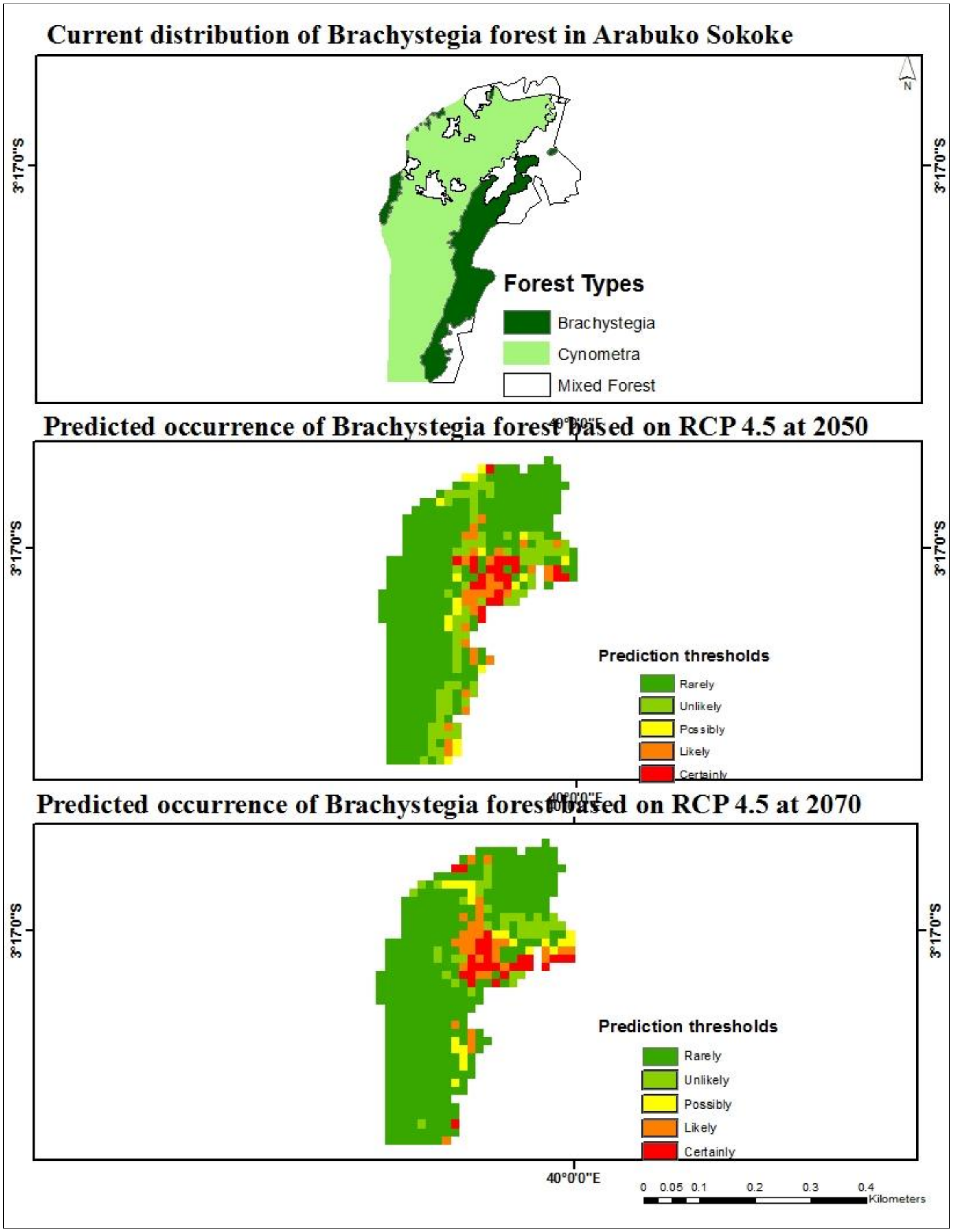

Figure 31: Climate suitability map for brachystegia forest based on current conditions and RCP 4.5 at 2050 and 2070 in Arabuko Sokoke forest reserve

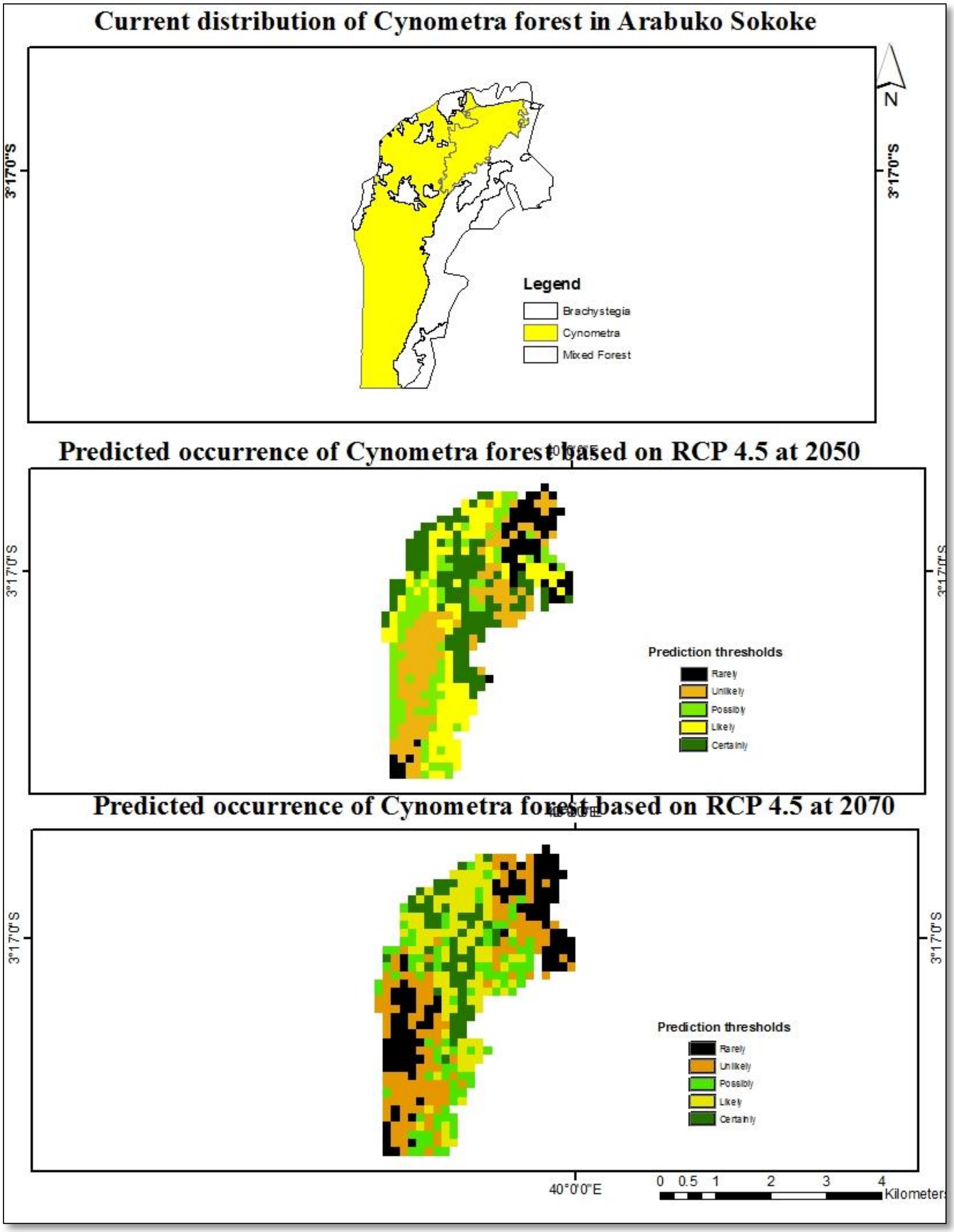

Figure 32: Climate suitability map for cynometra forest based on current conditions and RCP 4.5 at 2050 and 2070 in Arabuko Sokoke forest reserve

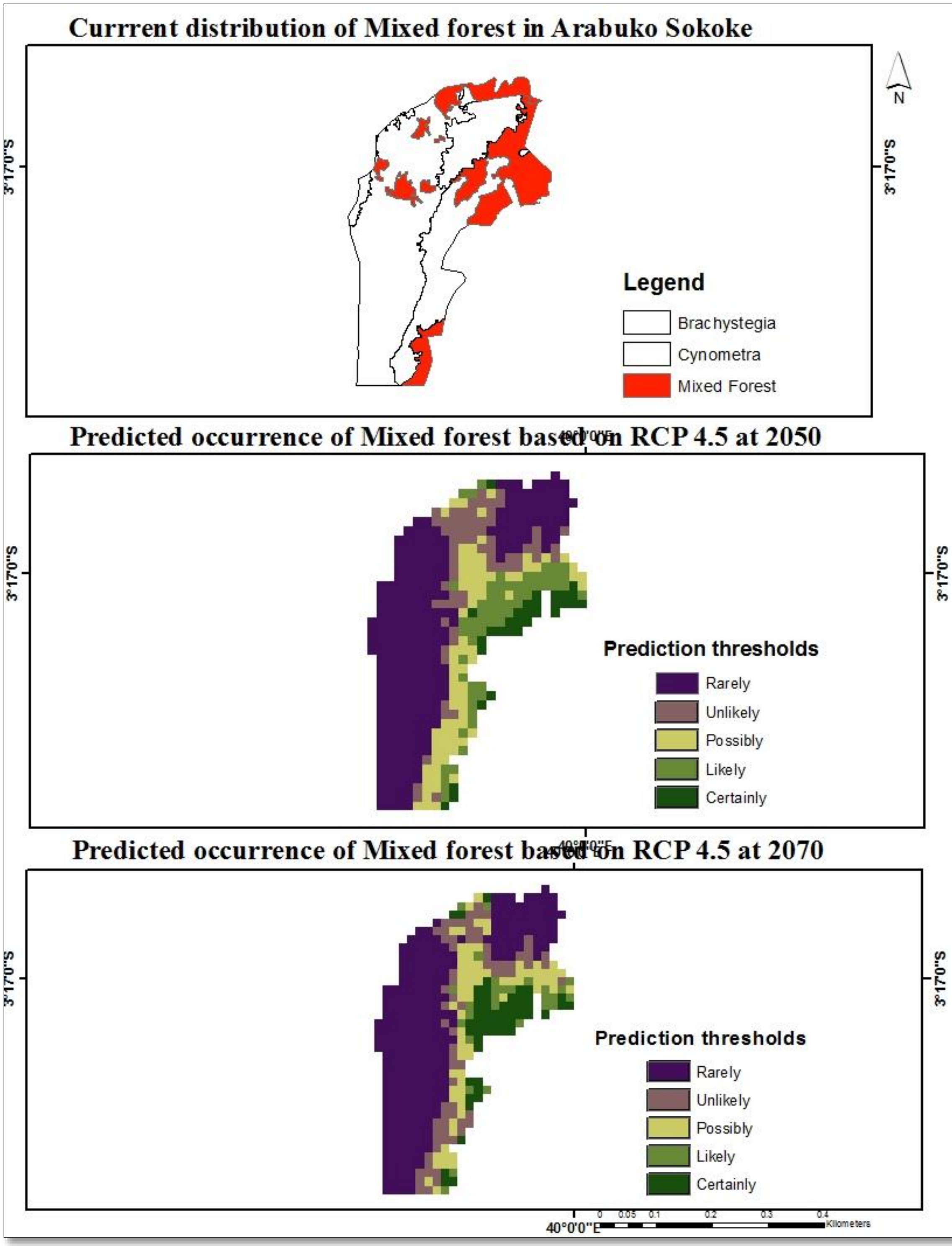

Figure 33: Climate suitability map for mixed forest based on current conditions and RCP 4.5 at 2050 and 2070 in Arabuko Sokoke forest reserve

4.4.1.3 Analysis of variable contributions based on RCP 4.5 at 2050

The future distribution of brachystegia forest based on RCP 4.5 at 2050 modeling will be influenced by temperature and precipitation variables. A total of six (6) variables contributed to the brachystegia forest model based on RCP 4.5 at 2050. The bioclimatic variables BIO8 and BIO2 were the top two contributors to the prediction model with 61.2% and 19 % respectively (Table 3), while BIO 17 had 13.3%.

Table 3: Selected environmental variables with percent contribution to the model for brachystegia forest based on RCP 4.5 at 2050

Environmental Variable	**Percent contribution**
Mean Temperature of Wettest Quarter (Bio8)	61.2
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio 2)	19
Precipitation of Driest Quarter(Bio 17)	13.3
Annual Mean Temperature(Bio 1)	3.8
Precipitation of Driest Month(Bio 14)	2.2
Annual Precipitation(Bio 12)	0.5

The predicted distribution of cynometra forests based on RCP 4.5 as at 2050 will be determined by precipitation and temperature variables. A total of eight (8) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 19 and BIO 1 were the biggest contributors with 35.9% and 16.1% respectively (Table 4)

Table 4: Selected environmental variables with percent contribution to the model for cynometra forest based on RCP 4.5 at 2050

Environmental Variable	**Percent contribution**
Precipitation of Coldest Quarter(Bio19)	35.9
Annual Mean Temperature(Bio 1)	16.1
Mean Temperature of Driest Quarter(Bio9)	15.4
Temperature Annual Range (BIO5- BIO6)(Bio7)	14.1
Max Temperature of Warmest Month(Bio 5)	13.1
Precipitation of Driest Quarter(Bio 17)	4.3
Isothermality (BIO2/BIO7) (* 100)(Bio 3)	1
Temperature Seasonality (standard deviation *100)(Bio 4)	0.1

Nine (9) bioclimatic variables contributed to the mixed forest prediction model based on RCP 4.5 at 2050.The highest contribution was from bioclimatic variable BIO8 ,followed by BIO5 with least being from BIO14 and BIO7(Table 5)

Table 5: Selected environmental variables with percent contribution to the model for mixed forest based on RCP 4.5 at 2050

Environmental Variables	Percent Contribution
Mean Temperature of Wettest Quarter (Bio8)	65.5
Max Temperature of Warmest Month(Bio 5)	19.3
Mean Temperature of Coldest Quarter(Bio11)	5.4
Mean Temperature of Warmest Quarter(Bio10)	4.6
Precipitation of Driest Quarter(Bio 17)	4.3
Mean Temperature of Driest Quarter(Bio9	0.4
Annual Precipitation(Bio 12)	0.3
Precipitation of Driest Month(Bio 14)	0.1
Temperature Annual Range (BIO5- BIO6)(Bio7)	0.1

4.4.1.4 Jackknife test for variables based on RCP 4.5 at 2050

The jackknife test estimates how the model will perform if new data or observation is input into it. The stepwise approach of removing bioclimatic variables indicates the Mean Temperature of Wettest Quarter (Bio8) had the highest gain when used alone, while Mean Diurnal Range (Mean of monthly (max temp - min temp) (Bio 2), decreases in gain the most when it is omitted for brachystegia forest (Figure 34). The jackknife test shows that in the cynometra forest Annual Mean Temperature (Bio 1) records highest gain when applied alone. Precipitation of Coldest Quarter (Bio19) decreased the gain the most when it is omitted (Figure 35).

The jackknife results for mixed forest shows that the highest gain in variable when used alone is that of Mean Temperature of Wettest Quarter (Bio8) while at the same time shows a drastic decreases when it is omitted in the model (Figure 36).

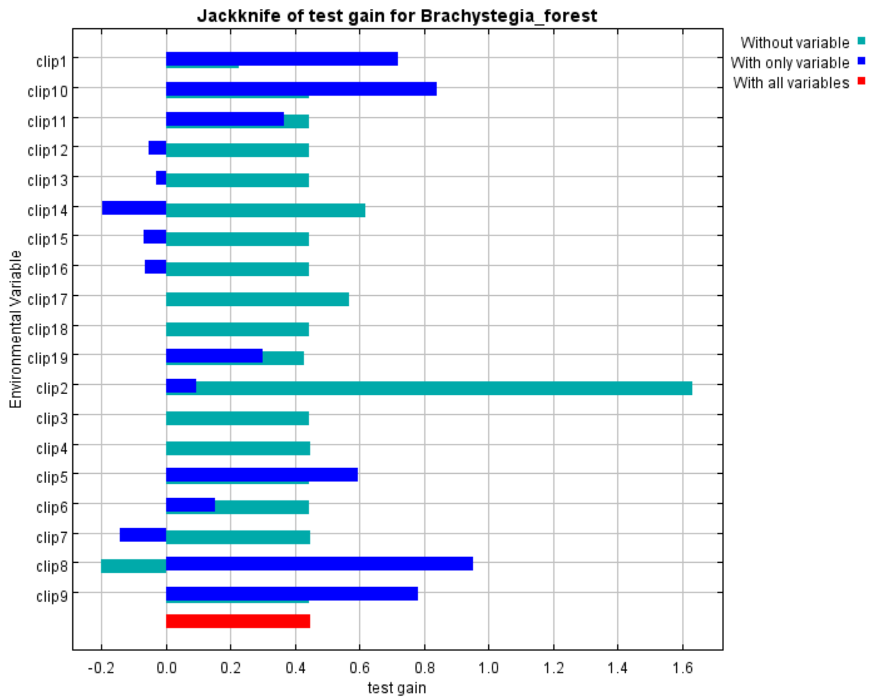

Figure 34: Predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 4.5 at 2050

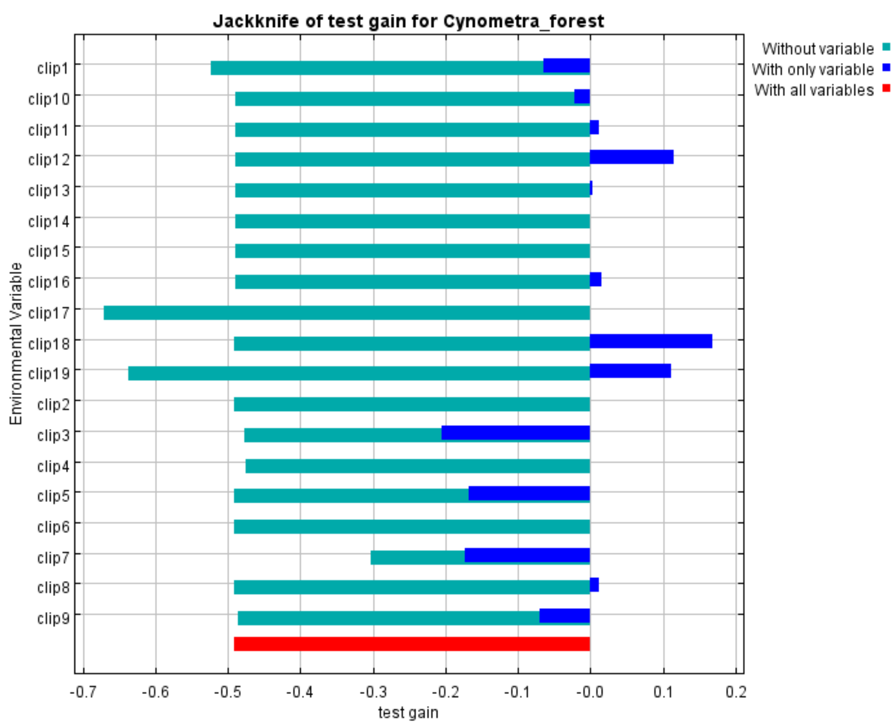

Figure 35: Relative predictive power of different bioclimatic variables based on the jackknife test for cynometra forest based on RCP 4.5 at 2050

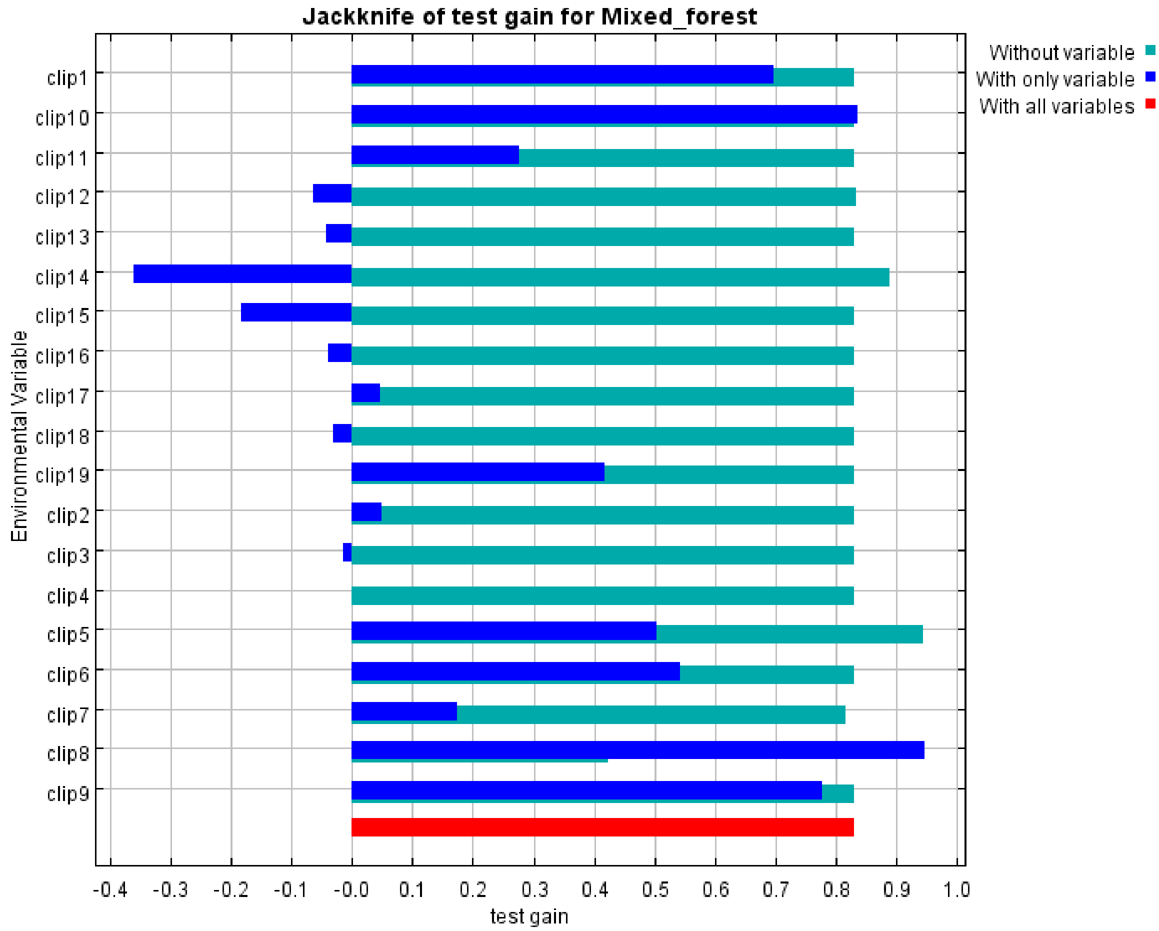

Figure 36: Relative predictive power of different bioclimatic variables based on the jackknife test for mixed forest based on RCP 4.5 at 2050

4.4.2 Impacts of climate change based on RCP 4.5 at 2070

The results below documents MaxEnt model outputs analyzed from forest occurrence data and bioclimatic variables based on RCP 4.5 at 2070. RCP 4.5 postulates a future where a raft of proactive policies and strategies will be deployed to address the greenhouse gases by 2100.

4.4.2.1 Analysis of sensitivity and specificity based on RCP 4.5 at 2070

The AUC for brachystegia forest model as determined by climatic factors associated with RCP 4.5 at 2070 was 0.95 and 0.89, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had 'good' predictive accuracy and it can be used for predicting the geographic distribution of brachystegia forest in Arabuko Sokoke forest reserve (Figure 37)

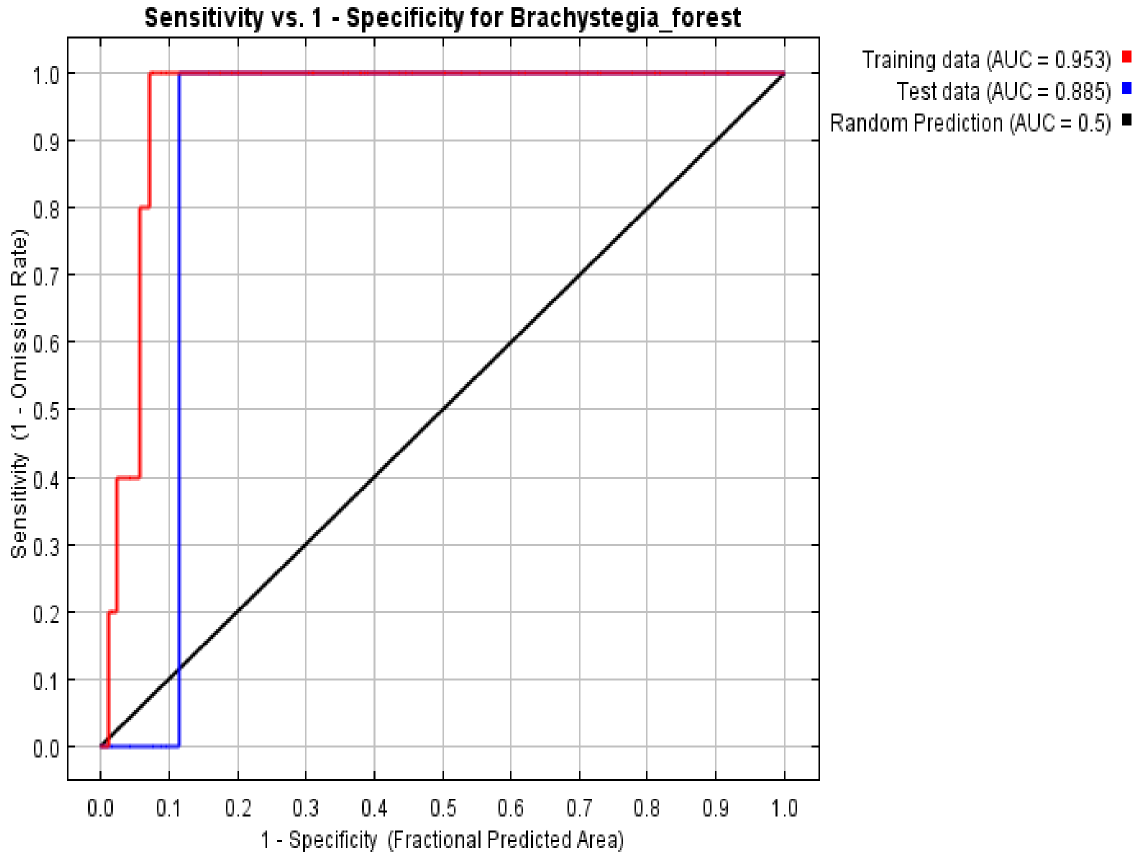

Figure 37: ROC curve of sensitivity versus specificity for brachystegia forest based on RCP 4.5 at 2070

The cynometra forest model as per climatic factors associated with RCP 4.5 at 2070 had an AUC of 0.92 and 0.58, for training and test data, respectively. This AUC value indicated that the constructed model cannot be used predicting the suitable areas for brachystegia forest in Arabuko Sokoke forest reserve (Figure 38) because it has failed the predictive accuracy

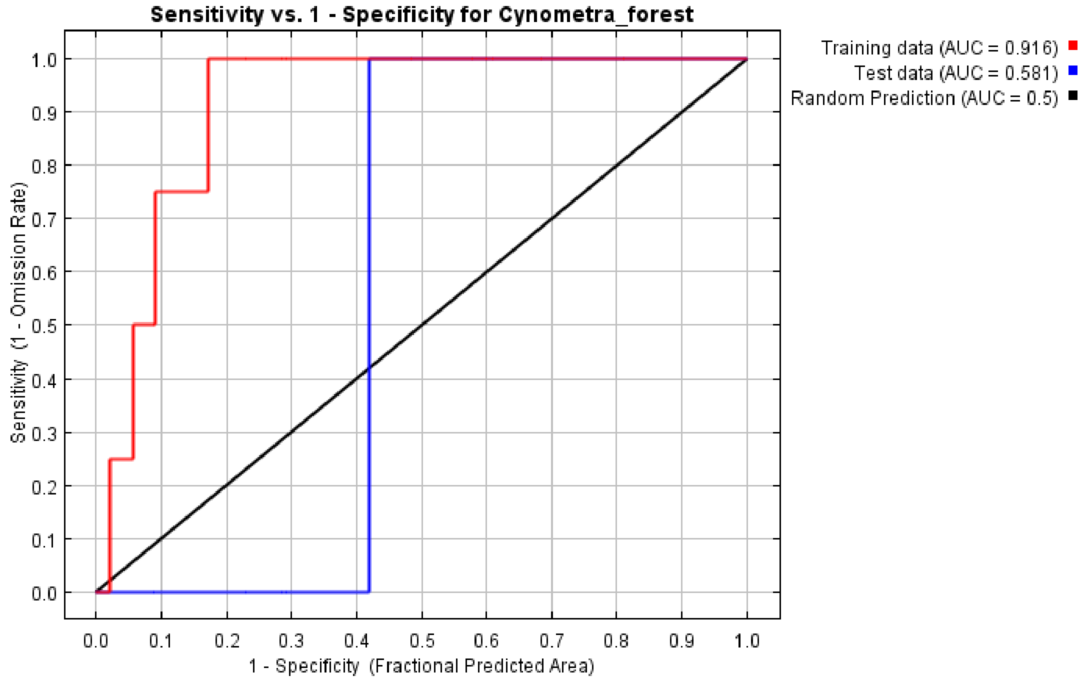

Figure 38: ROC curve of sensitivity versus specificity for cynometra forest based on RCP 4.5 at 2070

The AUC for mixed forest model based on the climatic variables associated with RCP 4.5 at 2070 was 0.96 and 0.87, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had ‘good’ predictive accuracy and it useful in predicting the geographic distribution of mixed forest in Arabuko Sokoke forest reserve (Figure 39)

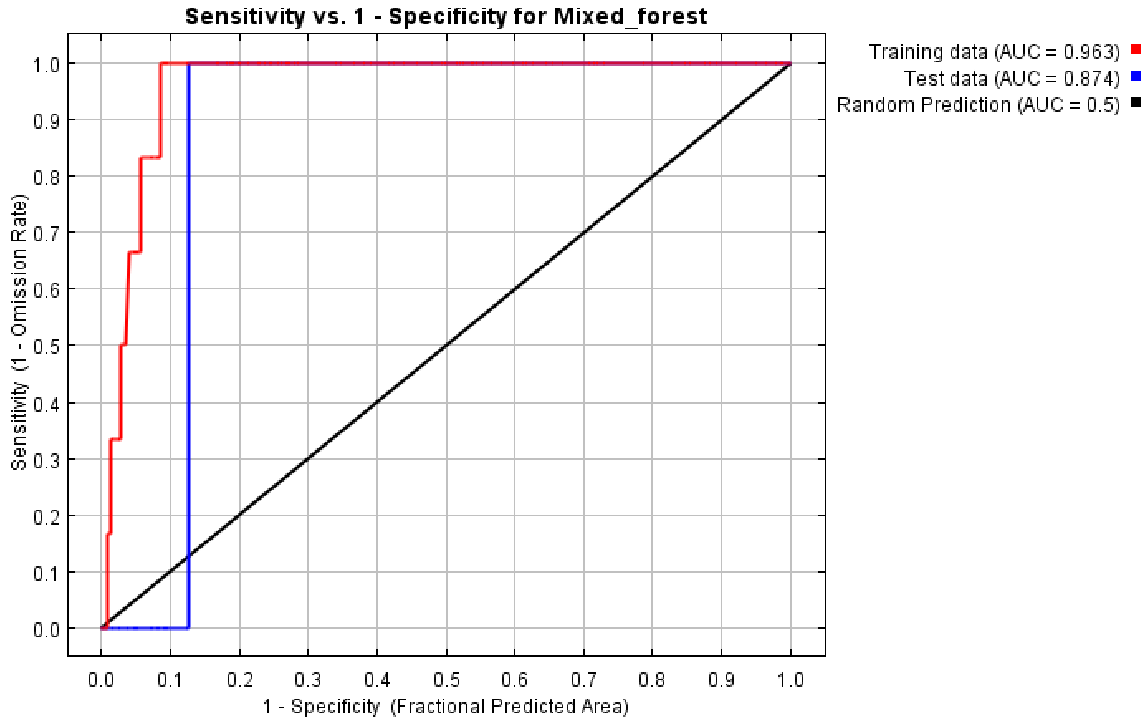

Figure 39: ROC curve of sensitivity versus specificity for mixed forest based on RCP 4.5 at 207

4.4.2.2 Analysis of variable contributions based on RCP 4.5 at 2070

Table 6 below indicates that the predicted distribution of brachystegia forests based on RCP 4.5 at 2070 will be determined by temperature and precipitation variables. Nine (9) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 8 and BIO 1 were the biggest contributors with 53% and 24.7% respectively

Table 6: Selected environmental variables with percent contribution in the model for brachystegia forest based on RCP 4.5 at 2070

Environmental Variable	Percent contribution
Mean Temperature of Wettest Quarter(Bio 8)	53
Annual Mean Temperature(Bio 1)	24.7
Mean Temperature of Coldest Quarter(Bio 11)	9.8
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio2)	4
Precipitation of Warmest Quarter(Bio 18)	3.7
Precipitation of Driest Month(Bio14)	3.1
Isothermality (BIO2/BIO7) (* 100)(Bio 3)	1.3
Mean Temperature of Warmest Quarter(Bio 10)	0.2
Annual Precipitation(Bio12)	0.2

The selected environmental variables (Table 7) shows that the predicted distribution of cynometra forests based on RCP 4.5 at 2070 will be determined by temperature and precipitation variables. Seven (7) bioclimatic variables contributed to the prediction model. With bioclimatic variable BIO 9 and BIO 2 being the biggest contributors with 48.1% and 21.2% respectively

Table 7: Selected environmental variables and their percent contribution in MaxEnt model for cynometra forest based on RCP 4.5 at 2070

Environmental Variable	Percent contribution
Mean Temperature of Driest Quarter(Bio9)	48.1
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio2)	21.2
Temperature Annual Range (BIO5- BIO6)(Bio7)	15.8
Precipitation of Warmest Quarter(Bio 18)	7.7
Temperature Seasonality (standard deviation *100)(Bio4)	4.4
Min Temperature of Coldest Month(Bio6)	1.5
Precipitation Seasonality (Coefficient of Variation)(Bio 15)	1.3

Nine bioclimatic variables contributed to the prediction model for mixed forest based on RCP 4.5 at 2070.The mean Temperature of Wettest Quarter (Bio 8) and Annual Mean Temperature (Bio 1) were the largest contributors with 37.8% and 37.2 % respectively (Table 8)

Table 8: Selected environmental variables and their percent contribution in MaxEnt model for mixed forest based on RCP 4.5 at 2070

Environmental Variable	**Percent contribution**
Mean Temperature of Wettest Quarter(Bio 8)	37.8
Annual Mean Temperature(Bio 1)	37.2
Precipitation of Driest Month(Bio14)	10.1
Mean Temperature of Driest Quarter(Bio9)	4.8
Isothermality (BIO2/BIO7) (* 100)(Bio 3)	4.4
Precipitation of Warmest Quarter(Bio 18)	3.5
Min Temperature of Coldest Month(Bio 6)	1.2
Mean Temperature of Coldest Quarter(Bio 11)	0.8
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio2)	0.3

4.4.2.3 Jackknife test for variables based on RCP 4.5 at 2070

Jackknife test estimate the performance of models when subjected to new data, and in this study the jackknife results for brachystegia shows that mean Temperature of Wettest Quarter (Bio8) had with highest gain when used alone, while Mean Temperature of Coldest Quarter (Bio 11), had decreases in gain the most when it is omitted (Figure 40)

In the cynometra forest, the Mean Temperature of Driest Quarter (Bio9) had higher gain when applied in isolation and it decreased drastically in the gain omitted in the prediction model. (Figure 41)

The jackknife test analysis for mixed forest indicates that higher gain is expected where Mean Temperature of Wettest Quarter (Bio8) is used alone while Precipitation of Driest Month (Bio14) led to decreased gain the most when left out in the prediction model (Figure 42)

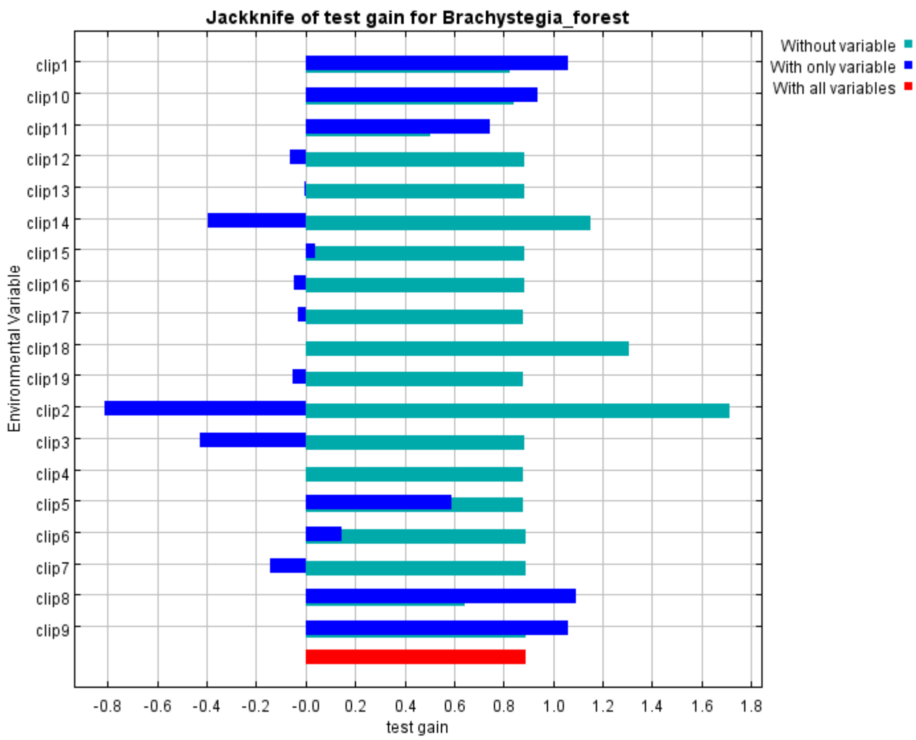

Figure 40: Relative predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 4.5 at 2070

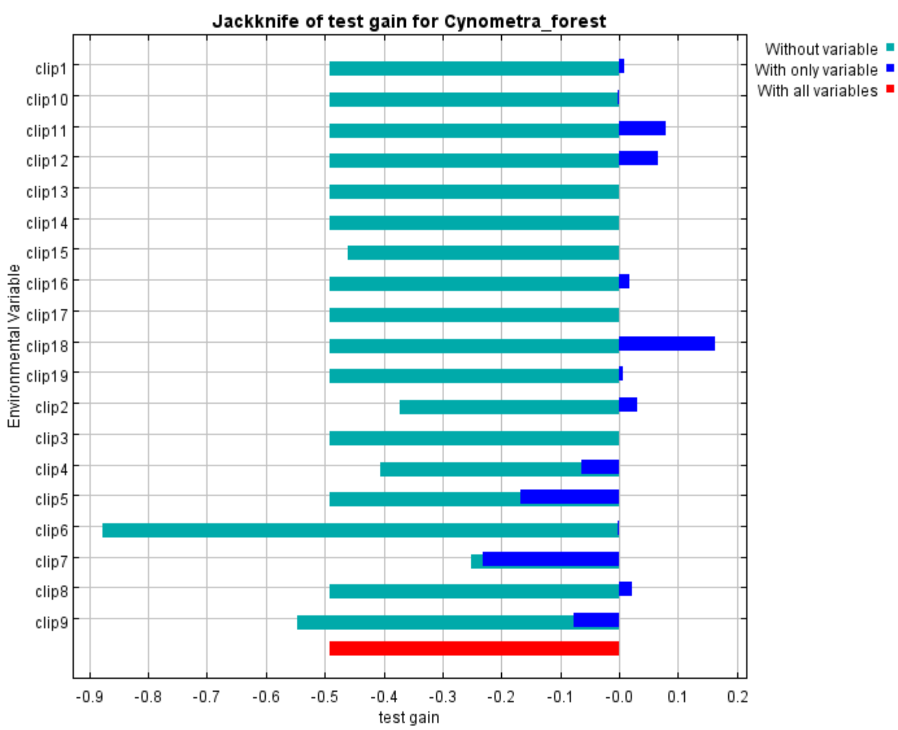

Figure 41: Relative predictive power of different bioclimatic variables based on the jackknife test for cynometra forest based on RCP 4.5 at 2070

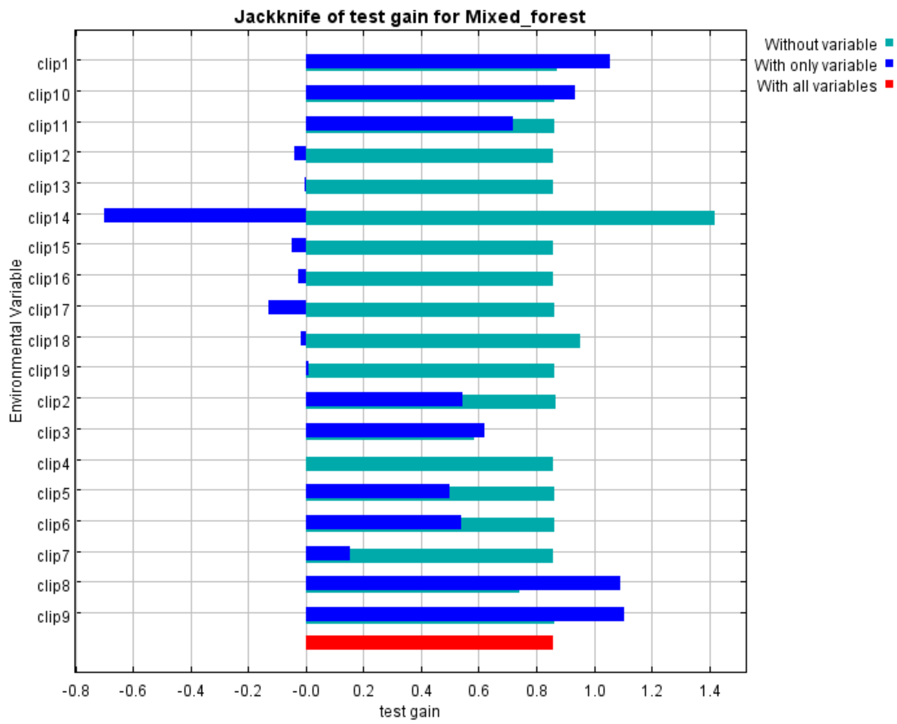

Figure 42: Relative predictive power of different bioclimatic variables based on the jackknife test for mixed forest based on RCP 4.5 at 2070

4.4.3 Impacts of climate change based on RCP 8.5 at 2050

The MaxEnt model outputs analyzed from forest occurrence data and bioclimatic variables based on RCP 8.5 at 2050 are presented in the below sections.

4.4.3.1 Analysis of sensitivity and specificity based on RCP 4.5 at 2050

The AUC for brachystegia forest model based on RCP 8.5 at 2050 was 0.96 and 0.86, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had ‘good’ predictive accuracy and useful in site suitability determination for brachystegia forest in Arabuko Sokoke forest reserve (Figure 43)

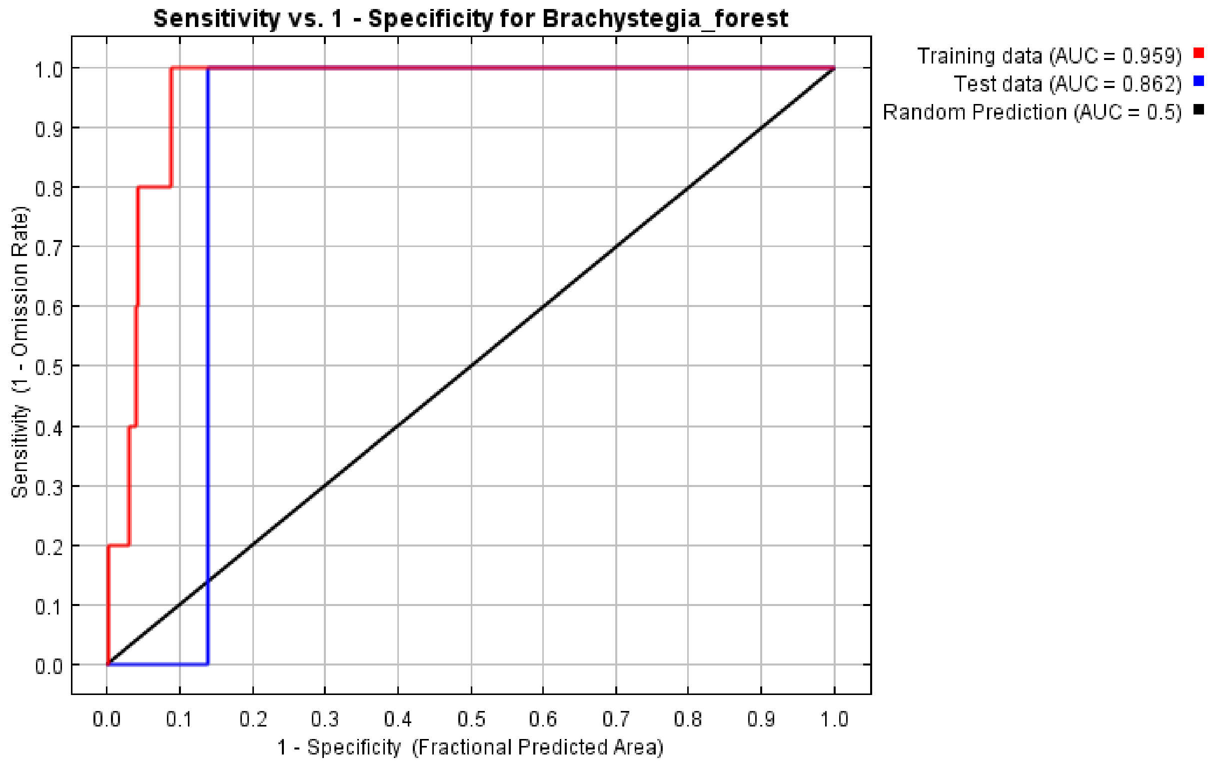

Figure 43: ROC curve of sensitivity versus specificity for brachystegia forest based on RCP 8.5 at 2050

The AUC for cynometra forest model based climatic factors associated with RCP 8.5 at 2050 was 0.93 and 0.55, for training and test data, respectively. This AUC value indicated that the constructed model is not better then random data and has 'fail' predictive accuracy and it is not suitable for predicting the geographic distribution of cynometra forest in Arabuko Sokoke forest reserve (Figure 44)

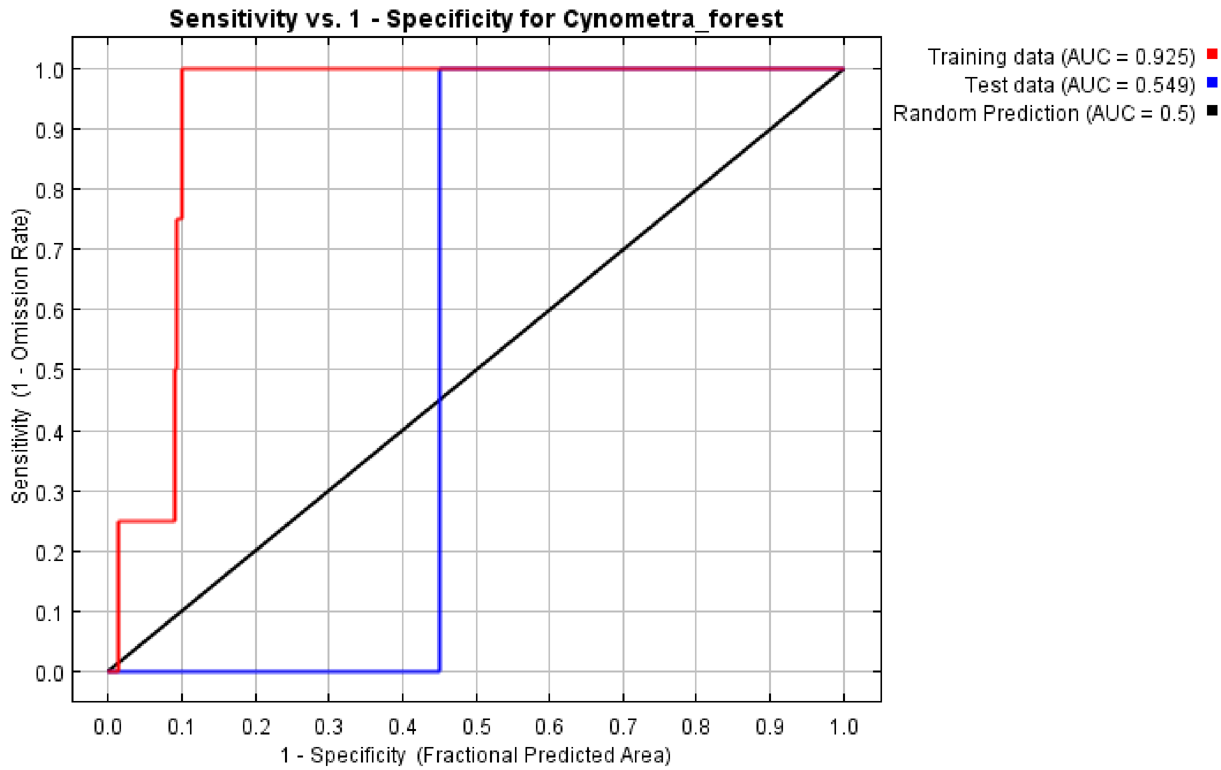

Figure 44: ROC curve of sensitivity versus specificity for cynometra forest based on RCP 8.5 at 2050

The AUC for mixed forest c model based RCP 8.5 at 2050 was 0.95 and 0.90, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had ‘good’ predictive accuracy and therefore it was robust in predicting suitable forest areas for mixed forest type in Arabuko Sokoke forest reserve (Figure 45)

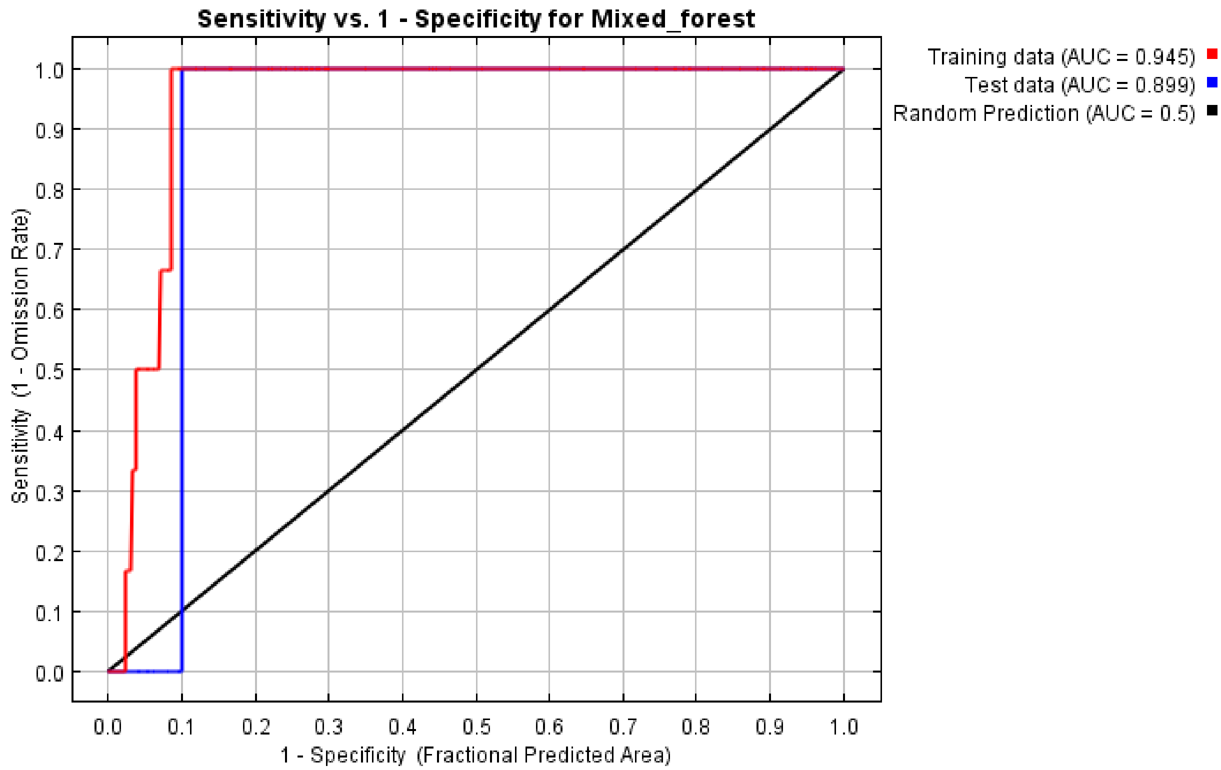

Figure 45: ROC curve of sensitivity versus specificity for mixed forest based on RCP 8.5 at 2050

4.4.3.2 Climate suitability maps generated from MaxEnt and Arc Gis based on RCP 8.5 at 2050

The future suitability zones were derived for RCP 8.5 in 2050, based on the existence probability of, determined through MaxEnt. The geographical ranges of the certainly (0.6-1.0), likely (0.45-0.60), possibly (0.30.-0.45), unlikely (0.2-0.3) and rarely (0.00-0.17) are shown in the climate suitability map with different colours (Figures 44, 45 and 46). The red colour indicates zones of unsuitability while green colour depicts highly suitable areas for brachystegia forest based on RCP 8.5 in2050 and 2070.In the cynometra forest, the blue colour shows areas of higher suitability while orange colour indicates zones of unsuitability based on RCP 8.5in 2050 and 2070.while for mixed forest based on RCP 8.5 in 2050 and 2070 red colour depicts suitable area and shades of grey for unsuitable areas respectively

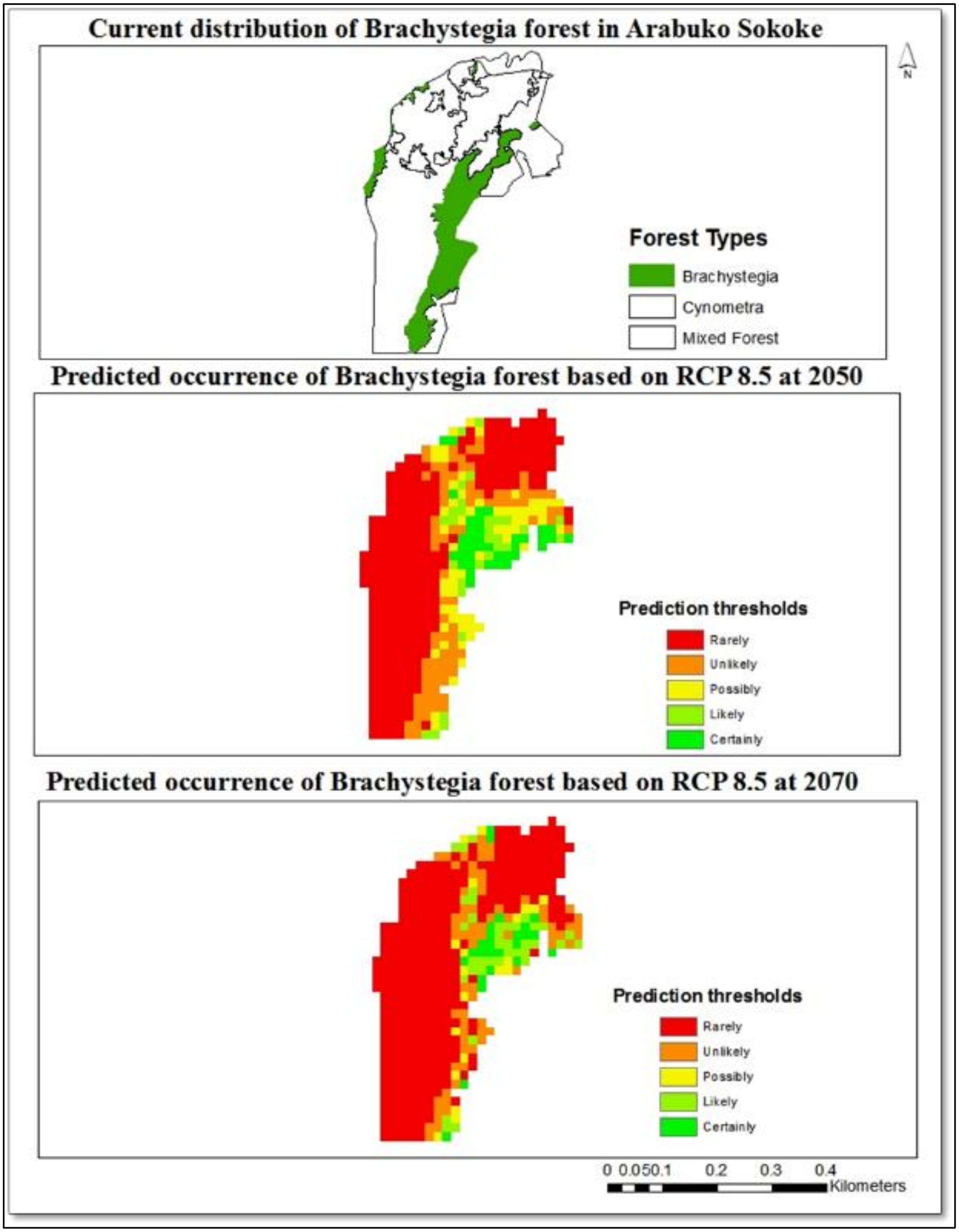

Figure 46: Climate suitability map for brachystegia forest based on current conditions and RCP 4.5 in 2050 and 2070 in Arabuko Sokoke forest reserve

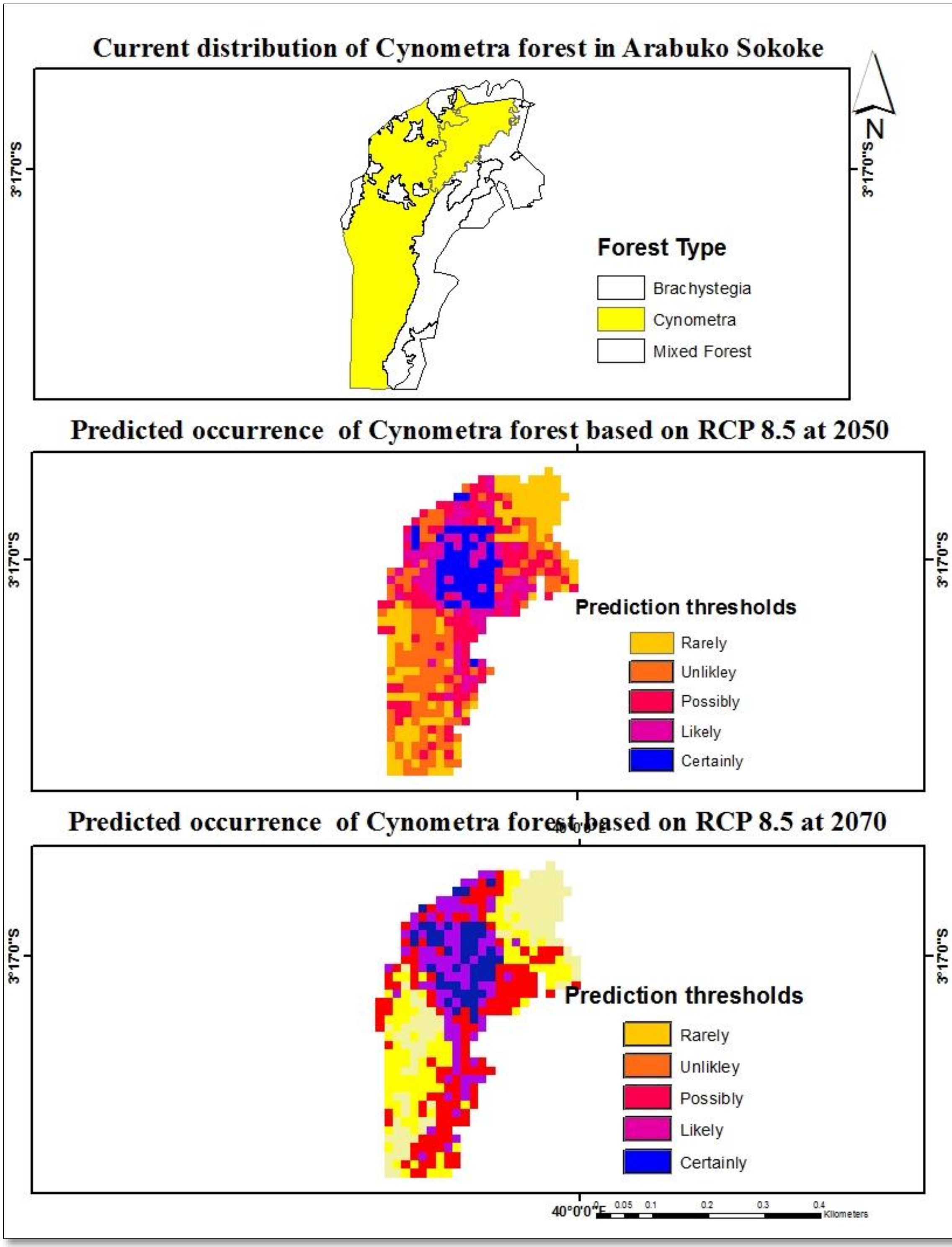

Figure 47: Climate suitability map for cynometra forest based on current conditions and RCP 4.5 in2050 and 2070 in Arabuko Sokoke forest reserve

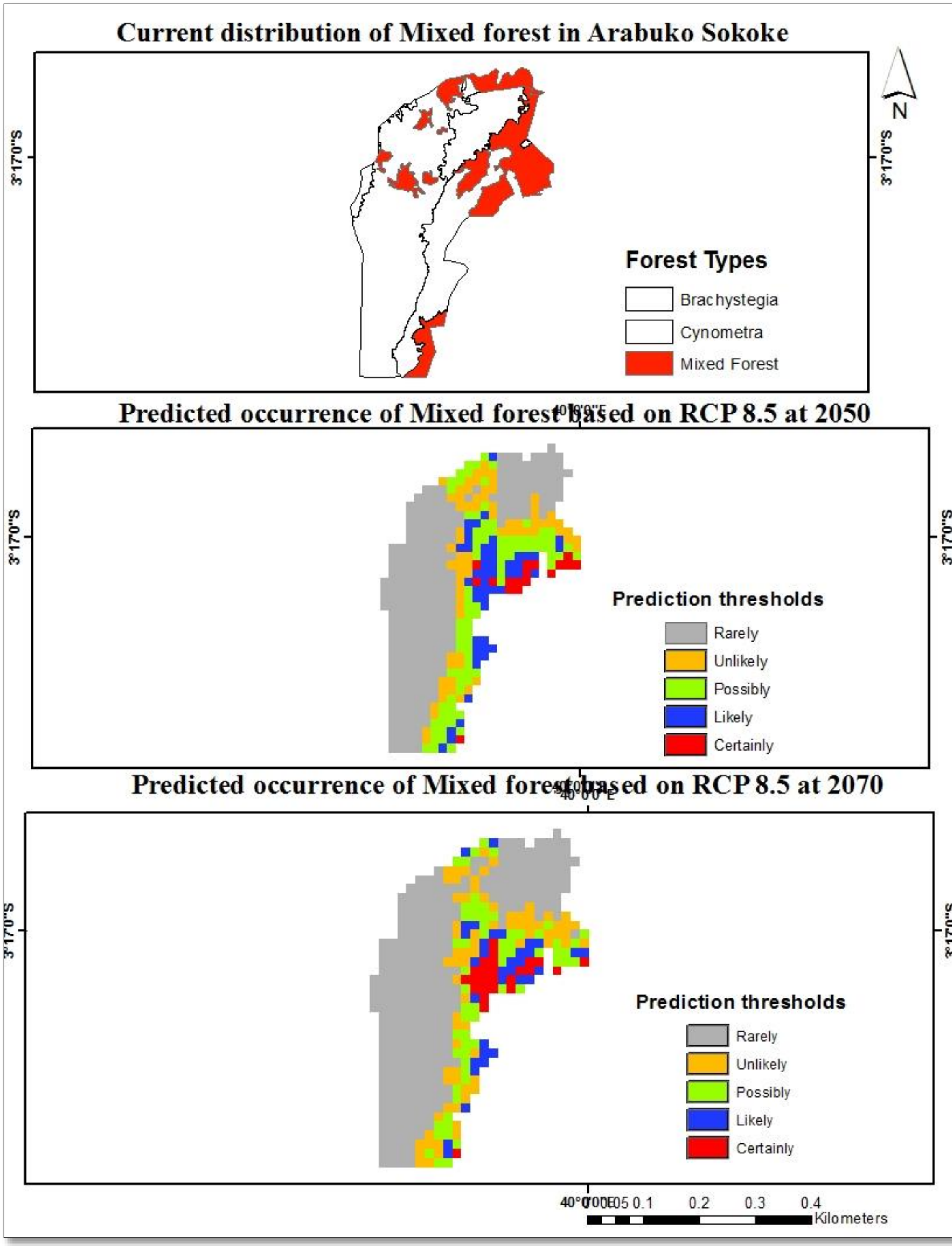

Figure 48: Climate suitability map for mixed forest based on current conditions and RCP 4.5 in 2050 and 2070 in Arabuko Sokoke forest reserve

4.4.3.3 Analysis of variable contributions based on RCP 8.5 at 2050

The predicted distribution of brachystegia forests based on RCP 8.5 at 2050 will be determined by temperature and precipitation variables. Nine (9) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 8 and BIO 14 were the biggest contributors with 53.1% and 19% respectively (Table 9)

Table 9: Selected environmental variables with percent contribution to the model for brachystegia forest based on RCP 8.5 at 2050

Environmental Variable	Percent Contribution
Mean Temperature of Wettest Quarter (Bio8)	53.1
Precipitation of Driest Month(Bio 14)	19
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio 2)	8.4
Max Temperature of Warmest Month(Bio 5)	7.5
Annual Precipitation(Bio 12)	7.1
Mean Temperature of Warmest Quarter(Bio 10)	2.7
Precipitation of Coldest Quarter(Bio 19)	1.8
Temperature Seasonality (standard deviation *100)(Bio 4)	0.3
Precipitation of Driest Quarter(Bio 17)	0.2

Table 10 below documents predicted distribution of cynometra forests based on RCP 8.5 in 2050. Seven (7) bioclimatic variables contributed to the prediction model with bioclimatic variable BIO 7 and BIO 5 being biggest contributors with 46.6% and 29.5% respectively.

Table 10: Selected environmental variables and their percent contribution in MaxEnt model for cynometra forest based on RCP 8.5 at 2050

Environmental Variable	Percent Contribution
Temperature Annual Range (BIO5- BIO6)(Bio7)	46.6
Max Temperature of Warmest Month(Bio 5)	29.5
Mean Temperature of Driest Quarter(Bio 9)	11.9
Temperature Seasonality (standard deviation *100)(Bio 4)	10.8
Precipitation of Coldest Quarter(Bio 19)	0.7
Precipitation of Driest Quarter(Bio 17)	0.5
Precipitation of Wettest Month(Bio 13)	0.1

The predicted distribution of mixed forests based on RCP 8.5 in2050 shows that temperature and precipitation are the largest variables. Six (6) bioclimatic variables contributed to the prediction model with bioclimatic variable BIO 5 and BIO 9 being biggest contributors with 75.9% and 8.4% respectively.

Table 11: Selected environmental variables with percent contribution to the model for mixed forest based on RCP 8.5 at 2050

Environmental Variable	Percent Contribution
Max Temperature of Warmest Month(Bio 5)	75.9
Mean Temperature of Driest Quarter(Bio9)	8.4
Precipitation of Driest Quarter(Bio 17)	7.8
Precipitation of Driest Month(Bio 14)	4.6
Precipitation of Coldest Quarter(Bio 19)	2.9
Mean Temperature of Wettest Quarter (Bio8)	0.4

4.4.3.4 Jackknife test for variables based on RCP 8.5 in 2050

The results of the jackknife test for brachystegia shows that mean Temperature of Wettest Quarter (Bio8) had higher gain when singly used in the model, while Precipitation of Driest Month (Bio 14), mostly decreased when omitted in the model (Figure 49)

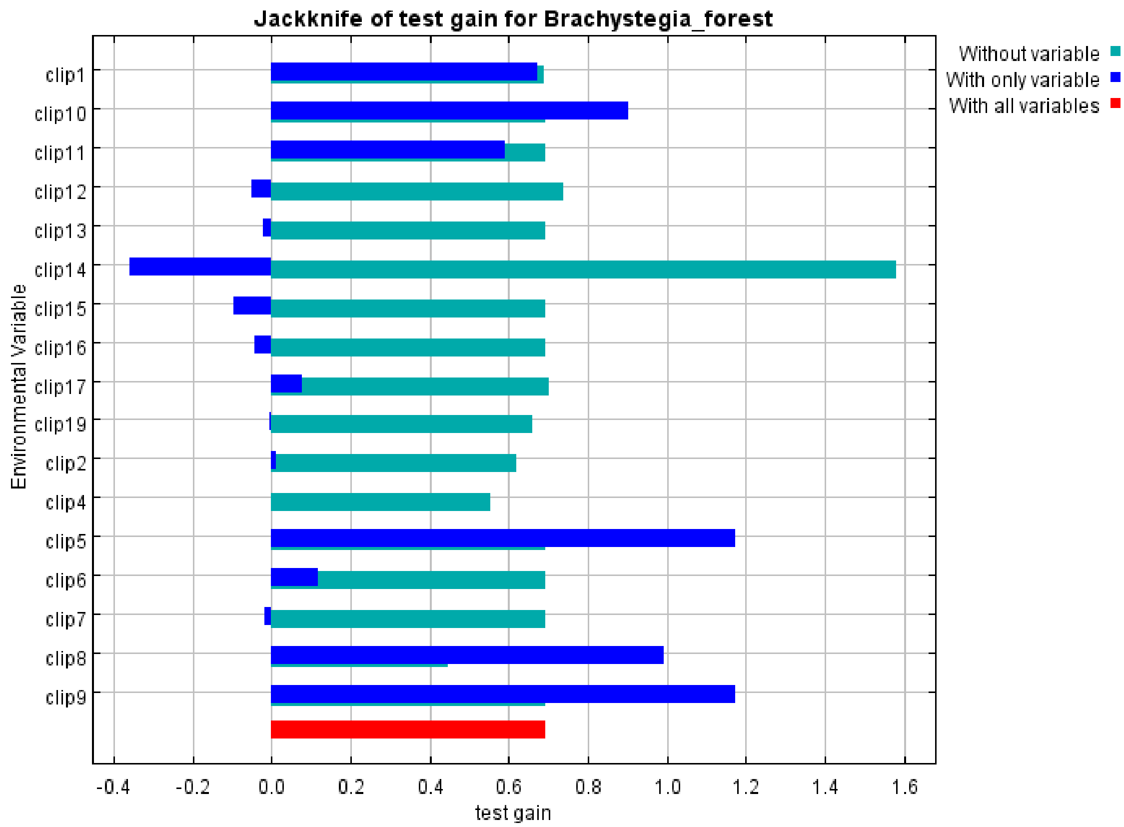

Figure 49: Relative predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 8.5 at 2050

In the cynometra forest the jackknife test indicates that the Temperature Annual Range (BIO5- BIO6) variable had highest gain when used alone and whiles at the same time it decreased the gain the most when it is omitted in the prediction model (Figure 50)

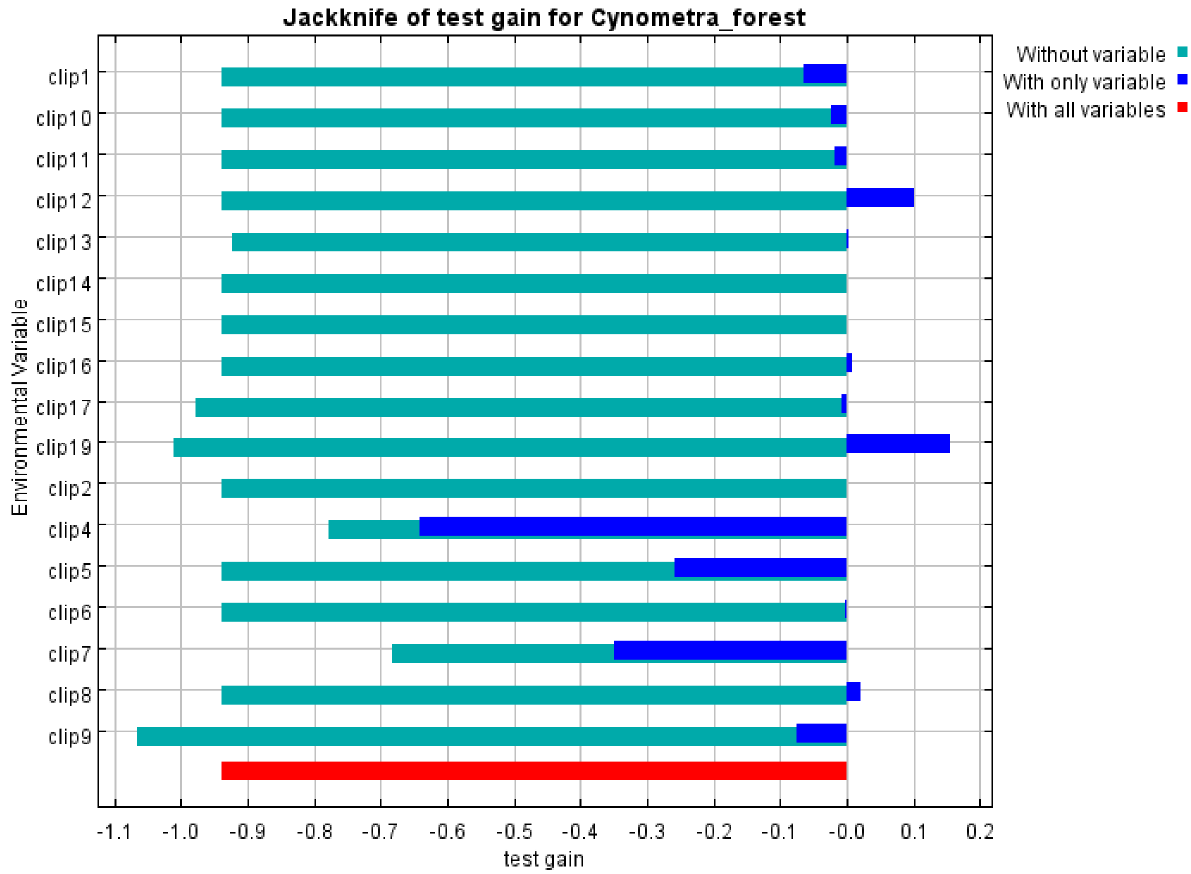

Figure 50: Relative predictive power of different bioclimatic variables based on the jackknife test for cynometra forest based on RCP 8.5 at 2050

The jackknife results for mixed forest shows that the highest gain for a bioclimatic variable when used in isolation is that of Mean Temperature of Driest Quarter (Bio9) while Max Temperature of Warmest Month (Bio5) decreased the most in the gain when omitted in the prediction model

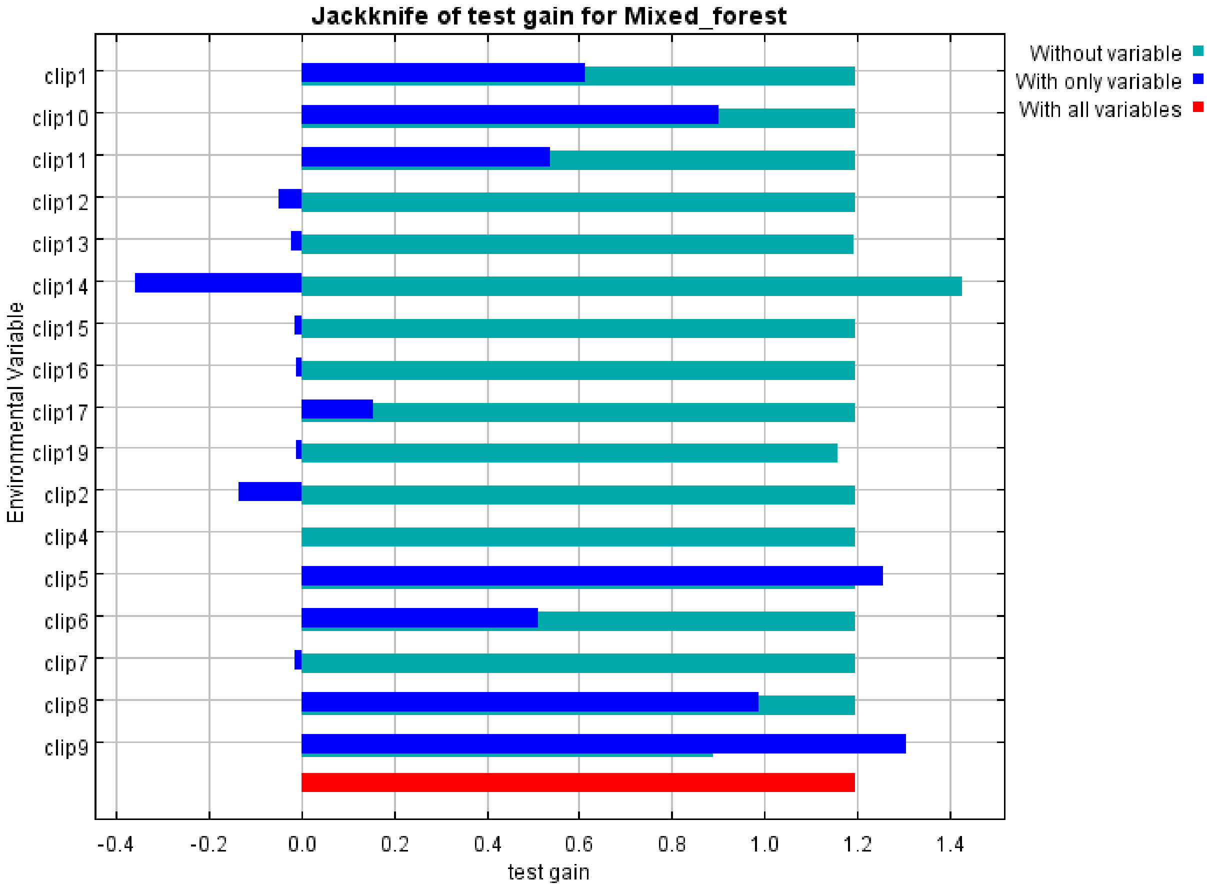

Figure 51: Relative predictive power of different bioclimatic variables based on the jackknife test for mixed forest based on RCP 8.5 at 2050

4.4.4 Impacts of climate change based on RCP 8.5 in 2070

The section below details the results of MaxEnt model analysis of forest occurrence data and bioclimatic variables from RCP 8.5 at 2070.

4.4.4.1 Analysis of sensitivity and specificity based on RCP 8.5 at 2070

The AUC for brachystegia forest model based on RCP 8.5 at 2070 was 0.95 and 0.93, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had 'excellent' predictive accuracy and therefore it was suitable in showing future geographic distribution of brachystegia forest in Arabuko Sokoke forest reserve (Figure 52)

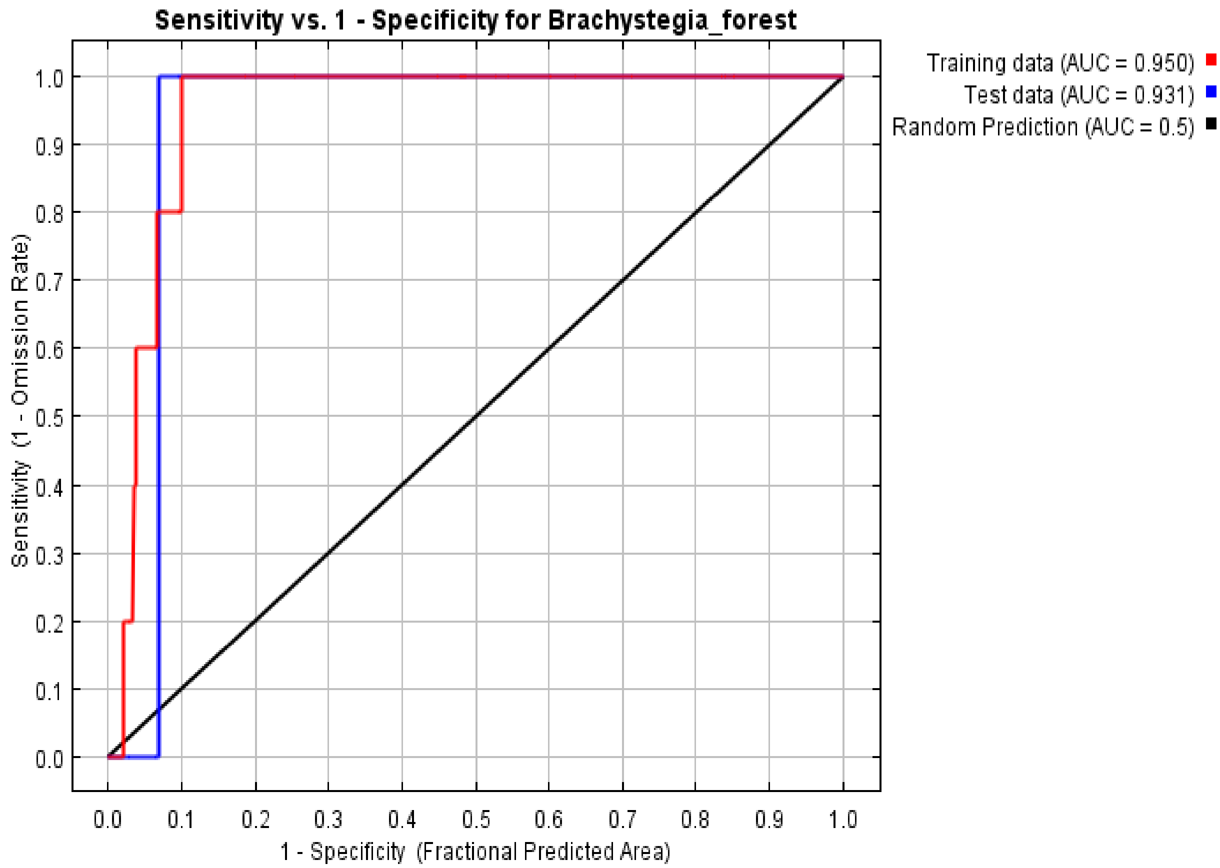

Figure 52: ROC curve of sensitivity versus specificity for brachystegia forest based on RCP 8.5 at 2070

The AUC for cynometra forest model based on RCP 8.5 at 2070 was 0.91 and 0.65, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had 'excellent' predictive accuracy and therefore it was suitable in identification of predicted sites of brachystegia forest in Arabuko Sokoke forest reserve (Figure 53)

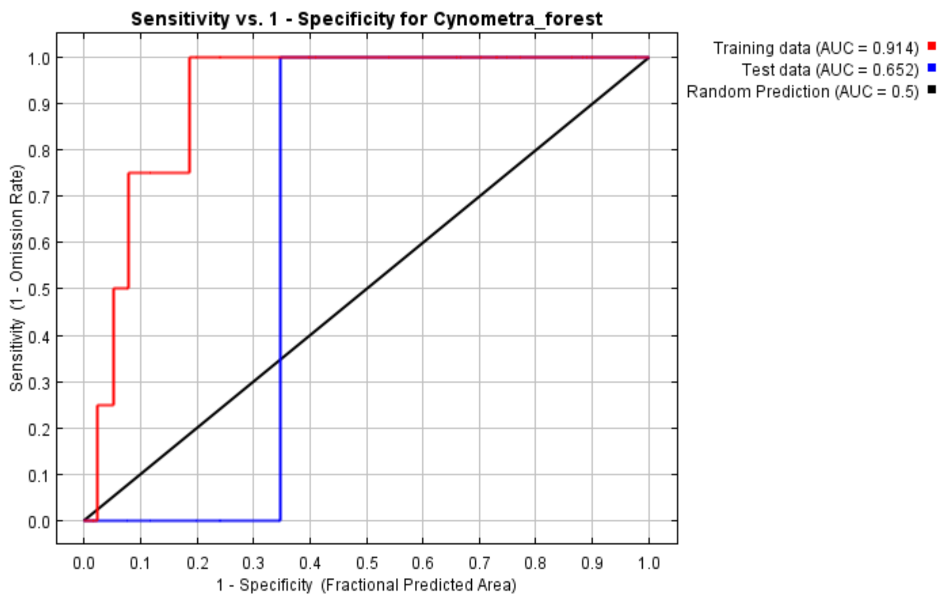

Figure 53: ROC curve of sensitivity versus specificity for cynometra forest based on RCP 8.5 in 2070

The AUC for mixed forest model based on factors associated with RCP 8.5 at 2050 was 0.97 and 0.95, for training and test data, respectively. This AUC value indicated that the constructed model is applicable and had 'excellent' predictive accuracy and therefore it was suitable for predicting the geographic distribution of brachystegia forest in Arabuko Sokoke forest reserve (Figure 54**)**

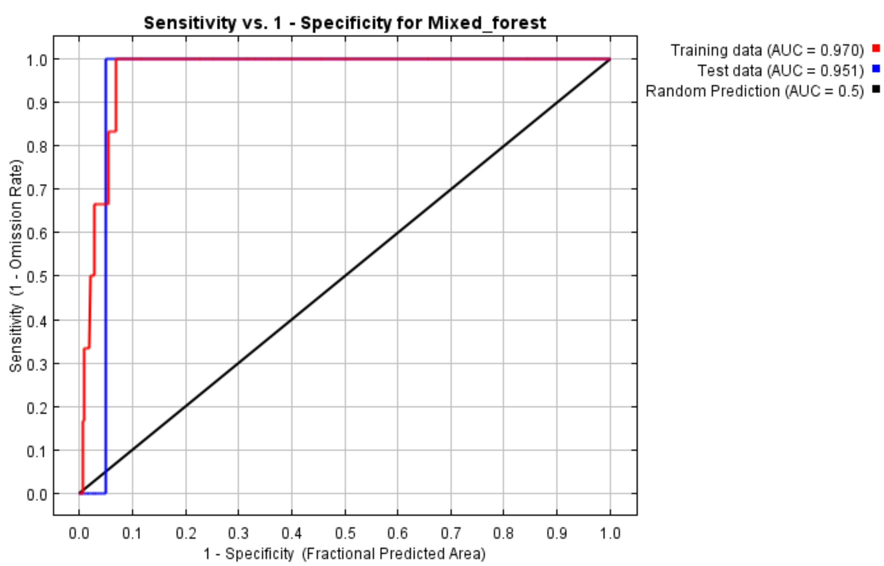

Figure 54: ROC curve of sensitivity versus specificity for mixed forest based on RCP 8.5 in 2070

4.4.4.2 Analysis of variable contributions based on RCP 8.5 at 2070

Table 12 below indicates that the predicted distribution of brachystegia forests based on RCP 8.5 in 2070. Six (6) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 8 and BIO 2 were the biggest contributors with 86.3% and 11.4% respectively

Table 12: Selected environmental variables and their percent contribution in MaxEnt model for brachystegia forest based on RCP 8.5 in 2070

Environmental Variable	Percent contribution
Mean Temperature of Wettest Quarter (Bio8)	86.3
Mean Diurnal Range (Mean of monthly (max temp - min temp))(Bio 2)	11.4
Annual Mean Temperature(Bio 1)	1.2
Temperature Seasonality (standard deviation *100)(Bio4)	0.5
Precipitation of Driest Quarter(Bio 17)	0.5
Isothermality (BIO2/BIO7) (* 100)(Bio 3)	0.1

The predicted distribution of cynometra forests based on RCP 8.5 in 2070 will be determined by temperature and precipitation variables. Six (6) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 7 and BIO 9 were the biggest contributors with 42.2% and 40.7% respectively (Table 13)

Table 13: Selected environmental variables with percent contribution to the model for cynometra forest based on RCP 8.5 in 2070

Environmental Variable	Percent Contribution
Temperature Annual Range (BIO5- BIO6)(Bio7)	42.2
Mean Temperature of Driest Quarter(Bio9)	40.7
Annual Mean Temperature(Bio 1)	6.5
Precipitation of Warmest Quarter(Bio 18)	6.1
Min Temperature of Coldest Month(Bio 6)	4.1
Temperature Seasonality (standard deviation *100)(Bio 4)	0.3

Table 14 below indicates that the predicted distribution of mixed forests based on RCP 8.5 in 2070 will be determined by temperature and precipitation variables. Seven (7) bioclimatic variables contributed to the prediction model. The bioclimatic variable BIO 8 and BIO 3 were the biggest contributors with 69.2% and 10.8% respectively

Table 14: Selected environmental variables with percent contribution to the model for brachystegia forest based on RCP 8.5 in2070

Environmental Variable	Percent contribution
Mean Temperature of Wettest Quarter (Bio8)	69.2
Isothermality (BIO2/BIO7) (* 100)(Bio 3)	10.8
Mean Temperature of Driest Quarter(Bio9)	8.9
Mean Temperature of Coldest Quarter(Bio11)	4.9
Precipitation of Driest Month(Bio 14)	2.8
Annual Precipitation(Bio 12)	2.6
Mean Temperature of Warmest Quarter(Bio10)	0.7

4.4.4.3 Jackknife test for variables based on RCP 8.5 in2070

The jackknife results shows how the model behaves when variables are independently assessed to show new dataset will respond. In the brachystegia forest the Mean Temperature of Driest Quarter (Bio9) had highest gain when used alone and while it decreased the most in gain when it is omitted within the prediction model. (Figure 55)

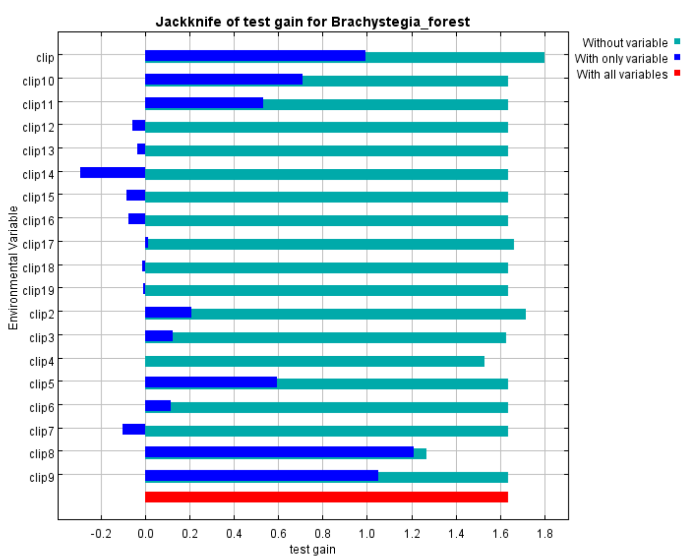

Figure 55: Relative predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 8.5 in 2070

In the cynometra forest the jackknife results indicates the highest gain existed when Mean Temperature of Driest Quarter (Bio9) is used alone while the Min Temperature of Coldest Month (Bio6) decreased the gain a lot when omitted in the prediction model (Figure 56)

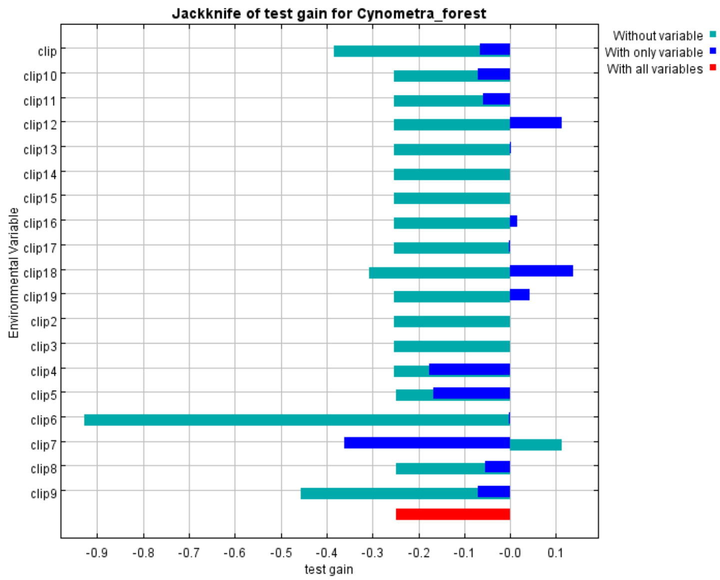

Figure 56: Relative predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 8.5in 2070

In the mixed forest the Mean Temperature of Wettest Quarter (Bio8)) had higher gain when it was singly used and it decreased the gain the most when it was omitted (Figure 57)

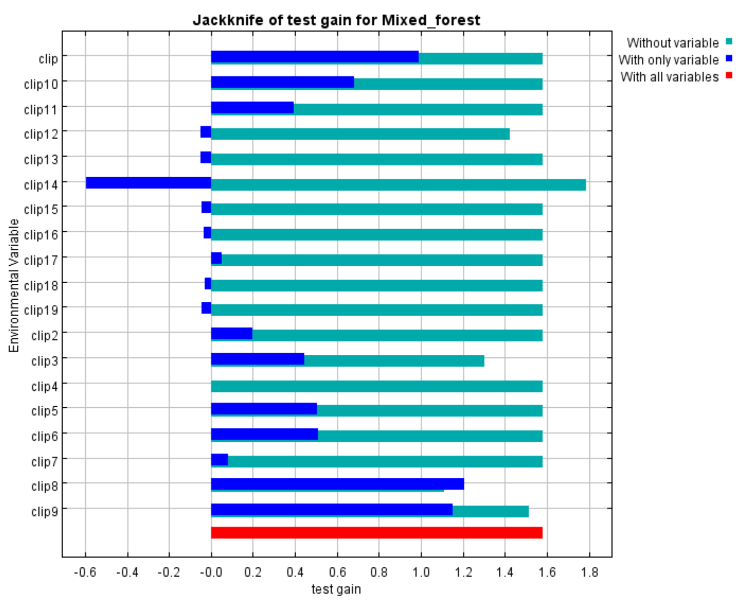

Figure 57: Relative predictive power of different bioclimatic variables based on the jackknife test for brachystegia forest based on RCP 8.5 in 2070

CHAPTER FIVE: DISCUSSION

5.1 Tree biomass accumulation in Arabuko Sokoke forest

The study finding indicates tree biomass in Arabuko Sokoke forest accumulated time. The different vegetation had different levels of biomass, with brachystegia forest recording higher total tree biomass, followed by mixed forest and cynometra forest in 2015 and 1990. Mixed forest had higher total tree biomass in 2004, followed by brachystegia forest and cynometra forest. This noted variance is supported by (Gray *et al.*, 2016) observations, that different species have varying growth, longevity and decomposition rates. Similarly (Krankina *et al.*, 2005) noted that specific tree species could be instrumental in determining how biomass changes in varied ways .For example coniferous species which are higher longevity (pine, Siberian pine, and larch) tends to accumulate more biomass in comparison to hardwood species such as aspen and birch which are short lived.

There is an increasing interest in understanding how forest biomass accumulate because of its role in regulating cycling of carbon and nutrients (Cairns *et al.*, 1997). Forest can achieve higher level of carbon sequestration but can also rapidly lose the stored carbon (Mckinley *et al.*, 2011). In the absence of anthropogenic drivers, the level of carbon storage and lose is determined by available resources and environmental resources, this two factors influences the net primary productivity and heterotrophic respiration of a forest (Gray *et al.*, 2016). However due to diverse forest species composition variance in maximum attainable stocks is expected even is similar sites due to difference in species growth, longevity and decomposition rates(Gray *et al.*, 2016). forest ecosystems show variation in tree biomass and carbon stocks due to distinction in forest type, species diversity, age, growth stage of the species, biotic and a biotic conditions of the site, precipitation pattern and topographical conditions (Gairola *et al.*, 2011;Zhao *et al.*, 2014).

The varying biomass levels in brachystegia, cynometra and mixed forests as documented by this study could be due to difference site conditions (Glenday, 2008). Forest managers have historically used empirical relationships of site conditions or index and community classifications, localized variations, to project forest productivity and evaluate a suite of management actions (Gray *et al.*, 2016).

The study documents higher biomass levels in 2015 than 1990, a possible indicator of net increase in biomass. The rate of biomass accumulation rate tends to changes with forest age and successional stage, as determined by plant process specifically the net primary productivity and respiration (Gray *et al.*, 2016)

Furthermore the results show a slight drop in biomass levels for brachystegia and cynometra between 1990 and 2004. The noted change coincides with (Glenday, 2008) study that had observed the forest was facing disturbance during that study period, in fact the study noted then that the disturbance was likely to cause an associated loss of stored carbon stock in disturbed parts of the forest.

The higher biomass levels in 2015 in the three vegetation types shows a forest that regenerated rapidly; as new forest vegetation regenerate in disturbed forest site, biomass accumulation tends to climax early in the forest as net primary productivity approaches a plateau soon after canopy closure by trees (Ryan *et al.*, 2004;Mckinley *et al.*, 2011). The above observation is enhanced by assertion that improved management of harvesting and rehabilitation (Glenday, 2008) in Arabuko Sokoke forest could lead to higher biomass.

A number of challenges to associate with accuracy of tree biomass and its change exist. But more definitive estimates can be achieved through longer remeasurement time spans (Krankina *et al.*, 2005); therefore the need for long term monitoring plots in our diverse forests that differ in accumulation rates due to variance in site productivity, species mix and ages.

5.2 Temporal climate pattern of Arabuko Sokoke forest

Intergovernmental Panel on Climate Change (IPCC), have documented unique trend of warming in 20th century (Desktop *et al.*, 2010;Field *et al.*, 2014). Estimating the spatial distribution of climatic pattern has become a cornerstone of studies helping in understanding climate change and its effects throughout the world (Price *et al.*, 2000).

The study findings indicates that mean annual rainfall trend for Arabuko Sokoke was not significant (S = -11, p = 0.10 and had a weak Kendall’s tau (-0.21). The analysis points at a statistically significant decreasing trend (Sen’s Slope= -0.50) and confidence intervals (-

0.67,-0.37). There were variation in the amount of rainfall received in 1990 to 2014 period, a total of 18 different years recorded a below mean annual rainfall. These results indicates interannual variability which was noted by another study (Hulme *et al.*, 2001) in their review study of observed conditions (1900–2000) and projected future (2000–2100) in changes temperature and rainfall within the whole of Africa where they noted that interannual rainfall variability is large over most of Africa and for some regions.

The findings indicates that minimum temperature anomaly in Arabuko Sokoke had a significant positive trend (S = 34, p = 0.00) and a strong Kendall's tau (0.64) based on the Mann-Kendall test. There was a statistically significant increasing trend of mean annual minimum temperature in Arabuko Sokoke forests (Sen's Slope= 0.03) and confidence intervals (0.03, 0.04). The analysis shows a continuous 13 year above mean annual temperature in Arabuko Sokoke forest (Figure 16) similar to other studies (Ongoma and Onyango, 2014)The maximum temperature in Arabuko Sokoke had no significant trend (S=77, p=0.24) based on Mann-Kendall trend test and had a weak Kendall's tau (0.15). Figure 13 indicates a significant increasing trend of mean annual maximum temperature in Arabuko Sokoke forests and it was confirmed by Sen's Slope (0.01) and confidence intervals (0.00, 0.01).

The anomaly analysis for temperature indicates variability around the mean, this scenario is within the observation of other studies (Desktop *et al.*, 2010;Field *et al.*, 2014). For example (Mccarthy, 2001) study in Africa using predictive models indicated that the warming of within 0.2°C per decade (low scenario) to more than 0.5°C per decade (high scenario) is possible. These climate models shows a possible increase in future mean annual temperature to within ranges of 1° to 3.5°C by the 2050s (Kebede *et al.*, 2010)

5.3 Comparison of total tree biomass based on temporal climate pattern in Arabuko Sokoke

The distribution of plants forms, species types, and plant productivity within and across continents and vast geographic regions can be broadly determined by climate (Krankina *et al.*, 2005) through influencing plant photosynthesis and respiration. The climatic parameters associated with temperature and precipitation determines plant growth and respiration processes to a major degree. (Jarvis and Linder, 2000) observed that when temperature increases the available nutrient in the soil is likely to be affect through the enhancement of organic matter decomposition and mineralization process. Temperature is an important factor in all plant metabolic processes that includes uptake, respiration, and carbon storage. When higher temperatures complement with adequate precipitation without limitation then increased tree metabolic processes are expected. This higher tree metabolic activity will results in higher tree growth (Luo *et al.*, 2000;Mcmahon *et al.*, 2010) an indicating that global temperature is an important determinant of spatial distribution of biomass.

The study findings indicates a significant relationship between biomass (Mixed, Cynometra and Brachystegia) with temperature existed, which conforms to (Delpierre *et al.*, 2009) observational studies correlating temperature and three deciduous in France. However, temperature may reduce productivity in warmer areas through increased rates of evaporation and stomatal closure due to higher vapor pressure deficits.

Water availability influences carbon stocks principally by determining structural area of forests. This expectation is reinforced by the global pattern of covariation of ecosystem carbon turnover times with both precipitation and climate (Carvalhais *et al.*, 2014;Álvarez-Dávila *et al.*, 2017). In contrast water deficits due to occasional or regular droughts are well-known to drive mortality, particularly of larger trees and these mortality impacts may be limiting AGB in our forests too (Phillips *et al.*, 2002)

In this study a significant relationship between rainfalls with mean total tree biomass in the forest was established. These results pinpoint observation that were noted by (Malhi *et al.*, 2008); where their showed precipitation in the drier quarter in Amazonian forest were positively correlated with above ground biomass. While consensus exist on the role precipitation play in determining biomass accumulation through influencing seed germination, seedling growth and survival, phenology and species richness which all contribute forest productivity (Rivas-Arancibia *et al.*, 2006;Padilla and Pugnaire, 2007;Quevedo-Robledo *et al.*, 2010).

In contrast, it's been noted that rainfall may not provide an explanation to the interannual variation in primary productivity at local scales (Knapp and Smith, 2001;Swemmer *et al.*, 2007;Yan *et al.*, 2015) and this observation may explain the absence of significant relationship between cynometra forests and mean annual rainfall. (Duncan and Woodmansee, 1975;Yan *et al.*, 2015) observed that the yield of annual grasses correlated poorly with rainfall in any particular month of the growing season.

According to studies (Agnew *et al.*, 2000;Lin *et al.*, 2010;Yan *et al.*, 2015) there was no relationship between above ground biomass of annuals plants and precipitation in the Chihuahuan desert. Other unique observations include (Salve *et al.*, 2011;Yan *et al.*, 2015) concluded that higher total rainfall reduces the aboveground biomass of annuals. Therefore its apparent that biomass is influenced by the amount of rainfall and temporal patterns in a geographical location (Yan *et al.*, 2015).

Water supply and temperature have multiple impacts on both growth and mortality processes, and so are likely to exert major control on above ground biomass. This expectation is reinforced by the global pattern of covariation of ecosystem carbon turnover times with both precipitation and climate (Carvalhais *et al.*, 2014). The study results points out the role precipitation and temperature play in determining biomass accumulation, this is through the significant relationship forest biomass and climatic parameter had at landscape levels. Though at species level the relationship was significant for brachystegia and mixed forests, the cynometra forest had a weak relationship, however the poor correlation between biomass accumulation and climate could be an indicator of how hard it is to project the function of plants on land and their interaction with global carbon cycle using various climate change scenarios.

In essence the most challenging issues is the ability to pinpoint changes that are caused by climate change from those associated with process of recovery from disturbance, variation in edaphic conditions, diversity of species and historical climate (Mcmahon *et al.*, 2010).

5.4 Projection on impacts of climate change on tree species distribution

Biomass in trees are as a result of elaborate biological and resource portioning processes and therefore it can easily be affected by tree distribution in a forest (Pan *et al.*, 2013).

However scientific consensus shows that; climate is the primary determinant of forest distribution at global and continental scales, but it changes at the scales of landscapes and stands, to topography, soil, species interactions, and disturbance that define additional complexity in forest assemblages and structures (Pan *et al.*, 2013). Results show that the future distribution of tree species in Arabuko Sokoke will be determined by climatic variables majorly those associated with temperature and rainfall. (Lin *et al.*, 2010) indicates that experimental warming increased biomass in certain species and lead to suppression biomass accumulation is some species for instance climate warming stimulated seed plant biomass but suppressed the growth of spore plants. The study results shows that the predictive model for brachystegia and mixed forests was good, while cynometra forest had a poor model, this disparity could be due to (Lin *et al.*, 2010) observation, where climate change will enhance the development of biomass in brachystegia and mixed forest, while suppressing in cynometra a suggestion that seems to agree with a the higher tree biomass for both brachystegia and mixed forest in 2015.

The ROC curve is generally utilized in evaluation of the simulation accuracy of the model while the area below the ROC curve, the value of area under curve (AUC) indicates the predictive accuracy of the model (He and Zhou, 2012). The results indicates the constructed model for brachystegia and mixed forest for RCP 4.5 and RCP 8.5 at 2050 and 2070 were good, while cynometra forest at RCP 4.5 and RCP 8.5 at 2050 and 2070 had a poor model fit. This observation is explained by the how climatic parameters correlate with tree biomass, where the biomass for brachystegia and mixed forests are impacted by climatic parameters, while poor relationship was noted for the cynometra forest.

However, (Norby and Luo, 2004) study concludes that ecosystem responses to future climate change involve multiple environmental factors, rather than just climate warming or increases in atmospheric CO_2 concentration and this may be the reason why cynometra forest was not modeled to a good level. Another possibility of poor model performance revolves around absence of critical variables in model analysis or use of either inaccurate or unreliable field data. Additionally trees adaptation mechanism to complex matrix of climate, forest processes and perturbations, could end up producing a distribution of plant assemblage and structure with a locality (Pan *et al.*, 2013). (Glenday, 2008) noted a section of Arabuko Sokoke faced disturbances in the past and the cynometra forest was part of the forest affected and therefore it's postulated that its recovery process may have created a complex geographical pattern and therefore closer observation is recommended.

The predictive MaxEnt models based on brachystegia, cynometra, and mixed forests recorded higher AUC values in 2070 for RCP 4.5 and 8.5 than in 2050 for RCP 4.5 and RCP 8.5; this generally indicates that key variables that are related to suitable habitat and the characteristics of the tree species were identified successfully by the analyses (Boyce *et al.*, 2002;Mckenney and Pedlar, 2003;Gibson *et al.*, 2004)

The species suitability maps based on RCP 4.5 at 2050 and 2070 indicates variation in species predicted occurances.The cynometra forest suitability map shows that the area of occurrence will reduce, leaving the species to occur at the central part of the forest by 2070, similarly the mixed forest will record reduction in area of coverage and shifting of species to the eastern side of the forest and brachystegia will shift upwards and see reduction of areas. These results show that the climatic conditions will be unfavorable to Arabuko Sokoke forest species range, pointing to observation of other studies. (Thompson *et al.*, 2009;Remya *et al.*, 2015) observed that some of the major considerations when looking at how climate change will impact on floral biodiversity include how species are changing phonologically and spatially, increased rate of species extinction and longevity of the plant growing season..

In contrast the species occurrence and area under coverage will increase and shift for mixed and cynometra forests under RCP 8.5 at 2050 and 2070, while brachystegia forest will experience shifting and reduction in area of occurrence. These results postulates that climate scenario based on RCP 8.5 will be favorable to cynometra and mixed forest though possibly causing extinction of some species or reduction in suitable ecological conditions for some current species in Arabuko Sokoke.

The prediction model utilized bioclimatic variables in determining suitable habitat and the potential distribution of vegetation types in Arabuko Sokoke. MaxEnt is among the common species distribution modeling (SDM) tools utilized by natural resource managers in predicting species suitable areas by utilizing a set of records and environmental predictors (Fourcade *et al.*, 2014). The predictive model for the three vegetation types in

Arabuko Sokoke forest had various bioclimatic variables. These variables contributed differently to the model and they represent annual trends, seasonality and extremities of temperature and rainfall parameters. These climatic parameters are supported by (Jarvis and Linder, 2000) study that noted the role climatic parameters associated with temperature and precipitation plays in determining plant growth and respiration processes.

Due to the fact that MaxEnt use only presence data, the estimation of the species fundamental niche (different from occupied niche) rather than realized niche (Kumar and Stohlgren, 2009;Yang et al., 2013). To understand the fundamental niche normally a set of deterministic parameters are analyzed through statistical inference to understand associated bias and standard error in a statistic, when using a random sample of observed or measured data compute (Phillips et al., 2006). The jackknife tests for the vegetation types confirms previous findings showing that variables associated with annual trends, variability and anomalies of temperature and rainfall parameters contributed to the predictive model and determines forest biomass growth (Jarvis and Linder, 2000),

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

Based on the study findings tree biomass in Arabuko Sokoke has significantly accumulated over time for brachystegia and mixed vegetation types. Though the cynometra forest has insignificant relationship with time, it had higher biomass in 2015.

The evidence provided by this study indicates significant anomalies and trends existed in climatic variable namely; temperature and rainfall between 1990 and 2014 for Arabuko Sokoke forest. The temporal variation in rainfall and temperature points at effects of climate. There was significant relationship between tree biomass and climatic parameters, the findings indicates rainfall and temperature significantly related with biomass across the forest landscape. Based on the results MaxEnt model can be used to predict geographical distribution of mixed and brachystegia vegetation based on general climate model scenarios of RCP 4.5 and RCP 8.5.The species distribution predictive model for Arabuko Sokoke was strongly influenced by annual trends, seasonality and extremities of temperature and rainfall parameters.

6.2 Recommendations of the study

The role and contribution of the forests in the climate change mitigation and adaptation cannot be over emphasized. The impacts of climate on forest ecosystem have been well documented, but the scale and magnitude is still an ongoing debate. Based on the study findings postulated species shift and niche reduction in Arabuko Sokoke based on representative pathway concentration scenarios of 4.5 and 8.5. The study recommends;

- That the forest managers consider development of strategies to deal with possible shift species and fundamental niche reduction for key species in Arabuko Sokoke forest
- Communities are advised to diversify their sources of livelihoods and reduce their dependency on forest in the event the predicted shift of species range sets in
- Carbon accounting systems and GHG systems should take into consideration carbon accumulation and possible impacts of climate change on tree biomass in Arabuko Sokoke

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