CARBON SEQUESTRATION DYNAMICS AND ITS IMPLICATION ON CLIMATE VARIABILITY IN THE SOUTH WEST MAU FOREST, KENYA

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Carbon Sequestration Dynamics and its Implication on Climate Variability in the South West Mau Forest, Kenya

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

I dedicate this work to the entire Kigomo family, my wife Beatrice Wambui, my sons Herbert and Hubert and my late Aunt Teresia Njoki.

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ACRONYMS AND ABBREVIATIONS

AGB	Above Ground Biomass
AVHRR	Advanced Very High Resolution Radiometer
CASA	Carnegie-Ames-Stanford Approach
FAO	Food and Agriculture Organization
FLDAS	Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System
FPAR	Fraction of photosynthetically active radiation
GOK	Government of Kenya
IPCC	Intergovernmental Panel on Climate Change
KFWG	Kenya Forests Working Group
LUE	Light use efficiency
NASA GES DISC	National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center
NOAA	National Oceanic and Atmospheric Administration
NDVI	Normalized Difference Vegetation Index
NPP	Net primary production
PAR	Photosynthetically Active Radiation
SWM	South West Mau Forest
UNEP	United Nations Environment Programme

UNFCCC	United Nations Framework Conventions on Climate Change

ABSTRACT

Forests are important for regulation of the global carbon balance and climate stabilization. Increase in forest biomass enhances atmospheric carbon sequestration decreasing climate variability, while decrease in forest biomass contributes to carbon dioxide emissions increasing climate variability. World over, forest biomass has been declining due to forest loss and degradation. The South West Mau has experienced significant forest loss since 1964. The decline is posited to have significant impacts on carbon sequestration, carbon storage, carbon dioxide emissions, status of atmospheric carbon dioxide, and consequently localized climatic conditions. This study assessed interannual trend and variability as well as change point detection in carbon sequestration, average annual air temperature and annual total surface precipitation in South West Mau Forest, Kenya between 1985 and 2015. Covariance analysis was performed between carbon sequestration dynamics and the climate variables to establish their relationship. Above ground biomass carbon sequestration was quantified based on the Carnegie-Ames-Stanford Approach (CASA) and carbon fraction for tropical climate domain. Carbon sequestration dynamics were characterized by increase-decrease cycles of approximately 3 years and low interannual variability (CV= 9.13). It emerged that South West Mau Forest was a net carbon emitter with a carbon sequestration balance of -588.3996 Kg/ha between 1985 and 2015. Annual average air temperature over the South West Mau forest pointed towards climate warming of 0.0188^0C per year (Kendall's tau = 0.3677, p value = 0.0033) but with low interannual variability (CV= 0.11%). A shift in the annual average air temperature of 0.368^0C at p= 0.0051 was detected between 1985-1998 and 1999- 2015. There was a weak positive anomaly in the annual average air temperature with a slope of 0.0192 and $R^2 = 0.3074$. There was an increasing trend in the annual total surface precipitation (Kendall's tau = 0.4968, Sen's slope = 71.455, and p = 0.0001) with moderate interannual variability (CV=27.9%). A shift in the total surface precipitation with increase of 1611mm was detected between 1985-2003 and 2004 -2015. There was moderately strong positive anomaly in the total surface precipitation with a slope of 79.791 and $R^2 = 0.5$. A weak negative covariance between above ground carbon sequestration and annual average air temperature (r = -0.1563, R^2= 0.0244) and a weak positive covariance between above ground carbon sequestration and annual total surface precipitation (r = 0.3408, R^2= 0.1162) were established. This indicated that variability in carbon sequestration were inversely related to variability in annual average air temperature and directly related to variability in annual total surface precipitation. The study concluded that the above ground biomass pool in South West forest was a net carbon emitter. The region experienced climate warming and increased total surface precipitation. Overall, the results of this study demonstrate that variability in above ground carbon sequestration explained only 2.4% inter annual variability in average air temperature and 11.62% interannual variability in total surface precipitation.

CHAPTER ONE

INTRODUCTION

1.1 Background

Forest represents the largest terrestrial carbon sink and accounts for about 90 percent of all living terrestrial biomass (Dixon et al., 1994; Tan et al., 2007; Bajracharya, 2008). They store about 80 percent of all above-ground biomass (FAO, 2005; IPCC, 2006) and are thus important for regulation of the global carbon balance and stabilization of climate regimes through carbon sequestration and carbon dioxide emission (Nasi, et al., 2002; Backeus, 2009). They act as carbon sink through the increase in cover (Ponce-Hernandez, 2004; Bajracharya, 2008) or as carbon source through the decrease in cover (Pareta & Pareta, 2011). Forests as carbon sinks, account for 50 percent of global carbon (Kindermann et al., 2008) capturing about 2.4 gigatonnes of carbon per year from the atmosphere (Jordan et al., 2018).

Forests' role in the global carbon balance and stabilization of climate regimes depend on the succession stage, specific disturbance regime and management activities. All these result in temporal forest carbon dynamics characterized by long periods of gradual build-up of biomass, alternated with short periods of massive biomass loss. Increase in forest biomass enhances atmospheric carbon sequestration, whereas the decrease in forest biomass due to deforestation and forest degradation causes carbon dioxide emissions back to the atmosphere resulting in elevated atmospheric carbon dioxide and consequently altering climatic regimes (Sitaula et al., 2005; Bajracharya, 2008).

Albeit forests' importance in global carbon balance and stabilization of climate regimes, forest cover has been reported to be declining globally, nationally and at ecosystem level (Bonino, 2006; FAO, 2006; FAO, 2010). According to FAO State of the World's Forests report of 2018 forest cover globally decreased from 31.6 percent of the global land area to 30.6 percent between 1990 and 2015. In the sub-Saharan Africa it decreased from 30.6 percent of the total land area to 27.1 percent between 1990 and 2015. Nelson (2008) estimated Kenya's gazetted forests cover at a total of

1.4 million hectares representing about 1.7 percent of total land area, which is way below the internationally recommended minimum of 10 percent of country forest cover and places Kenya among the countries with low forest cover of less than 3 percent of the total land area (Obare & Wangwe, 2008). Between 1990 and 2010 Kenya lost an average of 12,050 hectares or 0.32 percent annually. In total, between 1990 and 2010, Kenya lost 6.5 percent of its forest cover which corresponds to 241,000 hectares (Saatchi, 2012).

Across the globe land conversion is the main reason for 93.4 percent of the annual net forest loss, while conversion to forest plantation explains the other 6.6 percent (FAO, 2006; Samalca, et al., 2007; FAO, 2010; FAO, 2018). Deforestation, degradation and poor forest management reduce carbon sequestration and storage in forest biomass, increases carbon dioxide emission to the atmosphere and also destroy the mechanism for controlling atmospheric carbon (Tutu, 2008).

The world's forests stored 289 Gigatonnes of carbon in their biomass alone for the period 2005 to 2010 a slight increase from 283 Gigatonnes of carbon from the period 1990 to 2005. Forest biomass decreased by 1.1 Gigatonnes of carbon annually for the period 1990 - 2005, owing to continued deforestation and forest degradation and 0.5 Gigatonnes of carbon annually during the period 2005 to 2010 due to reduction in global forest area. Carbon in forest biomass decreased in Africa, Asia and South America in the period 1990–2010, but increased in all other regions (FAO, 2006; FAO, 2010).

Although forest carbon in sensitive to a number of controls including climate, topography, soils, plants and microbial characterisitcs antropogenic impacts and distrubance regimes, FAO (2006) and (2010) attributes the decline in forest carbon to forest loss due to disturbance regimes and antropogenic impacts. Although there is a correlation between forest area and fixed carbon, Millennium Ecosystem Assessment (2005) noted that the rate of decline in fixed carbon has been greater than the rate of decline in forest area. All together, it is estimated that forestry contributes an average 6.7 billion tons of carbon emissions reductions annually, with over two-thirds of this potential coming from tropical nations (Baldwin & Richards, 2010). Understanding the exchange of carbon dioxide between forests and the atmosphere is key to understanding and modifying the global carbon cycle and climate variability (Jarvis & Fowler, 2001; Kindermann, et al., 2008). The foregoing literature demonstrate that the spatial extent of forests and their growing stock reflect their amounts of biomass and carbon and have a crucial role in the context of the global carbon cycle, climate change and stabilization.

Carbon dioxide is one of the most abundant greenhouse gases and a primary agent of global warming. It constitutes 72 percent of the total anthropogenic greenhouse gases, causing between 9-26 percent of the greenhouse effect (Samalca et al., 2007). IPCC (2006) reported that the amount of carbon dioxide in the atmosphere has increased from 280 parts per million in the pre-industrial era (1750) to 379 parts per million in 2005, and is increasing by 1.5 parts per million per year. The elevation in atmospheric carbon dioxide concentration has raised concerns over global warming and climate change. It is liable for the alterations in surface temperature, precipitation, latent heat flux, and albedo among other weather parameters (Skole et al., 1997). Bajracharya (2008) and UNEP (2007) indicates that for the last few decades, as a result of anthropogenic activities including deforestation and forest degradation, release and concentrations of carbon dioxide in the atmosphere, has been increasing, causing rapid changes in the climate. These arguments from actual assessments and projected situations of climate sensitivity to carbon dioxide emissions due to changing global forest status informed this study to assess the implications of interannual forest carbon sequestration dynamics on climate regimes in the South West Mau forest.

1.2 Statement of the problem

The Mau forest complex has been under intense pressure from forest degradation and deforestation leading to a decline in forest cover (Sena, 2010). According to the Kenya Forests Working Group report (KFWG, 2001), the Mau forest complex, decreased in area by approximately 9 percent (34,000 hectares) from 1964 to 2000 as plantation forests were replaced by small-scale subsistence agriculture. GOK (2009) report of the prime minister’s task force on the conservation of Mau forest complex reported that the Mau forest complex declined by approximately 25 percent (107,000 Ha) for the last 15 year up to 2009. Approximately 58 percent (61,586.5 Ha), of that decline occurred in the year 2001 (Nabutola, 2010).

The South West Mau Forest is the largest forest block of the Mau forest complex with remnant natural forest and is classified as critically endangered (WWF, 2001). It has experienced significant forest loss from deforestation and degradation specifically from forest excision since 1964 (Matiru, 2000). The decline which is directly linked to decline in forest biomass (Obati, 2007), is likely to impact on forest carbon sequestration capacity, carbon storage, carbon dioxide emissions, status of atmospheric carbon dioxide, and consequently localized climatic conditions. As such, this study assessed above ground carbon sequestration dynamics and how it influenced climate variability in the South West Mau Forest between 1985 and 2015 with annual average air temperature and annual total surface precipitation being the indicator climate parameters.

1.3 Research objectives

The overall objective of this study was to evaluate the contribution of fluctuations in above ground forest carbon sequestration to climate variability in South West Mau Forest, Kenya between 1985 and 2015. The overall objective was achieved through the following specific objectives.

i). To assess above ground carbon sequestration dynamics in South West Mau Forest between 1985 and 2015

ii). To assess variability and trend in the interannual average air temperature and total surface precipitation in South West Mau Forest between 1985 and 2015

iii). To assess the response of interannual average air temperature and total surface precipitation to above ground carbon sequestration dynamics in South West Mau Forest between 1985 and 2015

1.4 Research hypothesis

i). Above ground carbon sequestration variations in South West Mau Forest between 1985 and 2015 are not significant

ii). There is no significant variability and trend in the interannual average air temperature and total surface precipitation in South West Mau Forest between 1985 and 2015

iii). There is no significant response by interannual average air temperature and total surface precipitation to above ground carbon sequestration dynamics in South West Mau Forest between 1985 and 2015

1.5 Justification of the study

Forests are important sinks and sources of atmospheric carbon dioxide and present opportunities for mitigation of climate change. Managing forest to retain and increase their stored carbon will help reduce the elevation in atmospheric carbon dioxide and stabilize climate regimes. Monitoring carbon dioxide exchanges between forests and the atmosphere and the resultant climatic influence is imperative and deserves conscious effort. Reliable information on forest carbon fluxes and the resultant influence on climate variability is important for guiding forest and climate management policies and programmes. This study was constructed on this posit and thus holds great potential for guiding forest and climate management policies and programmes. The results of this study deepen understanding of interactions between forest carbon stocks and climate variability and thus contribute to building of scientific knowledge in the assessment of forest ecosystem services in Kenya. The results also provide an inventory of carbon sequestration of South West Mau Forest from 1985 to 2015.

1.6 Scope

The study involved assessment of above ground biomass carbon sequestration dynamics – climate interaction in South West Mau Forest between 1985 and 2015. Above ground carbon sequestration dynamics assessment mainly involved estimation carbon fixed in the above ground biomass pool from year to year and analysis of variations in the same using trend analysis, change point detection and anomaly analysis. The assessment was based on the Carnegie-Ames-Stanford Approach (CASA) biogeochemical model using remote sensing data. Assessment of trend and variability in annual average air temperature and annual total surface precipitation involved evaluating the behavior of these parameters around their climatological mean, evaluation of extreme events and evaluation of upward or downward trend or no trend. In this study carbon sequestration dynamics were treated as the independent variable and trends in annual average air temperature and annual total surface precipitation as the dependent variables. Co-variation of carbon sequestration dynamics with trend in annual average air temperature and annual total surface precipitation aimed at establishing the nature, strength and direction of their relationship.

1.7 Limitation

This study was based on modeled meteorological data due to the lack of complete, consistent and homogenous data from weather gauging stations. Although the modeled data is acceptable for bioclimatic studies due to consistency and homogeneity (Asfaw et al., 2018), it provides more generalized results. Secondly, NDVI data from medium to high resolution satellite imagery was limited in temporal year to year coverage of the study area due to low temporal resolution and complications imposed by cloudy conditions. Use of this data could have resulted in reporting unlikely changes in above ground net primary production. As such, NDVI data from the NOAA AVHRR which is widely accepted and used as a potential tool for monitoring dynamics in vegetation production because of it suitable radiometric and daily temporal resolution (Didhan & Fagan, 2004), was used for this study although it has course spatial resolution (0.05^0).

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews carbon cycling, historical elevation in carbon dioxide and how these are related to the climate system at the global level and at the forest ecosystem level. At the forest ecosystem level emphasis in laid on processes related to vegetation dynamics and carbon exchanges and their relation to climate system.

2.2 Global carbon cycling

The atmosphere stores approximately 750 gigatonnes of carbon in the form of carbon dioxide and is increasing by 3 gigatonnes of carbon per year. Figure 2.1 shows carbon pools and carbon dioxide fluxes between the earth and the atmosphere. The land (soils and vegetation) and ocean floor store both organic and inorganic carbon. Organic carbon is derived from the decomposition plant and animal materials while inorganic carbon is extracted from ores and minerals. Oceans, water bodies and groundwater reservoirs store dissolved inorganic carbon. Carbon contained in the oceans and land is linked to atmospheric carbon through photosynthesis, respiration extraction and combustion. The oceans, vegetation and soils exchange carbon with the atmosphere constantly on daily and seasonal time scales. On the other hand, carbon from fossil fuels, formed over millions of years, is not exchanged with the atmosphere, but is transferred in a one way direction over time (IPCC, 2006; Folger, 2009).

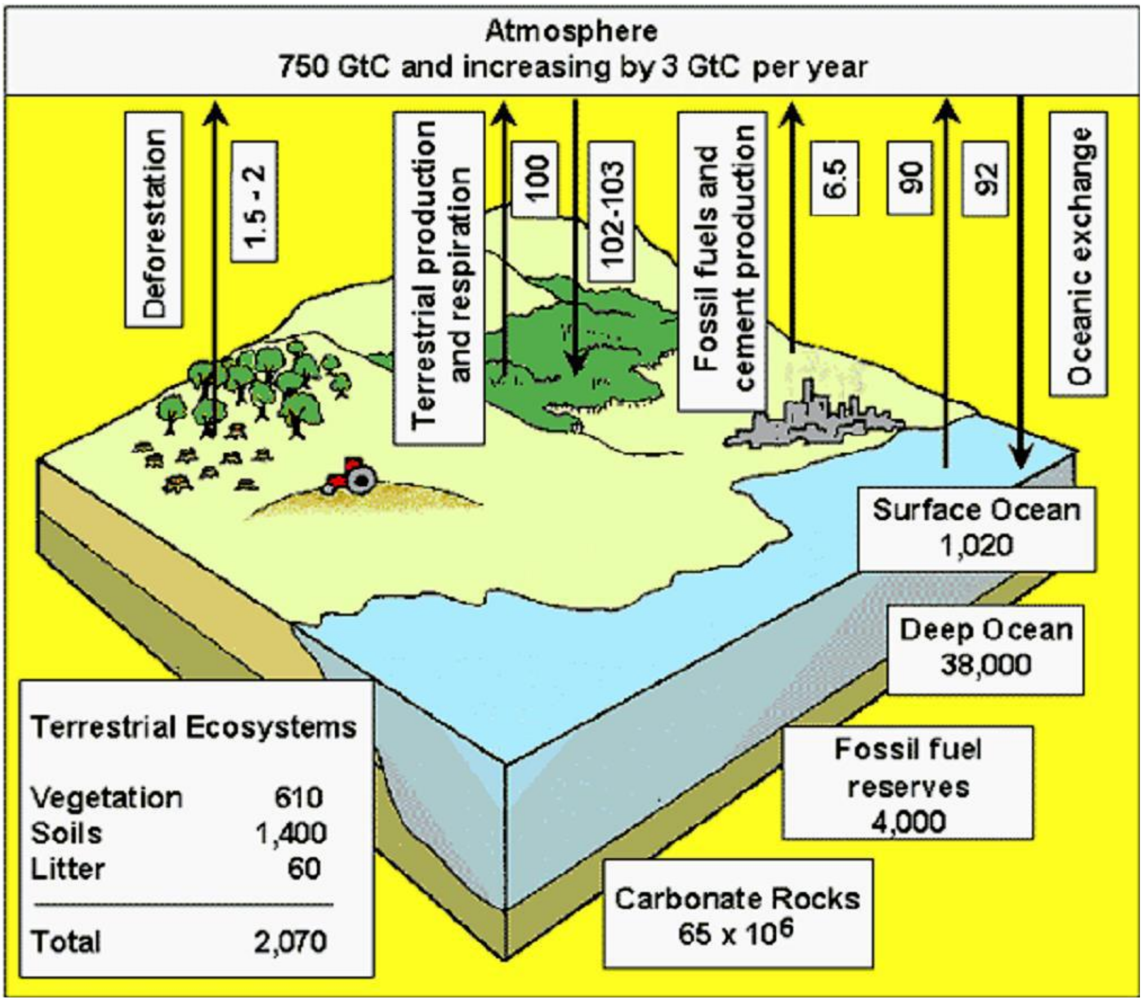


Figure 2.1: Carbon pools and carbon dioxide fluxes between the earth and atmosphere

(Source: Edinburgh centre for carbon management)

The concentration of carbon dioxide in the atmosphere has been fairly constant at approximately 280 parts per million. Human activities such as burning of fossil fuels, deforestation and other land use activities have significantly altered the carbon cycle. Large volumes of fossil carbon have been tapped for energy and are thus transferred into the atmosphere over a relatively short period of time yet it took millions of years to accumulate them in the underground. Atmospheric concentration of carbon dioxide has risen by over 35 percent since the industrial revolution and are now greater than 380 parts per million (Folger, 2009). Notwithstanding the growing concentration of atmospheric carbon, it is important to emphasize that there are two different stable carbon isotopes present in the atmospheric carbon dioxide, that is, carbon 13 and carbon 12. Sinks in terrestrial ecosystem and more specifically vegetation discriminate against carbon 13, which means that the carbon dioxide they fix is enriched with carbon 12 (Dawson et al., 2002). Oceans, vegetation and soils do not take up carbon released from human activities quickly enough to prevent carbon dioxide in the atmosphere from increasing (Folger, 2009).

2.3 Forest biomass and forest carbon cycling

Forest carbon cycling is defined by changes in forest stand type and eco-physiological behavior (Fahey, 2001; FAO, 2001; Jarvis & Fowler, 2001; Folger, 2009). Changes in forest stand type are expressed in terms of species, age, composition and structure. The eco-physiological behavior of forest is described by morphology and anatomy of the leaves, photosynthesis, transpiration, water relations, respiration, phenology and growth (Fahey, 2001). The changes in forest stand type and eco-physiological behavior are influenced by natural succession, deforestation, aforestation, reaforestation, harvesting, burning and other forms disturbance (Fahey, 2001; FAO, 2001; Folger, 2009). The changes in forest stand type and eco-physiological behavior subsequently affect drivers and processes involved in forest – carbon dioxide interactions (Sanderson et al, 2012).

Photosynthesis and respiration are the driving process behind carbon capture and storage in forest biomass. During photosynthesis, light absorbed by chlorophyll drives a transfer of electron and hydrogen from water to combine with carbon dioxide from the atmosphere to create carbohydrates. Through these processes, carbon dioxide is removed from the atmosphere and is sequestered into organic molecules already present in the plant's chlorophyll a process often referred to as carbon fixation (Campell & Reece, 2002). This capture of carbon dioxide by forests from the atmosphere through photosynthesis and the subsequent sequestration in the structure of plant tissue where it resides for years, decades or centuries makes forests carbon sinks while the eventual release through death, decay, harvesting or burning makes forests sources of carbon emission.

Changes in forest stand type and eco-physiological behavior affect the amount of carbon-assimilating photosynthetic tissue in a forest and as such, a forest will show a net gain or loss of carbon based on the amount of carbon-assimilating photosynthetic tissue. Undisturbed mature forest stands with closed canopies and high leaf area indexes have large amounts of carbon-assimilating photosynthetic tissue and therefore fix more carbon dioxide in forest biomass while disturbed forest stands with open canopies and low leaf area indexes have low amounts of carbon-assimilating photosynthetic tissue and as a result fix less carbon dioxide in forest biomass (Diaz, 2001). The forest canopy is the photosynthetic power house and over 90 percent of photosynthesis occurs in the upper 20 percent of the tree crown which has high leaf area index. It is also in the canopy that 60 percent of the total organic carbon in forests is fixed and stored (Didhan & Fagan, 2004).

Respiration involves three processes namely glycolysis, kreb cycle and electron transport. During these stages glucose is oxidized to produce carbon dioxide. Some fraction of this carbon dioxide is used in photosynthesis while some fraction is released to the atmosphere as a product of metabolism. Plant respiration represents approximately half of the carbon dioxide that is returned to the atmosphere in the terrestrial portion (Campell & Reece, 2002). In principle the capture of carbon dioxide by forests from the atmosphere through photosynthesis and release through respiration is considered to take place on a short time scale of seconds to minutes resulting in the accumulation of biomass over time, what is often referred to as net primary production (NPP).

Forest conservation and restoration lead to maintenance and enhancement of photosynthetic and respiration capacity of a forest and eventual gain in the capacity to fix carbon from the atmosphere. Disturbance and degradation result in the loss of photosynthetic and respiration capacity of a forest and eventual loss in the capacity to fix carbon from the atmosphere (Didhan & Fagan, 2004; Kindermann et al., 2008). Amongst all kind of plants, forests have the greatest ability to store or sequester large amounts of carbon and at the same time release large amounts of carbon to the atmosphere when they respire, die, decay are harvested or burned on account of having large amount of foliage and woody stems (Millennium Ecosystem Assessment, 2005; FAO, 2006; Zhu, et al., 2010). Emission and sequestration of carbon dioxide in turn influence atmospheric concentration of carbon dioxide (Diaz, 2001).

2.3.1 Field Measurements of above ground Biomass/Carbon

Conventional methods of measuring biomass values in the field are the most accurate and reliable method although they are time consuming, labour intensive and cannot cover spatial distribution of biomass in larger areas (Brown, 1997; FAO, 2008). These methods are considered as either destructive or non-destructive. The destructive method involves felling down specific number of sample trees, which are weighed to make biomass equations which are then used to derive forest above ground biomass (Brown, 1997).

In nondestructive methods, regression equations are developed (Foody et al. 2003; Bajracharya, 2008) based on data from felled trees using some easily measurable dimension such as diameter (Brown 1997). Since biomass and trunk diameter are highly correlated, regression models can be used to convert trunk diameter data to biomass data (Brown, 1997; Gledy, 2005; Havemann, 2009). Allometric equations that relate biomass of tree components to diameter at breast height (dbh) are used to calculate biomass values. Other variables such as height can also be used in the regression equations; however the most simple and commonly used technique for deriving forest above ground biomass is through the use of diameter at breast height (dbh) based allometric equations (Brown, 1997; Subedi et al., 2010).

2.3.2 Remote sensing for mapping of biomass/carbon

Optical, laser and radar remote sensing techniques have been identified as potentially important tools and have been widely used in quantification of above-ground biomass stocks and associated changes (Roy & Ravan, 1996; Yang et al., 2001; Lu et al., 2002; Namayanga, 2002; Rokhmatuloh, 2007; Bajracharya, 2008; Tutu, 2008;

Tripathi et al., 2011). The optical remote sensing measures reflectance from red, green and near infrared section of the electromagnetic spectrum which contains considerable information about forest biomass. It provides more accurate estimates of structural and eco-physiological properties of forest canopies. Laser remote sensing measures vertical height from ground to canopy and radar remote sensing is excellent for estimating canopy structure (Didhan & Fagan, 2004; Bajracharya, 2008). Because of its capability to measure accurately structural and eco-physiological properties of forest canopies, optical remote sensing was used in this study for estimation of biomass/carbon.

A major benefit of using remote sensing data is that it can cover a large area and provide systematic observation systems and historical archives of data (Yang, et al., 2001). Although various optical remote sensing approaches such as crown cover, LAI, and stand volume (Brown, 1997) have been used extensively for vegetation mapping and forest biomass assessment, this study focuses on the use of reflection coefficients and solar radiations. This involved the use of NDVI and PAR (Namayanga, 2002; Tripathi et al., 2011).

2.4 Trends in climate change and variability

Climate change is the long term shift in the climate of a specific area and is manifested by change in features associated with average weather such as temperature, and precipitation among others. To visualize climate change there is need to compare two or more different periods of time. Climate variability describes how much the weather and extreme events vary around the averages. It is important to understand that variability in climate is also considered climate change since the average change is a product of the cumulative variability. Statistically climate change and variability may be described using measures of central tendency, measures of dispersion and measures of distribution at different spatial and temporal scales (Folland & Karl, 2001; IPCC, 2007; Dinse, 2011).

Either as a coincidence or consequence, globally there has been an increasing trend in temperature since the late 19th century. Between 1910-1945 temperature increases of about 0.14^{0}C per decade were detected. From 1976 temperature increases of about

0.17^0C per decade were detected (Folland & Karl, 2001). In tropical Africa, temperature increases of about 0.15^0C per decade were detected for the period between 1979 and 2010. The increase in temperature was attributed to both natural and anthropogenic processes (Emmanuel et al., 2019). In Kenya mean annual temperatures increased by 1.0^0C between1960 and 2006 which translates to 0.21^0C per decade (McSweeney et al., 2010). For the decade from 1995 to 2005, the growth rate of carbon dioxide in the atmosphere led to a 20 percent increase in its radiative forcing (IPCC, 2014). Again, as a coincidence or consequence, the period between 2011 to 2015 was considered the hottest period on record and 2015 as the hottest since modern observation began in the late 1800s (IPCC, 2007; Nouaceur & Murarescu, 2016).

Precipitation is not only a major component of the hydrological cycle but is also a key parameter in the context of climate and weather. It is commonly defined as any product of atmospheric water vapour deposited at the earth surface and includes rain, sleet, snow, drizzle, hail, ice, snow pellets, diamond dust and freezing rain (Eva et al., 2018). Patterns in precipitation variability are generally considered feedback responses of surface temperature and key biogeophysical processes. Increasing surface temperature leads to changes in biogeophysical processes mainly land surface albedo, land surface latent heat, surface roughness, surface energy fluxes and cloud formation (Kiehl & Trenberth, 1997; Samalca et al., 2007). Increases in temperature lead to increases in the moisture-holding capacity of the atmosphere. These alter precipitation in terms of amount, frequency, intensity, duration, type and extremes events. Overall increased water vapour leads to more intense precipitation, but reductions in duration and/or frequency, given that total amounts do not change much (IPCC, 2007).

As these changes in biogeophysical process take place surface humidity generally increases. These leads to increased atmospheric water vapour leading to increased moisture available for precipitation. As a matter of fact, surface specific humidity has been increasing since 1976 in resonance with higher temperature over both land and ocean. The total column of water vapour also increased by 1.2 ± 0.3percent per decade (α =0.05) from 1988 to 2004. This significantly increased the global precipitation but spatial and temporal variations were observed in different regions. Global land precipitation is reported to have increased by approximately 2 percent from 1900 (Folland & Karl, 2001). Remarkably, analysis of interannual variability in precipitation in different part of the world reveal that during hotter years precipitation increases while during colder years precipitations decreases. In many regions global warming translates into wetter conditions as well as in precipitation increase and repeated occurrence in extreme precipitation events (Nouaceur & Murarescu, 2016). As noted in (Desanker & Justice, 2001) many extreme climate events will increase or get more intense in the future under changing climate attributed to anthropogenic modification of land surface.

2.5 Attributing climate change and variability to forest carbon fluctuation

The earth's global mean climate is determined by incoming solar energy and by the properties of the earth and its atmosphere. Changes occurring in the atmosphere and at the surface of the earth alter the radiation, transmission, absorption, reflection and re-radiation of solar energy and subsequently affect climatic parameters such as temperature and precipitation among others. Among these changes is the continual elevation in atmospheric greenhouse gases concentrations. Greenhouse gases act primarily to increase the atmospheric absorption of outgoing radiation and in so doing contribute directly or indirectly to changes in climate and weather parameters. Carbon dioxide, which is the focus of this study, is an important greenhouse gas and is extremely effective in absorbing and trapping heat within the earth's atmosphere and is thus an important radiative forcing agent (IPCC 2007, Blunden et al., 2016).

As carbon dioxide concentration grows it increases the degree to which the atmosphere traps incoming radiation from the sun resulting in increased surface temperature, increase in heat waves and droughts and change in precipitation rate (FAO, 2006; IPCC, 2006; IPCC, 2007; Samalca et al., 2007; Bajracharya, 2008; Baldwin & Richards, 2010). The concentration of carbon dioxide in the atmosphere has been fairly constant at approximately 280 parts per million over several thousands of years. However, it has risen by over 35% since the 1900 and is now greater than 380 parts per million, a trend closely matched by increased surface temperature (Folger, 2009).

Fluctuations in atmospheric concentration of carbon dioxide due to changes in forest biomass modifies climate parameters among them solar radiation, air temperature, rainfall and air humidity (Jarvis & Fowler, 2001; IPCC, 2007; Sanderson et al., 2012). Figure 2.2 shows the effect of changes in forest stand on carbon stock and subsequent impact on weather. Changes in carbon dioxide concentration influences temperature through its capacity to absorb infrared radiation. Increase in atmospheric carbon dioxide increases the absorption of outgoing infrared radiation and in so doing contribute directly or indirectly to elevation in surface and column temperatures. Decrease in atmospheric carbon dioxide decreases the absorption of outgoing infrared radiation and results in reduced surface and column temperatures (IPCC, 2007). Changes in carbon dioxide concentrations influence precipitation through its effects on stomatal opening. As carbon dioxide concentrations increase the size of the stomatal openings decreases resulting in reduced evapotranspiration and as carbon dioxide concentrations decrease the size of the stomatal openings increases resulting in increased evapotranspiration. Increased evapotranspiration makes more moisture availability as precipitation and decreased evapotranspiration results in less moisture available as precipitation (Sanderson et al., 2012).

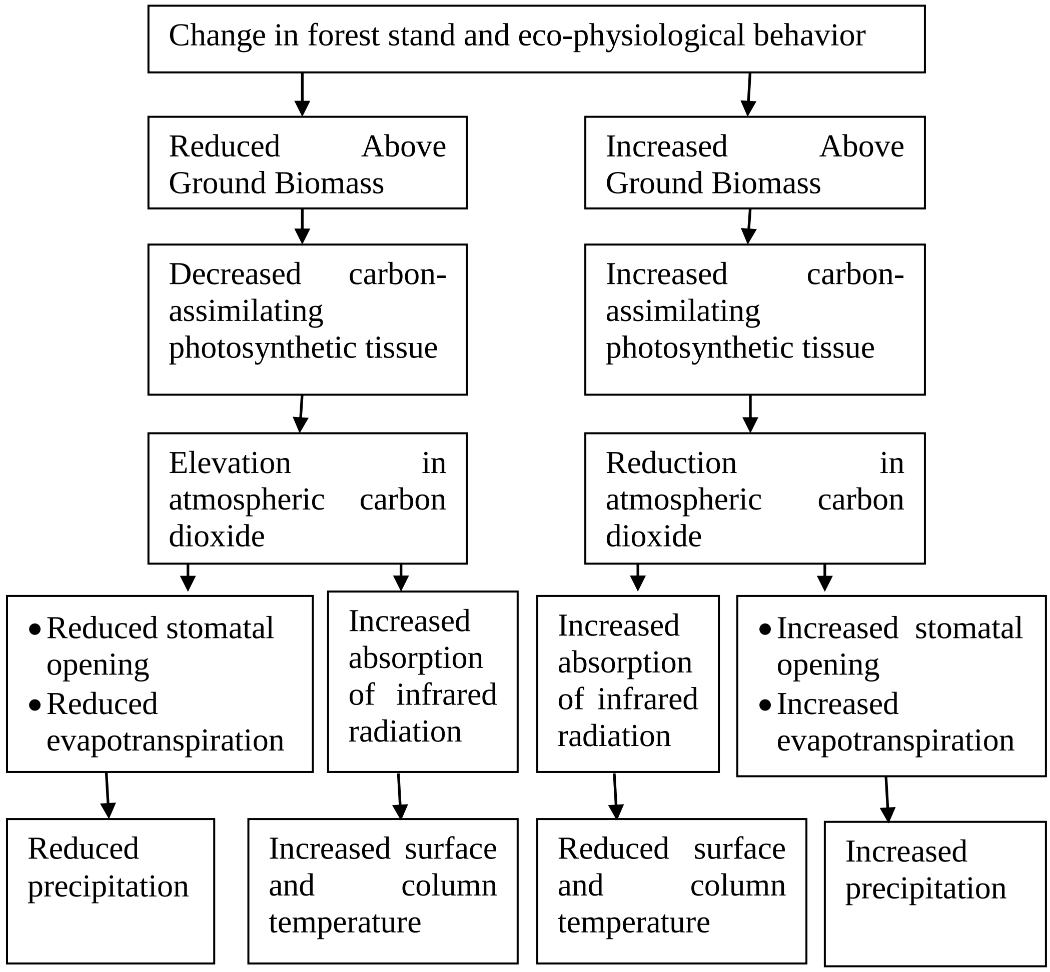


Figure 2.2: Effect of changes in forest stand on carbon stock and subsequent impact on weather

As from 1990 tropical deforestation has been responsible for the largest share of carbon dioxide release to the atmosphere releasing approximately 1.6 gigatonnes of carbon per year (Folger, 2009). The continual emission of carbon dioxide by forests and its subsequent elevation in the atmosphere is one of the major contributors to climate change and variability (Didhan & Fagan, 2004; Mitchell et al., 2017). As at 2000 and relative to pre-industrial era, deforestation accounted for 26 percent of the total carbon dioxide emissions and an enhanced greenhouse effect of 15 percent (Moutinho & Schwartzman, 2005)

2.6 Research gaps

Linking forest carbon to climate change has largely been done at global and regional scales and at time scales of over 50 years. Not as much of focus is accorded to attributing climate change and variability at smaller scales and over time scales of less than 50 years with limited exceptions. Additionally, although the main mechanisms by which forests modify climate are known, they have, with limited exception, not been studied in isolation (IPCC, 2007). Partitioning climate variability between the main mechanisms by which forests modify climate is a major objective for climate change attribution (Sanderson et al., 2012). This study endeavored to close in on these gaps by establishing forest carbon-climate interactions at ecosystem scale over a period of 31 years.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study area

South West Mau Forest is one of the 22 blocks that comprise the Mau Forest Complex (Figure 3.1).

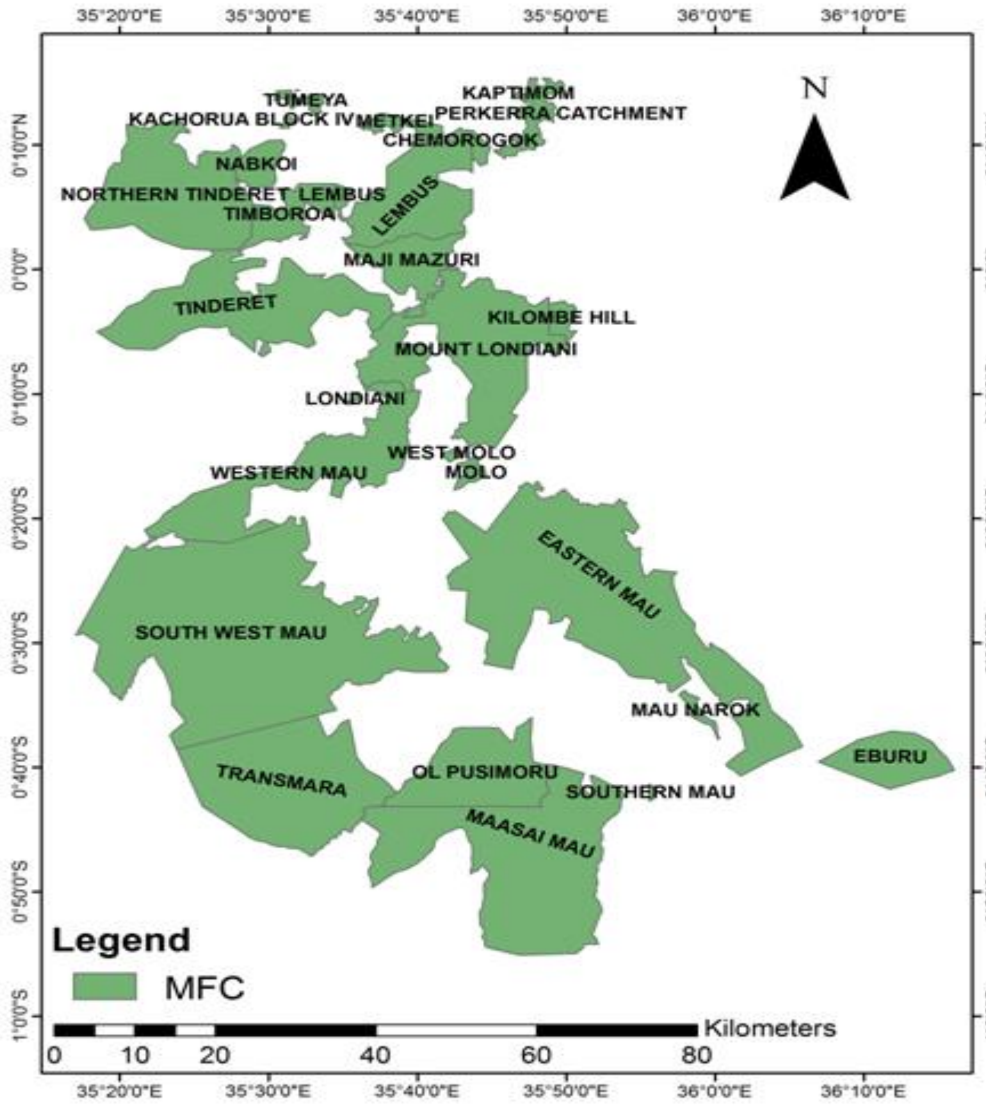


Figure 3.1: Map of Mau Forest Complex

It lies on longitudes $35^0 15'00''$E and $35^0 40'00''$E and latitudes $0^0 20'00''$S and $0^0 45'00''$S (Figure 3.2). It covers an area of approximately 84000 ha (Obati, 2007). The forest reserve extends over four counties namely Narok, Nakuru, Kericho and Bomet.

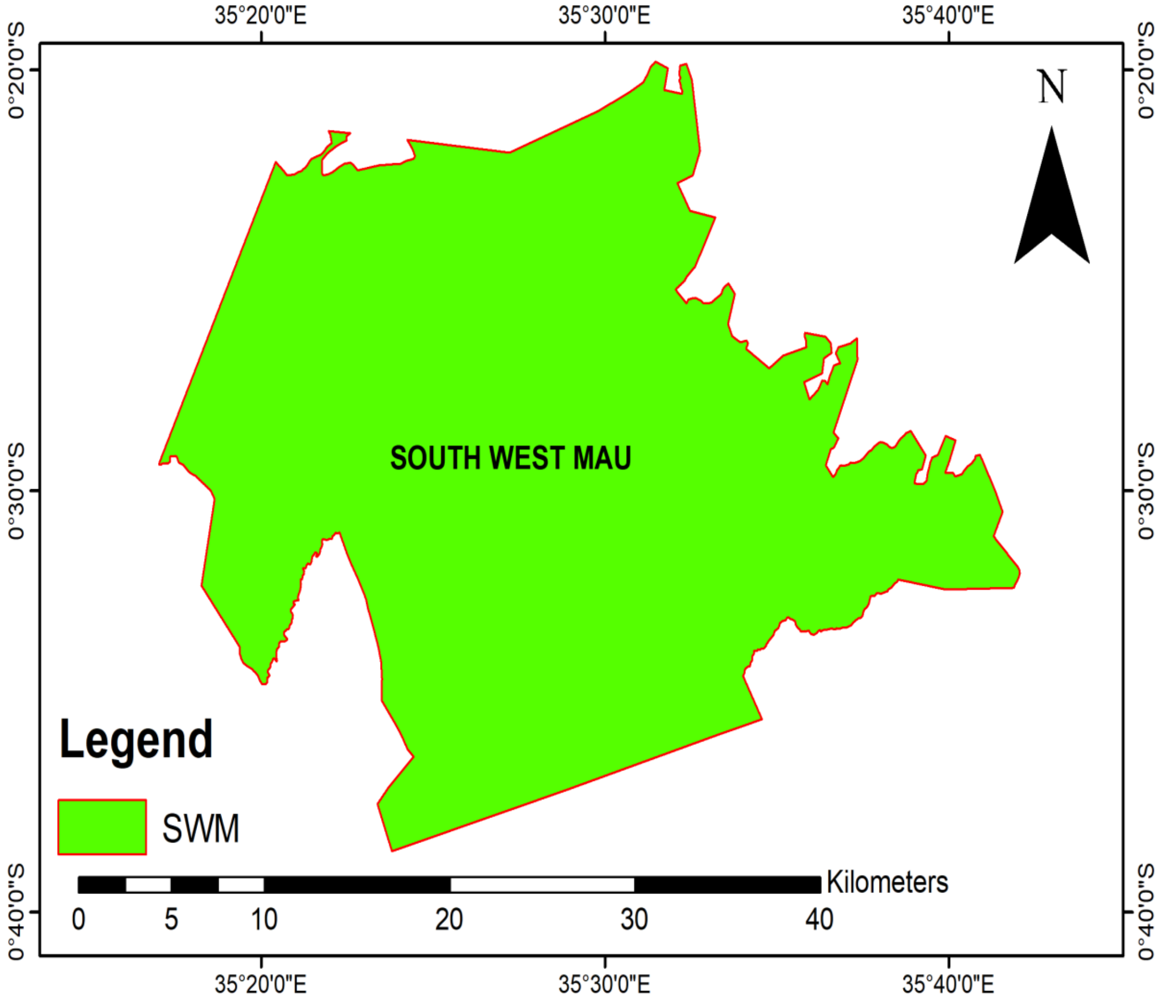


Figure 3.2: Location of South West Mau Forest

The altitude (Figure 3.3) rises from 1934 meters above sea level in the South west to 2653 meters above sea level in the North east. The slope tends from North East to South West characterized by deeply incised valleys starting from the escarpment and joining towards the south west.

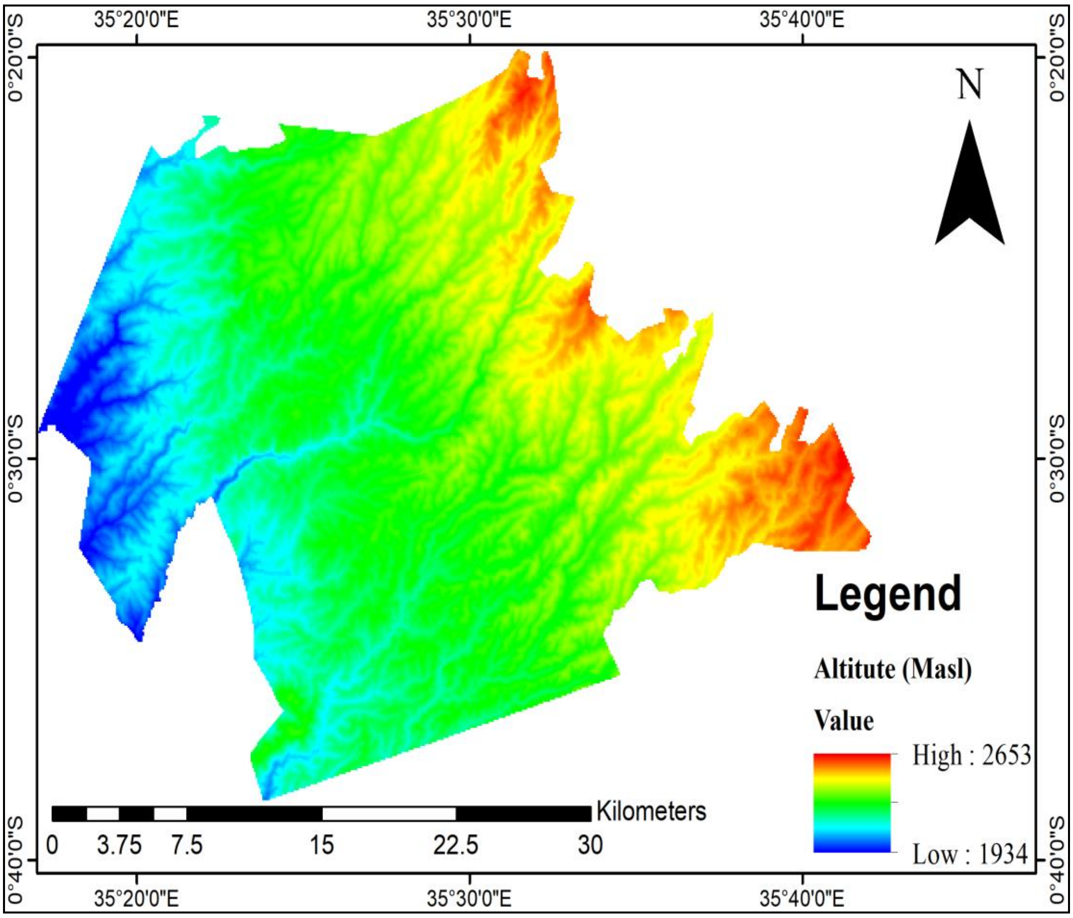


Figure 3.3: Topography of South West Mau

South West Mau is part of indigenous montane ecosystem in Eastern Africa. It falls under the tropical climate domain and tropical montane climate region described by FAO (2001). Annual rainfall which is more or less continuous round the year is between 1000 - 2700mm (GOK,1980; Bennun & Njoroge, 1999; KFWG, 2008). The long rains start from mid-march to June with the peak in April, while the short rains occur between the months of September and December. The average annual potential evaporation is between 1200-2000mm (GOK, 1980). According to the agro-climatic map of Kenya (GOK 1980), about 80 percent of the Forest falls under the upper highlands with the remaining 20 percent being categorized as lower highlands (Figure 3.4).

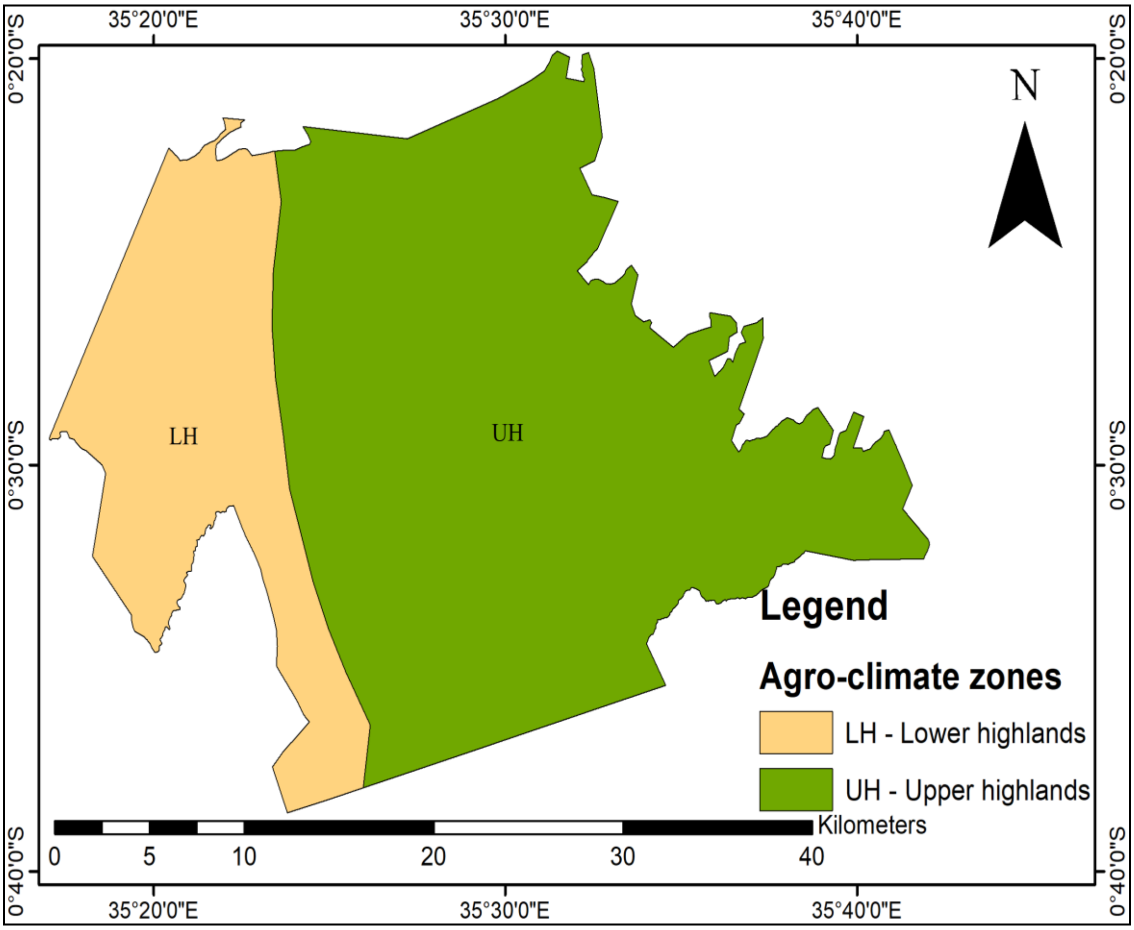
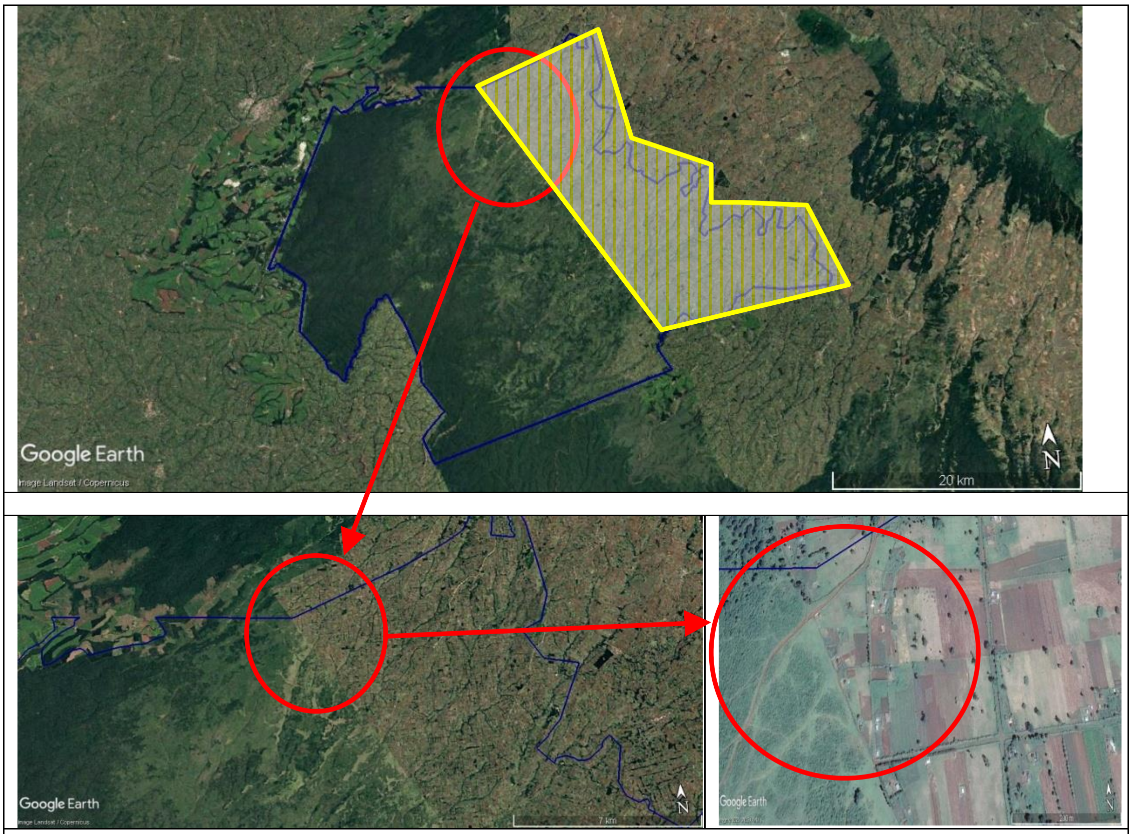


Figure 3.4: Agro-ecological zones of South West Mau Forest

The upper highlands have mean annual temperature of between 12-16^{0}C with the mean minimum temperatures ranging between 4-6^{0}C and the mean maximum between 16-20^{0}C and is classified as very cool to cool. The lower highlands have mean annual temperature of between 14-18^{0}C with the mean minimum temperatures ranging between 8-12^{0}C and the mean maximum between 20-24^{0}C and is classified as fairly cool to cool temperature. In general, the average temperatures are in the range of 12-16^{0}C but fall below 10^{0}C during the cold season (Obati, 2007) and the climate in the South West Mau Forest is classified as being humid (GOK, 1980).

According to the agro-climatic map of Kenya (GOK 1980), South West Mau Forest is classified as a Moist forest with very high potential for plant growth. The vegetation exhibit a broad altitudinal zonation from west to east, with lower montane forest below 2,300 m giving way to thickets of bamboo (*Arundinaria alpine)* mixed with grassland, and finally to montane sclerophyllous forest near the escarpment crest. There are over 37 species of woody vegetation with the major tree species being *Aningeria adolfi-friedericii, Strombosia scheffleri, Tabernaemontana stapfiana*, *Syzygium guineense, Neoboutonia macrocalyx*, *Olea capensis, Prunus africana* and *Albizia gummifera* (Bennun & Njoroge, 1999; Obati, 2007; KFWG, 2008).

In terms of land use and social economic activities, the communities adjacent to the forest practice crop and animal production. Dominant crops include tea, maize and potatoes among other farm produces. Animals reared include local and exotic shoat and cattle as well as donkeys. To the west are mainly large scale tea plantations. On the eastern side, most of the farmlands are smallholder and were curved out from the forest. It is in this area that 22797 hectares of forest land were excised to form settlement schemes in the year 2001 although this was contested in court. Much of these encroachments had already taken place before the year 2001. As at December 2015 encroachment had extended beyond the excision boundary. The encroachments are mainly characterized by conversion of forest into farmlands (Figure 3.5).



The area with the yellow mask is the contested excised area. The Red circles are extracts of the continued encroachments as at December 2015.

Source of image: Google earth 2015

Figure 3.5: Encroachment into South West Mau Forest

Ground truthing visits conducted in July and August 2015 in Kabongoi and Silibwet areas revealed that extraction of forest products mainly firewood, poles and timber (Figure 3.6 b, c and d) and encroachments into the forest (Figure 3.6 a) are the major cause forest loss and degradation in South West Mau forest. The loss translates to loss in standing biomass and consequently loss of photosynthetic capacity and as such reduced above net primary production.

a. Encroachment by farms

b. Extraction of poles

c. Firewood collection

d. Illegal logging for timber

Figure 3.6: Encroachment and destructive extraction of forest products

3.2 Data collection

This study was based on above ground biomass carbon sequestration, annual average air temperature and annual total annual surface precipitation data. The data collection and derivation process is described in details in the subsequent section.

3.2.1 Estimation of above ground carbon sequestration in South west Mau Forest

Above ground carbon sequestered (Table 3.4) in South West Mau Forest for the period between 1985 and 2015 was quantified from above ground net primary production. Above ground net primary production (ANPP) is the increment in biomass per unit area over a given period of time (An et al., 2013; Zhang, et al., 2017). It is the balance between photosynthesis and respiration and it reflects the net carbon input from the atmosphere to terrestrial ecosystems (Diaz, 2001; et al., 2017). It is dependent on the initial amount of carbon assimilating tissue and the rate at which new biomass is produced. Stands with large standing biomass show higher above ground net primary production (ANPP) than stands with lower standing biomass (Diaz, 2001).

The above ground net primary production (ANPP) was estimated based on the Carnegie-Ames-Stanford Approach (CASA) light use efficiency model (equation 1) (Namayanga, 2002; Masek & Collatz, 2006; Garbulsky et al., 2008; Goerner et al., 2011; Raza & Mahmood, 2018). Light use efficiency model exemplify photosynthesis theoretically based on the assumptions that under optimal environmental conditions, that is, temperature water and soil fertility, vegetation production is influenced only by absorbed photosynthetically active radiation (Running et al., 2000). Above ground net primary production provides an accurate regular measure of biomass which subsequently is important for defining terrestrial carbon fluxes (Lu et.al., 2002; Namayanga, 2002; Bonino, 2006; Rokhmatuloh, 2007; Bajracharya, 2008; Tripathi, et.al., 2011). The above ground net primary production data is presented in table 3.4.

$NPP \equiv AGB = FPAR * PAR * LUE$……………………….………. Equation 1

Where:

NPP is above ground net primary production also referred as increment in above ground biomass (AGB). For this study NPP was expressed in Kg/ha.

FPAR is the fraction of photosynthetically active radiation absorbed by the canopy. It is expressed as a unitless fraction of incoming radiation received by the land surface (Eisfelder, 2013).

PAR is the incident photosynthetically active radiation. For this study PAR was expressed in $Mj/m^2/yr$. LUE is the light use efficiency. For this study LUE was expressed in $gCMJ^{-1}$.

Computation of fraction of photosynthetically active radiation (FPAR)

In the Carnegie-Ames-Stanford Approach (CASA) light use efficiency model, the fraction of photosynthetically active radiation absorbed by plants depends on the vegetation type and cover and its maximum value does not exceed 0.95 (Running et al., 2000). The fraction of photosynthetically active radiation absorbed by the canopy (FPAR) can be directly quantified using the normalized differential vegetation index (Goward, 1989; Myeni & Williams, 1994; Gabriela & Ana Maria, 2004; Glenn et al., 2008; An et al., 2013;) as was the case in this study (equation 2). The fraction of photosynthetically active radiation data used for this study is presented table 3.4.

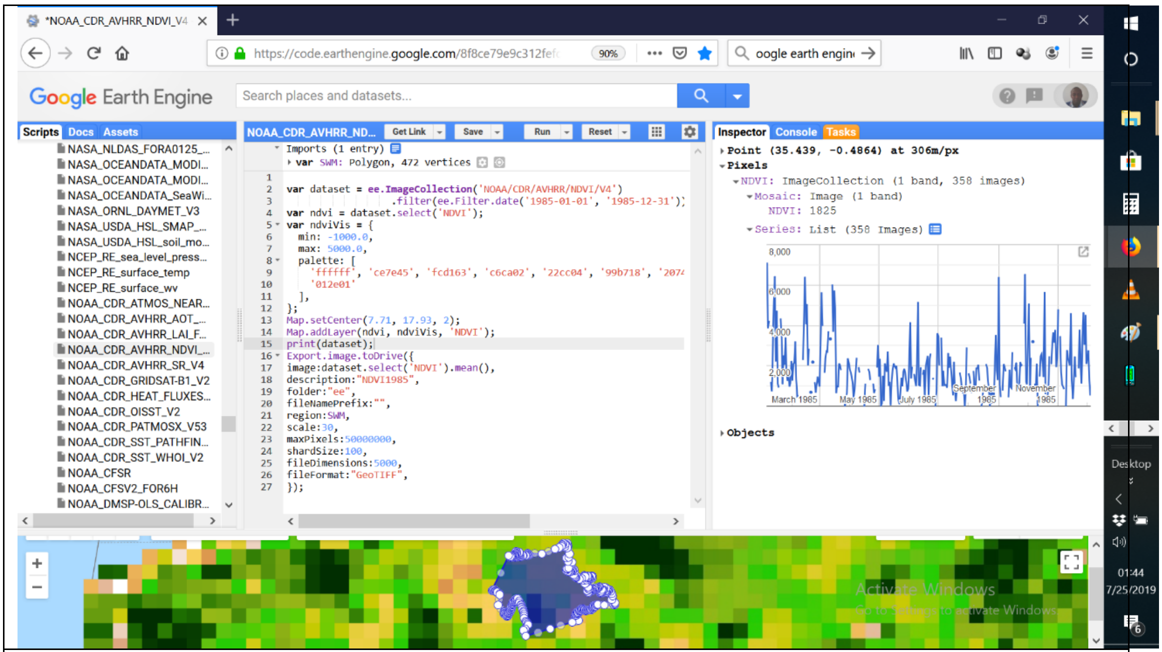
$FPAR \sim NDVI$………………………………………………………… Equation 2

Where: NDVI is the Normalized Difference Vegetation Index. In this study NDVI describes the mean annual NDVI.

Normalized Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum to analyze whether the target being observed contains live green vegetation or not (Holme et al., 1987; Meneses-Tovar, 2011). It is based on the principle that actively growing green plants strongly absorb radiation in the visible region of the spectrum while strongly reflecting radiation in the Near Infrared region (Holme et al., 1987; Ryan, 1997). NDVI is known to respond to change in canopy cover and structure, biomass and chlorophyll content (Anyamba & Tucker, 2005; Glenn et al., 2008) and it is a good estimator of the rate of photosynthesis (Namayanga, 2002).

The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands (Garbulsky et al., 2008; Goerner et al., 2011; Pareta & Pareta, 2011; Hashimoto et al., 2012). NDVI values range from -1 to +1 with extreme negative values representing water, values around zero represent bare soil, values over 0.6 represent dense green vegetation and +1 value represents strongest vegetative growth (Ryan, 1997). More precisely, values between 0.2 and 0.4 represent shrub and grassland, and higher values represent temperate and tropical rainforests (Holme et al, 1987; Ryan, 1997). Vegetation indices studies (Anyamba & Tucker, 2005; Endeleo, 2010; Kinyanjui, 2010; Loranty et al., 2018; VITO, 2020) observed that forest NDVI values on average range from 0.42 to 0.88 with the lower limit corresponding to open forests while the upper limit correspond to closed forest. Fraction of photosynthetically active radiation (FPAR) values for forests, range from 0.411 to 0.780 as well (Field et al., 1995). Considering that South West Mau Forest is composed of closed undistributed forest and open disturbed forest, NDVI threshold of 0.42 was used to represent threshold fraction of photosynthetically active radiation (FPAR).

Gridded daily normalized difference vegetation index (NDVI) data from National Oceanic and Atmospheric Administration Climate Data Record (CDR) Advanced Very High Resolution Radiometer (NOAA AVHRR) NDVI product was used to compute average annual NDVI using Google Earth Engine Code Editor (figure 3.7). The average annual NDVI is known as integral NDVI (NDVI-I) and has been used widely as a proxy for the annual fraction of photosynthetically active radiation to estimate above ground net primary production (Goward, 1989; Myeni & Williams, 1994; Paruelo et al., 1997; Gabriela & Ana Maria, 2004; Glenn et al., 2008; An et al., 2013). The computed yearly NDVI-I was used in this study to estimate annual fraction of photosynthetically active radiation for each year between 1985 and 2015.




```
var dataset = ee.ImageCollection('NOAA/CDR/AVHRR/NDVI/V4')
                  .filter(ee.Filter.date('1985-01-01',
'1985-12-31'));
var ndvi = dataset.select('NDVI');
var ndviVis = {
  min: -1000.0,
  max: 5000.0,
  palette: [
    'ffffff', 'ce7e45', 'fcd163', 'c6ca02', '22cc04',
'99b718', '207401',
    '012e01'
  ],
};
Map.setCenter(7.71, 17.93, 2);
Map.addLayer(ndvi, ndviVis, 'NDVI');
print(dataset);
Export.image.toDrive({
image:dataset.select('NDVI').mean(),
description:"NDVI1985",
folder:"ee",
fileNamePrefix:"",
region:SWM,
scale:30,
maxPixels:50000000,
shardSize:100,
fileDimensions:5000,
fileFormat:"GeoTIFF",
});
```

Figure 3.7: Generation of NDVI-I for 1985 from the google earth engine code editor

The NDVI data from the NOAA AVHRR spans from June 1981to date and it has a gridded spatial resolution of 0.05° which is nominally 1km × 1km or 100 Ha per pixel (An et al., 2013). Although NOAA AVHRR is able to capture daily NDVI data some data is not cloud free. As such data was not obtained for all days in a year. Table 3-1 shows the number of days per year that had cloud free gridded daily NDVI data used to compute integral NDVI (NDVI-I). The presented integral NDVI (NDVI-I) is the area averaged for South West Mau Forest between 1985 and 2015.

Optical satellite data is the regularly used remote sensing data used to estimate structural properties of canopies and much more accrulately aspects of leaf physiology and chemistry including photosynthesis , transpiration and pigment concentration as compared to laser and radar remote sensing data (Didhan & Fagan, 2004). Several studies (Paruelo et al., 1997; Song et al., 2014; Zhang et al., 2017) have observed that there is a strong positive relationship between NDVI from NOAA AVHRR and either biomass or annual above ground net primary production for different geographical areas and ecosystems. Considering that the study focused on above ground biomass from forest canopy, the data was considered most appropriate to provide an accurate estimation of above ground biomass quantified as average annual above ground net primary production.

Table 3.1: Number of days per year used to derive NDVI-I for SWM

Year	Days /year	Area averaged NDVI-I for SWM
1985	308	0.6270021
1986	321	0.6847957
1987	327	0.7227584
1988	340	0.5804357
1989	351	0.6426169
1990	341	0.7304784
1991	350	0.6519468
1992	344	0.7047745
1993	335	0.7512
1994	231	0.7713
1995	348	0.6371143
1996	311	0.6903479
1997	342	0.7343181
1998	332	0.7441793
1999	331	0.6786857
2000	326	0.6140528
2001	361	0.737714
2002	361	0.6449999
2003	358	0.7673173
2004	356	0.7209874
2005	350	0.7307156
2006	356	0.7420117
2007	363	0.6969447
2008	358	0.7025648
2009	359	0.6450145
2010	360	0.725795
2011	362	0.6910188
2012	356	0.7405
2013	335	0.7648386
2014	363	0.7037088
2015	361	0.7112675

Computation of photosynthetically active radiation (PAR)

Photosynthetically active radiation (PAR) is part of the incoming short-wave solar radiation that is used for photosynthesis (Namayanga, 2002; Tripathi et al., 2011). Approximately 45 to 50 percent of the incoming short wave solar radiation in the range of 0.4 – 0.7 μm of the electromagnetic spectrum is generally accepted to represent Photosynthetically Active Radiation (PAR) for a 24-hour average condition (Namayanga, 2012; Hasenauer et al., 2012). For tropical countries a PAR value of 0.51 or 51% of the incoming short-wave solar radiation is generally accepted for clear skies (Tripathi et al., 2011). For this study a PAR of 51% of the incoming short-wave solar radiation was used to represent average 24 hour conditions in South west Mau forest as shown in equation 3 assuming clear skies.

$$PAR = 0.51K_{24}\ (Wm^{-2}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation } 3$$

Where:

K_{24} is the average 24 hour incoming short-wave solar radiation.

Mean annual incoming short-wave solar radiation data generated from mean monthly incoming short-wave solar radiation data (Appendix I) was used to compute mean annual photosynthetically active radiation (PAR) (Table 3.4). The mean monthly incoming short-wave solar radiation data was acquired from Giovanni, National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center (NASA GES DISC). Table 3.2 below illustrates the features of the mean monthly short wave solar radiation data.

Table 3.2: Features of Average Incident Shortwave on Land for SWM (1985-2015)

Variable	**Incident short-wave solar radiation (FLDAS_NOAH01_C_EA_M v001)**
Units	Wm^{-2}
Source	MERRA-2 MODEL M2TMNXLFO v5.12.4
Temporal resolution	Monthly
Land region	Sub-Saharan Africa
Spatial resolution	0.5 x 0.65 deg
Observations	Satellite and land surface models
Begin data	1985-01-01
End date	2015-12-31

Computation of Light use efficiency (LUE)

Growth and production by trees and stands is defined by the amount of light or radiation absorbed by leaves, the efficiency of converting absorbed light into biomass, and the allocation of photosynthate to various tissues (Binkley et al, 2011; Boschetti et al., 2011). The efficiency of converting absorbed light into biomass is referred to as Light use efficiency (LUE) and it is expressed in mass and energy units (gC Mj^{-1}). Light use efficiency can be determined by use of agro-meteorological parameters (Namayanga, 2002; Tripathi et al., 2011) or by use of vegetation indices (Agapiou, et al., 2012). In this study Light use efficiency (LUE) (Table 3.4) was computed using agro-meteorological parameters (Appendix 2) as shown in equation 4.

$LUE = \varepsilon_{max} * T1 * T2 * \omega$……………………………………….…… Equation 4

Where:

$\boldsymbol{\varepsilon}_{max}$ is the maximum light use efficiency under ideal conditions, and the adopted value for this study was $0.389gMJ^{-1}$.

T1, T2 and $\boldsymbol{\omega}$ are the limitations imposed by temperature and water stress on the optical energy utilization rate and relate to plant growth regulation (acclimation) by temperature.

T1 reflects the limitation imposed by the biochemical actions of plant photosynthesis at low and high temperatures and it is computed as shown in equation 5.

$\mathrm{T1} = 0.8 + 0.02 * \mathrm{T_{opt}} - 0.0005 * \mathrm{T_{opt}}^2$………………..………… Equation 5

Where:

T_{opt} is the monthly average temperature (appendix 3) in the month in which NDVI reaches maximum in a given year and a specific place. June for South West Mau has maximum NDVI.

T2 defines how light use efficiency decreases as the environmental temperatures deviates from the optimal temperature T_{opt} and is computed as shown by equation 6.

$T2 = 1.185/ (1+e^{(0.2Topt-10-T)})/ (1+e^{(-0.3Topt-10+T)})$……………………… Equation 6

Where:

T is the average annual air temperature as presented in table 3.6 and described in table 3.7.

The water stress factor (**ω**) reflects the influence of effective water utilization by plants on the optical energy conversion rate. For this study, water stress factor (**ω**) was equated to evaporative fraction (Bastiaanssen & Ali, 2001) computed as shown in equation 7.

$$\omega = \Lambda = \frac{LE}{LE + H} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 7}$$

Where:

Λ is the evaporative fraction which is defined as the energy used for the evaporation process divided by the total amount of energy available for the evaporation process.

LE is the latent heat flux. H is the sensible heat flux.

Mean monthly latent heat flux and sensible heat flux data (Appendices 4 and 5 respectively) were acquired from Giovanni, National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center

(NASA GES DISC). Table 3.3 below illustrates the features of the mean monthly latent heat flux and sensible heat flux data.

Table 3.3: Features of latent heat flux and sensible heat flux data for SWM (1985-2015)

Variable	**Latent heat flux (FLDAS_NOAH01_C_GL_M v001)** **Sensible heat flux (FLDAS_NOAH01_C_GL_M v001)**
Units	Wm^{-2}
Source	FLDAS model
Temporal resolution	Monthly
Land region	Sub-Saharan Africa
Spatial resolution	0.1^0
Observations	Satellite and land surface models
Begin data	1985-01-01
End date	2015-12-31

Conversion of above ground net primary production to sequestered carbon

The above ground net primary production was converted to sequestered carbon (Table 3.4) using 0.47 carbon fraction which is the most suitable for tropical climate domain and tropical montane climate region (Brown, 1997; CMFP, 2000; FAO, 2001; IPCC, 2006; Subedi et al., 2010).

Table 3.4: Mean above ground net primary production and sequestered carbon in SWM (1985-2015)

YEAR	Mean annual LUE gC Mj^{-1}	Annual PAR (MJ m^{-2} yr^{-1})	Mean annual FPAR (Unitless fraction)	Mean annual ANPP (g m^{-2})	Mean annual ANPP (Kg ha^{-1})	Mean annual Sequestered Carbon (Kg ha^{-1})
1985	0.32	4270.00	0.63	854.95	8549.48	4018.26
1986	0.31	4296.34	0.68	924.66	9246.60	4345.90
1987	0.33	4355.15	0.72	1038.90	10389.03	4882.84
1988	0.34	4267.98	0.58	853.99	8539.85	4013.73
1989	0.35	4248.43	0.64	954.18	9541.82	4484.66
1990	0.35	4085.11	0.73	1029.84	10298.40	4840.25
1991	0.32	4223.21	0.65	881.04	8810.42	4140.90
1992	0.32	4212.66	0.70	957.21	9572.05	4498.87
1993	0.33	4301.98	0.75	1073.35	10733.48	5044.74
1994	0.31	4316.20	0.77	1042.76	10427.58	4900.96
1995	0.32	4238.17	0.64	873.93	8739.29	4107.47
1996	0.34	4175.28	0.69	982.31	9823.13	4616.87
1997	0.32	4265.41	0.73	1016.70	10167.00	4778.49
1998	0.37	4106.10	0.74	1126.44	11264.36	5294.25
1999	0.32	4298.89	0.68	937.17	9371.68	4404.69
2000	0.29	4370.38	0.61	791.28	7912.78	3719.01
2001	0.35	4163.41	0.74	1086.94	10869.43	5108.63
2002	0.34	4319.96	0.64	936.63	9366.28	4402.15
2003	0.34	4238.68	0.77	1105.51	11055.08	5195.89
2004	0.34	4218.49	0.72	1038.65	10386.46	4881.64
2005	0.33	4247.59	0.73	1011.77	10117.69	4755.32
2006	0.33	4023.09	0.74	987.35	9873.54	4640.57
2007	0.37	4099.78	0.70	1051.39	10513.92	4941.54
2008	0.31	4070.33	0.70	897.60	8976.01	4218.73
2009	0.29	4200.11	0.65	783.90	7839.00	3684.33
2010	0.37	3890.43	0.73	1053.51	10535.08	4951.49
2011	0.35	3983.63	0.69	968.45	9684.50	4551.71
2012	0.36	3996.50	0.74	1073.43	10734.33	5045.14
2013	0.37	3922.78	0.76	1101.39	11013.93	5176.55
2014	0.36	3934.20	0.70	998.99	9989.93	4695.26
2015	0.34	4062.22	0.71	980.14	9801.40	4606.66

The mean annual above ground net primary production net primary production results for for SWM from 1985 to 2015 are comparable to those reported by other studied (Table 3.5). The difference can be explained by differences in levels of disturbance and degradation for the areas of study.

Table 3.5: Review of ANPP estimations from previous studies

No.	Author	Vegetation type	annual average NPP	Data	MODEL
1	(Goetz, et al., 1999)	Boreal forest in Central Canada	235 $gCm^{-2}yr^{-1}$	NOAA AVHRR	GLO-PEM2
2	(Zhu, et al., 2017)	Deciduous Coniferous forest in the Greater Khingan Mountain region	760 $gCm^{-2}yr^{-1}$	NOAA AVHRR	CASA
3	(Rasib, et al., 2008)	Tropical rain forest in Pasoh forest reserve, Malaysia	392.16 - 710.36 $gCm^{-2}yr^{-1}$	MODIS	CASA
4	(Chirici, et al., 2015)	Italian Forests	700 - 1800 $gCm^{-2}yr^{-1}$	SPOT	Modified C-fix BIOME-BGC
5	(Chen, et al., 2016)	Sub tropical evergreen broadleaf forest, subtropical deciduous broadleaf forest, subtropical needle leaf forest and moso bamboo forest in Tianmu mountain nature reserve, China	708 $gCm^{-2}yr^{-1}$	MODIS	CASA
6	(Waring, et al., 1998)	Evergreen in Oregon, Deciduous forest in Oregon and Massachusetts, Pine plantations in New South Wales and *Nothofagus* forest in South Island of New Zealand	45-1291 $gCm^{-2}yr^{-1}$		

3.2.2 Annual average air temperature for South West Mau (1985-2015)

Annual average air temperature (Table 3.6) for South West Mau was generated from averaged air temperature monthly data (Appendix III).

Table 3.6: Annual average air temperature for South West Mau (1985-2015)

YEAR	Annual average air temperature (^0C)
1985	15.4762
1986	15.7695
1987	16.0201
1988	15.9009
1989	15.3989
1990	15.5457
1991	16.1317
1992	16.0466
1993	15.8773
1994	16.1001
1995	15.9786
1996	15.9068
1997	16.1472
1998	15.9006
1999	16.1010
2000	16.5212
2001	15.9964
2002	16.3765
2003	16.2448
2004	16.4333
2005	16.6826
2006	16.3523
2007	15.9410
2008	16.0881
2009	16.5965
2010	15.8521
2011	16.1075
2012	15.9282
2013	15.9180
2014	16.3115
2015	16.6069

The data was acquired from Giovanni, National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center (NASA GES DISC). Table 3.7 below illustrates the features of the average air temperature data. FLDAS stands for Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System. This is a drought monitoring system which rely on satellite remote sensing and land surface models to produce multi-model and multi-forcing estimates of hydro-climate states and fluxes over semi-arid regions of Africa (McNally et al., 2017).

Table 3.7: Features of average air temperature data for used for the study

Variable	**Air temperature (FLDAS_NOAH01_C_EA_M v001)**
Units	Degree Celsius
Source	FLDAS model
Temporal resolution	Monthly
Land region	Sub-Saharan Africa
Spatial resolution	0.1^0
Observations	Satellite and land surface models
Begin data	1985-01-01
End date	2015-12-31

3.2.3 Annual total surface precipitation for South West Mau (1985-2015)

Annual total surface precipitation (Table 3.8) was generated from total surface precipitation monthly (Appendix VI) for the period between 1985 and 2015.

Table 3.8: Annual total surface precipitation for South West Mau (1985-2015)

YEAR	Annual total surface precipitation (mm)
1985	3153.1440
1986	3184.4525
1987	3033.3967
1988	3629.0715
1989	2998.9209
1990	3902.1848
1991	2865.9646
1992	2929.5766
1993	2448.8581
1994	2892.4787
1995	3151.7846
1996	3050.8290
1997	3501.0718
1998	3469.4971
1999	2750.8865
2000	1694.8050
2001	3357.4177
2002	2948.7907
2003	3208.2428
2004	3371.8963
2005	3641.7285
2006	5176.6818
2007	4077.6083
2008	3864.8943
2009	3683.9481
2010	5963.0981
2011	4909.9476
2012	5149.7256
2013	5659.5448
2014	5222.1964
2015	5350.6775

The data was also acquired from Giovanni, National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center (NASA GES DISC). Table 3.9 illustrates the features of the total surface precipitation data. MERRA-2 stands for Modern-Era Retrospective Analysis for Research and Applications, Version 2. Retrospective analysis (reanalysis) data products are based on the assimilation of a large amount of in situ and remote sensing observations into an atmospheric general circulation model (AGCM) and are among the most widely used datasets in Earth science (Reichle et al., 2017).

Table 3.9: Features of total surface precipitation data used for the study

Variable	**Total surface precipitation (M2TMNXFLX v5.12.4)**
Units	mm/month
Source	MERRA-2 model
Land region	Africa
Observations	Satellite and NOAA Climate Predictor Center Unified (CPCU) gauge data
Correction method	Full correction to observations
Temporal resolution	Monthly
Spatial resolution	$0.5x0.625^0$
Begin data	1985-01-01
End date	2015-12-31

The average air temperature and total surface precipitation data from Giovanni, National Aeronautics and Space Administration Goddard Earth Science Data and Information Services Center (NASA GES DISC), is complete and homogenous and therefore most suitable for hydro-meteorological analysis as compared to data acquired from weather gauging stations which is characterized by long periods of missing data, as is the case for SWM forest.

3.3 Data analysis

Data analysis was conducted using XLSTAT Add In software for Microsoft EXCEL 2007. The specific analyses employed in this study were aligned to the research objectives and are presented in details in the subsequent sections.

3.3.1 Analysis of carbon sequestration dynamics in the AGB pool of SWM Forest (1985-2015)

The quantified above ground carbon sequestration was subjected to time series visualization, spectral analysis, change point detection and variability analysis for the period between 1985 and 2015. Time series visualization was performed to describe interannual pattern in carbon sequestration. Spectral analysis was performed to describe interannual cycling in carbon sequestration. The results from spectral analysis show whether the series varies with regular cycles (Shumway & Stoffer, 2000). Petit test was used to detect significant changes in the above ground carbon sequestration for South West Mau forest between 1985 and 2015 and when they exactly occurred (Jaiswal & Tiwari, 2015; Pohlert, 2018). Variability analysis was performed using coefficient of variation to explained the degree of variability in inter annual carbon sequestration from 1985 to 2015 by comparing the standard deviation ($\boldsymbol{\delta}$) in the time series relative to the mean (μ) as shown in equation 9 (Asfaw, et al., 2018; Ukhurebor & Abiodun, 2018).

$$CV = \frac{\delta}{\mu} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Equation 8}$$

Coefficient of variability (CV) values below 10.7 percent indicated low variability, values between 10.7 percent and 15.4 percent indicated moderate or average variability, value between 15. 4 percent and 17.7 percent indicated high variability, while values above 17.7 percent indicated very high variability. This classification was computed using the mean and standard deviation of coefficient of variability for above ground carbon sequestration in South West Mau forest between 1985 and 2015and based on the criteria proposed by Garcia in 1989 (Couto et al., 2013; Vaz et al., 2017; Ferreira et al., 2018). The criteria are presented in table 3-10. The mean and standard deviation of coefficient of variation for above ground carbon sequestration in South West Mau forest between 1985 and 2015 were 13.07 and 2.33 respectively.

Table 3.10: Criteria of classification of coefficient of variation

Coefficient of variation classification criteria	Classification
CV $\leq$ (A- 1B)	Low
(A-1B) < CV $\leq$ (A+1B)	Moderate or average
(A+1B) <CV$\leq$ (A+2B)	High
CV > (A+2B)	Very high

Where A and B are the mean and standard deviation of the coefficient of variation respectively

3.3.2 Analysis of climate variables in SWM Forest (1985-2015)

Annual average air temperature and annual total surface precipitation were all analysed for trend, change point detection and variability. Trend was analysed using Mann Kendall test which is a non-parametric test that is used to assess whether data points in a data series have a significant monotonic upward or downward trend. A positive value indicates upward or increasing trend, while a negative value indicates downward or decreasing trend in the time series (Jaiswal & Tiwari, 2015; Asfaw et al., 2018; Pohlert, 2018; Ukhurebor & Abiodun, 2018). Mann Kendall showed whether the temperature was tending towards warming or cooling and the significance of the trend. For annual total surface precipitation, Mann Kendall trend test was used to test existence of increasing or decreasing precipitation trends denoted by a positive and a negative value respectively. Change point detection followed the same procedure explained in section 3.3.1. Petit test established whether there were break or change point in average annual air temperatures and in annual total surface precipitation time series.

Variability analysis performed using anomaly analysis and coefficient of variation. Anomaly (A) testing is computed by subtracting the time series mean (μ_{30}), from yearly mean (X_i) (equation 8). It returns values that are either higher than the time series mean designated by a positive value or values that are lower than the time series mean designated by a negative value (Ukhurebor & Abiodun, 2018). Anomaly analysis enabled the detection of average annual air temperatures and annual total surface precipitation that were higher than the climatological normal designated by positive values and those that were lower than the climatological normal designated by negative values.

$$A = X_i - \mu_{30} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \text{Equation 9}$$

Coefficient of variability for both average annual air temperature and annual total surface precipitation from 1985 to 2015 were computed as illustrated by equation 8 in section 3.1.1. For average annual air temperature, the criteria proposed Garcia in 1989 was also used. The temperature data was converted from degree Celsius to Kelvin since coefficient of variability is meaningful only for data measured on a ratio scale. Temperature data in degree Celsius is considered as data with interval scale and as such it has no real zero or meaningful zero (Abdi, 2010). The mean and standard deviation of coefficient of variability for average annual air temperature in South West Mau forest between 1985 and 2015 were 0.0036 and 0.0006 respectively. Coefficient of variability (CV) values below 0.30 percent indicated low variability, values between 0.30 percent and 0.42 percent indicated moderate or average variability, value between 0.42 percent and 0.48 percent indicated high variability, while values above 0.48 percent indicated very high variability. Coefficient of variability classes for annual total surface precipitation was adopted from previous studies (Asfaw, et al., 2018; Ukhurebor & Abiodun, 2018). Coefficient of variability (CV) values below 20 percent indicated low variability, values between 20 percent and 30 percent indicated moderate variability, values between 30 percent and 40 percent indicated normality, while values above 40 percent indicate high variability.

3.3.3 Analysis of climate variables response to above ground carbon sequestration dynamics in SWM Forest (1985-2015)

Analysis of annual average air temperature and annual total surface precipitation response to carbon sequestration dynamics was performed using co-variation testing. Co-variation involves measuring the likelihood of a linear relationship between variables or the tendency of variables varying together (joint variation of the variables). Joint variation is a potential exhibit that variables have some level of dependence (Hassard, 1991; Kothari, 2004). The values of covariance statistics show positive covariance, negative covariance or zero covariance. Positive covariance indicate that higher than average values of one variable tend to be paired with higher than average values of the other variable. Negative covariance indicate that higher than average values of one variable tend to be paired with lower than average values of the other variable. Zero covariance indicate that the two random variables are either independent or that a nonlinear relationship exist between them.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Inter-annual above ground biomass carbon sequestration dynamics in SWM (1985-2015)

The mean carbon sequestered by the above ground pool of South West Mau forest between 1985 and 2015 was 4,611.21 Kg/ha with a standard deviation of 428.11 kg/ha. The maximum and minimum sequestered carbon were 5,294.25 Kg/ha in 1998 and 3,684.33 Kg/ha in 2009 respectively. Figure 4-1 below is a visualization of the time series for South West Mau forest for the period between 1985 and 2015.

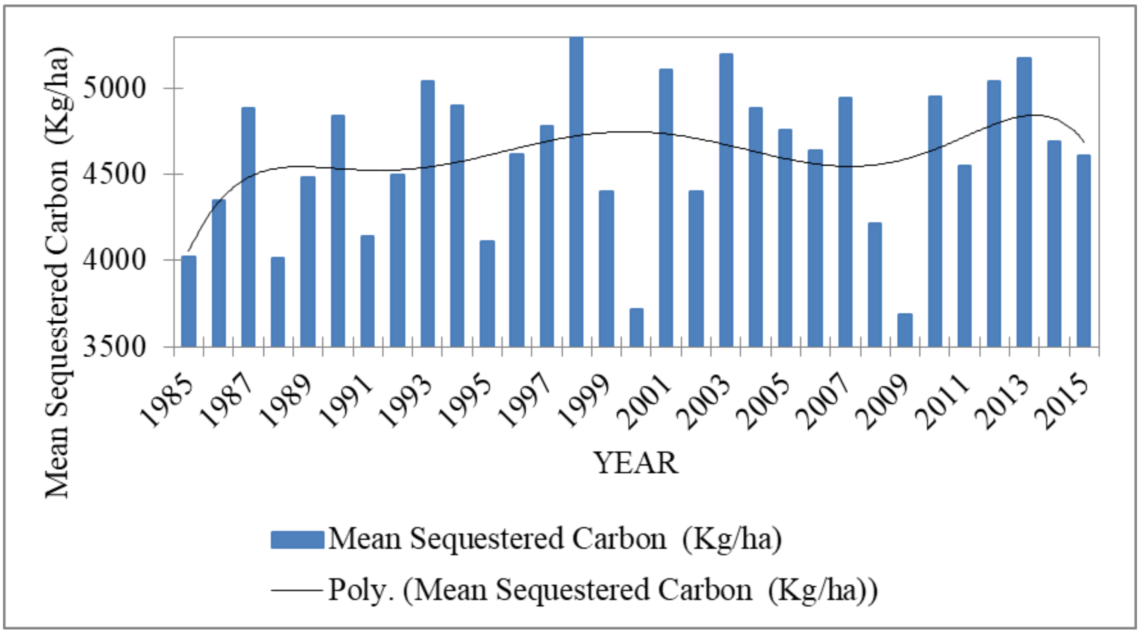


Figure 4.1: Time series of the mean carbon sequestration in South West Mau forest (1985-2015)

The mean annual above ground carbon sequestration in South West Mau forest fluctuated from year to year characterized increases that saturated at some point followed by decreases. A sequence of three years increase in carbon sequestration and eventual saturation followed by a decrease between 1985 to1987, 1988 to 1990 and 1991 to 1993 was noted. There was then a sequential decrease in carbon sequestration for two year from 1994 to 1995 followed by a sequence of three year increase and eventual saturation from 1996 to 1998 and thereafter a decline in 1999 and 2000. From 2001 to 2004 there was an annual transposition between increases and decreases in carbon sequestration. The decrease continued from 2004 to 2009 with a one year interruption of this pattern by an increase in 2007. There was an annual transposition between carbon sequestration increase and decrease in 2010 and 2011 followed by a two years increase between 2012 and 2013. The period between 2014 and 2015 continued to show decrease in carbon sequestration. The fluctuations in above ground carbon sequestration in the South West Mau forest had a negative balance of -588.3996 Kg/ha for the period between 1985 and 2015 signifying that above ground biomass pool was generally a carbon emitter.

Six order polynomial trend line (Figure 4-1) showed that the mean annual above ground carbon sequestration in South West Mau forest for the period between 1985 and 2015 had smooth periodic oscillations depicted by the trend line equation $y = -0.0003x^6 + 0.028x^5 - 1.0305x^4 + 18.192x^3 - 158.87x^2 + 652.38x + 3541.9$. Spectral analysis showed that the mean annual above ground carbon sequestration spectral density peak corresponded to a period of 2.8 years (Figure 4-2), signifying that mean annual above ground carbon sequestration in the South West Mau varied with quite regular cycles of approximately 3 years. This also suggested that the sequestered above ground biomass carbon had a residence time of approximately three years.

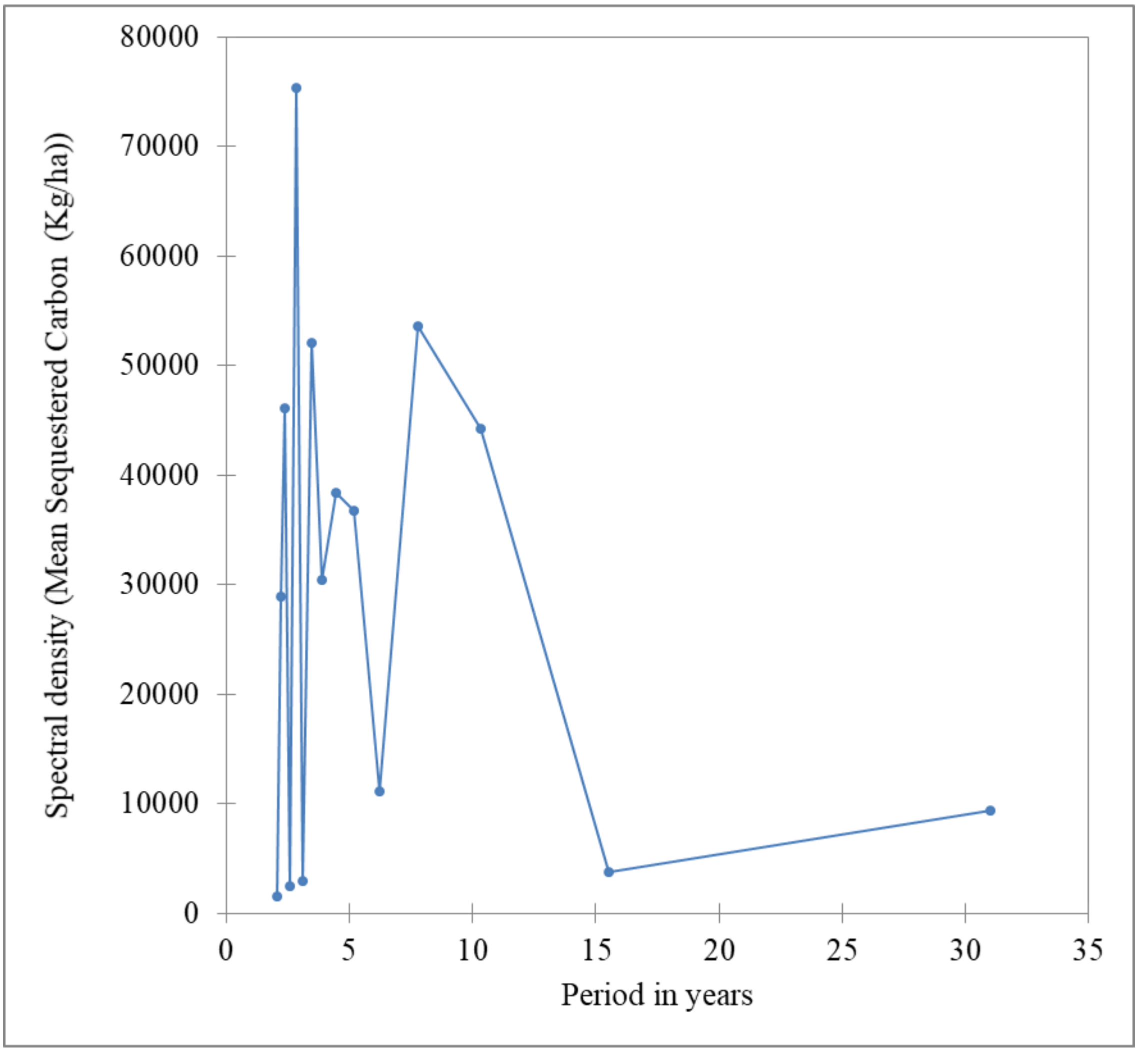


Figure 4.2: Periodicity of above ground carbon sequestration in SWM Forest (1985-2015)

Results from Petit test showed that there was no break point in interannual carbon sequestration in the South West Mau forest between 1985and 2015 (Figure 4-3). The null hypothesis that data are homogenous was accepted at P-value (two tailed) equal to 0.3481 and alpha set at 0.05.

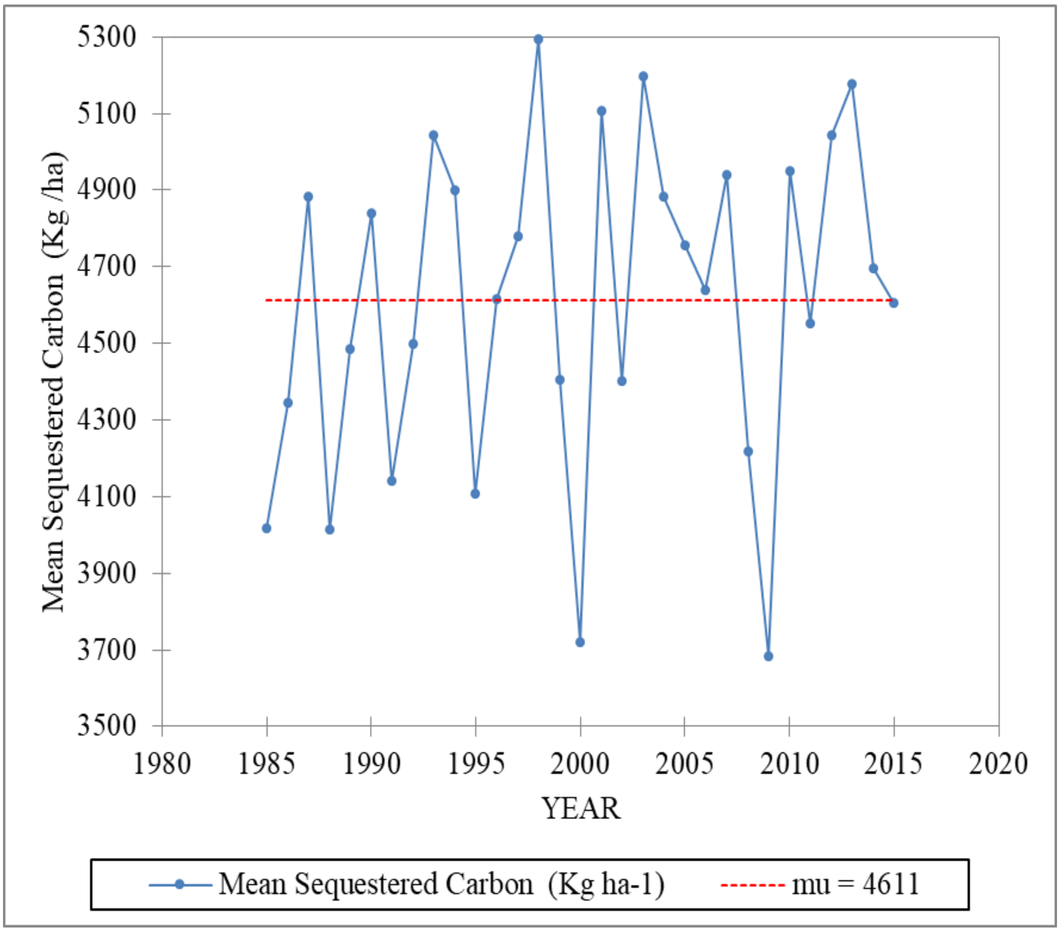


Figure 4.3: Change point analysis of the mean annual carbon sequestration in the South West Mau forest (1985-2015)

Coefficient of variability was at 9.13 percent indicating low variability in the interannual carbon sequestration for South west Mau Forest between 1985 and 2015. Overall, the results indicated that the above ground biomass pool of the South West Mau forest for the period between 1985 and 2015was a net carbon emitter with low inter-annual variability in above ground carbon sequestration which followed a sinusoidal waveform with a repeat cycle or wavelength of three years. This was associated with natural and anthropogenic disturbance and regeneration events that took place in the forest between 1985 and 2015.

4.2 Variability and trend in annual average air temperature of SWM forest

The climatological normal (mean annual average air temperature between 1985 and 2015) in the SWM forest was 16.0728^{O}C with 0.3144^{O}C standard deviation. The maximum annual average air temperature was 16.6826^{O}C experienced in 2005 while the minimum annual average air temperature was 15.3989^{O}C experienced in 1989. Inter annual time series analysis (Figure 4-4) using Mann-Kendall test at 5 percent confidence interval revealed a statistically significant increasing trend in the annual average air temperature in the South West Mau forest for the period between 1985 and 2015, with a Kendall's tau of 0.3677, Sen's slope of 0.0188, p value (two tailed) of 0.0033. The results signify that there is trend towards climatic warming in the South West Mau forest between 1985 and 2015.

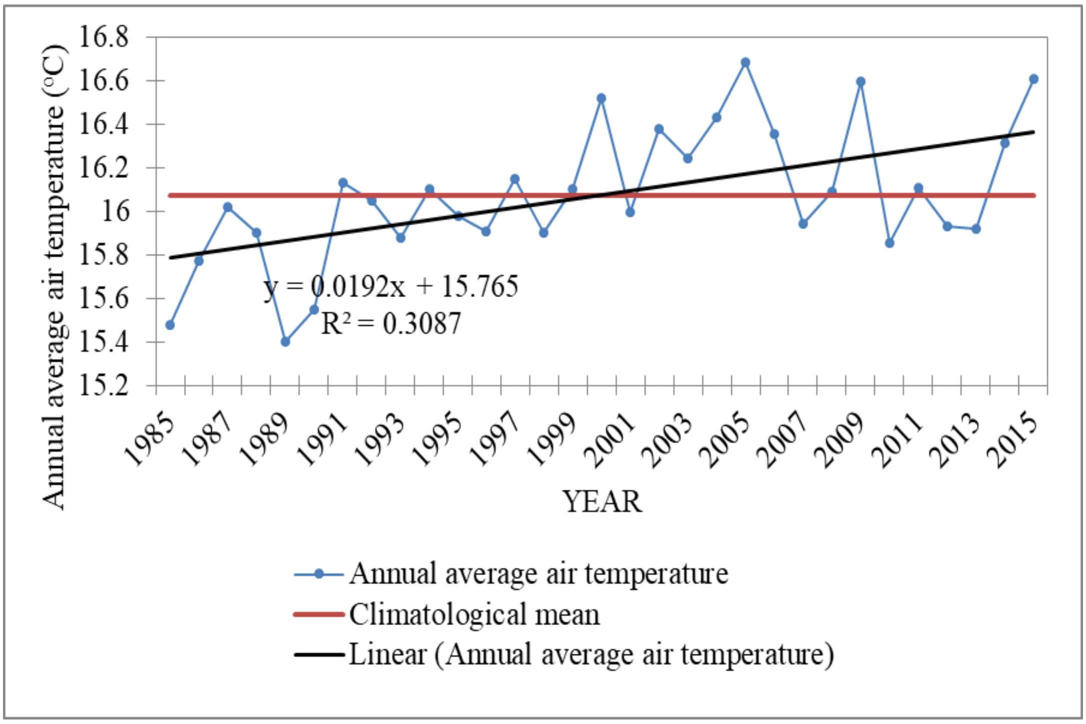


Figure 4.4: Inter annual time series of average air temperature in SWM (1985-2015)

Petit test of homogeneity revealed that there was a change point of 0.368^{0}C in the interannual average air temperature in 1998 with a p value (two tail) of 0.0051 at 99 percent confidence level. This implied that the observed increase in annual average air temperature occurred in two distinct periods, the first beginning in the year 1985 and ending in 1998 and the second being from1999 to 2015 (Figure 4-5). The means in annual average air temperature of the two periods were 15.871^{0}C and 16.239^{0}C respectively. The results from the Petit test supported the indication that there was significant climate warming over the South West Mau Forest for the period between 1985 and 2015.

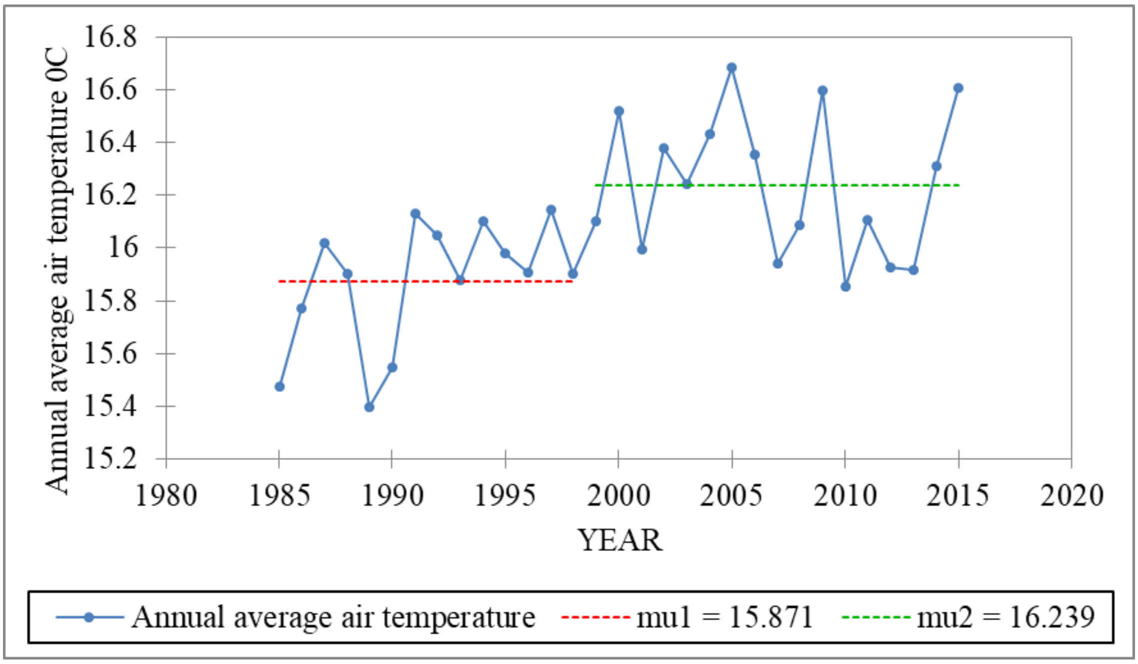


Figure 4.5: Shift in inter annual average air temperature in SWM (1985-2015)

Inter annual average air temperature anomalies in the South West Mau between 1985 and 2015 (Figure 4-6) had a gradient of 0.0192 implying an overall positive anomaly which pointed towards climatic warming. The results showed that 48 percent of the years had an annual average air temperature with a positive anomaly and 52 percent had an annual average air temperature with a negative anomaly. Although there were more cooler years than warm years, the warm years had more extreme anomalies resulting in the trend towards warming the average annual temperature were higher. Extreme positive anomalies in annual average air temperatures were prominent for the years 2000, 2005, 2009 and 2015 while the extreme negative anomalies in annual average air temperatures were prominent for the years 1985, 1989 and 1990.

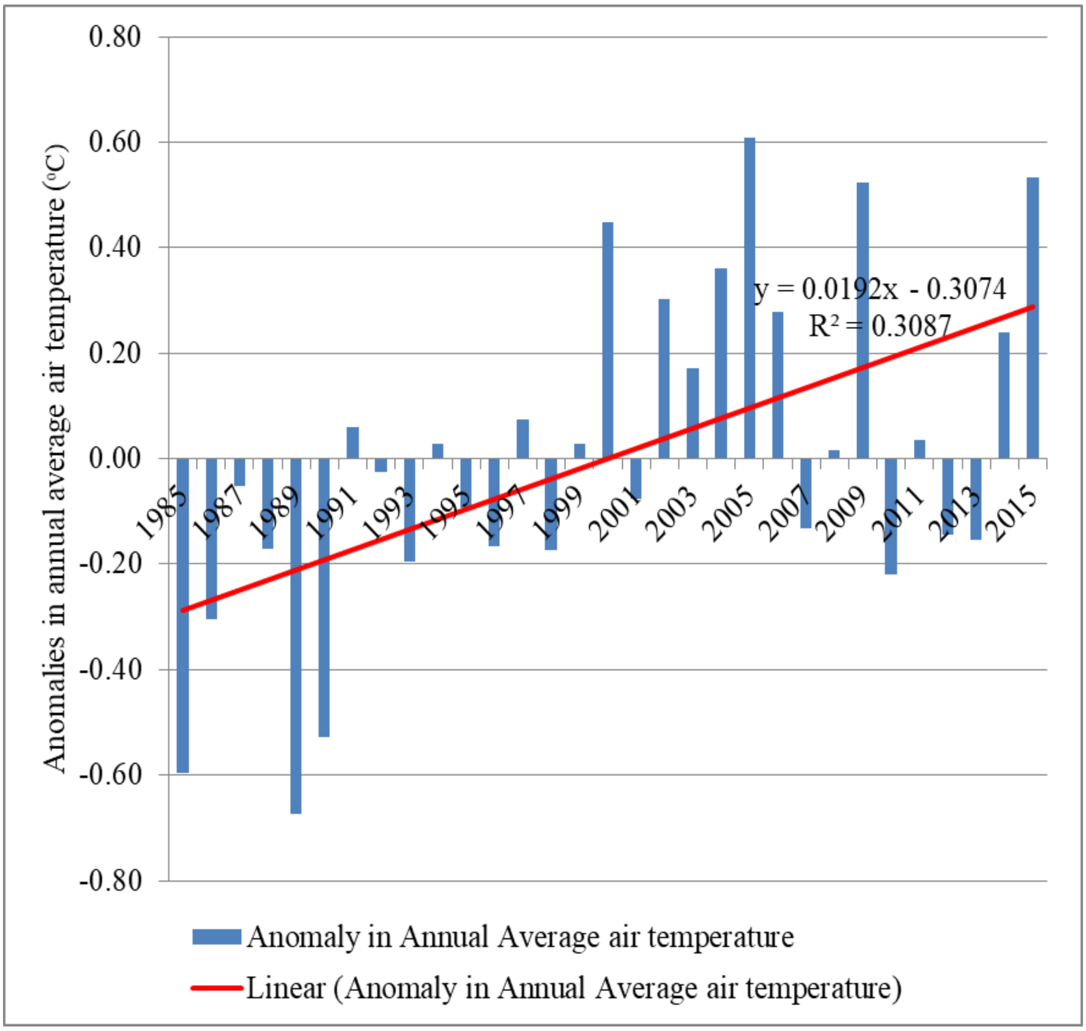


Figure 4.6: Anomalies in annual average air temperature for SWM (1985-2015)

Further scrutiny of the results revealed that annual average air temperatures between 1985 and 1998 with the exception of 1991, 1994 and 1997 had a negative anomaly an indication of cooling with reference to the climatological normal. Annual average air temperatures between 1999 and 2015 with the exception of 2001, 2007, 2010, 2012, and 2013 had a positive anomaly and indication of warming with reference to the climatological normal. The observation made is that cooling occurred early in the time series while warming occurred late in the time series. These results are in agreement with those from Petit test that there is a shift from cool conditions to warmers conditions. The coefficient of variability was 0.11 percent implying a low variability in the annual total surface precipitation in the South West Mau forest between 1985 and 2015.Overall all the results pointed towards climatic warming in the South West Mau between 1985 and 2015 with low year to year variability

4.3 Variability and trend in annual total surface precipitation of SWM forest

The climatological normal annual total surface precipitation for South West Mau Forest was 3685.2684mm with 1028.5410mm standard deviation. The maximum annual total surface precipitation was 5963.0981mm experienced in 2010 and the minimum was 1694.8050mm experienced in 2000. Inter annual time series results (Figure 4-7) from Mann-Kendall test at 5 percent confidence interval revealed a statistically significant increasing trend in the annual total surface precipitation in the South West Mau forest for the period between 1985 and 2015, with a Kendall's tau of 0.4968, Sen's slope of 71.455, p value (two tailed) of < 0.0001and alpha of 0.05.

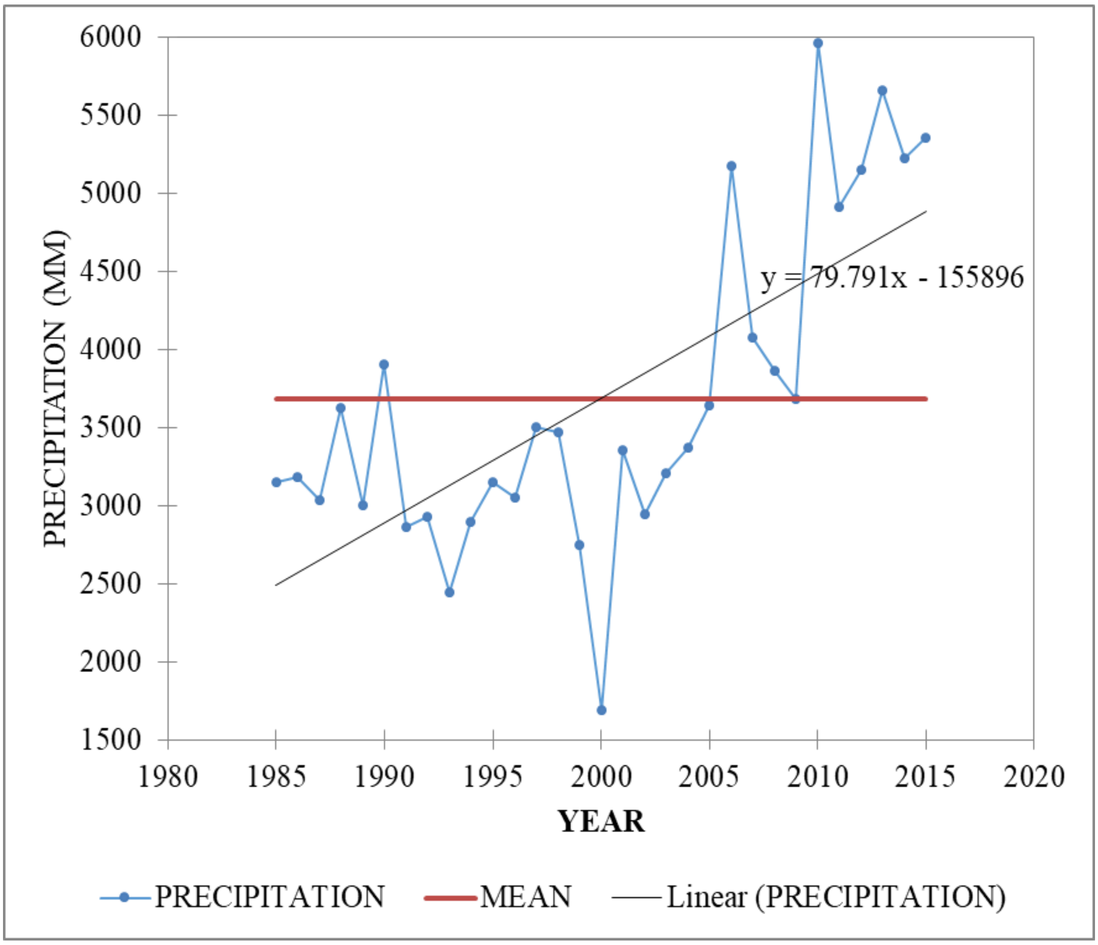


Figure 4.7: Inter annual time series of total surface precipitation in SWM (1985-2015)

Petit test of homogeneity revealed that there was a change point of 1611mm in the annual total surface precipitation in 2003 with a p value (two tail) of 0.0001 at 99 percent confidence level. This implied that the observed increase in annual total surface precipitation occurred in two distinct periods; the first beginning in the year 1985 to 2003 and the second being from 2004 to 2015 (Figure 4-8). The means in annual total surface precipitation of the two periods were 3062mm and 4673mm respectively. The results from the Petit test also resonate with the observation that there was significant increase in the annual total surface precipitation over the South West Mau Forest for the period between 1985 and 2015.

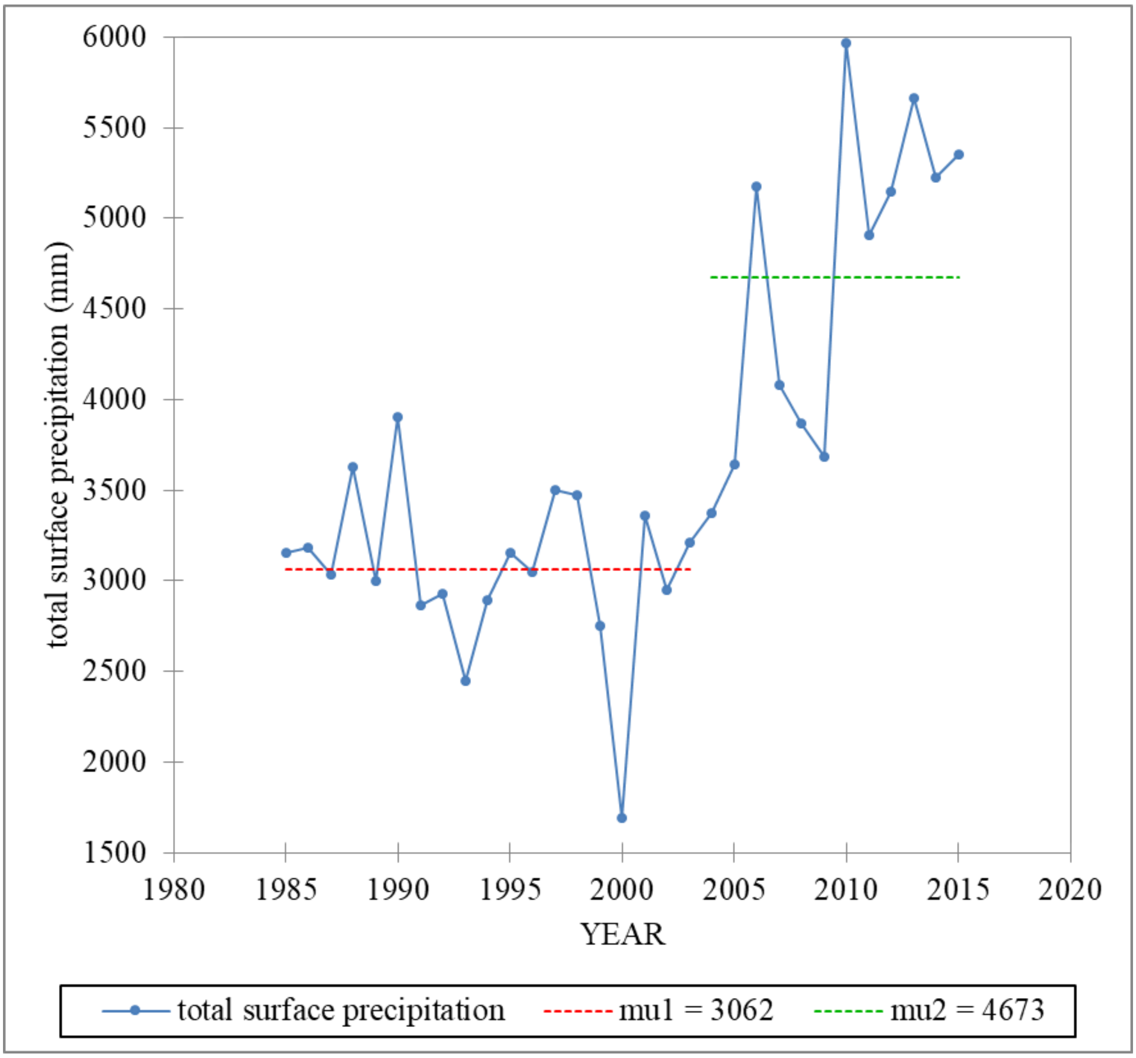


Figure 4.8: Shift in inter annual total surface precipitation in SWM (1985-2015)

Anomaly analysis presented in figure 4-9 showed that 68 percent of the years had an annual total surface precipitation lower than the climatological normal and only 32 percent had an annual total surface precipitation higher than the climatological normal.

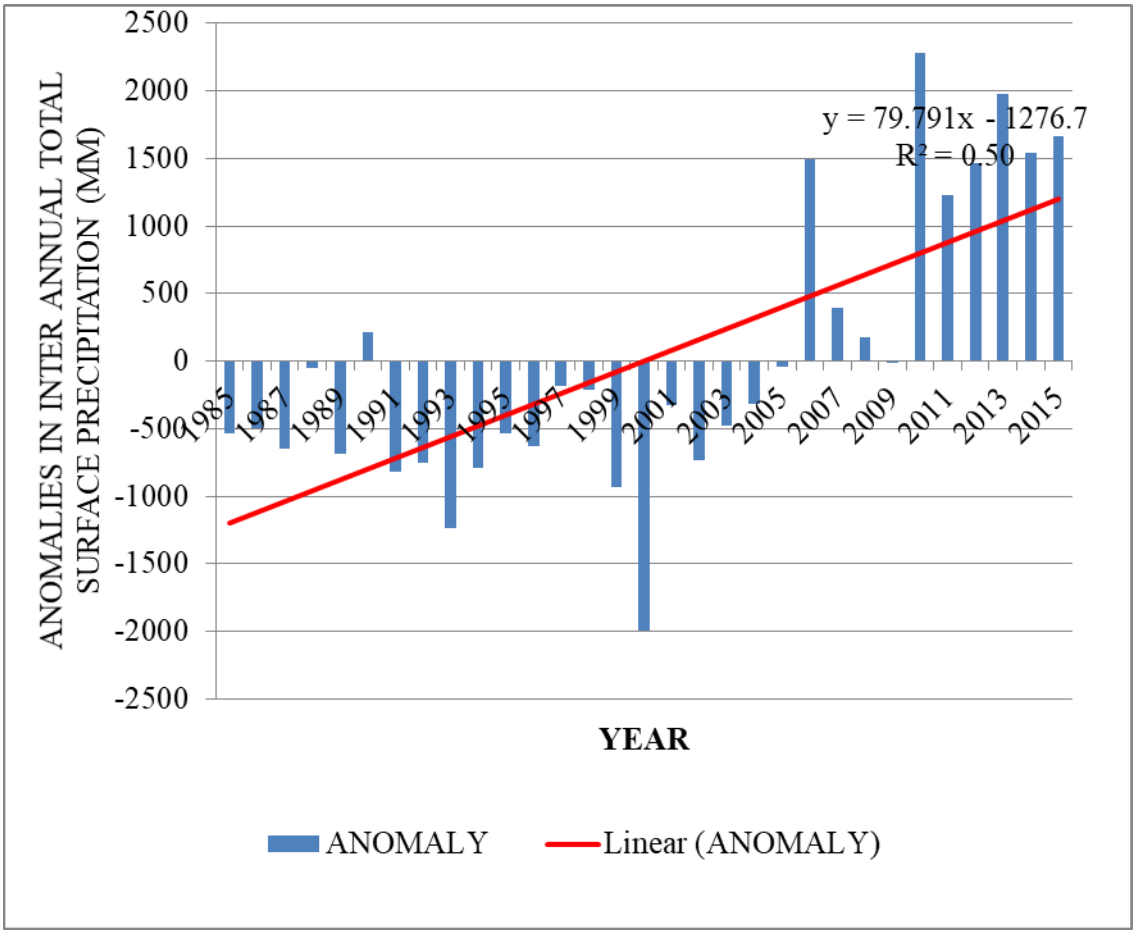


Figure 4.9: Anomalies in annual total surface precipitation for SWM (1985-2015)

Annual total surface precipitation between 1985 and 2005 with the exception of 1990 had a negative anomaly while annual total surface precipitation between 2006 and 2015 with the exception of 2009 had a positive anomaly. The prominent positive anomalies in annual total surface precipitation were experienced in 2006, 2010, 2013, and 2015. The prominent negative anomalies in annual total surface precipitation were experienced in 1990 and 2000. Many wet but less extreme conditions were experienced in the early section of the time series while fewer wet but more extreme conditions were experienced in the late section of the time series. This indicated a shift from less wet conditions to wetter conditions. The annual total surface precipitation for the period between 1985and 2015 had a gradient of 79.791

implying a positive anomaly for the entire period. These results indicated an increase in the amount of total surface precipitation over the South West Mau Forest between 1985 and 2015. The coefficient of variability was 27.9005 percent implying a moderate variability in the annual total surface precipitation in the South West Mau forest between 1985 and 2015. The coefficient of variability result is consistent with the anomaly and interquintile range results and indicates that there is a significant variability in the total surface precipitation in South West Mau for the period between 1985 and 2015.

4.4 Covariation of AGB carbon sequestration with annual average air temperature over SWM (1985-2015)

Covariance analysis of above ground carbon sequestration and annual average air temperature over the South West Mau Forest between 1985 and 2015 exhibited a weak negative relationship (r = -0.1563). The negative covariance implied that positive anomalies in carbon sequestration were paired with negative anomalies in annual average air temperature. In other words, increases in above ground biomass carbon sequestration was matched by a decline in annual average air temperature and a decrease in above ground biomass carbon sequestration was matched by a rise in annual average air temperature. The coefficient of determination R^2= 0.0244 indicated that the above ground carbon sequestration dynamics explained only 2.44% of the variability in annual average air temperature in South West Mau forest between 1985 to 2015. The remainder 97.56% of the variability was assumed to be due to some other explanatory variables that were not measured by this study. Overall, the results indicate a weak association that points towards climate warming that is matched by losses in above ground biomass carbon stock and climate cooling that is matched by gains in above ground biomass carbon stock over the South West Mau forest between 1985and 2015. It is therefore reasonable to argue that above ground biomass carbon fluxes were not the major mechanism that influenced the observed variability in annual average air temperature over the South West Mau forest between 1985 and 2015. It is likely that other forest related mechanisms that modify climate namely surface albedo, latent heat, sensible heat, aerodynamic effects and emission of hydrocarbon were likely agents of variability in annual average air temperature over the South West Mau forest between 1985 and 2015.

4.5 Covariation of AGB carbon sequestration with annual total surface precipitation over SWM (1985-2015)

Covariance analysis of above ground carbon sequestration and annual total surface precipitation over the South West Mau Forest between 1985 and 2015 exhibited a weak positive relationship ($r = 0.3408$). The positive covariance implied that positive anomalies in carbon sequestration were paired with positive anomalies in annual total surface precipitation. In other words, increases in above ground biomass carbon sequestration was matched by increases in annual total surface precipitation and a decrease in above ground biomass carbon sequestration was matched by a decline in annual total surface precipitation. The coefficient of determination $R^2= 0.1162$ indicated that the above ground carbon sequestration dynamics explained only 11.62% of the variability in annual total surface precipitation in South West Mau forest between 1985 to 2015. The remainder 88.38% of the variability was assumed to be due to some other explanatory variables that were not measured by this study. This is a weak relationship and it means that the variability in annual total surface precipitation over the South West Mau Forest between 1985 and 20015 were influenced more by other mechanisms other than carbon fluxes. These perhaps include transpiration and evaporation, feedback effects from latent heat and sensible heat, and aerodynamic effects.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Based on the observed results the study concluded that the above ground biomass pool in South West Mau forest was a net carbon emitter with low variability in sequestered above ground biomass carbon for the period between 1985 and 2015. The variability suggested that above ground biomass carbon had a residence time of approximately 3 years. The variability was linked to changes in forest physiological process resulting from natural and anthropogenic disturbances that occurred in the forest between 1985 and 2015. With regard to climate variability the region experienced climate warming with low interannual variability. It also experienced increased total surface precipitation with low interannual variability over the same period. Overall, above ground biomass carbon sequestration dynamics had a weak influence on climate variability. Other mechanisms by which forests modify climate are likely to have more influence on climate variability over the South West Mau Forest between 1985 and 2015 as compared to above ground biomass carbon fluxes. These mechanisms include surface albedo, latent heat, sensible heat, transpiration and evaporation, feedback effects from latent heat and sensible heat, aerodynamic and emission of hydrocarbon effects.

5.2 Recommendations

Based on these findings, it is recommended that the impact on climate variability by surface albedo, latent heat, sensible heat, transpiration and evaporation, feedback effects from latent heat and sensible heat, aerodynamic and emission of hydrocarbon effects be studied cumulatively or in isolation to help in understanding and attributing climate variability over the South West Mau Forest between 1985 and 2015. There is need also to upscale estimation of carbon sequestration to capture all the blocks of the Mau Forest Complex and other forest ecosystems in Kenya.

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APPENDICES

Appendix I: Mean monthly incoming short-wave solar radiation (Wm^{-2}) on land for SWM (1985-2015)

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1985	303	286	308	255	248	231	221	251	278	280	245	271
1986	298	341	315	233	250	223	227	257	265	275	259	255
1987	278	302	316	265	242	217	245	251	278	298	248	302
1988	284	326	294	219	224	248	245	255	273	277	258	274
1989	267	313	315	260	245	252	228	233	261	267	260	262
1990	298	243	273	216	232	236	236	236	287	255	257	269
1991	310	332	308	275	233	213	222	227	265	252	242	265
1992	303	318	314	252	253	206	227	233	258	245	265	260
1993	261	300	335	283	240	214	227	253	291	277	261	261
1994	307	305	317	276	240	214	225	247	295	282	228	276
1995	312	304	299	287	255	228	222	252	250	241	226	278
1996	289	318	308	289	234	202	222	225	240	262	235	283
1997	301	342	313	227	252	241	218	244	309	272	224	235
1998	241	271	310	249	203	219	221	235	280	259	264	303
1999	299	343	290	263	239	256	243	226	284	287	219	252
2000	320	325	330	270	253	220	210	243	259	277	260	286
2001	262	334	301	272	245	225	206	248	255	242	218	292
2002	272	336	306	268	244	242	255	235	304	276	253	228
2003	305	326	321	261	223	217	225	207	270	263	249	290
2004	274	297	289	234	235	242	250	243	262	273	263	277
2005	298	326	302	265	207	226	230	236	251	269	258	293
2006	307	312	288	230	217	223	195	217	261	292	216	236
2007	288	272	307	268	249	188	188	215	244	275	270	287
2008	284	303	269	268	262	215	188	214	246	238	248	295
2009	295	314	314	255	216	256	240	237	262	244	266	232
2010	281	261	236	243	224	213	207	229	252	232	236	282
2011	303	315	295	285	230	175	216	197	234	253	209	253
2012	316	314	312	192	219	191	202	220	254	261	248	246
2013	270	317	263	198	253	201	220	216	237	275	237	232
2014	299	255	288	261	238	204	200	203	242	251	235	249
2015	312	314	299	227	225	194	228	246	255	255	223	246

Appendix II: Parameters used to compute of mean daily light use efficiency for SWM (1985-2015)

YEAR	ε max (g /MJ)	T1 (^{0}C)	T2 (^{0}C)	ω
1985	0.389	0.980101	1.19556	0.70057
1986	0.389	1.017955	1.19433	0.66454
1987	0.389	1.014487	1.21103	0.6906
1988	0.389	1.017616	1.19821	0.72679
1989	0.389	1.007945	1.2212	0.72992
1990	0.389	1.011993	1.21034	0.72431
1991	0.389	1.021636	1.18897	0.67721
1992	0.389	1.02058	1.19092	0.6819
1993	0.389	1.019834	1.19002	0.70353
1994	0.389	1.022483	1.18539	0.66434
1995	0.389	1.018259	1.19754	0.68231
1996	0.389	1.017448	1.1989	0.71821
1997	0.389	1.020981	1.19153	0.68592
1998	0.389	1.022631	1.18061	0.78492
1999	0.389	1.01662	1.20541	0.67383
2000	0.389	1.024758	1.18579	0.62377
2001	0.389	1.015874	1.20597	0.74258
2002	0.389	1.00692	1.24082	0.69163
2003	0.389	1.025147	1.17905	0.72292
2004	0.389	1.016747	1.21072	0.71314
2005	0.389	1.025807	1.18518	0.68927
2006	0.389	1.015659	1.21291	0.6902
2007	0.389	1.015387	1.20657	0.7721
2008	0.389	1.017611	1.20185	0.65976
2009	0.389	1.020251	1.20205	0.60653
2010	0.389	1.014151	1.20904	0.78223
2011	0.389	1.007098	1.23636	0.72634
2012	0.389	1.014088	1.21068	0.75948
2013	0.389	1.011938	1.21763	0.76588
2014	0.389	1.007579	1.23787	0.74372
2015	0.389	1.013409	1.22395	0.70306

Appendix III: Average air temperature monthly (^0C) for SWM (1985-2015)

YR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1985	17	16	17	16	15	15	14	14	15	16	16	16
1986	17	18	18	16	15	14	14	15	15	16	16	16
1987	16	17	17	17	16	15	15	15	16	17	16	17
1988	17	18	18	17	16	15	14	15	15	16	16	16
1989	15	16	17	16	15	15	14	14	15	16	16	16
1990	16	17	16	16	16	15	14	14	15	16	16	16
1991	17	18	18	17	16	16	14	15	16	16	16	16
1992	17	18	19	17	16	15	14	14	15	16	16	16
1993	16	16	17	17	16	15	14	14	15	16	16	16
1994	18	18	18	17	15	15	14	15	16	16	16	16
1995	17	17	17	17	16	15	14	15	16	16	16	16
1996	16	17	18	17	16	15	14	15	15	16	16	16
1997	17	18	19	16	15	15	14	15	17	16	16	16
1998	16	17	17	17	16	15	14	14	15	16	16	16
1999	17	18	17	17	16	15	15	15	16	17	16	16
2000	17	18	19	17	17	15	15	15	16	17	16	17
2001	16	17	18	17	16	15	14	15	16	16	16	16
2002	16	18	18	17	16	15	16	15	16	17	16	16
2003	17	18	18	17	16	15	14	15	16	17	16	16
2004	17	17	18	17	16	15	15	15	16	17	17	17
2005	17	19	18	18	16	15	15	15	16	17	17	17
2006	18	19	18	16	16	15	15	15	16	17	16	16
2007	16	16	17	17	16	15	14	15	16	16	16	16
2008	17	17	17	16	16	15	14	15	16	16	16	17
2009	17	17	19	17	16	16	15	16	17	16	16	16
2010	16	17	17	17	16	15	14	15	15	16	16	16
2011	17	17	18	17	16	16	15	15	16	16	16	16
2012	17	17	18	16	16	15	14	15	16	16	16	16
2013	17	17	18	16	16	15	15	15	16	16	16	16
2014	17	17	17	17	16	16	15	15	16	16	16	16
2015	17	19	18	17	16	15	15	16	17	17	16	16

Appendix IV: Mean monthly latent heat flux (Wm^{-2}) for SWM (1985-2015)

YEAR	JAN	FEB	MAR	APR	MAY	JUNE	JUL	AUG	SEP	OCT	NOV	DEC
1985	72	86	92	136	131	112	110	125	129	116	104	105
1986	83	86	80	107	125	109	98	114	111	118	108	92
1987	86	97	106	114	126	106	113	110	109	122	116	115
1988	103	97	94	111	118	121	121	130	132	133	118	103
1989	93	115	111	122	126	118	109	108	120	123	114	121
1990	116	100	129	116	123	117	110	99	120	93	97	102
1991	96	90	86	124	116	110	100	100	113	103	98	101
1992	84	96	77	105	116	86	109	113	118	116	116	111
1993	111	137	119	113	137	108	106	105	114	98	94	83
1994	74	71	98	106	120	107	107	117	124	111	101	113
1995	91	94	108	123	123	105	100	103	109	106	97	109
1996	97	105	100	126	118	93	108	104	115	127	112	117
1997	93	86	63	109	121	111	101	110	124	108	112	120
1998	126	132	126	124	112	112	113	120	133	123	121	110
1999	96	79	110	118	116	115	97	103	114	112	90	94
2000	96	72	68	104	102	92	91	99	86	108	117	114
2001	104	123	101	127	127	110	101	118	114	115	105	127
2002	107	108	111	113	122	116	117	102	111	107	100	89
2003	115	102	78	111	124	111	107	106	134	123	108	116
2004	101	109	101	124	123	118	112	103	105	106	102	113
2005	91	95	99	112	108	108	108	107	111	109	101	104
2006	78	69	99	114	115	110	97	102	113	107	96	106
2007	138	130	127	123	126	96	92	108	121	126	116	110
2008	82	89	73	109	123	91	80	94	103	105	106	112
2009	79	83	64	92	108	112	92	85	97	96	85	92
2010	106	106	108	134	128	113	107	113	124	116	111	120
2011	106	95	85	102	120	89	105	98	122	122	106	124
2012	119	85	94	104	117	102	111	114	132	131	118	104
2013	109	117	98	107	135	105	108	107	114	136	108	105
2014	115	109	107	114	123	101	92	100	115	113	97	108
2015	97	84	72	103	122	104	111	113	115	101	102	108

Appendix V: Mean monthly sensible heat flux (Wm^{-2}) for SWM (1985-2015)

YEAR	JAN	FEB	MAR	APR	MAY	JUNE	JUL	AUG	SEP	OCT	NOV	DEC
1985	88	75	82	25	29	33	27	30	39	49	42	53
1986	80	92	94	37	31	33	39	41	43	43	47	58
1987	73	76	71	48	28	28	35	42	57	52	35	57
1988	60	80	74	29	27	33	30	28	39	33	38	59
1989	60	62	69	37	26	35	34	37	36	38	43	38
1990	50	44	37	20	25	30	34	47	51	56	59	53
1991	76	90	85	47	30	27	34	41	39	45	45	52
1992	80	80	93	50	36	41	32	33	38	31	41	44
1993	42	41	66	55	16	27	35	43	55	61	58	63
1994	91	91	81	62	31	30	30	36	50	56	39	51
1995	75	76	63	52	40	34	36	48	45	40	38	54
1996	67	73	77	49	30	34	32	33	32	31	29	48
1997	73	87	103	33	32	37	35	36	54	53	28	26
1998	23	28	55	32	21	26	25	29	38	34	37	58
1999	66	92	61	45	33	37	47	35	52	52	42	51
2000	73	91	110	55	50	39	37	47	65	53	37	54
2001	47	63	71	40	27	29	29	34	41	32	31	43
2002	46	73	67	54	23	32	36	40	61	58	52	48
2003	55	70	94	45	18	28	34	28	32	35	41	47
2004	56	60	65	24	21	28	37	41	53	52	52	49
2005	74	74	72	47	23	32	34	35	41	47	50	53
2006	86	97	66	31	22	28	28	31	43	60	38	36
2007	36	27	48	41	30	21	27	28	28	39	45	53
2008	72	78	79	51	39	39	37	37	42	38	42	55
2009	80	87	108	56	27	42	46	56	57	50	67	48
2010	52	48	35	21	15	22	25	31	32	28	36	45
2011	63	75	82	67	25	25	28	25	27	30	25	33
2012	49	82	77	19	20	19	21	24	25	31	31	45
2013	50	57	59	20	22	23	28	29	32	29	35	37
2014	54	39	59	42	27	25	31	25	28	40	43	38
2015	70	85	89	34	21	20	30	34	36	50	34	41

Appendix VI: Total surface precipitation monthly (mm) for SWM (1985-2015)

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1985	243	126	100	458	300	370	328	174	191	139	509	216
1986	79	19	80	653	395	334	278	230	176	231	308	402
1987	131	117	153	298	516	599	242	241	185	64	436	53
1988	82	40	192	1196	606	270	176	241	137	149	335	206
1989	73	143	98	417	307	201	278	338	382	227	324	212
1990	212	192	439	941	506	226	194	295	92	328	286	191
1991	41	8	152	241	357	480	242	343	200	328	271	203
1992	53	55	45	412	447	392	258	200	242	341	168	317
1993	249	190	47	146	258	419	165	185	133	154	181	323
1994	29	52	67	383	295	528	205	208	130	126	731	139
1995	29	118	182	169	310	347	308	210	360	402	560	156
1996	81	74	234	136	275	469	321	540	387	170	256	107
1997	40	1	171	800	369	329	386	323	50	161	529	341
1998	509	205	185	412	875	397	182	182	137	176	169	39
1999	149	3	275	330	225	125	178	330	115	119	556	347
2000	23	12	37	113	201	200	245	173	181	196	200	114
2001	184	31	221	349	275	244	394	264	289	357	653	95
2002	249	56	182	363	576	199	149	240	71	171	281	410
2003	152	13	140	461	500	520	195	455	156	205	294	118
2004	245	92	211	640	613	221	170	208	320	214	260	180
2005	312	68	200	388	664	304	223	349	316	295	427	97
2006	77	132	247	689	658	359	518	579	318	108	891	600
2007	84	268	98	445	616	574	421	569	503	198	186	117
2008	95	125	322	454	139	324	593	383	524	463	331	112
2009	165	52	260	379	590	128	205	317	254	329	333	672
2010	262	346	1126	618	645	506	393	329	413	596	596	132
2011	70	90	449	174	488	758	363	617	534	280	714	374
2012	12	83	97	1044	728	600	365	394	294	416	652	465
2013	228	105	507	1241	282	559	217	564	518	202	631	605
2014	100	246	212	491	374	618	431	532	498	688	682	351
2015	35	110	242	769	502	524	425	314	345	406	1013	665