ASSESSING THE VULNERABILITY OF MAIZE PRODUCTION TO CLIMATE CHANGE IN TRANS NZOIA, UASIN GISHU, NAKURU AND NAROK COUNTIES

BY

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DECLARATION

DECLARATION

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

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ABSTRACT

Quantification of vulnerability and its components is currently an integral part of providing information to policy makers and stakeholders in an attempt to appropriately assess climate change consequences and support effective risk management and spatial planning.

The aim of this study was to assess the vulnerability of maize production to climate change in Trans Nzoia, Uasin Gishu, Narok and Nakuru Counties. The trend of baseline climate patterns (1981-2010) and projected climate under RCP4.5 and RCP8.5 (2021-2050) was also assessed. Further, the relationship between climate parameters and total maize yields for the period between 2000 and 2015 was determined. The study used historical climate data obtained from Kenya Meteorological Department (KMD), simulated climate data from CORDEX for CNRM model for the period between 2021 and 2050, and biophysical and socioeconomic data from Kenya National Bureau of Statistics (KNBS), Ministry of Agriculture, Livestock and Fisheries (MOALF), and Tegemeo Institute of Agricultural Policy and Development (TIAPF).

The trend analysis revealed that temperatures increased significantly while rainfall recorded a general increase which was not significant during the baseline period. Based on RCP4.5, rainfall is expected to record upward mean shift and trend patterns that will be non-significant. As for RCP8.5, the results showed that a significant upward trend of minimum and maximum temperature will be recorded in all counties during the simulation period. The correlation results showed that there was a relationship between maize yields and climate. The strength and direction of the association was varied across the maize growth stages.

The results of vulnerability assessment showed that due to its least exposure index (0.19) and considerably high adaptive capacity index (2.58), Trans Nzoia registered the lowest vulnerability index of -0.21. Narok recorded the highest vulnerability index of 1.51 because of its high exposure index (1.03) which contributed greatly to potential impacts of climate stressors and hence increased its vulnerability. Moreover, its negative adaptive capacity index (-2.28) was the least among the four counties. Therefore, the county had no capacity to withstand or cope with impacts of climate change. Nakuru had the second highest vulnerability index (0.35) while Uasin Gishu was the second least vulnerable county (-0.12).

Generally, counties with considerable socioeconomic and infrastructural development recorded high adaptive capacity which reduced their vulnerability significantly. Hence, in order to reduce the vulnerability of most vulnerable maize producing counties, climate change policies and strategies should prioritize adaptive capacity enhancement through socio economic development initiatives such as irrigation, rural infrastructural development and educational programs.

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ACRONYMS AND ABBREVIATIONS

CCC	-	Canadian Climate Centre
CCCMA	-	Canadian Centre for Climate Modelling and Analysis
CO_2	-	Carbon Dioxide
CERES	-	Coalition for Environmentally Responsible Economies
CNRM	-	National Centre for Meteorological Research
CORDEX	-	Coordinated Regional Downscaling
ESMS	-	Earth System Models
ERDAS	-	Earth Resource Data Analysis System
ETM	-	Enhanced Thematic Mapper
FAO	-	Food and Agriculture Organization
GDD	-	Growing Degree Days
GDP	-	Gross Domestic Product
GFDL	-	Geophysical Fluid Dynamics Laboratory
GHG	-	Green House Gases
GIS	-	Geographical Information Systems
GPS	-	Global Positioning System
GRADS	-	Grid Analysis and Display System
HadCM3	-	Hadley Centre Coupled Models, version 3
HDI	-	Human Development Index
IPCC	-	Intergovernmental Panel on Climate Change
JJA	-	June, July, August
KNBS	-	Kenya National Bureau of Statistics
KSH	-	Kenyan Shillings
LULC	-	Land Use Land Cover
MAM	-	March, April, May
MEMR	-	Ministry Of Environment and Mineral Resources
MIROC	-	Model for Interdisciplinary Research on Climate
MOALF	-	Ministry of agriculture, Livestock and Fisheries
MOHC	-	Met Office Hadley Centre,
MPI	-	Max Plank Institute
NCC	-	National Climate Centre
NCPB	-	National Cereals and Produce Board
NOAA	-	National Oceanic and Atmospheric Administration
OLI	-	Operational Land Imager
OND	-	October, November, December
PCA	-	Principal Component Analysis
RCM	-	Regional Climate Model
RCP	-	Representative Concentration Pathways
RCMRD	-	Regional Centre for Mapping of Resources for Development
RMSE	-	Root Mean Square Error
SOBJ	-	Specific Objective
SRES	-	Special Report Emissions

SPSS	-	Statistical Package for the Social Sciences
SSA	-	Sub Saharan Africa
TIAPD	-	Tegemeo Institute of Agricultural Policy and Development
TM	-	Thematic Mapper
UNDP	-	United Nations Development Program
UNDP	-	United Nations Development Program
VI	-	Vulnerability Index

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

Over the last three decades, the earth's surface has successively been warming up at the highest rate compared to the preceding decades since 1850. The Fifth Assessment Report by Intergovernmental Panel on Climate Change (IPCC), shows that the global averaged land and ocean surface temperature increased by 0.85°C (0.65°C - 1.06°C) from 1880 to 2012 (Pachauri *et al.*, 2014). In comparison to the base period between 1986 and 2005, the increase in global mean surface temperature by the end of the century has been projected to be in the range of 0.3^0C to 4.8^0C (Pachauri *et al.*, 2014).

Climate change is largely driven by the increasing emission of greenhouse gases (GHGs) that emanate from anthropogenic activities (Parry, 2007; Stocker *et al.*, 2013). Although there are concerted efforts to reduce the emission of GHGs, global temperatures are still expected to continue increasing and therefore there is urgent need to explore mechanisms for adapting to the continuing change in climate, specifically for developing countries which face the biggest brunt of the adverse impacts of climate change (Ahumada-Cervantes *et al.*, 2015). Other than decreasing the frequency of frost, cold nights and cold days, escalating global temperatures have increased the occurrence of heat waves, hot nights and hot days globally (Adhikari *et al.*, 2015). Additionally, it has caused atmospheric water vapour increase, widespread melting of ice, soil moisture variation and deviation of runoff which have significantly interfered with the hydrological cycle (Bates *et al.*, 2008; Hartmann *et al.*, 2013). Climate projections up to 2050 reveal that rising mean global temperatures will cause increased weather variability, which will in turn affect the type and distribution of agricultural production worldwide (Parry, 2007). Due to the impacts of climate change, global food production is expected to reduce by up to 30% (Parry *et al.*, 2004)

The high temperatures and increased frequency of extreme weather events due to climate change, are bound to jeopardize agricultural production and as a result compromise food security in Africa (Conway, 2009). Particularly, the high temperatures are likely to hinder crop development as most crops in Africa are cultivated close to their thresholds of thermal tolerance (Collier *et al.*, 2008). For instance, at a 5^0C global warming, East Africa is expected to experience a reduction in maize production by 19% (Thornton *et al.*, 2011). Notably, some areas in Africa are likely to benefit from the escalating temperatures. This includes the highlands of East Africa where the increased temperatures are expected to favour maize production. However, in the long run, the temperature rise will exceed the optimal temperature for maize production in the highlands and varieties that are tolerant to high temperatures will be the only remedy for sustaining optimal yields (Thornton, 2012). Large areas of marginal agricultural production may be forced out of production due to continuous increase of temperatures and higher frequency of droughts brought about by climate change (Conway, 2009).

In Kenya, the suitable maximum and minimum temperature for maize growth in high altitude areas (1500m-2100m) is 28^{0} C and 8^{0} C respectively. Optimal production of maize in these areas requires rainfall amounts ranging from 800mm to 1500mm (Schroeder et al., 2013). Temperature has notable impact on maize production than precipitation in Kenya (Wandaka, 2013). In particular, the increasing temperatures during the long rain season affect maize production by disrupting crop development during its formative stages which occurs between March and May (Ojwang *et al.*, 2010; Kabubo-Mariara & Karanja, 2007; Wandaka, 2013). It is predicted that by the year 2020, yields resulting from maize farming that is rain-fed will decline by half (Ojwang *et al.*, 2010). Therefore, there is need for sustainable strengthening of maize production, by increasing the yields per unit land and improving the ecological condition while at the same time averting the adverse impacts of climate change on agricultural production (Khan *et al.*, 2014).

The availability of locally produced maize determines Kenya's food security nationally and at the household level since it is the staple food, and accounts for up to more than one third of the caloric intake of food in the country (Ariga *et al.*, 2010; Mohajan, 2014; Kirimi *et al.*, 2011; Omoyo *et al.*, 2015) . Counties found in Kenya's Rift Valley region are the major source of maize in the country which contributes significantly to the food security and national strategic food reserves. In particular, Uasin Gishu, Trans Nzoia, Nakuru and Narok are the among the top maize producing counties in the region (Ministry of Agriculture, 2015).

1.2 Problem Statement

In Sub-Saharan Africa, climate change is already threatening food security by causing damaging impacts on cereal production in the region (Khan *et al.*, 2014). Over the years, Kenya's maize production has been fluctuating due to erratic weather and climate patterns which have significantly interfered with maize production locally and hence jeopardized Kenya's policy on food (Mati, 2000). Mapping of vulnerability and its components is currently an integral part in providing information to policy makers and stakeholders in an attempt to appropriately assess climate change consequences and support effective risk management and spatial planning (Preston *et al.*, 2011; López-Carr *et al.*, 2014). However, there are very few studies done on vulnerability to climate change in Kenya (Mwangi & Mutua, 2015 ; Opiyo *et al.*, 2014; Yohe *et al.*, 2006) of which none has focussed on the vulnerability of maize production to climate change in Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties. Therefore, there is urgent need to establish the degree of vulnerability of maize production to climate change in these counties which contribute significantly to locally produced maize and hence the food security of the country.

1.3 Objectives of the Study

The main objective of the study was to assess the vulnerability of maize production to climate change in Trans nzoia, Uasin Gishu, Nakuru and Narok Counties.

The specific objectives were to:

a) Characterize climate change in Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties between 1985-2015, and 2021-2050 for RCP4.5 and RCP8.5 during annual MAM, JJA, and OND.
b) Determine the relationship between climate and maize production in Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties between 2000 and 2015
c) Develop vulnerability indices for Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties using the indicator approach
d) Generate maize vulnerability maps for Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties.

1.4 Research Questions

a) What are the characteristics of climate change in Trans Nzoia, Uasin Gishu, Nakuru and Narok counties?
b) What is the relationship between maize yields and climate in Trans Nzoia, Uasin Gishu, Nakuru and Narok counties?
c) What is the degree of vulnerability of maize production to climate change in Trans Nzoia, Uasin Gishu, Nakuru and Narok counties?
d) How can the vulnerability in Trans Nzoia, Uasin Gishu, Nakuru and Narok counties be classified?

1.5 Justification of the Study

Ultimately, the current and projected trends of climate change necessitate the adoption of elaborate measures in order to reduce the degree to which maize production is susceptible to adverse impacts of climate change and adapt to the changes. Vulnerability indices have the ability of capturing the multi-dimensional nature of vulnerability in a form that is understandable (Leichenko & O'brien, 2002). The maps and indices generated from vulnerability assessments are of great significance in decision making processes for identifying various areas of varied degrees of vulnerability that require implementation of specific adaptation and mitigation interventions (Emebet, 2013). Information generated from this assessment will be prerequisite for formulation of policies aimed at lowering the degree to which maize production is predisposed to climate change consequences and appropriately allocate resources meant for impact reduction. Consequently, maize production will be sustained in the study counties, hence improving food security in the country. Additionally, the country will avert the economic expense that comes with sourcing of maize from other countries in an effort to bridge the local deficit brought about by climate change induced crop failure.

1.6 Conceptual Framework

The IPCC framework of vulnerability assessment formed the basis for vulnerability assessment in this study. Vulnerability is dependent on various biophysical and socio-economic factors clustered under exposure, sensitivity and adaptive capacity (Sehgal *et al.*, 2013; Shukla *et al.*, 2015). It is a function of the character, magnitude and climate fluctuation rate to which a system is exposed, its sensitivity and adaptive capacity (Parry, 2007; Binita *et al.*, 2015). Whereas exposure and sensitivity contribute to the potential impact of climate related stressors and increases vulnerability, adaptive capacity has an inverse relationship with vulnerability (Smit & Pilifosova, 2003).

The change rates of temperature and rainfall, and the frequency of extreme weather events during the baseline period between 1981 and 2010, were considered as climate change indicators and denoted the changes in climate. Ecological and demographic indicators were regarded as sensitivity indicators. Adaptive capacity indicators were represented by socio-economic factors (Sehgal *et al.*, 2013).

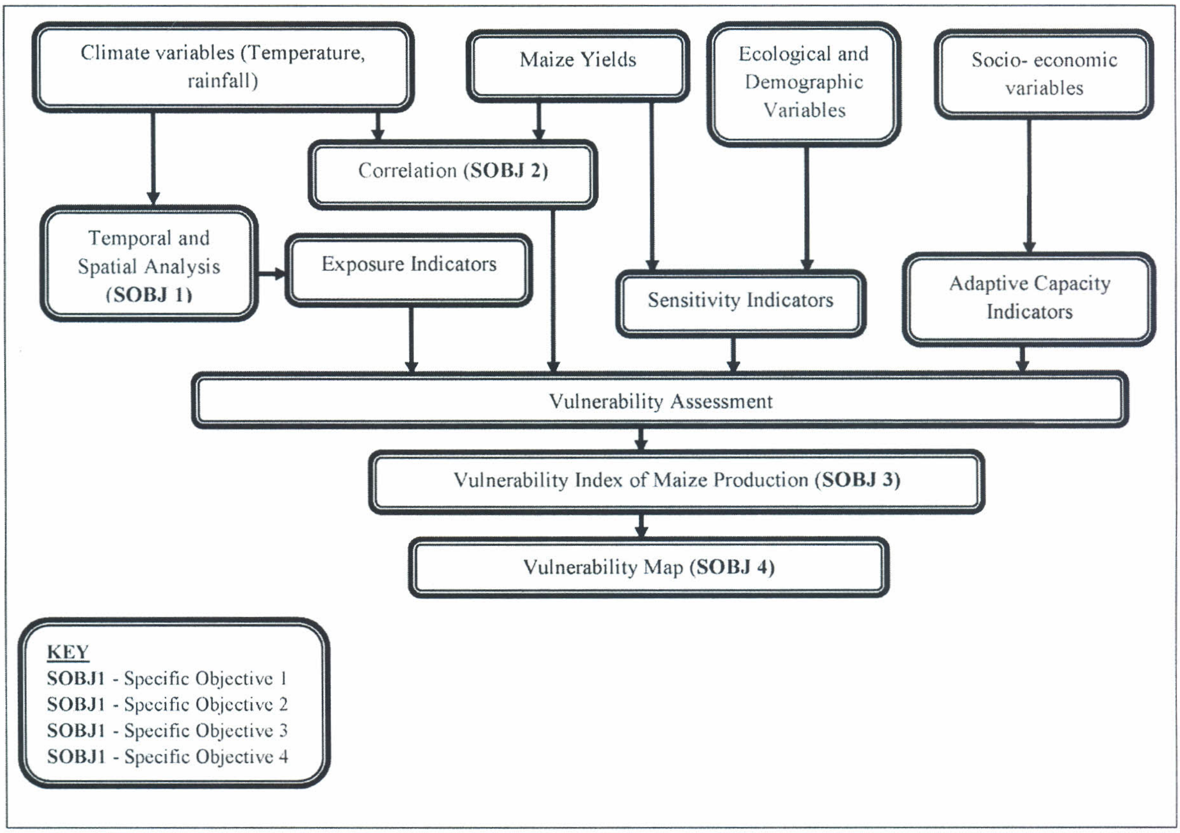

Figure 1: Conceptual Framework

CHAPTER TWO

2.0 LITERATURE REVIEW

This chapter presents a review of literature on vulnerability and impacts of climate change on agriculture, including the approaches and methods used for vulnerability assessment. The chapter also presents climate change scenarios that are crucial for future climate change projections.

2.1 Climate Change in Kenya

In the recent decades, Kenya has recorded, noticeable changes in climate (Parry *et al.*, 2012). Since 1960, the mean temperatures have increased by about 1^0C representing a decadal increase of approximately 0.21^0C. Warming has increased by 0.29^0C during the hotter months (December-January-February) and by 0.25^0C during the cooler months (June-July-August). Daily maximum temperatures indicate that the frequency of warm days has increased while the frequency of cold days has decreased (Gosling *et al.*, 2011).

Although rainfall changes have been noticed since 1960s, the changes do not show obvious tendency towards increasing or decreasing amount of rainfall nationally. Observations have shown that rainfall has increased throughout the short rainy season (October-November-December), while the long rainy season (March-April-May) has recorded reduced rainfall and become less reliable (Parry *et al.*, 2012).

2.1.1 Impacts of Climate Change on Crop Production

Impacts of climate change on agricultural production that considerably reduce crop yields include reduced season duration, intensified water shortage and escalated frequency of pests, diseases and weeds occurrence (Barros *et al.*, 2014). Generally, heat stress and water shortage are regarded as manifestations of climate change with the most adverse impacts on crop production (Prasad *et al.*, 2008).

Occurrence of heat stress during development phases causes growth of fewer and smaller plant organs, reduced crop leaf area that decreases light interception, and variation in photosynthesis, respiration and transpiration (Stone, 2000). Low quality crop yields result from occurrences of heat stress throughout the flowering and grain filling stages, which result into diminished grain count and weight (Bita & Gerats, 2013). Increase in atmospheric vapour pressure due to escalated temperatures can raise the evaporative demand that may prompt plants to close their stomata, hence decreasing the rate of photosynthesis and escalating propensity to heat damage (Lobell & Gourdji, 2012). Additionally, crop yields are significantly reduced when short periods of heat stress coincide with the reproductive stages (Teixeira *et al.*, 2013).

Water stress causes a decline in quality and quantity of crop yields by shortening the crop reproduction stage, increasing the pollen sterility, decreasing the leaf area and shutting of stomata to lessen water loss (Adhikari *et al.*, 2015; Alqudah *et al.*, 2011; Barnabás *et al.*, 2008; Teixeira *et al.*, 2013). Damage to agricultural systems can occur due to pest, disease and weed infestation that is caused by excessive water and heat induced by climate change in areas with excess water and heat (Ziska *et al.*, 2011).

Maize crop requires significant rainfall amount for optimal development and production but is sensitive to excessive continuous rainfall on a daily basis during the rainy season (Paul & Oluwasina, 2011). According to (White & Reynolds, 2003), increased temperatures shortened the growth cycle duration of maize including the grain filling stage, hence reducing the maize yields significantly. A study by (Schlenker & Roberts, 2008) revealed that an increase in maize yields occurred when temperatures increased until a specific threshold temperature which is considered conducive for optimal maize production. Any further increase beyond the threshold, impacted negatively on maize production. Cool night temperatures lead to reduced accumulation rate of growing degree days (GDD) hence lengthening grain filling and enhancing accumulation of dry matter and grain yields. Additionally, low minimum temperatures reduced foliar disease and pest infestation (Hoeft *et al.*, 2000). A study by (Nanticha *et al.*, 2017) found out that increased minimum temperatures during the grain filling phase accelerated respiration rate of a maize plant leading to increased utilization of sugar which reduced the amount of sugar deposited in the kernel as starch . They also established that escalated minimum temperatures caused the maize plant to mature faster because the phenological growth was accelerated. As a result, the physiological processes occurred hurriedly and inefficiently, hence the reduced maize yields (Nanticha *et al.*, 2017).

In Kenya's highlands increase in temperature is expected to open up new grounds for agriculture; hence increase crop yields in these areas (Adhikari *et al.*, 2015). However, increased temperatures will exacerbate water stress in lowlands and considerably reduce crop yields from these areas. An increase in frequency of floods and droughts due to climate change will hamper agricultural production to a great extent (Pachauri & Reisinger, 2007). As a result of drought, the productivity of rain fed agriculture will be hampered due to reduced availability of crop water. Increased temperatures will cause a shift of high potential agro-ecological zones to low potential zones therefore reducing the value of agricultural lands (Kurukulasuriya & Mendelsohn, 2008). Intensified floods will increase the frequency and intensity of soil erosion.

Whereas climate change affects crop production adversely, its impacts are diverse depending on the response of the crops and regions to climate stimuli (Thornton *et al.*, 2006). A study in China revealed that wheat yields would decrease by 3%-10% due to a temperature increase of 1^0C during the period of plant growth (You *et al.*, 2009). In Turkey, shorter growth periods and decrease in rainfall caused by climate change would reduce wheat yields by a percentage that is more than 20% (Özdoğan, 2011). A study carried out to assess how global food security was affected by climate change, found out that food access, availability and utilization will be adversely affected. Nevertheless, the impacts across different regions will be subject to the policies and strategies that will be adopted to counter climate change. Additionally, the study indicated that the dependence of developing countries on imports will increase especially for Sub-Saharan countries (Schmidhuber & Tubiello, 2007).

Climate change has impacted negatively on Kenya's agricultural production, with high temperatures during the planting period (March to May) having great potential in decelerating or preventing crop growth, while greatly benefiting crops during the ripening and harvesting season (June to August) (Kabubo-Mariara & Karanja, 2007).

2.1.2 Climate Change Impacts on Maize Production.

Maize is not only considered as the principal source of carbohydrates in the world but also the major food commodity that takes up a significant share of global markets (80%). Additionally it is cultivated on more than 100 million hectares especially in developing countries (Tripathi *et al.*, 2016). Studies have shown that in Africa, every 1^0C rise in temperature above 30^0C will result into a 1% to 1.7% decrease of maize yields under most favourable rainfall and drought requirements (Lobell *et al.*, 2011).

A study carried out in Iran's Zayandeh-Rud River Basin revealed that maize yields would decrease from 5.7% to 19.1% due to a temperature increase from 1.1^0C to 1.5^0C and rainfall decline from 11% to 31% during the period from 2015 to 2035 (Gohari *et al.*, 2013). In the northern plains of China, studies have shown that a 2.4% to 45.6% decrease in maize yields will be recorded due to higher temperatures induced by climate change (Tao & Zhang, 2010). It is estimated that climate change will result into a 22% reduction in maize production by mid-century (Schlenker & Lobell, 2010). The influence of climate change on agricultural production in Latin America and Africa was assessed through a research carried out by (Jones & Thornton, 2003). They found out that, by 2055, maize production in these regions, will record an overall reduction of 10% which will be equivalent to an annual monetary loss of two billion dollars. However, technological advancement and superior crop varieties may be used to minimize the reduction.

A projection using the HadCM3, on how agricultural production in Sub-Saharan Africa (SSA) would respond to impacts caused by climate change showed that whereas CO_2 fertilization and planting of most productive crop varieties will improve productivity, the potential of agricultural land in the region will reduce by 11% and the potential of maize producing regions will reduce by 7% by 2080. (Edame *et al.*, 2011).

In Kenya, research has shown that the temperature increase throughout the long rain season (March to May) impacted negatively on maize production. This is because high temperatures during the long rain season interrupted crop growth by causing growth of fewer and smaller plant organs, reduced crop leaf area and decline in grain count and weight, which in turn reduced the maize yield considerably (Stone, 2000; Bita & Gerats, 2013). On the other hand, maize production benefited from increase in rainfall during the short rain season. In comparison, temperature affects maize production to a greater extent than rainfall. Maize production is expected to reduce by 23% by 2100 as noted by simulations from climate scenarios (Kabubo-Mariara & Karanja, 2007; Wandaka, 2013).

In Central, Western and Eastern Kenya, a research was carried out in two agro-ecological zones to ascertain the probable impacts of climate change on agricultural production using climate change scenarios obtained from GFDL and CCC models. A simulation of the changes in maize yields was performed using the CERES-Maize model. The study revealed that different climate change scenarios impacted negatively on maize production in the two agro-ecological zones. It also found out that while climate change caused an increased maize production in semi humid zones, it reduced maize production in semi-arid ecological zone. As a way of adapting to the changes, it was suggested that farmers should plant maize during the short rain season in Eastern Kenya, grow maize varieties that mature early and plant early (Mati, 2000).

2.1.3 Impacts of Land Use/Land Cover on Agricultural Production.

Studies have been done on the relationship between land use changes and agricultural production. Specifically, research work has been revolving around the impact of changes in forest land and cropland on total yields. For instance, it has been observed that loss of cereal yields resulted from anthropogenic driven loss of forests in the Sahel (Stephenne & Lambin, 2001). In Cameroon the increase of area under maize production at the expense of forest areas, led to higher maize yields in the short term. This is was due to increased cropland which expanded the area under which maize was grown. As a result more maize crops were grown leading to increased yields. In the long run, steady decrease of forest land resulted into notable decrease of maize yield. This was because the forest area that had been cleared for cropping became more susceptible to erosion and low storage capacity of soil nutrients which reduced its productivity, hence low maize yields (Epule & Bryant, 2014). Additionally, clearing of forest for cropland expansion interrupted the water cycle and exacerbated water scarcity. Hence cereal production and specifically maize production, encountered insufficiency of water that is crucial for their subsistence (Epule *et al.*, 2011; Lobell *et al.*, 2011).

2.2 Vulnerability Assessment Approaches

Socioeconomic and environmental factors of different areas determine their degree of vulnerability to climate change. Different social groupings exhibit distinctively varied socioeconomic and environmental features which determine their vulnerability extents and adaptive capacity to climate change (Adger *et al.*, 2004; Rajesh *et al.*, 2014)

Vulnerability is defined as the susceptibility degree of a system that renders it incapable of withstanding the unfavourable effects of climate change including variations of climate and severe weather events (McCarthy, 2001). It is dependent on the exposure to climate stressors, sensitivity and adaptive capacity of a given system. The nature and extent to which climatic variations affect a system is called exposure (Parry, 2007). The degree to which a system takes advantage of or is adversely affected by climate change is called sensitivity (Parry, 2007). A systems potential to adjust in order to minimize probable harm, take advantage or cope with consequences of climate change, variability and extremes is referred to as adaptive capacity (Parry, 2007).

Socioeconomic and biophysical variables form the basis on which indices are developed. These variables are translated into indicators of adaptive capacity, sensitivity and exposure. Vulnerability assessments are normally carried out at varied spatial scales. Assessment of vulnerability due to climate change can be conducted using three major conceptual approaches as outlined below.

2.2.1 Socio-economic Approach

Socio economic and political status of individuals or groups of people forms the basis of socio-economic vulnerability assessment approach (Adger & Kelly, 1999; Füssel, 2007). The level of vulnerability of different individuals in a community varies depending on factors that differentiate them which include gender, health status, technology and information access, level of education, wealth, accessibility to credit and political power. Specifically, vulnerability is described as a system's initial situation or condition prior to it encountering an event that is harmful (Kelly & Adger, 2000). As a result, vulnerability is shaped by institutional and economic changes within a society (Adger & Kelly, 1999). However, this approach ignores the intensities, frequencies and probabilities of environmental stresses caused by environmental factors. It also overlooks the capability of the community to use any available natural resources to neutralize the adverse impacts of environmental disaster.

2.2.2 Bio-Physical Approach

Biophysical vulnerability assessment approach focuses on examining the destruction level caused by a specific environmental disaster on biological and social systems (Kaly *et al.*, 1999). For instance, so as to quantify the impact of climate change on agriculture in monetary terms, one can simulate the connection linking income generated from farming and climate variables (Polsky & Easterling, 2001). Climate prediction models provide forecasts that are used to estimate damage caused by environmental stresses (Kurukulasuriya *et al.*, 2008).

Estimation of the damages can also be achieved by creating sensitivity indicators through identification of potential or real hazards including their frequencies (Cutter *et al.*, 2000). According to (Füssel ,2007), this approach is a risk-hazard approach and has been used in various disciplines including research work on natural hazards where the vulnerability connection with the hazard is termed as hazard- loss relationship. Also, it has been applied in epidemiology as exposure-cause relationship. In macroeconomics, the approach is described as a damage function. This approach is also referred to as the end point analysis answering various research questions like "How extensive is the climate change problem?" (Kelly & Adger, 2000). Despite its informative nature, the biophysical approach has a limitation of only considering the physical damages like yield reduction.

2.2.3 The Integrated Assessment Approach

In this method, determination of vulnerability is based on integration of socio-economic and biophysical approaches. The hazard-of-place model uses this approach by logically aggregating biophysical and socio-economic indicators in determining vulnerability (Cutter *et al.*, 2000). It is also possible to integrate the biophysical and socio-economic indicators and use the outcome to determine the degree of vulnerability using mapping (o'Brien *et al.*, 2004). This approach was incorporated into IPCC's definition of vulnerability (2001) which stated that adaptive capacity, sensitivity and exposure were the key determinants of vulnerability (Füssel & Klein, 2006; Füssel, 2007)

Absence of standard for integrating the biophysical and socio-economic data sets is the main limitation of this approach. The data sets used in this approach have different and unknown weights. This approach has no common metric for assessing the relative significance of individual variable or the relevance of social and biophysical vulnerability (Cutter *et al.*, 2000). Inability for this method to account for dynamism in vulnerability is the other limitation.

This integrated approach was used for vulnerability assessment in this study because of is applicability in policy formulation and decision making process.

2.3 Methods for Measuring Vulnerability to Climate Change

Vulnerability can be quantified using various methods. The econometric and indicator method are the main methods used for measuring vulnerability to climate change.

2.3.1 Econometric Method

In this method, data from household socio-economic survey is used in the analysis of vulnerability level. The method considers vulnerability as expected poverty, low expected utility and assured exposure to risk (Emebet, 2013). These categories are used to develop a welfare loss measure caused by shocks (Hoddinott & Quisumbing, 2003).

One of the limitations of this approach is that it depends on observed data and can only use climate data that has already been observed to measure vulnerability to climate change. It operates on high data requirements and an assumption must be made concerning the utility function (Sofie, 2012).

2.3.2 The Indicator Method

Vulnerability can be quantified using this method by choosing a set of potential indicators and then merging them systematically, so as to show the degree of predisposition. It generates composite indices which have the capability of characterizing the multi-dimensional nature of vulnerability in a form that is comprehensible (Leichenko & O'brien, 2002). This method presents two options for calculating vulnerability levels. In the first option an assumption is made that all vulnerability indicators have equal significance hence generate weights that are equal (Cutter *et al.*, 2000). To avoid the uncertainty of equal weighting, the second option assigns different weights to the variables considering that they have differential influence on vulnerability.

Various methodological approaches that are in agreement with the latter method have been recommended to explain the difference in weights of vulnerability indicators. The fuzzy logic (Eakin & Bojorquez-Tapia, 2008);expert judgement (Kaly & Pratt, 2000); principal component analysis (Cutter *et al.*, 2003; Easter, 1999) and relationship with historical disaster occurrences (Brooks *et al.*, 2005); are just but few of the approaches that can be used. The appropriateness of each of these approaches remains doubtful although they try to assign weights to the variables. This is because no standard weighting method exists that can be used to test the precision of the approaches.

Just like the other methods, the indicator method has its own limitations which include subjective identification of indicators and their weights, data accessibility at different scale, and difficulty in testing or validating different metrics. Despite its limitations, many researchers have used the approach in quantifying vulnerability because of its transparency (Rama Rao *et al.*, 2016). In Ethiopia, vulnerability indices were developed using the integral approach and used to rank seven states (Deressa *et al.*, 2009). An assessment of climate change vulnerability on a district level using this approach revealed that higher vulnerability levels were recorded in districts located in the western and peninsular India (Rama Rao *et al.*, 2016). In South Africa, this method revealed that vulnerability to climate change of the farming areas varied spatially necessitating the development of region specific adaptation options and policies to address climate change at provincial level (Gbetibouo *et al.*, 2010).

For the purposes of this study, the integrated approach and the indicator method were adopted to assess vulnerability of maize production to climate change within the major maize producing counties in the Rift Valley.

2.3.3 Principal Component Analysis

Variables do not contribute equally to vulnerability (Hebb & Mortsch, 2007). Statistical methods such as Principal Component Analysis can be used to assign weights to variables identified for vulnerability assessment (Cutter *et al.*, 2003; Thornton *et al.*, 2008). Principal Component Analysis (PCA) is an variable reduction method used to reduce multivariate set of data to data that has fewer dimensions which capture the maximum information from the original set of data (Abdi & Williams, 2010; Collins *et al.*, 2001). It is an analytical method that reorients a set of variables that are redundant and correlated into fewer uncorrelated variables called principal components (Abson *et al.*, 2012;Ravindranath *et al.*, 2011). It extracts fewer perpendicular linear combinations of variables that characterize the maximum information from the original set of variables. The first principal component account for the highest variability while the subsequent components explain the remaining variability in the data set (Gbetibouo *et al.*, 2010). It is the most suitable method of assigning weights because it ensures that large variations in any indicator do not improperly dominate the contribution of other relevant indicators and cause distortion in inter areal comparisons (Emebet, 2013). Unfortunately, vulnerability is a function of relevant variables that have been identified and therefore cannot be verified statistically. The implication is that determination of vulnerability index using this method is on a judgement basis. PCA is not only advantageous in terms of its objectivity in assigning weights to variables, but also in estimating the input of each variable to the core phenomenon (Emebet, 2013)

2.4 Empirical Studies of Vulnerability in Kenya

A study carried out to classify the global distribution of vulnerability based on consequences and adaptive capacity to climate change of various countries, categorized Kenya as extreme vulnerable under varied emission scenarios and moderately vulnerable when mitigation strategies were factored in the study (Yohe *et al.*, 2006).

The multifactor approach applied to model Kenya's vulnerability to climate change using GIS revealed that, out of the total area of Kenya; 0.28% was least vulnerable, 14.82% moderately vulnerable, 79.9% highly vulnerable and 5.01% had the highest vulnerability (Mwangi & Mutua, 2015).

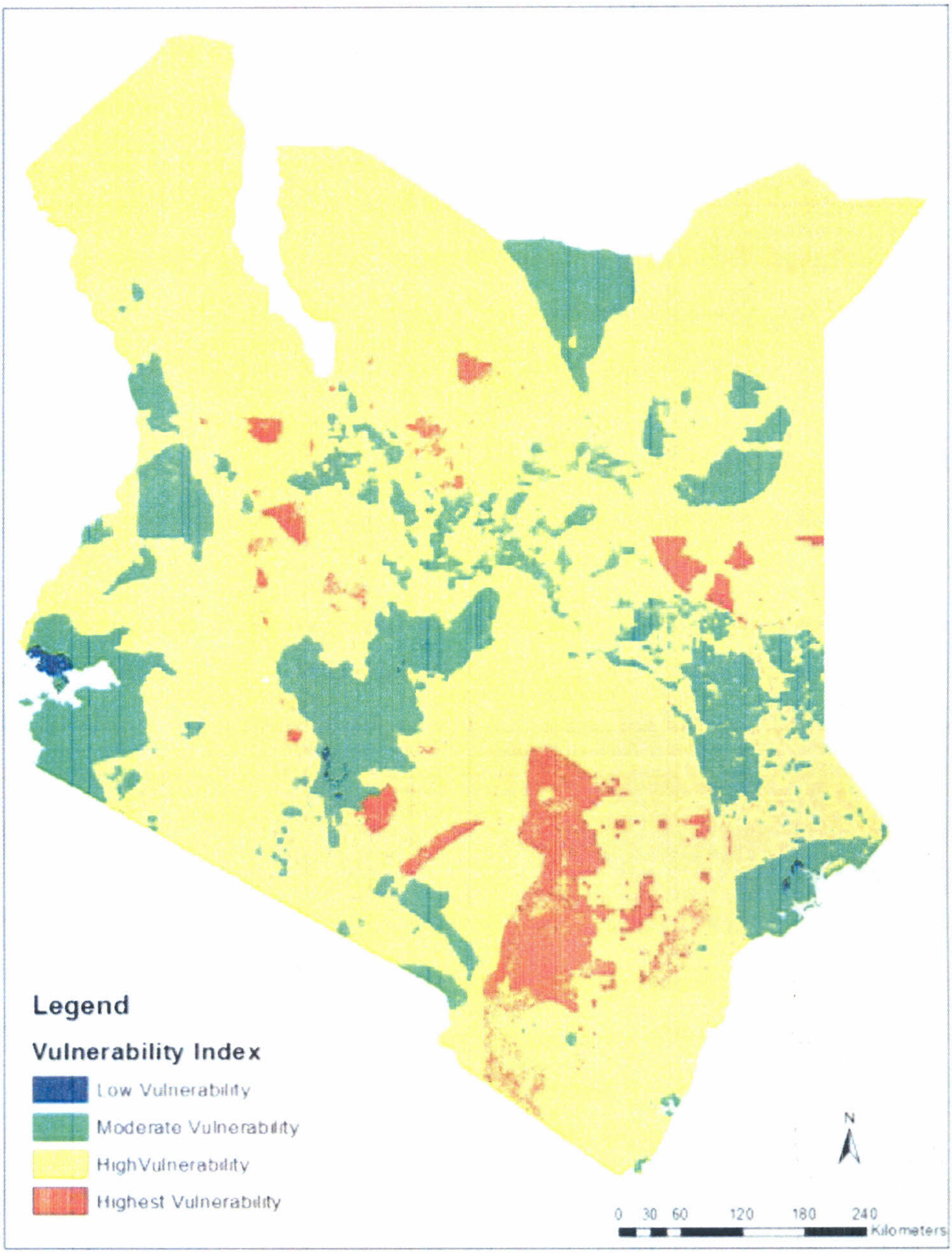

Figure 2: Map of Vulnerability in Kenya (Source: Mwangi & Mutua, 2015)

However, it would be difficult to apply the outcome of this study to various disciplines because climate change vulnerability is dependent on the causal factors which are distinct for every discipline. Additionally, it is difficult to delineate areas from the vulnerability map and accurately determine their degree of vulnerability.

2.5 Climate Change and Emission Scenarios

The variation between probable scenarios of future climates can be represented using climate change trajectories developed in consideration of projections from climate system response to scenarios of GHGs and aerosol emissions using simulations of climate models and the baseline climate (Rwigi, 2014). The scenarios give a credible account of predictions of global climate states by using logical and internally consistent array of hypotheses regarding driving forces and their relationships (Miller & Yates, 2005). Precise investigation of possible impacts of human induced climate change requires development of such scenarios.

Socio-economic and technological developments originating from human activities are the main sources of increased levels of GHGs and aerosols which are the driving forces of anthropogenic climate change (Solomon *et al.*, 2007). Studies have shown that anthropogenic activities have greatly impacted on climate and will continue to influence climate into the future resulting into unidentified scenarios of climate (Mitchell *et al.*, 1999). Developing future climate change scenarios that result from human activities is a prerequisite in assessing environmental, social and economic impacts of climate change so as to formulate appropriate strategies for adaptation and mitigation (Rwigi, 2014).

Climate change scenarios are the best tools that can be used to simulate the climate resulting from different levels of GHGs emission caused by anthropogenic and natural emissions (Rwigi, 2014). Due to the apparent uncertainty surrounding future changes in anthropogenic emissions, IPCC constructed and adopted the Representative Concentration Pathways (RCPs) which represent four distinct pathways of GHGs emissions and atmospheric concentrations, emission of air pollutant and land use. Integrated Assessment models were used to generate the RCPs which are imputed in various simulations of climate models so as to predict how they are going to impact the climate system (Pachauri *et al.*, 2014).

RCPs are inclusive storylines constructed on the basis of the parallel approach using aerosol, income, population, emission and energy variables which describe the different paths of radiative forcing (Van Vuuren *et al.*, 2011). Essentially, four scenarios of the future climates are projected from the RCPs and they are characterised by escalating radiative forcing level (Moss *et al.*, 2010). The RCPs are described in detail in Table 1.

Table 1: Description of Representative Concentration Pathways (Source: Moss *et al.*, 2010).

Parameter	Description	Radiative forcing(Wm^{-2})	CO_2 concentration(ppm)	Pathway
RCP 2.6	The lowest scenario that depicts concerted efforts to reduce GHG emissions and increase carbon sequestration.	$3Wm^{-2}$ before 2100 and reduces	490ppm before 2100 then declines	Peak and decline
RCP 4.5	A low scenario characterized by stabilization of GHG emissions by mid-century followed by a sharp decline subsequently.	4.5 Wm^{-2} before 2100 then declines	490ppm before 2100 and reduces	Stabilization without overshoot
RCP 6.0	An intermediate scenario that denotes a steady increase in GHG emissions that stabilizes in the last decade of the 21st century	$6Wm^{-2}$ at stabilization after 2100	650ppm (at stabilization after 2100)	Stabilization without overshoot.
RCP 8.5	The highest scenario that presumes continuous increase in emissions of GHG up to 21st	8.5 Wm^{-2} in 2100	1370ppm in 2100	Rising

The assessment of how climate will be responsive to human induced forcings like rising GHG emissions, land use changes and atmospheric aerosol concentrations has for a very long time been done using Earth System Models (ESMS) (Hargreaves & Annan, 2014). However, the ESMS have course horizontal resolution (100km-200km) hence they cannot account for local forcings like topographical features and characteristics of the land surface which are vital in altering climate (Döscher *et al.*, 2017). So as to overcome this inadequacy, Regional Climate Models of higher grid resolution are used to downscale simulations from ESMs (Döscher *et al.*, 2017). Coordinated Regional Downscaling Experiment (CORDEX) is a regional climate modelling and downscaling framework that is made up of various Regional Climate Model (RCM) projections (Nikulin *et al.*, 2012). The GCMs that form part of this framework include Canadian Centre for Climate Modelling and Analysis (CCCMA), National Centre for Meteorological Research (CNRM), Model for Interdisciplinary Research on Climate (MIROC), Met Office Hadley Centre (MOHC), Max Plank

Institute (MPI), Norwegian Climate Centre (NCC), and National Oceanic and Atmospheric Administration (NOAA) model. The framework uses a rotated grid with horizontal resolution of 0.44^0 in generating their simulations which is approximately 44 kilometres grid resolution (Giorgi *et al.*, 2009). Projections of green house gases, feedback mechanisms and carbon cycle also form part of the CORDEX framework (Taylor *et al.*, 2009).

The operations of CORDEX focussed on scenario simulations that were based on RCPs. RCPs are trajectories which describe the levels of equilibrium of radiative forcing by the end of the 21st century due to emission and concentration GHGs (Giorgi *et al.*, 2009). The four RCPs that form part of the framework include RCP2.6, RCP4.5, RCP6.0 and RCP8.5 which represent a radiative forcing of 2.6W/m^2, 4.5W/m^2, 6.0W/m^2 and 8.5W/m^2 respectively (Giorgi *et al.*, 2009). The study used RCP4.5 and RCP8.5 for climate simulation for the period between 2021 and 2050. This was to compare the extent of climate change in a scenario where climate change policies are imposed and also in a scenario where there is no climate change mitigation measures employed to reverse the ascending trend of change in climate by the end of the 21st Century. Based on RCP4.5, it is expected that by the end of the 21st century, the radiative forcing will be stabilized at 4.5Watts/m^2 (Thomson *et al.*, 2011) . This will be as a result of climate change policies which will encompass global green house gas emission prices imposed to ensure the limitation of emissions, concentrations and radiative forcing (Peters *et al.*, 2013) . As for RCP8.5, the temperature will continue rising steadily up to the end of the century as there will be no mitigation measured to limit emissions of GHGs (Giorgi *et al.*, 2009; Van Vuuren *et al.*, 2011).

Africa was the initial prime target for the CORDEX framework since most economic activities depend on natural resources and lack adaptive capacity which predisposes the continent to climate change impacts. Moreover, the continent has very few simulations generated from regional climate model downscaling (Giorgi *et al.*, 2009; Nikulin *et al.*, 2012; Thomson *et al.*, 2011).

CHAPTER THREE

3.0 DATA AND METHODOLOGY

3.1 Area of Study

Uasin Gishu County lies between longitudes 34^0 50'' East and 35^0 37" West and latitudes 00^0 03" South and 00 55" North and has a total area 3,327 km^2 (Osundwa *et al.*, 2013). Its altitude ranges between 1500 metres and 2700 metres. The county an receives annual rainfall ranging from 624.9mm to 1560.4mm. The dry spells commence in November and end in February. Temperatures range from 8.4^0 C to 26.1^0C with a mean of 18^0C (Korir, 2011). The main crops grown in the county are maize, sunflower, wheat, pyrethrum, potatoes and barley. The population of the county stood at 894,179 in during the 2009 Census (Korir, 2011; Osundwa *et al.*, 2013; Uasin Gishu County Government, 2013).

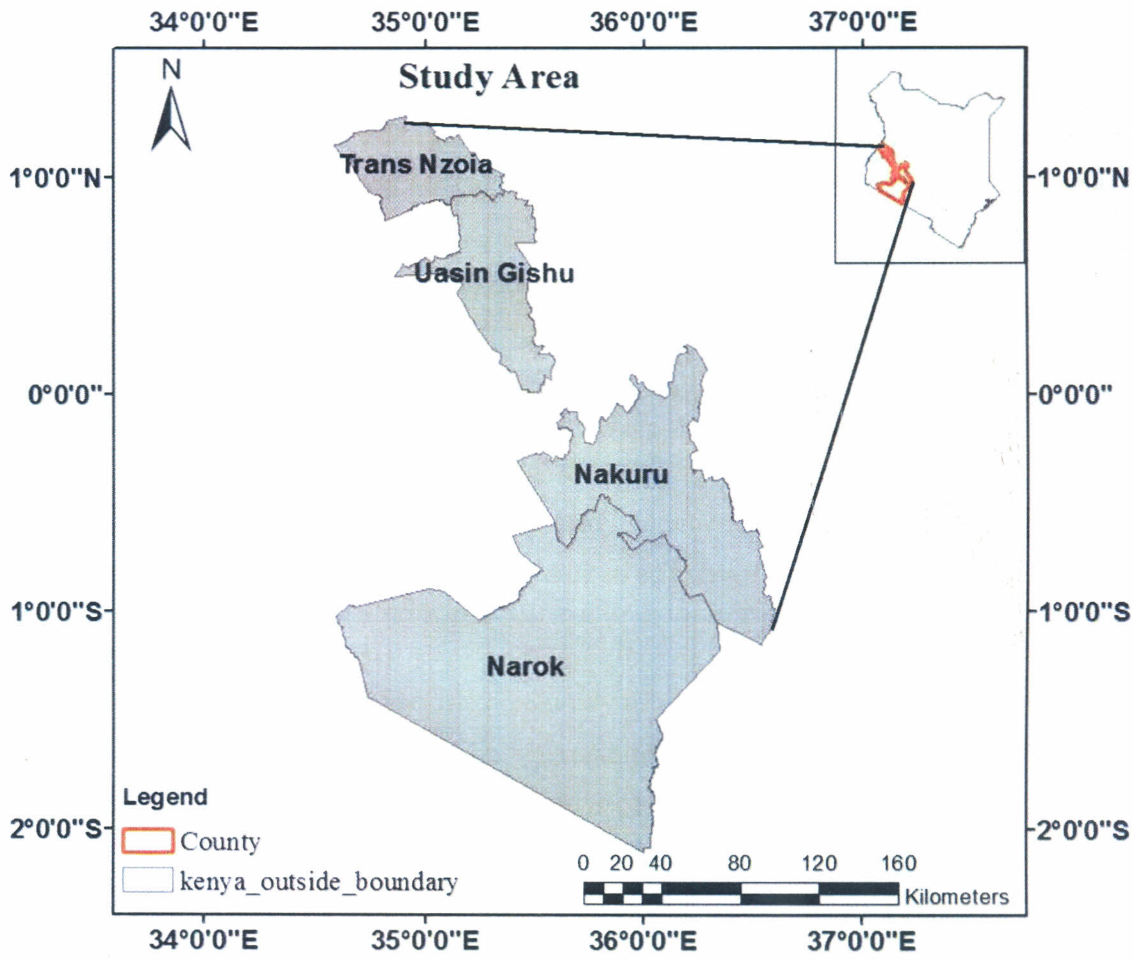

Figure 3: Map of Study area

Trans Nzoia County has an area of 2,467 km^2 and an average altitude of 1800 metres. Its coordinates lie between latitude 00 38'' and 10^0 18'' North of the equator and longitudes 34^0 38" and 35^0 23" East. The county receives a mean annual rainfall of 1,296.1mm and a mean temperature of 18.6^0C. Maize production is the main farming activity and accounts for the greatest acreage of arable land. By the year 2009, the total population of Tran Nzoia was 818, 757 (Mungo, 2014; Trans Nzoia County Government, 2013).

Nakuru County has an area coverage of 7,495.1 km^2 and an altitude of 2,000 metres (Nakuru County Government, 2013). It lies between longitude 35^0 28'' and 35^0 36'' East and latitude 0^0 13'' and $1^0$10'' south (Sangori, 2012) . The county experiences high temperatures of 29^0C (December-January-February) and low temperatures of 12^0C (June-July). Most farmers in the county grow wheat, maize and horticultural crops (Dennis, 2010). By the year 2009, the population of the county was 1,603,325 people (Nakuru County Government, 2013)

Narok County lies between latitudes 0^0 50'' and 1^0 50'' South and longitude 34^0 28'' and 36^0 25'' East and has an area coverage of 17,944 km^2. Its average elevation is 1827 metres above sea level. The population of the county in the year 2012 was estimated to be 850,920. Generally the county receives a mean annual rainfall ranging from 500mm to 1800mm with temperatures ranging from 12^0C to 28^0C. Crops that are mainly grown in the county include barley, wheat, maize, beans, and Irish potatoes. Out of these crops, the highest revenues are realized from maize and wheat that are widely grown by most of the farmers in the county (Narok County Government, 2017)

3.2 Sampling Procedure and Sample Selection

Purposive sampling was used to select the study counties depending on their maize production levels and availability and completeness of data so as to have a varied climatic condition.

3.3 Data Types and Sources.

A literature survey identified specific commonly used socioeconomic and biophysical indicators that were applicable in assessing the vulnerability of maize production to climate change (Gbetibouo *et al.*, 2010; Ahumada-Cervantes *et al.*, 2015; Li *et al.*, 2016; Binita *et al.*, 2015; Shukla *et al.*, 2015; Deressa, 2010; Emebet, 2013). These indicators had some connection that was logical with the phenomena under study that clearly showed their state, causes and results (Scholes *et al.*, 2010; Ash *et al.*, 2010). Vulnerability indicators were chosen considering: suitability of the indicator in terms of its theoretical basis in the framework of vulnerability, definite direction of influence between the indicator and easy access to data on the indicator (Gbetibouo *et al.*, 2010).

The variables that were applicable in maize production were identified and clustered into three dimensions of vulnerability

3.3.1 Climate Data

Eldoret, Kitale, Nakuru and Narok meteorological stations were chosen to represent Uasin Gishu, Trans Nzoia, Nakuru and Narok County respectively. Monthly observed data on temperature and rainfall for the meteorological stations was obtained from Kenya Meteorological Department for the baseline period between 1981 and 2010. Dekadal historical data for rainfall and temperature was obtained from Kenya Meteorological Department for the period between 2000 and 2015.

The performance of GCMs represented in CORDEX was assessed using root mean square error (RMSE) and coefficient of determination (R^2). The simulated rainfall data for the period between 1981 and 2010 for Nakuru, Narok, Kitale and Eldoret meteorological stations was obtained from the GCMs that form part of the CORDEX framework and compared to the observed rainfall data for the same period and stations. This was done so as to determine the appropriate model whose simulated climate data was similar to the observed data during the baseline period. The model with the highest coefficient of determination and the least RMSE value was selected. The results revealed that the National Centre for Meteorological Research (CNRM) had the highest R^2 value of 0.152 and the least RMSE of 67mm.

Table 2: Assessment of Model performance using Correlation and Root Mean Square Error

MODEL	Correlation Coefficient	Coefficient of Determination	RMSE
CCMA	0.165	0.027	100
CNRM	0.3899	0.152	67
MIROC	0.22	0.048	76
MOHC	0.17	0.029	73
MPI	0.216	0.047	75
NCC	-0.012	0.000144	84
NOAA	0.28	0.078	271

Therefore CNRM was selected as the model whose climate simulations would be used to assess the trend of temperature and rainfall patterns during the simulation period between 2021 and 2050 based on RCP4.5 and RCP8.5.

The simulations from CNRM model were downloaded for the period between 2021 and 2050 and used to obtain the climate data for Eldoret, Kitale, Nakuru and Narok meteorological stations. A script was generated and run using Grid Analysis and Display System (GRADS) so as to extract the simulated climate data based on RCP4.5 and RCP8.5 for the stations that represented the counties under study.

3.3.2 Maize Data

The annual maize yields for the four counties were obtained from the Ministry of Agriculture the period between 2000 and 2015.

3.3.3 Exposure Indicators

The exposure indicators included rates of change of rainfall, minimum and maximum temperature, and frequency of droughts and floods. In order to get the rate of change of temperature and rainfall, the historical data of each county was analysed using Sen's Slope estimator. The change rate of rainfall and temperature was used as the exposure variable in computation of exposure and vulnerability indices. Standard Precipitation Index was used to analyse observed rainfall data of each station so as to get the frequency of droughts and events that were anomalously wet. The results from analysis were compared to the SPI value table to determine the number of values that corresponded to extremely wet and extremely dry categories.

Land use/Land cover was also used as a vulnerability indicator for exposure. The land use/land cover of the counties was assessed using satellite images for the year 1984, 2000 and 2015. The images had an interval of fifteen years (1984 TM, 2000ETM and 2015OLI) with spectral resolution of 30 metres. Ground truthing was done using a GPS tool. The images were obtained from SERVIR.

3.3.4 Sensitivity Indicators

The sensitivity indicators were grouped into ecological and demographic sensitivity indicators. Ecological sensitivity was determined by the percentage dependency on rain- fed agriculture, total annual maize yields, annual maize yields per hectare and agricultural area under maize production. Density of rural population, percentage of farmers who practice maize farming and percentage of people living under poverty line constituted the demographic sensitivity.

3.3.5 Adaptive Capacity Indicators

Adaptive capacity indicators were collectively grouped as social-economic capacity indicators which included; social capital (percentage share of farmers in farm organisations), literacy rate, financial capital (percentage of farmers who save money, off farm income , farm income, farm land holding size, farm assets, net house hold income, remittances and percentage of farmers who had access to credit) and physical capital (distance to motorable roads, distance to National Cereals and Produce Board(NCPB) depot, distance to tarmac road , distance to farm produce market, use of chemical fertilizers, rate of irrigation and use of improved seeds).

The data on sensitivity and adaptive capacity variables was obtained from the Kenya National Bureau of Statistics (KNBS), Ministry of agriculture, Livestock and Fisheries (MOALF) and Tegemeo Institute of Agricultural Policy and Development (TIAPD). Table 2 shows the vulnerability indicators, their unit of measurement and functional relationship with vulnerability. The sources of data for the component variables are listed in Table 3.

Table 3: Component variables and their relationship with vulnerability

Vulnerability Component	Component Variables	Indicator description/Unit of Measurement	Functional Relationship
Exposure	Rainfall	Rate of change of rainfall(1981-2010)	↑
	Maximum Temperature	Rate of change of maximum temperature(1981-2010)	↑
	Minimum Temperature	Rate of change of minimum temperature(1981-2010)	↑
	Extreme Climate events (droughts)	Number of droughts	↑
	Extreme Climate events (floods)	Number of flood	↑
Sensitivity	Agricultural area under maize production	Hectares	↓
	Maize yields per acre	Tonnes/ Hectare	↓
	Total annual maize production	Tonnes	↓
	% dependency on rain- fed agriculture	Percentage of farmers who rely on rainfall (%)	↑
	Density of rural population	Number of people per km^2	↑
	People living under poverty line	Number of people who are unemployed	↑
	% farmers who practice maize production	Percentage	↑
Adaptive Capacity	% of farmers who belong to agricultural organisations	Percentage	↓
	% Literacy rate	Percentage of people who can read and write(%)	↓
	Off farm Income	Income generated from none agricultural activities(KSH)	↓
	% of farmers who save money	Percentage	↓
	Farm Income	Income generated from none maize production(KSH)	↓
	Ownership of farmland	Acres	↓
	Farm assets	Kenyan Shillings	↓
	Access to credit	Percentage of maize farmers who can access credit	↓
	Remittances	Kenyan Shillings	↓
	Net House Hold Income	Kenyan Shillings	↓
	Distance to farm produce market	Kilometres	↑
	Distance to NCPB	Kilometres	↑
	Distance to motorable road	Kilometres	↑
	Distance to tarmac road	Kilometres	↑
	% rate of irrigation	Percentage of maize farmers who irrigate their farms(%)	↓
	use of improved seed	Percentage of maize farmers who use improved seeds(%)	↓
	Use of chemical fertilizers	Percentage of maize farmers who use chemical fertilizers(%)	↓

Key

↑ - Vulnerability increases

↓ - Vulnerability decreases

Table 4 : Source of data on the vulnerability indicators

Vulnerability Component	Component Variables	Data Source
Exposure	• Rate of change of rainfall(1981-2010) • Rate of change of maximum temperature(1981-2010) • Rate of change of in minimum temperature(1981-2010)	Kenya Meteorological Department
	• Number of droughts • Number of flood	Standard Precipitation Index
Sensitivity	• Agricultural area under maize production • Maize yields per acre • Total annual maize production	Ministry of Agriculture and Fisheries
	• % dependency on rain- fed agriculture • Density of rural population • People living under poverty line	Kenya National Bureau of Statistics
	• % farmers who practice maize production	Tegemeo Institute of Agricultural Policy and Development
Adaptive Capacity	• % of farmers who belong to agricultural organisations • % Literacy rate • Off farm Income • % of farmers who save money • Farm Income • Ownership of farmland • Farm assets • Access to credit • Remittances • Net House Hold Income • Distance to farm produce market • Distance to NCPB • Distance to motorable road • Distance to tarmac road • % rate of irrigation • use of improved seed • Use of chemical fertilizers	Tegemeo Institute of Agricultural Policy and Development

3.4 Methodology

Various methods were used to achieve the objectives set out in the study as described in the following section.

3.4.1 Mann-Kendall Test

Generally, in most climatologic studies, Mann-Kendall test has been used for determining the trend patterns in climatologic time series (Kahya & Kalaycı, 2004; Mavromatis & Stathis, 2011). This method is advantageous because it is non parametric and the data used need not be normally distributed. The test has minimal sensitivity when dealing with an inhomogeneous time series that has abrupt breaks. Moreover, a general value that is lesser than the least observed figure in the data set is allotted to any data points that are reported as non-detects (Karmeshu, 2012). While carrying out the test, it is theorized that the null hypothesis, H_0, assumes absence of trend and that the data is independent and randomly structured. The null hypothesis is checked against an alternate hypothesis which supposes that there exists trend in the data set. Commonly, the process used for computation in Mann-Kendall test takes into account a time series of n data values and T_i and T_j as two data subsets (i = 1,2,3,..., n-1 and j = i+1, i+2, i+3, ..., n). The evaluation of values within the data was done by considering them as ordered time series and each value was compared to all other preceding or consequent data values in the data set. The statistic value S computed as given in equation (1).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(T_j - T_i) \qquad \text{Eqn (1)}$$

Where, S is the Mann-Kendall statistic.

$$Sign(T_j - T_i) = \begin{cases} 1 \; if(T_j - T_i) > 0 \\ 0 \; if(T_j - T_i) = 0 \\ -1 \; if(T_j - T_i) < 0 \end{cases} \qquad \text{Eqn (2)}$$

Where T_j and T_i are annual values in years j and i , j>i respectively.

An increasing value S implied that the data value from a later time period was higher than a data value from the earlier time period. Conversely, if the statistic S decreased, the data value from a later time was considered to be lower than the data value sampled earlier on. The final value of S was considered to be the result of the decrements and increments (Kundu *et al.*, 2014; Mishra *et al.*, 2014; Pingale *et al.*, 2014) . An increasing trend was denoted by a positive value of S while a negative value of S indicated a decreasing trend. The observed trend was considered to be statistically significant when the p- value was smaller than the level of significance value of 0.05.

3.4.2 Pettit's Test

In order to identify the sudden change in records of climatic parameters, Pettit's test for change detection was applied. It is a non parametric test that is highly sensitive to breaks in a data set and is used to distinguish points of change in a set of continuous climate data (Jaiswal *et al.*, 2015; Pohlert, 2016; Zarenistanak *et al.*, 2014). Essentially, a notable shift in the mean of the time series is detected by this method especially when the precise instance of mean deviation is unidentified (Jaiswal *et al.*, 2015). Suppose a series of observed data is $x_1, x_2, x_3 \ldots\ldots x_n$ has a change point at t, such that the distribution function of $x_1, x_2 \ldots, x_t$ is $F_1(x)$ and the second part of the series x_{t+1}, x_{t+2}, x_n has a distribution function of $F_2(x.)$, then Pettit's test computes a parameter, U_t, using equation (3).

$$U_{t=\sum_{i=1}^{t}\sum_{j=t+1}^{n}} sign(x_t - x_j) \qquad \text{Eqn (3)}$$

$$sign(x_t - x_j) = \begin{cases} 1\ if(x_t - x_j) > 0 \\ 0\ if(x_t - x_j) = 0 \\ -1\ if(x_t - x_j) < 0 \end{cases} \qquad \text{Eqn (4)}$$

The test statistic and the associated confidence level (ρ) for the sample length (n) were computed using equations (5) and (6) respectively.

$$K = Max|U_t| \qquad \text{Eqn (5)}$$

$$\rho = \exp\left(\frac{-K}{n^2 + n^3}\right) \qquad \text{Eqn (6)}$$

The null hypothesis was rejected whenever ρ was smaller than the specific confidence level. The significance probability (p) for a change-point was estimated using equation (7).

$$p = 1 - \rho \qquad \text{Eqn (7)}$$

3.4.3 Sen's Slope Estimator

The slope of the linear trend line was calculated in order to determine the rate of change of weather parameters per unit time using the non-parametric method that was developed by Sen in 1968 (Drápela & Drápelová, 2011; Gocic & Trajkovic, 2013). The form of liner model that was used is given in equation (8).

$$f(t) = Qt + K \qquad \text{Eqn (8)}$$

Where Q is the slope

K is the constant

In order to approximate the slope, Q, a computation of slopes for all data pairs was carried out using equation (9).

$$Q_i = \frac{x_j - x_k}{j-k} \qquad \text{Eqn (9)}$$

Where *i=1,2,........N, j>k*

In a case where there were *n* values of *x* then the number of slopes that would estimate Q_i were given by equation (10).

$$N = \frac{n(n-1)}{2} \qquad \text{Eqn (10)}$$

The N values of Q_i were ranked from least to highest and the slope median (Sen's slope estimator) was calculated using equation (11).

$$Q = \begin{cases} Q_{\frac{N}{2}} if\ N\ isodd \\ \frac{1}{2}\left(Q_{N/2} + Q_{N+2/2}\right) if\ Nis\ even \end{cases} \qquad \text{Eqn (11)}$$

3.4.4 Standard Precipitation Index

Standard precipitation Index was used to analyse observed rainfall data of each station so as to get the frequency of droughts and events that were anomalously wet. The rainfall data for the meteorological stations was subjected to a 3 month- SPI computation using a program provided by the World Meteorological Organisation that is recommended for calculation of SPI (Svoboda *et al.*, 2012). The results from analysis were compared to the SPI table value to determine the number of values that corresponded to extremely wet and extremely dry categories (Svoboda *et al.*, 2012)

Table 5: Standard Precipitation Index values

2.0 +	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

3.4.5 Analysis of Satellite Images

Satellite images of the counties were pre-processed so as to point out and demarcate varied land use/land cover (LULC) units. Further categorization of satellite images was done using supervised classification method. In comparison, the interpretation and classification of recent satellite images taken during the research period can be directly ground truthed as opposed to satellite images taken before the recent time. In order to ascertain the classification of satellite images that were taken during the research period, eight numbers of classes were selected for each LULC unit as a training area. This was done depending on the nature of reflectance signature in the study area. Maximum likelihood classification method was used to identify the land use/land cover classes. The maximum likelihood classification is a supervised classification method drawn from the Bayes theorem which states that the a posterior distribution, $P(i|\omega)$, which is the probability that a pixel with feature vector ω belongs to class i, is given by

$$P(i|\omega) = \frac{P(\omega|i)P(i)}{P(\omega)} \quad \text{Eqn (12)}$$

Where

$P(\omega|i)$ is the likelihood function.

$P(i)$ is the priori information (probability that class i occurs in the study area).

$P(\omega)$ is the probability that ω is observed which is given by equation (13) below.

$$P(\omega) = \sum_{i=1}^{M} P(\omega|i)P(i) \quad \text{......Eqn (13)}$$

Where M is the number of classes

Normally $P(\omega)$ is regarded as a standardization constant to make sure $\sum_{i=1}^{M} P(i|\omega)$ sums up to 1. Pixel **x** is allocated to class i based on the following rule.

$\boldsymbol{x} \in \boldsymbol{i}$, if $P(\omega|i) > P(j|\omega)$ for $j \neq i$

The Maximum likelihood classification presumes that the distribution of data within a specific class i, conforms to the multivariate Gaussian distribution. Every pixel is allocated to the class with the maximum likelihood. In case the pixels have probability values that are lower than the set limit then it is categorized as unclassified (Asmala, 2012)

.

Land use/land cover maps were generated from 1984, 2000 and 2015 satellite images of the study area during the post-interpretation and classification phase. ArcGIS 10 and ERDAS Imagine 10 were used for land cover land use classification.

3.4.6 Spearman's Correlation

Spearman's correlation was used to determine the relationship between climate and maize yields in Trans Nzoia, Uasin Gishu, Nakuru and Narok Counties. It is a non-parametric measure of association between two paired variables (Gautheir, 2001). It shows the degree and direction of correlation between two variables that are on scale. The spearman's correlation coefficient, ρ , is the measure of the strength of association between two ranked pairs and ranges between 1 and -1 (Chok, 2010). For instance, given two variables X and Y, the relationship between them can be determined using equation (14) below.

$$\rho = 1 - \frac{\sum_{i=1}^{n} D^2}{n(n^2-1)} \quad \text{......Eqn (14)}$$

Where,

D is the difference between the paired ranks

n is the number of rank pairs

3.4.8 Root Mean Square Error

Root Mean Square error is a statistical method that is used to assess the performance of a model by computing the differences between the observations and forecasts from the model (Chai & Draxler, 2014; Sagero, 2012). RMSE can be determined using Equation (15) below.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}(F_i - OBS_i)^2}{N}} \quad \text{.. Eqn (15)}$$

Where F_i is the predicted value from the model, OBS_i is the observations and N is the number of observations.

3.4.9 Indicator Approach

The suitability of data for climate change vulnerability analysis in maize production requires standardization because they are all in different measurement units. According to (Vincent, 2004), standardization of the indicators eliminates differences in scales, and makes sure that they are comparables and dimensionless. It was important to establish the functional relationship that existed between an indicator and vulnerability. The method that United Nation Development Program (UNDP) used to compute Human Development index (HDI) was used for normalization in this study (UNDP, 2002). In cases where vulnerability increased when the value of the indicator increased, then equation (16) was used for normalization.

$$X_{normalized} = \frac{X_{ij} - MinX_{ij}}{MaxX_{ij} - MinX_{ij}} \quad \text{.. Eqn (16)}$$

Conversely, if vulnerability reduced with an increase in a specified indicator then normalization was done using equation (17).

$$X_{normalized} = \frac{MaxX_{ij} - X_{ij}}{MaxX_{ij} - MinX_{ij}} \quad \text{.. Eqn (17)}$$

Where,

X_{ij} is the value of the i^{th} indicator for the j^{th} county

Normalization of the data was followed by ranking of the indicators where unequal weights were assigned to each of them using the principal component analysis method. For instance, if there is a collection of N variables ($a^{\#}_{1j}$ to $a^{\#}_{Nj}$), PCA can be used to normalize each variable using its average and standard deviation as given in equation (18) (Deressa, 2010).

$$a_{1j} = \frac{a^{\#}_{1j} - a^{\#}_{1}}{s^{\#}_{1}} \qquad \text{Eqn (18)}$$

Where,

$a^{\#}_{1}$ is the mean of over the region and its standard deviation is $s^{\#}_{1}$.

For each county, j, a linear combination of a set of core components was used to express the selected variables (Deressa *et al.*, 2008; Deressa, 2010).

$$a_{1j} = V_{11}A_{1j} + V_{12}A_{2j} + \ldots V_{1N}A_{Nj}, \; j=1 \qquad \text{Eqn (19)}$$

$$a_{Nj} = V_{N1}A_{1j} + V_{N2}A_{2j} + \ldots V_{NN}A_{Nj} \qquad \text{Eqn (20)}$$

Where,

A's are the components.

V's are the coefficients on each component for each variable.

The solution to this equation is undefined because the only part of the equation that is known is the left hand side which is basically the actual value of the vulnerability variable. So as to surmount this challenge, PCA was used to obtain a linear combination of variables with highest variance termed as the first principal component (A1j). Subsequently, the second principal component generated using PCA was orthogonal to the first principal component and accounted for the remaining maximum variance et cetera. This method provided a theoretical solution in the equation $(R - \lambda_n I)\, v_n = 0$, for v_n and λ_n . In this equation, each variable's correlation with the n^{th} component was represented by the matrix R. A solution of this equation presented the value of λ_n (Eigen values) which was the typical root of R and their associated Eigen vectors, vn. Scaling the vns so that the total of their square adds up to the total variance, produced the final set of estimates. This was another restriction imposed to achieve determinacy of the problem (Deressa, 2010).

Equation (19) above implies inverting of the system which allows for the recovery of the scoring factors from the model. Consequently, a set of estimates for each K principal components is yielded.

$$A_{1j} = f_{11}a + f_{12}a_{2j} + \ldots\ldots\ldots\ldots f_{1N}a_{Nj} \quad \text{Eqn (21)}$$

$$A_{Nj} = f_{N1}a + f_{N2}a_{2j} + \ldots\ldots\ldots\ldots f_{NN}a_{Nj} \quad \text{Eqn (22)}$$

Based on Equation (23) below, the index of each county is the first principal component, expressed in terms of the initial variables that have not been normalized.

$$A_{1j} = \frac{f_{11}(a^{\#}_{1j} - a^{\#}_{1})}{s^{\#}_{1}} + \ldots\ldots \frac{f_{1N}(a^{\#}_{Nj} - a^{\#}_{N})}{s^{\#}_{N}} \quad \text{Eqn (23)}$$

The weights obtained from PCA were multiplied by their respective normalized values of each variable under the three components of vulnerability. Thereafter, the products were summed up and divided by the total weight of variables under each component as given by Equation (24) to (26) (Emebet, 2013).

$$E_C = \frac{\sum_{i=1}^{j} P_i Y_E}{\sum_{I=1}^{J} P_1} \quad \text{Eqn (24)}$$

$$S_C = \frac{\sum_{i=1}^{j} P_i Y_S}{\sum_{I=1}^{J} P_1} \quad \text{Eqn (25)}$$

$$AC_C = \frac{\sum_{i=1}^{j} P_i Y_{AC}}{\sum_{I=1}^{J} P_1} \quad \text{Eqn (26)}$$

Where:

- AC_c is the adaptive capacity of the County
- S_c is the sensitivity of the County
- E_c is the exposure of the county
- Y_E, Y_S and Y_{AC} are standardized values of variables under exposure, sensitivity and adaptive capacity respectively.

- P_i is the weight of the indicators.

The vulnerability index of the counties (VI_c) was computed by summing up S_c and E_c and then subtracting the AC_c as shown in equation (27) (Ahumada-Cervantes *et al.*, 2015).

$$VI_c = \frac{E_c+S_c-(1-AC_c)}{3} \quad \text{Eqn (27)}$$

Where:

- VI_c is the vulnerability of the county
- AC_c is the adaptive capacity of the county
- S_c is the sensitivity of the county
- E_c is the exposure of the county

The vulnerability indices were normalized further so as to get the final value on a scale of 0-5 as shown in equation (28) (Ravindranath *et al.*, 2011).

$$VI_{normalized} = 5\left(\frac{VI-V_{min}}{VI_{max}-VI_{min}}\right) \quad \text{Eqn (28)}$$

Five categories were created to classify the normalized VIs. These included: very high ($4\leq VI_{normalized} <5$), high ($3\leq VI_{normalized} <5$), moderate ($2\leq VI_{normalized} <3$), low ($1\leq VI_{normalized} <2$) and very low ($0\leq VI_{normalized} <1$). The $VI_{normalized}$ values were plotted to generate the spatial patterns of vulnerability for each county using GIS (Ahumada-Cervantes *et al.*, 2015).

CHAPTER FOUR

4.0 RESULTS AND DISCUSSIONS

In this chapter, a detailed discussion of the results obtained from the analysis of this study is presented. This includes trend and mean shift of baseline and simulated climate, correlation of weather parameters and annual maize yields, exposure, sensitivity, adaptive capacity and vulnerability indices for baseline period.

4.1 Trends and Patterns of Baseline Climate

4.1.1 Rainfall Trends and Patterns

Nakuru and Narok stations experienced an increasing trend and an upward mean shift in the observed annual rainfall while Eldoret and Kitale stations registered decreasing trend patterns and downward mean shift for the baseline period between 1981 and 2010 (Figures 4 and 5).

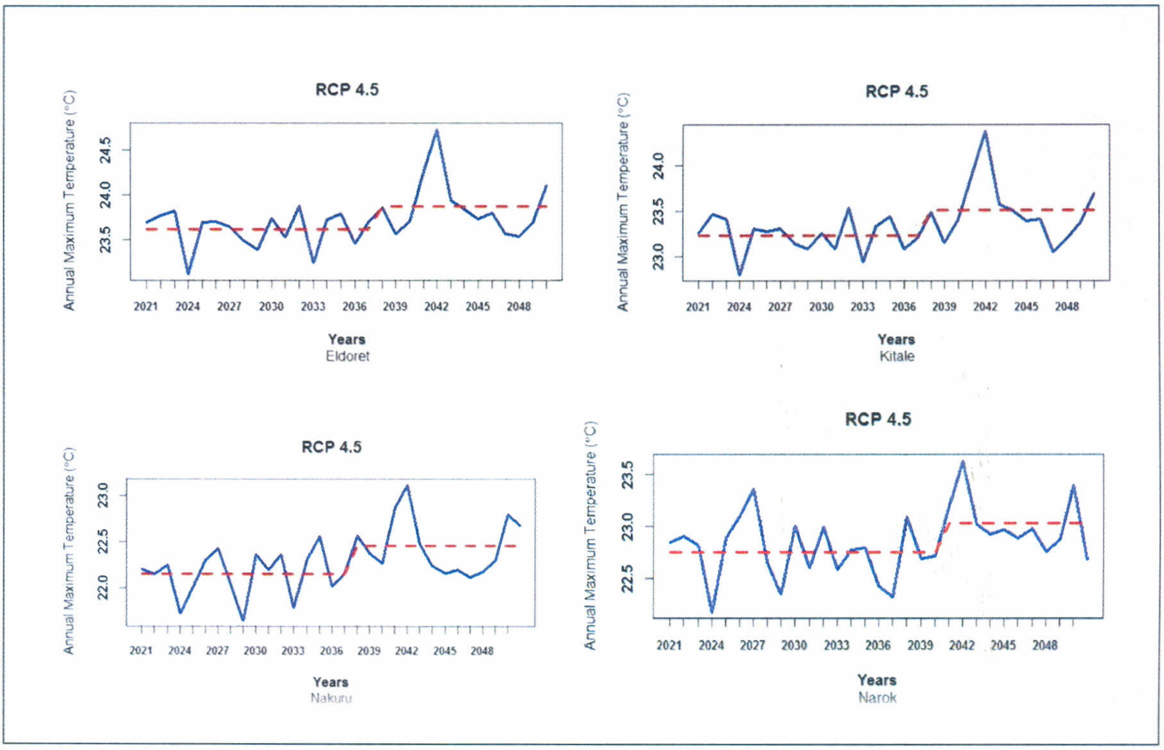

Figure 4: Trend of annual rainfall for Eldoret, Kitale, Nakuru and Narok stations (1981-2010)

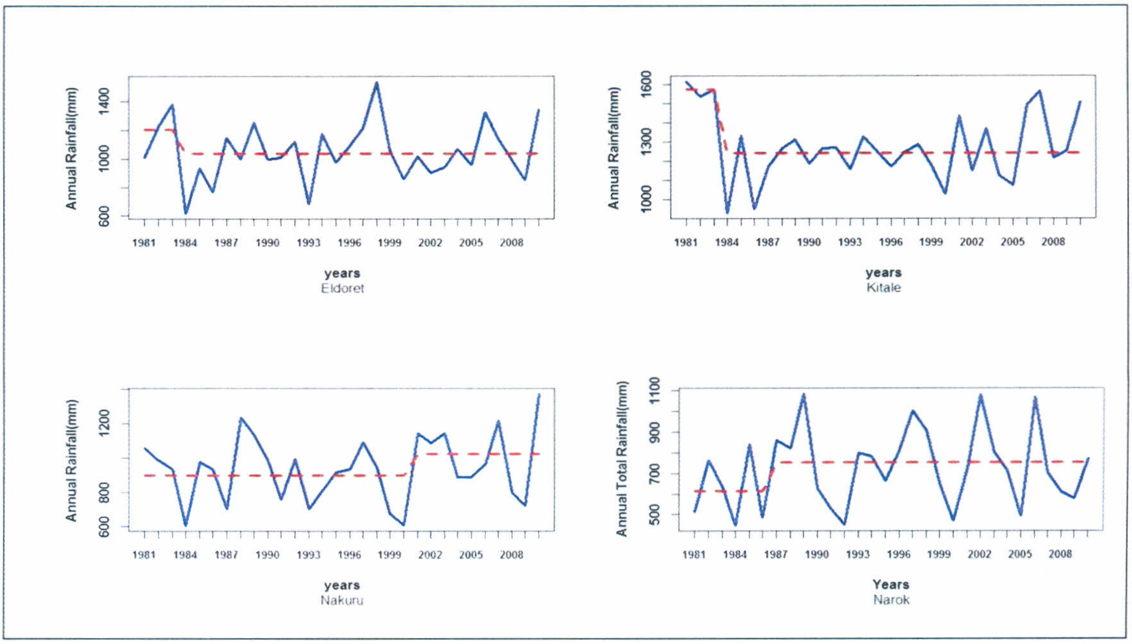

Figure 5: Mean shift of annual rainfall for Eldoret, Kitale, Nakuru and Narok stations (1981-2010)

The highest mean seasonal rainfall for Eldoret was recorded during JJA rainy season (Table 6). Kitale had the highest mean rainfall among the four meteorological stations across the seasons. Nevertheless, the station recorded declining trends in seasonal mean rainfall during MAM and JJA. Its OND season had the highest rate of change among the four stations of +4.7mm/year. Rainfall patterns in Nakuru indicated a general increasing trend except for JJA rainy season. In this station, the OND rainy season recorded the highest rate of change despite it having the lowest seasonal rainfall mean. Out of the four stations, the lowest seasonal mean rainfall during JJA was recorded in Narok.

In general, the OND rainy season exhibited an increasing trend in rainfall amounts across all the study stations. Notably, the trend patterns and mean shifts of baseline rainfall were not statistically significant as depicted by the p-values of Mann-Kendall and Pettit's test which were higher than the significance level value (α=0.05).

From the rainfall analysis, Uasin Gishu and Trans Nzoia recorded reducing rainfall trends during the season of MAM with negative rates of change of -2.9mm/year and -3.2mm/year respectively. Consequently, maize production encountered water stress which caused a decline in quality and quantity of crop yields.

Table 6: Characteristics of baseline rainfall for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Mean Rainfall(mm)	Score	P- value (MK test)	P- value (P test)	Sen's Slope Value
Eldoret	MAM	331.0	-61	0.28	0.8	-2.9
	JJA	415.1	9	0.89	1.3	0.7
	OND	166.0	35	0.54	1.0	1.3
	Annual	1054.5	7	0.91	1.3	1.1
Kitale	MAM	449.2	-59	0.3	0.5	-3.2
	JJA	386.2	-17	0.78	1.2	-0.6
	OND	324.6	45	0.43	0.8	4.7
	Annual	1275.5	-19	0.75	0.5	-1.0
Nakuru	MAM	314.2	37	0.52	0.4	1.3
	JJA	272.6	-15	0.8	1.4	-0.8
	OND	271.4	97	0.09	0.4	4.1
	Annual	939.1	17	0.78	0.9	0.9
Narok	MAM	314.3	19	0.75	1.0	0.6
	JJA	66.0	-47	0.41	0.3	-0.7
	OND	205.4	45	0.43	1.0	1.8
	Annual	724.6	23	0.69	0.9	2.4

Nakuru and Narok had increasing trend of rainfall during MAM season. It was also noted that Uasin Gishu had an increasing rainfall trend during JJA season with a positive rate of change of 0.7mm/years. As for OND season, the trend of rainfall patterns was increasing in all counties with Kitale and Narok recording the highest rates of change.

Studies revealed that rainfall had increased throughout the short rainy season (OND), while the long rainy season (MAM) has recorded reduced rainfall and become less reliable (Parry *et al.*, 2012). In Uasin Gishu and Trans Nzoia rainfall reduced during MAM season which is in agreement with the findings of the study by (Parry *et al.*, 2012). However, the results of rainfall trend in Nakuru and Narok showed that rainfall had increased in the two counties during MAM which was contrary to findings by (Parry *et al.*, 2012). All counties recorded an increase in rainfall during OND season which is agreement with findings by (Parry *et al.*, 2012).

4.1.2 Trends of Maximum Temperature

The maximum temperature depicted increasing trend and upward mean shift during the baseline period over all the study stations for all seasons. Generally, the maximum temperature increased at change rates ranging between $+0.044^{0}$C/years and $+0.056^{0}$C/years (Figures 6 and 7, Table 7).

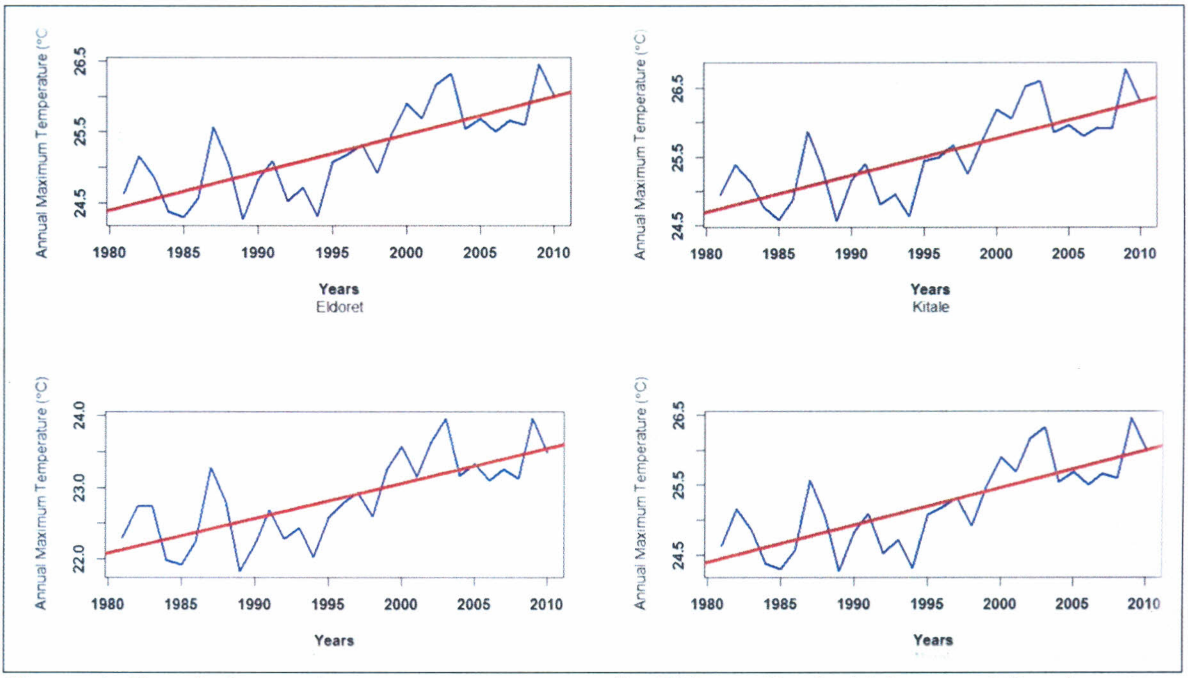

Figure 6: Trend of annual maximum temperature for Eldoret, Kitale, Nakuru and Narok stations (1981-2010)

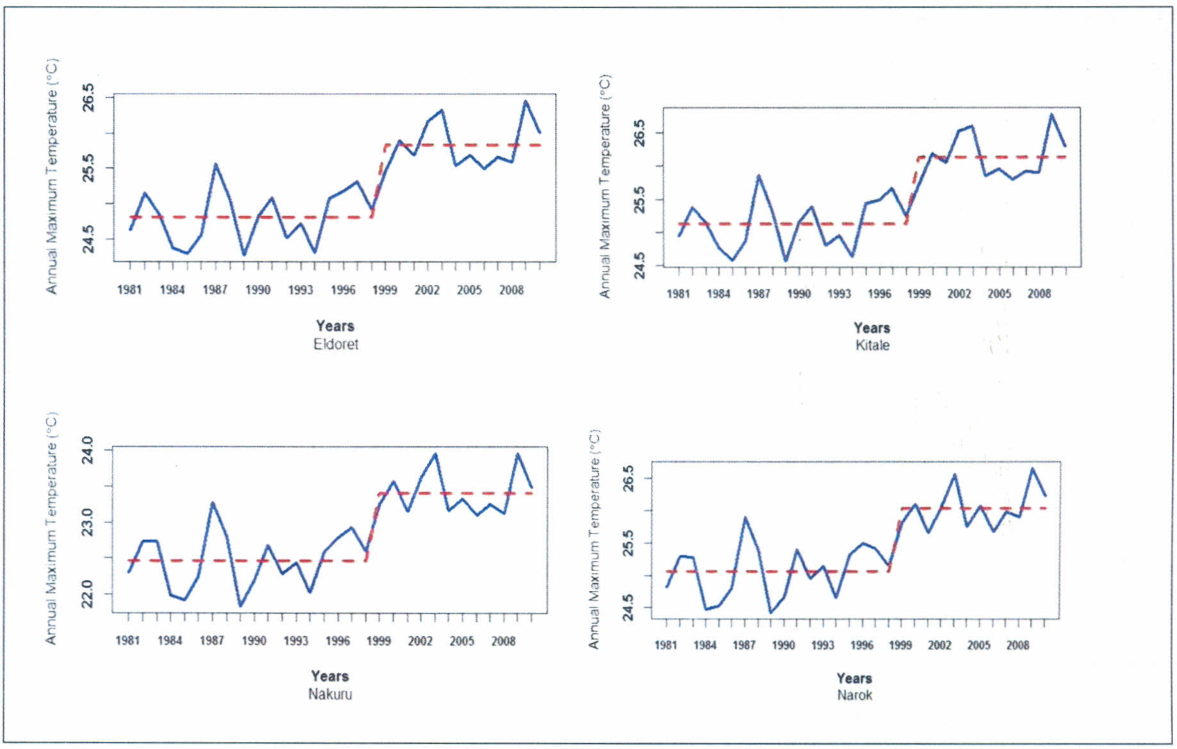

Figure 7: Shift in mean of annual maximum temperature for Eldoret, Kitale, Nakuru and Narok stations (1981-2010)

Table 7: Characteristics of baseline maximum temperature for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Maximum Temperature (^{0}C)	Score	P- value (MK test)	P- value (P test)	Sen's Slope Value
Eldoret	MAM	25.9	204	0.0003	0.0003	0.054
	JJA	23.8	190	0.0007	0.0057	0.053
	OND	25.3	196	0.0005	0.0053	0.052
	Annual	25.2	245	<0.0001	0.0002	0.054
Kitale	MAM	26.2	198	0.0004	0.0002	0.056
	JJA	24.0	188	0.0008	0.0046	0.055
	OND	25.6	200	0.0004	0.0043	0.052
	Annual	25.5	251	<0.0001	0.0002	0.054
Nakuru	MAM	23.6	189	0.0008	0.0012	0.054
	JJA	21.5	187	0.0009	0.0016	0.044
	OND	22.6	183	0.001	0.0114	0.052
	Annual	22.9	225	<0.0001	0.0003	0.051
Narok	MAM	25.4	174	0.002	0.0022	0.048
	JJA	24.1	208	0.0002	0.0007	0.051
	OND	26.3	191	0.0007	0.0218	0.056
	Annual	25.5	255	<0.0001	0.0002	0.056

The increasing trend and mean shift of the maximum temperature was statistically significant with p- values generated from Mann-Kendall and Pettit's test being much less than significance level value of 0.05.

The result of maximum temperature trend agrees with studies done by (Parry *et al.*, 2012), which had shown that in Kenya, temperature had increased by 1^{0}C since 1960.

4.1.3 Minimum Temperature Trends

Minimum temperature recorded an ascending trend pattern and an upward mean shift for the period between 1981 and 2010 in all the stations during all seasons (Figure 8 and 9, Table 8). The minimum temperature increased at rates between +0.039^{0}C/years and +0.055^{0}C/years during the base line period.

The increasing trends in minimum temperature patterns noted in all the study counties were statistically significant as depicted by very small p-values of Mann-Kendall test compared to the significance level value of 0.05. In addition, the Pettit's test yielded p-values that were less than the value of the significance level (α =0.05) thereby indicating a significant change in the mean values of the sample data sets.

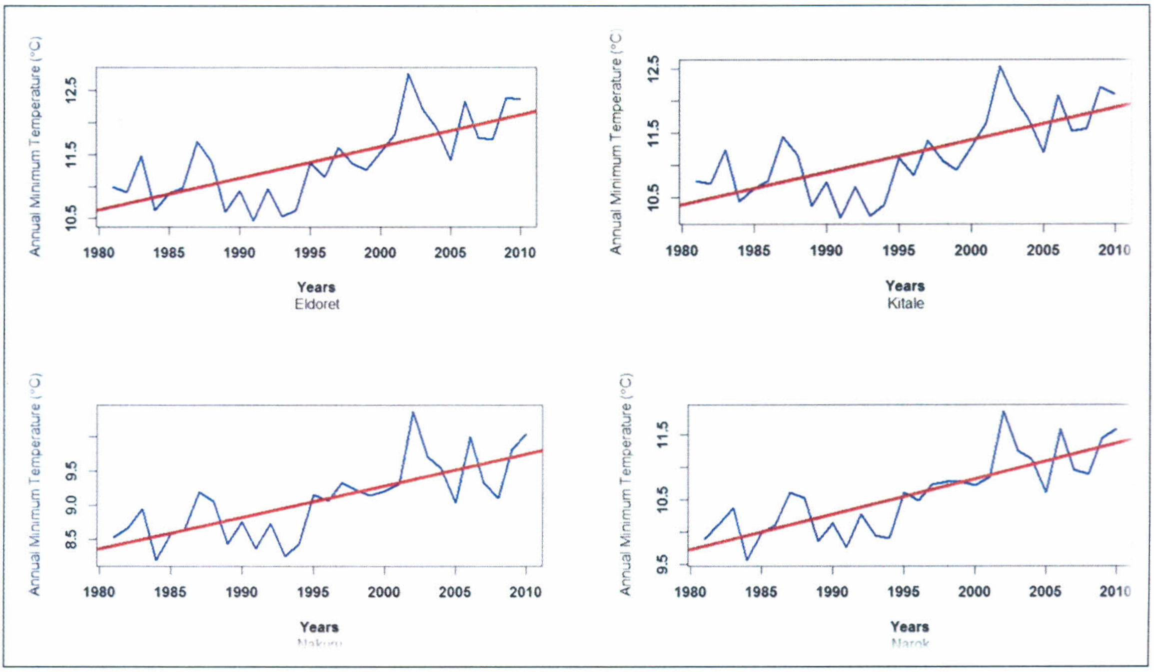

Figure 8: Trend of annual minimum temperature for Eldoret, Kitale, Nakuru and Narok stations (1981-2010).

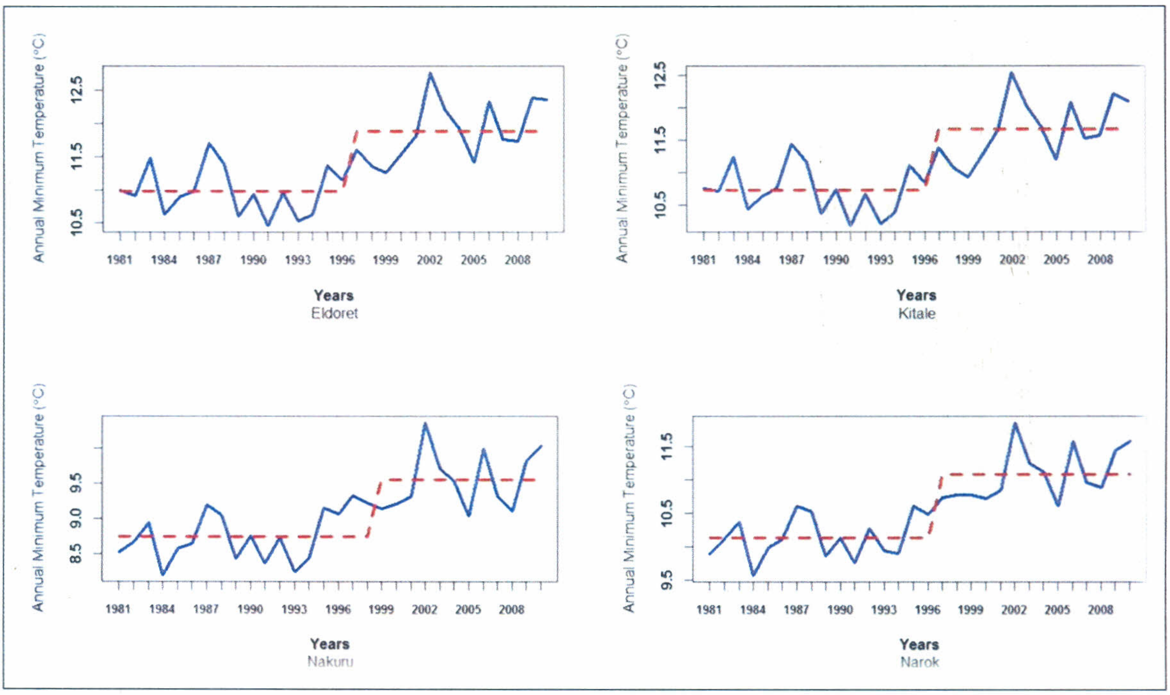

Figure 9: Shifts in annual mean minimum temperature for Eldoret, Kitale, Nakuru and Narok stations (1981-2010).

Table 8: Characteristics of baseline minimum temperature for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Minimum Temperature (⁰C)	Score	P- value (MK test)	P- value (P test)	Sens Slope Value
Eldoret	MAM	12.2	166	0.003	0.001	0.05
	JJA	11.0	201	0.0004	0.003	0.042
	OND	11.2	153	0.007	0.025	0.046
	Annual	11.4	222	<0.0001	0.0004	0.046
Kitale	MAM	11.9	168	0.003	0	0.05
	JJA	10.9	199	0.0004	0.002	0.042
	OND	10.9	154	0.006	0.025	0.045
	Annual	11.2	221	<0.0001	0.0004	0.049
Nakuru	MAM	10.0	174	0.002	0.002	0.043
	JJA	8.6	208	0.0002	0.001	0.039
	OND	9.0	150	0.008	0.033	0.042
	Annual	9.1	240	<0.0001	0	0.045
Narok	MAM	12.0	195	0.0005	0.001	0.05
	JJA	9.5	225	<0.0001	0.0003	0.049
	OND	10.2	186	0.0009	0.014	0.046
	Annual	10.6	275	<0.0001	0.001	0.055

4.2 Trends Patterns of Projected Climate for RCP4.5 Emission Scenario

4.2.1 Rainfall Pattern

Under RCP4.5 emission scenario based on the CNRM model outputs, rainfall is projected to increase over the study area for the period between 2021 and 2050 (Figures 10 and 11). These figures clearly show an increasing trend pattern and a shift in the mean of annual precipitation. Table 9 shows the characteristics of rainfall patterns for the simulation period for the study stations.

At Eldoret station, all seasons are projected to register an increase in rainfall except JJA rainy season. The highest rate of change and seasonal rainfall are expected to occur during the MAM rainy season at this station. Kitale station is expected to experience the most notable changes in its rainfall characteristics. It is expected to receive the highest amount of seasonal rainfall of 781.2mm during MAM rainy season which will have increased at a rate of +6.4mm/year between 2021 and 2050. The highest annual total precipitation of 2265.3mm is projected for this station with a positive rate of change of +14.1mm/year.

Figure 10: Trend of rainfall based on RCP4.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050)

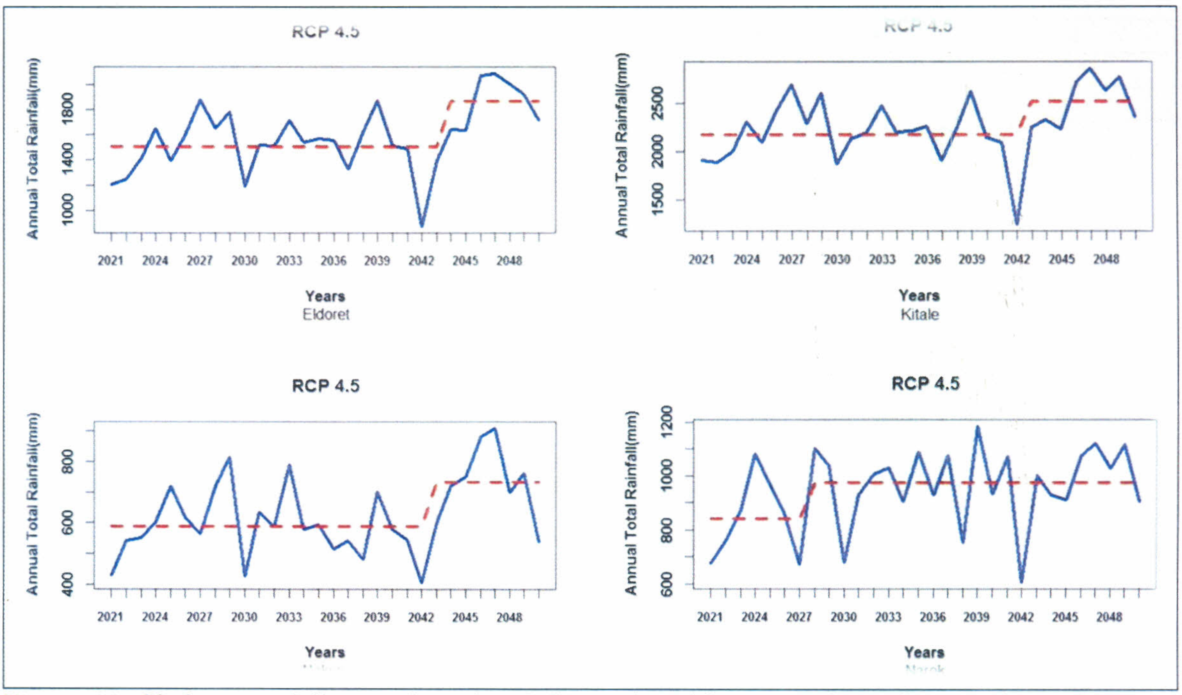

Figure 11: Shift in rainfall mean based on RCP4.5 for Eldoret, Kitale, Nakuru and Narok stations

Nakuru station is projected to experience increasing trend of rainfall patterns. The low projected values are an indication that Nakuru station will receive the lowest rainfall among the study stations. In addition, Nakuru is the only station that is expected to record an increasing trend during JJA rainy season. Narok station is expected to record the smallest rate of change during MAM rainy season as well as the lowest seasonal mean precipitation during the JJA rainy season. The JJA rainy season in this station is projected to register a decreasing trend pattern of rainfall.

Based on RCP4.5, the increasing trend and positive shifts in rainfall patterns will not be statistically significant as denoted by the p-values from Man-Kendall and Pettit's test which were higher than the significance level value.

Table 9: Characteristics of projected rainfall based on RCP4.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050)

Station	Season	Mean Rainfall(mm)	Score	P- value (MK test)	P- value (P test)	Sen's Slope Value
Eldoret	MAM	592.3	65	0.254	0.97	5.8
	JJA	289.8	-31	0.592	0.95	-1.4
	OND	468.7	43	0.454	0.34	3.4
	Annual	1587.7	125	0.269	0.06	12.9
Kitale	MAM	781.2	71	0.212	0.88	6.4
	JJA	528.9	-49	0.392	0.74	-2.7
	OND	611.4	23	0.695	0.39	3.1
	Annual	2265.3	133	0.019	0.09	14.1
Nakuru	MAM	233	35	0.544	0.68	1.2
	JJA	106.9	15	0.803	1.17	0.2
	OND	200.5	81	0.154	0.13	1.8
	Annual	627.2	81	0.154	0.21	4.8
Narok	MAM	414.5	13	0.830	1.32	0.6
	JJA	71.6	-5	0.943	0.88	-0.01
	OND	357.1	117	0.038	0.25	4.5
	Annual	944.6	91	0.108	0.45	5.4

4.2.2 Projected Maximum Temperature under RCP4.5

An analysis of projected climate under RCP4.5 shows that the four counties will experience an increasing trend and an upward shift in mean of annual maximum temperature for all the seasons (Figures 12 and 13, Table 10).

Figure 12: Trend of projected maximum temperature based on RCP4.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050).

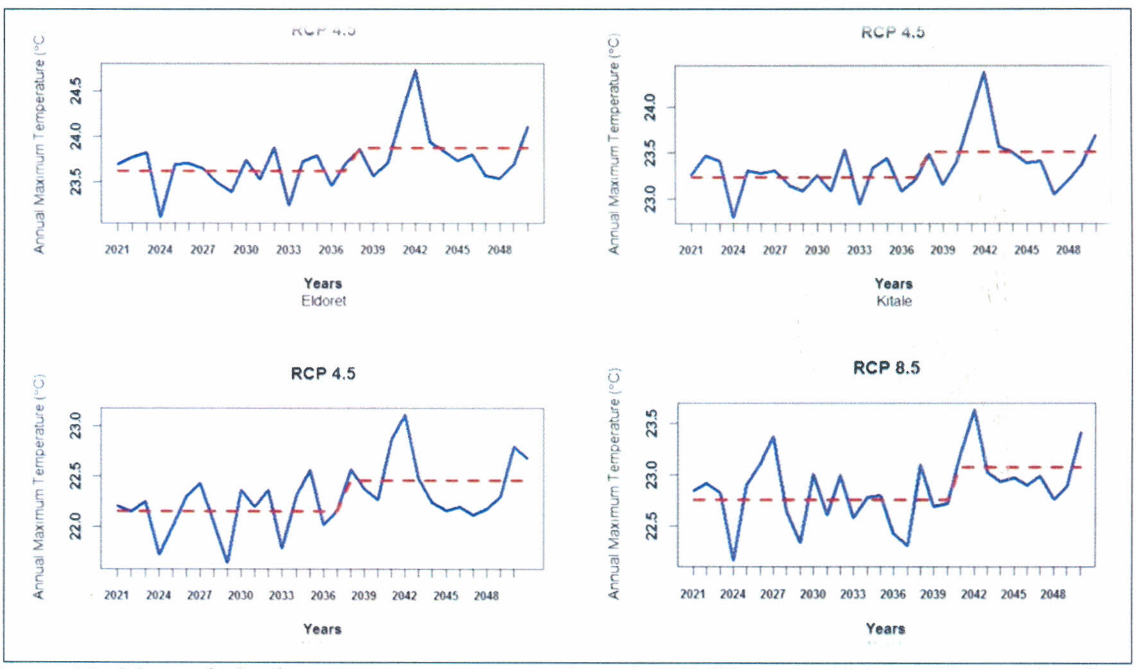

Figure 13: Mean shift of maximum temperature based on RCP4.5 for Eldoret, Kitale, Narok and Nakuru stations (2021-2050)

Generally, the p-values from Pettit's test for the stations were significantly higher than the level of significance value of 0.05. This indicates that the shift in the mean maximum temperatures will not be significant for projected climate under RCP4.5. The p-values from Mann Kendall test for Eldoret, Kitale and Nakuru during JJA season (Table 10) indicate that the increasing trend of maximum temperature under RCP4.5 is expected to be statistically significant between 2021 and 2050. Annual maximum temperature in Nakuru will register an increasing trend which is expected to be statistically significant.

Table 10: Characteristics of projected maximum temperature based on RCP4.5 for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Maximum Temperature (^{0}C)	Score	P- value (MK test)	P- value (P test)	Sens Slope Value
Eldoret	MAM	24.6	1	1	0.97	0.007
	JJA	22.8	116	0.04	0.11	0.025
	OND	22.4	7	0.91	0.92	0.003
	Annual	23.7	79	0.16	0.20	0.007
Kitale	MAM	24.4	-29	0.62	1.32	-0.006
	JJA	22.1	109	0.05	0.14	0.022
	OND	22.0	1	1	1.04	0.002
	Annual	23.4	85	0.13	0.11	0.007
Nakuru	MAM	23.0	59	0.32	0.61	0.009
	JJA	21.6	149	0.01	0.07	0.026
	OND	21.1	17	0.79	0.61	0.002
	Annual	22.3	119	0.04	0.13	0.006
Narok	MAM	23.3	1	1	1.02	0.001
	JJA	22.5	81	0.17	0.07	0.023
	OND	21.8	-7	0.91	1.51	-0.001
	Annual	22.9	17	0.79	0.13	0.006

4.2.2 Projected Minimum Temperature based on RCP4.5

Based on RCP4.5, annual minimum temperatures are projected to register an increasing trend (Figure 14) and a shift in the mean across the study stations (Figure 15).

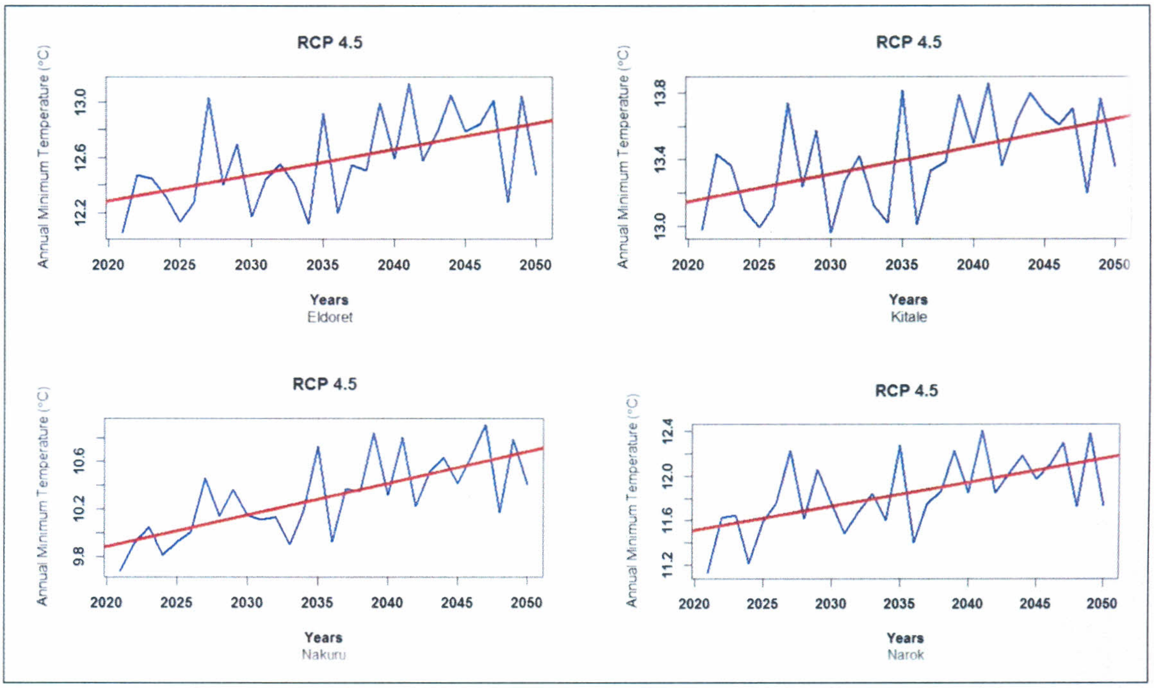

Figure 14 Trend of projected annual minimum temperature under RCP 4.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050).

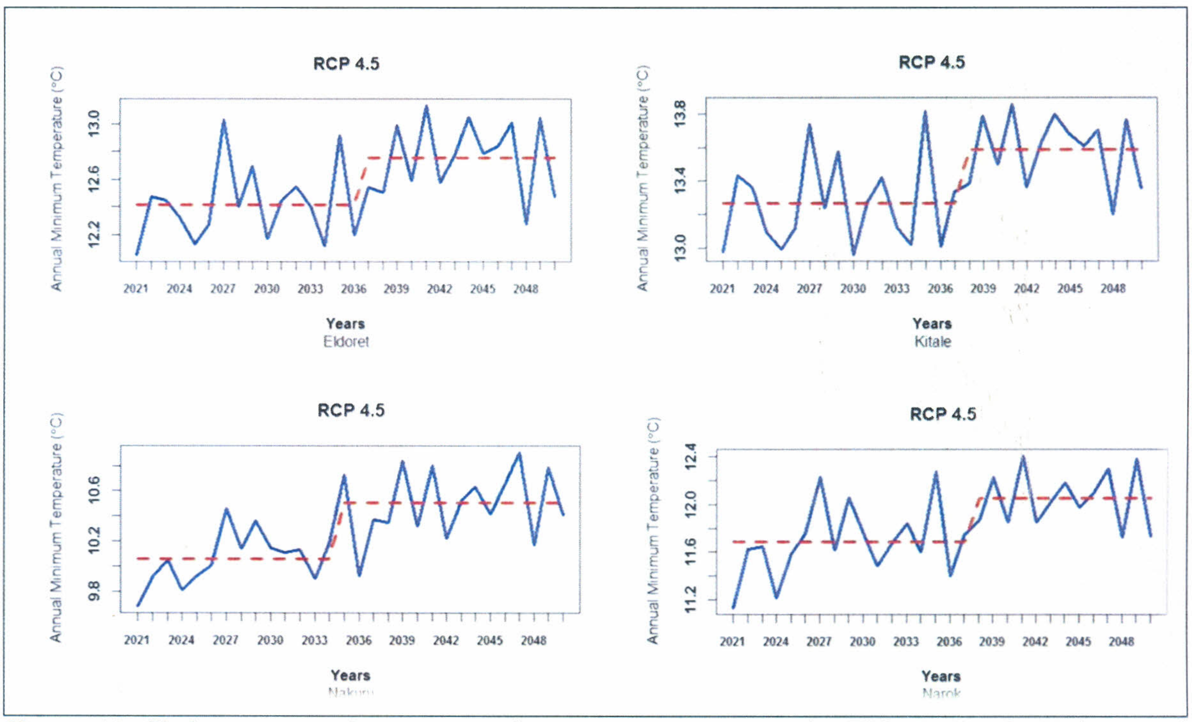

Figure 15: Shift in projected mean annual minimum temperature for Eldoret, Kitale, Nakuru and Narok stations between 2021 and 2050 (RCP4.5).

Generally, minimum temperature is projected to increase as illustrated by positive values of the scores (Table 11).

It is also apparent that the rate of change is projected to be positive for each of the seasons in all the study stations. The highest minimum temperature is projected for the MAM rainy season ranging from 10.7^{0}C to 14.0^{0}C. Notably, the p- values generated from Mann- Kendall test for projected minimum temperature over Nakuru station for annual and MAM are very much smaller than the value of the significance level (0.05) hence it is expected that its increasing trend of minimum temperature will be statistically significant. Annual and OND's minimum temperature in Eldoret, will have significant mean shift and trend patterns. Kitale and Narok will record increasing annual minimum temperature that will be statistically significant.

Table 11: Characteristics of projected minimum temperature under RCP 4.5 for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Minimum Temperature (^{0}C)	Score	P- value (MK test)	P- value (P test)	Sens Slope Value
Eldoret	MAM	13.2	77	0.175	0.15	0.016
	JJA	12.5	51	0.372	1.04	0.012
	OND	12.0	137	0.015	0.03	0.018
	Annual	12.6	167	0.003	0.02	0.020
Kitale	MAM	14.0	73	0.199	0.16	0.015
	JJA	13.9	61	0.284	0.64	0.013
	OND	12.5	91	0.108	0.11	0.015
	Annual	13.4	129	0.030	0.03	0.019
Nakuru	MAM	10.7	171	0.002	0.04	0.028
	JJA	10.0	147	0.009	0.16	0.028
	OND	10.2	153	0.007	0.04	0.0257
	Annual	10.3	231	0.000	0.00	0.028
Narok	MAM	12.7	85	0.134	0.23	0.014
	JJA	10.3	91	0.108	0.51	0.020
	OND	12.2	104	0.066	0.26	0.014
	Annual	11.8	179	0.001	0.01	0.022

4.3 Trends and Patterns of Projected Climate based on RCP8.5

4.3.1 Rainfall Trend

Projections under RCP8.5 that were obtained from CNRM model showed that in Eldoret and Kitale, annual rainfall will increase while Nakuru and Narok will register decreasing trend (Figure 16). Figure 17 shows that a general shift in the annual mean rainfall will be recorded for the period between 2021 and 2050.

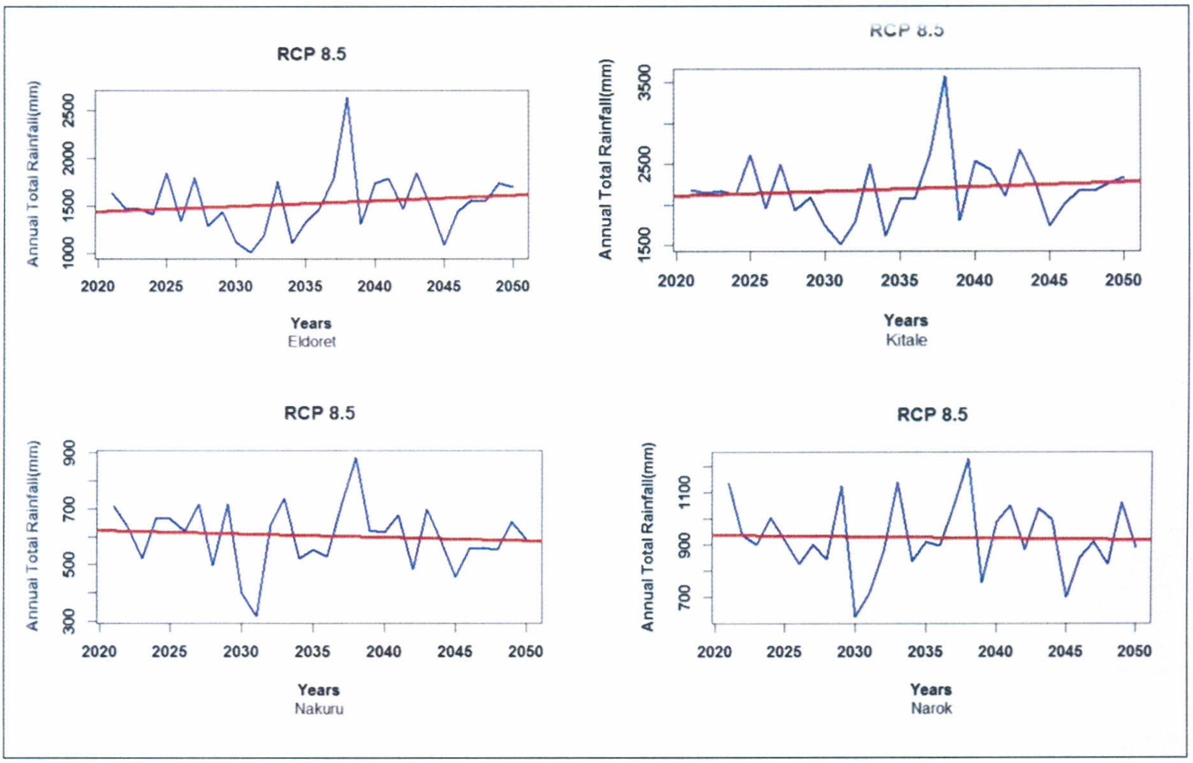

Figure 16: Trend of annual rainfall patterns under RCP8.5 for Eldoret, Kitale, Nakuru and Narok (2021-2050)

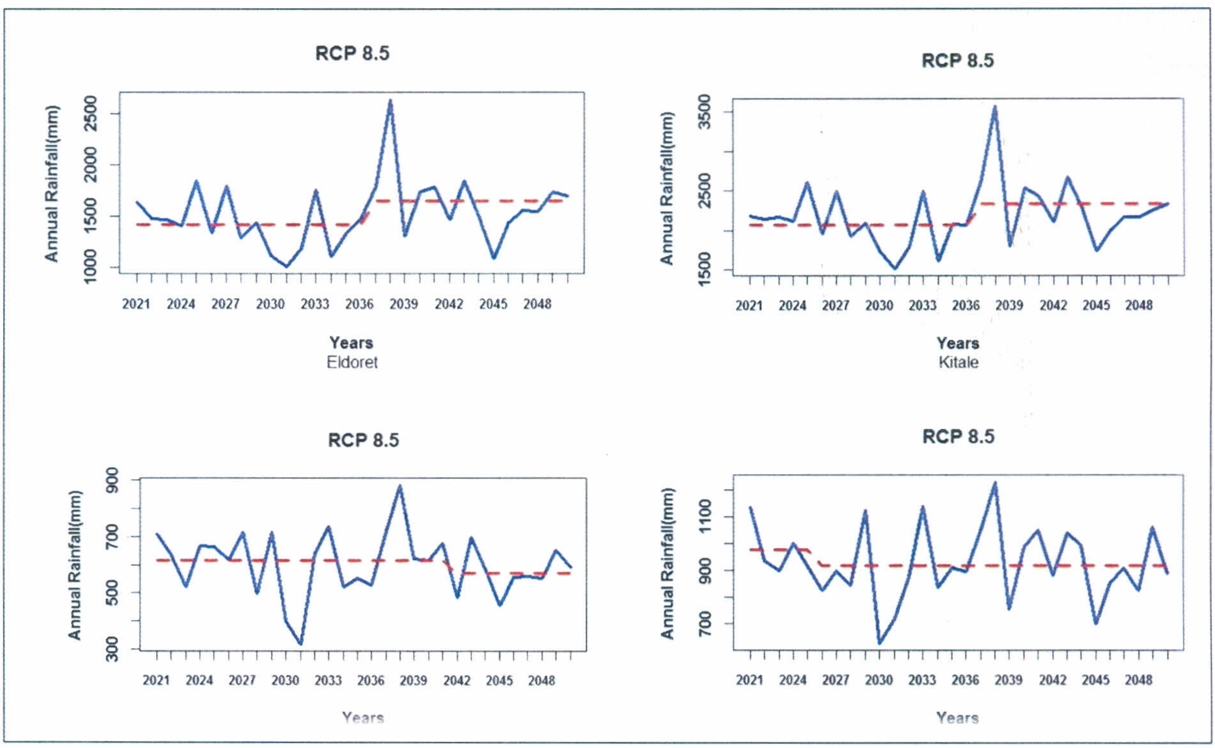

Figure 17: Mean shift of annual rainfall under RCP8.5 for the period between 2021 and 2050 for Eldoret, Kitale, Nakuru and Narok

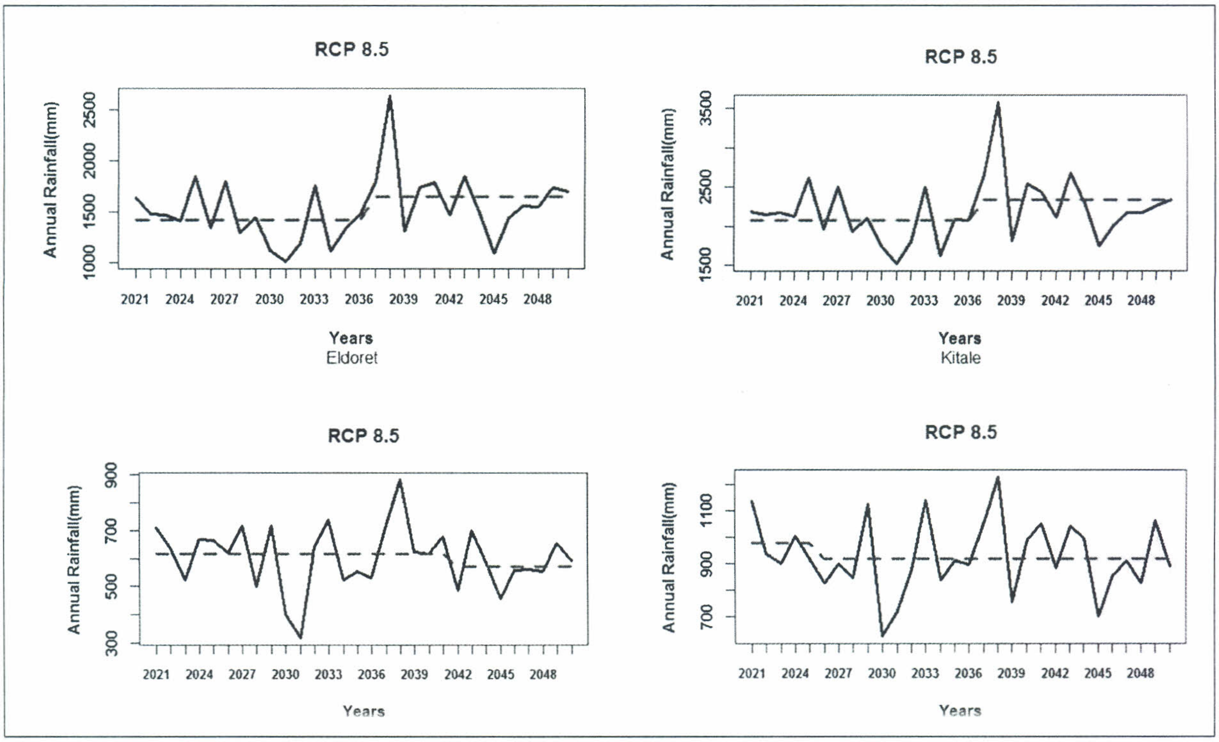

Figure 17: Mean shift of annual rainfall under RCP8.5 for the period between 2021 and 2050 for Eldoret, Kitale, Nakuru and Narok

Table 12 indicates that the rainfall patterns during MAM season in Eldoret, Kitale and Nakuru will have a declining trend. It was also noted that Eldoret and Kitale stations will have increasing rainfall trends during JJA and OND seasons with positive rates of change.

Table 12: Analysis results of projected rainfall under R.C.P 8.5 for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Mean Rainfall(mm)	Score	P- value (MK test)	P- value (P Test)	Sen's Slope Value
Eldoret	MAM	551.2	-39	0.50	0.52	-2.0
	JJA	320.8	45	0.43	0.54	2.2
	OND	425.8	63	0.27	0.54	4.27
	Annual	1525.4	39	0.50	0.30	5.1
Kitale	MAM	729.0	-41	0.48	0.31	-3.1
	JJA	2391.5	45	0.43	0.83	1.5
	OND	576.2	85	0.13	0.25	3.5
	Annual	2198.5	31	0.59	0.28	3.6
Nakuru	MAM	219.1	-35	0.54	0.76	-0.7
	JJA	117.4	41	0.48	0.54	0.6
	OND	188.7	-37	0.52	1.02	-0.7
	Annual	603.7	-41	0.48	0.99	-2.2
Narok	MAM	241.5	19	0.75	1.29	0.4
	JJA	82.5	63	0.27	0.51	1.1
	OND	343.4	-57	0.32	0.32	-1.2

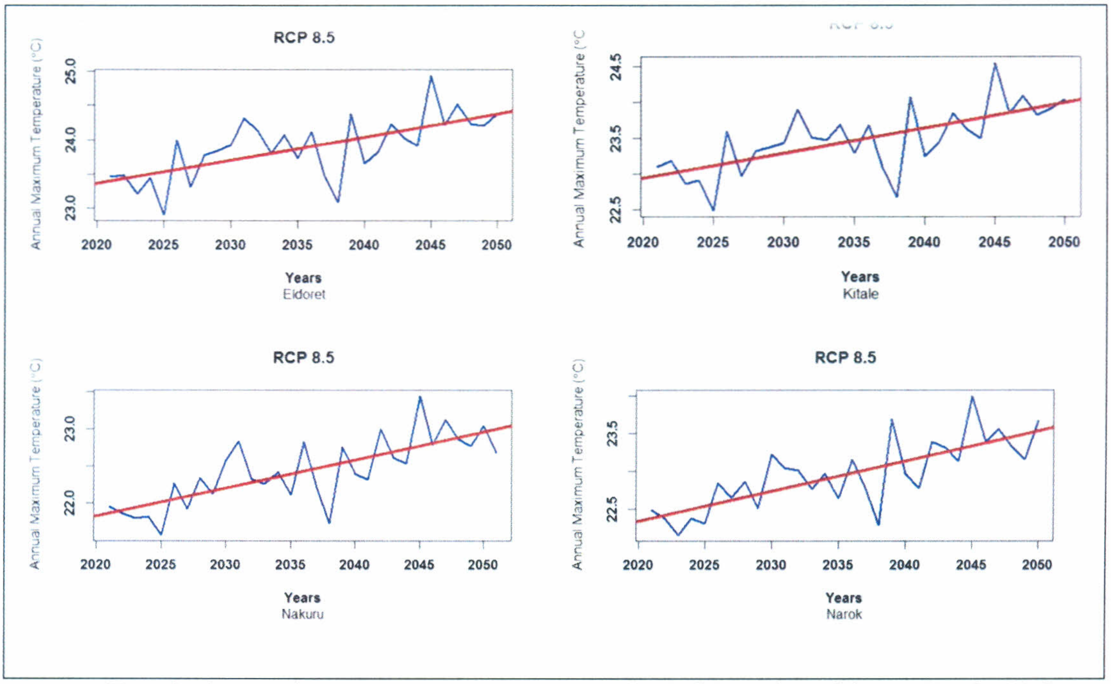

Figure 18: Trend of annual maximum temperature under RCP8.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050)

The mean shift of maximum temperature in Eldoret, Kitale and Narok, for annual and JJA are expected to be statistically significant. In Nakuru, it is only OND which is projected register mean shift of maximum temperature that will not be significant. Generally the p-values from Mann-Kendall were smaller than the significant level value of 0.05 denoting that the trend pattern of maximum temperature under RCP8.5 is expected to be significant in all stations.

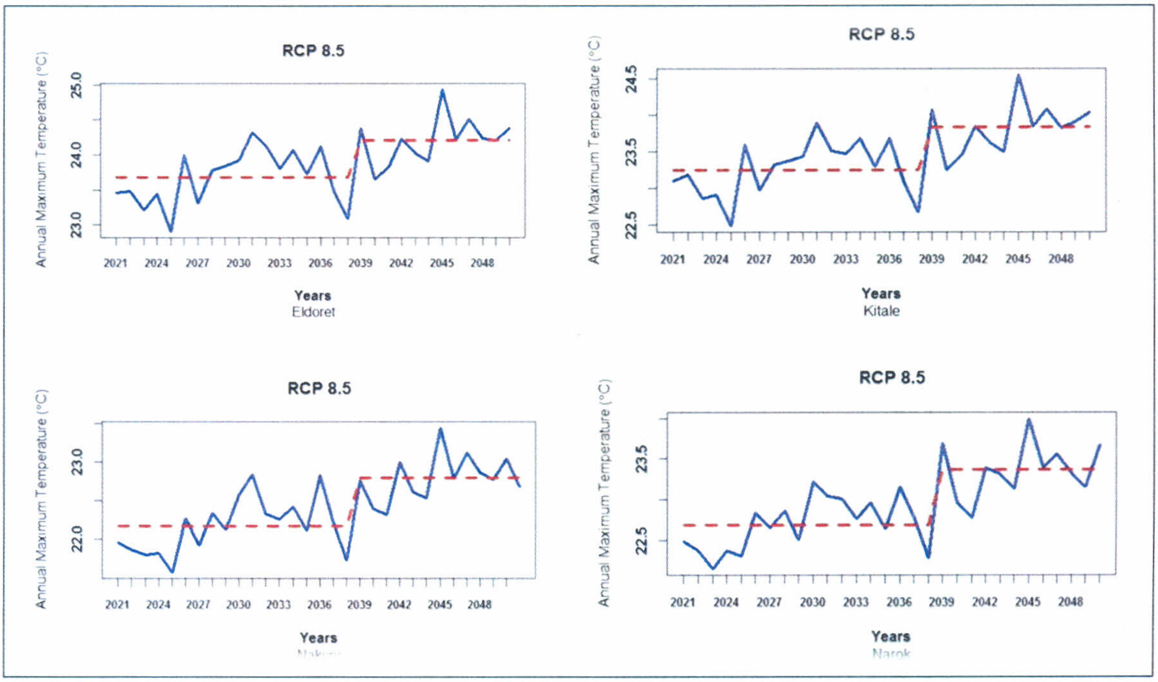

Figure 19: Mean shift of annual maximum temperature based on RCP 8.5 for Eldoret, Kitale, Nakuru and Narok stations (2021-2050)

Table 13: Analysis results of projected maximum temperature under RCP 8.5 for Eldoret, Kitale, Nakuru and Narok stations

Station	Season	Maximum Temperature (^{0}C)	Score	P- value (MK test)	P- value (P test)	Sens Slope Value
Eldoret	MAM	24.7	161	0.0043095	0.073	0.045
	JJA	22.9	207	0.0002	0.014	0.035
	OND	22.7	73	0.20	0.578	0.018
	Annual	23.9	207	0.0002	0.012	0.032
Kitale	MAM	24.5	151	0.007	0.086	0.044
	JJA	22.2	197	0.0005	0.014	0.035
	OND	22.2	77	0.18	0.578	0.017
	Annual	23.5	223	<0.00001	0.007	0.035
Nakuru	MAM	23.2	185	0.002	0.020	0.046
	JJA	21.7	253	0.00002	0.004	0.038
	OND	21.3	129	0.03	0.263	0.027
	Annual	22.5	249	0.00002	0.002	0.036
Narok	MAM	23.4	157	0.005	0.011	0.046
	JJA	22.1	211	0.0002	0.006	0.040
	OND	21.9	177	0.002	0.056	0.036
	Annual	23.0	237	0.00003	0.001	0.038

In Eldoret and Kitale stations, the mean shift of maximum temperature for annual and JJA season is expected to be significant. Significant mean shift of maximum temperature under RCP8.5 is expected in Nakuru and Narok for Annual, MAM and JJA seasons.

4.3.3 Minimum Temperature Characteristics of Projected Climate based on RCP 8.5

Figure 20 shows that the annual trend patterns of minimum temperature are expected to record an increasing trend. It is also expected that the mean of annual minimum temperature will shift upwards as illustrated by Figure 21. The results also showed that the four stations will register increased maximum temperature during all the seasons for the period between 2021 and 2050 (Table 14).

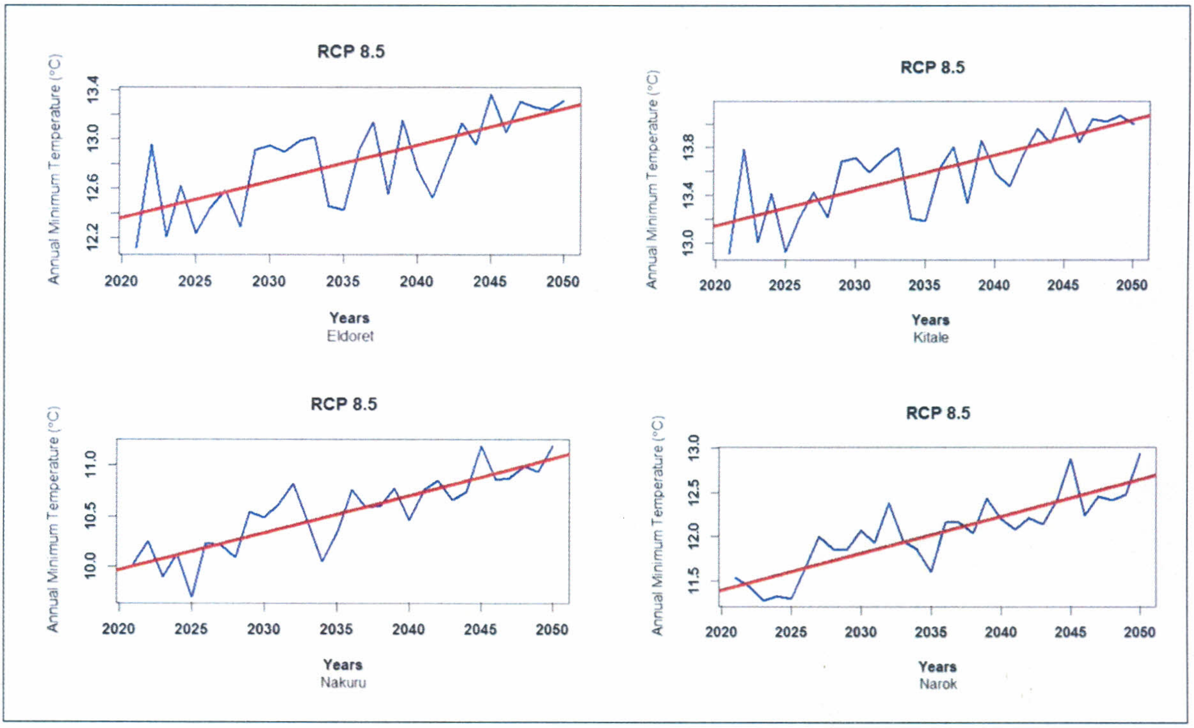

Figure 20: Trend of annual minimum temperature between 2021 and 2050 for Eldoret, Kitale, Nakuru and Narok stations (RCP 8.5)

Figure 21: Mean shift of annual minimum temperature between 2021 and 2050 for Eldoret, Kitale, Nakuru and Narok stations (RCP8.5)

In reference to Table 14, the minimum temperature is expected to increase at positive rates of change and have ascending trends. It is noticeable that the highest minimum temperature of 14.1^{0}C will occur during MAM season in Kitale.

Table 14: Minimum temperature characteristics for Eldoret, Kitale, Nakuru and Narok stations between 2021 and 2050 (RCP8.5)

Station	Season	Minimum Temperature (^{0}C)	Score	P- value (MK test)	P- value (P test)	Sens Slope Value
Eldoret	MAM	13.4	127	0.02	0.02	0.026
	JJA	12.9	207	0.0002	0.09	0.038
	OND	12.2	155	0.006	0.010	0.024
	Annual	12.8	237	0.00003	0.008	0.029
Kitale	MAM	14.1	131	0.02	0.02	0.027
	JJA	14.1	135	0.02	0.19	0.028
	OND	12.7	217	0.0001	0.01	0.025
	Annual	13.6	255	0.00006	0.002	0.030
Nakuru	MAM	11.1	183	0.001	0.005	0.031
	JJA	10.3	253	0.00002	0.003	0.040
	OND	10.5	301	<0.000001	0.0004	0.036
	Annual	9.0	150	0.008	0.03	0.042
Narok	MAM	12.8	197	0.0005	0.005	0.033
	JJA	10.6	197	0.0005	0.003	0.058
	OND	12.3	104	0.07	0.003	0.029
	Annual	12.1	311	< 0.00001	0.0004	0.039

The table also showed that results from Mann- Kendall and Pettit's test yielded p-values that were generally smaller than the significance level value of 0.05. Therefore, the upward trend patterns and mean shift of minimum temperature will be statistically significant.

4.4 Comparison between the Baseline and Projected Climates

4.4.1 Rainfall

Figure 22 shows bar plots of change rates of annual and seasonal rainfall for baseline and projected climate under RCP4.5 and RCP8.5.

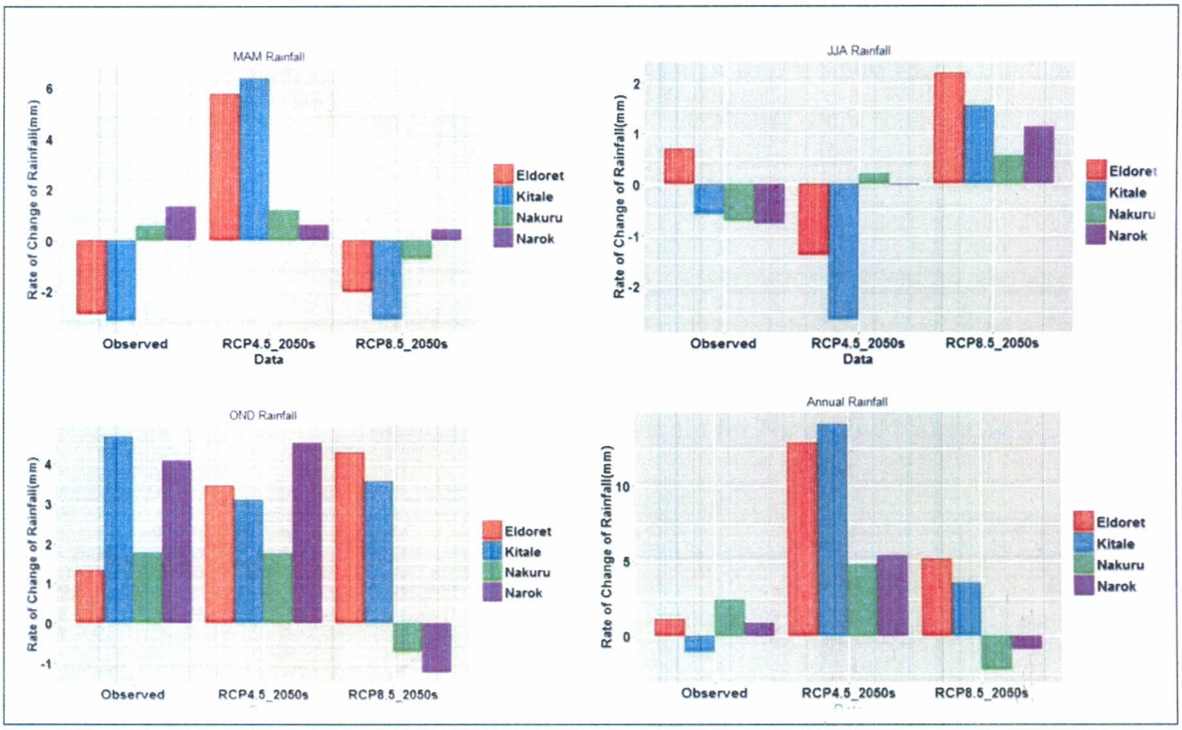

Figure 22: Barplots of change rates of annual and seasonal precipitation

Generally, Uasin Gishu and Trans Nzoia recorded a decrease in rainfall during MAM season throughout the baseline period. As for Narok and Nakuru, rainfall increased in the same season for the period between 1981 and 2010. During JJA season, Uasin Gishu recorded an increase in rainfall. All counties registered an increase in rainfall amounts during OND season under the baseline period. Climate simulations based on RCP4.5 for the period between 2021 and 2050 indicated that rainfall is expected to increase in all counties during MAM season. Nakuru is the only county whose JJA season is expected to record an increase in rainfall. All counties are expected to experience a rise in seasonal rainfall during OND. Under RCP8.5, rainfall is expected to decrease during MAM in all counties except Narok. It was noted that rainfall amount expected to experience a rise in seasonal rainfall during OND. Under RCP8.5, rainfall is expected to decrease during MAM in all counties except Narok. It was noted that rainfall amount will be on the rise during JJA in all counties. Whereas Nakuru and Narok are expected to have a decrease, Trans Nzoia and Uasin Gishu will experience a rise in rainfall throughout OND based on RCP 8.5. As for annual rainfall, increasing trend patterns were recorded in all counties except Kitale which had negative score value of -19 during the base line duration. Notable increase in annual rainfall is expected under RCP4.5 in all stations for the period between 2021 and 2050. While Uasin Gishu and Trans Nzoia are expected to register upward trend of annual rainfall based on RCP8.5, Narok and Nakuru will record negative change rates for the period between 2021 and 2050. Notably, the rainfall patterns and mean shift under the baseline period, RCP4.5 and RCP8.5 had p-values that were higher that the significance level value of 0.05 and hence were found not to be statistically significant.

According to a study done by (Parry *et al.*, 2012), observations showed an increase in rainfall during the short rain season(OND). Similarly, trend analysis in this study indicated a rise in rainfall during OND in all counties. Further, (Parry *et al.*, 2012) noted that rainfall reduced during MAM season. This was true for Uasin Gishu and Kitale but not for Narok and Nakuru.

4.4.2 Temperature

The comparison of maximum and minimum temperature for baseline, RCP4.5 and RCP8.5 is shown in Figures 23 and 24.

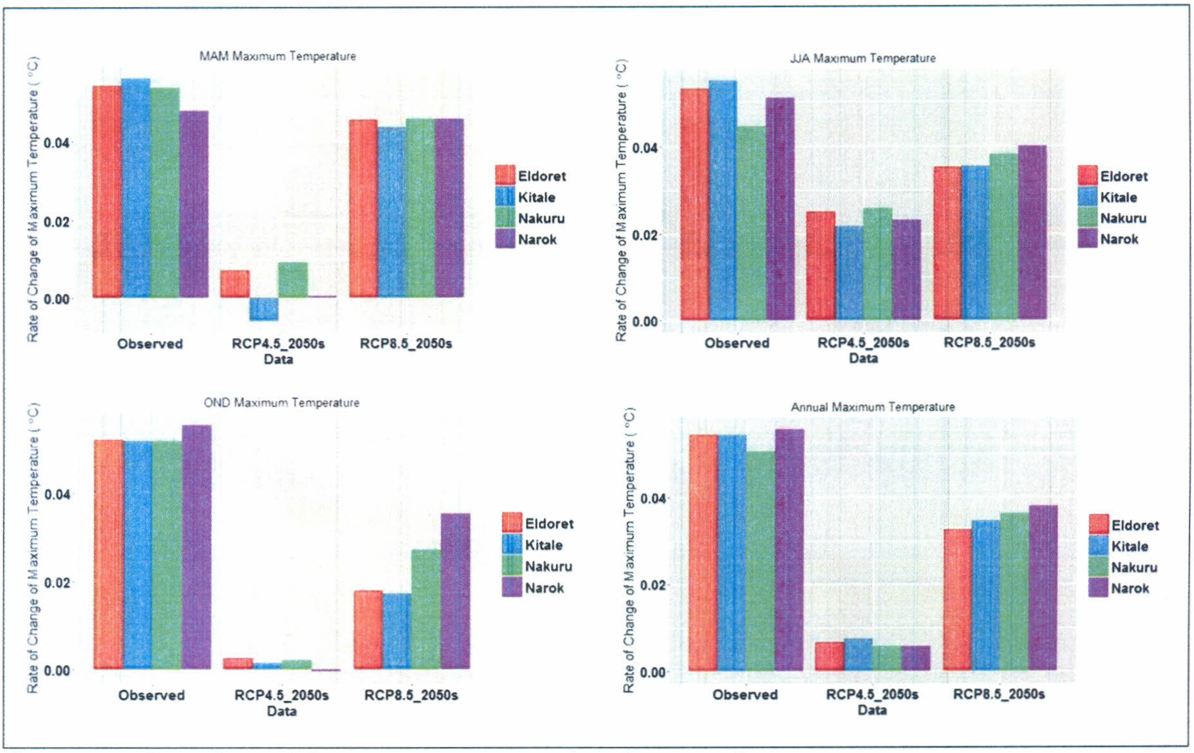

Figure 23: Bar plots of change rates of annual and seasonal maximum temperature.

During the baseline period, there was a notable mean shift and ascending trend patterns of maximum temperature in all counties during all seasons. Similarly, minimum temperature recorded an ascending trend pattern and mean shift that was significant in all counties throughout all seasons between 1981 and 2010. Generally, the rate change of minimum and maximum temperature under the base line period was between 0.042^{0}C and 0.058^{0}C. It is expected that based on RCP4.5, maximum temperature will record an increasing trend and mean shift that will not be significant during the simulation period between 2021 and 2050. Notably, Kitale will have a declining change rate in MAM while Narok will record a negative change rate during OND. Kitale, Narok and Nakuru are expected to record annual mean shift and trend patterns of minimum temperature that will be statistically significant. The mean shift and upward trend patterns of minimum temperature in Eldoret for annual and OND are predicted to be significant. The change rates of temperature are expected to range between 0.001^{0}C and 0.028^{0}C for projected climate under RCP4.5. Based on RCP8.5, the results revealed that maximum and minimum temparature will record significant ascending trend patterns and mean shift in all stations throughout all seasons. The temperature under this scenario will change at a rate ranging from 0.017^{0}C to 0.058^{0}C.

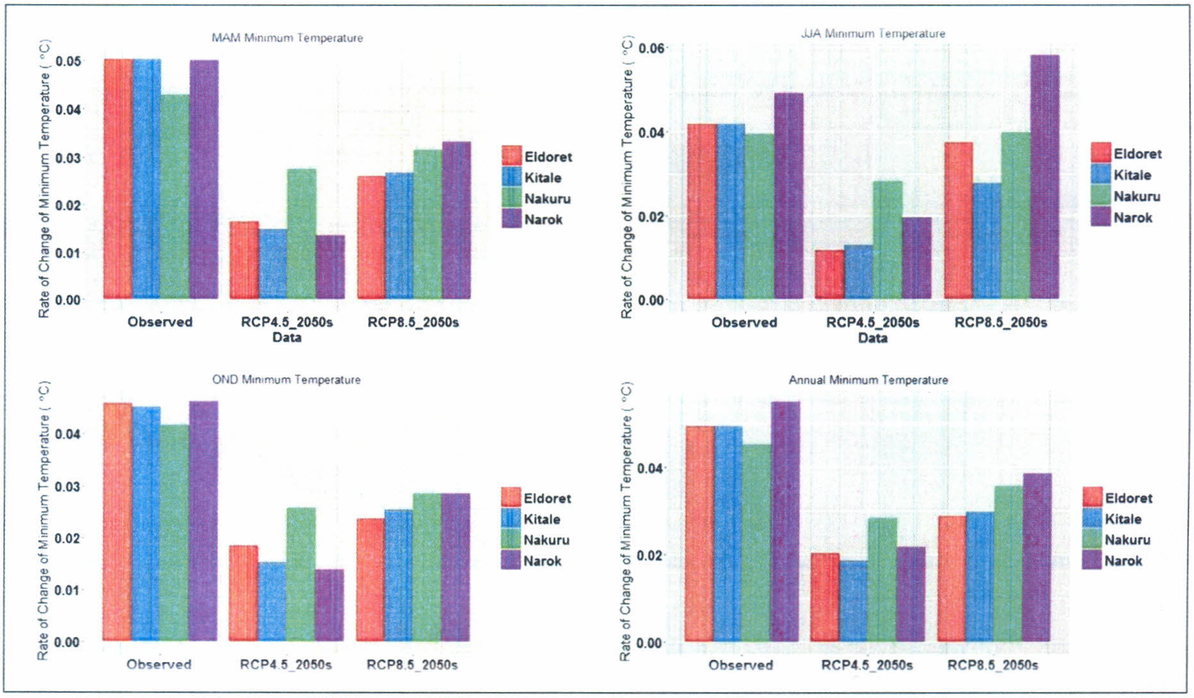

Figure 24: Bar plots of change rates of annual and seasonal minimum temperature.

In summary, the deduction that can be made from baseline and projected climate analysis is that the emission and concentration of GHGs have a profound influence temperature . It is also clear that the mitigation policies imposed to manage climate change under RCP4.5 will reduce the change rate at which temperature will increase in the study counties. On the contrary, a scenario under RCP8.5 means that the emmsions and concentration of GHGs will increase continually leading to temperatures increasing upto 2050.

4.5 Land Use/Land Cover Trends (1984, 2000, 2015)

An analysis of changes in land use and land cover was carried out using satellite images obtained from Landsat 5 (1984 TM), Landsat 7 (2000 ETM) and Landsat 8 (2015 OLI), whose resolutions were 30 metres. The results revealed eight classes under which land use/land cover in the study area was categorized. These classes encompassed forestland, shrub land, grassland, cropland, water body, wetland, built up area and bare land (Figure 25).

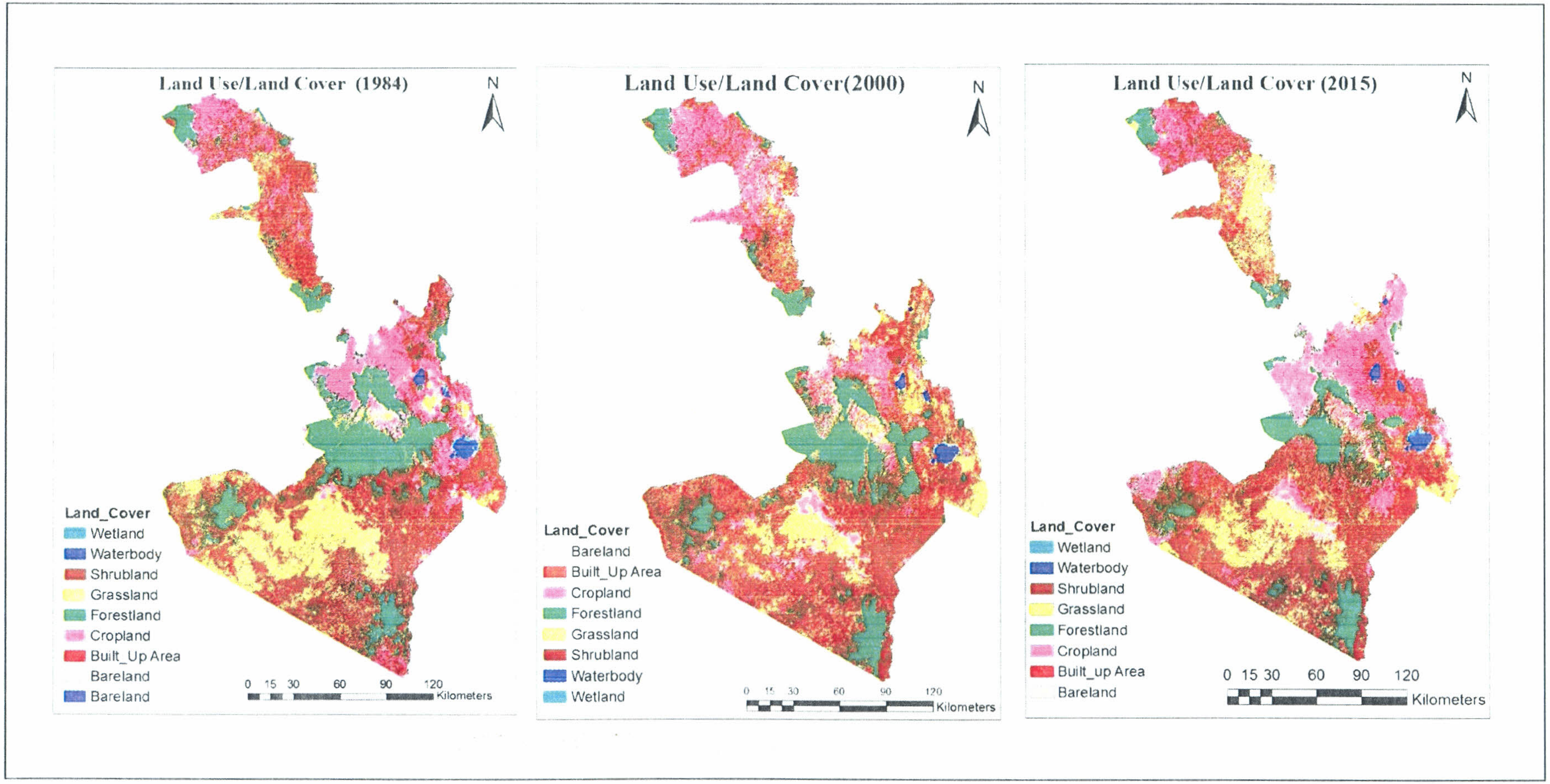

Figure 25: Classification of Land use/Land Cover for 1984, 2000 and 2015

Figure 26, 27 and 28 illustrate the percentage area coverage of land use/land cover classes for 1984, 2000 and 2015 respectively. It is apparent that shrub land covered the largest portion of land in the study area. Notably, its area coverage increased in 2000 and reduced by 2015. The area coverage of forest land declined significantly with the largest decrease occurring in 2015.

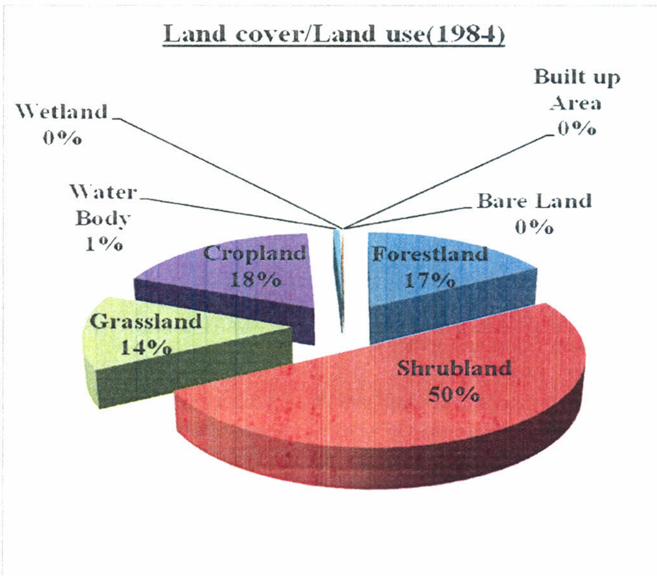

Figure 26: Pie chart for percentage area coverage of Land use/Land cover classes in 1984

The trend of crop land reduced slightly in 2000 as compared to its cover in 1984. However, by 2015, the percentage of land used for cropping had increased to 21% from a coverage of 17% that was observed in 2000.

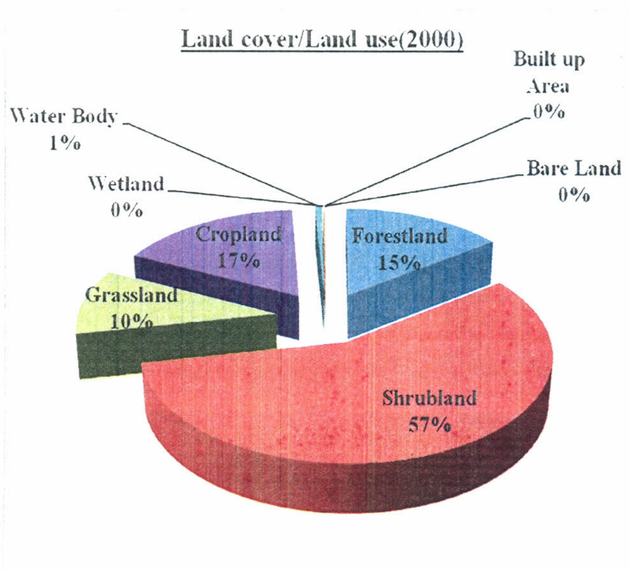

Figure 27: Pie chart for percentage area coverage of Land use/Land cover classes in 2000

In 2000, part of the grass land had been taken up by other land uses which reduced its coverage from 14% in 1984 to 10% in 2000. Despite this, the acreage covered by grass had an upward trend in 2015. Although its percentage area coverage was significantly minimal, the built up area was the only land cover classification that recorded an ascending trend throughout.

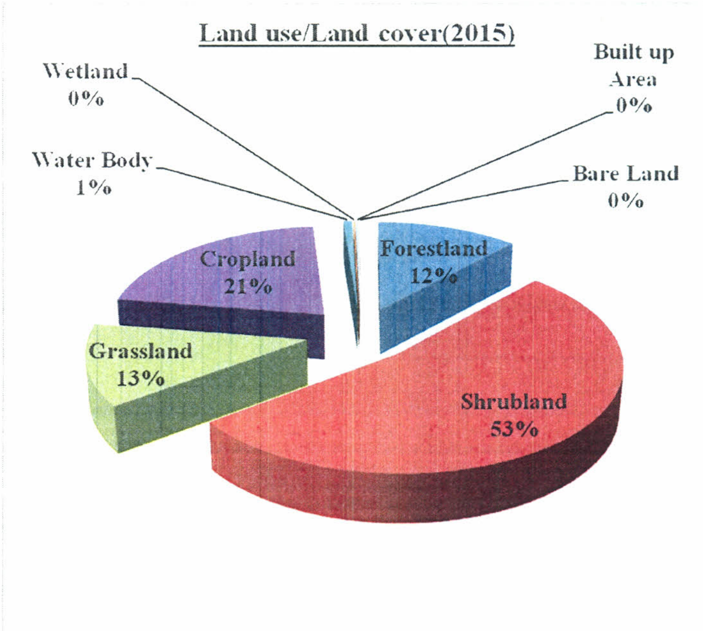

Figure 28: Pie chart for percentage area coverage of Land use/Land cover classes in 2015

In summary, forestland, cropland, shrub land and grassland were the main classes of land use in the study area which had notable variation in percentage coverage. Water body, built up area, bare land and wetlands accounted for only 1% of the total acreage in the study area. Although built up area increased steadily, its percentage coverage was greatly small. There was a decrease in forest land and crop land in 2000 as compared to their percentage coverage in 1984. By 2015, cropland had increased significantly while forests registered notable declining trend. In reference to Figure 25, it is obvious that areas that were initially forests had been replaced by cropland. This implies that the reduction of forest lands was a result of expansion of acreage under crop production.

The land use/ land cover results show that forest land was converted into cropland in the study area. This increased the maize production in the short term and hence the yields. However, over time, water scarcity increased and the frequency of extreme weather events escalated. As a result, the exposure of the study area to negative impacts of climate change increased, hence increasing the vulnerability of the area. The results agree with earlier studies by Epule *et al* (2011), Lobell *et al (*2011), Epule & Bryant (2014), and Stephenne & Lambin (2001).

4.6 Relationship between Annual Maize yields and Observed Climate.

The correlation analysis revealed that the relationship between maize yields and rainfall had a notable positive correlation coefficient of 0.51 during the seedling and grain filling, and maturity growth stages in Nakuru County (Table 14). Also, maize yields and minimum temperature had a positive relationship with significant coefficients during the seedling growth stage (0.45) and vegetative growth stage (0.56). Narok had a negative correlation coefficient of -0.39 between rainfall and maize yields during the vegetative growth stage. It was in the same county that maximum temperature and maize yields had positive relationship with coefficients of 0.52 and 0.50 for the vegetative growth and flowering and fertilization stages respectively. In Trans Nzoia County, rainfall and maize yields had positive correlation coefficients of 0.64 and 0.55 during seedling growth and grain filling, and maturity stages respectively. The most notable correlation coefficient between maize yields and maximum temperature in the county was realized during the vegetative growth stage (0.50). Uasin Gishu registered a correlation coefficient of 0.52 between maize yields and rainfall during the grain filling and maturity stage which was highest amongst the four growth stages. Maximum temperature had the most notable influence on maize yields during the vegetative growth stage (0.60).

Table 15: Spearman's Correlation Coefficient

County	Correlation	Seedling Growth	p-value	Vegatative Growth	p-value	Flowering % Fertilization	p-value	Grain filling% Maturity	p-value
Nakuru	Rfall /Yield	0.51	0.03	-0.18	0.86	0.16	0.25	0.51	0.08
	Tmax/Yield	0.12	0.92	-0.07	0.26	0.07	0.63	-0.24	0.48
	Tmin/Yield	0.45	0.27	0.56	0.20	0.29	0.72	-0.01	0.81
Narok	Rfall/Yield	0.24	0.11	-0.39	0.56	0.09	0.77	-0.05	0.67
	Tmax/Yield	-0.23	0.85	0.52	0.66	0.50	0.59	-0.05	0.46
	Tmin/Yield	0.19	0.55	-0.06	0.98	0.18	0.50	0.24	0.59
Trans Nzoia	Rfall/Yield	0.64	0.07	0.09	0.69	0.23	0.35	0.55	0.18
	Tmax/Yield	-0.22	0.25	0.50	0.22	-0.04	0.73	-0.13	0.94
	Tmin/Yield	-0.04	0.82	-0.20	0.87	0.08	0.90	0.26	0.29
Uasin Gishu	Rfall /Yield	0.28	0.24	-0.14	0.75	0.11	0.65	0.52	0.24
	Tmax/Yield	-0.13	0.62	0.60	0.28	-0.43	0.05	-0.35	0.80
	Tmin/Yield	-0.20	0.92	0.08	0.87	0.15	0.73	0.16	0.78

4.7 Vulnerability of Maize Production to Climate change.

PCA resulted into three major principal components whose Eigen values were greater than one. These components explained 100% of the variation in the data set with 51.2%, 25.3% and 23.5% of the variation being accounted for by the first, second and third component respectively. The first principal component was used to develop the vulnerability indices. The weights of the vulnerability indicators in the first component were multiplied by their respective normalized values and later aggregated to obtain the indices. The exposure, sensitivity, adaptive capacity and vulnerability indices for each county are recorded in Table 16.

Table 16: Exposure, Sensitivity, Adaptive capacity and Vulnerability indices

County	Exposure Index	Sensitivity Index	Adaptive Capacity Index	Vulnerability Index
Nakuru	0.48	0.71	1.13	0.35
Narok	1.03	0.21	-2.28	1.51
Trans Nzoia	0.19	0.75	2.58	-0.21
Uasin Gishu	0.61	0.64	2.60	-0.12

4.7.1 Exposure Indices

The exposure indices for the counties ranged from 0.19 to 1.03 (Table 16, Figure 29). Narok had the highest exposure index of 1.03 while Trans Nzoia emerged as the least exposed county with an index of 0.19. The second and third highest exposure indices were recorded in Uasin Gishu (0.61) and Nakuru (0.48) respectively. The growth and development of crops is highly dependent on prevailing climate conditions(temperature and rainfall patterns) and extreme weather events (Li *et al.*, 2015). Climate change exacerbates the exposure of farmers by triggering new and unknown alterations in temperature and rainfall patterns including increased recurrence rate of droughts and floods (Gbetibouo *et al.*, 2010). In comparison, temperature affects maize production to a greater extent than precipitation (Kabubo-Mariara & Karanja, 2007). Evidently, Narok recorded the highest change rate of maximum temperature (0.056^{0}C/year) and minimum temperature (0.055^{0}C/year). Also, it recorded a total of five floods and six droughts during the baseline period. Trans Nzoia registered the second highest change rates of maximum temperature and minimum temperature of 0.054^{0}C/year and 0.049^{0}C/year respectively. A total of three droughts and five floods were observed in the county between 1981 and 2010. Evidently, the peak exposure index realized in Narok was as a result of its high temperature variation which was highest among the four counties.

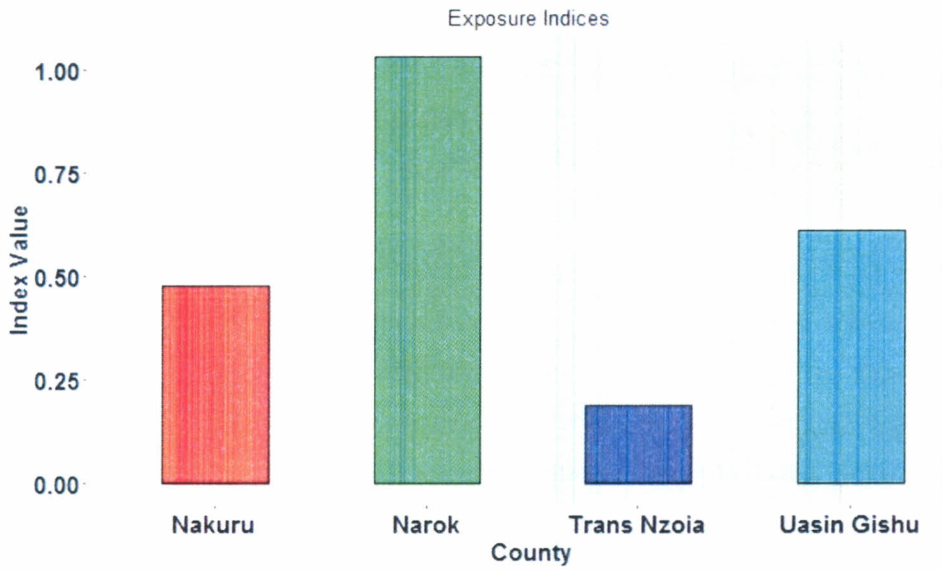

Figure 29: Exposure indices by County.

Additionally, the considerably high frequency of extreme weather events contributed significantly to the peak exposure index in the county. Although Trans Nzoia had the second highest change rates in maximum and minimum temperature, it emerged as the least exposed county due to least frequency of droughts and floods during the baseline period. The least change rates of maximum temperature (0.051^{0}C/year) and minimum temperature (0.045^{0}C/year) were observed in Nakuru County. Uasin Gishu had the same rate of change of minimum temperature with Trans Nzoia (0.54^{0}C/year) and the third highest minimum temperature change rate (0.046^{0}C/year). Notably, Nakuru and Uasin Gishu recorded the highest number of droughts (6) and floods (7). Uasin Gishu and Nakuru recorded higher exposure indices than Trans Nzoia due to their peak frequency of extreme weather events. The results obtained in this study for exposure indices agree with the observation made by (Gbetibouo *et al.*, 2010) that farming areas with high variability in climate patterns and peak occurrence rate of extreme weather events are likely to be highly exposed to climate change.

4.7.2 Sensitivity Indices

Sensitivity indices for the study counties ranged from 0.21 to 0.75 (Figure 30). Trans Nzoia emerged as the most sensitive county with an index of 0.75. The minimal sensitivity was recorded in Narok County with a value of 0.21. The second highest and the second least sensitivity indices were recorded in Nakuru (0.71) and Uasin Gishu (0.64) respectively. Trans

Nzoia recorded the highest percentage of farmers who practiced maize production (98%), density of rural population (328 people/km^2), percentage of people living under poverty line (50.1%) and absolute reliance of maize production on rainfall (100%). As a result, more people were at the risk of being adversely affected by change in climate and hence exhibited higher sensitivity levels. Narok recorded the least density of rural population (48people/km^2), percentage of farmers who practiced maize production (85.7%) and percentage of people living under poverty line (33.7%). Thus fewer people were exposed to impacts of climate change hence the minimal sensitivity recorded in the county.

The results in this study were consistent with research findings by (Yusuf & Francisco, 2009) and (Hegglin & Huggel, 2008) on sensitivity. These studies found out that the degree of sensitivity was dependent on the number of people that were at risk of being affected by climate change. Nakuru had a lower percentage of rural population density, people living under poverty line and maize farmers compared to Uasin Gishu. However, the percentage dependency of maize production on rainfall was 100% in Nakuru and 99% in Uasin Gishu. Therefore, farmers in Uasin Gishu were not entirely dependent on rainfall for maize production and could lessen the impacts of climate change induced water stress by using irrigation which reduced their sensitivity. This is in line with findings by (Emebet, 2013) who stated that sensitivity to temporary rainfall variability would be reduced by irrigation in a given area.

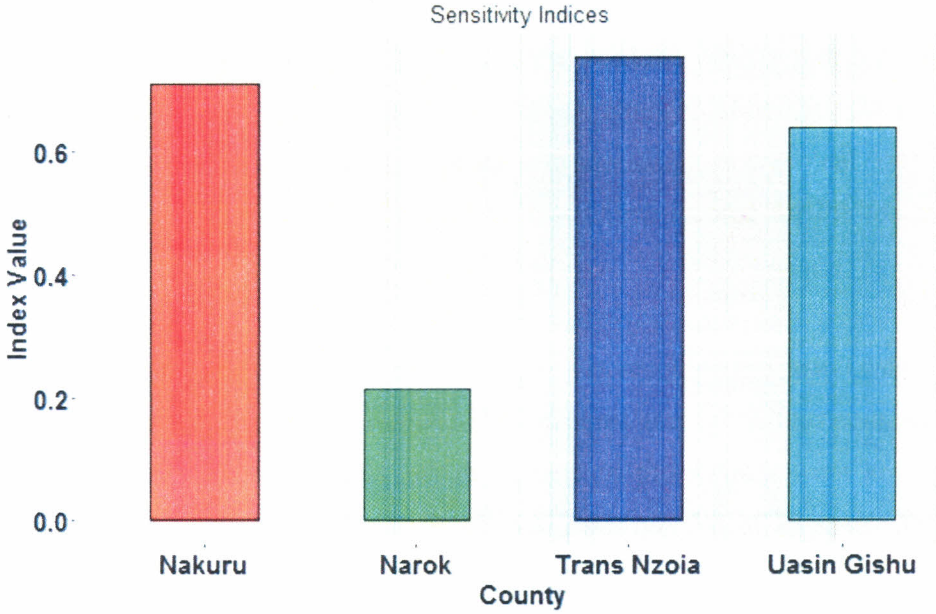

Figure 30: Bar plots of Sensitivity indices

4.7.3 Adaptive Capacity Indices

The comparison of adaptive capacity indices for the study counties are presented in Figure 31. Narok had the minimal adaptive capacity index of -2.28. Not only did Narok record the least percentage of farmers in agricultural organisations (33.3%) but it also had the lowest literacy rate among maize farmers (53.7%). Membership of farmers in agricultural organisations creates a societal network that acts as a platform that facilitates cash flow and transfers which eliminates financial barriers for farmers (Deressa *et al.*, 2008). Also, literacy rates determine the ability of farmers to access knowledge and information and hence improve their coping capability to unfavourable consequences of climate change (Brooks *et al.*, 2005). As a result, in Narok, fewer farmers accessed climate change information and were not able to fully understand, interpret and implement it to improve maize production, hence the low adaptive capacity realized in the county.

The wealth status of farmers can be ascertained by considering the value of farm assets, farm, off farm and net income. Such wealth enables farmers to access resources like markets and technology which are vital in improving their adaptive capacity (Brenkert & Malone, 2005). The net income that accrued from farm and off farm activities was least in Narok County. Therefore, the maize farmers lacked financial capacity to adapt to impacts of climate change. For farmers to access markets to sell their produce, there must be quality and dense infrastructure network in form of roads and other transport routes (Adger *et al.*,2004). Narok had the furthest distance to farm produce outlets, NCPB depots, motorable and tarmac roads. As a result, farmers incurred higher costs in transporting their maize to nearest markets which reduced their revenue considerably and made them more vulnerable to climate change. Although 100% of farmers in the county used improved seeds, lack of irrigation and low usage of chemical fertilizers limited the total annual maize yields which translated to lesser farm income for the maize farmers in Narok.

The peak adaptive capacity during the baseline period was recorded in Uasin Gishu (2.60).It had the highest farm asset value, farm, off farm and net incomes among the four counties. Therefore, in the face of climate change impacts, maize farmers in this county were able to promptly address financial constrains posed by erratic climate patterns. Out of all maize farmers in the county, 91% were literate, 53.1% were members of agricultural organisations and 59.4% saved their income. This meant that a greater portion of maize farmers had access to climate information and could understand, interpret and implement the information for improvement of maize production against a wave of changing climate patterns. Besides, the farm produce markets were closer to farmers in Uasin Gishu and therefore more farmers were able to sell their produce without incurring a lot on transport expenses. The second and third highest adaptive capacity were recorded in Trans Nzoia (2.58) and Nakuru (1.13) respectively.

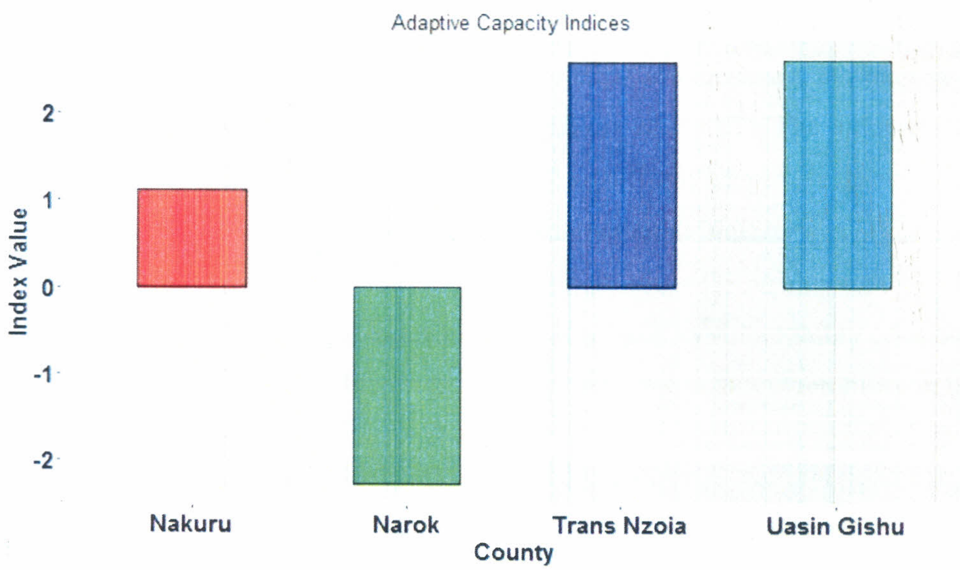

Figure 31: Bar plots of Adaptive Capacity indices

the second highest adaptive capacity index (2.58) which reduced its vulnerability considerably. Uasin Gishu County recorded a vulnerability index of -0.12 making it the second least vulnerable county. Much as the highest adaptive capacity was realised in this county, the combined effect of its sensitivity and exposure created a greater climate change potential impact and hence increased its vulnerability. Narok registered the highest vulnerability index of 1.51. This is because the significant values of exposure index recorded in the county, contributed greatly to potential impacts of climate stressors and hence increased its vulnerability to a great extent. Moreover, its negative adaptive capacity index meant that the county lacked capability to adjust in order to minimize probable harm, take advantage or cope with consequences of climate change and extremes events. The second most vulnerable county was Nakuru with a vulnerability index of 0.35.

The overall vulnerability is a function of magnitude of exposure, sensitivity and adaptive capacity for the system or area under study (Ezra, 2016; Yusuf & Francisco, 2009). Areas that are highly exposed to climate change and have low adaptive capacity depict peak vulnerability levels (Li *et al.*, 2015). Narok recorded the least vulnerability index because it had the least adaptive capacity and highest exposure. Highly exposed areas or communities do not necessarily have low adaptive capacity or high sensitivity to climate change (Gbetibouo *et al.*, 2010; Islam *et al.*, 2014). As much as Narok was the most exposed county, it registered the least sensitivity and adaptive capacity index. Also, Trans Nzoia was the most sensitive county, but had the second highest adaptive capacity. Vulnerability increases when sensitivity and exposure increases, but reduces as adaptive capacity increases and vice versa (Ahumada-Cervantes *et al.*, 2015). The vulnerability in Trans Nzoia and Uasin Gishu was considerably reduced by significant adaptive capacity realized in the counties. The sensitivity and exposure of Uasin Gishu (potential impact) was higher than in Trans Nzoia. This had an increasing effect on the vulnerability in Uasin Gishu although it had the highest adaptive capacity. The high exposure index in Narok increased its vulnerability considerably while the negative adaptive capacity was inconsequential in reducing peak vulnerability in the county.

4.8 Vulnerability Maps

Based on a scale of 0-5, three categories of normalized vulnerability indices of the study counties were identified (Table 17).

Table 17: Normalized vulnerability classes

Vulnerability class	County
Very low ($0 \leq VI_{normalized} < 1$)	Trans Nzoia, UasinGishu
Low ($1 \leq VI_{normalized} < 2$)	Nakuru
Very high ($4 \leq VI_{normalized} < 5$)	Narok

Trans Nzoia County was classified under the very low category ($0 \leq VI_{normalized} < 1$). Uasin Gishu County scored a normalized vulnerability index that lay between 1 and zero (0.3) and therefore was classified under the same vulnerability class as Trans Nzoia County. The vulnerability in Nakuru County was classified as low ($1 \leq VI_{normalized} < 2$) due to its normalized vulnerability index of 1.6. Narok County had a normalized vulnerability index of 5 and therefore was classified as very high category of vulnerability ($4 \leq VI_{normalized} < 5$). Based on these vulnerability categories, a vulnerability map for the study counties was developed (Figure 34).

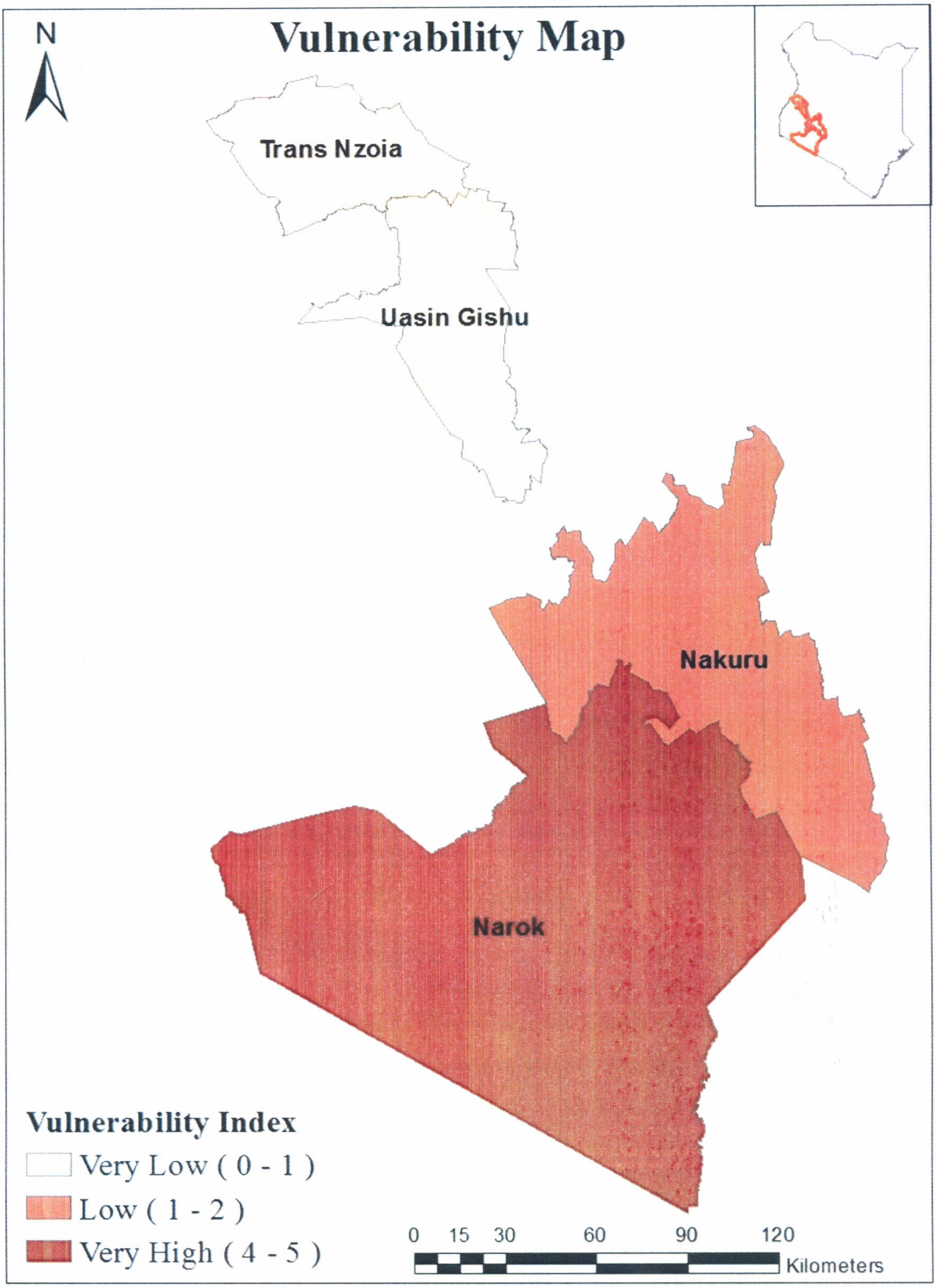

Figure 32: Vulnerability map

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The results showed that climate had changed in the four counties between 1981 and 2010. Temperatures increased considerably and recorded notable upward mean shift over all the stations in the four counties under study during the baseline period. Although reducing trend patterns were observed during MAM rainy season in Uasin Gishu and Trans Nzoia, Nakuru and Narok recorded an increase in rainfall during the same season under the baseline period. Rainfall increased during OND rainy season over all the study counties. As for annual rainfall, increasing trend patterns were recorded in all counties except Trans Nzoia.

Based on RCP4.5 and RCP8.5, it is expected that there will be changes in climate between 2021 and 2050. Under RCP4.5 scenario, rainfall is expected to increase over all the counties during MAM and OND seasons. Nakuru is the only county that is expected to record a upward trend during JJA season. Notable increase in annual rainfall is expected under RCP4.5 in all stations for the period between 2021 and 2050. Generally, maximum and minimum temperature are expected to record upward trend patterns that will not be significant under RCP4.5. Based on RCP8.5 scenario , rainfall is expected to decrease during MAM in all counties except Narok. All counties are expected to register increased rainfall during JJA under this scenario. Whereas Nakuru and Narok are expected to have a decrease, Trans Nzoia and Uasin Gishu will experience a rise in rainfall during annual and OND rainy season based on RCP8.5. Temperatures are expected to increase in all the counties under study based on RCP8.5.

From the correlation analysis, the results showed that there existed a relationship between climate and maize yields. However the direction and strength of correlation between maize yields and climate (temperature and rainfall) varied depending on the growth stage of the maize crop.

Vulnerability analysis for the four counties showed that each of them had distinct vulnerability index which was dependent on the degree of exposure, sensitivity and adaptive capacity of each county. Narok emerged as the most vulnerable county among the four counties under study. Consequently, maize production in the county would be adversely affected by climate change. The county lacked the adaptive capacity that is prerequisite for vulnerability reduction. Trans Nzoia was the least exposed and most sensitive county. However, it recorded the second highest adaptive capacity which reduced its vulnerability considerably. The combined effect of sensitivity and exposure in Uasin Gishu was higher than in Trans Nzoia, making it the second least vulnerable county despite its highest adaptive capacity. Nakuru was the second most vulnerable county to impacts of climate change.

5.2 Recommendations

- It was noted that in all the counties, maize production was dependent on rainfall which increased the sensitivity of maize farmers to severe impacts of erratic rainfall fluctuations. Being that it is a primary requirement of maize production, it is imperative to ensure that water availability and supply remains constant regardless of the prevailing climate. Therefore, harvested rainfall, surface and ground water should be utilized for irrigation in order to suppress water stress situations like drought and inadequate rainfall during the rainy seasons that are brought about by the increasing temperatures. Irrigation can also be used to increase the number of growing seasons and hence increase maize yields. Consequently, the sensitivity of maize farmers in the study counties and hence vulnerability will be minimized.

- Availability of climate, biophysical and socioeconomic data is imperative for vulnerability assessments. There is need to increase the number of weather stations so as to gather meteorological data that will be more representative of the region under study. Regular surveys need to be carried out to build up real time data on biophysical and socioeconomic indicators.

- Improvement of the maize farmers' adaptive capacity is fundamental as it reduces vulnerability to a great extent. Adaptive capacity of the most vulnerable counties can be improved by implementing socio-economic and rural infrastructural developments. Educational programs can be part of social programs initiated to improve the literacy levels of the maize farmers. Improvement of rural infrastructure should entail expansion and upgrading of the road network and building farm produce outlets that can easily be accessed by the farmers.

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