UNIVERSITY OF NAIROBI

ASSESSMENT OF THE VULNERABILITY OF SMALLHOLDER MAIZE PRODUCTION TO THE ADVERSE EFFECTS OF CLIMATE CHANGE IN SOUTHERN NYANZA REGION, KENYA

BY

FREDRICK GIKEMI

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Department of Earth and Climate Sciences

Faculty of Science and Technology

University of Nairobi

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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 or institution. and that all the sources used herein have been dully acknowledged and referenced in strict adherence to the standards and requirements of the University of Nairobi.

Fredrick Gikemi Signature Date

I54/12205/2018 26/07/2022

Department of Earth and Climate Sciences

This Dissertation has been submitted for examination with our approval as university Supervisors:

Mr. Cromwell Lukorito Signature Date

Department of Earth and Climate Sciences

University of Nairobi 26/07/2022

Prof. Christopher Oludhe Signature Date

Department of Earth and Climate Sciences

University of Nairobi. ------------------- *26/07/2022*

DEDICATION

To my parents and siblings for their unwavering and unconditional support, encouragement, and constant source of inspiration and hope.

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ABSTRACT

Vulnerability assessment is critical towards helping policy makers understand and quantify the impacts and consequences of climate change. Therefore, this study sought to assess the vulnerability of smallholder maize production to adverse climate change impacts in Southern Nyanza region. The study data included historical climate data for the period 1983-2016 for temperature, and 1988-2018 for rainfall obtained from CHIRTS and CHIRPS daily data respectively. Time periods for temperature and rainfall data were different since CHIRTS data was only available from 1983-2016. Climate projections for the period 2022-2051 was done using data extracted from CORDEX Africa family of models under RCP4.5 and RCP8.5 emission scenarios. Socioeconomic and biophysical data were sourced from the Ministry of Agriculture, Livestock, Fisheries and Cooperatives, Tegemeo Institute of Agricultural Policy and Development, Kenya National Bureau of Statistics, and Kenya Institute for Public Policy Research and Analysis. The trends and mean shifts of baseline rainfall and temperature were statistically significant as depicted by the p-values of Man-Kendall and Pettit's tests that were smaller than the significance level value ($\alpha = 0.05$). Similarly, all the projections showed a general decreasing trend in rainfall, with an increasing significant trend in maximum and minimum temperatures. The results of the correlation analysis indicated that there was a significant relationship between maize yields and climate variables (maximum and minimum temperature, and rainfall) across the various stages of growth of maize. The vulnerability indices for the study counties were driven mainly by maize productivity, infrastructural, and socioeconomic development levels. Migori County recorded the highest vulnerability (0.72), followed by Homabay County (0.48), Kisii County (-0.29), and Nyamira County (-0.74). Smallholder maize production in Southern Nyanza region was generally vulnerable to climate change owing to the significant increase in temperature. These trends are expected to persist into the future, thus increasing the vulnerability of smallholder maize production in Southern Nyanza region. The findings of this study will go a long way in helping smallholder farmers identify relevant adaptation strategies to help them reduce the vulnerability of maize production to adverse climate change effects. The findings of this study will also assist agricultural extension officers and other relevant stakeholders in identifying the most vulnerable counties to adverse climate change effects, and enable them make recommendations that would support the implementation of appropriate climate change policies to cushion smallholder maize production systems against adverse climate change effects in order to achieve sustainable maize productivity and food security.

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ABBREVIATIONS AND ACRONYMS

CCCma	The Canadian Centre for Climate Modelling and Analysis
CHIRPS:	Climate Hazards Group InfraRed Precipitation with Station Data
CHIRTS	Climate Hazards Group InfraRed Temperature with Station Data
CNRM:	National Centre for Meteorological Research
CORDEX:	Coordinated Regional Downscaling Experiment
CSIRO:	Commonwealth Scientific and Industrial Research Organisation
GDP:	Gross Domestic Product
ICHEC	High-resolution Climate Projections for Ireland
IPCC:	Intergovernmental Panel on Climate Change
IPSL	Institut Pierre Simon Laplace Climate Model
JJA:	June July August
KIPPRA	Kenya Institute for Public Policy Research and Analysis
KIPPRA:	Kenya Institute for Public Policy Research and Analysis
KNBS	The Kenya National Bureau of Statistics
LULC	Land Use Land Cover
MAM:	March April May
MIROC	Model for Interdisciplinary Research on Climate
MOALFC:	Ministry of Agriculture, Livestock, Fisheries and Cooperatives
MOHC	Met Office Hadley Centre
MPI	Max Plank Institute
OND:	October November December
PCA:	Principal Component Analysis
RCP:	Representative Concentration Pathway
RMSE:	Root Mean Square Error
SPI:	Standard Precipitation Index
TIAPD:	Tegemeo Institute of Agricultural Policy and Development

CHAPTER ONE

1.0 Introduction

This chapter presents a description of background information to this study, the statement of the problem being addressed, the study objectives, justification and the conceptual framework that was used in this study.

1.1 Background information

In Kenya, agriculture is a key driver of the economy and contributes approximately 31.5% to the national GDP and 50% of the country's total export (Ochieng *et al.*, 2016). Moreover, the sector creates 18% of formal jobs, 70% of informal jobs and contributes approximately 65% of the County's total export earnings (Mumo *et al.*,2018). Similarly, the livelihoods of nearly all rural places of Kenya are primarily sustained by agriculture.

Agricultural production in Kenya is largely carried out in small land holdings of between 0.2 and 3 hectares. Small-holder farming in Kenya accounts for 78% and 70% of agricultural production and commercial agricultural respectively. Small-holder farmers are therefore the main stakeholders in the agricultural industry (Salami et al., 2010). Therefore, smallholder farming has potential to significantly contribute towards poverty alleviation in Kenya (World Bank, 2018).

83% of Kenya's land area is occupied by fragile dry lands and receives between 300 and 500 millimetres of rainfall annually. Despite receiving such low amounts of rainfall, they are prone to flooding hence affecting crop farming. Major droughts have been reported to occur every decade while the minor droughts occur every four years. Consequently, these droughts have continued to spread, thereby hampering agricultural production in the country. As such, climate change presents a formidable threat towards Kenya's agricultural prosperity (Herrero *et al.*, 2010).

With the ongoing accelerated global warming rates, the associated climate change impacts are presenting formidable threats to human, environmental, and socioeconomic systems of the world. Many countries across the globe are currently experiencing increased fluctuations in temperature and rainfall characteristics including amounts, distribution and extremes. These variabilities have inevitably led to poor, unreliable and occasionally failed food production locally and even globally (Ochieng *et al*, 2016). Moreover, surface temperatures in both land

and oceans have increased from 0.65^0C to 1.06^0C representing an overall increase of 0.85^0C from the year 1880 to 2012 (Masambaya, 2018).

Concomitantly, temperatures in Kenya have risen by approximately 1^0C above the 1960 level (Masambaya, 2018). Given the highest sensitivity of agriculture to variation in temperature, it is very likely that these conditions will lead to decreased agriculture productivity and exacerbate food insecurity nationally, locally and down to household level (Hatfield and Prueger, 2015). Changes in climate inevitably lead to undesired ramifications in the agriculture sector. Furthermore, climate change exacerbates climate related disasters particularly droughts and floods; increased prevalence of livestock and crop pests and diseases; substantial loss in crop yields; and crop failure among others (Jamshidi *et al*.,2019).

Globally, it is approximated that 475 million farmers practice small-holder farming, each cultivating parcels of land that are less than 2 hectares (Harvey *et al*.,2018). Similarly, 80% of farmers in Sub Saharan Africa are actively involved in small-holder farming, representing approximately 33 million small-holder farmers (Pratt *et al.,* 2017). In Kenya, smallholder farming is carried out in small parcels of land that do not exceed 3 hectares (Kogo *et al.,*2021). Donatti *et al.,* (2019) affirms that small-holder farmers are severely affected by climate variability and change. Therefore, any decline in agricultural productivity will adversely affect the small-holder farmers by impoverishing and imposing household food insecurity (Jamshidi *et al*., 2019).

Worldwide, maize ranks third in consumption, whereas wheat ranks second (Ramirez *et al*, 2017). However, in Kenya and Africa, maize ranks first. In this regard, maize is considered as the chief source of calories in most parts of Africa (Adhikari *et al*., 2015). Unfortunately, many small-holder farmers in Kenya have continued to experience declines in maize yields due to invasion of their crops by crop pests such as fall armyworms which thrive in hot and moist climatic conditions (State Department of Crops Development, 2019). Climate change would therefore greatly undermine global, regional and local efforts to combat food insecurity and poverty due to increased pest infestations following rising temperatures. In Southern Nyanza region (Kisii, Nyamira, Migori and Homabay County), rain-fed agriculture significantly contributes towards socio-economic development of the region, with the bulk of farming being carried out on small-holder farms (less than 2 hectares). Climate change would therefore impose and exacerbate existing socioeconomic vulnerabilities of small-holder maize production.

This study, therefore assessed vulnerability of small-holder maize production to the adverse effects of climate change in Southern Nyanza region.

1.2 Problem Statement

Climate change continues to adversely affect rain-fed smallholder farming systems in Kenya and Southern Nyanza region in particular. Notable climate change impacts in this region include declining maize yields, disruptions in cropping seasons' patterns due to erratic rainfall patterns associated with fluctuations in rainfall onset and cessation dates, and overall planting seasons for various cereals, including maize. The resultant declines in crop yields and complete crop failure in extreme cases is aggravating the vulnerability of smallholder maize farmers, thus leading to deterioration of livelihoods and enhancing poverty and food insecurity.

1.3 Objectives of the Study

The overall objective of this study was to assess the vulnerability of smallholder maize production to the adverse effects of climate change in Southern Nyanza region of Kenya.

The specific objectives were to:

i. Determine the trends and patterns of temperature and rainfall in Kisii, Nyamira, Homabay, and Migori County under current (1988-2018) and future climate (2022-2051) under RCP 4.5 and RCP 8.5 emission scenarios
ii. Establish the relationship between climate variables and smallholder maize productivity in Kisii, Nyamira, Homabay, and Migori County between 1988-2018.
iii. Determine the vulnerability of smallholder maize production to climate change impacts in Kisii, Nyamira, Homabay, and Migori County.
iv. Develop Vulnerability Index Maps for Kisii, Nyamira, Homabay, and Migori County under current climate

1.4 Research Questions

i. What are the trends and patterns of temperatures and rainfall in Kisii, Nyamira, Homabay, and Migori County for the period 1988-2018?
ii. How did climate variables affect smallholder maize production in Kisii, Nyamira, Homabay, and Migori County over the period 1988-2018?
iii. What is the extent of vulnerability of smallholder maize production to climate change impacts in Kisii, Nyamira, Homabay, and Migori County?

iv. How is the vulnerability of smallholder maize production distributed over Kisii, Nyamira, Homabay, and Migori County?

1.5 Justification

In Africa and Kenya in particular, maize farming is mainly practised on smallholder basis, and relies heavily on rainfall. This is also the case in Southern Nyanza region where nearly every farmer grows maize (Berazneva *et al.,* 2018). However, with climate change, notable decline in maize production has been observed by various studies. According to Thornton *et al*., (2009) crop yields will drop by as much as 10-20% by the year 2050 in Africa, including Kenya.

Many studies focusing on the influence of climate change on agriculture have been done in Southern Nyanza region and Kenya at large (Ochieng *et al.,* 2016; Mugwika, 2019; Ogenga *et al.,* 2018). However, none has attempted to assess the vulnerability of smallholder maize production. Therefore, vulnerability assessment of smallholder maize production in the study area will avail useful information that can be used by relevant stakeholders and policy makers in planning and implementing effective climate specific response measures that would enhance resilience of smallholder maize production systems.

Moreover, mapping of vulnerability and its components will stimulate development of programs and activities aimed at increasing the resilience of smallholder maize production thus shaping policies geared towards achieving local and international sustainable development goals on food security and poverty alleviation.

1.6 Conceptual Framework

This study adopted the IPCC 2007 framework for vulnerability assessment in which vulnerability was conceptualized as the total adverse impacts to any given system due to exposure to hazards. This framework accounted for vulnerability based on exposure, sensitivity and adaptive capacity by carefully selecting a group of measurable indicators for each of these components (Sharma and Ravindranath,2019).

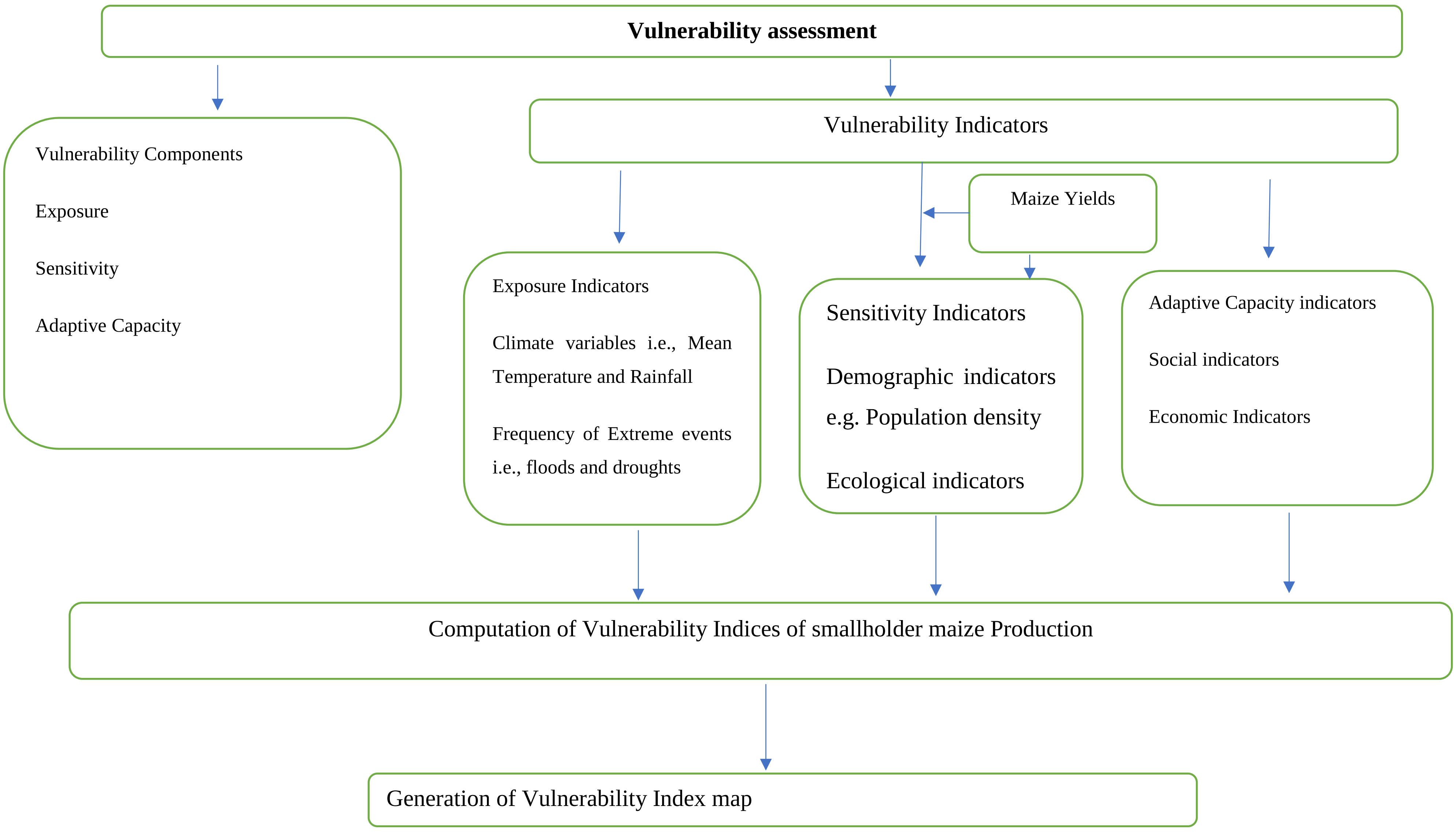


Figure 1: Conceptual Framework

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

In this chapter, pertinent literature on previous research works on impacts of climate fluctuations and change on agriculture in Kenya and the vulnerability of the sector to the adverse climate impacts have been presented. Besides, the various approaches used to assess vulnerability, including scenarios used to predict future changes in climate have been discussed.

2.2 Climate Change in Kenya

With each passing day, losses and damages caused by steady changes in climate are becoming more apparent. In Kenya, evidence of climate change and variability manifests in changing seasonal patterns and intra-seasonal characteristics. The occurrence of extreme climatic events has been increasing. Notably, the severity and frequency of droughts has increased while ground water levels and volumes in Lakes and rivers has substantially decreased. Consequently, 752 Ha of land have been exposed to anthropogenic degradation due to the reduction in water levels in Lake Victoria (Okotto *et al.*, 2018)

Mean surface temperature in Kenya changed at a rate of 0.15^0C/decade between 1951 and 2010 (Ongoma *et al*., (2018). These researchers also noted that Kenya experienced an upward shift in mean (+0.5^0C), minimum (+0.4^0C) and maximum (+0.5^0C) temperatures between 1982 and 2012 compared to 1951-1981. Consequentially, this led to undesired ramifications such as poor agricultural production leading to loss of income, loss of livelihoods and food insecurity. Nonetheless, the country has also witnessed a dip in the production of Hydro-electric power as well as destruction of ecosystems, wildlife and forest resources with adverse consequences on tourism. For instance, the droughts witnessed in Kenya in 2004 and 2009 significantly affected a vast majority of Kenyans leading to loss of livestock resources, water and energy rationing, reduced industrial activity as well as poor agricultural production. Additionally, the droughts experienced in the year 2006 affected approximately 723,000 Kenyans (Bobadoye, 2016; SEI, 2009).

Other adverse impacts include disasters related to floods that have resulted into destruction of infrastructure and human settlement, agricultural losses, forced migration, and disease epidemics that have resulted into mortality and increased cost of health care. The growing adverse climate change impacts present great potential to deter and cripple Kenya's future economic growth and impede the desired sustainable development. For instance, Kenya experienced economic losses amounting to USD 1.2 billion, caused by floods in the region in 1997/98 (SEI, 2009).

Furthermore, extreme climatic conditions are expected to burden Kenya's economy causing losses estimated at 2% of the Kenyan gross domestic product (SEI, 2009). Therefore, climate change and variability are a significant threat towards Kenya's economic and social development agendas, particularly the vision 2030 blueprint and the big four agenda.

2.3 Climate change and agriculture

Climate change is currently unequivocal globally with immense ramifications on agricultural, natural and human systems. Consequently, these fluctuations in climate have sharply crippled efforts towards achieving global food security owing to their adverse impacts on food production systems. Subsequently, many sectors including agriculture, have significantly been affected by these changes. Moreover, many livelihoods that rely on agriculture have deteriorated immensely.

Furthermore, agriculture contributes significantly to food security and provides a major revenue stream in most Kenyan households. For instance, approximately 85% of Kenyan households rely entirely on rain for farming (Kogo *et al*., 2021). Unfortunately, the agricultural sector in Kenya continues to be exposed to adverse climate change impacts, thereby making it more vulnerable hence destroying means of livelihoods. According to IPCC (2007, 2014), crop production is expected to show a decreasing trend due to the projected rise in global temperatures.

Concomitantly, the expected increase in levels of CO_2 concentration will increase water use efficiency in C_4 plants such as maize (Betts *et al.*, 2007). However, despite the increase in water use efficiency in maize, it is considered as one of the most vulnerable crops to water stress compared to other C_4 plants owing to its unique floral structure that contains separate female and male structures (Huang *et al*., 2006). In Kenya and Africa at large, fluctuations in climate has caused shortening of the growing season for most cereal crops as well as creating suitable warm conditions that have enhanced the spread of crop pests, diseases and weeds (IPCC, 2014).

Similarly, changes in Kenya's climate have exacerbated the occurrence of extreme weather episodes, particularly floods and droughts, thus hindering the growth of the agricultural sector. For instance, between 2008-2009, the Kenyan agricultural sector recorded the lowest reduction in its growth by approximately 6% because of droughts. On the other hand, the floods witnessed in 1997/98, 2002, and 2013 reduced Kenya's agricultural growth by approximately 4% (Kogo *et al*., 2021).

2.3.1 Crop Production under Changing Climate

The present fluctuations in climate have severely impacted crop farming. Some of the impacts include a decrease and/or complete loss of crop yields as a result water stress for most crops such as cereals (Hatfield and Prueger, 2015). Climate change also gives rise to conducive conditions for weed infestations and enhances the outbreak of crop pests and diseases, that act singly or in combination to limit crop growth and productivity (Cilas *et al*.,2016). Furthermore, climate change due to rising temperatures increase evapotranspiration rates that exacerbate water stress. This reduces the ability of crops to produce high yields (Sadras *et al*.,2016).

Besides, crops in rain fed farming systems rely on precipitation for moisture, and also depend on temperature for conditioning the processes of growth and development. Thus, any slight changes in these climatic elements can lead to devastating effects on crop production. Likewise, low temperature stress before flowering in wheat plants generally hinders the synthesis of starch and sugar, including nitrogen compounds, in the vegetative organs, while low temperatures after flowering significantly reduce grain number and the grain filling rate in wheat plants. (*Liu et al.,2019*).

Frost conditions lead to sterility in wheat plants while excessive heat greatly reduces the grain filling period (Liu *et al*.,2019). Nonetheless, heat stress in most crops affect their flowering stage by destroying the viability of pollen, thereby hindering yields. Heat stress also affects the physiological processes that take place in crops (Hatfield and Prueger, 2015).

Although various crops respond differently to heat stress, most of them generally experience a decline in leaf area hence low rates of capture of the photosynthetically active radiation and increased rates of leaf senescence, thereby leading to decreased crop productivity (Hatfield and Prueger, 2015). Similarly, heat stress before or after anthesis in cereal crops dramatically reduces grain number and grain weight. (Barlow *et al*.,2015).

Furthermore, prevailing high temperatures lead to increased saturation vapor pressure that increases evaporative demand of the atmosphere. Under limited soil moisture conditions, plants will tend to close their stomata thereby affecting the rate of photosynthesis (Hatfield and Prueger, 2015). Since water influences virtually all the morphological and physiological processes in plants, water stress will therefore cause a reduction in the quantity of harvestable yield.

Moreover, changes in climate exacerbate distribution of various crop pathogens, diseases and pests, thereby affecting crop production. Variations in humidity and temperature can modify fungal growth, insect growth and multiplication, as well as their renewal rates. Ultimately, agricultural systems and processes are adversely affected by these agents, thus inhibiting plant growth, development and productivity (Cilas *et al*.,2016).

2.3.2 Climate change and Maize Production

Maize, just like any other crop, is extremely sensitive to fluctuations in temperature and precipitation. Despite consideration of several factors including farm management and technology as being crucial towards enhancing and sustaining maize production, climate change still remains the greatest threat to maize farming (Mumo *et al*.,2018). Furthermore, variations in patterns of cold and heat stress spells, wet and dry spells within a cropping season would reduce growth rate of maize especially during the flowering phase and thereby reduce the accumulation of biomass. Furthermore, the viability of maize pollen decreases significantly when exposed to temperatures above 35^0C (Hatfield and Prueger, 2015).

Consequently, during the reproductive phase, the viability of maize pollen grains is negatively affected since their viability depends on the moisture content of the pollen grains which in turn is highly dependent upon the deficit in vapor pressure (Fonseca and Westagate,2005). Jones *et al* (1984) indicated that kernels of maize reduced in size when an increase in temperature from 30^0C to 35^0C occurred during the divisional phase of the endosperm. Furthermore, rainfall amounts have continued to decline at a rate of 3.3% per decade, thus catalysing occurrence of droughts and drought conditions which eventually stifle maize farming (Kimani, 2017).

According to Muchow *et al* (1990), maize yields will increase with an increase in temperature up to 29^0C, beyond which a sharp decline in maize yields would occur. Thus, any temperature increases beyond 29^0C eventually reduces maize yield even under conditions of optimal rainfall (Lobell *et al*., 2011). Similarly, Brown (2009) indicates that any increase in temperature above optimal reduces maize yields by approximately 10%. Nevertheless, highland areas will benefit from the positive effects of rising temperatures above historical levels, thus enhancing maize yields.

However, maize production in the low land areas will plummet because of water deficiency, and temperature rises beyond current levels that are threatening to overrun crop thresholds of temperature which are already high. The high variability in precipitation amounts and distribution is a major precursor for water stress and water logging for maize crops leading to low yields in quantity and quality, and in extreme cases complete crop failure.

2.4 Vulnerability of Small-holder Maize farming in Kenya

Maize farming in Kenya is largely carried out on smallholder basis across the country on farms not exceeding one hectare. Farming households depend on the maize grown for both consumption and income generation. This presents maize among this segment of society as a means of livelihoods. Therefore, the role of smallholder maize farming in fighting food insecurity and poverty in Kenya is underscored in this study. For instance, between 2005 and 2015, smallholder farming was largely responsible for the reduction of poverty levels in Kenya and hence improved the living standards of the farming households (World Bank, 2018).

However, the vulnerability of the smallholder maize farmers has increased due to climate related risks particularly floods, crop pests and diseases, and droughts that hamper food production while worsening poverty level among households. Moreover, extreme weather events witnessed annually in Kenya have inadvertently led to the destruction of critical agricultural infrastructure hence increasing the vulnerabilities of smallholder maize farming. For instance, floods have led to the destruction of crops, farm roads, irrigation systems, maize storage facilities as well as enhancing soil erosion, water logging and leaching of nutrients necessary for crop production. Similarly, wet conditions have exacerbated post-harvest losses through rotting of the harvested crops as well as enhancing contamination by aflatoxin. On the other hand, drought conditions have led to water stress in maize crops hence declining maize yields. Consequently, maize yields in Kenya have continued to decline every ten years representing a loss of 0.07 tons/ha. This has increased the vulnerability of small-holder maize farmers (Mumo *et al.*, 2018)

Furthermore, there is marked variability in rainfall across agro-ecological zones during the planting seasons that in turn influences the varietal choices of maize seeds planted. In western and North Rift Valley regions of Kenya, long duration high yielding hybrid maize varieties are preferred. On the other hand, the early maturation maize varieties are recommended for farmers in dry regions (Mbithi and Huylenbroeck, 2000).

Smallholder maize farming in Kenya is usually done through intercropping with other crops, notably, legumes such as common beans and cowpeas. This practice enables farmers to derive maximum output from their farms as well as enhance their resilience. Moreover, intercropping cushions smallholder farmers against risk of crop failure and enhances food security and nutrition. However, the high potential regions such as western Kenya and Rift Valley have the least intercropping practices (Nying'uro, 2020).

2.5 Kenya's Vulnerability to climate Change

Kenya has continued to experience climate extremes that lead to adverse impacts. Studies conducted have integrated land use data, climate data as well as socioeconomic data by utilizing geospatial techniques hence making it possible to spatially reveal Kenya's vulnerability to climate change (Mwangi and Mutua, 2015). According to these authors, 47.36% of Kenya is sensitive to climate change while only 1.65% of the country has a higher threshold to withstand the negative consequences initiated by changes in climate.

In another study conducted by Marigi (2017) on Kenya's climate change vulnerability assessment, the eastern, northern, south-eastern and the southern part of the Kenyan Coast have the highest exposure to negative fluctuations in climate. Similarly, this study observed that the southern coast and northern Kenya recorded the highest sensitivity to climate change, and also identified northern Kenya as having the least adaptive capacity. Consequently, the southern coast and northern Kenya exhibited the highest vulnerability whereas the least vulnerability was recorded in Western and Central Kenya.

2.6 Household Vulnerability Assessment

Most of the vulnerability assessment studies done in Kenya have mainly focused on macro-level vulnerability assessment. As such, there is scanty literature on vulnerability assessment among households. However, vulnerability assessment among households is highly invaluable in obtaining a deep understanding of the extent and depth of a family's vulnerability, and is highly instrumental in shaping local plans and policies.

In a study by Opiyo *et al.*, (2014) assessing household vulnerability in Kenya's pastoral rangelands, 27% of the households were found to be highly vulnerable, 44% of the households were considered moderately vulnerable, whereas 29% exhibited minimal vulnerability. The integrated vulnerability assessment approach adopted for the study constituted both internal and external stressors that influence the vulnerability of any given system. However, this approach lacks the ability to account for the dynamic changes that are commonly linked with vulnerability. To this end, vulnerability at the household level can significantly be reduced by improving literacy rates and education in families, having multiple sources of income as well as encouraging programmes and policies aimed at empowering women.

2.7 Vulnerability Assessment

Vulnerability to climate change is “the degree to which a system is susceptible to, and unable to cope with the adverse effects of climate change, including climate variability induced extremes, and is viewed as a function of the characteristics, magnitude, and rate of climate change and variability to which a system is exposed, its sensitivity, and its adaptive capacity” (IPCC, 2007). In agriculture, sensitivity refers to how crops respond to fluctuations in climate as manifested in their growth and yields, as well as overall plant development (Mallari, 2016). Exposure is “the nature and the degree to which a system is exposed to significant climatic variations” (IPCC, 2007). Finally, “adaptive capacity” is “the ability of a system to adjust to climate change (including climate variability and extremes) to moderate potential damages, to take advantage of opportunities, or to cope with the consequences” (IPCC, 2007).

There is a robust demand for vulnerability assessments addressing climate change impacts. In most studies, vulnerability assessment is considered as an invaluable undertaking that can be used to determine the probability and potential of harm to any given ecosystem and human/ community as a result of a hazard. Moreover, vulnerability assessments help in understanding specific needs of ecosystems, farming systems and communities (Preston *et al.*, 2011).

2.8 Approaches for Vulnerability Assessment

The role of vulnerability assessment in shaping current and future planning and policies can only be underscored. Moreover, vulnerability assessment provides crucial information that can be used in identifying vulnerable groups and thereafter help in offering relevant adaptation strategies. In most cases, environmental and socioeconomic factors greatly influence vulnerability. The subsections that follow describe some of the approaches used for vulnerability assessment.

2.8.1 Socio economic Approach

This method uses social, economic, political and institutional changes to compute vulnerability. According to this approach, the economic vulnerability of any given region depends on the amount of wealth found in that particular region. Additionally, the vulnerability of a given community will be influenced by factors such as the level of their interactions with climate sensitive environments, their literacy levels, health status, political power, access to credit, their political systems, cultural systems as well as their geographical location (Esperón *et al*.,2016).

The socio-economic approach assesses vulnerability by developing a Socioeconomic Vulnerability Index. Knowledge obtained from local experts is then used to identify vulnerability indicators. Subsequently, weights are assigned to each indicator and thereafter used to compute the index (Ahsan and Warner, 2014). In this regard, social vulnerability can therefore be defined as the exposure of any given community or individual to external risks mostly from adverse changes in climate. Going by this definition, the social vulnerability of a particular community or group of individuals can be assessed based on their resilience capacity or their ability to adapt to external stressors. However, this approach measures vulnerability purely on the basis of social and individual variations. As such, it overlooks the role played by biological and physical environmental factors including natural events and disasters in influencing variations within and among societies and individuals.

2.8.2 The Impact Assessment Approach

The impact assessment approach, also known as the biophysical approach, assesses and measures vulnerability based on the impact that natural and environmental calamities have on social systems or biological systems (Kaly *et al*., 1999). This approach assumes that the physical-environmental facet of vulnerability largely accounts for climatic harm. For instance, the productivity of agricultural systems is largely dependent on climate variables. Therefore, climatic shocks can lead to impacts that can severely affect farming systems hence making them vulnerable.

Moreover, the distribution and spread of disease vectors can closely be tied to the biophysical dimension of climate change. Nonetheless, biophysical vulnerability can also be assessed by adopting a risk-hazard approach. This approach measures vulnerability based on the occurrence of hazards in a given area or community. The resulting damages are then quantified by developing sensitivity indicators obtained from the hazard analysis (Füssel, 2007).

In economics, this approach can be used to assess the vulnerability of economies to disasters. In engineering, the approach has also been used to estimate the vulnerability of the built infrastructure to disasters (Downing *et al*.,2005). From the foregoing, the impact approach largely lays emphasis on how biophysical indicators influence vulnerability. However, despite the numerous advantages of this approach, it is not in sync with the complex dynamics that surround climate change vulnerability since it only focuses on the environmental and physical dimensions of vulnerability. This approach also ignores the structural and behavioural factors that influence vulnerability since it only underscores the impacts of extreme events.

2.8.3 The Integrated Approach

According to Cutter *et al*., (2000), this approach assesses vulnerability by integrating both the biophysical and the socioeconomic approaches to vulnerability assessment by systematically combining both the socioeconomic and biophysical indicators and thereafter computing a vulnerability index.

Furthermore, this approach has the capacity to account for both the internal and external stressors that make a system vulnerable and hence favoured in most studies (Cutter,2003; Fussel 2007). However, most of the socioeconomic and the biophysical data has different weights and lacks a clear and concise framework of integrating the two data sets (Cutter *et al*.,2000). Moreover, this approach is unable to account for the constant changes that are associated with vulnerability.

2.9 Methods for Climate Change Vulnerability Assessment

This section presents and discusses the most preferred methods for assessing vulnerability.

2.9.1 Vulnerability variable assessment method

Under this method, the welfare loss of the variables under study are assessed in relation to a specific set of stressors that the system is exposed to. Examples of variables may include agricultural yields and household consumption, while on the other hand, a stressor can include climate change. Once all the variables and stressors have been identified, vulnerability metrics are then developed to help in assessing the vulnerability of any given location of interest (Gbetibouo *et al*.,2010). This method is mostly favoured in economic and agricultural studies. Some generic metrics assess vulnerability by working out the probability that the variables identified will cross the set threshold.

Vulnerability is then assessed depending on how the system responds and adapts to the changing conditions subjected to it. However, this method works best for systems that are subjected to multiple stressors with multiple variables (Luers *et al*.,2003)

2.9.2 The Indicator Method

Under this method, vulnerability is quantified by calculating indices, averages or weighted averages obtained from a potential set of indicators that are carefully chosen to suit the study area (Leichenko and O'brien,2002). This method is favoured in most studies since it is applicable at any given scale, i.e., locally or nationally.

The indicator method can also allow for data aggregation and disaggregation, and hence can be used to assess vulnerability at any given scale. This is done by generating composite vulnerability indices obtained from weighted or averaged standardized vulnerability variables which finally gives us one vulnerability index (Leichenko and O'brien,2002). Moreover, the indicator approach relies heavily on the statistics obtained both at the micro and macro levels in order to compute the vulnerability indices.

According to Cutter *et al* (2000), two approaches can generally be used to compute the vulnerability indices. The first approach assumes that all the weights generated are equal hence the vulnerability indicators have the same level of significance. The second approach recognizes that the vulnerability indicators influence vulnerability differentially hence the need to assign them different weights. The weights assigned can be a source of uncertainty during the study. In order to overcome this, various methods such as the principal component analysis, expert judgment and the fuzzy logic among others can be used to account for the differences in weights (Masambaya, 2018).

However, the indicator approach comes along with certain limitations. For instance, the selection of the vulnerability indicators and the subsequent assigning of weights is a highly subjective process (Gbetibouo *et al*.,2010). To this end, this study employed both the indicator and integrated method.

2.10 Climate Projections and Emission Scenarios

Emission scenarios project global climate based on a consistent set of systematic and internal hypothesis determined by the driving forces as well as the relationships they exhibit. Concomitantly, the difference between future climate scenarios can be represented well using climate projections against the baseline climate using climate models (Rwigi,2014).

Over the recent past, advances in technology have spurred economic development thus intensifying emissions of greenhouse gases hence influencing global climate. Unfortunately, the influence of man on the climate system is projected to intensify into the future, thus causing climate uncertainties (Mitchell *et al*, 1999).

However, due to the complexities and difficulties involved in determining the future changes in anthropogenic emissions, the IPCC adopted the Representative Concentration Pathways (Rwigi, 2014). Representative concentration pathways primarily consist of four pathways, namely, RCP2.6, RCP4.5, RCP6.0 and RCP8.5 (IPCC, 2014; Van Vuuren *et al.*,2011). Representative concentration pathways are generated from a collaboration of models such as Integrated Assessment Models, Terrestrial Ecosystem Models, Climate Models, as well as emission inventory experts. Additionally, the representative concentration pathways have four climate scenarios constructed using variables such as energy, aerosols, emission, income and population (Van Vuuren *et al*.,2011), and this provides the basis for climate modelling, in climate studies.

High emission scenario is represented by RCP 8.5. It describes a rising radiative forcing of 8.5 W/m^2 with a CO_2 concentration of 1370 ppm by 2100. RCP 6.0 represents a stabilization pathway without an overshoot and a radiative forcing of 6 W/m^2 and a CO_2 concentration of 850 ppm at stabilization after 2100. RCP 4.5 has a radiative forcing of 4.5 W/m^2 and a stabilization pathway without an overshoot in CO_2 concentration of 650 ppm and stabilization just after 2100 (Clarke *et al*. 2007; Fujino *et al*., 2006; Riahi *et al.* 2007). RCP 2.6 represents a low emission scenario. Before circling back to 2.6W/m^2 by the year 2100, this scenario projects the level of Radiative forcing to reach a value close to 3.0W/m^2 at CO_2 concentration of 490 ppm (Moss *et al*.,2010).

2.10.1 Trends and patterns in Historical Temperature and Rainfall in Kenya

This section presents synthesis of the existing literature on the trends and patterns in historical temperature and rainfall in Kenya.

2.10.1.1 Trends and Patterns in Temperature

Temperature and rainfall are important determinants for any gains and prospects from farming systems dependent on rainfall, particularly in Kenya and Sub-Saharan Africa.

Muhati *et al.,* (2018) noted an annual significant increase in historical mean temperature of 0.84^{0}c for the period 1974 to 2011. These authors used observed daily temperature data for the period 1974 to 2011 to determine the trends and patterns in temperature in North Eastern

Kenya. The study further noted a decrease in temperature in the 1970s and 1980s, representing a decrease of 0.05^0C and -0.03^0C respectively per decade. Conversely, the decadal temperature rose significantly in the 1990s and 2000s at rates of $+0.013^0$C and $+0.07^0$C respectively.

Temperatures were observed to increase during the historical period 1979 to 2012 in North western Kenya (Opiyo, 2014). The study employed the Mann-Kendall trend test to analyze the trends and variability in temperature in Turkana, North western, Kenya. The Mann-Kendall trend tests revealed positive and statistically significant trends for all seasonal maximum temperature values at $p< 0.05$. Gichangi *et al.,* (2015) assessed Intra-seasonal climate variability in semi-arid eastern Kenya. The results revealed increased year-to-year variation in annual temperatures. Concomitantly, increased trends in maximum temperature were noted during the study period.

Kaoga *et al.,* (2021) determined the long-term spatial-temporal temperature characteristics in Kajiado county. The study employed the STATA statistical package to analyze the trends in temperature. The analysis of temperature trends indicated that temperatures increased significantly for the period 1983 to 2014 representing an increase of 1.37^0C. Samwel (2021) observed that mean temperature, minimum and maximum temperature in Kisii revealed increasing trends. This study employed the Mann-Kendall test statistic to reveal a significant upward trend in temperature in Kisii at 95% confidence level for the period 1983-2013.

2.10.1.2 Trends and Patterns in Historical Rainfall

Between 1950 and 2012, Lodwar exhibited a positive but insignificant rise in its total annual rainfall (Opiyo, 2014). The study further revealed slight negative seasonal trend in rainfall for the MAM rainfall season and slight positive trend in OND rainfall for period 1950 to 2012.

Ayugi et al., (2016) noted that Kenya has experienced a significant decline in rainfall trends between 1971 and 2010. Trend analysis of rainfall in Kisii for the period 1983-2013 revealed lack of increasing or decreasing trends in rainfall as the computed p value from the Mann-Kendall test statistic of 0.590 was greater than the significance level value of $p< 0.05$ (Samwel, 2021).

2.10.1.3 Trends and Patterns in Projected Rainfall and Temperature under RCP 4.5 and RCP 8.5 in Kenya.

Ongoma (2017) forecasted increasing rainfall over the entire region of East Africa, with the increases of rainfall being higher during OND compared to MAM rainy season under the RCP

4.5 and RCP 8.5 emission scenarios. However, the increase in rainfall was insignificant. This implies that the projected wetting under RCP 8.5 will be greater than under RCP 4.5.

Consequently, the 21st century is projected to exhibit temperature increase in relation to the 20th century. As such, temperatures are projected to rise by +0.2^{0}C and +0.5^{0}C every decade for the period 2006 to 2100 under the RCP4.5 and RCP8.5 scenarios respectively. Northern Kenya is expected to experience the highest warming (Ongoma, 2017).

Projections done using CMIP5 model show that Northern Kenya will exhibit an increase in annual and decadal rainfall. The seasonal increase in rainfall will be higher during the OND season under both RCP4.5 and RCP8.5 scenarios (Muhati, 2018). These results corroborate with those of the study by Ongoma *et al.,* (2017) that also noted higher increases in OND seasonal rainfall than the MAM seasonal rainfall.

2.10.2 Relationship between Climate Variables and Maize Production

Rainfall and temperature are critical in influencing crop yields particularly around the tropical areas (Mumo *et al.,* 2018). These authors further noted that most crops grown within the tropics are extremely sensitive to temperature hence extreme fluctuations in temperature will adversely impact their yields.

Cereal crops are projected to experience a 10% decline in yields for every 1^{0}C increase in temperature except in the high latitude areas (Mumo *et al.,* 2018; Lobell, 2011). The study by Lobell (2011) further projects that the present farming land under optimum rain-fed conditions or drought conditions in East Africa is projected to decrease by 65%. East Africa is projected to lose 40% of maize yields by the end of the 21st century. Jones and Thornton (2003) further projected a 10-20% decrease in crop yields in Africa by the year 2055. This decline in crop yields is attributed to limited growing season length, heat stress, increased water and moisture stress, and high pests, diseases and weeds prevalence as a result of increasing temperatures (Mumo *et al.,* 2018; Ziska *et al*., 2011).

Rise in global average temperatures will increase crop yields particularly in the highland areas and adversely impact yields in the lowland areas due to increased water and moisture stress. The timing of crop stress is crucial if gains are to be realized in crop yields (Mumo *et al.*, 2018). Within the tropical regions, maize crop usually grows close to its threshold temperature of between 28- 32^{0}C (Schlenker and Roberts, 2009; Conway, 2009). As such, maize is extremely sensitive to any slight rise in temperature not coupled by an increase in rainfall amounts.

2.11 Climate Change Vulnerability in Smallholder farming in Africa

Smallholder farming in Africa continues to deteriorate as a result of being exposed to climate risks and stressors such as droughts and floods. In this regard, many smallholder farmers have witnessed a decline in crop yields (Derbile *et al*.,2022). Nonetheless, the vulnerability of the smallholder farmers is greatly influenced by their farming systems and number of stressors and risks that they are exposed to. Therefore, smallholder farmers that have diverse systems of farming and higher levels of exposure to risks, coupled with poor access to farming resources are considered the most vulnerable (Williams *et al.*, 2018).

Smallholder farming in Africa ranks as the most vulnerable owing to the erratic rainfall patterns received in the region (IPCC,2014). Moreover, smallholder farming in Africa completely relies on rainfall for farming, hence any slight changes in precipitation significantly affects smallholder farming. However, smallholder farmers that have higher adaptive capacity tend to exhibit very low vulnerability (Hitayezu *et al.*, 2014). Similarly, fluctuations in climate severely impact smallholder farming in rural Africa owing to the prevailing low rates of adaptive capacity (Mashizha,2019).

Consequently, the vulnerability of smallholder farming in Africa is highly influenced by social, economic and demographic factors. As such, strong economies increase the resilience of farmers. Conversely, poverty-stricken farmers have very limited opportunities and resources hence rendering them vulnerable. (Dumenu *et al.*,2020).

Kanchebe *et al.,* (2022) notes that smallholder maize production in Africa is severely affected by droughts, high temperatures, and floods respectively. The drought conditions lead to excessive heat which in turn discourages farmers from carrying out their farming activities. Moreover, the high temperature conditions lead to drying and wilting of crops, thus affecting their farming income. Additionally, high temperatures also lead to bush fires which eventually destroy crops.

CHAPTER THREE

3.0 DATA AND METHODOLOGY

3.1 Introduction

This chapter presents methods and data that were utilised to address the specific study objectives, including a description of the location of the area of study. The description of the area of study is first presented.

3.1.1 Area of Study

South Nyanza consists of four counties namely, Kisii, Nyamira, Homabay and Migori. Kisii County is located in South Nyanza region between latitudes 0º 40’ South and 38.4’ South, and longitudes 34º 34’ East and 46º 61” East (Kisii County Government, 2018). The annual rainfall received in Kisii County is approximately1500mm. Conversely, the ranges of maximum and minimum temperature are 210C-300C, and 150C-200C respectively. The average household farm size in Kisii County is approximately 0.5 ha, indicating that the farming population in the County is predominantly smallholder (Wamalwa *et al*, 2016). Most of the smallholder farmers mainly grow maize, beans, vegetables, fruits such as bananas and avocados, tea and coffee, sorghum and sweet potatoes.

Nyamira County lies between latitudes 0º 30' and 0º 45' South, and longitude 34º 45' and 35º 00' East with an altitude that ranges between 1,250-2,100 metres above sea level. The County receives up to 2,100 mm of rainfall annually. Farmers mainly grow tea, coffee, fruits, sugarcane, sweet potatoes, maize, beans, pyrethrum, sorghum and vegetables (Momanyi, 2016).

Homabay County lies between latitude of 0^o 15’ South and 0^o 52’ South, and longitudes 34^o East and 35^o East. It covers approximately 4,267.1 Km2 including the water surfaces (Ongeko *et al.*,2017). The County experiences both short and long rainy seasons and with elevation of 1146 m above sea level (Ogenga *et al.*,2018). Homabay residents are predominantly fishermen and smallholder farmers growing maize, cassava, millet, and sunflower.

Migori County lies between latitude 1^o24’ South and 1^o40’South and longitude 34^o East and 34^o 50’East with an estimated land and water area of 2,596.5 km^2. Farmers in this County grow sugar cane, maize, sweet potato, tobacco, sunflower, cassava, and beans, among other crops. (Migori County Government, 2018).

Figure 2 shows the geographical location of the area of study.

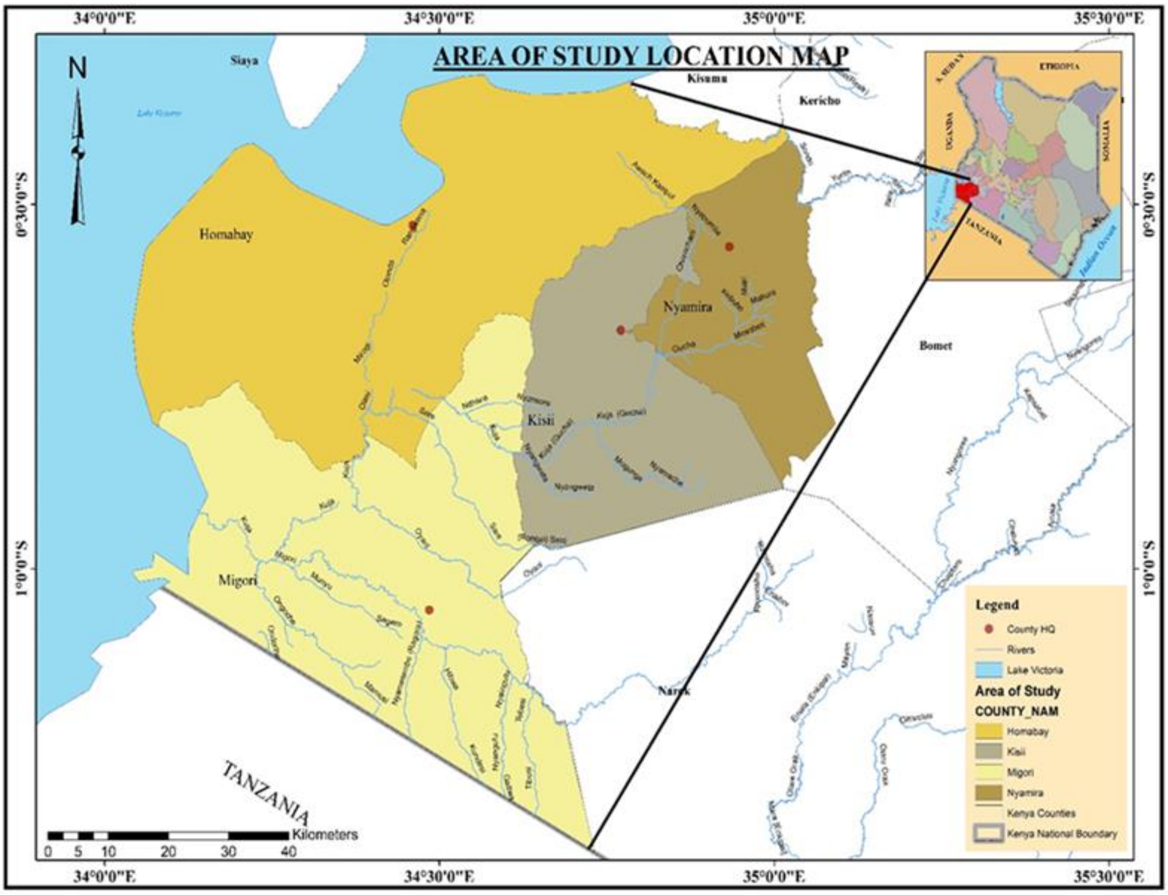


Figure 2: Area of study

3.2 Types and Sources of Data

This section presents the data types used in this study with their sources. Data on climate is first presented.

3.3 Climate Data

Due to scarcity and inconsistency of observed climate data in the study counties, climate data that were used in this study were obtained from satellite derived estimates. Data for daily and monthly rainfall were obtained from CHIRPS with a resolution of 0.05° for the period 1988-2018, whereas daily and monthly minimum and maximum temperature were acquired from CHIRTS at a resolution of 0.05° for the period 1983-2016. Observed data from Kisii Meteorological Station were used to validate the satellite estimates from CHIRPS and CHIRTS platforms.

3.3.1 Climate Hazard Group Infrared Precipitation with Stations (CHIRPS)

CHIRPS rainfall data was used for climate analysis and to validate the model outputs gridded at a resolution of 0.05ºx0.05º. CHIRPS is a global dataset that spans from 50°N to 50°S, with a resolution of 0.05º. This data was obtained from the "IGAD Climate and Application Centre (ICPAC)". Four stations were used represented in Counties and due to scarcity of data in the area of study, available data from Kisii Meteorological station were used to validate the satellite estimates for both rainfall and temperature. Table 1 indicates the stations used in the study, their locations, and the distribution of data.

Table 1: Coordinates of Meteorological Study Stations used in the area of study

No.	Station Identification		Location			Distribution			Missing Range (%)
	Name	**Code**	**Lat.**	**Lon.**	**Elev. (m)**	**Start**	**End**	**Length (yrs.)**	
1.	KISII MET Station.	9034088	0.67S	34.77E	1649	1981	2018	37	3.2%
2.	NYAMIRA	-	0.56S	34.94E	1960	1981	2018	37	-
3.	MIGORI	-	1.06S	34.47E	1377	1981	2018	37	-
4.	HOMABAY	-	0.53S	34.46E	1194	1981	2018	37	-

3.3.2 CHIRTS

This study used CHIRTS daily temperature data for climate analysis. CHIRTS data were also obtained from the "IGAD Climate and Application Centre (ICPAC)" . CHIRTS is also a global data set that comprises daily minimum and maximum temperatures covering areas ranging from latitudes 60°S to 70°N, and has a high resolution of 0.05ºx0.05º.

3.3.3 Climate Projection Datasets

This study used Coordinated Regional Downscaling Experiment (CORDEX) to simulate scenarios based on the four distinct Representative Concentration Pathways (RCPs) described in chapter 2 of this dissertation. CORDEX was preferred for this study since it accounts for the local forcing which influence climate change at a local scale. In order to simulate climate change between 2022 and 2051, this study employed the RCP4.5 and RCP8.5 to represent the medium stabilization and high emission scenarios respectively. Furthermore, RCP 4.5 and RCP 8.5 allowed for a comparison to be made between scenarios where there are climate change policies to curb climate change and a scenario where there are no climate change policies, mitigation and adaptation measures (Van Vuuren *et al*.,2011). A list of the CORDEX-Africa General Circulation Models extracted over a box covering the area of study is indicated in Table 2 below.

Table 2: Global Climate Models used with CORDEX

Model	Maximum Temperature		Minimum Temperature		Rainfall	
	Correlation Coefficient	**RMSE**	**Correlation Coefficient**	**RMSE**	**Correlation Coefficient**	**RMSE**
CNRM	0.38	1.7	0.35	2.2	0.33	89.8
CSIRO	0.51	1.1	0.38	1.4	0.18	96.2
ICHEC	0.42	1.4	0.31	1.8	0.26	90.4
CCCma	0.36	2.2	0.24	3.3	0.12	100.7
MOHC	0.43	1.6	0.34	2.6	0.18	99.6
MPI	0.39	1.3	0.18	1.9	0.21	102.9
MIROC	0.26	2.6	0.28	2.5	0.16	100.9
IPSL	0.41	1.9	0.27	2.8	0.12	103.8

CNRM model mimicked well the observed rainfall and was therefore selected to provide for climate projections. CSIRO on the other hand performed well in simulating historical temperature and was therefore used to provide future climate projections over the area of study. The simulations from both models were done for the period 2022 to 2051.

3.3.4 Maize Yield Data

Data on the annual maize yield between 1988-2018 was obtained from the "Ministry of Agriculture, Livestock, Fisheries and Cooperatives".

3.3.5 Satellite Imagery Data

The Imagery acquired for this research was obtained from Landsat 5, Landsat 7 and Landsat 8 satellites. The imagery used were for the year 1986, 2001 and 2018. The Images were downloaded and pre-processed; geographically corrected and layer-stacked (band compositing) using Google Earth Engine (GEE). Table 3 below depicts the specifications of the satellite platform used and images acquired for this study.

Table 3: Landsat Imagery Specifications

LANDSAT IMAGERY SPECIFICATIONS					
Sensor	**Year of imagery**	**Spatial Resolution**	**Spheroid and Datum**	**UTM Zone**	**False colour band combination**
Landsat 5 TM	1986	30m	WGS 1984	36 South	4,3,2
Landsat 7 ETM+	2001	30m	WGS 1984	36 South	4,3,2
Landsat 8 OLI-TIRS	2018	30m	WGS 1984	36 South	7,6,4

3.3.6 Data on Indicators

This section contains all the vulnerability indicators that were used in this study.

3.3.6.1 Exposure Indicators

Exposure indicators for this study included the rates of change of warming, frequency of floods and droughts, land use and land cover, and the rate of change in rainfall. Rate of change of temperature and rainfall was determined using the Sen Slope Estimator. Baseline rainfall data for each station was analysed using Standardized Precipitation Index so as to obtain the frequency of floods and droughts. Thereafter, the results were compared against the Standardized Precipitation Index value table so as to identify values that correspond to floods and droughts.

3.3.6.2 Adaptive Capacity Indicators

Adaptive capacity indicators used included: rate of literacy, farm income, farm assets, percentage of farmers in farm organizations, percentage of farmers who save money, income from other sources including farming, household net income, percentage of farmers who access credit, proximity to "National Cereals and Produce Board" depots, proximity to markets, distance to tarmac roads, utilisation of inorganic fertilizers and hybrid seeds, and levels of irrigation. These indicators were obtained from "Tegemeo Institute of Agricultural Policy and Development (TIAPD)".

3.3.6.3 Sensitivity Indicators

In this study, sensitivity indicators comprised demographic and ecological indicators. Demographic indicators included rural population density, percentage of farmers planting maize and the percentage of people living in hardcore poverty. Ecological indicators included area of land under maize farming, annual maize yields, and the percentage dependency on rainfall. Sensitivity indicators were obtained from the “Ministry of Agriculture, Livestock, Fisheries and Cooperatives (MOALFC)”, the “Kenya Institute for Public Policy Research and Analysis (KIPPRA)”, the “Kenya National Bureau of Statistics(KNBS)”, and “Tegemeo Institute of Agricultural Policy and Development (TIAPD)”. Table 4 indicates the variables and the indicators used in this study to compute “Exposure, sensitivity and adaptive capacity” indices.

Table 4: Variables and indicators used to compute Exposure, Sensitivity and Adaptive Capacity Indices

Components of Vulnerability	Vulnerability Indicators	Indicator Description/Measurement	Functional Relationship between the indicators used and vulnerability	Sources of Data
	Extreme climate events	Frequency of occurrence of floods and droughts (Number of floods and droughts)	High frequency of floods and droughts, denotes high vulnerability and vice versa	Standard Precipitation Index (SPI)
		Rate of change of maximum temperature (1983-2016)	The higher the rate of change of maximum temperature, the higher the vulnerability	Sen Slope Estimator
		Rate of change of minimum temperature (1983-2016)	The higher the rate of change of minimum temperature, the higher the vulnerability	Sen Slope Estimator
Exposure	Climate change	Rate of change of rainfall (1988-2018)	The higher the rate of change of rainfall, the higher the vulnerability	Sen Slope Estimator
	Population density	Number of people per square km	The higher the density, the higher the vulnerability	Kenya National Bureau of Statistics
	% of farmers who depend on rainfed agriculture	% Of farmers who depend entirely on rainfall for farming	The higher the %, the higher the vulnerability	Tegemeo Institute of Agricultural Policy and Development
	Hardcore poverty rates (%)	Number of people living in extreme/abject poverty	The higher the %, the higher the vulnerability	Kenya National Bureau of Statistics
	Total area under maize production	Acres	The higher the area, the lower the vulnerability	"Ministry of Agriculture, Livestock Fisheries and Cooperatives"
	Quantity of maize harvested per acre	Kilogram/acre	The higher the yield, the lower the vulnerability	Ministry of Agriculture, Livestock Fisheries and Cooperatives.
	Total annual maize production	Kilograms	The higher the yield, the lower the vulnerability	Ministry of Agriculture, Livestock Fisheries and Cooperatives
Sensitivity	Farmers who practise maize farming (%)	Percentage (%)	The higher the %, the higher the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Use of chemical fertilizers	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Irrigation rates	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Distance to NCPB	Kilometres	The longer the distance, the higher the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Distance to farm markets	Kilometres	The longer the distance, the higher the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	% of farmers in farming groups	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	% of maize farmers that use improved seeds	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	% of farmers with savings account	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
Adaptive Capacity	Rate of Literacy	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	% of maize farmers who access credit	Percentage (%)	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Remittances	Kenya Shillings	The higher the %, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Value of farm assets	Kenya Shillings	The higher the value, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"
	Total farm land holding	Acres	The larger the land holding, the lower the vulnerability	"Tegemeo Institute of Agricultural Policy and Development"

	Total net off-farm income	Income generated from other activities other than agriculture in Kenya Shillings	The higher the income, the lower the vulnerability	“Tegemeo Institute of Agricultural Policy and Development”
	Net Farm Income	Income generated from agricultural activities except maize farming in Kenya Shillings	The higher the farm income, the lower the vulnerability	“Tegemeo Institute of Agricultural Policy and Development”
	Distance (in Km) from homestead to a motorable road	Kilometres	The longer the distance, the higher the vulnerability	“Tegemeo Institute of Agricultural Policy and Development”
	Distance (in Km) from homestead to a tarmac road	Kilometres	The longer the distance, the higher the vulnerability	“Tegemeo Institute of Agricultural Policy and Development”

3.4 Sample Selection and Sampling Procedure

The study counties were selected using purposive sampling while considering the level of smallholder maize production in the region. Availability of Data was also used to select the area of study.

3.5 Methodology for Data Analysis

This sub-section presents in detail the methods that were utilized to address the specific objectives of this study. Methods used to assess trends in historical climate is first presented.

3.5.1 Determination of the Trend in the Climate Variables

Trends in the climate series were determined by timeseries analysis. This involves plotting data against time, and is a crucial process since it helps to detect trends, periodicities and cycles including seasonality (Rwigi, 2014).

The non-Parametric Mann-Kendall Test was used to determine the trend in the historical climate data in order to tackle problems that could arise due to data skewness (Mondal *et al,* 2012) and data that is randomly distributed. The assumptions made in this analysis was that the data used was randomly distributed and independent (Partal and Kahya, 2006).

The trend test was performed on a time series of *n* data values, with T_i and T_j as two data sub sets (i= 1, 2, 3..., n) and (j= i+1, i+2, i+3…. n). Values within the data were considered as ordered time series for evaluation purposes. The Mann-Kendall Statistic S was computed using equations 1 and 2.

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

$$\text{Sign}(T_J - T_I) = \begin{cases} 1 \; if(T_J - T_I) > 0 \\ 0 \; if(T_J - T_I) = 0 \\ -1 \; if(T_J - T_I) < 0 \end{cases} \quad \text{Eqn (2)}$$

Where; T_J = annual values in jth years and T_I = annual values in ith years, and j>i

The value of S was then interpreted to give the trend. For instance, S> 0 indicated increasing trends in the time series data, values of S< 0, indicated decreasing trends in the time series data, while S= 0, indicated that there was no trend in the time series data (Partal and Kahya, 2006). The computed p-values of the Mann-Kendall test were then compared to the significance level value of α= 0.05. The trend was considered statistically significant if the p-values of the Mann Kendall test were less than 0.05 significance value.

3.5.2 Determination of Rate of Change of the Climate Variables

Rate of change of climatic data was determined using the Sen Slope Estimator, a non-parametric method developed by Sen in the year 1968. The slope of the linear trend was computed so as to establish rate of change of the climate variables per unit time (Gocic, andTrajkovic,2013) as given by equation 3.

$f(t) = Qt + K$ ……………………………………...Eqn (3)

where $\boldsymbol{Q}$ =slope of the trend line, $\boldsymbol{t}$ is time and $\boldsymbol{K}$ is the constant

Equation 4 was used to obtain the slopes for all the pairs of data used as a measure for the parameter Q in equation 3.

$$Qi = \frac{x_j - x_k}{j - k} \quad \text{……… Eqn (4)}$$

Where Qi is the slope of all data pairs, i=l, 2…..N, and j>k

The number of slopes needed to estimate Qi was determined using equation 5.

$$N = \frac{n(n-1)}{2} \quad \text{……… Eqn (5)}$$

N=the number of slopes needed.

Upon ranking the N values of Qi in equation 5, the Sen's Slope estimator was computed using equation 6.

$$Q = \begin{cases} Q_{\frac{N}{2}} \ N \ is \ odd \\ \frac{1}{2}\left(Q_{N/2} + Q_{N+2/2}\right) \ N \ is \ even \end{cases} \quad \text{……… Eqn (6)}$$

Where Q is the Sen's Estimator of Slope, N is odd means the N value is not divisible by two, whereas N is even, refers to N value divisible by two.

3.5.3 Standardized Precipitation Index (SPI)

Rainfall data from each County was analysed using the three-month Standardized Precipitation Index (SPI) program developed by the World Meteorological Organization so as to obtain the frequency of floods and droughts. Subsequently, the results obtained from the above analysis were compared to the SPI values in Table 5 in order to identify dry and wet periods within the data (Svoboda *et al*., 2012). Normal rainfall ranged between -1 and +1. Values above +1 depicted floods whereas values below -1 indicated drought. Table 5 presents the standardized precipitation index values that were used in this study.

Table 5: Standardized 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

3.5.4 Determination of the relationship between climate variables and maize productivity

The degree and nature of the relationship between climate variables and maize yields was determined using the Spearman's correlation coefficient, $\boldsymbol{\rho}$, that ranges between -1 to 1, computed using equation 7 (Zhao *et al*., 2015).

$$\boldsymbol{\rho = 1 - \frac{\sum_{i=1}^{n} D^2}{n(n^2-1)}} \quad \text{Eqn (7)}$$

Where: $\boldsymbol{D}$ is the difference between the paired ranks, and $\boldsymbol{n}$ is the number of paired ranks

The Spearman's correlation coefficient, $\boldsymbol{\rho}$, was then interpreted to give the nature of the relationship between maize yields and climate variables. Where, $\boldsymbol{\rho}$ **=0,** there was no association between the study variables, where $\boldsymbol{\rho}$ **= -1 or +1,** means there was a perfect monotonic relationship, thus implying that each of the variables was a perfect monotone function of the other.

3.6 Determination of Change in Climatic Parameters in Climate Records

Points of change in the climate data sets were identified using the Pettit test owing to its high sensitivity to breaks in any given data set. This method was used to compute parameter Ut, as given by equations 8 and 9 (Pohlert, 2016).

$$U_t = \sum_{i=1}^{t} \sum_{j=t+1}^{n} \text{Sign}(X_t - X_j) \quad \text{Eqn (8)}$$

$$\text{Sign}(X_t - X_j) = \begin{cases} 1 \ if \ (x_t - x_j) > 0 \\ 0 \ if (x_t - x_j) = 0 \\ -1 \ if \ (x_t - x_j) < 0 \end{cases} \quad \text{Eqn (9)}$$

Where, $\boldsymbol{X_t}$ and $\boldsymbol{X_j}$ are the sequential data values, and **T** is the number of the recorded data, **t** and **j** are coefficients of the sequential data values.

Equations 8 and 9 were used to detect a single change point in climate series with continuous data. The null hypothesis that was tested was H_0: the variables follow one or more distributions that have the same location parameters against the alternative hypothesis H_1: there is an existence of change point.

The data series was divided into two parts. In the first part, it was assumed that a series of baseline data *X1, X2……Xn* had a change at point t, and associated with a distribution function F1(x). The second part of the time series, xt+x1, *xt+x2, xn* was considered to have a distribution function, *F2(x)*. The test statistic and the confidence level ($\boldsymbol{\rho}$) for a sample length, n was computed using equation 10 and 11 (Pohlert, 2016).

$$K = \text{Max}|U_t| \quad \text{Eqn (10)}$$

The change point of the series is located at K_T, provided that the statistic is significant. The significance of probability of K_T is approximated for $p \leq 0.05$ using equation 11.

$$\rho = exp\left(\frac{-K}{n^2+n^3}\right) \quad \text{Eqn (11)}$$

Where ρ = test statistic

The result from equation 11 above was used to compute the probability value in equation 12 that was used to test for the significance of the difference between the two data sets.

$p=1-\rho$………………………………………………………………………. Eqn (12)

where p, is the required probability value. A p-value greater than 0.05 was considered to indicate a significant change in the climatic data sets.

3.7 Analysis of Satellite Images

The pre-processed images were loaded onto ArcGIS software where image classification was undertaken. Supervised classification method was used to categorise the satellite images. Additionally, the satellite images that were taken during the study period were ascertained by coming up with two classes for each Land Use and Land Cover unit using the maximum likelihood classification method (Sisodia *et al*.,2014) using equation 13.

$P(i|\omega) = \frac{p(\omega|i)p(i)}{p(\omega)}$………………………………………………………………… Eqn (13)

Where, $\boldsymbol{i}$ is class, $\boldsymbol{\omega}$ is a feature vector, $\boldsymbol{P(i|\omega)}$, is the likelihood function, $\boldsymbol{p(i)}$ is the Probability that class i will occur in the study area, and $\boldsymbol{p(\omega)}$ is the probability that ω will be observed and was computed using equation 14.

$p(\omega)=\sum_{i=1}^{M} p(\omega|i)p(i)$ ………………………………………….… Eqn (14)

Where M is the number of classes, $\boldsymbol{p(\omega)}$ is a standardization constant that ensures that $\boldsymbol{\sum_{i=1}^{M} p(\omega|i)p(i)}$ adds to 1.

Nonetheless, the rule set by equation 15 was used to allocate pixel x to class i.

X ϵ I, if $p(\omega|i)> p(j|\omega)$ given j≠I ……………………………………….…... Eqn (15)

The maximum likelihood method assumes that data distribution in a given class i, was in tandem with the multivariate Gaussian distribution. In the instances where the probability values of the pixels were less than the limits set by the pixels, the pixels were considered unclassified. Each pixel was attached to a class that had the maximum likelihood. Finally, land use and land cover were classified using ERDAS Imagine 10 and Arc GIS 10. The trends in Land Use and Land Cover were analysed using nine classes as illustrated in figure 3.

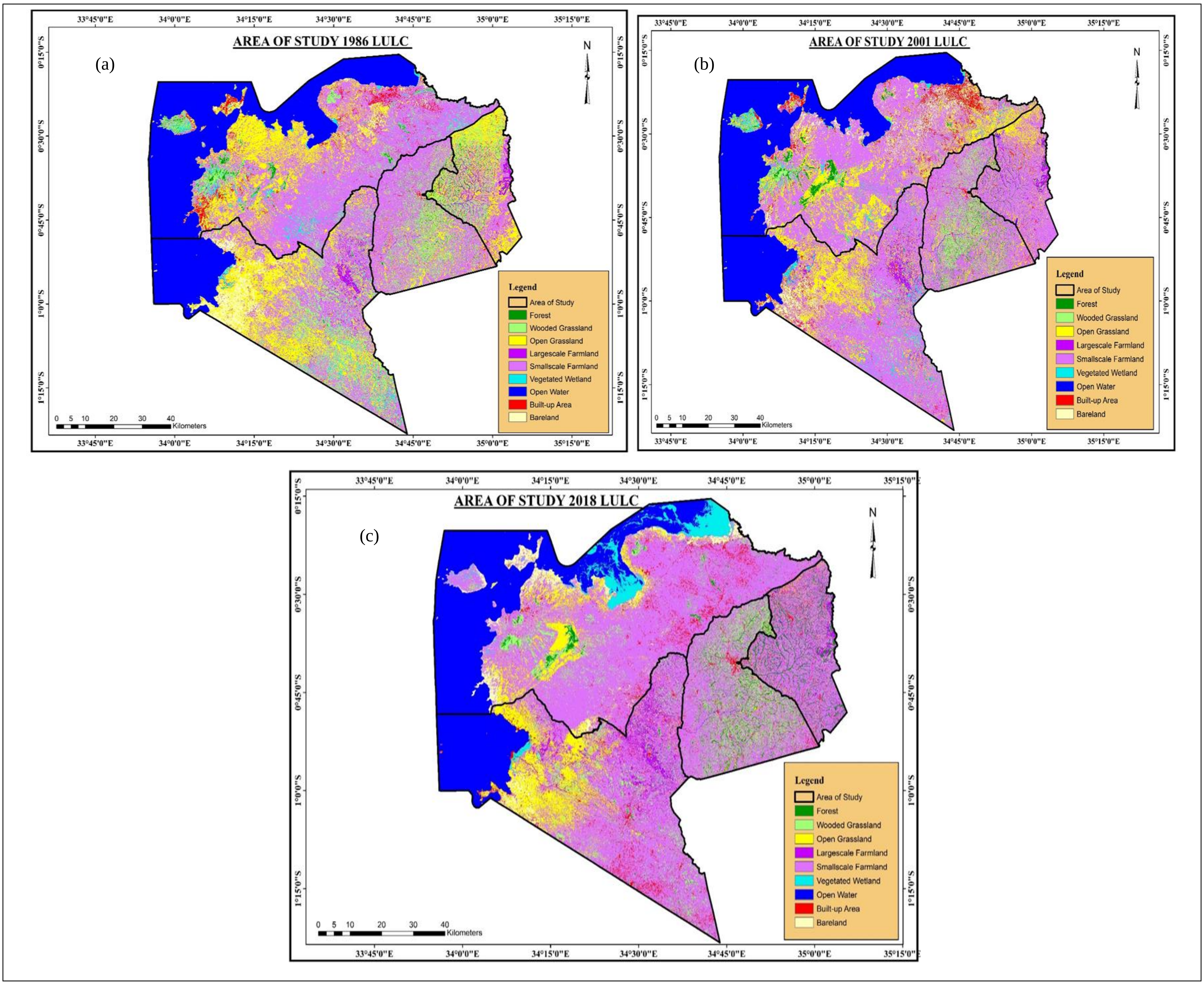


Figure 3: LULC for the years 1986 (a), 2001 (b) and 2018 (c) over the area of study

3.8 Determination of Vulnerability Index for the Study area

Any increase in vulnerability due to increase in the value of indicators was normalized using equation 16.

$$X_{normalized} = \frac{Xij - minxij}{maxXij - minXij} \quad \text{Eqn (16)}$$

Where:

X_{ij} is the value of the ith indicator for the jth County

On the other hand, any reduction in vulnerability caused by a decrease in a given indicator was normalized using equation 17.

$$X_{normalized} = \frac{maxxij - xij}{maxxij - minxij} \quad \text{Eqn (17)}$$

Where X_{ij} represented the value of the ith indicator for the jth County.

Principal Component Analysis (PCA) was then performed so as to rank the data by assigning unequal weights to each of the indicators using the standard deviation and mean of each indicator for normalization. A given group of N variables ($\boldsymbol{a_{1j}^{\#}}$ **to** $\boldsymbol{a_{Nj}^{\#}}$ **)** was normalized using a similar approach to that of Masambaya (2018) given by equation 18.

$$a_{1j} = \frac{a_{1j}^{\#} - a_{1}^{\#}}{s_{1}^{\#}} \quad \text{Eqn (18)}$$

Where, $\boldsymbol{a_{1}^{\#}}$ is the mean of the region and $\boldsymbol{s_{1}^{\#}}$ is the standard deviation of the region

The selected variables were expressed by linearly combining a set of the main components as shown in equation 19.

$$a_{1j} = v_{11}A_{1j} + V_{12}A_{2j} + \ldots V_{1N}A_{NJ}, \text{ J=1} \quad \text{Eqn (19)}$$

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

Where, A’s are the components, V’s are the coefficients of each component for each variable used and a1j, is the first principal component from a set of N variables (attributes) of each region, j, and aNj, is the Nth principal component.

Principal Component Analysis (PCA) was used to determine the first principal component (a1J) which basically represented variables with the highest variance obtained through a linear combination. A second principal component was determined so as to account for the other maximum variance. The PCA method, provided a theoretical solution in the equation $(R-\lambda_n 1)$ v_n=0, for v_n and λ_n.The Matrix R in the equation showed how each variable correlated with the nth component. A solution to this equation gave rise to the values of λ_n presented as the typical root of R and the associated Eigen vectors Vn. The final estimates were then obtained by scaling the Eigen Vectors and thereafter obtained a sum of their square to obtain the total variance.

The scoring factors from the model were recovered by inverting the system presented in equation 19. This yielded a set of estimates for each of the N components

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

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

The f's are the factor scores. Following Deressa (2010), the first principal component, expressed in terms of the original variables, was considered as an index for each region in the study counties presented in equation 23.

$$A_{1j}=\frac{f_{11}(\boldsymbol{a_{1j}^{\#}}-\boldsymbol{a_{1}^{\#}})}{\boldsymbol{s_{1}^{\#}}}+\ldots\ldots\frac{f_{1N}(\boldsymbol{a_{Nj}^{\#}}-\boldsymbol{a_{N}^{\#}})}{\boldsymbol{s_{N}^{\#}}}\ldots\ldots \text{Eqn (23)}$$

The normalized values of each component variables were multiplied by their respective PCA weights. Consequently, the products were added together and divided by the total weight of the variables under each component as presented in equations 24 to 26.

$S_C=\frac{\sum_{i=1}^{j}P_iY_S}{\sum_{I=1}^{j}P_1}\ldots\ldots$ Eqn (24)

$E_C=\frac{\sum_{i=1}^{j}P_iY_E}{\sum_{I=1}^{j}P_1}\ldots\ldots$ Eqn (25)

$A_{C\,C}=\frac{\sum_{i=1}^{j}P_iY_{AC}}{\sum_{I=1}^{j}P_1}\ldots\ldots$ Eqn (26)

Where, ***Ec*** = exposure of the County, ***Sc*** =sensitivity of the County, ***ACc***= adaptive capacity of the County, $\boldsymbol{Y_{AC}}$, $\boldsymbol{Y_S}$ ***and*** $\boldsymbol{Y_E}$ = Standardized values of variables, namely, adaptive capacity, sensitivity and exposure in that order, and ***Pi*** = weight of the indicators.

The vulnerability index of the County (VIc) was then computed by obtaining the sum of Ec and Sc and then subtract the adaptive capacity (ACc) as shown in equation 27.

$$VI_C = \frac{E_{C+S_C} - (1 - AC_C)}{3} \quad (27)$$

Where;

VIc is the vulnerability index of the County, ACc is the adaptive capacity of the County, Sc is the sensitivity of the County, while Ec is the exposure of the County.

To obtain a more valid vulnerability index, the vulnerability index obtained in equation 27 was normalized as shown in equation 28 to get a final value that range between 0-5 (Masambaya, 2018).

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

The resultant vulnerability in equation 28 was normalized on a scale of 0-5 and thereafter used to characterize vulnerability in each County as categorized in Table 6.

Table 6: Categorization of Vulnerability

No.	Normalized VI	Category
1	$4 \leq VI_{Normalized} < 5$	Very high
2	$1 \leq VI_{Normalized} < 2$	Low.
3	$0 \leq VI_{Normalized} < 1$	Very low

The resulting categories of vulnerability in each County were then used to generate a vulnerability index map. The vulnerability indicators were statistically developed by different methods highlighted in the various sections discussed under section 3.4, and the different indicators mathematically combined to develop an index map. Spatial analysis function of the Geographical Information System (GIS) tool was used to draw spatial maps, which were overlaid with the different indices to determine the geographical location of the most vulnerable areas and their exposure to climate hazards.

CHAPTER FOUR

4.1 RESULTS AND DISCUSSION

4.2 Introduction

This chapter presents results of the analysis of the specific objectives of this study and their discussion. It details the trends and mean shifts of baseline and projected climate; correlation coefficients between weather variables and annual maize yields, “exposure, sensitivity, adaptive capacity” and vulnerability indices for the study counties.

4.3 Validation of the CHIRPS and CHIRTS datasets

A comparison between the observed baseline climate and the satellite data was done for both rainfall and temperature for Kisii Meteorological station between 1981 to 2018 for rainfall and 1983-2016 for temperature. Table 7 indicates the relationship between satellite datasets with the observed station data for Kisii Meteorological station.

Table 7: Validation Coefficients

Parameter	Correlation coefficient (r)
Rainfall	0.65
Maximum Temperature	0.72
Minimum Temperature	0.69

Rainfall had a correlation coefficient (R^2) of 0.65 (65%), whereas maximum and minimum temperature had a correlation coefficient (R^2) of 0.72 (72%) and 0.69 (69%) respectively. The correlation coefficients were good hence CHIRPS rainfall and CHIRTS temperature data can be used in the study area.

4.4 Trends and Patterns of Baseline and Future Climate

The trends and patterns of observed rainfall and temperature for the baseline (1988-2018) and future (2022-2051) under RCP4.5 and RCP8.5 emission scenarios are contained in this section.

4.4.1 Baseline Trends for the Annual Rainfall

Figure 4 presents the mean shifts in total annual rainfall for the period 1988-2018 for Homabay, Kisii, Migori and Nyamira Counties respectively. Homabay, Kisii, Migori and Nyamira Counties exhibited an upward/ increasing mean shift in annual rainfall for the baseline period (1988-2018). All the study counties depicted an increasing trend in the total annual rainfall.

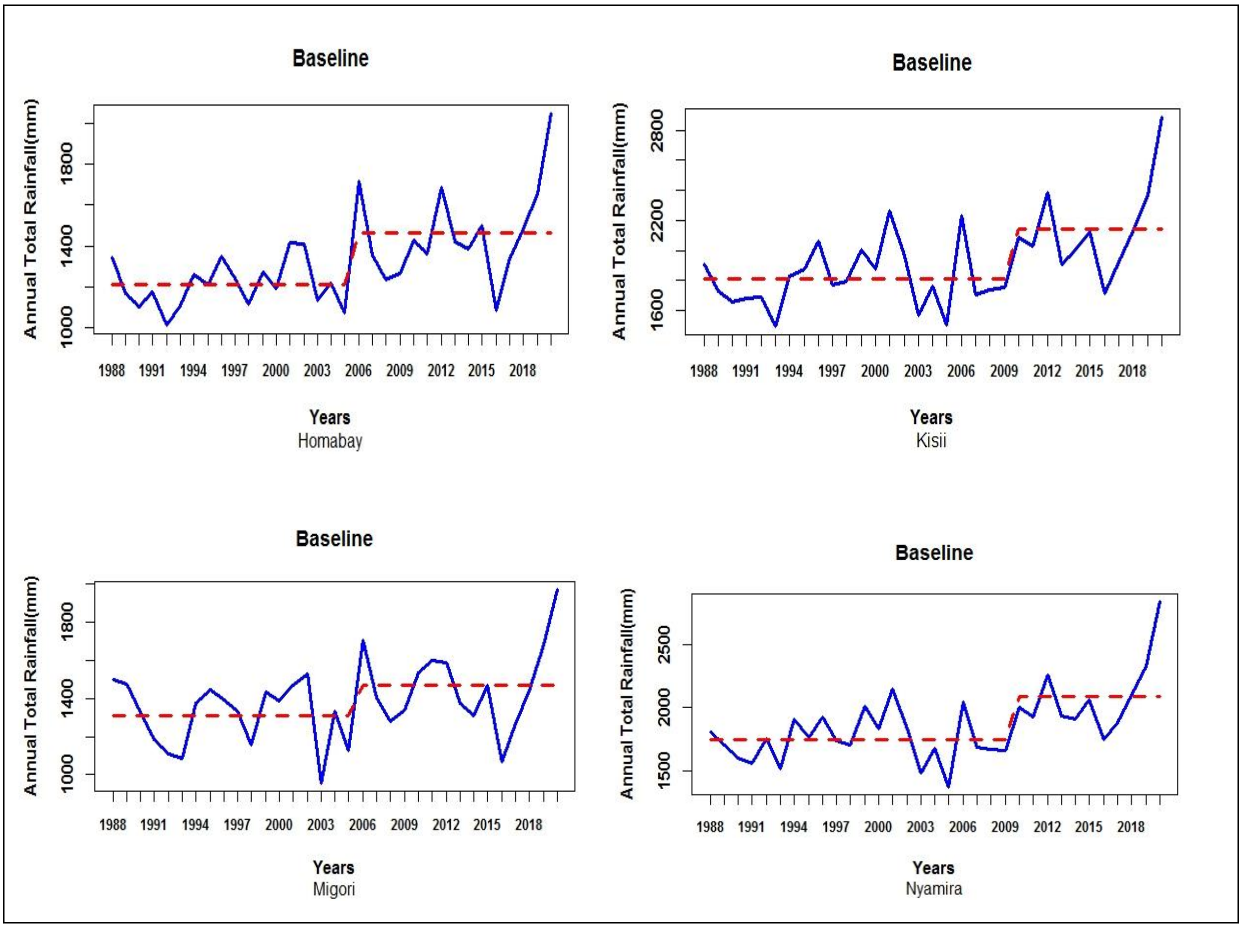


Figure 4: *Mean shifts in annual rainfall for Homabay, Kisii, Migori and Nyamira (1988- 2018*).

Figure 5 presents the baseline Trends in annual rainfall for Homabay, Kisii, Migori and Nyamira counties.

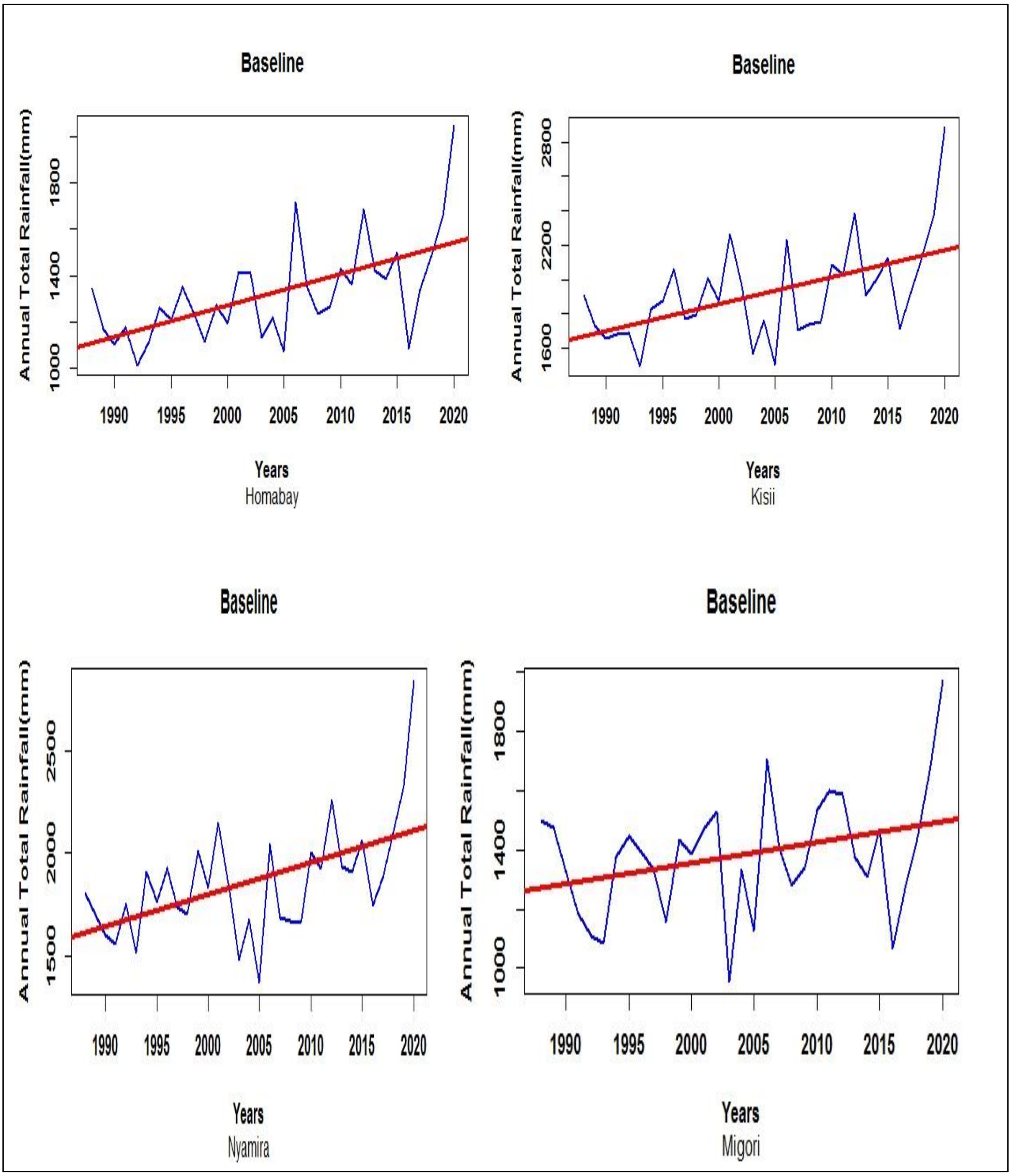


Figure 5:Baseline Trends in annual rainfall for Homabay, Kisii, Migori and Nyamira

Over the period 1988-2018, all the four counties experienced increasing trends in annual rainfall totals. This implies increasing prospects for agricultural activities including maize production.

Figure 6 presents the mean shift in MAM rainfall for Homabay, Kisii, Migori and Nyamira counties.

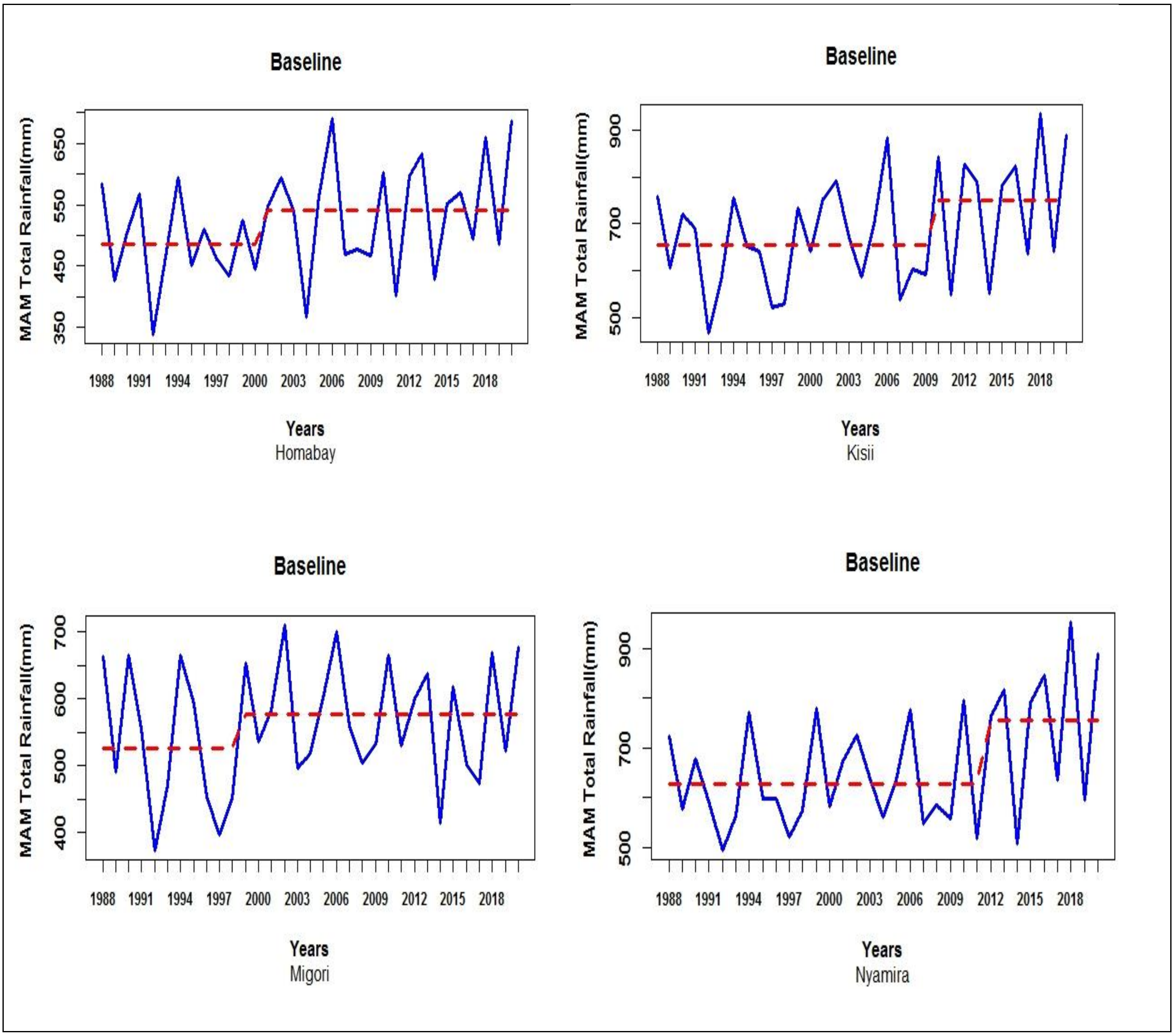


Figure 6: Baseline Mean shifts in MAM rainfall for Homabay, Kisii, Migori and Nyamira

Over the baseline period, Homabay, Kisii, Migori and Nyamira counties experienced increasing mean shift during MAM rainfall season for the period 1988-2018, implying increasing MAM total rainfall.

Figure 7 presents trends in MAM seasonal rainfall in Homabay, Kisii, Migori and Nyamira counties.

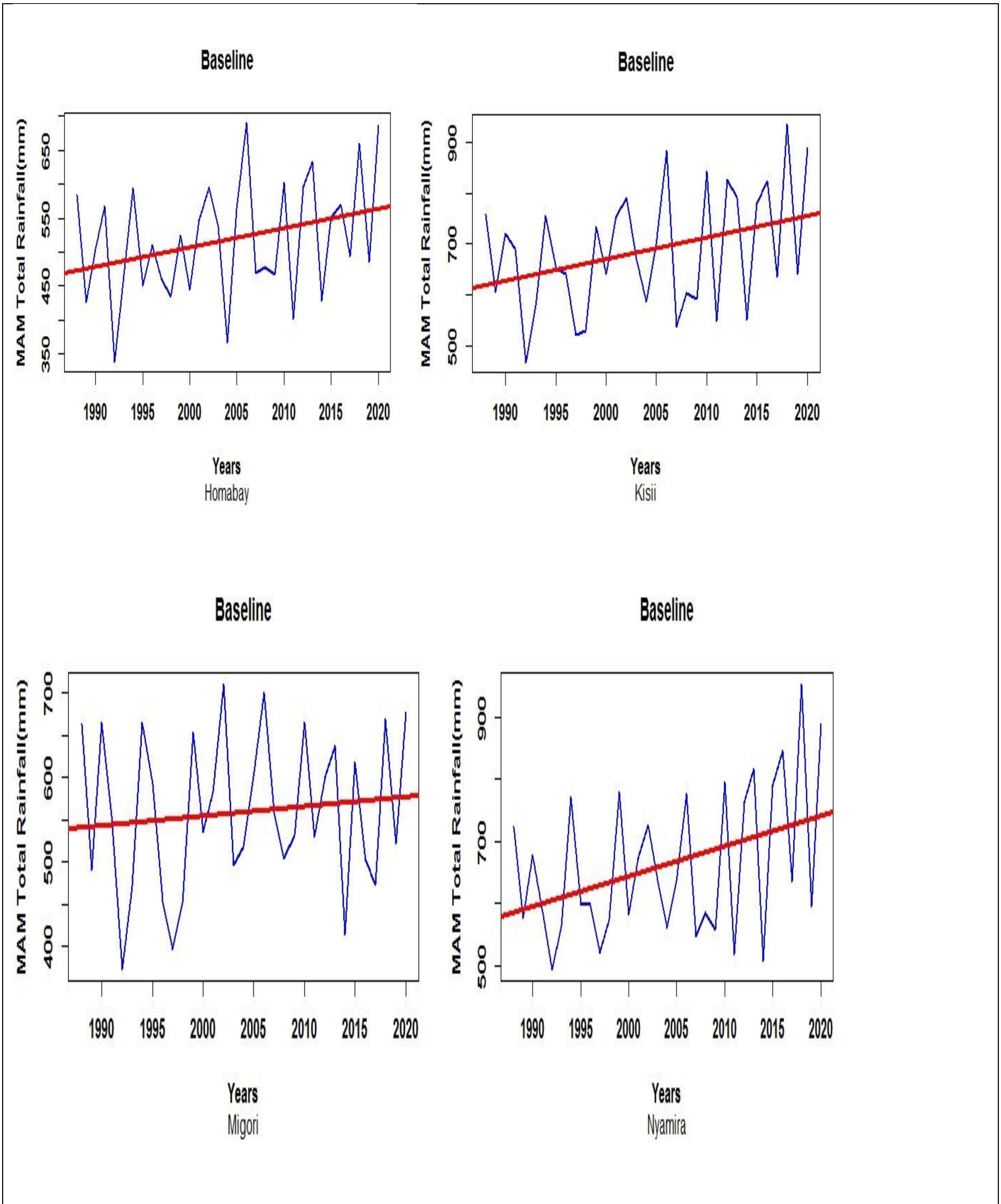


Figure 7: Baseline Trends in MAM rainfall for Homabay, Kisii, Migori and Nyamira

Homabay, Kisii, Migori and Nyamira counties exhibited increasing trends in MAM rainfall season for between 1988 to 2018.

Figure 8 presents the mean shift in June-July-August (JJA) rainfall season for Homabay, Kisii, Migori and Nyamira counties.

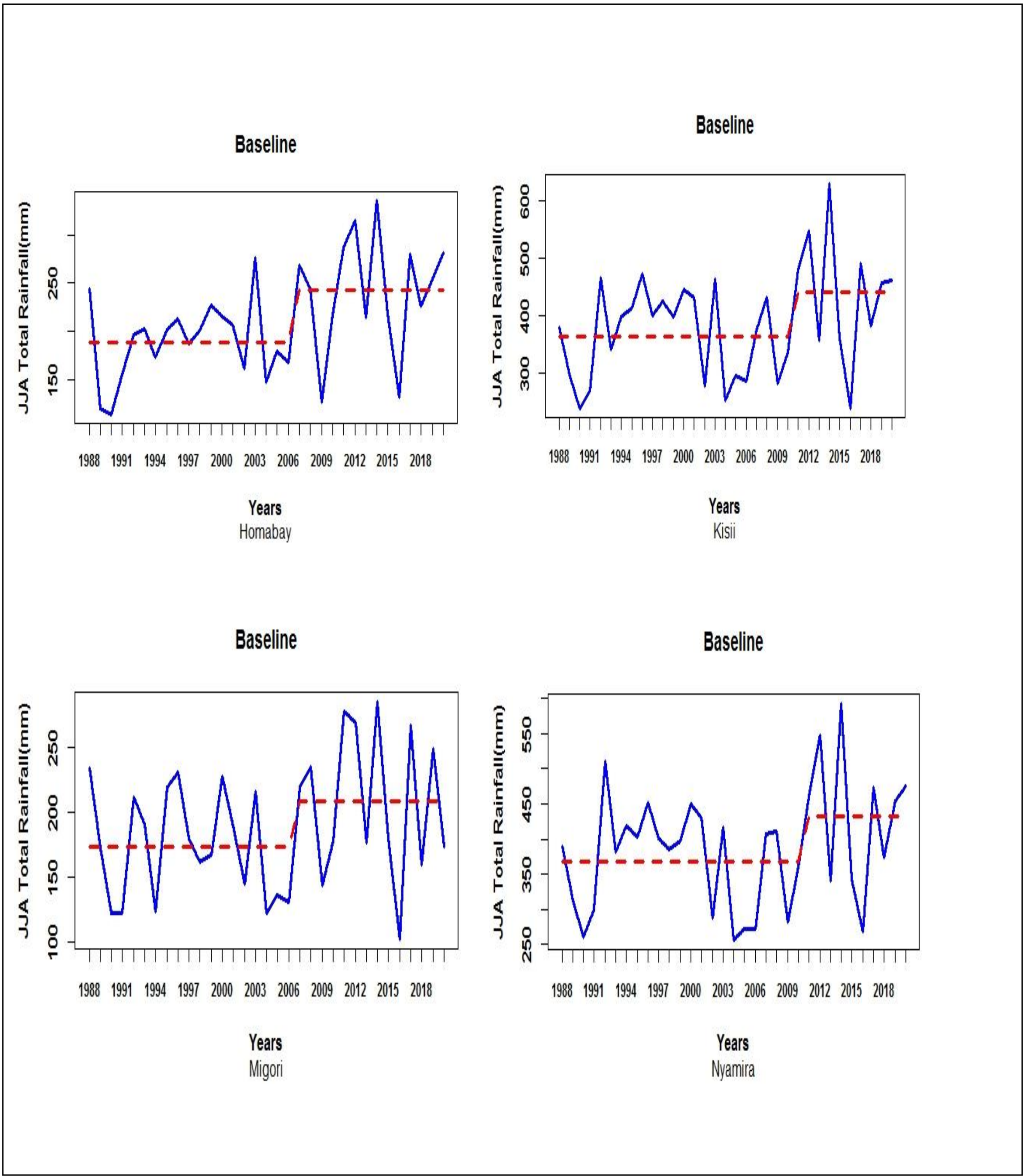


Figure 8: Baseline Mean shifts in JJA rainfall for Homabay, Kisii, Migori and Nyamira

Homabay, Kisii, Migori and Nyamira experienced an upward mean shift in JJA total seasonal rainfall for the period 1988-2018.

Figure 9 presents the trends in mean JJA rainfall for Homabay, Kisii, Migori and Nyamira counties.

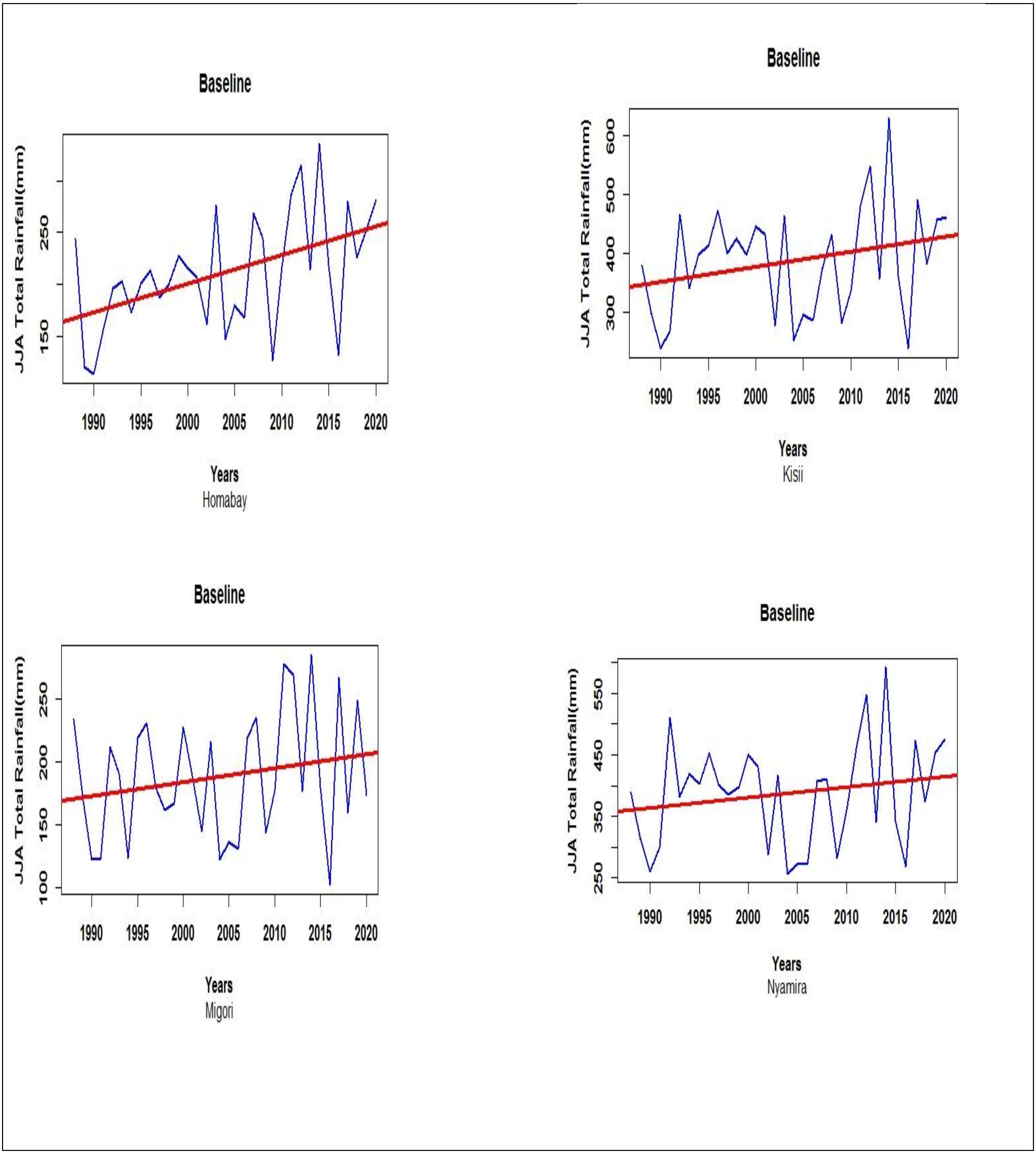


Figure 9: Baseline Trends in mean JJA seasonal rainfall for Homabay, Kisii, Migori and Nyamira.

Homabay, Kisii, Migori and Nyamira experienced increasing trends in mean total JJA rainfall for the period 1988-2018, implying increased wetness and prospects for crop production during this season.

Figure 10 presents the mean shift in total rainfall for OND rainy season in Homabay, Kisii, Migori and Nyamira counties.

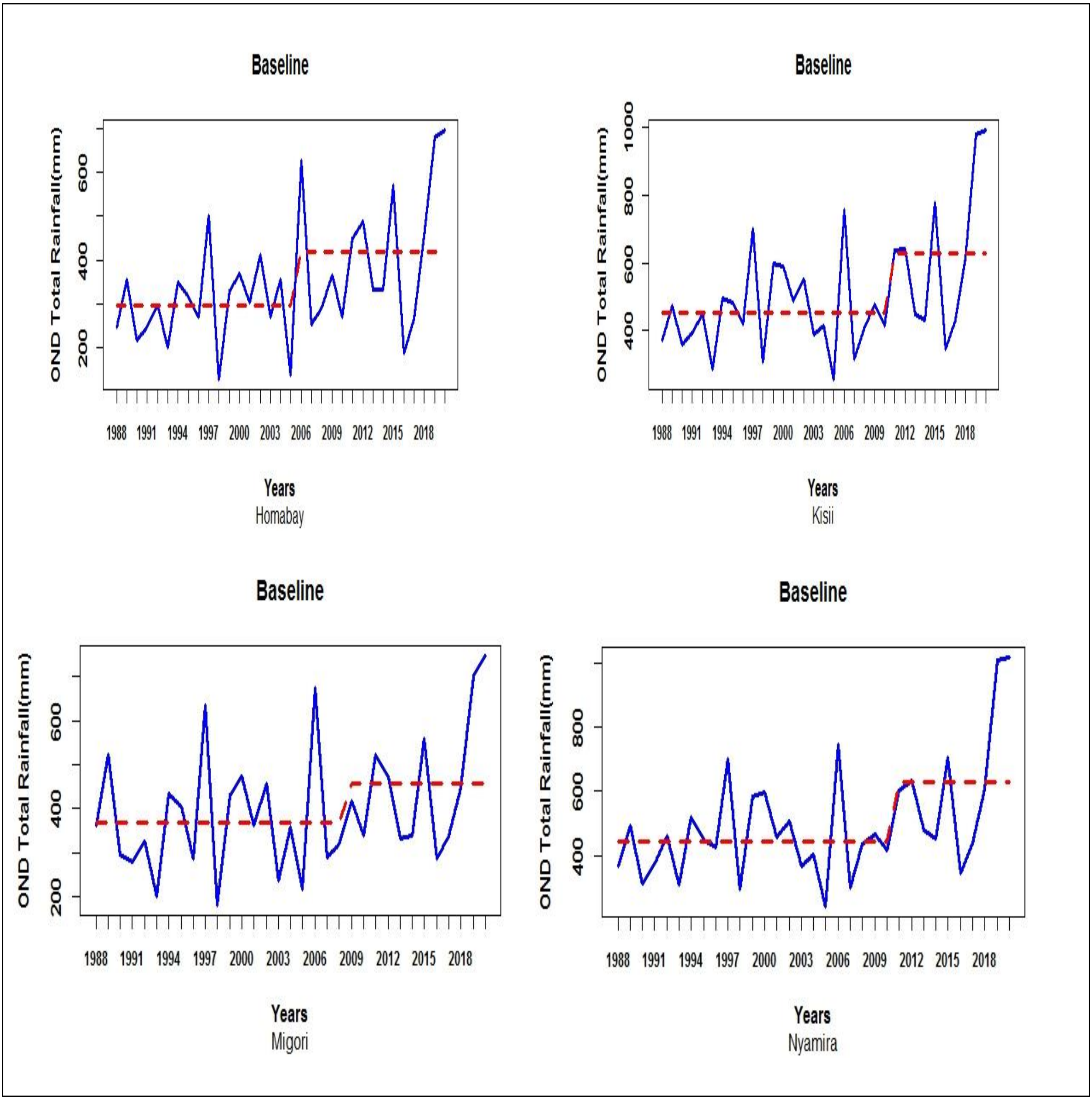


Figure 10: Baseline Mean shifts in OND rainfall for Homabay, Kisii, Migori and Nyamira

Homabay, Kisii, Migori and Nyamira experienced an upward shift in OND rainfall totals for the period 1988-2018, implying that OND rainfall was increasing during this period. This observation agrees with the findings of Ongoma and Chen (2017) that indicate increasing trends in OND rainfall amounts across East Africa.

The corresponding trend lines for total rainfall amounts for Homabay, Kisii, Migori and Nyamira are presented in Figure 11.

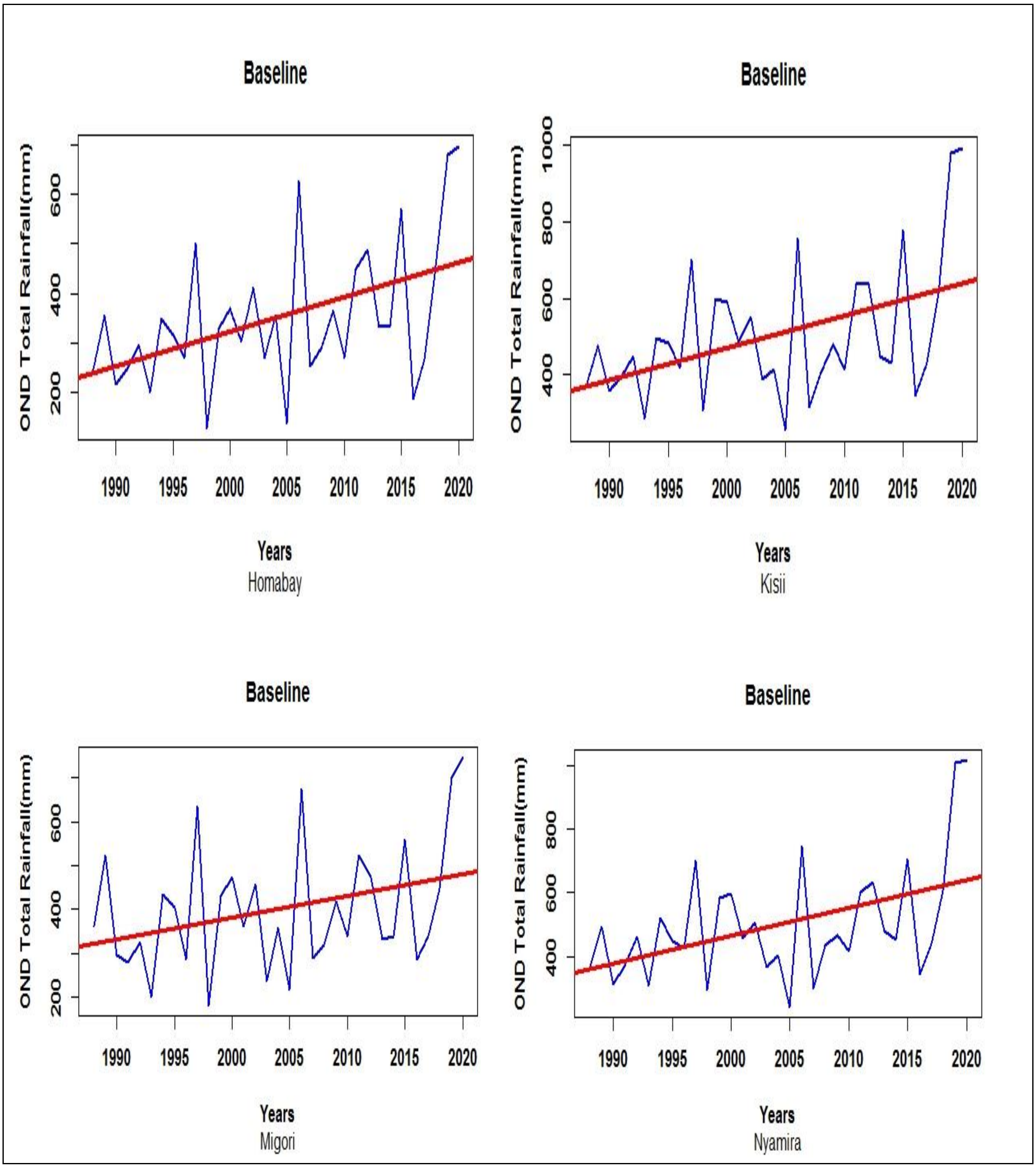


Figure 11: Trends in mean OND rainfall for Homabay, Kisii, Migori and Nyamira.

As with the shifts in the mean total rainfall, all the study counties (Homabay, Kisii, Migori and Nyamira) depicted increasing trends in mean total OND rainfall.

Table 8 presents the Mann-Kendall test statistics and Sen's slope values for the trends in mean total annual and seasonal rainfall for Homabay, Kisii, Migori and Nyamira counties.

Table 8: Characteristics of baseline rainfall for Homabay, Kisii, Migori and Nyamira

Station	Season	Mean Rainfall (mm)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Kisii	MAM	687.3	106	0.104	0.324	4.2
	JJA	387.4	94	0.150	0.396	2.5
	OND	504.8	142	0.029	0.226	6.1
	Annual	1921.0	194	0.003	0.026	14.6
Nyamira	MAM	662.7	112	0.085	0.010	3.9
	JJA	387.6	70	0.285	0.507	1.7
	OND	499.4	142	0.029	0.166	6.7
	Annual	1859.8	178	0.006	0.226	12.6
Migori	MAM	560.1	50	0.448	0.673	1.1
	JJA	188.2	64	0.329	0.422	1.1
	OND	401.0	100	0.125	0.507	4.5
	Annual	1383.9	88	0.178	0.396	5.8
Homabay	MAM	519.0	118	0.070	0.371	2.7
	JJA	211.6	192	0.003	0.026	3.0
	OND	350.7	158	0.015	0.262	6.0
	Annual	1326.0	236	0.000	0.004	12.0

Kisii station recorded the highest mean annual rainfall (1921mm), mean seasonal (MAM) rainfall (687.3mm) and mean seasonal OND rainfall (504.8mm) among all the study counties, with the highest rate of change of +14.6mm/year. Migori County recorded the least rate of change in MAM and JJA season rainfall of 1.1mm/year. The station also recorded the least mean seasonal rainfall in JJA of 188.2mm.

Homabay station exhibited increasing trends in the mean annual and seasonal rainfall for JJA. The trends and mean shifts of baseline rainfall were statistically significant as depicted by the p-values of Pettit's and Man-Kendall tests, that were less than the significance level value (α= 0.05). The station had statistically significant trend in its OND seasonal rainfall based on p-values of the Man-Kendall test (0.015) that was less than the significance level value (α= 0.05). However, the mean shift in OND rainfall was statistically insignificant based on the p-value of the Pettit's test (0.262) that was greater than the significance level value (α= 0.05).

Kisii station recorded statistically significant increase in the trend and mean shift of annual rainfall based on the p-values of Pettit's (0.010) and Man-Kendall test (0.003), that were less than the significance level value (α= 0.05).

Generally, all the study counties indicated increasing trends in the annual, MAM, JJA and OND seasonal rainfall. These findings also concur with those of Ayugi *et al* (2016). Moreover, all the study counties recorded an increase in mean MAM seasonal rainfall. Increasing rainfall trends in MAM and OND seasons in all the study counties increase the prospects for crop production, due to enhanced rainfall and moisture availability for crop growth, development and productivity.

4.4.2 Baseline Trends for Minimum Temperature

Figures 12 and 13 present the trends and mean shift in minimum temperature for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016. Temperature data used for the study was only available for the period 1983-2016

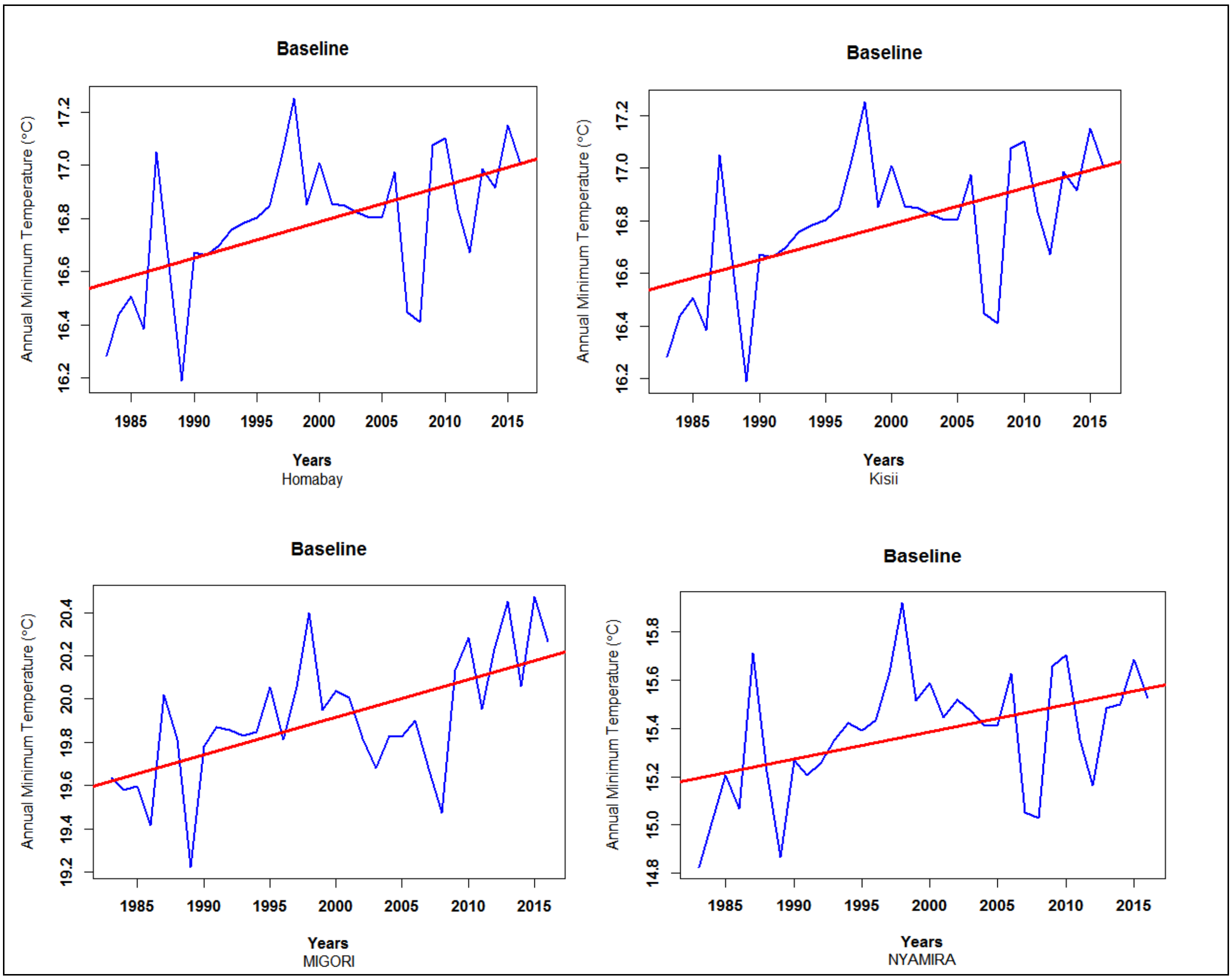


Figure 12: Trends in mean annual minimum temperature for Homabay, Kisii, Migori and Nyamira.

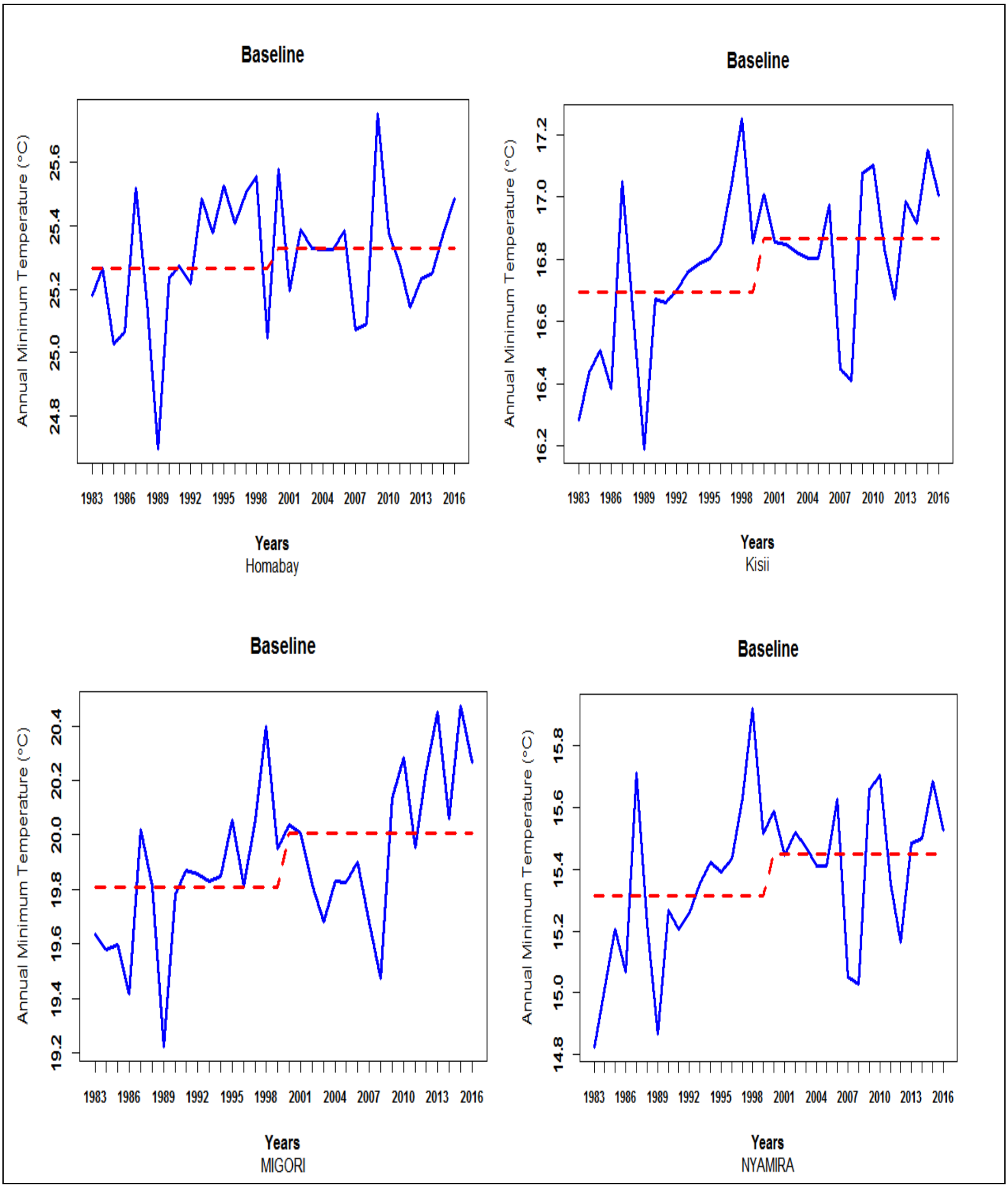


Figure 13: Mean shifts in mean annual minimum temperature for Homabay, Kisii, Migori and Nyamira.

Annual mean minimum temperatures across the study counties indicate an increasing trend and an upward shift in mean annual minimum temperature for the period 1983-2016. The increasing trends and mean upward shifts in annual minimum temperatures imply increasing mean annual minimum temperatures.

Figure 14 presents the trends in mean MAM minimum temperatures for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

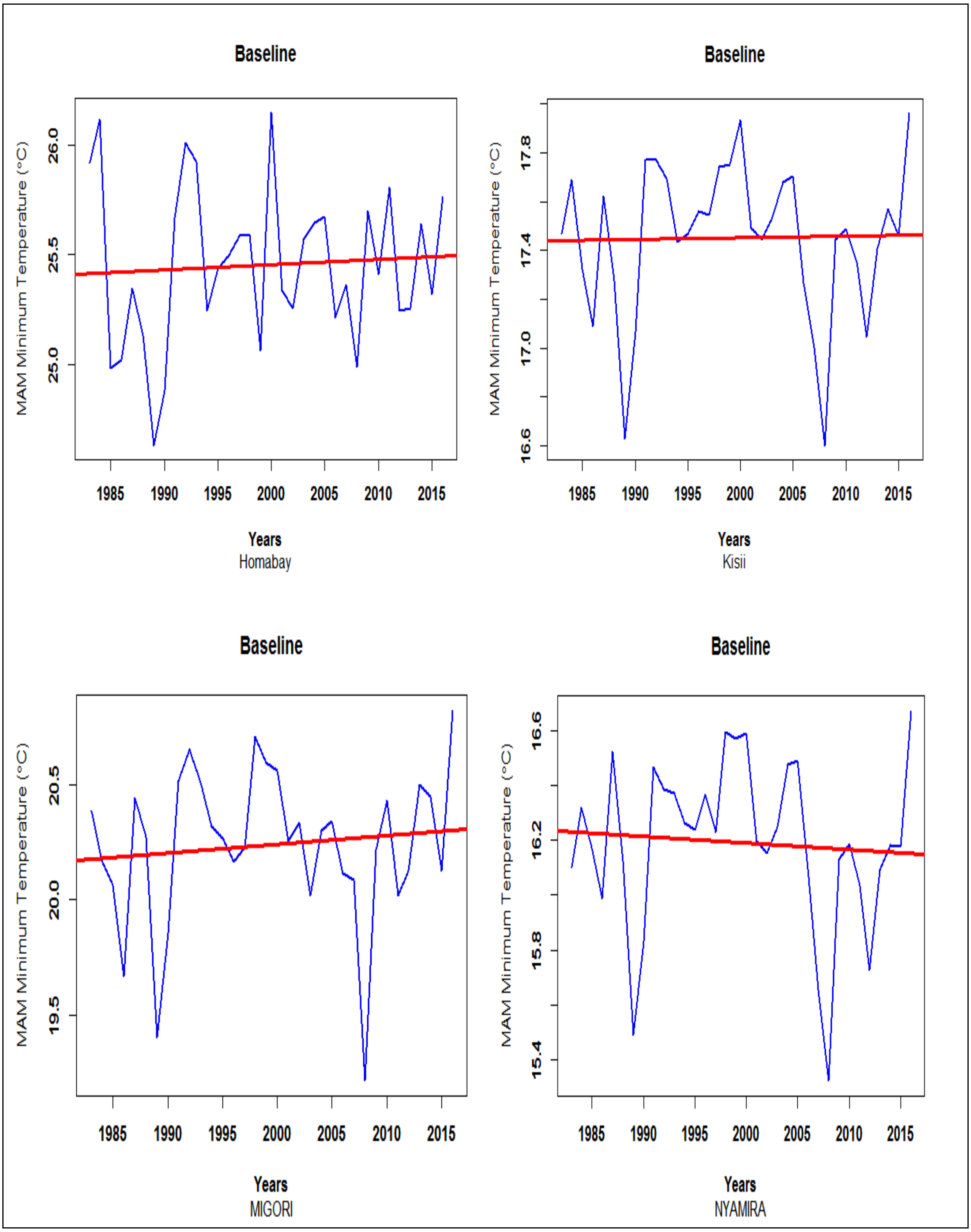


Figure 14: Trends in mean MAM minimum temperature for Homabay, Kisii, Migori and Nyamira.

Homabay and Migori exhibited increasing trends in mean seasonal minimum temperature during MAM rainy season for the period 1983-2016, signifying increasing minimum temperatures in MAM season. However, Kisii and Nyamira exhibited a decreasing trend in mean seasonal minimum temperature during MAM season.

Figure 15 presents mean shifts in MAM season mean minimum temperature for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

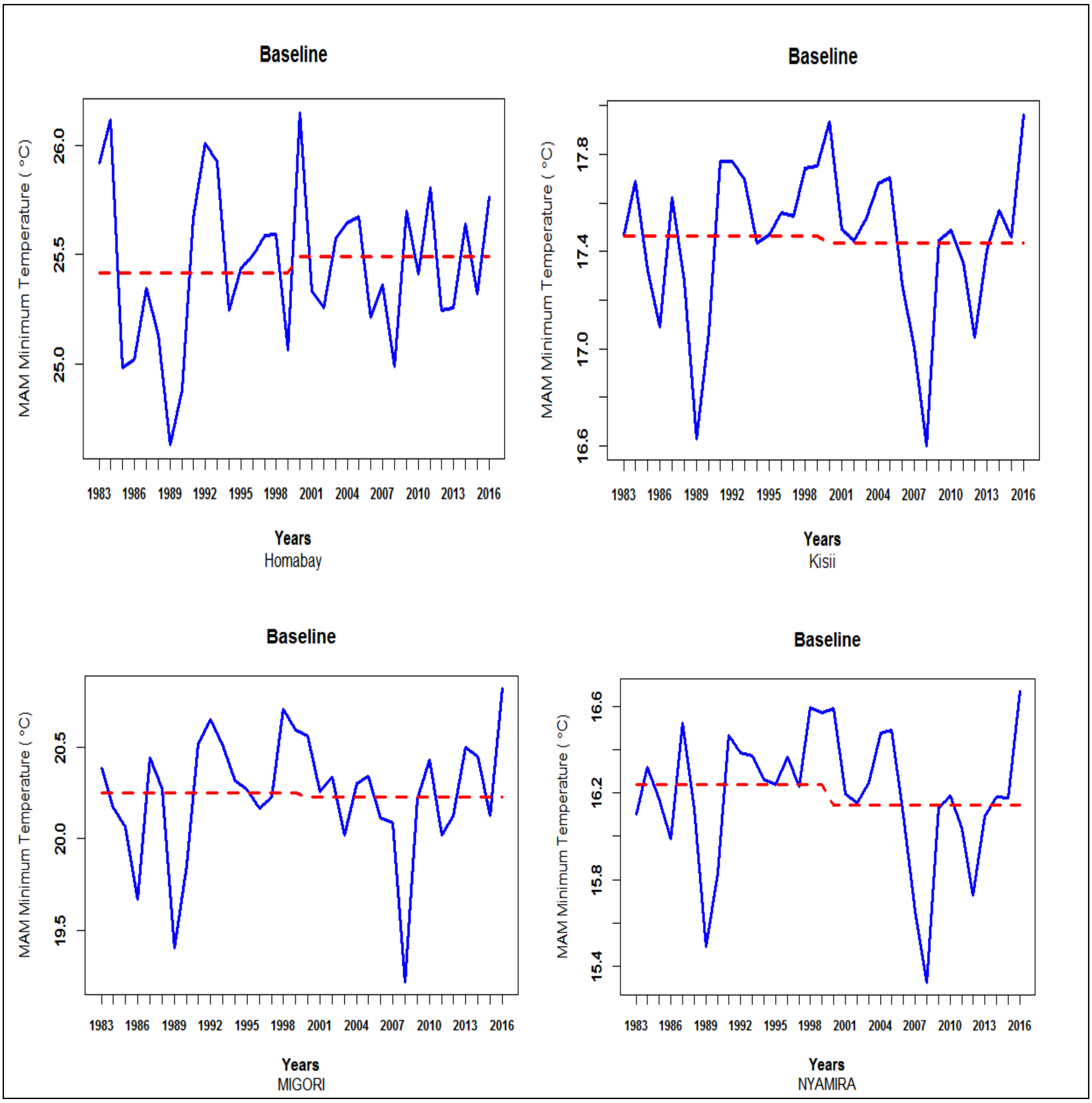


Figure 15: Mean shifts in MAM season mean minimum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period 1983 to 2016.

Homabay experienced an upward mean shift in the mean MAM minimum temperatures. On the contrary, Kisii, Migori and Nyamira exhibited a downward mean shift in the mean MAM minimum temperature.

Figure 16 presents the trends in mean JJA seasonal minimum temperature for the study counties for the period 1983-2016.

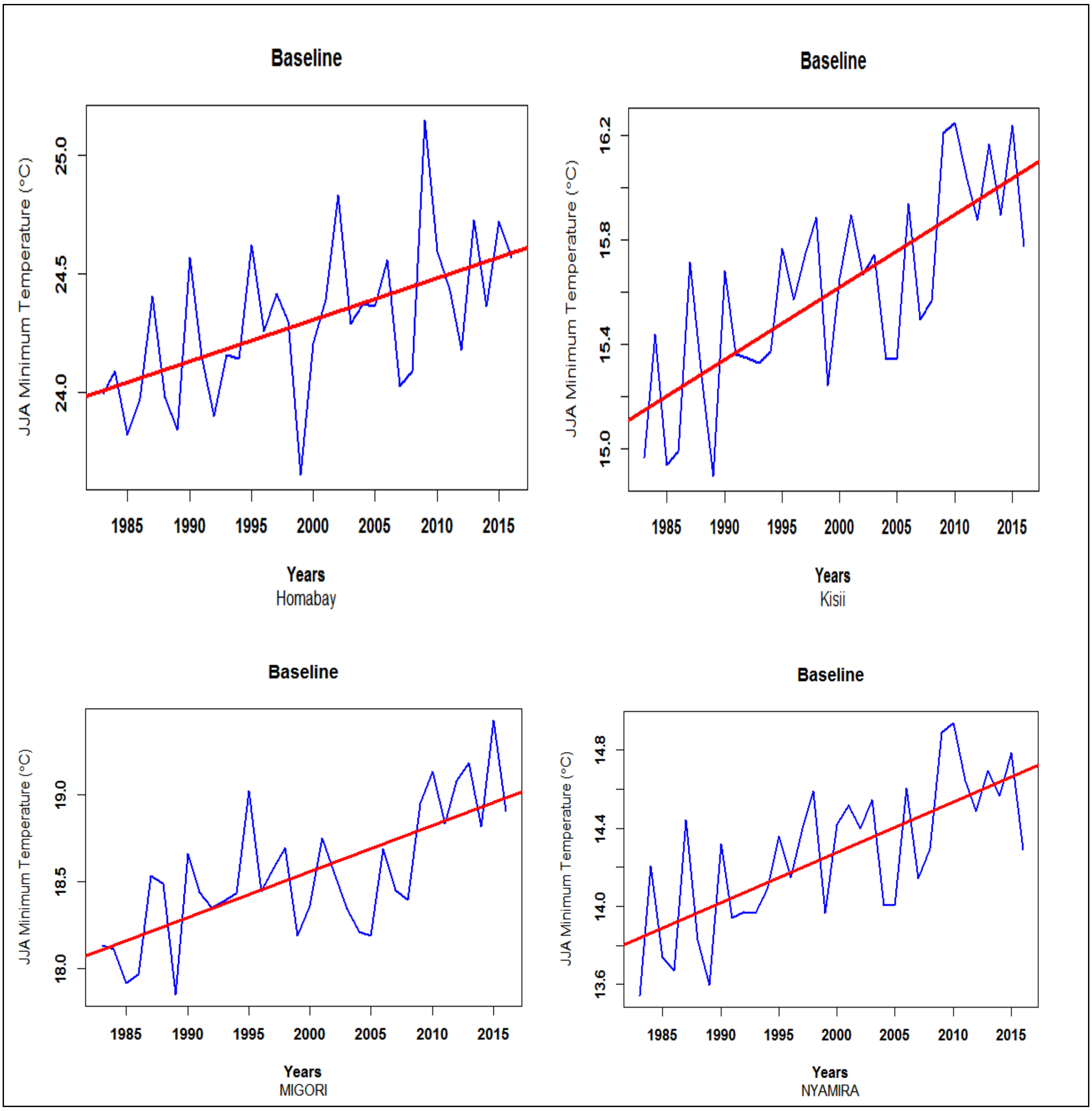


Figure 16:Trends in mean JJA minimum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period 1983 to 2016.

. All of the study counties exhibited increasing trends in mean JJA minimum temperatures. This implies rising mean JJA minimum temperatures for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

Figure 17 presents the mean shifts in mean JJA minimum temperature for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

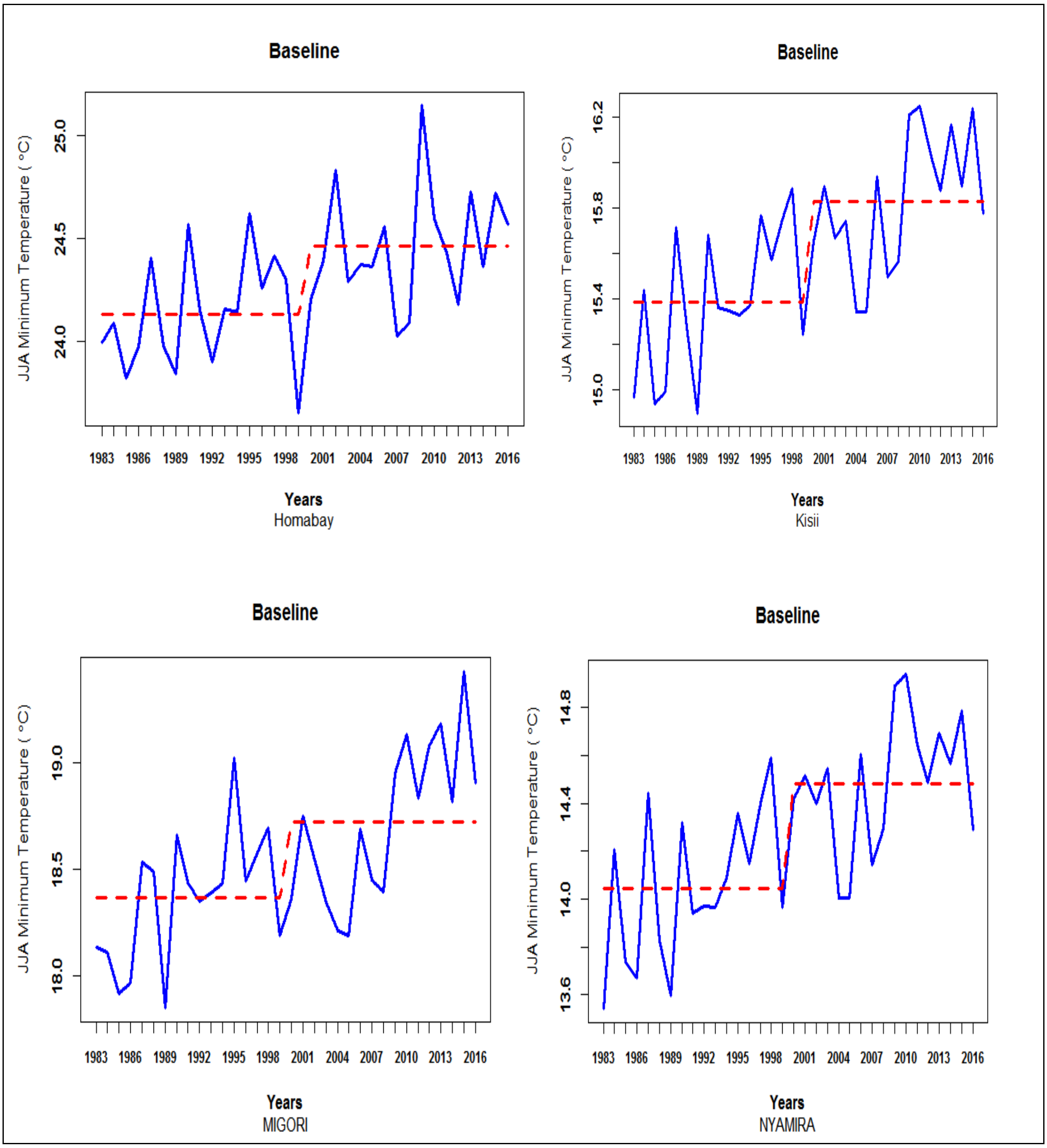


Figure 17: Mean shifts in JJA season mean minimum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period 1983 to 2016.

An upward mean shifts in mean JJA minimum temperatures across the study counties was depicted, signifying increasing minimum temperatures during JJA season in Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

Figure 18 presents the trends in mean OND minimum temperature for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

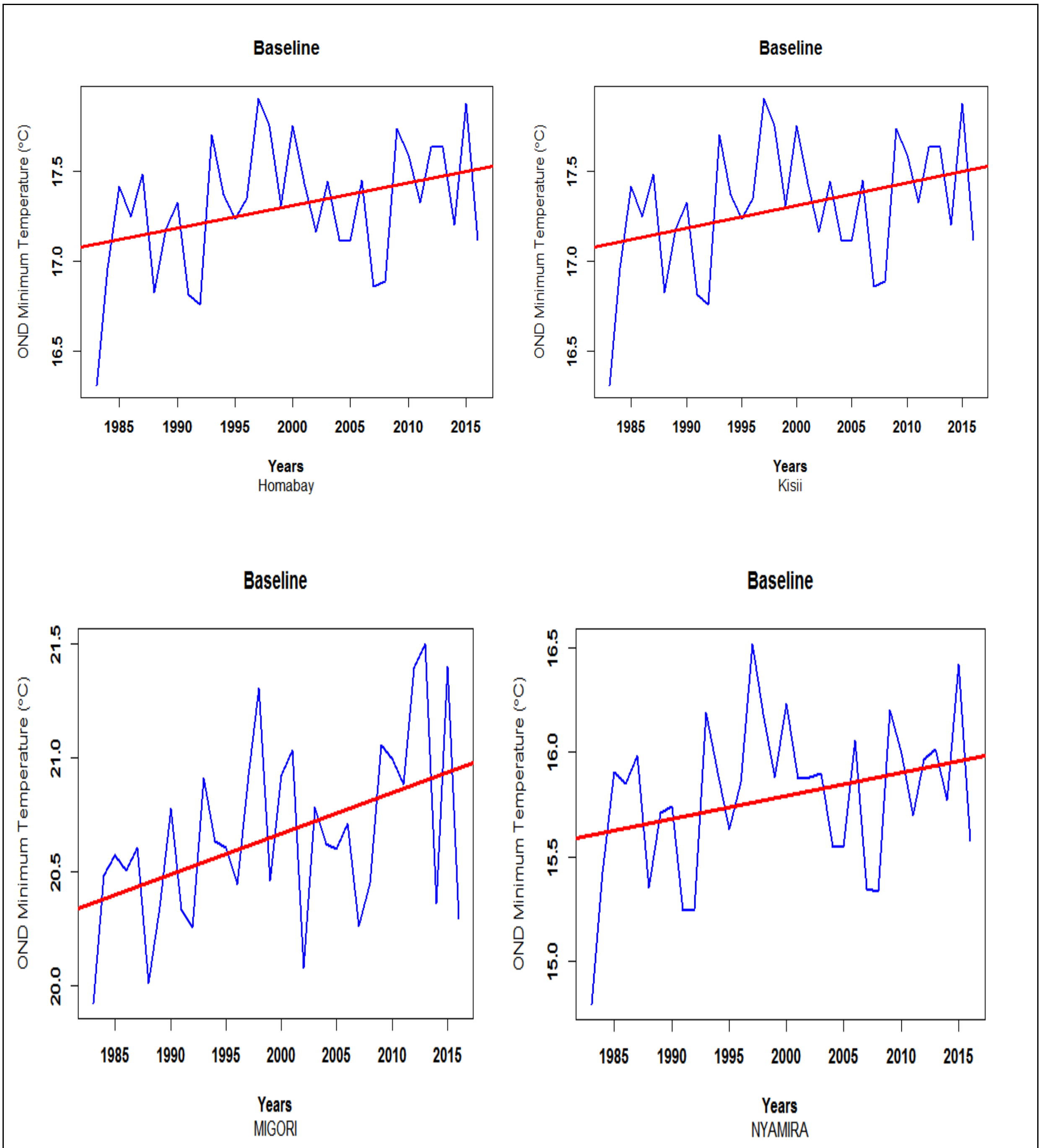


Figure 18: Trends in mean OND minimum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period 1983 to 2016.

Homabay, Kisii, Migori and Nyamira stations depicted increasing trends in mean OND minimum temperatures, implying rising mean minimum temperatures in OND season for the period 1983-2016.

Figure 19 presents the mean shifts in OND minimum temperature for Homabay, Kisii, Migori and Nyamira counties for the period 1983-2016.

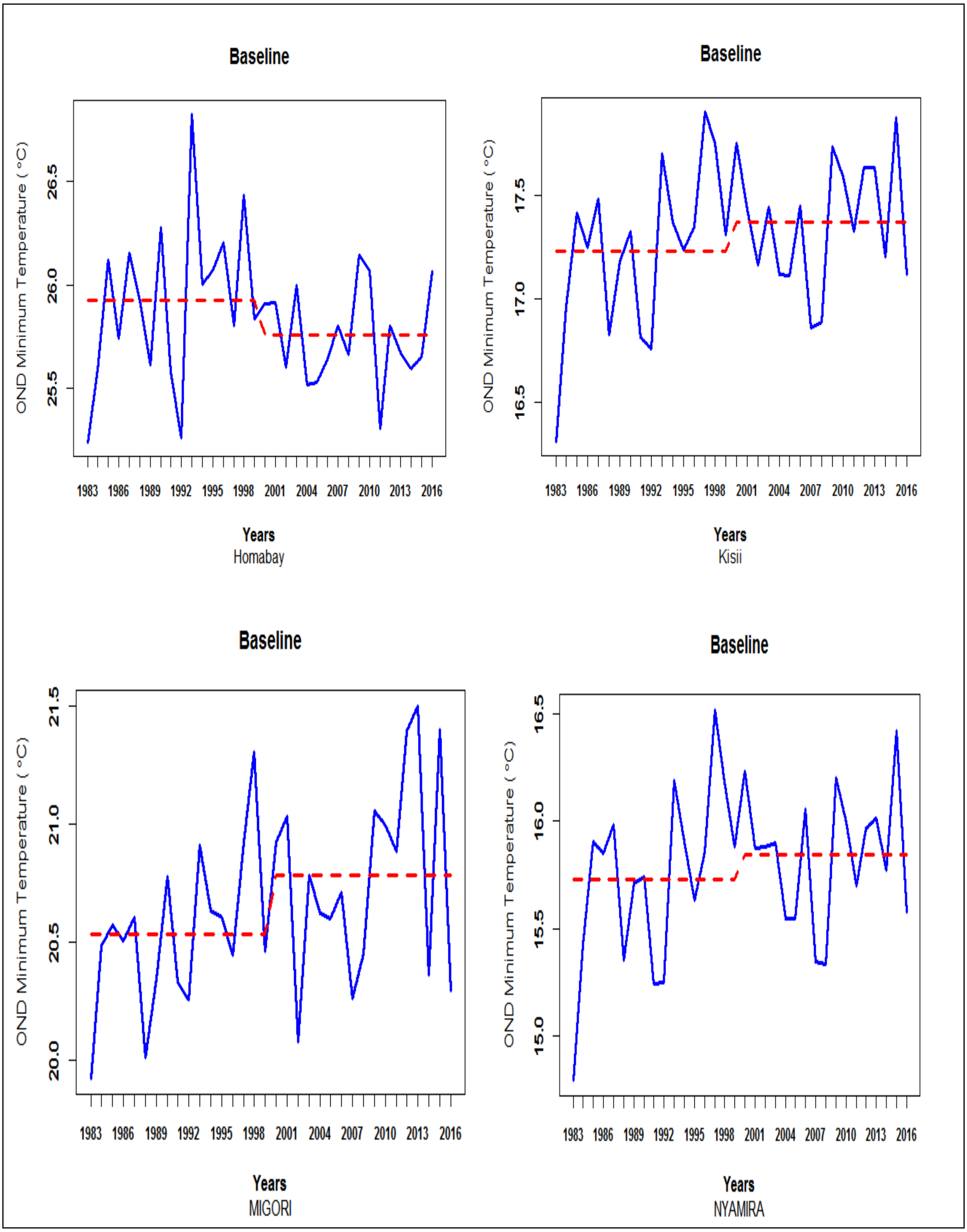


Figure 19:Mean shifts in OND season mean minimum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period.

Kisii, Migori and Nyamira counties exhibited an upward mean shift in OND season minimum temperatures, signifying rising minimum temperatures. Conversely, Homabay County showed a downward shift in OND season minimum temperatures.

Table 9 presents the Mann-Kendall test statistics and Sen's slope values for the trends in mean annual and seasonal Minimum Temperature for Homabay, Kisii, Migori and Nyamira counties.

Table 9: Characteristics of Baseline Minimum Temperature for Homabay, Kisii, Migori and Nyamira stations.

Station	Season	Mean Tmin(°C)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Kisii	MAM	17.45	-17	0.81251	0.366	-0.001
	JJA	15.61	291	0.00002	0.366	0.029
	OND	17.30	103	0.13051	0.140	0.011
	Annual	16.78	235	0.00052	0.007	0.016
Nyamira	MAM	16.17	-47	0.49529	0.281	-0.003
	JJA	14.26	301	0.00001	0.002	0.027
	OND	15.77	107	0.11609	0.092	0.010
	Annual	15.39	195	0.00403	0.024	0.015
Migori	MAM	20.24	15	0.8356	0.602	0.002
	JJA	18.54	265	0.0001	0.005	0.025
	OND	20.66	169	0.0128	0.092	0.018
	Annual	19.91	243	0.0003	0.012	0.018
Homa Bay	MAM	25.45	45	0.5142	0.634	0.006
	JJA	24.30	227	0.0008	0.018	0.019
	OND	25.84	-43	0.5335	0.555	-0.004
	Annual	25.30	77	0.2599	0.151	0.004

Homabay and Migori exhibited increases in minimum temperatures at the rates of between 0.004^0C/year and 0.018^0C/year for the period 1983-2016. The rates of increase of between $+0.002^0$C/year for Migori and $+0.006^0$C/year for Homabay were observed. Kisii and Nyamira depicted decreasing trends in mean MAM minimum temperatures, signifying decreasing mean minimum temperatures at rates of between -0.001^0C/year for Kisii and 0.003^0C/year for Nyamira during MAM season. All the study counties exhibited increasing minimum temperatures during OND at the rates of between $+0.010^o$C/year and 0.019^0C/year for the period 1983-2016. On the contrary, Homabay station depicted a downward mean shift in OND minimum temperature at a rate of -0.004^oC/year for the baseline period 1983 to 2016.

Kisii, Nyamira and Migori counties exhibited increasing trends and upward shifts in mean annual minimum temperatures for the period 1983-2016. These increasing trends and upward shifts in mean annual minimum temperatures were statistically significant owing to the smaller p-values of the Man-Kendall test and Pettit's test compared to the significance level value (α = 0.05).

The observed increasing trends and upward shift in JJA season mean minimum temperatures for Nyamira, Homabay and Migori counties were statistically significant, given that the p-values of the Man-Kendall test and Pettit's test statistics were smaller compared to the significance level value of 0.05. Kisii County exhibited a statistically significant trend line in mean JJA minimum temperature owing to the smaller p-value of Mann-Kendall test compared to the significance level value of 0.05.

4.4.3 Baseline Trends for Maximum Temperature

This section presents results for the trends and shifts in mean maximum temperature for Homabay, Kisii, Migori and Nyamira counties between 1983-2016. Figure 20 presents trends in annual maximum temperature for the study stations for the period 1983-2016.

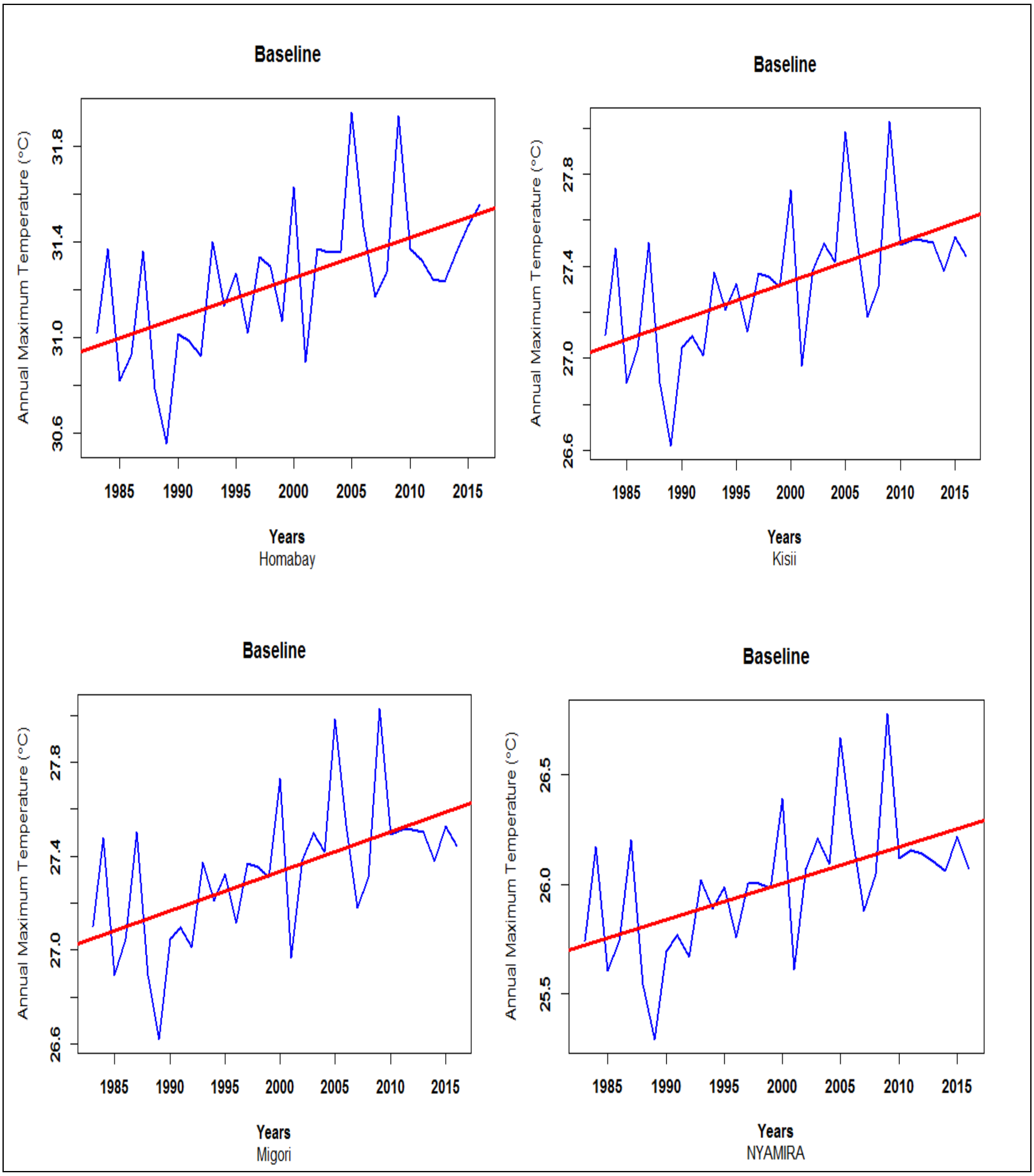


Figure 20: Trends in mean annual maximum temperature for Homabay, Kisii, Migori and Nyamira stations.

All counties exhibited rising trends in mean annual maximum temperatures, signifying increasing annual maximum temperatures for the period 1983-2016. Increasing maximum temperature will inevitably reduce the growth duration of maize crops thus reducing yields. Moreover, rising maximum temperature will enhance evapotranspiration, thus limiting the availability of moisture necessary for plant growth and development.

Figure 21 presents the shifts in mean annual maximum temperatures for the period 1983-2016.

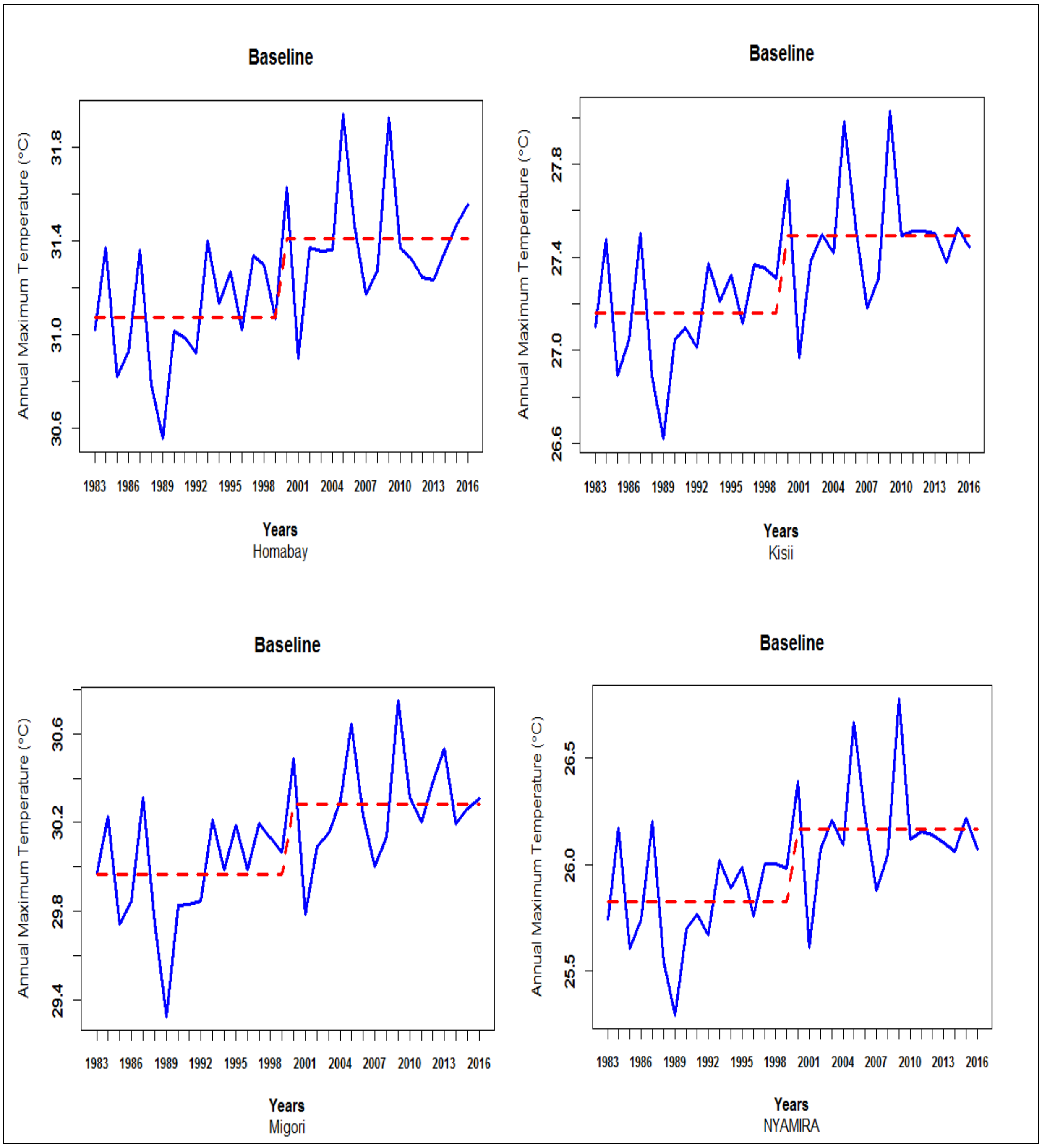


Figure 21: Shifts in mean annual maximum temperatures for Homabay, Kisii, Migori and Nyamira stations for the historical period

All the study counties depicted an upward shift in mean annual maximum temperature between 1983 and 2016.

Figure 22 presents the trends in mean MAM maximum temperature for Homabay, Kisii, Migori and Nyamira counties for the baseline period 1983-2016.

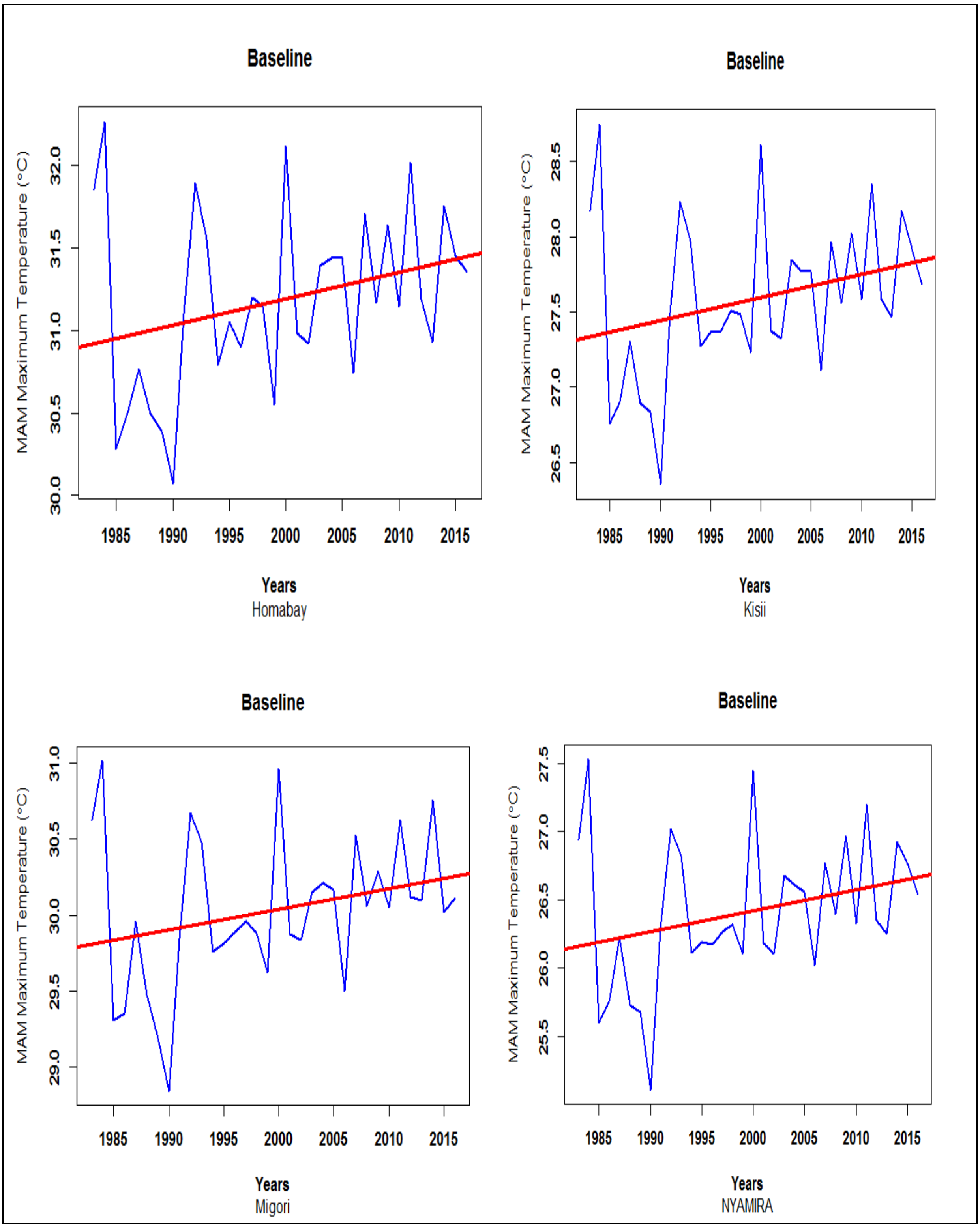


Figure 22: Trends in mean MAM maximum temperature for Homabay, Kisii, Migori and Nyamira stations for the historical period 1983 to 2016.

Homabay, Kisii, Nyamira and Migori counties exhibited increasing trends in mean MAM maximum temperature for the period 1983-2016, signifying rising mean maximum temperatures in the MAM season. This will decrease yields because of the negative effects of rising maximum temperature through enhanced evapotranspiration rates, including reduction in leaf area, thus inhibiting maize growth and development. Consequently, this will cause food insecurity since maize is their staple food.

Figure 23 presents the shifts in mean MAM maximum temperature for the study stations for the period 1983-2016.

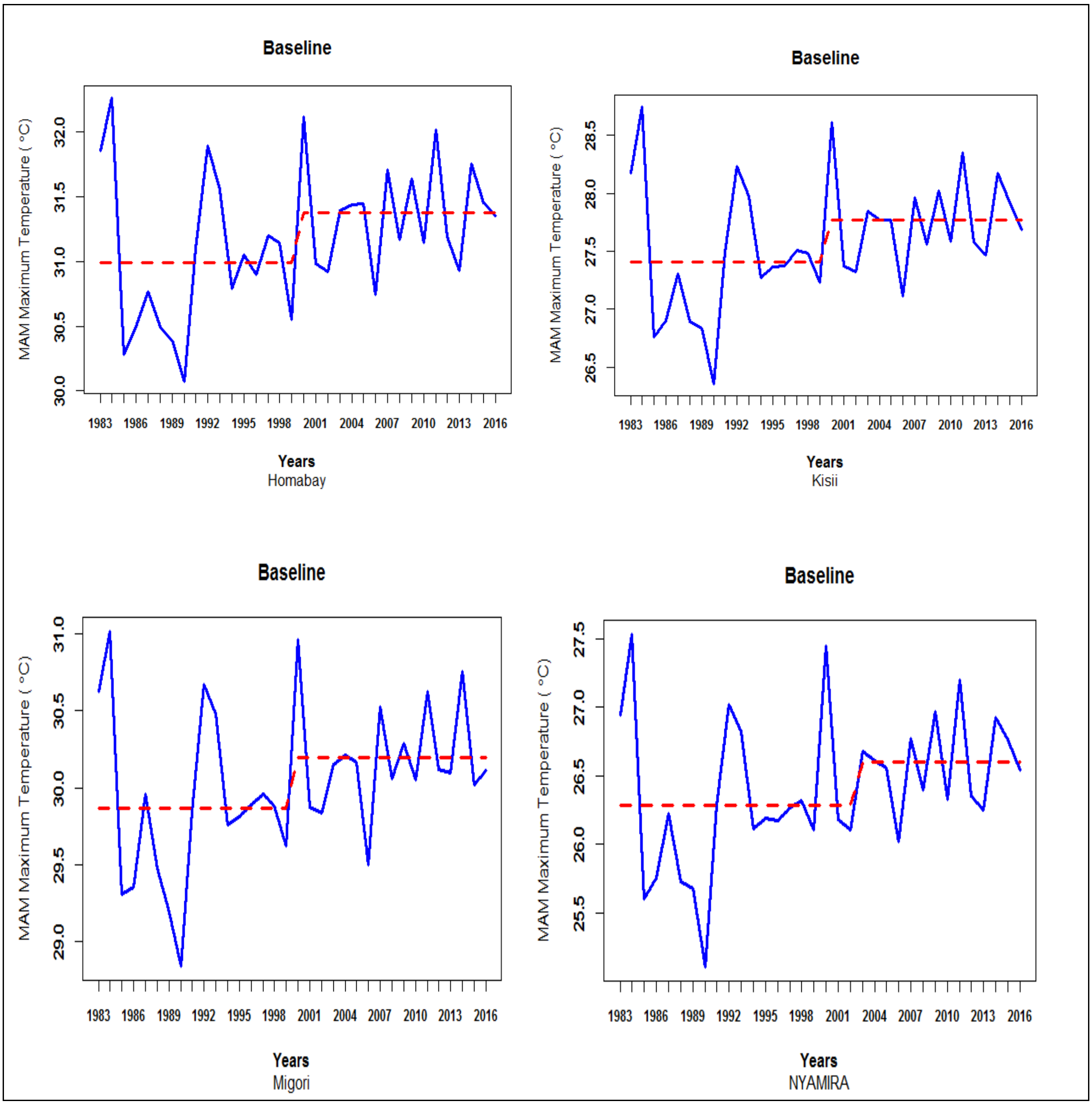


Figure 23: Shifts in mean MAM maximum temperature for Homabay, Kisii, Migori and Nyamira stations for the baseline period.

All the study counties experienced an upward shift in mean maximum temperature during MAM season, implying rising mean MAM maximum temperatures for the period 1983-2016.

Figures 24 and 25 present the trends and shifts in mean JJA maximum temperatures for the period 1983-2016 respectively.

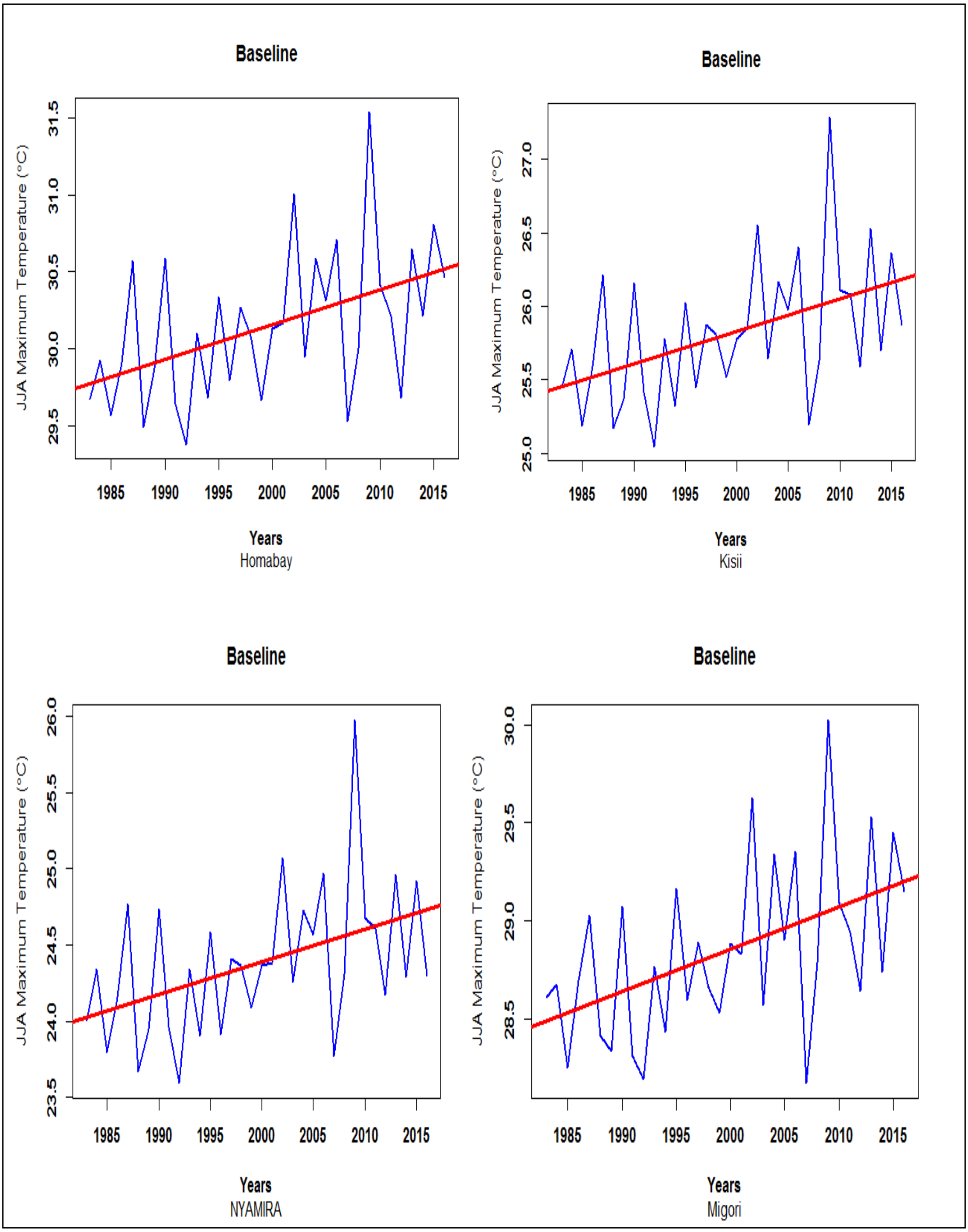


Figure 24: Trends in mean JJA maximum temperature for Homabay, Kisii, Nyamira and Migori stations for the baseline period

Maximum temperatures depicted an increasing trend, signifying increasing mean JJA maximum temperatures for the period 1983-2016.

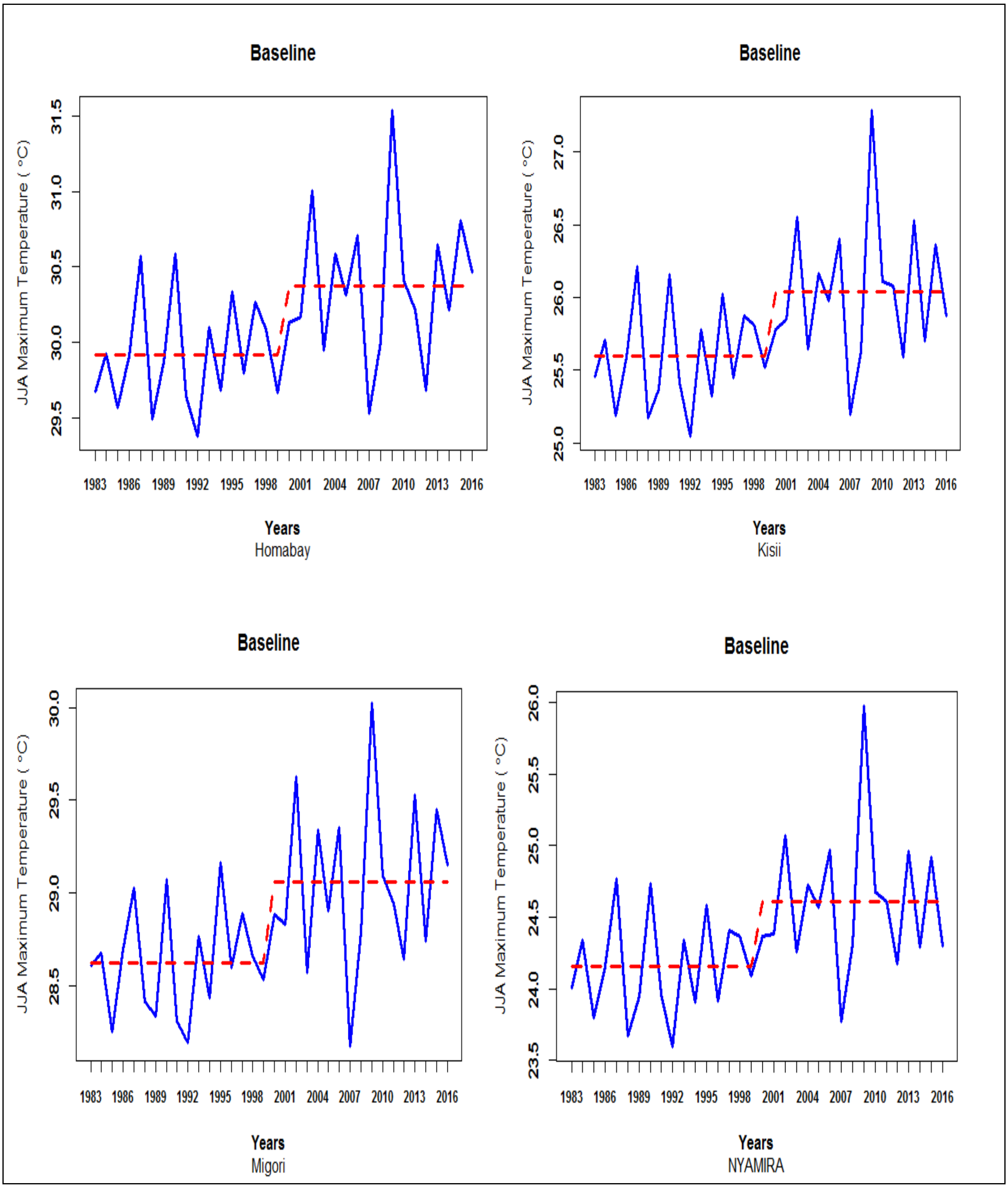


Figure 25: Shifts in mean JJA maximum temperature for Homabay, Kisii, Migori and Nyamira for the baseline period.

Maximum temperature for Homabay, Kisii, Migori, and Nyamira depicted an upward mean shift during the JJA season for all the study counties, signifying increasing mean JJA maximum temperatures for the period 1983-2016.

Figures 26 and 27 present the trends and shifts in mean OND maximum temperatures for the period 1983-2016 respectively.

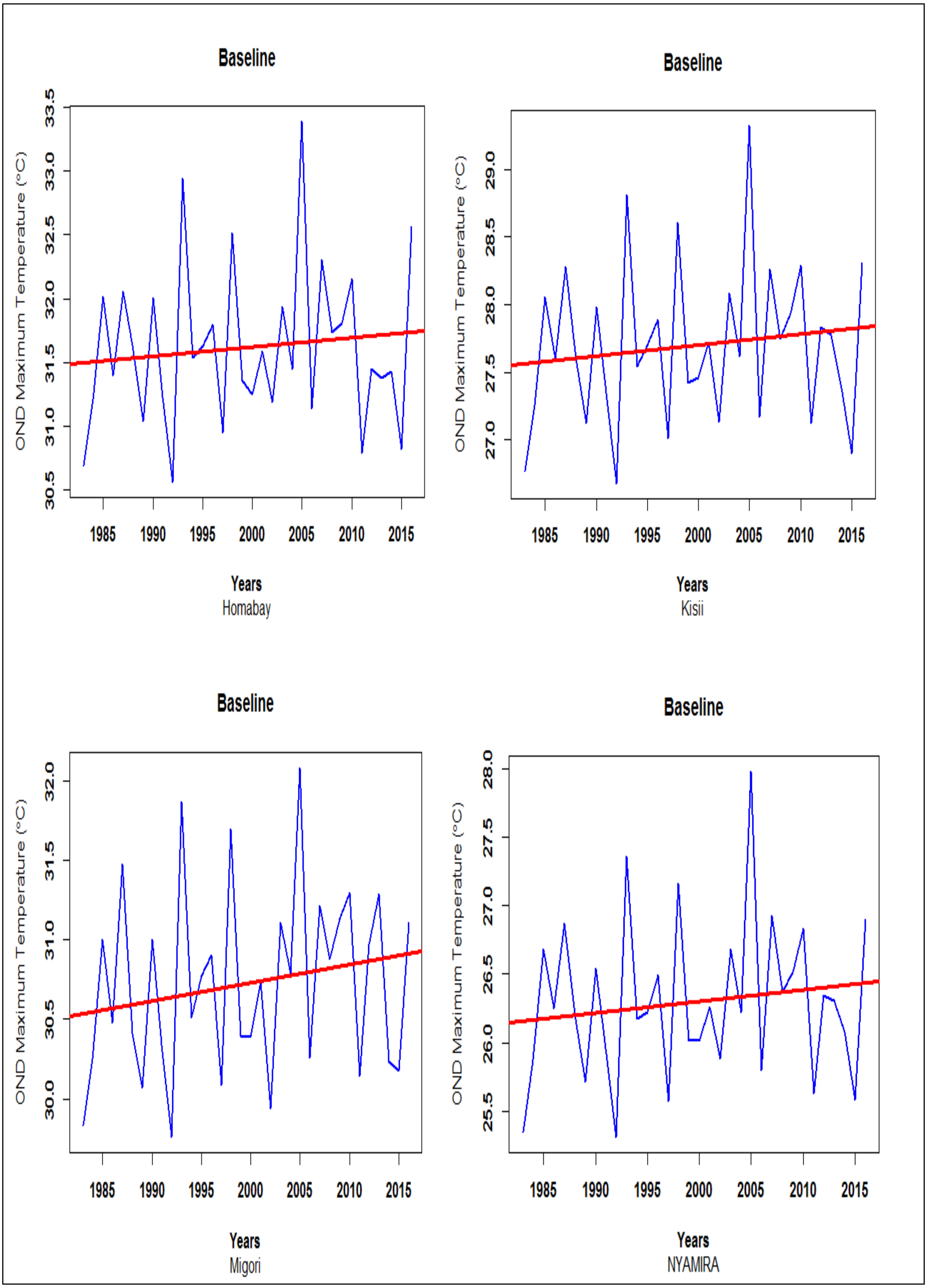


Figure 26: Trends in mean OND maximum temperatures for Homabay, Kisii, Migori and Nyamira stations for the baseline period.

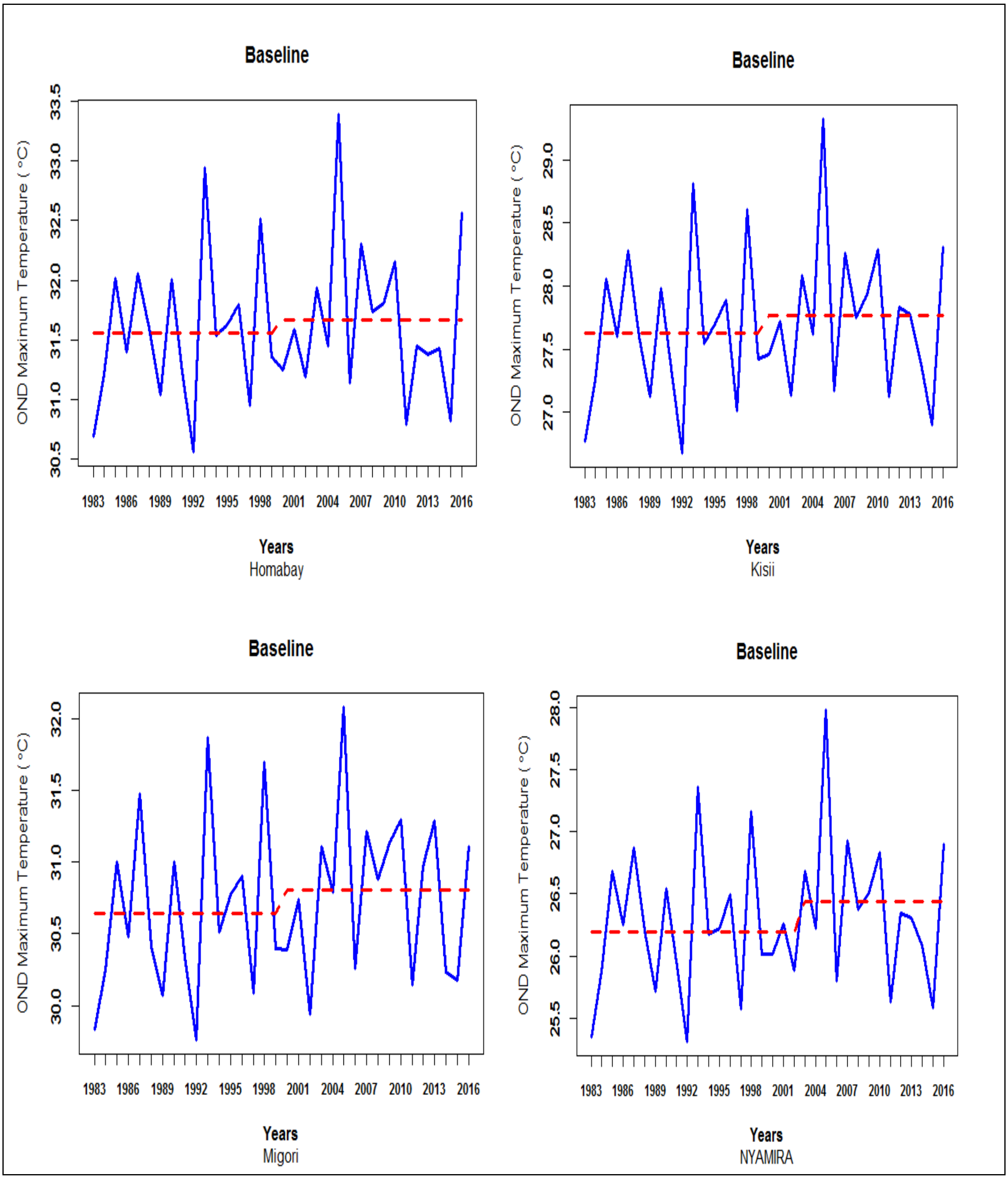


Figure 27: Shifts in mean OND maximum temperatures for Homabay, Kisii, Migori and Nyamira stations for the baseline period.

All the counties exhibited rising trends and upward shifts in maximum temperatures during OND season for the period 1983-2016, signifying rising mean maximum temperatures during this season.

Table 10 presents the Mann-Kendall test statistics and Sen's slope values for the trends in mean annual and seasonal Maximum Temperatures for Homabay, Kisii, Migori and Nyamira counties.

Table 10: Characteristics of Baseline Maximum Temperatures for Homabay, Kisii, Migori and Nyamira

Station	Season	Mean Tmax (°C)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Kisii	MAM	27.6	152	0.026	0.145	0.023
	JJA	25.8	179	0.008	0.043	0.021
	OND	27.7	65	0.343	0.888	0.009
	Annual	27.3	249	0.000	0.003	0.015
Nyamira	MAM	26.4	131	0.054	0.190	0.020
	JJA	24.4	159	0.019	0.057	0.020
	OND	26.3	55	0.423	0.888	0.007
	Annual	26.0	239	0.000	0.000	0.015
Migori	MAM	30.0	137	0.044	0.134	0.018
	JJA	28.8	193	0.004	0.029	0.019
	OND	30.7	81	0.236	0.570	0.016
	Annual	30.1	249	0.000	0.006	0.017
Homa Bay	MAM	31.2	147	0.030	0.197	0.025
	JJA	30.1	191	0.005	0.035	0.024
	OND	31.6	33	0.635	1.090	0.006
	Annual	31.2	211	0.002	0.013	0.016

Maximum temperatures increased in all the three seasons (MAM, JJA, OND) and annually in all the study counties at rates of between 0.006^0C/year and 0.025^0C/year. The increasing trends and upward shifts in JJA and annual maximum temperatures were statistically significant for all the study counties, given that the p-values for the Man-Kendall and Pettit's test statistics were less than the significance level value of 0.05. Kisii, Migori and Homabay counties exhibited statistically significant trends in mean MAM maximum temperatures, given that the p-values of the Man-Kendall test statistics were less than the significance level of 0.05.

Increasing mean maximum temperatures will adversely affect the soil-water balance parameters hence negatively impact maize growth, development and the resultant yields. These would exacerbate the vulnerability of maize production by small-holder farmers to the adverse impacts of climate change within the study counties.

4.5 Trends and Patterns in the Projected Climate based on RCP4.5 and RCP8.5 Emission Scenarios

This section describes the trends and patterns in projected climate under RCP 4.5 and RCP 8.5 emission scenarios.

4.5.1 Validation of the Skill of CORDEX Models used for projecting future climate

Table 11 presents the correlation coefficients and the root mean square error that formed the basis for assessing the skill of the CORDEX models in simulating rainfall and temperature in Homabay, Kisii, Migori and Nyamira counties.

Table 11:Correlation and root mean square error for CORDEX models in simulating rainfall and temperature in Homabay, Kisii, Nyamira and Migori counties

	Maximum Temperature		Minimum Temperature		Rainfall	
Model	Correlation Coefficient	RMSE	Correlation Coefficient	RMSE	Correlation Coefficient	RMSE
CNRM	0.38	1.7	0.35	2.2	0.33	89.8
CSIRO	0.51	1.1	0.38	1.4	0.18	96.2
ICHEC	0.42	1.4	0.31	1.8	0.26	90.4
CCCma	0.36	2.2	0.24	3.3	0.12	100.7
MOHC	0.43	1.6	0.34	2.6	0.18	99.6
MPI	0.39	1.3	0.18	1.9	0.21	102.9
MIROC	0.26	2.6	0.28	2.5	0.16	100.9
IPSL	0.41	1.9	0.27	2.8	0.12	103.8

The CSIRO model gave rise to the highest correlation coefficients between the observed and the forecasted climate elements and least mean square error in simulating maximum and minimum temperature, hence having the best skill in simulating temperature. Therefore, CSIRO model temperature outputs were used to assess the trend and shifts in the projected temperature for the period 2022-2051 under both RCP4.5 and 8.5 emission scenarios. CNRM model had better skill in simulating precipitation compared to the rest of the CORDEX models. Consequently, CNRM model outputs for rainfall were used to assess the trend and shifts in future rainfall for the period 2022-2051 under both RCP4.5 and 8.5 emission scenarios.

4.5.2 Projected Minimum Temperature based on RCP4.5 emission scenario

Figure 28 presents the trends in projected minimum temperature under RCP4.5 emission scenario for Homabay, Migori, Kisii and Nyamira counties.

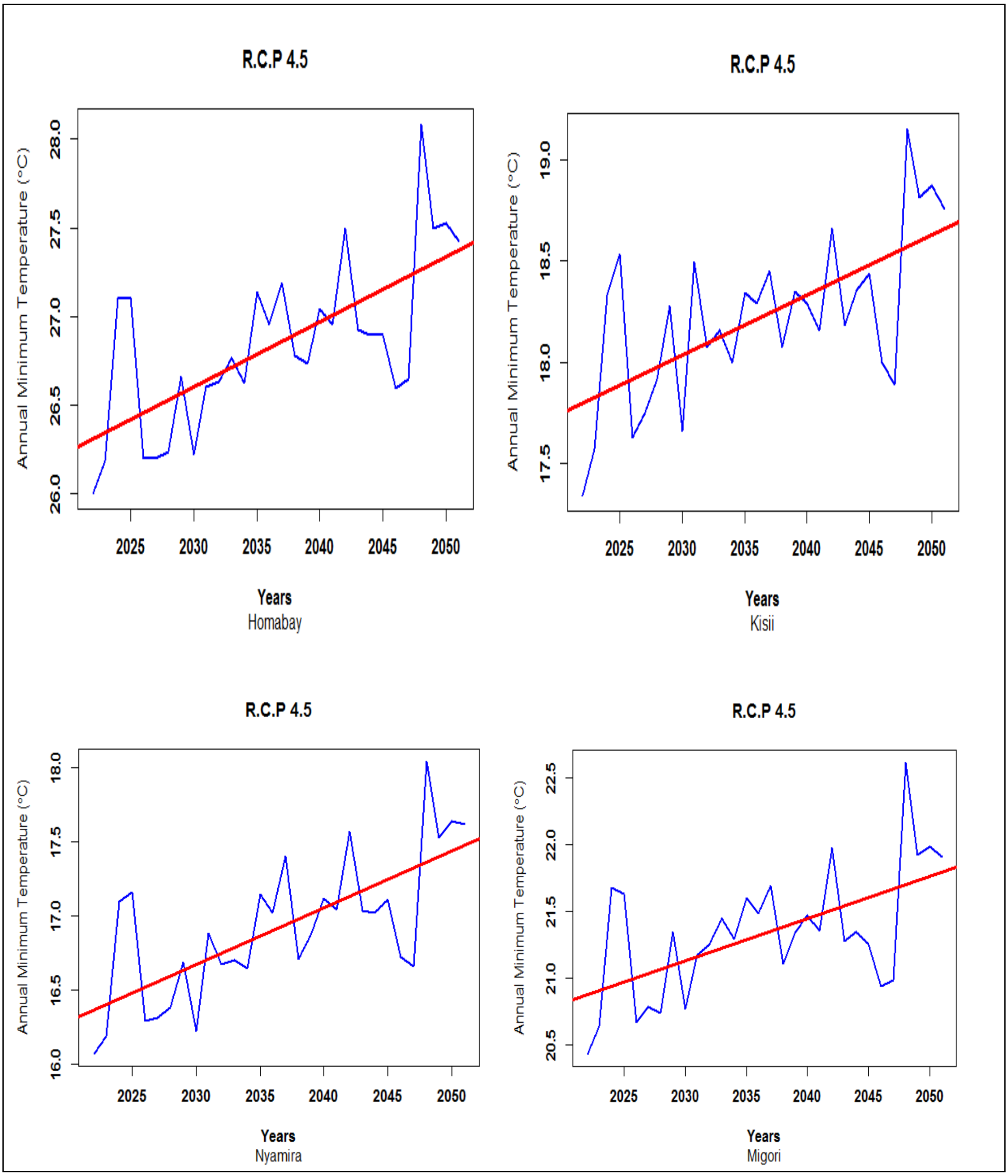


Figure 28: Trends of projected annual minimum temperature for Homabay, Kisii, Nyamira and Migori stations.

Under RCP4.5 emission scenario, all the four study counties of Homabay, Kisii, Nyamira and Migori exhibit increasing trends in the projected annual minimum temperature. This is expected to increase daily average temperature in future, thus increasing vulnerability of small holder maize farming in all the four counties.

Figure 29 presents the shifts in projected annual minimum temperature for Homabay, Kisii, Migori and Nyamira counties under RCP4.5 emission scenarios.

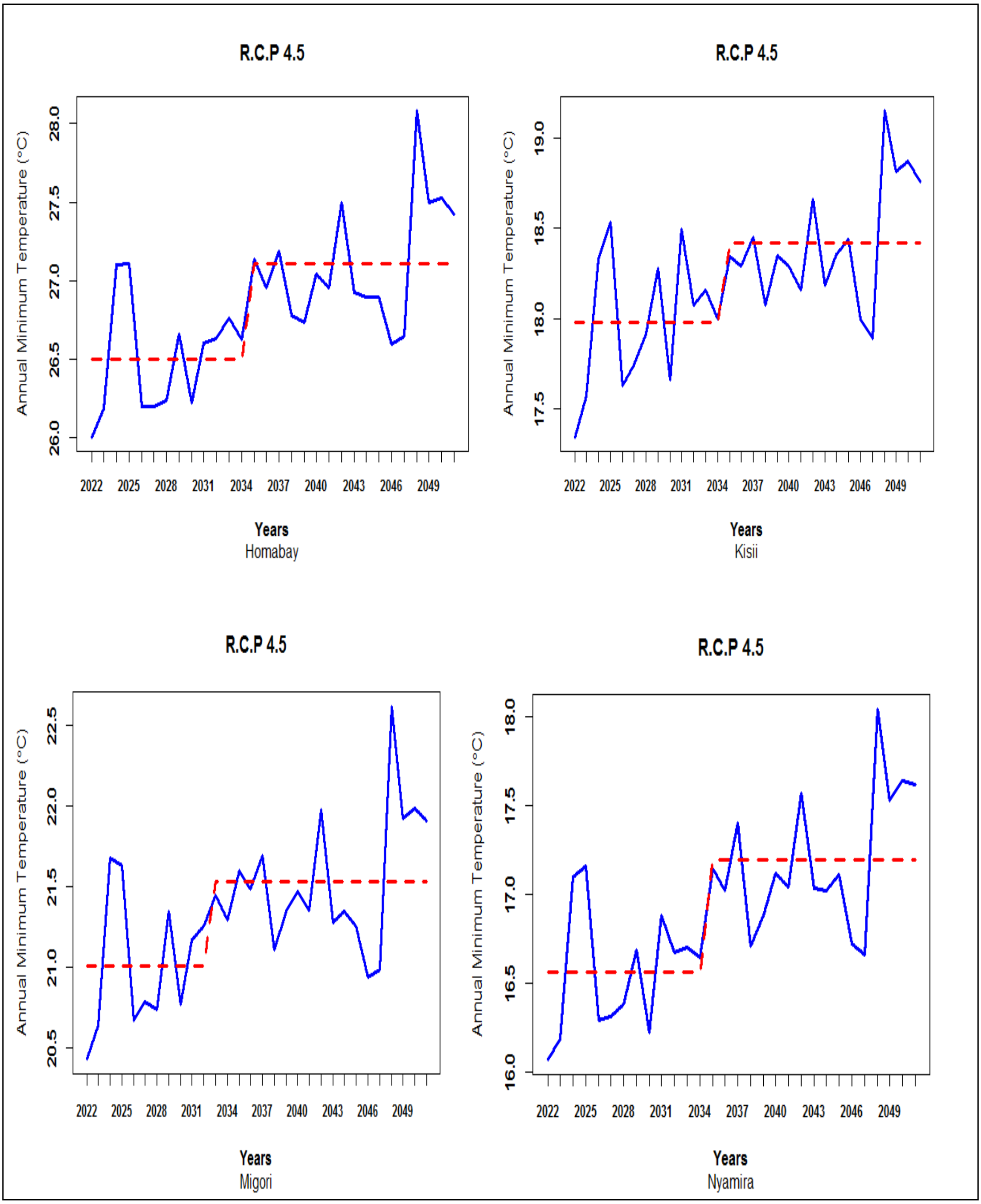


Figure 29: Shifts in projected annual minimum temperature for Homabay, Kisii, Migori and Nyamira stations.

The projected annual minimum temperatures depicted upward shifts in the means of the annual minimum temperatures in all the study counties of Kisii, Homabay, Nyamira and Migori.

Table 12 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean annual and seasonal minimum temperature based on RCP 4.5 Emission Scenario for Homabay, Kisii, Migori and Nyamira Counties respectively.

Table 12: Characteristics of projected minimum temperature based on RCP 4.5 Emission Scenario

Station	Season	Mean Tmin(°C)	Score	p- value (MK test)	p- value) (Pettit's Test)	Sens Slope Value
Homa Bay	MAM	26.9	159	0.0048	0.0087	0.0421
	JJA	26.2	233	0.0000	0.0011	0.0591
	OND	26.9	37	0.5207	1.3440	0.0074
	Annual	26.8	205	0.0003	0.0057	0.0399
Kisii	MAM	18.9	157	0.0044	0.0397	0.0340
	JJA	17.5	241	0.0000	0.0024	0.0627
	OND	18.3	69	0.2251	0.7617	0.0095
	Annual	18.2	185	0.0010	0.0499	0.0334
Migori	MAM	21.7	130	0.0213	0.1284	0.0335
	JJA	20.3	233	0.0000	0.0015	0.0637
	OND	21.6	-5	0.9431	1.2190	-0.0014
	Annual	21.3	161	0.0043	0.0446	0.0336
Nyamira	MAM	17.8	165	0.0034	0.0130	0.0476
	JJA	16.1	241	0.0000	0.0002	0.0608
	OND	16.9	45	0.4325	1.0680	0.0098
	Annual	16.9	217	0.0001	0.0037	0.0428

Minimum temperatures are projected to increase based on CSIRO model projections under RCP 4.5 emission scenario for all the seasons in the four study counties at rates of between 0.0074^0C/year and 0.0637^0C/year, except for OND season in Migori County, where minimum temperatures are projected to decrease at a rate of -0.0014^0C/year.

The projected increasing trend and upward shift in MAM, JJA and annual minimum temperatures were statistically significant, given that the p-values of Mann-Kendall and Pettit's tests statistics were less than the significance level of $\alpha=0.05$. The trend and shift in OND minimum temperatures were statistically insignificant.

4.5.3 Projected Maximum Temperatures based on RCP4.5 emission Scenario

Figure 30 presents the trends in projected maximum temperature based on CSIRO projections under RCP4.5 for Homabay, Kisii, Migori and Nyamira counties.

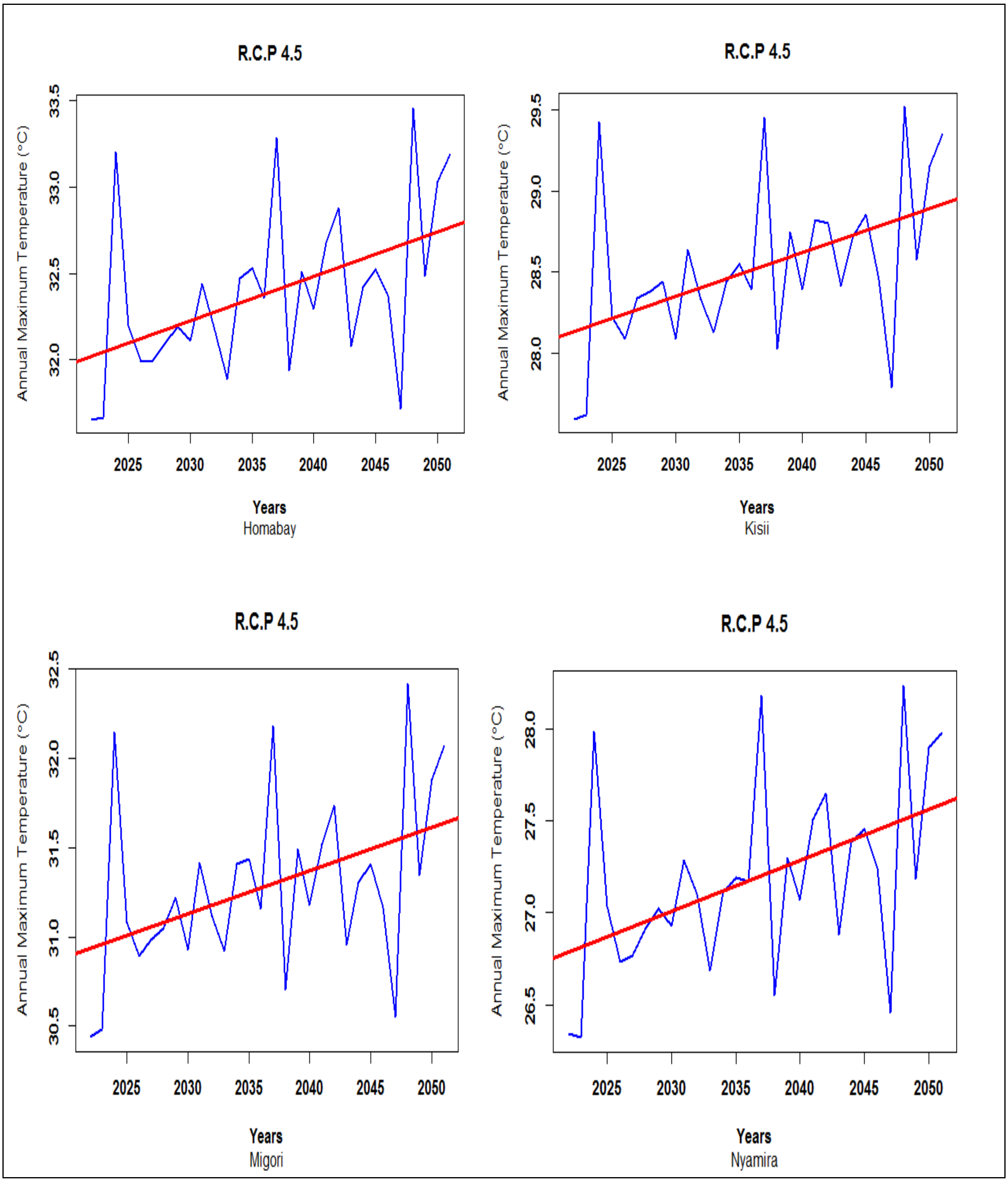


Figure 30: Trends in projected maximum temperatures under RCP 4.5 emission scenario for Homabay, Kisii, Migori and Nyamira.

Annual maximum temperatures are projected to have increased trends based on CSIRO model projections under RCP4.5 emission scenario. This implies increasing temperatures in Homabay, Kisii, Migori and Nyamira counties. The increase in maximum temperatures is expected to accelerate evapotranspiration hence reducing the amount of moisture needed for maize production.

Figure 31 presents the shifts in the projected annual maximum temperature for Homabay, Kisii, Migori and Nyamira counties under RCP4.5 emission scenario.

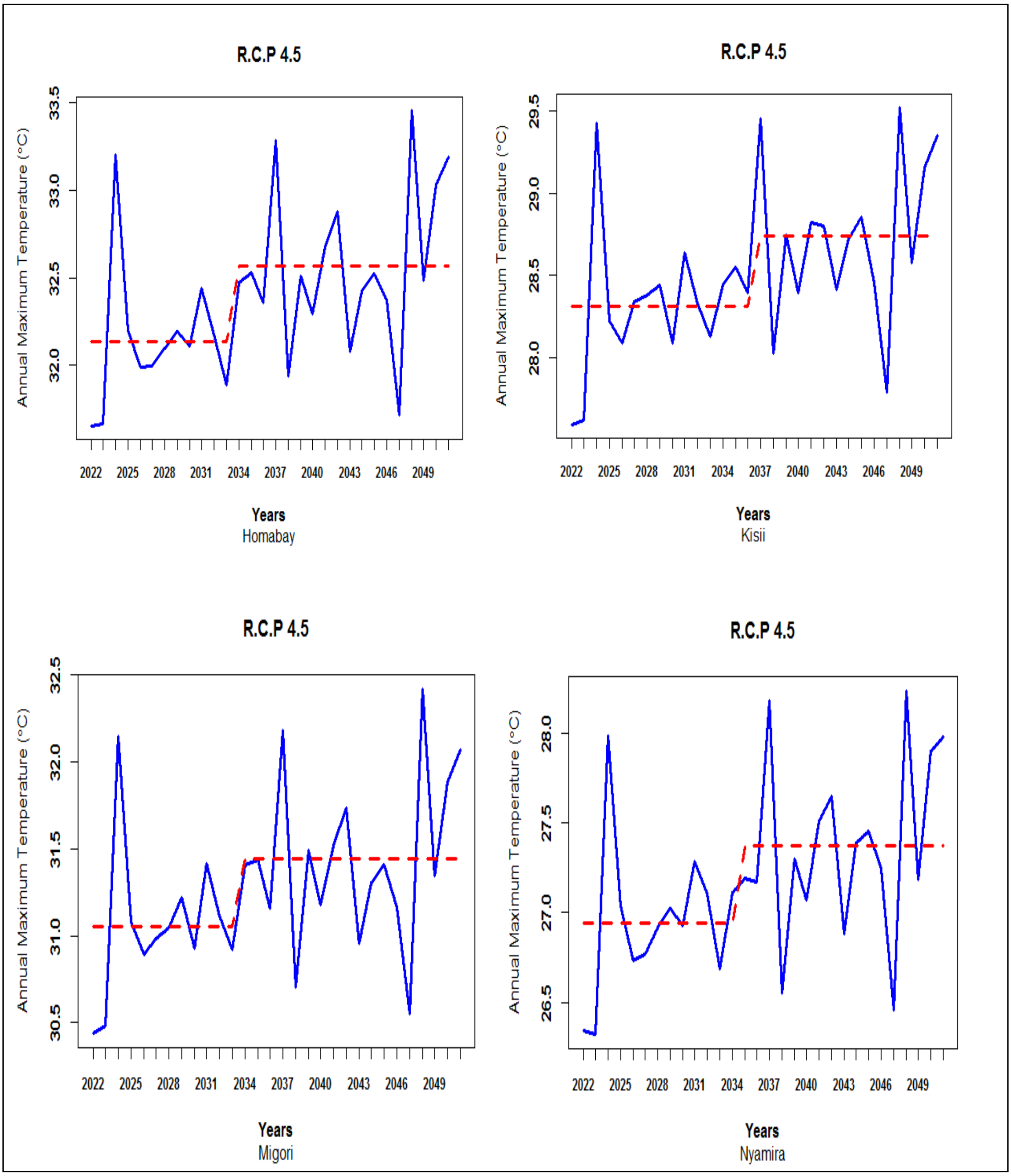


Figure 31: Shifts in projected annual maximum temperature under RCP4.5 for Homabay, Kisii, Migori and Nyamira.

All the study counties depicted an upward shift in the mean projected annual maximum temperatures based on CSIRO model projections under RCP4.5 emission scenario thus implying increased vulnerability of smallholder farming systems.

Table 13 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean annual and seasonal Maximum Temperature under RCP 4.5 Emission Scenario for Homabay, Kisii, Migori and Nyamira counties.

Table 13: Characteristics of Projected Maximum Temperature under RCP 4.5 Emission Scenario for Homabay, Kisii, Migori and Nyamira.

Station	Season	Mean Tmax(°C)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Homa Bay	MAM	32.2	117	0.0385	0.0314	0.0507
	JJA	31.7	251	0.0000	0.0001	0.0563
	OND	32.8	-97	0.0868	0.1284	-0.0269
	Annual	32.4	167	0.0031	0.0528	0.0306
Kisii	MAM	28.6	137	0.0153	0.0314	0.0486
	JJA	27.6	247	0.0000	0.0002	0.0486
	OND	28.9	-63	0.2687	0.1954	-0.0172
	Annual	28.5	183	0.0012	0.0558	0.0334
Migori	MAM	31.1	111	0.0497	0.0952	0.0446
	JJA	30.5	253	0.0000	0.0001	0.0566
	OND	31.9	-97	0.0868	0.0904	-0.0362
	Annual	31.3	153	0.0067	0.1107	0.0279
Nyamira	MAM	27.4	111	0.0497	0.0623	0.0487
	JJA	26.1	247	0.0000	0.0002	0.0589
	OND	27.5	-67	0.2390	0.2644	-0.0214
	Annual	27.2	173	0.0022	0.0773	0.0333

Maximum temperatures are projected to increase in MAM and JJA seasons and also annually in all the study counties at rates of between 0.0279^0C/year and 0.0589^0C/year based on CSIRO model projections under RCP4.5 emission scenario. On the contrary, maximum temperatures are projected to decrease in all the study counties during OND season at rates of between -0.0172^0C/year and -0.0362^0C/year. The decrease in maximum temperature during the OND season is expected to enhance retention of soil moisture, hence enhancing maize growth and development. The trends and shifts in MAM and JJA maximum temperatures for Homabay and Kisii counties were statistically significant based on the p-values of the Man-Kendall and Pettit's tests statistics that were less than the significance value of 0.05.

All the study counties depicted statistically significant trends in their MAM, JJA and annual maximum temperatures, given that the p-values of the Man-Kendall test were less than the significance level of 0.05. Migori and Nyamira counties had statistically significant trends and shifts in maximum temperatures during JJA season, based on their smaller p-values of the Man-Kendall and Pettit's tests compared to the significance level of 0.05. During the OND season, all the study counties had statistically insignificant trends and shifts in the mean maximum temperatures.

4.6 Projected Rainfall based on RCP4.5 Emission Scenario

Figure 32 presents the trends in projected annual rainfall based on CNRM model projections under RCP4.5 emission scenario for Homabay, Kisii, Migori and Nyamira counties.

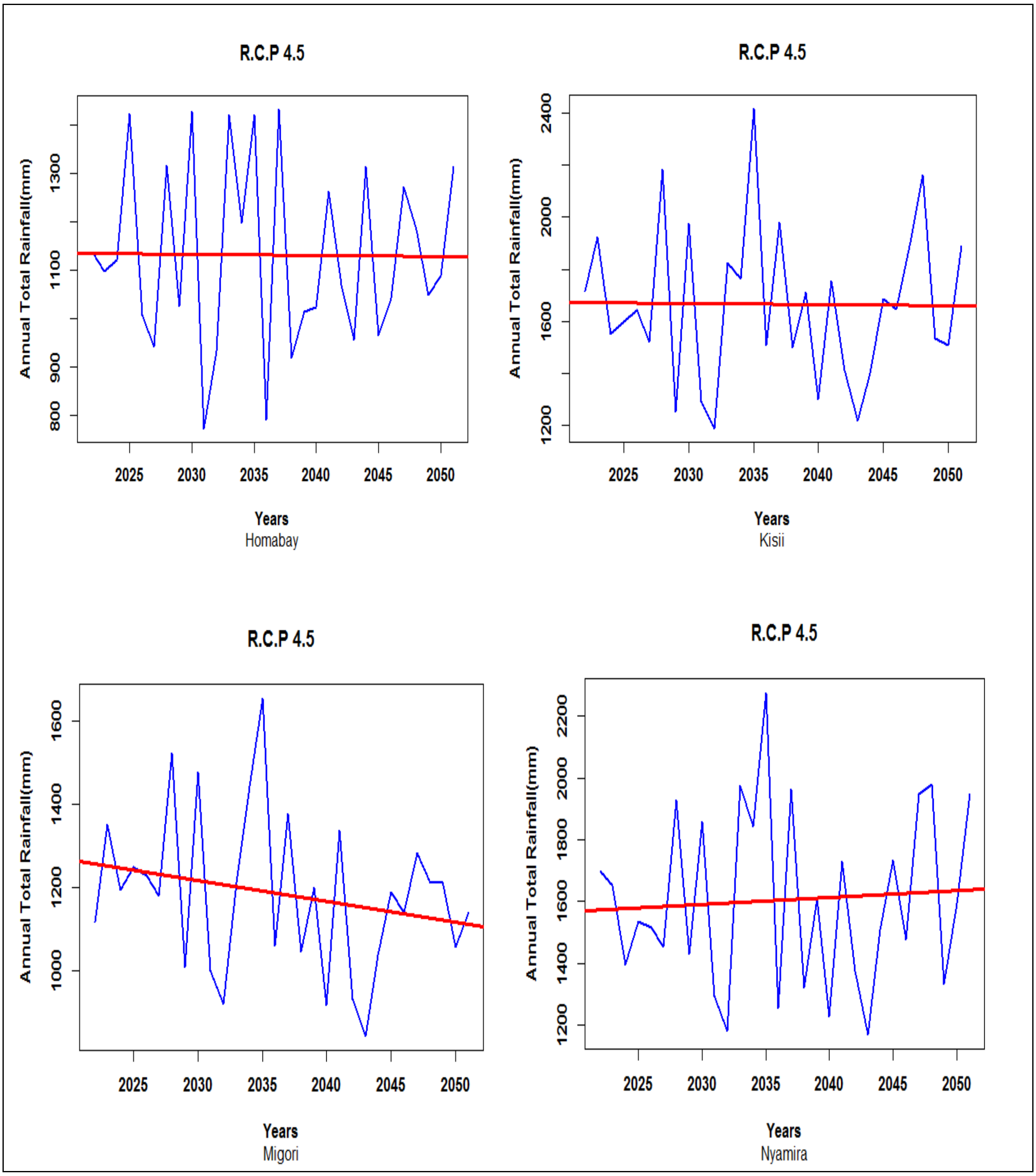


Figure 32:Trends in projected annual rainfall under RCP4.5 for Homabay, Kisii, Migori and Nyamira.

Homabay, Kisii and Migori counties depicted decreasing trends in the projected annual rainfall based on CNRM model projections under RCP4.5 emission scenario, implying declining annual rainfall. On the contrary, Nyamira county exhibited a rising trend in projected annual rainfall. Decreasing rainfall in Homabay, Kisii and Migori counties imply a decrease in soil moisture which in turn negatively affects smallholder maize farming. On the other hand, increasing annual rainfall in Nyamira county will enhance prospects for maize farming.

Figure 33 presents the shifts in projected annual rainfall based on CNRM model under RCP4.5 for Homabay, Kisii, Migori and Nyamira Counties.

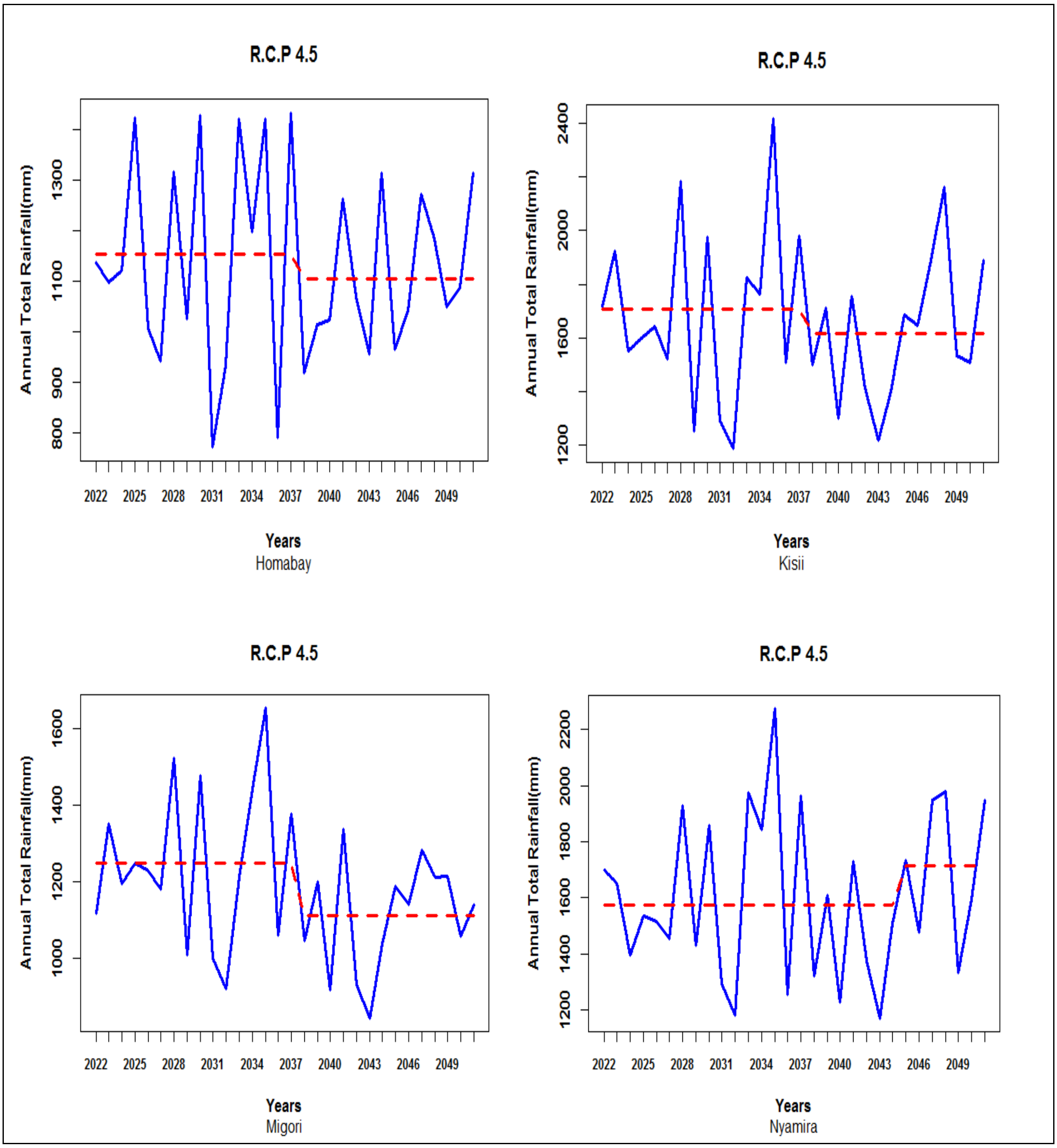


Figure 33: Shifts in projected annual rainfall under RCP4.5 for Homabay, Kisii, Migori and Nyamira

Homabay, Kisii and Migori counties exhibited downward shifts in projected annual rainfall under RCP4.5 emission scenario. Nyamira depicted an upward mean shift in projected annual rainfall.

Table 14 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean total annual and seasonal rainfall under RCP4.5 for Homabay, Kisii, Migori and Nyamira counties.

Table 14: Characteristics of projected rainfall under RCP4.5 for Homabay, Kisii, Migori and Nyamira.

Station	Season	Mean Rainfall (mm)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Homa Bay	MAM	422.4	-57	0.318	0.505	-2.3
	JJA	203.3	85	0.134	0.311	3.7
	OND	200.0	18	0.762	1.093	0.3
	Annual	1132.2	6	0.929	1.466	0.8
Kisii	MAM	581.0	-89	0.116	0.081	-5.7
	JJA	292.5	93	0.101	0.214	5.2
	OND	407.8	10	0.872	1.019	0.4
	Annual	1665.5	-14	0.817	1.319	-1.2
Migori	MAM	388.4	-153	0.007	0.019	-6.0
	JJA	161.3	95	0.094	0.243	3.4
	OND	310.3	-18	0.762	0.559	0.7
	Annual	1184.4	-64	0.261	0.378	-4.3
Nyamira	MAM	562.3	-95	0.094	0.056	-4.2
	JJA	323.8	121	0.032	0.195	6.5
	OND	329.7	70	0.218	0.254	1.8
	Annual	1606.9	14	0.817	1.044	1.6

All the study stations are projected to experience decreasing rainfall during MAM season at rates of between -2.3mm/year and -6mm/year. Decreasing rainfall amounts during the main growing season (MAM) will exacerbate the sensitivity of maize production to the adverse impacts of climate change within the study counties. The trends and shifts in the projected

MAM rainfall for Migori are statistically significant given that the p-values of Man-Kendall and Pettit's tests statistics that are less than the significance level of 0.05.

However, the decreasing trends and shifts in the projected JJA, OND and annual rainfall are not statistically significant based on the p-values of Man-Kendall and Pettit's tests statistics that are larger than the significance level of 0.05. This implies that the decline in rainfall in the JJA and OND season will be inconsequential and insignificant with regard to smallholder maize production.

4.7 Trends and Patterns of Projected Climate Based on RCP 8.5 Emission Scenario

This section presents the trends and patterns of projected rainfall and temperature based on RCP8.5 Emission Scenario.

4.7.1 Projected Maximum Temperatures based on RCP8.5 emission scenario.

Figure 34 presents the trends in projected annual maximum temperatures under RCP8.5 emission scenario for Homabay, Kisii, Migori and Nyamira Counties.

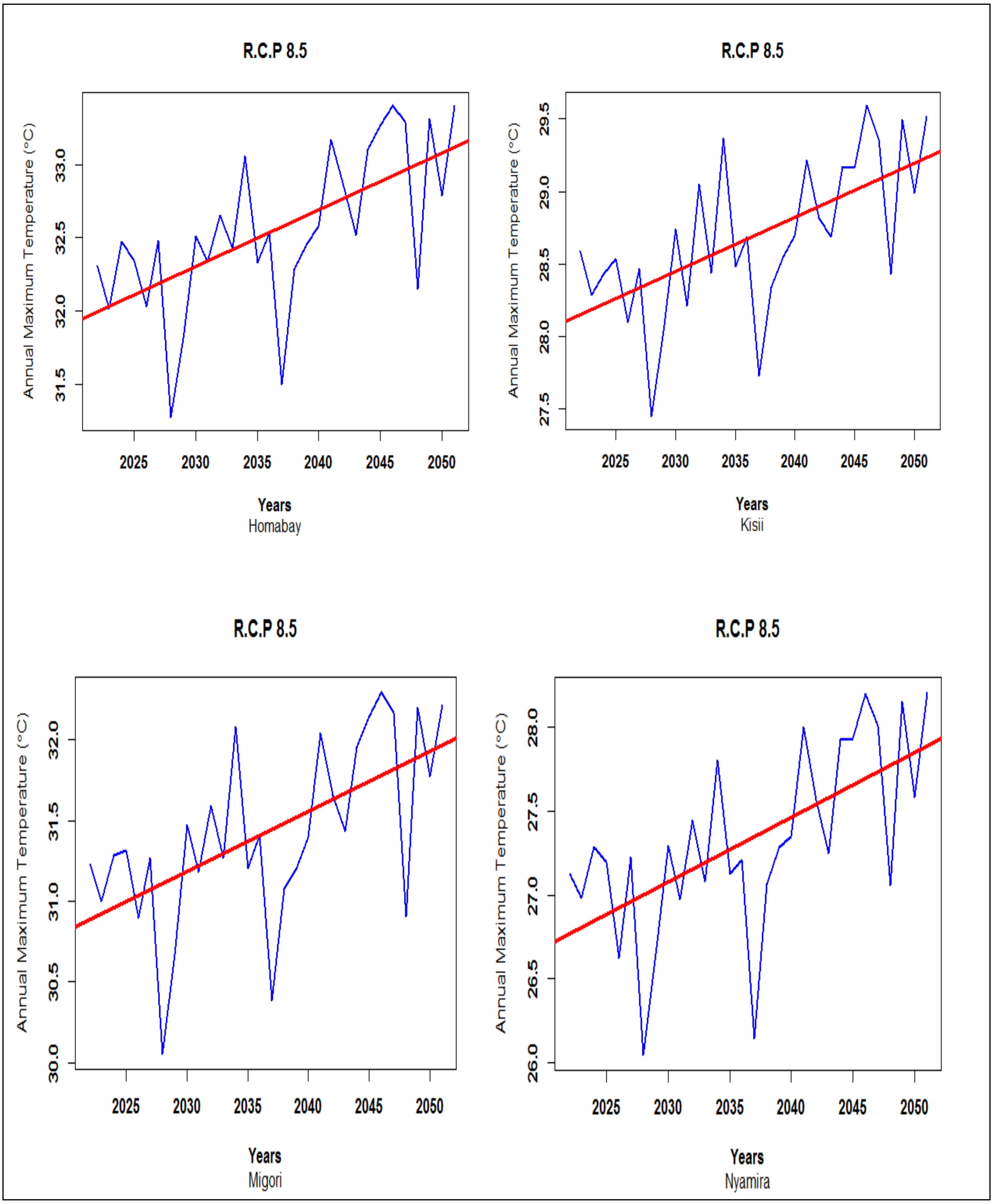


Figure 34: Trends in projected annual maximum temperature based on RCP8.5 for Homabay, Kisii, Migori and Nyamira

All counties exhibited rising trends in annual maximum temperatures based on RCP8.5 emission scenario, implying rising annual maximum temperatures.

Figure 35 presents the shifts in forecasted annual maximum temperature under RCP8.5 for Homabay, Kisii, Migori and Nyamira Counties.

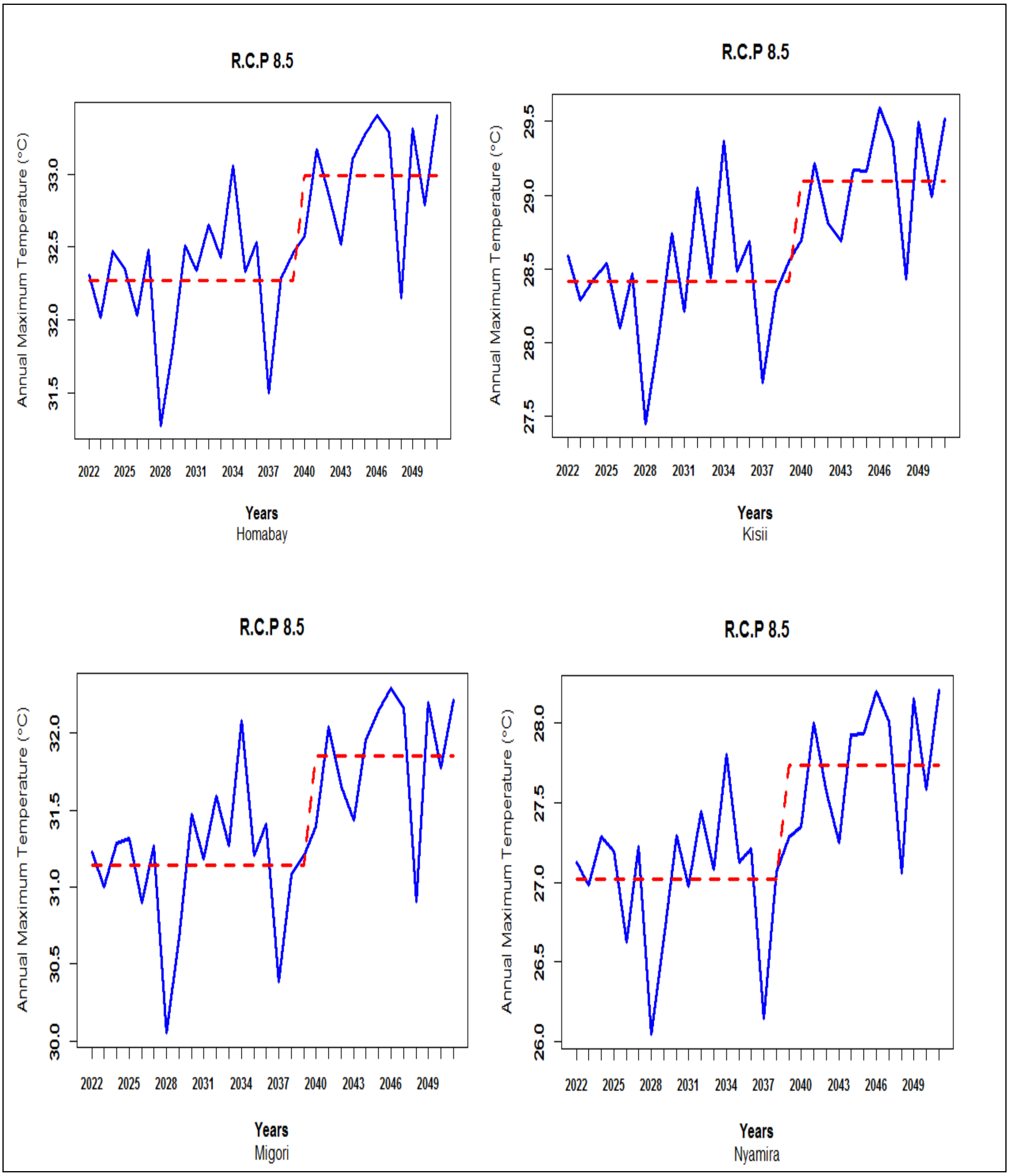


Figure 35: Shifts in projected annual maximum temperature based on RCP8.5 for Homabay, Kisii, Migori and Nyamira

All the study counties depicted an upward shift in the annual maximum temperatures based on RCP8.5 emission scenario.

Table 15 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean annual and seasonal maximum temperature based on RCP 8.5 emission scenario for Homabay, Kisii, Migori and Nyamira Counties.

Table 15: Characteristics of projected maximum temperature based on RCP 8.5 emission scenario for Homabay, Kisii, Migori and Nyamira.

Station	Season	Mean Tmax(°C)	Score	p- value (MK test)	p- value (Pettit's test)	Sens Slope Value
Homa Bay	MAM	32.2	103	0.0688	0.0952	0.0409
	JJA	31.9	275	0.0007	0.0003	0.0585
	OND	32.9	99	0.0804	0.1053	0.0447
	Annual	32.6	219	0.0001	0.0026	0.0395
Kisii	MAM	28.5	117	0.0385	0.0658	0.0431
	JJA	27.7	293	0.0000	0.0002	0.0678
	OND	29.0	81	0.1535	0.1284	0.0400
	Annual	28.7	197	0.0005	0.0062	0.0395
Migori	MAM	31.0	95	0.0935	0.1347	0.0410
	JJA	30.6	281	0.0000	0.0001	0.0607
	OND	31.9	95	0.0935	0.1284	0.0433
	Annual	31.4	193	0.0006	0.0053	0.0375
Nyamira	MAM	27.3	101	0.0744	0.0658	0.0435
	JJA	26.2	293	0.0000	0.0002	0.0648
	OND	27.6	93	0.1007	0.1053	0.0471
	Annual	27.3	213	0.0002	0.0024	0.0395

Under RCP 8.5 emission scenario, maximum temperatures is projected to increase in all the seasons for all the study counties at rates between 0.0375^0C/year and 0.0678^0C/year. The increasing trends and upward shifts in the annual and JJA maximum temperatures were statistically significant, given that the p-values of Man-Kendall and Pettit's tests statistics were less than the significance level of 0.05. The projected increase in maximum temperature will exacerbate water stress, hence increase sensitivity of maize production within the study counties to adverse changes in climate. Consequently, smallholder maize production is expected to decline, since the rise in temperature will negatively impact maize production by increasing water stress, hence reducing biomass production, and eventually reduce maize yields.

4.7.2 Projected Minimum Temperatures based on RCP8.5 emission scenario.

Figure 36 presents the trends in the forecasted annual minimum temperature under RCP8.5 for Homabay, Kisii, Migori and Nyamira Counties.

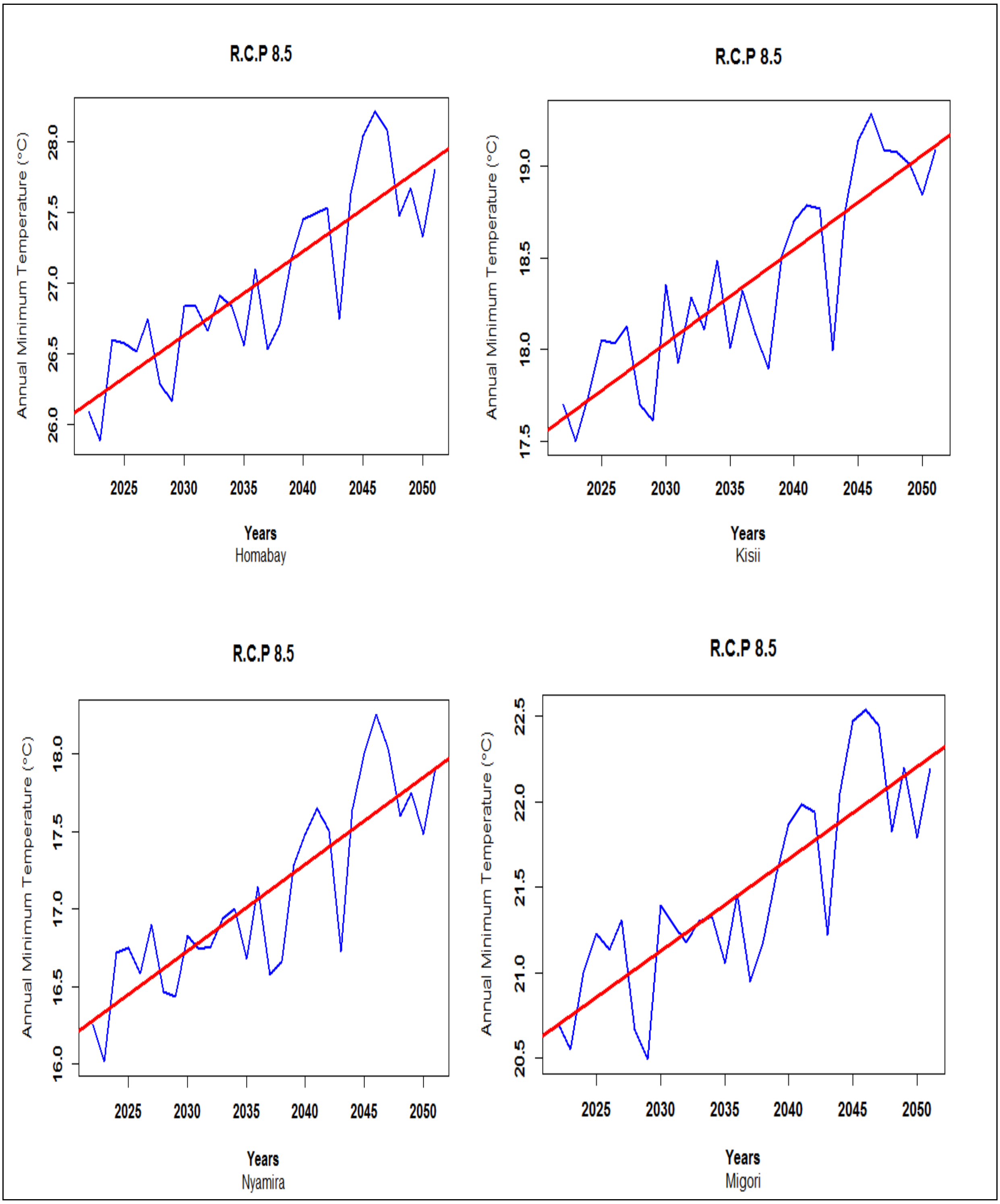


Figure 36: Trends in projected annual minimum temperature based on RCP8.5 emission scenario for Homabay, Kisii, Migori and Nyamira.

All the study counties depicted increasing trends in the forecasted annual minimum temperature under RCP8.5 emission scenario, signifying rising minimum temperatures. Figure 37 presents the shifts in the projected annual minimum temperatures based on RCP8.5 for Homabay, Kisii, Migori and Nyamira Counties,

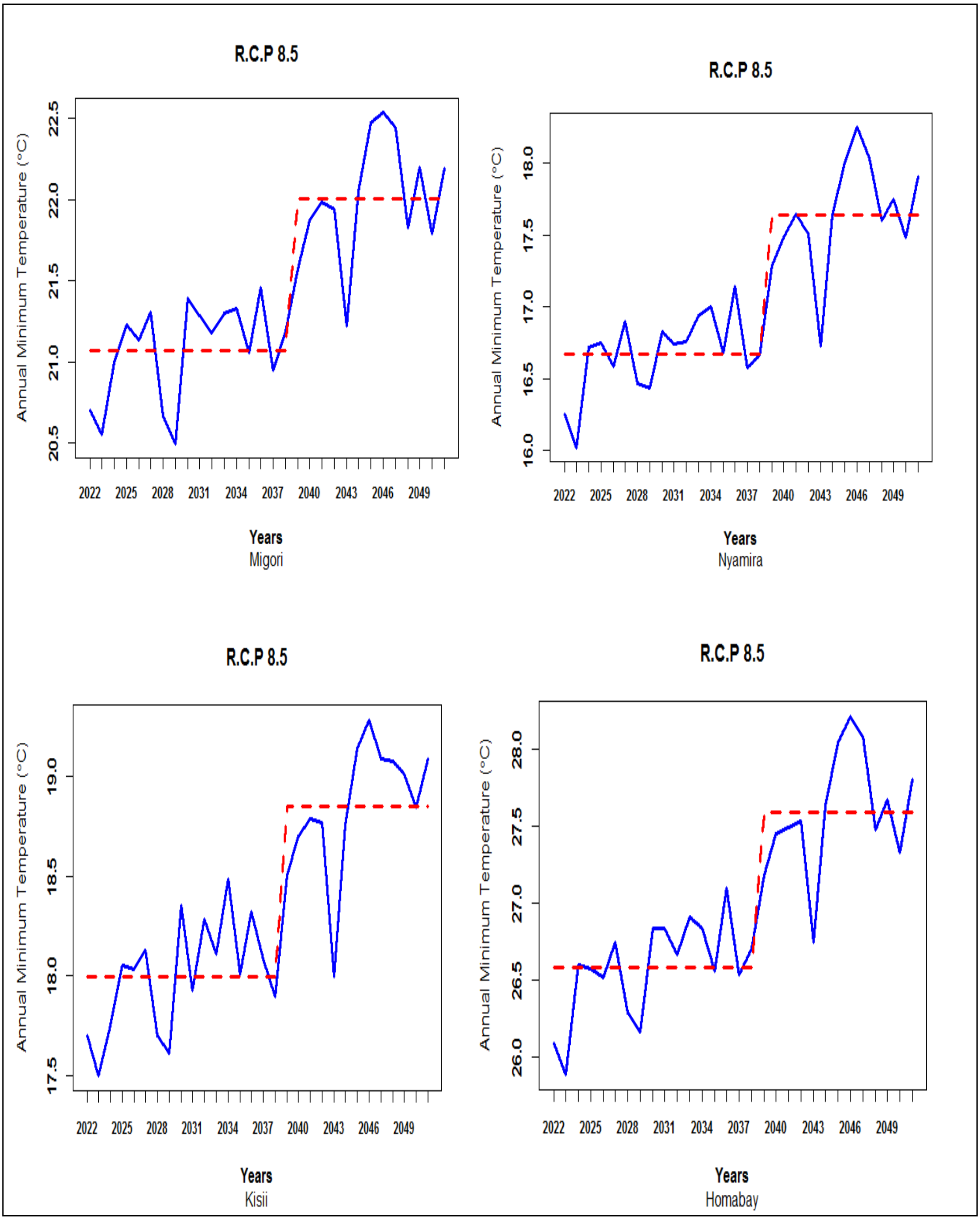


Figure 37: Shifts in projected minimum temperatures based on RCP8.5 for Homabay, Kisii, Migori and Nyamira.

Under RCP8.5 emission scenario, all the study counties will experience an upward mean shift in the projected minimum temperature.

Table 16 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean annual and seasonal minimum temperature based on RCP8.5 emission scenarios for Homabay, Kisii, Migori and Nyamira Counties.

Table 16: Characteristics of projected minimum temperature based on RCP8.5 emission scenario for Homabay, Kisii, Migori and Nyamira

Station	Season	Mean Tmin(°C)	Score	p- value (MK test)	p- value (Pettit's Test)	Sens Slope Value
Homa Bay	MAM	27.0	189	0.0008	0.0100	0.0496
	JJA	26.5	253	0.0000	0.0006	0.0711
	OND	27.2	205	0.0003	0.0016	0.0536
	Annual	27.0	285	0.0000	0.0001	0.0575
Kisii	MAM	18.8	197	0.0005	0.0107	0.0459
	JJA	17.7	275	0.0000	0.0005	0.0736
	OND	18.5	186	0.0010	0.0024	0.0432
	Annual	18.4	275	0.0000	0.0003	0.0504
Migori	MAM	21.6	163	0.0038	0.0231	0.0437
	JJA	20.6	235	0.0000	0.0007	0.0670
	OND	21.8	175	0.0019	0.0046	0.0544
	Annual	21.5	263	0.0000	0.0002	0.0522
Nyamira	MAM	17.8	201	0.0004	0.0071	0.0514
	JJA	16.3	275	0.0000	0.0005	0.0697
	OND	17.2	199	0.0004	0.0010	0.0566
	Annual	17.1	273	0.0000	0.0002	0.0570

Under RCP8.5 emission scenario, minimum temperatures will increase in all seasons across the study counties at rates of between 0.0432^0C/year and 0.0736^0C/year. JJA season will experience the highest rates of increase in minimum temperature for all the study counties at rates of between 0.0670^0C/year and 0.0732^0C/year. The increasing trends and upward shifts in the projected minimum temperatures in all the seasons are statistically significant based on the smaller p-values of Man-Kendall and Pettit's tests compared to the significance level of 0.05. The increase in minimum temperatures will increase the daily average temperatures, hence reducing prospects for smallholder maize production in all the study counties.

4.7.3 Projected Rainfall under RCP 8.5 Emission Scenario

Figure 38 presents trends in projected annual total rainfall under RCP 8.5 emission scenario for Homabay, Kisii, Migori and Nyamira Counties.

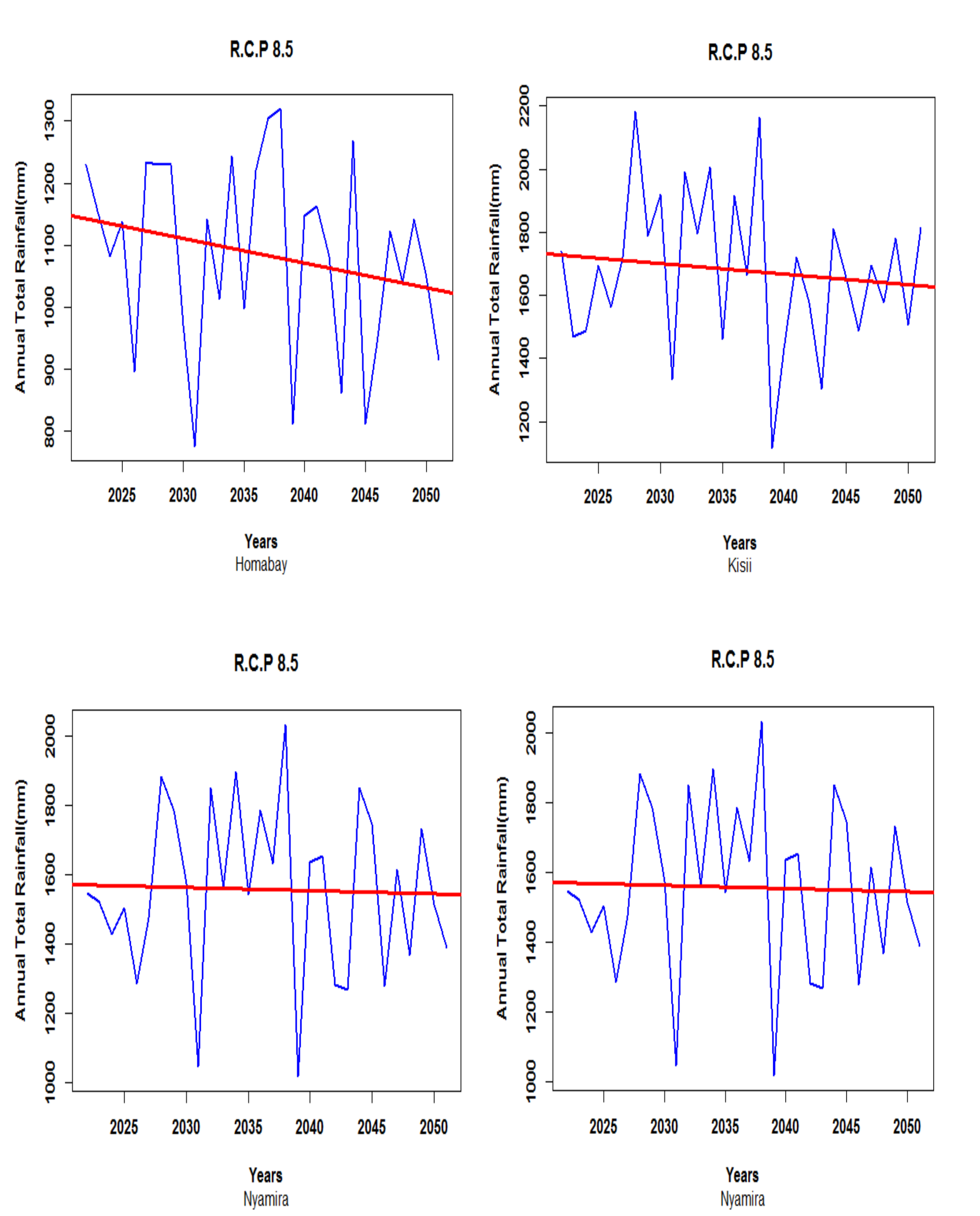


Figure 38: Trends in annual total rainfall based on RCP8.5 for Homabay, Kisii, Migori and Nyamira.

Under RCP8.5 emission scenario, the projected annual total rainfall exhibit decreasing trends for all the study Counties. Figure 39 presents the shifts in the projected annual total rainfall under RCP8.5 emission scenario.

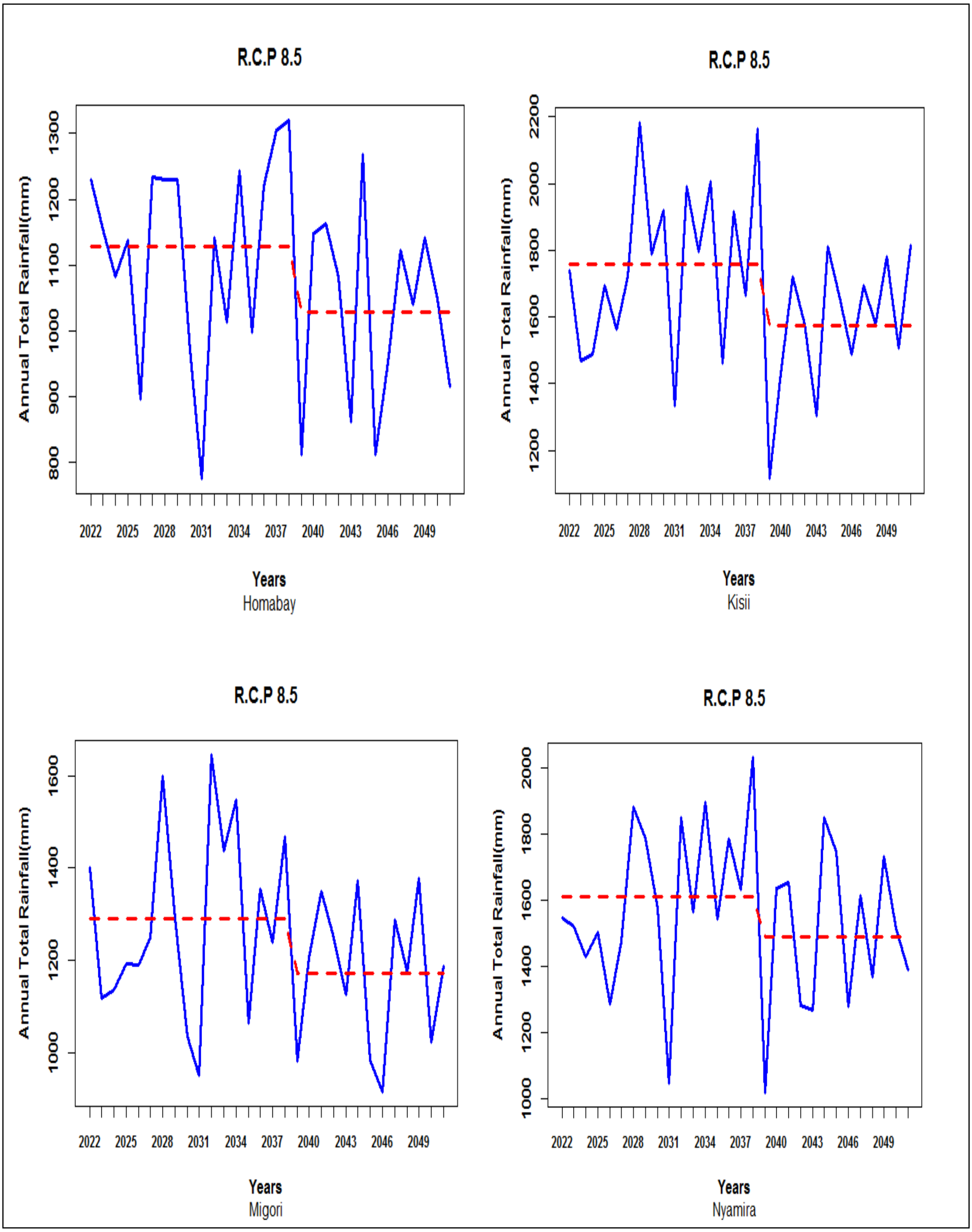


Figure 39: Shifts in annual total rainfall based on RCP8.5 for Homabay, Kisii, Migori and Nyamira.

Homabay, Kisii, Migori and Nyamira exhibit a downward shift in annual total rainfall under RCP8.5 emission scenario. Table 17 presents the Mann-Kendall test statistics and Sen's slope values for the trends in projected mean total annual and seasonal rainfall based on RCP 8.5 emission scenario for Homabay, Kisii, Migori and Nyamira Counties.

Table 17: Characteristics of projected rainfall based on RCP 8.5 emission scenario for Homabay, Kisii, Migori and Nyamira.

Station	Season	Mean Rainfall (mm)	Score	p- value (MK test)	p- value (P test)	Sens Slope Value
Homa Bay	MAM	413.1	43	0.454	1.044	1.6
	JJA	185.7	-21	0.721	1.044	-0.4
	OND	310.2	-35	0.544	0.578	-1.5
	Annual	1084.579	-65	0.3	0.423	-4.2
Kisii	MAM	573.9	-25	0.669	0.740	-1.5
	JJA	320.9	79	0.164	0.740	3.4
	OND	498.1	27	0.643	0.378	1.1
	Annual	1679.3	-15	0.803	-1.191	-1.2
Migori	MAM	444.1	5	0.943	0.676	0.2
	JJA	167.2187	57	0.3	0.676	1.7
	OND	432.0	-31	0.592	0.899	-1.2
	Annual	1238.3	-45	0.432	0.636	-3.5
Nyamira	MAM	537.1	41	0.475	1.168	1.2
	JJA	319.1	31	0.592	1.168	1.4
	OND	469.8	5	0.943	1.319	0.3
	Annual	1557.3	-9	0.887	0.852	-0.2

Homabay, Migori and Nyamira counties depicted increasing trends in MAM total rainfall. However, Nyamira and Kisii Counties exhibited increasing trends in JJA and OND rainfall. The observed trends and mean shifts in rainfall are statistically insignificant, given that the p-values of Man-Kendall and Pettit's tests statistics are greater than the significance level of 0.05. Increasing rainfall during MAM and OND seasons will increase the prospects for maize production in the affected Counties.

4.8 Comparison between Baseline and Projected Climates

This section presents a comparison between the baseline and projected climates under both RCP 4.5 and RCP 8.5 emission scenarios.

4.8.1 Maximum Temperature

Table 18 presents the change in maximum temperature from the baseline level under RCP 4.5 and RCP 8.5 emission scenarios for Homabay, Kisii, Migori and Nyamira Counties.

Table 18: Comparison between the baseline and future maximum temperatures due to climate change.

Station	Season	Baseline	RCP 4.5	RCP8.5	Change	
					RCP4.5 - Baseline	RCP8.5 - Baseline
Kisii	MAM	27.6	28.5	28.6	0.9	1
	JJA	25.8	27.6	27.7	1.8	1.9
	OND	27.7	28.9	29.0	1.2	1.3
	Annual	27.3	28.5	28.7	1.2	1.4
Nyamira	MAM	26.4	27.4	27.3	1	0.9
	JJA	24.4	26.1	26.2	1.7	1.8
	OND	26.3	27.5	27.6	1.2	1.3
	Annual	26.0	27.2	27.3	1.2	1.3
Migori	MAM	30.0	31.1	31.0	1.1	1
	JJA	28.8	30.5	30.6	1.7	1.8
	OND	30.7	31.9	31.9	1.2	1.2
	Annual	30.1	31.3	31.4	1.2	1.3
Homa Bay	MAM	31.2	32.2	32.2	1	1
	JJA	30.1	31.7	31.9	1.6	1.8
	OND	31.6	32.8	32.9	1.2	1.3
	Annual	31.2	32.4	32.6	1.2	1.4

Maximum temperatures are projected to increase in all seasons under both RCP 4.5 and RCP 8.5 emission scenarios across the study counties. The rise in maximum temperature under RCP 8.5 emission scenario will be greater compared to RCP 4.5. The JJA season will experience the highest change in maximum temperature of between 1.6^{0}C and 1.9^{0}C by the year 2051, compared to the other seasons for all the study counties under RCP 4.5 and RCP 8.5 emission scenarios. Maximum temperatures will rise by 0.9^{0}C and 1.9^{0}C by the year 2051 under RCP 4.5 and RCP 8.5 respectively. Increasing temperatures will negatively affect the soil-water balance, with severe impacts on maize crop growth, development and productivity due to the water scarcity caused by the associated high evapotranspiration rates. Crops will likely face increased water/moisture stress during their growth and development phases. These will exacerbate the vulnerability of the maize production systems.

4.8.2 Rainfall

Table 19 compares baseline rainfall and projected rainfall under RCP4.5 and RCP 8.5 emission scenarios for Homabay, Kisii, Migori and Nyamira Counties.

Table 19: Comparison between baseline rainfall and projected rainfall based on RCP 4.5 and RCP 8.5 emission scenarios.

Station	Season	Baseline	RCP 4.5	RCP8.5	Change	
					RCP4.5 - Baseline	RCP8.5 - Baseline
Kisii	MAM	687.3	581.0	413.1	-106.3	-274.2
	JJA	387.4	292.5	185.7	-94.9	-201.7
	OND	504.8	407.8	310.2	-97.0	-194.5
	Annual	1921.0	1665.5	1584.6	-255.5	-336.4
Nyamira	MAM	662.7	562.3	537.1	-100.4	-125.6
	JJA	387.6	323.8	319.1	-63.7	-68.5
	OND	499.4	329.7	469.8	-169.7	-29.7
	Annual	1859.8	1606.9	1557.3	-253.0	-302.6
Migori	MAM	560.1	388.4	444.1	-171.7	-116.0
	JJA	188.2	161.3	167.2	-26.9	-21.0
	OND	401.0	310.3	302.0	-90.7	-99.0
	Annual	1383.9	1184.4	1238.3	-199.6	-145.7
Homa Bay	MAM	519.0	422.4	413.1	-96.6	-105.9
	JJA	211.6	203.3	185.7	-8.3	-25.9
	OND	350.7	200.0	310.2	-150.7	-40.4
	Annual	1326.0	1132.2	1084.6	-193.8	-241.4

Rainfall will decline in all seasons across all the counties. Under RCP 4.5 emission scenario, rainfall will change by between -8.3mm and -255.5mm by the year 2051. The decline in rainfall under RCP 8.5 emission scenario will be greater compared to RCP 4.5. Under RCP 8.5 emission scenario, rainfall will change by between -21mm and -336.4mm by 2051. The decrease in rainfall will be greater on annual basis and during the MAM season. Decreased rainfall during MAM season will increase the sensitivity of maize production to adverse climate change impacts, thus decreasing the prospects for maize crop production during this season.

4.8.3 Minimum Temperature

Table 20 compares the baseline minimum temperature and the projected minimum temperature under RCPs 4.5 and 8.5 emission scenarios for Homabay, Kisii, Migori and Nyamira Counties.

Table 20: Comparison between baseline minimum temperature and projected minimum temperature based on RCP 4.5 and RCP 8.5 emission scenarios.

Station	Season	Baseline	RCP 4.5	RCP8.5	Change	
					RCP4.5 - Baseline	RCP8.5 - Baseline
Kisii	MAM	17.4	18.8	18.9	1.4	1.5
	JJA	15.6	17.5	17.7	1.9	2.0
	OND	17.3	18.3	18.5	1.0	1.2
	Annual	16.8	18.2	18.4	1.4	1.6
Nyamira	MAM	16.2	17.8	17.8	1.6	1.6
	JJA	14.3	16.1	16.3	1.8	2.1
	OND	15.8	16.9	17.2	1.1	1.4
	Annual	15.4	16.9	17.1	1.5	1.7
Migori	MAM	20.2	21.6	21.7	1.4	1.5
	JJA	18.5	20.3	20.6	1.8	2.1
	OND	20.7	21.6	21.8	0.9	1.1
	Annual	19.9	21.3	21.5	1.4	1.6
Homa Bay	MAM	25.5	26.9	27.0	1.5	1.5
	JJA	24.3	26.2	26.5	1.9	2.2
	OND	25.8	26.9	27.2	1.1	1.3
	Annual	25.3	26.8	27.0	1.5	1.7

Under both RCPs 4.5 and 8.5 emission scenarios, projected minimum temperatures will rise in all the seasons by between 0.9^0C and 2.2^0C by the year 2051 across the study counties. JJA season will experience the greatest increase in minimum temperature of between 1.8^0C and 2.2^0C by 2051. OND season will experience the least increase in minimum temperature of between 0.9^0C and 1.4^0C by 2051. The change in minimum temperature will be higher under RCP 8.5 emission scenario compared to RCP 4.5 emission scenario. This will be the case because of the low "business as usual (BAU)" mitigation pathways under RCP 8.5 emission scenario.to abate global warming. Under RCP 8.5 emission scenario, minimum temperatures will rise by 1.1^0C to 2.2^0C by 2051. Increasing minimum temperatures during MAM and OND seasons will present favourable conditions for optimum maize crop production, with optimum rainfall conditions.

4.9 Relationship between Annual Maize Yields and Observed Climate variables

Table 21 presents the spearman's correlation coefficients between observed study climatic parameters and maize yields during the maize seedling, vegetative, flowering and fertilization, and grain filling and maturation phases in Homabay, Kisii, Migori and Nyamira Counties during the MAM rainfall season.

Table 21: Spearman's Correlation Coefficients for the MAM Season

County	Climatic parameter	Seedling Growth	P-value	Vegetative Growth	P-value	Flowering & Fertilization	P-value	Grain filling & Maturity	P-value
Homabay	Maximum temperature/Yield	-0.07	0.7	0.03	0.89	-0.19	0.32	0.07	0.73
	Minimum temperature/Yield	0.09	0.64	0.08	0.66	-0.22	0.24	0.11	0.59
	Rainfall/Yield	0.01	0.97	0.08	0.65	0.06	0.76	-0.18	0.32
Kisii	Maximum temperature /Yield	-0.30	0.11	-0.28	0.14	-0.09	0.65	-0.32	0.09
	Minimum temperature/Yield	0.11	0.56	0.01	0.96	-0.03	0.87	0.06	0.74
	Rainfall/Yield	0.30	0.10	0.19	0.30	0.33	0.07	0.14	0.44
Migori	Maximum temperature /Yield	-0.18	0.36	-0.04	0.85	-0.33	0.08	-0.39	0.04
	Minimum temperature/Yield	0.10	0.60	0.32	0.09	-0.22	0.26	-0.12	0.52
	Rainfall/Yield	0.08	0.66	0.03	0.87	0.04	0.83	0.09	0.64
Nyamira	Maximum temperature /Yield	-0.28	0.14	-0.12	0.54	-0.12	0.54	-0.09	0.66
	Minimum temperature/Yield	-0.01	0.94	0.06	0.75	-0.05	0.79	-0.12	0.54
	Rainfall/Yield	0.30	0.11	0.00	0.98	-0.17	0.37	0.01	0.94

Maximum temperature during seedling stage exerted negative but insignificant influence on maize yields across the study counties at the p=0.05 significance level. Maximum temperature during the vegetative stage resulted into decreased maize yields in all Counties except in Homabay, where an increase though insignificant was found. Maximum temperature reduces the rate at which maize nodes and leaves appear, hence reducing maize yields. During flowering and fertilization stage, maximum temperature depressed maize yields in all the study counties, although the associated correlation coefficients were statistically insignificant at the P=0.05 level. This is because high temperatures during the flowering and fertilization stage reduce the viability of maize pollen grains, hence reducing the potential maize yields. During the grain filling and maturity stage, maximum temperature depressed maize yields in all Counties, except in Homa Bay County where an increase, though statistically insignificant was noted.

There was a statistically significant negative correlation coefficient (-0.39) between maximum temperature and maize yields during grain filling and maturity stage in Migori County. There was a statistically significant positive correlation coefficient (0.32) between minimum temperature and maize yield during vegetative growth, and a statistically significant negative correlation between minimum temperature and maize yield during flowering and fertilization stage (-0.22) in Migori County. The most statistically significant correlation between rainfall and maize yields was realized during flowering and fertilization (0.33) and seedling growth (0.30) in Kisii County. The most significant correlation coefficient in Nyamira County was between maximum temperature and maize yields during seedling growth, which resulted into poor sprouting of maize seedlings hence reducing maize yields.

4.10 Vulnerability of Small-holder Maize farming to impacts of climate change

All the indices that were used to assess vulnerability of small-holder maize farming in each County are presented in this section. Negative indices showed a decline in the vulnerability components. Conversely, positive indices indicated an increase in the vulnerability components.

4.10.1 Sensitivity Indices

Table 22 presents the sensitivity indices for Migori, Homabay, Nyamira and Kisii counties.

Table 22: Sensitivity Indices

County	Sensitivity Index
Migori	-0.55
Homabay	0.34
Nyamira	1.22
Kisii	1.42

Kisii County had the highest sensitivity index (1.42) whereas Migori County recorded the least sensitivity (-0.55), with Homa Bay and Nyamira Counties having sensitivity indices of 0.34 and 1.22 respectively.

The high sensitivity recorded in Kisii County is attributed to the County's high population density of 958 people/km^2 compared to Migori County with a population density of 427 people/km^2. In addition, Kisii County had the highest percentage of farmers (100%) practising rain-fed maize farming and the highest rates of poverty (7.5%). Conversely, Migori County with the least sensitivity had the lowest poverty rate (3.6%) and 98.7% of its farmers practicing rain-fed maize farming compared to Nyamira (99.8%) and Homa Bay (99.1%). These observations agree with those of Yoo *et al.,* (2011), who concur that areas with high population densities tend to show high levels of sensitivity to fluctuations in climate. Therefore, areas with high population densities dependent on rain-fed socioeconomic activities such as Kisii County will be more vulnerable to the adverse impacts of climate change.

Since small-holder maize farming in Kisii County is purely rain-fed, maize production in this County is therefore highly sensitive to climate change impacts. Conversely, Migori County experienced the least sensitivity owing to its least proportion of farmers (98.7%) depending on rain fed maize production, and the highest percentage of farmers practicing irrigated maize farming (1.3%). Generally, maize farming is extremely sensitive to fluctuations in climate, thus fluctuations in climate variables, particularly temperature and rainfall, affect maize production (Lobell *et al*., 2011).

Figure 40 presents the sensitivity map for the area of study.

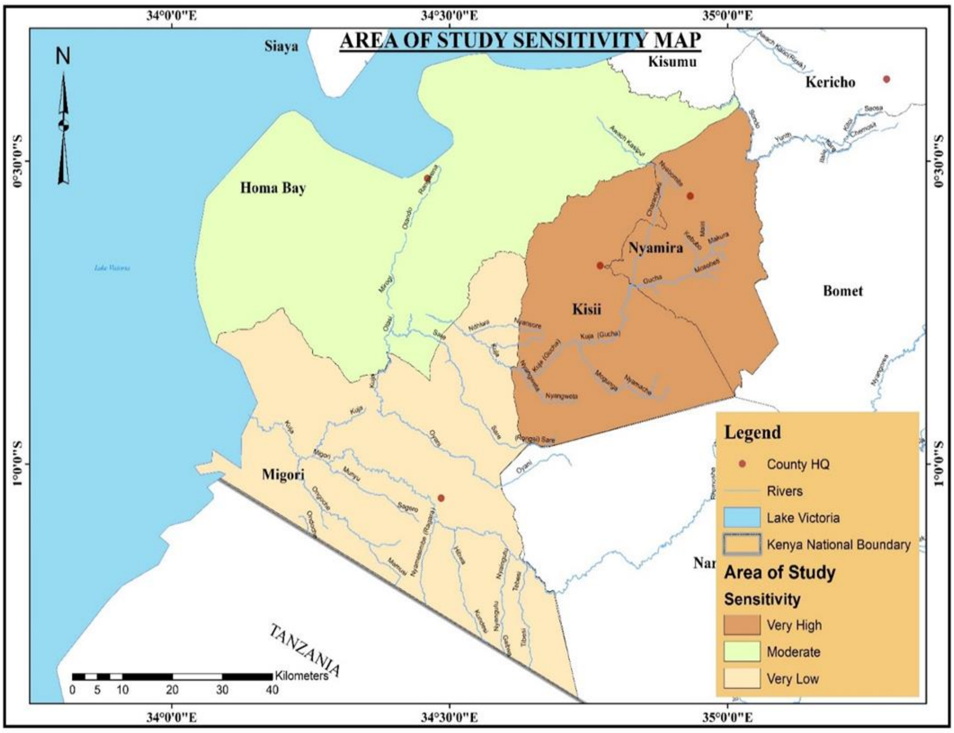


Figure 40: sensitivity index map for the study Counties.

The map categorizes Kisii and Nyamira as Counties in Southern Nyanza region characterized by very high sensitivity to the adverse changes and impacts in climate. This is largely influenced by high population densities in the two Counties and highest dependency on rain fed socioeconomic activities. On the other hand, the sensitivity in Homa Bay and Migori Counties were classified as moderate and very low respectively owing to their low population densities, lower rates of poverty as well as lower dependency on rain fed socioeconomic activities.

4.10.2 Exposure Indices

The exposure indices for the study Counties including frequency of occurrence of dominant extreme climate/hazardous events are presented in Table 23. Negative exposure indices indicated a decrease in exposure levels whereas positive exposure indices implied an increase in exposure levels.

Table 23: Exposure Indices

County	Exposure Index	Dominant climate hazards	
		Drought	Floods
Nyamira	-1.56	3	10
Kisii	-1.08	4	10
Homabay	0.6	5	6
Migori	2.25	6	11

Migori County presented the highest exposure index while Nyamira County exhibited the least exposure index of -1.56, followed by Kisii (-1.08) and Homa Bay (0.60). The least exposure index in Nyamira County is closely tied to its low frequency of droughts (3) and floods (10). The highest frequency of floods and droughts in Migori County accounted largely for its highest exposure index. The exposure indices generally reflect how the various Counties are exposed to hazardous climate variables particularly extreme temperature and rainfall events that manifest in frost and heatwaves, and droughts and floods for temperature and rainfall respectively. In as much as Homabay County had a lower number of floods (6) compared to Nyamira (10), it still had a higher rate of change in Maximum temperature of 0.016^{o}C/year compared to the change in Maximum temperature of 0.015^{o}C/year in Nyamira County. This warming is likely to have exacerbated drought conditions due to enhanced evapotranspiration rates, thus increased exposure of the County to drought conditions. Conversely, Migori County had the highest exposure index of 2.25, arising from the highest observed number of floods (11) and droughts (6) associated with the highest rate of change in both maximum temperature (0.017^{0}C/year) and minimum temperature (0.018^{0}C/year).

Figure 41 presents the exposure index map for the study Counties.

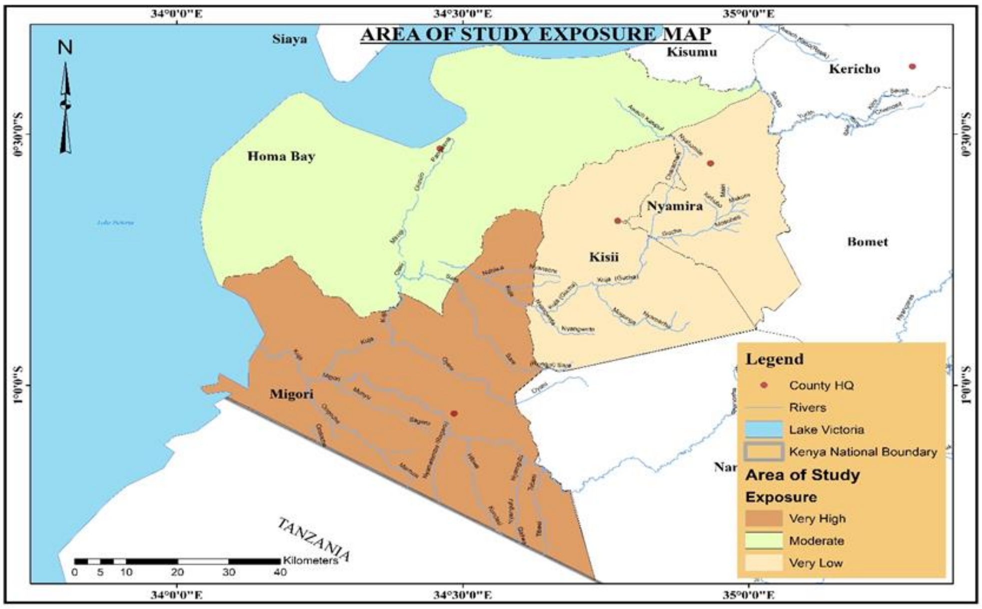


Figure 41: Exposure Index Map

The results in Figure 41 classified the exposure in Migori County as very high, whereas Homa Bay County was categorized as moderately exposed. Therefore, Migori County stands a greater risk of exposure to extreme climate events, particularly droughts and floods. Conversely, exposure in Kisii and Nyamira County was classified as very low, implying minimal exposure to adverse climate conditions.

4.10.3 Adaptive Capacity Indices

Table 24 presents the adaptive capacity indices for each of the study Counties. Negative adaptive capacity indices indicate lower adaptive capacity levels whereas positive adaptive capacity indices implies higher adaptive capacity levels.

Table 24: Adaptive Capacity Indices

County	Adaptive Capacity Index
Homa Bay	-0.5
Migori	-0.46
Kisii	1.21
Nyamira	1.89

Nyamira County exhibited the highest adaptive capacity of 1.89, followed by Kisii County (1.21), Migori County (-0.46) and finally Homa Bay County with the least adaptive capacity (-0.50). Across the study Counties, small-holder maize farming in Nyamira County is better adapted to fluctuations in climate because of farmers' adoption of improved technologies and farming practices involving use of improved seeds, chemical fertilizers, and pesticides. The percentage of small-holder maize farmers who use improved maize seeds (75%) and chemical fertilizers (96.1%) was highest in Nyamira County compared to the rest of the study Counties. These technologies increase maize yields and also help in managing crop pests and diseases, and hence strengthening the adaptive capacity of the maize production (Fadina, and Barjolle,2018). However, Nyamira County had the lowest quantity of maize produced since it had the lowest area under maize cultivation relative to the rest of the Counties.

Nonetheless, Nyamira County had the highest percentage of small-holder farmers (62.8%) who operated saving bank accounts, thus enabling them to easily access agricultural financing. This translates into higher capacity of these farmers to respond to negative impacts of climate change. In addition, increased savings and access to agricultural financing generally enhances the ability of smallholder farmers to access and purchase better seed varieties, fertilizers and other agrochemicals, in addition to improving their livelihoods.

Furthermore, markets in Nyamira County are also situated closer to the farmers (1.82km) compared to other Counties in the study area such as Kisii (2.14km), Migori (2.32), and Homa Bay (2.38km). This implies that farmers in Nyamira travel the shortest distance to access farm inputs including seeds and fertilizers, as well as to deliver their farm produce to the market. Moreover, shorter distances to markets allow farmers to conveniently sell their farm produce by cutting down on transportation costs, thereby boosting their revenue (Hassan and Nhemachena, 2008).

Figure 42 presents the adaptive capacity index map for the study Counties.

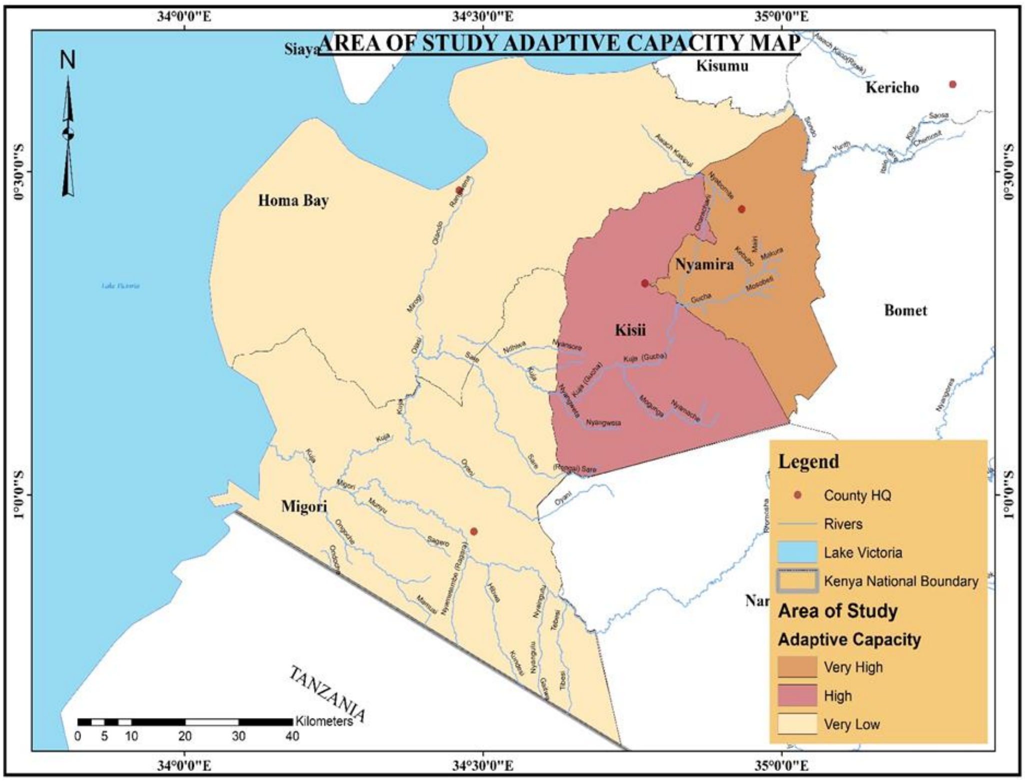


Figure 42: Adaptive Capacity Index Map

The adaptive capacity in Nyamira County was categorized as very high while that of Kisii County was categorized as high. As such, smallholder maize farming in Nyamira and Kisii Counties is well adapted to withstand the adverse impacts of changes in climate. Conversely, Migori and Homa Bay Counties were classified as having very low adaptive capacities thereby increasing their vulnerability.

4.10.4 Vulnerability Index

Table 25 presents the vulnerability indices of the study counties.

Table 25: Vulnerability Indices

County	Vulnerability Index
Nyamira	-0.74
Kisii	-0.29
Homa Bay	0.48
Migori	0.72

Migori County recorded the highest vulnerability index of 0.72 followed by Homa Bay County (0.48), Kisii County (-0.29) and Nyamira County (-0.74). These results indicate that Counties that generally had low adaptive capacities and high exposure levels such as Migori and Homa Bay tended to exhibit higher vulnerability levels than those that had low exposures and higher adaptive capacities such as Nyamira and Kisii Counties.

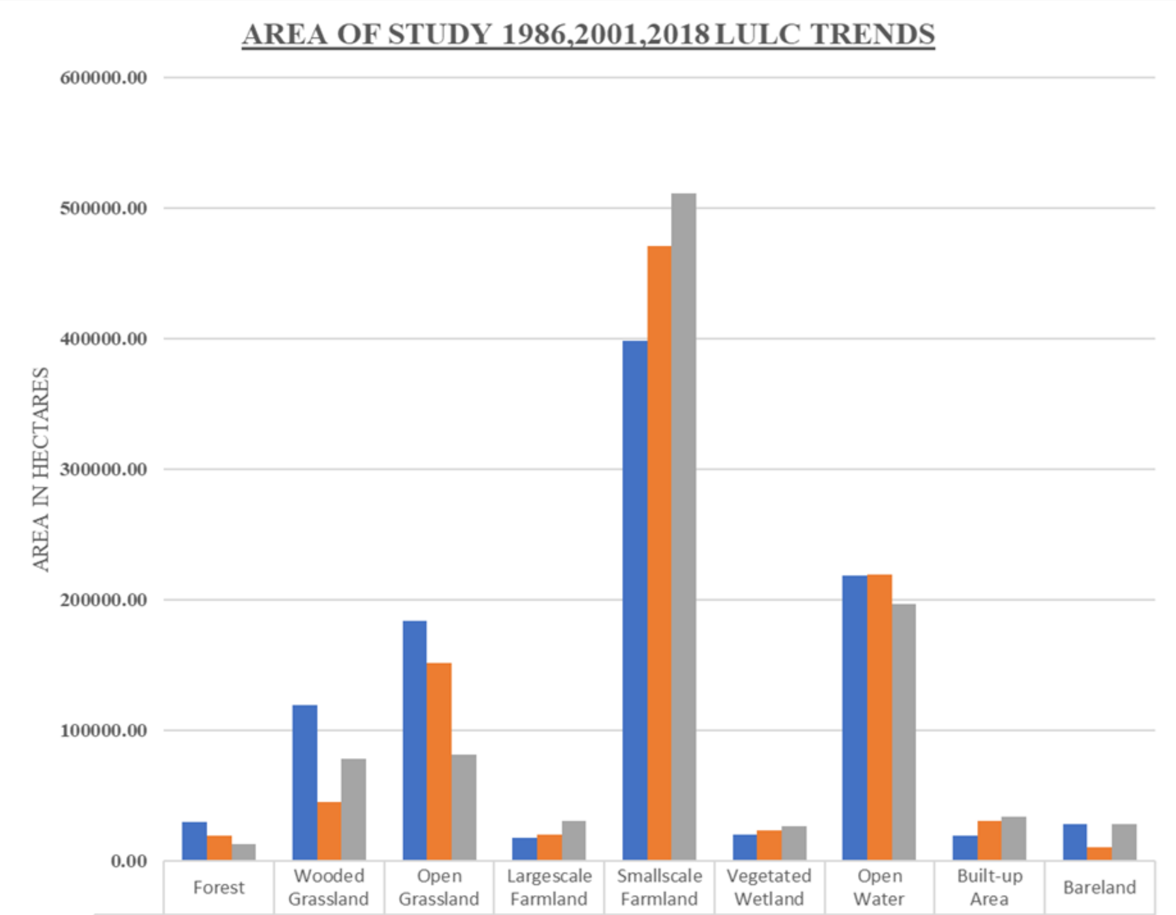
Counties that had low adaptive capacities such as Homa Bay (-0.5) and Migori (-0.46) recorded the highest values of vulnerability index and hence were generally more vulnerable. Therefore, small-holder maize farmers in these Counties are highly prone to suffer from unexpected climate change related shocks such as extremes of weather and climate, specifically floods and droughts, long-term and short-term shifts in mean annual rainfall and temperature, as well as seasonal variations in the amounts of rainfall received (Challinor *et al.*, 2007).

Although Migori County had the least sensitivity score of -0.55, it exhibited the highest vulnerability index owing to its highest levels of exposure and lowest adaptive capacity that compounded to give rise to this effect. Counties such as Nyamira and Kisii that had higher sensitivity indices also exhibited higher adaptive capacity indices, signifying high levels of preparedness for impending hazards and hence lowering their vulnerability to adverse climate change impacts. Kisii and Nyamira Counties had higher sensitivity indices of 1.42 and 1.22 respectively, and high adaptive capacity indices of 1.21 (Kisii) and 1.89 (Nyamira). Thus, exposure and sensitivity are two closely related characteristics of any given system that are nearly inseparable (Smit and Wandel, 2006).

This study, therefore, reveals that small-holder maize farming is most vulnerable to adverse climate change impacts in Migori County (0.72) and least vulnerable in Nyamira County (-0.74) due to the relative differences in the degree of warming of the counties that gave rise to different levels of drying arising from enhanced evapotranspiration rates. Migori County recorded the highest rate of increase of maximum temperature (0.017^0c/year) and minimum temperature (0.018^0c/year). Consequently, the highest exposure index in Migori County implies that small-holder maize farming in Migori stands a greater risk of being adversely affected by climate change through enhanced water scarcity/stress. This is consistent with various studies that confirm that maize farming is highly fragile to changes in climate variables, particularly temperature (Muchow *et al.,* 1990; Liu *et al.,* 2008; Lobell *et al*., 2011)

4.11 Land Use and Land Cover change for the study area

The Land Use and Land Cover change for the classification images for 1986, 2001, and 2018 are presented in Figure 43.



	Forest	Wooded Grassland	Open Grassland	Largescale Farmland	Smallscale Farmland	Vegetated Wetland	Open Water	Built-up Area	Bareland
1986	30003.84	119326.95	183707.37	17628.48	398175.30	19825.65	218196.00	19489.95	27877.50
2001	19567.89	44929.71	151255.17	20261.43	471512.52	23445.63	219396.78	30225.87	10255.77
2018	12679.11	78378.12	81277.83	30379.77	511688.16	26594.28	196479.63	33928.56	28116.27

Figure 43: LULC for the years 1986, 2001 and 2018 for the area of study

It is evident in this study that the increase in population coupled with the farming-based livelihood and the demand for produce in response to the needs of the growing population have reduced the area under natural vegetation (Forests, wooded grassland and open grassland) and the subsequent increase in built-up areas, and both largescale and small-scale farming. Open water surfaces have been decreasing due to the rapid increase in invasive species of Water hyacinth (*Eichhornia crassipes*) in L. Victoria. This has increased the area under wetland vegetation in the study Counties.

Figure 44 presents the percentage area coverage of each of the LULC class in 1986.

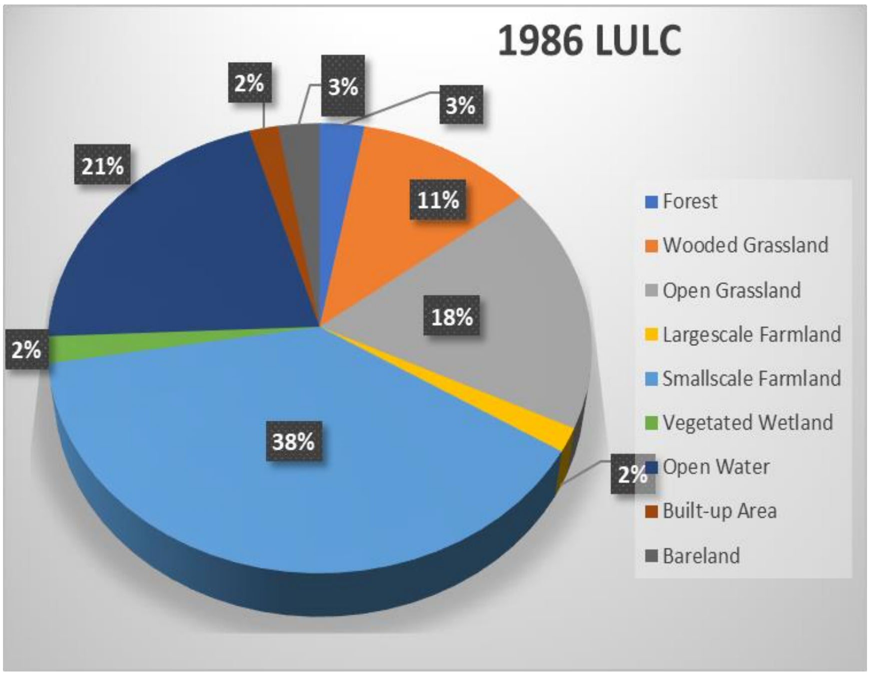


Figure 44: Percentage Area Coverage for each LULC class in 1986

During the base year (1986), forests were shown to cover 30,003.84 Ha that corresponded to only 3% of the total land area. Wooded Grassland constituted 119,326.95 Ha translating into 11% of the total land cover, while Open Grassland covered 183,707.37 representing 18% of total land cover. Largescale Farmlands covered 17,628.48 Ha representing 2%, while Small-scale Farmland covered 39,8175.30 Ha, representing 38% of total land area. Vegetated Wetlands covered 19,825.65 Ha, equivalent to 2% of the land area. Open Water sources covered 218,196.00 Ha representing 21%. The built-up Area constituted 19,489.95Ha, representing 2% while bare land covered 27,877.50 Ha, representing 2% of the total land area.

Figure 45 shows the area coverage for each LULC Class in 2001.

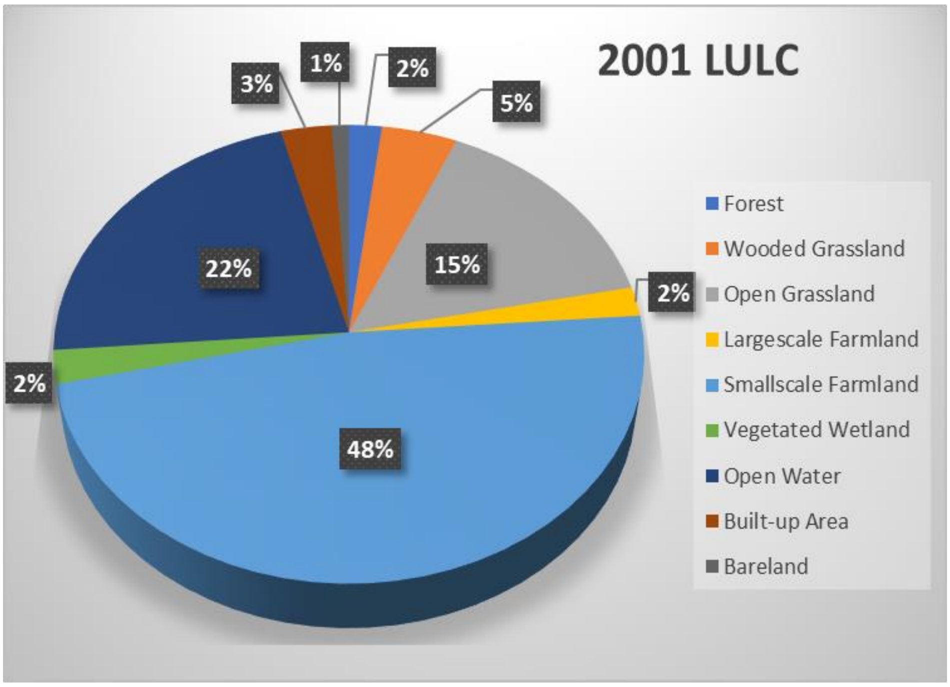


Figure 45: Percentage Area coverage for each LULC Class in 2001

Due to changing anthropogenic activities, the areas under various LULC in 2001 indicate variations in land areas across LULC classes covered. Small-scale farmland experienced a drastic increase in the land area covered (471,512.52 Ha) above that of 1986, representing 48% of the total land area. The 10% increase is tantamount to 73,337.22 Ha in actual land area conversion to smallholder farming. This is in stark contrast to the decrease in forest area over the baseline to 19,567.89 (2%) in 2001. This implies that deforestation was done in favor of land conversion to arable land use in response to the growing demand of the land resource by the rapidly growing population. Alongside forests, acreage under both Wooded Grassland and Open Grassland areas experienced a reduction in their land areas in 2001 relative to the same areas in 1986. These could have also constituted sources of the additional arable lands in the study Counties. However, there were other natural land uses that did not show significant signs of either degradation or rehabilitation. For instance, vegetated wetland covered 23,445.63 Ha in 2001 compared to 19,825.65 Ha in 1986, signifying positive restoration effort. However, despite this increase in vegetated wetland, most likely from management of water hyacinth encroachment, the area covered by wetland in both years still remained at 2% of the total land area.

In 2018, the area coverage for each LULC Class also changed as shown in Figure 46.

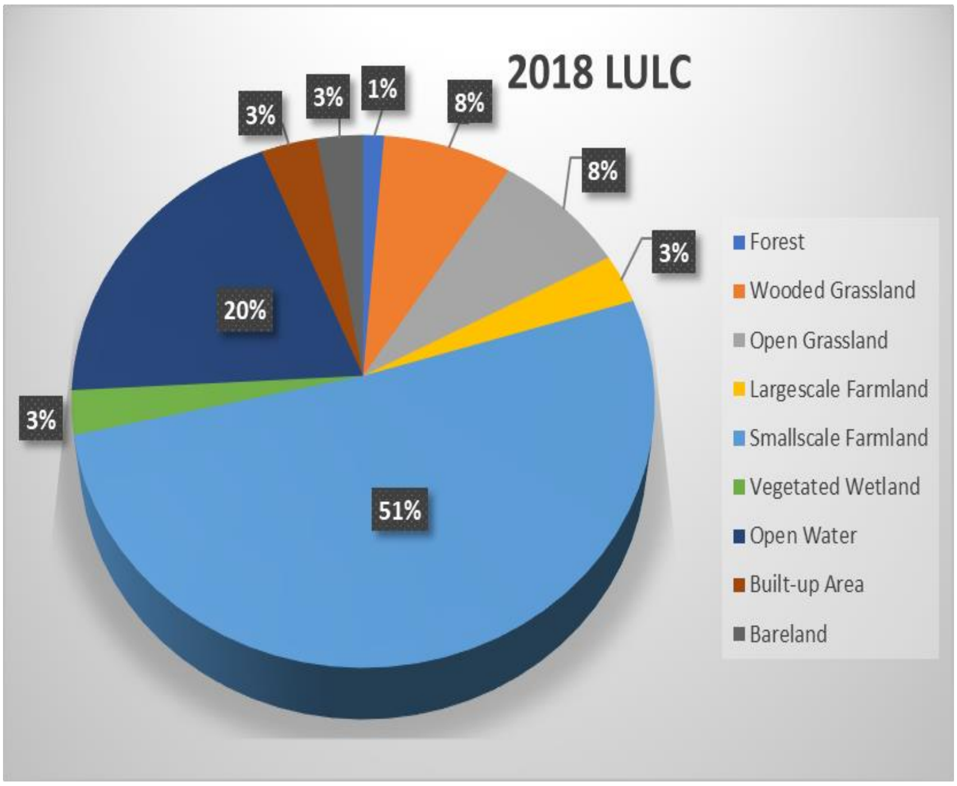


Figure 46: Percentage Area Coverage for each LULC class in 2018

The area under small-scale farmland increased from 471,512.52 Ha (48%) in 2001 to 511,688.18 Ha (51%) in 2018. This 3% increase in area coverage translated to 40,175.66 Ha from 2001 to 2018, and 113,512.88 Ha increase from the original LULC coverage in 1986. Moreover, the area under small-scale farmland increased by over half the total land area in the area standing at 51%. Conversely, the area under forest and open grassland decreased in 2018. Forest area coverage decreased by 1% of its area to stand at 12,679.11 Ha compared to 19,567.89 Ha in 2001. On the other hand, the proportion of open grassland decreased from 15% in 2001 to 8% in 2018, representing an equivalent decrease from 151,255.17 Ha in 2001 to 81,277.83 Ha in 2018. This was the largest reduction in LULC acreage under all classes over the years.

The areas under Wooded Grassland and Bare land exhibited variability in LULC. Both experienced a decrease in 2001 and an increase in 2018. These changes are attributed to the maize crop farming practices of the study Counties that involved leaving large tracts of land fallow in between years to allow for soil fertility regeneration, and also for breaking pest and diseases cycles.

Open Water surfaces continued to decrease in the same way as between 1986 and 2001. The period 2001 to 2018 experienced a 1% decrease in the LULC class that translated to an absolute decrease of 22,917.15 Ha. Nevertheless, vegetated wetlands increased by 1% over the same period, pointing at continued invasion of water hyacinth in Lake Victoria and other wetland areas in the study Counties.

4.12 Vulnerability Index Map for the Study area

Figure 47 presents a vulnerability map for the study Counties.

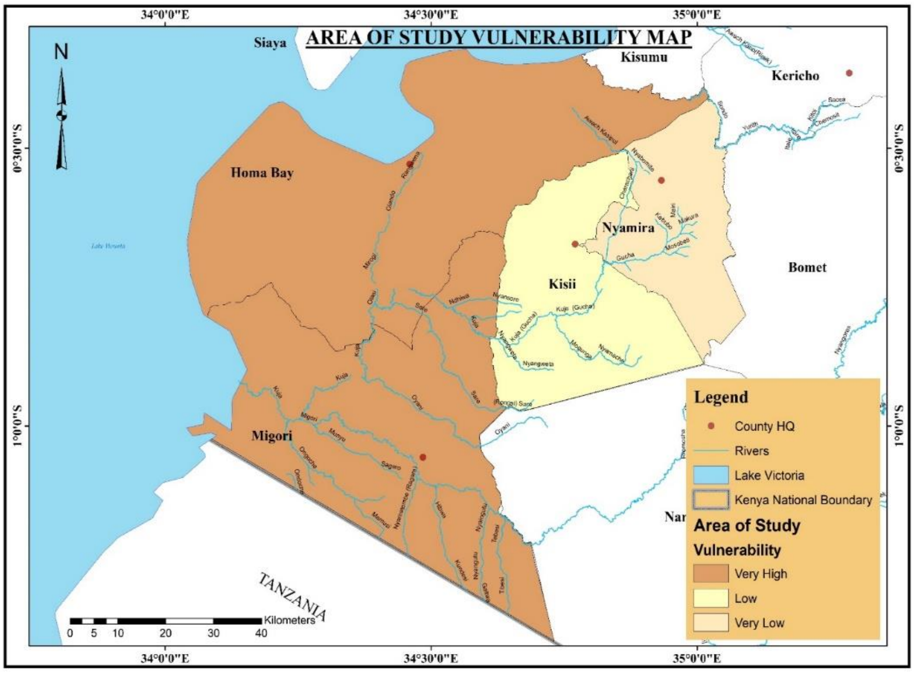


Figure 47: Vulnerability Index Map for study Counties

Migori and Homa Bay Counties recorded the highest normalized vulnerability indices of 5 and 4.17 respectively. On the other hand, Kisii County had a normalized index of 1.54 and hence was categorized as having low vulnerability, whereas the vulnerability of Nyamira County with the lowest normalized index of 0, was categorized as having very low vulnerability among all the Counties studied. The vulnerability index map generated herein indicates that Counties that have low adaptive capacities coupled with higher levels of exposure to climate hazards tend to have very high vulnerability levels with regard to the adverse climate change impacts. Similarly, Counties that have high adaptive capacities and lower levels of exposure to climate hazards tend to generally have low to very low levels of vulnerability. This is attributed to the fact that areas that have high adaptive capacities are better placed in terms of resources and technology to respond to the adverse climate change impacts.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents major conclusions and recommendations drawn for the key results of this study.

5.2 Conclusion

All the study Counties experienced significant increasing trends and mean shifts in baseline rainfall and temperature. Similarly, all the projections show a general decreasing trend in rainfall, with an increasing significant trend in maximum and minimum temperatures. Current vulnerability of smallholder maize production in Southern Nyanza is expected to persist, with prospects of increasing in the future, owing to the steady increase in annual and seasonal minimum and maximum temperatures, and declining rainfall which inadvertently affect soil water balance through increased evapotranspiration.

Maize yields in the study counties of southern Nyanza region are strongly influenced by the variability in climate variables (maximum and minimum temperature, and rainfall) observed during the various growth stages of the maize crop.

The vulnerability indices of maize production varied across the study counties and were influenced by their levels of exposure, adaptive capacity and sensitivity. Counties that had high exposure and sensitivity indices, coupled with lower adaptive capacity indices recorded the highest vulnerability indices. In contrast, counties that had higher adaptive capacity indices and low exposure indices recorded the lowest vulnerability indices.

5.3 Recommendations

Based on the conclusions of this study, the following recommendations are made:

- The county governments in southern Nyanza region, in collaboration with the national government should enact and enforce water harvesting and use policies for irrigated agriculture to adapt maize production systems to drought and other water stress related impacts associated with climate change, for improved and sustainable crop yields.

- With the projected decline in annual and seasonal rainfall amounts, and the subsequent increase in both maximum and minimum temperatures, there is need for the county governments in Southern Nyanza region to invest in research aimed at breeding early maturation, drought tolerant, and efficient water use maize varieties for increased and sustainable maize productivity.

5.4 Suggestions for future work

- Future vulnerability assessment studies should be cascaded down to household/ farm level to capture the differentiated levels of sensitivity, exposure and adaptive capacity across the Nyanza region.
- Future research should address future vulnerability of smallholder maize production, taking into consideration socioeconomic, biophysical and climate data in the midterm (2022-2051) and long term (2052 to 2100).

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