UNIVERSITY OF NAIROBI

ASSESSMENT OF THE TEMPORAL AND SPATIAL CHARACTERISTICS OF DROUGHTS IN KENYA

BY

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DECLARATION

I hereby declare that this dissertation is my original work and has not been presented in any University or learning institution for any academic award. Where other people's work has been used, this has properly been acknowledged and referenced in accordance with the University of Nairobi requirements.

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This Dissertation has been submitted with our approval as University Supervisors.

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DEDICATION

I dedicate this project to my mother, husband and children for their continued support and resilient prayers

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ABSTRACT

Drought in Kenya is ranked among the top and most expensive natural disaster to deal with due to its creeping phenomena. The frequency and intensity of droughts in the country have been increasing in recent years leading to great social, economic and environmental impacts. A lot of effort has been made to assess past droughts in the country with little or no information on the occurrence of future droughts. The studies carried out have only used rainfall to characterize droughts yet droughts are caused by a combination of many factors. The objective of this study was to assess the temporal and spatial characteristics of drought in the study area using a combined drought index (CDI) that incorporated three drought indices; the Precipitation Drought Index (PDI), the Humidity Drought Index (HDI) and the Temperature Drought Index (TDI). In this study, relative humidity was used instead of NDVI because NDVI is used as a proxy to monitor the condition of vegetation which is determined by the amount of soil moisture available. Information on soil moisture can better be obtained from a combination of rainfall falling in an area, temperature and relative humidity because the amount of water lost into the atmosphere through evapotranspiration depends on the amount of humidity in the atmosphere.

Data used in the study was obtained from the Kenya Meteorological Department (KMD) from 1979 to 2015 and included observed annual and dekadal rainfall, dekadal maximum temperature and dekadal relative humidity at 1200 GMT.

To achieve the objective of the study, the country was first delineated into climatologically homogenous zones using the Principal Component Analysis (PCA) after which the principal of communality was used to pick the representative station in each homogenous zone. The drought characteristics in each zone were determined using various drought categories based on CDI values. A drought forecast model was then developed using past CDI values and stochastic time series modelling (Auto Regressive Model). Nine homogenous rainfall zones with distinct rainfall characteristics were delineated by PCA. Rainfall in the zones showed high spatial and temporal variability with the highest variability being observed over the northern parts of the country, while the lowest variability was observed over the coast, western and central parts of the country. CDI is able to effectively capture drought characteristics in the study area.

The country experiences all categories of droughts (mild, moderate, severe and extreme) with the mild category being dominant in most of the zones. CDI and time series modelling can be used to develop a drought forecast model in the study area. Drought forecasts in the study area can be made with reasonable accuracy up to the ninth dekad which marks the end of a season. Since the more severe drought categories tend to be experienced during the major rainfall season of MAM, there is need for drought assessment both on the short and long term basis. Dekadal data therefore should be used in conjunction with monthly and annual data to take care of both the short and long term drought characteristics. In order to fully capture all aspects of droughts, more parameters should be incorporated into the CDI.

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LIST OF ACRONYMS AND ABBREVIATIONS

ACF	Auto Correlation Function
AMSL	Above Mean Sea Level
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ASAL	Arid and Semi-Arid Lands
APARCH	Asymmetric Power Autoregressive Conditional Heteroskedasticty
AVHRR	Advanced Very High Resolution Radiometer
CDI	Combined Drought Index
CORDEX	Coordinated Regional Downscaling Experiment
CMI	Crop Moisture Index
CSIRO	Commonwealth Scientific and Industrial Research Organization
CV	Coefficient of Variation
DI	Drought Index
DJF	December January February
DMC	Drought Monitoring Centre
DSI	Drought Severity Index
ECMWF	European Centre for Medium range Weather forecasts
ENSO	El Nino Southern Oscillation
ESP	Ensemble Streamflow Prediction
FAO	Food Agricultural Organization
FAPAR	Fraction Absorbed Photo synthetically Active Radiation
GMT	Greenwich Meridian Time
GDP	Gross Domestic Product
GHA	Greater Horn of Africa
GIS	Geographical Information System

HDI	Humidity Drought Index
HSS	Hit Skill Score
ICPAC	IGAD Climate Prediction and Applications Centre
IGAD	Inter-Governmental Authority on Development
IP	Interest Period
ITCZ	Inter Tropical Convergence Zone
JF	January February
JJA	June July August
JJAS	June July August September
KMD	Kenya Meteorological Department
KM	Kilometres
LEV	Logarithm of Eigen Value
LTM	Long Term Mean
m	Metres
MAM	March April May
mm	Millimeters
MS	Micro Soft
NASA	National Aeronautics and Space Administration
NDMA	National Drought Management Authority
NDVI	Normalized Drought Vegetation Index
NHMs	National Hydrological and Meteorological services
NIR	Near Infra-Red
NSE	Nash-Sutcliffe model efficiency Coefficient
OND	October -November -December
PACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
PDI	Precipitation Drought Index

PDSI	Palmer's Drought Severity Index
PRECIS	Providing Region Climate for Impact Studies
RL	Run Length
RACF	Residual Auto Correlation Function
RPCA	Residual Partial Auto Correlation Function
RPC	Rotated Principal Component
SPI	Standardized Precipitation Index
SACF	Sample Autocorrelation Function
SPACF	Sample Partial Autocorrelation Function
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
SON	September -October -December
SWALIM	Somali Water And Land Information Management
SWSI	Surface Water Supply Index
TDI	Temperature Drought Index
TFRCD	Task-Force for Regional Climate Downscaling
UNDP	United Nations Development Program
UNICEF	United Nations International Children Emergency Fund
USA	United States of America
UN	United Nations
VDI	Vegetation Drought Index
WFP	World Food Program
WHO	World Health Organization
WMO	World Meteorological Organization

CHAPTER ONE: INTRODUCTION

1.0 Background

There are many types of natural hazards that have negative impacts on both humans and the environment. Some of the most common hazards incorporate geological and meteorological phenomena and include droughts, floods, cyclonic storms, volcanic eruptions, earthquakes, wildfires and landslides. Among all these hazards, drought is the most devastating because of its creeping phenomena. Drought creeps in gradually without being noticed and its impacts are cumulative, making it one of the most expensive natural disasters to deal with. Droughts have been experienced worldwide for a very long time. From 1900 to date, more than eleven million people have died globally as a result of drought and more than 2 billion have been affected by drought more than any other hazard (Zahid *et al* 2016).

Kenya like other East African countries is susceptible to drought due to its eco-climatic conditions. Nearly 80% of Kenya's land mass is arid and semiarid characterized by mean annual rainfall of between 200-500 millimeters (mm). Over the years, Kenya has experienced droughts of various intensity. The drought cycle has become shorter with droughts becoming more frequent and intense. During the 1960's/70's, Kenya experienced one major drought in each decade which increased to once every five years in the 1980's. In the 1990's, the droughts occurred once every two to three years and their frequency of occurrence became increasingly unpredictable from 2000 (Huho and Mugalavai, 2010). According to Balint *et al*., 2011, Kenya has been experiencing drought almost every year since 2000. The 2010/2011 drought that affected over 3.7 million people in Kenya was the worst in sixty years. (World Food Program report, 2011).

Since drought is a problem that affects many people all over the world than any other natural hazard, a lot of studies have been carried out worldwide on drought. Drought is a short term anomaly caused by oscillation of climatic parameters. Therefore, a long term oscillation of these parameters in any part of the world will lead to droughts. In this study, the drought characteristics were assessed using a revised combined drought index that incorporated rainfall, temperature and relative humidity.

1.1 Characteristics of Drought

Drought is a very complex natural phenomenon that is usually characterized by lower than average precipitation, high temperatures, high wind speeds, low relative humidity, reduced cloud cover and long periods of sunshine (Wilhite, 1993). In general terms, drought refers to a shortage in precipitation over a prolonged period of time, usually a season, year or more which leads to water shortage and has adverse effects on vegetation, animals and/or people. Drought is characterized with reference to a certain amount of rainfall that falls during a given period of time in a given area commonly referred to as normal. Deviations from the normal leads to extremes with amounts above normal leading to floods and those below normal leading to droughts.

1.2 Problem Statement

Droughts have increased in frequency, magnitude and severity over several parts of the world, Kenya included leading to great economic, social and environmental impacts in the affected areas. Most of the studies carried out in the region to assess droughts are based on rainfall. Yet development of drought is caused by a combination of many climatic variables such as high temperature, strong winds, less cloud cover, long periods of sunshine and the amount of humidity in the atmosphere.

Using only one parameter to assess drought fails to fully trace the footprints of drought. Use of temperature, rainfall and relative humidity in this study have taken into more than one climatic variables that lead to drought development thus capturing more drought aspects. Most of the studies have concentrated on past drought characteristics, hence give us a better understanding of past droughts. However, their usefulness is limited due to lack of forecasting skills which would enhance our preparedness in dealing with future droughts. Planning for future droughts would reduce the impacts associated with them. Hence the need to develop a drought forecast model that can accurately predict droughts.

1.3 Objectives of the Study

The main objective of this study was to assess the temporal and spatial characteristics of droughts in Kenya. The specific objectives of this study are:

(i) To determine Kenya's dominant homogenous rainfall zones and the associated rainfall characteristics in each zone.
(ii) To determine drought characteristics and the relative frequency of droughts using the revised combined drought Index.
(iii) To develop a drought forecast model using the revised combined drought index.

1.4 Justification and Significance of the Study

Drought is one of the most complex and expensive natural disasters to deal with due to its creeping phenomena. It sets in gradually without being noticed and its impacts are cumulative. In Kenya, drought is a major concern and is ranked among the top natural disasters. From 1990 to 2017, droughts accounted for seven out of the nine natural disasters that were declared as national disasters. These include the 1992-93, 1995-96, 1999-2000, 2004-06, 2008-09, 2010-11 and 2016-17 droughts. The other two were floods that were experienced in 1997-98 and 2003 respectively.

In Kenya, droughts affect many economic sectors and especially agriculture which is the back bone of the country's economy leading to economic instability. Droughts can easily be misunderstood due to their complexity and this can lead to poor or inappropriate decision making by policy makers. Thus the occurrence of frequent droughts in most parts of the country and the negative socio economic impacts associated with it requires that more research on drought be carried out and especially drought forecasting. The results obtained from this study will help reduce the impacts of droughts as the appropriate measures can be put in place once it is known where and when droughts are likely to occur.

1.5 Area of Study

This subsection describes the location, topography and climatology of the study area.

1.5. 1 Geographical Location of the Study Area

Kenya lies on both sides of the equator between Longitudes 34^0 E to 42^0 E and latitudes $5.5^{\,0}$ N to 5^0 S. It is bordered to the west by Uganda, to the east by Somalia, to the north by Ethiopia and parts of South Sudan and to the south by Tanzania and Indian Ocean. The country's total area is 582,646 Kilometres squared (km^2) (Figure 1).

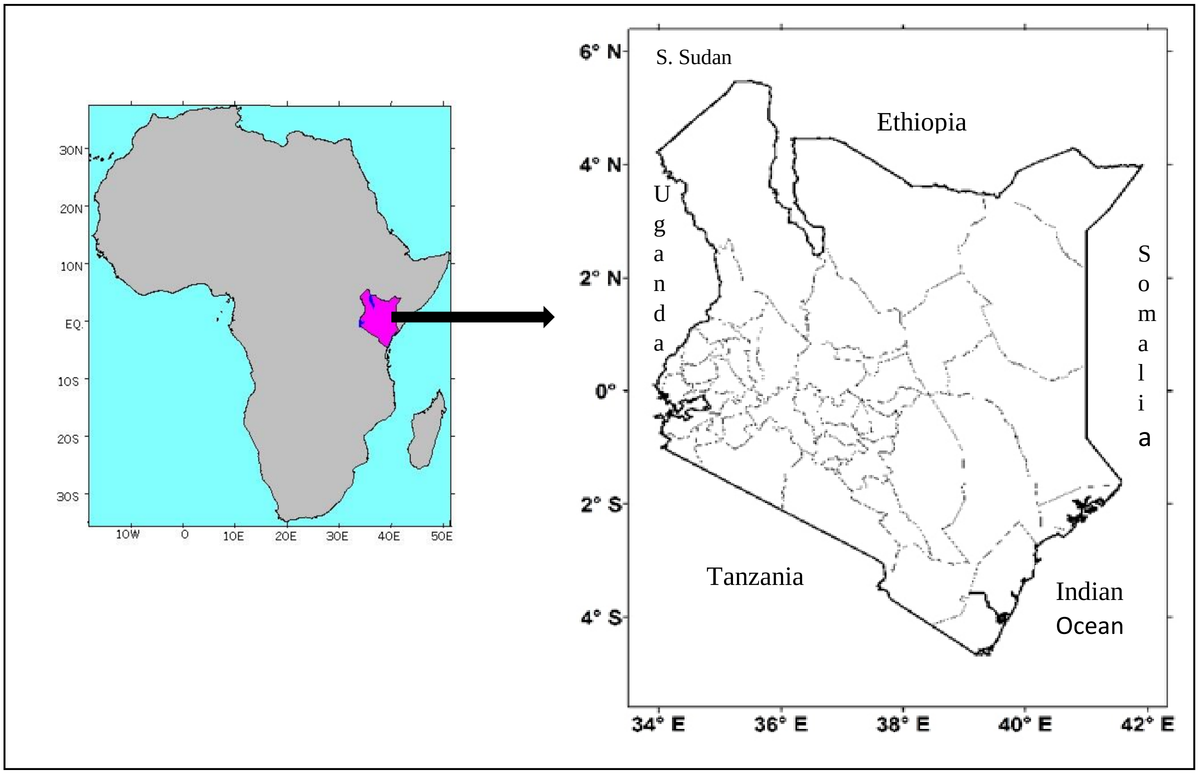

Figure 1: Map of Africa showing the position of Kenya

1.5. 2 Topography

Kenya has tremendous topographical diversity as a result of volcanic eruptions and slow tectonic movements that occurred during the formation of the Great Rift Valley, a trough that runs through Kenya from north to south and divides the country into two. From the eastern coastal line of the Indian Ocean, the country rises gradually from 5 metres Above Mean Sea Level (AMSL) through the south-eastern lowlands which ranges from 500-1600m to the central highlands up to about 5199m (Mt. Kenya). From the central highlands, the land falls off steadily to the west of Rift Valley to about 1200m around the Kenyan part of the Lake Victoria. North of the Lake, the land again rises gently up to about 4321m around Mt. Elgon that lies along the Kenya Uganda Border and falls again around Lake Turkana and areas bordering south western Ethiopia. The southern part of the country bordering northern Tanzania is characterised by high altitude above 3800m in areas neighbouring Mt. Kilimanjaro. The north eastern parts of the country constitutes mainly of low lying land below 500m, except areas east of Lake Turkana (Marsabit and Moyale) where the land rises above 800m. (Figure 2).

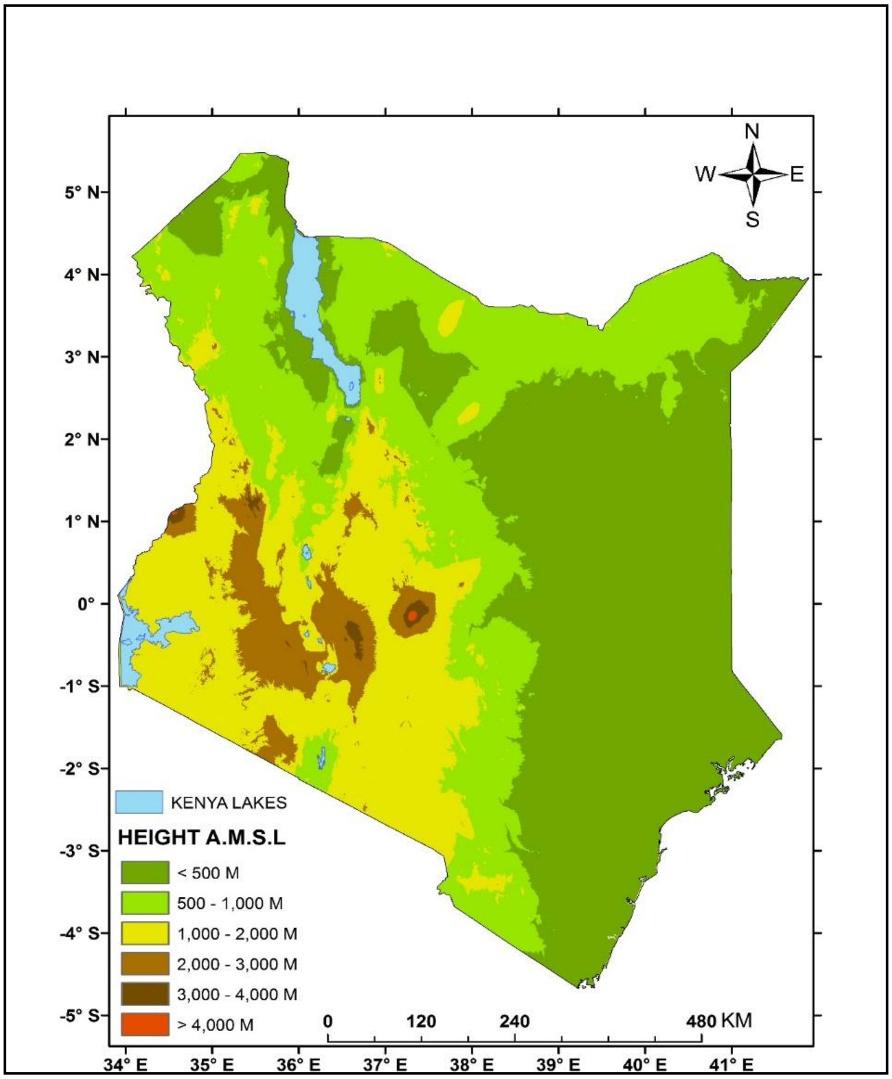

Figure 2: Map showing the Topography of the study region

1.5. 3 Climatology of the Study Area

This sub section gives a brief summary of the climatology of the study area.

1.5. 3.1 Rainfall

Rainfall over the study area is governed by large scale (global), synoptic and mesoscale factors. The large scale factors arise from global teleconnections which are in turn brought about by hemispheric abnormalities in the general circulation of the atmosphere and include the El Nino Southern Oscillation (ENSO), Quasi-Biennial Oscillation (QBO) and Madden Julianne Oscillation (MJO) among others. The synoptic factors include the Inter Tropical Convergence Zone (ITCZ), subtropical anticyclones, tropical cyclones, jet streams, easterly waves, upper air troughs and extra tropical weather incursions.

The most significant synoptic feature responsible for the seasonal variation of rainfall in the study area is the ITZC. This is a belt of low pressure where the northeast and southeast trade winds from both hemispheres converge. The ITCZ follows the northward and southward movement of the sun with a lag of approximately two to three weeks and brings rainfall to the study area twice in a year. The position of ITCZ is mainly determined by the overhead sun as well as by the position, intensity and orientation of the Azores and Arabian high pressure cells to the north and the Mascarene and Saint Helena high pressure cells to the south.

Most parts of the country experiences a bimodal rainfall distribution with two rainy seasons and two dry seasons. The long rain season is experienced from March to May when the ITCZ is moving north and is locally referred to as MAM. The short rain season is experienced from October to December when the ITCZ is moving to the south and is locally referred to as OND. The two dry periods run from mid-December to February and from June to September. However, areas west of the Rift Valley, Isolated areas over the central highlands (Nyahururu) and over the coast experience a third rain season from June to August, locally referred to as JJA. Rainfall over Kenya is further modified by local factors such as large water bodies (Indian Ocean and Lake Victoria) which induce land-sea breeze circulations, Orography, Marsabit Jetstream and the Great Rift Valley among others.

The rainfall is highly variable both in time and space with some regions west of the Rift Valley experiencing high amounts of rainfall annually, while others especially in the Arid and Semi-Arid Lands (ASALs) receiving very low rainfall. For example Kisii Meteorological station receives over 2000mm of rainfall annually, while Lodwar Meteorological station receives about 200mm of rainfall annually.

1.5. 3.2 Temperature

Temperatures in Kenya are modified by orography, water surfaces and wind flow patterns. They vary from one area to another and from season to season. In general, high maximum temperatures of above 30 degrees Celsius (^{0}C) are recorded over the north western parts of the country (Lodwar Meteorological station) and parts of northeast (Garissa, Wajir and Mandera Meteorological stations) during the December, January February (DJF) season. The northern parts of the country have less cloud cover during this season, hence receive maximum insolation which leads to high day time temperatures.

The lowest maximum temperatures below 20 degrees Celsius (^{0}C) are recorded over the central highlands during the June July August (JJA) season depicting the influence of high altitudes and low insolation on temperature. The highest minimum temperatures of about 24^0C are recorded along the coast, parts of northeast and northwest most of the year showing the effect of water bodies (Indian Ocean and Lake Turkana) and low altitude on temperature. The lowest minimum temperature of less than 10^0C are recorded over the highlands during the DJF season. Compared to lowlands and water surfaces, highlands undergo more radiational cooling as the downslope winds (Katabatic) descend over the highlands at night and early morning causing low night time temperatures.

1.5.3.3 Relative Humidity

Relative humidity varies from one place to another and from season to season. Generally it is high around large water bodies such as the Indian Ocean and Lake Victoria and also over areas characterized by convergence such as the highlands. It is low over the lowlands which are mainly characterized by divergence. Relative humidity tends to be high during the wet season and low during the dry seasons.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This section gives an overview of drought concepts as well as drought studies that have been carried out in the study area and other parts of the world.

2.1 Drought Definition

There is no precise and universally accepted definition of drought (WMO report, 2006). Developing a universal and precise definition of drought is difficult because definitions are governed by among other things discipline, varying frequency with which drought occurs, time of scale, location, land use and the context of the impacts (Yevjevich, 1967; Wilhite and Glantz, 1985, Wilhite, 1992; Sepulcre *et al*, 2012) Lack of a universal drought definition is a major problem especially to policy makers who do not understand the concepts of drought (Glantz and Katz 1977). This is because they can fail to take action when it is needed or come up with unplanned responses which they don't understand especially in the context of social and environmental implications associated with them (Wilhite *et al,* 1984).

In general, drought can be defined as "extreme persistence of precipitation deficit over a specific region for a specific period of time" ((Gonzalez and Valdes, 2006, Correia *et al*, 1994, Beran and Rodier, 1985). Drought definitions are broadly grouped in two categories: Conceptual and operational definitions (Wilhite and Glantz, 1985). Conceptual definitions are formulated in general terms to assist people understand the concept of drought and establish drought policies (National Drought Mitigation Centre, NDMC, 2006b). They are of the "Dictionary" type and vary from one dictionary to another. Conceptual definitions offer little guidance to real time drought assessment. Operational definitions quantitatively define the criteria for the onset, development, cessation and severity of drought events for a particular application (Wilhite, 2000; Mishra and Singh, 2010; Balint *et al*, 2011). They vary from one discipline to another.

2.2 Types of Droughts

Droughts can be classified as Meteorological, agricultural, and hydrological. Meteorological droughts compare the duration and extent of dryness in an area to the normal conditions for that area. Agricultural droughts arise when Meteorological droughts affect soil moisture, evapotranspiration and plant development. Hydrological droughts deals with effects of precipitation deficits on surface and/or subsurface water supply (Wilhite, 1993). Different types of droughts therefore reflect the same process but at different stages. Meteorological drought explains the primary cause of this process, while agricultural and hydrological drought describes the impacts associated with this process (Balint *et al*, 2011). This relationship has been illustrated in Figure 3.

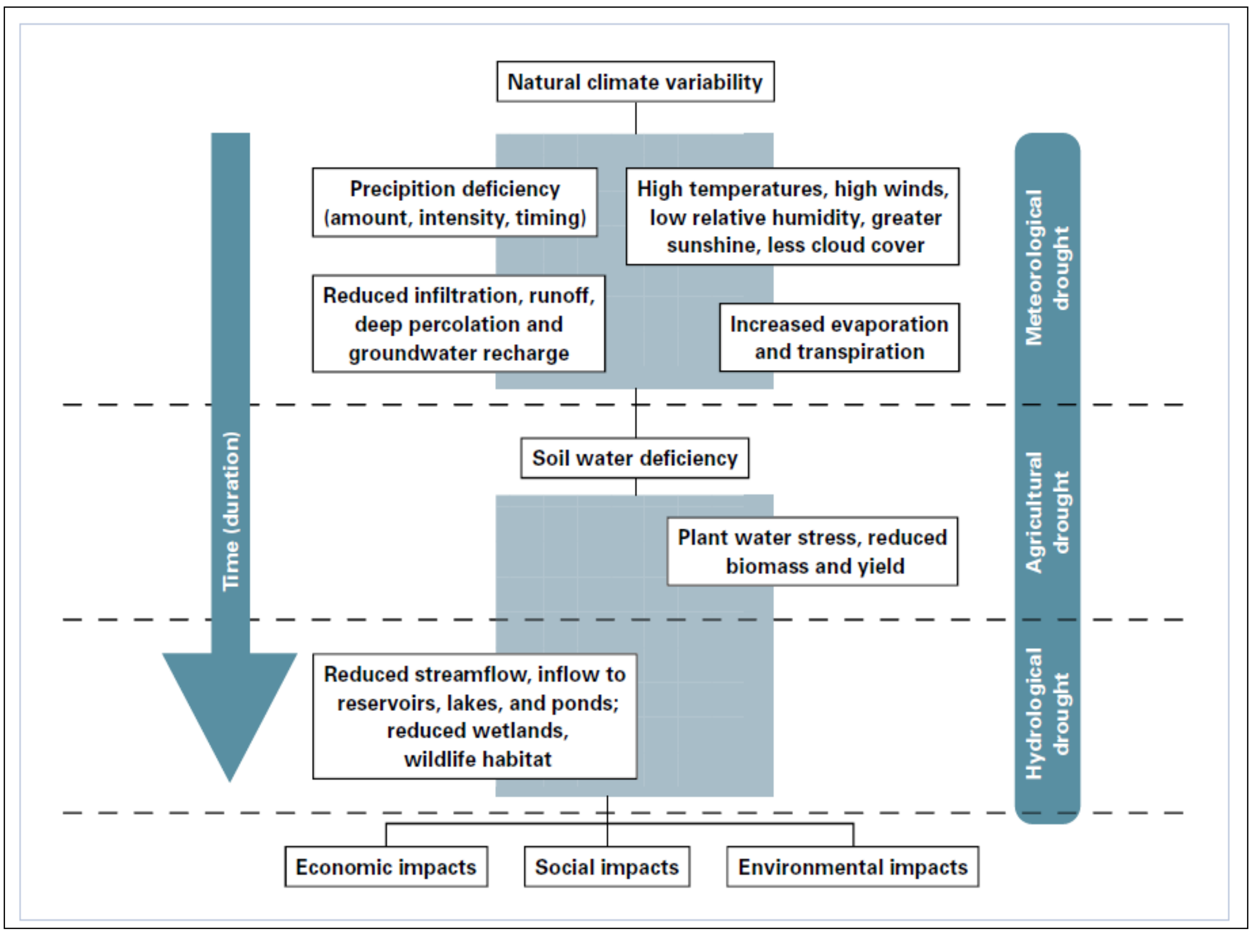

Figure 3: Sequence of drought occurrence and impacts for commonly accepted drought types ***(Source: WMO-No 1006, 2006)***

2.3 Drought Indices

The process of monitoring how drought evolves is intricate and involves measuring and calculating all variables integrated in the definition of drought. This is done through the use of drought indices which are computed by integrating various drought indicators into a single numerical value. These indices provide a broad picture for the analysis of drought and decision making that is more practical than that provided by raw data from indicators (Hayes, 2006). Numerous drought indices have been developed in different parts of the world to measure the magnitude of drought (Szinell *et al*., 1998, Wu *et al*., 2001, Morid *et al*., 2006, Shakya and Yamaguchi, 2010). Currently, there are more than one hundred and fifty drought indices being used (Niemeyer, 2008) and more are being proposed (Cai *et al*., 2011, Karamouz *et al*., 2009, Rhee *et al*., 2010, Vicentre- Serrano *et al*., 2010; Vasiliades *et al*., 2011). While none of these indices is superior to the rest in all situations, certain indices are suitable in specific areas than others.

Drought indices are broadly divided into two groups: statistical indices which are based on time series analysis and indices based on water balance calculations. Most statistical indices are based on one or two climatic variables, mostly rainfall and occasionally temperature. Examples include the Standardized Precipitation Index (SPI) (McKee *et al*., 1993) and Percent Normal Index. Water balance indices are based on several climatic and physical variables. The main objective of water balance indices is to determine the water deficit of the crop at a given time and space based on a distributed parameter model. Examples include the Palmer Drought Severity Index (PDSI) (Palmer, 1965), Crop Moisture Index (CMI) (Palmer, 1968) and Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982).

Drought indices can also be classified according to the impacts associated with them (Zargal *et al*, 2011) variables they relate to (Steinemann *et al*, 2005) and by use of disciplinary data (Niemeyer, 2008). The most common categories are Meteorological, Agricultural and Hydrological. However indices can also be classified as comprehensive, combined and remotely sensed drought indices (Niemeyer, 2008). Comprehensive indices take into account multiple meteorological, hydrological and agricultural parameters to describe drought. An example in this category is the United States Drought Monitor, USDM (Svoboda *et al,* 2002).

Combined indices integrate several drought indices into a single index such as the CDI (Balint *et al*, 2011). Remotely sensed indices uses data obtained from remote sensors to map the situation on the ground. An example is the Normalized Difference Vegetation Index, NDVI (Tarpley *et al*, 1984; Kogan, 1995). Table 1 gives a summary of selected drought indices highlighting the advantages and disadvantages of each. However, more information on other drought indices can be obtained from the handbook of drought indicators and indices (WMO, G & GWP, G, 2016).

Table 1: Summary of selected drought indices

DI , Source and parameters	**Advantages**	**Disadvantages**
Percent of Normal Precipitation	-Quick and easy to compute -Flexible time scales -Effective in a single location, season or particular time in the year	-Not suitable for comparison in different climatic systems -Difficult to differentiate normal precipitation from its mean -Assumes a normal distribution
SPI (McKee *et al*, 1993) Precipitation	-Useful in all climate regimes -Effective in areas with poor data network; -Determines the duration, magnitude and intensity of droughts -Effective for both solid and liquid precipitation	-Assumes a theoretical probability distribution -Inaccurate in arid areas and during dry periods -Requires long periods of data -Incapable of identifying drought prone areas
Deciles (Gibbs and Maher 1967), Precipitation	-Flexible hence can be applied in many situations. -Suitable for both wet and dry conditions	-Requires data for a long period. -Ignores other factors that contribute to drought
PDSI (Palmer, 1965) Precipitation and temperature	-Effective in detecting drought anomalies in a region -Provides both the temporal and spatial representation of past droughts	-Lags in drought detection -Not suitable for frozen ground and/or precipitation -Does not incorporate stream flow, longer term hydrologic impacts, lake and reservoir level and snow -underestimates runoff condition
USDM (Svoboda *et al*, 2002) Several drought indicators	Robust and flexible since it uses multiple indices and indicators	-Requires expert interpretation of results -Accuracy depends on the most current inputs
NDVI (Several) Visible Red and NIR bands (Tarpley *et al*,1984; Kogan, 1995)	-High resolution and covers a big land area -Efficient in differentiating between vegetated and non-vegetated surfaces -Measures actual droughts and does not interpolate or extrapolate droughts	-Values may vary with differences in soil moisture -Not accurate in riparian buffer zones and urban areas; -Assumes vegetation stress is caused by soil moisture alone -Tends to saturate in areas with large biomass.
CDI (Balint *et l*,2011) Precipitation, Temperature and NDVI	-Takes into account effects of temperature and soil moisture -Effective in data scarce areas	-Works well with daily and dekadal data only. Not very accurate with time scales of one month and above

(Source Zargar *et al*, 2011)

2.4 Evolution of Drought

Drought is considered as a hydro meteorological risk as it has an atmospheric or hydrological origin (Landsberg, 1982). Therefore, it becomes difficult to isolate the onset of a drought as its development is only recognized when human activities and/or the environment are affected (Serrano and Sergio, 2006). In addition, the impacts of a drought can continue for many years after its cessation (Changnon and Easterling, 1989). Droughts are different from other natural disasters in that they do not occur suddenly but evolve over a long period of time (Rossi, 2003). Like any hydro-meteorological event, drought evolution depends on the intial conditions and climate forcings as discussed by among others Wood and Lettenmaier, 2008; Shukla and Lettenmaier, 2011.

The spatial evolution of drought is complicated because of the intricacy of atmospheric circulation patterns and also by the fact that droughts cannot be linked to a single type of atmospheric condition. (Serrano and Sergio, 2006). Droughts in different parts of the world have been attributed to more than one atmospheric circulation patterns. In Kenya, droughts have been attributed to the El Nino Southern Oscillation (ENSO) and particularly La Nina **(**Ininda *et al*., 2007; Okoola *et al*., 2008 and Ngaina and Mutai, 2013). Shanko and Camberlin, 1998 attributed droughts in East Africa to variations in the regional atmospheric circulation and associated rain generating weather systems.

Several studies in the United States attributed the 2012 flash droughts to "the development of a persistent upper tropospheric ridge that inhibited convection and caused exceptionally warm temperatures to occur across the region for several months'' (Kumar *et al*., 2013; Wang et al., 2014; Hoerling *et al*.,2014. In Moldova, Bogdan *et al*., 2008 and Corobov *et al*., 2010 attributed the 2007 drought to a heat wave that resulted from persistent anticyclonic conditions that favoured the advection of dry air mass. Studies have shown that it is possible for an area to experience drought while neighbouring areas experience normal or humid conditions (Oladipo, 1995; Nkemdirim and Weber, 1999; Fowler and Kilsby, 2002). On the other hand, temporal evolution of drought can vary significantly and a drought event can be restricted to distinct areas (Serrano and Sergio, 2006).

2.5 Drought Monitoring

Zahid *et al.*, 2016 used the 12 month SPI to assess the temporal and spatial characteristics of meteorological droughts in Sindh province in Pakistan and found that meteorological drought events in Sindh province had increased from the year 2000 as compared to previous years. In the 1980's Sindh province suffered only one drought in 1988. No drought was recorded in the 1990's but in the 21st century, the province experienced three major droughts in 2000, 2002 and 2004. According to their findings, these droughts were caused by, high temperatures, low rainfall and variability in the rainfall patterns. Using the 12 month SPI may not capture short term droughts that occur within the year. The authors also attributed the droughts to high temperatures and SPI uses rainfall for drought assessment.

Jahangir *et al*., 2013 carried out a research in Barind region in Bangladesh using SPI and Markov chain model to monitor meteorological and agricultural droughts respectively. They found out that these two drought indices exhibited a statistically significant temporal correlation but poor spatial correlation especially during the pre-monsoon season. Meteorological drought exhibited a similar pattern in pre-monsoon season but during the monsoon season, rainfall deficits varied from time to time and was recurrent in some areas of Barind than others. On the other hand, agricultural drought exhibited a prolonged pattern during the pre- monsoon season over the entire Barind region but during the monsoon season, it had a low prevalence and it varied from one region to another. They established that meteorological drought does not always lead to agricultural drought but prolonged agricultural drought can occur due to rainfall deficit. They also noted that the frequency of meteorological drought was increasing in the 1990's compared to the 1970's and 1980's. SPI is only useful when dealing with long term droughts and tends to ignore short term droughts.

Sepulcre *et al.*, 2012 used a Combined Drought Indicator comprising of SPI 3, soil moisture anomalies and Fraction of Absorbed Photo synthetically Active Radiation (FAPAR) to detect agricultural drought in Europe. They noted that the CDI was able to illustrate the spatial extent of a drought condition and give a general idea of the possible consequences for agriculture. Using the 2000-2011 drought events in Europe, they demonstrated the indicator's ability to differentiate between areas affected by agricultural droughts. They noted that in some areas such as Romania, short but very extreme precipitation deficit accompanied by high temperatures can have significant agricultural impacts. They adopted this indicator as an operational and early warning indicator for drought. Like in many countries they noted that drought occurrence in Europe increased after the 21st century. This approach is good as it incorporated various drought indicators. However it used a single SPI value which may not work in all situations and is incapable of representing situations that may roll over from one season to another.

Habibi *et al.*, 2018 used the SPI, Markov chain model, the Drought Index (DI) and time series modelling to characterize Meteorological drought in Cheliff Zahrez basin in Algeria. Using SPI, they found that droughts in this basin have been increasing since 1970 in most of this region. The DI which was derived from transition probabilities of wet and dry years was used to classify areas that are prone to drought. The probability of occurrence of consecutive droughts was investigated using the Markov Chain model which showed that the southern basins were likely to experience droughts every two years. The SPI was used as input data for stochastic modelling of the return period of droughts in the area of study. The researchers used various statistical models and found out that the Asymmetric Power Autoregressive Conditional Heteroskedasticty (APARCH) model was the best in representing the return periods of drought. The approach is good as it incorporated two drought indices to assess drought. However it used SPI which is more appropriate in long term drought assessment.

Hassan *et al*., 2014 used the 3 month (SPI-3) and 12 month (SPI-12) to study drought patterns along the coast of Tanzania and found that this region experienced numerous meteorological droughts ranging from mild, moderate, severe and extreme in the course of both the short and long rains growing seasons. They noted that drought duration, intensity and frequency varied from one area to the other. Even though Tanzania’s mainland experienced droughts less frequently as compared to other areas, it experienced the highest occurrence of extreme droughts They also discovered that the droughts were more prominent during OND than in MAM. In addition they noted that the drought duration, intensity and extent during the study period (1952-2011) was increasing with time. The study fails to capture meteorological drought in other seasons/months which may aggravate the impacts of droughts experienced during MAM and OND. It also fails to capture short term droughts that may occur within the seasons. It also uses one parameter to quantify drought.

Awange *et al.,* 2007 used the percent normal and the Drought Severity Index (DSI) to investigate drought frequency and severity in the Lake Victoria region of Kenya and found out that the 1980's and 1990's were drier decades as compared to the 1960's and 1970's. The 1980's had the most severe droughts during the study period starting from 1961 to 1999. According to their findings, the return period for severe droughts varied from one season to the other and ranged from three to eight years. The September October November (SON) season had the shortest return period of three to four years, while the December January February (DJF) season had the longest return period of seven to eight years. MAM season had a return period of three to eight years, while JJA had no clear return cycle. This approach is good as it used more than one drought index.

Balint *et al*., 2011 used a Combined Drought Index (CDI) that incorporated a precipitation, temperature and vegetation component to study drought in three areas with different climatic characteristics (arid, semi-arid and sub-humid) in Kenya, The study showed that the CDI values changed more rapidly in dry areas than in wet areas. A comparison between the dekadal and monthly values of the CDI showed that the 5- dekadal analysis exhibited the highest fluctuation, while the 3-month analysis was much smoother. However they established that the 5-dekadal analysis detected short term droughts, while the long term droughts were detected by the 9-month analysis. The study noted that the number and frequency of severe and/or extreme droughts were increasing with more intense droughts being experienced from the 1980's to 2000's. Using Embu station, they concluded that the CDI could be used for short term forecasts and early warning tool up to the end of the season. The approach was good as it incorporated various drought indices to quantify droughts. However, it concentrated more on past droughts and only mentioned that CDI could be used to forecast short term droughts without showing how.

Wanjuhi, 2016 used both observed and downscaled ensemble rainfall data from the Coordinated Regional Climate Downscaling Experiment (CORDEX) and SPI to assess past and future drought characteristics over north eastern Kenya. His study found out that the region experiences two categories of drought, the mild and moderate during the two rain seasons of MAM and OND. He however noted that the mild category had a higher probability of occurrence in both seasons as compared to the moderate category.

Projected SPI analysis showed that droughts are expected to increase both in magnitude and frequency. The moderate category is expected to have a higher probability in both seasons than the mild category. Droughts of varying intensity are also expected to last for several seasons once they occur. This study looked at both the past and future characteristics of droughts in the study area hence useful in drought preparedness. However, it used rainfall only to characterize drought.

Onyango, 2014 used the 3-month SPI (SPI-3) to investigate the drought characteristics over the northeastern region comprising of Wajir, Garissa, Mandera and Moyale in both MAM and OND seasons. The study showed that this region experiences two categories of droughts, mild and moderately dry conditions. Mild drought had a high probability of occurrence in both seasons across the whole region with Wajir recording the highest probability. The probability of occurrence of moderate drought varied from one station to another and from season to season. The study also noted that the duration of droughts varied from year to year and from one season to another. Like in many studies, the frequency of drought increased during the period 1998- 2008 which experienced nine drought events in 1999-2001 and 2004-2008. The researcher noted that there was need to use other indices to monitor drought in this region since SPI could not explain the water shortage caused by evapotranspiration, deep filtration, runoff, soil moisture and recharge. The study concentrated on past drought characteristics and gave no indication of future drought occurrence. It also left out drought characteristics in other seasons/months outside MAM and OND and only used one parameter to quantify droughts.

Ngaina *et al*., 2014 investigated the past, present and future drought characteristics in Tana River County using the 12 month SPI and model data from Providing Region Climate for Impact Studies (PRECIS) and the Commonwealth Scientific and Industrial Research Organization (CSIRO). They noted that rainfall and temperature have been increasing monotonically, with rainfall exhibiting the highest spatial variability. From the past drought patterns, droughts have been increasing with time from only two droughts in the 1970's to four in 1980's and early 2000's. According to the research, the magnitude and frequency of these drought events are expected to increase in future despite the fact that wet and dry conditions are expected to alternate in almost equal magnitude and frequency.

They also noted that the central and northern parts of Tana River will be more prone to drought occurrence than any other part of the county. The study looked at both the past and future drought characteristics. However, it used the 12 month SPI which does not capture drought patterns within the year. It also utilized SPI as a drought indicator and drought is caused by a combination of other meteorological parameters.

2.6 Drought Forecasting

Using a stochastic approach based on analytical derivation of transition probabilities of different drought categories at different time scales and auto covariance matrix of monthly SPI time series, Cancelliere *et al*, 2005 developed a suitable model to predict short medium term droughts in Sicily Italy. The study showed that the observed and forecasted values were fairly close and hence adopted the model for short medium term forecasting tool in Italy. The study used precipitation only to characterize drought.

Using the SPI at different time scales (3, 6, 9, 12 and 24 months) as a drought quantifying parameter, Mishra and Desai, 2005 developed an Auto Regressive Integrated Moving Average (ARIMA) and the Seasonal Auto Regressive Integrated Moving Average (SARIMA) models to predict droughts in Kansabati river basin (India). The study showed that the ARIMA model predicted droughts with reasonable precision up to two months lead time in all the timescales. However, the accuracy of the forecast decreased with increasing lead time, especially for the lower SPI series (3 and 6). For higher SPI series (9, 12 and 24), drought prediction would be reasonably accurate up to 3 months lead time. The study is good as it used SPI at different time scales, hence captured various drought durations. However, it used precipitation only to characterize drought.

Karavitis *et al*, 2015 showed that the 24 months Seasonal Auto Regressive Intergrated Moving Average (SARIMA) model was more reliable in predicting droughts up to the first 6 months in Greece both at regional and country levels. Using monthly SPI as input data to various models, they found out that the 24 month SARIMA model had the best fit both at the local and national level and picked it to forecast drought using SPI 6 and SPI 12. Comparative analysis based on Krigging approach in a GIS environment between the observed and forecasted SPI values showed that SPI 6 predicted droughts accurately for the first few months both nationally and regionally, while SPI 12 underestimated droughts at both levels. This study used precipitation only to characterize drought.

Aghakouchak, 2015 investigated the possibility of producing persistent based drought predictions in the Greater Horn of Africa (GHA) using the Ensemble Streamflow Prediction (ESP) and the Multivariate Standardized Drought Index (MSDI). His study showed that this model was able to forecast drought severity, persistence as well as the probability of drought occurrence with a lead time of four months, Using the 2010-2011 droughts in east Africa, he demonstrated that the multi-index, multivariate drought predictions from MSDI and ESP were consistent with the observations and concluded that the model could be used for probabilistic drought early warning in the study region. The study used multivariate drought index that incorporated both precipitation and soil moisture hence predicting two types of droughts simultaneously.

Using dynamical seasonal model forecasts from the European Centre for Medium range Weather Forecasts (ECMWF) and SPI, Mwangi *et al*., 2014 showed that it is possible to forecast the duration, magnitude and spatial extent of droughts in GHA. The prediction skill was found to be higher during the OND than in MAM season and decreased with increasing lead time. They found out that ECMWF rainfall seasonal forecasts had significant skills for the major rain seasons (MAM and OND) in East Africa when evaluated against observed rain gauge data but could not give adequate information on drought. However, when SPI was used instead of raw rainfall data, information on the intensity and spatial extent of drought was obtained. They therefore concluded that the use of drought indices such as SPI in conjunction with seasonal rainfall forecasts would go a long way in the drought decision making process. The study used precipitation only to characterize and predict drought.

In Kenya, drought forecasting is carried out indirectly by KMD and the IGAD Climate Prediction and Application Centre (ICPAC) through the generation of seasonal rainfall forecasts. However, these forecasts give the general performance of rainfall and do not indicate if droughts will occur or not. Drought thresholds can only be obtained from rainfall performance and may be user specific. The forecasts produced by ICPAC are too general as they cover the Greater Horn of Africa (GHA) and do not concentrate on any particular country.

2.7 Conceptual Frame Work

The conceptual frame work of the study is displayed in Figure 4. The study used standardized annual rainfall anomalies for specific objective one and dekadal rainfall, temperature and relative humidity for specific objective two. Output from specific objective two were then used together with time series modelling for specific objective three. The output of the study was past drought characteristics over the study area and a drought forecasting model was also developed.

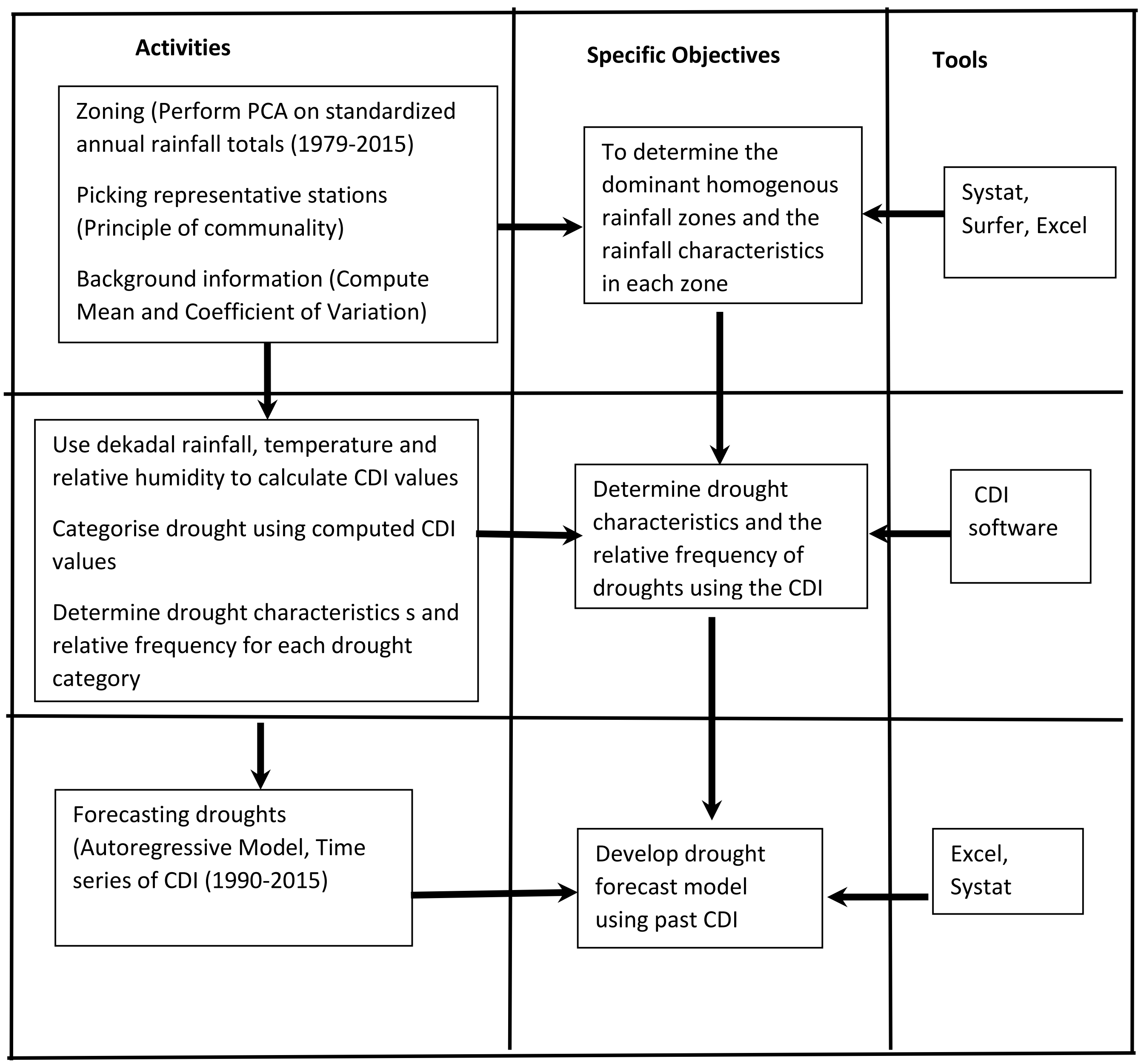

Figure 4: Conceptual framework of the study

CHAPTER THREE: DATA AND METHODOLOGY

3.0 Introduction

This section describes the data and the various methods that were used in the study to achieve the objectives described in section one.

3.1 Data

This study used observed rain gauge data, maximum temperature and Relative Humidity at 1200 GMT obtained from the Kenya Meteorological Department.

Two sets of rainfall data were used in this study. The first set composed of annual rainfall totals from the period 1979-2015 from twenty eight meteorological stations. Kenya Meteorological Department has over one hundred rainfall stations spread all over the country. However, most of the stations do not have up to date records and the concentration of these stations is around the high potential areas of western, Lake Basin and central highlands with very few stations over the northern parts of the country. Thus, based on data availability and considering that using the many stations concentrated in the high potential areas may not add value to the study, twenty eight stations with reliable data were picked.

Table 2 gives a summary of the stations used while figure 5 shows their spatial distributions. The second set of data was dekadal rainfall data from the period 1990-2015 from nine representative stations. Dekadal maximum temperature and dekadal relative humidity for the period 1990-2015 from nine representative stations was also used.

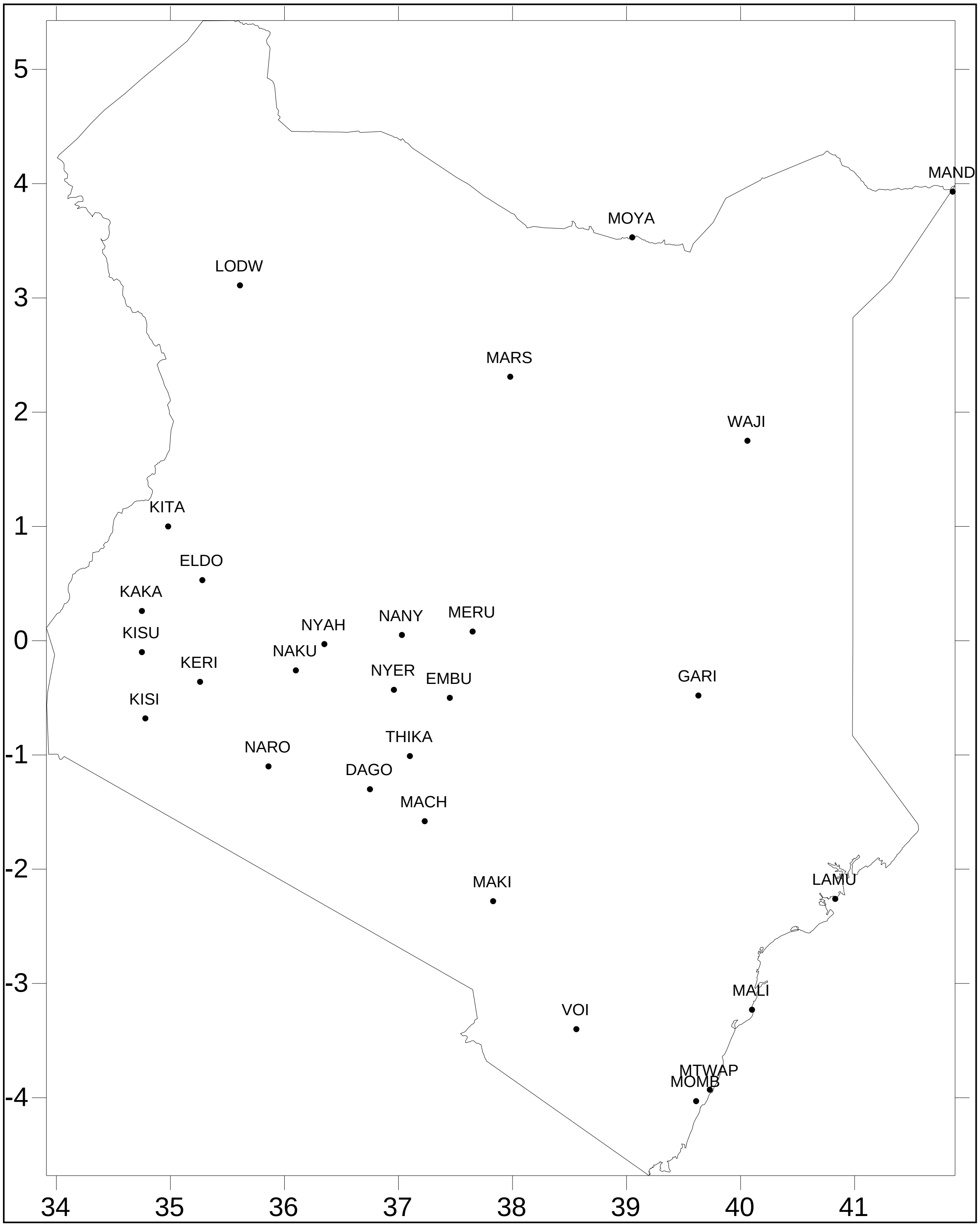

Figure 5: Spatial Distribution of stations used to delineate the study area into homogenous zones

Table 2: Summary of stations used to delineate the study area into homogenous zones

S/No	Station Number	Station Name	Latitude	Longitude	Altitude in metres	Long Term Annual Mean
1	8635000	Lodwar	3.11N	35.61E	505	207
2	8639000	Moyale	3.54N	39.05E	1110	650
3	8737000	Marsabit	2.31N	37.98E	1345	739
4	8641000	Mandera	3.93N	41.86E	330	273
5	8840000	Wajir	1.75N	40.06E	244	323
6	9039000	Garissa	0.48S	39.63E	128	347
7	9240001	Lamu	2.26S	40.83E	6	996
8	9340009	Malindi	3.23S	40.10E	20	1039
9	9439021	Mombasa	4.03S	39.61E	5	1065
10	9339036	Mtwapa	3.93S	39.73E	21	1319
11	9137020	Machakos	1.58S	37.23E	1600	681
12	9237000	Makindu	2.28S	37.83E	1000	568
13	9338001	Voi	3.40S	38.56E	558	572
14	8937065	Meru	0.08N	37.65E	1524	1301
15	9037112	Embu	0.50S	37.45E	1494	1251
16	9036288	Nyeri	0.43S	36.96E	1798	967
17	9136164	Dagoretti	1.30S	36.75E	1798	1017
18	9137048	Thika	1.01S	37.10E	1463	952
19	9135001	Narok	1.10S	35.86E	1585	742
20	8937022	Nanyuki	0.05N	37.03E	1890	636.3
21	9036135	Nyahururu	0.03S	36.35E	2377	992
22	9036020	Nakuru	0.26S	36.10E	1901	944.6
23	8935181	Eldoret	0.53N	35.28E	2120	1077
24	8834098	Kitale	1.00N	34.98E	1840	1280
25	8934096	Kakamega	0.26N	34.75E	1582	1956
26	9034025	Kisumu	0.10S	34.75E	1149	1356
27	9035279	Kericho	0.36S	35.26E	1976	1988
28	9034001	Kisii	0.68S	34.78E	1771	2036

3.1.1 Estimation of Missing Data and Quality Control

The data was subjected to quality control measures where any stations with more than 10% data missing was disregarded. Missing data was estimated using the correlation and regression method. In this method the correlation between pairs of stations is computed using (Equation 1) and the station that is highly correlated to the station with missing data.is picked and used to compute the missing record using the relationship in equation 2. For zones with only one station, the long term mean was used to fill the missing gaps. Consistency of the data was carried out using the single mass curve. In a single mass curve cumulated values for each station are plotted against time. A regression line is then drawn through the scatter diagram. A straight line shows a consistent record.

$$r = \frac{N\sum XY-(\sum X)(\sum Y)}{\sqrt{[\sum X^2-(X)^2][N\sum Y^2-(\sum Y)^2]}} \qquad \text{.................... (1)}$$

$$SA_i = r_{AB*S_{BI}} \qquad \text{..................................... (2)}$$

Where S_{Ai} is the missing record in station A, R_{AB} is the correlation coefficient of station B that is highly correlated with the station A that has missing data and S_{BI} is the value of the data from station B that has full record.

3.2 Data Analyses

The various methods used in the study are described in this subsection.

3.2.1 Demarcating Kenya into Homogenous Rainfall Climatic Zones.

In order to achieve this objective, the annual rainfall totals were first standardized and PCA performed on the standardized rainfall anomalies to come up with the homogenous zones. The number of significant principal components were determined using the Kaisers criterion method while the representative stations were picked using the principal of communality.

3.2.1.1 Standardization

The standardized yearly anomaly indices for each year and station were obtained using Equation 3.

$$\boldsymbol{Z_{ij}} = \frac{\boldsymbol{T_{ij}-\bar{T}}}{\boldsymbol{\sigma_j}} \qquad \text{.............................. (3)}$$

Where (Z_{ij}) is the standardized rainfall anomaly, T_{ij} is the annual rainfall totals for a station i in a given year j, T bar is the long term mean of rainfall and σ is the standard deviation. Standardization is done to ensure the rainfall totals have a mean of zero and a unit variance.

3.2.1.2 Regionalization

Kenya has previously been demarcated into homogenous rainfall zones using different time scales. (Agumba, 1988; Barring, 1988; Ogallo, 1989; Indeje *et al*, 2000 and Drought Monitoring Centre, DMC 2000, 2001). This demarcation was carried out using rainfall data ranging from 1922 to 2000. This study thus aimed at demarcating the country into homogenous zones using annual rainfall totals from 1979-2015 to account for the most recent changes in rainfall patterns. Several methods are used to zone a country into homogenous zones such as the graphical method, cluster and discriminant analysis and the Principal Component Analysis (PCA). Of all these methods, PCA is the most popular and has been used in Kenya and East Africa in general to come up with homogenous zones. (Ogallo, 1980 and 1989; Oludhe, 1987; Basalirwa; 1991, Ininda, 1994; Okoola, 1996) among others.

In this study, PCA was used to delineate the country into homogenous zones. This is a data compression skill where a large data set is reduced to a small data set while maintaining most of the information in the original data set. PCA uses an orthogonal transformation to convert a set of variables that are correlated to a set of linearly uncorrelated variables called principal components. The first principal component accounts for the highest possible variance in a data set, with each subsequent component accounting for the remaining variance. According to Richman 1986, PCA can be performed in various ways which are determined by the way in which the input matrix of observation is organized. If the parameter being studied is fixed, then one can either use the S or T mode.

In the S- mode, the correlation data matrix is produced between locations over a set of periods. This mode therefore produces a group of localities with similar temporal patterns. In the T- mode, the correlation matrix is produced between periods over a set of localities. Thus this mode produces a group of periods with the same spatial patterns (Ogallo, 1989).

In this study, the S- mode was used to demarcate Kenya into homogenous rainfall zones. The basic PCA model for any variable j is given by Equation 4.

$$\boldsymbol{Z_j = \sum_{k=1}^{m} a_{jk} F_k \qquad (j = 1, 2, \dots \dots m)} \qquad \text{……..} \ \textbf{(4)}$$

Where Z_j is the variable j (rainfall) in standardized form, F_k is the hypothetical factor k and A_{jk} is the standardized multi-regression coefficient.

3.2.1.3 Number of Significant Principal Components

Since there are as many principal components as there are stations in the matrix data, it is important to select the number of significant principal components to be used in the study. Many methods have been proposed by several authors on how this can be done. They include but not limited to the Kaisser's criterion (Kaiser 1959), Scree's test (Cattell, 1966), Logarithim of Eigen value (LEV) method (Craddock, 1973) and the Sampling Errors of Eigenvalues (North *et al*, 1982). This study used the Kaisser;s criterion method, which assumes that all principal components whose values are equal to or greater than one are significant. Thus it only retains those PCs that excerpt variance at least as much as that equal to the intial variable.

3.2.1.4 Rotation of Principal Components

Eigenvectors are mathematically orthogonal and the underlying processes related to the variables are not orthogonal, hence there is need to adjust the frames of references of the eigenvectors through rotation in order to overcome the uncertainties produced by direct solutions of eigenvectors. Several authors have shown that rotated solutions describe the interrelations among variables better than unrotated solutions (Hsu and Vallace, 1985; Richman, 1981, 1986; Barnston and Livezey, 1987).

There are two main methods of rotation, the orthogonal and oblique rotations .In orthogonal rotation, the reference axes are retained at 90 degrees such that each factor is orthogonal to all other factors. Examples include Varimax, quartimax, equimax, orthomax, among others. In oblique rotation, the rotated factors are allowed to identify the extent to which they are correlated. Examples include Oblimax, Oblimin, Quartimin, covarimin among others. Details about these rotations can be obtained from Richman, 1986.

In this study, Kaisser’s Varimax rotation was used. The significant rotated components were mapped using the Surfer software in order to delineate the homogenous climatic zones.

3.2.1.5 Picking Representative Stations

After the climatic zones were delineated, representative stations were picked from each zone. Basalirwa, 1979 and Ouma, 2000 have described the various methods that can be used to pick a representative station. They include the unweighted Arithmetic mean method, use of PCA weighted Averages and the principle of communality. In order to identify the most representative station within each homogenous zone, the principal of communality was applied. The communality C_j for any given locality j in a homogenous zone is given by Equation 5.

$$C(\boldsymbol{j}) = \sum_{\boldsymbol{k=1}}^{\boldsymbol{m}} (\boldsymbol{ajk})^{\boldsymbol{2}} \; (\boldsymbol{j} = \boldsymbol{1}, \boldsymbol{2}, \dots . \boldsymbol{n}) \qquad \textbf{…….. (5)}$$

Where:

ajk is the standardized multiregression coefficient of variable j on factor k (factor loading)

m is the number of significant principal components, n is the number of variable

The communality of a variable, in this case a station represents the degree of a station's association with other stations in the zone. Child, 1990 showed that Cj gives the extent to which the various variables are interrelated. Thus the location with the highest value of Cj in any homogenous zone can imply that this location is highly correlated with all the other stations within the homogenous region. The best representative station will therefore be the one with the highest communality in the homogenous zone. This principle has been used in the country to pick representative stations (Ogallo, 1980 and Opere 1998).

3.2.2 Determining Past Drought Characteristics and Their Respective Relative Frequency

3.2.2.1 General overview of the CDI Software

The CDI software is a Microsoft (MS) excel- based software that was developed by Balint *et al*, 2011 in conjunction with the Food Agricultural Organization Somalia Water and Land Information Management (FAO-SWALIM) as a tool to improve drought monitoring in the data scarce areas of the Greater Horn of Africa (GHA). It provides an easier way of computing drought indices and was initially designed to compute four drought indices; the Precipitation Drought Index (PDI), Temperature Drought Index (TDI), Vegetation Drought Index (VDI) and the Combined Drought Index (CDI) which incorporates all the three preceeding drought indices.

The CDI is a statistical index that measures how much the current hydro meteorological conditions depart from the long term mean during a certain interest period. It combines three drought indices the PDI, HDI and TDI. In simple words, the index for the various components of the CDI can generally be expressed by Equation 6.

$$\boldsymbol{Drought\ index} = \frac{\boldsymbol{Actual\ average\ for\ IP}}{\boldsymbol{LTM\ for\ IP}} * \sqrt{\frac{\boldsymbol{Actual\ length\ of\ continous\ deficit\ or\ excess\ in\ the\ IP}}{\boldsymbol{LTM\ length\ of\ continous\ deficitor\ excess\ in\ the\ IP}}} \quad \ldots\ldots \textbf{(6)}$$

Where IP refers to the interest period (9 dekads in this study), LTM is the long term mean and deficit applies to rainfall and relative humidity while excess applies to temperature.

Computation of the CDI was done using six different time series which include the following

(i) Dekadal (10 day) rainfall data

(ii) Time series of the rainfall run lengths ($RL^{(p)}$) for a particular interest period (IP)

(iii) Dekadal Relative Humidity

(iv) Time series of the humidity run lengths ($RL^{(H)}$) for a particular interest period (IP)

(v) Dekadal Temperature

(vi) Time series of the temperature run lengths ($RL^{(T)}$) for a particular interest period (IP)

The run length in the time series describes the persistence of the unfavourable weather conditions in the course of continuous drought occurrence. For rainfall, the run length is the duration within the IP in which the rainfall is constantly below the long term average value. For humidity, the run length is the duration within the IP in which the humidity is constantly below the long term average value. For temperature, the run length is the length of time within the IP in which the temperature is constantly above the long term average value representative of the same time unit such as a dekad, month or year. The time series described above can be grouped into two classes A and B. In A, small values of the data specify dry conditions while larger values specify wet conditions. Rainfall and relative humidity belong to this group. In B, large values in the time series point to conditions that may cause drought, while small values indicate better than drought conditions. Temperature belongs to this category.

Since the drought indices described above are used to compare the actual drought conditions with the long term average conditions, it is necessary to standardize the data used in CDI computation in order to attain homogenous mathematical interpretation. In this study, this was achieved by shifting the X-axis to the level of $(T_{max} + 1)$ for temperature, $(RL_{Max} + 1)$ for run length and $(RH_{Min} - 0.01)$ for relative humidity, where T_{max} is the maximum temperature, RL_{max} is the longest run length in the complete data set used and RH_{min} is the minimum relative humidity for the station being considered. For rainfall, the X-axis was shifted by adding one millimeter (mm) to the actual rainfall amount. This was necessary because some parts of the study area (northern parts of the country) are characterized by prolonged dry seasons with no rain. In these areas, one may find a whole period characterized by zero values, including the LTM, which can result to unrealistically large values when dividing by very small values close to zero. This standardization ensured that no parameter would be divided by zero, hence simplified the calculation process. The X-axis shift gave rise to modified data series given by Equations 7a to 7d.

$$T^* = (T_{max} + 1) - T \quad \text{.......... (7a)}$$

$$RL^* = (RL_{max} + 1) - RL \quad \text{......... (7b)}$$

$$RH^* = RH - (RH_{min} - 0.01) \quad \text{......... (7c)}$$

$$P^* = P + 1 \quad \text{........ (7d)}$$

Where T^*, RL^*, RH^* and P^* are the standardized temperature, run length, relative humidity and precipitation respectively.

3.2.2.2 Computation of PDI, TDI and HDI

The formula for computing individual drought indices for year i and dekad m are given by Equations 8 to 10.

$$\boldsymbol{PDI_{i,m}} = \frac{\frac{1}{IP}\sum_{j=0}^{IP-1} P^*_{i,(m-j)}}{\frac{1}{(n\times IP)}\sum_{k=1}^{n}\left[\sum_{j=0}^{IP-1} P^*_{(m-j),k}\right]} * \sqrt{\left[\frac{RL_{m,j}^{(P^*)}}{\frac{1}{n}\sum_{k=1}^{n} RL_{m,k}^{(P^*)}}\right]} \quad \text{............ (8)}$$

$$\boldsymbol{TDI_{i,m}} = \frac{\frac{1}{IP}\sum_{j=0}^{IP-1} T^*_{i,(m-j)}}{\frac{1}{(n\times IP)}\sum_{k=1}^{n}\left[\sum_{j=0}^{IP-1} T^*_{(m-j),k}\right]} * \sqrt{\left[\frac{RL_{m,j}^{(T^*)}}{\frac{1}{n}\sum_{k=1}^{n} RL_{m,k}^{(T^*)}}\right]} \quad \text{............ (9)}$$

$$\boldsymbol{HDI_{i,m}} = \frac{\frac{1}{IP}\sum_{j=0}^{IP-1} H^*_{i,(m-j)}}{\frac{1}{(n\times IP)}\sum_{k=1}^{n}\left[\sum_{j=0}^{IP-1} H^*_{(m-j),k}\right]} * \sqrt{\left[\frac{RL_{m,j}^{(H^*)}}{\frac{1}{n}\sum_{k=1}^{n} RL_{m,k}^{(H^*)}}\right]} \quad \text{....... (10)}$$

Where IP is the interest period (9 dekads)

n is the number of years where relevant data is available (25 years)

j is the summation running parameter covering the IP

k is the summation parameter covering the years where relevant data are available

$RL^{(p*)}$ is the run length which describes the maximum number of consecutive dekads below long term mean rainfall in the interest period

RL $^{(T*)}$ is the maximum number of consecutive dekads above long term mean maximum temperature in the interest period

RL (H*) is the run length which describes the maximum number of consecutive dekads below long term mean relative humidity in the interest period

PDI, TDI, and HDI represent the precipitation, temperature, and humidity drought indices respectively. These indices are dimensionless and measure the severity of droughts in a certain IP, where smaller values indicate serious drought conditions while large values indicate mild drought conditions.

The actual drought index signifies the severity of drought for the IP terminating in time unit m. In this study, since the IP was nine dekads, an index value say of 0.25 indicates the real drought conditions from the first to the ninth dekad of a given month and year.

Each of the indices has two components. The first component (part of the indices' equation without the square root) represents the ratio of the seasonal performance of the mean modified rainfall, temperature and humidity to the overall performance of the same parameters over all the years under consideration. The numerator measures the present conditions while the denominator gives the LTM of each parameter. The second component (Part of equation under the square root sign in all the equations) represents the ratio of the drought run length in a given season to the average run length over the years in that season and it measures the persistence of dryness.

3.2.2.3 Computation of the CDI

After individual drought indices were computed by the software, the CDI was then computed as a weighted average of the PDI, TDI and HDI as shown by Equation 11

$$\boldsymbol{CDI_{i,m} = w_{PDI} * PDI_{i,m} + w_{TDI} * TDI_{i,m} + w_{HDI} * HDI_{i,m}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textbf{(11)}$$

Where w are the weights of the individual drought index.

The intial weights as designed by Balint *et al*, 2011 for PDI was 50%, TDI 25% and NDVI 25%. In the case of missing data for temperature and NDVI, then the weight for PDI was assigned 67%, while all the others were allocated a weight of 33%. In this study, the coefficient of variation (CV) computed by dividing standard deviation with the mean (Equation 12) was used as a guide to assign the weights to individual drought indices. Different sets of weights were assigned to PDI, TDI and HDI and CDI time series for every set was developed. A total of twelve different sets of weights were used to develop twelve CDI time series. The CV for each CDI series was then calculated and the series that had the lowest CV was picked to assign the weights that were used in the final calculation of CDI.

$$CV = \frac{\sqrt{\frac{1}{N}\sum_{i}^{N}(X_i - \bar{X})^2}}{\bar{X}} \qquad \text{……………………} \; \textbf{(12)}$$

The numerator is the standard deviation and the denominator is the mean. In the numerator, N is the sample size, Xi is the selected value and Xbar is the mean.

3.2.2.4 Assessing Drought Characteristics

To assess the drought characteristics in the study area, the corresponding values of the CDI in the various representative stations were interpreted using Table 3.

Table 3: Classification of drought categories based on CDI

CDI Value	**Drought Severity**
>1	No Drought
>0.8 - ≤ 1	Mild drought
> 0.6 - ≤ 0.8	Moderate drought
>0.4 - ≤ 0.6	Severe drought
< 0.4	Extreme drought

The annual drought characteristics were determined by counting the number of dekads that were affected by different categories of droughts per year. In order to determine how the droughts were spread out in each season, the number of droughts computed as a percentage of total droughts in each drought category was determined using Equation 13.

$$D_s = \frac{d_c}{N} * 100 \qquad \textbf{…………} \; \textbf{(13)}$$

Where D_s is the percentage of droughts in a given season, dc is the number of dekads affected by a drought category c and N is the total number of droughts observed during the study period. The various drought categories in the study area were mapped using the Geographical Information System (GIS) and in particular the Inverse Distance Weighting (IDW) interpolation technique. In order to determine whether droughts are becoming more severe or not, the whole time series was divided into five years period and the number of moderate to extreme droughts cumulated over every five years.

3.2.2.5 Comparison of Droughts Computed by CDI with Previous Drought Reports in the Country

In order to know if the CDI captured droughts well in the study region, all the years which were affected by more than 18 dekads of droughts in each zone were tabulated and the results compared with previous drought reports issued by the government**.**

3.2.2.6 Drought Relative Frequency

If the number of times a certain drought category occurs is denoted by m and the total number of droughts recorded in a given station is denoted by N, then the relative frequency of drought category RF_c is given by Equation 14.

$$\boldsymbol{RF_c = \frac{m}{N}} \qquad \text{.....................} \ \textbf{(14)}$$

Relative frequency was used to approximate the probability that a certain drought category will affect a certain area at any given time in the study area.

3.2.3 Developing a Drought Forecast Model.

Three major steps were carried out in order to achieve this specific objective and include model selection, fitting, diagnostic and forecasting.

3.2.3.1 Model Selection

Model selection involves identifying a suitable ARIMA model that best represents the behaviour of the time series. Graphical analysis is an important tool in model identification as it easily identifies patterns and anomalies in a time series. (Chatfield, 2000). In this study, the correlogram which is a plot of the sample autocorrelation at lag k (r_k) against the lags was used to look for seasonality, trend and stationarity and also to identify the type of model to be used in the study. In general, a high value of r_k at a particular time indicates the presence of seasonality at that particular time. The tendency of r_k not coming down to zero until a high lag (more than half of the length of time series) is attained may indicate the presence of trend in a time series.

Stationarity was checked using the sample Auto Correlation Function (SACF) which were computed by the Systat software. Since the stochastic process that governs a time series is usually unknown, SACF are computed from the time series and used instead of the theoretical ACF. The theoretical autocorrelation function denoted by p_k at lag k is given by Equation 15.

$$p_k = \frac{Y_k}{Y_0} \qquad \text{………………… } \mathbf{(15)}$$

Where Y_k is the theoretical auto covariance coefficient at lag K for K=0, 1, 2....n and Y_0 is the auto covariance at lag zero (Variance of the time series). The SACF is given by Equation 16.

$$r_k = \frac{C_k}{C_o} \qquad \text{………………… } \mathbf{(16)}$$

Where r_k is the sample Auto correlation function, C_k is the sample auto covariance at lag k and C_o is the sample auto covariance at lag 0. It has been shown that for data from a stationary process, the correlogram usually provides an approximation of the theoretical ACF (Chatfield, 2000). Thus the plot of ACF against lag can be used to check if the time series is stationary or not.

It has been shown (Box and Jenkins, 1976; 1994 Chatfield, 2000) that for an AR (p) process, the roots of the characteristic equation of the ACF must lie outside the unit circle for the series to be stationary. For an MA (q) process, the roots of the characteristic equation of the ACF must lie outside the unit circle for the time series to be invertible. Therefore to know if the time series is stationary or not, the estimated ACF ($r_{k)}$ was plotted against the lags and the nature of this plot investigated. Since the estimated ACF tends to behave like the theoretical ACF (P_k), the tendency of r_k not dying off rapidly will show that the time series is not stationary and may have to be differenced to make it stationary. Also if the series is stationary, the first few values of r_k show a short term correlation where the first few values of r_k are significantly different from zero (Chatfield, 2000).

The SACF and the Sample Partial Autocorrelation Function (SPACF) plots were then used to identify the model type and order. For a stationary AR process, the ACF will tail off at lag p while its PACF will have a cut off at lag p. For a stationary Moving Average (MA) process, the ACF will have a cut off after lag q, while its PACF will tail off after lag q. For a mixed process, both the ACF and PACF will tail off. Besides determining the class of the ARIMA models to use, PACF is also useful in determining the order of the model. The PACF of an AR (p) process will be zero at all lags larger than p. Thus the order of the model will be given by the lag value where the PACF is significantly different from zero. The converse is true for an MA process and the order of the model will be the lag value where the PACF tails off. Thus graphical analysis of ACF and PACF were used to identify the model to be used in the study.

3.2.3.2 Model fitting

Model fitting involves looking for a suitable method to estimate model parameters. There are three basic methods that are used to estimate parameters in stochastic modelling. These include the maximum likelihood estimate, least squares estimate and the Yule Walker estimates (Box and Jenkins, 1976). For this particular study, model fitting was carried out using the Least squares method. This method involves minimizing the sum of all the squares of the deviations of the observed points. For a given function, the sum to be minimized is given by Equation 17.

$$s = \sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 = \sum_{i=1}^{N}\left(Y_i - F(X_i, \alpha, \beta\ )\right)^2 \text{ ………………… } \mathbf{(17)}$$

Where Xi and Yi are coordinates of the observed points, Ŷ is the mean value of Y, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are parameters and N is the sample size. Equation 17 is then differentiated with respect to the parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ and equated to zero as shown in Equation 18

$$\partial \sum_{i=1}^{N} \frac{(Y_i - \hat{Y}_i)^2}{\partial \alpha} = 0,\ \ \partial \sum_{i=1}^{N} \left(\frac{(Y_i - \hat{Y}_i)}{\partial \beta}\right)^2 = 0 \quad \text{ …………………..… } \mathbf{(18)}$$

The solutions obtained from solving the above equation gives the number of parameters to be estimated. The number of parameters to be used in fitting the model was determined by looking at the P value, where parameters with a small value of p (as close to zero as possible) were picked

3.2.3.3 Model Diagnostics

This step looks at the shortfall of the fitted model and any possible modifications to the model. There are various methods that are used to test the goodness of fit of a model such as examining the residuals for the analysis of Variance as discussed by Anscombe and Turkey, 1963, over fitting (Box and Jenkins, 1976) and also the criticism of factorial experiments, leading to Normal plotting (Daniel, 1959). Over fitting involves fitting a model that has a higher order than the model being diagnosed and examining whether the additional parameters are significant. It is useful in improving model adequacy as it detects inadequacies that may not be identified by examining the residuals. However, over fitting is suitable only when the nature of the high order model is known and in most cases, this information is not known and hence other methods need to be used in conjunction with over fitting.

Residuals refer to the difference between the observed and the fitted value and their analysis is a very useful tool in model diagnostic. When fitting data to a model, it is assumed that the error term has a mean of zero and a constant variance, the errors are not correlated and they are normally distributed. Examination of residuals therefore checks if the assumptions made to the data are true. If the residuals tend to behave like the random errors, then the model is taken to be adequate. Analysis of residuals can be done either using numerical or graphical methods or a combination of both.

In this study, both the numerical and graphical methods were used. The numerical method used was the Nash- Sutcliffe model efficiency coefficient (NSE) that was developed by Nash and Sutcliffe in 1970. NSE is calculated using Equation 19.

$$NSE = 1 - \left(\frac{\frac{1}{N}\sum_{i=1}^{n}\left(Y_o - Y_p\right)^2}{\frac{1}{N}\sum_{i=1}^{n}(Y_o - \bar{Y})^2} \right) \qquad \text{.....................} \ \mathbf{(19)}$$

Where N is sample of the test size, Y_o is the observed value, Y_p is the predicted value and Y bar is the mean of the observed data. NSE ranges from -1 to 1.A good model should have an NSE close to 1. Moriasi *et al*, 2007, Carpena and Ritta, 2013 suggested that for a model to be adequate, NSE thresholds values should range between 0.5 and 0.65. In this study, the CDI time series was divided into the training and validation sets where the training set was used to fit the model and the resulting parameters used to validate the model. The NSE for both the training and validation sets were then compared. If the model is adequate, the difference in the NSE value should be minimal.

Graphical analysis was carried out using plots of Residual Autocorrelation Function (RACF), Residual Partial Autocorrelation Function (RPACF) and plots of residuals against fitted values. RACF and PACF plots were developed using Systat, while excel was used to develop plots of residuals against fitted values. For the RACF and PACF plots, if the residuals are significantly different from zero, then the model is inadequate. In the plot of residuals against fitted values, the residuals should be evenly distributed around the mean if the model is adequate. (Mishra and Desai, 2005).

3.2.3.4 Forecasting Droughts

After confirming that the model was adequate, the fitted model was used to produce forecast at lead 0, which is simply the fitted values. Forecasts at consecutive leads up to lead 11 were produced using the previous lag's predicted values as the input parameters to the model. The coefficient of determination (R^2) for each lead time was computed and a graph of R^2 against the leads was drawn for every station to determine how far into the future the model could forecast. The forecast accuracy was evaluated using the coefficient of determination (R^2) and the Hits Skill Score (HSS**).** R squared and the HSS for every lead time were computed and their respective values compared to see if they were consistent. The higher the value of HSS and R^2, the more accurate the forecast was and vice versa. A Hit was realized any time the model predicted a drought category that was similar to the observed data. An alarm was realized when the model predicted a drought category that was different from the observed data.

3.3 Data Requirements and Limitations

Data used in the study has been described at the introductory part of this section (3.1) and include rainfall annual totals, dekadal rainfall, maximum temperature and relative humidity at 1200 GMT. A few limitations were however encountered throughout the study.

(i) There were very few stations over the northern parts of the study area. Hence the spatial rainfall characteristics over this area may not have been accurately represented.

(ii) The CDI used in the study incorporated three climatic variables (temperature, rainfall and humidity). Since drought is caused by more variables, all aspects of droughts were not taken into account

(iii)The CDI utilized dekadal data in its computation thus only short term drought prediction was carried out.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.0 Introduction

This section gives a detailed discussion of the results obtained from all the methods used in the study. These include results from regionalization, historic drought characteristics obtained using CDI, model building and forecasting.

4.1 Results from Data Quality Control

Results from the single mass curves displayed in this subsection for rainfall, temperature and humidity show that the data was consistent in all the zones (Figures 6 to 8). However, only three single mass curves from three stations randomly selected are displayed as examples. They include Lodwar for temperature, Kericho for rainfall and Garissa for relative humidity. All the other single mass curves can be found in the appendix

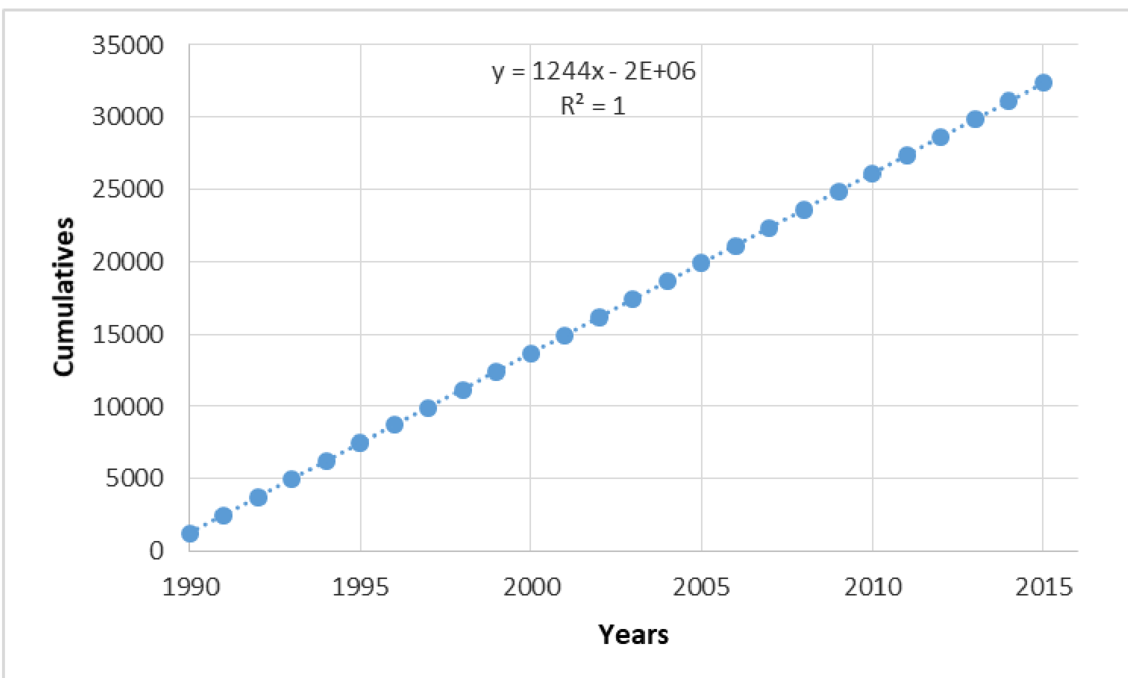

Figure 6: Single mass curve for Lodwar Temperature

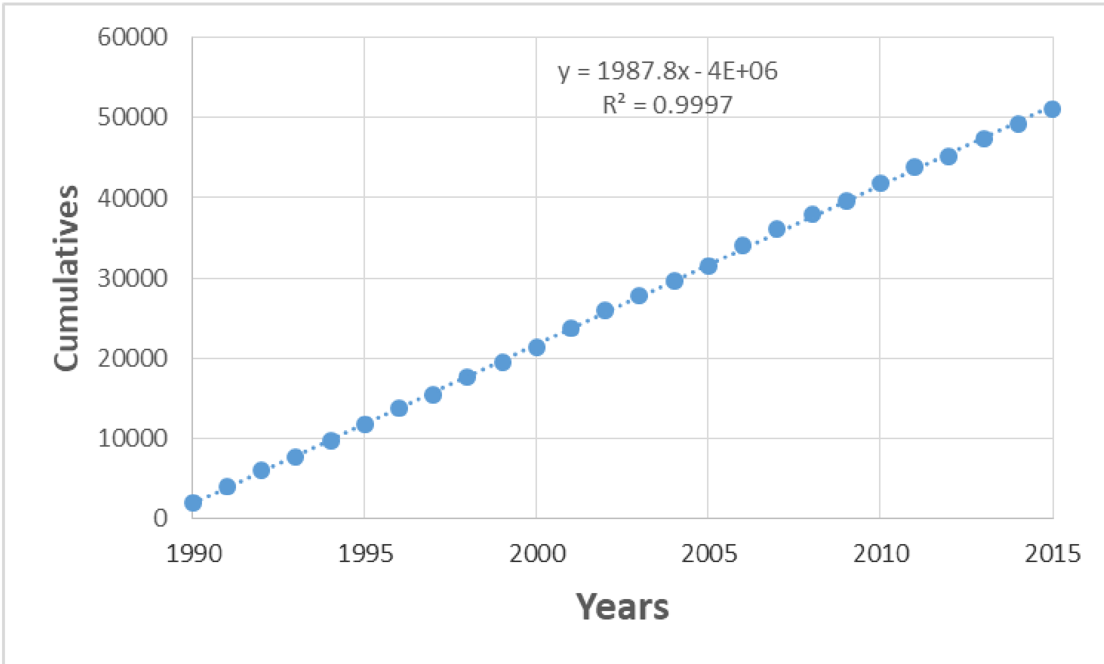

Figure 7: Single mass curve for Kericho rainfall

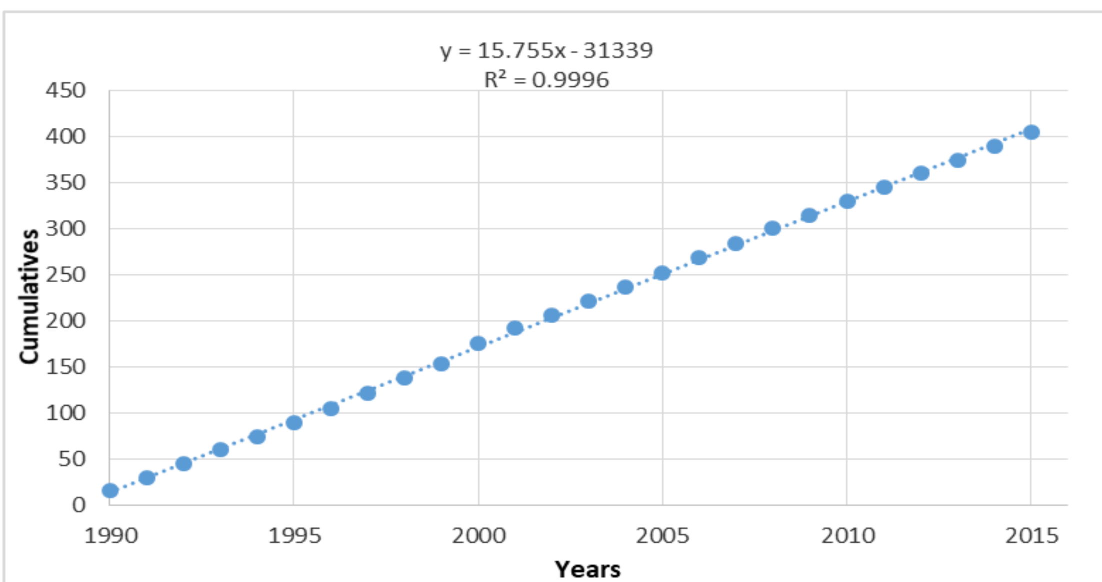

Figure 8: Single mass curve for Garissa Relative Humidity

4.2 Delineation of The Study Area into Rainfall Homogenous Zones

This section presents the results obtained from PCA of the standardized annual rainfall totals. The rotated PCA factor loadings were mapped to examine the spatial variability of rainfall in the study area. Results from Kaiser's criterion show that six components accounting for a total variance of 81% were significant (Table 4). The rotated PCAs tend to reflect the influence of local and regional factors such as topography, large water bodies and other thermally induced circulations such as the mountain/valley winds and land/sea breeze on the rainfall patterns of the study area. Use of annual rainfall totals to perform PCA tends to filter out seasonal characteristics (Ogallo, 1980), thus results from this study may not accurately represent the seasonal rainfall characteristics of the study region but give a general classification of areas that have the same annual rainfall characteristics.

Table 4: Statistical characteristics of annual rainfall in the study area

Factor	Percent of Total Variance
1	42.2
2	15.6
3	7.5
4	6.1
5	5.7
6	4.0

The spatial distribution of the RPCs are shown in Figure 9. The first component was dominant over the coast (zone 4) reflecting the interaction of the Indian Ocean and the local land/sea breeze circulations over this region. The second and third components were dominant over the highlands and southeastern lowlands (zones 8 and 5) respectively. These components depict the influence of high/ low topography on the rainfall patterns.

The fourth component was dominant over the Lake Basin (zone 9) reflecting the effect of the Lake Victoria on the rainfall patterns in this region. The fifth and sixth components were dominant over north east and north west (zones 3 and 1) respectively. These two regions are in the arid category and their spatial distribution reflects the effect of both topography on rainfall as well as the influence of the Turkana- Marsabit jet. Using the six RPCs and comparing the spatial distribution of the dominant PCA components as well as considering other factors, nine homogenous zones were derived as shown in Figure 10. These zones and their representative stations are shown in Table 5

The additional three zones (2, 6 and 7) that were not represented by the six RPCs were picked according to their annual rainfall amounts and altitude. Moyale and Marsabit could not be classified with Mandera, Wajir and Garissa because their altitude is 1110m and 1345m respectively compared to between 128-330m in Garissa Wajir and Mandera. The total annual rainfall for Moyale and Marsabit is 650 and 739mm respectively while those of Mandera, Wajir and Garissa range from 273 to 347mm. Zone 7 comprising of Meru, Embu, Nyeri, Dagoretti and Thika could not be grouped with Narok (zone 6) because its annual rainfall is 742mm compared with a range of 1463 to 1798mm in zone 7. Information on the altitude and annual rainfall totals of the stations can be obtained from table 2 in section 3(data and methods of analyses section).

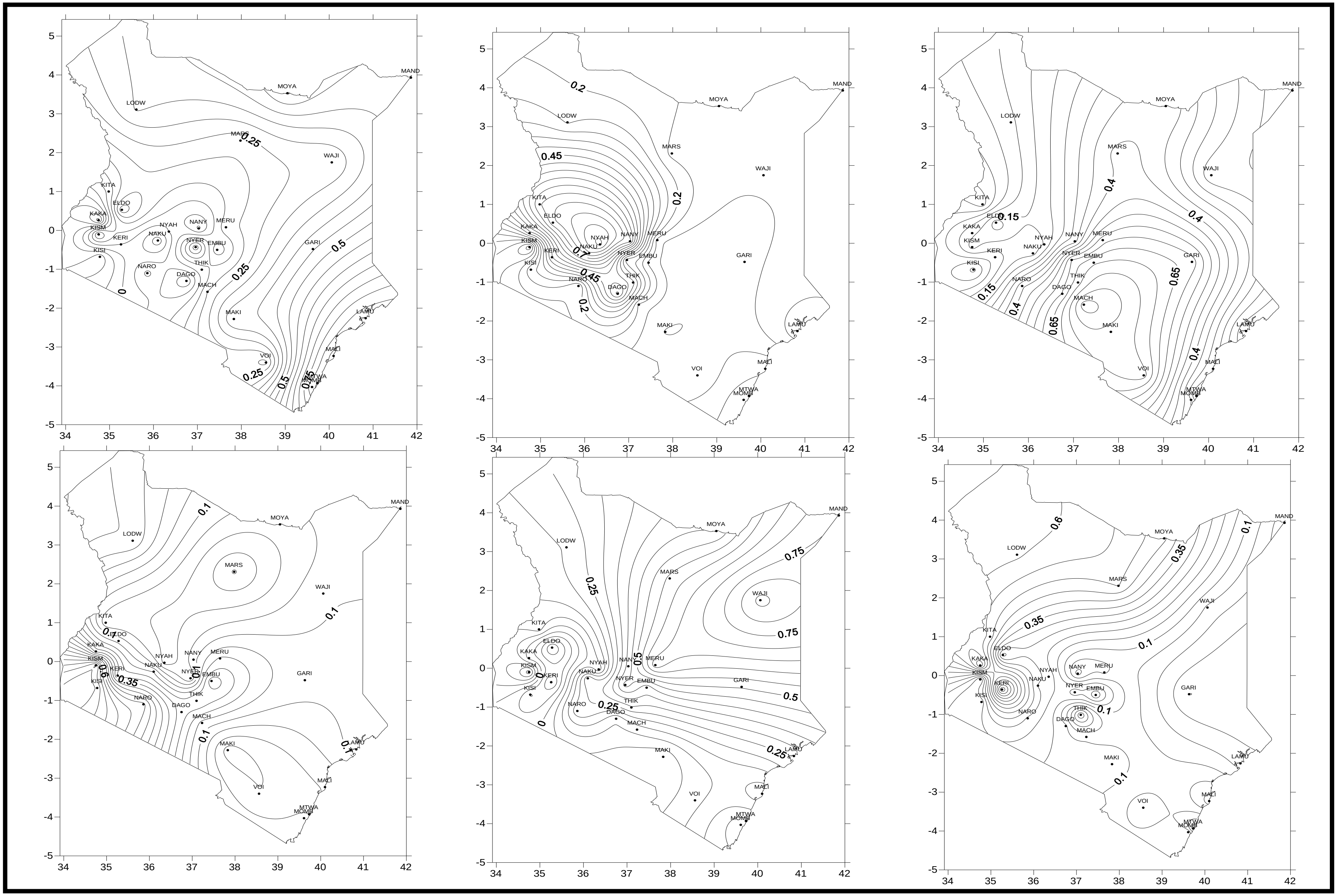

Figure 9: Spatial distribution of the First to Sixth Rotated Principal Components

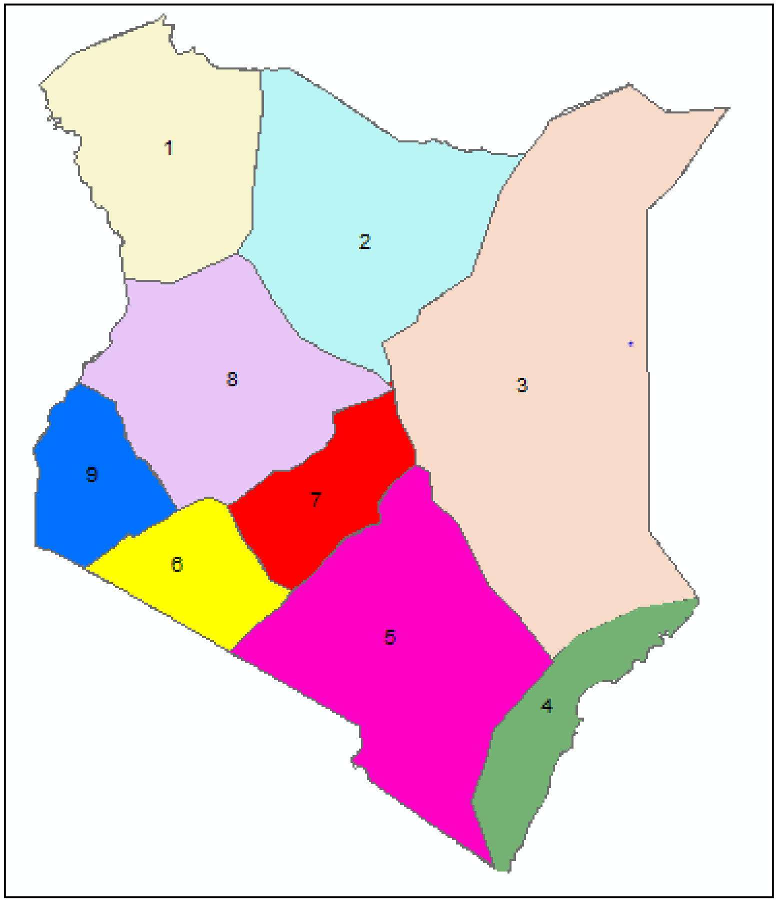

Figure 10: Homogenous zones of the twenty eight stations derived from the annual rainfall totals

Table 5: List of Homogenous zones with their representative stations

Zones	Stations	Factors squared	Representative station
Zone1	Lodwar	0.69	**Lodwar**
Zone 2	Moyale	0.85	**Moyale**
	Marsabit	0.82	
Zone 3	Garissa	0.88	
	Wajir	0.87	
	Mandera	0.78	
Zone 4	Malindi	0.87	**Malindi**
	Mombasa	0.86	
	Lamu	0.85	
	Mtwapa	0.81	
Zone 5	Machakos	0.87	**Machakos**
	Makindu	0.79	
	Voi	0.65	
Zone 6	Narok	0.62	**Narok**
Zone 7	Meru	0.89	**Meru**
	Thika	0.85	
	Embu	0.84	
	Nyeri	0.83	
	Dagoretti	0.78	
Zone 8	Nyahururu	0.92	**Nyahururu**
	Nakuru	0.83	
	Nanyuki	0.81	
	Kitale	0.79	
	Eldoret	0.76	
Zone 9	Kericho	0.88	**Kericho**
	Kakamega	0.81	
	Kisumu	0.80	
	Kisii	0.74	

4.2.1. Rainfall Characteristics

The characteristics described in this subsection include the variability and long term monthly mean of rainfall in the zones.

4.2.1.1. Coefficient of Variability.

The coefficient of variability (CV) of the zones showed that precipitation in the study area is highly variable both in space and time. Figures 11 shows the CV for the various zones.

Zone 1

This zone shows high rainfall variability with CV values ranging from 0.9 in the month of April to 2.5 in the month of September. Highest variation occurs between the months of June to February, with a slight reduction of variability in July and October, while the lowest is observed during the MAM season. This zone therefore experiences high variability throughout the year.

Zone 2

Rainfall in this zone is highly variable with the highest variability being observed in Marsabit over most of the months except July and August when Moyale has the highest variation. The CV values range from 0.5 in Moyale in the month of April to 2.0 in Marsabit in February. Highest variation occurs from May to February (excluding November). The lowest variation is seen in the months of April and November. Thus this zone is characterized by high rainfall variability most of the year.

Zone 3

In this zone Mandera meteorological station shows the highest rainfall variability with CV values ranging from 0.5 in April to 4.7 in February. Wajir and Garissa show more or less a similar pattern in rainfall variability as compared to Mandera. Highest variation occurs from January to March and again from May to October, while the lowest occurs in April and November. This zone therefore is characterized by high rainfall variability throughout the year except the peak months of April and November.

Zone 4

The variation of rainfall in this zone is not much across all the stations throughout the year except over Mtwapa which exhibits inconsistency in January and February. CV values range from 0.4 in Malindi Meteorological station in May to 3.4 in Lamu in January. Lamu shows the highest variation of rainfall throughout the year except February when the highest variation is observed in Mtwapa Meteorological station.

Zone 5

The highest variation in this zone is observed in Makindu Meteorological station throughout the year except in February when Voi shows the highest variation. CV values range from 0.4 in Machakos in April and November and 2.5 in Makindu in August. More variation is observed from June to October and in January and February as compared to MAM, November and December.

Zone 6

In this zone, rainfall varies highly throughout the year with CV values ranging from 0.5 in April to 1.1 in July. Highest variation occurs from June to February with a slight reduction in August and November. Lowest variation is observed during the MAM season, indicating that rainfall in this season varies highly throughout the year except during MAM.

Zone 7

This zone is characterized by an almost similar pattern in rainfall variability throughout the year except Nyeri and Embu which shows a different pattern in January and February and Dagoretti which exhibits a different pattern from May to October. Thika exhibits the highest variation throughout the year except in January, February, November and December when Dagoretti and Embu record the highest variability respectively. CV values range from 0.4 in Embu and Meru during the months of April and November to 1.7 in Embu in February. Less variation is observed during MAM and OND as compared to JJAS and the months of January and February.

Zone 8

Variation of rainfall among the stations in this zone is not much from the month of October to April except Nakuru which shows inconsistency in January and February. Nyahururu shows the highest variation in most of the months, except June to August when Nanyuki exhibits the highest variation. CV values range from 0.3 over Kitale in April, July and August to 1.5 over Nyahururu in January. Highest variation occurs in the months of January and February.

Zone 9

In this zone, Kisumu shows the highest variation throughout the year except in January and March when Kericho records the highest variation. CV values range from 0.3 to 0.6 throughout the year except the relatively dry months of January February and December when the CV values range from 0.7 to 0.9 in all the stations except Kisii which exhibits low variation below 0.6 throughout the year. This zone records the lowest rainfall variability across the study area.

In general, the highest rainfall variability is observed in the arid areas over the northern parts of the country, while the lowest variability is observed over the highlands, Coast and the Lake Basin. The variability is more pronounced during the dry months of January, February and from June to September in most of the zones except zone 9 which shows relatively low variability in JJAS. MAM and OND are characterized by generally low rainfall variability. However zones 1 and 3 shows high variability throughout the year except in April and November.

Figure 11: Coefficient of variability for the zones

4.2.1.2. Long Term Monthly Mean

The long term monthly mean of the zones are displayed in figure 12 and show the annual rainfall distribution across the study area.

Zone 1

This zone exhibits a tri modal rainfall distribution with a major peak during MAM and two minor peaks in JJAS and OND. The highest monthly rainfall above 38 millimeters (mm) is recorded in April, while the lowest amount less than 4mm being recorded in February.

Zone 2

A bimodal rainfall distribution is observed in this zone during MAM and OND with Marsabit recording both the highest and lowest amount of rainfall in April and September respectively. The period from June to September and January to February remain generally dry with monthly rainfall of less than 20mm.

Zone 3

This zone is characterized by a bimodal rainfall distribution with two wet seasons (MAM and OND) across all the stations. The highest monthly rainfall of about 100mm is recorded in Garissa during the month of November, while the lowest monthly rainfall of less than a millimeter is recorded in Mandera in the month of August.

Zone 4

The monthly patterns in this zone shows a tri modal rainfall distribution during MAM, JJA and OND. However, MAM is the major season in this zone with JJA and OND remaining relatively wet. The highest monthly rainfall of about 350mm is recorded in Mtwapa in the month of May, while the lowest monthly rainfall of 2mm is recorded in Lamu in the month of February. January and February remain generally dry with monthly rainfall of less than 30mm.

Zone 5

This zone is also characterized by two wet seasons (MAM and OND) and two dry seasons (JF and JJAS). However the OND season is more conspicuous than the MAM season. The highest monthly rainfall (160mm) is recorded in Makindu in November and the lowest monthly rainfall of less than a millimeter is recorded in Makindu in July.

Zone 6.

The monthly means in this zone show two wet seasons (MAM and OND) and one major dry season (JJAS). January and February are relatively wet compared to JJAS recording monthly rainfall of 79 and 69 mm respectively. The highest monthly rainfall above 130 mm is recorded in April, while the lowest monthly rainfall below 20 mm is recorded in July.

Zone 7

This zone is characterized by two wet seasons (MAM and OND) and two dry seasons (JF and JJAS). Meru records both the highest and lowest monthly rainfall above 300 mm in November and less than 15 mm in June and July.

Zone 8

Most of the months in this zone remain relatively wet throughout the year with monthly rainfall of above 40mm except January and February where rainfall is below 40mm across all the stations. However major rainfall seasons are observed in MAM, JJAS and OND even though Nanyuki and Nakuru records relatively low amounts during the JJA season. The highest monthly rainfall above 180mm is recorded in Kitale in April, while the lowest is recorded in Nanyuki in February (Less than 15mm).

Zone 9

This zone is characterized by wet conditions throughout the year with monthly rainfall amounts above 50mm. However, three major wet seasons are observed in MAM, JJAS and OND. The highest monthly rainfall above 160mm is recorded in Kakamega and Kisii in April, while the lowest is recorded in Kisumu in February(less than 65mm). In general Kisumu records the lowest monthly rainfall throughout the year.

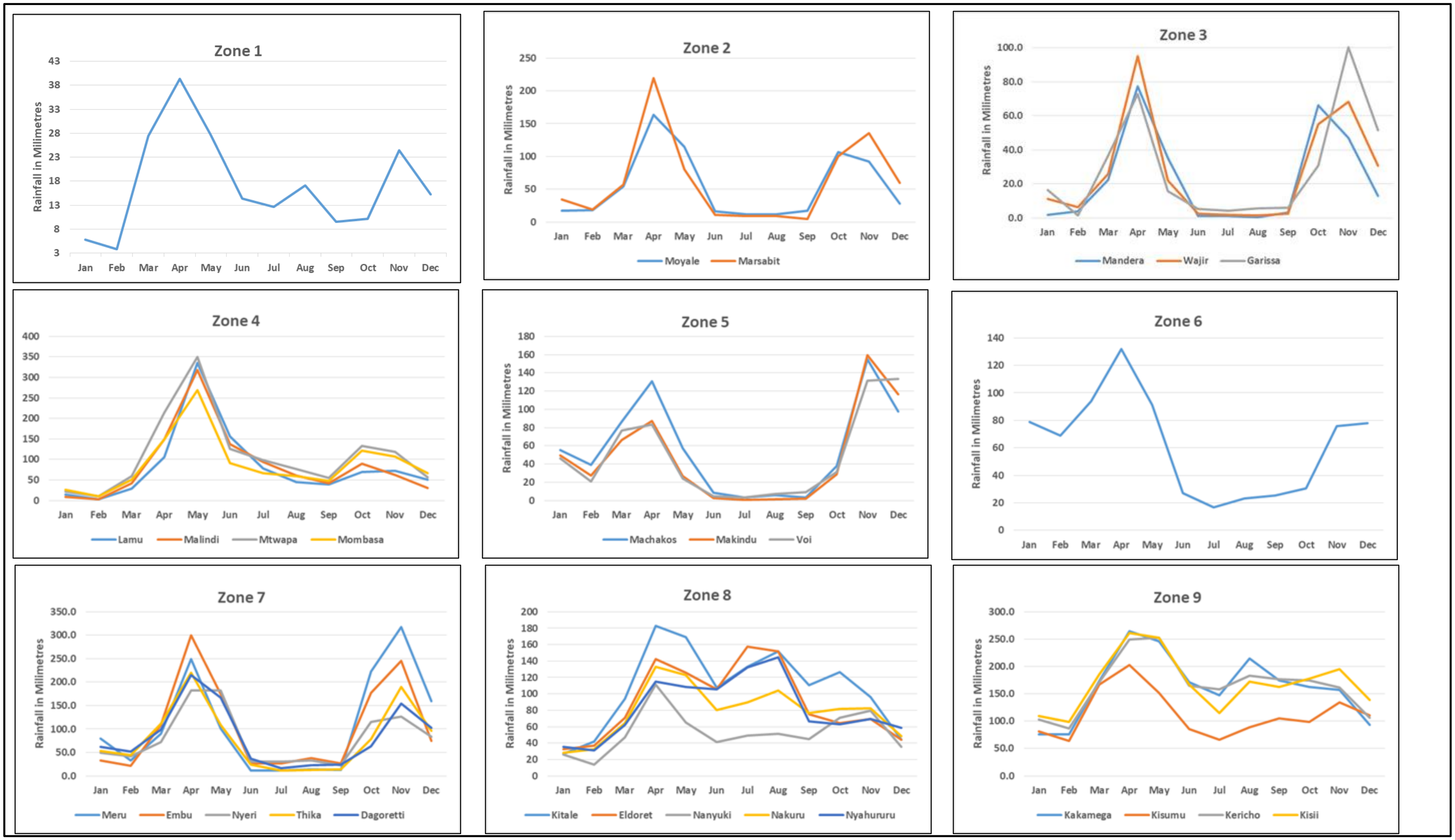

Figure 12: Monthly long term mean for the zones

The monthly long term means across the country depicts a bimodal rainfall distribution with two rainy seasons (MAM and OND) and two dry seasons (JF and JJAS) in most of the zones except zones 4, 8 and 9 which shows three wet seasons (MAM, JJAS and OND) and only one dry season in January and February. The peaks months in MAM and OND in most of the zones are April and November respectively, except in zone 4 where the peak months are realized in May and October. April, May and November are the wettest months in the country while February, June, July, August and September are the driest months. The highest monthly rainfall in the whole country is recorded in the month of May in zone 4(Mtwapa station with a LTM of 350mm). The lowest monthly rainfall is recorded in the month of August in zone 3 (Mandera station with a LTM of 0.6mm). Zone 1 shows the lowest monthly rainfall totals ranging from 4mm in February to less than 40mm in April. Zone 9 records the highest monthly rainfall totals ranging from 64 mm in Kisumu during the month of February to 265 mm in Kakamega during the month of April.

4.3 Droughts Characteristics as Measured by the CDI

This section describes results obtained from calculation of CDI which include weighting, drought characteristics and drought relative frequency.

4.3.1. Weighting

Results from the twelve models that were assigned different weightings indicated that the model that assigned temperature the highest weighting had the lowest CV (2 and 7), while those that assigned rainfall the highest weighting had the highest CV (1, 4 and 5). Relative humidity also affected the outcome and in general models that assigned relatively higher weightings to relative humidity also had low CV but not as low as those that assigned temperature more weighting (3 and 9). Models 2 and 7 had the lowest CV value of 0.32 and since temperature contributed most to low CV followed by relative humidity, model 7 was picked for CDI computations with a weight of 0.2, 0.5 and 0.3 for rainfall, temperature and relative humidity respectively. The results of the weighting are displayed in Table 6.

Table 6: Results from different models used for weighting

Model	Rainfall	Temperature	Relative humidity	CV
1	0.6	0.2	0.2	0.62
2	0.2	0.6	0.2	0.32
3	0.2	0.2	0.6	0.34
4	0.5	0.3	0.2	0.54
5	0.5	0.2	0.3	0.54
6	0.3	0.5	0.2	0.39
7	0.2	0.5	0.3	0.32
8	0.3	0.2	0.5	0.40
9	0.2	0.3	0.5	0.33
10	0.4	0.3	0.3	0.46
11	0.3	0.4	0.3	0.39
12	0.3	0.3	0.4	0.39

4.3.2. Drought characteristics

Results from CDI computations displayed in figures 13 to 21 shows that CDI is able to capture the various drought categories as well as climate variability and especially variability in rainfall. The high CDI values in all the zones correspond to extremely wet periods while the very low values corresponds to extremely dry periods such as those associated with El Nino and La Nina respectively.

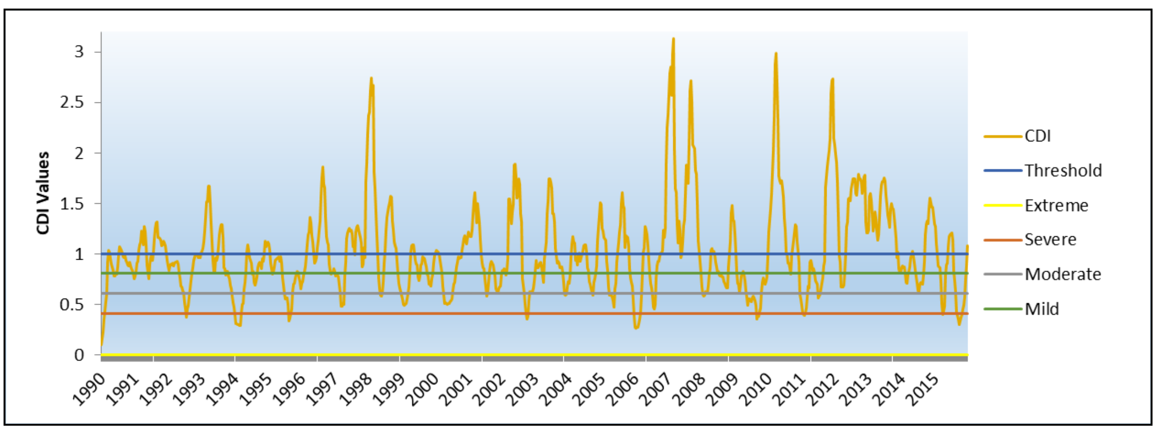

Figure 13: CDI Time series for Lodwar

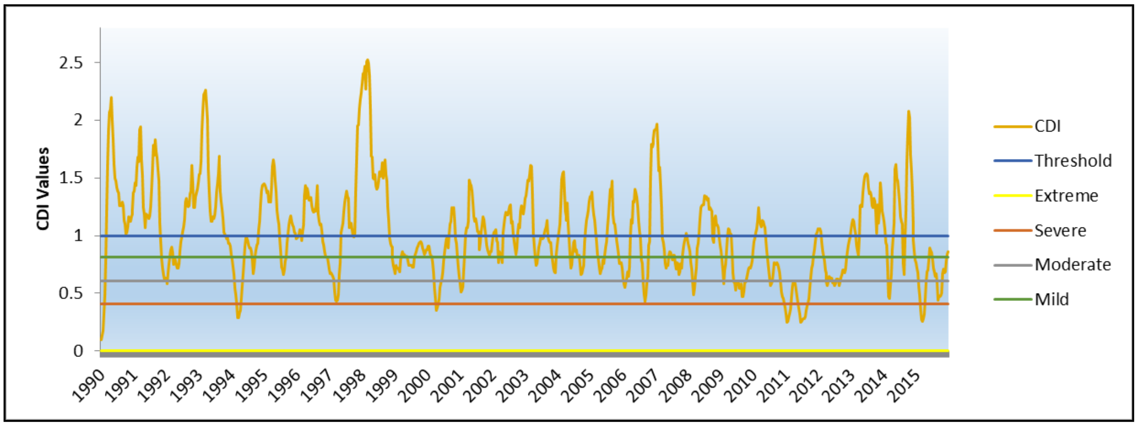

Figure 14: CDI Time series for Moyale

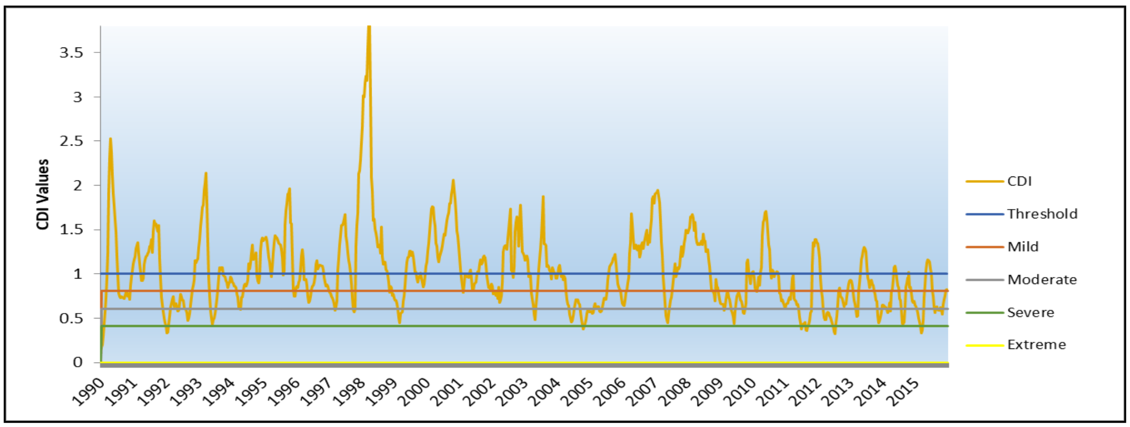

Figure 15: CDI Time series for Garissa

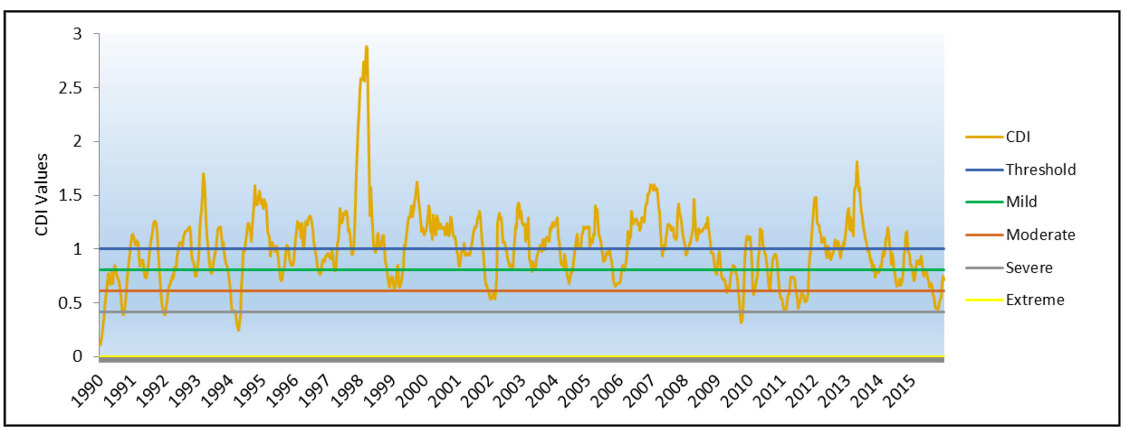

Figure 16: CDI Time series for Malindi

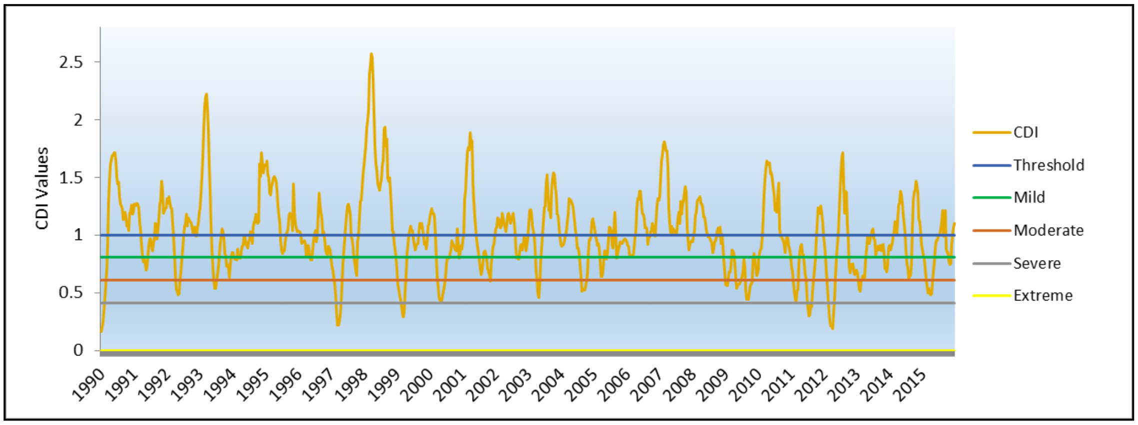

Figure 17: CDI Time series for Machakos

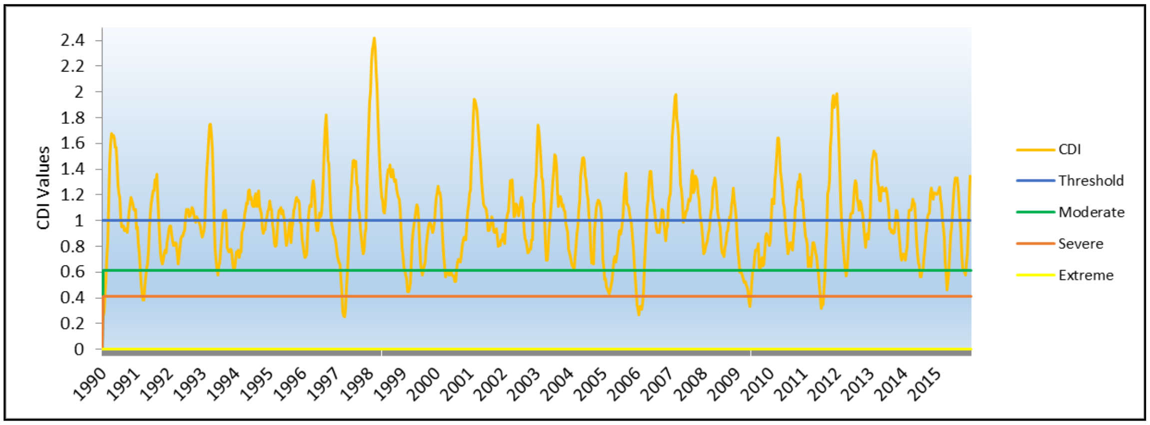

Figure 18: CDI Time series for Narok

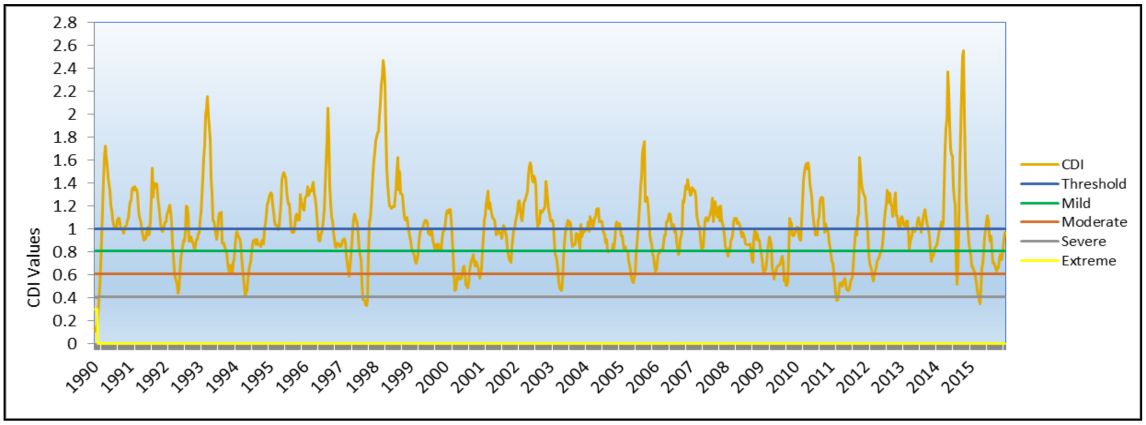

Figure 19: CDI Time series for Meru

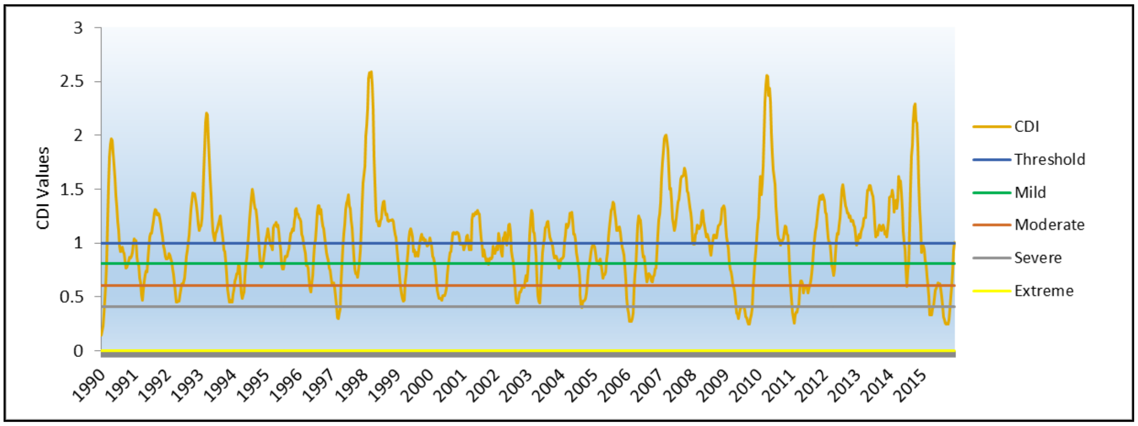

Figure 20: CDI Time series for Nyahururu

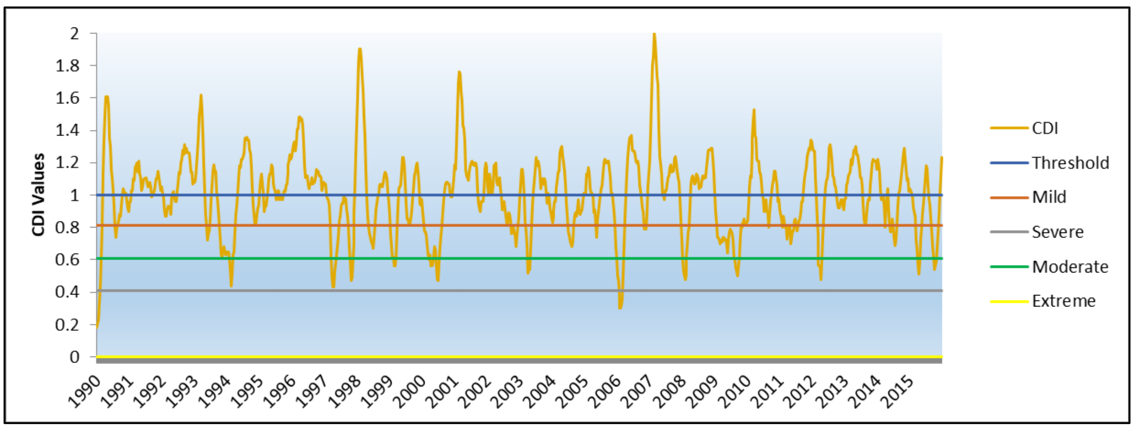

Figure 21: CDI Time series for Kericho

Table 7 shows the number of dekads that were affected by each drought category and the total number of dekads affected by droughts throughout the study period. From the table, it is evident that most parts of the country are affected mainly by mild droughts except zone three which experiences mild and moderate droughts almost equally at 186 and 188 dekads respectively. Most of the zones experienced drought more than half of the period under study (more than 450 dekads) except zones 4, 8 and 9. The highest drought prevalence was recorded in zone 1 with 521 out of 900 dekads of droughts throughout the study period, while the lowest drought prevalence was recorded in zone 9 with 424 dekads of droughts recorded during the study period.

Table 7: Summary of droughts in the study area

Zones	Mild	Moderate	Severe	Extreme	Total Number of dekads affected by droughts
1	222	174	94	31	521
2	202	182	80	31	495
3	186	188	116	10	500
4	219	150	58	11	438
5	267	139	70	20	496
6	208	173	59	18	458
7	263	138	59	10	470
8	169	127	93	44	433
9	242	128	49	5	424

The spatial distribution of the various categories of droughts is displayed in figure 22. From the figure, the lowest prevalence of the mild category is around zone eight represented by Nyahururu, while the highest prevalence is in zones five and seven represented by Machakos and Meru respectively. In the moderate category, the Lake basin and the highlands (zones nine, eight and seven) represented by Kericho, Nyahururu and Meru respectively record the lowest prevalence while the highest prevalence is over the northeastern parts of the country (zones two and three) represented by Moyale and Garissa respectively. Zone nine represented by Kericho records the lowest incidences of the severe category and zone three represented by Garissa records the highest incidences. In the extreme category, the lowest occurrence is recorded in zone nine represented by Kericho, while the highest occurrence is recorded in zone eight represented by Nyahururu.

In general, zone nine represented by Kericho records the lowest incidences of most of the drought categories except the mild category which is lowest in zone eight represented by Nyahururu. It is important to note that even though zone eight reports the lowest incidences of the mild and drought categories, it experiences the highest incidences of the most devastating drought category (extreme). This should be of concern because this zone is in the food basket of the country hence occurrence of extreme droughts in this region can have adverse effects on food security. Even though zone one experiences the highest number of dekads affected by droughts (Table 7), the individual drought categories tend to occur moderately over this region.

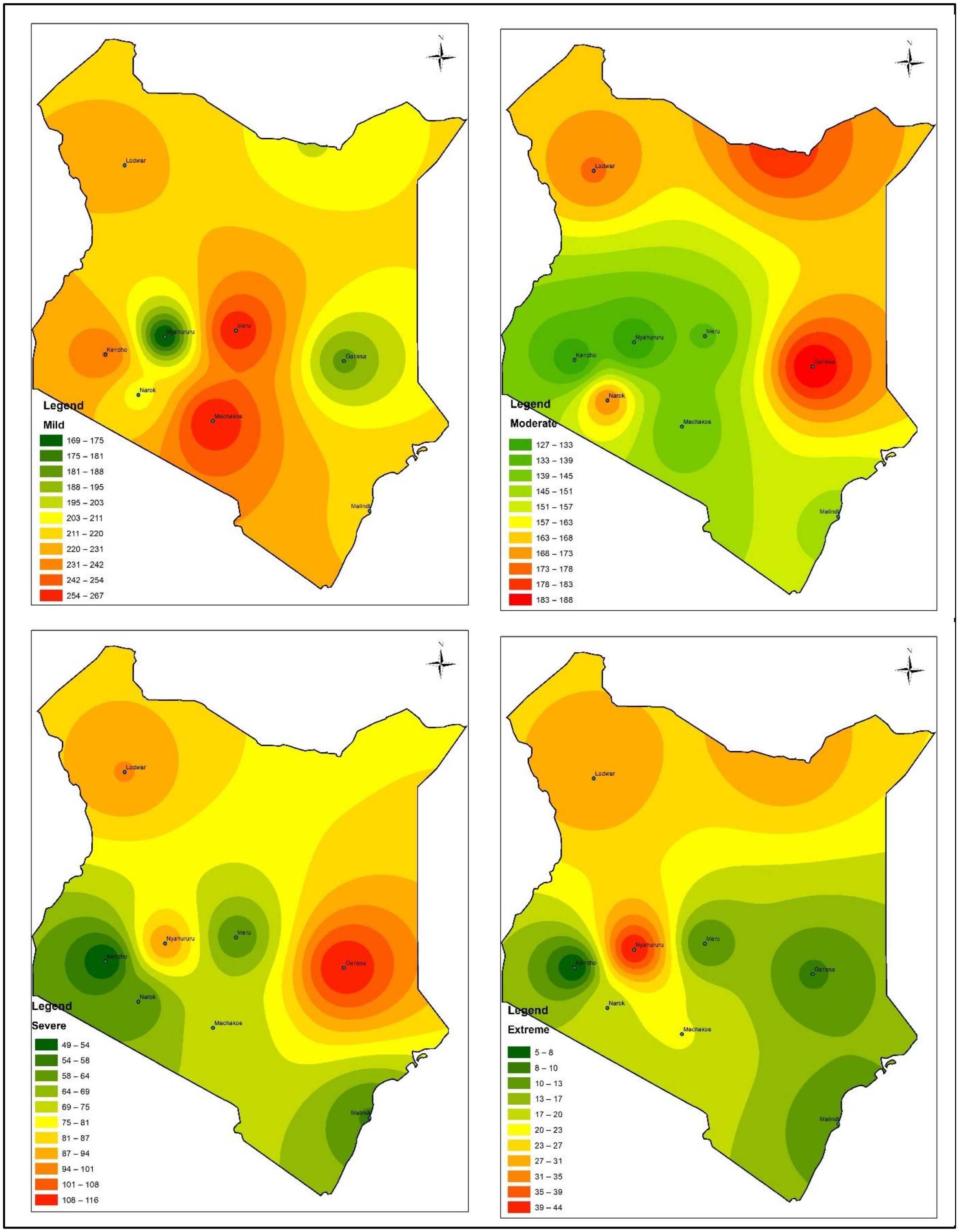

Figure 22: Spatial distribution of Mild to Extreme categories of droughts

Table 8 shows how droughts are spread out within the zones in different seasons of the year.

In zone 1, the prevalent drought category in most of the seasons is the mild category with above 40% except in JJA where moderate droughts prevail at 40%. Moderate to extreme droughts during this season accounts for 66%, implying more severe droughts during the JJA than in any of the other seasons.

In zone 2, the mild category dominates in all the seasons with above 40% except MAM where moderate droughts dominate at 37% with the mild category accounting for 30%. Moderate to extreme droughts during this season is at 70%, showing that this zone is prone to more severe droughts during the MAM season.

In zone 3, the mild category is dominant during the SON and DJF seasons with 44 and 40% respectively. In MAM and JJA, the moderate category prevails at 40 and 35% respectively. The moderate to extreme droughts in MAM and JJA account for 68% showing more severe droughts during these seasons.

In zone 4, mild droughts are dominant in MAM, SON and DJF at 53, 58 and 43% respectively. In JJA the moderate category dominates at 47% with the mild category following at 46%. However, more severe droughts are experienced during DJF as the moderate to extreme droughts take up 57% of all the droughts.

Mild droughts are dominant in **zone 5** in all the seasons accounting for above 50% of the drought categories except MAM which takes up 38%. The moderate to extreme drought categories however take the highest percentage (62) in MAM indicating that droughts are more severe in MAM. Mild droughts are more dominant in **zone 6** in most of the seasons ranging from 45% in JJA, 46% in DJF and 59% in SON. However, in MAM moderate droughts prevail at 36% with the mild category at 31%. Moderate to extreme droughts take up 69% during MAM in this zone, implying the severity of droughts is more pronounced in MAM than in any seasons in this zone.

In zone 7, mild droughts prevail in all the seasons with a higher percentage (above 60) except in MAM where mild droughts account for 36%. Even though the mild droughts are dominant, the moderate and severe droughts also take a big percentage of the total droughts experienced during this season at 31% and 30% respectively. Drought are more severe in this season as moderate to extreme droughts account for 64%.

In zone 8, the mild category dominates in DJF (59%), SON (40%) and JJA (38%). In MAM the moderate category prevails at 36% with the severe category following closely at 34%. The moderate to extreme droughts during MAM accounts for 81%, the highest in the country. This zone records the highest percentage of severe droughts (34% during MAM) and the highest percentage of extreme droughts (14% during SON).

In zone 9, the mild drought category prevails in most of the seasons with a higher percentage (above 60%), except during MAM where moderate droughts prevail at 48% with the mild category at 36%. Moderate to extreme droughts account for 48%, the lowest in the country.

In general, even though most of the zones experiences mainly mild droughts in most of the seasons, the severity of these droughts is more pronounced in MAM than in any other season. Moderate to extreme droughts are more in MAM in most zones except zones 1and 4 which have more moderate to extreme droughts in JJA and DJF respectively. Zone 8 experiences the highest moderate to extreme droughts at 81% during the MAM season, while zone 4 experiences the lowest moderate to extreme droughts at 47% during the same season.

Table 8: Seasonal Analysis of Droughts in the zones

Zone	Season	Mild (%)	Moderate (%)	Severe (%)	Extreme (%)
1	**MAM**	48	27	23	2
	JJA	34	40	24	2
	SON	47	35	9	9
	DJF	42	31	16	
2	**MAM**	30	37	21	12
	JJA	42	36	15	7
	SON	48	37	15	0
	DJF	43	38	13	6
3	**MAM**	32	40	27	1
	JJA	32	35	29	4
	SON	44	31	23	2
	DJF	40	42	17	1
4	**MAM**	53	35	7	5
	JJA	46	47	7	0
	SON	58	23	16	3
	DJF	43	33	22	2
5	**MAM**	38	28	23	11
	JJA	59	28	9	4
	SON	61	29	10	0
	DJF	58	27	14	1
6	**MAM**	31	36	28	9
	JJA	45	34	18	3
	SON	59	40	1	0
	DJF	46	40	9	5
7	**MAM**	36	31	30	3
	JJA	64	23	12	1
	SON	60	30	6	4
	DJF	64	33	3	0
8	**MAM**	19	36	34	11
	JJA	38	33	22	7
	SON	40	27	19	14
	DJF	59	22	10	9
9	**MAM**	36	43	20	1
	JJA	64	30	6	0
	SON	65	25	10	0
	DJF	65	22	9	4

4.3.3 Drought Relative Frequency

The relative frequency of droughts in the region vary from one category to another and from one zone to the other. Table 9 shows the relative frequency in percentage for each drought category in each zone. The highest relative frequency is observed in the mild category, while the lowest is in the extreme category. In the mild category, the relative frequency is below 50% in most of the zones except zones 9, 7, 5 and 4 which are at 57, 56, 53 and 50% respectively. The lowest in this category is observed in zone 3 at 37%. In the moderate category, the relative frequency ranges from 29 to 38% with zone 3 recording the highest frequency at 38% while zones 5, 7 and 8 recording the lowest at 29% each. In the severe category the relative frequency is below 20% in most of the zones except zones 3 and 8 which have a relative frequency of 23 and 22% respectively. The relative frequency in the extreme category is below 10% in most of the zones except zone 8 which is at 10%. From the table it is clear that even though the country is mainly affected by mild droughts, the more severe categories take a higher percentage with more than half of the country having relative frequency above 50% in the moderate to extreme droughts.

Table 9: Relative Frequency of Droughts in the study area

Zones	Mild (%)	Moderate (%)	Severe (%)	Extreme (%)
1	43	33	18	6
2	41	37	16	6
3	37	38	23	2
4	50	34	13	3
5	53	29	14	4
6	45	38	13	4
7	56	29	13	2
8	39	29	22	10
9	57	30	12	2

4.3.4 Comparison of Droughts Computed by CDI with Previous Drought Reports in the Study Area

A comparison of the droughts computed by CDI and drought reports in the country showed some similarity. Table 10 gives a summary of the areas that were affected by droughts for more than half of the year from 1991 to 2015. Table 11 gives a history of the incidences of droughts in the country. From the two tables, the years 1992 -1994, 1996, 2004, 1999-2000 and 2011 were adversely affected by droughts. The differences in both the temporal and spatial droughts between the CDI droughts and previous drought reports in the country are due to the fact that droughts in the country are only documented when they become a national disaster and also because droughts in these reports are quantified through their associated impacts which vary from one region to the other. On the other hand, CDI detects droughts as soon as they start to occur and uses values to quantify droughts. An example of these differences is in 2009 when the CDI captured droughts all over the country but the report from the government did not include this year as one of the worst years affected by droughts.

Table 10: Summary of areas affected by droughts more than half of the year

Year	Regions affected
1991	Coast and Rift valley
1992	Widespread except northeast and southeast
1993	Widespread except central
1994	Widespread except zones coast and south rift valley
1996	Widespread except coast, south rift valley and central Kenya
1997	Widespread except the northern and coast
1999	Widespread except Coast
2000	Widespread except coast and parts of northeast (zone 3)
2001	Widespread except south Rift Valley and parts of northeast (zone 2)
2002	Northwest, Coast and Rift Valley
2003	Northwest, Coast, Central and north Rift Valley
2004	Widespread except central Kenya and south rift valley
2005	Widespread except northeast, southeast and coast)
2006	Widespread except Coast, southeast and northeast
2008	Northwest and central Kenya
2009	Widespread (All zones)
2010	Coast and parts of northeast (zone 2)
2011	Widespread (All zones)
2012	Widespread except northwest and Rift valley)
2013	Northeast and Southeast
2014	Northern, Coast and South Rift Valley
2015	Widespread (All Zones)

Table 11: History of drought incidences in Kenya (1980-2011)

Year	**Region**	**Remarks**
1980	Widespread	40,000 people affected
1983/1984	Central, Rift Valley eastern and northeastern	Severe food shortages in eastern province and less in central
1987	Eastern and central province	4.7 million people dependent on relief power and water rationing
1991/1992	Northeastern, Valley eastern and coast provinces	1.5 million people affected
1993/1994	Northern, central and eastern provinces	
1995/1996	Widespread	1.41 million people affected
1997	Northern parts of the country	2 million people affected
1999/2000	Countrywide except west and coast provinces	4.4 million people affected (worst drought in 37 years)
2004	Widespread	2.3 million people affected
2005	Northern parts of Kenya	2.5 million people affected
2010/2011	Widespread	3.5 million people affected

Source: Republic of Kenya (2004), Republic of Kenya (2011)

4.3.5 Severity of Droughts Computed by CDI

Table 12 shows that drought severity in most of the zones have been increasing over the years except the period between 2001 to 2005 when the number of moderate to extreme droughts decreased all over the country except zones 3 and 4 which recorded the least number of moderate to extreme droughts in the period 1996 to 2000. The highest number of moderate to extreme droughts was recorded from 2011 to 2015 in most of the zones except zones` 6, 9 and 1 which recorded their highest number of moderate to extreme droughts in the period 1996 to 2000 and 2006 to 2010 respectively.

Table 12: Number of moderate to extreme droughts per 5 year period

Zones	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
1	59	58	58	71	53
2	37	46	31	84	95
3	52	32	63	54	113
4	45	22	28	51	73
5	29	44	36	36	82
6	47	60	41	49	55
7	29	49	27	34	67
8	50	53	48	52	61
9	21	50	22	44	40

4.4 Developing a Drought Forecast Model.

The results discussed in this subsection include results from model selection, fitting, diagnostic and forecasting.

4.4.1 Model Selection.

The CDI time series were examined by use of ACF plots to check for stationarity, seasonality, trend, and also to determine the appropriate model to represent the CDI series. The model order was determined using PACF plots. The results are discussed below with corresponding ACF and PACF plots shown in figures 23 and 24 respectively.

The results for stationarity analysis from the ACF plots showed that the series were stationary as R_k tapered off rapidly indicating that none of the roots of the characteristic equation was close to the boundary of the unit circle. (Box and Jenkins, 1976). Only a few values of r_k (up to lag 7) are significantly different from zero depicting a short term correlation among the r_{ks} and hence stationarity. (Chatfield, 2000). Most of the ACF values are within the red dotted line indicating that the local mean is not changing and hence stationarity (Chatfield, 2000). The plot did not show any evidence of seasonality as there were no large positive values of r_k at any point during the whole length of the CDI series. Finally, there were no systematic trend as the correlogram came down to zero at lag 6 in most of the zones except zone 2 (Moyale) where it came down at lag 7. In a series with trend the correlogram comes down to zero at high lags (more than half the length of the series). The SACF plots decayed rapidly with a mixture of exponential and sine waves indicating an AR (p) model. The SPACF plots indicated that the SPACF had significant spikes up to lag 10 for some stations and lag 11 for others indicating an AR model of order 10 and 11 respectively.

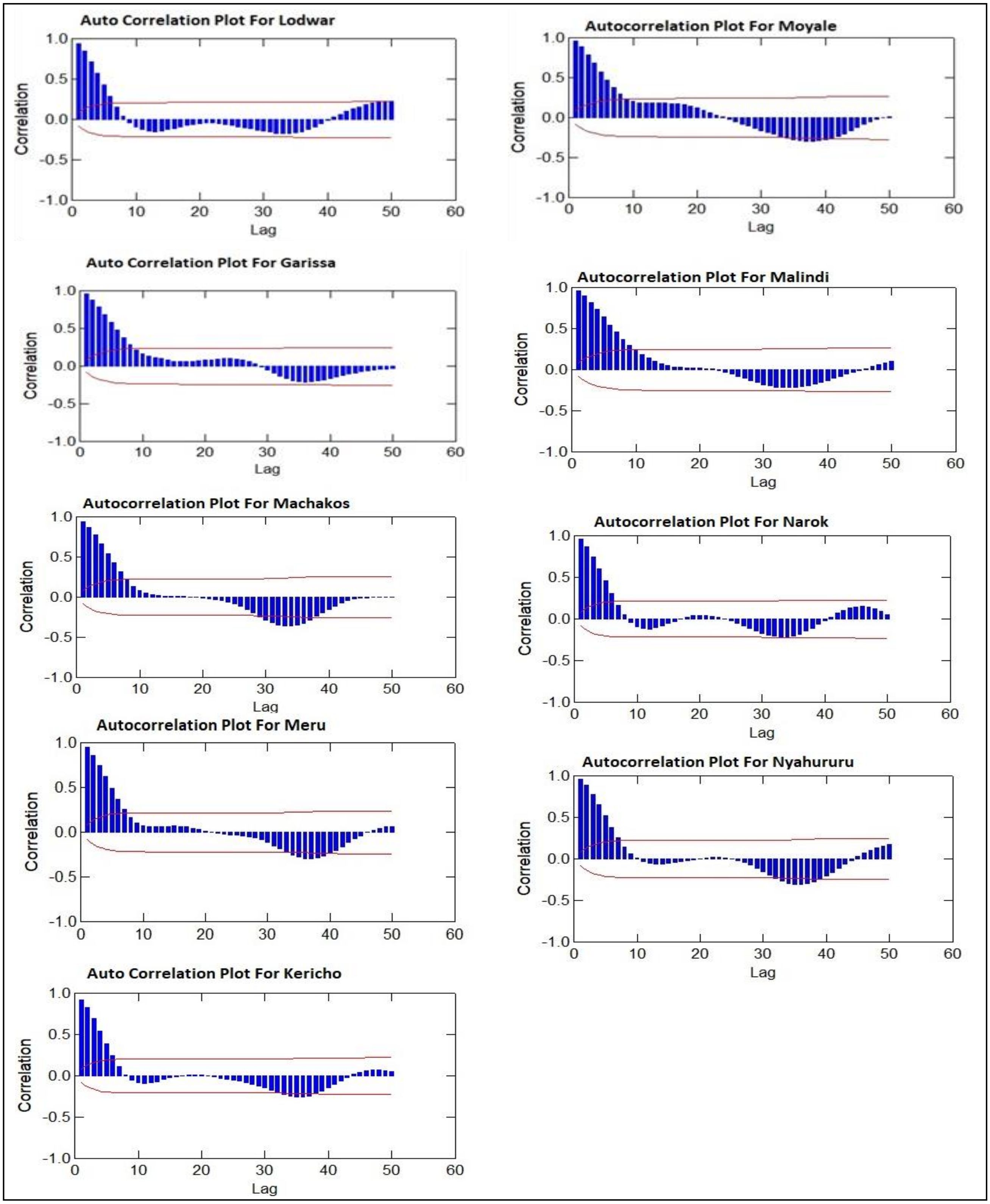

Figure 23: Auto Correlation Function for the Zones

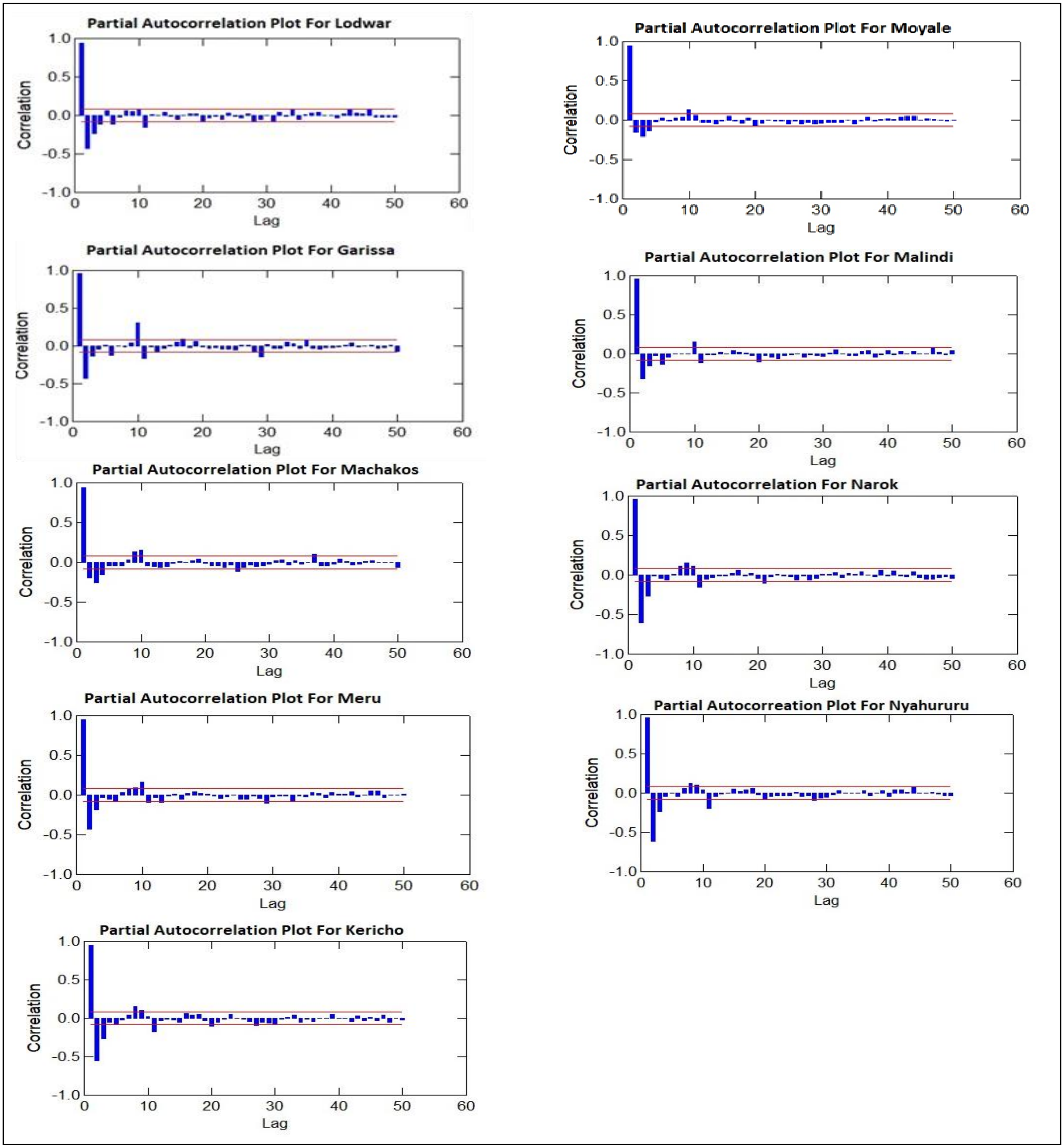

Figure 24: Partial Auto Correlation Function for the zones

4.4.2 Model Fitting

After determining the type and order of the model, model parameters were estimated using the least squares method. The statistical analysis of the parameters for each zone are shown in Table 13. The estimates that were selected to fit the model were those whose P value was less than or equal to 0.05 and whose standard errors were less than the model values. In most of the zones, the first three parameters and one of the last three parameters (7, 8 or 9) were used to fit the model implying that the first three dekads and one of the last three dekads in a season may play a role in drought development and cessation.

Table 13: Statistical analysis of parameters used to fit the models in the zones

Zone/Station	Model Parameter	Parameter Values	Standard Error	T-Stat	P-Value
Lodwar	A0	0.0849	0.0146	5.8049	0.0000
	A1	1.2711	0.0400	31.7526	0.0000
	A3	-0.2618	0.0609	-4.2984	0.0000
	A5	0.1629	0.0614	2.6554	0.0081
	A7	-0.1464	0.0614	-2.3849	0.0174
	A10	-0.2407	0.0606	-3.9683	0.0001
	A11	0.5872	0.0614	9.5668	0.0000
Moyale	A0	0.0406	0.0123	-7.1276	0.0000
	A1	1.2969	0.0399	3.3003	0.0010
	A2	-0.1537	0.0661	32.4707	0.0000
	A3	-0.1674	0.0665	-2.3273	0.0203
	A9	-0.2857	0.0661	-2.5189	0.0120
	A10	0.2739	0.0393	-4.3201	0.0000
Garissa	A0	0.0633	0.0140	4.5317	0.0000
	A1	1.3698	0.0408	33.5746	0.0000
	A2	-0.3442	0.0661	-5.2057	0.0000
	A9	-0.4113	0.0652	-6.3064	0.0000
	A10	0.5471	0.0657	8.3246	0.0000
	A11	-0.1886	0.0399	-4.7266	0.0000
Malindi	A0	0.0673	0.0133	5.0506	0.0000
	A1	1.2673	0.0412	30.7540	0.0000
	A2	-0.1957	0.0653	-2.9965	0.0028
	A3	-0.1737	0.0650	-2.6705	0.0078
	A9	-0.2505	0.0651	-3.8466	0.0001
	A10	0.3456	0.0654	5.2830	0.0000
	A11	-0.1261	0.0411	-3.0708	0.0022
Machakos	A0	0.0621	0.0135	4.5998	0.0000
	A1	1.2521	0.0412	30.3619	0.0000
	A3	-0.1925	0.0647	-2.9738	0.0031
	A8	-0.1274	0.0650	-1.9607	0.0504
Narok	A0	0.0597	0.0115	5.1858	0.0000
	A1	1.4404	0.0405	35.5605	0.0000
	A2	-0.2406	0.0694	-3.4664	0.0006
	A3	-0.3160	0.0698	-4.5269	0.0000
	A8	-0.1714	0.0704	-2.4341	0.0152
	A10	0.4876	0.0690	7.0693	0.0000
	A11	-0.2295	0.0401	-5.7275	0.0000
Meru	A0	0.0583	0.0145	4.0270	0.0001
	A1	1.3038	0.0408	31.9281	0.0000
	A2	-0.2330	0.0676	-3.4477	0.0006
	A3	-0.1712	0.0683	-2.5062	0.0125
	A9	-0.1350	0.0677	-1.9931	0.0467
	A10	0.1753	0.0405	4.3257	0.0000
Nyahururu	A0	0.0538	0.0094	5.7334	0.0000
	A1	1.4875	0.0399	37.2866	0.0000
	A2	-0.3161	0.0711	-4.4472	0.0000
	A3	-0.2013	0.0723	-2.7852	0.0055
	A8	-0.1593	0.0726	-2.1961	0.0285
	A10	0.4663	0.0710	6.5633	0.0000
	A11	-0.2857	0.0394	-7.2524	0.0000
Kericho	A0	0.0741	0.0118	6.2544	0.0000
	A1	1.4015	0.0396	35.4355	0.0000
	A2	-0.2056	0.0682	-3.0151	0.0027
	A3	-0.2637	0.0687	-3.8395	0.0001
	A7	-0.1617	0.0690	-2.3438	0.0194
	A10	0.4299	0.0680	6.3228	0.0000

4.4.3 Model Diagnostics

After the models were fitted, the NSE and graphical residual examination were used to check if the models were adequate or not. The NSE for both the training and validation periods were computed and compared to check if there was consistency among the two. The higher the NSE and the lower the disparity between the training and validation sets, the more adequate the model. Table 14 below shows that the NSE for both the training and validation period was high and the two did not have a large variation indicating the models were adequate.

Table 14: Nash-Sutcliffe Model Efficiency coefficient for training and validation

Zone	**Nash Sutcliffe model efficiency coefficient For Training**	**Nash Sutcliffe model efficiency coefficient For Validation**
1	0.935	0.935
2	0.956	0.945
3	0.948	0.942
4	0.927	0.937
5	0.939	0.923
6	0.957	0.949
7	0.936	0.905
8	0.853	0.869
9	0.964	0.958

The plots of RACF and RPACF **(**Figure 25) showed that there was no significant correlation among the residuals as most of the values in most zones were within the confidence intervals (red line). Only a few values appeared large compared to the confidence intervals and this is expected in large lags. This indicates that the models were adequate. The plots of residuals against fitted values (figure 26) showed that most of the residuals are evenly distributed around the mean indicating that the models were adequate.

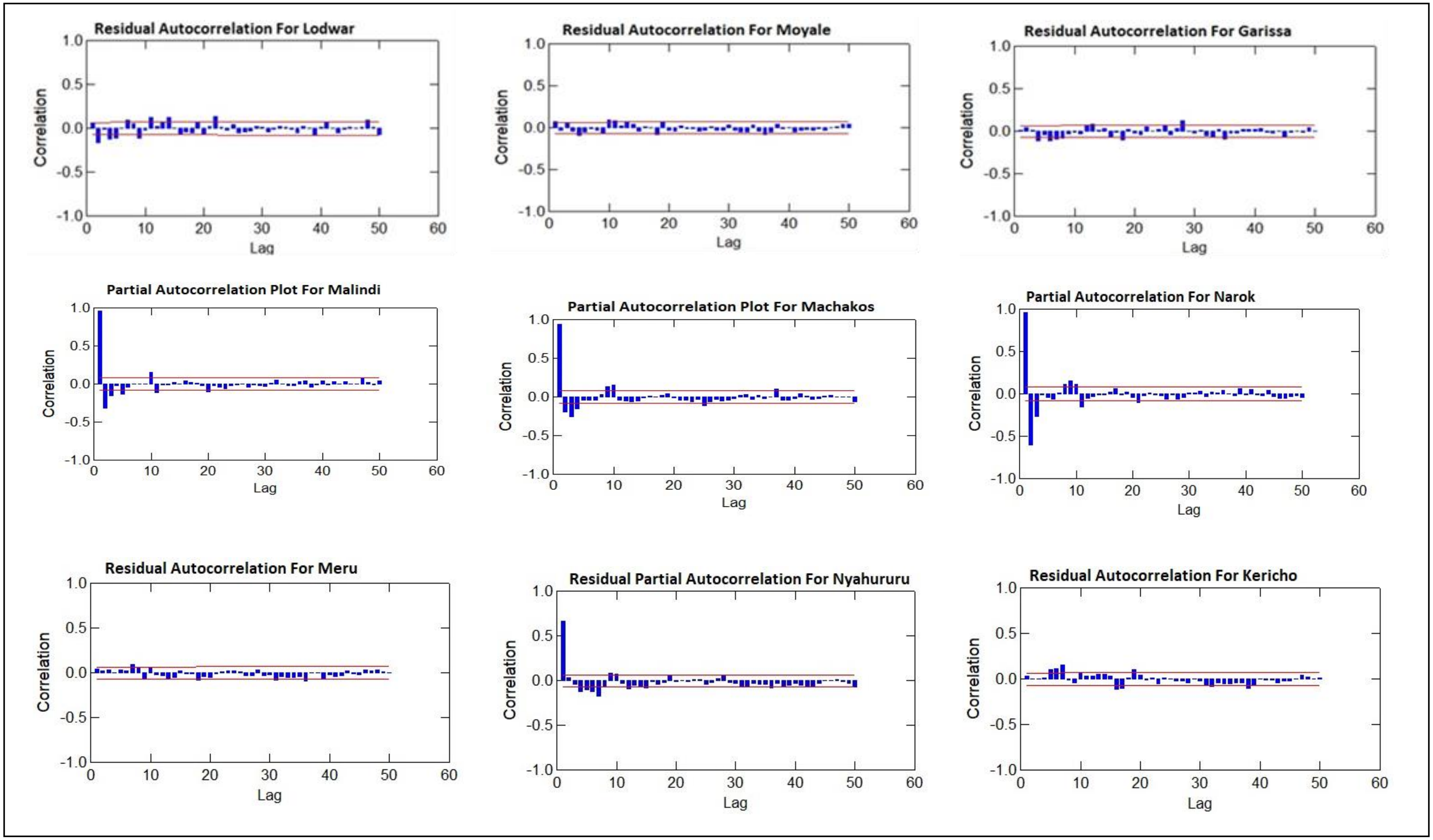

Figure 25: Residual Auto Correlation Function and Partial Auto Correlation Function for the zones

Figure 26: Plots of residuals against fitted values for the zones

4.4.4 Forecasting Droughts and Evaluating Forecasts Accuracy

After ascertaining that the model was adequate, forecasts at every lead were produced as discussed in section three above. The model produced forecasts at eleven leads but only nine leads are displayed in the results because after lead nine, the model started a new cycle that was similar to the first cycle from leads ten and eleven. Thus it was concluded that the model could forecast droughts up to lead nine which marks the end of the season. From the high values of R squared in Table 15, it is seen that the model could predict droughts with reasonable accuracy. The table shows an almost similar pattern in all the zones where the value of R squared in lead one decreases and picks in lead two and remains constant from leads 3 to 8 in most zones and reduces again in lead 9. However in zones 5, 6 and 9, the R squared starts decreasing in lead 7 and 8 respectively. This implies that the developed model's ability in predicting the onset of droughts may not be as good as compared to when the drought sets in.

Table 15: R squared for the nine leads in the zones

Zone	Lead 0	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5	Lead 6	Lead 7	Lead 8	Lead 9
1	0.94	0.86	0.86	0.93	0.93	0.93	0.93	0.93	0.93	0.78
2	0.96	0.92	0.94	0.95	0.95	0.95	0.95	0.95	0.95	0.85
3	0.85	0.81	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.62
4	0.93	0.86	0.90	0.91	0.91	0.91	0.91	0.91	0.91	0.78
5	0.94	0.93	0.94	0.94	0.94	0.94	0.94	0.94	0.92	0.87
6	0.95	0.80	0.90	0.92	0.92	0.92	0.92	0.92	0.80	0.80
7	0.97	0.82	0.93	0.98	0.98	0.98	0.98	0.98	0.98	0.95
8	0.98	0.93	0.98	0.97	0.97	0.97	0.97	0.97	0.92	0.91
9	0.96	0.85	0.93	0.96	0.96	0.96	0.96	0.90	0.90	0.90

The contingency tables show that in most of the zones, the model is able to forecast most of the drought categories with relatively high hits and low alarms at the beginning of a season. At the end of the season, the model predicts the severe and extreme categories with relatively low hits but is good at the other categories both at the beginning and at the end of the season. (Tables 16 and 17) as examples. However, in some zones (zone 4 and 5), the model is only able to predict the no drought category with high hits and low alarms both at the beginning and end of the season. For all the other categories, the model predicts with low hits and high alarms. (Tables 18 and 19) as examples.

Table 16: Contingency Table for Nyahururu lead 1

		FORECASTS					
		NO	MILD	MODERATE	SEVERE	EXTREME	TOTAL
OBSERVATIONS	NO	455	20	0	0	0	475
	MILD	69	113	5	0	0	187
	MODERATE	2	48	69	5	0	124
	SEVERE	0	0	29	60	7	96
	EXTREME	0	0	1	18	24	43
	TOTAL	526	181	104	83	31	925
	PERCENT CORRECT	77.9	NO	MILD	MODERAT	SEVERE	EXTREME
	POST AGREEMENT(%)		86.5	62.4	66.3	72.3	77.4
	FAR(%)		13.5	37.6	33.7	27.7	22.6
	POD - HIT RATE(%)		95.8	60.4	55.6	62.5	55.8
	BIAS		1.1	1.0	0.8	0.9	0.7
	CSI		0.8	0.4	0.4	0.5	0.5
	HSS		0.66				

Table 17: Contingency table for Nyahururu lead 9

		FORECASTS					
		NO	MILD	MODERATE	SEVERE	EXTREME	TOTAL
OBSERVATIONS	NO	443	32	0	0	0	475
	MILD	64	107	16	0	0	187
	MODERATE	3	53	63	5	0	124
	SEVERE	0	2	52	42	0	96
	EXTREME	0	0	1	28	14	43
	TOTAL	510	194	132	75	14	925
	PERCENT CORRECT	72.3	NO	MILD	MODERATE	SEVERE	EXTREME
	POST AGREEMENT(%)		86.9	55.2	47.7	56.0	100.0
	FAR(%)		13.1	44.8	52.3	44.0	0.0
	POD - HIT RATE(%)		93.3	57.2	50.8	43.8	32.6
	BIAS		1.1	1.0	1.1	0.8	0.3
	CSI		0.8	0.4	0.3	0.3	0.3
	HSS		0.57				

Table 18: Contingency table for Malindi lead 1

		FORECASTS					
		NO	MILD	MODERATE	SEVERE	EXTREME	TOTAL
OBSERVATIONS	NO	453	10	0	0	0	463
	MILD	165	66	3	0	0	234
	MODERATE	11	110	31	0	0	152
	SEVERE	0	10	46	8	0	64
	EXTREME	0	0	4	8	0	12
	TOTAL	629	196	84	16	0	925
	PERCENT CORRECT	60.3	NO	MILD	MODERATE	SEVERE	EXTREME
	POST AGREEMENT(%)		72.0	33.7	36.9	50.0	#DIV/0!
	FAR(%)		28.0	66.3	63.1	50.0	#DIV/0!
	POD - HIT RATE(%)		97.8	28.2	20.4	12.5	0.0
	BIAS		1.4	0.8	0.6	0.3	0.0
	CSI		0.7	0.2	0.2	0.1	0.0
	HSS		0.33				

Table 19: Contingency table for Malindi lead 9

		FORECASTS					
		NO	MILD	MODERATE	SEVERE	EXTREME	TOTAL
OBSERVATIONS	NO	426	36	1	0	0	463
	MILD	125	102	7	0	0	234
	MODERATE	13	93	43	3	0	152
	SEVERE	0	5	53	6	0	64
	EXTREME	0	0	6	6	0	12
	TOTAL	564	236	110	15	0	925
	PERCENT CORRECT	62.4	NO	MILD	MODERATE	SEVERE	EXTREME
	POST AGREEMENT(%)		75.5	43.2	39.1	40.0	#DIV/0!
	FAR(%)		24.5	56.8	60.9	60.0	#DIV/0!
	POD - HIT RATE(%)		92.0	43.6	28.3	9.4	0.0
	BIAS		1.2	1.0	0.7	0.2	0.0
	CSI		0.7	0.3	0.2	0.1	0.0
	HSS		0.38				

The Hit Skill Score (HSS) shown in Table 20 also shows that the model is capable of producing forecasts with reasonable accuracy up to the end of the season.

Table 20: Hit Skill Score for the leads

Zone	Lead 0	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5	Lead 6	Lead 7	Lead 8	Lead 9
1	81.8	67.6	67.6	77.4	77.4	77.4	77.4	77.4	77.4	63.4
2	84.9	76.4	80.8	82.8	82.8	82.8	82.8	82.8	82.8	68
3	79.2	64.2	76.2	78.1	78.1	78.1	78.1	78.1	78.1	61.8
4	77.3	60.3	64.2	65.7	65.7	65.7	65.7	65.7	65.7	62.4
5	74.3	56.9	59.1	59.1	59.9	59.9	59.9	59.9	59.8	61.2
6	81.4	63.1	70.8	74.2	74.2	74.2	74.2	74.2	65.2	65.2
7	87.8	69.9	81.3	88.8	88.8	88.8	88.8	88.8	88.8	82.4
8	85.3	77.9	83.4	81	81	81	81	81	73.1	72.3
9	83.9	65.4	74.2	81	81	81	81	75.5	75.5	75.5

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.0. Introduction

This section provides conclusions derived from all the results obtained in the study as well as give recommendations for future work and also for policy makers.

5.1. Conclusion

Regionalization based on PCA of standardized annual rainfall data delineated the study area into nine homogenous zones with distinct rainfall characteristics. The rainfall is highly variable both in space and time. The highest variability occurs over the northern parts of the country and the southeastern lowlands, while the lowest variability occurs over the highlands, Coast and the Lake Basin. Rainfall is also highly variable during the dry months of June to September and Mid December to February in most of the zones except zone 9 which exhibits low variability most of the year.

The region is mainly characterized by a bimodal rainfall distribution with two wet seasons (MAM and OND) and two dry seasons (JF and JJAS) except over the Coast, highlands west of Rift Valley and Isolated areas in the highlands east of Rift Valley which experience a third season from June to August. The CDI is able to capture drought characteristics in the study area effectively as well as climate variability. The region is mainly affected by mild drought but the droughts have been shifting from the mild to more severe drought categories. The severe categories are more dominant during the long rain season of MAM than in any other season.

An effective drought forecasting model can be developed using CDI, dekadal data and Time series modelling in the study area. Dekadal data has been shown to predict droughts with reasonable accuracy up to the end of the season. Hence it is useful in short term drought prediction.

5.2. Recommendations

The use of twenty eight stations to carry out regionalization may not have brought out the spatial rainfall distribution especially over the northern parts of the country where stations are sparsely distributed. It is therefore recommended that regionalization be carried out using blended satellite data which will take care of the spatial disparity over the study region.

Drought is caused by a combination of more than one climatic variable. Hence it is important for the CDI to use more parameters such as wind, sunshine duration and cloud cover in order to effectively capture all aspects of droughts. Since droughts in the study area tend to be more severe during the long rain season of MAM, there is need for frequent drought assessment both on a short and long term basis. Therefore, dekadal data should be used in conjunction with both monthly and annual data to take care of the short and long term droughts

Results obtained from this study show that drought can be forecasted with reasonable accuracy up to the end of the season. Since drought can extend beyond a season, there is need for further studies to explore the possibility of forecasting droughts beyond a season. Results obtained from this study can be used to make timely decisions and reduce the socio- economic impacts of droughts.

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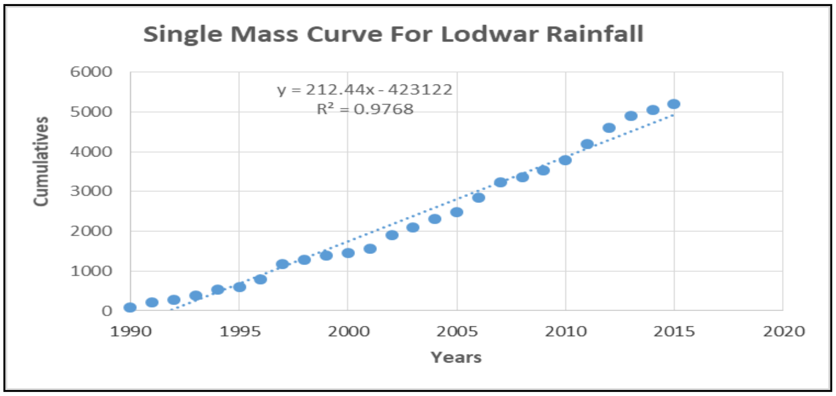
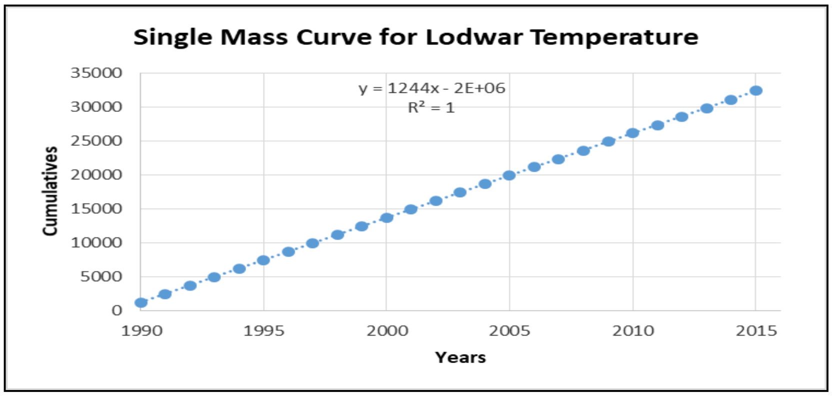
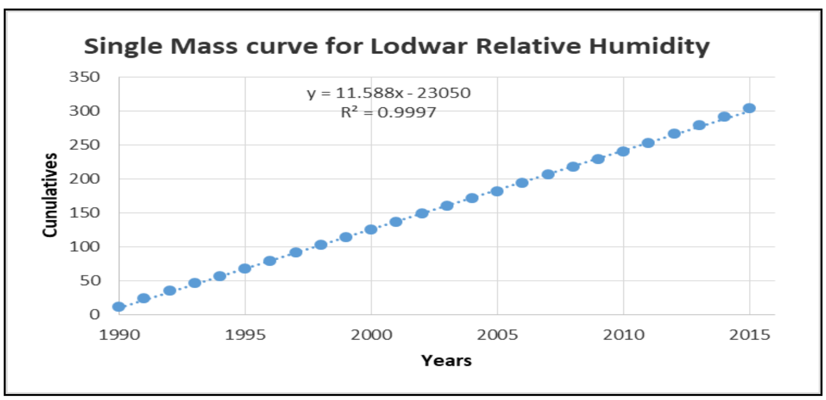
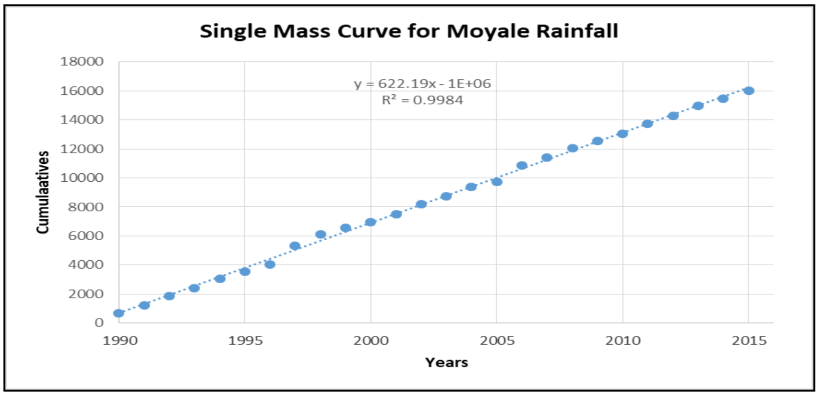
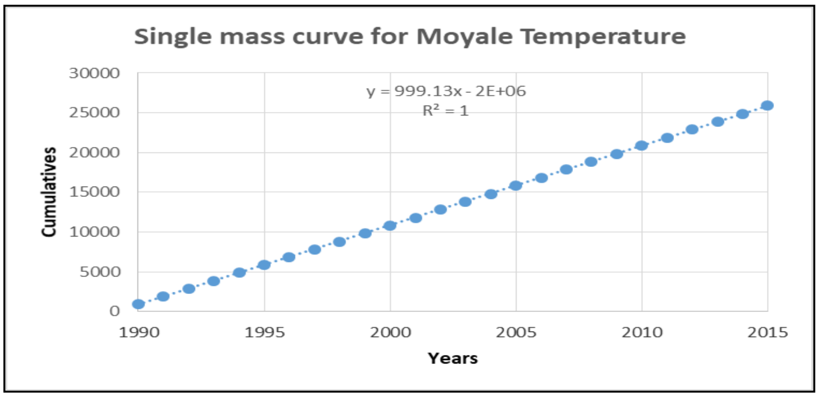
APPENDIX: Single mass curves for Rainfall, Temperature and Relative humidity for the Zones

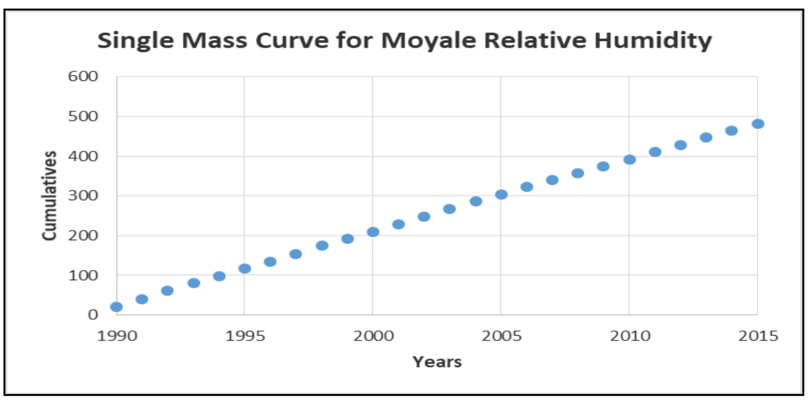


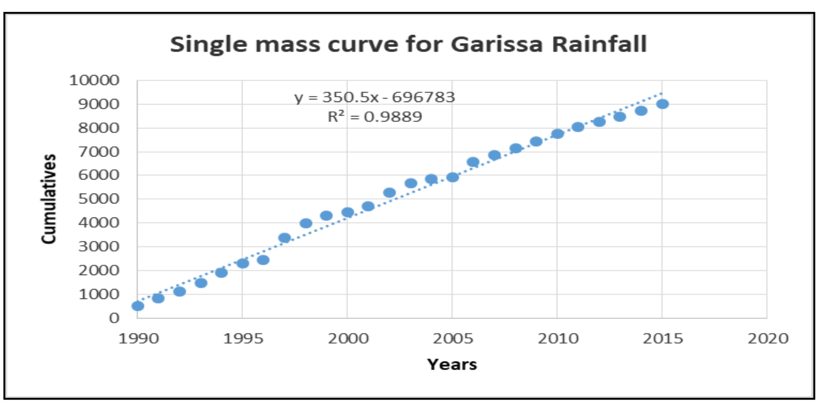


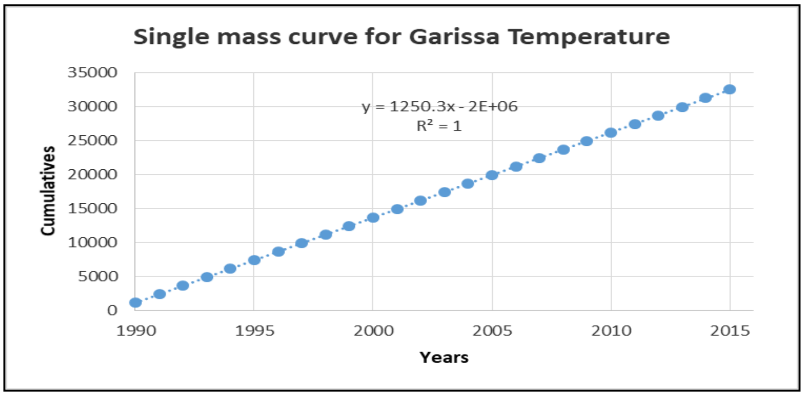


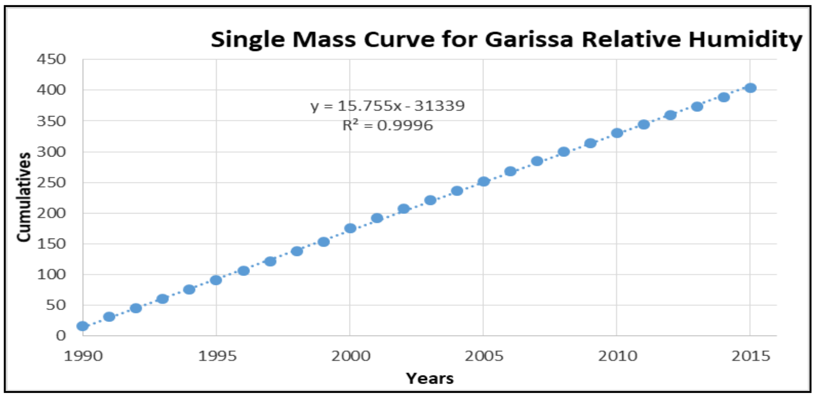

Single Mass Curve for Moyale Rainfall
y = 622.19x - 1E+06
R² = 0.9984
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1990
1995
2000
2005
2010
2015
Cumulaatives
Years

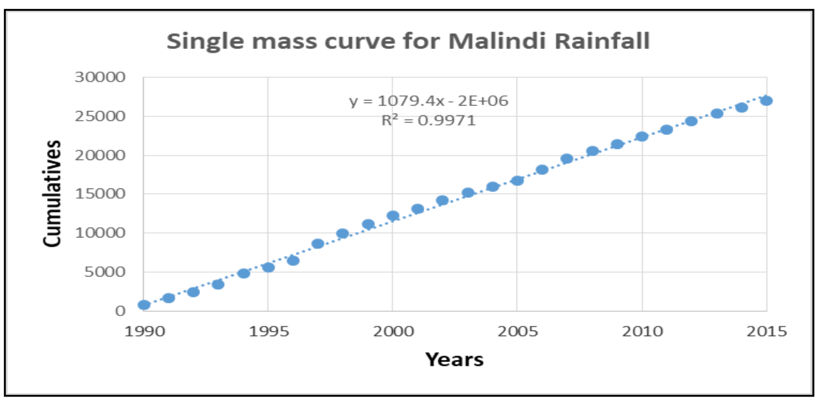

Single mass curve for Moyale Temperature
y = 999.13x - 2E+06
R² = 1
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years

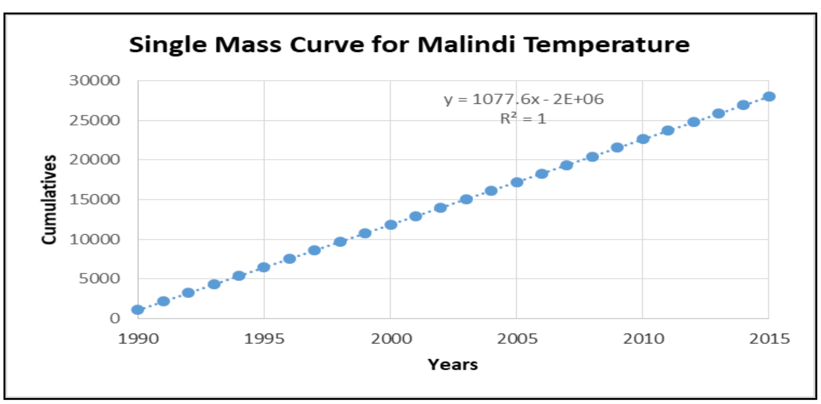

Single Mass Curve for Moyale Relative Humidity
600
500
400
300
200
100
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years

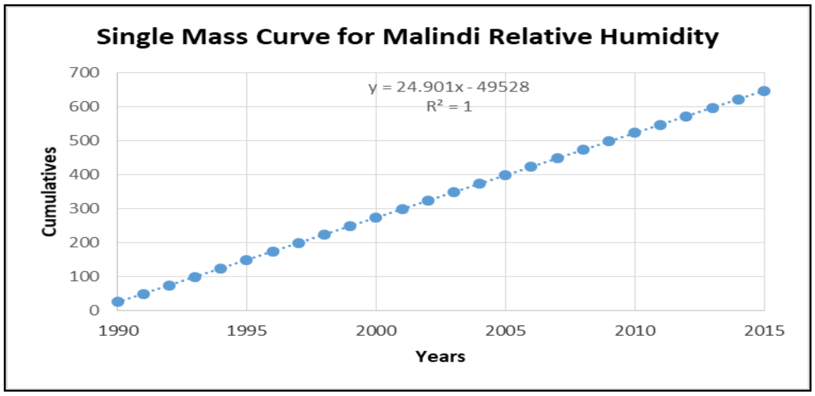

Single mass curve for Garissa Rainfall
y = 350.5x - 696783
R² = 0.9889
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1990
1995
2000
2005
2010
2015
2020
Cumulatives
Years

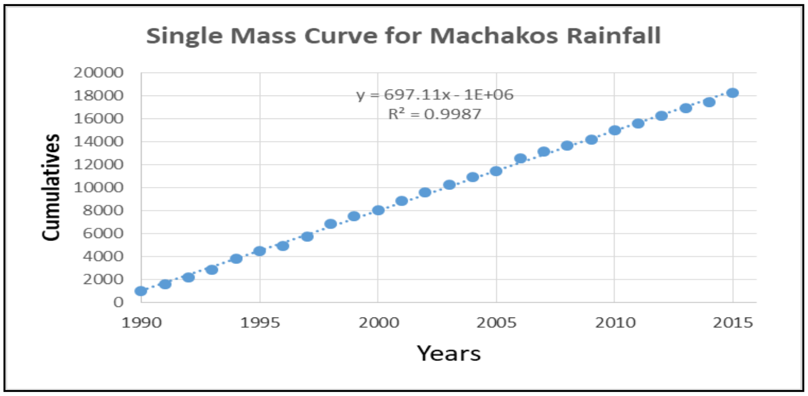

Single mass curve for Garissa Temperature
35000
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years
y = 1250.3x - 2E+06
R² = 1

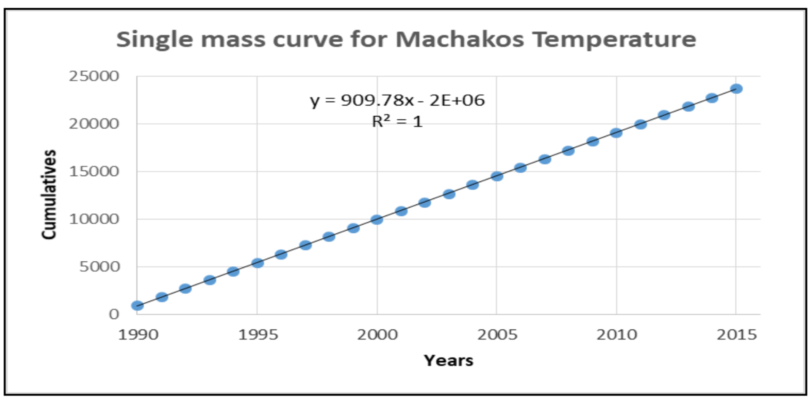

Single Mass Curve for Garissa Relative Humidity
450
400
350
300
250
200
150
100
50
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years
y = 15.755x - 31339
R² = 0.9996

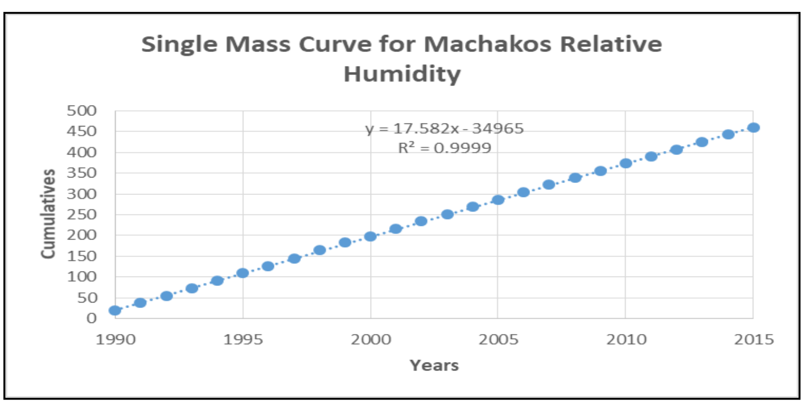

Single mass curve for Malindi Rainfall
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years
y = 1079.4x - 2E+06
R² = 0.9971

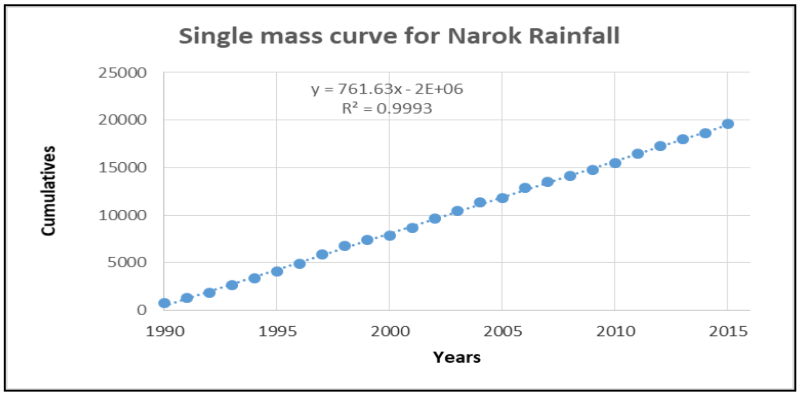

Single Mass Curve for Malindi Temperature
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015
Cumulatives
Years
y = 1077.6x - 2E+06
R² = 1

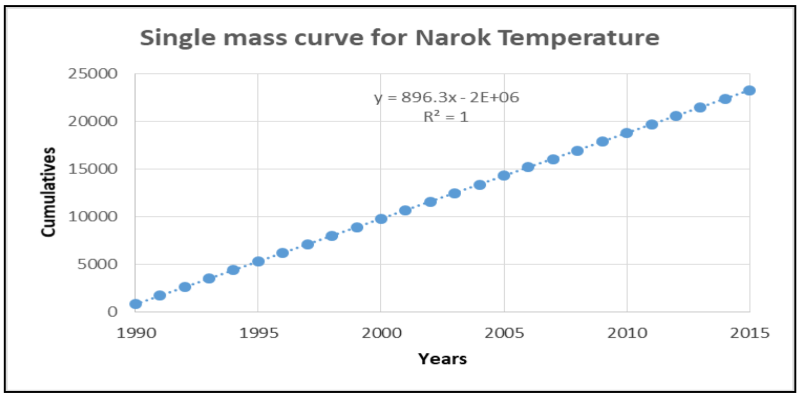

Single Mass Curve for Malindi Relative Humidity
y = 24.901x - 49528
R² = 1
Cumulatives
Years
0
100
200
300
400
500
600
700
1990
1995
2000
2005
2010
2015

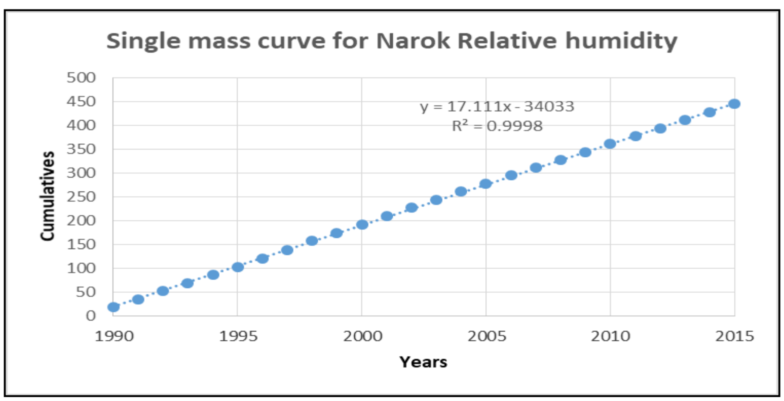

Single Mass Curve for Machakos Rainfall
y = 697.11x - 1E+06
R² = 0.9987
Cumulatives
Years
0
2000
4000
6000
8000
10000
12000
14000
16000
18000
20000
1990
1995
2000
2005
2010
2015

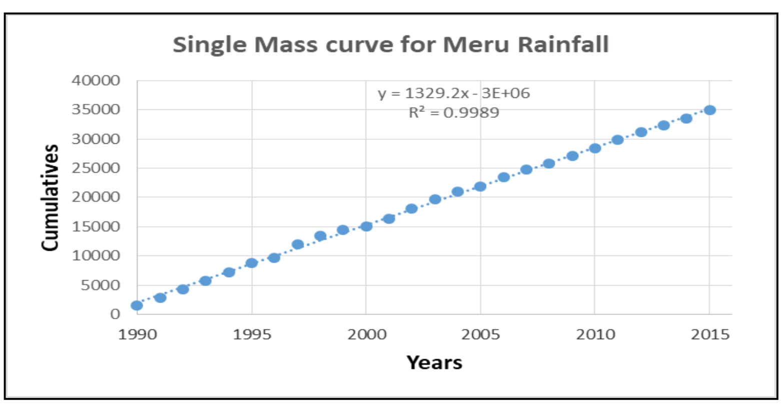

Single mass curve for Machakos Temperature
y = 909.78x - 2E+06
R² = 1
Cumulatives
Years
0
5000
10000
15000
20000
25000
1990
1995
2000
2005
2010
2015

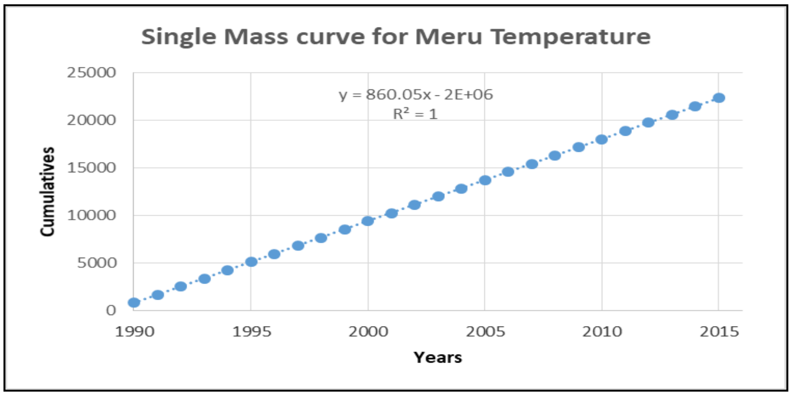

Single Mass Curve for Machakos Relative Humidity
y = 17.582x - 34965
R² = 0.9999
Cumulatives
Years
0
50
100
150
200
250
300
350
400
450
500
1990
1995
2000
2005
2010
2015

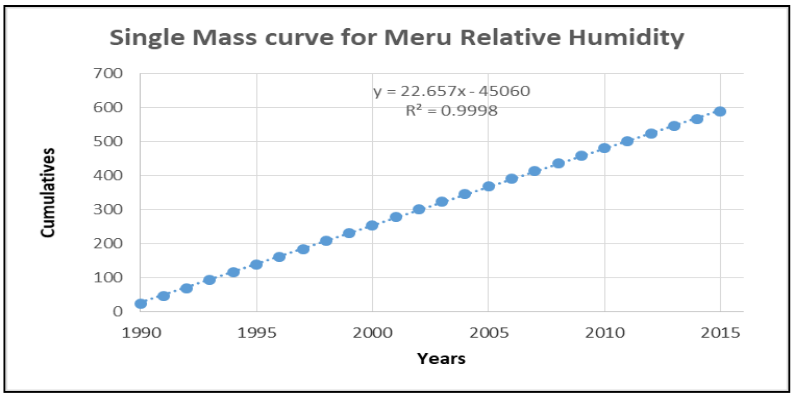

Single mass curve for Narok Rainfall
y = 761.63x - 2E+06
R² = 0.9993
25000
20000
15000
10000
5000
0
Cumulatives
1990
1995
2000
2005
2010
2015
Years

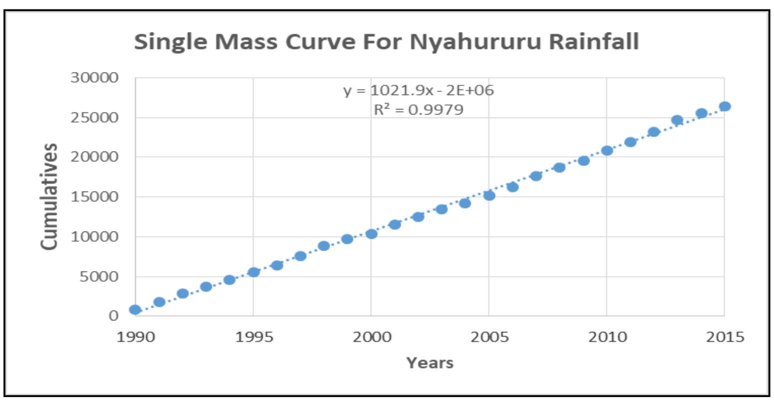

Single mass curve for Narok Temperature
y = 896.3x - 2E+06
R² = 1
25000
20000
15000
10000
5000
0
Cumulatives
1990
1995
2000
2005
2010
2015
Years

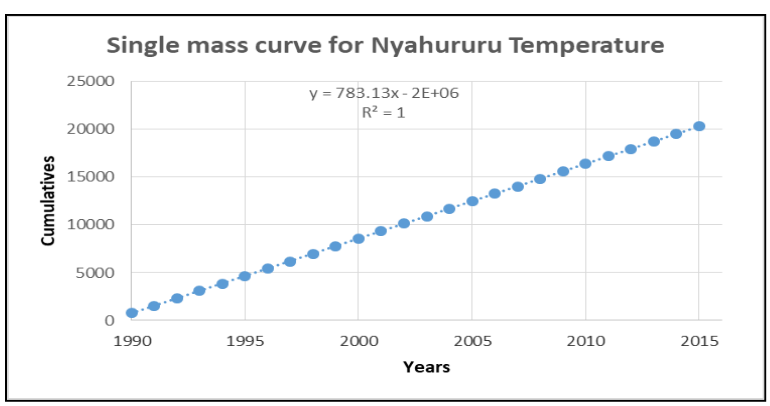

Single mass curve for Narok Relative humidity
y = 17.111x - 34033
R² = 0.9998
500
450
400
350
300
250
200
150
100
50
0
Cumulatives
1990
1995
2000
2005
2010
2015
Years

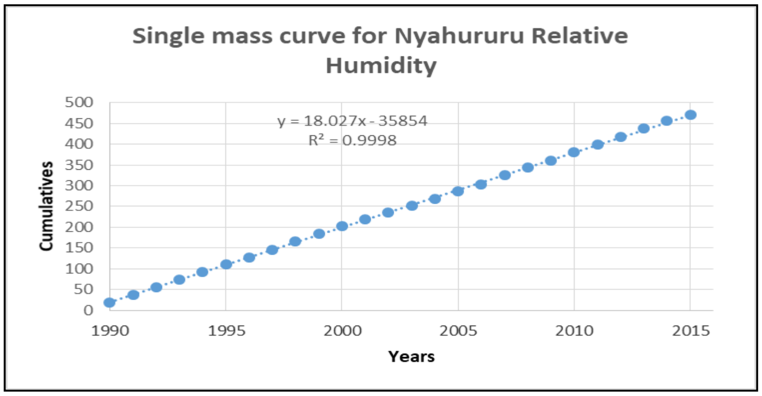

Single Mass curve for Meru Rainfall
y = 1329.2x - 3E+06
R² = 0.9989
40000
35000
30000
25000
20000
15000
10000
5000
0
Cumulatives
1990
1995
2000
2005
2010
2015
Years

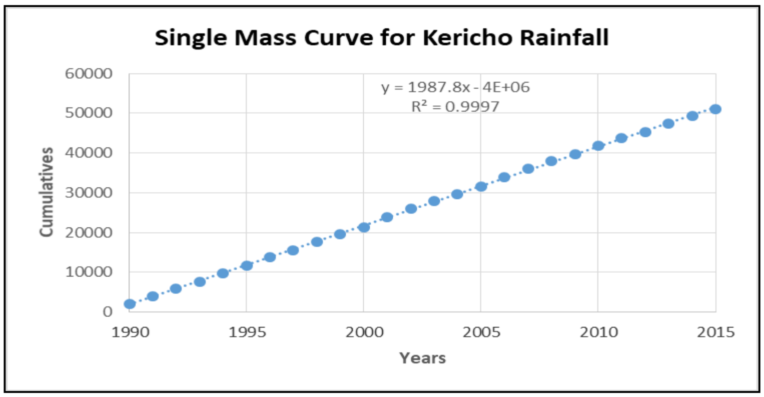

Single Mass curve for Meru Temperature
y = 860.05x - 2E+06
R² = 1
Cumulatives
Years
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015

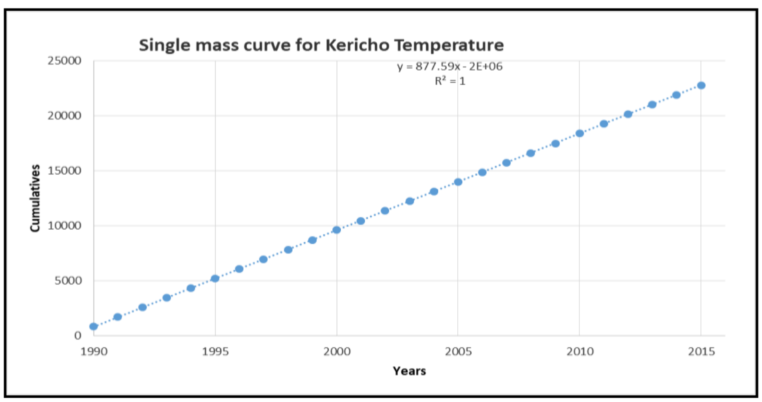

Single Mass curve for Meru Relative Humidity
y = 22.657x - 45060
R² = 0.9998
Cumulatives
Years
700
600
500
400
300
200
100
0
1990
1995
2000
2005
2010
2015

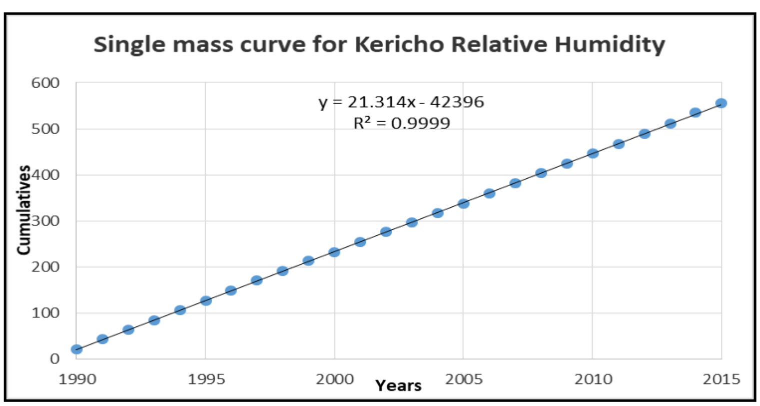

Single Mass Curve For Nyahururu Rainfall
y = 1021.9x - 2E+06
R² = 0.9979
Cumulatives
Years
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015


Single mass curve for Nyahururu Temperature
y = 783.13x - 2E+06
R² = 1
Cumulatives
Years
25000
20000
15000
10000
5000
0
1990
1995
2000
2005
2010
2015


Single mass curve for Nyahururu Relative Humidity
y = 18.027x - 35854
R² = 0.9998
Cumulatives
Years


Single Mass Curve for Kericho Rainfall
y = 1987.8x - 4E+06
R² = 0.9997
Cumulatives
Years


Single mass curve for Kericho Temperature
y = 877.59x - 2E+06
R² = 1
Cumulatives
Years


Single mass curve for Kericho Relative Humidity
y = 21.314x - 42396
R² = 0.9999
Cumulatives
Years