THE USE OF REMOTE SENSING PRODUCT TO MONITOR METEOROLOGICAL DROUGHT IN EAST AFRICA

By

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DECLARATION:

I declare that this is my original work and has not been presented for a degree in this or any other University

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ABSTRACT

Most drought studies have been dependent on limited rainfall data that is available in most parts of Africa. The new developments in space technology, especially satellite derived products now provide new opportunities that can be used to study space-time characteristics of drought. Thus the main objective of this study is to assess the potential of using satellite-derived products to enhance the monitoring of meteorological drought within the East Africa. This involved the validation of the satellite products using some available rainfall records.

Rainfall data used in this study was obtained from IGAD Climate Prediction and Application Centre (ICPAC) and was from 2000 to 2009 for East Africa. The other data is a (10-day) dekadal composite of Normalized Difference Vegetation Index (NDVI) images of the East Africa obtained from VGT4Africa website. It contains a spatial resolution of 1 kilometer by 1 kilometer with an accuracy of 300m and runs from year 2000 to 2009 for the east Africa region.

The methods used in this study included the calculation of satellite based drought indices using Vegetation Productivity Index from Normalized Difference Vegetation Index (NDVI) values. These were then compared with drought severity index (DSI) derived from rainfall records using some standard statistical methods.

The study has shown that drought indices based on Vegetation Productivity Index can provide some realistic estimates of drought indices. There were however some challenges in some stations where vegetation cover are not mainly dependent on rainfall but relied on irrigation. The study has therefore provided some alternative methods that could be used for regional drought monitoring.

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CHAPTER ONE

INTRODUCTION

1.0 Background

Droughts are like a cancer on the land with seemingly no recognizable beginning (Mather, 1985); unlike floods, earthquakes, or hurricanes, during which violent events of relatively short duration occur. Droughts covering a few hundred square kilometers do exist but these are usually of limited duration and modest severity. It is more common for droughts to cover relatively vast areas, a significant proportion of a continent or sub-continent approaching millions of square kilometers (Mather, 1985).

Drought can be categorized broadly as either conceptual or operational (Wilhite and Glantz, 1985). The encyclopedia of Climate and Weather (Schneider, 1997) defines drought as "an extended period - a season, a year, or several years – of deficient rainfall relative to the statistical multi-year mean for a region". Operational definitions attempt to identify the onset, severity and termination of drought episodes. As result it is frequently defined according to disciplinary perspective, i.e. Subrahmanyam (1967) has identified six types of drought: meteorological, climatological, atmospheric, agricultural, water-management and hydrological.

According to Wilhite and Glantz (1985) Meteorological drought is defined as a period when rainfall is significantly less than the long-term average or some designed percentages, or less than some fixed value.

Drought is basically associated with a period of abnormally dry weather compared with averaged condition, which further results in a change in vegetation cover condition (Heim, 2002; Tucker & Choudhury, 1987). Drought is part of the environment. It occurs in every part of the globe and adversely affects the lives of a large number of people, causing considerable damage to economies, the environment, and property. It also affects countries differently, having a greater impact on countries with poor economic conditions (IDIC,NDMC,1995).

Repeated drought in Africa in the last 30 years has had a disastrous effect on an economic and social situation that already has serious problems. Today, in the aftermath of these devastating droughts, planning and preparedness have become more important. Like most disasters, droughts are inevitable in this part of the continent. Thus competent governments, given foresight and funds, can build defenses against them. The enormous physical consequences of drought and the huge financial cost of relief efforts (compared to prevention) have led Africa to improve its drought management and preparedness scheme regularly.

East African countries; Tanzania, Kenya and Uganda are always suffering severe droughts as a result of failed annual rains. With crops unable to grow, many people have been left without enough food to eat. Examples of such drought years which have occurred are like early 2002 and 2009. In the 1970s there was one major drought. In the 1980s this quickened to once every seven years, in the 1990s, once every five years (Howden, 2008). The 2009 year's drought is presumed to be the worst in east Africa since 2000, and possibly since 1991.

In Great Horn of Africa, drought usually affects several million people via its effects on agriculture, water resources, fisheries, public health among many other sectors and quite often results into loss of human and livestock lives. Droughts of 1983/84, 1998-2000, 2004-2005 resulted into serious environmental, social and economic consequences. Furthermore, droughts have often wiped out decades of national development investments and infrastructures in the region. Thus drought monitoring has become a central component in current strategies for managing and monitoring environmental changes.

Traditionally, drought monitoring in the region has been based on the use of limited rainfall observations. However, this method is deficient of continuous spatial coverage needed to characterize and monitor the detailed spatial pattern of drought conditions. An alternative method of monitoring is therefore necessary to counter this problem. The advancement in the concept of vegetation monitoring or mapping which has greatly increased research on land cover change to provide an accurate evaluation of the spread and growth of the world's vegetation cover has been enabled by the use of satellite monitoring. This has become an important priority and thus this study will enhance a drought monitoring system using vegetation that will examine and highlight the possibility of having the same mechanisms used in drought monitoring using rainfall.

With the current technological advances in communication and computers, remote sensing has greatly improved our ability to measure the important characteristics and impacts of weather related disasters. A well-integrated use of ground observations and earth- observation satellite products can improve drought monitoring.

Ground observations of rainfall so far have a tremendous potential to analyze past, present, and future weather conditions. But observations from meteorological satellites routinely provide more complete, timely, and finer spatial coverage of terrestrial information. This information is normally produced by transformation of the observed radiance into environmental variables such as clouds, snow cover, sea ice, temperature, vegetation, and other meteorological and geophysical components. Developed techniques transform the satellite-observed radiance into more complex environmental phenomenon such as drought (Kogan, 1991).

Examples of drought monitoring methods based on satellite derived data used are like modified perpendicular drought index (MPDI): which is a real-time drought monitoring method that introduces vegetation fraction, which takes into account both soil moisture and vegetation growth. Other indices are Enhanced vegetation index (EVI), Vegetation Health Index (VHI) and Vegetation condition index (VCI). Limitation of the VCI comes in when deviation from the mean does not take into account the standard deviation, and hence the index can be misinterpreted when variability in the vegetation conditions in a region is very high in any one given year (Thenkabail, *et al.*, 2004)

Different Satellite derived indices measure drought in different ways, and no single index works under all circumstances (Heim, 2002). Another limitation in drought monitoring using satellite data is the apparent time lag between a rainfall deficit and vegetation response [Reed, 1993; Di, 1994; Wang, *et al.*, 2001]. Note that due to these limitations other ways have been developed in drought monitoring, like blending science and art since there is no one 'correct' way to measure drought.

Unlike above, this study will use drought indices derived from satellite observation alone to study drought characteristics. Since soil moisture and vegetation growth are vital and important indicators of drought events, an understanding of vegetation and water spectral behavior is critical in estimating drought conditions.

1.1 Objectives

The main objective of this study is to assess the potential use of satellite-derived product, Vegetation Productivity Index (VPI) in regional meteorological drought monitoring. The study will focus on comparison of rainfall and satellite derived products for the case of SOND seasons. To achieve this, the study will specifically:

(i) Indentify drought periods using rainfall drought severity index (DSI);

(ii) Generate Vegetation Productivity Index (VPI);

(iii) Compare VPI and DSI drought products.

1.3 Justification of the study

Insufficient rainfall records from ground stations calls for alternative methods for drought monitoring. This reason, together with the creeping phenomenon of drought makes the accurate prediction of either its onset or end a difficult task. Since droughts are natural events whose occurrences in time and space are complex and not fully understood, rainfall measurements are always limited in spatial extend thus remote sensing allows investigation of a larger portion of the East African countries than previously possible through station observations.

There is a need to keep track of drought conditions or effects and environmental changes for the intention of monitoring and predicting the production of the marginal agricultural areas, whether they are the result of shifting climate, human actions or a combination of these.

Much of the environmental research over the past decade has been focused on investigating the entire region using the satellite technology. This region, to human observers, appears quite large and due to the limitation of ground station observations it is hard to understand the complex interactions between the region's land mass, lakes and the ocean strip, including the surrounding atmosphere.

The ability to address challenges of drought monitoring is limited both by the invisibility of the changes and by uncertainty in our ability to have an early warning on them. This emphasizes the importance of improving our understanding on vegetation changes and its relationship to drought. The use of remote sensing products in East Africa during SOND season can give detailed measurements, data and the information needed to begin to understand, describe, and model the various trends of drought in the Eastern Africa region using productivity classes.

East Africa is characterized by widely diverse climates ranging from semi arid to forest over relatively small areas. Rainfall seasonality is complex, changing within tens of kilometers. The annual cycle of East African rainfall is bimodal, with wet seasons from March to May and October to December. The Long Rains (March to May) contribute more to the annual rainfall than the Short Rains (September to December). Much of the interannual variability comes from the Short Rains (coefficient of variability = 74% compared with 35% for the Long Rains) (WWF, 2006). Therefore, it's important to monitor Short Rain season which is crucial for marginal areas. On synoptic view, this dissertation facilitates the study of meteorological drought during the Short Rains (September to December) in a wider spatial and temporal extend which will be very useful for studying landscape dynamics; that is phenological variations of vegetation in respect to drought severity index.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter discusses the studies that have been done previously.

2.1 literature Review

Common to all types of drought is the fact that they originate from a deficiency of precipitation that result in water shortage for some activity (Wilhite and Glantz 1985). Nearly all drought indices are based on rainfall observations and drought definitions included this variable either singly or in combination with other meteorological elements (World Meteorological Organization 1975a). Early meteorological drought definitions incorporated some measure of precipitation over a given period of time (Tannehill 1947; World Meteorological Organization 1975a; Wilhite and Glantz 1985).

A drought would exist if the criteria defining the drought were met, and the index would then be a measure of the drought's duration and/or intensity. During the first decade of the twentieth century, the U.S. Weather Bureau identified drought as occurring during any period of 21 or more days with rainfall 30% or more below normal for the period (Steila 1987). During this time, a drought measure frequently used was the accumulated precipitation deficit, or the accumulated departure from normal. Most of these definitions were valid only for their specific application in their specific region. Indices developed for one region may not be applicable in other regions because the meteorological conditions that result in drought are highly variable around the world.

Indices developed to measure the intensity of meteorological drought, for instance, were inadequate for agricultural, hydrological, or other applications. These deficiencies were recognized early (Henry 1906). The problems with developing an agricultural drought index, for example, include consideration of vegetation, soil type, soil moisture and evapotranspiration as influenced by wind speed and the temperature and humidity of the air. Many of these climatic elements were not widely measured, or could not be incorporated into a drought index. But over time other indices were brought into picture and interest in satellite observation and subsequent evaluation of drought were attributed to several characteristics of remote sensing. These include the fact that remote sensing provides an advantage in permanent record or data archive, extra visual information, and cost effectiveness in many cases (Johnson, *et al.*, 1993).

From 1970's, studies have used satellite land observation data to monitor a variety of dynamic land surface processes [e.g., Anderson, *et al.*, 1976; Reed, *et al.*,1994; Yang, *et al.*, 1998; Peters, *et al.*, 2002]. Satellite remote sensing provides a general view of the land and a spatial context for measuring drought impacts. Effects of drought are evident on vegetation. Reduced biomass production, increased fire danger, and other long-term changes can often be linked to drought events as Peters, *et al.*, (1993) has shown. Satellite observations of vegetation can thus be used to monitor drought. One of the most popular product used is the Normalized Difference Vegetation Index (NDVI).

The Normalized Difference Vegetation Index (NDVI) is used extensively in ecosystem monitoring. The NDVI measures the changes in chlorophyll content (via absorption of visible red radiation) and in spongy mesophyll (via reflected NIR radiation) within the vegetation canopy. As a result, higher NDVI values usually represent greater vigor and photosynthetic capacity (or greenness) of vegetation canopy [Tucker, 1979]. NDVI's role in drought monitoring and assessment has been described several times during the last decade [Kogan, 1991; Kogan, 1995; Yang, *et al.*, 1998; Ji and Peters, 2003; Wan, *et al.*, 2004].

In contrast to above, clouds, water and snow have larger visible reflectance than those of near-infrared (Ch 2). Thus, those features yield negative index values. Rock and bare soil covered areas have similar reflectances in the VIS/NIR bands and result in vegetation indices near zero. Because of these properties, NDVI has become the primary tool for mapping changes in vegetation cover and analysis of the impacts of environmental phenomena.

The NDVI can be used not only for accurate description of continental land cover, vegetation classification and vegetation phenology (Tucker, *et al.* 1982, Justice, *et al.* 1985) but it is also effective for monitoring rainfall and drought, estimating net primary production of vegetation, crop growth conditions and crop yields, detecting weather impacts and other events important for agriculture, ecology and economics (Kogan 1987a).

Most of research and projects on vegetation monitoring from satellite observation are based on NDVI calculated from data collected by the Advanced Very High Resolution Radiometer (AVHRR) sensor. NDVI has been calculated from AVHRR data for more than 20 years, creating a useful time-series for monitoring. However, one limitation of NDVI for drought monitoring is the apparent time lag between a rainfall deficit and NDVI response [Reed, 1993; Di, *et al.*, 1994; Rundquist and Harrington, 2000; Wang, *et al.*, 2001]. Undoubtedly, NDVI is especially useful for picking up seasonal and inter-annual variations in the overall condition of vegetation, especially in relation to drought.

The science of remote sensing has been applied in vegetation monitoring with remarkable successes, that isNOAA Advanced Very High Resolution Radiometer satellite data are and have been applied to regional vegetation monitoring in Great Horn of Africa. The collected data from vegetation monitoring using remote sensing have been correlated with vegetation measures such as biomass and leaf area index (Tucker 1979; Hatfield; and Holben, *et al.*, 1980).

Studies which have been done on vegetation variation using satellite data include Tucker

(1991), who did a study on contraction and expansion of the Sahara desert which extends between ~7,000,000 and ~9,000,000 km^2 in area. According to Tucker, information got suggests that the Sahara has expanded toward the south. He alleged expansion was attributed by climate variation (droughts) and also due to land mismanagement such as overgrazing, increased cultivation, and firewood cutting. However, a 1984 field study by Hellden in the same area found little evidence of such an expansion.

Patterns of vegetative cover in most places in East Africa are dependent on rainfall with some exceptions of some irrigated areas. Rainfall is the key limiting factor in crop production. Increasingly dense and accurate rainfall observations that can be analysed in real time are required to monitor closely the progression of the cropping season. This is because in areas such as arid land, great spatial and temporal variability of rainfall mean that interpolating between rain gauge values to obtain estimates of the rainfall at a particular point can give rise to serious errors. Proper monitoring for these regions therefore requires an impractically large number of gauges. Even if such dense coverage were possible, the rainfall data on its own is insufficient to draw useful information regarding the status of the plants.

Drought monitoring and mitigation in the Eastern Africa has remained largely responsive and based on reaction after a drought has occurred. Consequently, it is not surprising that related losses are much more than those caused by most of the other natural disasters (Ogallo, *et al.* 2004). The recurrent climate extremes like droughts in eastern Africa are largely associated with rainfall anomalies.

Drought monitoring, climate prediction and timely early warning based on SSTs, Indian Ocean Dipole, El Nino / La Nina events El Nino / La Nina events, and other predictable climate signals can be used as one of the best strategies for mitigating the negative impacts of drought and also for taking advantage of the good years, and / or good rains that may be received in other parts of the country / region (Ogallo, *et al.* 2004). In any precondition season, it is common to find that while one part of the eastern Africa is under severe drought stress, other parts of the region are doing well. This might be due to the complexity in the climate patterns associated with complex physical terrain, Ogallo (2003).

Drought has an impact on water sources like rainfall, ground water, reservoir storage and streamflow. Therefore, the impacts of water deficit are a complex function of water source and water use. The time scale over which precipitation deficits accumulate becomes extremely important and functionally separates different types of drought. Agricultural droughts, for example, typically have a much shorter time scale than hydrologic droughts.

The relationship of NDVI to rainfall is used as a basis for employing NDVI as an indicator of meteorological drought. The onset of suitable moisture conditions for vegetation causes the emergence and growth of plants. The resulting increase in the amount of vegetation and in the photosynthetic activity leads to a consistent increase in the NDVI. When these conditions cease, the resulting moisture stress will reduce biophysical rates (photosynthetic rate and transpiration) which will result in a substantial fall in the NDVI (Bonifacio, *et al.*, 1993a).

The vegetation response to rainfall is well marked; a good example is in the Sahel where detailed studies of the relationship between NDVI and biomass have been undertaken (Justice and Hiernaux, 1986). The integrated NDVI over a suitable base or background value has been used previously as a measure of total biomass production (Tucker, 1986).

2.2 Area of study

The region of East Africa is located within latitudes 5° N to 12° S, and longitudes 29° E to 42° E. It consists of three countries namely Kenya, Tanzania and Uganda.

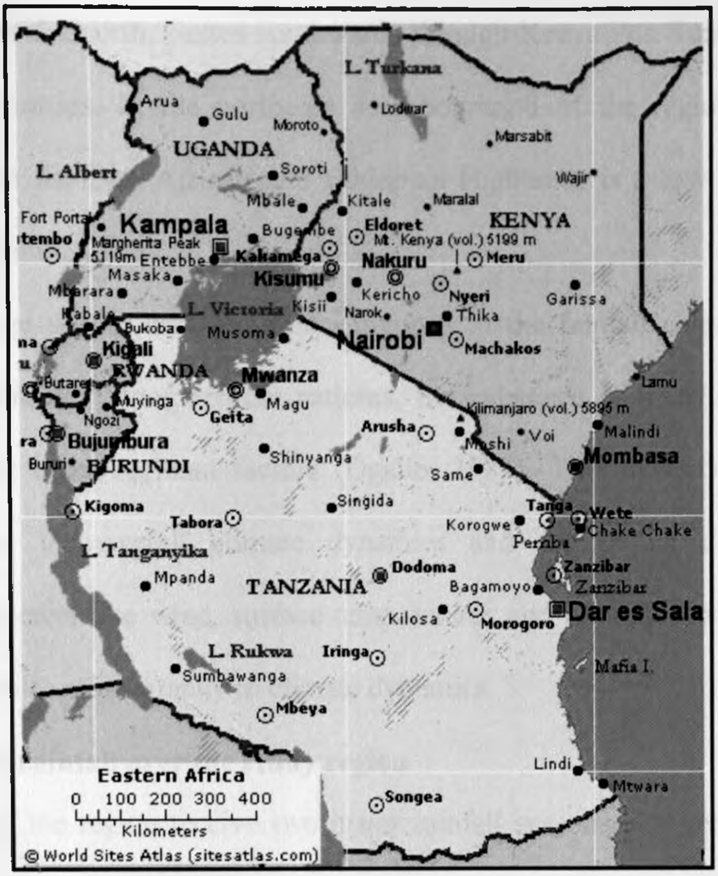

Figure 1a: Map of the study region showing the East African countries

2.2.1 Physical features of the study region

The region is found in the eastern part of the African continent with the eastern side of it Indian Ocean is located. The region is composed of the low lands, East Africa highlands, riftvalley and the highest mountains in Africa. that isMt. Kilimanjaro (5895m) and Kipengere Ranges in south-western Tanzania, Mt. Kenya (5199m), and Mt. Elgon (4321m) in Kenya together with Mt. Ruwenzori (5109) in Uganda.

The region has several lakes, the major one being Lake Victoria at 1132m above mean sea level covering an area of 68,000km^2 and is the second largest fresh water lake in the world. Others are lakes Turkana and Tanganyika found within the floor of the Great Rift Valley. The central highlands make up the eastern and western escarpments of the Great Rift Valley, which enters the region from the north, passes southwards through Kenya into Tanzania and runs into the South Africa countries. In the northeast neighbourhood of the region is the Ethiopian highland and between the East African and Ethiopian Highlands is a low level valley region called the Turkana Channel.

There are large spatial and temporal variations in the rainfall characteristics over the region due to the complex topographical patterns, the existence of many large inland lakes, together with several other regional factors (Ogallo, 1982). The diversity in orography has profound effects on the overall climate dynamics and the spatial distribution of key meteorological parameters like wind, surface temperatures and rainfall. Indeje, *et al.* 2000 has stated the dominant roles of orography in climate dynamics.

2.2.2 Climatology of rainfall over the study region

Most parts of the region receive two major rainfall seasons in a year which follow the movement of the ITCZ which lags behind the overhead sun. This is called bimodal rainfall distribution (two rainy seasons and two dry seasons). The two dry periods, over most parts of east Africa, run from mid-December to late February and from June to late September. The two major rainfall seasons experienced over East Africa are locally referred to as the long rains (March-May) and the short rains (October-December) with high rainfall areas concentrated over the highlands and near the large water bodies. Large areas of the region including Eastern and Northern Kenya, North Eastern Uganda, and Central Tanzania receive low rainfall.

The western parts of the region experience effects of Congo Airmass. Close to the equator, bimodal regimes are well marked with the long rainfall concentrated within March to May (MAM) while the short rainfall season occurring in late September to November/early December (SOND). Regions in southern Tanzania experience their rainfall within a single season spanning the period November to March and this has been referred to as unimodal regime (Ogallo, 1980).

Coastal regions and Western Kenya have three wet seasons exhibiting a trimodal regime. This third rainfall peak within the year occurs from July to August mainly around the coastal and western regions. Areas close to the water bodies receive substantial rainfall throughout the year, Ininda (1995) Ogallo (1980). The regional features in the region interact with both the synoptic and the large-scale systems to produce the observed rainfall distribution (Mukabana, 1992; Asnani, 1993).

2.2.2.1 Inter Tropical Convergence Zone (ITCZ)

It is a boundary of meeting of hemispheric winds near the surface as a result of inter-hemispheric monsoon wind systems over the region. It is the main synoptic scale system that controls seasonal rainfall over the eastern Africa. The ITCZ is however noticeable in the wind field near 700mb (Kiangi, *et al.*, 1981). Over East Africa, the ITCZ has two unique components; the normal east-west orientation called the zonal component and the north-south oriented component referred to as meridional component in around November to March months.

2.2.2.2 Indian monsoons

The monsoon winds flow in response to the differential heating between continent and ocean. The East Africa region experiences northeast monsoons in December-February and the Southeast monsoon in June-August. The continental heating is strongest when the sun is overhead at any given location twice a year. This causes low-level hemispheric airmass convergence called ITCZ. During March-May and September-November both monsoonal wind currents are present with one withdrawing while the other advancing.

In transitional seasons, a strong zonal component brings equatorial warm and moist air into the Equatorial East Africa region from the Indian Ocean. Sadler, *et al*., (1987) have shown warm surface waters (SST) over equatorial Indian Ocean during the transition months of April and November. This moist equatorial air has a conditionally unstable lapse rate and responds rapidly to low-level convergence with widespread cloudiness, showers and thunderstorms. The east African monsoons are associated with relatively little rainfall.

2.2.2.3 Tropical cyclones

Tropical cyclones origins are almost invariably in the low latitudes between 5 and 20 degrees North or South of the equator. In these latitudes, the deviating Coriolis force is sufficiently large to produce cyclonic circulation. According to World Meteorological Organization (WMO) Intense depressions occur in several tropical southern/western Indian Ocean regions during certain periods of the year and these are popularly known as cyclones in the southwest Indian Ocean and Arabian Sea.

The tropical cyclones that influence weather in eastern Africa form in the West Indian Ocean, equator ward of 20 degrees latitude. North of the equator, they form in northern spring and late fall and move northward into the Arabian Sea. There are other names given to this weather system elsewhere in the world. These systems rarely reach the East Africa coast, however, there have been few occasions (e.g. October 1972, 1984) when cyclones in the region reached the coast and caused increased rainfall as far as Somalia and northern Kenya. But their effects is felt and can cause heavy precipitation for one or two days, when 200 km away from the East African coast. Tropical cyclones cause severe weather that is destructive to both life and property.

2.2.2.4 Global and Regional-scale Teleconnections

These include; El Niño Southern Oscillation (ENSO), global Sea Surface Temperatures

(SSTs), Quasi-Biennial Oscillation (QBO), subtropical anticyclones and the Indian Ocean Dipole mode are the major climatic systems that affect rainfall over eastern Africa region through Teleconnections.

2.2.2.4.1 El Niño Southern Oscillation

Although research has long established that it is a global scale phenomenon (Wallace, *et al*., 1998); The El Niño/Southern Oscillation (ENSO) phenomenon has been studied largely in the context of the Pacific Ocean and adjacent regions. It is the most noteworthy interannual climate variability which occurs as a result of instabilities in air-sea interaction in the Pacific Ocean and it has impacts on regional climate extremes in many parts of the globe. Its episodes lead to massive displacements of rainfall regions of the tropics, bringing drought to vast areas and torrential rains to otherwise dry regions.

The most prevalent mode of interannual climate variability appears to be ENSO in sub-Sahara Africa. It is characterized by rainfall anomaly pattern over eastern and southern Africa. Tropical eastern Africa is one of the areas where global ENSO impacts have been reflected in both precipitation and temperature anomalies. Interannual variability in rainfall over East Africa during the October to December season correlates strongly with the Sea Surface Temperature (SST) changes in the tropical Pacific associated with the ENSO phenomenon (Ogallo, 1988).

Many studies have investigated the relationship between rainfall received in east Africa with ENSO (Ogallo, 1988; Indeje, 2000; Mutemi, 2003, among others). Mutemi (2003) for example, found a strong relationship between rainfall over East Africa and evolutionary phases of ENSO.

Ogallo, *et al*. (1988) correlated the global SST anomalies within the latitude 30° north and south of the equator with the rotated principal component analyses (RPCA) modes of the

Northern Hemisphere autumn rainfall over Eastern Africa for the period 1950-79. The study suggested that about 36% of the short rainfall variation in East Africa could be explained by SST variations in western Pacific and most of Indian Ocean where correlation values are near 0.6.

2.2.2.4.2 Global Sea Surface Temperatures (SSTs)

Ogallo, *et al.*, (1988) and Ogallo (1988) have shown that rainfall in the coastal and western parts of East Africa has significant correlation with the Southern Oscillation Index and SST over parts of the Pacific and Indian Oceans. In a study by Nicholson and Entekhabi (1987) investigation of interannual variability of surface fields over the Indian Ocean, Cadet (1978) indicated that Indian Ocean parameters might have significant influence on East African weather.

2.2.2.4.3 Quasi-Biennial Oscillation

The Quasi-Biennial Oscillation (QBO) is the alternation in phase of the zonal winds in the lower stratosphere with period of 26-30 months. There is vertical propagation in the phases of the zonal winds leading to changes in vertical wind shear and the associated stability. Several studies have reported the presence of the QBO in various atmospheric parameters and at different regions of the globe. Indeje, *et al.*, (2000) found a statistical association between rainfall over East Africa and QBO to be strongest during the boreal summer season (June-August) and weakest in boreal winter (December-February).

CHAPTER THREE

DATA AND METHODOLOGY

3.0 Introduction

This chapter outlines the data sets which were used and the methods of analysis adopted to achieve the objectives of the study.

3.1 Data

The data used here include dekadal NDVI and rainfall records for the period 2000 - 2009. Details of each are presented independently in the following.

3.1.1 Normalized Difference Vegetation Index (NDVI)

The data used in this study are (10-day) dekadal composites of NDVI images obtained from Vegetation for Africa (www.vgt4africa.org) website. NDVI is a vegetation sensitive indicator that reflects the pattern of spectral responses of ground objects in the visible and near-infrared regions of the electromagnetic spectrum. It is found to be a good indicator of the vegetation characteristics over land surface. For example, Rouse, *et al*. (1974) defined NDVI as (NIR-R)/ (NIR+R) where, NIR and R are the radiances or reflectances in the near- infrared and red spectral channels respectively.

Chlorophylls in plant leaves causes considerable absorption in the red light region of the electromagnetic spectrum in the incoming light while plant spongy mesophyll leaf structure creates considerable reflectance in the near infra-red region of the spectrum (Tucker, 1979; Jackson, *et al*, 2004, Tucker, *et al*, 1991). As a result, vigorously growing healthy vegetation has lower reflectance in the red light region and a higher reflectance in the near infra red region of the spectrum. This ultimately results in higher NDVI values for the vigorously growing healthy vegetations and it tends to become lower as the greenness of the vegetation decreases.

These NDVI values are given the range of -1.0 to 1.0. Increasing positive NDVI values indicates increasing amounts of healthy and vigorous green vegetations. The values closer to zero and decreasing negative values indicate non vegetated features such as barren surfaces and water, snow, ice and clouds. So, green and healthy vegetation reflects much less solar radiation in the visible-red (Ch 1) compared to those in near-infrared (Ch 2). More importantly, when vegetation is under stress, Ch 1 values may increase and Ch 2 values may decrease as stated earlier.

The Normalized Difference Vegetation Index (NDVI) is defined as

$$\mathbf{NDVI = (Ch\ 2 - Ch\ 1) / (Ch\ 2 + Ch\ 1)} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where near-infrared and visible-red are the radiation measured in channels 2 and 1, respectively. The Vegetation NDVI product from VGT4AFRICA (ten day synthesis) is composed by merging atmospherically corrected segments (data strips) acquired over a ten days interval. All the segments of this period (dekad) are compared again pixel by pixel to pick out the 'best' ground reflectance values. These dekadal products provide data from all spectral bands, the NDVI and auxiliary data on image acquisition parameters.

The NDVI data, which is disseminated via VGT4AFRICA, contains a spatial resolution of 1 kilometer by 1 Kilometer, an accuracy of 300m and runs from April 1998 to date. Note that the Vegetation Productivity Indicator (VPI) is used to assess the overall vegetation condition and is a categorical type of difference vegetation index, whereby the actual NDVI is referenced against the NDVI percentiles of the historical year.

The VPI method was originally developed by Sannier, *et al.*, (1998) based on NOAA AVHRR data for a study area in Zambia, and later on implemented by Herman Eerens for

Europe for Monitoring Agriculture with Remote Sensing STATistics (MARS-STAT) and Africa Monitoring Agriculture with Remote Sensing FOOD (MARS-FOOD) / Global Monitoring for Food Security (GMFS) Boogaard, *et al.*, 2004 based on Satellite Pour l'Observation de la Terre (SPOT) -VEGETATION data. It is commonly used in hydrology for the prediction of extreme events.

The dekadal NDVI product used for this study was grouped into monthly averages which were later clustered to give an averaged condition for the SOND season for the east Africa region. This was done for the period between years 2000 to 2009.

3.1.2 Rainfall Data

Monthly rainfall data were obtained from IGAD Climate Prediction and Applications Centre (ICPAC). The data used were from year 2000 to 2009 for the SOND season. ICPAC database contains rainfall data from various locations of the Greater Horn of Africa (GHA). In some cases, some stations were within the same homogeneous rainfall regimes. This led to classify stations within similar homogeneous rainfall regimes in order to get a representative station in the location used.

The stations used are:

Table 1: List of station used in the study

Station	Station Name	Long.	Lat.
1	ARUA	30.917	3.05
2	KASESE	30.1	0.183
3	ENTEBBE	32.45	0.05
4	MANDERA	41.867	3.933
5	MARSABIT	37.9	2.3
6	WAJIR	40.067	1.75
7	KISUMU	34.75	-0.1
8	KISII	34.783	-0.667
9	KERICHO	35.35	-0.367
10	NAKURU	36.1	-0.267
11	NYERI	36.967	-0.5

12	EMBU	37.45	-0.5
13	GARISSA	39.633	-0.467
14	DAGORETTI	36.75	-1.3
15	WILSON	36.817	-1.317
16	MALINDI	40.1	-3.233
17	MOMBASA	39.617	-4.033
18	BUKOBA	31.81	-1.333
19	MUSOMA	33.8	-1.5
20	MWANZA	32.917	-2.467
21	KIGOMA	29.633	-4.883
22	TABORA	32.833	-5.083
23	DODOMA	35.767	-6.167
24	MBEYA	33.467	-8.933
25	SONGEA	35.583	-10.683
26	MTWARA	40.183	-10.267

The following map shows the stations used and are numbered as they appear in Table. 1

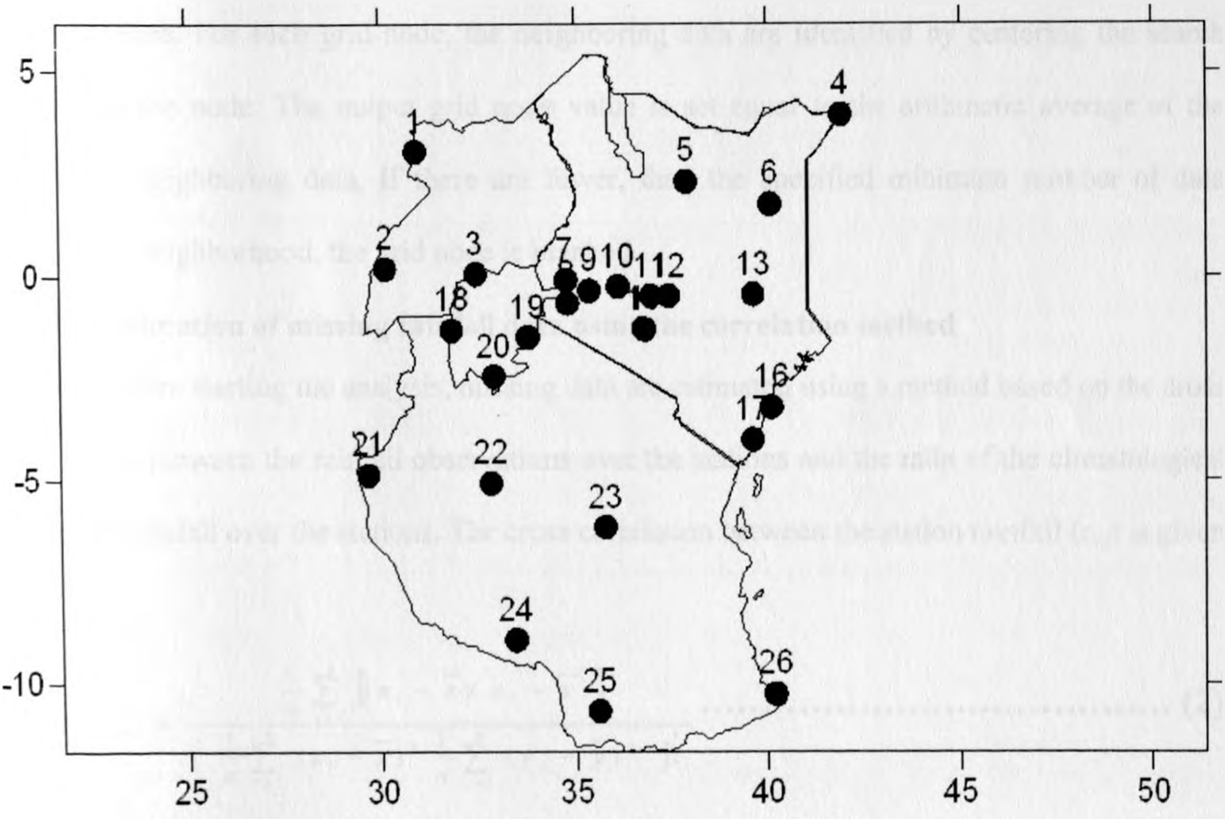

Figure 1b: Map of the stations used in the study

3.2 Methodology

This section discusses the various methods that were employed to address the overall and specific objectives of the study.

3.2.1 Estimation of missing data

3.2.1.1 Estimation of missing vegetation data using moving average method

The most common method used for interpolation from images or grid points is based on the computation of a weighted average of a representative sample of images or points in the vicinity of the needed data. The interpolation method which will be used to estimate missing grid points in case of missing data is moving average method. The Moving Average method assigns values to grid nodes by averaging the data within the grid node's search ellipse (Franke, 1980). To use Moving Average, a search ellipse must be defined and the minimum number of data to use, specified. For each grid node, the neighboring data are identified by centering the search ellipse on the node. The output grid node value is set equal to the arithmetic average of the identified neighboring data. If there are fewer, than the specified minimum number of data within the neighborhood, the grid node is blanked.

3.2.1.2 Estimation of missing rainfall data using the correlation method

Before starting the analysis, missing data are estimated using a method based on the cross correlation between the rainfall observations over the stations and the ratio of the climatological values of rainfall over the stations. The cross correlation between the station rainfall (r_{xy}) is given by:

$$r_{xy} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left[(x_i - \overline{x})(y_i - \overline{y})\right]}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2\right]^{\frac{1}{2}}} \quad \text{..................................} (2)$$

To compute these correlations between all the stations, a block of the data was taken over a sub-period where the most of the data was available. If station Y_i has a missing value at a certain year, and the station is best positively correlated with station X which has available data (X_a), the formula used to estimate Y_i is:

$$Y_i = X_a \frac{\overline{Y_i}}{\overline{X_a}} \quad \text{...} \quad (3)$$

Where , $Y_i =$ the missing data

$X_a =$ the available data of the station with the highest correlation with station whose data is missing.

$\overline{X_a} =$ the mean value for the station with complete data

$\overline{Y_a} =$ the mean value for the station with missing data

3.2.2 Homogeneity test

Homogeneity test was necessary for detection of errors in data and ensured that the data sets were free from errors. The cumulative mass curve technique was used in this study. It is a technique that involves accumulating monthly records for each station and plotting these values against time. A single straight line indicates a homogeneous record whereas homogeneity tendency is indicated by existence of one line fitted to the graphical plots of the cumulative data, WMO (1970, 1986), Siegel (1956) and Basalirwa (1991).

3.2.3 Drought severity index

Various drought indices have been developed and used in many parts of the world (including Africa) to monitor the spatial extent and severity of drought conditions. Generally, drought indices are developed based on cumulative precipitation deficit. These provide guidance for the use of mitigation measures during a drought. In this study, rainfall data was used to calculate drought severity index which responds well with the increase and decrease of vegetation and as result drought detection through it. Periods associated with drought and its effects are going to be monitored using the drought index.

The drought index is going to measure how much precipitation for the September - December season has deviated from established averaged condition. The index is calculated by dividing actual precipitation (observed) by the long term precipitation average (30 years) and multiplying by 100%.

$$\left\{ {}^{P\,(i)} / {}_{P\,(a)} \right\} * 100 \quad \text{.......................................} \quad (4)$$

Where,

P (i) = Actual precipitation (observed)

P (a) = Long term precipitation average (30 years)

This will be calculated for SOND season putting in mind that normal precipitation for a specific location is considered to be 100%.

The Drought Severity Index Values are given as follows.

5 which is >175%	Very wet (wettest on record)
4 which is 125-175%	Wet
3 which is 75-125%	Near normal
2 which is 25-75%	Dry
1 which is 10-25%	Generally dry
-1 which is <10%	Extremely dry (driest on record)

Drought Severity Index is used to determine the drought periods. This meteorological drought index responds to weather conditions that have been abnormally dry or abnormally wet.

3.2.4 Vegetation Productivity Index

Vegetation Productivity Index (VPI) gives the overall vegetation condition of the region in probability classes. This was possible by taking the actual NDVI readings and referencing it against the NDVI percentile of an averaged image of a determined period for the best condition, normal condition and worst condition for the whole region. The general principle of VPI is explained in the Fig. 2. The green line represents the cumulative histogram, which is derived from the historical NDVI values available for the considered period. The red line, which connects the selected set of percentiles, forms an approximation of the true histogram.

Current observations are referenced to this approximate histogram, which allows deriving their historical probability. Example, the blue point has a relatively high NDVI and hence a high probability (89%). Sannier, *et al.* 1998, classified the probabilities in 5 groups (0-20%... 80-100%). However, the original values are kept and the VPI is calculated based on the NDVI values. NB: The VPI is produced based on SPOT-VGT NDVI values.

Source: SPOT-VEGETATION

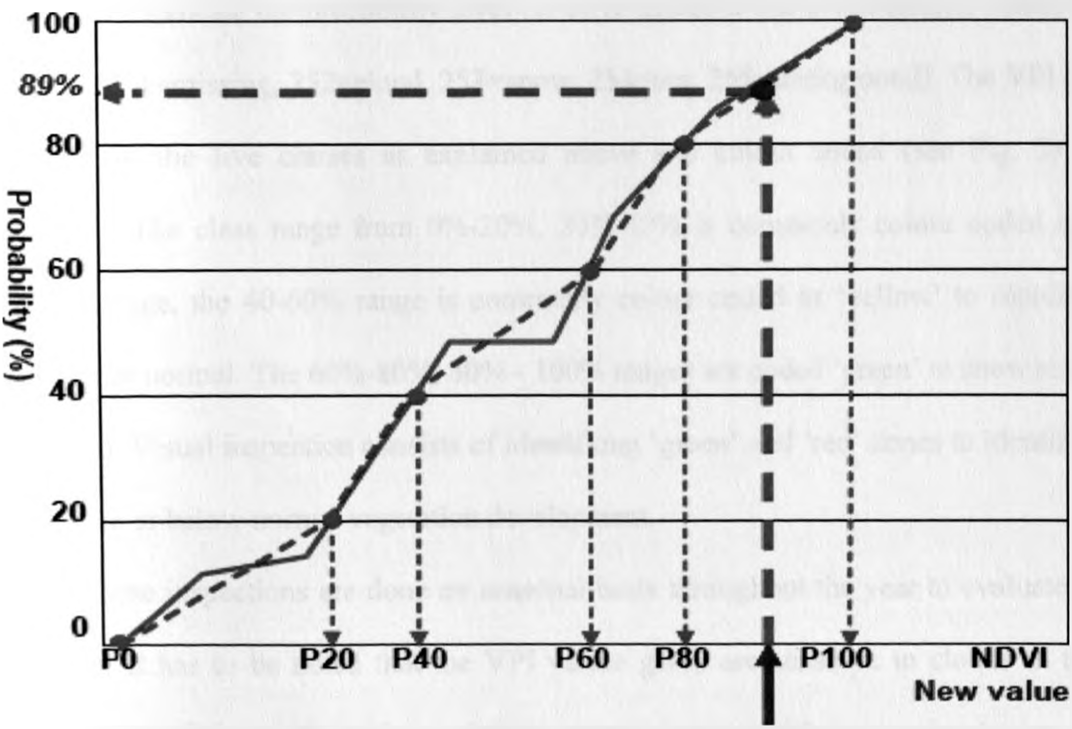

Figure 2: Comparison of NDVI value and VPI Probability Class from VGT4Africa (Sannier, et al., 1998b).

VPI-maps are created as follows for every period: For each pixel, the NDVI-percentiles are read from the following 6 percentiles of the historical period that is0%, 20%, 40%, 60%, 80% and 100%. By comparing the pixel's actual NDVI-value with these percentiles, it is assigned to one of the five percentile groups ("productivity classes"). Note that VPI is used to qualitatively identify areas with below normal vegetation development possibly linked to low vegetation productivity as compared to what can be expected based on the historical range. VPI is used to identify drought affected areas (Sannier, et al., 1998b).

The decoded VPI percentages indicate the probability of getting a lower NDVI value based on historical analysis of the NDVI values. Thus, a probability of 50% indicates that there is a 50% chance of getting a lower value (and thus 50% chance of getting a higher value) compared to the historical value range, indicating a fairly normal/average situation.

The VPI data generated contains continuous values from 0-255, whereas values ranging from 10-210 indicate the probability level (to be re-scaled to the 0-100 range), values above 250 are flags (251=missing, 252=cloud, 253=snow, 254=sea, 255=background). The VPI is typically classified in the five classes as explained above and colour coded (see Fig. 3) for visual inspection. The class range from 0%-20%, 20%-40% is commonly colour coded as 'red' for below average, the 40-60% range is commonly colour coded as 'yellow' to represent neutral condition or normal. The 60%-80%, 80% - 100% ranges are coded 'green' to show above normal vegetation. Visual inspection consists of identifying 'green' and 'red' zones to identify the zones with above or below normal vegetation development.

These inspections are done on seasonal basis throughout the year to evaluate the season condition. It has to be noted that the VPI values given are sensitive to clouds in the original NDVI image. This might lead to a below normal value which is not due to low vegetation

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These inspections are done on seasonal basis throughout the year to evaluate the season condition. It has to be noted that the VPI values given are sensitive to clouds in the original NDVI image. This might lead to a below normal value which is not due to low vegetation activity but due to the interference. Because of this, it is important to consider multiple periods to see if the same trends persist.

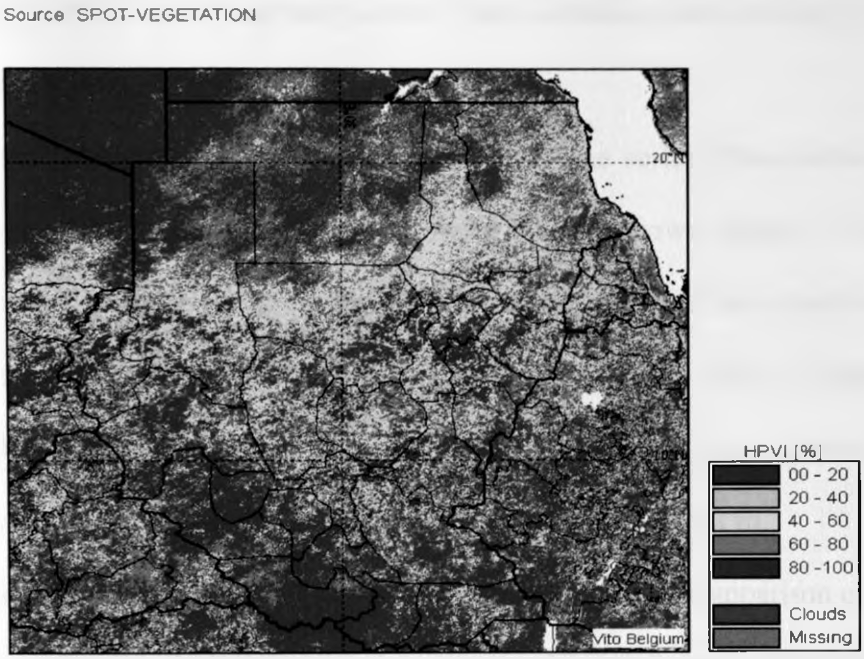


Figure 3: Example of a VPI Image from SPOT-VEGETATION used in VGT4Africa (Sannier, et al., 1998b).

3.2.5 VPI drought identification

Vegetation responds well to rainfall in the east African region, this is well portrayed during the rainfall seasons; this is the duration when farming is intensified. The NDVI is a direct measure of the radiative response to the vigour of the surface vegetation, and so will respond indirectly to rainfall; this brings in the idea of monitoring meteorological drought using satellite data.

Just like the drought index, Images were grouped from dekadal products to monthly averages then SOND averages, where the average of each yearly SOND was obtained and data extracted to give the actual VPI values. Using these values, VPI productivity classes were specified and the readings were recorded to the required category. The final products were used for comparison with the SOND DSI results.

3.2.6 Trend analysis

SOND average time series were obtained from the rainfall drought index and the same was repeated for VPI for each year and plotted. Then combining and checking the variation of both indices, trends were observed and results given.

Trend analysis is the long-term movement in a time series. Examination of the trend component in any time series analysis is significant since it shows whether the time series is stationary or non-stationary. Trend can be linear or non-linear, and the objective approach to examine this is through graphical and statistical approaches (WMO 1966). A graph of the time series can indicate whether or not a linear relationship provides a good approximation to the long-term movement, regression analysis may give the curve of the best fit.

Graphical approach method was used to examine trends and comparison of the DSI trend and vegetation productive classes were employed to test the significance of the observed trends.

3.2.6.1 Graphical approach

In graphical method, the trend is visualized from the graphical representation of time series. In time series, the trend at any point in time is represented by a weighted average of the observed values near that point. The idea behind using time series is to allow a preliminary view of the temporal evolution of rainfall drought severity index in respect to VPI classes. The graphical method adopted in the study included plotting of time series through which by visual examination an approximation of whether or not a general trend to the long-term movement can be inferred. Also during the extraction of VPI values, images got allow easy determination of variation of yearly SOND season with respect to the decadal average in wider spatial extend.

3.2.6.2 Statistical approach

The visual methods of determining trends from graphs are very subjective and therefore the objective approach towards determining the trend of any time series is to examine the significance of any trend observed in the time series. Since some form of trend is the most likely alternative to randomness in climatological time series, statistical tests are usually applied to check the presence or the absence of trend (linear or non-linear).

3.2.6.2.1 Linear Regression

Linear Regression is a parametric statistical procedure that is typically used for analyzing trends in data over time. However, with the usual approach of interpreting the slope of the regression line, concentration trends may often be obscured by data scatter arising from non ideal conditions, sampling and analysis conditions, etc.

If we expect a set of data to have a linear correlation, the simplest way to get the regression formula for your data is to create a simple XY chart and add the Trendline formula and correlation values from the Options dialogue. Also it is not necessary for us to plot the data in order to determine the constants *m* (slope) and *b* (y-intercept) of the equation

$$y = mx + b \qquad \text{..} (5)$$

Instead, we can apply a statistical treatment known as linear regression to the data and determine these constants. NB: Given a set of data (x_i, y_i) with *n* data points, the slope, y-intercept and correlation coefficient, *r*, can be determined using the following:

$$m = \frac{n\sum(xy) - \sum x \sum y}{n\sum(x^2) - \left(\sum x\right)^2} \qquad \text{..} (6)$$

$$b = \frac{\sum y - m\sum x}{n} \quad \text{...} (7)$$

$$r = \frac{n\sum(xy) - \sum x \sum y}{\sqrt{\left[n\sum(x^2) - \left(\sum x\right)^2\right]\left[n\sum(y^2) - \left(\sum y\right)^2\right]}} \quad \text{........................} (8)$$

3.2.6.2.2 Coefficient of Variation (CoV)

To determine the Coefficient of Variation (CoV) calculation of average and standard deviation was done. The arithmetic mean of a sample of n values of a variable is the average of all the sample values written as

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad \text{..} (9)$$

The standard deviation is the square root of the average of the square of the deviations from the sample mean written as

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \quad \text{...} (10)$$

The standard deviation is a measure of how the value fluctuates about the arithmetic mean of the data. The Coefficient of Variation (COV) is a statistical measure of how the individual data points vary about the mean value. The coefficient of variation, defined as the standard deviation divided by the average or

$$C.O.V. = \frac{s}{\bar{x}} \quad \text{.......................................} (11)$$

Values less than or near 1.00 indicate that the data form a relatively close group about the mean value. Values larger than 1.00 indicate that the data show a greater degree of scatter about the mean.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

This chapter presents and discusses the results that were obtained from the various methods that were used to address the objectives of this study.

4.1 Results of estimation of missing vegetation data using interpolation method

Only one dekad in the stations used in the region had missing data for Entebbe region recording 251 in NDVI value. The missing value for Entebbe region for dekad 3 in September 2006 was estimated using moving average method and the result was found to be 175.

4.2 Homogeneity results

Homogeneity test was done to check for consistency in the data in all the station used. Results from the mass curves indicated that in general only straight single lines could be fitted to all of the monthly seasonal cumulative rainfall records of the stations, which is indicative of homogeneity of the records used in the study. Examples of the derived mass curves are shown in figure 4 to 11. The results were indicative of good quality of rainfall records.

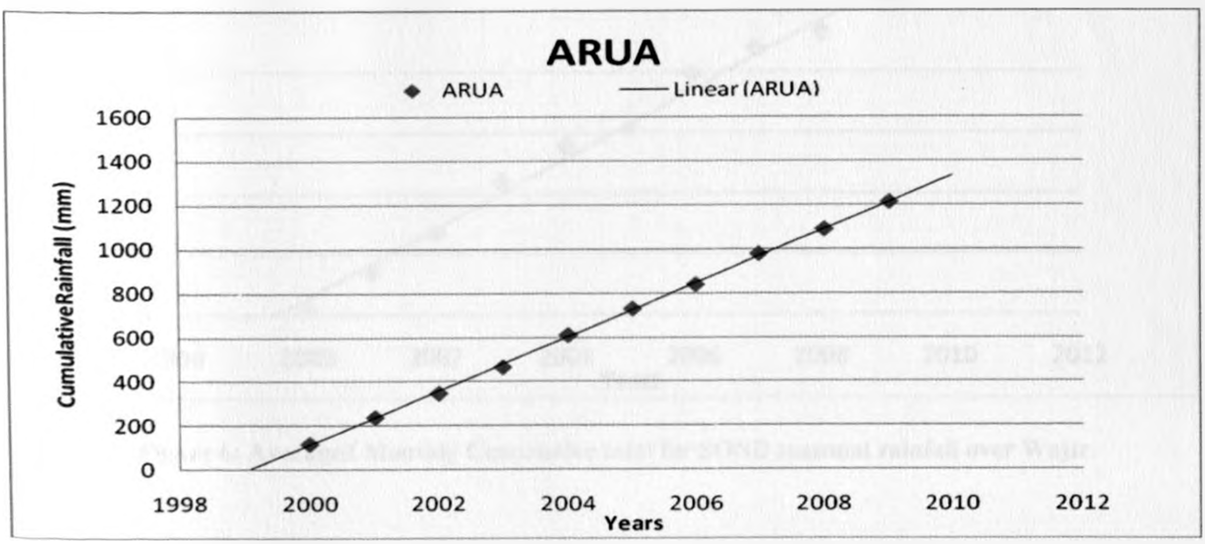


Figure 4: Averaged Monthly Cumulative total for SOND seasonal rainfall over Arua

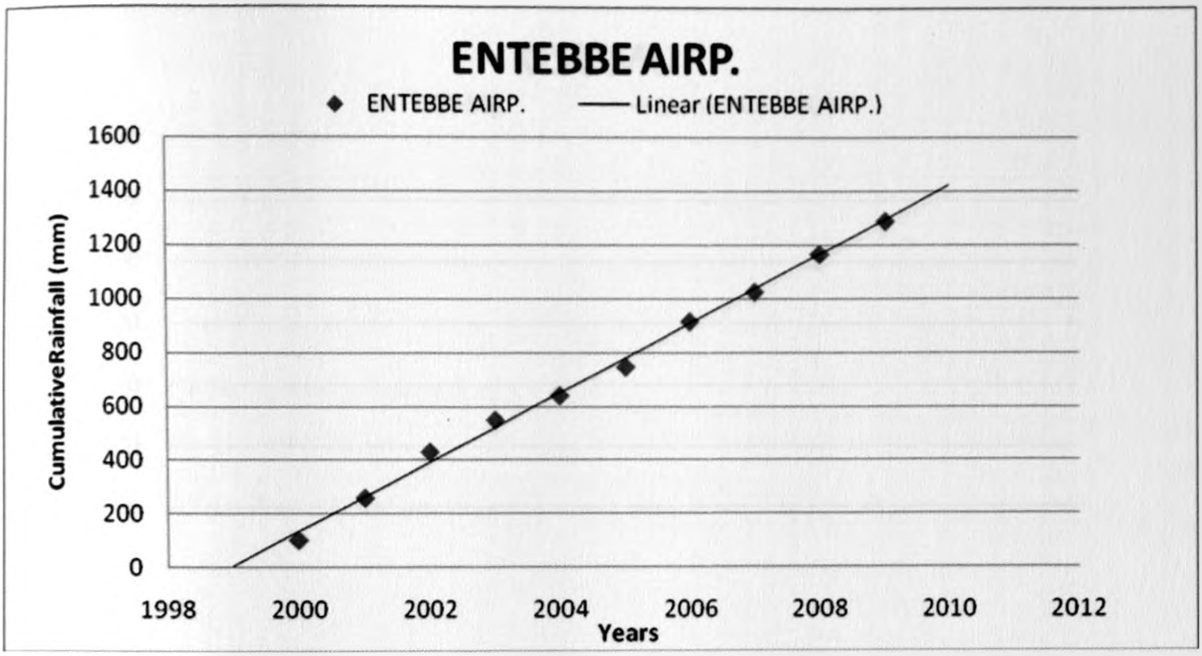


Figure 5: Averaged Monthly Cumulative total for SOND seasonal rainfall over Entebbe

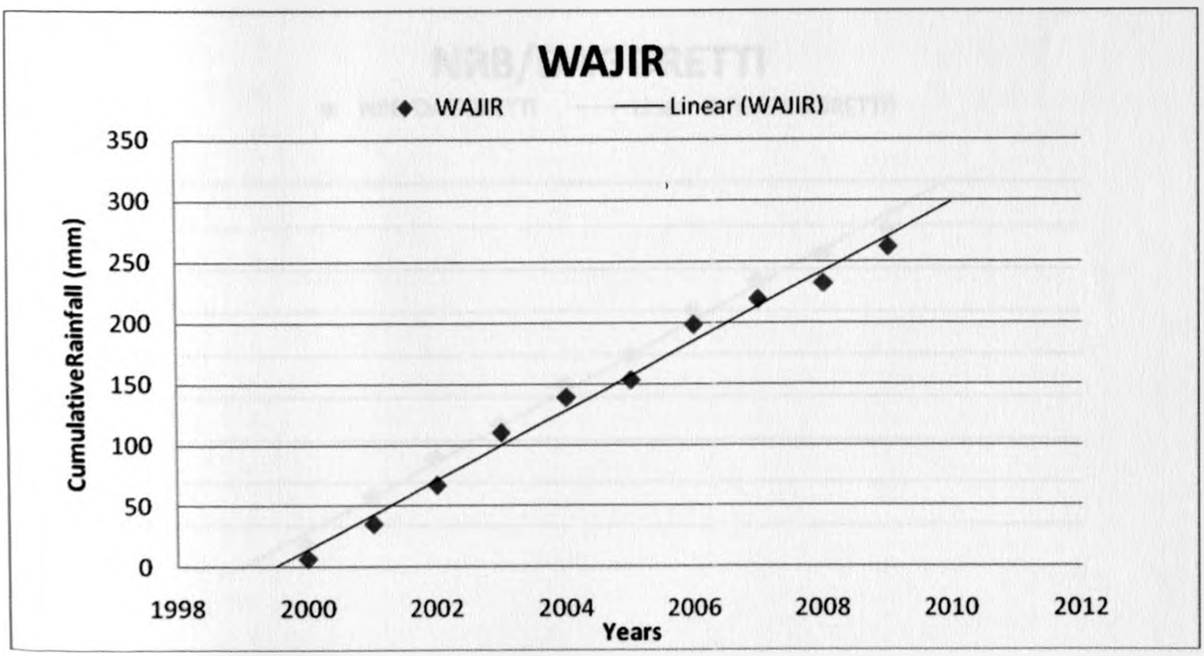


Figure 6: Averaged Monthly Cumulative total for SOND seasonal rainfall over Wajir

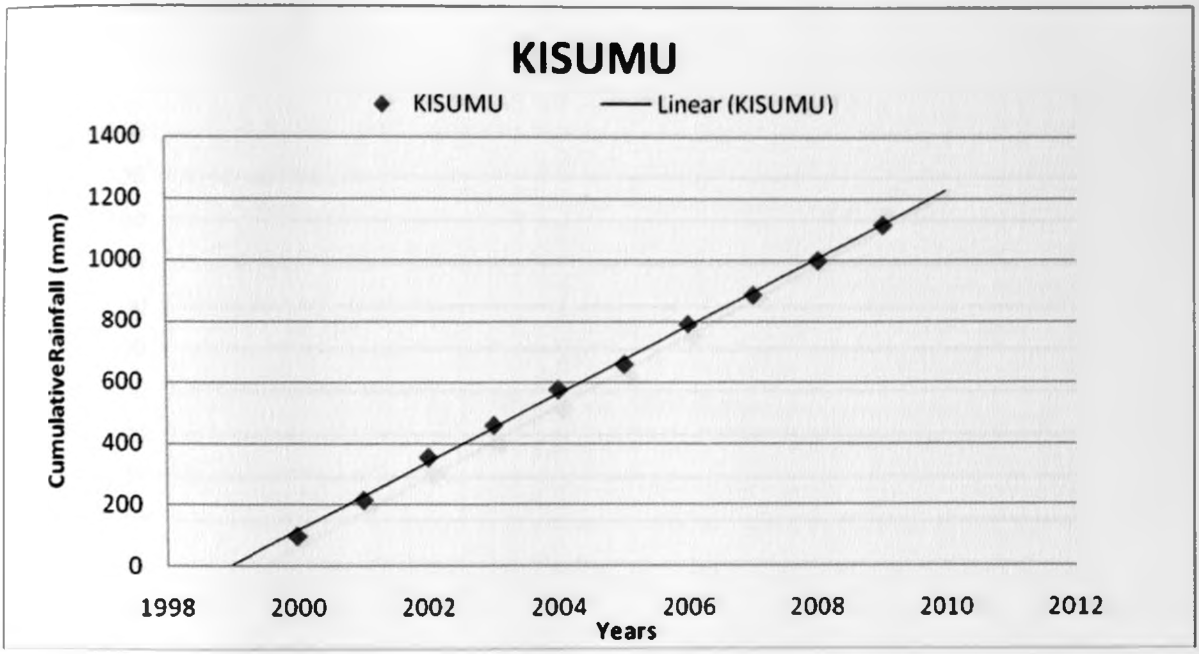


Figure 7: Averaged Monthly Cumulative total for SOND seasonal rainfall over Kisumu

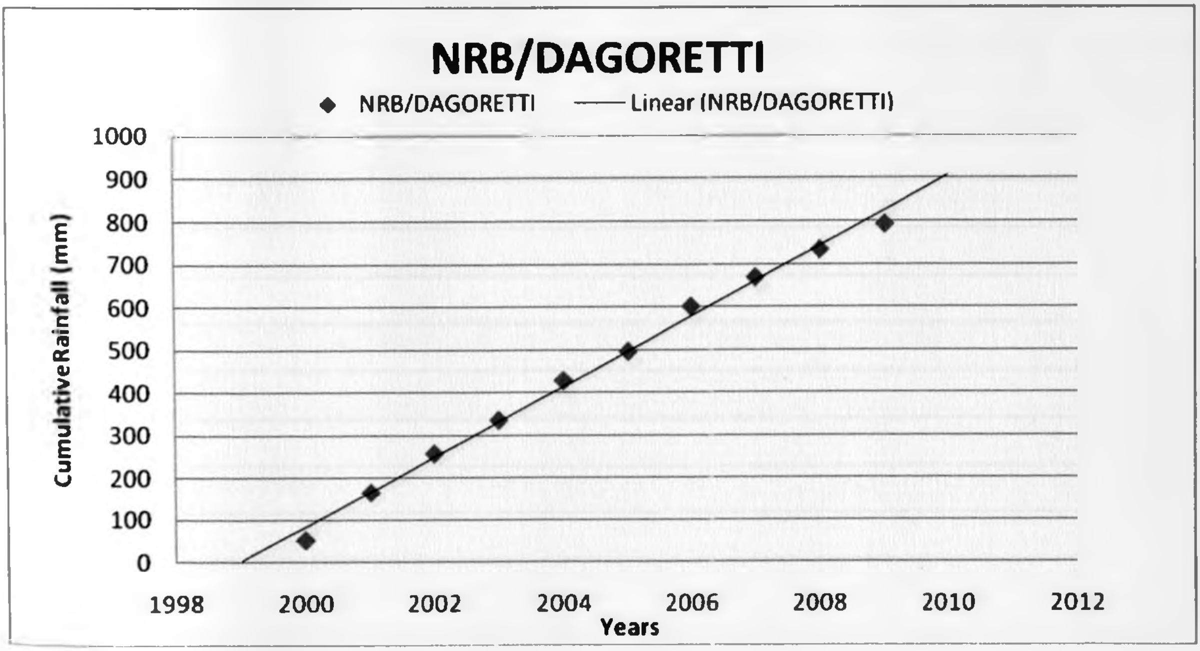


Figure 8: Averaged Monthly Cumulative total for SOND seasonal rainfall over Dagoretti

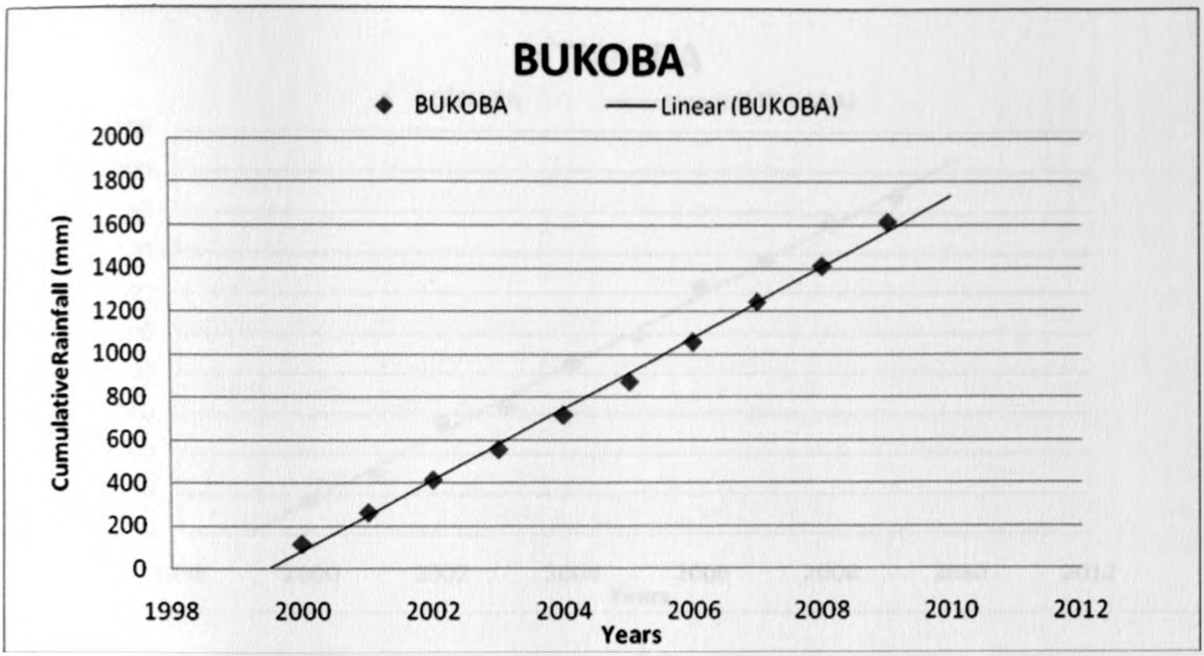


Figure 9: Averaged Monthly Cumulative total for SOND seasonal rainfall over Bukoba

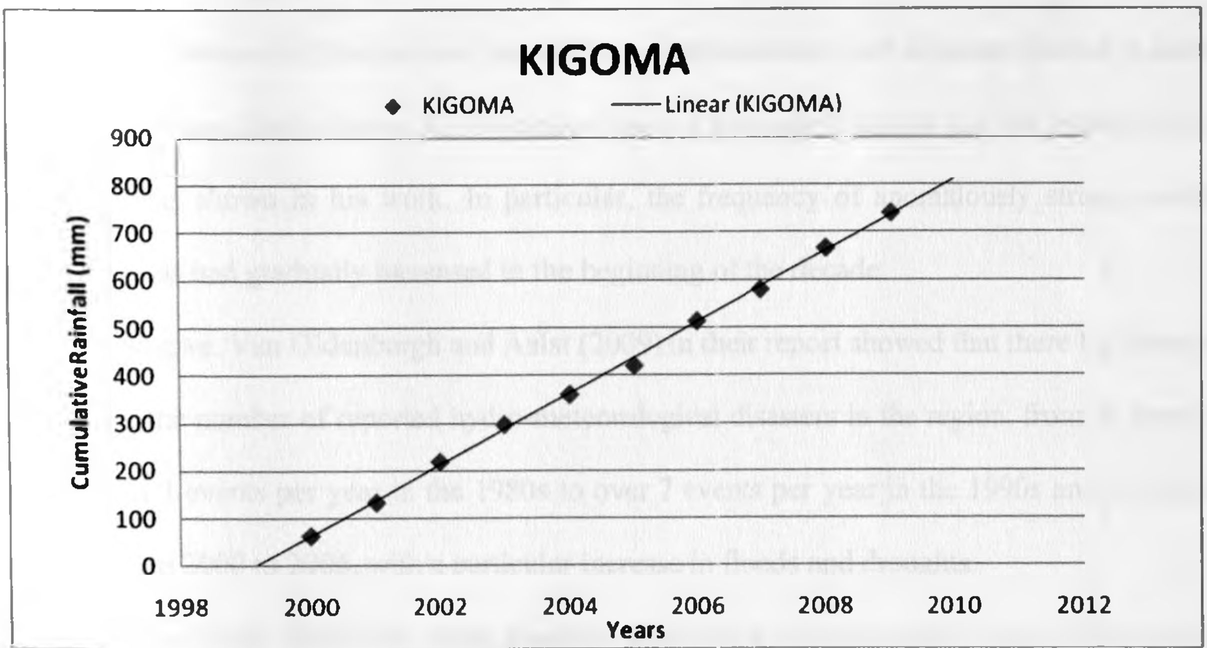


Figure 10: Averaged Monthly Cumulative total for SOND seasonal rainfall over Kigoma

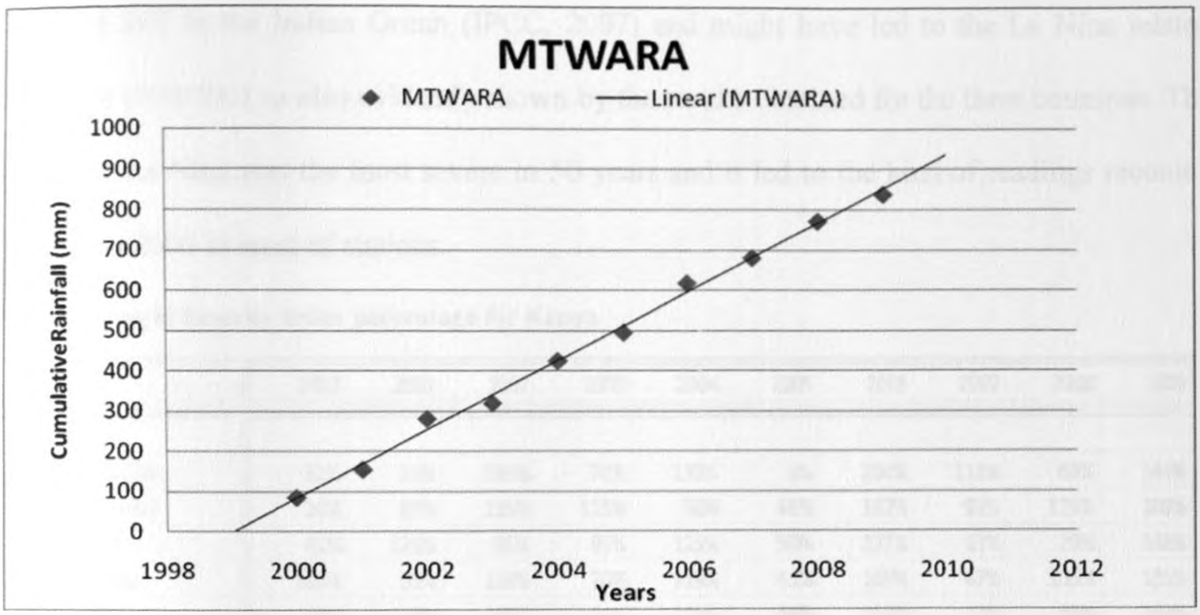


Figure 11: Averaged Monthly Cumulative total for SOND seasonal rainfall over Mtwara

4.3 Results for identifying drought periods using drought severity index

Using drought index the following SOND results were obtained. The results in this section show that east Africa has had variability in both excessive and deficient rainfall in recent years. This is specifically shown for the earlier years of the current decade just like Hastenrath, et al. (2007) has shown in his work. In particular, the frequency of anomalously strong rainfall causing floods had gradually increased in the beginning of the decade.

Shongwe, Van Oldenborgh and Aalst (2009) in their report showed that there had been an increase in the number of reported hydro-meteorological disasters in the region, from an average of less than 3 events per year in the 1980s to over 7 events per year in the 1990s and 10 events per year from 2000 to 2006, with a particular increase in floods and droughts.

In the period 2000-2006 these disasters affected on average almost two million people per year. The major historical droughts in the last 20 years in the region were in: 1983/84, 1991/92, 1995/96, 1999/2001, 2004/2005 (led to famine) i.e. results for Kenya, as show in table.2. Also the El-Nino related floods of 1997/98 were very severe enhanced by unusual pattern of SST in the Indian Ocean (IPCC, 2007) and might have led to the La Nina related drought of 1999/2001 as also evidently shown by the results obtained for the three countries. The 1999/2000 La Nina was the most severe in 50 years and it led to the kind of readings recorded for the year 2000 in most of stations.

Table 2: Drought Severity Index percentage for Kenya

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
KENYA										
63624 MANDERA	91%	21%	139%	74%	139%	6%	204%	113%	69%	144%
63641 MARSABIT	24%	87%	135%	113%	98%	46%	167%	93%	129%	109%
63671 WAJIR	41%	125%	85%	89%	125%	56%	227%	85%	29%	138%
63708 KISUMU	106%	95%	110%	70%	119%	45%	169%	47%	105%	135%
63709 KISII	119%	136%	106%	94%	113%	64%	113%	73%	81%	102%
63710 KERICHO	71%	88%	85%	86%	71%	47%	114%	81%	93%	263%
63714 NAKURU	78%	88%	128%	74%	87%	86%	124%	94%	134%	107%
63717 NYERI	75%	65%	120%	112%	123%	37%	196%	101%	76%	96%
63720 EMBU	65%	72%	99%	103%	137%	60%	204%	114%	65%	82%
63723 GARISSA	43%	75%	161%	80%	61%	14%	221%	164%	71%	111%
63741 NRB/DAGORETTI	101%	71%	149%	90%	98%	54%	172%	59%	115%	91%
63742 NRB/WILSON	87%	92%	159%	63%	80%	37%	180%	65%	135%	102%
63799 MALINDI	71%	34%	168%	67%	118%	36%	200%	92%	51%	164%
63820 MOMBASA	66%	51%	145%	36%	132%	99%	236%	84%	52%	100%

Table 3: DSI grouped to classes for Kenya

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
KENYA										
63624 MANDERA	3	1	4	2	4	-1	5	3	2	4
63641 MARSABIT	2	3	4	3	3	2	4	3	4	3
63671 WAJIR	2	3	3	3	3	2	5	3	2	4
63708 KISUMU	3	3	3	2	3	2	4	2	3	4
63709 KISII	3	4	3	3	3	2	3	2	3	3
63710 KERICHO	2	3	3	3	2	2	3	3	3	5
63714 NAKURU	2	3	4	2	3	3	3	3	4	3
63717 NYERI	2	2	3	3	3	2	5	3	3	3
63720 EMBU	2	2	4	3	4	2	5	3	2	3
63723 GARISSA	2	2	4	3	2	1	5	4	2	3
63741 NRB/DAGORETTI	3	3	4	3	3	2	4	2	3	3
63742 NRB/WILSON	3	3	4	2	3	2	4	2	4	3
63799 MALINDI	2	2	4	2	3	2	5	3	2	4
63820 MOMBASA	2	2	4	2	4	3	5	3	2	3

Just like year 2000, year 2001 was another worst hit SOND season with a dry period lasting longer than any other SOND season in Kenya in the period of study. All the stations in this year show varying conditions on average as shown in Table. 2. Garissa and Mandera were the worst hit in year 2005 and show the lowest recordings in the region. Year 2000 drought might have been attributed to the warming episodes in the Niño 3.5 region in the pacific. The whole East Africa region in this year experienced the worst drought in the decade. Year 2002, 2004, 2006 and 2009 SOND seasons were wet but in year 2004 there was a tendency for near normal conditions. Year 2003 and 2008 had near normal conditions, but year 2008 was having some variations.

Table 4: Drought Severity Index percentage for Uganda

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
UGANDA										
63602 ARUA	94%	127%	82%	74%	117%	114%	88%	96%	105%	103%
63674 KASESE	109%	93%	96%	67%	132%	87%	105%	123%	105%	84%
63705 ENTEBBE AIRP.	44%	126%	153%	88%	81%	46%	172%	78%	76%	135%

Table 5: DSI grouped to classes for Uganda

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
UGANDA										
63602 ARUA	3	4	3	2	3	3	3	3	3	3
63674 KASESE	3	3	3	2	4	3	3	3	3	3
63705 ENTEBBE AIRP.	2	4	4	3	3	2	4	3	2	4

From the three stations used for Uganda, near normal conditions were observed throughout the decade with the Entebbe region experiencing four wet years in year 2001, 2002, 2006 and 2009. Dry SOND seasons were recorded in 2000, 2005 and 2008. It is also evident that year 2003, 2004 and 2007 were near normal and around the Entebbe region variability was well characterized in the great part of the decade. Year 2003 for these stations shows drought prevalence and it is the lowest recorded in the last ten years.

Table 6: Drought Severity Index percentage for Tanzania

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	101%	74%	109%	97%	87%	58%	142%	115%	88%	129%
63733 MUSOMA	119%	82%	161%	54%	57%	56%	128%	97%	97%	149%
63756 MWANZA	73%	103%	106%	76%	110%	84%	136%	97%	86%	128%
63801 KIGOMA	115%	77%	96%	84%	97%	73%	159%	111%	106%	81%
63832 TABORA	102%	108%	125%	70%	149%	35%	156%	70%	86%	100%
63862 DODOMA	168%	48%	95%	127%	108%	46%	83%	70%	67%	187%
63932 MBEYA	155%	87%	64%	89%	115%	59%	153%	87%	89%	101%
63962 SONGEA	98%	53%	110%	92%	95%	38%	179%	132%	92%	113%
63971 MTWARA	111%	72%	177%	22%	223%	26%	174%	37%	97%	61%

Table 7: DSI grouped to classes for Tanzania

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	3	2	3	3	3	2	4	3	3	4
63733 MUSOMA	3	3	4	2	2	2	4	3	3	4
63756 MWANZA	2	3	3	3	3	3	4	3	3	4
63801 KIGOMA	3	2	3	3	3	2	4	3	3	3
63832 TABORA	3	3	3	2	4	2	4	2	3	3
63862 DODOMA	4	2	3	4	3	2	3	2	2	5
63932 MBEYA	4	2	2	3	3	2	4	3	3	3
63962 SONGEA	3	2	3	3	3	2	5	4	3	3
63971 MTWARA	3	2	5	1	5	2	4	2	3	2

On average Tanzania shows a fairly near normal tendency, this is recorded for year 2002, 2007 and 2008. Year 2001 and 2005 were far the driest SOND seasons in the decade having year 2005 as the worst drought experienced for the country. Unlike 2001 and 2005, 2006 SOND season was the wettest in all stations during the period chosen for study. It is noted that changes characterized in the great part of the decade. Year 2003 for these stations shows drought prevalence and it is the lowest recorded in the last ten years.

Table 6: Drought Severity Index percentage for Tanzania

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	101%	74%	109%	97%	87%	58%	142%	115%	88%	129%
63733 MUSOMA	119%	82%	161%	54%	57%	56%	128%	97%	97%	149%
63756 MWANZA	73%	103%	106%	76%	110%	84%	136%	97%	86%	128%
63801 KIGOMA	115%	77%	96%	84%	97%	73%	159%	111%	106%	81%
63832 TABORA	102%	108%	125%	70%	149%	35%	156%	70%	86%	100%
63862 DODOMA	168%	48%	95%	127%	108%	46%	83%	70%	67%	187%
63932 MBEYA	155%	87%	64%	89%	115%	59%	153%	87%	89%	101%
63962 SONGEA	98%	53%	110%	92%	95%	38%	179%	132%	92%	113%
63971 MTWARA	111%	72%	177%	22%	223%	26%	174%	37%	97%	61%

Table 7: DSI grouped to classes for Tanzania

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	3	2	3	3	3	2	4	3	3	4
63733 MUSOMA	3	3	4	2	2	2	4	3	3	4
63756 MWANZA	2	3	3	3	3	3	4	3	3	4
63801 KIGOMA	3	2	3	3	3	2	4	3	3	3
63832 TABORA	3	3	3	2	4	2	4	2	3	3
63862 DODOMA	4	2	3	4	3	2	3	2	2	5
63932 MBEYA	4	2	2	3	3	2	4	3	3	3
63962 SONGEA	3	2	3	3	3	2	5	4	3	3
63971 MTWARA	3	2	5	1	5	2	4	2	3	2

On average Tanzania shows a fairly near normal tendency, this is recorded for year 2002, 2007 and 2008. Year 2001 and 2005 were far the driest SOND seasons in the decade having year 2005 as the worst drought experienced for the country. Unlike 2001 and 2005, 2006 SOND season was the wettest in all stations during the period chosen for study. It is noted that changes in season in rainfall intensity tend to contribute towards determining a wet or dry year. Also anomalously wet seasons are typified by more evenly distributed rains, whereas for drier than average years the reverse tends to be true.

4.4 Results for vegetation productivity index generation

The yearly VPI images derived from the NDVI images are shown below (fig. 12 to 22) these images were placed alongside to rainfall anomalies and ENSO charts for comparison. The most prevalent mode of interannual climate variability appearing to be influential in this rainfall season is ENSO. Since its effect characterizes rainfall anomaly pattern over eastern Africa, charts have been drawn to show this. ENSO charts drawn show the warm and cold episodes which are based on a threshold of +/- 0.5oC for the Oceanic Niño Index (ONI) which is a 3 month running mean of Extended Reconstruction Sea Surface Temperature (ERSST.v3b) SST anomalies in the Niño 3.4 region (5^{o}N-5^{o}S, 120^{o}-170^{o}W)], based on the 1971-2000 base period. The cold and warm episodes are defined when the threshold is met for a minimum of 5 consecutive over-lapping seasons. Note that also rainfall anomalies plotted below show regions of above normal rainfall (green), near normal (cyan) and below normal rainfall (yellow).

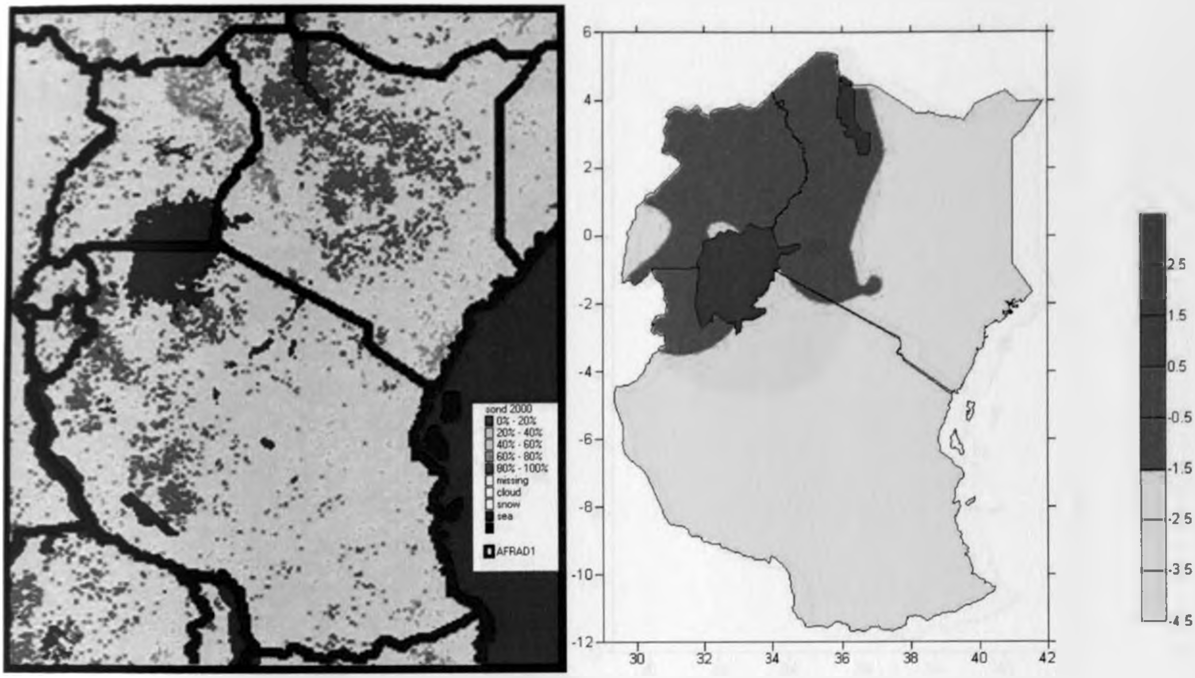
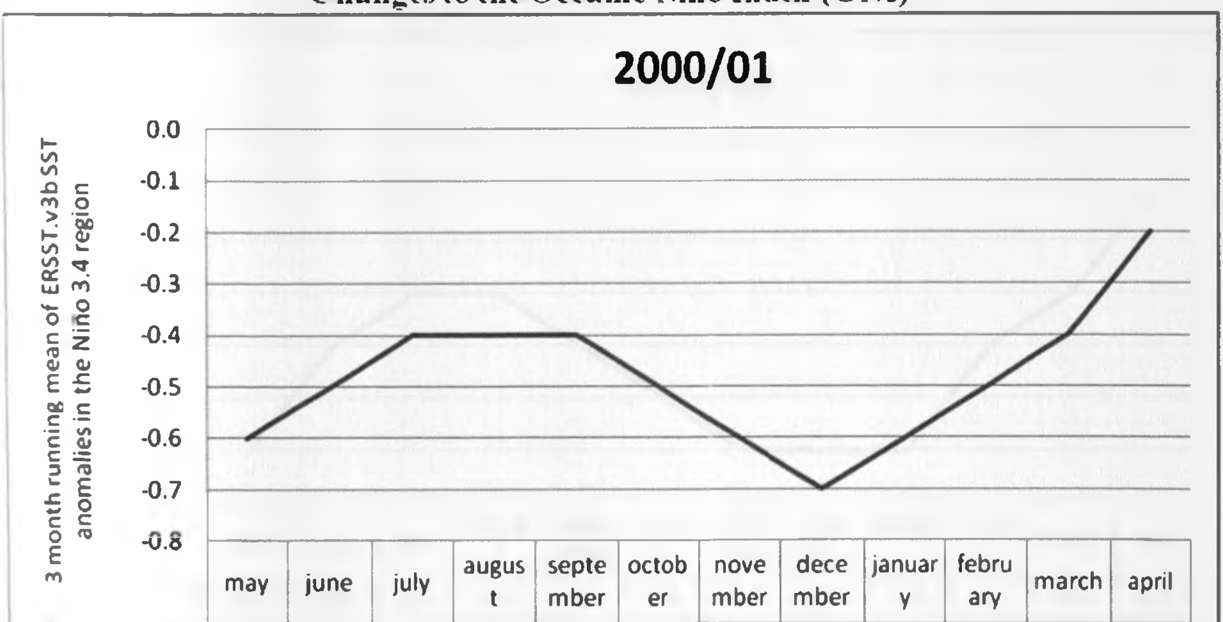


Figure 12: Year 2000 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)



	may	june	july	augus t	septe mber	octob er	nove mber	dece mber	januar y	febru ary	march	april
2000/01	-0.6	-0.5	-0.4	-0.4	-0.4	-0.5	-0.6	-0.7	-0.6	-0.5	-0.4	-0.2

Figure 13: Time evolution of changes to the oceanic Nino Index in 2000/01

Its observed that during a dry period in East Africa the oceanic nino index records the lowest in the SOND period (Figure 12).

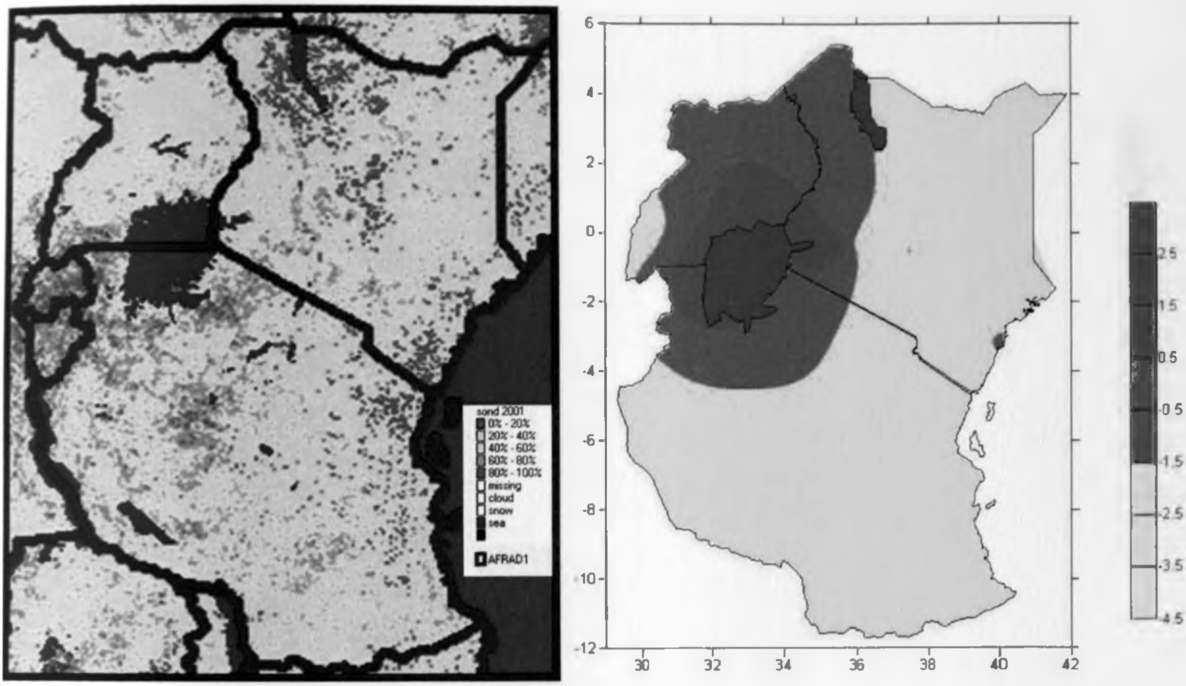
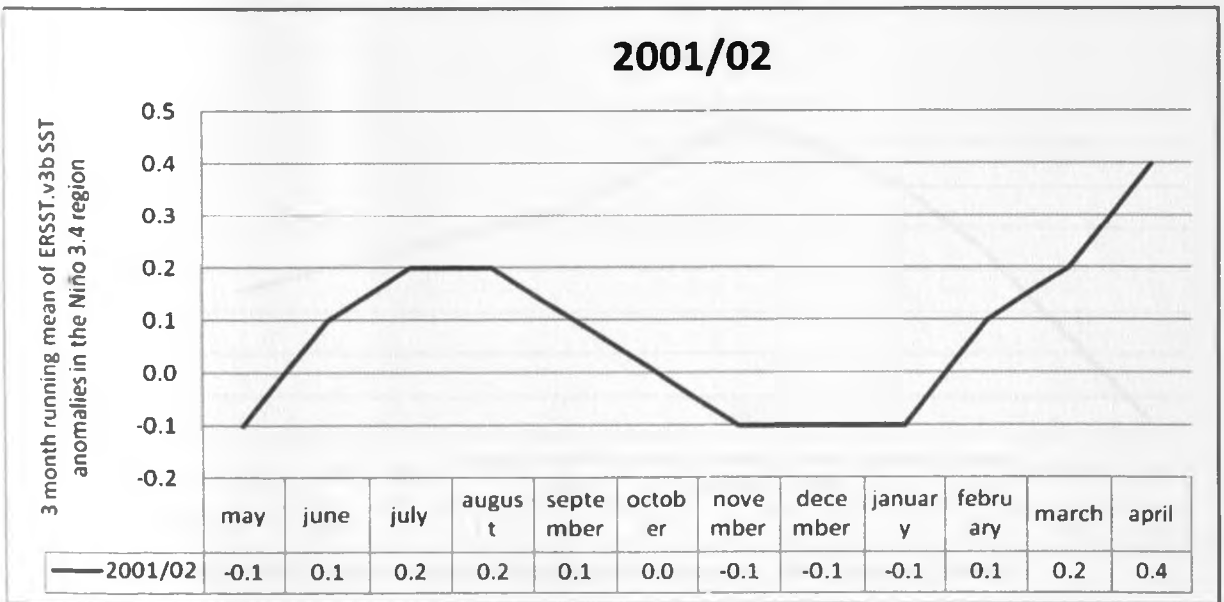


Figure 14: Year 2001 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)



	may	june	july	august	september	october	november	december	january	february	march	april
2001/02	-0.1	0.1	0.2	0.2	0.1	0.0	-0.1	-0.1	-0.1	0.1	0.2	0.4

Figure 15: Time evolution of changes to the oceanic Nino Index in 2001/02

Just like time evolution of changes to the oceanic Nino Index in 2000/01, 2001/2 follows the same trend resulting to a dry period in East Africa.

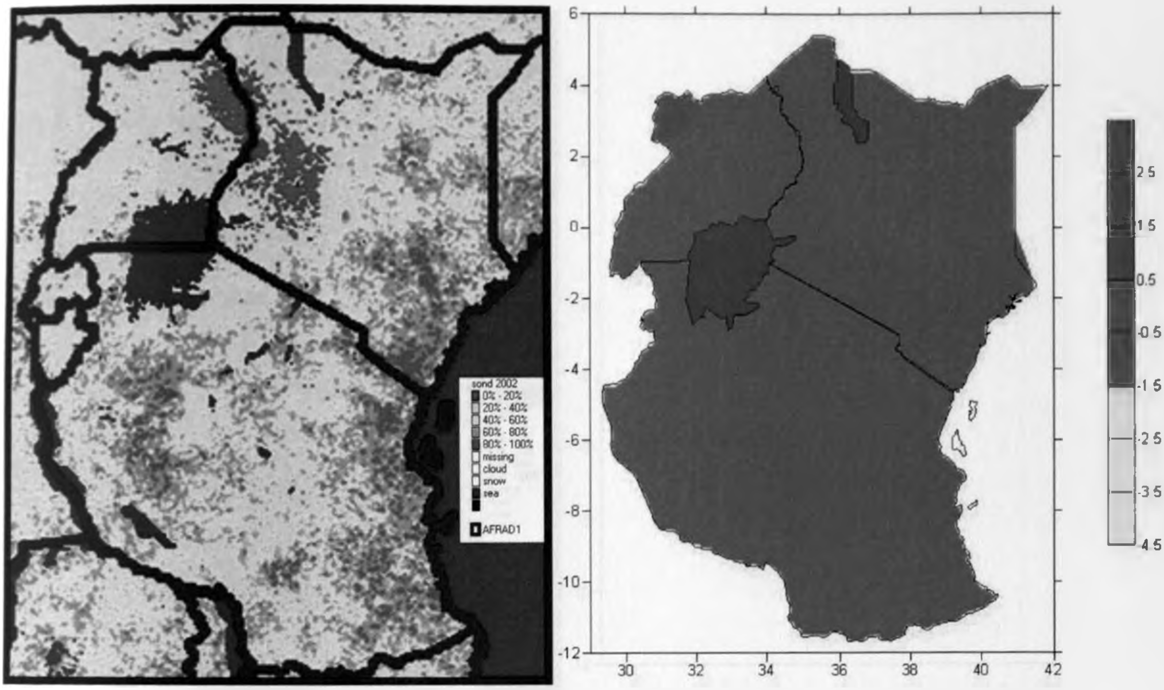
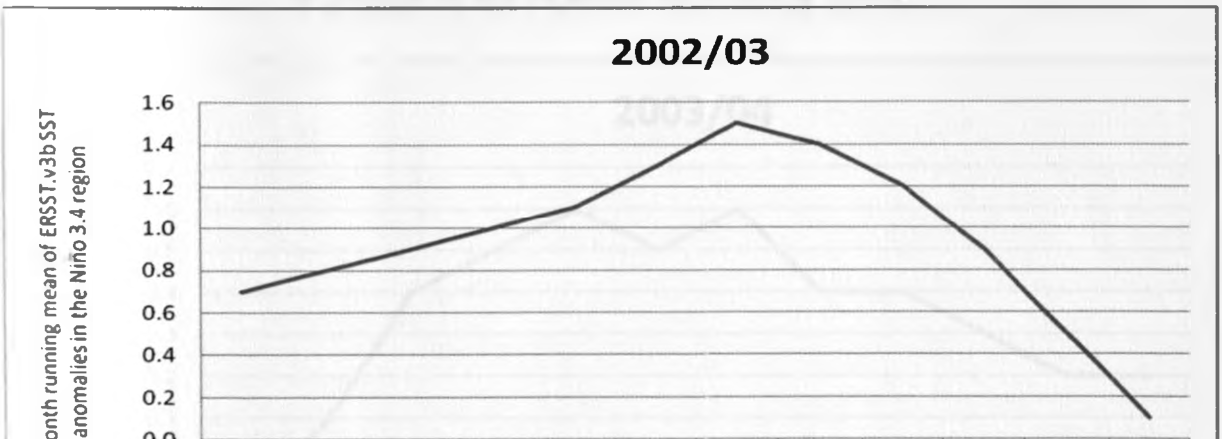


Figure 16: Year 2002 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)



	may	june	july	august	september	october	november	december	january	february	march	april
2002/03	0.7	0.8	0.9	1.0	1.1	1.3	1.5	1.4	1.2	0.9	0.5	0.1

Figure 17: Time evolution of changes to the oceanic Nino Index in 2002/03

An increase in oceanic Nino Index shows a corresponding increase in the vegetation cover in East Africa region. This is because rainfall received is a function of the nino index change.

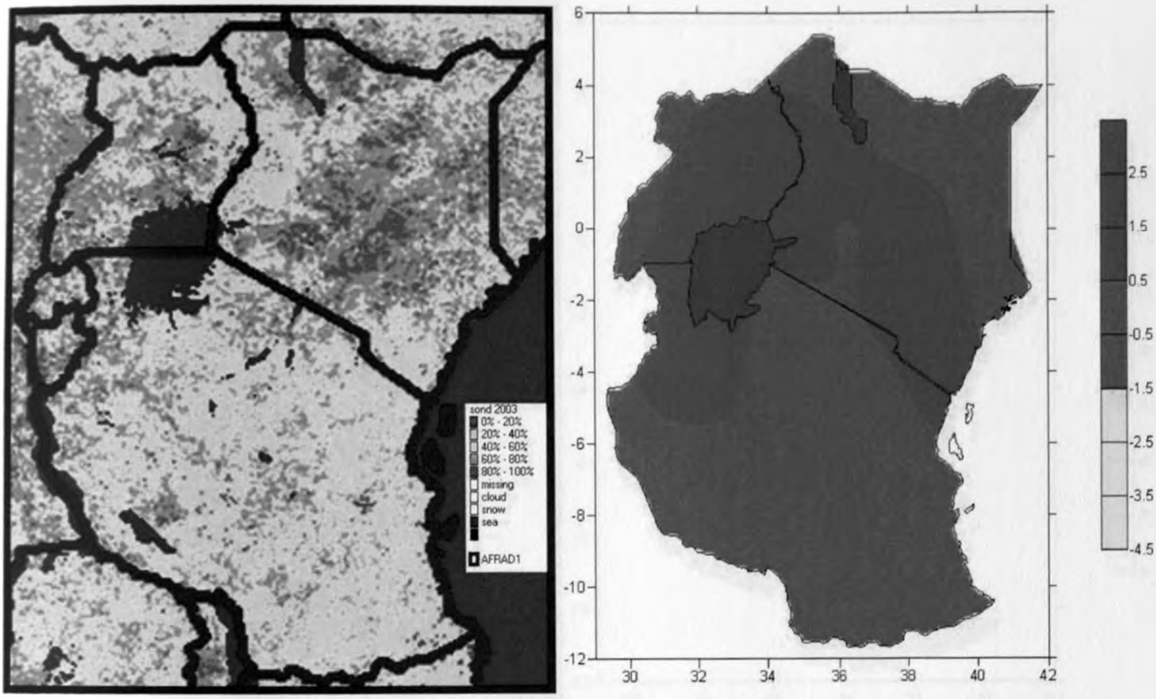
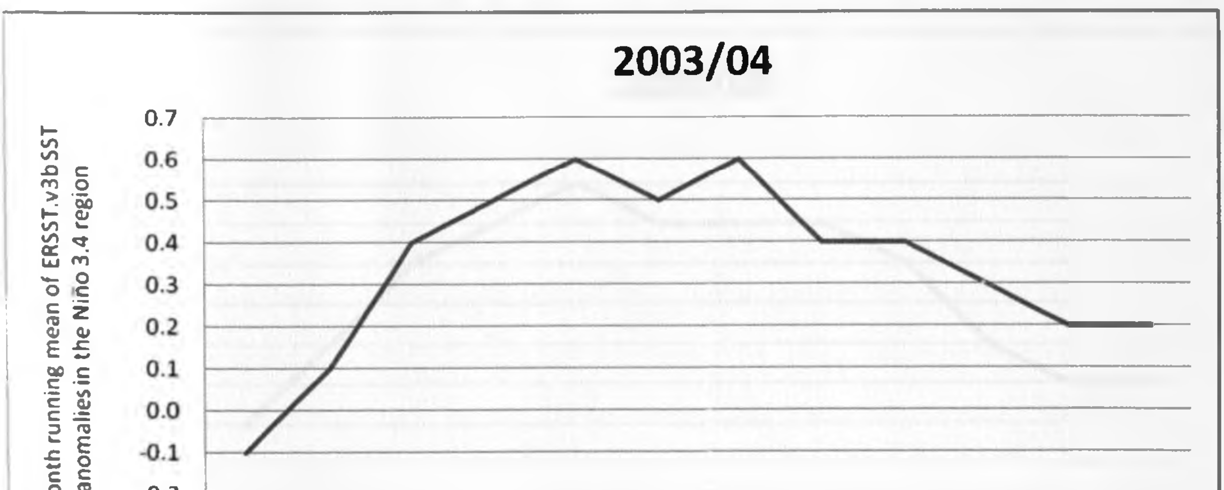


Figure 18: Year 2003 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)



	may	june	july	augus t	septe mber	octob er	nove mber	dece mber	januar y	febru ary	march	april
2003/04	-0.1	0.1	0.4	0.5	0.6	0.5	0.6	0.4	0.4	0.3	0.2	0.2

Figure 19: Time evolution of changes to the oceanic Nino Index in 2003/04

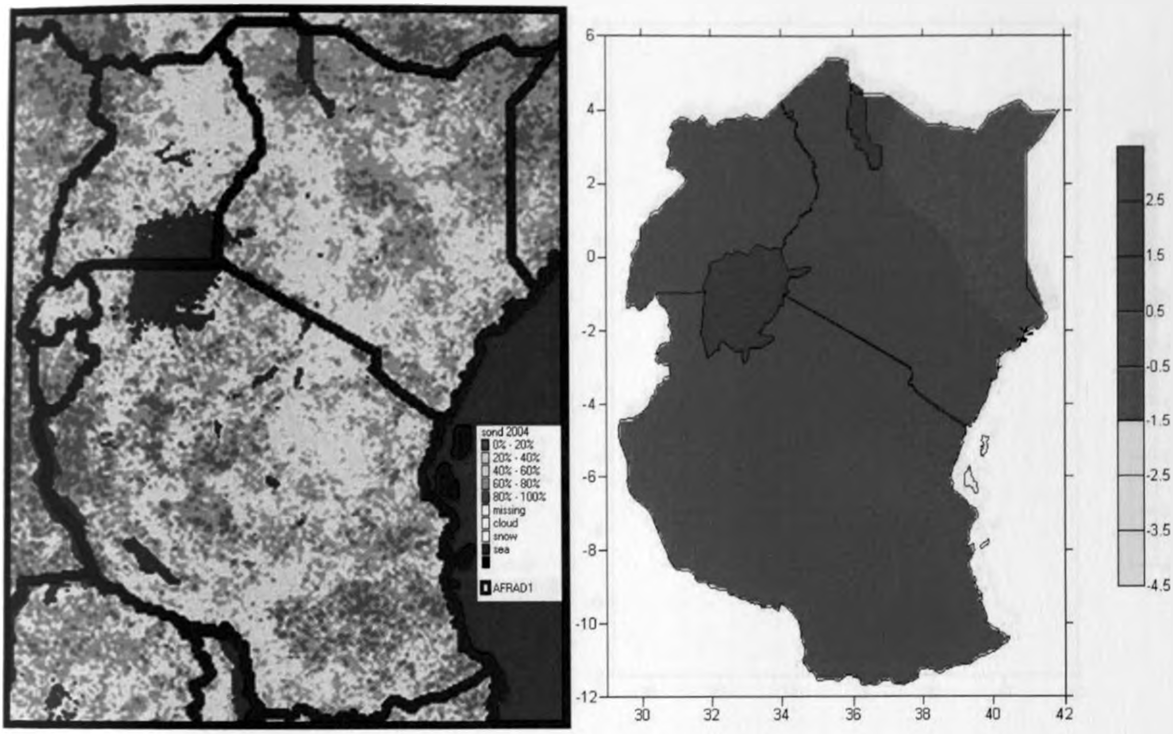
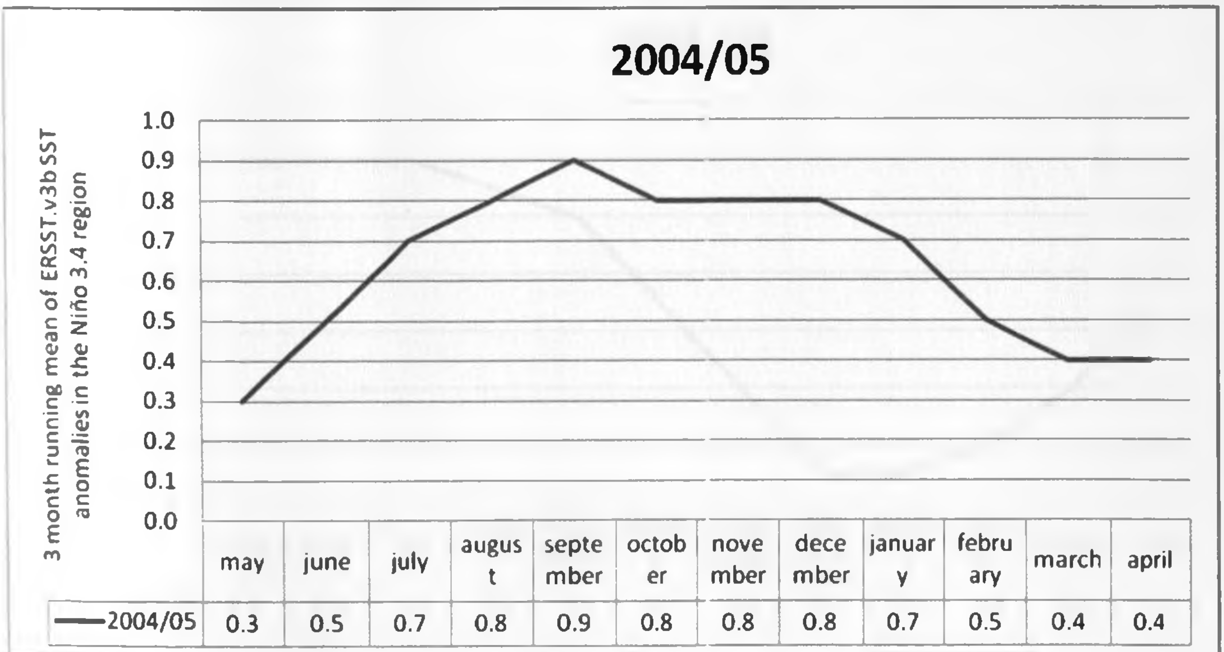


Figure 20: Year 2004 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Nino Index (ONI)



	may	june	july	augus t	septe mber	octob er	nove mber	dece mber	januar y	febru ary	march	april
2004/05	0.3	0.5	0.7	0.8	0.9	0.8	0.8	0.8	0.7	0.5	0.4	0.4

Figure 21: Time evolution of changes to the oceanic Nino Index in 2004/05

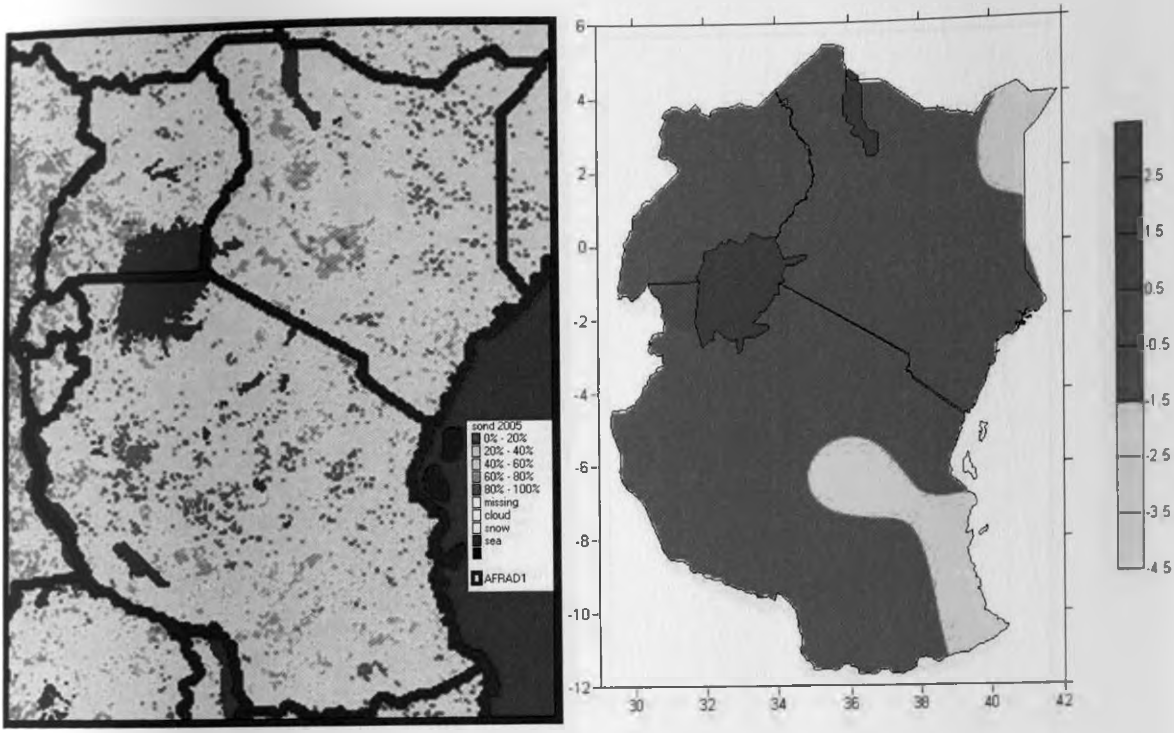


Figure 22: Year 2005 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)

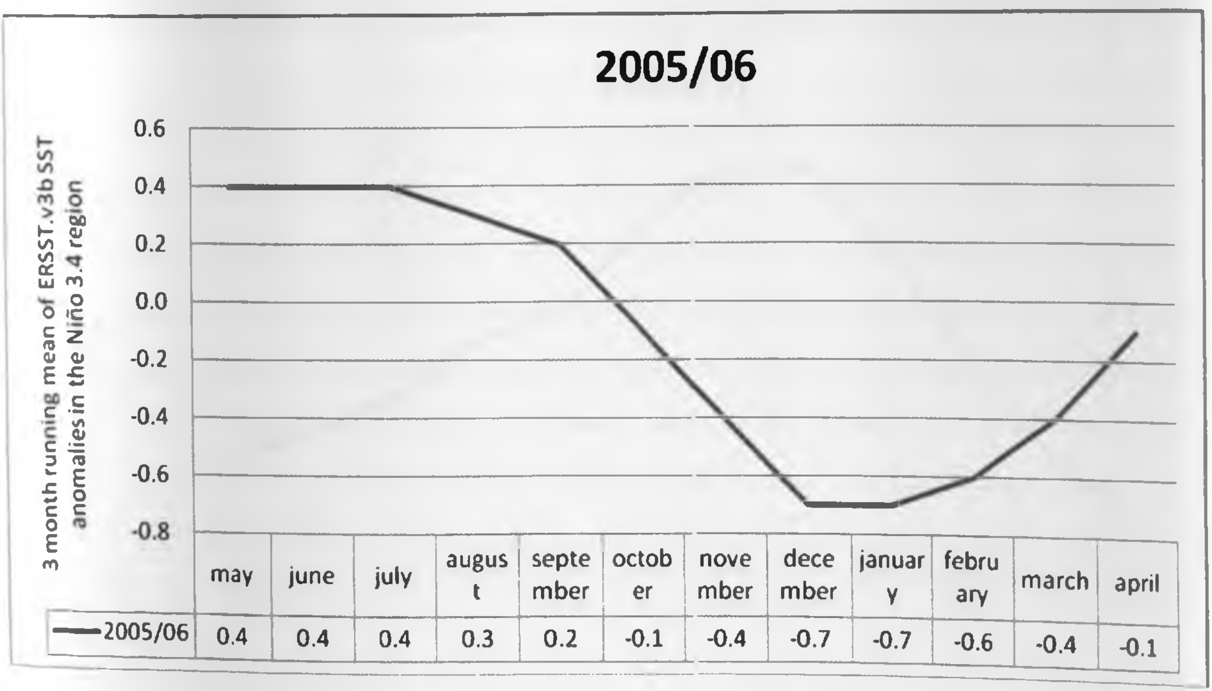


Figure 23: Time evolution of changes to the oceanic Nino Index in 2005/06

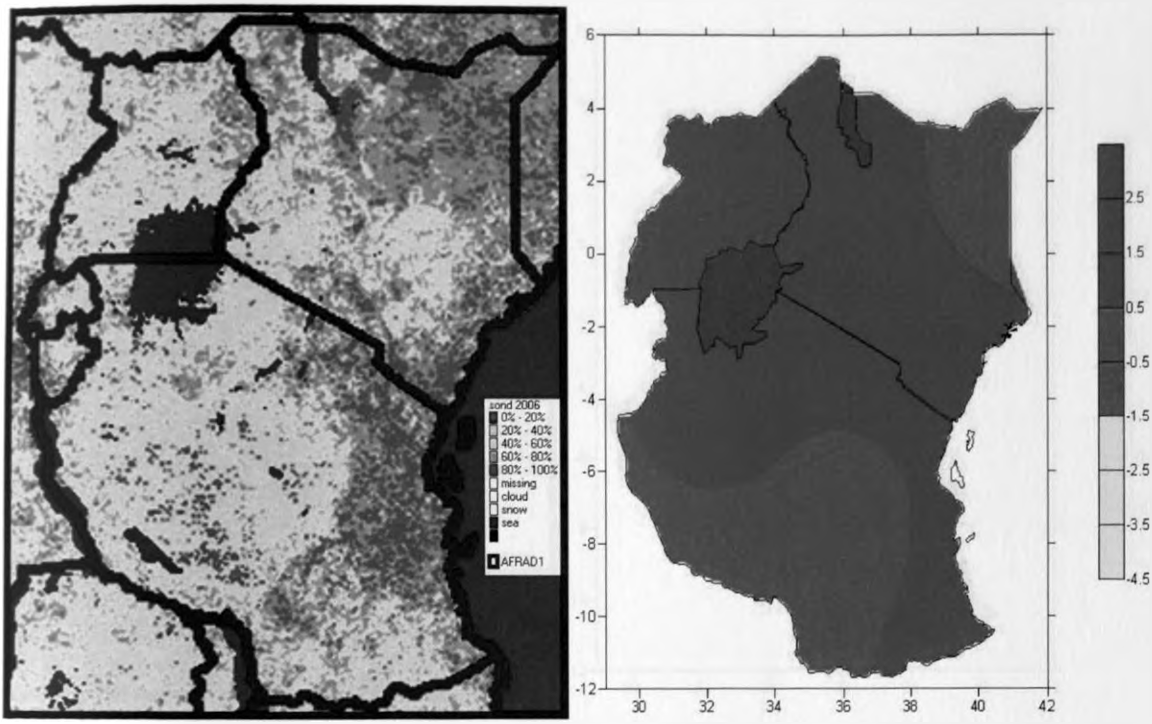


Figure 24: Year 2006 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)

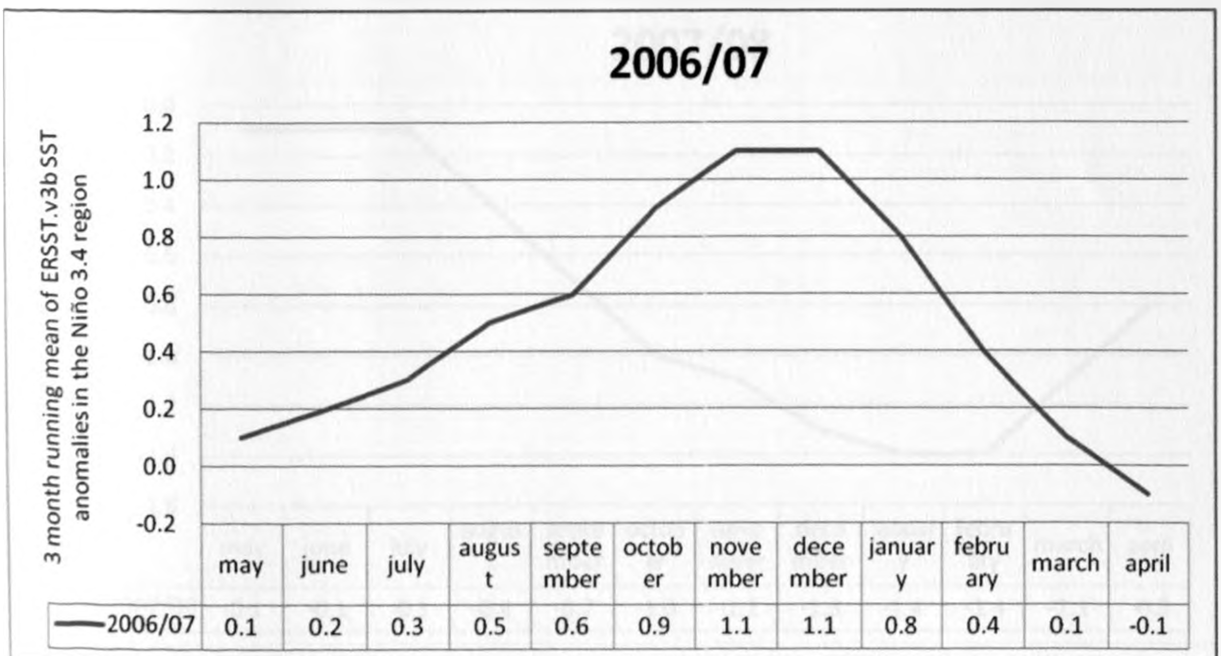


Figure 25: Time evolution of changes to the oceanic Nino Index in 2006/07

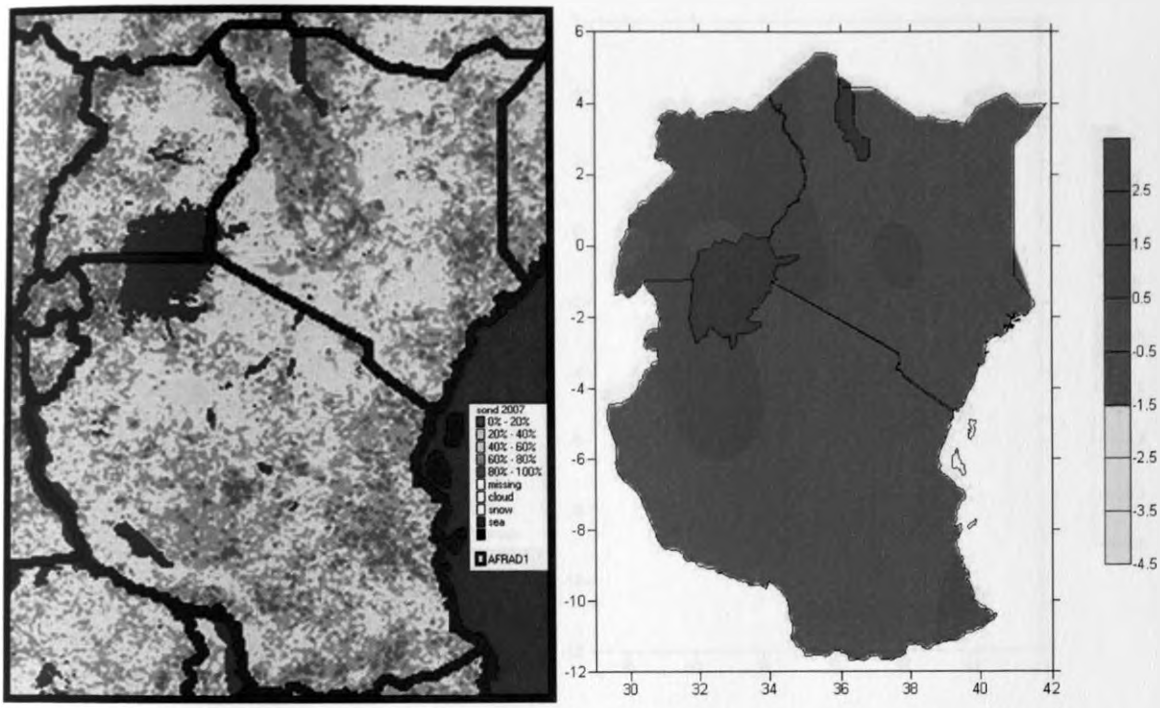


Figure 26: Year 2007 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)

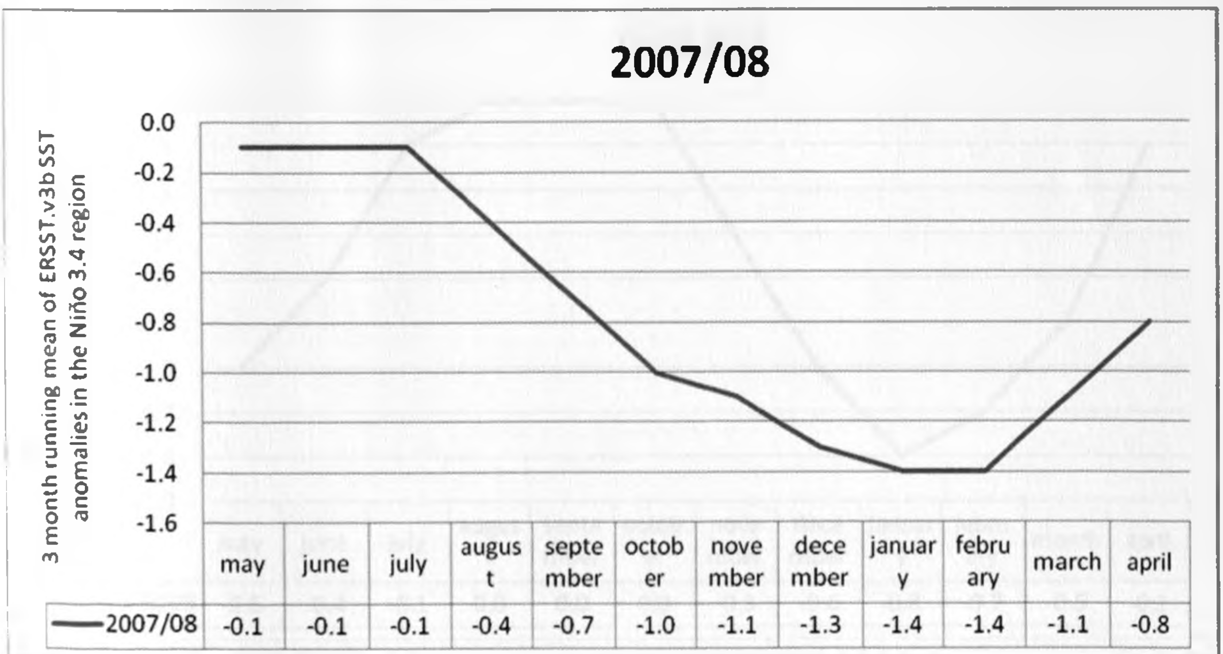


Figure 27: Time evolution of changes to the oceanic Nino Index in 2007/08

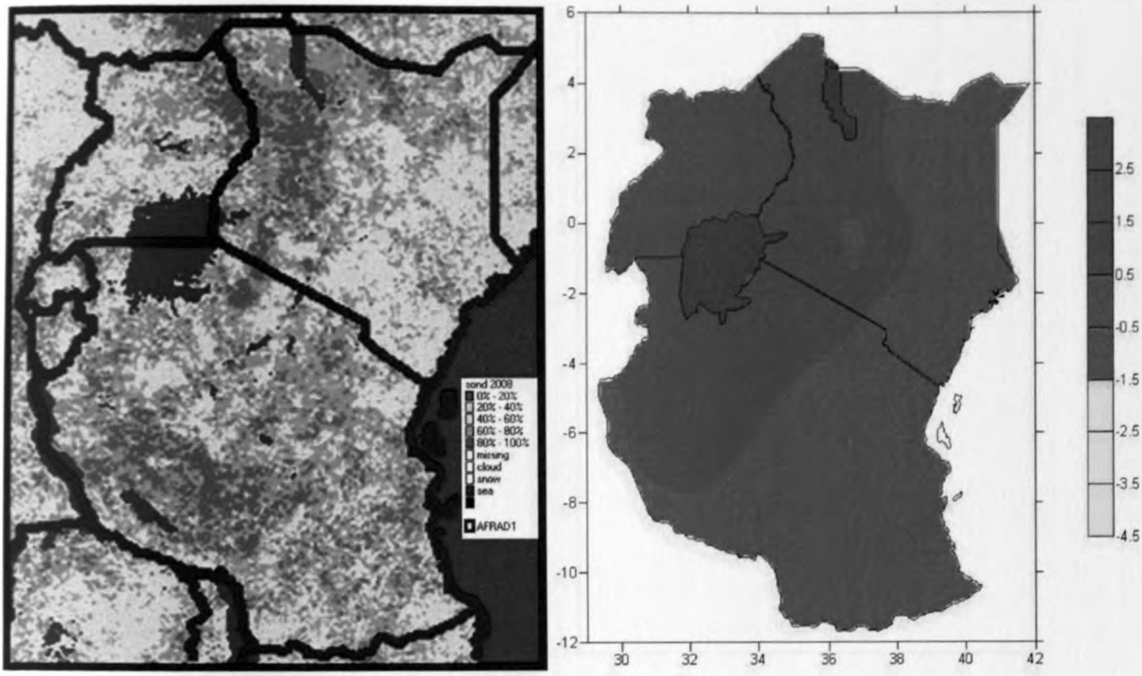


Figure 28: Year 2008 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)

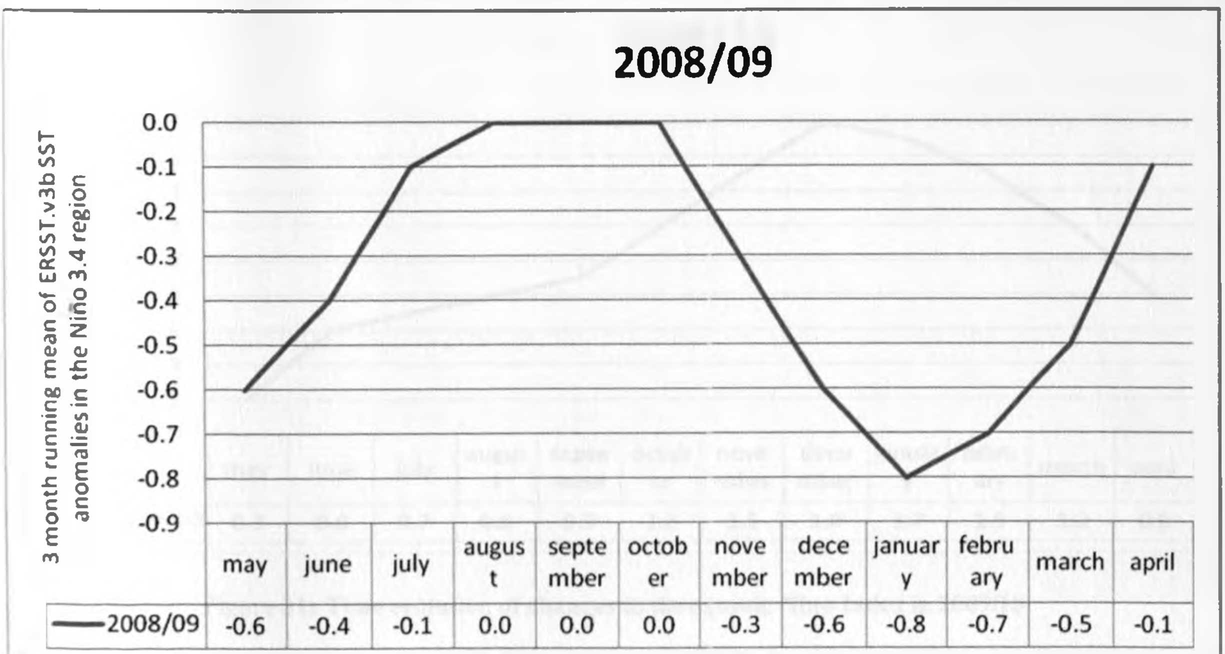


Figure 29: Time evolution of changes to the oceanic Nino Index in 2008/09

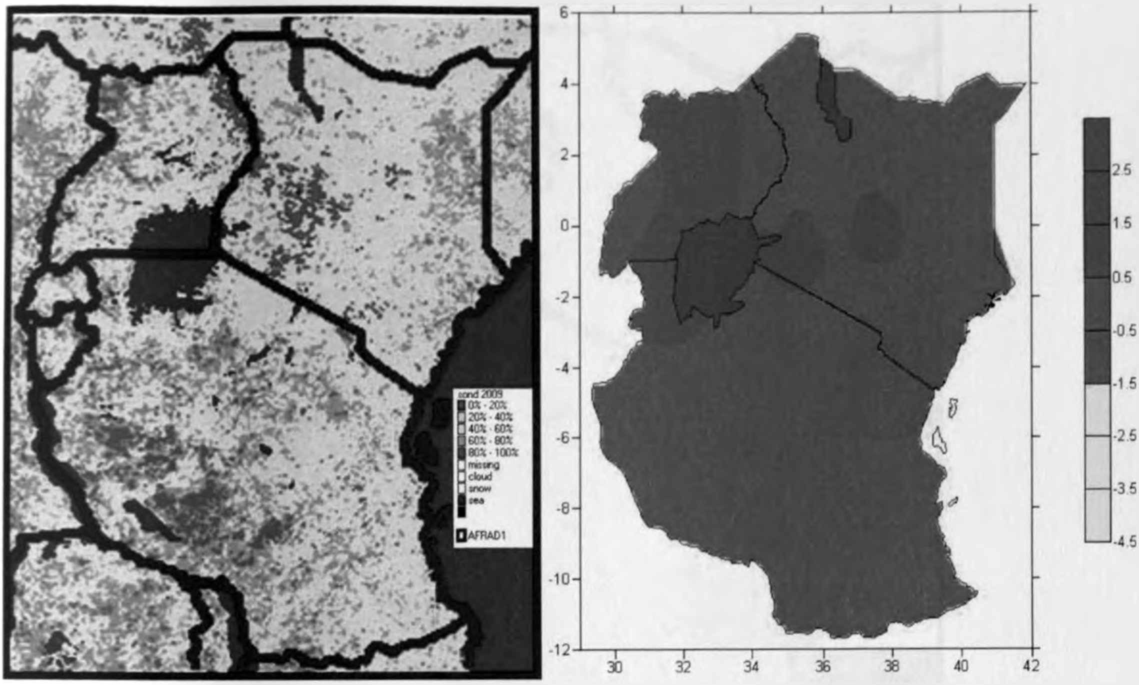


Figure 30: Year 2009 SOND averaged VPI image and Rainfall Anomaly

Changes to the Oceanic Niño Index (ONI)

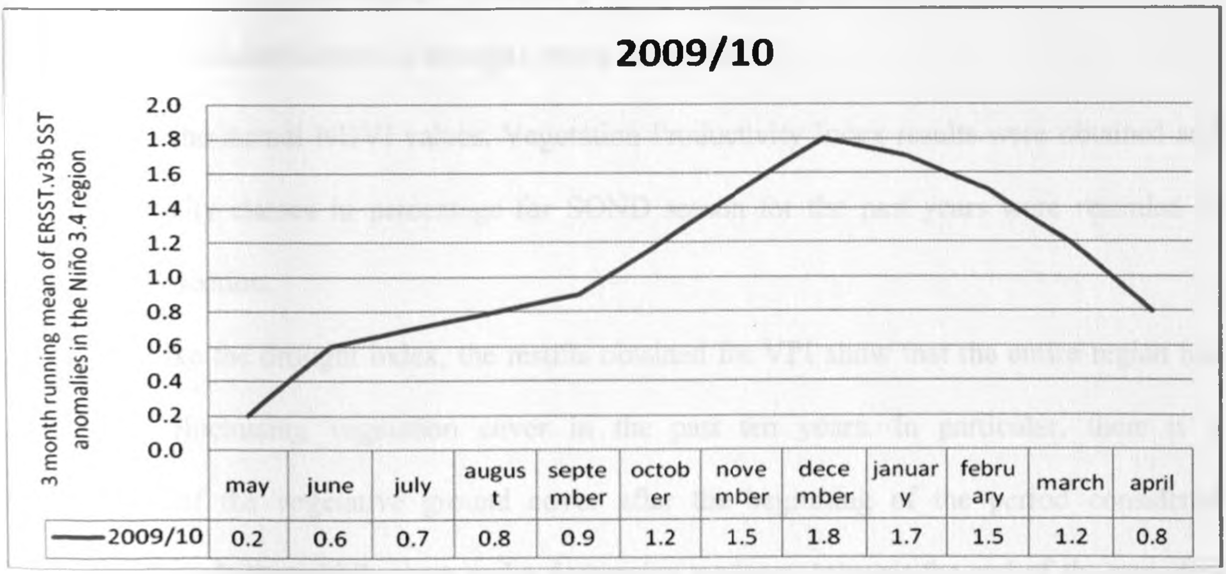


Figure 31: Time evolution of changes to the oceanic Nino Index in 2009/10

Note that the historical image referred is a SOND averaged situation for the whole 10 year period of study which is represented by the following image

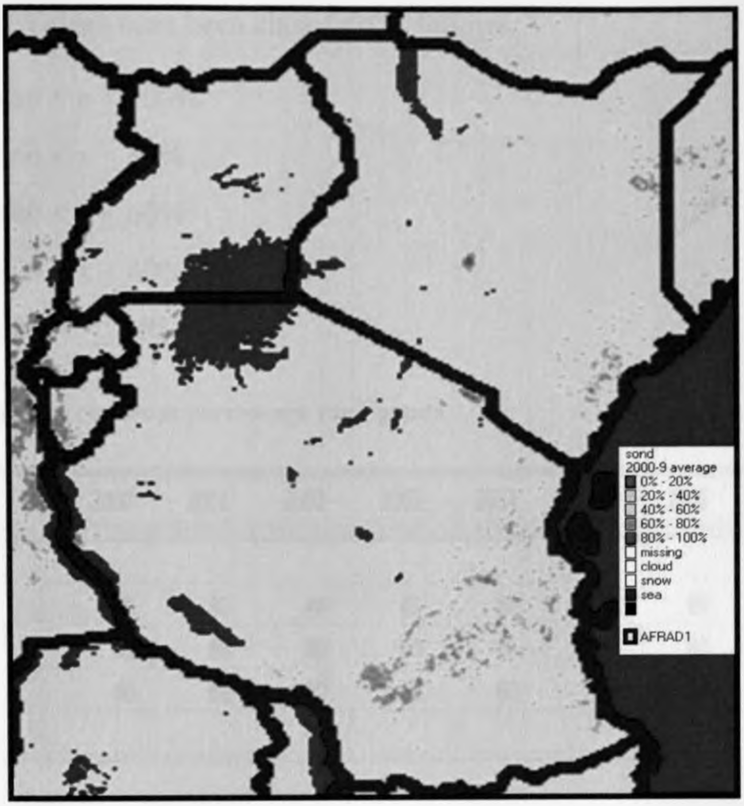


Figure 32: year 2000 to 2009 SOND averaged VPI image

4.5 Results for identification of drought years using VPI

From the Actual NDVI values, Vegetation Productivity Index results were obtained and VPI productivity classes in percentage for SOND season for the past years were recorded as shown in this section.

Just like the drought index, the results obtained for VPI show that the entire region has experienced fluctuating vegetation cover in the past ten years. In particular, there is a regeneration of the vegetative ground cover after the beginning of the period considered especially towards the middle years and a decreasing tendency towards the end of the period in most stations.

The obtained measurements are in support of the droughts we experienced in the beginning of the decade and also towards the later years of the same decade. The Vegetation

Productivity Index Values have been classified as follows.

- 5 which is $80 < x \leq 100\%$
- 4 which is $60 < x \leq 80\%$
- 3 which is $40 < x \leq 60\%$
- 2 which is $20 < x \leq 40\%$
- 1 which is $0 < x \leq 20\%$

Table 8: VPI productivity classes in percentage for Uganda

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
	UGANDA										
63602	ARUA	60	80	40	40	60	60	80	60	40	60
63674	KASESE	60	60	80	60	60	80	80	60	60	60
63705	ENTEBBE AIRP.	40	60	80	60	60	40	80	60	60	60

Table 9: Classified VPI productivity classes for Uganda

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
	UGANDA										
63602	ARUA	3	4	2	2	3	3	4	3	2	3
63674	KASESE	3	3	3	3	4	3	4	3	3	3
63705	ENTEBBE AIRP.	2	3	4	3	3	2	4	3	3	3

Just like the rainfall drought index, VPI productivity classes in table 6 above shows neutral conditions throughout the decade with Arua region experiencing below average vegetation cover in year 2002, 2003 and 2008 during the decade. The Entebbe region had a bad year in 2000 and 2005. Most stations in Uganda were characterized by a higher productivity rate thus giving higher VPI index values; this is specifically noted in year 2001, 2004 and 2006. Year 2006 was the most vegetated in the duration of consideration with year 2001, 2004 and 2009 giving neutral conditions throughout the decade.

Table 10: VPI productivity classes in percentage for Kenya

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
	KENYA										
63624	MANDERA	40	20	60	60	80	60	100	80	40	60
63641	MARSABIT	20	60	60	40	80	40	80	60	60	60
63671	WAJIR	40	60	60	80	60	60	80	60	60	60
63708	KISUMU	40	60	80	40	60	60	80	60	60	80
63709	KISII	60	80	60	40	80	40	80	40	80	60
63710	KERICHO	40	60	60	60	60	60	60	60	80	80
63714	NAKURU	40	60	60	60	40	60	60	60	80	60
63717	NYERI	40	60	60	60	60	60	60	100	80	60
63720	EMBU	40	40	60	60	60	40	80	80	60	40
63723	GARISSA	40	40	60	60	40	40	80	80	40	60
63741	NRB/DAGORETTI	60	80	80	60	60	20	80	40	60	40
63742	NRB/WILSON	60	60	80	40	40	20	80	40	60	40
63799	MALINDI	40	60	80	40	60	40	80	80	60	80
63820	MOMBASA	40	40	80	20	80	40	100	100	40	80

Table 11: Classified VPI productivity classes for Kenya

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
	KENYA										
63624	MANDERA	2	1	3	3	4	3	5	4	2	3
63641	MARSABIT	1	3	3	2	4	2	4	3	3	3
63671	WAJIR	2	3	3	4	3	3	4	3	3	3
63708	KISUMU	2	3	4	2	3	3	4	3	3	4
63709	KISII	3	4	3	2	4	2	4	2	4	3
63710	KERICHO	2	3	3	3	3	3	3	3	4	4
63714	NAKURU	2	3	3	3	2	3	3	3	4	3
63717	NYERI	2	3	3	3	3	3	5	4	3	3
63720	EMBU	2	2	3	3	3	2	4	4	3	2
63723	GARISSA	2	2	3	3	2	2	4	4	2	3
63741	NRB/DAGORETTI	3	2	4	3	3	1	4	2	3	2
63742	NRB/WILSON	3	3	4	2	2	1	4	2	3	2
63799	MALINDI	2	3	4	2	3	2	4	4	3	4
63820	MOMBASA	2	2	4	1	4	2	5	5	2	4

Just like year 2000 in the rainfall drought index, year 2000 VPI readings show that it was the worst hit with a dry conditions lasting longer than any other SOND season in the country during the decade. All the stations in this year show dry conditions on average. Year 2006 was the best in ground vegetation cover showing a higher VPI percentage in the entire region while year 2001, 2003, 2007 and 2009 shows varying VPI values in the region across the country.

Year 2000 conditions might have led to the worst drought in the decade at the time. Year 2002, 2004, 2006 and 2008 were above average years for Kenya but year 2009 had some stations record below average conditions. Results also show that above neutral conditions were well characterized in the great part of the decade but with one dry SOND year in 2000 and one densely vegetated year in 2006.

Table 12: VPI productivity classes in percentage for Tanzania

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	60	20	40	80	60	60	60	80	60	60
63733 MUSOMA	60	40	60	60	40	60	60	80	60	60
63756 MWANZA	40	60	60	60	60	80	80	80	40	60
63801 KIGOMA	40	40	60	40	40	20	80	60	60	60
63832 TABORA	60	40	80	60	60	40	60	60	60	80
63862 DODOMA	60	40	60	60	80	60	20	60	40	80
63932 MBEYA	80	60	40	40	60	60	60	60	60	60
63962 SONGEA	40	40	60	60	60	60	60	80	60	60
63971 MTWARA	60	40	80	40	60	60	80	60	60	40

Table 13: **Classified VPI productivity classes for Tanzania**

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
TANZANIA										
63729 BUKOBA	3	1	2	4	3	3	3	4	3	3
63733 MUSOMA	3	2	3	3	2	3	3	4	3	3
63756 MWANZA	2	3	3	3	3	4	4	4	2	3
63801 KIGOMA	2	2	3	2	2	1	4	3	3	3
63832 TABORA	3	2	4	3	3	2	3	3	3	4
63862 DODOMA	3	2	3	3	4	3	1	3	2	4
63932 MBEYA	4	3	2	2	3	3	3	3	3	3
63962 SONGEA	2	2	3	3	3	3	3	4	3	3
63971 MTWARA	3	2	4	2	3	3	4	3	3	2

On average, Tanzania has neutral conditions but having year 2001 and 2002 as dry years. Year 2002, 2006 and 2007 were above average years showing a much improvement in the region. Tanzania has a dry and below neutral condition in the beginning of the period of study but showing regenerating characteristics throughout the decade especially in year 2007.

Fairly near normal condition in the past ten years have been noted in year 2000, 2003, 2004, 2005, 2008 and 2009 but with a tendency of below average expectancy as you go towards the end of the decade. Also noted is that for the most part of the decade, Tanzania has recorded small variations in most of the stations and this might be due to human influence or irrigation might have been used or both while an increasing trend from the beginning of the decade is observed but decreasing gradually in the last two years. Note that the VPI percentages and are derived from the actual VPI readings which have been extracted from NDVI values.

4.6 Trend analysis results

4.6.1 Graphical approach

Except for some few years, in Uganda vegetation probability index has well mapped the same trends noted in the drought severity index. This result shows that VPI can also be appropriate for drought monitoring in the stations adopted in the study since vegetation in the region is slightly variable compared to the rainfall received.

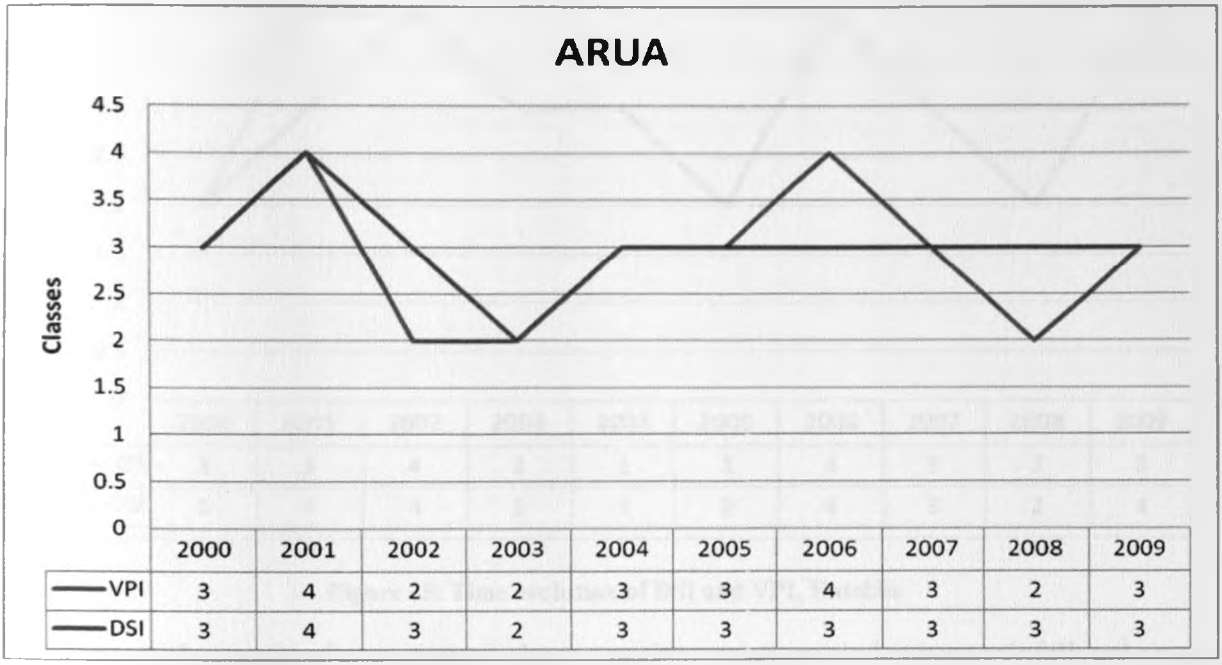


Figure 33: Time evolution of DSI and VPI, Arua

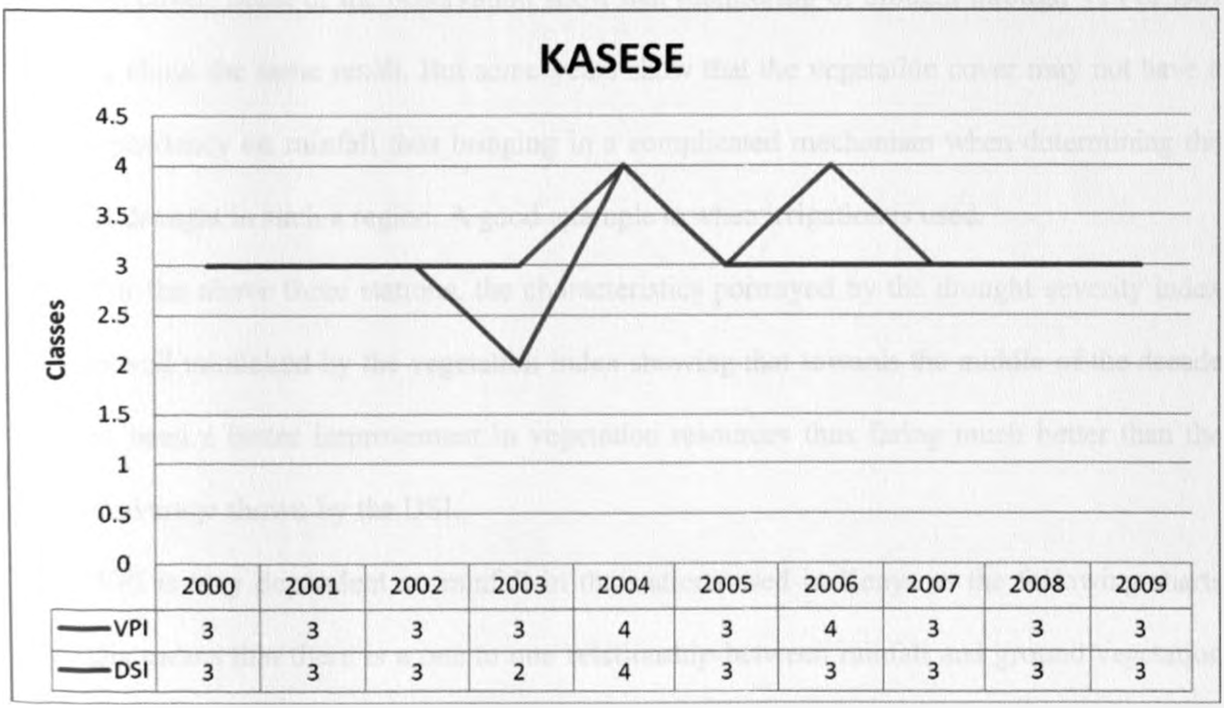
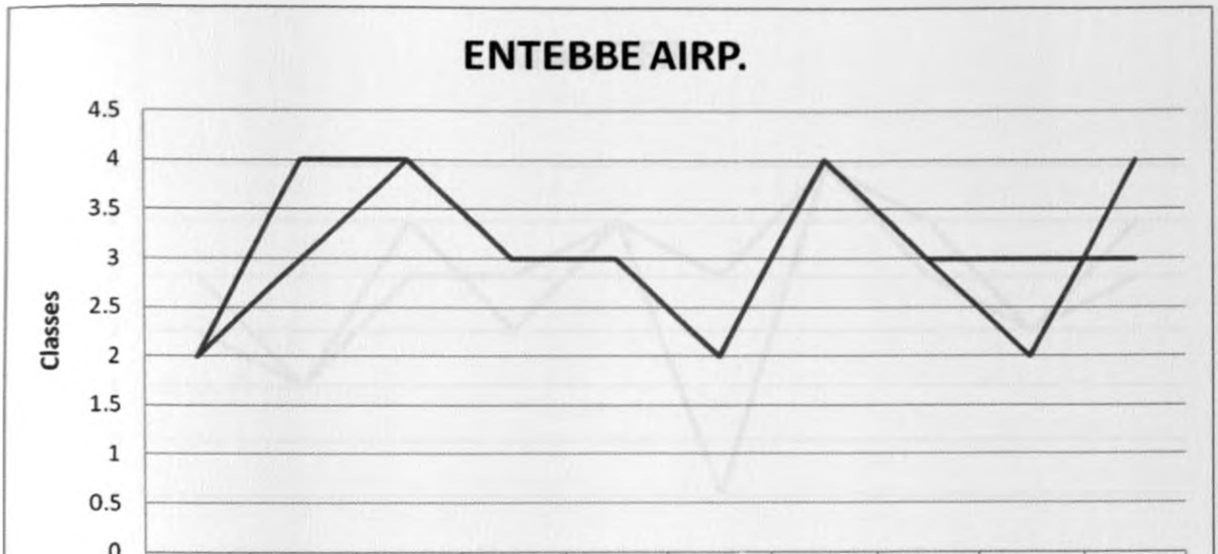


Figure 34: Time evolution of DSI and VPI, Kasese



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	4	3	3	2	4	3	3	3
DSI	2	4	4	3	3	2	4	3	2	4

Figure 35: Time evolution of DSI and VPI, Entebbe

From the graphs above, stations show a positive relationship between rainfall and ground vegetation cover. Most of the observation show that monitoring of drought through VPI or DSI can bring about the same result. But some years show that the vegetation cover may not have a direct dependency on rainfall thus bringing in a complicated mechanism when determining the effects of drought in such a region. A good example is when irrigation is used.

For the above three stations, the characteristics portrayed by the drought severity index has been well mimicked by the vegetation index showing that towards the middle of the decade there has been a better improvement in vegetation resources thus faring much better than the expected average shown by the DSI.

VPI is very dependent on rainfall in the stations used in Kenya as the following charts show, this means that there is a one to one relationship between rainfall and ground vegetation cover.

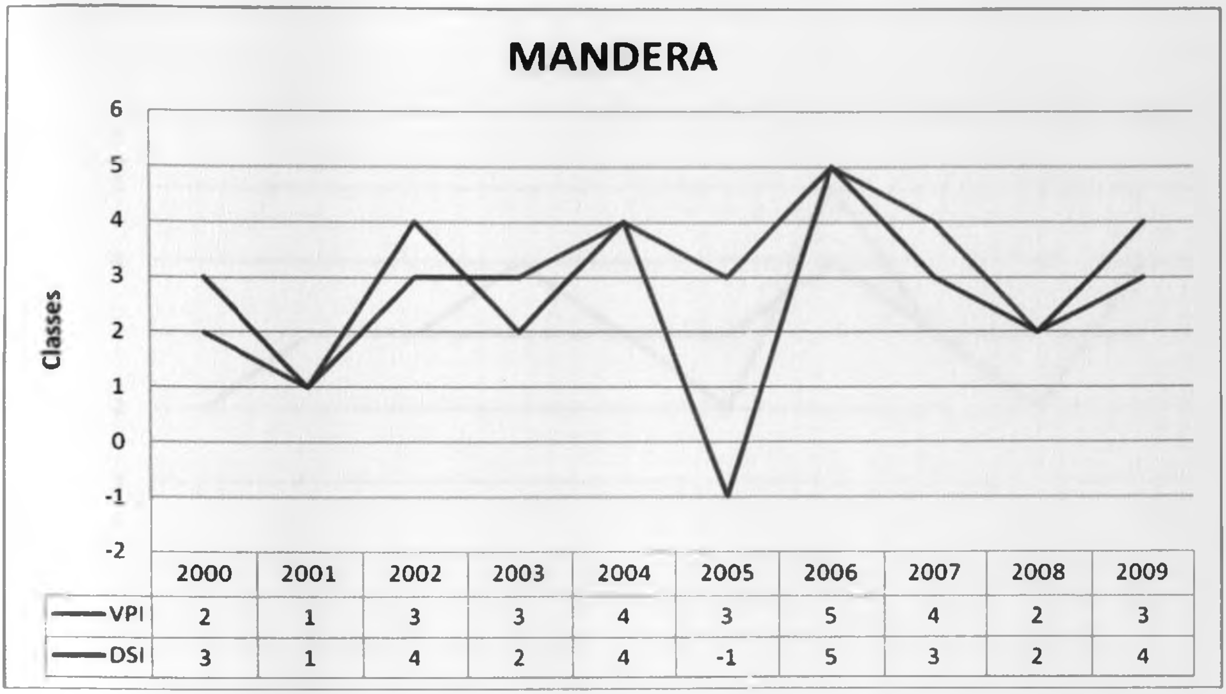


Figure 36: Time evolution of DSI and VPI, Mandera

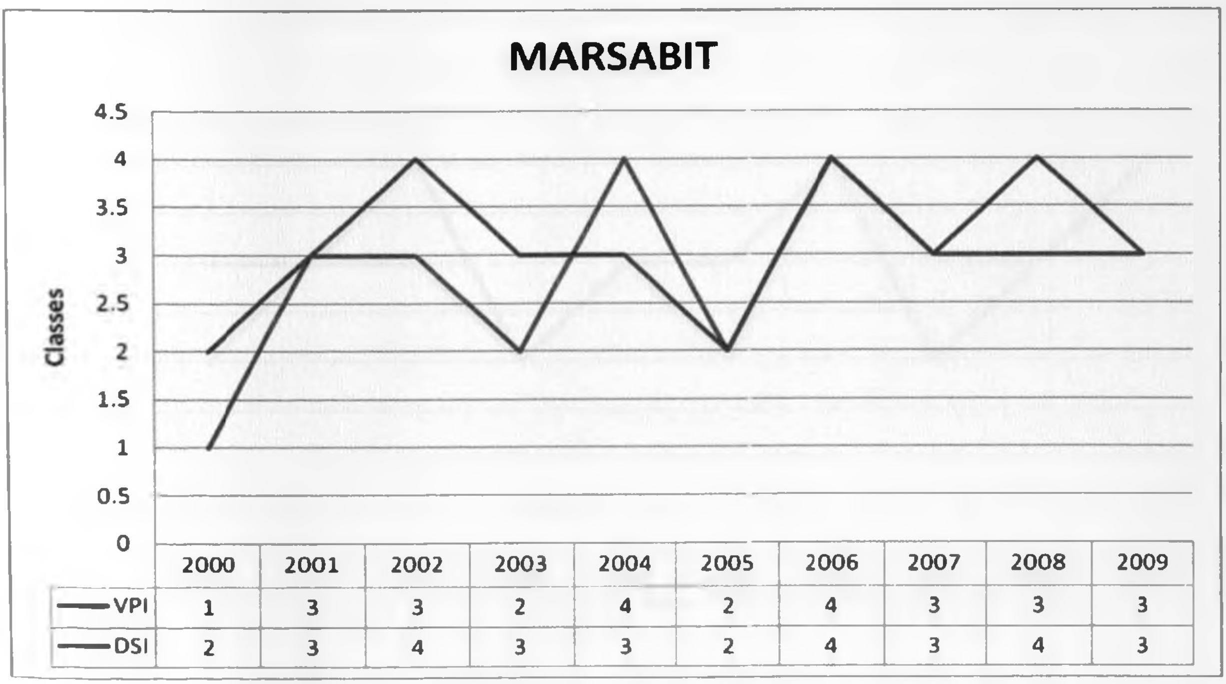
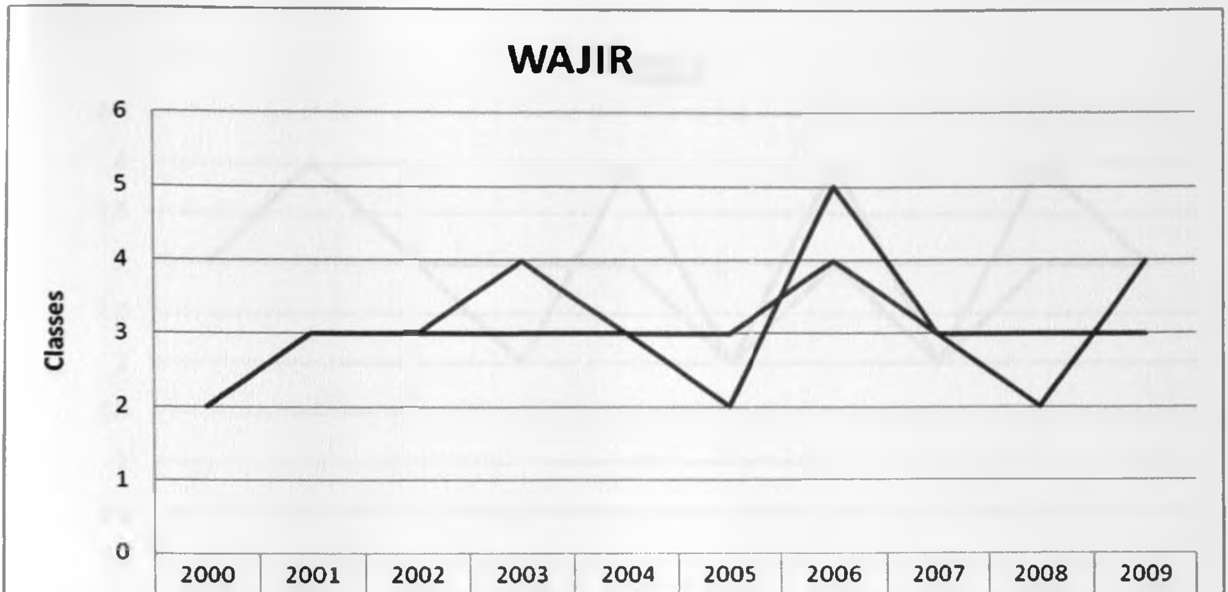
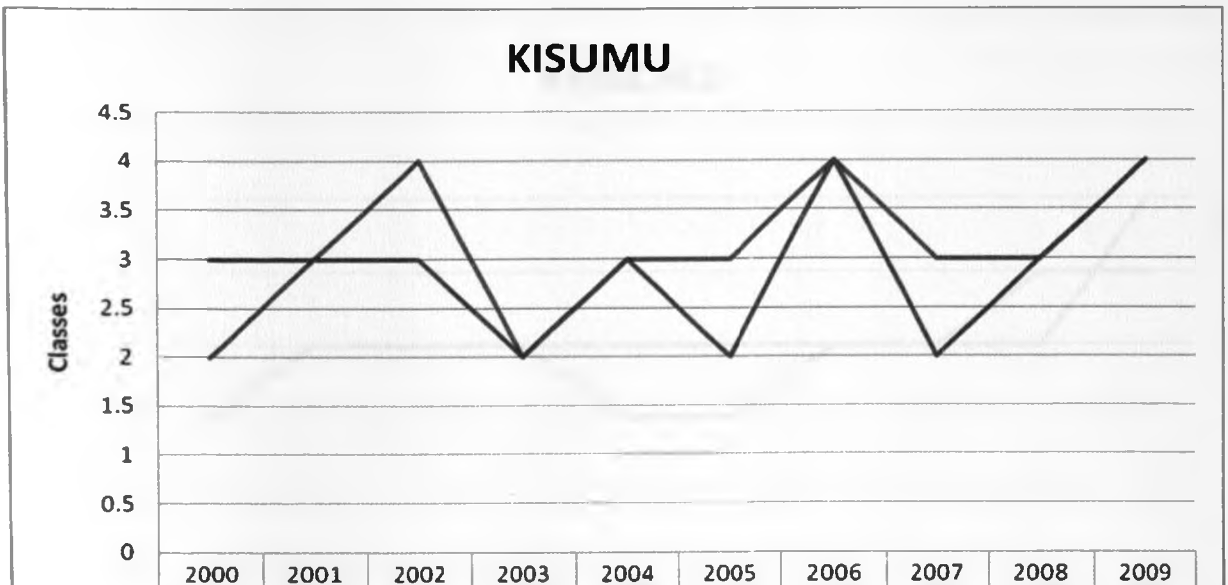


Figure 37: Time evolution of DSI and VPI, Marsabit



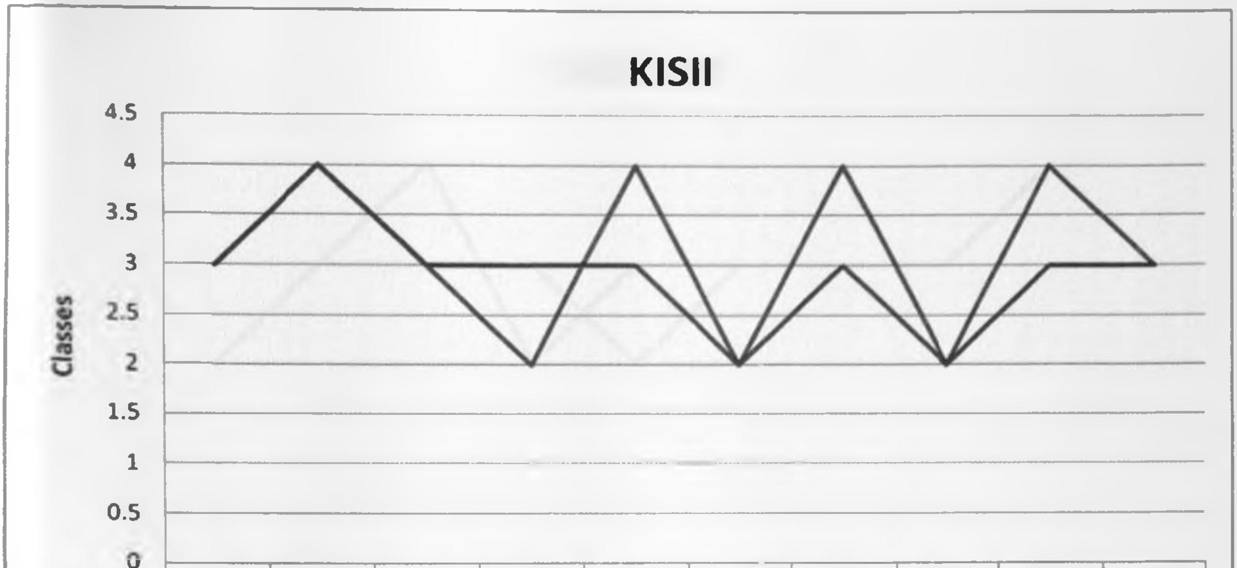
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	3	4	3	3	4	3	3	3
DSI	2	3	3	3	3	2	5	3	2	4

Figure 38: Time evolution of DSI and VPI, Wajir



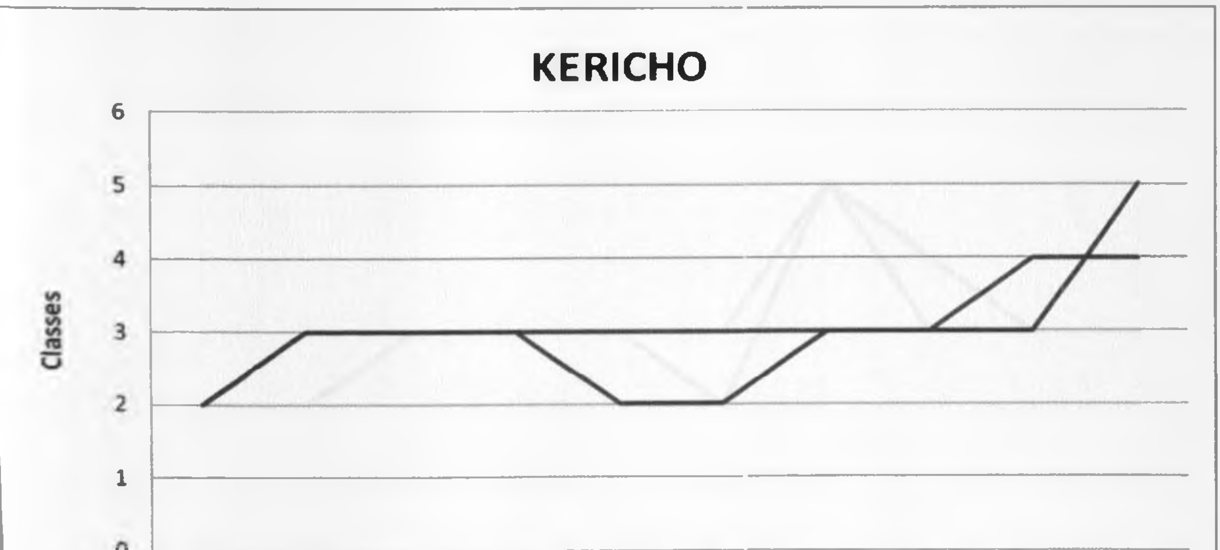
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	4	2	3	3	4	3	3	4
DSI	3	3	3	2	3	2	4	2	3	4

Figure 39: Time evolution of DSI and VPI, Kisumu



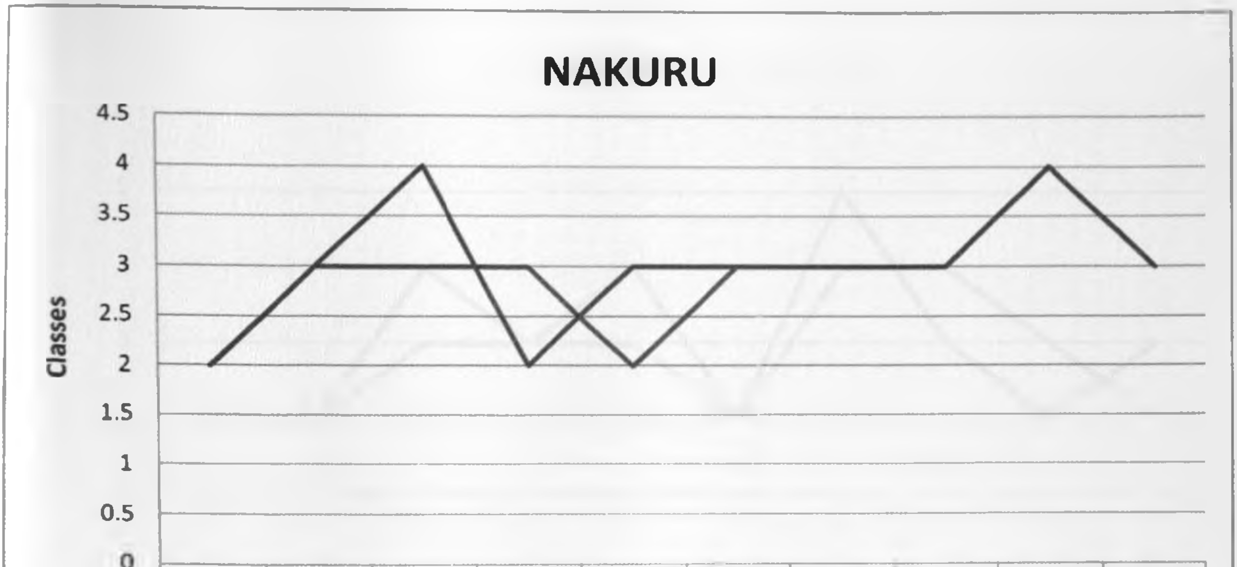
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	4	3	2	4	2	4	2	4	3
DSI	3	4	3	3	3	2	3	2	3	3

Figure 40: Time evolution of DSI and VPI, Kisii



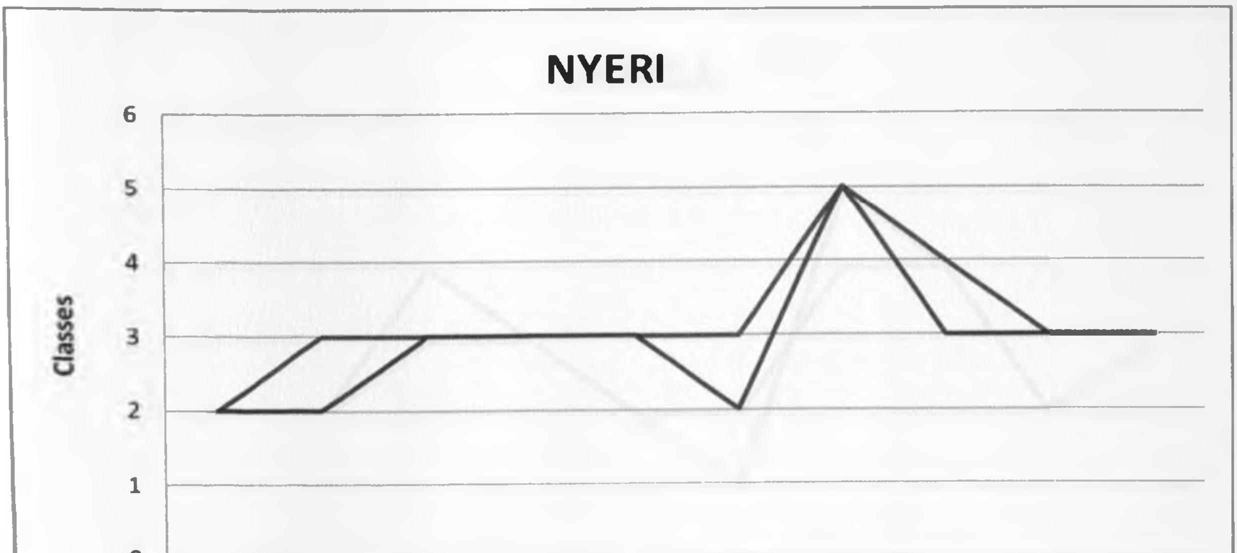
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	3	3	3	3	3	3	4	4
DSI	2	3	3	3	2	2	3	3	3	5

Figure 41: Time evolution of DSI and VPI, Kericho



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	3	3	2	3	3	3	4	3
DSI	2	3	4	2	3	3	3	3	4	3

Figure 42: Time evolution of DSI and VPI, Nakuru



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	3	3	3	3	5	4	3	3
DSI	2	2	3	3	3	2	5	3	3	3

Figure 43: Time evolution of DSI and VPI, Nyeri

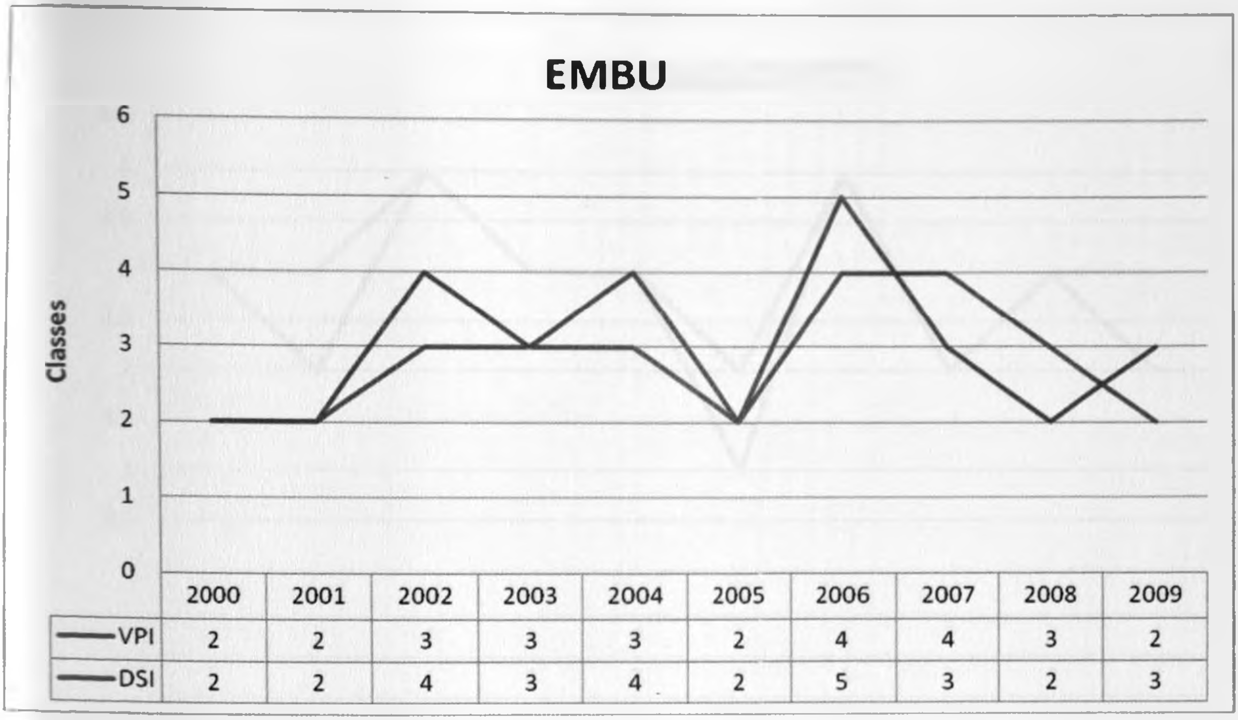


Figure 44: Time evolution of DSI and VPI, Embu

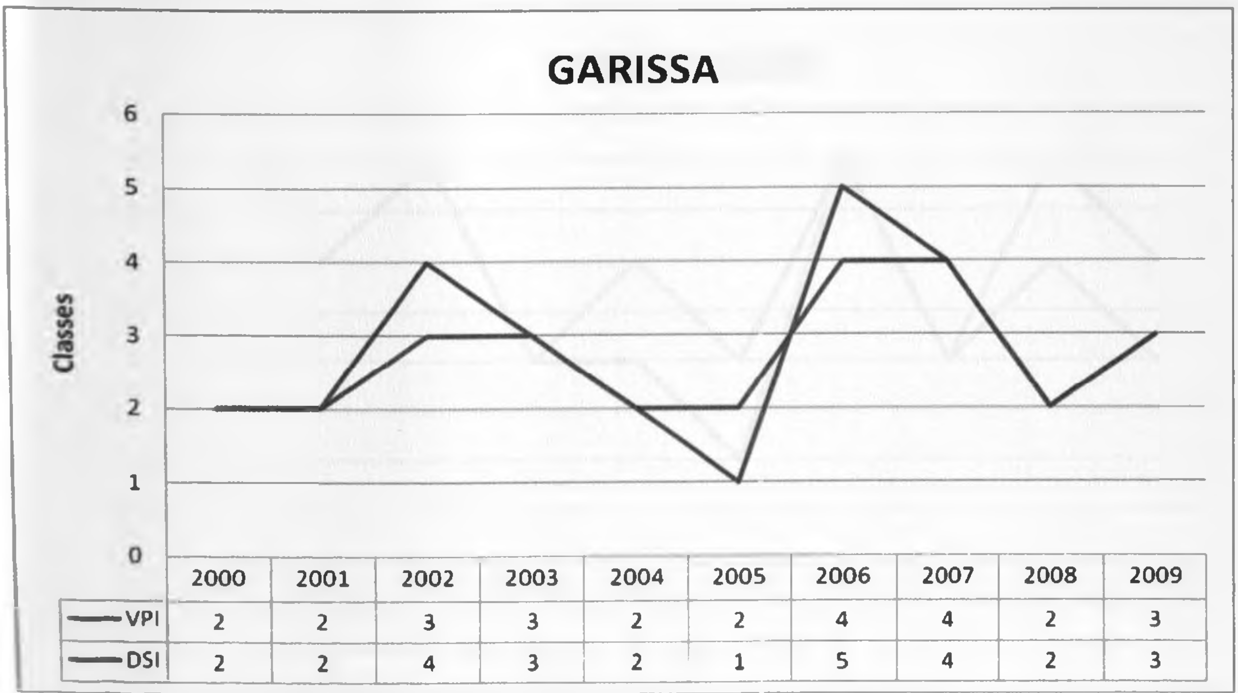
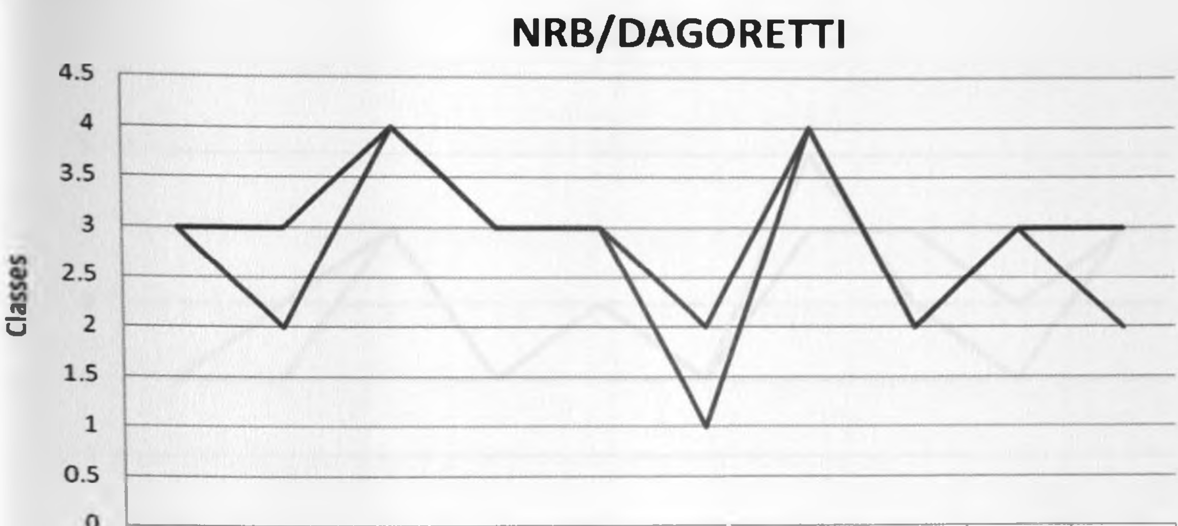
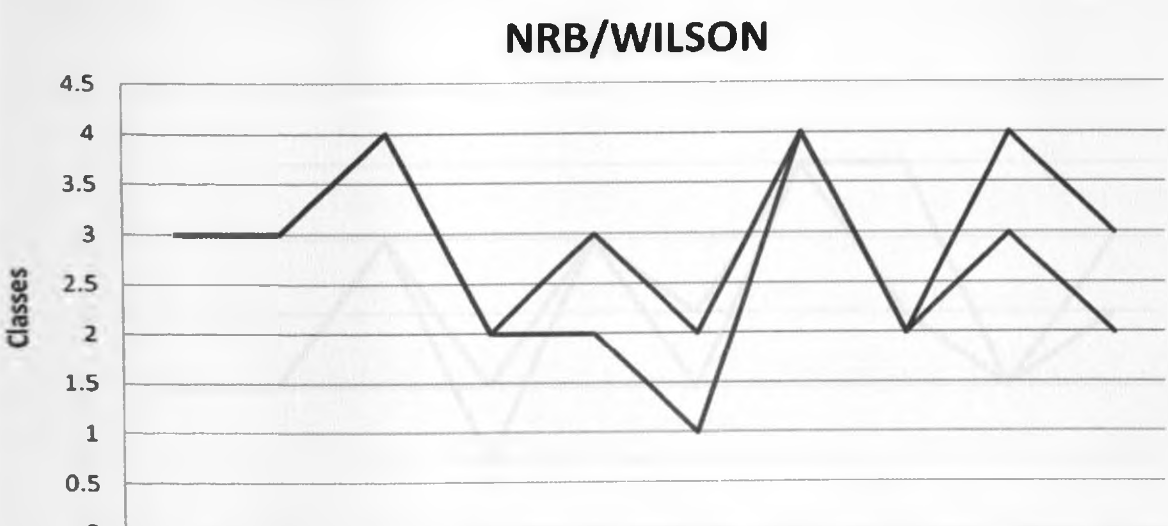


Figure 45: Time evolution of DSI and VPI, Garissa



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	2	4	3	3	1	4	2	3	2
DSI	3	3	4	3	3	2	4	2	3	3

Figure 46: Time evolution of DSI and VPI, Dagoretti



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	3	4	2	2	1	4	2	3	2
DSI	3	3	4	2	3	2	4	2	4	3

Figure 47: Time evolution of DSI and VPI, Wilson

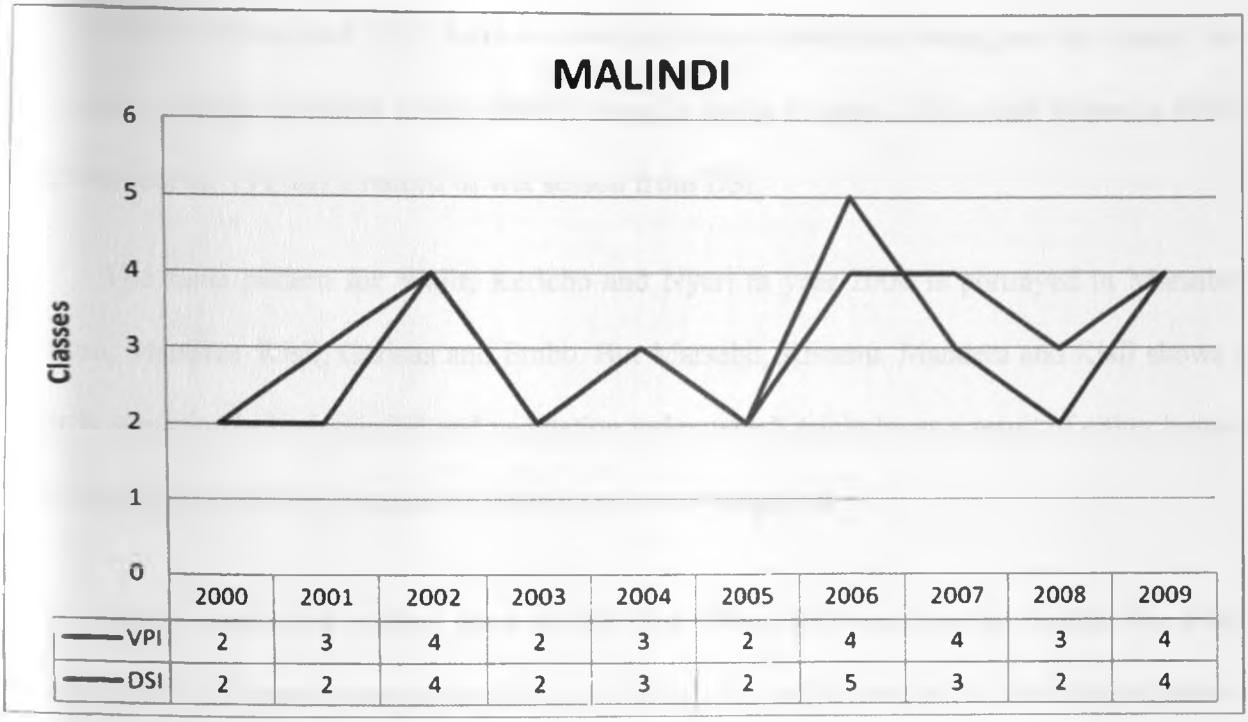


Figure 48: Time evolution of DSI and VPI, Malindi

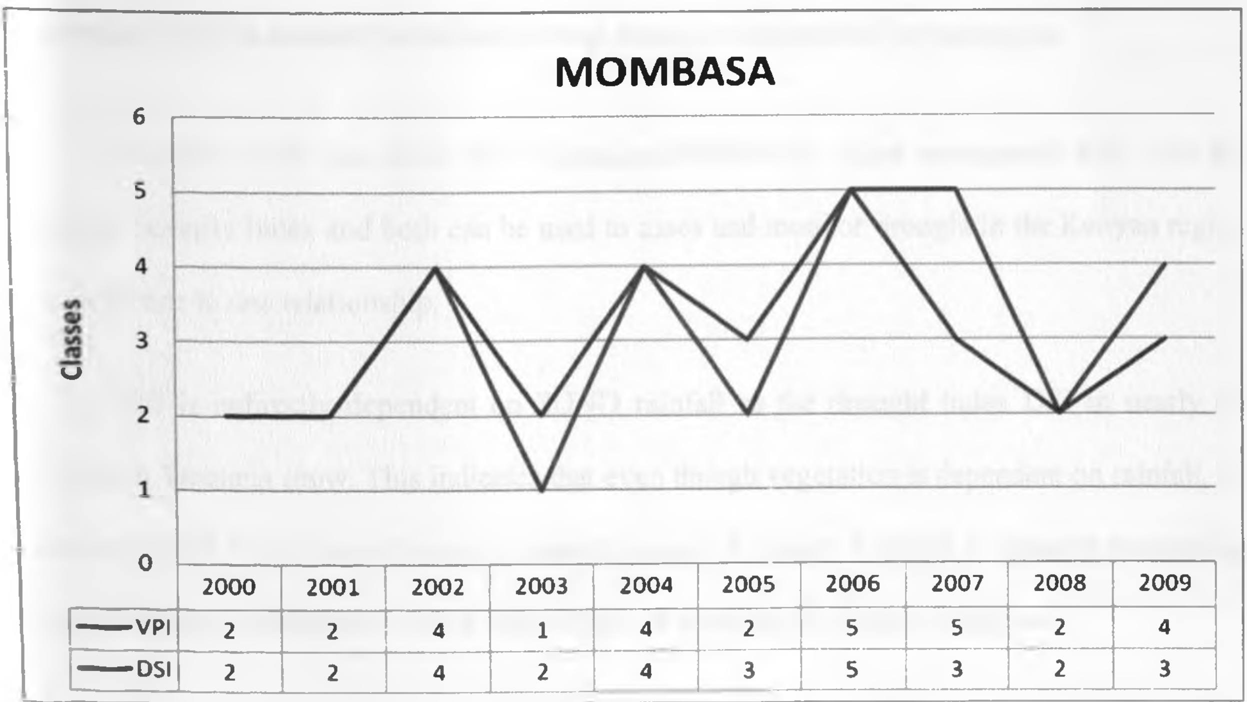


Figure 49: Time evolution of DSI and VPI, Mombasa

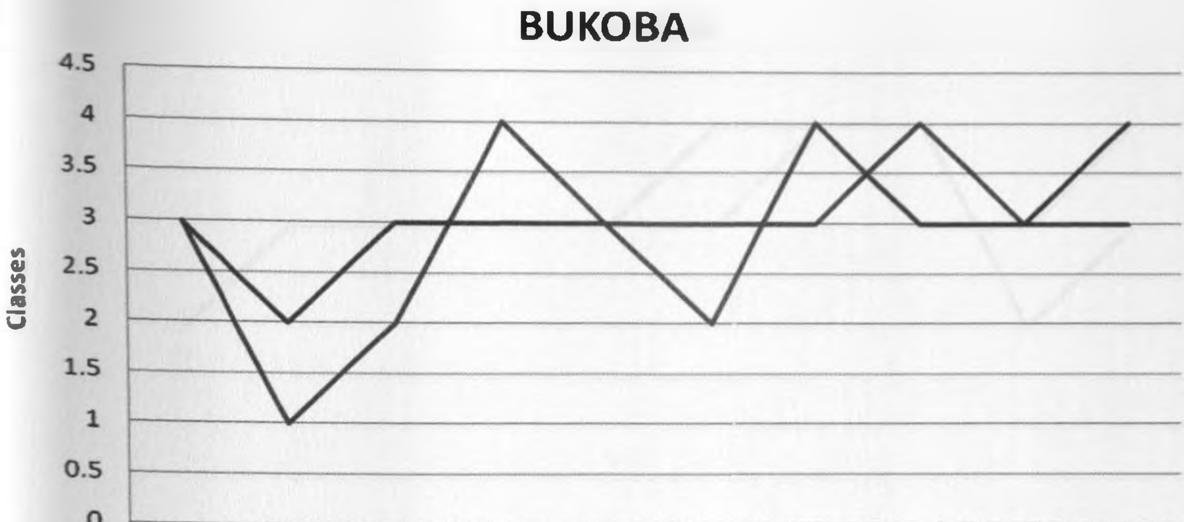
Wajir, Kericho and Nyeri have an averaged neutral condition throughout the decade but with some slightly variation in the rainfall drought index in year 2006 which shows a 100% improvement on VPI and a record of wet season from DSI.

The same pattern for Wajir, Kericho and Nyeri in year 2006 is portrayed in Marsabit, Kisumu, Mandera, Kisii, Garissa and Embu. But Marsabit, Kisumu, Mandera and Kisii shows a slightly variation in both rainfall and vegetation index which might be as a result of either human interference like farming, vegetation clearing or use of irrigation.

Most reports and studies done on the East Africa region show that despite the small percentage SOND season annual rainfall contribution received in most parts, there is a vegetation dependence in the season's rainfall received for its growth. This is evident from the charts plotted above (fig. 33 to 49) which supports the results of these findings and also brings in a vegetation factor to consider while monitoring drought using rainfall in the region.

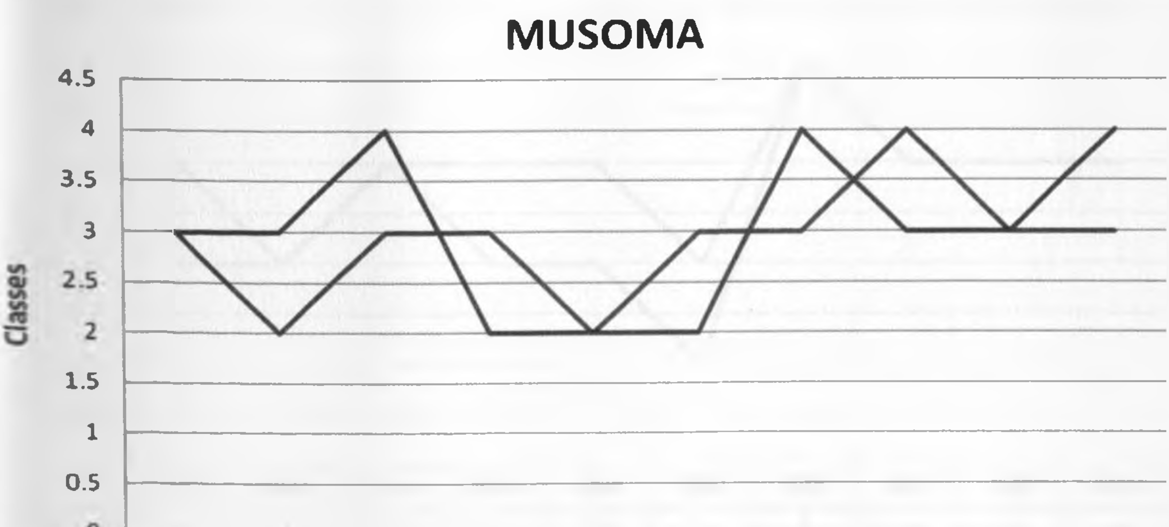
The time series also show that Vegetation Productivity Index corresponds well with the Drought Severity Index and both can be used to asses and monitor drought in the Kenyan region due to its one to one relationship.

VPI is indirectly dependent on SOND rainfall as the drought index DSI in nearly all stations in Tanzania show. This indicates that even though vegetation is dependent on rainfall, its variation might be influenced more by human means. So when it comes to drought monitoring we must be also considerate to see a factor that will consider this human influence.



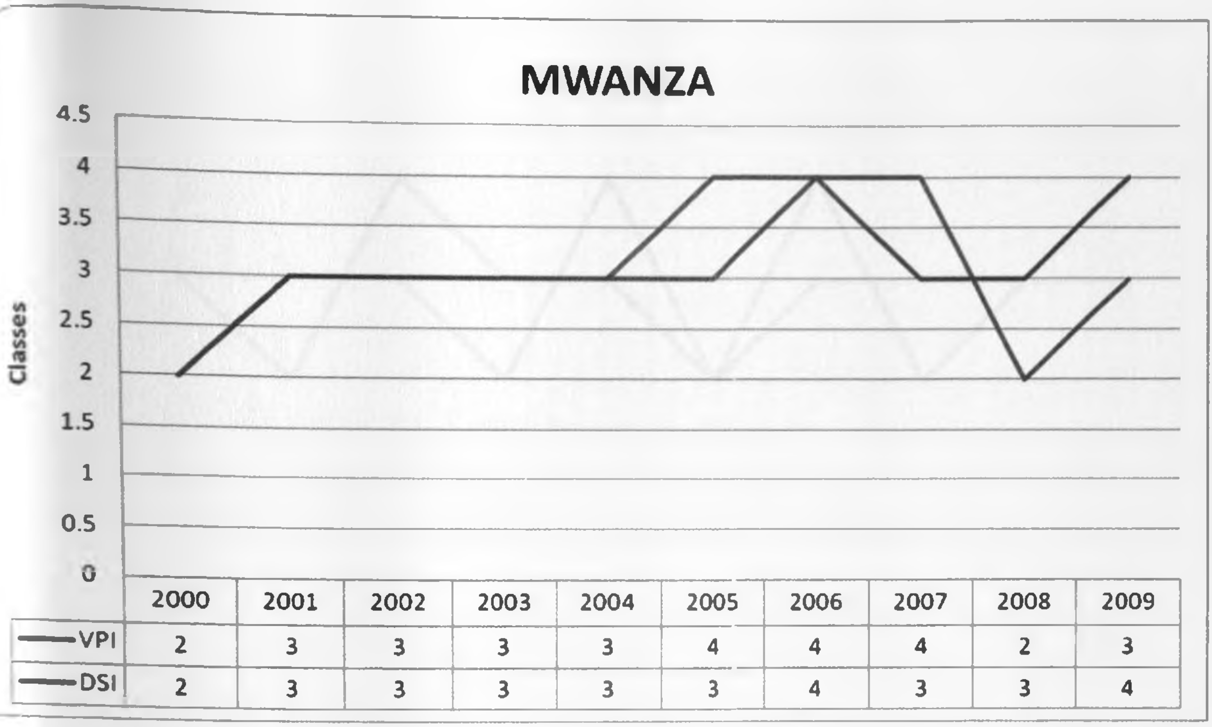
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	1	2	4	3	3	3	4	3	3
DSI	3	2	3	3	3	2	4	3	3	4

Figure 50: Time evolution of DSI and VPI, Bukoba



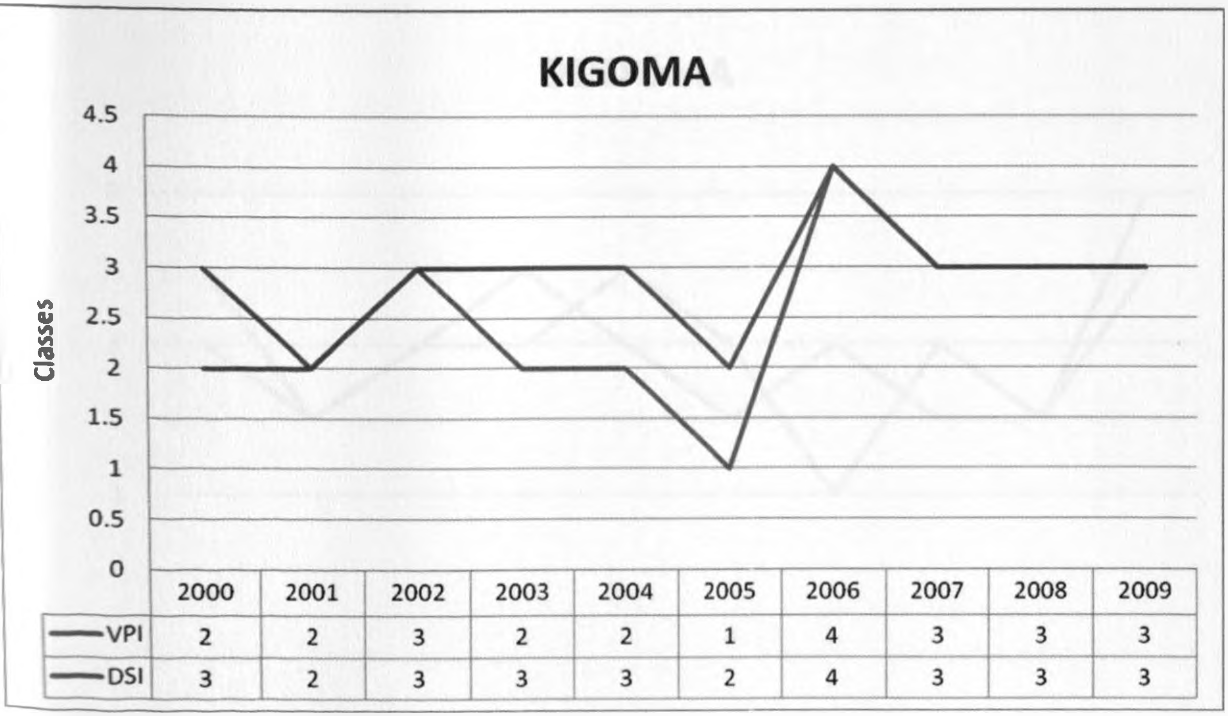
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	2	3	3	2	3	3	4	3	3
DSI	3	3	4	2	2	2	4	3	3	4

Figure 51: Time evolution of DSI and VPI for Musoma



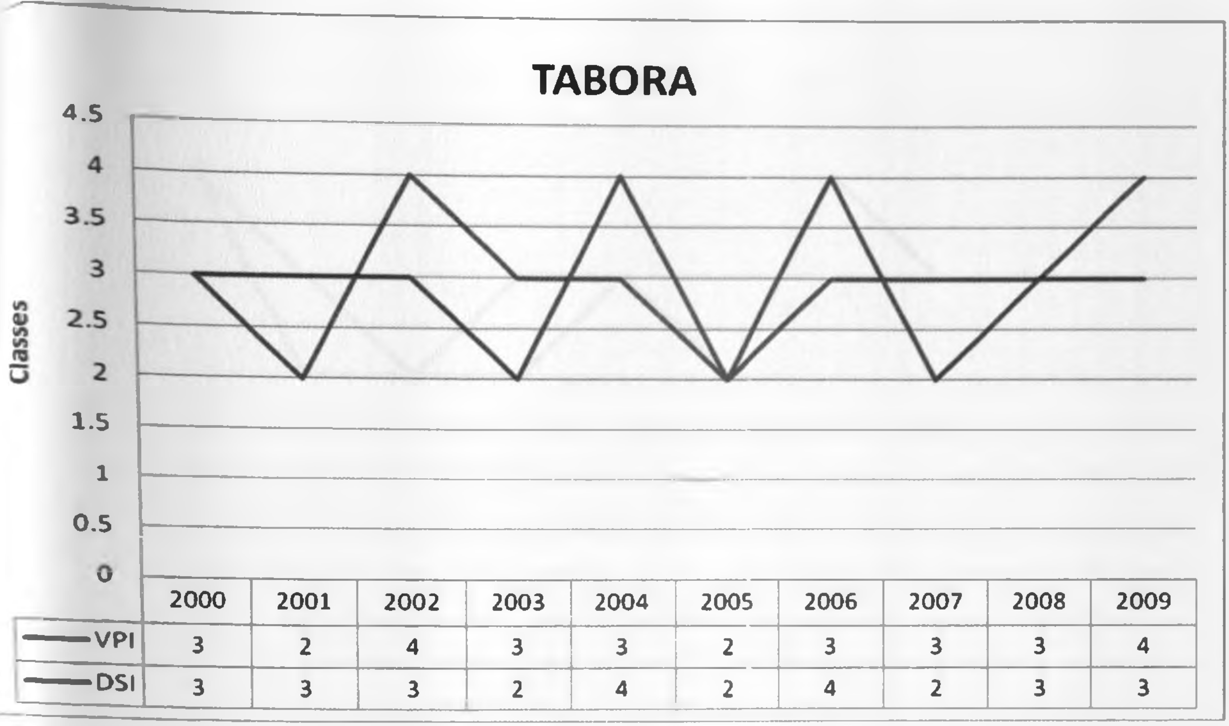
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	3	3	3	3	4	4	4	2	3
DSI	2	3	3	3	3	3	4	3	3	4

Figure 52: Time evolution of DSI and VPI for Mwanza



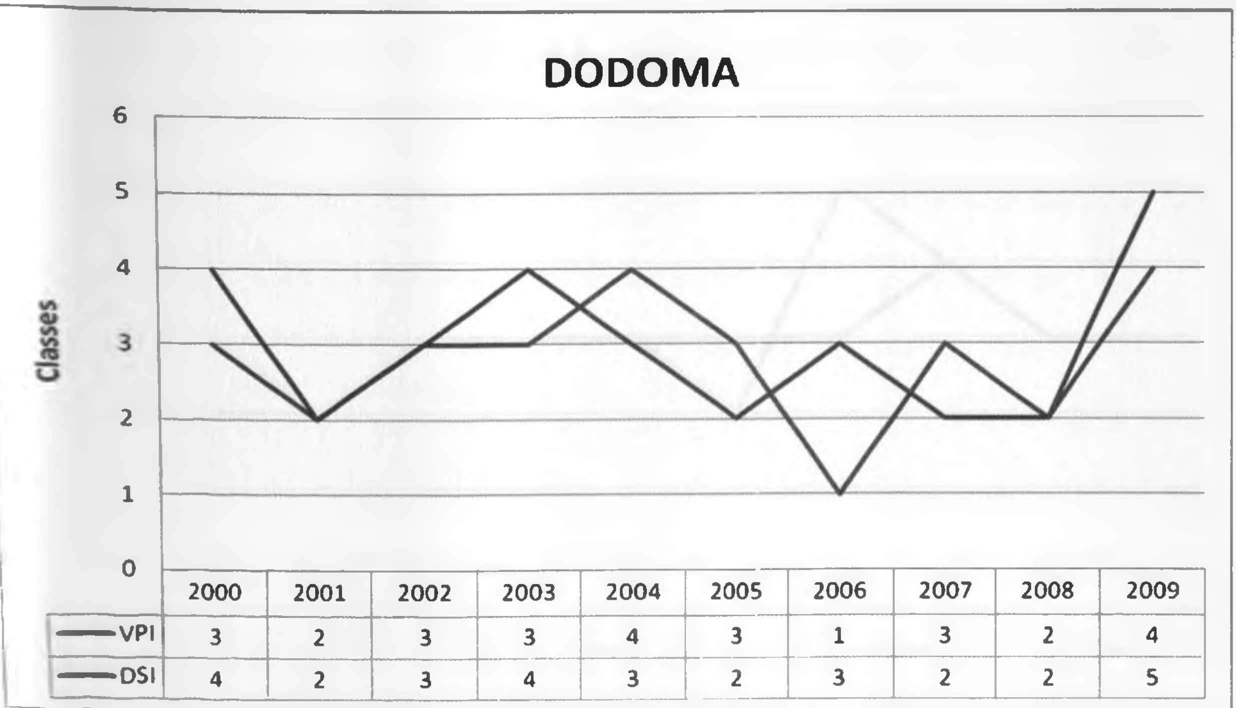
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	2	2	3	2	2	1	4	3	3	3
DSI	3	2	3	3	3	2	4	3	3	3

Figure 53: Time evolution of DSI and VPI for Kigoma



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	2	4	3	3	2	3	3	3	4
DSI	3	3	3	2	4	2	4	2	3	3

Figure 54: Time evolution of DSI and VPI for Tabora



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	2	3	3	4	3	1	3	2	4
DSI	4	2	3	4	3	2	3	2	2	5

Figure 55: Time evolution of DSI and VPI, Dodoma

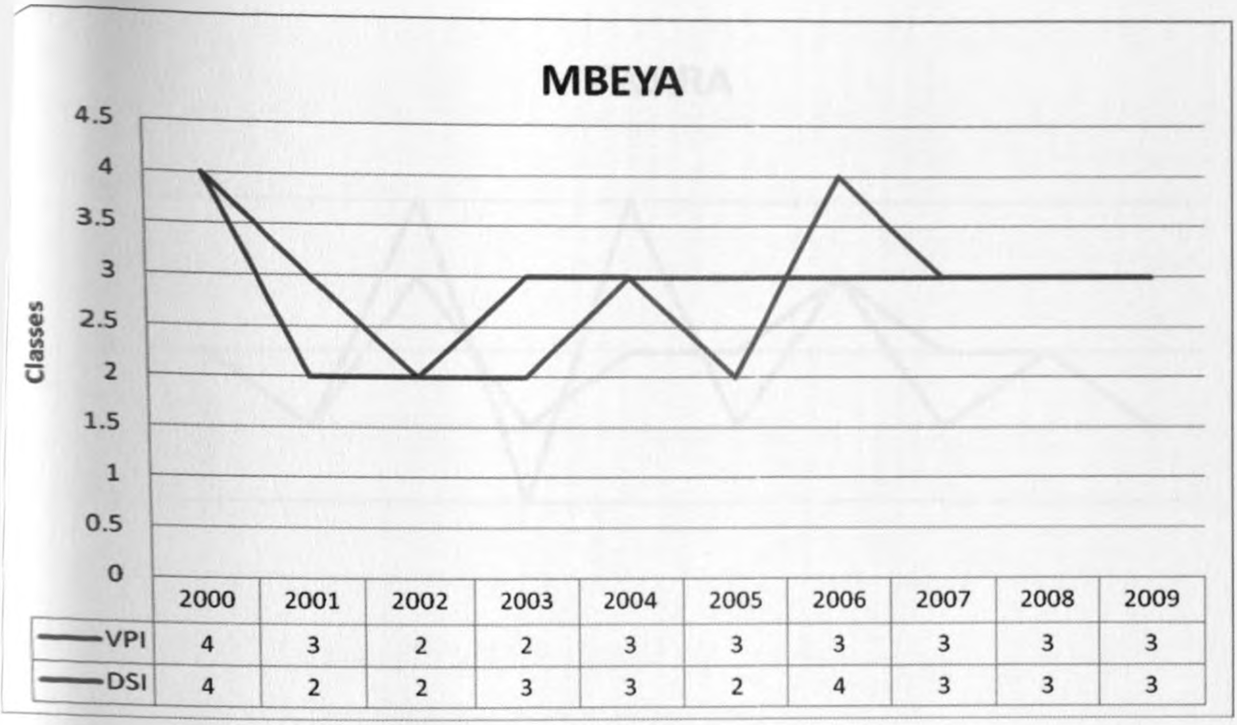


Figure 56: Time evolution of DSI and VPI, Mbeya

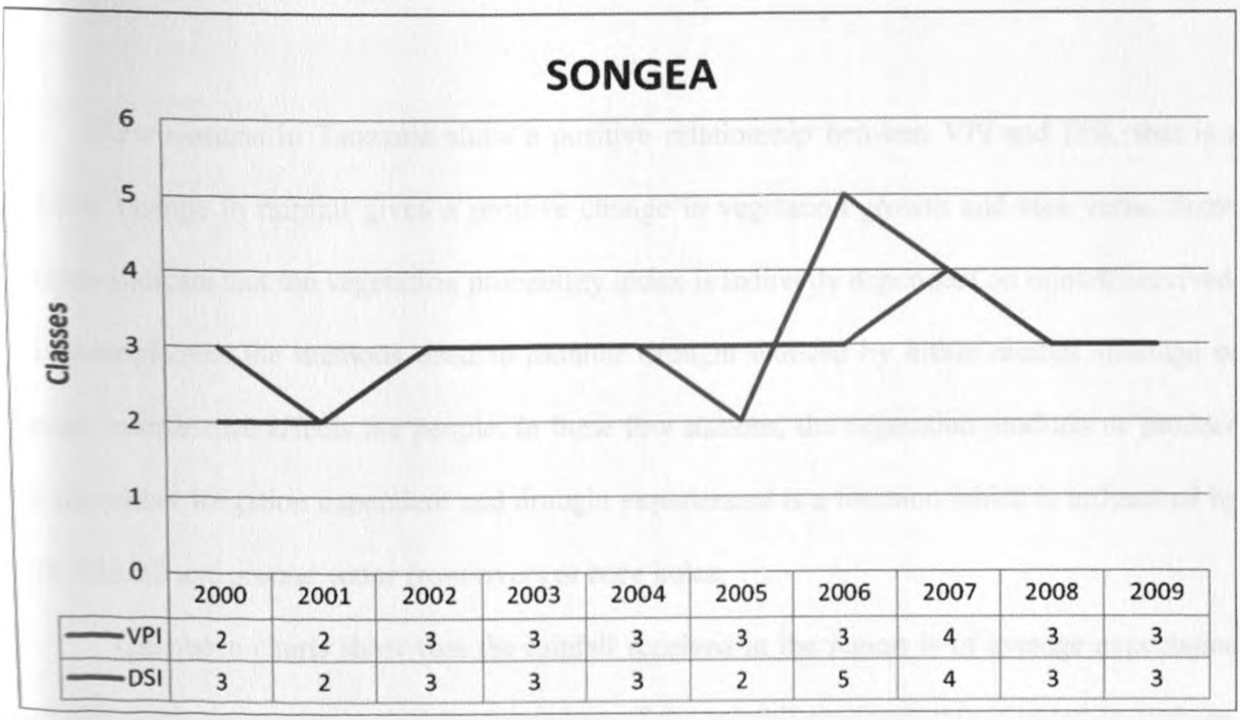
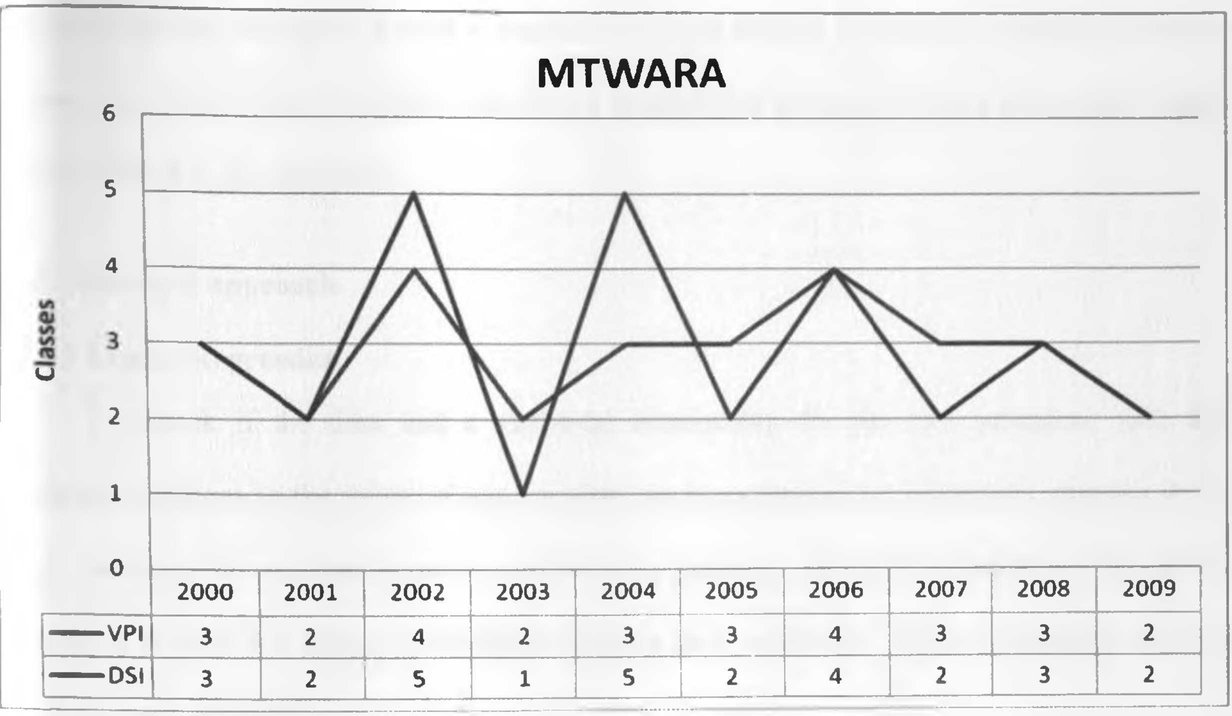


Figure 57: Time evolution of DSI and VPI, Songea



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
VPI	3	2	4	2	3	3	4	3	3	2
DSI	3	2	5	1	5	2	4	2	3	2

Figure 58: Time evolution of DSI and VPI, Mtwara

Few stations in Tanzania show a positive relationship between VPI and DSI, that is a positive change in rainfall gives a positive change in vegetation growth and vice versa. Some stations indicate that the vegetation probability index is indirectly dependent on rainfall received. This complicates the methods used to monitor drought induced by either rainfall shortage or human interference affects the people. In these few stations, the vegetation products or produce got are either irrigation dependent and drought experienced is a function which is influenced by both rainfall and ground water from rivers or bore holes.

The above charts show that the rainfall received in the region is of average expectation and the vegetation cover is slightly dependent of the rainfall received, this is noted in Bukoba, Musoma, Kigoma, Songea, Dodoma and Mtwara. Also just like the rainfall drought index, the vegetation probability index in Mwanza, Tabora and Mbeya are characterized by a variation om the expected average but with a tendency of going back to its normal condition. Dodoma, ongea and Mtwara show a nearly one to one relationship between the two indices but with a light variation in the extremes.

4.6.2 Statistical approach

4.6.2.1 Linear Regression

To check if the data had a statistical relationship for the two indicators such that systematic changes in the value of one variable are accompanied by systematic changes in the other, the simplest way used to get this was through plotting a regression formula for the data by creating a simple XY chart, a Trendline formula and correlation values calculation and the following was obtained.

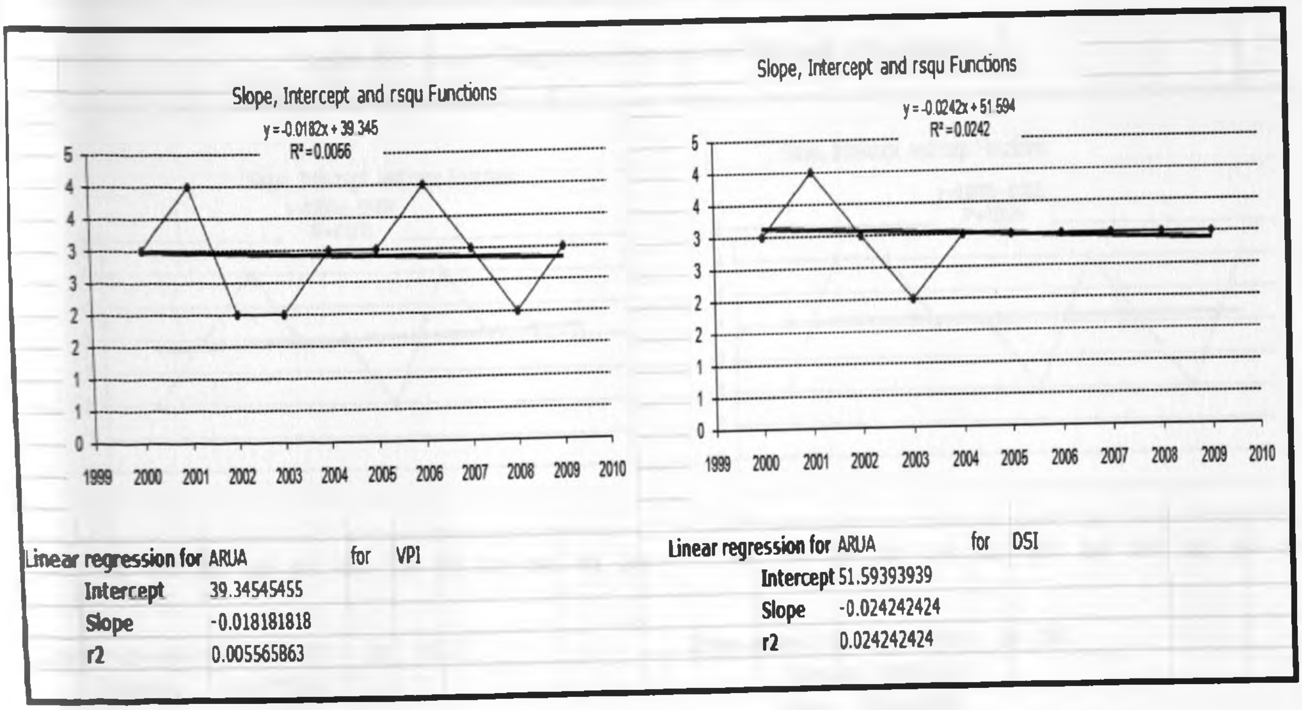
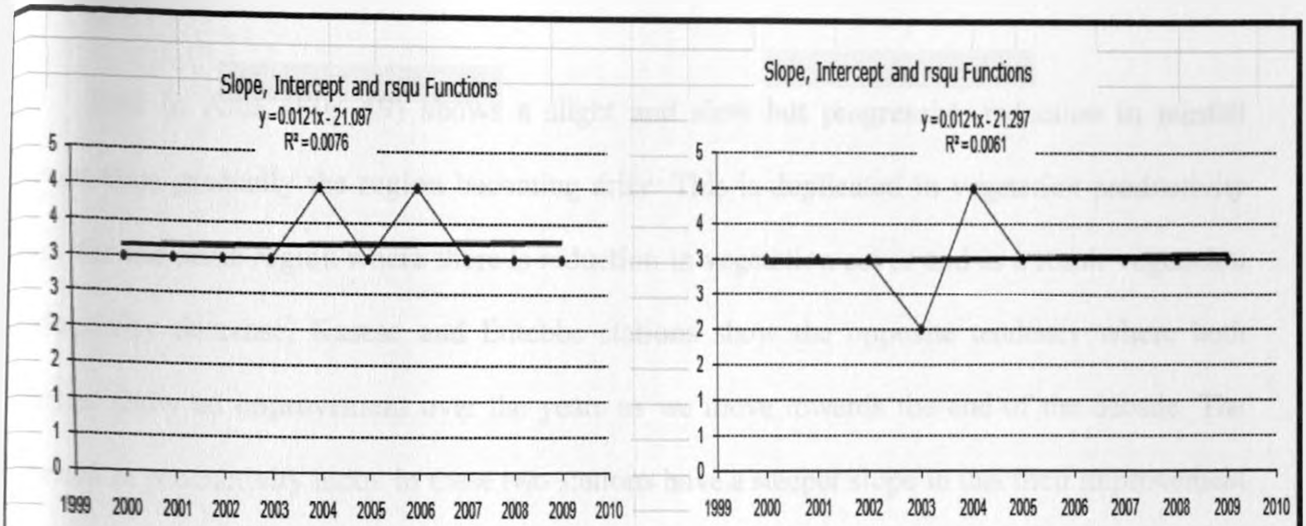


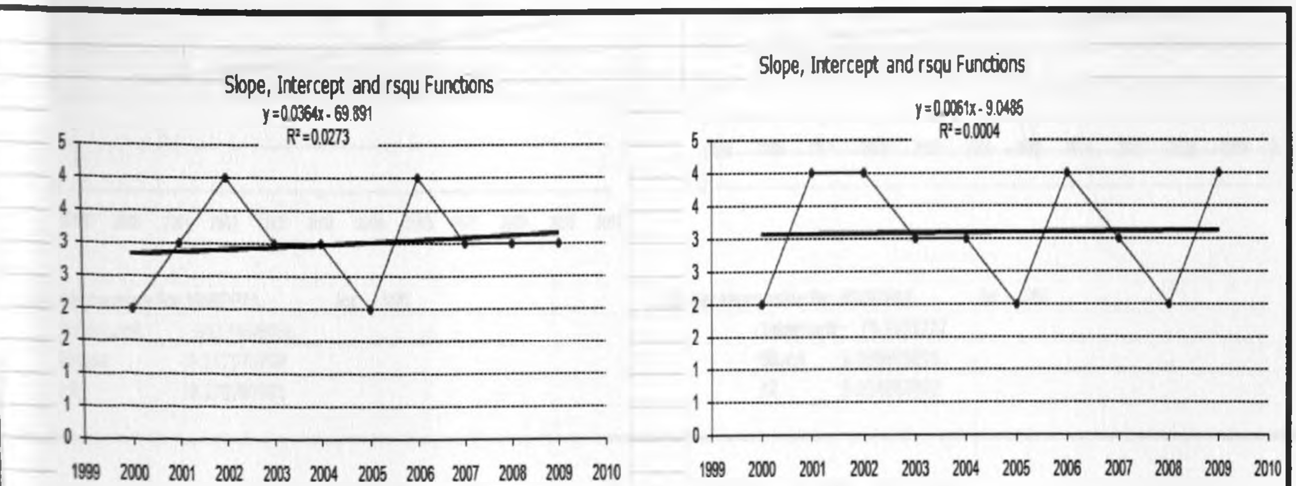
Figure 59: Linear Regression graphs of DSI and VPI, Arua



Linear regression for	KASESE	for	VPI
Intercept	-21.0969697		
Slope	0.012121212		
r2	0.007575758		

Linear regression for	KASESE	for	DSI
Intercept	-21.2969697		
Slope	0.012121212		
r2	0.006060606		

Figure 60: Linear Regression graphs of DSI and VPI, Kasese



Linear regression for	ENTEBBE AIRP.	for	VPI
Intercept	-69.89090909		
Slope	0.036363636		
r2	0.027272727		

Linear regression for	ENTEBBE AIRP.	for	DSI
Intercept	-9.048484848		
Slope	0.006060606		
r2	0.000439174		

Figure 61: Linear Regression graphs of DSI and VPI, Entebbe

DSI in Arua (Fig. 59) shows a slight and slow but progressive reduction in rainfall amount thus gradually the region becoming drier. This is duplicated in vegetation productivity index for the same region where there is reduction in vegetation cover and as a result vegetation productivity decrease. Kasese and Entebbe stations show the opposite tendency where both indexes show an improvement over the years as we move towards the end of the decade. The vegetation productivity index in these two stations have a steeper slope in that their improvement is faster in comparison to rainfall drought index improvement.

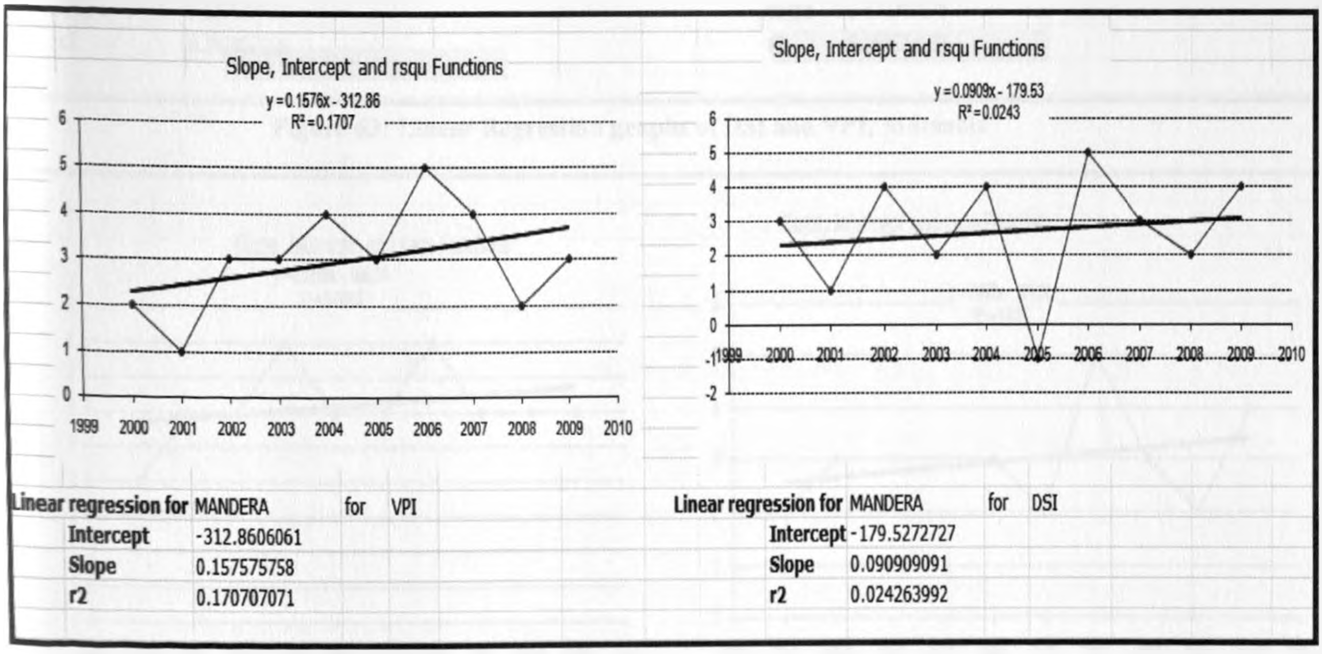


Figure 62: Linear Regression graphs of DSI and VPI, Mandera

In kenya, vegetation productivity index and drought severity index portray an increasing, neutral and decreasing trends in the stations used for the study. For example: Mandera (Fig. 62), Marsabit (Fig. 63), Wajir (Fig. 64) and Kisumu (Fig. 65) show a steady increase in both rainfall and vegetation cover in their region.

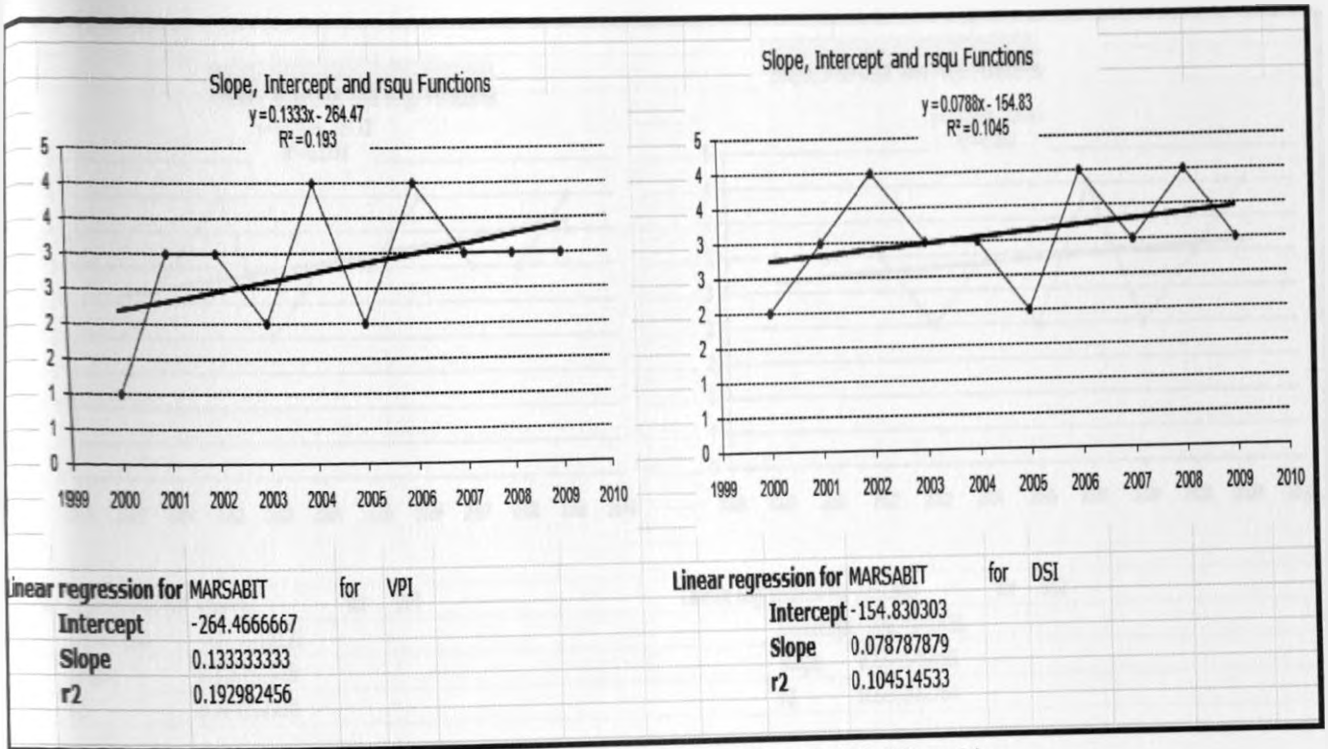


Figure 63: Linear Regression graphs of DSI and VPI, Marsabit

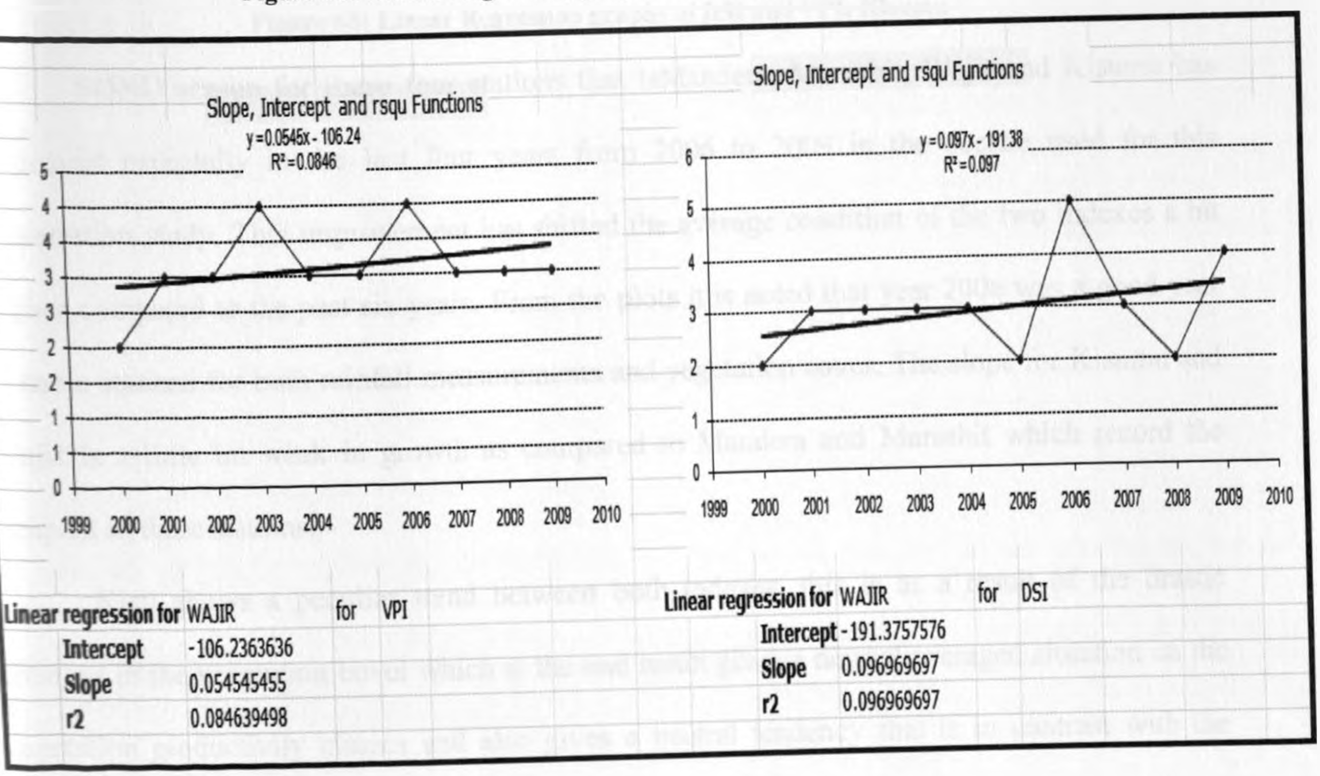


Figure 64: Linear Regression graphs of DSI and VPI, Wajir

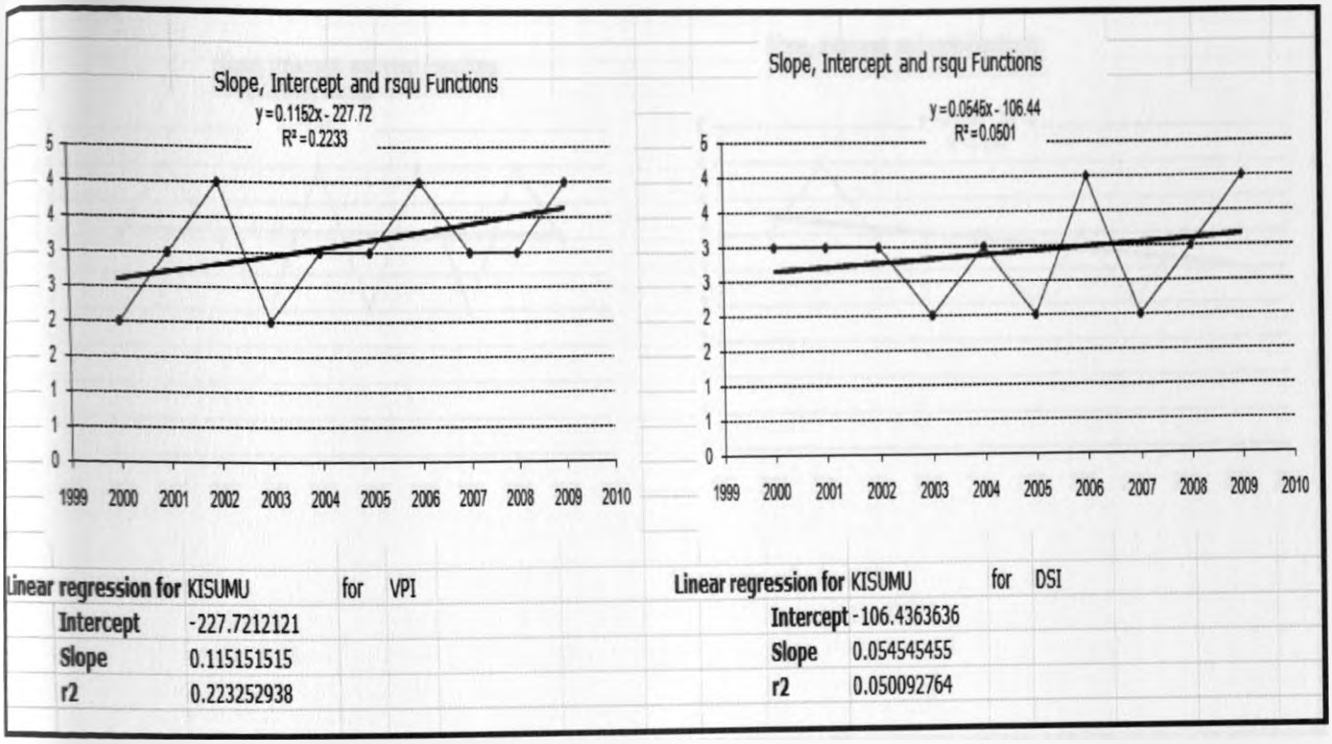
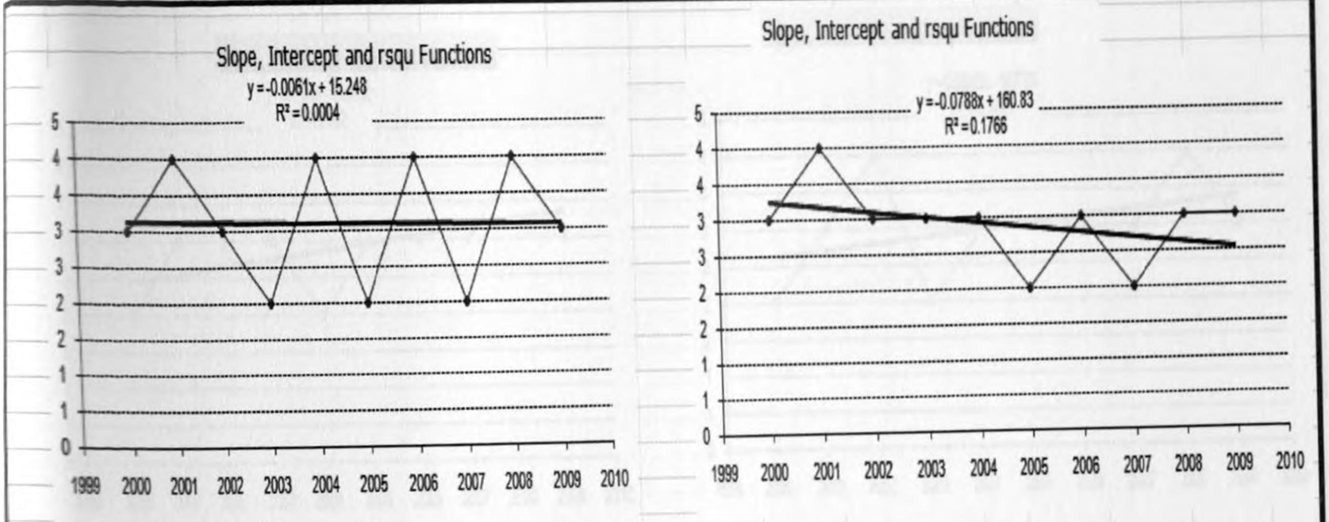


Figure 65: Linear Regression graphs of DSI and VPI, Kisumu

SOND season for these four stations that isMandera, Marsabit, Wajir and Kisumu has improved especially in the last four years from 2006 to 2009 in the decade used for this dissertation study. This improvement has shifted the average condition of the two indexes a bit higher compared to the past six years. From the plots it is noted that year 2006 was a good year in these stations for both rainfall measurements and vegetation cover. The slope for Kisumu and Wajir is a little bit weak in growth as compared to Mandera and Marsabit which record the steepest in these stations.

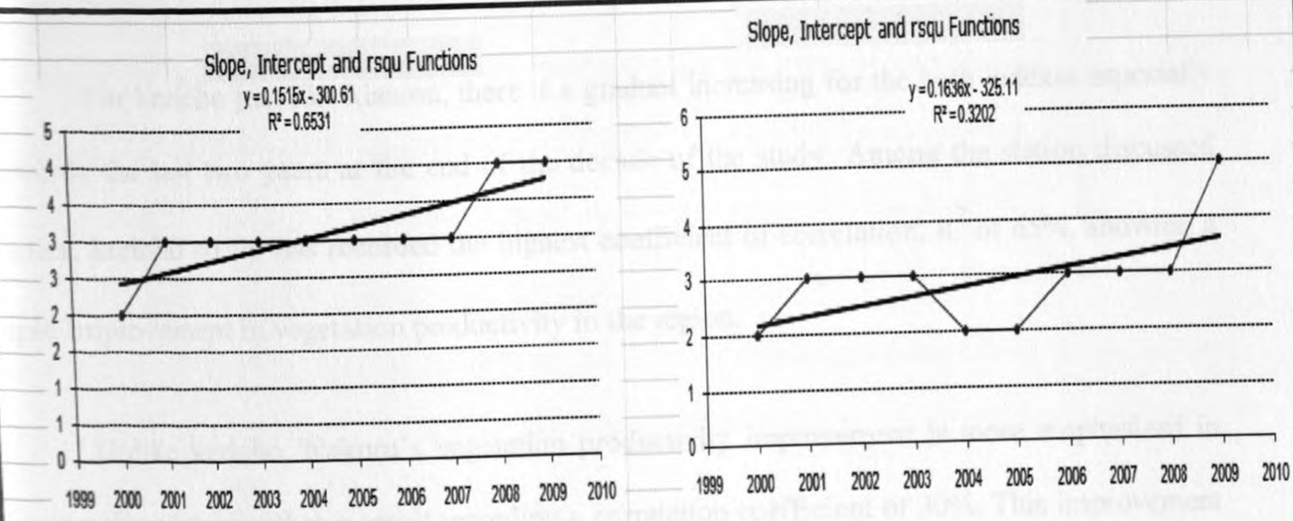
Kisii shows a peculiar trend between both indexes, this is as a result of the drastic changes in the vegetation cover which at the end result gives a neutral averaged situation on the vegetation productivity classes and also gives a neutral tendency that is in contrast with the decreasing rainfall recordings. The DSI shows a gradually growing drought phenomenon in the decreasing drought index from above normal readings to below normal rainfall recordings.



Linear regression for	KISII	for	VPI
Intercept	15.24848485		
Slope	-0.006060606		
r2	0.000439174		

Linear regression for	KISII	for	DSI
Intercept	160.830303		
Slope	-0.078787879		
r2	0.176593521		

Figure 66: Linear Regression graphs of DSI and VPI, Kisii



Linear regression for	KERICHO	for	VPI
Intercept	-300.6121212		
Slope	0.151515152		
r2	0.65308255		

Linear regression for	KERICHO	for	DSI
Intercept	-325.1090909		
Slope	0.163636364		
r2	0.320158103		

Figure 67: Linear Regression graphs of DSI and VPI, Kericho

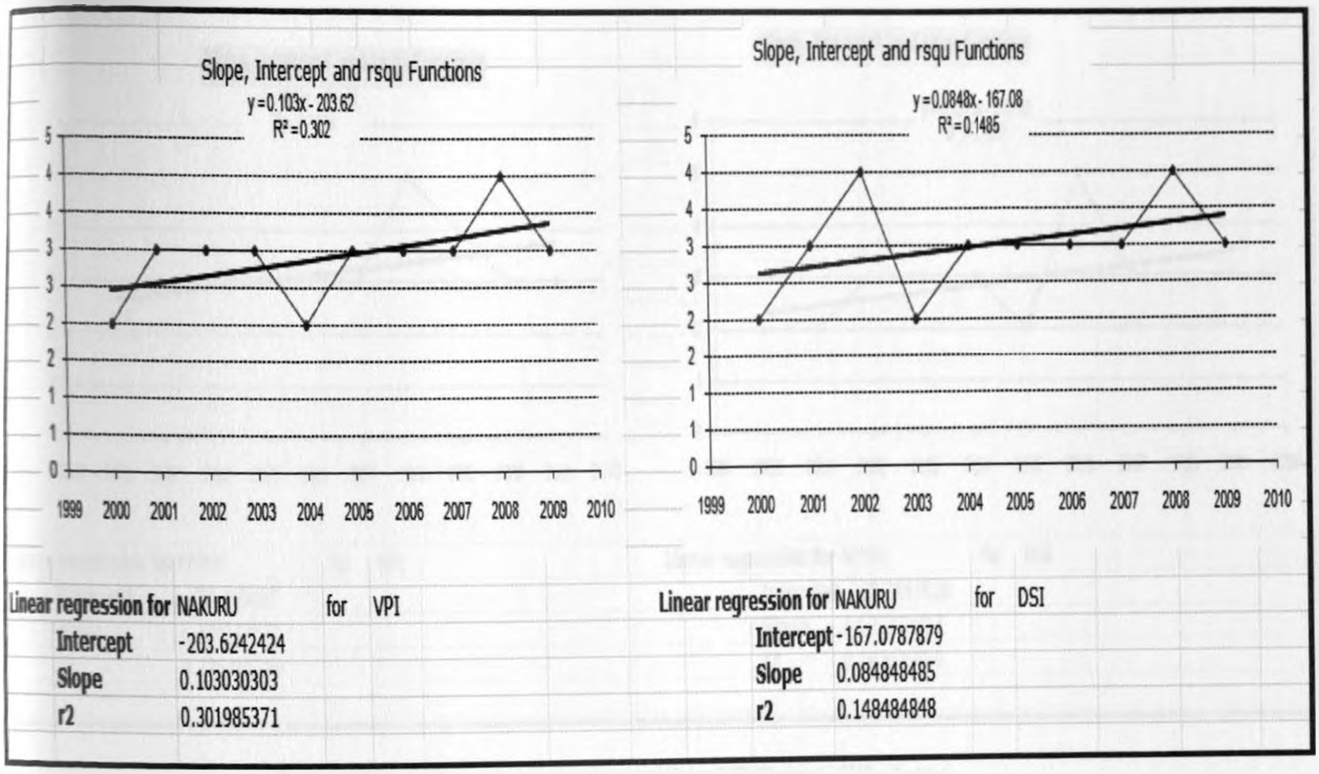


Figure 68: Linear Regression graphs of DSI and VPI, Nakuru

For kericho just like kisumu, there is a gradual increasing for the both indexes especially towards the last two years at the end of the decade of the study. Among the station discussed earlier, kericho so far has recorded the highest coefficient of correlation, R^2 of 65%, showing a rapid improvement in vegetation productivity in the region.

Unlike kericho, Nakuru's vegetation productivity improvement is more emphasized in the last three years and as a result recording a correlation coefficient of 30%. This improvement is also noticed in the rainfall drought index, that is the results show that as much as the rainfall alters, the vegetation productivity rate also alters in the same direction. Positive for positive slope and negative slope for negative slope in the other.

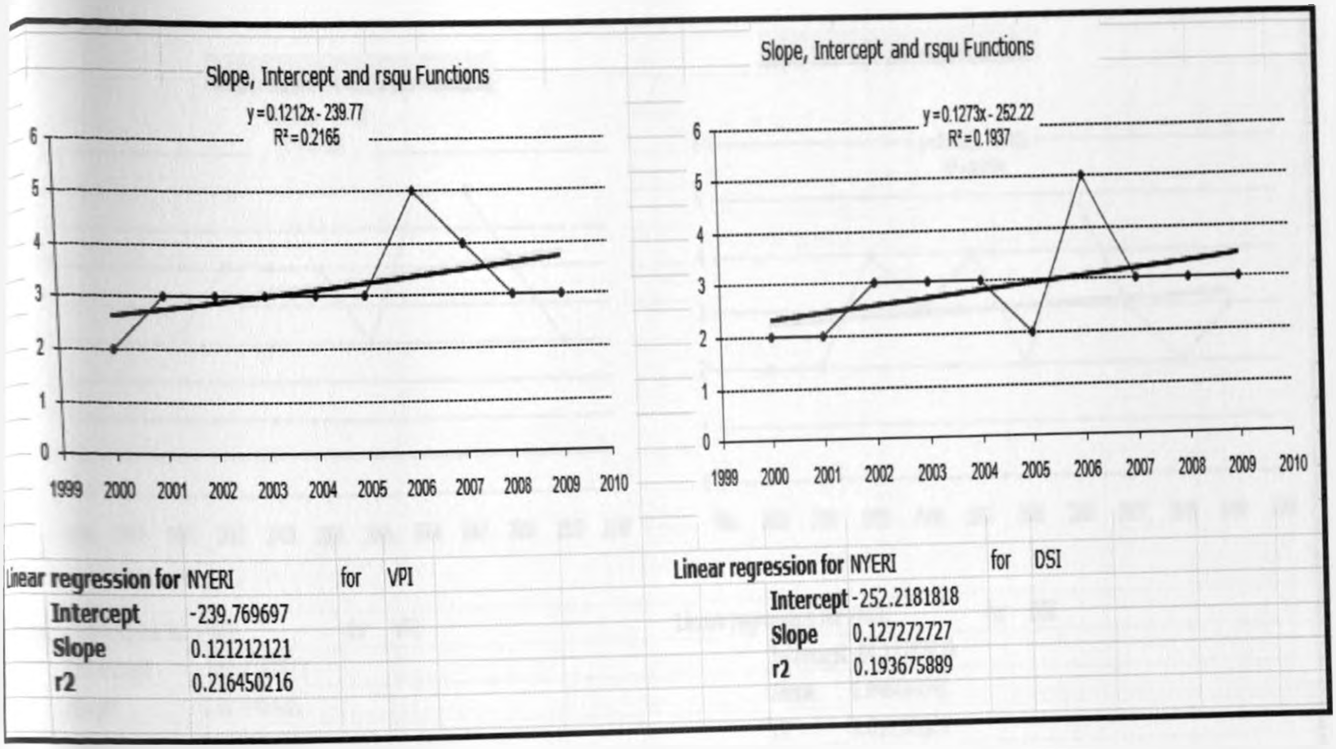


Figure 69: Linear Regression graphs of DSI and VPI, Nyeri

Nyeri records highest vegetation productivity class giving an 80% to 100% in the VPI legend. This is the highest in the region and supports the kind of measurements of rainfall recorded during the SOND season in year 2006. The region's trend analysis show gradual increase with a tendency a neutral position in most years in the decade of the study.

Despite the gradual increase in vegetation productivity rate in Embu, the rainfall received on average gives a near normal status with year 2006 giving a higher recording of the wettest year so far in the country in the decade of the study. This is also noted for Garissa for both the wettest year and gradual improvement in vegetation productivity.

Dagoretti and Wilson airport stations show a drastic decrease in vegetation productivity rate thus resulting to a decreased vegetation cover. Even though the rainfall drought index in these stations records a near normal rainfall, vegetation productivity decrease raises an alarm for the environmental conservation in the region.

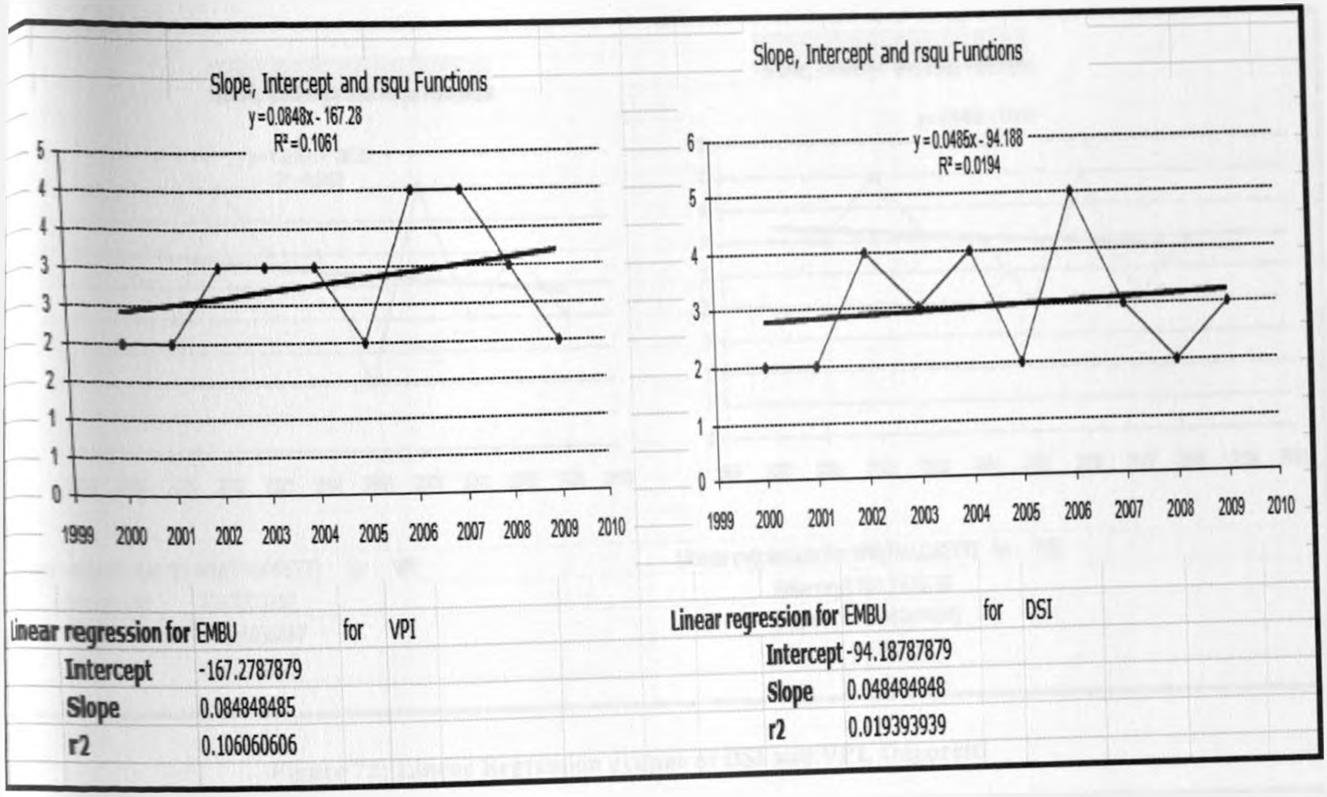


Figure 70: Linear Regression graphs of DSI and VPI, Embu

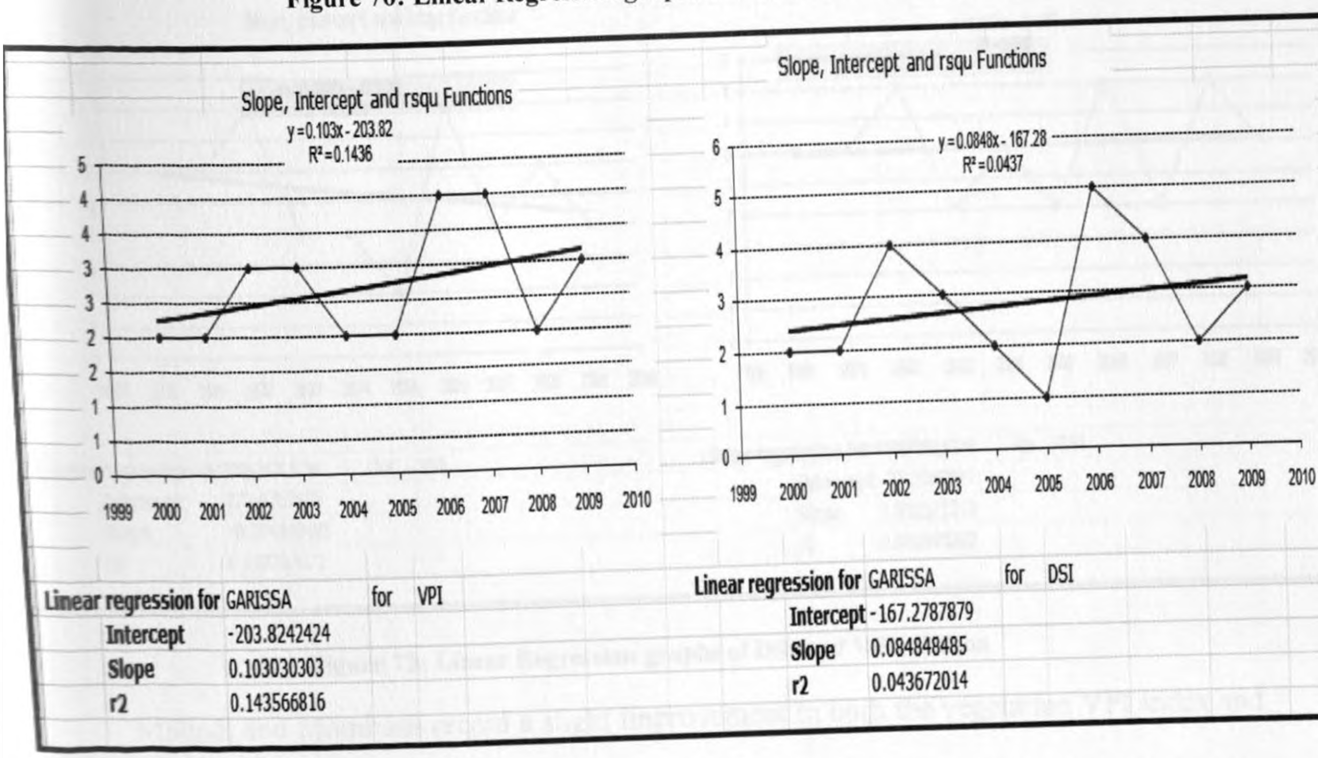


Figure 71: Linear Regression graphs of DSI and VPI, Garissa

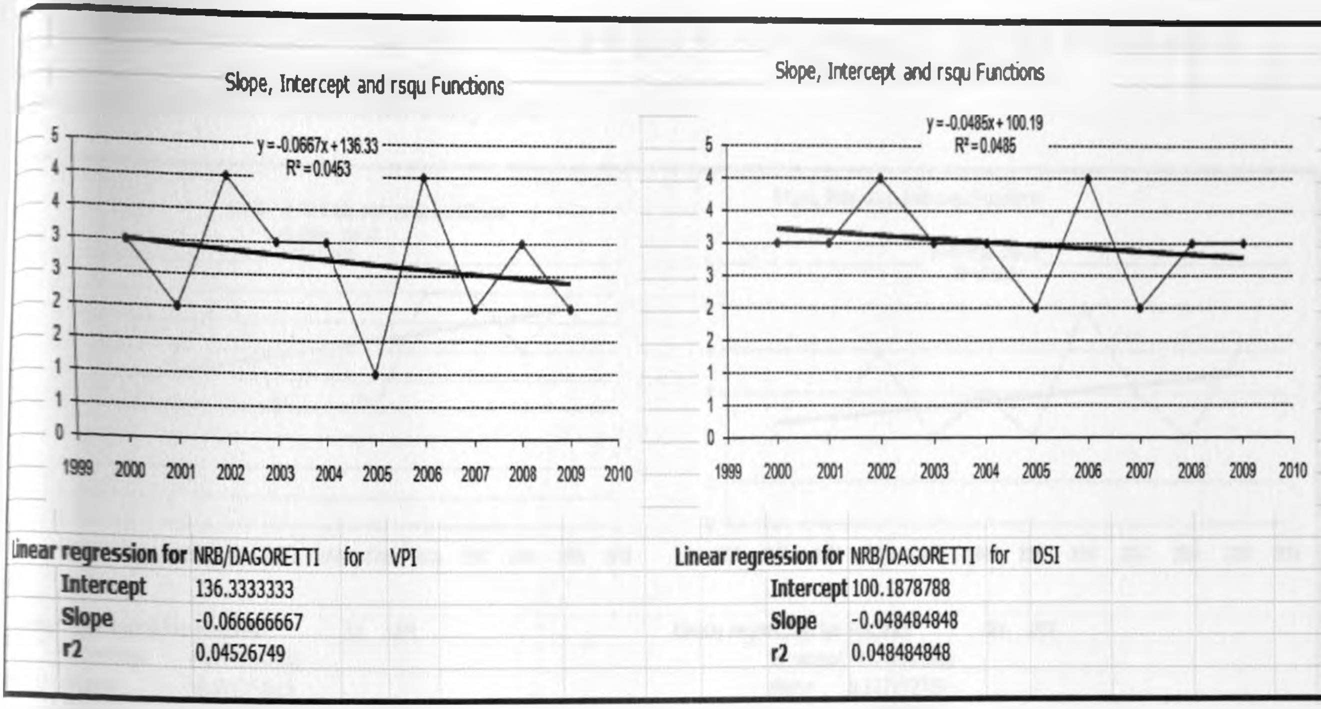


Figure 72: Linear Regression graphs of DSI and VPI, Dagoretti

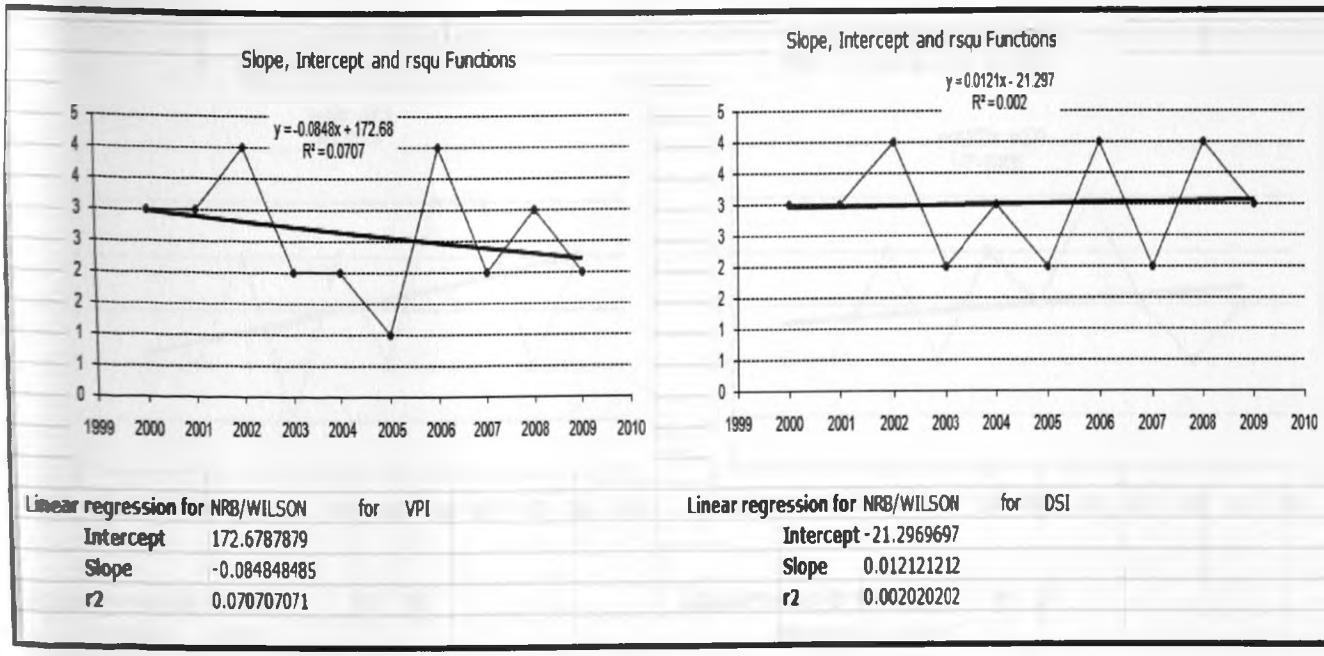
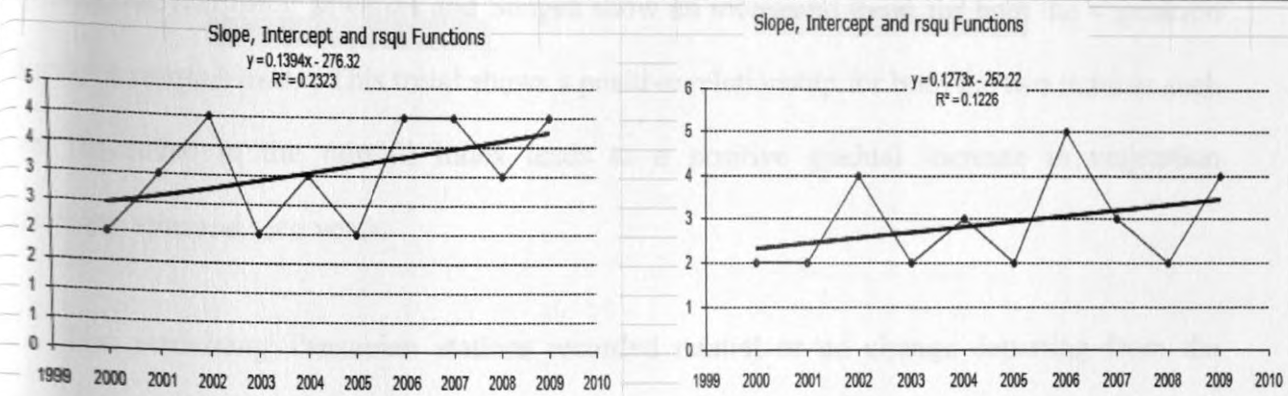


Figure 73: Linear Regression graphs of DSI and VPI, Wilson

Malindi and Mombasa record a slight improvement in both the vegetation VPI index and rainfall DSI index. This gives an increasing trend to the plotted charts for Malindi and Mombasa.

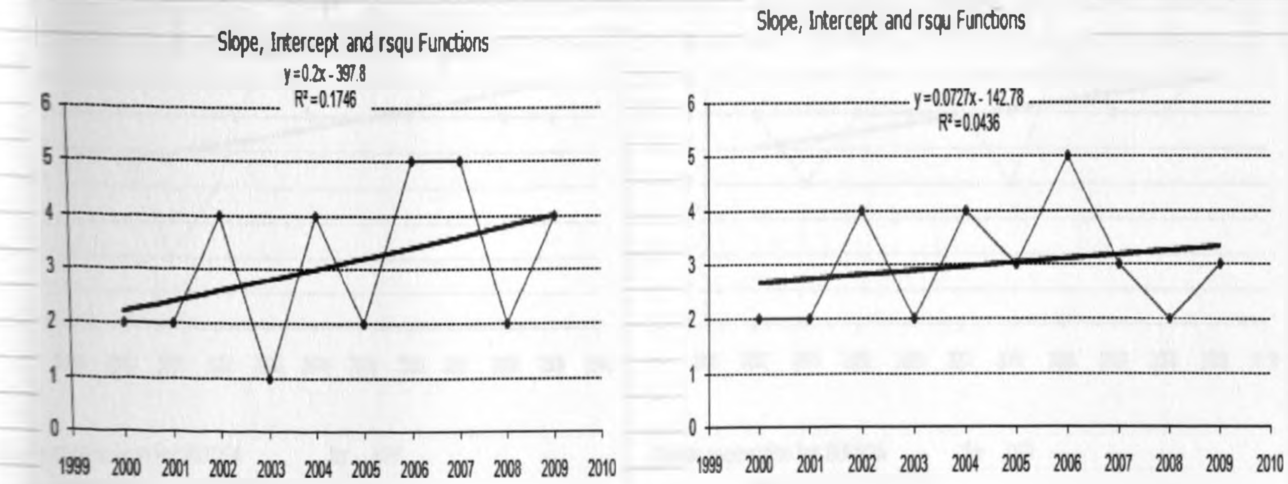
increasing rainfall and vegetation trend was due to an occurrence of El Niño that started in ember 2006band lasted until early 2007.



Linear regression for MALINDI	for VPI
Intercept	-276.3151515
Slope	0.139393939
r2	0.232323232

Linear regression for MALINDI	for DSI
Intercept	-252.2181818
Slope	0.127272727
r2	0.122602168

Figure 74: Linear Regression graphs of DSI and VPI, Malindi



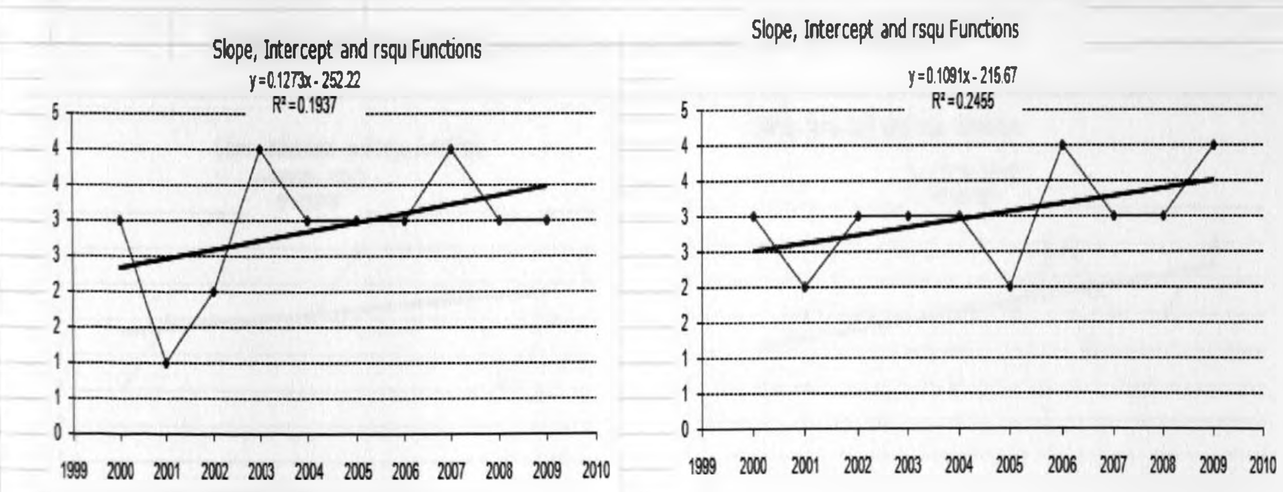
Linear regression for MOMBASA	for VPI
Intercept	-397.8
Slope	0.2
r2	0.174603175

Linear regression for MOMBASA	for DSI
Intercept	-142.7818182
Slope	0.072727273
r2	0.043636364

Figure 75: Linear Regression graphs of DSI and VPI, Mombasa

The Tanzanian stations used in the study show a particular trend in their observed recordings. These stations are divided into two groups, that is an increasing trend and a neutral trend. Bukoba, Musoma, Mwanza and Songea show an increasind trend for both the vegetation and drought rainfall index. This trend shows a positive relationship for both the two indexes such that an increase in the rainfall index leads to a positive gradual increase in vegetation productivity rate and vice versa.

The remaining Tanzanian stations recorded neutral or no change departing from the average condition. This is evident in Tabora, Dodoma, Mbeya and Mtwara.



Linear regression for BUKOBA	for VPI
Intercept	-252.2181818
Slope	0.127272727
r2	0.193675889

Linear regression for BUKOBA	for DSI
Intercept	-215.6727273
Slope	0.109090909
r2	0.245454545

Figure 76: Linear Regression graphs of DSI and VPI, Bukoba

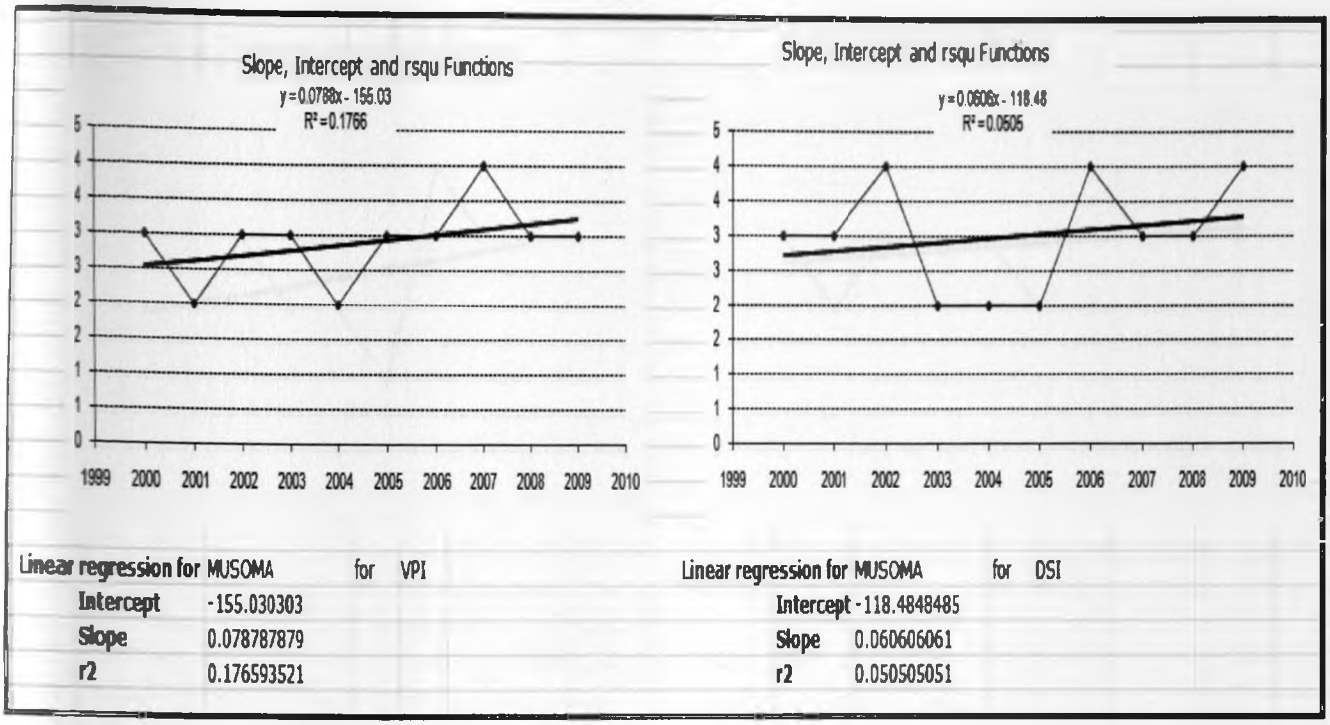


Figure 77: Linear Regression graphs of DSI and VPI, Musoma

Figure 78: Linear Regression graphs of DSI and VPI, Mwanza

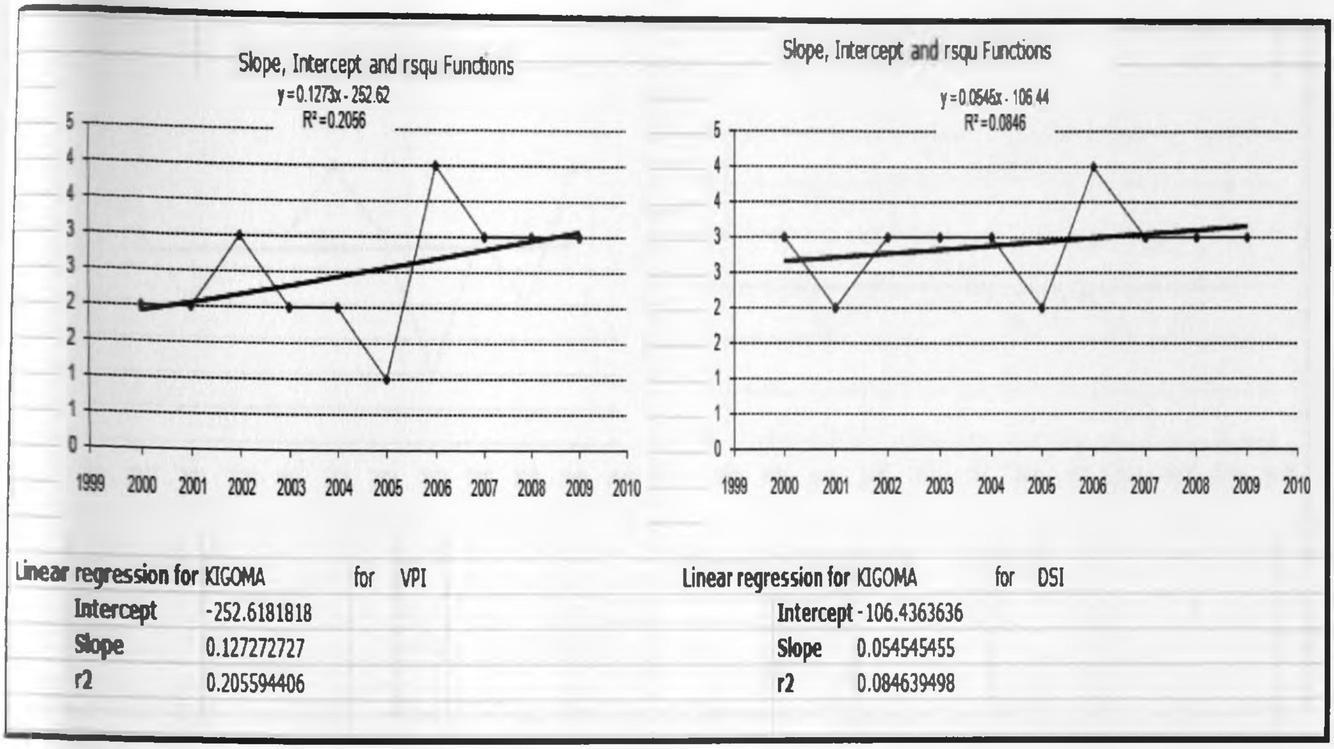


Figure 79: Linear Regression graphs of DSI and VPI, Kigoma

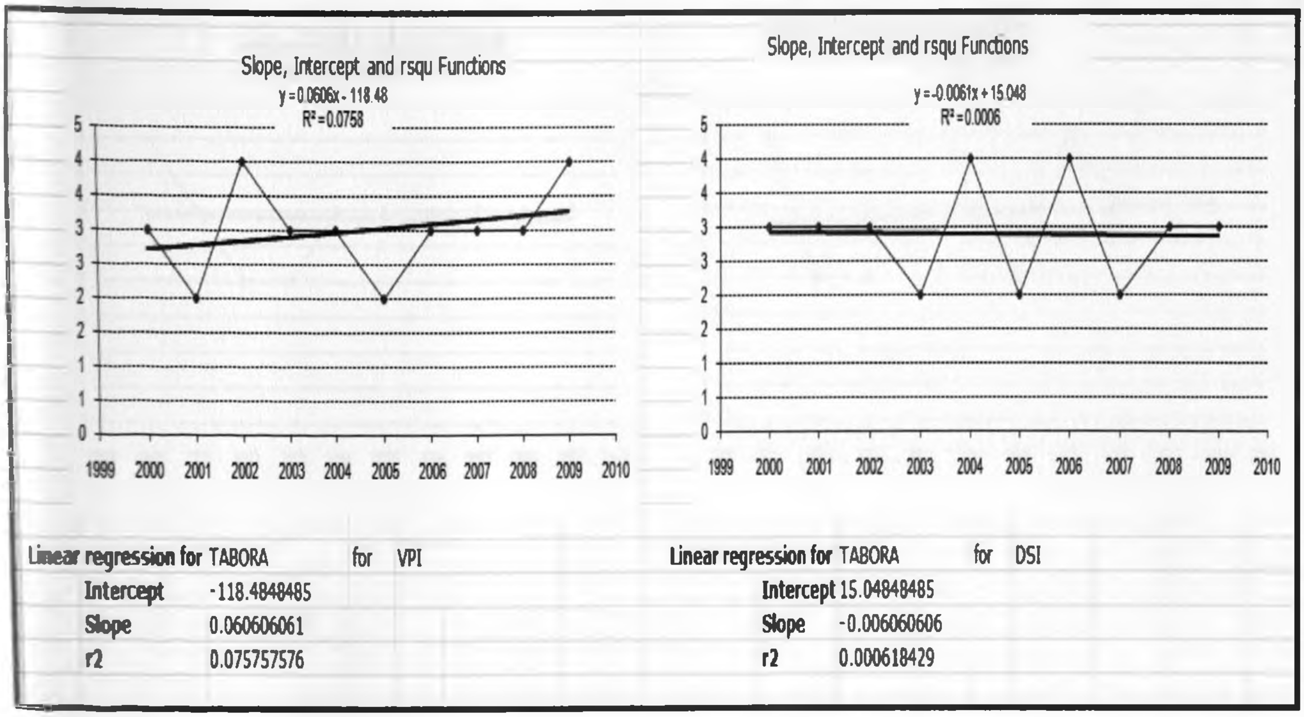


Figure 80: Linear Regression graphs of DSI and VPI, Tabora

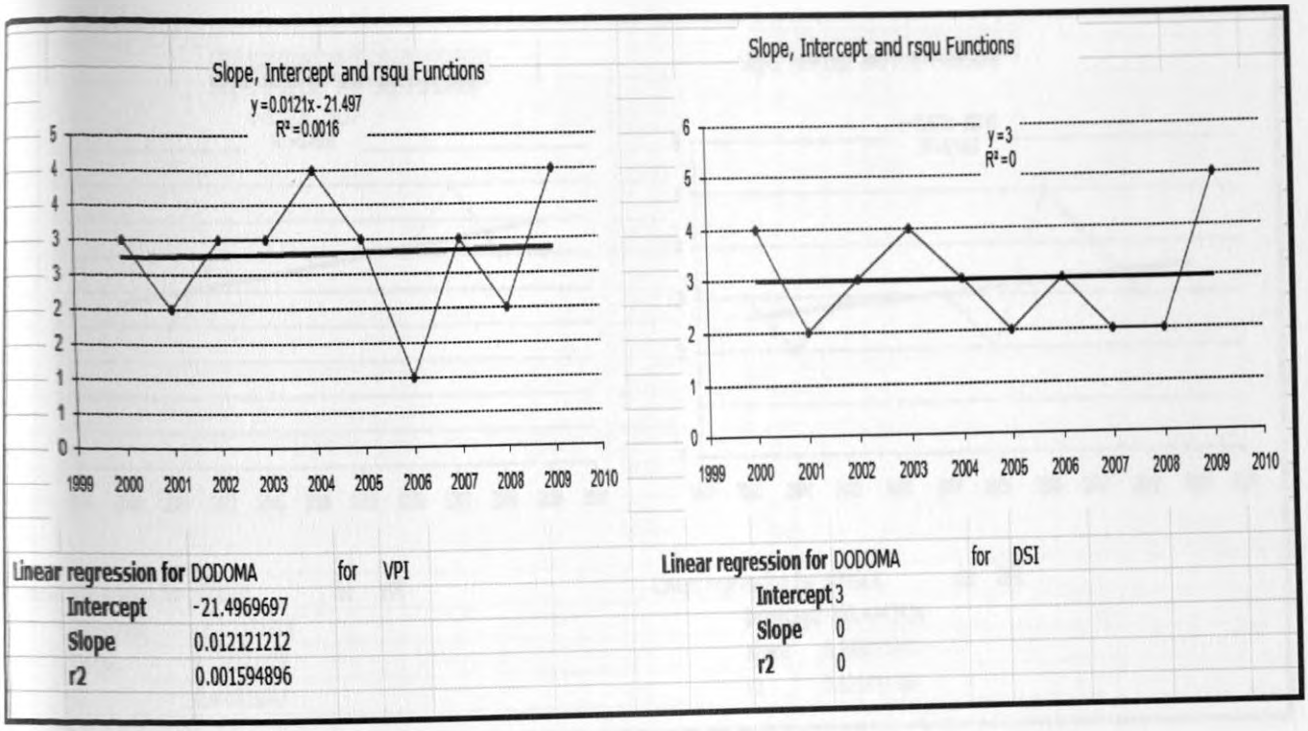


Figure 81: Linear Regression graphs of DSI and VPI, Dodoma

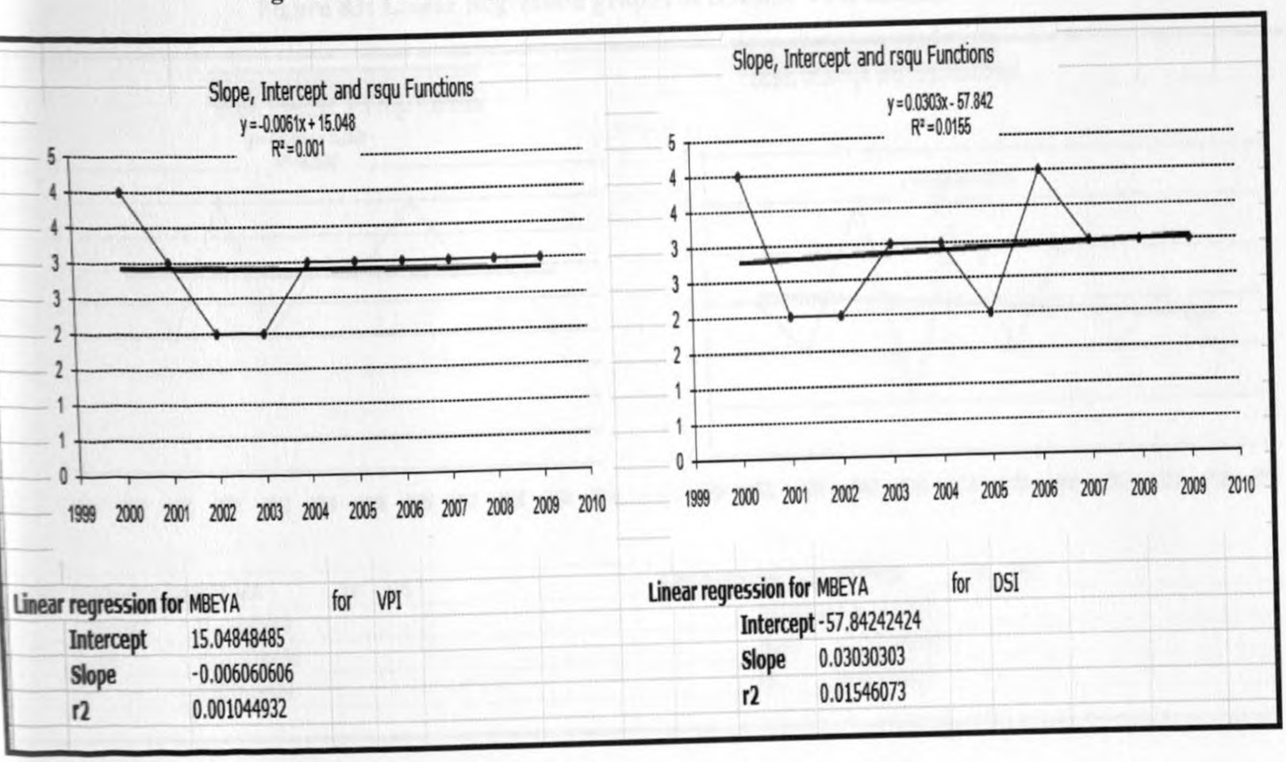
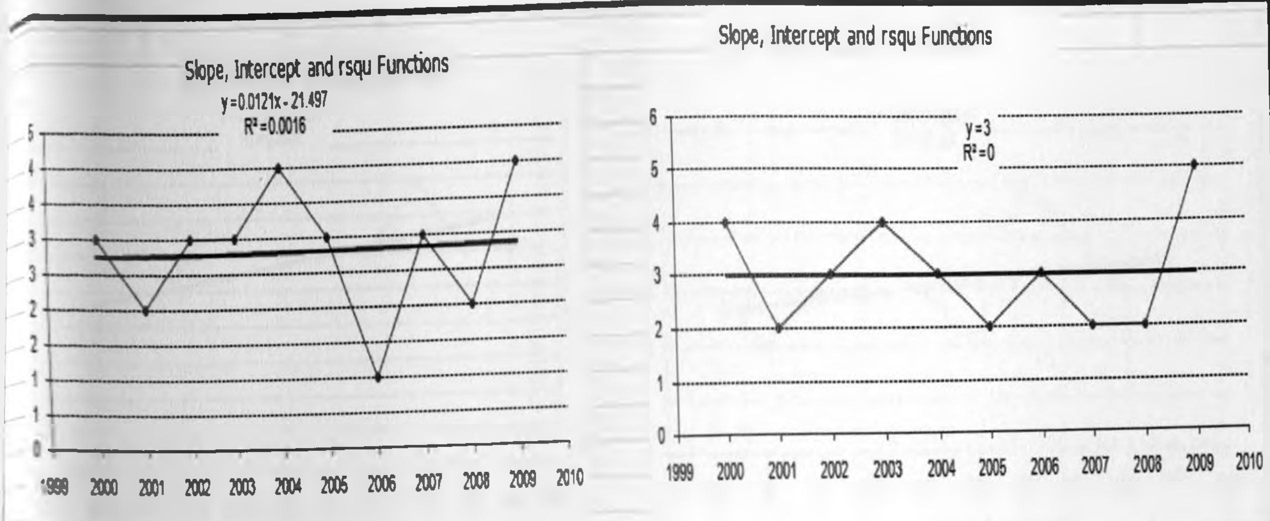


Figure 82: Linear Regression graphs of DSI and VPI, Mbeya



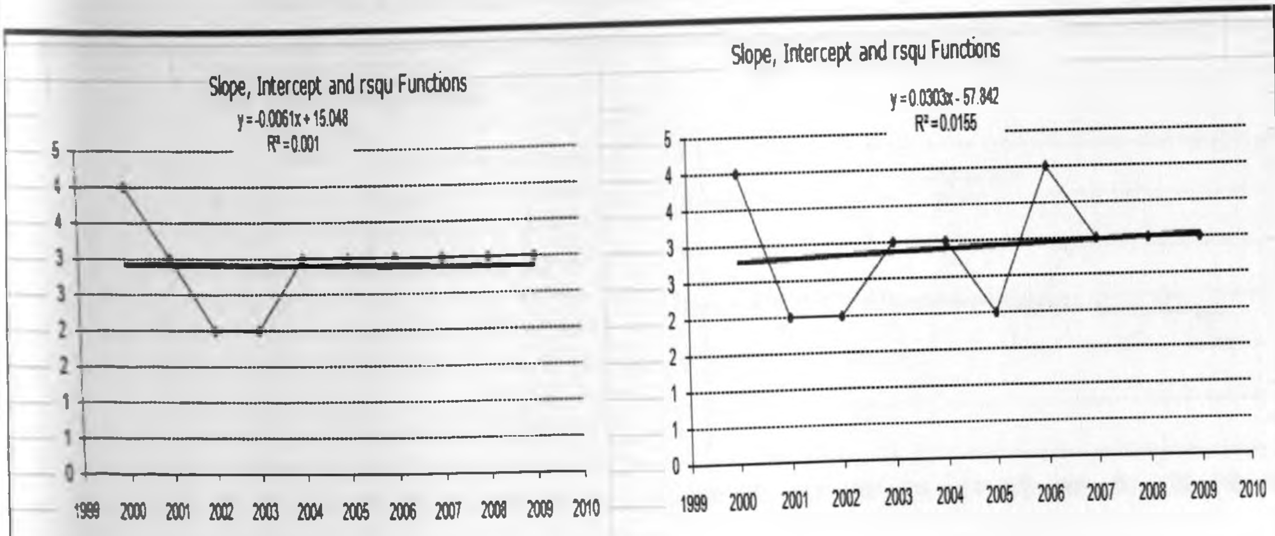
Linear regression for DODOMA for VPI

Intercept	-21.4969697
Slope	0.012121212
r2	0.001594896

Linear regression for DODOMA for DSI

Intercept	3
Slope	0
r2	0

Figure 81: Linear Regression graphs of DSI and VPI, Dodoma



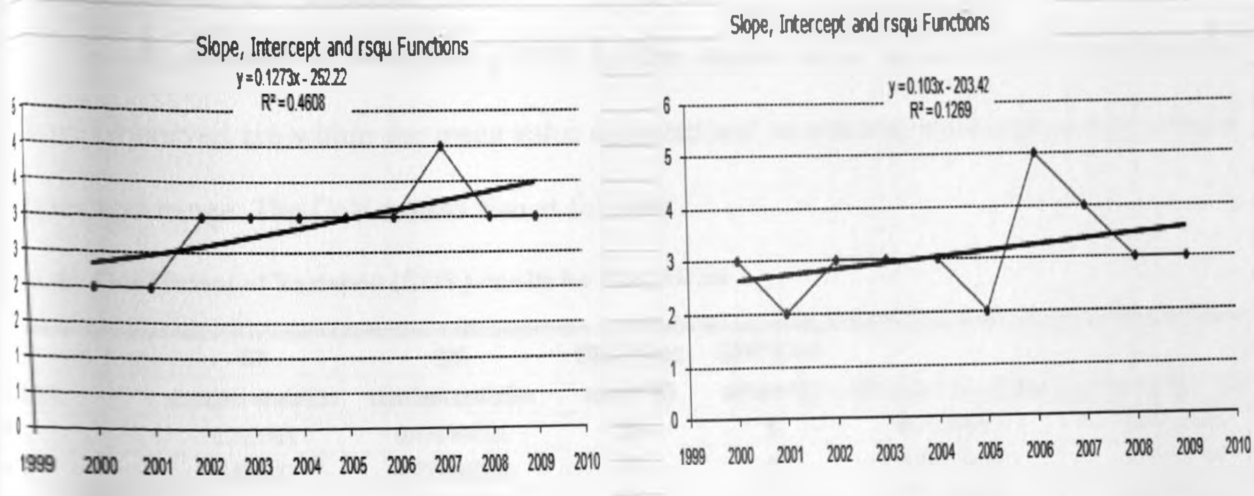
Linear regression for MBEYA for VPI

Intercept	15.04848485
Slope	-0.006060606
r2	0.001044932

Linear regression for MBEYA for DSI

Intercept	-57.84242424
Slope	0.03030303
r2	0.01546073

Figure 82: Linear Regression graphs of DSI and VPI, Mbeya



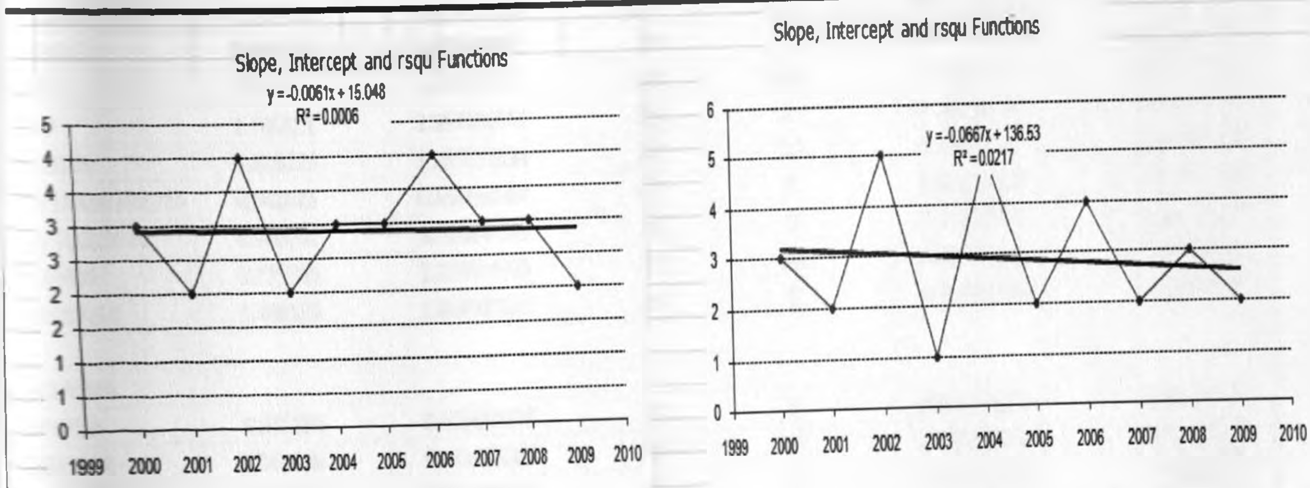
ear regression for SONGEA for VPI

Intercept	-252.2181818
Slope	0.127272727
r2	0.460815047

Linear regression for SONGEA for DSI

Intercept	-203.4242424
Slope	0.103030303
r2	0.126921388

Figure 83: Linear Regression graphs of DSI and VPI, Songea



inear regression for MTWARA for VPI

Intercept	15.04848485
Slope	-0.006060606
r2	0.000618429

Linear regression for MTWARA for DSI

Intercept	136.5333333
Slope	-0.066666667
r2	0.021696252

Figure 84: Linear Regression graphs of DSI and VPI, Mtwara

4.2.2 Coefficient of Variation (CoV)

The Coefficient of Variation (COV) for the stations used in this study show that the variation observed are within the mean value expected and no extreme were such severe beyond the expected range. The CoV results also as follows:

Table 14: Coefficient of Variation (COV) results for East Africa

UGANDA	VPI standard deviation	DSI standard deviation	SOND mean xmean VPI	SOND mean xmean DSI	CoV VPI= STDDEV/MEAN	CoV DSI= STDDEV/ME
ARUA	0.737865	0.471404521	2.9	3	0.254436134	0.15713484
KASESE	0.421637	0.471404521	3.2	3	0.131761569	0.15713484
ENTEBBE AIRP.	0.666667	0.875595036	3	3.1	0.222222222	0.282450012
KENYA						
MANDERA	1.154701	1.766981104	3	2.7	0.384900179	0.654437446
MARSABIT	0.918937	0.737864787	2.8	3.1	0.328191637	0.238020899
WAJIR	0.567646	0.942809042	3.1	3	0.183111681	0.314269681
KISUMU	0.737865	0.737864787	3.1	2.9	0.238020899	0.254436134
KISII	0.875595	0.567646212	3.1	2.9	0.282450012	0.195740073
KERICHO	0.567646	0.875595036	3.1	2.9	0.183111681	0.301929323
NAKURU	0.567646	0.666666667	2.9	3	0.195740073	0.222222222
NYERI	0.788811	0.875595036	3.2	2.9	0.246503324	0.301929323
EMBU	0.788811	1.054092553	2.8	3	0.281718085	0.351364184
GARISSA	0.823273	1.229272594	2.7	2.8	0.304915779	0.439025927
NRB/DAGORETTI	0.948683	0.666666667	2.7	3	0.351364184	0.222222222
NRB/WILSON	0.966092	0.816496581	2.6	3	0.371573763	0.272165527
MALINDI	0.875595	1.100504935	3.1	2.9	0.282450012	0.37948446
MOMBASA	1.449138	1.054092553	3.1	3	0.467463766	0.351364184
TANZANIA						
BUKOBA	0.875595	0.666666667	2.9	3	0.301929323	0.222222222
MUSOMA	0.567646	0.816496581	2.9	3	0.195740073	0.272165527
MWANZA	0.737865	0.567646212	3.1	3.1	0.238020899	0.183111681
KIGOMA	0.849837	0.567646212	2.5	2.9	0.339934634	0.195740073
TABORA	0.666667	0.737864787	3	2.9	0.222222222	0.254436134
DODOMA	0.918937	1.054092553	2.8	3	0.328191637	0.351364184
MBEYA	0.567646	0.737864787	2.9	2.9	0.195740073	0.254436134
SONGEA	0.567646	0.875595036	2.9	3.1	0.195740073	0.282450012
MTWARA	0.737865	1.370320319	2.9	2.9	0.254436134	0.472524248

Limitation of the study

One of the disadvantages of using drought severity index is that the mean, or average, precipitation is often not the same as the median precipitation, which is the value exceeded by 50% of the precipitation occurrences in a long-term climate record. The reason for this is that precipitation on monthly or seasonal scales does not have a normal distribution. Use of the percent of normal comparison implies a normal distribution where the mean and median are considered being the same.

Satellite derived products are known to be affected by topography, variations in viewing and illumination angles, atmospheric influences, and variations in soil brightness, and since NDVI has been for many years the Earth observation workhorse to quantify vegetation amount and radiation absorbed it is therefore affected by this factors. For example, some authors have shown how NDVI is increasing in the northern hemisphere, and they have deduced that photosynthesis is therefore increasing. This observation might be accelerated by these factors.

There are also many complications, limitations and causes of error associated with satellite data, including sensor resolution and calibration, digital quantization errors, ground and atmospheric conditions and (orbital and sensor) degradation. But NDVI data sets are generally well-documented, quality-controlled and have been pre-processed to reduce many of these problems. However, some noise is still present in the data sets. Such noise is mainly due to remnant cloud cover, water, snow, or shadow, sources of errors that tend to decrease the NDVI values. False highs, although much less frequent, can also occur at high solar or scan angles (in which case the numerator and denominator in the NDVI ratio are both near zero) or because of transmission errors, such as line drop-out.

To minimize the problem of false highs, the data are generally based on low-angle ervations wherever possible. Most errors thus tend to decrease NDVI values. This unusual error structure, with high NDVI values being more trustworthy than low ones, breaks the assumptions of many standard statistical approaches. Further complications can arise because the error structure can vary in time and space.

CHAPTER FIVE
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Summary

Meteorological drought in the three countries shows equal chances of occurrence in all ion used. This is shown by the average VPI image for the SOND season, the whole region of stern Africa has a 50% chance of improving vegetation cover and same chance in performing orly. But an exception is noticed in the Kenyan highlands, north eastern parts of Kenya, astal areas in Kenya and Tanzania and parts of southern Tanzania with a small portion in Mt. ilimanjaro. This gives a negative implication in that the greater part of east African region is ubject to effects of drought as the satellite product suggests.

It is shown that the conclusion for year 2000 is that the north eastern part of Uganda, Mt. Elgon region and coastal strip of Kenya experienced a positive regeneration as compared to the emaining regions of East Africa. This implies that drought effects were more felt and experienced in the later regions where degeneration was dominant.

In year 2001, rift valley around Lake Turkana, some parts of central Kenya and the coastal strip along Kenya-Tanzania border were hard hit by drought conditions as VPI shows in figure 14 where the regions recorded 0-20% in the productivity class of VPI and had an 80-100% chance of improvement. The other parts recorded a good productivity rate of 60-80% with few places having 40-60% in the same year.

In 2002, the eastern and southern sector of East Africa had a good year with a 60-80% reading while the whole north eastern parts in Uganda and western side of Kenya performed poorly, this is shown in figure 16. From year 2003, regeneration of vegetation picked up in the whole region with a maximum record being observed in year 2004. In 2005, few places in central ya and north eastern Kenya recorded a low productivity rate while majority of the region neutral conditions except for Kenyan highlands, western parts of rift valley, southwest ia and southern Tanzania which had 60-80% productivity class

In 2006 SOND season, major improvement of 60-100% was recorded in most places with entral and western Tanzania recording neutral and low productivity rate. This shows that ght was not experienced in Kenya, Uganda and eastern and southern Tanzania during this season.

The best condition in east Africa was recorded in year 2007 where majority of the region rded a 60-80% and even some places had 80-100%, meaning that no more improvement ld be got at the time. This persisted to year 2008 where a maximum was recorded in the tral parts of the region. Year 2009 was bad for Kenyan central rift valley which recorded a 0-% in VPI productivity class; this is similarly experienced in some parts of Tanzanian coast. e rest of region recorded 40 to 80%.

Conclusions

In conclusion, from the study it is found that drought can basically be monitored by atellite products which are associated with a period of abnormally dry weather which results in a change in vegetation cover condition. Remote sensing showed that meteorological drought can be monitored using VPI index and it can be concluded that VPI index is more sensitive and perform well with small changes of vegetation; this shows that meteorological drought affects vegetation cover in the stations used and thus monitoring of this effects are very crucial. The results conclude that drought occurs nearly in every part of the region and adversely affects the lives of a large number of people, causing considerable damage to economies, the environment, and property of the region. It also affects the stations differently, having a greater impact on the ependent on rainfall.

East African countries experience severe droughts as a result of failed rains. With crops to grow, many people have been left without enough food to eat. Examples of these ght years indentified by the study which have occurred are in year 2000, early 2002 and . Note that also year 2009 drought is presumed to be the worst in east Africa since 2000 as n by the satellite product used in the study.

The evaluation of the potential use of satellite-derived products in regional drought itoring focusing on comparison of rainfall and satellite derived products for the case of ND season demonstrates that VPI is a good indicator of vegetation response to rainfall nges and thus also to rainfall drought index. It can be concluded that the VPI is a useful tool d is capable of providing a good monitoring satellite system on drought.

When used along with traditional drought indices, based on rainfall or other weather and cillary information, VPI contributes toward the development of an operational drought index at aid in making appropriate and timely decisions in response to drought. From the results oted in the study, it is possible to state that satellite monitoring of drought is realistic and can be sed in its monitoring. This has been proved by results of the objectives of this study.

.2 Recommendations

The recommendations of this study are directed towards climate research scientists, environmental scientist, environmental centres, Meteorological and Hydrological Services (NMHSs), ICPAC and various professionals in all sectors that are affected by drought and its results.

5.2.1 Recommendations to climate research scientists

- The data for this study was carried for the whole East Africa region and further study can be done for a specific region within the region for verification i.e. an individual country.

- Further enhancement of the vegetation index used in monitoring drought in the study should be encouraged such that scenario development and modelling at regional and even local levels are explored by the scientists aiming to have a good early warming mechanism.
- More validation of the satellite products should be done since human influence in vegetation growth is difficult to analyse or separate from the main data.

5.2.2 Recommendation to Meteorological and Hydrological services

- Since satellite products are difficulty or expensive to get, meteorological and hydrological centres should make them available with ease since most of them are linked to the satellite data providers.

5.2.3 Recommendation to Research institutions

- Different research institutions within African countries should encourage collaborating together to determine what is needed to promote the convergence of satellite monitoring networks within Africa i.e. A good example is like what African Monitoring of The Environment for Sustainable Development (AMESD) is doing.
- It is also recommended that research institution within the east African region work together to develop a regional data base and data assimilation capability that highlights land surface coverage for vegetation and water cycle processes using satellite products for research colleges which can't obtain the data from foreign data bases i.e. in Europe, Asia or USA.
- There are a large number of experimental and operational products that are produced by satellite monitoring that could benefit the non-governmental organizations (NGOs) if extended or made available with clear understanding thus they should increase Capacity building

According to reports from bodies like IPCC - Intergovernmental Panel on Climate Change on climate change, climate variability and the frequency of extremes are expected to increase in general. In order to more effectively contribute to the understanding of droughts, a better way of understanding the urgency of such extreme events workshops should be conducted by these institutions to educate the public.

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