TREND ANALYSIS AND ASSESSMENT OF METEOROLOGICAL DROUGHT: A CASE STUDY OF NZOIA BASIN

By

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DECLARATION

I declare that this project is my own work and has not been submitted by anybody else to the best of my knowledge.

Sign…………………………………   Date………………………………………..

JILLIAN WANGARI MWANGI

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Finally, my thanks go to all the people who have propped me up to complete the research work directly or indirectly.

Abstract

In this study, meteorological drought in Nzoia Basin was assessed using the Standardized Precipitation Evapotranspiration Index (SPEI) with a 3-month timescale and 30 years length of rainfall data from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) data and temperature data from the Climate Research Unit (CRU), both recorded between 1988 and 2018. Both datasets were extracted for every grid point within the basin. Principal component analysis (PCA) was applied to the 3-month gridded SPEI data of the entire basin and was used to assess the temporal and spatial patterns of dry and wet events i.e. to characterize the Meteorological Drought. This was then followed by the determination of dry/wet trends using the Mann Kendall Trend Test and subsequently, the frequency of occurrence identified using Fourier Transforms. The PCA showed that there were two leading components which explained over 89.8% of the spatial variation of dry and wet events in the basin. Meteorological drought was characterized to mainly affect the central region of the study basin as displayed by the first PC loadings map. Dry events dominated the period between 1988 and 2006 while wet events were dominant in the period between 2006 and 2018. This was also true in the wet/dry trend test, in that, 1988 to 2006 showed an upward trend in dry periods and a downward trend in the dry period from 2006 to 2018. Cycles of drought i.e. mild, moderate and severe were observed in three dominant cycles of 1.3, 2.5 and 3.3 years respectively. Overall, this study provides evidence that meteorological drought does occur in areas that are regarded by most as high rainfall yielding areas such as the Nzoia Basin. This information is of high value for setting up adaptation and mitigation strategies related to forest conservation, farming and natural resources preservation.

CHAPTER ONE: INTRODUCTION

BACKGROUND

Drought is a major environmental disaster in many parts of the world. Knowledge about the timing, severity and extent of drought can aid planning and decisionmaking. It is considered as one of the major natural environmental hazards, which severely affects the water resources and vegetation throughout the history of mankind. Drought indicates the deficit of rainfall, runoff, water availability, soil moisture, ground water, surface water and crop yield. Droughts have significant economic and humanitarian impacts because rain-fed agriculture is the backbone of most economies in East Africa (Mwangi et al., 2014). Drought is a temporary aberration, unlike aridity which is a permanent feature of climate which occurs in both high and low rainfall areas and virtually all climate regimes (WMO, 2006). Assessment of drought impacts thus requires the understanding of regional historical droughts as well as the behavior of human activities during their occurrences (Naumann et al., 2014).

Drought is directly or indirectly the indicator of climate change (Ghebrezgabher et al., 2016) and is classified into Meteorological drought, hydrological drought and agricultural drought. Meteorological drought is a situation when the actual rainfall is significantly lower than the climatologically expected rainfall over a wide area. Meteorological drought may start any time, last indefinitely and attain many degrees of severity (Mulinde, Majaliwa, Twesigomwe, & Egeru, 2016). Hydrological drought is associated with marked depletion of surface water and consequent drying up of lakes, rivers, and reservoirs etc. This occurs if meteorological drought is sufficiently prolonged. Agricultural drought is a condition in which there is insufficient soil moisture available to a crop and results in reduction of yield.

Agricultural drought is the end effect of meteorological and hydrological drought and its severity is assessed from the crop yield. The economic, social and environmental impacts of drought are cumulative and vary greatly according to the prevailing climatic conditions and national wealth/vulnerability of the society to the event. The effects are most evident in Least Developed Countries that have the least capacity to prepare and build resilience. Although droughts can persist for several years, even a short, intense drought can cause significant damage and harm the local economy (Mulinde et al., 2016).

Drought indices are designed to provide a concise overall picture of droughts which are often derived from massive amounts of hydro-climatic data and are used for making decisions on water resources management and water allocations for mitigating the impact of droughts (Yagoub et al., 2017). The commonly used techniques in drought assessment are based on water supply indices derived from rainfall data (Tefera et al., 2019a). However some empirical studies (e.g. (Tefera et al., 2019); (Polong et al., 2019)) have shown that although rainfall is the main variable determining drought/floods conditions, the rise in temperature has important effects on the severity of dry/ wet events (Polong et al., 2019). Among the numerous indices that have been developed and are in use over the years for the identification and characterization of droughts, the Standardized Precipitation Index (SPI) has been the most used. However, the SPI does not take into account the impact of increased temperature (Tefera et al., 2019a) thus the Standardized Precipitation Evapotranspiration Index was developed. It is an extension of the widely used SPI but differ in that it is designed to consider both precipitation and potential evapotranspiration (PET) in determining drought conditions. It is thus a more suitable index to assess the impacts of global warming-induced climate change on drought (Shiru et al., 2018). This study thus implements SPEI.

PROBLEM STATEMENT

Drought in Africa has been associated in the Sahel region which extends from West coast of Africa to the East Coast of Africa (Carré et al., 2019), that is, the Sahel Complex. Kenya lies within the Sahel Complex with "rainfall isles" like the Kenyan Highlands and the Lake Victoria Basin which are the main food producing areas hence the need to assume drought as a problem of national importance when such areas are affected. In search areas the most affected people are farmers who rely heavily on rainfall as their main source of water and are not able to carry out irrigation. Drought indices have been used to characterize drought conditions in dry regions successfully however, their use in humid regions is limited (Rhee, Im, & Carbone, 2010). Nzoia Basin is mostly linked to cases of flooding but drought is somehow overlooked as the other types of drought, that is, agricultural and hydrological droughts are not usually/mostly experienced in the region. This however does not guarantee that meteorological drought is non-existence and if not properly monitored will result in the cases of the other forms of drought. This will then result in losses as the area's main economic activity is farming.

Drought unlike other natural disasters lacks the sudden and quick identification. Furthermore, the onsets and termination of droughts have proven difficult to monitor as they vary widely in terms of severity, duration, and areal extent depending on the geographical area and the climatological factors of the area at that specific duration. Kenya being an agricultural country, land is judged by its ability to sustain cultivated agriculture whereas drought being a meteorological phenomenon that is very difficult to determine and predict with high levels of accuracy, it often results in a lack of appropriate drought management strategies thus leading to disastrous effects like famine and desertification.

In Africa, Kenya included, droughts have been severe in the Sahel Complex (Carré et al., 2019) thus most studies have been done in this zone especially in ASAL lands. Drought is often associated only with arid, semi-arid and sub-humid regions by scientists, policymakers and the public. In reality, drought occurs in most countries, in both dry and humid regions (WMO, 2006).The possibility of drought occurrences in the high potential lands i.e. in terms of agricultural production, rainfall amount and distribution is to a greater extent ignored especially when dealing with severe meteorological drought. Yet, such areas are the major agricultural lands hence the need to investigate and identify characteristics of the drought periods. In doing so, the established information can be used in designing appropriate drought management strategies in an attempt to minimize the effects of the Meteorological drought in such areas.

OBJECTIVES OF THE STUDY

Main Objective

To investigate the meteorological drought cycles over Nzoia Basin by using the Standardized Precipitation Evapotranspiration Index (SPEI) during the period 19882018.

Specific Objective

- To characterize meteorological drought over Nzoia Basin from the year 1988-2018
- To analyze meteorological drought trends from the year 1988-2018
- To model recur rate/periodicity of the meteorological drought over the basin.

RESEARCH QUESTIONS

The following questions were motivated by the shortcomings discussed in the problem statement section above and were the basis of the formulation of the above objectives;

i. Does meteorological drought exist in regions that are considered to be high potential areas, that is, areas of high yields and rainfall? And if so, what magnitudes have been occurring i.e. mild, moderate, severe or extreme meteorological drought.
ii. What are the spatial and temporal patterns of the meteorological drought across the entire study area
iii. What has been the general trend in dry/wet periods over the study area within the study time frame
iv. What was the recur rate of the dominant meteorological drought magnitudes

SIGNIFICANCE OF THE STUDY

Most research on meteorological drought or drought in general has been carried out on arid and semi-arid regions due to the common nature of drought occurring in these areas. This study however goes beyond the norm to study high potential regions (regions that are considered by many to be of high yield and rainfall), how often the meteorological droughts occur and their severity. The need to study meteorological drought is important as most research on drought is associated with only the physical aspects of drought, that is, famine and desertification thus leaving a gap for further study on this type of drought (meteorological drought).

This study is to draw attention to scientists and interested parties/people to the fact that drought should be expected anywhere on the surface of the earth (WMO, 2006) in whatever form, that is, meteorological, hydrological or agricultural droughts. Drought strategies should thus not only be part of the overall planning in marginal lands but also high potential lands (WMO, 2006). In this case our high potential land is Nzoia Basin. This study will aid to improve the basin's coping mechanism towards droughts and water-related stress and thus, reducing its vulnerability to the projected climate change. In planning for drought mitigation, it is important to understand the drought characteristics through drought analysis (Mulinde et al., 2016). It consists of reliable information as the primary factor in the decision-making process (Polong et al., 2019). Analysis of drought based only on rainfall data has been frequently utilized since, in many areas, as rainfall data are more available than other meteorological or remote sensing data but the need to include Evapotranspiration data will aid in providing a more accurate result in the determination of drought intensity in the area of study (Tefera et al., 2019b). Drought monitoring and early warning is essential for decision making by concerned subjects, farmers and national policy makers.

CHAPTER TWO

LITERATURE REVIEW

Several studies have been carried out in an effort to understand the characteristics of droughts. This section provides review of literature that are relevant to the current study.

Drought is a condition on land characterized by recurring scarcity of water that falls below normal average levels of the region. It is a naturally re-occurring climatic variability (Wang et al., 2003). Due to its accumulating impacts over time and slow onset, drought remains the most devastating but least understood weather phenomena (Opiyo et al., 2015). Drought is directly or indirectly the indicator of climate change (Ghebrezgabher, Yang, & Yang, 2016) Moreover, drought lasts for extended periods of time and distresses large areas. Presently, droughts are expected to increase in severity and frequency and thus to impact environmental, social and economic sectors of vulnerable populations.

Owing to the rise in water demand and looming climate change, recent years have witnessed much focus on global drought scenarios. As a natural hazard, drought is best characterized by multiple climatological and hydrological parameters. An understanding of the relationships between these two sets of parameters is necessary to develop measures for mitigating the impacts of droughts.

Drought may be categorized into three classes, including meteorological drought, hydrological drought and agricultural drought. In meteorological drought, the actual rainfall is significantly lower than the climatologically expected rainfall over a wide area. The second category, hydrological drought, is associated with the depletion of surface water and consequent drying up of surface water bodies. Whenever meteorological drought becomes too prolonged, then hydrological drought occurs. Lastly, agricultural drought occurs when the soil moisture available for crops is insufficient such that there is a reduction in the crop yield. Agricultural drought is the cumulative effect of hydrological and meteorological drought and its severity is assessed from the crop yield. Thus, the periodical drought assessment in a region must be necessary to take the management measures.

Opiyo et al. (2015) attributed crop failure in the North-Eastern region to lack of surface water resources, or failure of water resources systems to meet demands. Other studies define normal meteorological drought as a condition where observed rainfall is less than 75% of the climatological normal (Opiyo et al., 2015).

Drought characteristics are critical in design, planning, and management of water resources (Kyambia et al., 2014). The term “drought” and its features have been defined differently in numerous applications (Wambua et al., 2014a, 2014b).

Drought proxies include the use of indices involving precipitation deficit, soil-water deficit, low stream flow, low reservoir levels and low groundwater level.

WMO defines four major drought types: agricultural, meteorological, socioeconomic and hydrological. Notably, all droughts result from a deficiency of precipitation and begin as meteorological drought. Other types of drought and their impacts cascade from meteorological drought to other forms (WMO, 2006). The ability of societies to reduce drought effects and build resilience is a significant grave concern on a global level. The WMO and other United Nations agencies promote an implementation of National Development Plan (NDP) that will provide insight into science-based actions useful to address key drought issues (WMO, 2006).

An effective drought monitoring and early warning system is a way to prevent or reduce drought impacts. An effective drought tracking system can deliver an early warning in a case of the drought’s onset, successfully measure drought severity and spatial extent, and communicate facts to decision-making groups promptly.

The experiences of regional drought management programs can thus inform the development of National programs. Figure 1 below shows the relationship between climate change variability and drought.

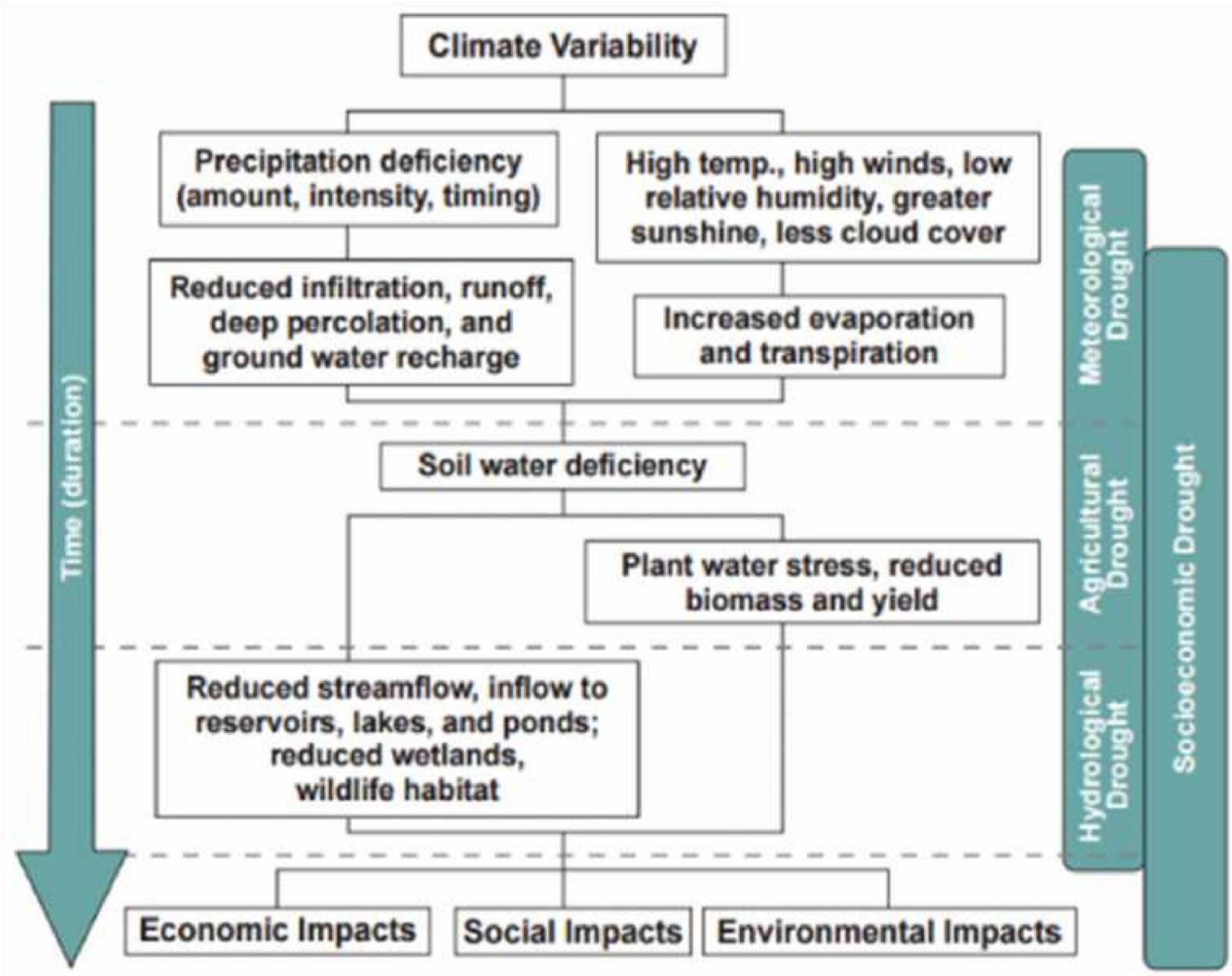

Figure 1: The flow chart shows a sequence of drought types occurrences and impacts

(Source: Diagram courtesy of National Drought Mitigation Center)

Definable characteristics of drought include intensity, duration, spatial extent, and timing (Tefera et al., 2019a). Intensity commonly refers to the magnitude of the precipitation deficit and how quickly it develops. History shows us that each drought is unique, but common features of the most severe droughts include long duration, and large moisture deficits with a large areal extent, particularly during a climatological wet season.

The adverse effect of climate change on agriculture might be minimized through the introduction of dry resistance crops and modifying the type of crops/seeds; for instance, replacing long growing season crops by short growing season crops and applying modern type of agriculture such as irrigation by constructing water reservoirs/dams may help to tackle food problems. Therefore, well preparation prior to dry periods is needed and increasing awareness of the people and encouragement may help to protect land degradation (Ghebrezgabher et al., 2016). Although there is no universal definition of drought the common factor is a deficit in normal precipitation over an extended period sufficient to cause adverse impacts. The term "drought" and its features have been defined differently in numerous applications (Wambua et al., 2014). However, it is a challenge to define the term quantitatively.

Drought trends in Kenya do not have a fixed pattern and tend to fluctuate from time to time (Mutsotso, Sichangi, & Makokha, 2018). Areas along the coast, western, Nyanza and Rift valley tending to be wet whereas the ASAL (Arid and Semi-Arid Lands) that forms about 80% of the total Kenya's land cover are always dry. This has led to effects of non-uniformity in drought detection (Mutsotso et al., 2018). Temporal and spatial drought is influenced by both climate and land use/cover changes (Wambua et al., 2014).

Drought proxies include the use of indices involving precipitation deficit, soil-water deficit, low stream flow, low reservoir levels and low groundwater level. Impacts are the primary ways to measure drought severity. The choice of indices for drought monitoring should be based on the quantity and quality of available climate data, purpose of the study, computational simplicity and its ability to consistently detect spatial and temporal variations of a drought event (Mohammed, Yimer, Tadesse, & Tesfaye, 2018).

According to Wanjuhi (2016), drought index is a variable which characterizes droughts on their intensity, duration, and severity at a given location and time. An index should, therefore, be able to quantify drought for a variety of time scales to address different kinds of drought phenomena, e.g. meteorological drought. Drought indices are designed to provide a concise overall picture of droughts which are often derived from massive amounts of hydro-climatic data and are used for making decisions (Yagoub et al., 2017).

When a drought index such as the SPI is used in place of raw precipitation data to generate a "proxy" of the consensus maps, then not only do the maps become spatially homogeneous as expected but also information about the intensity of the conditions expected in the coming season are made available. Such information could be used to support the decision process when issuing advisories for policy actions within the region (Mwangi, Wetterhall, Dutra, Di Giuseppe, & Pappenberger, 2014).

The SPEI is recommended as an alternative to SPI to quantify anomalies in accumulated climatic water balance, incorporating potential evapotranspiration as SPI does not account for atmospheric conditions, other than precipitation, that may affect drought severity such as temperature, wind speed, and humidity (Tefera et al., 2019b). SPEI results can be rated as being superior as the element of temperature variation is taken into consideration (Mutsotso et al., 2018). A study by Tefera et al., (2019b) showed results of SPI and SPEI to be different in that, SPEI identified higher number of drought years that occurred. However, SPI performed as well as SPEI did and captured most of the major drought occurrences. The only occasion that SPEI and SPI were equally able to identify drought was only during a cool period. This showed the inability of SPI to consider the effects of global temperature change in drought modelling (Tefera et al., 2019b). The existence of differences between SPI and SPEI values doesn't mean that they give completely different results. This is evident when places experience low temperature variations, SPI works as well as SPEI does. This is an advantage for example, in the absence of temperature data and/or appropriate analyses tools to carry out SPEI, SPI can thus be used to assess drought in a study area and at various time scales.

In a study by Aladaileh et al. (2019), drought indices were used for calculating the meteorological SPI on an annual (SPI12), 6-months (SPI6), and 3-months basis (SPI3) and found that although there are few variances between annual, 6-months, and 3-months basis SPI, however, the various scaled SPI provides a better understanding of drought occurrences, magnitudes, and severity. The variability of drought events demonstrates the need to have a monitoring program to investigate the direct and indirect impacts on all related sectors, and to develop proactive risk management measures and preparedness plans at various physiographic regions.

When using Combined Drought Index (CDI) one is able to capture drought characteristics in the study area as well as climate variability. However to effectively capture all the aspects of drought, CDI could use more parameters such as wind, sunshine duration and cloud cover.

The comparison of multiple drought indicators suggests that precipitation-based indices, while useful, do not provide a more complete picture of long-term drought trends, soil moisture is also affected by surface drying and other hydrological processes (e.g., deep percolation) that remove water from the soil. Therefore, it is recommended that multiple drought indicators be used during water policy planning and management endeavors (Temam, Uddameri, Mohammadi, Hernandez, & Ekwaro-Osire, 2019). The significance of global scale drivers of climatology such as ENSO (El Niño Southern Oscillation) and regional scale drivers of climatology such ITCZ (Inter Tropic Convergence Zone) on East African climate are also not to be looked down upon and have significant effect on the region (Karanja, Ondimu, & Recha, 2017).

Drought Monitoring and Prediction

Various drought indicators are used as a proxy for different types of drought. Droughts can develop quickly in some climatic regions, but usually require a minimum of two to three months to become established (Tsakiris, 2017). The magnitude of drought impacts is closely related to the timing of the onset of the precipitation shortage, its intensity and the duration of the event. There are many tools to identify drought characteristics. The choice depends on the hydroclimatology of the region, the type of drought, the vulnerability of the society, the purpose of the study and the available data. Not only do the timing and duration associated with drought matter but also the amount of rainfall associated with them. Among other things, drought prediction plays a critical role in the planning and management of the now scarce water resource (Tsakiris, 2017).

Drought indicators commonly computed include severity, duration, the location of the drought in absolute time (initial and termination time points), magnitude/density of the drought calculated by getting the ratio of severity to duration and area affected by drought. Studies on drought are aimed at understanding the causes of droughts, describing and understanding impacts of droughts, looking at the frequencies and severity of droughts, and looking at responses, appropriate mitigation, and preparedness strategies (Tsakiris, 2017)

This research focuses on a reduction of the impacts associated with drought. Therefore, puts more focus on severity, duration, frequency, persistence and probability of occurrence. The development and advancements in space technology, to address issues like drought detection, monitoring and assessment have been dealt with very successfully and helped in the formulation of plans to deal with this slow onset disaster (Dinku et al., 2018)

Drought can be detected four (4) to six (6) weeks earlier than before with the help of environmental satellite, and delineated more accurately. There is no uniform method to characterize drought conditions, and there are a variety of drought indices used as tools to monitor meteorological drought (Quiring, 2009). The input variables required for the calculation of meteorological drought indices vary depending on the drought index in question but include precipitation, temperature, available waterholding capacity of the soil and others that are representative of the moisture in the system. Drought indices such as Standardized Precipitation-Evapotranspiration Index (SPEI) and Standardized Precipitation Index (SPI) have been developed to accommodate the multi-scalar properties of drought that are applicable and temporally flexible to different types of drought. A study by Tefera et al. (2019b) has also reviewed numerous studies on drought indices.

Despite the advancements in computer technology (for example, availability of powerful computers) and simulation algorithms/models, scientists are only able to provide indications of drought trends and never the actual values. Models for predicting drought duration are more developed; however, those for predicting drought severity are still fraught with great difficulty and yet the latter is of paramount importance (Tsakiris, 2017).

Direct impacts of drought include death/malnutrition in animals/humans, decline in food yield, forest and greenbelt; worsening water/air quality and sanitation; and higher fire prevention risk. Indirect effects include price upsurge; reduction of income; loss of jobs; and degradation of living standards among others. Drought occurrence has become increasingly severe in the Horn of Africa during the last decade (Opiyo et al., 2015). The regularity of drought events and the subsequent recovery period means Kenya is expected to incur substantial economic costs and reduced long-term growth every 3 to 4 years (Polong et al., 2019).

CHAPTER THREE

DATA AND METHODOLOGY

STUDY AREA

Nzoia River Basin

River Nzoia is one of the largest and longest rivers in western Kenya and lies between latitude 0° 02’N; 01°14’N and 33° 54’E; 35° 35’E in the northern parts of the Lake Victoria Basin. It is 334 km long and has a catchment area of 12,903 km2 with an annual discharge of 1777 x 106 m3/year. Source of river Nzoia are the Mt Elgon, Cherangani and Mau water towers. River Nzoia transverses Trans Nzoia, Bungoma, Mumias, Siaya and Busia counties. The Nzoia River empties into the Lake Victoria in the Southwestern corner of Lake Victoria North catchment area. The economy of the region is still largely rural, and more than 90 percent of the population earns its living from subsistence agriculture. The farms are privatelyowned ranging from 1 – 3 ha. Districts such as Trans Nzoia and Uasin Gishu are characterized by large commercial farms with an average of 50 – 100 ha or more. There are two rainfall peaks in the catchment; the first peak comes in the months of April to June, while the other occurs in July to September. December through March are dry months in Nzoia. Compared to other parts of Kenya, the basin receives high rainfalls. The mean annual rainfall is 1400mm.

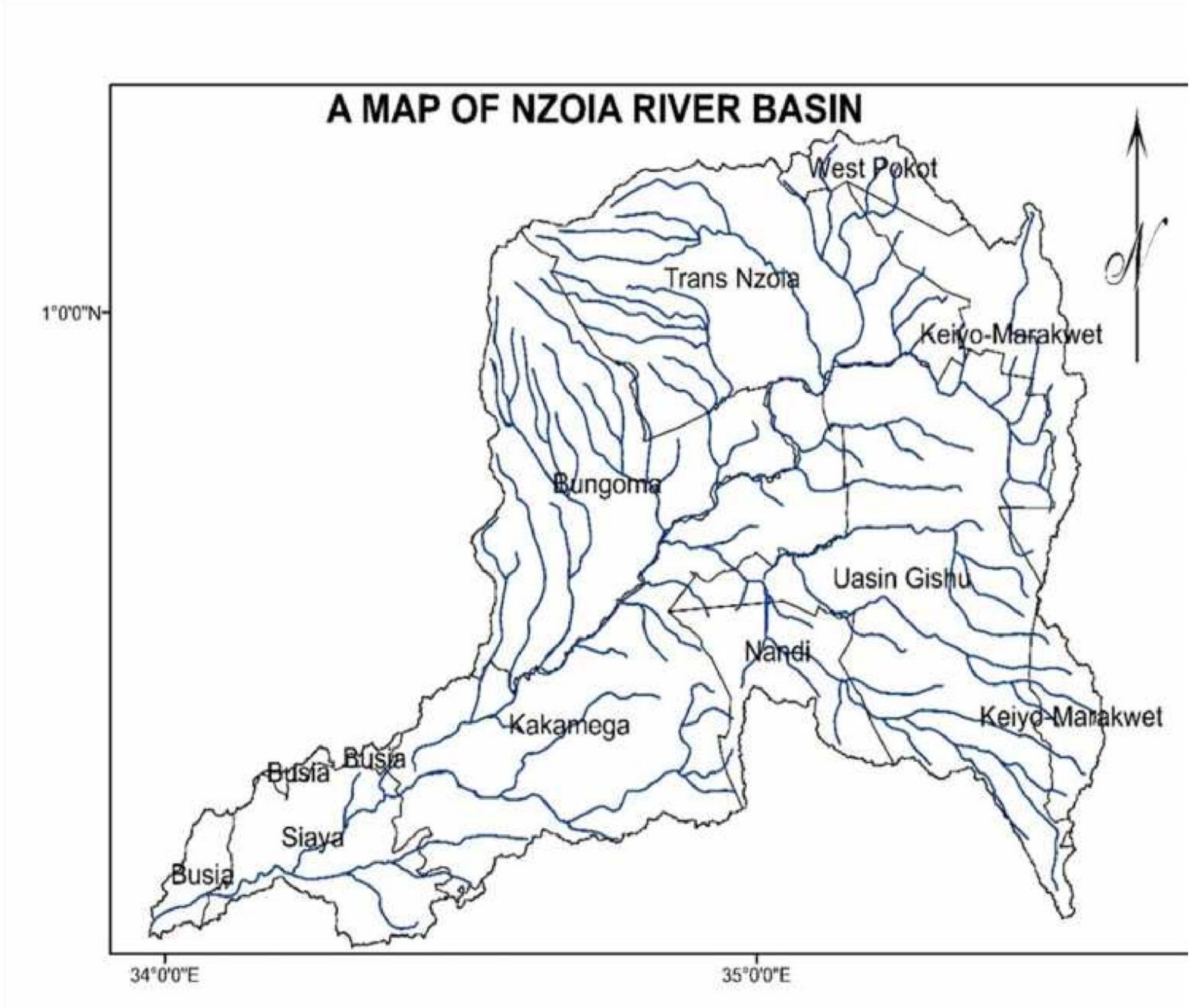

Figure 2: Image showing the administrative boundary and rivers within Nzoia Basin

Data

The following data sets of Nzoia Basin from the year 1988-2018 were used:

- *Monthly precipitation data/rainfall data from CHIRPS*

Gridded precipitation data from Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) was used. CHIRPS was created by a collaboration of scientists at the USGS Earth Resources Observation and Science (EROS) center to support the United States Agency for International Development Famine Early Warning Systems Network (FEWS NET) by providing reliable, complete and up-todate data for objectives such as trend analysis and seasonal drought monitoring. CHIRPS is a new quasi-global (500S-500N), and high spatial resolution (0.05^0) satellite–derived rainfall product produced from five main data sources (Funk et al., 2015) that ranges from 1981 to near-present. It incorporates climatology, CHPclim, 0.05^0 resolution satellite imagery and in-situ station data to create gridded rainfall time series. Monthly rainfall data sets from the year 1988-2018 was acquired from https://climateserv.servirglobal.net/ to carry out trend analysis of meteorological drought in Nzoia Basin. Choice of CHIRPS data was based on that it offers data at high resolution, long period records and offers quasi-global coverage. Chirps data has been valid in Eastern Africa through various studies such as that performed by (T. Dinku et al., 2018) which assessed the validation of the CHIRPS satellite rainfall estimates over eastern Africa which proved its significance and validity of use within the region.

- *Monthly temperature data from CRU*

Gridded Climatic Research Unit (CRU) Time-series (TS) data version 4.03 datasets was acquired from CEDA archive through the link http://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.03 on monthly basis as gridded data of high resolution spatial 0.50^0 x 0.50^0. The gridded CRU TS 4.01 data are month-by month variations in climate over the period January 1901 to December 2018, provided and produced by CRU at the University of East Anglia (Harris and

Jones, 2017). This dataset was chosen for its wider application in numerous studies and spatial and temporal coverage. CRU datasets vary in versions each with different temporal timescales thus due to the temporal coverage required for this study that is 1988-2018 the CRU TS 4.03 was selected and used.

The two datasets have been successfully used and documented by a number of recent studies over East Africa including a study by Dinku et al., (2018) that validated CHIRPS for use over eastern Africa and a study by Ongoma & Chen (2017), that used CRU data in East Africa to carry out Temporal and Spatial variability of Temperature and rainfall in the region.

Methodology

Figure 3 below shows the general methodology flowchart used in the achievement of project objectives and outputs.

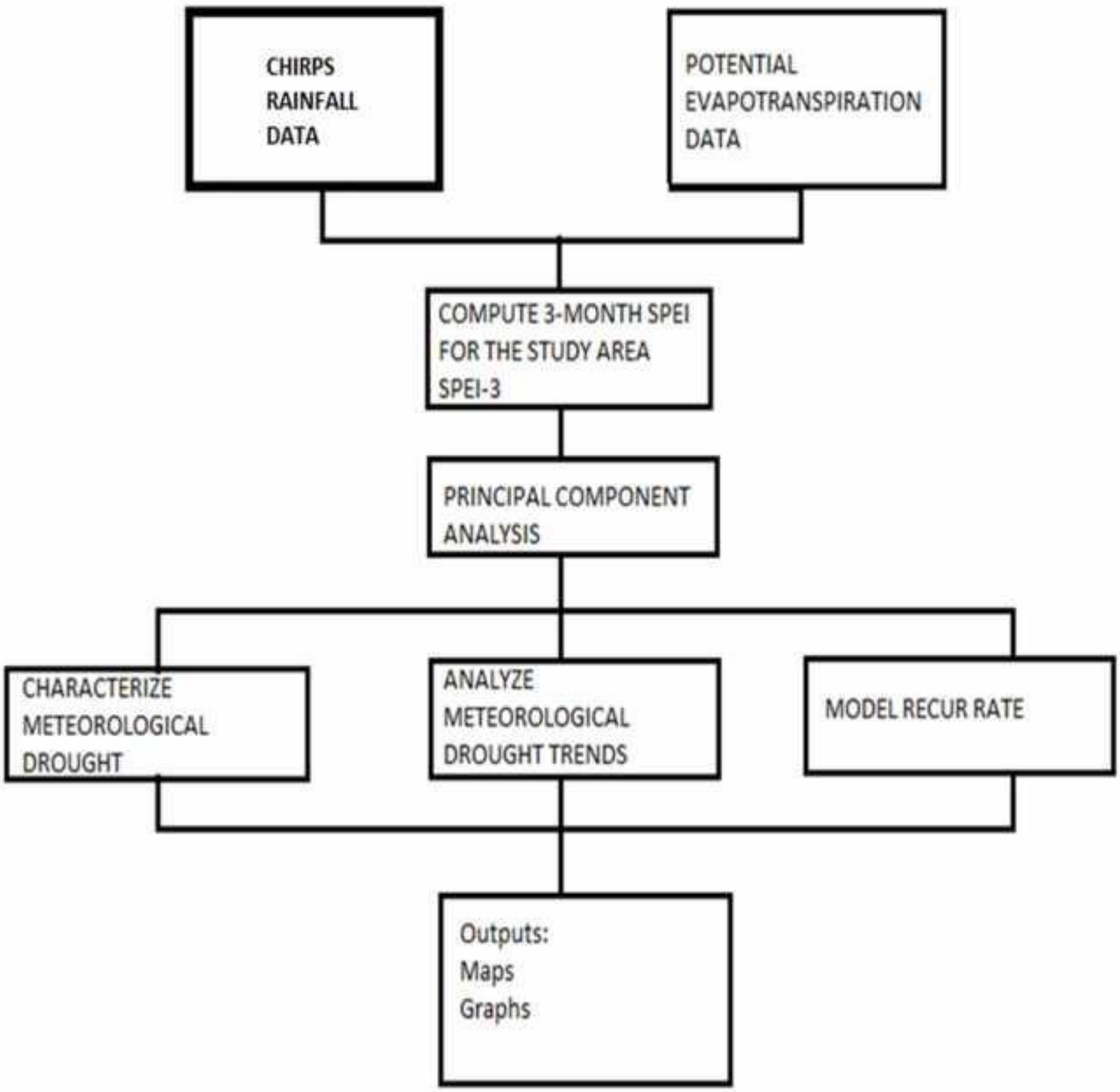

Figure 3: Methodology Flowchart

Standardized Precipitation Evapotranspiration Index (SPEI)

The choice of drought index for any drought monitoring should be based on the study purpose, quantity and quality of available climate data, computational simplicity and its ability to consistently detect spatial and temporal variations of a drought event (Mohammed et al., 2018). SPEI is recommended as an alternative to SPI to quantify anomalies in accumulated climatic water balance, incorporating potential evapotranspiration as SPI does not account for atmospheric conditions, other than precipitation, that may affect drought severity such as temperature, wind speed, and humidity (Tefera et al., 2019b). Meteorological drought in this study will thus be analyzed by the use of SPEI for the duration.

Generally, SPEI is calculated using the formula:

$$SPEI = W - C_0+C_1W+C_2W^2/1+d_1W+d_2w^2+d_3W^3 \ldots\ldots \text{ Eqn (i)}$$

Where

$$W= \sqrt{-2\ln (P)} \text{ for } P \leq 0.5$$

0.5

P is the exceeding probability of the difference (D) value; specifically $P=1-(x)$. P can be replaced by $1-P$ when $P > 0.5$, and the sign of the resultant SPEI is reversed, and $C_0= 2.515517$, $C_1=0.802853$, $C_2= 0.010328$, $d_1=1.432788$, $d_2= 0.189269$, and $d_3= 0.001308$.

SPEI is also considered being the difference between the precipitation (P) and PET for the month I, and is also calculated as:

$$SPEI = P - PET \quad \ldots$$

…… Eqn (ii)

Where the Monthly PET is calculated by the Thorn Thwaite equation as:

$$PET = 16K\,(10T^{m}/I) \quad \text{…. Eqn (iii)}$$

Where I refer to the heat index, the sum value of 12 month i T is monthly temperature value, and “m” and “K” imply coefficient and correction coefficient, respectively.

Drought occurs when the SPEI is continuously below zero and reaches a value of -1.0 or below and ends when SPEI value becomes zero or above (Lweendo et al., 2017) for not less than a month’s time. These periods can last for months or years.

Dry spells are referred to as periods of prolonged dry weather (often 15 or more consecutive days).

Table 1: Categories of drought based on SPEI value (Masupha, 2017)

SPEI Value	Drought Type
0 to -0.99	Mild Drought
-1.00 to -1.49	Moderate Drought
-1.5 to -1.99	Severe Drought
≤ -2	Extreme Drought

Severity is the cumulative sum of the index value based on the duration extent

$$S = \sum_{i=1}^{Duration} Index \quad \text{… Eqn (iv)}$$

Intensity of an event is the severity divided by the duration

$$I = Severity/Duration \quad \text{….Eqn (v)}$$

Principal component analysis (PCA)

Principal component analysis is a way of identifying patterns in climatic data and expressing the data in such a way that highlights their similarities and differences (Polong et al., 2019). PCA analysis is considered a data reduction method. Principle Components (PCs) from PCA are used to explain the correlation among several random uncorrelated variables without loss of information. For this case study, Principal Component Analysis was used to portray both the spatial and temporal pattern variation of dry/wet periods in the study region based on the SPEI series at each grid cell. The original inter-correlated SPEI variables at different grid cells are Xi, 1, Xi, 2,….., Xi, k where k is the number of the grid cells in the basin and i represents the length of SPEI series at each grid cell. The principal components (PCs) are produced for the same time Yi, 1, Yi, 2, … , Yi, k using linear combinations of the first ones(Polong et al., 2019):

Yi, 1 = a11Xi; 1 þ a12Xi; 2 þ ... þ a1kXi; k Yi;
2 ¼ a21Xi; 1 þ a22Xi; 2 þ ... þ a2kXi; k
⋮ Eqn...(vi)

Y1; k ¼ ak1Xi; k þ ak2Xi; 2 þ ... þ akkXi; k

In the above equation (vi), the Y values are orthogonal and an uncorrelated variable, such that Yi, 1 explains most of the variance, Yi, 2 explains the remainder and so on. The coefficients of the linear combinations are called "loadings" and represent the weights of the original variables in the PCs (Santos et al. 2010).

Temporal pattern explains the dominant temporal variation of time series in all grids, whereas spatial patterns explains how strong the PCs depend on the geographical nature of the basin such that maps are produced from loadings of each principal components**.** The first PC has the highest variance, thus the first leading components of PCs contain the highest values of the total variance and so on. Such a transformation is a linear one and depends on the eigenvectors of a covariance or correlation matrix (Mathbout et al. 2018). In order to produce more localized spatial regions, the Varimax orthogonal rotation method was applied to the ‘‘loadings’’ i.e. the correlation matrix between the SPEI time series at single grid and the corresponding PCA; because it simplifies the structure of the patterns by forcing the value of the loading coefficients towards zero or ± 1 (Tian and Quiring, 2019). The resulting spatial patterns were normalized by dividing with their respective standard deviations and were then used to plot spatial distribution maps. Similarly temporal patterns were achieved from the first two PCs which were also normalized by division with their standard deviations and plotted to give temporal graphs.

Trend Analysis

To compute the trend of the time series, Mann-Kendall rank statistics will be used. This is due to its use in determining monotonic trends (variable consistently increases/decreases through time, but the trend may or may not be linear), is able to test the correlation between a sequence of pairs of values (precipitation/temperature & time) and it requires fewer assumptions than parametric tests.

The Mann Kendall test statistics S is calculated as:

$$S = \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} sgn(Xk - Xj) \ \ldots \ \text{Eqn (vii)}$$

where xj and xk are time series value of the jth and kth years (k,j) and n is the length of time series. The sgn(x_k- x_j) is sign function

Where: $(x_k - x_j) = +1$, if $(x_k - x_j) > 0$ …. Eqn (viii)

$(x_k - x_j) = 0$, if $(x_k - x_j)$ …. Eqn (ix)

$(x_k - x_j) = -1$, if $(x_k - x_j) < 0$ …. Eqn (x)

tistic (ZS):

$$Zs = \frac{S-1}{\sqrt{Var(S)}}, \text{ if } S > 0 \ \ldots \ \text{Eqn (xi)}$$

$$Z = 0, \text{ if } S = 0 \ \ldots \ \text{Eqn (xii)}$$

$$Zs = \frac{S-1}{\sqrt{Var(S)}}, \text{ if } S < 0 \ \ldots \ \text{Eqn (xiii)}$$

Standard normal test statistic (ZS):

Var(S)=variance of S.

A positive ZS indicates an upward trend and a negative value indicates a falling/downward trend.

Periodicity/Recur rate

The repetitive oscillations about a trend line/curve is generally known as Periodicity which is done to determine the recurrence of an oscillation and in this case the recurrence of Meteorological drought (Onyango OA, 2014). Fourier series is the preferred choice for this case study.

$$f_{xy}=1/2\prod \sum_{r=-\infty}^{\infty} e^{-i\omega r}\rho_{xy}(r) \;\ldots\; \text{Eqn (xiv)}$$

$$f_{(w)}=1/2\prod \sum_{r=-\infty}^{\infty} e^{-i\omega r}\rho(r) \ldots \; \text{Eqn (xv)}$$

Where:

$(-\pi \leq \omega \leq \pi)\rho xy\ r)$= lag) xy( )= lagged correlation

r=the lag

ω = frequency

(ω) =spectral density function

(r)=autocorrelation function

CHAPTER 4: RESULTS

3-month SPEI

The evolution of the 3-month SPEI over a 30-year timescale i.e. 1988-2018 was computed through the averaged values over all the grid cells of the Nzoia Basin. Figure 4 shows the resulting timescale graph representing the evolution of mean SPEI across the study area.

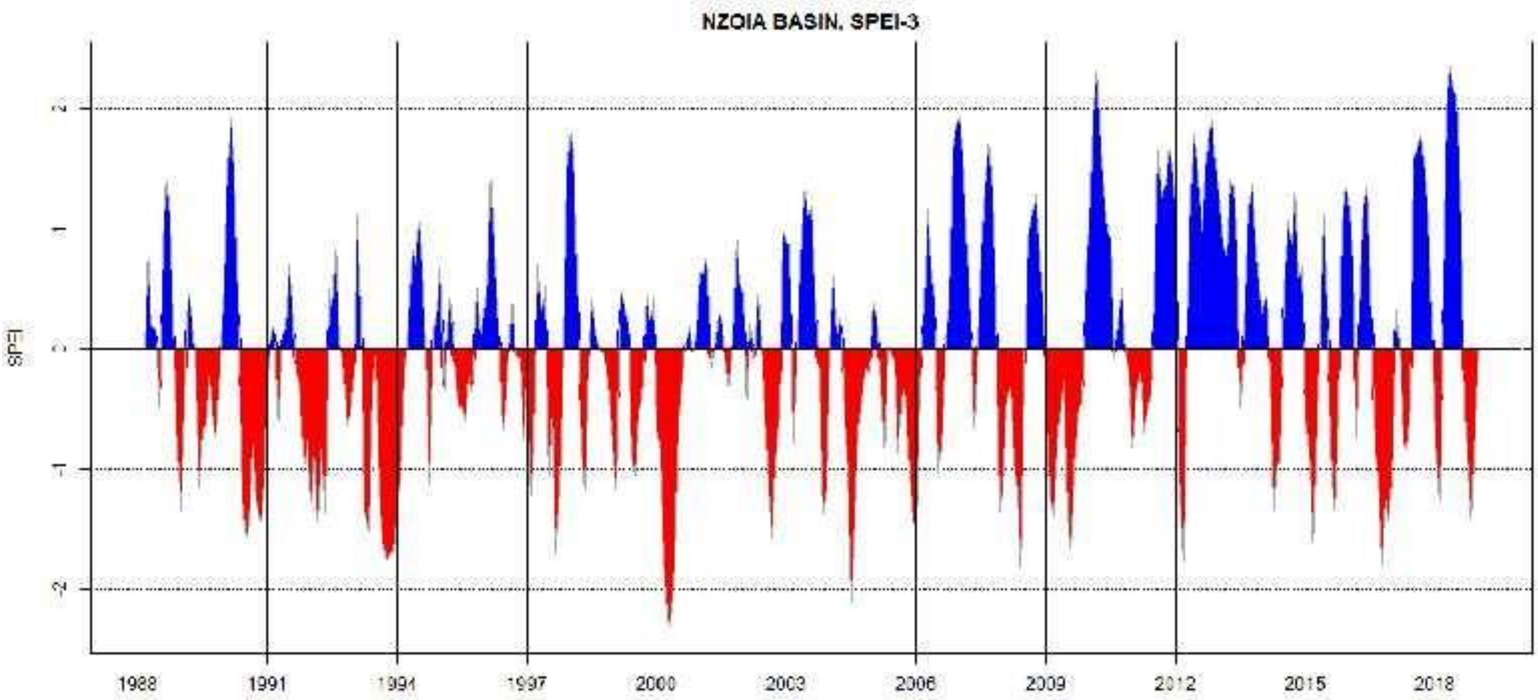

Figure 4: Evolution of mean 3-month SPEI across Nzoia Basin showing the variation in the duration, severity and intensity of dry and wet events

According to the figure 4 above, 3-month SPEI graph of across the basin, the years 1990-1995 and 2000-2006 experienced the worst and frequent times of meteorological drought within the 30 years of the case study. This evidence proves that the region though a high potential land which receives a lot of rainfall and experiences flooding also experiences times of meteorological drought. Due to this finding, a Principal Component Analysis (PCA) was done on the SPEI time series made from each cell grid of the study region for better understanding of both the temporal and spatial pattern experienced in the region

Spatial patterns of SPEI in Nzoia Basin

From the numerous grid cells within the study area, PCA was computed from the SPEI series extracted for the period 1988-2018. This resulted in the acquisition of many Principle Components (PCs) but only the first two PCs were picked. The first PC1 explains 81.5% and 89.8% for the combined two PCs. PC1 has spatially homogenous negative values over the entire basin where the PC2 loadings showed both positive and negative values. The PC2 showed a smaller percentage of variance, that is, 8.2% suggesting this PC represents a more localized spatial pattern and possibility of having dry areas during specific periods while the other areas are experiencing wet periods.

Table 2: Variabilities explained by first two Principal Components

	PC1	**PC2**
Standard deviation	18.24067	5.788259
Proportion of Variance	81.549 %	8.2120 %
Cumulative Proportion	81.549 %	89.7610 %

<u>Spatial Patterns from the first two PC Loadings</u>

According to the first loading of 3-month SPEI as shown in the below figure 5 (a), it highlights the middle part. The PC1 loadings for SPEI3 shows high values concentration in the middle part of the basin (and the negative values of the PC1 loadings) suggesting that this part of the region is mainly associated with low rainfall and have been affected by more frequent dry events.

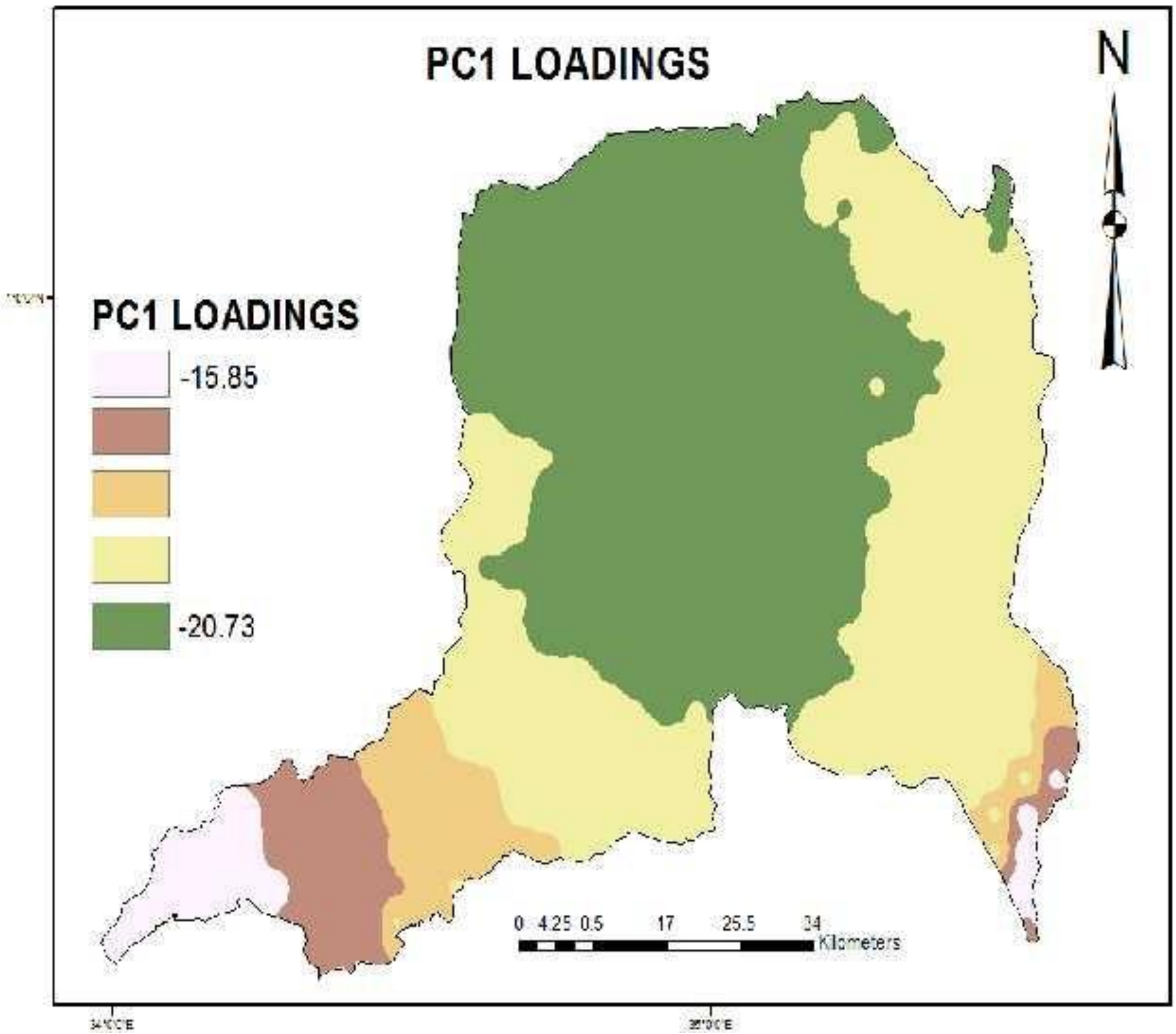

Figure 5 (a): A graphical representation of the spatial distribution of the first Principle Component Loadings

Figure 5 (b) below represents a spatial map of the second PC loading which shows lows on the south western part of the basin.

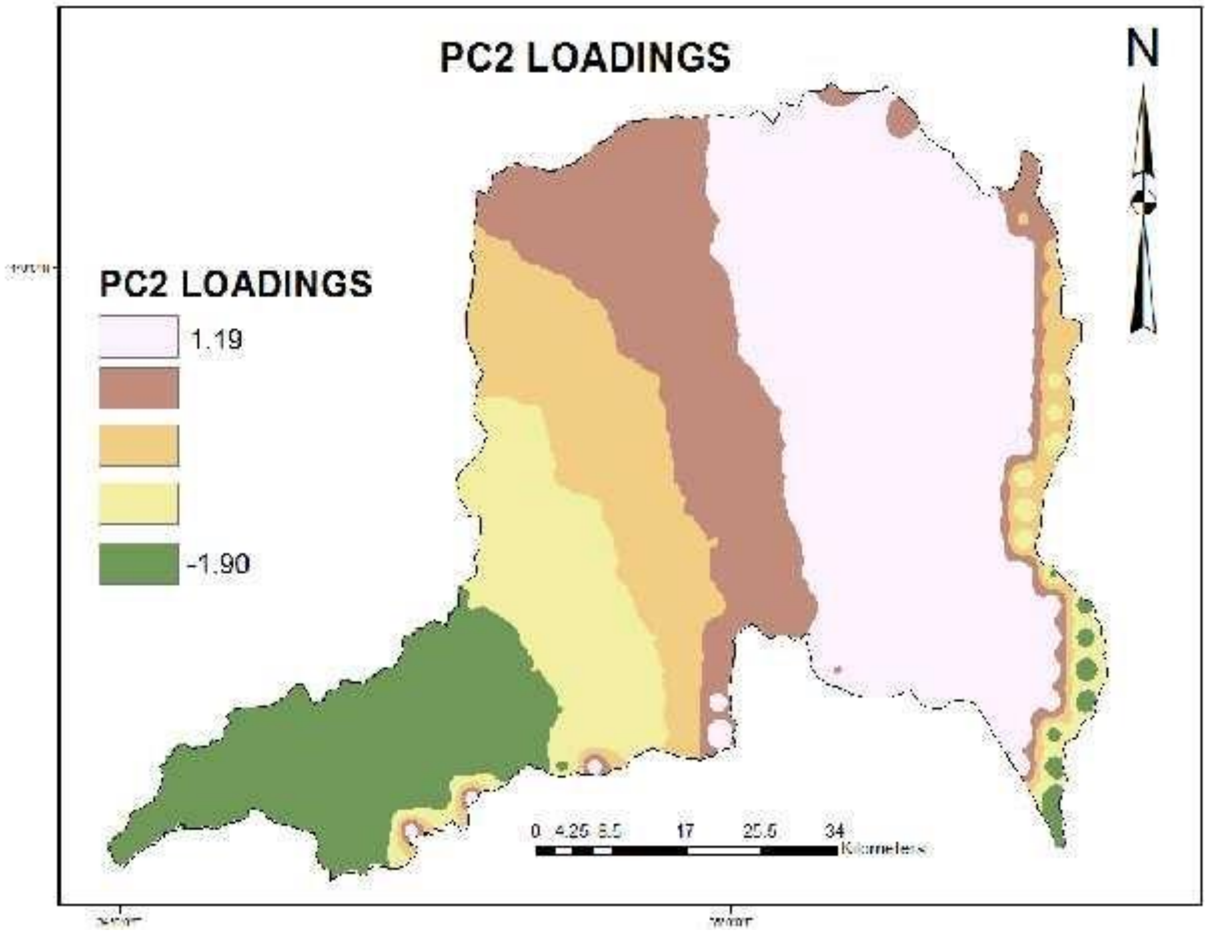

Figure 5 (b): A graphical representation of the spatial distribution of the second Principle Component Loadings

Temporal Patterns

The Principle Components scores, especially PC1 score represented by figure 6 below describes the temporal behavior of the SPEI in the basin. The scores show a pattern of downward (negative) trend from 2005 to 2012, followed by an upward (positive) trend from 2012 to 2015 and finally another downward (negative) trend from 2015 to the end of the time series. The years 1993, 2000, 2001, 2005 and 2009 were the wettest periods while the years 1991, 1998, 2007, 2010, 2013 and 2018 were the driest periods.

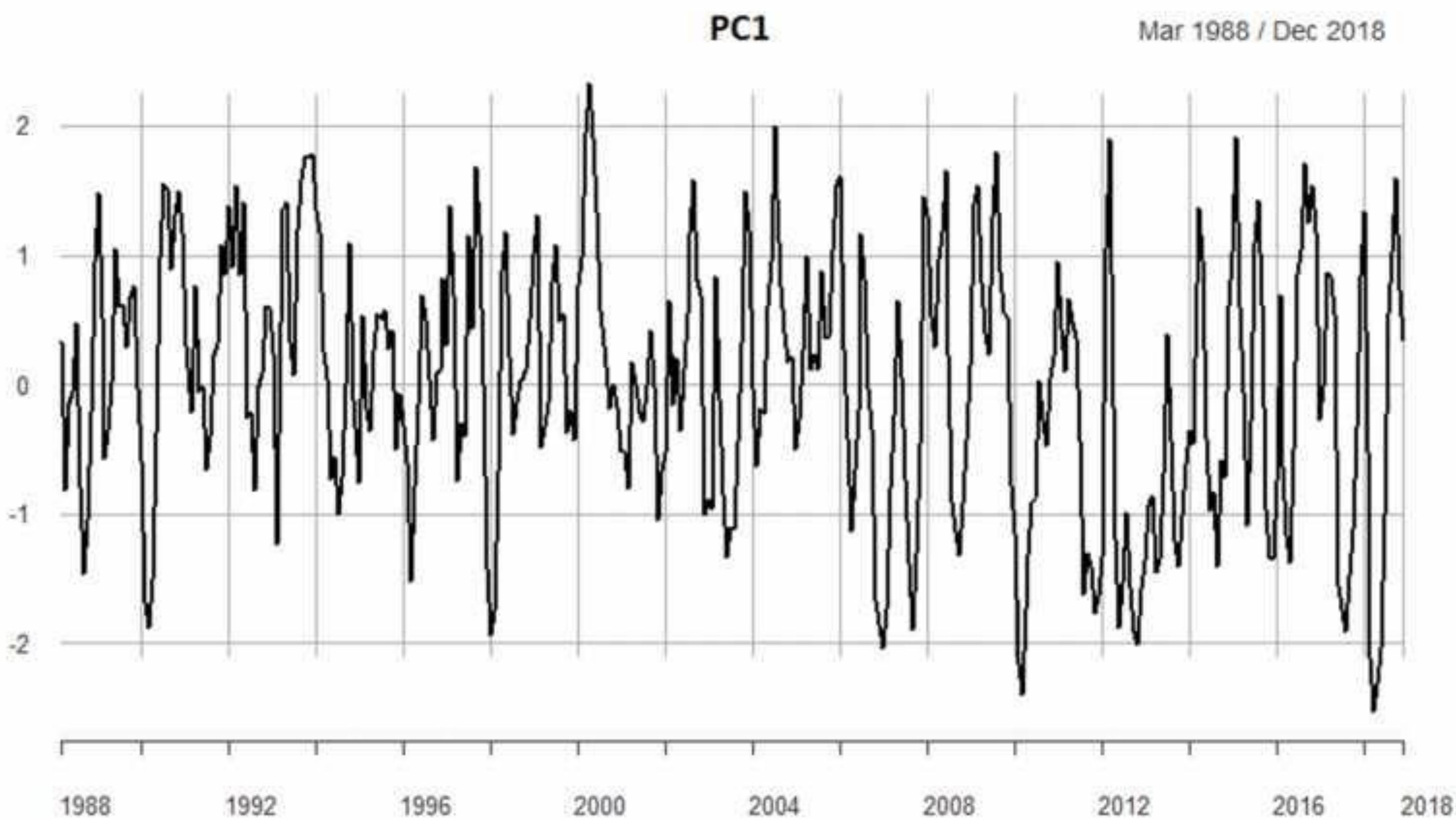

Figure 6: Temporal pattern from the first Principal Components. *The graph shows changes in dry and wet periods across the study region with time over the 30 years of the study period i.e. the dominant temporal trends of the data*

The second PC scores (figure 7 below) show high frequency oscillation without any noticeable trend from 1988 to around 2014 followed by a noticeable upward trend from 2014 to the end of the period.

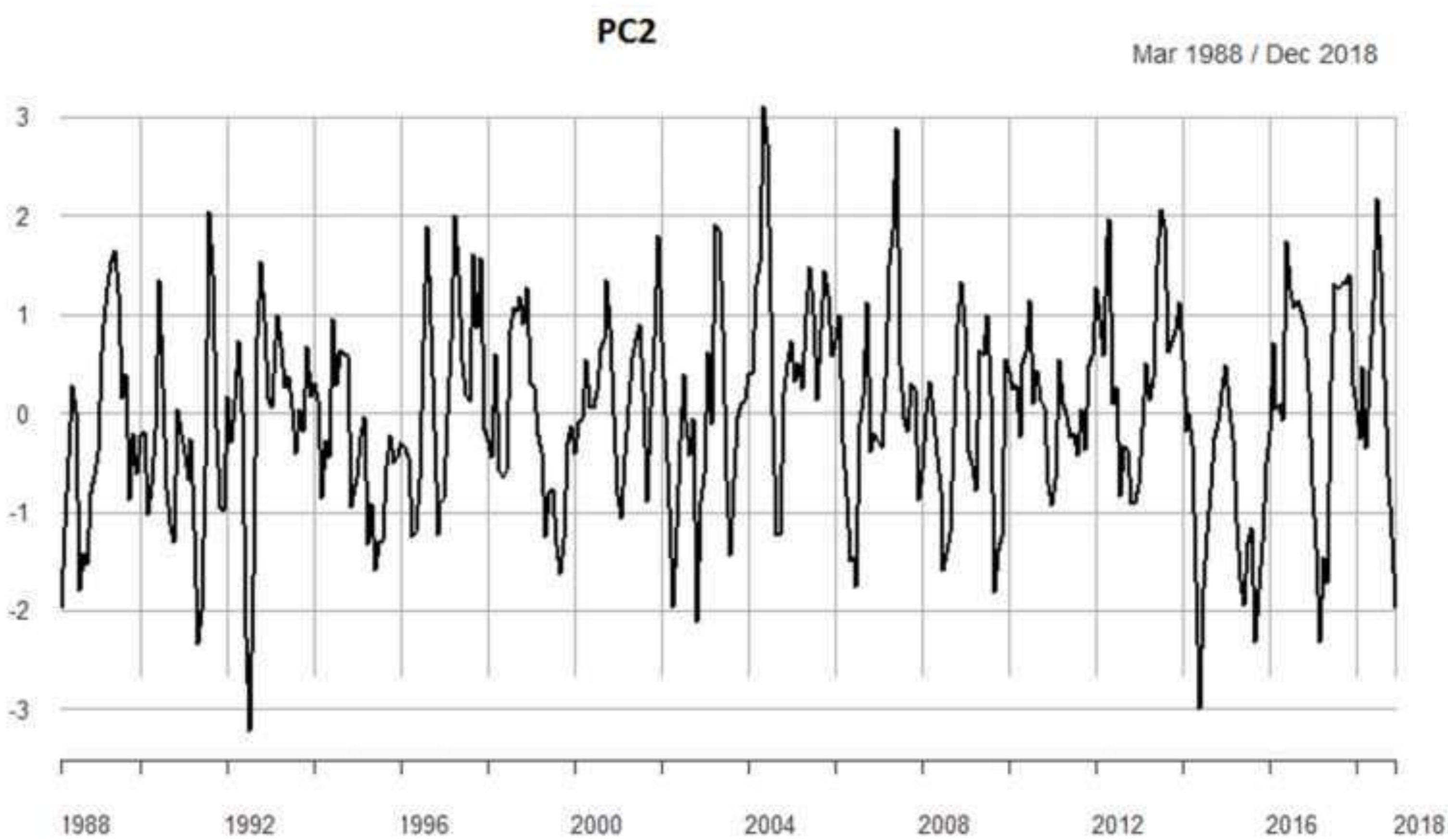

Fig. 7: Temporal pattern from the second Principal Component. Shows the second dominant temporal trends of the data

Mann-Kendall Trend Test

Mann-Kendall test also known as MK Test was carried out on cumulated Principal Component (PC1) thus would better show the trend of the data. MK test simply calculates whether a trend is increasing or decreasing with respect to time. A negative value of S or tau is a sign of decreasing trend and vice versa. First the cumulated Principal Component (PC1) was converted to Time Series data as in figure 8:

Fig. 8: Cumulative Principle Component Time Series Graph. This graph provides a graphical representation of cumulated PC scores over the 30 year study period

From figure 8 of the cumulative Principle Component time series graph, two noticeable trends are observed on the plotted time series, that is, from 1988 to 2006 and from 2006 to 2018 as shown by figures 9 and 10

Fig. 9: First Part of Trend. Represents the first half of the Cumulative Principle Component Time Series Graph to be tested of any significant trend using Mann-Kendall trend test

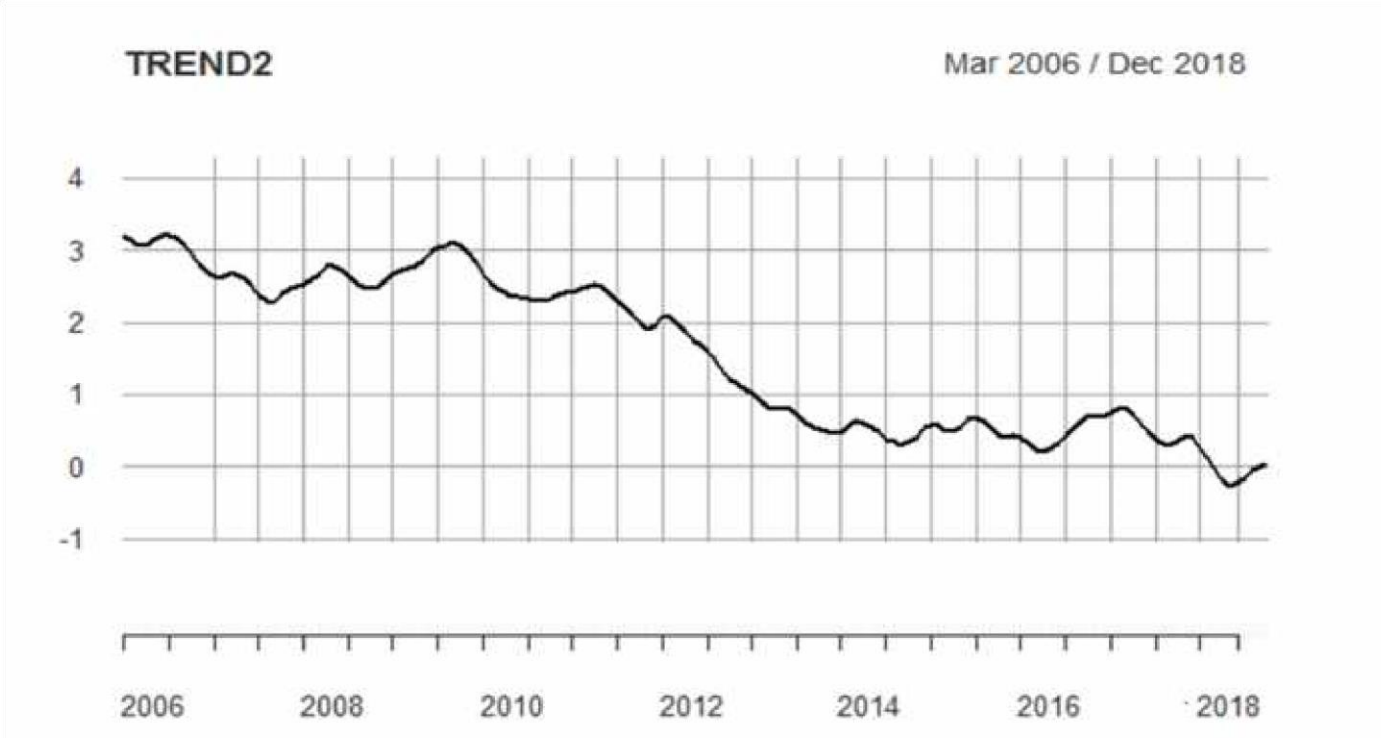

Fig. 10: Second Part of Trend. Represents the second half of the Cumulative Principle Component Time Series Graph to be tested of any significant trend using Mann-Kendall trend test

Before performing the Kendall's Test, the time series data was first tested for significant correlation i.e., both Partial and Autocorrelation as shown in the figures 11.1, 11.2, 12.1 and 12.2:

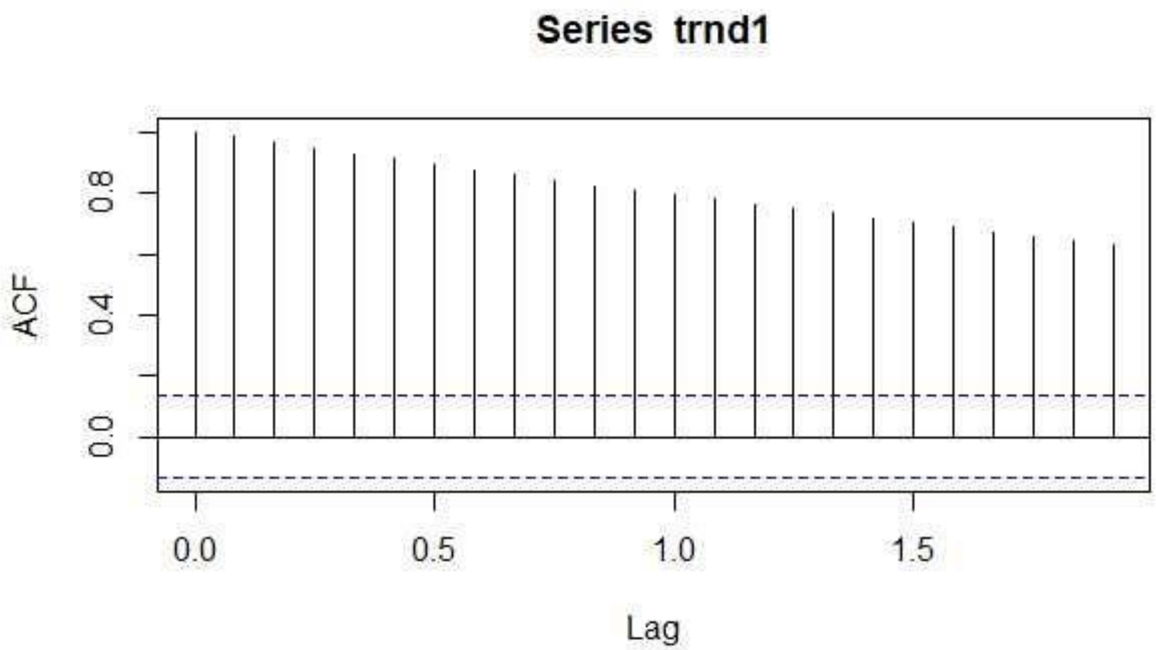

Figure 11.1: Autocorrelation Test of the first part of the trend. Shows signuficant Autocorrelation in the first half of the Cumulative Principle Component Time Series Graph.

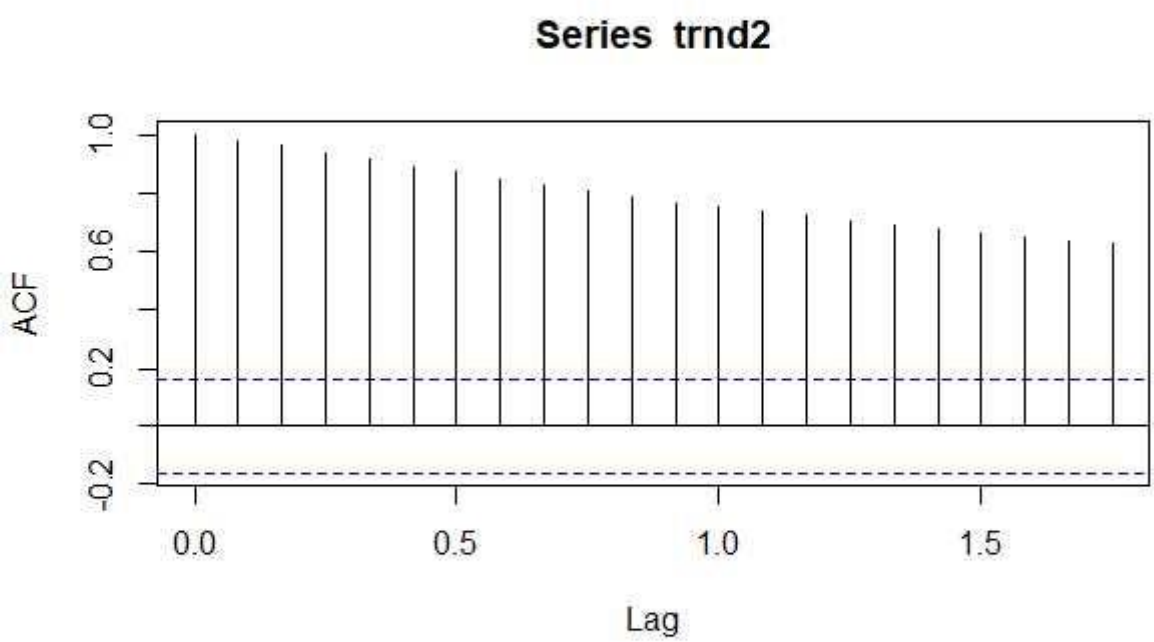

Figure 11.2: Autocorrelation Test of the second part of the trend. Shows signuficant Autocorrelation in the second half of the Cumulative Principle Component Time Series Graph.

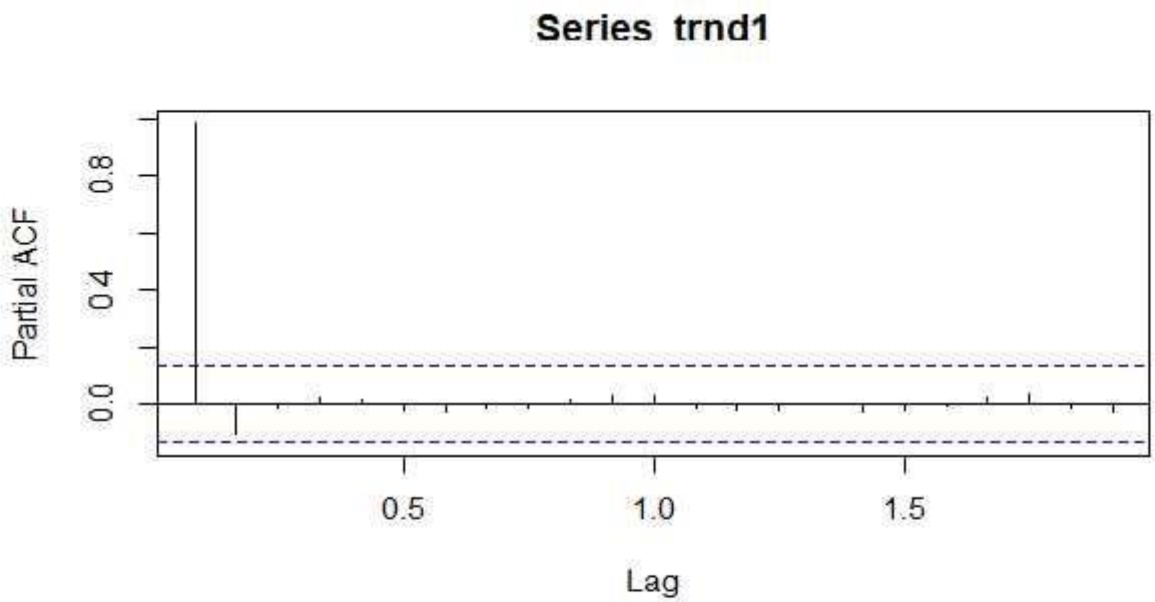

Figure 12.1:Partial Autocorrelation Test of the first part of the trend. Shows insignuficant Partial Autocorrelation in the first half of the Cumulative Principle Component Time Series Graph.

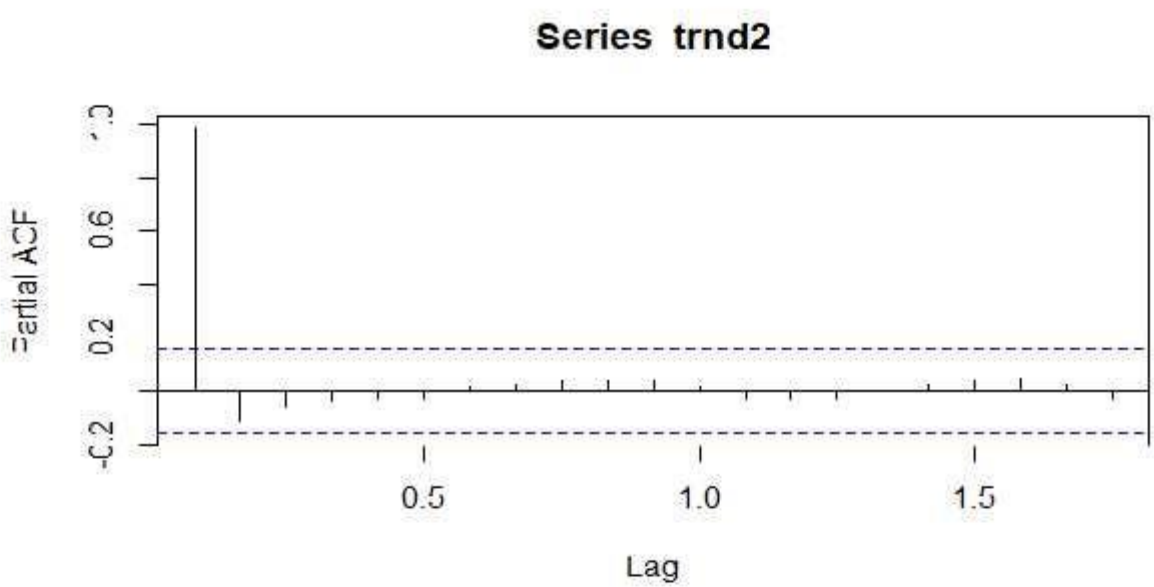

Fig. 12.2: Partial Autocorrelation Test of the second part of the trend. *Shows insignuficant Partial Autocorrelation in the first half of the Cumulative Principle Component Time Series Graph.*

From the ACF and Partial ACF test it was found that the series did appear to have significant correlation. This is true as most of the vertical lines in the ACF plots fall outside the horizontal band (Blue Dotted Lines) thus requiring the need for corrections of autocorrelation. The results of the test were as shown in the table 3:

Table 3: Results of Bootstrap Statistics in Mann Kendall Test

1st Trend	2nd Trend
Bootstrap Statistics : original bias std. error t1* 0.8293712 -0.8238053 0.0981002 Intervals : Level Percentile 95% (-0.2160, 0.1743) MKtau(trnd1) 0.8293712	Bootstrap Statistics : original bias std. error t1* -0.7606316 0.7629985 0.1180371 Intervals : Level Percentile 95% (-0.2281, 0.2169) MKtau(trnd2) -0.7606316

From the above results, Nzoia Basin is experiencing both an upward (increasing) trend and a downward (decreasing) trend in drought. The upward trend confirms meteorological drought was becoming an issue in the area thus the region was experiencing more frequent drought spells due to dry weather patterns dominating the region. The downward trend from the year 2006 is associated with high rainfall that occurred in the region. The same period of low drought was associated with high rainfall occurring in the basin.

Recur rate

The modeling of recur rate was tackled using Fourier Transforms on PC Temporal pattern using **fft** package in R. Fourier Analysis allows on to understand the frequency components in your data by transforming time-domain data into the frequency domain (E. Moreira et al., 2015). A periodogram was created from the Fourier transform and used to identify the dominant periods of the time series. The periodogram was generated in R using spectrum. Period (T) is the number of time periods required to complete a single cycle whereas Frequency is = 1/T, that is, it is the fraction of the complete cycle that's completed in a single time period. The scale of the horizontal axis is in cycles per unit of time; the value 6 at the right end is the Nyquist frequency (frequency $1/2T$ when T is the sampling rate of the series). The first three peaks showed cycles of drought of the range SPEI (-2, -1.5 & -1) respectively.

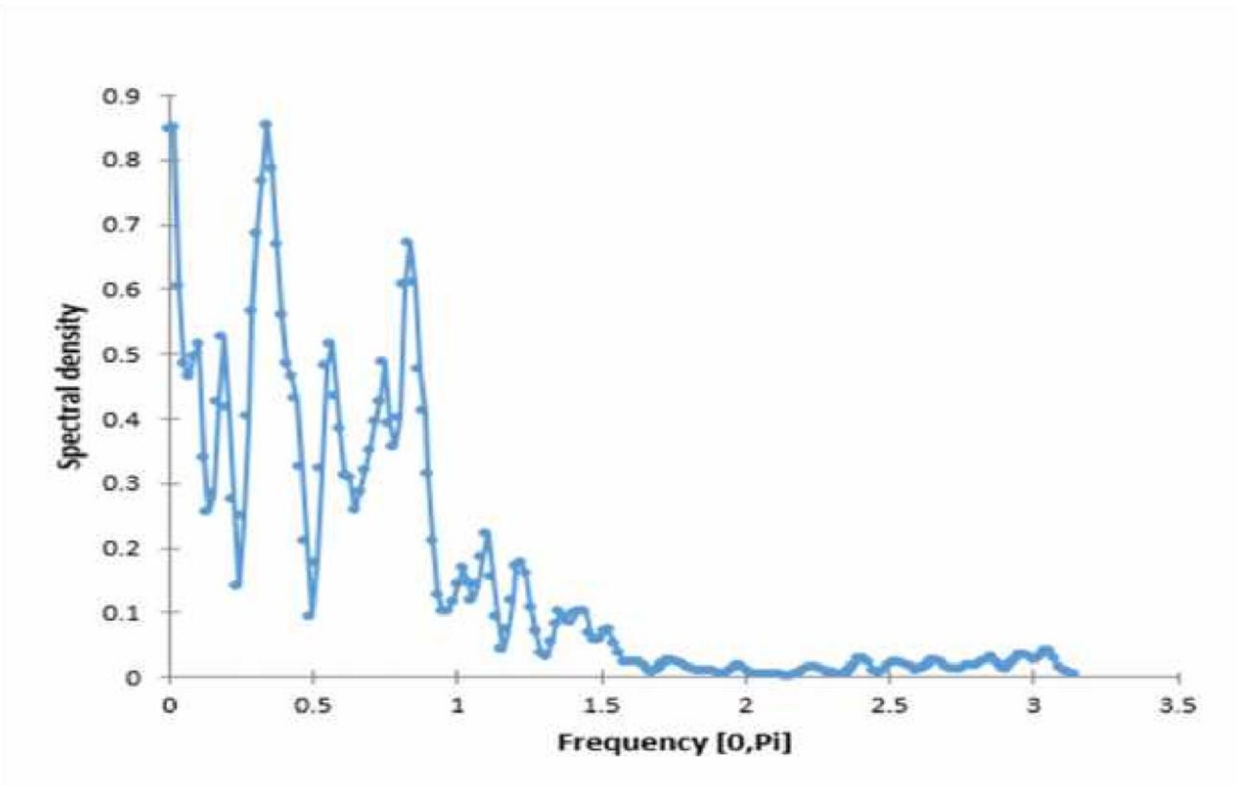

Fig. 13: Periodogram of drought cycles

From figure 13, the frequencies of the main three categories of drought were determined i.e. mild, moderate and severe meteorological droughts. The tallest peak at about 0.4 corresponds to about 0.4 cycles per unit of time which is equivalent to 2.5 years (represents moderate meteorological drought periods), 0.75 cycles is equivalent to 1.3 years (represents mild meteorological drought periods) and 0.3 cycles is equivalent 3.3 years (represents severe meteorological drought periods).

Discussion

Spatial/Temporal Patterns

SPEI was able to identify some of the documented major drought and flood episodes in Kenya for example 1991, 1998, 2007, 2010, 2013 and 2018 (for drought), and 1993, 2000, 2001, 2005 and 2009 (for floods) (Wambua et al. 2015). In general, the wettest period was between 2010 and 2017 in the entire basin clearly showing the effects of the El Niño rainfall that were experienced during the 2015-2016 period. It can be seen that on the study timescale, near normal and moderate events occur most frequently and extreme events occur least frequently. A 2–3 year period means that a year with positive SPEI is followed by a year with negative SPEI and then either immediately by a year with positive SPEI or by another year with negative SPEI and then a year with positive SPEI (Hartmann et al. 2012). Extreme meteorological drought was experienced in the following years; 2000 (April and May) and 2004 (January and July) which corresponds to results of a study by Wambua et al., (2018) which identified major droughts occurring between the years 1999-2007 and major wet periods between 2009-2016.

The pattern of the temporal evolution of dry/wet events in the basin can be due to the influence of the high variability of seasonal and annual rainfall in the East African region. Some studies e.g. Lyon (2014) had suggested that the increase in the frequency of drought conditions post 1998 in the East African region was due to multidecadal variability of Sea Surface Temperatures (SSTs) in the tropical Indian and Pacific oceans.

La Niña events significantly contributed to the occurrence of persistent dry events in Kenya in 2010/2011 while El Niño events of 1997 and 1998 caused extreme wet events during that period (Kisaka et al. 2015). This could also be the reason for the spatial heterogeneity and occurrence of dry/wet periods over the basin, where some extreme episodes were witnessed in specific periods over the basin while there were no dry/wet events corresponding to these episodes across other regions of the study area particularly the east and west side of the basin. The occurrence of long episodes of dry and wet events in the basin is an indication of climate variability and change.

Trends of drought

Mann Kendall trend tests carried out on the cumulated PC1 scores proved the existence of two trends at 95% confidence level. A positive trend with a Kendall's Tau factor of 0.829 and a negative trend with a Kendall's Tau factor of -0.761. These two trends can be associated with the climatological changes over the study area, that is, the increased trend may have been attributed by the reduced rainfall over the basin due to climatological events such as La Niña events, whereas the decreasing trend was caused by increased rainfall over the basin giving rise to a reduction in drought events. This decreased trend was also greatly influence by the El Niño rainfall that occurred during the 2015-2016 period which resulted in increased severe wet periods that resulted in cases of flooding in the study region.

Recur Rate

A visual relation was established between the Fourier waves and the events of drought that occurred during the study period. The correspondence between the sinusoidal waves and the drought cyclicity is not perfect because cycles in nature are only near-regular, thus not providing for a full agreement with regular waves (E. Moreira et al., 2015). Mild droughts had the highest repeat period of 1.3 years cycles, as the study area being a high rainfall receiving area doesn't experience severe/extreme meteorological drought cycles often. Moderate drought had a recur rate of 2.5 years whereas severe drought had a less frequent recur rate of 3.3 years.

The recur rates show that even though Nzoia Basin is a high rainfall receiving area it has an almost predictable cycle rate that can be used to aid farmers and other persons who depend on rain fed water to be able to utilise the most and prepare for times of low rainfall.

Conclusion

The study was carried out to determine the trend analysis of meteorological drought in Nzoia basin, while also carrying out spatio-temporal analysis of meteorological drought and the determination of the recur rate of the various meteorological drought categories experienced across the basin.

Spatially, meteorological drought was more dominant on the central part of the basin from the first PC loadings map suggesting that this part of the region is mainly associated with low rainfall and is frequently affected dry events and lows were observed on the south western part of the basin according to the second PC loading map. The two maps gave a clear representations of the spatial patterns. The temporal pattern of the meteorological drought within the basin was given by the first PC and a time series plot of the first PCs gave a visual representation of the temporal pattern. Results of the Mann Kendall trend test showed both an upward and downward trend in wet/dry periods thus the basin experienced two different trends over the 30 years study length. The first being an increased drought trend followed by a decrease in the drought trend. Fourier analysis was used to search for significant cycles that could relate to return periods of different drought categories i.e. mild, moderate and severe drought. The study did prove that areas considered to be high rainfall receiving areas such as this case study of Nzoia Basin are affected by meteorological drought often.

Recommendations

Such studies on other areas that are considered to be high rainfall receiving areas should be carried out in order to take charge and be able to capitalize on the high rainfall years. Further study may be carried out and include the forecasting of meteorological drought periods.

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