ASSESSMENT OF DROUGHT OCCURRENCE AND ITS IMPACTS ON RURAL LIVELIHOODS IN THE UPPER EWASO NG'IRO BASIN, KENYA

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Assessment of Drought Occurrence and its Impacts on Rural Livelihoods in the Upper Ewaso Ng'iro Basin, Kenya

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University

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DEDICATION

This work is dedicated to the Upper Ewaso Ng'iro River Basin communities.

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LIST OF ABBREVIATIONS AND ACRONYMS

ACAPS	Assessment Capacities Project
ASAL	Arid and Semi-Arid Land
ANN	Artificial Neural Network
ARIMA	Autoregressive Integral Moving Average
BP	Back Propagation
DI	Drought Index
EU	European Union
FEWSNET	Famine Early Warning Sign Network
FSNWG	The Food Security and Nutrition Working Group
GDP	Gross Domestic Product
GN	Generalized Normal
GWP	Global Water Partnership
IPCC	Intergovernmental Panel on Climate Change
KNBS	Kenya National Bureau of Statistics
LM	Levemberg Marquadt
MoALF	Ministry of Agriculture, Livestock and Fisheries
MSE	Mean Square Error
MSRRI	Multivariate Standardized Reliability and Resilience Index
NDMA	National Drought Management Authority
NDVI	Normalized Difference Vegetation Index
NDWI	Normalize Difference Water Index
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
PDSI	Palmer Severity drought Index
PET	Potential Evapotranspiration
RMSE	Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SPI	Standard Precipitation Index

SPEI	Standard Precipitation Evapotranspiration Index
SWSI	Surface water supply index
SSDWI	Standardized Supply and Demand Water Index
SRI	Standardized Runoff Index
SDI	Stream flow drought index
TRMM	Tropical Rainfall Measuring Mission
UNISDR	United Nations International Strategy for Disaster Reduction
UENB	Ewaso Ng'iro North River Basin
VCI	Vegetation Condition Index
WMO	World Meteorological Organization

ABSTRACT

Drought assessment is necessary for identifying adaptation and resilience measures for the livelihoods of the communities. There is therefore an urgent need for comprehensive research on drought impacts and adaptation strategies in the Upper Ewaso Ng'iro North Basin (UENB) in Kenya. The study assessed drought occurrence in the UENB aiming to provide insights into potential measures for safeguarding livelihoods in the region. This basin showcases varying regional characteristics, influenced by elements such as climate, environmental conditions, and human actions, all of which contribute to its multifaceted landscape and climatic fluctuations due to changes in elevation. This study assessed drought trends using the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). The data used in the study were monthly rainfall and monthly temperature data for ten stations in the basin for the period 1981 to 2020, 58 farmer surveys and key informant interviews. The results of SPI and SPEI demonstrated a 40% and 50% increase respectively in the severity of drought events in the UENB since 1999. Additionally, the study reveals that the SPI and SPEI indices differ in identifying temporal and spatial drought characteristics, with longer timescales showing improved accuracy. When modelling the indices, it was found that ANN performs well in the long term, and the accuracy decreases with a decrease in the time frame. Also, it performs better with SPEI than with SPI indicating a regression of 0.845 for SPI and 0.957 for SPEI. Farmer Surveys revealed that droughts affect the communities differently based on the geographical location. Farmers have encountered significant difficulties, with a noteworthy 45% experiencing total crop failure and 36% suffering substantial losses in livestock. Issues related to conflicts over water and grazing land have emerged as major concerns. Furthermore, a significant health issue has been the increased prevalence of malnutrition and the rise of pests and diseases affecting both crops and livestock. Different coping strategies have been employed: 50% of pastoralists have resorted to seasonal migration, while crop farmers have adapted by changing their crops (24%), and 30% have sought alternative employment opportunities. Despite the several adaptation strategies, they have proven inadequate. The study recommends integrating multiple drought indices for a comprehensive assessment. of drought in ASALS. The study also emphasizes on refurbishing existing water sources and implementing soil and water conservation strategies within the communities to alleviate the significant impact of limited access to water resources during drought.

CHAPTER ONE

INTRODUCTION

1.1 Background Information

Drought refers to an extended period of unusually dry conditions, characterized by precipitation levels falling below a specific threshold over a wide area and which persists for over a month (Integrated Drought Management Program (IDMP), 2022). Alternatively, it can be defined as significantly drier than typical conditions or as circumstances that restrict moisture availability to a potentially detrimental degree (World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016) or as scenarios marked by an extended absence or substantial shortfall in rainfall (Zargar et al., 2011). Drought is further characterized by reduced rainfall, elevated temperatures, strong winds, low relative humidity, and various aspects of rainfall patterns such as its onset, duration, intensity, and distribution (Mishra & Singh, 2010; Van Loon, 2015). As a global crisis, drought is the most devastating natural catastrophe with adverse impacts on water resources systems, ecosystems, and human populations (Intergovernmental Panel on Climate Change (IPCC), 2014).

According, IPCC Hoegh-Guldberg et al. (2018), globally, drought has frequently occurred in recent years. Drought-prone areas are becoming more vulnerable since the frequency and severity are increasing. Additionally, after 1970, droughts have become more intense and occur longer in drought prone areas like Africa. Drought occurrences are mainly due to increased water demand and climatic changes (Shamshirband et al., 2020).

There are increased drought events in Africa due to climate change (Hoffmann, 2022; Mwangi et al., 2014; Okoro et al., 2014). For example, in 2010-2011, the Horn of Africa experienced one of the most extreme drought events that affected more than thirteen million people and increased food insecurity to the level of famine in the region (Dutra et al., 2013; Mwangi et al., 2014). African countries are the most vulnerable to drought impacts because at least 70% depend on rainfall as a water source for food production and livestock. Okoro et al. (2014) projected that there will be a decrease in water availability and increased desertification due to reduced rainfall in dry seasons in Africa.

Situated in East Africa, Kenya grapples with a rising frequency of drought occurrences, exacerbated by the fact that 80% of its land is categorized as Arid and Semi-Arid Land (ASAL), as noted by the Government of Kenya (GoK), 2012). Drought and climate variability have significantly affected the river basins in Kenya (R. Wambua et al., 2014). Additionally, human activities such as deforestation to expand cropland areas, grazing areas, residential and commercial land have contributed to climate variability in these river basins, further straining water resources(Gichuki, 2006; Wamucii et al., 2023). Various sectors of Kenya's economy are expected to be impacted by drought and climate change. Notably, the impact of drought will extend to the country's key agricultural sector, which serves as the primary source of foreign exchange earnings, primarily driven by the export of tea and horticultural products (Lanari, Schuler, Kohler, & Liniger, 2018). As a result, economic development in the country will continue to face impediments.

Moreover, the Upper Ewaso Ng'iro River Basin (UENB), renowned for its thriving commercial horticultural farming conditions (Lanari et al., 2018), has played a pivotal role in enhancing the livelihoods of communities previously engaged in agro pastoralism, as noted by Ngigi et al. (2007). Horticultural farming has created employment opportunities, enhanced food security, and contributed to the area's infrastructure development. As a result, there has been an increase in population in the region (Kenya National Bureau of Statistics (KNBS) 2019a) that has resulted in a higher demand for limited natural resources, such as freshwater and land, driven by agricultural intensification (Lesrima et al., 2021). Consequently, the area has experienced environmental degradation, causing alterations in the hydrological cycle of the catchment, including changes in rainfall patterns, evaporation rates, and runoff in smaller catchments (Mutiga et al., 2011). Additionally, the water quality has been affected by the pollution from agricultural runoff reducing the access to domestic water (Lanari et al., 2018).

Following the emergence of horticulture as a lucrative industry in the 1980s, agricultural activities have seen a notable increase in the upper areas of the Ewaso Ng'iro basin, leading to substantial population growth and heightened pressures on water and land resources (Mukhwana, 2016). Based on studies by Gannon et al. (2020), Lanari et al. (2018), and Lesrima et al. (2021), the increasing demand for water and pasture has resulted in perennial conflicts between different communities within the basin, contending over river water. Moreover, the country's economy will be significantly affected by drought due to the basin's contributions to the gross domestic product (GDP) through agricultural production, tourism, and forestry (Gichuki, 2006; Mutiga, Mavengano, Zhongbo, Woldai, & Becht, 2010). Therefore, there is an urgent need to establish sustainable approaches to help communities effectively adapt to and manage unforeseen climate changes, enabling them to embrace beneficial transformations. (Crossman, 2018; Soanes et al., 2021).

To effectively manage and mitigate droughts, it is crucial to have early warning systems that rely on drought development information. Drought assessment, which uses drought indices and models, is crucial in monitoring droughts. Among the various drought indices available, the Standard Precipitation Index (SPI) and Standard Precipitation and Evapotranspiration Index (SPEI) are widely utilized (Mishra & Singh, 2010). SPI is favoured due to its minimal input requirements, while SPEI is preferred for its inclusion of potential evapotranspiration. This study used SPI and SPEI to characterize droughts in the basin. Physical and statistical models have been developed to predict future drought occurrences (Mishra & Desai, 2005). Statistical models, including time-series analysis, regression, and machine-learning techniques, are often preferred over physical models (Khan et al., 2020). Artificial Neural Networks (ANN), a machine learning method, is commonly favoured due to its simplicity in input requirements (Mulualem & Liou, 2020; Patil et al., 2020). The study will evaluate how ANN performs in modelling SPI and SPEI.

1.2 Statement of the Problem

Environmental deterioration in the Upper Ewaso Ng'iro North Basin (UENB) can be traced back to extensive alterations in land use, where natural forests and bushlands have been replaced by plantation forests, cultivated fields, grazing lands, and residential developments (Gichuki, 2006). Moreover, the basin's agricultural and horticultural sectors, which significantly improve livelihoods, generate employment opportunities, develop infrastructure, and ensure food security, require substantial irrigation. Unfortunately, the intensified agricultural and horticultural practices have resulted in excessive water extraction during dry seasons, reducing river flows and causing environmental degradation. Climate change, the unreliability of rainfall, and the basin's position on the leeward side of Mt. Kenya have worsened dry periods and contributed to a decrease in agricultural output.

There is a lack of comprehensive research information on the following: the impact of drought to the basin's communities', development, and current drought conditions. In order to address this critical knowledge gap, it is crucial undertake comprehensive research initiatives that encompass assessments of the drought events, the socio-economic and environmental impacts of drought, as well as the adaptive strategies employed by these communities to mitigate its effects and ensure sustainable development. Therefore, this study assessed the drought events, examined the impacts of droughts on the communities' livelihoods, and analysed the drought adaptation strategies employed by the communities in the basin.

1.3 Objectives

1.3.1 Main Objective

The main objective of this study was to determine the drought occurrences, identify their impacts on the livelihood of the communities and the community adaptation strategies in the Upper Ewaso Ng'iro North River Basin (UENB).

1.3.2 Specific Objectives

The specific objectives of this study were to:

1. Determine the trends of drought occurrences in the Upper Ewaso Ng'iro North River Basin (UENB) by using selected drought indices (DI) over the past 40 years.

2. Evaluate the trend of short-term, medium-term, and long-term drought conditions in the UENB using Artificial Neural Networks.
3. Identify the impact of drought events on the livelihoods of rural communities in the UENB.
4. Identify the drought adaptation and resilience strategies currently implemented by local communities in the UENB.

1.4 1.4 Research Questions

2. What are the historical drought trends in the past 40 years- from 1980-2020 based on the selected drought indices in the Upper Ewaso Ng'iro North River Basin (UENB)?
3. What is the trend of short-, medium- and long-term drought conditions as evaluated by Artificial Neural Networks?
4. What is the impact of drought events on the livelihoods of rural communities in the basin?
5. What are drought Adaptation and Resilience strategies currently implemented by local communities in the UENB?

1.5 Justification of the Study

The Upper Ewaso Ng'iro North River Basin faces challenges of uneven resource distribution, particularly water, due to varying climatic zones and increased climatic changes. These factors result in uneven rainfall patterns and frequent drought incidents in the basin, leading to prolonged hardships for marginalized communities (Kimwatu et al., 2021b; Lesrima et al., 2021). It is imperative to develop efficient strategies for enhancing drought resilience and enabling transformative adaptation among these affected communities. However, formulation of such strategies necessitates a thorough grasp of timely, precise, and dependable information on drought characteristics in the region (Jun et al., 2011).

By analysing drought characteristics in the UENB of between 1940 and 2020, this study will identify, classify, and quantify drought years in the Upper Ewaso Ng'iro North River Basin. Additionally, it will identify the impacts of drought events and the most preferred drought adaptation strategies employed by the local communities of Kisima, Lekurruki, and Leparua. The information generated from this study will be utilized by government agencies, water resource managers, and Non-Governmental Organizations (NGOs) to develop effective drought preparedness, mitigation, adaptation, and resilience strategies. Furthermore, there have been successful cases in Kenya where Artificial Neural Networks (ANN) have been utilized for drought forecasting (Kigumi, 2014; R. Wambua et al., 2014).

The findings of this study offer vital information to improve the management of drought risks, water resources, and river basins. Through a better grasp of drought patterns and their impacts, this research outcomes will aid in formulating policies and strategies that foster sustainable use of water resources and bolster the resilience of communities in the Upper Ewaso Ng'iro River Basin. Additionally, it provides insights into the pros and cons of using the SPI and SPEI drought indices for monitoring drought occurrences, benefiting both future research and real-world applications.

1.6 Scope and Limitations of the Study

This study focused on monitoring drought in the Upper Ewaso Ng'iro North basin using monthly rainfall and temperature data from 10 meteorological stations over a 40-year period, from 1980 to 2020. Specific regions within the basin were selected to examine the impacts of drought and the adaptation strategies: west Kisima in the semi-humid mountain region, North Lekurruki in the medium to low catchment region, and southeast Leparua Community in the arid areas. The impacts of drought were categorized into two main areas: household livelihoods, including income-generating activities, and the social well-being of the communities.

Due to limited data resources, the study was restricted to methods that do not require extensive data and resources. As a result, drought monitoring was based solely on rainfall and temperature events without considering climate change trends. The Thornthwaite method, which relies only on monthly mean temperatures, was used to calculate the Potential Evapotranspiration (PET). The limitations affected the comprehensiveness of the study by not incorporating long-term climate change trends, which might influence the depth of determining drought trends and the impact analysis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Drought Characteristics

Drought is a prolonged period of abnormally dry weather characterized by insufficient precipitation falling below a specific threshold over a significant area, typically lasting more than a month. This phenomenon may also encompass elevated temperatures, wind, and reduced relative humidity as contributing factors (Barua, 2010; Cook et al., 2014; Livneh & Hoerling, 2016; WMO, 2023). It can be further defined as either conceptual or operational. Operationally, it is defined scientifically by identifying the onset, severity and end of the drought period while conceptually as a non-analytic description such as “an arid year” (Mutiga et al., 2011). Operationally defined drought can be used to analyse the frequency of drought occurrence, how severe and the duration for a specific location (Mutiga et al., 2011).

Droughts are categorized into four distinct types: meteorological, hydrological, agricultural, and socio-economic, with classification based on their characteristics and impacts, making it difficult to assess and manage droughts (WMO & GWP, 2016). Meteorological drought arises from prolonged periods of dryness, limited precipitation, and extended high temperatures in a particular region (WMO & GWP, 2016). Insufficient rainfall reduces infiltration, decreases runoff, and diminishes groundwater recharge. High temperatures associated with meteorological drought contribute to changes in wind patterns, below-average relative humidity, and increased evapotranspiration.

Hydrological drought is characterized by reduced water availability in hydrological processes, resulting in decreased stream flow, lowered water levels in bodies of water, and diminished groundwater depth (Van Loon, 2015; WMO, 2023). Agricultural drought occurs when soil moisture levels decrease, leading to crop failure irrespective of surface water resources (García-león, Contreras, & Hunink, 2019). Socio-economic drought encompasses both water supply and demand challenges and arises when the demand for economic resources surpasses the available water supply within a particular basin (Kimwatu, Mundia, & Makokha, 2021a). This drought often increases food prices, unemployment, and heightened migration.

In addition to assessing drought, other crucial characteristics define droughts. The primary characteristics of drought include severity, duration, and intensity (IDMP, 2022; WMO & GWP, 2016). Drought duration refers to the continuous period during which drought conditions persist. Drought intensity measures the magnitude or strength of the drought. In contrast, drought severity represents the cumulative occurrence of drought over a specific period and is calculated by multiplying intensity and duration.

Several studies have been done in Kenya to identify drought characteristics over different time scales (Kigumi, 2014; Kimwatu et al., 2021a; R. Wambua et al., 2014; Wanjuhi, 2016). Wanjuhi (2016) study focused on assessing the temporal and spatial occurrence of drought in the Northeastern counties of Kenya. The research utilized precipitation data to understand the drought conditions in the region. The findings revealed that the drought conditions varied between mild drought and moderately dry conditions, indicating a range of severity. Furthermore, Wanjuhi's study classified drought events into different durations. Based on the available information, the drought conditions were grouped into three categories: 2 to 3 years, 4.5 to 7 years, and 8 to 12 years. This classification suggests that the region experienced drought events of varying lengths, which may have implications for water resource management and adaptation strategies.

2.2 Meteorological Drought

Meteorological drought always occurs at the beginning of all the other types of drought (Dalezios, 2014) and has different characteristics for different climatic regions. A threshold deficiency of precipitation for a period is first determined to identify meteorological drought using the meteorological indices. Due to the different meteorological characteristics, different regions will have their specified threshold levels. WMO & GWP (2016) grouped the indices into several classes based on their characteristics. The classes are atmospheric drought indices, precipitation anomaly indices, aridity indices, soil moisture indices and satellite indices.

2.3 Drought Assessment

Assessing and forecasting droughts are critical in preparing for, mitigating, and managing their impacts. This necessitates a comprehensive understanding of historical drought occurrences and their consequences (Mishra & Singh, 2010). Drought forecasting involves predicting various attributes of drought, including severity, onset, duration, and frequency (Hao, Singh, & Xia, 2018; Sharma & Panu, 2012a). Nevertheless, the intricate characteristics of droughts have presented obstacles for climatologists and decision-makers in accurately predicting such occurrences (Hao et al., 2018).

The assessment of drought entails the use of drought indices, which define and measure drought conditions (WMO & GWP, 2016). These indices encompass a range of climate variables and offer insights into drought attributes such as duration, severity, intensity, and geographic scope (Dalezios, 2014; Mishra & Singh, 2010). Depending on the specific index, they can also offer insights into historical drought patterns and trends (WMO & GWP, 2016). Multiple indices have been developed to cater to specific needs due to diverse applications and types of droughts. A summary of these drought indices can be found in Table 2.1.

These drought indices rely on diverse data inputs, including rainfall, temperature, soil moisture content, snow water content, stream flow, reservoir volume, potential evapotranspiration, and satellite data (Mishra & Singh, 2010). In Kenya, there exists a deficit in comprehensive data concerning the suitability and practicality of these indices for the purposes of drought prediction and evaluation (Wambua et al., 2014).

Table 2.1: Commonly used Drought Indices

Type	Index name	References
Meteorological drought	Standard Precipitation Index (SPI)	(Mishra & Singh, 2010)
	Standard Precipitation and Evapotranspiration Index (SPEI)	(Vicente-Serrano et al., 2010)
	Decile index (DI)	(WMO & GWP, 2016)
	Palmer Drought Severity Index (PDSI)	(Mishra & Singh, 2010)
Hydrological drought	Surface water supply index (SWSI)	(WMO & GWP, 2016)
	Standardized Runoff Index (SRI)	(Shukla & Wood, 2008)
	Stream Flow Drought Index	(Nalbantis & Tsakiris, 2009)
Agricultural drought	Normalized Difference Vegetation Index (NDVI),	(WMO & GWP, 2016)
	Vegetation Condition Index (VCI),	(Yang et al., 2011)
	Soil Moisture Deficit Index	(Narasimhan & Srinivasan, 2005)
	Normalize Difference Water Index (NDWI)	(WMO & GWP, 2016)
Social Economic drought	Multivariate Standardized Reliability and Resilience Index (MSRRI)	(Mehran et al., 2015)
	Standardized Supply and Demand Water Index (SSDWI).	(Zhou et al., 2022)

2.3.1 Palmer Drought Severity Index (PDSI)

Palmer's Drought Severity Index (PDSI) was formulated to estimate moisture supply and demand within a soil layer by Palmer (1965). It was developed to identify drought onset and end (Shamshirband et al., 2020). According to Wambua et al. (2014), it uses precipitation, temperature and soil moisture data as the input and does not consider other hydrometeorological variables and the human impacts that affect drought. From the Palmer Drought Severity Index, the Palmer Hydrological Drought Index (PHDI), which is more efficient and based on moisture flow, was developed (Mishra & Singh, 2010).

Wambua et al. (2014) points out that even though PDSI has been widely used in the USA, its application in other part of the world is limited. Barua (2010) and Mishra and Singh (2010) suggest that this could be attributed to its drawbacks, such as its poor indicator of short drought periods. Despite the mentioned disadvantages, the advantages of using PDSI are that it shows the current spatial and temporal drought conditions based on the historical drought conditions and measures the abnormality of weather conditions for a basin or region (Mishra and Singh 2010; Sivakumar et al. 2010).

2.3.2 Deciles Indices

Decile Indices are used for monitoring meteorological drought using a long-term average monthly precipitation (Barua, 2010; Gibbs & Maher., 1967). A cumulative frequency and distribution of the total rainfall is constructed using the data range from the highest to the lowest, and the median is used to identify the tendency of the records. The observations are categorized into deciles, with the fifth decile being the median. The current or previous rainfall values can be interpreted using the deciles. This approach will require a long historical rainfall record (R. Wambua et al., 2014).

The advantages of this approach are that they are simple to calculate and do not require multiple data (the precipitation data only). There are fewer assumptions compared to the other indices. Also, due to their flexibility in determining the threshold, they can be used for monitoring all types of drought (Dalezios, 2014).

2.3.3 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was originally developed by Mckee et al. (1993) in Colorado, USA, to quantify rainfall deficits and monitor drought conditions at several time scales. SPI is widely utilized worldwide and has been recognized by the World Meteorological Organization as the most suitable index for global drought monitoring and forecasting (Hayes et al., 2011). To calculate SPI, long-term complete monthly historical precipitation data spanning at least 20-30 years is required (Dalezios, 2014). Mckee et al. (1993) employed monthly time series of 3, 6, 12, 24, and 49 months to compute the SPI.

The calculation of SPI involves fitting the historical aggregated monthly rainfall data into a probability distribution function and converting it into a normal distribution function. Various distribution functions like Gamma, Pearson Type III, Lognormal, Extreme Value, and Exponential distribution functions can be used for this purpose (Dalezios, 2014; Khan et al., 2020; Patil et al., 2020). The Gamma probability distribution function is commonly preferred because it accommodates positive and non-zero values effectively (Khan et al., 2020). The gamma distribution function, (г(α)), is fitted into a dataset of rainfall with a shape factor α and a scale factor β. If the amount of precipitation is x, the probability density will be in the form of Equation 2.1:

$$f(x, a, \beta) = \frac{1}{\beta^{\alpha} T(\alpha)} x^{\alpha-1e^{-(\frac{x}{\beta})}} \tag{2.1}$$

for x, α, β>0

To obtain the values of the shape factor and scale factor Equations 2,2, 2.3, 2.4:

$$\alpha = \frac{1}{4A}(1 + \sqrt{1 + \frac{4A}{3}} \tag{2.2}$$

$$A = ln\bar{X} - \frac{\sum_{i=1}^{n} lnx}{n} \tag{2.3}$$

$$\beta = \frac{\bar{X}}{\alpha} \tag{2.4}$$

Where: $\bar{X}$ is the Mean rainfall (mm)

N is the number of months.

Following Mishra & Desai (2006) and Patil et al. (2020) study, the cumulative probability of the zero and non-zero values with undefined gamma function will be calculated using Equation 2.5:

$$H(x) = q + (1-q)\, f(x;\ \alpha, \beta) \tag{2.5}$$

Where: q is the probability of zero rainfall Equation 2.6.

$$q = \frac{m}{n} \tag{2.6}$$

Where: *m* is the number of zeros present in a rainfall time series,

H(x) will then be converted to SPI using Equation 2.7:

$$SPI = \pm(K - \frac{c_0 + c_1K + c_2K^2}{1 + d_2 + d_2K^2 + d_3K^3} \tag{2.7}$$

Where K is as Equation 2.8

$$K = \sqrt{ln(\frac{1}{(H(x))^2}} \tag{2.8}$$

According to the SPI, an event is classified as a drought when the SPI value remains consistently negative, and when it turns positive, it is considered the end of the drought event (Khan et al., 2020; McKee et al., 1993; Mishra et al., 2007; Mishra & Singh, 2010). Table 2.2 outlines the drought classification based on SPI (Mishra & Singh, 2010).

Table 2.2: Classification of Drought Based on SPI and SPEI

SPI Values	Class
<2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
- 0.9 to 0.99	Near Normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
>-0.2	Extremely dry

Mishra and Singh (2010) state that one of the key advantages of SPI is its versatility in being computed for different time scales, enabling it to effectively track short-term water resources like soil moisture. Patil et al. (2020) also state that the SPI is preferred because of its flexibility to be applied widely since it has a minimum input requirement compared to other indices. Based on studies by Anshuka et al. (2019), Khan et al. (2020); Mishra and Singh (2010); Mutiga et al. (2011); Wambua et al. (2014); WMO and GWP (2016), SPI has other advantages: it is not dependent on the geographical location because of its standardization, and it can show both long- and short-term drought for over time scales due to its statistical consistency.

However, based on Mishra and Singh's (2010) review of drought concepts, SPI was found to have a couple of disadvantages. These mainly occur during calculation of the SPI and are caused by the length of the precipitation record required and the nature of probability distribution. The review claims that the length of precipitation significantly impacts the SPI values. It further explains that sometimes, when computing SPI values using different lengths of record with similar gamma distributions over different times, similar and consistent results are observed. However, the SPI values will not be similar when using different gamma distributions. Therefore, while calculating using different lengths of record, one should note the differences in the SPI values.

The other limitation is using different probability distributions (Labudová et al., 2016; Mishra & Singh, 2010). Since SPI values are based on fitting a distribution to precipitation, the different probability distributions will affect the values observed. The problem arises when calculating SPI for long time scales fitting a distribution might be biased due to the limitation in data length and when finer resolutions of spatial analysis need to be investigated, and a long-term dataset is not available. The other issue is when calculating SPI values for areas with dry climates where seasonal precipitation and zero values are typical. Also, when a short time scale is used, the values may not be generally distributed because of highly skewed distribution. This may lead to significant errors while simulating precipitation distribution in dry climate areas; therefore, the researcher must be keen to calculate SPI values.

Therefore, it is evident that a long-term data series is suitable while calculating the SPI values.

The review of drought indices application by Ntale & Gan (2003) showed that of all the indices, SPI is more suitable for drought assessments and forecasting in East Africa. Ntale and Gan further explained that SPI is more adaptable to specific climates, has fewer data needs, is easy to interpret, and can be calculated for any time scale. SPI has been used to study different aspects of drought, i.e., forecasting, frequency analysis, spatial-temporal analysis, and climate impact studies. Karanja (2018) applied SPI to monitor the temporal drought trends in the Laikipia West sub-county from 1984 to 2014. Karanja reached the conclusion that drought occurrences in the region were on the rise, ultimately categorizing the drought events as severe in 2009. Additionally, Odhiambo et al. (2018) utilized SPI to evaluate the frequency and severity of drought in Isiolo, situated in the UENB. Odhiambo's study showed severe droughts ($-2<$SPI & SPEI≤-1.5) in 2004 and extreme (SPI & SPEI≤-2.0) droughts 2008/2009. The study also found that for drought incidents, the probability of recurrence of moderate droughts is once in 18 months and severe dryness at once in 5 years.

2.3.4 Effects of Probability Distribution and Parameter Estimation Errors

The computation of the Standardized Precipitation Index (SPI) hinges on theoretical probability distributions to fit cumulative precipitation data, as recommended by McKee et al. (1993), who advocate for a two-parameter gamma distribution. However, subsequent research underscores the necessity for flexibility in selecting distributions due to regional disparities and research objectives (Angelidis et al., 2012; Blain & Meschiatti, 2015; Sienz et al., 2012).

The choice of probability distribution (PD) significantly influences SPI values and drought characteristics, especially during extreme conditions, as demonstrated by Zhang & Li (2020). While normal and moderate classifications exhibit minimal disparities among PDs, significant variations arise as SPI values approach extremes. Diverse PDs yield marked differences in drought peak, event number, duration, and frequency. Additionally, studies by Angelidis et al. (2012); Vergni et al. (2017)

underscore the consistency of SPI across different distributions during normal periods but reveal increasing discrepancies during very dry or wet periods.

Parameter estimation errors further compound SPI uncertainty, particularly during extreme SPI values, as highlighted by Zhang & Li (2020). The confidence intervals expand with increasing or decreasing SPI extremes, contributing to larger intervals in drought event number and maximum drought duration compared to the variability caused by different PDs. As emphasized by Wu et al. (2005), parameter estimates with low confidence yield SPI values with low confidence. To ensure robust parameter estimates, a lengthy record of precipitation data is vital, as maximum likelihood estimation (MLE) exhibits instability with small samples and performs better with larger sample sizes (Beguería et al., 2014). Recommendations for an optimal record length vary, with McKee et al. (1993) suggesting a continuous period of at least 30 years for SPI calculation, while (Carbone et al., 2018) advocate longer record lengths of 40 to 80 years for parameter estimation stability. Carbone's study further notes that even over 60 years of records, extreme events significantly influence SPI estimates. Thus, the minimum record length depends on precipitation pattern changes and the desired level of parameter estimation confidence.

2.3.5 Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) was introduced by Vicente-Serrano et al. (2010) to detect periods of drought. SPEI incorporates the same principles as the Standard Precipitation Index (SPI) but additionally takes into account temperature (WMO & GWP, 2016). It requires complete monthly precipitation records and temperature data as input parameters. The computation of SPEI, as outlined by Vicente-Serrano et al. (2010), follows a similar process to SPI but involves calculating the monthly (or weekly) difference between precipitation and Potential Evapotranspiration (PET). According to Mishra & Singh (2010) and Vicente-Serrano et al. (2010), this calculation, performed at various time scales, yields the SPEI, representing a straightforward climatic water balance. SPEI is capable of quantifying drought severity based on intensity and duration while identifying the onset and cessation of drought events.

Vicente-Serrano et al. (2010) highlight the necessity of calculating PET as a precursor to computing SPEI. However, the study also acknowledges the challenges associated with PET calculation due to its reliance on multiple meteorological parameters. These parameters include surface temperature, air humidity, incoming radiation at the soil surface, water vapor pressure, and heat fluxes between the ground and the atmosphere. The study further underscores that the method chosen for PET computation depends on the availability of these meteorological parameters. These methods include physically based methods like the Penman-Monteith and empirical-related models. The study mentioned that the method of calculating PET does not affect the results; therefore, it is not of much concern. However, the study suggested that the ideal method uses the simple Thornthwaite method, which does not require multiple data inputs but uses monthly mean temperature.

Based on the study by Vicente-Serrano et al. (2010), PET in millimetres (mm) is calculated as Equation 2.9:

$$PET = 16K(\frac{10^T}{I})^m \quad (2.9)$$

Where: T= monthly mean temperature (^oC)

I-= heat index (calculated as some of the 12-month index values i)

The month index value i is calculated as Equation 2.10:

$$i = (\frac{T}{5})^{1.514} \quad (2.10)$$

m = coefficient (depending on I), Equation 2.11:

$$m = 6.75X10^{-7}I^3 - 7.71X\ 10^{-5}I^2 + 1.79X\ 10^{-2} + 0.492 \quad (2.11)$$

K= a correction coefficient (computed as a function of the latitude and month), 2.12:

$$K = (\frac{N}{12})(\frac{NDM}{30}) \quad (2.12)$$

NDM = the number of days of the month

N = the maximum number of sun hours, calculated as Equation 2.13:

$$N = \left(\frac{24}{TI}\right)\omega \tag{2.13}$$

ω = hourly angle of the sun rising, calculated as Equation 2.14:

$$\omega = arccos(tan\,\varphi\, tan\,\delta) \tag{2.14}$$

φ = latitude in radians

δ = solar declination in radians, calculated as Equation 2.15:

$$\delta = 0.4093\, sin\left(\frac{2\pi J}{365}\right) - 1.405 \tag{2.15}$$

J= the average Julian day of the month

After getting the value of PET, the difference between the precipitation P and PET for a month is then calculated using the Equation 2.16:

$$Di = Pi - PETi, \tag{2.16}$$

This will measure the water surplus or deficit for the specific month. These values of Di obtained are a combination of different time scales, similar to the SPI method. Dk i, j in a given month j and year i depends on the chosen time scale k. For example, the accumulated difference for one month in a particular year i with a 12-month time scale is calculated as the Equation 2.17:

$$X_{ij}^{k} = \sum_{l=13-k+j}^{12} D_{i-Ij} + \sum_{i-1}^{j} D_{il} \tag{2.17}$$

If j<K

Where D_{il} is the P -PET in the first month of the year i, in mm.

Vicente-Serrano et al. (2010) compared the SPI and SPEI calculation and found that SPI can be computed using a two-parameter distribution; SPEI requires a three-parameter distribution. In the three-parameter distributions, the variable x can take values in the range (γ>x< ∞) where range γ is the distribution's origin parameter. This means that x can take negative values common in D series. To model the Di values at different time scales, Vincente's study used the L-moment ratio diagrams since, with this method, the theoretical distribution of D at different timescales can be compared with the calculated frequency distributions of D. To create the L-moments ratio diagrams, L moments ratios L skewness t3 and L kurtosis t4 will be calculated as Equations 2.18 and 2.19:

$$\tau_3 = \frac{\lambda_3}{\lambda_2} \quad (2.18)$$

$$\tau_4 = \frac{\lambda_4}{\lambda_2} \quad (2.19)$$

Where: λ_2, λ_3, λ_4 are L moments of the D series obtained from probability-weighted moments (PWMs) are: $\lambda_1 = w_o$

$$\lambda_2 = w_o - 2w$$

$$\lambda_3 = w_o - 6w_1 + 6w_2$$

$$\lambda_4 = w_o - 12w_1 + 3w_2 - 20w_3$$

Where the probability-weighted moments of order s are calculated as Equation 2.20:

$$w_s = \frac{1}{N}\sum_{i=1}^{N}(1 - F_i)^5 Di \quad (2.20)$$

Where: F_i is a frequency estimator calculated using the Equation 2.21:

$$F_i = \frac{i-0.35}{N} \quad (2.21)$$

where i is the range of observations arranged in increasing order

N is the number of data points.

The probability density function of a three-parameter log-logistic distributed variable is as the Equation 2.22:

$$f(x) = \frac{\beta}{\alpha}(\frac{x-\gamma}{\alpha})^{\beta-11}[1 + (\frac{x-\gamma}{\alpha})^{\beta}]^{-2} \tag{2.22}$$

where a= scale, β= shape and γ= origin parameters, for D values in the range γ> D< ꝏ and they can be obtained as Equations 2.23, 2.24 and 2.25:

$$\beta = \frac{2w - w_o}{6w_1 - w_o - 6w_2} \tag{2.23}$$

$$\alpha = \frac{(w_o - 2w1)\beta}{\Gamma(1+\frac{1}{\beta})\Gamma(1-\frac{1}{\beta})} \tag{2.24}$$

$$\gamma = w_o - \alpha\Gamma(1 + \frac{1}{\beta})\Gamma(1 - \frac{1}{\beta}) \tag{2.25}$$

Where $\Gamma(\beta)$ is the gamma function of β.

Therefore, the probability distribution function of the D series is given by Equation 2.26:

$$F(x) = [1 + (\frac{\alpha}{x-\gamma})^{\beta}]^{-1} \tag{2.26}$$

From the F(x) the SPEI can be calculated as Equation 2.27:

$$SPEI = W - \frac{C_O + C_1W + C_2W}{1 + d_1W + d_1W^2 + d_3W^3} \tag{2.27}$$

Where W is given by Equation 2.28:

$$W = \sqrt{-2ln(p)} \tag{2.28}$$

For p ≥ 0.5

According to Vicente-Serrano et al. (2010) and WMO & GWP (2016), the main advantage of SPEI is the incorporation of temperature and precipitation data for measuring the effects of temperature on drought events. The study further stated that another strength is that the output can be used for all climate regimes, and the standardized results are easily comparable. Since SPEI uses temperature, they suggest that it can be a suitable index for identifying the impacts of climate change in model output under various predicted climate events Moreover, SPEI offers the flexibility to calculate measurements for periods as short as one month and up to 48 months, facilitating the comparison of drought severity across different time frames and geographical regions, even under diverse climatic conditions. The utilization of an extensive time series enhances the robustness of the results. Furthermore, the study noted that SPEI's versatility allows for the identification and monitoring of conditions related to various types of droughts and their implications for global warming. In their study, Vicente-Serrano et al. (2010) concluded that SPEI fulfils the requirements of a drought index because of its multi-scalar characteristics that enable it to be used by different scientific disciplines to detect, monitor and analyse drought events.

SPEI weaknesses, as identified by WMO & GWP (2016), are that due to the need for a complete temperature and precipitation dataset, some areas with incomplete datasets may be limited in their use. In addition, they noted that since SPEI is a monthly Index, it might not quickly identify the occurrence of rapid drought events. During their study, Vicente-Serrano et al. (2010) concluded that while calculating SPEI, it is difficult to determine a suitable distribution to model the D series since the four distributions are almost similar in their methods.

2.5 Drought Modelling

Together with the drought indices, drought modelling helps identify drought characteristics (Mishra & Singh, 2011). The outputs of drought modelling are severity, probability of occurrence, drought onset and end and spatial-temporal extent. Several drought modelling methods are used for drought forecasting: statistical methods, dynamic and hybrid methods (Hao et al., 2018; Mishra & Singh, 2011). However, the statistical models have been mostly preferred for drought forecasting since they are simple to implement and produce useful predictions (Hao et al., 2018; A. K. Mishra & Desai, 2006; Mishra & Singh, 2011). These techniques have been used to forecast the DI values to represent future drought.

Statistical techniques utilize historical data's empirical connections, taking into account diverse influencing factors as predictors. These statistical models offer multiple approaches to examine the associations between the drought indices to be forecasted and a range of historical predictors. These approaches encompass time series models, artificial intelligence models, Markov Chain models, and log-linear models.

2.5.1 Drought Modelling Techniques

2.5.2 Time Series Model

The technique of time series modelling utilizes stochastic methods to represent drought occurrences. The main models are the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA). These models have been used to forecast drought events based on SPI. The ARIMA technique combines an Autoregressive (AR) represented by the order p and a Moving Average (MA) model of order q. The equation for the ARIMA model (p, q) for a given time series x_t is defined as Equation 2.29 and ε_t as Equation 2.30:

$$x_t = \varphi_i x_{t-1} + \cdots + \varphi_p x_{t-1} + \varepsilon_{tj} - \theta_j \varepsilon_{ti1} - \ldots - \theta_j \varepsilon_{t-q} \quad (2.29)$$

$$\varepsilon_t = \sum_{i-1}^{p} \varphi_i x_{t-i} + \varepsilon_t - \sum_{j-i}^{q} \theta_j \varepsilon_{t-j} \quad (2.30)$$

x_t is usually =0,1,2…

ε_t is the independent error variable

φ_i and φ_p are the coefficients of the AR model

θ_j and θ_q are coefficients for the MA model.

The ARIMA model works very well with the SPI and PDSI drought indices since they use a longer series of data (Mishra & Desai, 2006). The primary drawback of this approach is its failure to account for nonlinear characteristics, as it operates under the assumption of a linear relationship between the predictions and the predictors

(Khan et al., 2020). Also, the model relies on persistent indicators; therefore, all the other factors affecting the drought events are ignored (Patil et al., 2020).

2.5.3 Markov Chain Model

Markov Chains uses stochastic processes to characterize and forecast meteorological drought (Wambua, 2014). Drought forecasting is based on the transitional probability defined by the condition of a drought category Cn + 1 for a period n + 1 given the drought category Cn for the period n (Barua, 2010; Hao et al., 2018). The drought category Cn is expressed as Equation 2.31

$$M_{ij} = P(C_{n-1} \ \ = J | C_n = i) \qquad (2.31)$$

Where: M_{ij} is the number of transitions from category j to I at time n+1($C_{n-1} \ \ = J$ to n$C_n = i$)

The transitional probabilities, which is the element of a transition matrix M in the equation is achieved through the conditional frequency, Equation 2.32:

$$M_{ij} = \frac{M_{ij}}{M_i} \qquad (2.32)$$

Where: M_i ,is the total number of transitions from category i to other categories.

The transitional matrix M can forecast the drought transitions and future series based on the historical drought indicators.

The Markov Chain model has been used for drought forecasting based on the PDSI, SPI and Standard Hydrological Index (SHI) (Moreira et al., 2008; Paulo & Pereira, 2007; Sharma & Panu, 2012). For example, a study by Paulo & Pereira (2007) predicted drought occurrence using the Markov Chain and SPI for 1-3 months. A significant limitation of this modelling is that it offers users predicted wet, dry, or normal drought conditions and their probabilities of occurrence, but it doesn't predict reservoir inflow discharge (Rezaeianzadeh et al., 2016). Furthermore, although the model is straightforward for making predictions, it does not provide explaining events (Sharma & Panu, 2012).

2.5.4 Log-Linear Model

The log-linear model is applied to Poisson-distributed data, as it expands the linear model to accommodate the Poisson distribution function (Barua, 2010; R. Wambua et al., 2014). It serves as an extension of the two-dimensional contingency table, where the relationship between discrete and categorical variables is determined by taking the natural logarithm of frequency entries in the table. This contingency table, a matrix displaying the frequency of distribution variables known as response variables, is fundamental to log-linear modelling. Log liner models have been used by Moreira et al. (2008) to forecast drought in a catchment in Portugal using 12-month SPI data. In a study by Moreira et al. (2008), utilized log-linear models to predict drought in a Portuguese catchment using 12-month SPI data. However, Moreira's study concluded that the log-linear approach is unsuitable for long-term drought modelling but is appropriate for short-term drought monitoring, typically spanning 1-2 months.

2.5.5 Artificial Neural Networks

An Artificial Neural Network (ANN) is a machine learning model developed to process information in a structure similar to the human brain. It has been defined by Gao et al. (2016) as a mathematical model of biological neurons that mimics their historical patterns and identifies patterns and relationships between processes. ANN's functionality has progressed using improved calibration techniques (Barua, 2010). It has been used to solve several problems, including drought forecasting, predicting water consumption, and water management.

Comprising a network of interconnected basic processing units termed neurons, artificial neural networks are designed to mimic the structure of human brain neurons, organized into layers (Dastorani & Afkhami, 2011; Patil et al., 2020). Each neuron is linked to others in adjacent layers, rather than within the same layer. In biological terms, neurons receive signal input and generate a response output. In the human brain, these inputs and outputs manifest as electrical impulses traveling through channels. Input pulses traverse dendrites, which contain synapses facilitating signal transmission, while output pulses exit through an axon channel.

Like the human brain, the ANN model is designed to have a cell body, several input channels where the input signals are passed to the neuron and one output channel. Each channel has a connection weight that enables it to select significant input signals by their weight values. The cell body is related to the neuron by a special input signal called the bias weight, which activates the synapse that allows or stops the input signals from passing through to the cell. When the input is a non-zero value, it can pass through and stop if it's zero (Mishra & Singh, 2011).

In the model, a mathematical function that allows mapping between the input and output signal called the activation function, is used to generate the output by adding all the input signals, as shown in Equation 2.33:

$$y = f(I) = f(\textstyle\sum_i^p w_i x_i + b) \qquad (2.33)$$

where x_i is the input signal *i*

w_i is the weight attached to the input signal *i*

p is the number of input signals

b is the bias weight at the cell of the body

y is the output signal

f is the activation function

According to Barua (2010), several activation functions, such as the non-linear sigmoidal, hyperbolic tangent and linear activation functions, can be used for the neurons. Moreover, several studies (Maier et al., 2010; Mishra & Desai, 2006) have shown that these activation functions were successful.

The prediction model *Y* is as Equation 2.34:

$$Y = f(X, W) + ^{\varepsilon} \qquad (2.34)$$

Y = Vector of model outputs

X = Vector of model inputs

W = Vector of model parameters (connection weights)

f(•) = Functional relationship between model outputs, inputs and parameters

ε = Vector of model errors

ANNs are classified based on three aspects: Topography, learning procedure and flow of information (Mulualem & Liou, 2020; Shanmuganathan, 2016). Based on topography, ANN is classified as single or multiple layers. A single layer consists of one input layer linked directly to the output layer, while the multiple layers consist of several hidden layers between the input and output layers. In addition, the multiple-layer ANN can model more than one linear and non-linear function.

ANNs are classified into three groups based on the flow of information: feed-forward, recurrent and hybrid networks (Anshuka et al., 2019). The feed-forward is a one-way network where the signal moves from the input to the output layer. In the recurrent network, the signal and information can move in all directions, forward and backwards. Here, the output layer may reverse the output into an input or a hidden layer. The hybrid model uses different modelling methods to model the scenario.

ANN works through a learning process classified into three: supervised, unsupervised and reinforcement learning (Anshuka et al., 2019; Khan et al., 2020). In supervised ANN, there is training data consisting of either input or targeted output variables that ANN uses to learn the input-output relationship. The network will process the inputs and then compare them with the target outputs provided. In case of errors, they are propagated back through the system, adjusting the weights that control the network, ensuring the network is refined every time it is adjusted. A learning algorithm that uses the input data to create output data for the training data. Examples of the learning algorithms are Levernberg-Mrquardt (LM), backpropagation (BP), Conjugate gradient (CG), Perceptron, Multi-layer perceptron (MLP) and genetic algorithms. In unsupervised ANN, self-train, the network will only have input variables and will learn and recognize the patterns of the input data on its own. It does this through a competitive learning rule, creating a neural network with an input and competitive layer. Data is introduced in the input layer, and the competitive layer's neurons compete on the response to the input data features. The competition happens in a way that the input vector is compared with the weight vectors connected to the competitive layer. The weight vectors that match the input are considered the winning neuron. Reinforced ANN uses the trial-and-error technique where an agent can perceive a given state and perform certain actions, after which a numerical output is provided. Numerous algorithms are used to select actions to explore the environment and gradually build an approach that gives maximum output.

2.5.6 Drought Assessment and Forecasting Using ANN

ANN has been applied globally for prediction modelling. Dastorani & Afkhami (2011) applied ANN to predict drought in Yazd meteorological station in Turkey. The study used different architectures of artificial neural networks as well as various combinations of meteorological parameters including 3-year precipitation moving average, maximum temperatures, mean temperatures, relative humidity, mean wind speed, direction of prevalent wind and evaporation from 1966 to 2000, as inputs of the models. Hao et al. (2018) study employed ANN to forecast drought based on monthly SPI values in Sivas Province, a semi-arid region in China. Hao's study examined various drought characteristics, such as duration, amplitude, and intensity, in different time spans. Additionally, Oguzturk et al. (2016) concentrated on evaluating water resources in the Qaidam Basin, northwest China, where gauge data was scarce or absent. They utilized areal precipitation derived from remote sensing data, sparse gauge data, and a combination of both via machine learning, specifically employing an ANN model.

ANN has been successfully used to assess and forecast drought in many river basins in Kenya. For example, Agwata et al. (2014) modelled the Tana River basin hydrological drought. The study fitted five frequency distributions to drought severity and duration based on discharge data on gauge stations in the basin. The study showed that the Generalized Normal (GN) distribution is the best, while the Pearson type III distribution is the poorest for both severity and duration. Another example is a study by Kigumi (2014) in Naromoru Sub catchment. The study used earth-observed data, i.e. TRMM and ANN, to predict the hydrological drought occurrence in the area. The study used the Levernberg-Marquadt (LM), Backpropagation (BP) and CG training algorithms. It showed that the feed-forward neural network (FFNN) with LM training algorithm is the best model for SPI and SDI.

Mulualem et al. (2020) conducted a study focusing on the Upper Blue Nile basin (UBN) of Ethiopia, utilizing Artificial Neural Networks (ANNs) to forecast the Standardized Precipitation Evapotranspiration Index (SPEI). The study involved the development of seven ANN predictive models incorporating various hydro-meteorological, climate, sea surface temperature, and topographic attributes to predict SPEI for seven stations in the area. The findings indicated that integrating large-scale climate indices led to accurate predictions of SPEI values. The study concluded that ANNs offer an alternative framework for forecasting the SPEI drought index, showcasing promising statistical achievements. Patil et al. (2020) conducted a comparison between Autoregressive Integrated Moving Average (ARIMA) models and Artificial Neural Network (ANN) models to predict drought across various timescales (1, 3, 6, 9, and 12 months) with a lead time of up to 6 months. Patil’s study found that both ARIMA and ANN models exhibited strong forecasting capabilities for drought at different scales, particularly up to a 2-month lead time. Additionally, the ANN model outperformed the ARIMA models across all stations. However, ARIMA showed better performance in forecasting at higher timescales.

Based on studies by Kigumi (2014), Mishra & Singh (2011), Mulualem & Liou (2020), Patil et al. (2020) and Wambua et al. (2014), the ANN model has several advantages over other methods:

a) They can process information based on their dynamic response to external input.

b) Unlike other techniques, they can model all the relationships, including non-linear functions.

c) It is a suitable model to provide effective analytical techniques in modelling and forecasting drought.

d) They can model both dynamic and stochastic time series variables.

e) Since they work as a black box, they are suitable for modelling complex processes that use large and long-term data sets, such as drought prediction.

The advantages mentioned have led to the popularity of ANN in many applications, including drought forecasting by many researchers (Barros & Bowden, 2008; Maity & Kumar, 2008; Mishra et al., 2007; Morid et al., 2007; Mulualem & Liou, 2020; Patil et al., 2020, Wambua et al., 2014). The major disadvantage of ANN is its inability to generalize, as it cannot accurately detect the values outside its training datasets. However, this can be corrected by using the correct number of neurons in the hidden layer and a large data set encompassing all the likely data points.

2.6 Impacts of Drought

The assessment of drought events involves evaluating factors such as their frequency, severity, affected area, and their impacts on the economy, environment, and society, as outlined by Mutekwa (2016). These occurrences have detrimental effects on various aspects, including food security, livestock, crops, water resources, education, energy, forestry, wildlife, health, nutrition, peace, and security, as the National Drought Management Authority (NDMA) (2017) reported. The ripple effects start with reduced agricultural output, resulting in unemployment, asset loss, decreased income, worsened living conditions, food insecurity, and diminished coping abilities, thereby heightening the vulnerability of impoverished communities to other hazards and increasing the risk of political instability, as highlighted by United Nations

International Strategy for Disaster Reduction (UNISDR) (2014). Collectively, these impacts often lead to financial and economic challenges for agriculture and agriculture-based businesses (Mutekwa, 2016).

The global increase in water demand due to population growth and economic progress has led to water scarcity challenges, significantly affecting various sectors (Lotfirad et al., 2022). Climate change patterns have caused a rise in the frequency and severity of droughts worldwide, impacting regions disparately (Hoegh-Guldberg et al., 2018). According to Adhikari (2018), nations like India, possessing substantial drought-prone land, have encountered more frequent and prolonged droughts since the mid-1990s. These droughts carry extensive consequences, impacting not just crop production and income but also access to domestic water, rural employment, and financial stability (Huho et al., 2009; Kalele et al., 2021; Karanja, 2018). This underscores the broader socioeconomic repercussions of drought. Similarly, India and Africa confront rising instances of drought, adversely influencing agriculture, water resources, human well-being, and industries. The repercussions of these droughts extend beyond direct effects on crops and income, encompassing challenges related to domestic water availability, rural employment, and economic pressure.

According to Mutekwa (2016), drought and desertification severely threaten sustainable development in Africa by negatively affecting population health and security, food security, economic progress, infrastructure, the environment, and natural resources. The study shows examples of how Africa's population has been significantly impacted by drought, resulting in famine and the loss of more than 500,000 lives in devastating drought events within the Sahel and Horn of Africa. According to a World Bank (2021) report, approximately 70% of Kenya's natural disasters are attributed to drought and climate change. Furthermore, the agricultural sector, which accounts for 80% of total employment in the nation, encompassing both urban and rural areas, is highly susceptible to droughts and other disasters. Consequently, drought events have harmful consequences on the livelihoods of those dependent on this sector.

2.6.1 Socio-Economic impacts

The economic consequences of drought encompass detrimental impacts on business operations and income generation for individuals. According to Mutekwa (2016) droughts reduce production figures, causing farmers to downsize their labour force, which results in elevated unemployment rates. Beyond joblessness, economic losses manifest as diminished income and decreased agricultural output. The escalating global demand for water due to population growth and economic progress has triggered water scarcity issues, particularly affecting various sectors, as highlighted by Adhikari (2018). Climatic shifts have heightened the frequency and severity of droughts worldwide, affecting regions disparately, according to the IPCC (2021).

Notably, countries like India, with a significant portion of drought-prone land, have encountered more frequent and extended drought episodes since the mid-1990s, as evidenced by the research of Dodamani & Pathak (2018). These droughts have far-reaching consequences, impacting crop production and income, access to domestic water, rural employment, and financial stability. This highlights the broader socioeconomic implications of drought, as demonstrated by Alawsi et al., 2022; Moghimi et al. (2020). India and Africa are similarly grappling with escalating drought occurrences, adversely affecting sectors such as agriculture, water resources, human health, and industries (Adhikari, 2018; Karanja, 2018). These drought-related impacts extend beyond immediate effects on crops and income to encompass issues like domestic water supply, rural employment, financial strain, and impacts on agricultural industries, land prices, financial institutions, closures, capital shortages, and reduced agricultural production.

Hugo and Mugalavai (2010) examined the impact of drought in Laikipia County, located within the Upper Ewaso Ng'iro river basin. The study found that drought leads to inadequate planting, wilting, and stunted growth of crops, with some failing to thrive altogether. During periods of drought-induced food scarcity, farmers resort to consuming stored supplies, including seeds, resulting in delayed and improper planting practices. This exacerbates severe famine, hunger, and dependence on relief aid. Moreover, food scarcity prompts wildlife encroachment and crop destruction, escalating tensions between local communities and wildlife, as observed by Karanja (2018).

In arid & semi-arid lands (ASALs), livestock production constitutes a major socio-economic activity, contributing to approximately 90% of employment and income opportunities, according to Huho & Mugalavai (2010). Drought-induced scarcity of both forage and water leads to livestock losses and diminishes quality and quantity. This, in turn, has adverse effects on daily activities like farming and herding, compelling communities to seek alternative sources of income such as sand mining, selling firewood and charcoal, and engaging in illegal logging. These activities exacerbate environmental deterioration and the spread of deserts due to deforestation. Additionally, Karanja (2018) highlighted that families in arid regions frequently turn to selling their livestock to generate income during drought periods.

In Isiolo and Samburu Counties in Kenya, livestock migrate in search of water and pasture during droughts, negatively affecting their condition and market price. This leaves pastoralists without access to markets, leading to a loss of income options for domestic needs, including school fee payment, as highlighted by the European Union (EU) & NDMA (2018) and NDMA (2015). The social impacts of drought directly influence rural livelihoods, resulting in reduced rural populations, restricted access to education and healthcare, and internal conflicts driven primarily by food insecurity and reduced water supply, according to Mutekwa (2016).

Communities living in the ASALs, particularly in the affected regions, have been profoundly impacted by drought, as illustrated by the research of Wambua et al. (2014) and Odhiambo et al. (2018). The 2008-2009 drought event adversely affected the livelihoods of pastoralists and agro pastoralists, affecting their access to food and water. This impact was similarly observed in Isiolo and Samburu counties, as documented by Odhiambo et al. (2018), where the reliance on livestock agriculture led to a severe toll on cattle and sheep populations, with over 50% of cattle and 60% of sheep succumbing to the conditions. Some communities were forced to migrate from their homes in search of sustenance and pasture for their livestock, as noted by FEWSNET (2020). The distance livestock needed to travel for water and grazing also significantly increased, nearly doubling the distance in Marsabit County, according to Huho et al. (2009) World Food Program (2022). Additionally, the 2021/2022 drought in the Horn of Africa caused a significant drop in maize cultivation by around 50% in less productive farming regions, as reported by the World Food Program (WFP) (2022).

Drought in the Upper Ewaso Ng'iro Basin disrupts trade, leading to a 10% to 23% year-on-year decline in livestock prices, attributed to oversupply and worsening livestock conditions due to scarce resources in rangelands, as observed by Kirui et al. (2022) and Musi et al. (2023). Decreased livestock and cereal transactions occur alongside rising staple food prices, reducing purchasing power for households, as reported by FEWSNET (2020). Thisforces impoverished households to sell livestock unsustainably for food or face food shortages. Consequently, thousands of people rely on relief aid, prompting mass migration from drought-affected homes to neighbouring towns and countries, leading to both intra- and inter-community conflicts, as highlighted by Hoffmann (2022); Lanari et al. (2018) and Lesrima et al. (2021).

In Isiolo County, severe droughts have caused children from vulnerable households to drop out of school due to lack of food and school fees, disrupting education and affecting access, equity, and retention, according to Assessment Capacities Project (ACAPS) (2022) and NDMA (2015). Furthermore, the well-being of individuals is affected, and social interactions within communities are disrupted. Mutekwa (2016) explains that people often experience stress and anxiety due to uncertainties about when the drought will end and how to mitigate its impacts. The likelihood of health consequences arising from drought varies significantly, primarily depending on drought severity, population susceptibility, pre-existing health and sanitation infrastructure, and the available resources to manage the unfolding effects.

The Centers for Disease Control and Prevention (CDC) (2012) indicates that specific health impacts related to drought become evident immediately and are easily observable and measurable. However, drought's gradual onset or prolonged duration can also lead to more complex, secondary health outcomes that are difficult to predict or manage. Stanke et al. (2013) identify several main categories of health effects resulting from drought, including nutrition-related effects like general malnutrition and micronutrient deficiencies. They also identify water-related diseases such as E. coli and cholera outbreaks and ailments linked to airborne particles and dust, like exposure to silo gas and coccidioidomycosis. Additionally, they note vector-borne diseases like malaria, dengue, and West Nile Virus, along with the impact on mental well-being, leading to feelings of distress and emotional consequences.

In Kenya's ASALs, the health consequences of drought are of notable significance. Research by organizations such as the NDMA (2021), United Nations Children's Fund (UNICEF) (2022) and United Nations Office for the Coordination of Humanitarian Affairs (OCHA) (2023) reveals that as drought severity intensifies, fewer individuals seek healthcare services from established health centres due to security concerns and the necessity to migrate in search of water and grazing grounds. This situation underscores the need for mobile health outreach initiatives to address malnutrition and disease outbreaks.

2.6.2 Environmental Impacts

Drought significantly impacts the environment by degrading soil quality, desiccating water bodies, and accelerating the process of desertification. Mutekwa (2016) and Vicente-Serrano et al. (2020) state that droughts reduce soil quality, diminishing organic activity, escalating wind erosion, and disrupting soil life. This phenomenon also results in habitat destruction, ecosystem disruption, and disturbances in the food chain. Consequently, animals are compelled to migrate to new areas for water, sustenance, and suitable habitats, as the World Food Program (2022) notes. Kenya's tourism industry, a major foreign exchange earner, is adversely affected by reduced biodiversity in areas like the Upper Ewaso Ng'iro Basin, which houses wildlife attractions (Mukhwana, 2016). There are also instances of heightened fire occurrences, soil erosion, and infrastructure destruction in specific regions due to drought events, as highlighted by Karanja (2018). The recurrent droughts have led to the intrusion of plant species incompatible with the native perennial grasses in certain areas (Huho et al., 2009).

Drought events have taken a toll on river basins in Kenya, resulting in acute water scarcity (Wambua et al., 2014). Over time, there has been a reduction in the water volume of the Ewaso Ng'iro River, causing segments like Buffalo Springs to desiccate (Bern & Notter, 2003; Gichuki, 2006). In the highland areas of the Upper Ewaso Ng'iro River Basin, there has been an increase in horticultural farming activity (Lanari et al., 2018). Due to decreased rainfall, farmers have initiated irrigation practices using river water. However, this practice has resulted in excessive water extraction from the river during dry periods, leading to conflicts between upstream and downstream users (Bern & Notter, 2003; Gichuki, 2006; Lanari et al., 2018; Mukhwana, 2016).

Human activities have contributed to reduced river streamflow through water withdrawals, but the amplified occurrence of floods and droughts due to climate change is predicted to compound the risks (Omwoyo et al., 2017). For instance, prolonged droughts in the Ewaso Ng'iro basin, like the one in 2008-2009, led to the depletion of water supply sources such as rivers and shallow wells, intensifying the impact of water scarcity and resulting in significant economic, social, and environmental losses. This insight is supported by studies conducted by Kimwatu et al. (2021b) and Odhiambo et al. (2018). Additionally, Odhiambo's study highlights that both surface and groundwater sources, including river intakes and shallow wells, have limited water resources that are only sufficient to sustain one dry season.

2.7 Adaptation to Drought

According to Yung et al. (2015) drought adaptation can be characterized as the capacity of a system to respond to climate change, encompassing climate variability and extreme events like drought. This response involves mitigating potential harm, capitalizing on favourable circumstances, or effectively managing the repercussions. This endeavour can be driven by either public or private interests, with governmental bodies across various levels overseeing public interests and private interests encompassing individuals, households, businesses, and corporations (Smit & Pilifosova, 2003).

Adaptive capacity, as outlined by Meybeck et al. (2012), is a dynamic concept denoting a system's ability to adjust, thus lessening vulnerability. It consists of two dimensions: the ability to manage shocks and the capability to evolve. This capacity is moulded by a complex interplay of environmental, social, cultural, political, and economic factors, which shape vulnerability through exposure and sensitivity. Adhikari, (2018) underscores the significance of adaptation in safeguarding livelihoods and food security in numerous developing nations. The study also contends that adaptation strategies, predominantly short-term endeavours, can be expanded into longer-term approaches, allowing systems to diminish risks and social vulnerability.

2.7.1 Strategies for Adapting to Drought

Various households employ distinct strategies to adapt to drought, influenced by their perceptions of drought's nature. According to (Kalele et al., 2021; Karanja, 2018), rural communities possess diverse viewpoints on drought, guiding their individual and local adaptation strategies. This implies that comprehending people's perceptions and concerns about extreme weather events is pivotal for designing and executing effective climate adaptation policies. Drought events are intricate for individuals, making understanding these perceptions crucial for effective drought adaptation.

In many African regions, farmers adapt to drought by changing their farming practices to withstand hot and warm climates (Gautier et al., 2016; Kalele et al., 2021). They would plant crops that require less water or are drought resistant, irrigation, change crop patterns and varieties, select different seeds, change planting calendars, plant near the river, and adopt soil and water conservation practices (Gautier et al., 2016; Mutekwa, 2016). Karanja (2018) asserts that commercial farmers have a higher advantage during drought than subsistence and small-scale farmers because they mostly have strong financial backups and good infrastructure. Some small-scale farmers will sell their products at the local shops at a much cheaper price. The study also cites that some livestock farmers and pastoralists sell their animals, buy fodder, feed the animals with crops that would have been sold and a combination of these mechanisms. Some pastoralists would sell the animals to reduce their herd size to buy fodder and generally compensate for the reduced income and save resources.

According to Mutekwa (2016) and Noble et al. (2015), people migrate from communal areas to urban areas to look for better livelihoods in dry areas. This reduces their risks of drought effects since they might get jobs in the new locations and send money back home. Other pastoralists also migrate with their herds in search of pasture and would remain there for as long as the drought lasts. As established by Mutekwa, (2016) and Olabanji et al. (2021), in some parts of South Africa, some pastoralists divide their herds into smaller units depending on the quality of the herds and the herders. Young herders would go to relatives and friends to request grazing fields. The studies also state that other pastoralists will reduce the number of people who depend on livestock for food. Women and children might be sent away to live with relatives and allies in towns and farming villages. This enables the herders to migrate further, save the milk for calves and generate money for food. Some nomads will take wage employment temporarily as they wait for rains to restore pastures so they can go back to pastoralism. During the 2005-2006 drought and famine in Kenya, herders formed corporate groups and put their livestock under the care of some selected herders (Huho & Mugalavai, 2010). This enabled them to move in search of food and other income-generating activities.

Mutekwa (2016) established that some households in rural communities in Zimbabwe had to reduce the quantity and number of meals during drought; most people would have two meals in a day to allow their food to last longer and to avoid expenditures on food. Also, in the Sahel region, as studied by Gautier et al. (2016), in addition to reducing consumption, most families used to buy and stock food in preparation. Furthermore, some studies (Kalele et al., 2021; Karanja, 2018; Olabanji et al., 2021) add that some farmers opt to practice crafting as a way of earning extra income; they would sell these products to tourists on the road and in towns. Some farmers also started harvesting indigenous and wild species like marula in Zimbabwe, wild yams and tree leaves in Burkina Faso.

Administration and institutions also play an important role in adaptation mechanisms in dry lands during drought (Udmale et al., 2014). For example, the studies mention that the government provides the communities with relief measures like food, water supply through tankers, agricultural loans, crop insurances and wave agricultural electrical bills in India. Based on Karanja (2018) study, Institutions like churches in the Laikipia West sub-county have created strategies that help the communities adapt to the impacts of climate change. They provide trainings that promote civic education, conflict resolution and democracy in areas affected by conflicts due to drought. They also provide food, shelter, and clothing to the victims of conflict and drought.

Through the National Climate Change Response Strategies (NCCRS, 2010), the government of Kenya has developed some adaptation strategies for vulnerable communities. The strategies have promoted irrigated agriculture by developing irrigation schemes along river basins, setting up measures to institutionalize early warning systems on drought, flood and disease outbreaks, and investing in programs to harvest and store fodder during dry seasons. Additionally, the Ministry of Agriculture, (2016) has promoted economic diversification among pastoral communities and awareness campaigns among the pastoralist communities on the importance of balancing stocking rates with available land resources to ensure sustainable pastoralism.

Rural communities in the parts of Upper Ewaso Ng'iro North River Basin have already perceived drought impacts in their areas and have applied a range of possible agricultural and non-agricultural adaptation measures based on their indigenous knowledge and experience (Gichuki, 2006; Huho et al., 2010; Lanari et al., 2018). They have used the available resources in the community and at the ecosystem level to design the adaptation strategies.

Adaptation efforts in the UENB involve the utilization of diverse knowledge sources, both traditional and contemporary, by both group ranches and individual members. Innovations like grazing committees and rangeland management coordinators build upon traditional rangeland management systems (Birch, 2018). An evolution from the earlier group ranches model to the adoption of conservancy models indicates progress, with most communities exploring and embracing a holistic management approach. These adaptation strategies are integrated into the system through various mechanisms, although their levels of adoption and implementation may vary.

According to The Kenya Ministry of Agriculture, (2016), county governments are enhancing livestock breeds as an adaptation strategy to climate-induced risks. Introducing breeds that require less feed and are disease-resistant addresses forage scarcity linked to climatic changes (Birch, 2018; Ontiri & Robinson, 2016). The introduction of dairy goats has also gained traction due to their efficient feed utilization. Complimentary vaccines are distributed among farmers to enhance livestock resilience against climate-related challenges. The Ministry of Agriculture shows that to combat forage shortages, some county governments are promoting commercial fodder cultivation and feed conservation. They are providing equipment like balers, rakes, and mowers at affordable rates to support hay production. Additionally, hay is being transformed into silage for longer storage and a more reliable fodder supply.

Crop farmers in the UENB primarily depend on agriculture for their livelihoods (Koech et al., 2020; Lanari et al., 2018; Ngigi et al., 2007). In response to climate change challenges, they are transitioning towards cultivating short-maturity crop varieties like sorghum, cowpeas, and green grams to maximize yields with reduced rainfall (Muthee, 2014; The Kenya Ministry of Agriculture, 2016). There's also diversification in dietary and crop choices, including previously underrepresented crops like cassava, sweet potatoes, and yams (Ministry of Agriculture, 2016). Additionally, farmers are embracing high-value traditional crops like sorghum, millet, cowpeas, pigeon peas, and green grams to reduce their reliance on maize as a staple, given these crops' shorter growth cycles and resilience to water stress. Despite this, the uncertain rainfall patterns associated with rain-fed agriculture have prompted a greater reliance on irrigation for sustainable production (Muthee, 2014) and innovative methods such as drip irrigation, water harvesting, and large water tanks. There's also a growing interest in greenhouses and hydroponic farming, offering controlled environments requiring minimal water. Farmers also adopt various practices to conserve soil and water resources, including minimum tillage, mulching, cover cropping, terracing, and herbicide-based weed control (The Kenya Ministry of Agriculture, 2016). Integrated soil and water conservation measures are emphasized, enhancing soil fertility and reducing runoff. Tree planting and woodlot establishment are common practices, and collaboration with the Kenya Forest Service has created Community Forest Associations (CFA). Farmers participate in tree planting on farms and nearby forests, contributing to diversified income sources and bolstering overall resilience against adverse weather impacts.

Collective efforts among farmers have resulted in cooperatives tailored to various value chains. These cooperatives offer services at reduced rates due to economies of scale, extending credit facilities and improving market access for members' produce. These structures function as safety nets and enhance overall adaptive capacity. Farmers can secure essential resources like seeds and fertilizers through collective action, especially during environmental hazards. While insurance options exist to mitigate climate-related risks, their adoption remains limited, with only 1% of households enrolled in agricultural insurance (GoK, 2014). Migration, both internal and international, shapes individual and societal adaptation. Well-managed migration can enhance resilience through diversified livelihoods, remittances, and expanded networks (Gannon et al., 2020).

2.7.2 Challenges and Opportunities for Adapting to Drought

The communities in the UENB are confronted with a spectrum of adaptation-related challenges. These challenges include inadequate pasture availability, water shortages, rangeland degradation, security concerns, competition for land use, conversion of land for agricultural purposes, and conflicts arising from neighbouring groups engaging in cattle theft (Ontiri & Robinson, 2016). The study found three main interconnected challenges: the scarcity of water for livestock, rangeland degradation leading to pasture shortages, and conflicts emerging from disputes over access to remote grazing lands. Such disputes often escalate into violence and threaten security, particularly in regions spanning county borders and inhabited by diverse ethnic groups (Lanari et al., 2018).

The degradation of rangelands is often attributed to practices of overstocking and overgrazing (Birch, 2018). Within the pastoral context, the ownership of substantial livestock herds serves as a coping mechanism during crises and a symbol of social status. Wealthier livestock proprietors tend to manage extensive herds, which, when coupled with insufficient mobility management, can lead to unsustainable grazing patterns and subsequent land degradation (Ontiri & Robinson, 2016). Such degraded land becomes susceptible to erosion during rainfall, causing gully erosion. Additionally, inadequate intervals between grazing events hinder the natural re-seeding of rangelands. Furthermore, the influx of migrants from neighbouring counties seeking land for agricultural pursuits compounds the issue of diminishing grazing land. Land subdivisions and the erection of fences further exacerbate this influx.

Numerous instances have shown that efforts to adapt to changing conditions are predominantly focused on local, regional, or national scales rather than on a global level, as discussed by Paavola and Adger in 2005. This emphasis on localized efforts leads to varying levels of vulnerability and capacity among communities, resulting in diverse impacts and adaptation requirements. As a result, adaptation initiatives often lack cohesion, spanning individual households, businesses, and organizations. Nonetheless, collaborative endeavours across different tiers also exist, as highlighted by Paavola and Adger (Gannon et al., 2020).

Multiple obstacles impede effective adaptation efforts, falling into distinct yet interconnected categories (Adhikari, 2018). Ecological and physical limitations encompass natural barriers that adaptation encounters, such as altitude, temperature, or thresholds for water availability. Human and information-based constraints arise due to gaps in knowledge, technological restrictions, and financial limitations, including policymakers' insufficient awareness of climate impacts. Social barriers encompass a range of factors, including cognitive and normative influences and institutional obstacles (Gannon et al., 2020).

Policymakers often misconceive the scope of adaptation, viewing it as separate from practical implementation (Meybeck et al., 2012). Integrating climate adaptation into development and adopting a technology-driven perspective becomes essential to reduce vulnerability and ensure resilient progress. Cultural barriers can also impede adaptation efforts, as strong attachments to specific locations create resistance to relocation. The changing socioeconomic landscape due to climate impacts has led to shifts in gender roles, particularly in rural contexts. With an increase in male outmigration, women shoulder the responsibilities of managing farmland, adapting to climate change, integrating into social networks, and handling household chores. Despite adding complexity, these challenges have improved women's societal decision-making roles (Huyer et al., 2021).

In climate adaptation, planning and executing strategies involve complex decision-making across individual, business, and governmental domains at various scales, ranging from local to international (Adhikari, 2018). Nevertheless, these strategies must account for various sectors such as irrigation, forestry, and livestock, necessitating interdisciplinary collaborations involving local organizations, farmers, and stakeholders. Successful adaptation planning requires coordination among institutions, but insufficient collaboration remains a concern. Integrating local knowledge into policies is crucial for effective planning. Collaborative partnerships between institutions are crucial for harmonizing adaptation efforts. Existing institutional structures and market mechanisms must be considered during adaptation planning—the success of adaptation hinges on addressing the underlying causes of vulnerabilities. Measures include providing financial assistance for agricultural adaptation, promoting off-farm employment, integrating adaptation into development plans, and enhancing access to information and training.

2.8 Research Gap

In summary, this chapter has thoroughly examined existing literature related to drought characteristics, assessment methods, droughts' impact on rural community livelihoods, and the strategies these communities employ to adapt. The review has confirmed that utilising the Standardized Precipitation Index (SPI) and the Standardized Precipitation-Evapotranspiration Index (SPEI) offers a viable approach to assessing African drought scenarios. Furthermore, it has been observed that

Artificial Neural Network (ANN) models present suitable alternatives to traditional regression models. Notably, no previous study has explored the application of SPI, SPEI, and the performance of ANN models in predicting these indices specifically for the Upper Ewaso Ng'iro North River Basin. Nevertheless, research by Mutiga et al. (2011) and Wambua et al. (2014) suggests that ANN models can effectively monitor and predict droughts in Kenya. The analysed literature also underscores the absence of comprehensive research examining meteorological drought monitoring across all Upper Ewaso Ng'iro North River Basin regions, particularly considering the diverse climatic zones within the basin.

While the reviewed studies have concentrated on the consequences of and adaptations to drought events in various locations, a comprehensive assessment of the entire Upper Ewaso Ng'iro North River Basin has not been done. Consequently, this study primarily centred on characterizing drought occurrences in this region while considering the varying climatic zones within the basin. Furthermore, the study identified the impacts of these droughts on rural community livelihoods and their adaptation strategies comparing both upstream and downstream effects.

2.9 Conceptual Framework

Figure 2.1 presents a conceptual framework of the study. It illustrates the interaction between drought events, drought modelling, effects of droughts, and drought adaptation strategies.

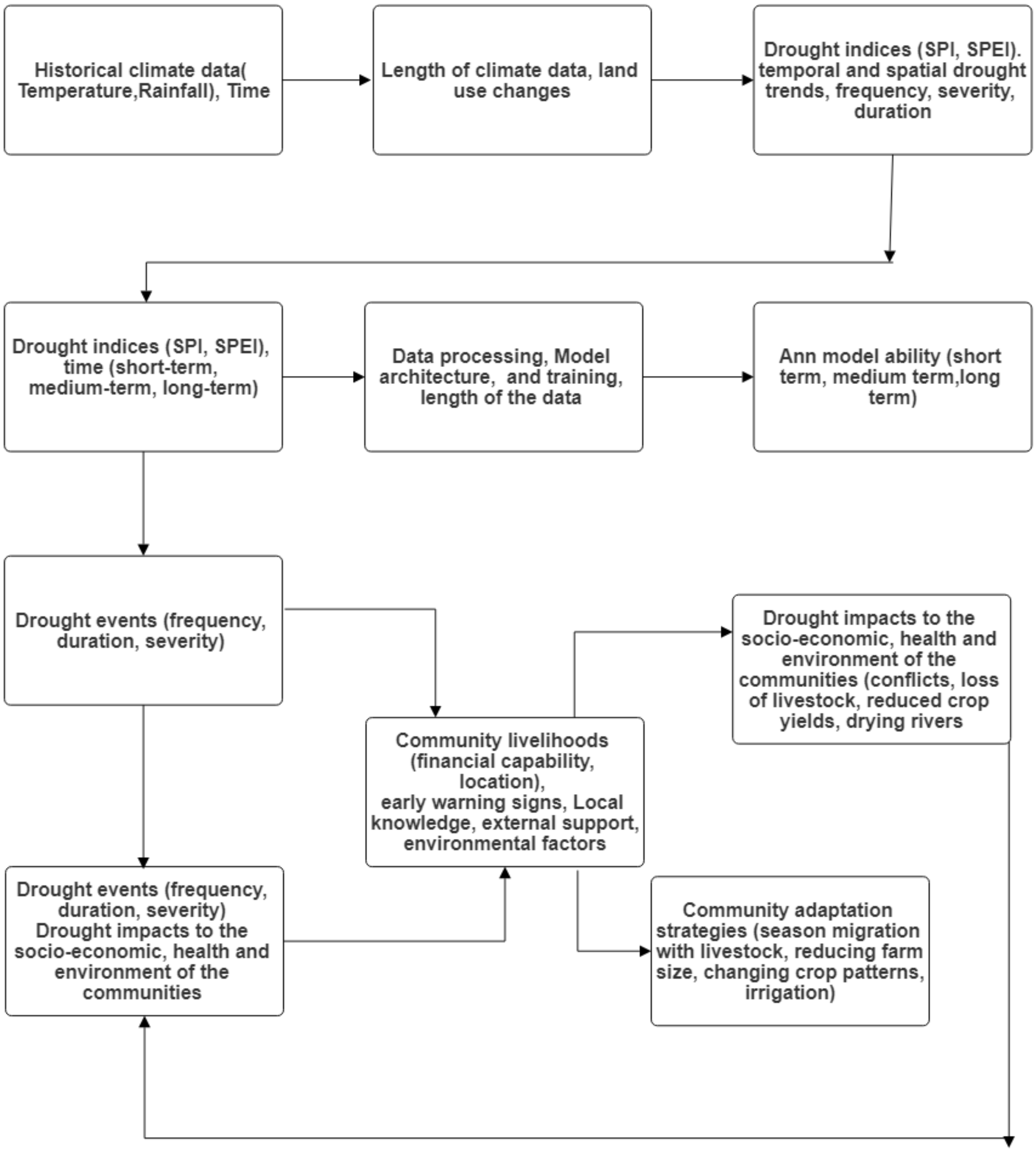

Figure 2.1: Conceptual Framework

CHAPTER THREE

MATERIALS AND METHODS

3.1 Study Area

The Upper Ewaso Ng'iro North River, covering an area of 15,251 km^2 is located between 0°15' south and 1°00' north, and 36°30' east and 37°45' east. This region is situated on the leeward side of Mount Kenya and the Aberdare's (Nyandarua) Ranges. The basin's diverse topography results in varying climatic zones due to altitudes ranging from 824 meters above sea level in the lowlands to 5,172 meters at the mountain's peak (Figure 3.1).

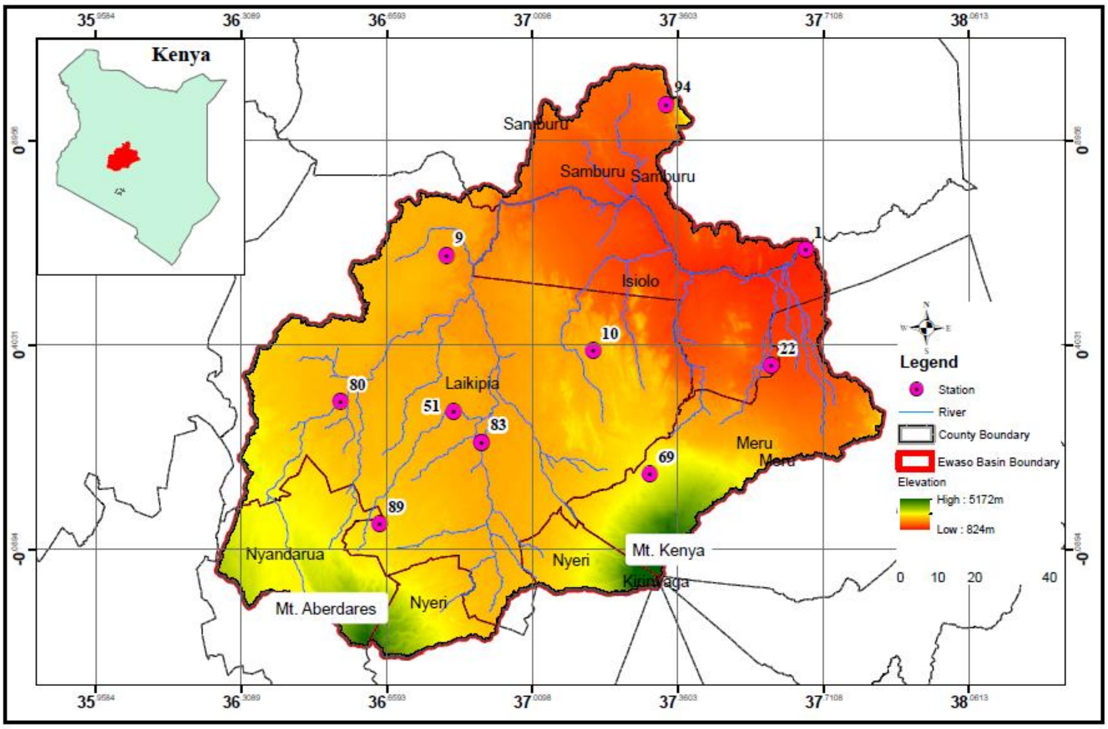

Figure 3.1: Location of the Upper Ewaso Ng'iro River Basin and the Meteorological Stations

This area exhibits a wide range of tropical highland-lowland characteristics, transitioning from the Alpine zone at the source of the Ewaso Ng'iro River in the Nyandarua Ranges and on Mount Kenya's slopes. The middle region is characterized by forested areas, woodlands, and bush vegetation. The transition extends further to a sub-humid zone in the lowland semi-arid plateau and eventually to arid plains (Kiteme, 2020).

The upper parts of the catchment experience annual temperatures ranging from 9°C to 22°C, while the lower parts range between 15°C to 29°C. The annual potential evapotranspiration (PET) in the basin varies from 1200 to 1800 mm/year. The basin exhibits spatial and temporal variations in annual rainfall, with values ranging from 300 mm in the northeast areas to 1500 mm at the source in the Nyandarua ranges (Ericksen et al., 2012). The rainfall pattern in the region is characterized by three distinct seasons, including long rains from April to June, short rains in October and December, and a brief rainfall season in August.

various traditional pastoral communities such as the Borana, Mukogodo, Maasai, Turkana, Samburu, Gabra, and Rendille residing in the lowlands. Additionally, the highlands are inhabited by the Kikuyu, Meru, and Europeans. As of 2019, the population of the basin was estimated to be around 334,405 individuals (KNBS, 2019a; Wamucii et al., 2023).

The primary land uses within the basin include livestock rearing, agriculture, and wildlife and forestry. Pastoralism is mostly practised in the drier lowlands while livestock ranches and agriculture are practised in the high rainfall areas around Mt Kenya and the Nyandarua Ranges. The Ranches are managed by commercial enterprises together with smallholder farmers and commercial agriculture enterprises oversee (Omwoyo et al., 2017). Agriculture in the basing includes commercial horticulture, floriculture and wheat farming alongside subsistence farming. Both government and private wildlife conservancies are responsible for wildlife and forest conservation efforts in the area.

3.2 Assessment of Drought Trends

3.2.1Collection Rainfall and Temperature Data

Monthly Rainfall and temperature data spanning the years 1981 to 2020 were acquired from ten meteorological stations. These data sources included the Kenya

Meteorological Department (KMD) and the Centre for Training and Integrated Research in ASAL Development (CETRAD). The stations, as designated by CETRAD, are shown in Figure 3.1, and listed in Table A1.

3.2.2 Data Cleaning

Missing data poses a significant obstacle to conducting trustworthy statistical analyses. Therefore, before computing the indices, the data underwent a thorough examination to identify any missing values, followed by a data reconstruction process. To achieve this, a comparison was made between the data from the stations and data from neighbouring stations, along with satellite data obtained from NASA's Langley Research Centre (LaRC) Prediction of Worldwide Energy Resource (POWER). The computations to handle missing data were performed in the R environment using the Multiple Imputation Chained Equations (MICE) technique implemented through the MICE package.

3.2.3 Standard Precipitation Index Analysis

Average monthly rainfall data from 1981-2020 were employed for the computation of the Standardized Precipitation Index (SPI). To calculate the SPI, a 40-year aggregated monthly rainfall data series was fitted into the Gamma probability distribution function and subsequent conversion into a normal distribution function, following the methodology outlined by Dalezios (2014).

The rationale behind selecting the gamma probability distribution function was supported by its capacity to accommodate both positive and non-zero values, as highlighted by Khan et al. (2020). Initially, the SPEI library in R was utilized to calculate the SPI indices. Various distributions, including Gamma and Pearson III, were initially tested in R to compare their functionalities and identify the most suitable distribution. Subsequently, the results were juxtaposed to determine the distribution that exhibited the best fit to the raw precipitation data. Additionally, sensitivity analysis was conducted using Excel to explore the impact of changes in distribution parameters on the outcomes. It was found that Gamma distributions outperformed the Pearson III distribution in fitting the precipitation data. This finding aligns with the conclusion drawn by Vergni et al. (2017) , who observed that the two-parameter gamma distribution yielded less reliable estimates of precipitation probability compared to Pearson type III and generalized normal distributions.

Based on Equation 2.7, computation of the 3-, 6-, and 12-month SPI values for this study was facilitated through the SPI packages available via the Comprehensive R Archive Network. In this analysis, a drought event is identified when the SPI value consistently remains negative. Conversely, the conclusion of a drought event is indicated when the SPI value turns positive, as discussed by Mishra and Singh(2010) and Khan et al. (2020). Table 2.2 shows the classification of drought based on SPI.

3.2.4 Standard Precipitation Evapotranspiration Index Analysis

Input parameters encompassed a comprehensive 40-year dataset of monthly precipitation alongside maximum and minimum temperature records. In the computation of the SPEI, the first step involved calculation of Potential Evapotranspiration (PET). Nevertheless, determining PET presents several complexities as it relies on a range of variables, including surface temperature, air humidity, incoming soil radiation, water vapor pressure, and ground-atmosphere latent and sensible heat fluxes. Various methods exist for PET calculation, contingent upon the accessibility of meteorological data. In this study, the Thornthwaite method, as introduced by Thornthwaite (1948), which relies on monthly mean temperature, was employed.

Negative values of the SPEI denoted drought conditions, while positive values indicated wetter or above-average conditions, as outlined in Table 2.2. The computation of SPEI values for all meteorological stations across 3-, 6-, and 12-month time scales was executed using Equation 27, leveraging the SPEI packages accessible through the Comprehensive R Archive Network.

3.2.5 Spatial Analysis of SPI and SPEI

Geographic Information Systems (GIS) was utilized to generate isopleth maps. To estimate SPI and SPEI values across the UENB, data from all ten monitoring stations underwent interpolation using the kriging interpolation method implemented in the Surfer Mapping Software. In kriging, a predefined radius was used to fit the weights of the ten known station points into a function, thereby deriving the output values for each station.

3.2.6 The Mann–Kendall Trend Test Method

To analyse drought trends based on SPI and SPEI characteristics, the Mann-Kendall (M-K) trend test was applied, alongside Sen's Slope (SS) estimator. The M-K trend test, recommended by the WMO for investigating trends in hydrological and meteorological variables was employed. Utilizing the formula provided by Khan et al. (2020), Pei et al. (2020), and Mehta and Yadav (2022), the Modified M-K (MMK) trend test package in the R programming language was utilized to assess drought trends across the ten stations within the study area. A significance level of 95% and a p-value of ≤ 0.05 were applied in this evaluation. In this context, positive SS values indicated an increasing trend, signifying a rise in wet conditions, while negative values denoted a decreasing trend, indicating an increase in dry conditions.

3.2.7 Assessment of the Linear Relationship Between SPI and SPEI

The Pearson correlation coefficient (r) is a statistical measure that helps us understand how two variables are related. It gives us a number between -1 (meaning a perfect negative relationship) and 1 (representing a perfect positive relationship), with 0 suggesting that there's no significant correlation between the variables. This coefficient provides insights into the strength and direction of the relationship between two variables (Mehr et al., 2020). In this study, the Statistical Package for the Social Sciences (SPSS) was employed to compute the coefficient and assess the SPI/SPEI relationship.

3.3.1 Artificial Neural Network Model Data Sources

SPI and SPEI were used as inputs for the ANN. Drought events were predicted based on drought indices on a range of short three months, medium six months, and long-term 12 months.

3.3 Drought Forecasting

3.3.2 Artificial Neural Network Model Development

To model the drought using the DIs, time-series data was partitioned into short three months, medium six months, and long-term 12 months (Figure 3.2). A dataset was prepared for each case involving the inputs and the corresponding output. The workflow of neural network design is summarised in Figure 3.2, 7 key stages including: 1) Collect data; 2) Create the network; 3) Configure the network; 4) Initialise the weights and biases; 5) Train the network; 6) Validate the network (post-training data); 7) Use the network.

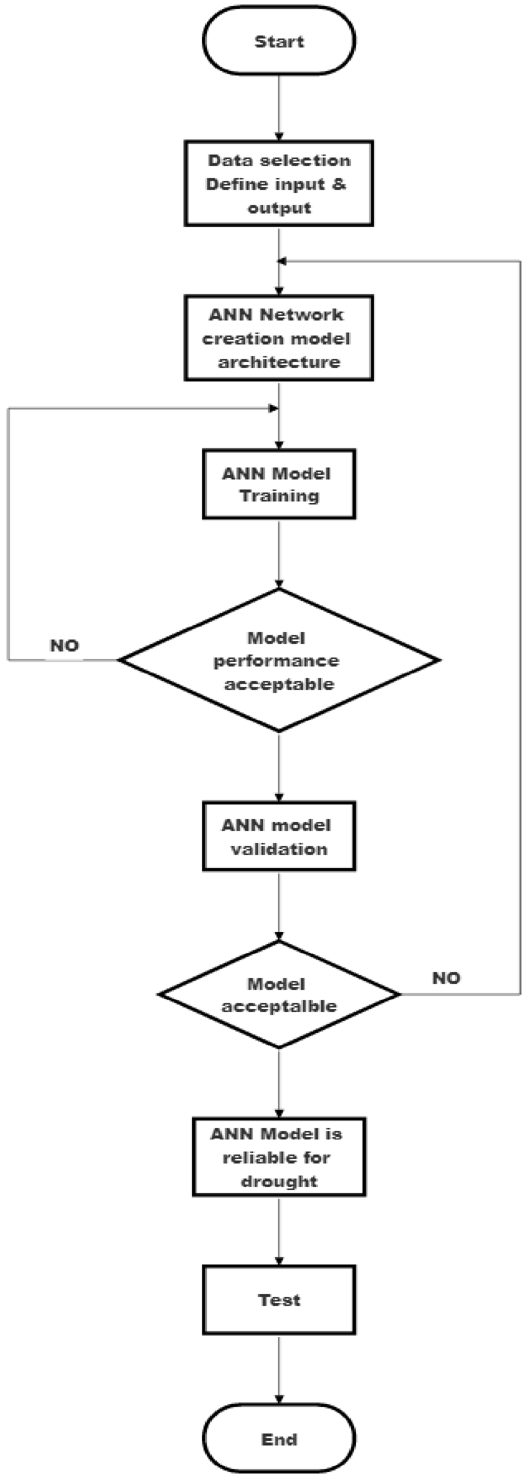

Figure 3.2: ANN Model Development Process

The SPI and SPEI data values for the different stations in the UENB were used to model the ANN program in the Matrices Laboratory (MATLAB). The first step, ANN network selection, involved creating and configuring the network. The feed-forward MATLAB function was used to create the network. The number of input neurons in the input layer and the number of hidden neurons in the hidden layer, equal to 2n+1, were selected. The data were then pre-processed and divided into three groups for training, testing and validating the model. Using the MATLAB divider and function, the data were randomly divided into groups for training, validating and testing on a ratio of 0.7: 0.15: 0.15. To configure the network, the inputs were identified, and the weights and biases were initialised. Figure 3.3 shows a basic multilayer ANN with 12 neurons in the hidden layer that was used in the study in MATLAB.

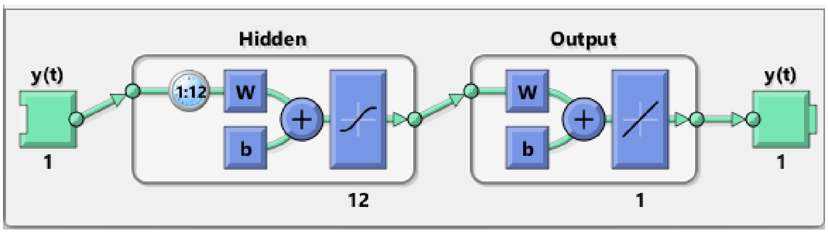

Figure 3.3: Basic Multilayer ANN

After initialisation, the network was then trained using the Levenberg-Marquardt training algorithm. The model training process involved adjusting the network parameters, i.e. the weights and biases, to optimise the network's performance. The validation dataset was used to validate the performance of the calibrated model and to check if the model outputs compare well with the desired targets. During this process, the error on the validation set was monitored, and at minimum error, the weights and biases were saved. After training, the test dataset was then used to test the model's performance. Mean square error (MSE) was used as the performance indicator. The MSE was monitored during the training session using the validation dataset; training stops when the value is the minimum and there is no further reduction.

By employing a trial-and-error approach, the quantity of hidden neurons was modified by either incrementing or decrementing it by a value of one relative to the previous quantity. The best ANN was selected by picking the model architecture with the best efficiency in forecasting the indices. This process was repeated for all the meteorological stations and different drought indices.

The three stages are plotted in curves and examined to evaluate the model's performance after the training. For training to be successful and sufficient, the testing and validation curves should have minimal differences (R. Wambua et al., 2014). According to Beale, Hagan, & Demuth (2014), the curves detect issues like overfitting and underfitting errors that might result from memorising the training examples by the network. The network fails to learn how to generalise new situations; thus, the training error becomes small, but with a new dataset, the error becomes large. This error was resolved by adjusting the number of hidden neurons and stopping training after validation when the MSE did not show any changes. This study adopted the ANN with the least MSE as the most efficient model. The other factor considered in the study was the regression coefficient. The Coefficient indicated the strength of the relationship between the output and the target. The closer the R-value to 1, the stronger the relationship, thus the better the model (Beale et al., 2014). Another model assessment plot is the model training performance curve. This indicated the reduction rate of MSE for the training, validation and testing datasets. If the training and validation curves have no significant differences, the model is regarded as well-trained and unlikely to suffer from overfitting.

3.4 Assessing the Impacts of Drought on the Livelihoods of Communities

3.4.1 Data Sources for Drought Assessment

Primary data on farmers' livelihoods and their strategies for adaptation were gathered through surveys and interviews with key informants. Additional secondary data was obtained from reviewing published literature such as books, reports and journals on drought modelling and livelihoods, impacts of drought and adaptation strategies. This was used to supplement the primary data collected.

3.4.2 Data Collection for Drought Assessment

Semi-structured questionnaires were used to collect data on farmers and their drought adaptation strategies. The semi-structured questionnaires focused on the effects of drought on the livelihoods and their adaptation strategies during drought events. Interviews with key informants selected based on their ability to inform study objectives were held. A standard interview guide was prepared before the interviews.

3.4.3 Sampling Procedure and Sample Size

A stratified random sampling survey acquired the population group of 58 individuals. The criteria for stratification were based on the economic activity in relation to agriculture. The population was first divided into two or more groups; for this study, the groups were the pastoralists, small-scale farmers and commercial farmers. The sub-groups identified were the people vulnerable to drought impacts. This method aimed to obtain the representation from the various subgroups in the basin. According to Mugenda & Mugenda (2003), the individuals should be selected so that the subgroups in the population are more or less reproduced in the sample, which means that the population sample should be made up of not less than two subgroups.

To determine the required sample size, Slovin's formula was used. It is an approach based on precision rate and confidence level. The sample size was calculated using Equation 3.1, assuming the population is too large to sample every member.

$$n = \frac{z^2pqN}{e^2(N-1)+z^2pq} \tag{3.1}$$

Where ***n*** is the size of the sample

N is the actual population (See table 3.1)

P is the sample proportion (assumed 0.05%)

q= *1-p*

z is the value of standard variate at a given confidence level calculated from the area under the normal curve table (1.96 at 95% confidence level).

e is the acceptable error (the precision) (the acceptable error is 5% which is 0.05)

The study took place in three villages in the UENB: Kisima, Lekurruki and Leparua conservancy in identified villages selected based on accessibility to the area and safety of the researcher. The villages are located in areas most prone to drought (NDMA, 2017). The selected sub-locations had a total household of 1003 (Kenya National Bureau of Statistics, 2019a), translating to 82 calculated households.

Table 3.1: Study location and sample size

County	**Sub-county**	**Villages**	**Total households(N) (KNBS, 2019b)**	**Sample households(n)**
Isiolo	Isiolo	Leparua Conservancy	358	30
Laikipia	Laikipia North	Lekurruki	286	22
Meru	Buuri	Kisima (Munyagalo)	359	30

Eighty-two questionnaires were administered to the selected household respondents for the household survey. Out of 82 questionnaires administered, some were incomplete and biased and could not be considered during analysis. During the data analysis phase, fifty-eight questionnaires were taken into account, indicating a 71% response rate. This response rate is deemed sufficient to draw conclusions for the study. As per Mugenda & Mugenda (2003), a 50% response rate is considered acceptable, 60% is viewed as favourable, and a response rate exceeding 76% is regarded as highly commendable.

3.4.4 Impacts of Droughts on the Livelihoods of the Communities

The effects of drought events that the participants can remember on their livelihoods were also evaluated. The questionnaire was analysed using SPSS, and the data was coded and categorized based on the responses. The evaluation of drought impacts on the communities' livelihoods involved assessing the perception of drought and the consequences of droughts on households using questionnaires. These effects encompassed aspects related to health, environment, and social well-being. The evaluation also considered the participants' recollections of drought events and their impact on livelihoods. The questionnaire responses were analysed using SPSS, with data being coded and categorized accordingly.

The data collected from the field was analysed based on the assigned codes from the questionnaire responses. Additionally, the questionnaire allowed participants to provide comments not covered in the closed-ended questions. SPSS was predominantly used to analyse the data, focusing on the percentage of participants who selected a specific option out of the total number of respondents, which amounted to 58 households.

3.5 Assessment of the Drought Adaptation Strategies by the Communities

For the community's adaptation strategies, similar to the assessment of drought impacts, an assessment was conducted using questionnaires that specifically targeted their responses to various drought events experienced in the region. The questionnaire data was analysed through SPSS, with coding and categorization employed to organize the responses.

3.6 Data Validation

Rainfall and temperature data were cleaned to prevent any missing data, as detailed in subheading 3.2.2. It's essential to highlight that this study solely focused on drought events based on rainfall and temperature data and did not consider climate change trends. This limitation was due to financial constraints and data availability, as analysing climate change trends requires extensive resources and data.

Additionally, the drought forecasting in this study specifically evaluated the performance of ANN in predicting SPI and SPEI values rather than utilizing climate change trends to forecast future drought events.

To ensure the validity of the research instruments, two steps were taken to validate the questionnaire. First, two expert reviews were conducted, followed by a pilot study in Meru, Timau area. This preliminary study helped refine the questionnaires, making them as clear as possible and avoiding uncomfortable questions before gathering primary data. The questionnaire was revised after the expert reviews and pilot study, and unclear questions were adjusted.

For the sample study group, there was a conflict over biased views and personal issues; hence, the study only selected the data that supported the main research argument. During data analysis for the impacts and adaptation, the frequency of responses for each factor was considered rather than the number of people who responded. This approach allows respondents to provide multiple responses to the same questions. For instance, an individual might be affected by drought in various ways, such as migrating in search of pasture and experiencing conflicts over water. Consequently, certain responses may exceed the number of respondents.

3.7 Ethical Considerations

This study adhered to three fundamental ethical principles in research: respect for persons, beneficence (concern for welfare), and justice and equity (Vanclay et al., 2013). Participation in the research by communities and other participants was entirely voluntary, and they were provided with all relevant information in an appropriate format before giving their consent. Research objectives and the use of the acquired information were orally explained to the participants. Written consent was obtained when possible, and in cases where it was not feasible, oral consent was recorded on the phone. Participants were assured of their right to withdraw from the study at any time.

To prioritize the welfare of the participants, the data collected was anonymized to ensure that their identities remained undisclosed. Information was presented in a generalized manner to protect individual privacy. Participants were fully informed about potential risks and benefits associated with the research, and those who might be negatively affected were not included in the study. Confidentiality was strictly maintained, and personal information, transcripts, audio and video recordings were kept in secure storage. Sensitive topics, like inter-communal conflicts, were avoided to prevent causing discomfort to participants. The opinions of women and youth were sought and included in the research to promote fairness and to ensure justice and equity.

3.8 Observation of COVID-19 Protocols

The field personnel strictly adhered to all health recommendations related to COVID-19 issued by the state, county, and town authorities at the research sites. They also followed the guidelines provided by the Ministry of Health (MOH) (2021). Before visiting the research areas, each researcher assessed COVID-19 symptoms. If any symptoms were present, they refrained from participating in the study. Throughout the research, the personnel ensured they had sufficient personal protective equipment and sanitation solutions and consistently wore masks when interacting with people. They maintained physical distancing, avoided overcrowding and body contact, and meticulously kept a log of all their movements, including dates, times, locations, and descriptions of interactions.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Drought Trends in the Upper Ewaso Ng'iro North Basin

4.1.1 Spatial-Temporal Drought Variations in the UENB

Figures 4.1, 4.2, and 4.3 depict the variation of SPI and SPEI at 3-, 6-, and 12-month scales. The results, observed across all stations, indicate an increase in dry periods, particularly after 1999. This monthly variation in SPI and SPEI highlights distinct shifts in dry and wet conditions each month. Post-2014, both indices exhibit a significant rise in dryness during certain months, leading to the identification of four drought characteristics: mild drought, moderate dryness, extreme dryness, and severe dryness (Figures 4.1 to 4.3).

The results reveal that SPEI identifies more drought years than SPI in the Northern (stations 1, 22, 94) and Central (10, 9, 80) parts of the basin. SPEI 3 detects additional drought years in 2002, 2007, and 2012, while SPEI 6 and 12 reveal droughts in 2017 and 2018 (see Figures 4.1 and 4.2 and Figure A2). Conversely, in the Southern region (stations 51, 69, 83, 89), closer to the river's source, both indices indicate fewer drought years compared to the North and Central parts. Here, SPI and SPEI show similar drought years (Figure 4.3). Notably, the study period between 2013 and 2019 witnesses an extended drought phase in the basin. SPEI identifies extreme droughts in 1987, 2000, 2004, 2006, 2009, 2014, 2018, and 2019, while SPI recognizes extreme droughts in 2000, 2004, 2009, 2014, 2018, and 2019 (Figures 4.1, 4.2, and 4.3).

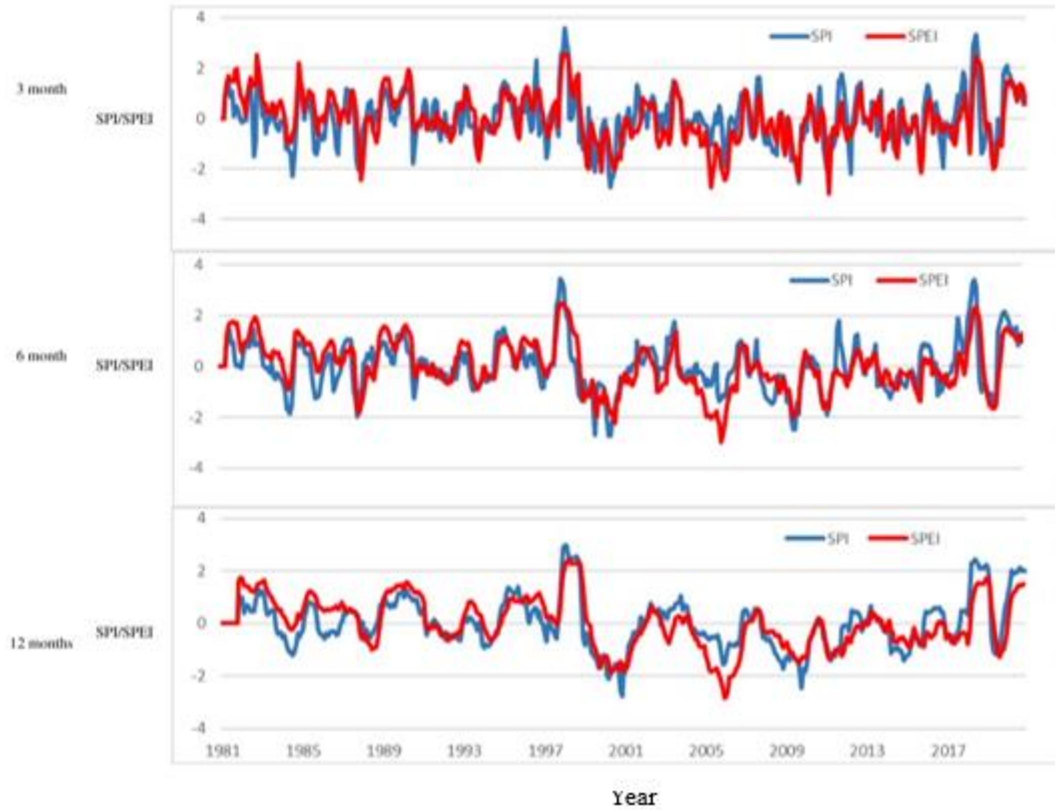

Figure 4.1: SPI and SPEI values for 3-, 6-, and 12-month timescales from 1981-2020 for Archer's Post Station (1).

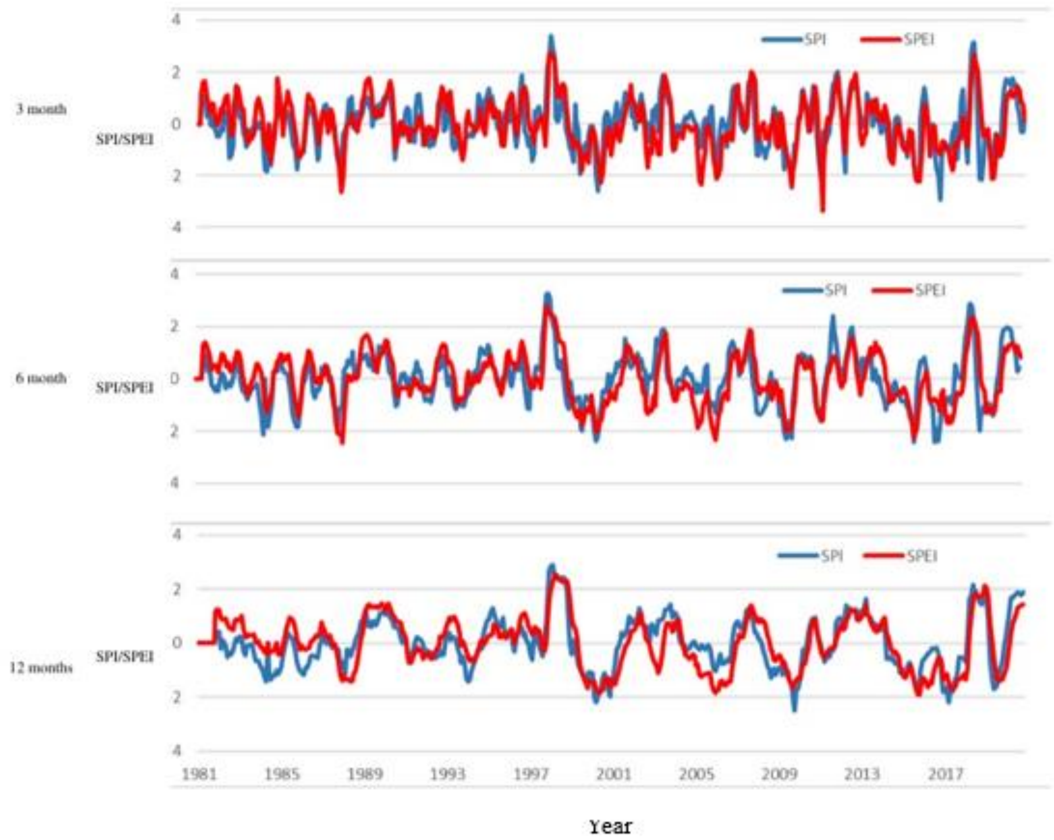

Figure 4.2: SPI and SPEI values for 3-, 6-, and 12-Month Timescales from 1981-2020 for Colcheccio Station (9).

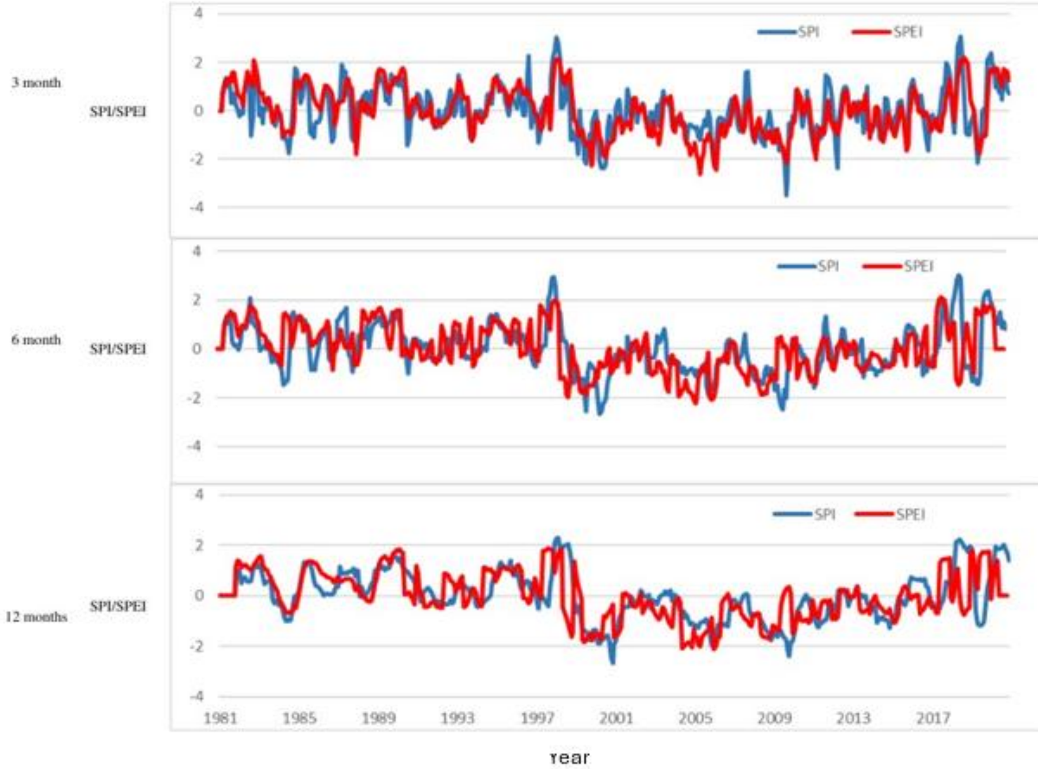

Figure 4.3: SPI and SPEI Values for 3-, 6-, and 12-Month Timescales from 1981-2020 for Mukogondo Station (69).

The spatial evolution of meteorological drought between 1981 and 2020, as revealed by SPI and SPEI, illustrates drought severity (Figures 4.4 and 4.5), duration (Figure 4.6), and intensity (Figure 4.7). Over a ten-year scale, the UENB exhibits an evident trend of increased drought intensity and severity in most regions from 1981 to 2020. SPI presents the highest drought values, ranging from -0.1 to -0.9 between 1981 and 2000, -0.6 to -1 from 2001 to 2010, and -0.8 to -1.5 from 2002 to 2020. In contrast, SPEI indicates severe drought values of -1 from 1981 to 1991, -1.5 to -2 from 1991 to 2010, and -2 to -2.5 from 2011 to 2020.

For SPI, the Northeast part of the UENB, the lowland, inherently the most arid, consistently leans towards extreme drought across all time scales, while the central and southeast regions, the higlands and mountain areas, tend towards mild drought. In the case of SPEI, extreme to severe droughts persistently manifest in the North, Northwest, Northeast, and Central parts of the basin, the Laikipia Plateau and lowlands, from 1981 to 2020, with the East and West experiencing moderate drought.

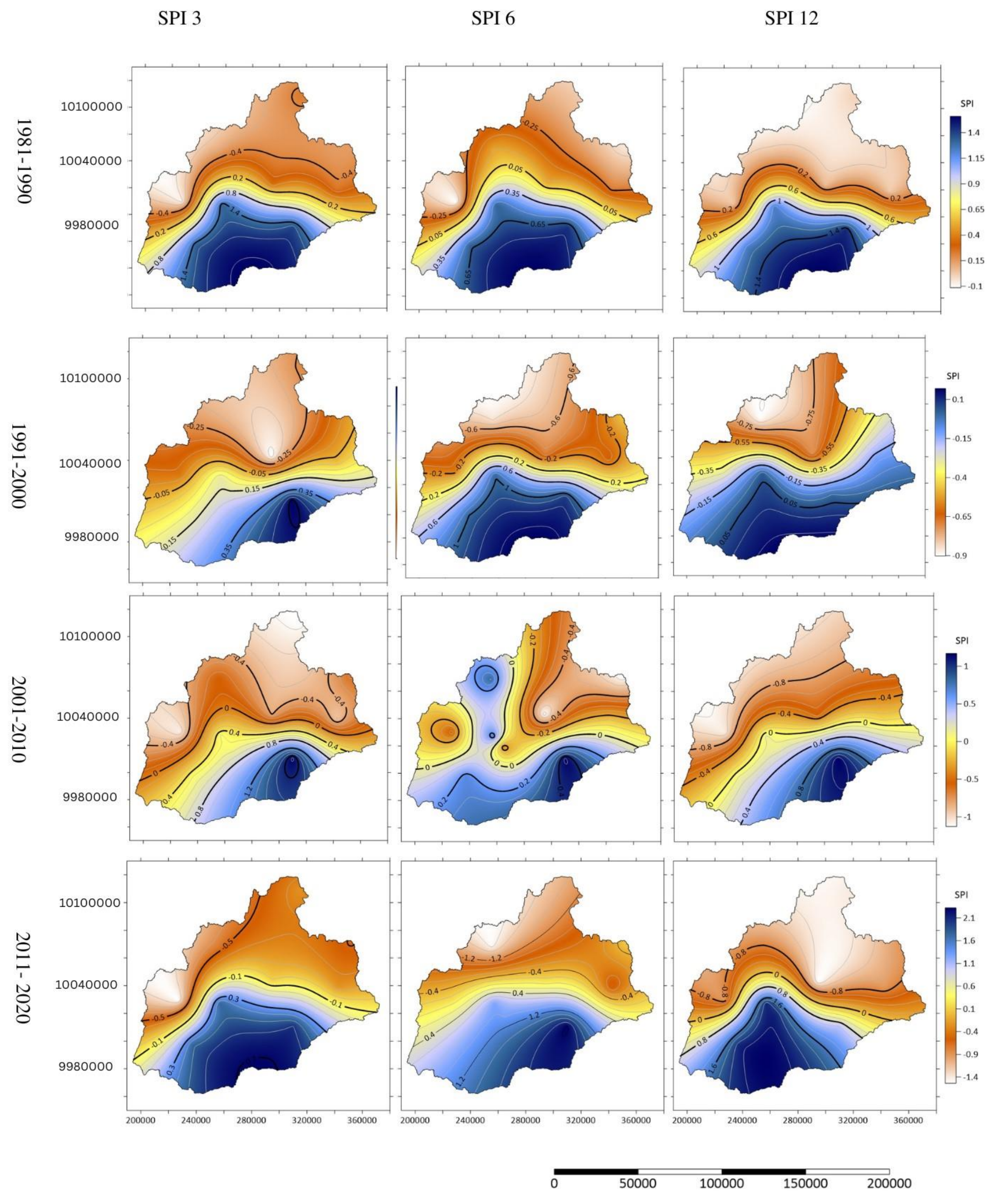

Figure 4.4: Spatial distribution of drought severity for SPI in the UENB.

At 6- and 12-month scales, the Northeast demonstrates extreme drought consistently from 1981 to 2020, while the Central area gradually experiences an escalation in severe to extreme drought across all time scales from 2001 to 2020. Overall, both indices indicate that the northern part of the basin, closer to the river's outlet, is highly susceptible to frequent droughts.this findings aligng with findings by Karanja (2018) and Odhiambo et al. (2018) who discussed that there has been an increase of drought occurrences in the Laikipia Plateau and the lowlands of the basin.

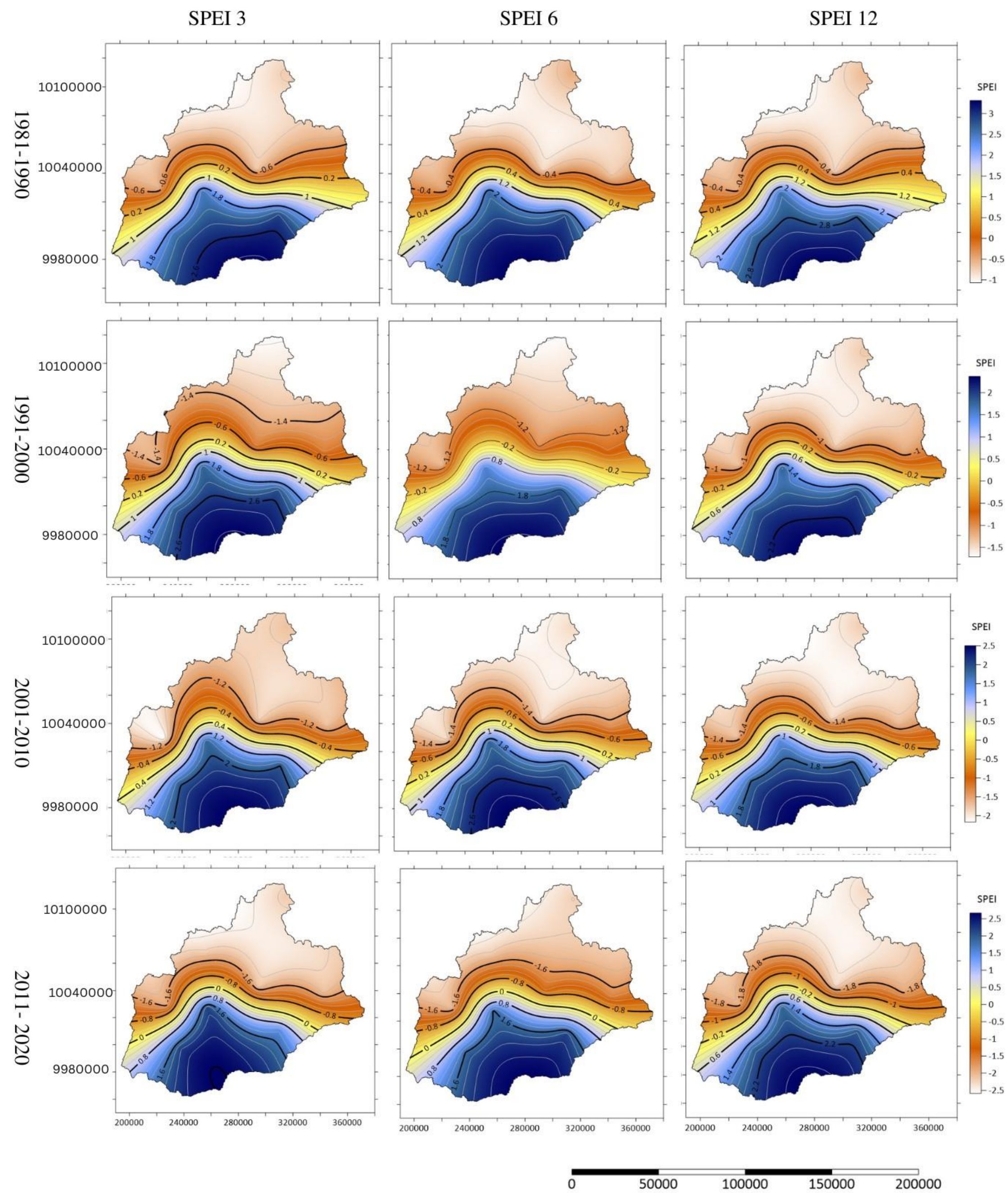

Figure 4.5: Spatial Distribution of Drought Severity for SPEI in the UENB.

Examining drought duration, in this case the duration of a historic drought event from 1980 to 2020 i.e., a total of 480, SPEI identifies the North and Central regions as experiencing the most prolonged periods, extending beyond 410 months (Figure 4.6). In contrast, the Southern areas have shorter drought periods, with approximately 380 months of drought, while the East, West, and parts of the lower Central region record drought durations ranging from 385 to 400 months. SPI exhibits a similar trend but with a lower number of drought months compared to SPEI. The North and West regions show 400 months, the Central and East range from 395 to 360 months, and the South region experiences less than 360 months of drought.

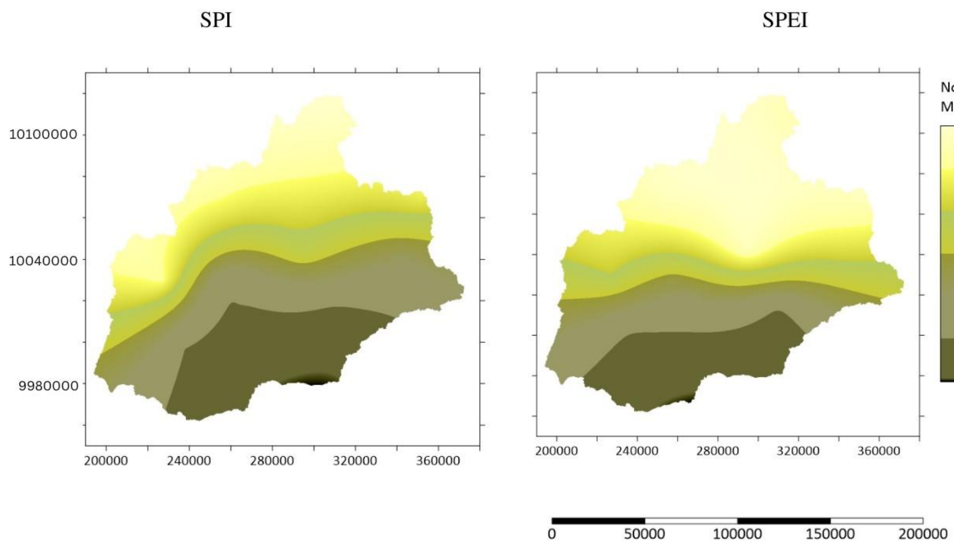

Figure 4.6: Spatial Distribution of Drought Duration in the UENB from 1981-2020.

Regarding drought intensity, represented by the number of events below -1.5 (Figure 4.7), drought intensity increases from South to North and with longer time scales. SPI indicates 16-31 months, 18-38 months, and 22-38 months, while SPEI shows 26-73 months, 26-40 months, and 26-42 months of high intensity for the -3, -6, and -12 timescales, respectively. Across both indices, it is consistently observed that the number of drought events with high intensity increases from the South to the North of the basin, with mountainous areas exhibiting fewer months of high intensity (22-26 months) and lowlands registering higher numbers (up to 42 months). The analysis reveals that drought severity, duration, and intensity in the UENB escalate from the South, near the river's source, to the North in the lowlands and the outlet.

Between the two indices, SPEI portrays drought intensity as more severe than SPI. SPEI outperforms SPI in detecting the spatial evolution of drought because it accounts for both temperature and rainfall changes. In summary, due to variations in SPI and SPEI values in time series, their drought characteristics differ in space across different timescales.

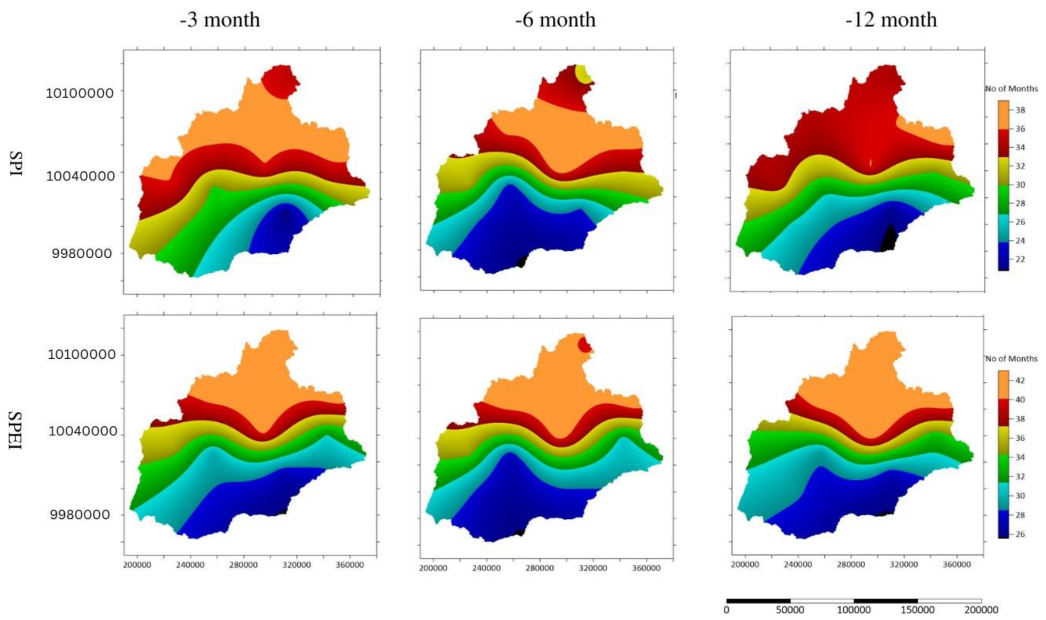

Figure 4.7: Spatial Distribution of Drought Intensity in the UENB from 1981-2020.

Since the start of the 21st century, drought events in the UENB have become more frequent. Notably, variations in SPI and SPEI are discernible across various time scales, signifying shifts in dryness and wetness each month. This shift is especially pronounced after 1999, with an increase in dryness observed in some months. it became evident that SPI and SPEI portrayed slightly distinct drought patterns each month similar to findings by Liang, Su, and Feng (2021) in their research conducted in the Jinta River basin in Northwestern China.

The study identifies moderate to extreme drought events in multiple years, including 1983/84, 1987, 1991/92, 1995/96, 1999, 2001, 2004/2005, 2006, 2007, 2008, 2009, 2011, 2014, 2016, 2017, and 2019. Among these, the droughts in 2007, 2011, and 2016/2017 are notably severe, aligning with previous studies by Karanja (2018) and Mwangi et al. (2014); NDMA (2017) and FEWSNET (2020). In fact, the 2016/2017 drought was designated a national disaster by the Kenyan government and incurred significant economic loss of up to US$ 12.1 billion (NDMA, 2017). Moreover, Mbogo et al. (2014) report that the 2011 drought affected more than 13.3 million people across Kenya, Ethiopia, and Somalia. Both SPI and SPEI highlight 2020 as a moderately wet year, consistent with reports by FEWSNET (2020) confirming it as a relatively wet.

Both SPI and SPEI identified the year 2010 as a non-drought year, which aligns with findings by Karanja (2018) and Odhiambo et al. (2018), who noted that areas around station 80 experienced heavy rainfall and subsequent flooding in that year. However, it should be noted that SPEI indicated moderate drought conditions in 2008/2009, consistent with the observations of Odhiambo et al. (2018), Mwangi et al. (2014), and NDMA (2017). In contrast, SPI also indicated a moderately wet season in 2007. This discrepancy may be attributed to SPI not accounting for PET (potential evapotranspiration).

Furthermore, both SPI and SPEI identified a severe drought in 2007, consistent with the findings of FEWSNET (2020) and Mbogo et al. (2014), which led to significant government expenditure on relief efforts. The study also identified drought events in previous years, including 1983/84, 1987/1988, 1991/92, 1995/96, 1999/2000, and 2004/2005, confirming that drought events have become increasingly severe over the past four decades. This is in line with predictions by FEWSNET (2022) and Mwangi et al. (2014) of more frequent drought events in the future. Additionally, as indicated by Famine Early Warning Sign Network (FEWSNET) (2020) and United Nations Environment Programme (UNEP) & GOK (2006) assessments, climate change is anticipated to bring about more severe drought occurrences in the basin, which will contribute to elevated water stress, decreased agricultural yields, heightened food insecurity, and malnutrition.

Regarding meteorological drought events in the UENB, an upward trend was observed, particularly after 1999, with an increase in drought frequency noted after 2004. This increase in drought intensity and severity varied across stations, with tropical forest regions (stations 51, 69, 83, 89) experiencing milder droughts compared to arid and semi-arid regions (stations 1, 9, 10, 22, 80, 94). This difference is attributed to the basin's topographical characteristics, where precipitation decreases with decreasing altitude while PET rises. Consequently, the downstream Northern region experiences more frequent and severe drought events, rendering it more vulnerable to drought. This aligns with the findings of Omwoyo et al. (2017), who also observed higher precipitation levels upstream compared to downstream in the basin. Both regions, however, face increasing drought challenges that significantly impact agriculture and socioeconomic activities (Huho et al., 2010; Karanja, 2018).

4.1.2 Consistency of SPI and SPEI

The consistency of SPI and SPEI was analysed through correlation coefficients (r) at different time scales, revealing significant positive correlations in all stations (Table 4.1). The strongest relationship (r = 0.876) was observed between SPI12 and SPEI12 in stations 51, 83, and 89. Longer time scales exhibited stronger correlations, while shorter time scales showed weaker correlations. This trend is consistent with the findings of Mehr et al. (2020) and Ojha et al. (2021), highlighting the importance of time scale in assessing the correlation between the two indices. Furthermore, the findings highlight that in arid regions such as the Northern area, encompassing stations 1, 9, 10, and 94, characterized by higher average temperatures and lower average precipitation levels, the correlation between SPI and SPEI tends to be lower compared to more temperate climatic zones. This outcome aligns with similar observations made by Homdee et al. (2016) and Lotfirad et al. (2022), suggesting that SPI's performance in arid and semi-arid regions, often referred to as ASAL (Arid and Semi-Arid Lands) regions, is relatively limited. This limitation arises from the SPI's simplistic approach, which solely relies on precipitation data without considering other factors contributing to drought dynamics. This discrepancy is further underscored by the fact that the SPEI incorporates evapotranspiration, a critical factor in drought assessment. SPEI tends to be higher in the Northern region (with an annual average of 1800 mm) compared to the Southern parts (with an annual average of 1200 mm), as discussed by Mehr et al. (2020) study of drought in Ankara Turkey.

Table 4.1: Pearson Correlation Coefficients of the SPI and SPEI Values.

Station ID	Station Name	SPI3/SPEI 3	SPI6/SPEI6	SPEI12/SPEI12
1	Archer's Post	0.737**	0.613**	0.813**
9	Colcheccio	0.729**	0.775**	0.793**
10	Dol Dol Dao	0.754**	0.764**	0.771**
22	Isiolo Dao	0.677**	0.761**	0.807**
51	Mukenya Farm	0.722**	0.786**	0.876**
69	Mukongondo Farm	0.771**	0.797**	0.823**
80	Rumuruti Mow	0.755**	0.794**	0.792**
83	Segera Plantations	0.722**	0.786**	0.876**
89	Suguroi Estate	0.722**	0.786**	0.876**
94	Wamba Do	0.581**	0.664**	0.703**

**. Correlation is significant at the 0.01 level (2-tailed).

4.1.3 SPI and SPEI Trends

The application of the Mann-Kendall (M-K) trend test and Sen's slope estimator revealed notable trends in drought occurrence.

Table 4.2 provides an overview of the drought trends and their magnitude in the UENB basin, as assessed through SPI and SPEI.

Table 4.2: SPI and SPEI Trend Analysis Results With Significance level (p) = 5%.

Station	Test	SPI3	SPI6	SPI12	SPEI3	SPEI6	SPEI12
Archer's Post	P value	0.548	0.354	0.296	0.029	0.026	0.009
	Sen's value	0.000	-0.001	-0.001	-0.002	-0.002	-0.003
Colcheccio	P value	0.802	0.912	0.619	0.019	0.020	0.019
	Sen's value	0.000	0.000	0.027	-0.001	-0.001	-0.002
Dol Dol Dao	P value	0.802	0.912	0.619	0.019	0.020	0.019
	Sen's value	0.000	0.000	0.000	-0.001	-0.001	-0.002
Isiolo Dao							
Isiolo Dao	P value	0.494	0.311	0.247	0.025	0.022	0.008
	Sen's value	0.000	-0.001	-0.001	-0.002	-0.002	-0.003
Mukenya	P value	0.144	0.149	0.161	0.138	0.134	0.114
Farm	Sen's value	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Mukongond	P value	0.110	0.099	0.108	0.040	0.070	0.083
o Farm	Sen's value	-0.001	-0.002	-0.002	-0.002	-0.002	-0.003
Rumuruti	P value	0.006	0.005	0.001	0.100	0.061	0.009
Mow	Sen's value	0.002	0.002	0.003	0.001	0.002	0.002
Segera	P value	0.144	0.149	0.161	0.138	0.134	0.114
Plantations	Sen's value	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Suguroi	P value	0.144	0.149	0.161	0.138	0.134	0.114
Estate	Sen's value	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Wamba Do	P value	0.547	0.827	0.794	0.000	0.000	0.000
	Sen's value	0.001	0.001	0.001	-0.002	-0.003	-0.003

Stations 1, 9, 10, 22, 69, and 94 exhibited a significant and consistent downward trend in drought when considering the SPEI over all the analysed time series.

However, no significant trend was observed for SPI at these same stations. On the other hand, at station 80, SPI displayed an increasingly significant trend across all time scales, while SPEI did not exhibit a significant trend. Conversely, stations 51, 83, and 89 did not show a discernible trend in either SPI or SPEI based on the Mann-Kendall test, but Sen's slope values (SS) indicated a negative trend, implying an increasing frequency of drought events. The overall trend within the basin suggests a rising occurrence of dry periods, indicating the potential for these periods to become more prevalent in the future. This analysis demonstrates that the trends in drought conditions vary across different stations and time scales, highlighting the complexity of drought patterns in the UENB basin.

When evaluating the suitability of SPI and SPEI for drought assessment, both indices offer distinct advantages and can generally serve as effective tools for monitoring regional drought conditions. However, it's essential to acknowledge that differences between the two indices are inevitable due to climate change and the varying climatic conditions present in different regions (Pei et al., 2020). In this study, SPEI emerged as the more robust indicator, revealing a higher frequency of drought events and a consistent upward trend in drought occurrence across all stations and time scales. SPEI's superior performance in arid areas can be attributed to its consideration of the Potential Evapotranspiration (PET) parameter, which plays a crucial role in detecting elevated evaporation rates resulting from higher temperatures and reduced rainfall (Vicente-Serrano et al., 2010; Homdee et al., 2016). Consequently, SPEI is deemed more suitable for monitoring drought in arid and semi-arid regions, particularly in the context of global warming (Mehr et al., 2020; Pei et al., 2020). For instance, at stations 10, 94, and 80, situated in the central, northern, and eastern parts of the basin, respectively, SPI failed to reflect severe and extreme drought conditions. In contrast, SPEI consistently indicated an escalating trend in drought severity across all time scales. This disparity can be attributed to the fact that these stations experience a warmer and drier climate, leading to higher evapotranspiration rates due to rising temperatures (Omwoyo et al., 2017; Kimwatu et al., 2021b). SPI, which does not account for evaporation effects, proved less effective in capturing the evolving nature of drought under these conditions.

4.2 Modelling Drought Using Artificial Neural Network.

This section presents the results of the performance of ANNs in modelling meteorological drought using the DI SPI and SPEI. In this study, the lead time was categorised into short (3 months), medium (6 months) and long (12 months).

The results of DIs under the meteorological drought were investigated. The performance of different ANN models in forecasting other drought indices at different meteorological stations is shown in Table A2 (in the appendices). The best-performing models at different timescales were selected based on the least MSE value in the training stage and the highest regression coefficient, R. The correlation coefficient values were used to measure the model's forecasting ability. The ANN architecture defines the number of neurons in the structure. For instance, architecture 1.13.1 means one neuron in the input layer, 13 in the hidden and 1 in the output of the ANN.

From the results summarised in Table A3, the highest coefficient of determination (0.993) and the smallest RMSE (0.0124) were captured at meteorological station 51 at SPEI 12. On the other hand, the ANN model resulted in minor predictions at meteorological station 22, as it provided a low coefficient of determination (0.818) and a high RMSE (0.319) at SPI 3. Nevertheless, the model performance metrics averaged over all stations confirmed that the ANN model accurately forecasted the drought index (Mulualem & Liou, 2020). Furthermore, the results show that R values increase, and MSE values decrease when forecast lead time increases. This suggests that the forecasting capability of ANN improves with longer lead times, agreeing with research conducted Anshuka et al. (2019), Kigumi (2014) and Santos et al. (2009).

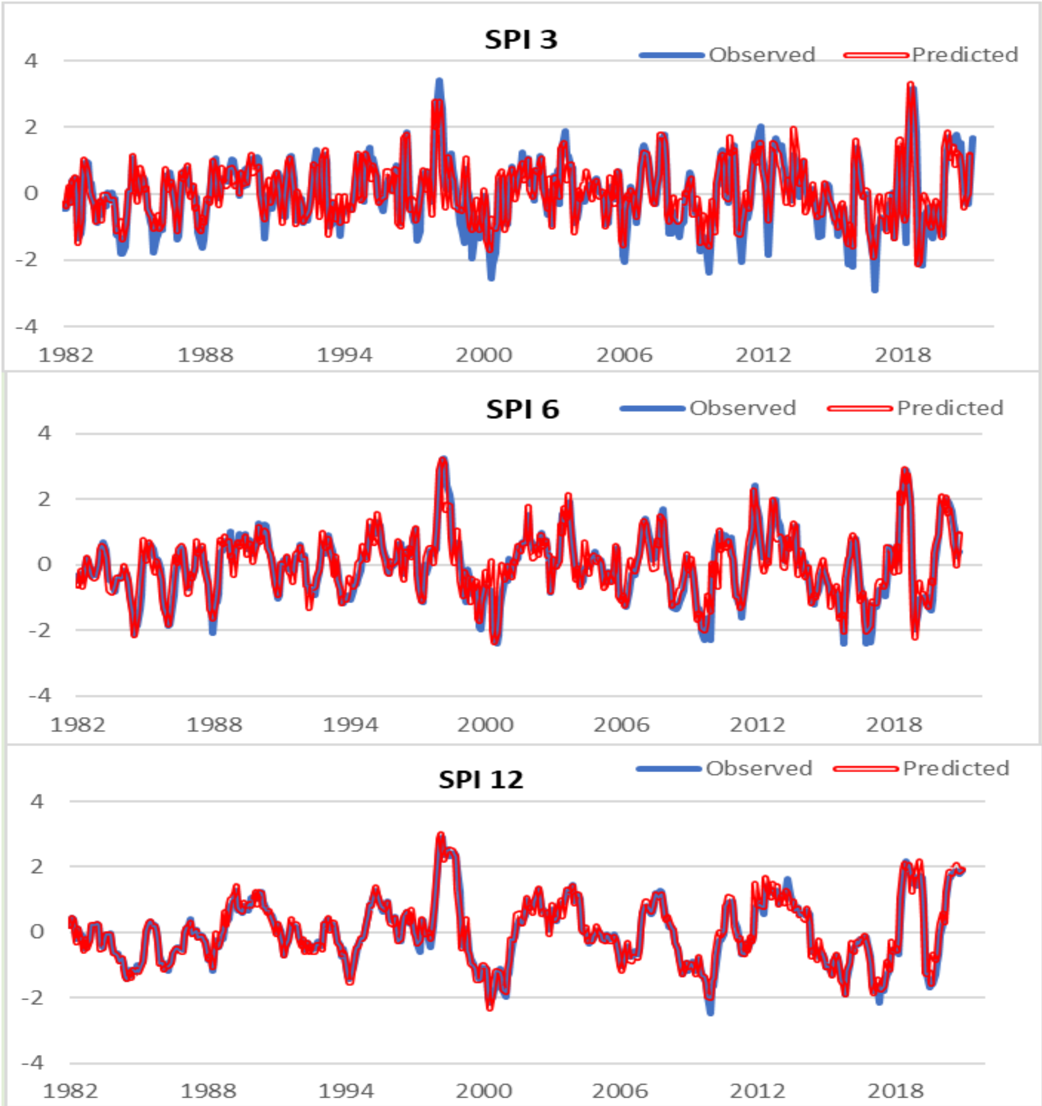

Figure 4.7: Observed Versus Predicted SPEI Values for Isiolo Dao Station (22)

The observed time series of the SPEI (Figure 4.7) and SPI (Figure 4.8) values against the forecasted values with 3, 6- and 12-month lead times at meteorological station 22 were plotted. Figures 4.7 and 4.8 show that although the model could predict the general trend, predictions deviate at extreme values, especially for SPI and SPEI 3. Additionally, the deviations between observed and predicted values are more apparent in SPI compared to SPEI. Poor prediction in the short term is due to the short observation record; it is challenging to derive enough drought events to characterize droughts identified from the rainfall data (Kigumi, 2014). However, it is deduced from the Figure that the predicted indices values are close to the observed values, slightly overestimating wet periods and underestimating the extreme periods.

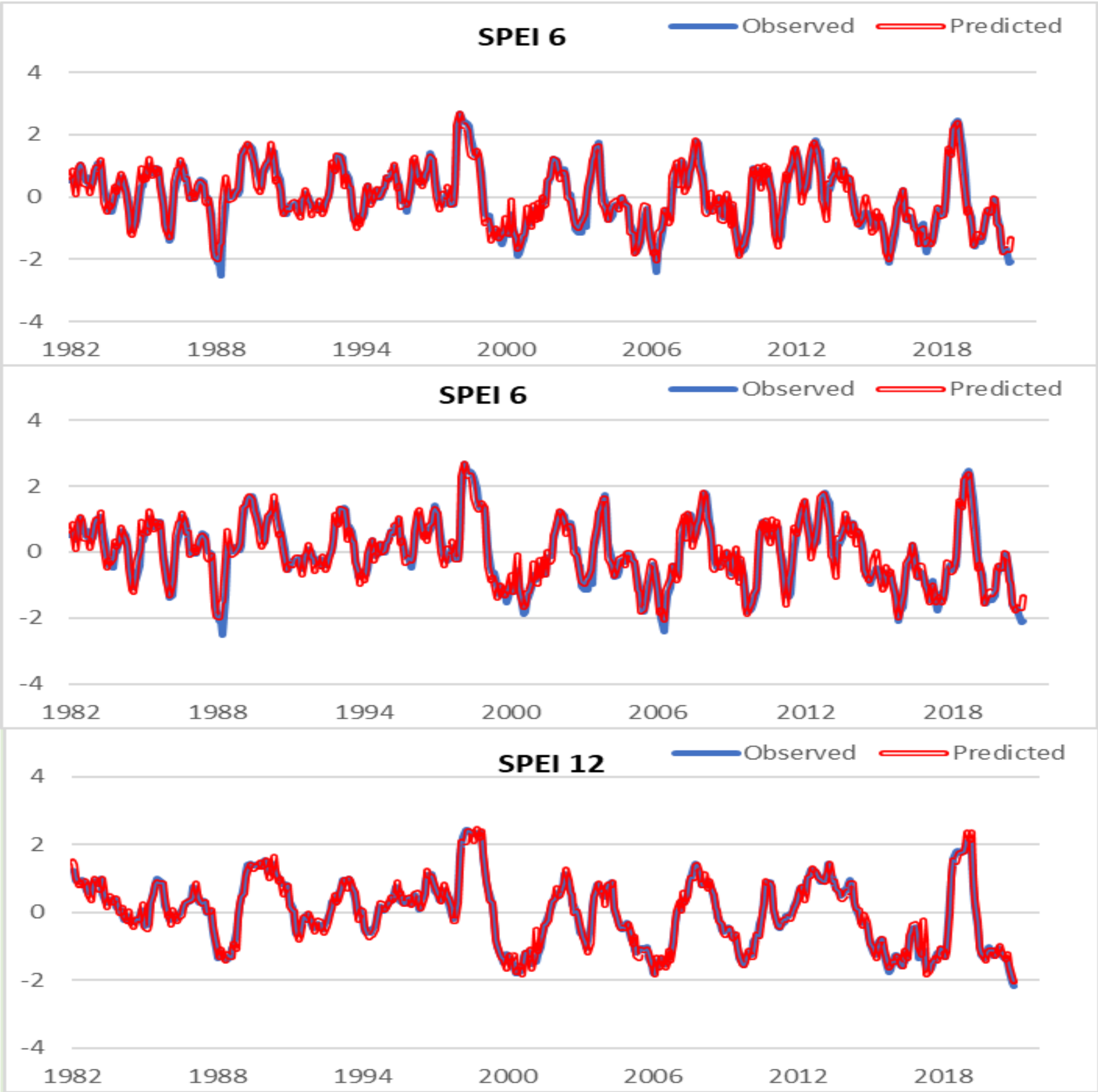

Figure 4.8: Observed Versus Predicted SPI values for Isiolo DAO Station (22)

When comparing the performance of ANN in predicting the two indices, SPEI forecasting performed better than SPI. For example, at station 89, the SPEI values show that the best forecasting models correlate 0.9576, 0.9863, and 0.9934 for 3,6 and 12 lead times, respectively. On the other hand, the corresponding R values for the same lead time series based on SPI are 0.8560, 0.9375 and 0. 9600, which is slightly lower than for SPEI. Additionally, the comparison of the performance of the SPI and SPEI in drought forecasting was illustrated by plotting the performance level versus the lead time for the meteorological stations 1 and 69, and results are given in Figure 4.9.

The results show that the SPEI's R is higher than those of the SPI for both stations. A similar trend is depicted in the other stations. This means that SPEI performs better than SPI in meteorological drought forecasting for the UENB. ANN performs better when estimating the SPEI because SPEI considers both temperature and rainfall data.

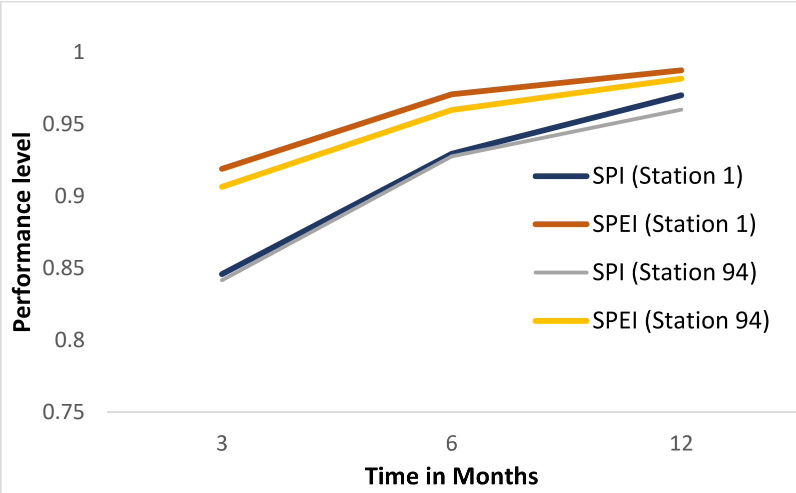

Figure 4.9: Performance level versus the lead time for the meteorological Archer's Post (1) Station and Wamba Dao station (94)

It may be seen that the forecasting effectiveness is lower in 3 months, reaching the best result in the forecast for 12 months. This is due to the high temporal variability in precipitation in SPI-3, while for the other scales, this variability is attenuated because more monthly data could be collected. Thus, while the time scale increases, the forecast is improved. It is also possible to see a significant increase in the mean square error occurs when the month horizon forecast is increased, which is very common in forecasting. This has been seen in studies by Litta et al. (2013). It can be observed that there are no significant differences in the forecast model performance when the meteorological zone is changed, which shows that the forecast SPI using the proposed ANN is not strongly affected by the rainfall regime of the region.

The other stations' results follow a similar trend but indicate different performance levels. As far as a practical application, accurate forecasting can inform water resources managers, agricultural systems and hydropower generation of the expected severities of particular droughts. Such information is helpful for the timely formulation of mitigation and coping mechanisms.

4.3 Impacts of Droughts on the Livelihoods of the Communities of the UENB

4.3.1 Demography of Respondents

The demographic composition of respondents in the surveyed communities' sheds light on several important trends, particularly in relation to age and gender dynamics. According to Figure 4.11, the predominant age group among respondents was 40-49 years old.

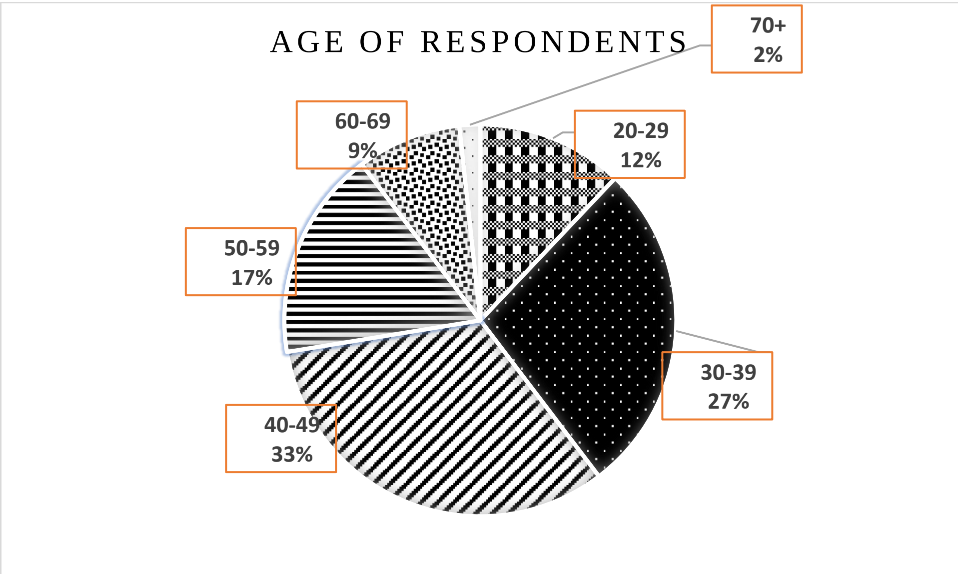

Figure 4.11: Age of respondents

This trend suggests a notable absence of younger participants, which could be indicative of a broader pattern of rural-to-urban migration among the youth population.

The fewer respondents below 30 years may be attributed to young people migrating to urban areas for employment and education opportunities. Many young individuals in the area showed little interest in traditional agricultural practices, preferring jobs or businesses in urban centres. Research studies have also shown an increasing rural-urban migration among young men and women seeking better prospects (Onyango et al., 2021; Research and Evidence Facility, 2020). The analysis indicates that the active farmers and pastoralists in the catchment mostly fall within the age range of 30-59. However, responses from the younger age group (below 30) were not as comprehensive in describing the impacts and adaptation strategies of the communities over the years. This observation resonates with the findings of Olabanji et al. (2021) in South Africa, indicating that age may shape economic perspectives vis-à-vis drought experiences.

Regarding gender, 51% of the respondents were women, while 49% were men. This balanced representation suggests an equitable involvement of both genders in the survey, providing diverse perspectives on the challenges and strategies related to drought in the studied communities.

The demographic makeup of respondents highlights the intricate interplay of age, gender, and socio-economic factors in shaping community resilience to drought. The overrepresentation of older age groups and women emphasizes the need for targeted interventions to enhance the participation of younger individuals, especially men, in discussions and initiatives aimed at developing sustainable adaptation strategies for rural communities facing environmental challenges United Nations Development Programme (UNDP), 2019).

4.3.2 Community Perceptions of Drought Events

Drought significantly affects farmers and pastoralists as they heavily rely on climate-sensitive factors like rain and water. Understanding their perspectives on climate change, especially drought, is essential for comprehending their adaptive behaviour (Olabanji et al., 2021). The respondents' viewpoints are closely related to their primary source of income, which influences the strategies adopted by different households (Table 4.3). According to the study by Karanja (2018), some farmers' perspectives are also shaped by information obtained from radio and TV.

Table 4.3: Household Perception of Drought

Villages	Kisima	Leparua	Lekurruki
Perception	Percent	Percent	Percent
Lack of rainfall	40.6	34.5	33.3
Lack of pasture	15.6	37.9	37.5
Lack of food	9.4	20.7	25.0
Drying of rivers	34.4	3.4	4.2
Other	0.0	3.4	0.0
Total%	100.0	100.0	100.0

Most respondents are aware of the climatic changes in the region and have distinct opinions about drought (Table 4.3). Farmers in Kisima predominantly perceive drought as a lack of rainfall, as they depend on rainwater for agriculture and pasture. In contrast, some farmers in Kisima view drought as the drying of rivers, particularly because they heavily rely on river water for irrigation and domestic needs due to unreliable rainfall.

For pastoralists in Leparua and Lekurruki villages, drought is often seen as a lack of pasture, given their dependence on livestock as a primary source of income and sustenance. Lack of food during drought is a major concern for women from nomadic pastoral communities, who are responsible for providing food to their families while the males search for pasture. Due to limited finances, these women resort to gathering wild fruits, vegetables, or herbs or rely on assistance from male family members to obtain food or money to buy food (Huho & Mugalavai, 2010; Karanja, 2018).

4.3.3 Effects of Drought on Household Livelihoods

The impact of drought on household livelihood in EUNB County was examined across four categories: crops, livestock, and health and social effects. The study specifically focused on the effects of the drought during the last decade, with most respondents referring to the droughts between 2015 and 2021.

4.3.4 Effects of Drought on Crops

Household survey results in Table 4.4 show that droughts reduced crop yield for the respondents from Kisima and Lekurruki who practised crop production. The main crops grown are in Table A4.2.

Table 4.4: Effects of Drought on Crops

Villages	**Kisima**	**Leparua**	**Lekurruki**
Effects on crops	Percent	Percent	Percent
No Yield	6.5	78.6	5
Reduced crop Produce	54.8	0.0	12.5
Increased crop pest	45.2	21.6	37.5
Total%	100.0	100.0	100.0

A study by Muthee (2014) also found that the farmers in Kisima experienced highly reduced crop production during dry seasons. Most crop farmers from Leparua and Lekurruki experienced crop failure. Some farmers reported an increase in crop pests and diseases during the drought, leading to total crop failure. Adhikari (2018) explains that the impact of reduced crop production and productivity is the consequence of reduced water availability for agricultural uses, hindrances in the operation of conventional irrigation systems, decreasing efficiency of water use, increasingly degrading agricultural land, and epidemics of diseases and pests. Adhikari further mentions that poor quality planting resources, technology and neglect of traditional crop cultivating methods could contribute to poor crop productivity.

4.3.5 Effects of Drought on Livestock

The findings in Table 4.5 illustrate the effects of drought on livestock based on the livestock kept in the basin shown in Table A4.2.

Table 4.5: Effects of Drought on Livestock

Villages	**Kisima**	**Leparua**	**Lekurruki**
Effects on Livestock	Percent	Percent	Percent
Normal produce	4.5	0.0	0.0
Reduced Livestock produce	54.5	0.0	0.0
Lost<25%	0.0	7.5	0.0
Lost=50%	0.0	17.5	14.7
Lost = 75%	0.0	20	32.4
Lost>100%	0.0	7.5	5.9
Increased livestock diseases	40.9	47.5	50
Total%	100.00	100.0	100.0

In Leparua, a notable proportion of respondents observed that drought led to significant livestock deaths, while a similar observation was made by respondents in Lekurruki. Furthermore, in Leparua and Lekurruki, respondents mentioned losing a substantial portion of their livestock. Some participants also reported a complete loss of all their animals during the drought, particularly in all the areas.

Farmers also pointed out an increase in the occurrence of livestock diseases during the drought period. This aligns with a report by the Government of Kenya (2021), which also observed a rise in livestock diseases during drought conditions. The compromised health and elevated mortality rate of animals due to lack of water and grazing areas could be exacerbated by the extended journeys undertaken in search of pasture and water, as indicated by FEWS NET (2022) and Karanja (2018).

The substantial number of respondents reporting animal deaths and diminished animal productivity underscores the profound impact of drought on livestock farming. It is important to note that even though these communities heavily rely on meat and milk production from their livestock (FEWSNET, 2022), only farmers from Kisima mentioned reduced livestock output. A few of the respondents did not address this aspect. Instead, they highlighted that they do not anticipate significant yields from their animals during the dry season due to their malnourished state. Their primary concern is to prevent the animals from perishing, allowing them to be sold to acquire other essential food items.

4.3.6 Effects of Drought on the Social Practices of Communities in UENB

Apart from the impact on agricultural and livestock activities, drought had significant social consequences for communities in the EUNB region. While food and water scarcity were prevalent issues (as indicated in Table 4.6), the most prominent problem was conflicts arising from competition over water and pasture.

Table 4.6: Social Impacts of Drought to Livelihoods of Communities

Villages	**Kisima**	**Leparua**	**Lekurruki**
Social Impacts of drought	Percent	Percent	Percent
Children miss School	0	14.9	18.2
Reduced interaction	9.5	6.00	5.5
Seasonal migration	0.0	22.4	21.8
Increased water distance	9.5	20.9	20.0
Animal attack	0.0	7.5	7.3
Conflict over water	81.0	25.4	25.5
Others	0.0	3.0	1.8
Total	100.0	100.0	100.0

This conflict was particularly pronounced in Kisima, Leparua, and Lekurruki. Studies by Kiteme (2020) and Lesrima et al. (2021) also confirm that water-related conflicts, especially during dry periods, are a major regional concern. These conflicts occurred between upstream and downstream users and among neighbouring communities. For instance, pastoralists in Leparua and Lekurruki often found themselves in conflicts with groups like the Maasai, Samburu, Turkana, and Borana. In Kisima, conflicts revolved around neighbours living near a stream (Kiteme, 2020).

Frequent seasonal migrations with livestock were a common practice among pastoralist communities. This migration pattern often separated families, with women and children remaining at home to manage the household. This situation sometimes led to shortages of food. Additionally, during these migrations, communities could encroach on each other's lands, sparking conflicts over pasture and even incidents of cattle theft (Lesrima et al., 2021). As the drought persisted, water scarcity forced individuals to travel longer distances to access water sources. Other studies also revealed the issue of long-distance travel in search of water (Hao et al., 2018; Mbogo et al.; 2014; Meybeck et al. 2012). Such extended travel exposed women to risks such as attacks by bandits, human trafficking, and, in some cases, desperation that drove them to resort to negative coping mechanisms, including engaging in transactional sex (OCHA), 2021).

Another significant social effect of drought was children missing school, with rates of 14.90% in Leparua and 18.2% in Lekurruki. The reasons for this absenteeism were primarily lack of food and school fees, which could be attributed to income loss due to the drought (NDMA, 2015; UNISDR, 2014). Older male children sometimes migrated with their fathers in search of pasture. In households led by single mothers, younger and older male children were forced to migrate to support their mothers. This phenomenon had been similarly observed in Lekurruki West by Karanja (2018), where school absenteeism often led to poor academic performance or dropouts. Moreover, insufficient food in schools could lead to more reported cases of dropouts, along with an increase in early child marriages and incidents of child labour (Kalele et al., 2021).

Another aspect highlighted by key informants was rural-urban migration. Drought directly impacts income-generating activities, prompting many young individuals, particularly men, to migrate to urban areas for alternative income sources. This migration often leads to permanent relocation, as these communities often follow patriarchal structures with men responsible for herding and cultivation, leaving the family with limited labour. Similarly, Adhikari (2018) noted in his study that male out-migration generates gendered vulnerabilities in agrarian societies.

Additional consequences of drought in the UENB included conflicts or attacks by wild animals and reduced social interactions (EU & NDMA, 2018; Karanja, 2018; The World Bank, 2013). Wild animals, particularly elephants, would attack homesteads and destroy crops. Predators like hyenas would target goats and sheep at night. Respondents mentioned that the Kenya Wildlife Service (KWS) did not adequately compensate them for crop or livestock losses due to wildlife attacks. Similarly, findings by Karanja (2018) highlighted that KWS would respond to wild animal attacks but not to property destruction. Rangers from conservancies noted that human-wildlife conflicts sometimes led to communities encroaching on preserved pasture for wild animals. Addressing these issues may require intervention from county authorities, religious leaders, community elders, and conservancy leaders. It was also noted that these conflicts occasionally led to conservancy rangers mistreating communities, potentially necessitating resolution through collective efforts (ACAPS, 2022).

4.3.7 Effects of Droughts on Livelihoods of the Communities

Given that agriculture and livestock keeping are the main income sources in the region (Table A4.1), drought significantly exposes communities to poverty. Understanding the adaptation strategies of these communities depends largely on their economic stability, making it crucial to examine how drought affects their economies. Analysing the economic impacts of drought on livelihoods will also guide the development of effective adaptation measures and equitable resilience policies in the area (Mutekwa, 2016).

Respondents frequently mentioned that during droughts, they experienced indirect financial losses due to diminished farm or livestock yields. As shown in Table 4.7, the highest economic impacts were reduced crop yields and livestock losses. In Kisima, crop failure was the second most significant effect. Both areas also faced considerable reductions in animal product yields. Respondents from Leparua and Lekurruki reported experiencing increased prices of goods, particularly food items. The rise in food prices or scarcity can be attributed to reduced production due to livestock and crop losses (Gautier et al., 2016; Kalele et al., 2021). These studies also pointed out that drought's impact on water indirectly affects livestock and crop production, potentially reducing herd sizes through animal deaths, sales, or sharing to cope with the consequences.

Table 4.7: Economic Impacts of Drought to Livelihoods of EUNB Communities

Villages	**Kisima**	**Leparua**	**Lekurruki**
Economic Impact	Percent	Percent	Percent
Reduced crop yield	27.9	6.3	1.9
Crop failure	25.0	6.3	5.7
Reduced animal production	19.1	23.8	24.5
Loss livestock	4.4	31.7	34.0
High cost of goods	7.4	19.0	18.9
Reduced wage	10.3	0.0	0.0
Loss of Business	4.4	9.5	15.1
Others	1.5	3.2	0.0
Total%	100.0	100.0	100.0

Furthermore, some respondents from pastoralist communities noted the absence of livestock markets, with the available markets offering low prices. Reports by FEWSNET (2020) and the World Food Program (2022) also highlighted reduced markets for livestock as a major drought problem in the Horn of Africa. This decline in market prices could be due to increased supply as individuals aim to sell their livestock due to drought-induced challenges or malnourishment (Crossman, 2018; Food Security and Nutrition Working Group (FSNWG), 2022; Kalele et al., 2021; NET & Organization, 2021; The Kenya Ministry of Agriculture (2016). Similarly, crop farmers expressed dissatisfaction with either a lack of markets or low product prices. Additionally, the country's COVID-19 lockdown measures in 2020 contributed to market shortages due to restrictions on intercounty movement of people and goods (ACAPS, 2022). Revenue from pastoralism declined by 50% in May 2020 from the same period in 2019 (Kirui et al., 2022). Low market prices during droughts could stem from poor product quality and excessive market supply (ACAPS, 2022; Gautier et al., 2016; Kalele et al., 2021). Alongside low selling prices, reduced production and losses lead to food scarcity, elevated prices and decreased consumption. For instance, according to ACAPS (2022), the 2021 drought in the Horn of Africa led to approximately 3.5 million people in the ASALs facing a food crisis, with a 75% increase projected for 2020. Decreased income levels in pastoral and agropastoral regions have diminished household purchasing power and intensified food insecurity (Kirui et al., 2022; World Food Program, 2022).

In regions like Kisima, casual farm work such as sowing, weeding, pruning, and harvesting often involves hiring individuals from other households to employ unskilled labour. However, during droughts, available work diminishes, leading to fewer employment prospects, reduced wages, and ultimately, job losses for many individuals (ACAPS, 2022; World Food Program, 2022). This downturn also impacts workers in larger commercial farms; for example, casual labourers in flower farms in Kisima reported experiencing job losses or reduced working hours accompanied by decreased pay.

Business community mentioned that during droughts, they experienced business losses primarily due to the lack of customers and high costs for goods, resulting in financial setbacks. Some businesspeople adjusted their ventures to align with available product and service demand. Due to financial challenges, some households, particularly in Kisima, resorted to borrowing loans from banks or self-help groups to buy cultivation supplies like improved seeds, fertilizers, or pesticides and purchase food. However, extended drought periods resulting in crop failures meant these households could not generate income to repay the loans. Consequently, they either failed to meet repayment obligations or borrowed more, leading to financial distress. The study by Mutekwa (2016) also found that due to droughts, some farmers who could not afford to repay their loans lost their properties attached as collateral for loans to financial institutions.

4.3.8 Effects of Drought to the Communities

Drought's impact on the livelihoods of communities also extended to health concerns, as indicated in Table 4.8. Some respondents noted an increase in human diseases and malnutrition. Gautier et al. (2016) study similarly revealed that drought-induced water scarcity led to a rise in diseases like Bilharzia in Ghana.

Table 4.8: Health Effects of Drought on Livelihoods of EUNB Communities

Villages	**Kisima**	**Leparua**	**Lekurruki**
Health Impacts	Percent	Percent	Percent
Increased human diseases	0.0	19.1	27.8
Increased malnutrition	15.8	57.1	55.5
No diseases and malnutrition	84.2	23.8	16.7
Total	100.0	100.0	100.0

Malnutrition emerged as a significant issue in the basin. Notably, most respondents from Kisima (84.2%) did not identify rising human diseases or malnutrition as a major problem, while Leparua and Lekurruki expressed similar sentiments. Food scarcity often leads families to reduce their consumption rates, with adverse implications for human health, including increased disease occurrence, mortality, and childhood malnutrition, affecting growth and cognitive development (Gautier et al., 2016; Stanke et al., 2013). Based on the report by ACAPS (2022), over 658,000 children and women in ASAL counties require treatment for acute malnutrition, with around 558,500 under-five children experiencing global acute malnutrition as of February 2022, marking a 20% increase from August 2021.

During droughts, inadequate water supply often results in poor hygiene standards, particularly in ASALs like Leparua Community and Lekurruki. However, communities in Kisima possess improved water management resources (FSNWG, 2022; OCHA, 2021). However, communities in Kisima possess improved water management resources (Odhiambo et al., 2018), which may account for the fewer reported cases of malnutrition and disease in the area. Respondents in Leparua mentioned sharing water sources with their livestock during droughts, which could lead to contamination and subsequently increase the risk of diseases for humans and animals. Karanja (2018) also highlighted that drought often entails compromised hygiene standards, undermining water quality and increasing human and livestock disease rates. Moreover, the study found that reduced water volumes in rivers and lakes during droughts led to higher concentrations of pollutants. The lack of access to hospitals likely compounds the issue of increased diseases in areas like Lekurruki and Leparua (FSNWG, 2022; Koech et al., 2020; Mutekwa, 2016).

4.3.4 Analysis of Drought Assessments and Impacts in the UENB

Comparing the outcomes of drought assessments and their consequences in the UENB basin unveils notable trends and variations. The analysis of drought occurrences during the study period showed an increasing frequency and severity of droughts in the UENB, evident through the SPI and SPEI indices (Huho et al., 2010; Karanja, 2018; Odhiambo et al., 2018). These findings agree with the observations of local farmers who have reported heightened drought impacts. These impacts manifest prominently in reduced crop yields and livestock losses, representing the most significant economic repercussions of drought, alongside social and health consequences, as illustrated in Tables 4.4 to 4.8. This concurs with earlier research conducted by Gichuki (2006) and Ngigi (2009), which shows the role of recurrent drought cycles in increased irregular rainfall distribution.

The UENB basin's diverse geography translates into distinct drought patterns and consequences. These distinctions become particularly apparent when comparing the lowlands (northern central and western regions), such as Leparua and Lekurruki villages, with the highlands (southern areas) like Kisima. These differences carry significant implications for the local communities and emphasize the necessity of devising location-specific strategies to address both the occurrence and effects of drought within the UENB basin. In the lowlands, notably in areas like Leparua and Lekurruki, susceptibility to severe and recurrent drought events is evident in the temporal and spatial distribution of drought results. Historical records chart an upward trajectory in drought frequency, culminating in prolonged water scarcity and livelihood challenges. The persistently arid conditions lead to protracted and severe drought episodes, significant livestock losses, an elevated occurrence of livestock diseases, resource conflicts, and difficulties in maintaining basic hygiene standards, exacerbating disease prevalence. The economic repercussions are profound, entailing reduced income levels and elevated food prices.

Conversely, in the highlands and mountainous regions, i.e. Kisima, the increase in drought severity is comparatively milder. These areas are less susceptible to prolonged and intense drought events, partly owing to the presence of nearby mountains that mitigate the severity and duration of droughts. Here, livestock losses are fewer, livestock diseases during droughts are less severe, access to water resources is relatively reliable due to mountain proximity, hygiene standards are higher, and disease prevalence during drought periods is lower. Although economic impacts are discernible, they are less severe when compared with the northern regions.

In summary, the study's findings substantiate farmers' perceptions of drought as a recurring event with the potential for devastating impacts on their livelihoods. Farmers are keenly aware of the multifaceted threats posed by drought to their food security, income, and way of life. The cumulative consequences of drought, compounded by limited water availability, pose a tangible risk of resource disparities within the basin, potentially leading to conflicts over natural resources among local communities, as previously noted by Gichuki (2006) and Lanari et al. (2018). Additionally, assessments by FEWSNET (2020) and the United Nations Environment Programme (UNEP) and GOK (2006) anticipate even more severe drought occurrences in the basin due to climate change. This predicts heightened water stress, diminished agricultural productivity, increased food insecurity, and heightened malnutrition.

4.4 Drought Adaptation Strategies of the Communities

4.41 Drought Preparedness Strategies

Table 4.9 illustrates that many households lacked adequate preparation for drought.

Table 4.9: Drought Preparation Strategies of EUNB Communities

Villages	**Kisima**	**Leparua**	**Lekurruki**
Drought preparedness strategies	Percent	Percent	Percent
Set aside some emergency fund	20.0	4.0	5.0
Preserve food supplies	20.0	24.0	10.0
Mobilize neighbours	12.0	0.0	0.0
Attend training on drought management	0.0	4.0	0.0
Women Group	0.0	4.0	15.0
Sell Livestock	0.0	16.0	5.0
Wait for relief food	0.0	4.0	5.0
Not Prepare	36.0	44.0	60.0
WRUAS Support	12.0	0.0	0.0
Total%	100.0	100.0	100.0

The unpreparedness among respondents primarily stemmed from an inability to predict drought early warning signs, with many traditional indicators no longer being reliable due to shifting climatic patterns. Instead, they often relied on delayed forecasting news from local radio stations. Financial constraints were another major factor hindering preparedness. Respondents noted that sufficient funds would allow them to purchase ample pasture and food and even invest in water harvesting and borehole construction during rainy periods in anticipation of droughts. A study by Kalele et al. (2021) also underscored that some individuals lacked traditional strategies to mitigate drought impacts.

In Kisima, households successfully stockpiled food supplies and allocated emergency funds for potential droughts. In contrast, in Leparua and Lekirruki, smaller proportions of households safeguarded food and set aside emergency funds. Some households opted to sell their livestock and save the proceeds to purchase food during drought, as described in Table 4.9. Additionally, these communities implemented various other preparatory measures. In Kisima, they collaborated with WRUAS to identify sustainable ways to utilize river water while anticipating rainfall. However, this approach predominantly benefited the upstream communities in Kisima, as indicated by Lesrima et al. (2021). Organizations like Caritas conducted training sessions on drought preparedness and adaptation in Leparua, although it was noted that only a limited number of individuals participated in these training programs. These findings are consistent with those of Karanja (2018), which suggests that churches and mosques provide educational opportunities to households.

Certain women formed community groups to save money, practice table banking, and sometimes provide food support to members during drought periods. Others focused on harvesting rainwater during the wet season for use during dry periods. Despite these efforts, area leaders highlighted that much lacked proper knowledge of effective water harvesting practices. A study by Kalele et al. (2021) also revealed that water conservation and harvesting activities were prominent adaptation strategies in the Kenyan ASALs.

Key informant interviews revealed additional strategies employed by households. Some relied on relief food from well-wishers and conservancies during droughts. (Huho et al., 2010) also found that during droughts, farmers have a high dependency on relief aid. Conservancies often reserved pastures and food for wildlife in anticipation of drought events, thereby preventing conflicts over grazing land with communities. At times, these resources were distributed to nearby households to reduce the temptation of farmers to take the pasture. This practice mitigated the potential for conflicts between humans and wildlife and minimized the chances of wild animals damaging crops and pastures.

4.4.2 Household Response to Drought

Household adaptation strategies in the EUNB region are intricately tied to their primary sources of income and livelihoods. The analysis findings (refer to Table

4.10) highlight UENB residents' diverse strategies to navigate droughts and enhance their agricultural and animal production.

Table 4.10: Drought Adaptation Strategies of Rural Communities in EUNB

Villages	**Kisima**	**Leparua**	**Lekurruki**
Response to drought	Percent	Percent	Percent
Sold livestock	2.94	11.84	10.29
Migrated with Livestock	0.00	25.00	25.00
Reduce stock- slaughtering	1.47	21.06	14.70
Preserve land	0.00	5.26	5.88
Steal Pasture from Conservancy	1.47	3.95	4.41
Irrigation	17.65	2.63	2.94
Change crop pattern	23.53	0.00	2.94
Reduce Farm size	10.29	0.00	2.94
Rehabilitation/ Construction of critical boreholes	2.94	0.00	0.00
Planting trees and reforestation	4.41	1.32	1.47
Searched for employment	13.23	9.22	7.35
Close Business	2.94	11.84	7.35
Stockpiling of cereals and grains	11.76	5.26	7.35
emergency aid	0.00	0.00	2.94
Other	2.94	2.63	4.41
Total %	100.00	100.00	100.00

Among pastoralists in Leparua and Lekurruki, a common practice is to engage in seasonal migrations with their livestock in search of suitable grazing land. Seasonal migration for pasture is a recognized and crucial adaptation strategy among pastoralists in arid and semi-arid areas, as indicated by research conducted by Huho et al. (2010), Karanja (2018); Kirui et al. (2022); Koech et al. (2020) and Mutekwa (2016). Some choose to reduce the size of their livestock herds by selling animals, while others opt to cull animals showing signs of decline. Notably, these pastoralists view selling their animals as a loss due to limited market access. Koech et al. (2020) also identified the lack of market access as a significant challenge in the region. Some households intentionally sell, cull, or give away animals as part of their efforts to reduce the size of their herds.

Farmers in Kisima adopt strategies like changing crops or reducing cultivated land in response to drought (Table 4.10). Reducing cultivated land aims to mitigate potential losses in case of crop failure. Some farmers diversify crops to those more suited to arid conditions or with deep root systems, hoping to yield better results with less water (Muthee, 2014). Those with access to river water engage in irrigation, even during dry seasons with water rationing. Some farmers, who once practised early planting up to 1-2 weeks before the rains to make the most of available moisture, no longer do so due to unpredictable rainfall onset, consistent with Muthee's (2014) findings. Those with access to river water might plant trees, especially fruit trees, to contribute to river conservation and mitigate drying. Households with non-functional boreholes would repair or drill new ones to obtain water.

Individuals with jobs or businesses initially stock up on food at the onset of drought. However, extended drought periods may deplete their supplies, prompting them to seek alternatives. Borrowing food and pasture from neighbours and relatives becomes a common strategy. Inhabitants turn to conservancies and private ranches for pasture. Some individuals, mainly those with only primary education, move to towns for casual jobs, reducing their reliance on agriculture and livestock. Others, especially young men, sell livestock to purchase motorbikes and venture into transport businesses. Businesspeople adapt by closing or changing their business types according to market demands.

In Lekurruki, some young individuals burn charcoal while women gather wild fruits and vegetables for sustenance. Artistic women, notably the Maasai and Samburu in the Lekurruki and Leparua Communities, engage in beadwork, selling their creations to tourists and businesses in urban centres. Some households set aside land during the rainy season to preserve grazing areas for drought. Key informant interviews revealed that women often join savings groups known as "*chama*" to secure funds for beadwork projects and small business loans. Gannon et al. (2020) report revealed that women's groups like table banking can potentially overcome barriers to entrepreneurship in ASALs. Some wealthier households send their children to boarding schools to ensure uninterrupted education. Beekeeping emerges as an alternative to rain-dependent activities, although a lack of expertise occasionally results in failures (Karanja, 2018).

4.4.3 Communities' Suggestions on Strategies to Enhance Adaptation

The respondents were also inquired about potential avenues through which local and national governments and well-wishers could support their adaptation to drought (Table 4.11).

Table 4.11: Communities' Recommendations on Strategies to Enhance Drought Adaptation.

Villages	**Kisima**	**Leparua**	**Lekurruki**
Strategies to enhance adaptation	Percent	Percent	Percent
Boreholes and water harvesting	82.6	60.9	33.3
Education of Children, Youth & Women group	0.0	8.7	11.1
Provide Drought resistant crops	8.7	13.0	29.6
Social amenities	0.0	8.7	9.3
Relief food	8.7	8.7	16.7
Total%	100.0	100.0	100.0

As highlighted in, a notable portion of respondents revealed their preferences for specific forms of assistance. Among these, the most prevalent requirement was for aid in establishing strategically positioned public boreholes near their residences. They believed these boreholes would yield improved access to water. Concurrent with the establishment of boreholes, these individuals sought instruction in techniques for harvesting water during rainy seasons. The Kenya Ministry of Agriculture (2016) has reported undergoing projects to focus on water harvesting, encompassing practices like roof water collection, river dams, water storage, and the creation of on-farm water pans to store water for future use and safeguard water sources. These initiatives aim to diminish conflicts arising from lack of access to water.

Addressing the issue of ensuring food security during drought emerged as another significant concern. A notable percentage of respondents in Leparua and Lekurruki (Table 4.11) emphasized the importance of having access to drought-resistant food crops and pastures. Their reasoning centred on the potential of these crops to serve as dependable sources of sustenance during drought periods, ultimately helping to mitigate losses in livestock and instances of malnutrition. This perspective aligns with MoALF (2016), which advocates for the promotion of alternative crops as a means of diversification, a strategy that offers protection against overreliance on specific crops susceptible to the impacts of climate change and variability.

Moreover, the respondents expressed the need for enhancements in fundamental infrastructure. Given the historical marginalization and insufficient representation in Kenya's arid and semi-arid lands (ASALs), these communities advocate for inclusion in decision-making processes and administrative structures. The communities suggest enhancements across infrastructure, services, and economic opportunities. This is primarily due to the substandard infrastructure and inadequate availability of sanitation, healthcare, and educational services, all contributing to heightened poverty levels and limited literacy rates (National Gender and Equality Commission (NGEC), 2017). For instance, they proposed the establishment of "nomadic schools" that would enable teachers to accompany students during droughts, ensuring uninterrupted learning.

Furthermore, they stressed the necessity of internet access, electricity, and improved road networks. Notably, young individuals highlighted a recurring issue where they missed job opportunities due to a lack of network coverage. They pointed out that potential employers might try to reach them via phone, but the absence of a signal renders them unreachable. Consequently, they are compelled to venture uphill in search of connectivity, often far from their residences. The challenging state of the roads adds an extra layer of difficulty, impeding their access to urban areas for employment prospects or the transportation of their goods to markets.

Other recommendations encompassed offering relief food, especially for children, and promoting free secondary-level education. Women's groups also conveyed a desire for instruction in alternative income generation methods and strategies for saving finances. Interestingly, the (Government of Kenya, 2021; Ministry of Agriculture Livestock and Fisheries (MoALF), 2016) aligns with these suggestions by emphasizing the importance of intensifying training like value addition training for farmers. This focus aims to empower them to attain improved returns from their agricultural outputs.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

1. Drought occurrences have consistently increased since 1999, with a prolonged drought period from 2012 to 2019. The trends indicate that the lowlands in Leparua Conservancy and Lekurruki have experienced more severe droughts compared to the highlands near the mountain, highlighting the complex drought patterns in the UENB basin.
2. The ANN model performed best at meteorological station 51 with the highest coefficient of determination (0.993) and the smallest RMSE (0.0124) at 12 months. Overall, the results showed that the ANN model accurately forecasted the drought index, with better performance for longer lead times, particularly for the SPEI index which includes both temperature and rainfall data.
3. Drought has severely impacted household livelihoods in the Upper Ewaso Ng'iro Basin (UENB). Crop yields dropped by 27.9%, with 25% of farmers in Kisima experiencing crop failures. Livestock losses were substantial, with 31% in Leparua and 34% in Lekurruki reporting deaths, leading to lower market prices and food scarcity. Water conflicts affected 81% in Kisima and 25.4% in Leparua and Lekurruki, straining community relations. Education and health also suffered, with increased school absenteeism due to food and fee shortages, and poor water quality leading to higher malnutrition rates.
4. Communities in the UENB adapted to drought based on their financial resources, but many strategies were unsustainable, leaving them vulnerable during extended droughts. Adaptations included migration, changing crops, reducing livestock, using irrigation or boreholes, storing cereals, and engaging in artistic activities. Despite these efforts, many faced significant economic losses and had to rebuild their livelihoods.

5.2 Recommendations

5.2.1 Recommendations from the Study

1. To alleviate the widespread consequences of drought on household livelihoods, the study recommends implementation of targeted support programs for affected communities. Programs like refurbishing existing water sources and implementation of soil and water conservation strategies within the communities.
2. To support the community's adaptation strategies through collaboration between Public and Private sectors investing in ASALS and enhance access to financial resources, infrastructure, healthcare, and education.

5.2.2 Recommendations for Further Studies

The following areas of study would help enrich the understanding of the drought discourse.

1. There is a need for further research on the relative effect of climate change and land use/cover change on drought based on climate models in the UENB. This could involve assessing the contribution of human-induced climate change to observed drought patterns. This research used precipitation and temperature data in assessing drought using the DIs.
2. For developing drought forecasting models, the study used the Levenberg-Marquardt (LM) training algorithm for calibration without exploring other alternatives. It's recommended to explore different training algorithms like backpropagation (BP), Conjugate gradient (CG), Perceptron, and Multi-layer perceptron (MLP) to evaluate the model's parameter robustness and reliability.
3. Future research could explore how gender dynamics and age intersect with drought effects and adaptation strategies. This could involve investigating differential experiences between women and men during droughts and assessing if adaptation measures adequately consider gender. Additionally, the research could examine age-related variations, comparing impacts and adaptation strategies among youth, children, and seniors.

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APPENDICES

Appendix I: Meteorological stations ID

Table A1**:** Meteorological Stations according to CETRAD

Station ID	Station Name	Longitude	Latitude
1	Archer's Post	37.6681	0.6335
9	Colcheccio	36.80318	0.61932
10	Dol Dol (Dao)	37.15697	0.38849
22	Isiolo (Dao)	37.58509	0.35384
51	Mukenya Farm	36.82054	0.24204
69	Mukongondo Farm	37.29269	0.09152
80	Rumuruti Mow	36.54844	0.26748
83	Segera Plantations	36.88782	0.1689
89	Suguroi Estate	36.64205	-0.02835
94	Wamba (Do)	37.33198	0.98218

Appendix II: SPEI and SPI Values

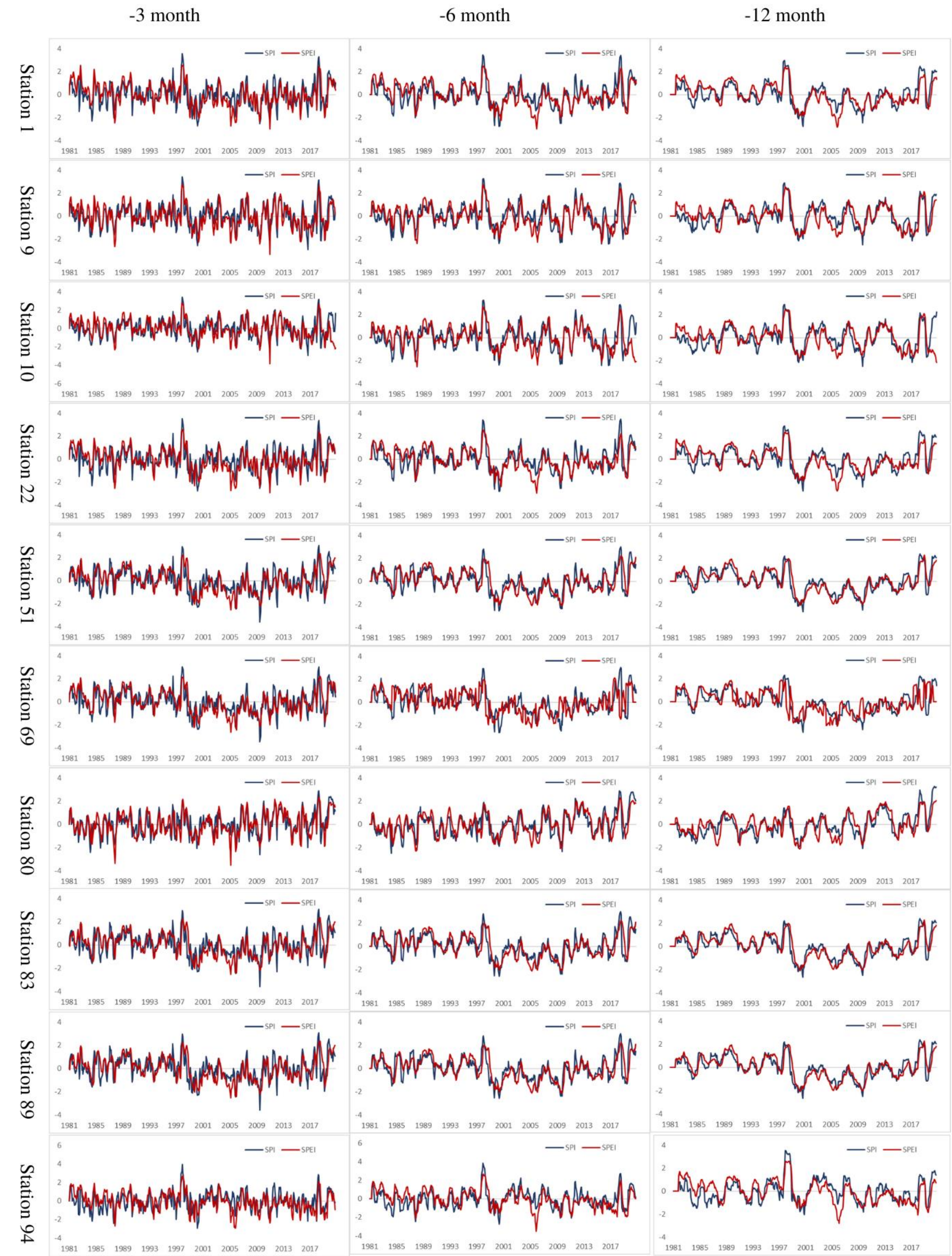

Figure A2: SPI and SPEI values for all stations

Appendix III: ANN Performance

Table A3: ANN performance

Station	SPI			SPEI		
	ANN Arch	R	MSE	ANN Arch	R	MSE
3Month						
1	1.11.1	0.82463	0.3132	1.13.1	0.91884	0.1529
9	1.12.1	1.84463	0.1646	1.13.1	0.9573	0.1592
10	1.10.1	0.84681	0.2851	1.13.1	0.9139	0.0729
22	1.10.1	0.81821	0.3187	1.10.1	0.93	0.1231
51	1.13.1	0.85234	0.2725	1.12.1	0.9561	0.0847
69	1.13.1	0.84126	0.2877	1.13.1	0.9489	0.0956
80	1.10.1	0.86169	0.2392	1.13.1	0.91722	0.1558
83	1.12.1	0.84816	0.2726	1.12.1	0.95967	0.0788
89	1.13.1	0.85603	0.2598	1.13.1	0.95763	0.0813
94	1.10.1	0.84171	0.2782	1.13.1	0.90638	0.1685
6month						
1	1.12.1	0.92942	0.1372	1.10.1	0.97063	0.0548
9	1.12.1	0.93747	0.1236	1.13.1	0.98203	0.0362
10	1.12.1	0.96114	0.0741	1.11.1	0.96302	0.0697
22	1.13.1	0.92742	0.1354	1.13.1	0.97122	0.0515
51	1.13.1	0.93859	0.1135	1.11.1	0.98522	0.0284
69	1.11.1	0.90315	0.1745	1.11.1	0.91129	0.1661
80	1.13.1	0.93454	0.1171	1.11.1	0.96945	0.0577
83	1.12.1	0.94123	0.1089	1.13.1	0.98608	0.0267
89	1.11.1	0.93753	0.1155	1.12.1	0.98632	0.0263
94	1.13.1	0.92754	0.12383	1.11.1	0.95983	0.0723
12 months						
1	1.10.1	0.96992	0.057	1.11.1	0.98731	0.2444

9	1.12.1	0.969501	0.0649	1.13.1	0.96381	0.0699
10	1.11.1	0.96408	0.0694	1.10.1	0.98191	0.3348
22	1.13.1	0.9693	0.0574	1.12.1	0.9867	0.0246
51	1.12.1	0.97701	0.0439	1.12.1	0.99352	0.0124
69	1.11.1	0.9762	0.0396	1.12.1	0.94367	0.1045
80	1.12.1	0.96742	0.0581	1.13.1	0.98245	0.0325
83	1.10.1	0.97868	0.0409	1.11.1	0.99351	0.0124
89	1.10.1	0.97745	0.0429	1.10.1	0.9934	0.0126
94	1.11.1	0.96002	0.736	1.12.1	0.98167	0.034

Appendix IV: Communities' Sources of Income

Table A4.1: Household Income sources

Household Income Sources	**Meru**		**Isiolo**		**Laikipia**	
	N	Percent	N	Percent	N	Percent
Crop production	19	41.3	11	28.9	5	16.7
Livestock	16	34.8	20	52.6	17	56.7
Business	7	15.2	5	13.2	6	20.0
Salaried employment	2	4.3	1	2.6	1	3.3
Casual labourer	2	4.3	1	2.6	1	3.3
Total %	46	100.0	38	100.0	30	100.0

Table A4.2: Summary of crops grown in EUNB

Crops Grown	**Meru**		**Isiolo**		**Laikipia**	
	N	Percent	N	Percent	N	Percent
Maize	9	11.3	11	45.8	5	45.5
Beans	3	3.8	10	41.7	4	36.4
Fruit trees	2	2.5	2	8.3	1	9.1
Vegetables	10	12.5	1	4.2	0	0.0
Carrots	16	20.0	0	0	0	0.0
Peas	4	5.0	0	0	0	0.0
Potatoes	18	22.5	0	0	0	0.0
Onions	2	2.5	0	0	0	0.0
Wheat	1	1.3	0	0.	1	9.1
French beans	10	12.5	0	0	0	0
Trees	3	3.8	0	0	0	0
Napier Grass	1	1.3	0	0	0	0
Oats	1	1.3	0	0	0	0
Total%	80	100.0	24	100.0	11	100.0

Table A4.3: Summary of Livestock in EUNB

Livestock		**Meru**		**Isiolo**		**Laikipia**	
		N	Percent	N	Percent	N	Percent
Livestock	Goat			21	39.6	18	36.0
	Sheep	1	5.3	9	17.0	9	18.0
	Cow	14	73.7	18	34.0	13	26.0
	Donkey	0	0.	2	3.8	3	6.0
	Camel	0	0.	3	5.7	4	8.0
	Bees	1	5.3	0	0.0	3	6.0
	Chicken	2	10.5	0	0.0	0	0.0
	Rabbit	1	5.3	0	0.0	0	0.0
Total %		19	100.0	53	100.0	50	100.0

Appendix V: Questionnaire

Understanding Drought Impacts: Community Survey in the Upper Ewaso Ng'iro North River Basin

Introduction

The survey is part of the research requirements for the award of a Master of Science degree. The objective of this research is to **investigate the effects of droughts to the livelihoods of rural communities in the Upper Ewaso Ng'iro North River Basin.** I am collecting information from households, government officials, and researchers to understand the effects of drought on their daily lives and their adaptation strategies. You have been randomly selected to participate in this survey, and I kindly request you to answer the following questions as appropriate. The data collected will be kept strictly confidential and findings will be used for academic purposes and if need be, will be availed to the community to help to improve livelihoods of the households and build coping capacity to deal with droughts in future.

The Language used for interviews was majorly Swahili with a few respondents in English. Some of the respondents also responded in Maasai and Samburu, then translated to English by a local translator.

<table>
<tr><th colspan="4">1. Personal Data</th></tr>
<tr><td>Village</td><td colspan="3"></td></tr>
<tr><td>Name of the Respondent (optional)</td><td colspan="3"></td></tr>
<tr><td>No of respondent</td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">Gender</td><td>Female</td><td rowspan="3">Year of birth</td><td rowspan="3"></td></tr>
<tr><td>Male</td></tr>
<tr><td>Other</td></tr>
</table>

2. Livelihood characteristics				
Livelihood *(Specify how long have you)*	Crop production			
	Livestock			
	Agro pastoral			
	Business			
	Salaried employment			
	Casual laborer			
	Other (Specify)			
Crop type	**Quantity**	**Usage (commercial (C)/ subsistence(S)**	**How do you describe your produce or harvest in the past few years?**	**number of bags of harvest or amount of animal product**
Livestock				
Cattle				
Sheep				
goats				
Donkey				
Camel				
Chicken				
Other(specify)				

3. Your perception and effects of drought (tick as appropriate)			
	Lack of rainfall		

What does drought mean to you?	Lack of pasture		
	Lack of food		
	Drying of rivers		
	Other Specify		
How frequent are drought episodes in this area?			
What was the impact of drought in your household? (tick as appropriate)			
Economic impact	Reduced crop yield		
	Crop failure		
	Reduced milk production		
	Loss of livestock		
	High cost of goods		
	Reduced salary/wage		
	Others (Specify)		
How was your crops/livestock impacted by drought? (Rate on the scale of 0-10, zero being not impacted and ten being serverly impacted)			
Crops		Livestock	
Social Impact	Children missed school for lack of food		
	Reduced interactions e.g., church gatherings		
	Seasonal migration with animals		
	Increased distance to the water point		

	Job losses in farms				
	Conflict over water				
	Others specify				
Health effects	Increased livestock diseases				
	Increased crop pest				
	Human diseases				
	Malnutrition				
	Human death				
	Others specify				
Environ mental impact	Drying of rivers				
	Increased cases of fires				
	Loss of vegetation/tree cover				
	Lack of household fuel				
	Others specify				

4. Adaptation strategies (tick as appropriate)		
How did you	Sold livestock	
	Migrated with the animals	

respond to the drought episode?	Searched for employment	
	Changed my source of income	
	Slaughtered the animals	
	Bought food supply	
	watered crops	
	Planting trees and reforestation	
	Stock piling of cereals and grains	
	Planted drought evading crops/ Changing cropping patterns	
	Rehabilitation/ Construction of critical boreholes	
	emergency aid	
	Irrigation of crops	
	Other (specify)	
What strategies do you use to prepare for drought	Set aside some emergency fund	
	Preserve food supplies	
	Mobilize my neighbours and discuss the way forward	
	Attend trainings on drought management	
	Seek information on drought preparedness	
	Wait for relief food	
	Other specify	
Which adaptation strategies did you use?		

5. What do you think can be done to help curb the impact of the drought to your livelihoods?

Appendix VI: Key Informants Interview Questions

The objective of this interview is to assess the drought effects on household livelihoods and adaptation strategies in County. The target populations are Chiefs, Elders, Ward Agriculture and livestock officers, ward devolution officers and NGO Officials

1. What does drought mean in Ewaso Ng'iro North River Basin (Or the specific county)?
2. What was the effect of the 2017 drought in the county?
3. How many livestock died during the 2017 drought?
4. How did crops perform during the 2017 drought period?
5. How many people needed food aid during the 2017 drought in this location?
6. What criteria do you use in distribution of relief food?
7. How many people died due to the 2017 drought in the location?
8. How did the households and Community respond during the 2017 drought?
9. What are the Community drought adaptations strategies used in the area?
10. What are the household drought preparedness and adaptation strategies in the Basin?
11. What are the government's drought disaster preparedness strategies?
12. Describe some of the activities undertaken to enhance drought preparedness?
13. What are the adaptation challenges facing household and community in the Basin?
14. What do you think should be done to enhance drought adaptation in the Basin?