MAKERERE UNIVERSITY

EXAMINING THE IMPLICATIONS OF PAST AND FUTURE EXTREME DROUGHT CHARACTERISTICS ON GRASSLANDS IN KIRUHURA DISTRICT

BY

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I, the undersigned, declare that to the best of my knowledge this work is original and has never been submitted anywhere for academic purposes or otherwise.

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DEDICATION

This work is dedicated to the Lord God Almighty and the Department of Meteorological Services (DMS), Ministry of Water and Environment (MWE) formally Uganda National Meteorological Authority (UNMA) for the financial and moral support towards this academic accomplishment.

Finally, I dedicate this work to my family and friends for your prayers, support and encouragement.

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LIST OF ACRONYMS AND ABBREVIATIONS

DSNO	Division of Station Networks and Observations
C/DMS	Commissioner Department of Meteorological Services
DMS	Department of Meteorological Services.
SVI	Standard Vegetation Index
NDVI	Normalized Difference Vegetation Index
EVI	Enhanced Vegetation Index
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
PDSI	Palmer Drought Severity Index
SMI	Soil Moisture Index
CMI	Crop Moisture Index
DSCI	Drought Severity and Coverage Index
CDI	Combined Drought Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FAO	Food and Agriculture Organisation
GPCC	Global Precipitation Climatology Centre
CMIP6	Coupled Model Intercomparison Project phase 6
WMO	World Meteorological Organisation
GCM	Global Circulation Model
SSP	Shared Social economic pathway
MODIS	Moderate Resolution Imaging Spectroradiometer
UBOS	Uganda Bureau of Statistics
FGD	Focus group discussions
KIIs	Key informative interviews
SSP245	Shared Socioeconomic Pathways
SSP585	Shared Socioeconomic Pathways

ABSTRACT

Drought is one of the major challenges in achieving sustainable development with impacts including; disruptions in the ecosystems, water and food resources among others. Understanding drought dynamics is therefore vital for protecting lives, securing food and water, preserving ecosystems and building climate resilience. This study investigated the characteristics and implications of past and future extreme drought on grasslands, with an aim of contributing towards building drought resilience of the cattle keeping communities in Kiruhura District. Specifically, the objectives of the study included; (1) examining the past and future extreme drought characteristics, (2) examining the impact of past extreme drought on spatiotemporal distribution of grasslands and (3) examining the projected impact of future extreme drought on the temporal distribution of the grasslands.

The research employed the Standardized Precipitation Index (SPI) to analyze past and projected drought conditions focusing on the duration, severity, and intensity of extreme drought events. The spatiotemporal changes in the Normalised difference vegetation index (NDVI) against the Standard precipitation index (SPI) were used to investigate the impacts of extreme drought on the grasslands. The results reveal that the grasslands were negatively impacted by extended extreme drought periods of 6 and 12 months. Both SPI indices had a statistically significant relationship shown by the Pearson moment correlation analysis. SPI6 and SPI12 having P-values of 0.0031 and 0.0022 respectively. In the future, under both SSP245 and SSP585 climate scenarios, the relationship between drought and NDVI was generally insignificant with Pearson moment correlation P-values between 0.33 - 0.84, way above the significance level of 0.05. Comparing the two projected climate scenarios, the implication of this relationship was much more pronounced under SSP585 as revealed by the time series analysis where NDVI showed to respond to longer – term droughts although not statistically significant.

Drawing from the study conclusions including the grasslands being resilient to short-term extreme droughts but vulnerable to prolonged droughts and the fact that no extreme drought control on grassland cover was evident in future projections. The study recommended grassland management policies that emphasize adaptive strategies such as controlled stocking rates, pasture rotation, restoration of degraded grasslands, and protection of key dry season grazing reserves to reduce vulnerability to prolonged and severe droughts to enhance resilience.

CHAPTER ONE: INTRODUCTION

1.1 Background

Drought, characterized by extended periods of unusually low rainfall, is a major environmental hazard that regularly jeopardizes the food security of farmers and livestock keeping communities (Carrão et al, 2016; Meza et al, 2020). Drought has been reported as one of the most severe climatic hazards that affects grassland ecosystems and pastoral livelihoods, especially in arid and semi-arid regions (Ndiritu, 2021). This is because cattle-keeping communities in most of these areas strongly depend on grasslands for pasture availability and livestock production. Pasture availability is highly influenced by seasonal variability in forage quantity and quality, water access, weather conditions, and topographic features that drive seasonal grazing patterns. (Lelenguyah et al., 2023; Kerven et al. 2016a, 2016b).

Drought impacts on agriculture, particularly grasslands and livestock systems, are extensive and growing due to climate variability and anthropogenic climate change (Thornton et al. 2009). Globally, droughts contribute significantly to reduced biomass production, desertification, and water scarcity, leading to declines in agricultural productivity and threatening food security (Wilhite et al. 2014). Grassland ecosystems, which support a large share of the world's cattle-rearing communities, are particularly vulnerable to drought because reduced precipitation and prolonged dry periods directly limit pasture growth, decrease forage quality, and diminish water availability, thereby threatening livestock productivity and the livelihoods of pastoral and agro-pastoral communities' dependent on these resources. (Reichstein et al. 2013). In addition, global warming is expected to lead to increased drought frequency, duration, and intensity in many regions, intensifying stress on grasslands and the livelihoods of pastoral communities (IPCC, 2022).

Africa is disproportionately impacted by drought due to its high climatic vulnerability, low adaptive capability, and significant dependence on rain-fed agriculture (IPCC, 2022). For example, Niang et al. (2014) observed that the African continent has experienced more frequent extreme droughts over the past decades, resulting in high livestock mortality, forced migration and conflict over grazing resources. These conditions not only erode the ecological stability of grasslands but also undermine the resilience of pastoralist livelihoods. In the Sahel, Horn of Africa, and Southern

Africa, recurrent droughts have led to widespread grassland degradation and water shortages, severely impacting livestock production (FAO, 2019).

In East Africa, semiarid areas like the cattle corridor increasingly experience recurring and prolonged drought episodes attributed to climate variability and change. The droughts severely impact grassland ecosystems, which are critical to the predominantly pastoral and agro-pastoral communities who depend on them for livestock rearing. According to Thornton et al. (2006), the frequency and intensity of drought in East Africa has contributed to a decline in grassland productivity, increased livestock mortality, and food insecurity among the cattle keeping communities.

In Uganda, droughts are becoming more frequent and intense, especially in the “cattle corridor”, a semi-arid belt stretching from the southwest to the northeast of the country (UNMA, 2020). Grasslands in these regions are vital for livestock, yet they are highly vulnerable to rainfall variability. The significant drought episodes in Uganda have been reported in 1999-2000, 2010-2011, and 2016-2017, all of which had adverse effects on pasture availability and water resources for both livestock and human use (UNMA, 2020). These climatic stresses undermine the resilience of cattle-keeping communities, particularly those relying heavily on natural pasture systems.

Kiruhura District in the cattle corridor is relatively dry and is home to extensive grasslands that are vital for the livelihoods of cattle keeping communities (Nampala et al. 2015). These communities rely heavily on livestock grazing for food, income generation, and cultural identity. However, the region is increasingly facing the challenge of recurring and intensifying droughts (Mubiru et al. 2018). As a result, drought-induced changes in grassland composition and coverage in Kiruhura have increased vulnerability among local cattle-keeping communities. The prolonged and intense droughts have led to losses of cattle due to forage and water scarcity. Since natural grasslands are the major source of feed for the animals, its sustainability in the face of diverse challenges including drought is therefore important (Nampala et al. 2015).

1.2 Research Problem

Drought poses a significant danger to the sustainability of grassland ecosystems by diminishing soil moisture, constraining plant development, and initiating degradation processes among others (Li et al., 2020). As prolonged dry conditions persist, the regenerative capacity of grasses diminishes, leading to biomass decline and shifts in species composition, which compromise both grazing quality and carrying capacity (Li et al., 2018). The sensitivity of grasslands to climatic stress underscores their vulnerability to drought events, particularly in semi-arid and arid environments like the cattle corridor where rainfall variability is already high (Knapp et al., 2008).

Studies in the region such as Nampala et al. (2015) and Mbuya et al. (2015) have focused on assessing the effects of climate variability on forage availability and herd dynamics in cattle corridor districts, including Kiruhura. These studies paid attention to historical impacts and adaptive responses among the cattle keeping communities. Other studies such as Twinamatsiko et al. (2020) and Njagi et al. (2022) have covered related aspects such as drought impacts, pasture management practices, and land cover dynamics within the grasslands ecosystem.

However, despite the availability of these studies and more on the subject, there remains a significant knowledge gap in understanding how extreme drought events particularly under projected future climate will affect the grasslands ecosystem in the cattle corridor. The interactions between droughts at different timescales and vegetation cover as well as resilience of pastoral systems under increasing climatic stress have not been thoroughly analyzed. Therefore, this study seeks to bridge the knowledge gap by examining the implications of past and future extreme drought on grasslands in Kiruhura District, with the goal to enhance early warning systems and inform strategies for drought resilience and sustainable grasslands management.

1.3 Main Objective

The main objective of this study was to contribute to building resilience of livestock farmers to the impacts of drought on grasslands in Kiruhura District.

1.4 Specific Objectives

1. To examine the past and future extreme drought characteristics in Kiruhura District.

2. To examine the impact of past extreme drought on spatiotemporal distribution of grasslands in Kiruhura District.

3. To examine the impact of future extreme drought on temporal distribution of grasslands in Kiruhura District.

1.4.1 Research Hypothesis

H_0: There is no statistically significant change in trend in the influence and measurable implication of extreme drought on grasslands conditions in Kiruhura District.

H_1: There is a statistically significant change in trend in the influence and measurable implication of extreme drought on grasslands conditions in Kiruhura District.

1.5 Significance

The cattle keeping communities in Kiruhura are constrained by the impacts of drought including diminishing animal forage and water resources. Consequently, at times the situation escalates into loss of livestock thereby breaking the economic backbone and security of these communities driving them into perpetual poverty. The cycle can be expected whenever climatic extremes including drought occur until resilience of these communities is built by availing an evidence based understanding of the implications of past and projected drought dynamics. This way, the study aligns itself to underwrite towards Sustainable Development Goal (SDG) 13 "taking urgent action to combat climate change and its impacts". The study will also contribute towards Uganda's Vision 2040 on climate change by providing information relevant for more effective policies on grassland management, guided practices and strategies for appropriate adaptation and mitigation to build more resilient cattle keeping communities.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter presents an in-depth review of the work done by scholars and researchers on the subject of drought and the implications on the grasslands and pasture availability as well as the mitigation strategies adopted by pastoralists to avert the implications.

2.1 Drought Definitions

Drought is one of the natural hazards that arise due to changes and variations in climate of the country (Zargar et al., 2011). It is a recurring natural phenomenon different from other natural hazards like floods because of its slow and accumulating process (Mulinde et al., 2016). In addition, it is associated with long lasting effects and damage which can be widespread leading to significant socio-economic losses especially in the agricultural sector (Paulina et al., 2017). This has made drought monitoring a major priority worldwide (Owrangi et al., 2011). Characteristics and impacts of drought are mostly determined by the hydrologic cycle; therefore they are not independent of factors such as temperature, wind speed, humidity, runoff, groundwater, soil moisture and snow, or human factors such as land and water management (Cook et al, 2014). Drought is majorly related to the timing of precipitation that is to say, it mainly results from deficiency of precipitation over an extended period of time like season or more (Dattatraya et al., 2016). Therefore, the drought impacts are controlled by the magnitude, duration, frequency and spatial extent of the rainfall deficit (Degefu & Bewket, 2013; Zargar et al., 2011). However, Wilhite and Glantz (1985) divides drought into four categories: meteorological drought, hydrological drought, agricultural drought and socio-economic drought.

A meteorological drought thus translates into an agricultural drought as the absence of precipitation and higher evapotranspiration rates impact agricultural production (Wang et al., 2016). Agricultural drought specifically focuses on the shortage of soil moisture, which can be detrimental to crop production. It occurs when the soil lacks sufficient moisture for crops to grow and develop. Further absence of precipitation with higher evapotranspiration depletes surface and subsurface water resources culminating into a hydrological drought.

A hydrological drought is thus related to the decreasing availability of surface water and groundwater (Van Loon, 2015). It occurs when the lack of precipitation results in lower streamflow, reduced reservoir levels, and declining groundwater tables. This type of drought affects water resources and can have long-term impacts on ecosystems and agriculture. When this water shortage negatively impacts the economy, then it is a socio-economic drought. This kind of propagation of drought is through stages with the first (1-3 months) being meteorological (Spinoni et al, 2013; Christina et al, 2017).

Socioeconomic drought refers to the impact of drought on human activities and communities (Van Loon, 2015). It encompasses water supply shortages, food security issues, and socio-economic consequences like job loss and reduced income. This type of drought often affects urban and rural populations differently.

Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels (WMO, 2005).

Ecological Drought: Ecological drought primarily affects ecosystems, including forests, wetlands, and wildlife. It occurs when reduced water availability leads to changes in the composition and health of natural ecosystems. These changes can have cascading effects on biodiversity and ecosystem services (Maxwell et al, 2019).

Consequences and after effects of droughts tend to persist even after drought duration (Begueria, 2003). Drought can have severe economic implications, particularly in regions heavily reliant on agriculture. Therefore, understanding the various definitions and types of droughts is crucial for effective monitoring, assessment, and mitigation. This literature review provides an overview of the definitions and types of droughts, offering insights into the evolving understanding of this complex phenomenon.

2.2 Drought characterization and monitoring Using Indices

Drought is a complex natural hazard with far-reaching environmental, social, and economic implications (Detges, 2017). Effective drought characterization and monitoring are essential for early warning, mitigation, and adaptive strategies. Spinoni et al (2013) characterized drought basing on frequency, intensity, duration and severity. Drought frequency, duration, severity and intensity can be illustrated by drought indices (Steinemann, 2003). Drought indices integrate thousands of bits of data on rainfall, streamflow, and other water supply indicators into a comprehensible big picture. A drought index value is normally a single number, far more suitable for decision making than raw data (WMO, 2005). Numerous indices have been established to identify the drought characteristics over the past few decades (Siyang et al., 2017). These indices include the following Standardized Precipitation Index, Palmer Drought Severity Index (PDSI), Percent of Normal and Deciles drought analysis method. However, the most used indices include; Palmer Drought Severity Index (PDSI); this was developed by Wayne Palmer in the 1960s. The Palmer Drought Severity Index is one of the earliest and widely used indices for drought assessment. PDSI considers temperature, precipitation, and soil moisture conditions to calculate drought severity (Ntale & Gan, 2003). It provides a standardized measure that allows for the comparison of drought events across different regions and time periods.

Standardized Precipitation Index (SPI); the Standardized Precipitation Index is a purely precipitation-based drought index that characterizes drought based on the probability of precipitation deficits (Musonda et al, 2020). SPI is versatile and can be computed for different timescales, making it useful for short-term and long-term drought monitoring. It has gained popularity for its simplicity and effectiveness in capturing meteorological drought.

Standardized Precipitation Evapotranspiration Index (SPEI); the Standardized Precipitation Evapotranspiration Index is an enhancement of SPI, as it incorporates evapotranspiration alongside precipitation data (Obubu et al, 2021). This index provides a more comprehensive assessment of hydrological drought by considering both water input (precipitation) and output (evapotranspiration).

Soil Moisture Index (SMI); Soil moisture is a critical component of drought monitoring, especially for agricultural and ecological applications. The Soil Moisture Index combines meteorological data with soil moisture measurements to assess drought conditions. It offers insights into the impacts of drought on soil moisture availability for vegetation and agricultural crops (Aghakouchak, 2015).

Crop Moisture Index (CMI); the Crop Moisture Index focuses on agricultural drought assessment. It considers factors such as precipitation and temperature to estimate the moisture condition of the soil as it relates to crop growth (Botai et al, 2016). CMI helps in predicting potential impacts on crop yields and is valuable for the agricultural sector.

Drought Severity and Coverage Index (DSCI); the Drought Severity and Coverage Index is designed to assess the spatial extent and severity of drought. It considers drought duration, intensity, and spatial distribution (Zhan et al, 2016). DSCI provides a comprehensive view of drought events and can assist in resource allocation for mitigation efforts.

Normalized Difference Vegetation Index (NDVI); NDVI is a normalized ratio of vegetation reflectance at two wavelength bands, i.e. the visible band and the near infrared bands. Many studies including (Tucker et al. 2005; Lunetta et al, 2006; Gamoyo et al. 2014; Son et al, 2014; Ndirima et al, 2020; FEWSNET. 2021), have studied changes in NDVI as an indicator for changes in vegetation and land use cover changes in relation to climate change and variability. Vegetation strongly absorbs the red wavelengths of sunlight and reflects in the near-infrared wavelengths making it different from other land surfaces. Since NDVI is indicative of the level of photosynthetic activity, it is used to monitor vegetation conditions. This way it effectively reflects levels of stress in vegetation and thereby, indicative of drought occurrence. Reduction in NDVI is expected in stressed vegetation conditions (; Bhuiyan, 2003; Makama-Massa et al, 2012).

Combined Drought Index (CDI); The Combined Drought index is used for Agriculture drought monitoring. It demonstrates that a reduction in precipitation leads to shortage in soil moisture resulting in vegetation failure (Copernicus, 2013; EDO, 2013). CDI combines measurements from SPI for meteorological drought, SMA for hydrological drought and FAPAR indicators. These measure precipitation, soil moisture and remote sensing vegetation growth anomalies. (De Jager et al, 2015) CDI therefore singles out regions of potential agricultural drought (watch - Mild), areas about to undergo drought (warning -Moderate), areas already under drought (Alert – Severe/Extreme) and those under recovery from drought.

Table 1: Drought severity legend adopted from Source: (Zoltan et al, 2013)

Drought severity legend					
Category	No Drought	Mild	Moderate	Severe	Extreme
colour code					
CDI	>1.0	1.0–0.8	0.8–0.6	0.6–0.4	<0.4

Standard Vegetation Index (SVI); this method of analysis supports drought monitoring and early warning was developed by Peters et al. (2002). The SVI is a z-score that differs from the mean in units of the standard deviation and is generated from the NDVI or EVI values for each given pixel of a composite period for each year during a stated period studied. It depicts, on a weekly time window, the likelihood that the NDVI will deviate from the mean over several years of data (such as 12 years) (UN-SPIDER, 2019).

Among all these drought characterizations and monitoring indices, this study preferred to use SPI index because of its simplicity to use in data scarce or resource limited environments and flexible across multiple timescales drought assessments (McKee, Doesken, & Kleist, 1993) The SPI method requires only precipitation as input and is recommended by the World Meteorological Organization (WMO) for use in climatic studies (WMO, 2012);

2.3 Drought trends

Several studies including (Easterling et al., 2000; Sheffield and Wood, 2008; Perkins et al., 2012; Trenberth et al., 2013; Aghakouchak et al, 2014; Ayugi et al, 2020) agree that global warming and the resultant increase in global temperatures increases the likelihood that climatic extreme events like droughts and heatwaves will occur with greater severity. Although it is quite evident that drought continues to be one of the most complicated environmental occurrences at all geographical scales including global, regional to the local. Drought trends at global scale are still highly debatable due to insufficient observations and a conflict in drought definitions. Meanwhile at regional level, many agree to an increasing trend in drought frequency and intensity (Dai, 2013; Sheffield, Wood, & Roderick, 2012; Trenberth et al., 2014; Naumann et al, 2018).

According to Gebremeskel et al, 2019, drought has occurred with greater frequency across most continents with devastating impacts within the last three decades. Approximately 55 million people are directly affected annually and a projection of 700 million at risk of displacement by 2030 globally. Many continents have been hit and affected with different drought magnitudes and levels of catastrophe. Without making mention of the human death tolls over the years, (Checchi and Robinson, 2013; Shukla et al, 2014) in their studies indicated that 40% of the global population had already been impacted by water scarcity under drought conditions by 2014.

In Africa, drought events recorded an increase in frequency, with some regions experiencing it in a cycle of three years instead of six years as previously experienced (Funk et al, 2014; Shukla et al, 2014). In every place drought has occurred, it was preceded by an entrainment of negative consequences. For example; Ethiopia alone lost up to 300,000 people in May 1983 and the most severe disaster of the century in 2011 directly affected 13 million people across the Horn of Africa (Shukla et al, 2014). Under ambitious mitigation targets, drought frequency is projected to multiply 5 – 10 times. While in stringent mitigation targets, doubling of drought magnitudes and duration were projected alongside warming (Naumann et al, 2018; Ayugi et al, 2020). Other studies including (Zhao and Dai, 2015; Gebremeskel et al, 2019) also projected an increase in drought frequency by 100% for agricultural and 50% for hydrological droughts by the year 2090.

In the East African region, studies like Ojara et al, 2022 have identified increases in drought duration, frequency and found out that during the period 1981 to 2017, most agricultural regions experienced up to 11 months of extreme droughts, 23 severe droughts and 47 moderate droughts. Nicholson, 2014; Gebremeskel et al, 2019 also highlighted an interesting fact that droughts occurred within the same years as flash floods like 2006, 2007, 2009 and 2010 escalating the climatic impacts on the ecosystems. Haile et al, 2020 indicated that by the 21 century, extreme drought spatial coverage is expected to increase by 54% under RCP 8.5 and 16% under 2.6 in EA. Drought duration, intensity and frequency were projected to increase in Tanzania, Somalia, Sudan and South Sudan while in Uganda and Kenya, will have a decrease.

In Uganda, a number of studies have documented hydro-climatic variability relevant to agricultural drought. Nsubuga and Rautenbach (2018) identified significant trends and variability in rainfall and temperature across Uganda, pointing to a high drought risk especially in semi-arid areas like the cattle corridor. According to (Kizza et al, 2009), there is a pronounced temporal rainfall variability in the Lake Victoria Basin. This variability translates into soil-moisture deficits and agricultural droughts downstream. At the level of the rangelands, (Nampala et al, 2015) provided evidence of drought impacts on pasture and livestock in Uganda's cattle corridor, linking rainfall anomalies to pasture degradation, reduced forage availability, and livestock productivity losses.

2.4 Causes of Droughts

According to Gebremeskel et al. (2019); Ayugi et al. (2020), droughts being one of the many extreme weather occurrences are notable consequences or implications of the changing climate. Many studies attribute this change in climate to both natural and human induced factors. WMO still acknowledges information gaps on the causes of droughts especially in regard to frequency, evolution and severity on a spatial scale. Researchers in regional contexts like East Africa, tie it to different geographical factors including coastal and oceanic exchanges alongside climate variability.

2.4.1 Anthropogenic causes

(Sheffield and Wood, 2011; Masih et al., 2014; Van Loon et al, 2016a; Ordway et al., 2017). Apart from natural causes, human activities have been shown to contribute towards climate change and the entrainment of extreme weather events such as droughts. Rapidly expanding populations multiply pressure on existing natural resources calumniating into excessive deforestation, land use change, fires, land degradation, mining, and overuse of water resources, urbanization, land reclamation and massive development projects are among many more activities that lead to droughts and other extreme events. Human water usage and consumption is closely related to hydrological cycle processes that show drought as a disruption in the processes (Zeng, 2003; AghaKouchak et al, 2015; Schubert et al, 2016; Gebremeskel et al, 2019).

2.4.2 Climate variability

According to Schreck & Semazzi (2004) and Nicholson (2017) zonal winds and low-level circulations are more reliable in drought seasonal forecasting than ENSO and SST in EA. But Lott et al (2013) insist La Nina is a primary cause of drought and deserves a lot of attention in EA. Studies by Funk, 2011; Lott et al., 2013; Dutra et al., 2013, also suggest La Nina is tightly linked to drought in the Eastern and central regions of East Africa. Like the 2010 – 2011 drought in the Horn of Africa was associated with a La Nina episode. However, Kiem et al, 2016; Schubert et al, 2016; Gebremeskel et al, 2019, suggested drought was caused by an integration of all factors Natural and human induced.

2.5 Implications of Droughts

Throughout time drought has impacted the ecosystem both positively and overwhelmingly negatively with disasters (Souverijns et al., 2016). Based on the study by Gu, 2015, 90% of the extremely disastrous climatic events between 1900 to 2006 were water related including droughts. (Spinoni et al, 2013) also noted that globally 2 billion people were affected by drought and 11 million of these lost lives between 1900 to 2011. Extreme climatic and weather events have always had profound impacts on the ecosystem, its management and the diverse species in it (Maxwell et al, 2019). In East Africa, projected impacts of drought are expected to follow the “wet gets wetted and dry gets drier” paradigm according to (Haile et al, 2020) in the study on future drought changes under different RCPs using CMIP 5 over East Africa.

2.5.1 Drought Implication on Vegetation

The Interactions between pastoralists, livestock and wildlife around pasture bands in grasslands and water resources amplify the competition for the decreasing resources in the rangelands (Reid et al, 2014; Kock et al, 2018). This culminates in an increase in disease transmission, a risk to more than 180 million pastoralists and cattle keepers globally (Galvin, 2009; Thornton et al, 2002).

Various studies have been carried out on the drought and implications on vegetation at different geographical scales. For example; Wang et al, 2015, investigated drought and implications on vegetation in China using SPI and NDVI anomaly. Gouveia et al, 2016, handled drought impacts in the Mediterranean basin. In both studies, revealed drought had a strong hold over huge vegetation cover areas but changes in spatial coverage were minimal in every 10 years.

Vulnerability assessments of grassland drought stress under climate change have become a high-profile concern (Li et al, 2022; Zeng et al, 2022). Quantifying the response of grassland vegetation to drought stress and identifying the area's most vulnerable to drought, as well as the types of grassland that respond most strongly to drought, are therefore critical to improving our understanding of the vulnerability of grasslands to climate change and taking appropriate measures to mitigate the effects of drought.

In Africa, Rijks et al, 2007, efforts were to develop a crop and rangeland monitoring system for Africa in order to keep abreast with the impacts of drought on semiarid vegetation.

In the East African region, examples of drought impact on vegetation in rangelands were identified in the Mukogodo Division in Kenya where gradual changes in rangelands vegetation occurred to the extent of turning palatable species into non-palatable ones based on the study by Herrero et al 2013. Reid et al, (2004) and Herrero et al (2013), pointed out that in East Africa, drought impacts on grasslands as a cattle feed resource are well pronounced, for example; in the West Pokot Region, due to the drought of 1999–2000. Restoration of pasture and graze for cattle failed, as a result hundreds of cattle keepers had to relocate into the nearby Trans-Nzoia district and Uganda.

In Uganda various studies on drought implications on vegetation have been carried out by studies including; (Isubikalu et al, 2012) that looked at predicted vegetation biomass under the 2071-2100 projected rainfall conditions in Uganda's cattle corridor. While (Byenkya et al, 2014) focused on land use and cover change in pastoral systems of Uganda: implications on livestock management under drought induced.

2.5.2 Drought implications on Agriculture and food security.

Drought impacts many sectors including; agriculture, tourism, health, ecosystems, water resources, energy with socioeconomic implications (Christina et al, 2017; Meza et al, 2020). However, of all these sectors, agriculture is most impacted by drought in many countries practicing rain fed agriculture, although ecosystems, economies and communities are all significantly affected. Since many African countries depend on rain fed agriculture, multiple famines resulting in food insecurity, starvation, hunger and malnutrition have affected numerous communities consequential to droughts (Rojas et al., 2011; Naumann et al, 2014). For example, in 2010 – 2011 drought in the great horn of Africa, had an estimate of 250,000 fatalities due to food shortage (O'Loughlin et al., 2012; Muller, 2014; Ayana et al., 2016; Vigaud, 2017). Some studies such as (Ayugi et al, 2020; Njouenwet et al, 2021; and Najjuma et al, 2021), have underscored the increasing impact of drought particularly on agriculture, water resources and ecosystems. These studies have highlighted drought implications that manifest in the form of decreased species richness, diminished plant cover, reduced tree density and overall depletion of natural resources.

The cattle corridor similar to other grassland regions in East Africa is significantly impacted by climate variability affecting resources like grass and water including regular supply of food and non-food demands Mbolanyi et al, (2014). According to Ogallo & Oludhe (2009) and Huho et al, (2011), pastoralists who happen to dwell in the regions with the lowest amounts of rainfall, any encounter with prolonged droughts results into substantial economic loss stemming from mortality of livestock Ongoma et al, (2015).

Drought has also been one of the main causes of socio-economic instability in various nations, including Ethiopia, Somalia and Kenya, Detges,(2017). For example; in northern Kenya Turkana pastoralists are forced to graze more regularly on the edges of their region, putting them at risk for attacks from Pokot and Toposa raiders. Like many other pastoral communities, the main obstacle to pastoralists in Mukogodo Division was drought, it always resulted in widespread livestock deaths and an overall decline in the pastoral economy among Maasai pastoralists

In the entire greater Horn of Africa, drought occurrences have been variable in space and time with varied impacts on people and their socio-economic livelihood as shown in Table 2.

Table 2: Summary of drought events recorded from 1900 – 2017 from EM-DAT database (EM-DAT, 2018) and from literature (e.g. Masih et al.,2014; Guha-Sapir et al., 2004). Source: (Gebremeskel et al., 2019)

Country	Drought years	Number of drought episodes	Number of deaths	Number of people affected (Million)	Economic loss (USD)
Burundi	1999, 2003, 2005, 2008, 2009, 2010	6	126	3.1	Not available
Djibouti	1980, 1983, 1988, 1996, 1999, 2005, 2007, 2008, 2010	9	0	1.2	Not available
Eritrea	1993, 1999, 2008	3	0	5.6	Not available
Ethiopia	1965, 1969, 1973, 1984, 1987, 1989, 1997, 1998, 1999, 2003, 2005, 2008, 2009, 2012 and 2015	15	402,367	77.1	1,492,600
Kenya	1965, 1971, 1979, 1983, 1991, 1994, 1996, 1999, 2004, 2005, 2008, 2010, 2012, 2014 and 2016	15	196	50.2	1500
Rwanda	1976, 1984, 1989, 1996, 1999, 2003	6	237	4.2	Not available
Somalia	1964, 1969, 1973, 1980, 1983, 1987, 1988, 1999. 2004, 2005, 2008, 2010, 2012, 2014 and 2016	15	19,673	18.4	Not available
South Sudan	2010, 2016	2	0	7.9	Not available
Sudan	1980, 1983, 1987, 1990, 1991, 1996, 1999, 2009, 2012 and 2015	10	150,000	31.5	Not available
Tanzania	1967, 1977, 1984, 1988, 1990, 1996, 2003, 2004, 2006, 2011	10	0	12.7	Not available
Uganda	1967, 1979, 1987, 1998, 1999, 2002, 2005, 2008, 2010	9	194	5.0	1800
EA		100	572,793	216.9	1,495,900

2.6 Drought under Projected climate scenarios

The Shared Socioeconomic Pathways (SSPs) are a set of five scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) to explore the possible trajectories of global development and their implications for climate change and associated risks, such as drought (O'Neill et al, 2014). These pathways range from sustainability-focused development (SSP1) to fossil-fueled development (SSP5), with intermediate scenarios such as SSP2 (middle of the road), SSP3 (regional rivalry), and SSP4 (inequality). In climate research, SSPs are combined with Representative Concentration Pathways (RCPs) to simulate future climate impacts.

SSP2-4.5 and SSP5-8.5 are two frequently used scenarios for analyzing future climate risks. SSP2-4.5 represents a moderate development pathway with medium challenges to mitigation and adaptation, while SSP5-8.5 represents a high-emission, fossil-fuel intensive future. Studies using these scenarios project increasing frequency and intensity of droughts under global warming, particularly in semi-arid and arid regions (Cook et al, 2020).

In the context of grasslands and pastoral systems, droughts under SSP5-8.5 are projected to cause more frequent vegetation stress, biomass loss, and livestock pressure, leading to ecological degradation and food insecurity (Spinoni et al, 2021). These effects are expected to be more pronounced in Sub-Saharan Africa due to higher exposure and lower adaptive capacity. Conversely, SSP2-4.5, though still associated with notable drought risks, offers a relatively moderate impact trajectory, supporting policy discussions around sustainable adaptation planning and early warning systems.

Research incorporating NDVI and SPI under SSP scenarios has shown a weakening of vegetation-drought correlations in high-emission futures, suggesting that other factors such as land use change, CO2 fertilization, and irrigation may increasingly mediate vegetation responses (Li et al., 2023). This implies the importance of integrated approaches combining climate modeling with local socioeconomic and land management dynamics.

Under future climate change scenarios, the frequency, intensity, and area of compound drought events (land-atmospheric water constraint) are expected to increase, leading to a decline in gross primary productivity (GPP) of grassland ecosystems (Karen et al, 2021). Additionally, warming and drought have been found to negatively impact biomass production, morphology, and nutritional quality of common pasture species, with drought having a stronger effect than modest levels of warming (Yuqian et al, 2022). The resistance and resilience of soil microbial communities to drought are influenced by historical precipitation regimes, with lower mean annual precipitation leading to more resistant and resilient bacterial communities (Miroslav et al, 2021). Furthermore, future climate change is projected to increase the exposure of European grasslands to heat and drought, particularly in southern and western regions (Wanqiang et al, 2023). Assessing grassland drought stress vulnerability is crucial for understanding the dynamics of drought stress and informing future management strategies**.**

However, there are levels of uncertainty associated with projections under SSP245 and SSP585 scenarios. These arise from internal climate variability, model structural differences and scenario uncertainty that increases toward mid late century as emissions pathways diverge (IPCC, 2021; Knutti & Sedláček, 2013; Tebaldi & Knutti, 2007). For drought, more uncertainty comes from precipitation biases and propagation errors introduced by downscaling and bias correction when deriving indices (Eyring et al., 2016; IPCC, 2021). However, many evaluations show CMIP6 models as reproducing seasonal precipitation over East Africa more realistically than earlier generations (Almazroui et al., 2020; Dosio et al., 2021). confidence in regional drought projections under SSP245/SSP585 remains medium due to persistent precipitation uncertainties and land-surface feedback complexities affecting grassland responses (IPCC, 2021; Dosio et al., 2021).

CHAPTER THREE: METHODOLOGY

3.0 Introduction

This chapter describes the study area, research design**,** data used for the study and the methods employed to achieve the specific objectives.

3.1 Study area

The study area is Kiruhura District located in the Southwestern subregion of Uganda between latitudes 00°12'S and 31°00'E (figure 2). The district has an average altitude of 1800 meters and a total surface area of 4608 km². It shares borders with Mbarara District to the West, Isingiro District to the south, Ibanda and Kamwenge to the North West, Rakai district to the South-East, Lyantonde District to the East, Kyenjojo to the North and Sembabule District to the North East (figure 2). Kiruhura has a population of 193,218 people settled in two counties; Nyabushozi and Kashongi.

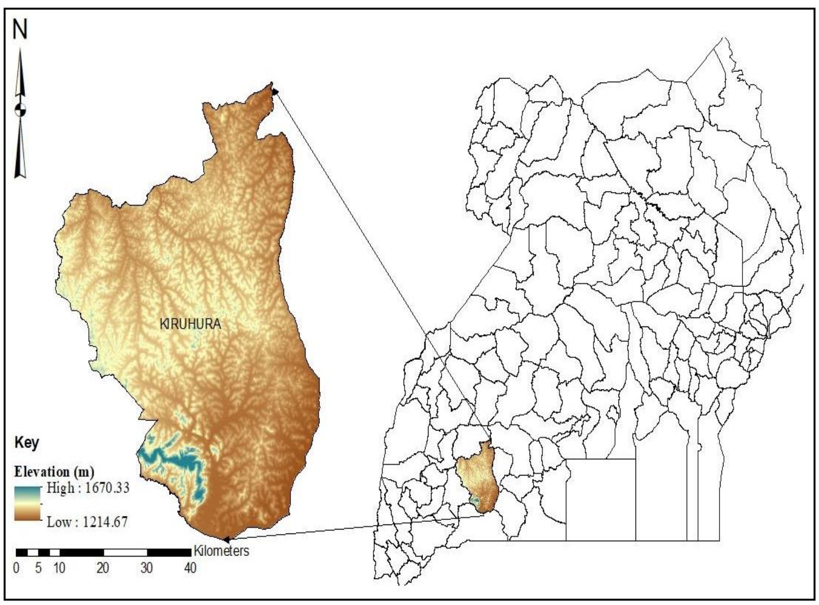

Figure 2: Map of Uganda indicating the location of the study area, Kiruhura District.

3.1.1 Climate of the study area.

The climate of Kiruhura District is defined by erratic and unreliable rainfall with 915mm as annual average rainfall (Nsubuga et al, 2014). The rainfall has a bi-modal seasonal pattern of March to May and August to November (Nsubuga et al., 2014). It has two distinct dry seasons from December toFebruary and from June to August. The dry periods are always associated with high temperatures and water scarcity impacting pasture availability and livestock making drought a concern in the district (Ampaire et al, 2017).

Average annual mean temperatures in Kiruhura range between 17°C and 29°C (Twinomuhangi & Bagonza, 2021). The area is considered warm on average, with the hottest months typically being January and February with mean monthly temperatures ranging from 27°C to 29°C, while the coolest months are June and July with mean monthly temperatures ranging from 17°C to 19°C (Uganda Bureau of Statistics UBOS, 2017; World Bank, 2021)

3.1.2 Vegetation of the study area.

The vegetation in Kiruhura District is dominated by savanna vegetation consisting of grasslands, shrubs and scattered trees (Mubiru et al, 2011; NEMA, 2010). Grassland savanna covers approximately 60 – 70% and supports its large cattle population. Bushlands and thickets occur in patches and cover about 15 – 20%. These are followed by wooded savanna covering 10% and wetland vegetation limited to 3 – 5% of the district land (MAAIF, 2019).

3.2 Research Design

The study adopted a quantitative research approach based on numerical data and statistical analysis of both primary and secondary datasets. In this approach, the climatic variable precipitation was used to derive the drought index Standard Precipitation index (SPI) for both past and projected climates in order to characterize extreme drought at the different SPI timescales. Statistical methods where used to investigate magnitude and direction of the relationship between NDVI distribution and extreme drought at the different SPI timescales.

3.3 Data and data sources.

The study utilized both historical and projected climate rainfall datasets as well as Normalised Difference Vegetation Indices (NDVI) from Satellite imagery. These datasets are explained in the preceding subsections.

3.3.1 Rainfall Datasets

This study used both historical and future rainfall datasets with the Global Precipitation Climatology Centre (GPCC) data as historical (1991-2020) and the Coupled Model Intercomparison Project phase 6 (CMIP6) as the future (2025-2055). The GPCC v.2022 is at a spatial resolution 0.25^o X 0.25^o (27.75km) and was downloaded from WMO world data center for climate (https://www.wmo.int/pages/prog/wcp/wcdmp/wcdo/welcome_en.php). The GPCC rainfall dataset was preferred because it has been widely used in climate research and has been found to capture fairly well the climatological rain fall dynamics in the region (Ngarukiyimana et al, 2016 and Ongoma & Chen, 2017). It is one of the most reliable, globally recognized gauge-based precipitation datasets. GPCC offers long-term, quality-controlled station data that is spatially interpolated to a regular grid (Schneider et al, 2017). This makes the dataset particularly suitable for climatic analyses where gauge accuracy and long-term consistency are critical. The dataset's coverage extends back to 1891, providing a strong baseline for establishing historical drought climatology and variability.

Future rainfall projections were derived from an ensemble of 15 CMIP6 GCMs (Table 3), downscaled and bias-corrected for East Africa by Ayugi et al. (2020) using the CORDEX-Africa framework at a 0.22° × 0.22° (~25 km) resolution. The models were dynamically downscaled via the Regional Climate Model (RCM) REMO, with empirical quantile mapping applied to reduce precipitation biases against observed CHIRPS data. CHIRPS was chosen because it blends high-resolution satellite imagery with in-situ station observations, achieving a finer spatial resolution (0.05° ~ 5.55km within the tropics) and strong performance in capturing spatial variability in East African rainfall (Funk et al, 2015). Its near-real-time updates and proven reliability for drought monitoring make it the most appropriate choice for calibrating and bias-correcting model outputs to reflect local rainfall patterns more accurately

For this study, point data was extracted for Kiruhura District (Latitude: -0.498; Longitude: 30.907) under two Shared Socioeconomic Pathways: SSP245 (intermediate emissions) and SSP585 (high emissions), enabling analysis of drought frequency/intensity shifts through standardized indices (e.g. SPI). The ensemble approach mitigates individual model uncertainties while preserving regionally projected trends in extreme rainfall variability.

Table 3: CMIP6 models used in the study, their modeling centers and the horizontal spatial resolution.

No	Models	Institution	Resolution	Reference
1	BCC-CSM2-MR	Beijing Climate Center (BCC) and China Meteorological Administration (CMA), China	1.13ºX1.13º	Wu et al., 2018
2	BCC-ESMI	Beijing Climate Center (BCC) and China Meteorological Administration (CMA), China	2.81ºX2.81º	(Zhang et al., 2018)
3	CanESM5	Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Victoria, Canada.	2.81ºX2.81º	(Swart et al., 2019)
4	CESM2	National Center for Atmospheric Research, USA	1.25ºX0.94º	(Danabasoglu et al., 2019)
5	CESM2-WACCM	National Center for Atmospheric Research, USA.	1.25ºX0.94º	(Danabasoglu et al., 2019)
6	CNRM-CM6-1	Centre National de Recherches Me'teorologiques (CNRM); Centre European de Recherches et de Formation Avanceeen Calcul Scientifique France.	1.41ºX1.41º	(Voldoire et al., 2019)
7	CNRM-ESM2-1	Centre National de Recherches Me'teorologiques, Toulouse, France	1.41ºX1.41º	(Seferian, 2018)
8	EC-Earth3-Veg	Consortium of European research institution and researchers, Europe	0.70ºX0.70º	(EC-EARTH, 2019a)
9	GFDL-CM4	Geophysical Fluid Dynamics Laboratory (GFDL), USA	2.50ºX2.00º	Krasting et al., 2018)

10	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory (GFDL), USA	1.25ºX1.00º	Guo et al., 2018)
11	IPSL-CM6A-LR	Institut Pierre Simon Laplace, Paris, France Fluid Dynamics Laboratory (GFDL), USA	2.50ºX1.26º	Boucher et al., 2018)
12	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	1.13ºX1.13º	Yukimoto et al., 2019)
13	NorESM2-LM	Norwegian Climate Centre/Norway	1.875ºX2.5º	(Seland et al., 2020)
14	SAM0-UNICON	Seoul National University, Seoul 08826, Republic of Korea.	1.25ºX0.94º	Park et al,.(2019)
15	UKESMI-0-LL	UK Met Office Hadley Center, UK	1.88ºX1.25º	Tang et al (2019)

3.3.2 NDVI Datasets.

The Normalised Difference Vegetation Index (NDVI) datasets were primarily derived from remote sensing satellites. This study used datasets from the Moderate Resolution Imaging Spectroradiometer (MODIS), which provides 16-day NDVI composites with a spatial resolution of 250 meters Zribi, (2019) and Myneni et al. (2015). This was accessed from the National Aeronautics and Space Administration (NASA) website; http://reverb.echo.nasa.gov/reverb/. The choice of this data source was based on the data consistency, uniformity and high temporal resolution (Myneni et al. 2015).

Historical climate and NDVI data (1990–2024) with a temporal consistency at a monthly resolution, was cleaned to handle missing values using linear interpolation for gaps <5%, while larger gaps were excluded to maintain data integrity. All climate variables were normalized to a [0,1] range using Min-Max scaling to prevent feature dominance in model training.

For future projections of NDVI, simulated datasets were obtained from Earth System Models (ESMs) that are part of the Coupled Model Intercomparison Project Phase 6 (CMIP6) framework. These models simulate vegetation dynamics under varying climate scenarios, including the Shared Socioeconomic Pathways (SSPs), allowing for comprehensive assessments of ecological responses to future climate conditions. The projections were accessed through the Earth System Grid Federation (ESGF) platform. Within this framework, Leaf Area Index (LAI) outputs from the ESMs were converted into NDVI using machine learning techniques that use Neural Network models, which have demonstrated high accuracy in modeling nonlinear relationships between vegetation indices and biophysical parameters (Zeng et al. 2020).

3.4 Data analysis Methods

This subsection will give details on the various methods of data analysis employed to achieve each specific objective.

3.4.1 Assessing the Past and future drought characteristics.

Standardized Precipitation index (SPI) was adopted for determination of drought characteristics for both the historical and future. The SPI expresses the actual rainfall as a standardized departure from rainfall probability distribution function (Kumar et al, 2009).

SPI values were computed at three time-scales of 1, 3, 6 and 12 using the inverse Gaussian Function (McKee et al, 1993; Heim 2003). The advantage of using SPI timescales of 1, 3, 6 and 12 is the ability to provide a multidimensional perspective on the drought dynamics. SPI 1 and 3 are effective for early warning and monitoring of agricultural drought. SPI 6 and 12 the longer timescales are effective for hydrological and ecological drought monitoring (McKee et al., 1993; Vicente-Serrano et al. 2010). This study sought a comprehensive perspective of drought dynamics from all the four timescales. The classes of drought severity based on SPI are summarized in table 4 indicating extreme drought as equal to a threshold value of SPI $\leq$ -2.0.

Table 4: Classification Scales of Drought Severity Using SPI/SPEI Drought Indices. source: McKee et al., 1993

Drought severity levels	SPI value
No drought/ Mild	SPI > −1
Moderate drought	−1.0 ≥ SPI> −1.5
Severe drought	−1.5 ≥ SPI > −2.0
Extreme drought	**SPI ≤ −2.0**

Drought was characterized into severity, intensity and frequency (figure.3) based on the different SPI timescales (SPI1, SPI3, SPI6 and SPI12). These characteristics were defined using equations 2–4 (Amirataee et al, 2018; Ayugi et al, 2020b).

i. Severity is the cumulative sum of the index value based on the duration extent (equation 1). Drought severity and duration were obtained by summation and count of occurrences of consecutive drought months using a pre-determined threshold value of SPI ≤-1 respectively.

$$Severity = \sum_{i=1}^{Duration} Index \qquad (2)$$

ii. Drought intensity is severity divided by the duration (equation 2). Droughts with short duration and high severity have high intensities.

$$Intensity = \frac{Severity}{Duration} \qquad (3)$$

iii. Drought frequency (Fs) is expressed as in equation (4):

$$F_s = \frac{n_s}{N_s} * 100\% \qquad (4)$$

where n_s is the number of drought events (SPI ≤ -1.0), N_s is the total number of dry months in the study period, and s is a grid cell representing a rain gauge station.

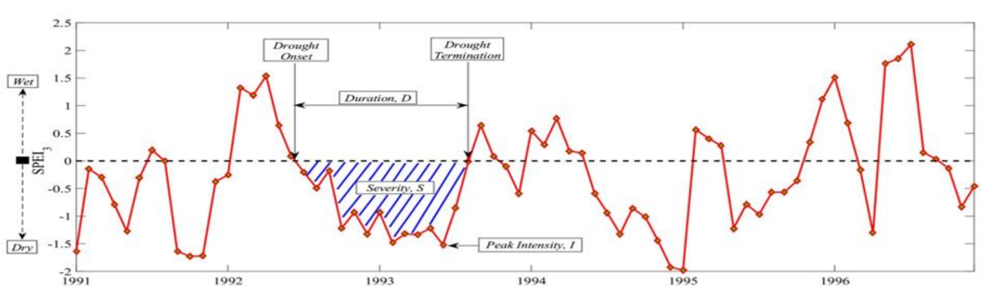

Figure 3: Definitions of drought severity, duration, frequency and intensity considered by the study.

3.4.2 Impact of past extreme drought on Spatiotemporal distribution of grassland

The study utilized the vegetation cover rate which is a quantitative measure that describes the proportion of a given land area to examine the Spatial temporal distribution variability of vegetation from 1991 to 2020. Since grassland degradation was actually a process of vegetation declination, the normalized difference vegetation index (NDVI) was used as an indicator of grassland degradation (Isubikalu et al, 2012). In order to capture the difference in vegetation density on ground, it was necessary to transfer NDVI into a cover rate for a better representation of the existing vegetation canopy (Zhang et al, 2017). Healthy green plants have a spectrum characterized with strong absorption in the red-light region and strong reflectance in the infrared region. Therefore, NDVI was generally computed as.

$$NDVI = \frac{R_2 - R_1}{R_2 + R_1} \qquad (5)$$

Where R1 and R2 were the reflectance of infrared and red bands of the MODIS data respectively, i.e. bands 1 and 2. The reflectance could be computed as follows:

$$R_I = RL_I * (DN_I - OS_I) \qquad (6)$$

In which RLi and OSi were the reflectance constants for band i of the MODIS images, and DNi was the digital number of image pixels for band i. The values of RLi and OSi could be obtained from the head file of each MODIS image. Theoretically the ground surface should have no vegetation cover when NDVI is in minimum while it should be fully covered with vegetation when NDVI was in maximum. As depicted in Table 5, the ground surface is bare without vegetation when NDVI was less than 0.1 while the vegetation was very dense with full canopy cover when NDVI was greater than 0.8 (Leeuwen et al, 1996).

Table 5: Examples of the different land cover based on respective NDVI ranges. Jensen, J. R. (2007)

Item	NDVI Range	Land cover	Examples
1	-1.0 to 0.0	Water Bodies	Lakes, Rivers and Oceans
2	0.0 to 0.1	Bare Soil/built up	Urban, roads and Non vegetated areas
3	0.1 to 0.2	Very Sparse veg	Desert areas
4	**0.2 to 0.3**	**Sparse vegetation**	**Grasslands and savannas**
5	0.4 to 0.5	Moderate Veg	Agricultural fields with crops
6	0.5 to 0.6	Moderate dense veg	Deciduous forests (growing season)
7	0.6 to 0.7	Dense Vegetation	Tropical rainforests (high Biomass)
8	0.7 to 0.8	Very Dense Veg	Dense tropical rainforests
9	Above 0.8	Extremely Dense Veg	Maximum vegetation cover

Therefore, we could compute vegetation cover rate as:

$$P_v = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (7)$$

where Pv was vegetation cover rate, $NDVI_{min}$ was the NDVI value of bare surface, which could be defined as 0.15, and NDVImax is the NDVI value of vegetation canopy, which could be defined as 0.8 (Qin et al. 2006). The value of Pv was with the range of 0 to 1, with Pv=0 for NDVI 0.8. Thus, the greater the P_v value, the better the vegetation cover in the region. Using this parameter, it was possible to map the spatial variation of vegetation for evaluation of pasture degradation.

Table 6 highlights two extreme drought periods; one in March 2012 and the other in December 2017. In order to investigate the impact of extreme drought on the spatial distribution of grasslands. Three NDVI classified maps were developed from composite satellite images. These were then analyzed to detect changes vegetation cover area for drought impact. One image before, during and after the extreme drought event. Using ArcGIS tools, maps of Kiruhura District at the defined periods (Table 6) were extracted and investigated to detect changes in vegetation coverage by area. For this analysis, the extreme drought event of 2017 was used because it had available preprocessed satellite images without gaps for the three required periods.

Table 6: The extreme drought event period and the details of the satellite images used in the impact assessment on grasslands area coverage.

Year	Extreme drought Event Period	Image - Before	Image - During	Image - After	Satellite	Path	Row
2012	March	February	March	April	Landsat 7	172	60
2017	December	November	December	Jan-18	Landsat 8	172	60

According to the study by (Njagi et al, 2022), Kiruhura has five major vegetative classes of those mentioned in table 5. Each vegetative class is within an NDVI range (table 7), as such this enabled unsupervised classification of the images in the production of the maps.

Table 7: Vegetative classes represented by the different NDVI ranges as depicted in the spatial maps after analysis.

	Vegetative Class	Colour	NDVI range
1	Bare ground & water	Purple	-1 – 0.1
2	Bushland & Shrub lands	Brown	0.1 – 0.19
3	Savannah Grasslands	yellow	0.2 – 0.39
4	Cultivable lands	Light green	0.4 – 0.49
5	woodlands	Dark green	0.5 – 0.6

Using ArcGIS, changes in grasslands area coverage due to the extreme drought event were investigated for the periods, before occurrence of the drought to a moment during the drought and to one after the drought event occurrence. Selection of the three periods was subjective to the availability of satellite images within the periods.

Investigating the impact of past extreme drought on the temporal distribution of grassland vegetation was through statistical analysis. The methods employed included; Pearson moment correlation analysis, a time series analysis, a Mann-Whitney U test and a Cross correlation analysis. The relationships between Normalized Difference Vegetation Index (NDVI) against extreme drought using SPI at different times scales was investigated. This method was also applied in the study by (Wang et al, 2003).

The Pearson moment correlation analysis was done between monthly NDVI series and different time-scales (1,3,6 and 12 months) SPI as:

$$R_{i,j} = cor(NDVI_i, SPI_{i,j}) 1 \leq i \leq 12, 1 \leq j \leq 24 \quad (8)$$

$$R_{max} = max_{1 \leq i \leq 12, 1 \leq j \leq 24}(R_{i,j})$$

where cor is Pearson correlation; i represents the ith month, ranging from 1st to 12th month; j is the drought time-scale, ranging from 1-24 months; $NDVI_i$ is the ith month NDVI series; i j, SPI is the ith month drought index with time-scale of j months; Ri j, is the Pearson correlation of $NDVI_i$ and i j, SPI; Rmax is the annual maximum correlation coefficient. To eliminate the influence of phenology on correlation analysis results, the monthly correlations were summarized annually. For this purpose, only the annual maximum correlation coefficient R_{max} was kept (Vicente-Serrano et al., 2013). And the corresponding SPI time-scale where R_{max} was obtained is considered as the time-scale of vegetation responding to drought. The subsequent analysis was done with focus mainly on R_{max} and the time-scales of vegetation response to drought.

3.4.3 Impact of future extreme drought on the temporal distribution of grasslands.

The Future NDVI (2025–2100) for both climate scenarios SSP245 and SSP585 was predicted using processed climate projections. This involved employing a deep learning-based modeling that uses a (sequence-to-value regression) to predict NDVI from the Leaf Area Index (LAI). The model that was used to execute this operation was the Neural Networks (NN) model ensemble preferred to other models because it's easy to interpret, and provides good spatiotemporal outputs from complex datasets according to Zeng et al. (2020). The process involved climatic inputs such as; longwave radiation (LWR), precipitation (pr), maximum and minimum temperatures (Tmax, Tmin), and relative humidity (RH), as well as applying a Monte Carlo dropout (20 forward passes) to estimate prediction uncertainty, generating 5th–95th percentile ranges. The methodology consisted of data preprocessing, model development, training, validation, and future projections, ensuring robust and biologically plausible NDVI predictions.

Using a multi-dimensional statistical approach to understand the impact of extreme drought on the spatiotemporal distribution of vegetation cover. This study employed four statistical methods including Pearson moment correlation, Time series analysis, Mann- Whitney U test and a cross-correlation analysis. The Pearson moment correlation was useful in giving the measure of the strength and direction of the linear relationship between vegetation cover (NDVI) and extreme drought severity. This way the study was able to identify the vegetation sensitivity to drought

(McKee et al, 1993; Kogan, 1995). The time series analysis was used to understand trends and seasonal patterns of both extreme drought severity using SPI at different timescales and the vegetation cover. Thus, revealing vegetation degradation and recovery patterns (Chatfield, 2003). The Mann-Whitney U test was used to make a statistical validation of the extreme drought induced changes in vegetation cover by comparing NDVI values during drought and non-drought periods. The test was used on the assumption that there is no normality in distribution and NDVI values between the two periods are not continuous (Laerd Statistics, 2025). This way testing the statistical significance of the drought impact (Wilcoxon, 1945). The cross-correlation analysis was used to determine time lag effects between extreme drought and vegetation cover. By this analysis, the study made conclusions on the vegetation response delay and recovery from effects of drought events (Shumway & Stoffer, 2017).

CHAPTER FOUR: RESULTS

4.0 Introduction

This chapter presents the findings and the discussion of the findings from the analysis carried out using the methods and tools explained in the previous chapter. The results are presented patterned after the study objectives.

4.1 Determination of Past and future extreme drought characteristics.

This subsection details the findings from analysis for past extreme drought characteristics including general drought timelines depicting occurrence of extreme events, number of extreme events, trends of drought duration, intensity and severity as well as future dynamics.

4.1.1 Past extreme drought Characteristics.

Historical timelines of drought events based on SPI at different timescales SPI1, SPI3, SPI6, and SPI12 spanning from 1990 – 2020 are presented in figure 4. Extreme drought is indicated by a marked threshold at SPI = - 2. The figure (top SPI1 to bottom SPI12) depicts frequent and short-lived drought events at SPI1. At SPI3 and SPI6, pronounced drought events are seen around 1999 – 2001, 2020 – 2011, and 2016 – 2017. At SPI12, the drought events are distinct and prolonged around 1998 – 2002. The extreme droughts are seen to increase in severity with increase in timescale evidenced in SPI3, SPI6 and SPI12.

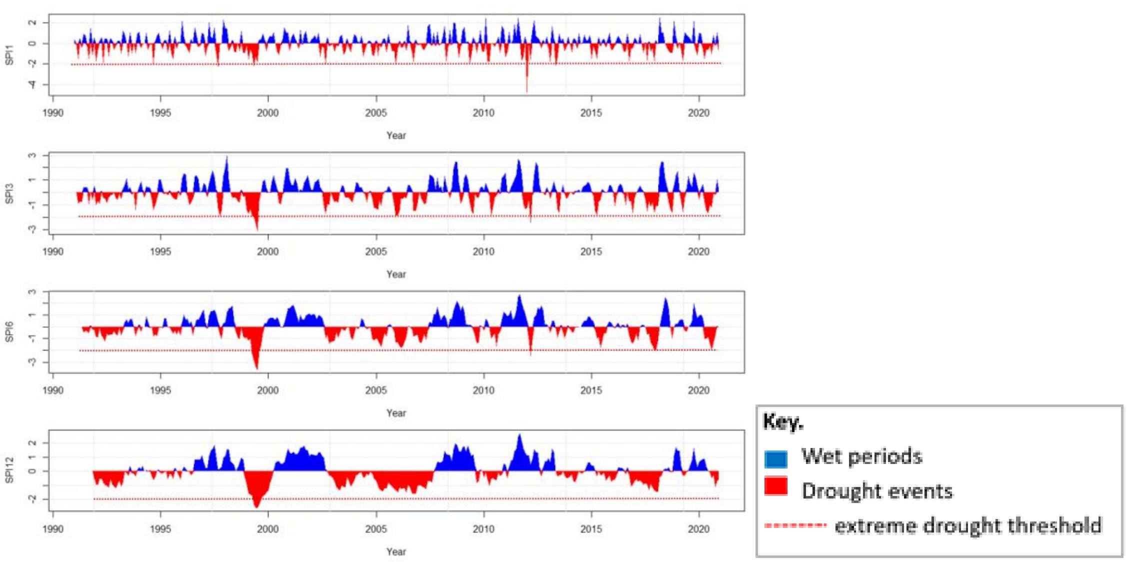

Figure 4: Historical timelines of drought events for the different SPI time scales, highlighting extreme droughts dips below the threshold (-2) marked by red dots.

Maximum changes in extreme drought characteristics (duration, intensity and severity) based on SPI timescales of SPI1, SPI3, SPI6 and SP112 for historical period 1990 – 2020 are shown in figure 5. Results show that at short term timescales (SPI 1 and SPI3) the maximum drought duration was variable between (1 to 12 months) over the years based on the fluctuations in the trends timeline. The maximum drought severity is relatively the same (-1) over the years for SPI1 but variable (-7.5 to -0.1) for SPI3. The maximum drought intensity was extreme upto (-1.2) for the two SPI short term timescales of SPI.

Long term timescales of SPI (SPI6 and SPI12) depicted drought durations which were prolonged. The drought severity and intensity were extreme but variable over the years. The extreme drought characteristics are variable over time, but the variability tends to increase with increase in SPI timescale. The variability is evident and well pronounced in maximum severity and duration at SPI6 and SPI12.

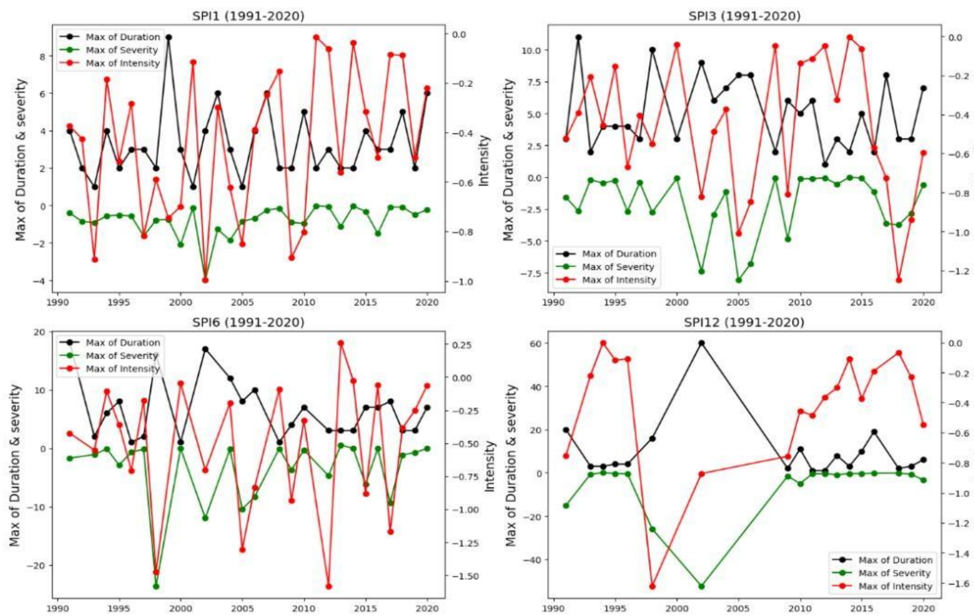

Figure 5: Plots of past extreme drought characteristics including; duration, severity and intensity for the period 1990 – 2020

Based on the results, the frequent and short-lived drought episodes in SPI1 are indicative of responsiveness to rapid weather fluctuation by this timescale. This shows SPI1 index as useful in identifying short term droughts and as such, may not be effectively useful in monitoring long term drought. However, SPI3 and SPI6 displayed pronounced droughts and may be effective in capturing seasonal droughts for grassland pasture and general agriculture monitoring and planning.

SPI12 revealed long term droughts like that of 1998 – 2002. This index seems to show cumulative precipitation deficits and as such usable in analyzing drought impacts to the grassland ecosystem, pasture resilience and available water resources.

4.1.2 Future extreme drought characteristics

Future drought events for the period 2025 to 2100 based on SPI timescales of SPI1, SPI3, SPI6 and SPI12 under two Climate projections SSP245 and SSP585 are given in Figure 6. Each column represents a future climate scenario and each row represents an SPI timescale SPI1, SPI3, SPI6 and SPI12. Under SSP245, results show a variable drought pattern at all SPI timescales, with extreme drought episodes indicated particularly at SPI6 and SPI12. However, the timeline depicts persistent and consistent moderate droughts throughout the century.

In comparison, the SSP585 climate scenario shows more frequent and prolonged drought events especially at SPI6 and SPI12 timescales where values are mostly below zero. SPI12 shows extended multi year drought periods towards the latter half of the century, indicating possible long term extreme droughts. The intensity and duration of the negative SPI values point towards persistent and prevalent extreme droughts under high emissions SSP585 pathway.

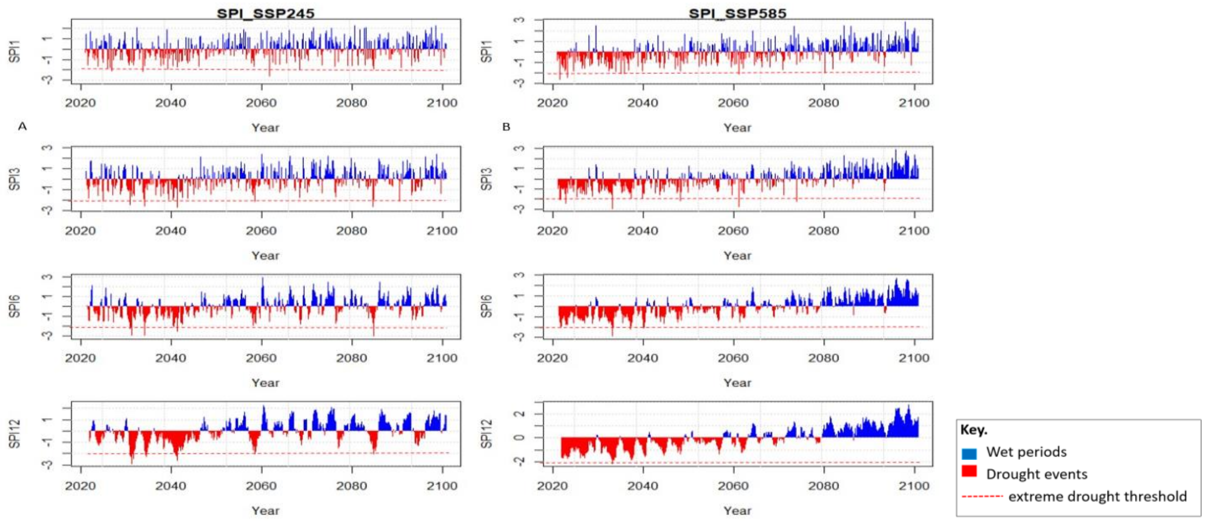

Figure 6: Future projections timelines of drought events from 2025 – 2100 under climate scenarios SSP245 and SSP585 based on SPI at Different timescales of SPI1, SPI3, SPI6 and SPI12. Highlighted are extreme droughts dips below the threshold (-2) marked by red dots.

Future maximum drought duration, intensity and severity for the period 2020 – 2050 at different SPI timescales SPI1, SP13, SPI6 and SPI12 under projected climate scenario SSP245 given in figure 7.

Results for SPI short term timescale indicate significant fluctuations in maximum drought duration and severity with reaching distinct peaks over the years. Intensity has less fluctuations compared to duration and severity and remains below zero but relatively moderate fluctuations for SPI 3. Long term SPI values indicated high variability in maximum drought duration and severity. Intensity has notable fluctuations although it remains below zero.

Overall, maximum drought duration and severity shows significant variability over the years. However, maximum drought intensity remains below zero and shows less variability over the years.

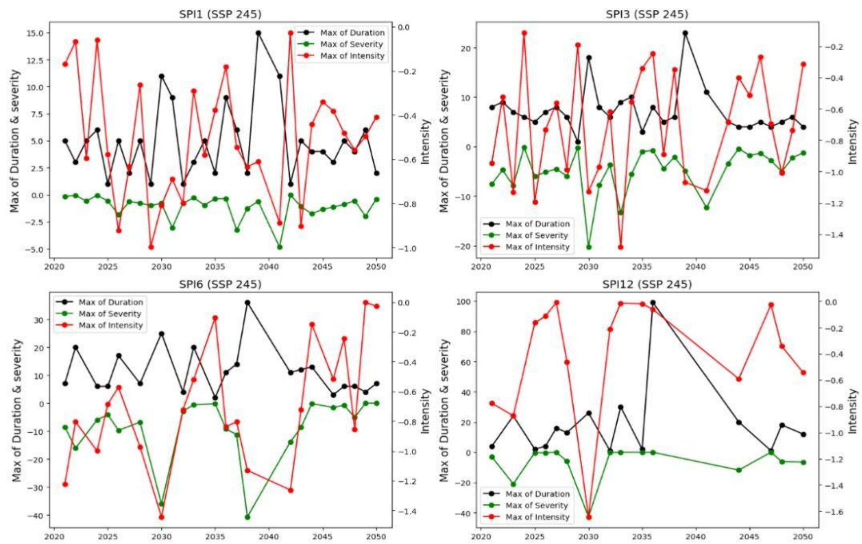

Figure 7: Future extreme drought characteristics including; duration, severity and intensity for the different SPI timescales under SSP245

Future maximum drought duration, intensity and severity for the period 2020 – 2050 at different SPI timescales SPI1, SP13, SPI6 and SPI12 under projected climate scenario SSP585 given in figure 8.

Results for SPI short term timescale indicate higher significant fluctuations in maximum drought duration and severity with reaching more distinct peaks over the years compared to SSP245. Maximum drought intensity is more variability compared to SSP245. Long term SPI values indicated high variability in maximum drought duration and severity over the years. Drought intensity is observed to have a higher variability under SSP585 compared to SSP245.

Although the entire time series shows significant variability over the years, long term SPI timescales SPI6 and SPI12 under SSP585 are shown to have extreme droughts with maximum drought duration, severity and intensity in the years 2030 and 2038.

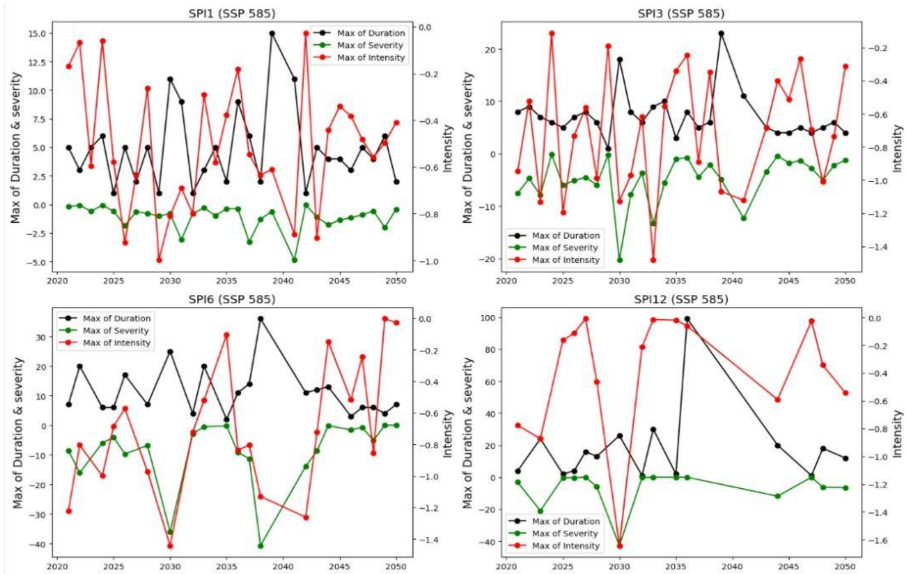

Figure 8: Future extreme drought characteristics including; duration, severity and intensity for the different SPI timescales under SSP585.

Analysis of projected Standardized Precipitation Index (SPI) values under SSP245 and SSP585 scenarios indicates a future rise in extreme drought episodes in Kiruhura District across multiple timescales. At shorter-term timescales (SPI1 and SPI3), both scenarios predict an increase in drought occurrences relative to historical records, with SSP245 showing marginally higher occurrences than SSP585. For longer-term timescales (SPI6 and SPI12), drought frequency under SSP585 surpasses SSP245.

Projected trends also reveal temporal variability in drought characteristics. Duration increases steadily until around 2033, after which it stabilizes by approximately 2048. Severity and intensity display cyclical rising in the early-to-mid 2030s before a gradual recovery and falling patterns before reaching stability.

4.1.3 Comparison of historical and future drought characteristics

This sub section gives a comparison of findings between historical and future extreme drought characteristics.

Table 8: Numbers of both past and future extreme drought events.

Number of Extreme Drought events

	Historical (1990 -2020)	Future SSP245	Future SSP585
SPI 1	6	11	7
SPI 3	2	8	7
SPI 6	3	5	4
SPI 12	1	3	2

The number of extreme drought events across the different SPI timescales (SPI1, SPI3, SPI6, and SPI12) for both time series, past (1990 – 2020) and future (2023 – 2053) under SSP145 and SSP285 projection scenarios are given in table 8 and figure 9.

The number of extreme drought events is higher at short term SPI timescales but gradually decreases (6 to 1) in long term SPI time scales across under both past and projected climate scenarios (11 to 3) under SSP245 and (7 to 2) under SSP585. However, the projected climate scenarios suggest more extreme drought events compared to the past climate with highest numbers expected under SSP245. All SPI timescales SPI1, SPI3, SPI6, and SPI12 show an increase in extreme drought episodes in the future under both projection scenarios, SSP245 and SSP585. For short term timescales (SPI1 and SPI3), the number of occurrences based on SSP245 is marginally more than that under SSP585.

However, for both future scenarios results depict a rise in the number of extreme drought occurrences at shorter term SPI timescales (SPI1 and SPI3). Although less marked but still noticeable for longer periods (SPI6 and SPI12).

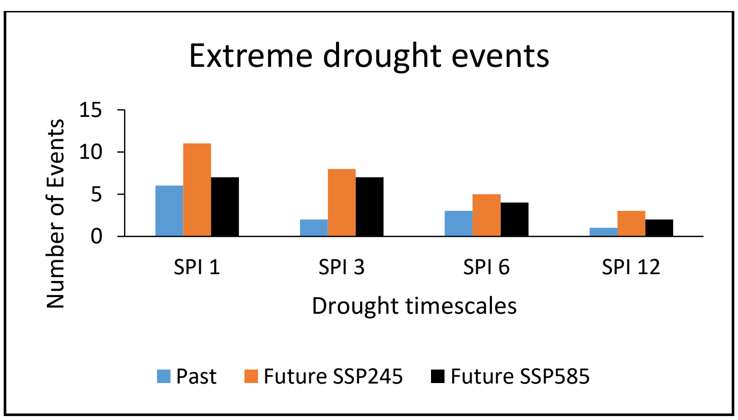

Figure 9: A graphical presentation of Extreme drought events at each SPI timescale for both past and future periods.

4.2 Implications of Past extreme drought on spatiotemporal distribution of grassland vegetation cover.

This section presents the results from investigations on the implications of extreme drought on grasslands vegetation cover in Kiruhura for the past period 1990 to 2020.

4.2.0 The past Spatiotemporal distribution of grassland vegetation cover (1990 – 2020).

The spatiotemporal distribution of grassland vegetation cover was investigated using annual means of NDVI at a five-year temporal resolution from 1990 to 2020 given in figure 10. Results show that in 1990 the southern part of the district had greener and healthier grasslands while the northern and central parts had much drier or non-green land cover. 1995 had a much better even distribution of grasslands compared to 1990. The years 2000 and 2005 depict a consistent pattern where the southern parts had greener grasslands and the northern and central non green land cover. In the years 2010 had an even distribution of green and healthier grasslands while in 2015, the shift was to the northern region with other regions tending to the non–green land cover. By 2020, most of the district had less green grasslands.

On the temporal scale, the year 2020 depicted a significant change to less green and much drier grasslands over the decade. Spatially, drier grasslands tend to dominate the district by 2020 compared to 2010 and 2015.

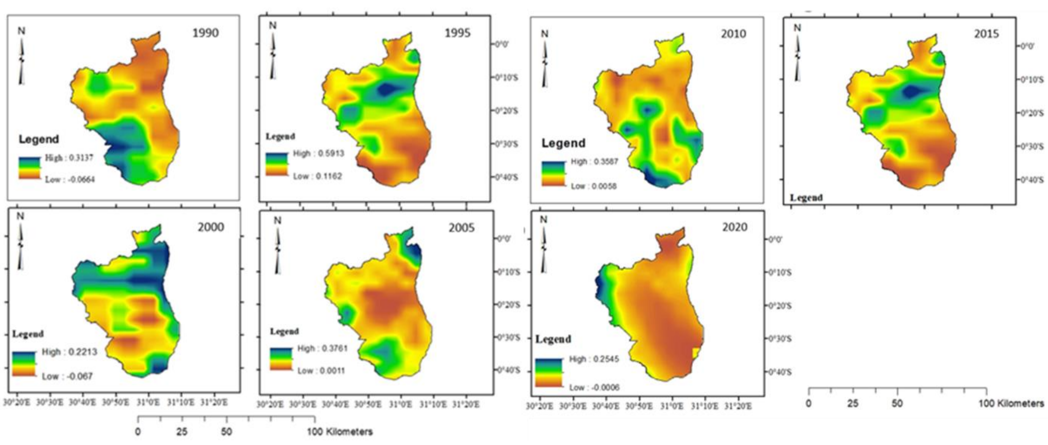

Figure 10: Kiruhura District depicting annual mean spatiotemporal changes in vegetation cover from 1990 – 2020.

4.2.1 Impact of extreme drought on grassland spatial distribution

Maps of Kiruhura District showing changes in vegetation cover due to the extreme drought event experienced in 2017 are given in figure 11. Results in Figure 11(a) shows vegetation cover before the occurrence of the extreme drought event. The landscape in Kiruhura was dominated by savannah grasslands and woodlands, indicating a well-vegetated environment with patches of bare ground & water and bushland & shrub lands, cultivable lands and woodlands distributed across the region.

Results in Figure 11(b) shows vegetation cover during the extreme drought. Compared to the previous map, there is a significant increase in bare ground suggesting severe vegetation loss due to drought-induced water stress. A reduction in savannah grasslands is evident, indicating degradation of pastures. Bushland & shrub lands expand in some areas, likely due to the dieback of grasslands and woodlands. Whilst the Cultivable lands shrink, suggesting reduced agricultural productivity, possibly due to crop failure. Results in Figure 11(c) shows a visible recovery of savannah grasslands and woodlands. Bare ground decreases, but some degraded areas remain, implying that certain ecosystems experienced permanent damage and cultivable lands reappear. Bushland & shrub lands remain in some areas, potentially replacing grasslands where regeneration was slower.

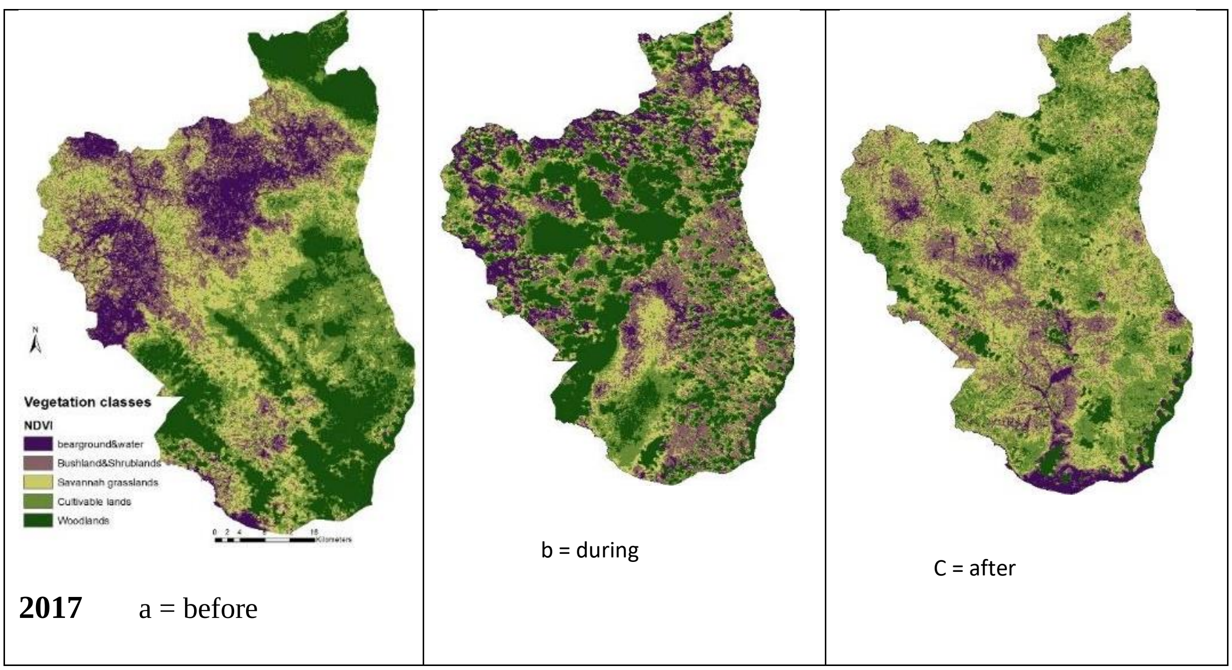

Figure 11: Kiruhura District depicting extreme drought impact on vegetation cover. Vegetation cover changes detected for the period before, during and after the extreme drought event in 2017.

For extreme drought impact assessment, the graph below shows the changes in vegetation area coverage for each of the five vegetation classes depicted in the maps.

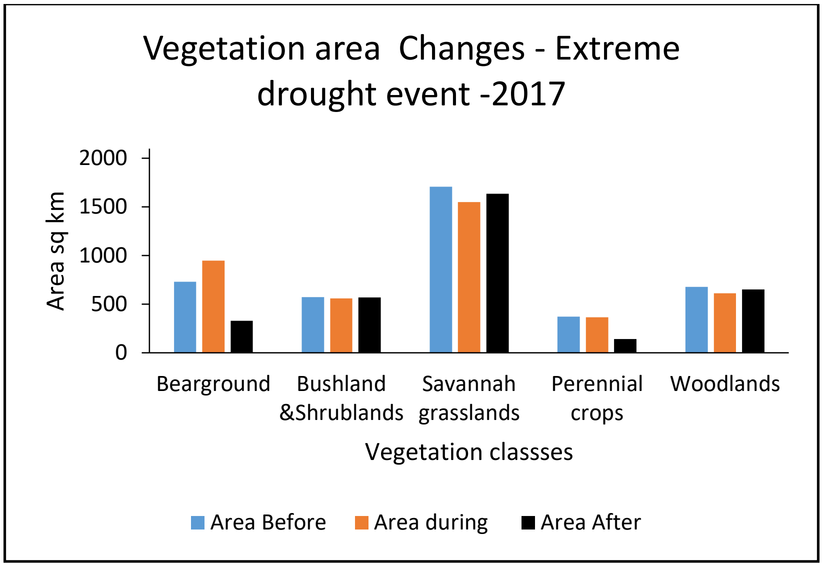

Figure 12: Changes in vegetative class area coverage as impacted by the extreme drought of 2017 in Kiruhura District.

The graphical changes in area coverage of each vegetation class before, during and after the extreme drought event of the year 2017 are displayed in figure 12. The results show that bare ground increased significantly in area during the drought event. After the drought, the bare ground area decreased but did not return to pre-drought levels.

Bushland & Shrublands showed minimal changes, with slight reduction during the drought. The area remained nearly stable before, during, and after the drought a trait for resilience vegetation types. Savannah Grasslands had one of the largest area coverage before the drought but a noticeable decrease during then an increase thereafter. Perennial Crops showed a decline in the area of perennial crops during the drought but the area remained low post drought.

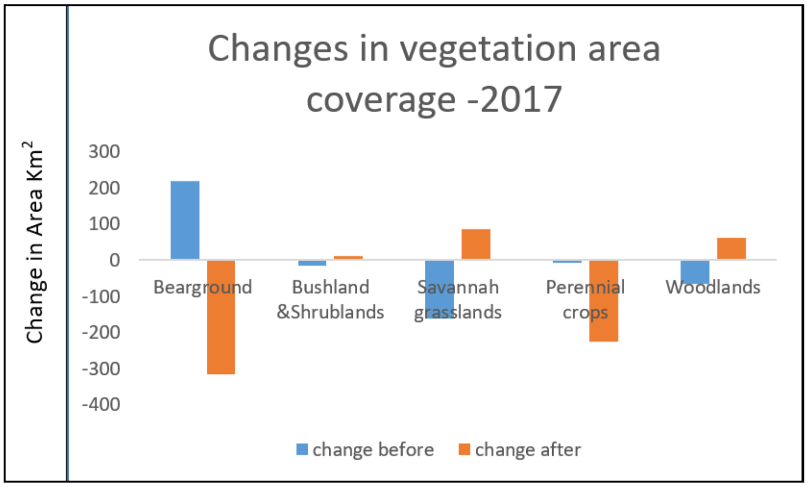

Figure 13: Vegetative class change in area (km^2) due to the 2017 extreme drought event.

This analysis established that savannah grasslands showed a significant response to the extreme drought event of 2017. During this period, approximately 2000 km² of grasslands savannah vegetative cover was diminished.

4.2.2 Impacts of past extreme drought on temporal distribution of grasslands.

Results presented in the subsection detail findings on the relationships established through the statistical analyses applied.

4.2.2.1 Strength and direction of the relationship between extreme drought and NDVI distribution.

In order to establish the linear association in terms of strength and direction of the relationship between extreme drought at different SPI time scales and vegetation response using NDVI, a Pearson moment correlation was performed. The results from the Pearson moment correlation analysis are given in table 9. The Pearson correlation value of 0.071 with a p-value of 0.1807 at SPI1 depicting a very weak positive correlation that is not statistically significant. The correlation of 0.0967 ($p = 0.0669$) at SPI3 is still weak but shows a trend toward statistical significance. The correlation strengthens to 0.1553 ($p = 0.0031$) at SPI6 timescale. This indicates a moderate and statistically significant positive relationship. SPI12 shows the highest correlation of 0.1608 ($p = 0.0022$), demonstrating the strongest and statistically significant relationship with NDVI.

Table 9: Results of a Pearson moment correlation for a relationship between extreme drought at different time scales and vegetation using NDVI.

SPI	Pearson Correlation	p value	Interpretation
SPI1	0.071	0.1807	Very weak positive, Not Significant
SPI3	0.097	0.0669	Weak positive, Marginally Insignificant
SPI6	0.155	0.0031	Moderate positive, Statistically Significant
SPI12	0.161	0.0022	Moderate positive, statistically Significant

4.2.2.2 Temporal relationship of extreme drought and NDVI distribution.

The figure13, shows plots depicting the relationship between NDVI and extreme droughts as portrayed using different SPI timescales (1, 3, 6 and 12months). The plots are structured in such a way that, on the y-axis are the NDVI values ranging (0.42 – 0.58), X –axis are the years (1990 – 2021). The blue line indicates the pattern of monthly NDVI values with time. Colored dots indicate extreme drought events when SPI is < -2 for each SPI timescale. The dashed line indicates the mean NDVI reference baseline for vegetation condition the entire time line.

The top left and right plots of NDVI during extreme droughts at SPI1 and SPI3. Show that many red dots appear showing frequent short-term droughts which correspond with a mix of NDVI below and above the mean. Some extreme droughts appear to occur when NDVI is relatively high. However, SPI3 reflecting seasonal drought on a 3month timescale, depicts extreme droughts as clustering around periods of reduced NDVI with a few exceptions above the mean.

The bottom left and right plots of NDVI during extreme droughts at SPI6 (mid-term droughts) and SPI12 (long- term droughts). SPI6 plot has green dots more aligned with dips in the NDVI curve often below the mean line. The extreme droughts, although fewer done the previous timescales, these often coincide with notable vegetation stress. The plot for long term extreme droughts shows purple dots appearing below the average during significant NDVI declines. The droughts seem to be rare but associated with substantial vegetation degradation.

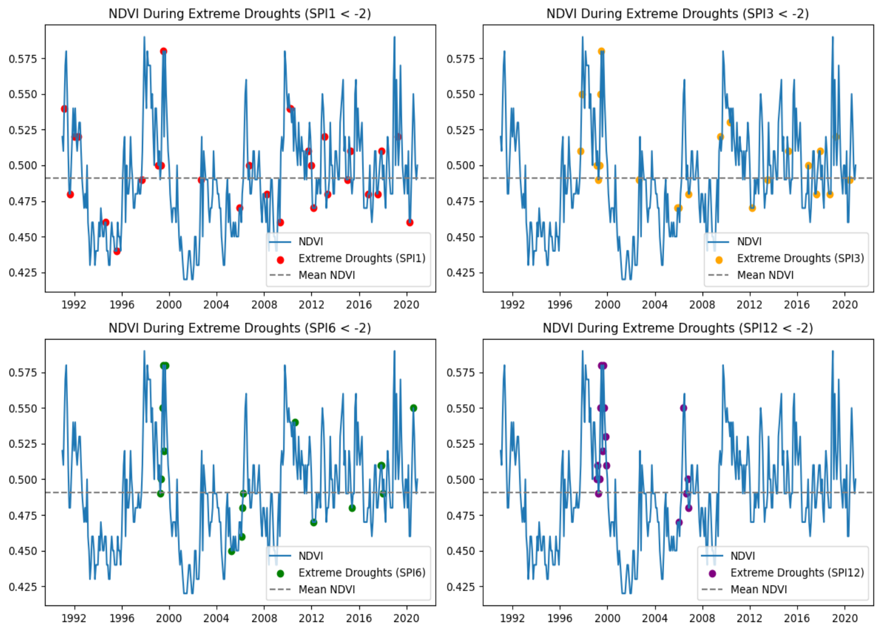

Figure 14: Shows historical time series analysis of extreme drought impact on vegetation for the different SPI timescales.

4.2.2.3 NDVI distribution during drought and non – drought periods.

Evaluated whether the distributions of NDVI values differ significantly during extreme droughts against non-drought periods.

Table 10: Shows results of a Mann-Whitney U test for significance of NDVI distributions during extreme drought and non-drought periods.

SPI	Mann Whitney U	P Value	Interpretation
SPI1	5741.0	0.1754	No statistically significant difference
SPI3	4723.0	0.0501	Borderline significance.
SPI6	3700.0	0.0638	Close to significance
SPI12	3996.5	0.0021	Statistically significant difference

During short-term extreme droughts (SPI1), NDVI remains relatively stable. During Seasonal droughts (SPI3), NDVI starts being affected but evidence may not be strong enough to confirm with confidence. However, SPI6 droughts indicated NDVI was very low and SPI12 droughts as well suggesting strong vegetation stress.

4.2.2.4 Lag response relationship between extreme drought and NDVI distribution responses.

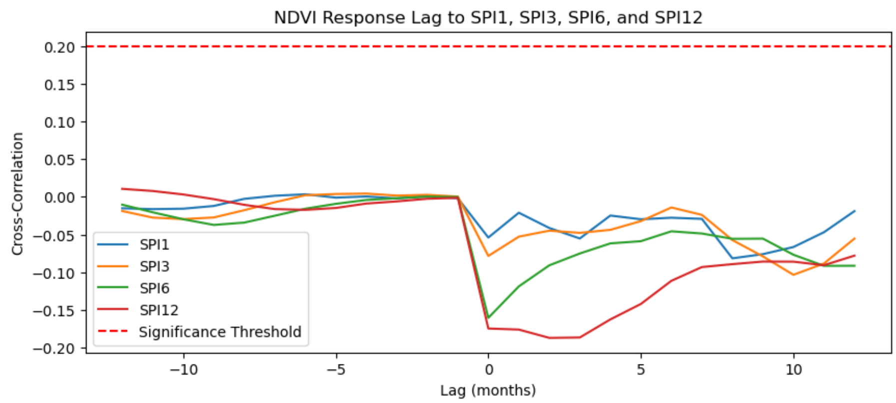

Figure 15: Vegetation response to extreme drought at different time lags and SPI timescales from across correlation analysis.

The cross-correlation analysis (Figure 15) indicates that negative lag values suggest SPI changes precede NDVI responses, meaning that past drought conditions influence future vegetation dynamics, and on the other hand, vegetation conditions can also provide signals that reflect preceding drought patterns. The red Dashed line (significance threshold) in the plot considers only correlations above it as statistically meaningful.

Based on the analysis, the cross correlation at SPI1 is weak and fluctuating about zero. At SPI3, cross correlation is stronger and more consistently negative around lags 0 to +6 months. At SPI6, there is an increasing negative correlation from lags 0 to +6 months. However, SPI12 suggests a stronger and more sustained negative correlation between lags 0 to +6 months suggesting Vegetation cover based on NDVI is more sensitive to cumulative drought over longer periods.

4.3 Impacts of Future extreme drought on the temporal grasslands distribution.

Using statistical analysis, the impact of future extreme drought on the temporal distribution of grasslands was examined under SSP245 and SSP585 climate scenarios. Below are the detailed findings.

4.3.1 Examination for impacts under projected climate scenario SSP245.

This subsection presents the results from each statistical analysis applied.

4.3.1.1 Strength and direction of the relationship between extreme drought and NDVI distribution

Using a Pearson moment correlation, the Table 11 presents the results.

Table 11: Shows results of a Pearson moment correlation for a relationship between extreme drought at different time scales and vegetation using NDVI.

SPI	Correlation	p-value	Interpretation
SPI1	-0.05	0.3334	Weak negative, not significant
SPI3	-0.10	0.0671	Weak negative, close to significant
SPI6	-0.05	0.3994	Very weak negative, not significant
SPI12	0.01	0.8431	No relationship, not significant

From the analysis, results present SPI1 and SPI6 as showing very weak negative correlations (-0.05), with p-values well above the 0.05 threshold, indicating no significant linear relationship between short-term or intermediate drought conditions and vegetation cover. SPI3 demonstrated a weak negative relationship (approximately -0.10), approaching marginal significance ($p = 0.0671$). On the other hand, SPI12 exhibited virtually no correlation (0.01), indicating minimal long-term influence of drought on NDVI.

4.3.1.2 The temporal relationship of extreme drought and NDVI distribution.

The figure 16, shows four subplots that present an analysis of the relationship between vegetation (NDVI) and extreme drought events using SPI at different time scales for the period 2024 to 2052. A description of the subplot for SPI1, shows extreme drought events being frequent and sporadically spread across the time. NDVI shows variability but during the extreme drought events, the values are often below average. The SPI3 plot of 3 months' cumulative extreme droughts show the events are less frequent compared to SPI1. NDVI is more below the mean during SPI3 than SPI1. The SPI6 cumulative droughts are sparse and often coincide with low NDVI values. SPI12 cumulative droughts are least frequent but on occurrence, NDVI tends to be consistently below average.

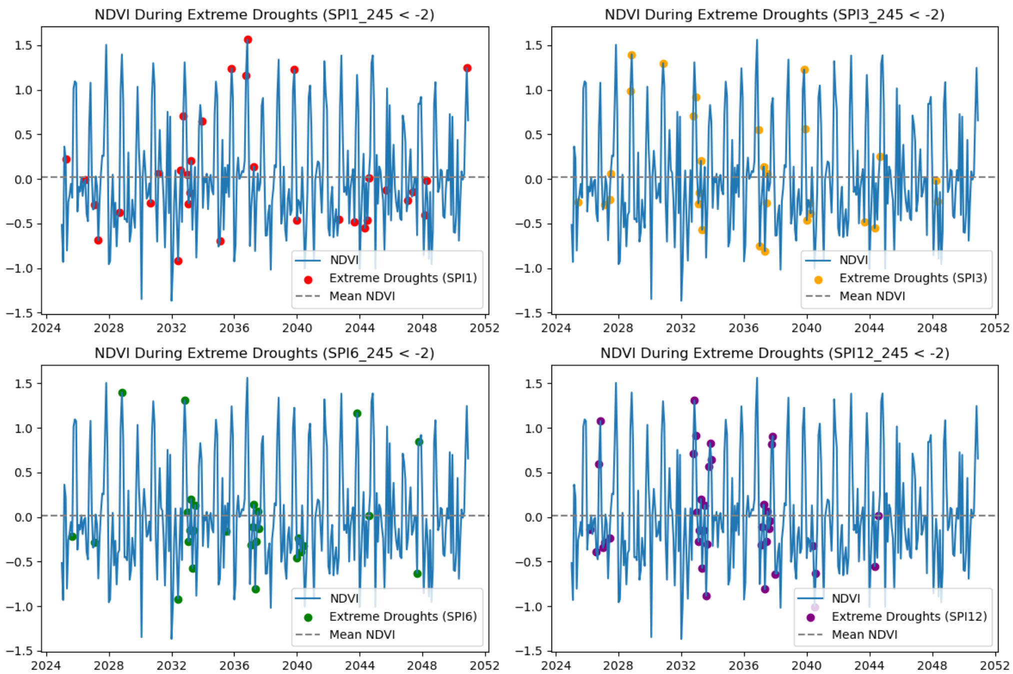

Figure 16: Future time series plots of extreme drought impact on vegetation for the different SPI timescales under SSP245 climate scenario.

4.3.1.3 NDVI distribution during drought and non – drought periods.

Using a Mann- Whitney U test, differences in distribution were probed. Below are the detailed results.

Table 12: Shows results of a Mann-Whitney U test for significance of NDVI distributions during extreme drought and non-drought periods.

SPI	Mann Whitney U test statistic	P Value	Interpretation
SPI1	4477.5	0.9288	No significant difference
SPI3	4050.0	0.8646	No significant difference
SPI6	3635.5	0.4525	No significant difference
SPI12	5105.0	0.8470	No significant difference

Results show all p-values are much greater than 0.05 meaning there is no statistically significant difference in NDVI values between extreme drought periods and non-extreme periods for all SPI time scales.

4.3.1.4 Lag response relationship between extreme drought and NDVI distribution

A cross correlation was used to probe the lagged relationships, below are the details.

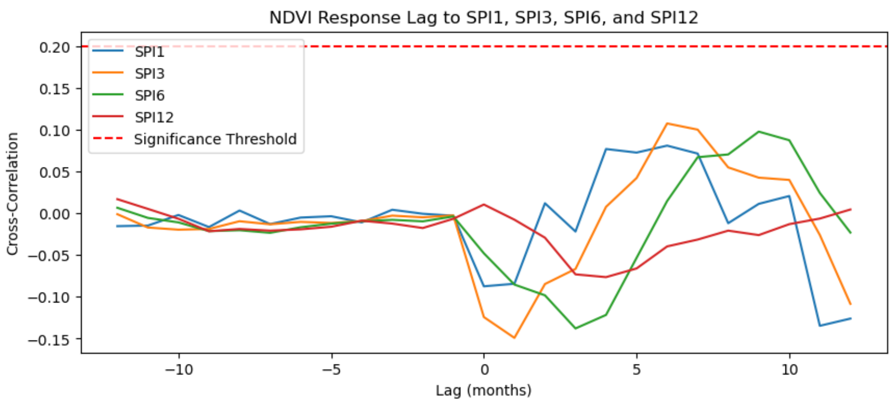

Figure 17: Vegetation response to extreme drought at different time lags and SPI timescales under SSP245 climate scenario from a Cross – Correlation analysis.

Figure 16, is a plot showing a cross-correlation analysis of the NDVI response lag to SPI timescales. At SPI1, the cross correlation is weak throughout, slightly peaking at lag 6 and small dips around Lag 0 and +11. SPI3 is observed to have a negative near lag 0, followed by a clear positive peak around lag 5-6. SPI6, has the strongest and broadest positive correlation that peaks at lag 7-8. A stronger response to longer term drought although delayed by 7-8 months. Correlations at SPI 12 are weak throughout. Peaking slightly at lag 4. This is indicative of very limited short term vegetation response to long term drought.

The plot revealed a delayed vegetation response to moderate duration droughts (SPI3 and SPI6), peaking 5 to 8 months later. At all SPI timescales, the relationship remains below the 0.2 significance threshold. However, short term droughts have minimal influence on long term NDVI changes. Long term droughts show weak correlation implying NDVI may adapt to more recent conditions.

4.3.2 Examination for impacts under projected climate scenario SSP585.

This subsection presents the results from the statistical analysis assessing the impact of extreme drought on temporal distribution of vegetation under the projected SSP585 climate scenario.

4.3.2.1 Strength and direction of the relationship between extreme drought and NDVI distribution

In order to understand whether a nonlinear relationship exists between SPI at different time scales and Vegetation using NDVI. A Pearson moment correlation was performed and the table below presents the results.

Table 13: Shows results of a Pearson Moment correlation for a relationship between extreme drought at different time scales and vegetation using NDVI.

SPI	Correlation	P-value	Interpretation
SPI3	0.10	0.0671	Weak positive, borderline significance
SPI1	0.05	0.3335	Very weak positive, not significant
SPI6	0.05	0.3994	Very weak positive, not significant
SPI12	-0.01	0.8432	Virtually no relationship, not significant

Among all the SPI timescales considered, only SPI3 shows a comparably strong positive correlation, that is close to statistical significance ($r= 0.10$, $p\approx 0.067$) with NDVI. The other SPI timescales, SPI1, SPI6 and SPI12 all show negligible correlations without any statistical significance. Under the projected climate scenario SSP585, NDVI and SPI show weak correlations with no statistical support for a significant relationship.

4.3.2.2 The temporal relationship of extreme drought and NDVI distribution.

The figure 17, shows four subplots that present an analysis of the relationship between vegetation (NDVI) and extreme drought events using SPI at different time scales for the period 2024 to 2052. Observations show that at short SPI1 extreme droughts occur frequently and randomly throughout the timeline. However, these show weak and irregular influence on vegetation. SPI3, NDVI shows a noisy pattern with some dips coinciding with droughts. The SPI6 plot shows fewer extreme drought events that tend to align with lower NDVI values a more consistent vegetation response. SPI12 shows less frequent but notable extreme drought events often coinciding with below-mean NDVI. Under the future extreme climate scenario SSP585, vegetation continues to show weak responses to short term droughts SPI1 and SPI3. Longer droughts SPI6 and SPI12 show more negative effects on NDVI with SPI12 indicating the most vegetation stress.

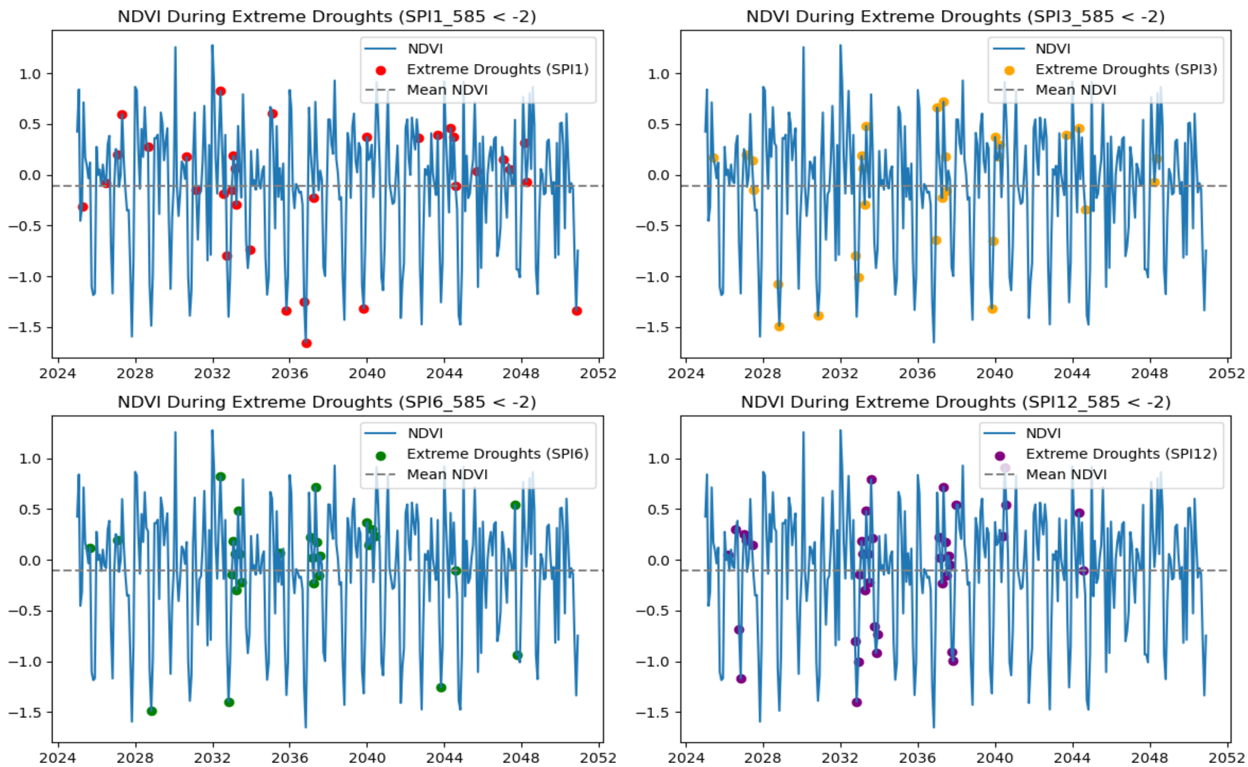

Figure 18: Future time series plots of extreme drought impact on vegetation for the different SPI timescales under SSP585 climate scenario.

4.3.2.3 NDVI distribution during drought and non – drought periods.

Results from the Mann Whitney U test in table 14 show that; for all the SPI timescales, p-values are well above 0.05 giving no statistically significant difference in NDVI between extreme drought and non-drought periods.

Table 14: Shows results of a Mann-Whitney U test for significance of NDVI distributions during extreme drought and non-drought periods.

SPI	Mann Whitney U test statistic	P Value	Interpretation
SPI1	4564.5	0.9288	No significance
SPI3	3896.0	0.8646	No significance
SPI6	4310.5	0.4525	No significance
SPI12	5307.0	0.8470	No significance

SPI12 has the highest U statistic of 5307.0 implying longer droughts seem to align more with NDVI drops although not statistically significant.

4.3.2.4 Lag response relationship between extreme drought and NDVI distribution

From figure 18, 1-month droughts (SPI1) plot depicts NDVI fluctuating considerably after lag 0. It peaks around +12 months but remains below significance threshold suggesting a weak correlation with a delayed NDVI response. SPI3 droughts have a stronger correlation with NDVI around lag 0 to +1, peaking near +1 month and Dips around +5 to +7 months suggesting NDVI responds quickly within 1 – 2 months to 3-month drought. At SPI6, NDVI shows the strongest peak between lags 1 – 3 and dips below zero around 6 -8 months. 12-month droughts are generally weak staying below 0.1 across all lags showing a weak direct relationship between 12-month SPI and NDVI.

All observed relationships are not statistically strong since no SPI lag exceeds significance 0.2. However, positive lags like SPI leading NDVI by 1-3 months tend to show the highest correlation.

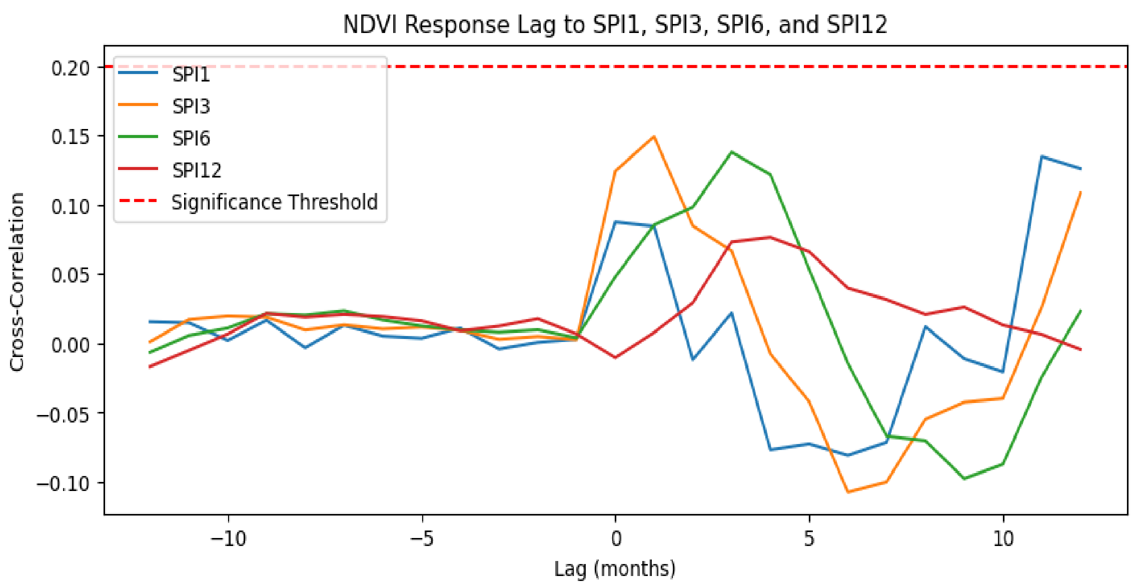

Figure 19: Vegetation response to extreme drought at different time lags and SPI timescales under SSP585 Climate scenario from a Cross-correlation analysis.

Comparison of results from the two emission scenarios SSP245 and SSP585 shows a likelihood for more pronounced extreme drought impacts under SSP585 especially in SPI12. NDVI variability here appears more erratic, possibly due to more intense climate extremes under this scenario.

In the context of the SSP585 high-emissions scenario, the relationship between the Standardized Precipitation Index (SPI) and the Normalized Difference Vegetation Index (NDVI) is generally weak. However, SPI3, which captures moderate-term drought conditions, demonstrated some statistical significance. Time series analysis indicated that NDVI responses to longer-term droughts, particularly SPI6 and SPI12, as being more pronounced compared to short-term droughts. The Mann-Whitney U test revealed that SPI12 had the highest U statistic, but the relationship was not statistically significant. Cross-correlation analysis demonstrated that NDVI responded most strongly to SPI3 and SPI6 with a short lag of 0 to 3 months.

CHAPTER FIVE: DISCUSSION OF RESULTS

5.0 Introduction

This chapter presents the discussion of the results presented in the previous chapter. The discussions are presented patterned after the results aligned with the study objectives.

5.1 Determination of Past and future extreme drought characteristics.

This subsection details the discussion for results of the past extreme drought characteristics.

5.1.1 Past extreme drought Characteristics.

Based on the results, the frequent and short-lived drought episodes in SPI1 are indicative of responsiveness to rapid weather fluctuation by this timescale. This shows SPI1 index as useful in identifying short term droughts and as such, may not be effectively useful in monitoring long term drought. However, SPI3 and SPI6 displayed pronounced droughts and may be effective in capturing seasonal droughts for grassland pasture and general agriculture monitoring and planning. The severity and clustering of drought events increase with timescale in SPI6 and SPI12 may point to the need for a multi timescale SPI analysis in drought monitoring. These findings are similar to Vicente-Serrano et al., (2010), who recommended use of multi-timescale drought indices for monitoring both short-term and long-term droughts. This is also in agreement with Zhang et al, (2012) whose study emphasized the capacity of short-term indices to detect rapid onset of droughts for early warning.

From the results, drought severity and duration become more pronounced with increase in SPI timescales. This variability was observed in SPI6 and SPI12 and as such underscores the need to use the integration of the different SPI timescales in drought early warning and monitoring efforts as suggested by (Naumann et al, 2015).

5.1.2 Future extreme drought characteristics

Results from the analysis of future SPI values under SSP245 and SSP585 scenarios indicates a future rise in extreme drought episodes in Kiruhura District across all timescales. At shorter-term timescales (SPI1 and SPI3), both scenarios predict an increase in drought occurrences relative to historical records, with SSP245 showing marginally higher occurrences than SSP585. This suggests that SSP245 pathway may experience more frequent short-term droughts, possibly due to variability in precipitation patterns and increased climate instability (Spinoni et al, 2020; Vicente-Serrano et al., 2010).

For longer-term timescales (SPI6 and SPI12), drought frequency under SSP585 surpasses SSP245, indicating that high-emission scenarios are more likely to exacerbate extended droughts. Although the increase is less marked than in shorter timescales, these projections still represent a rise compared to historical records (IPCC, 2021). This aligns with climate model studies showing that prolonged droughts are expected to intensify under higher greenhouse gas emissions (Cook et al., 2020).

Projected trends also reveal temporal variability in drought characteristics. Duration increases steadily until around 2033, after which it stabilizes by approximately 2048. Severity and intensity display cyclical rising and falling patterns before reaching stability, implying worsening drought conditions in the early-to-mid 2030s before a gradual recovery. At short-term timescales, drought severity may increase slightly, but duration and intensity remain relatively stable. Medium-term droughts are expected to intensify and lengthen before stabilizing, while long-term droughts will likely peak in duration, severity, and intensity in the 2030s, followed by a gradual decline. This pattern suggests that Kiruhura District should prepare for significant drought stress in the 2020s and 2030s, particularly at medium and long-term scales, with a possible stabilization in later decades.

Overall, these findings support existing literature that climate change will increase drought frequency, duration, and severity in sub-Saharan Africa, with varying effects across temporal scales (Niang et al, 2014; Masih et al, 2014).

5.1.3 Comparison of historical and future drought characteristics

All SPI timescales SPI1, SPI3, SPI6, and SPI12 showed an increase in extreme drought episodes in the future under both projection scenarios, SSP245 and SSP585. For short term timescales (SPI1 and SPI3), the number of occurrences based on SSP245 is marginally more than that under SSP585, this observation suggests that under a moderate emissions pathway, frequent and brief drought events may become more prevalent. This aligns with findings by Spinoni et al. (2018), who noted that short-term meteorological droughts are expected to increase in frequency under medium stabilization scenarios due to amplified variability in rainfall distribution.

However, for both future scenarios, results depicted a rise in the number of extreme drought occurrences at shorter term SPI timescales (SPI1 and SPI3). Although less marked but still noticeable for longer periods (SPI6 and SPI12), suggesting that extended droughts may also become more common in the future, especially under the high-emission SSP585 scenario. The severity and persistence of such drought events have major implications for grasslands water resource management and agricultural planning (Mukherjee et al, 2018).

With future scenarios indicating an increase in drought episodes relative to the past, particularly under greater greenhouse gas emission pathways, these results point to the possible effects of climate change on drought frequency across different timescale.

5.2 Implications of Past extreme drought on spatiotemporal distribution of grassland.

This sub section presents the discussion of results on past implications extreme drought on spatial distributions of grasslands in Kiruhura.

5.2.0 The past Spatiotemporal distribution of grassland vegetation cover (1990 – 2020).

Results from the analysis indicated the year 2020 depicted a significant change of less green and much drier grasslands over the decade. Spatially, drier grasslands tend to dominated the district by 2020 compared to 2010 and 2015. This may imply greener and healthier grasslands became less prominent with time particularly by the year 2020. These changes are likely due to a number of factors including Drought occurrence, land use cover changes and other ecological factors.

5.2.1 Implications on spatial distribution (Changes in area coverage) of grasslands vegetation cover.

Basing on the Maps in Figure 11, graphical changes in area coverage of each vegetation class before, during and after the extreme drought event of 2017 portrayed increased in bare ground area coverage into the extreme drought but a decrease during recovery period. This suggests that vegetation cover was lost due to the drought, leading to land degradation, but some recovery occurred afterward. The analysis established that savannah grasslands showed a significant response to the extreme drought. During this period, approximately 2000 km² of grasslands savannah vegetative cover was lost. However, there was gradual recovery after the extreme drought with the vegetation re-growing and the bear ground decreasing further. This suggests that grasslands are more sensitive to changes in water availability and can bounce back quickly when conditions improve, rather than just suffering from water shortages. (Vicente-Serrano et al, 2010).

5.2.2 Impacts of extreme drought on temporal distribution of grasslands vegetation cover.

Discussion of presented results on extreme drought and NDVI distribution on a temporal scale with emphasis on relationship strength and direction, distribution differences during drought and non-drought periods as well as response delays.

The Pearson Moment correlation analysis supports the idea that shows that longer durations of (SPI), specifically SPI6 and SPI12, have a stronger relationship with NDVI compared to shorter durations like SPI1 and SPI3. This finding aligns with research by Ji and Peters (2003), who also noted that SPI12 is a more reliable predictor of drought-related stress in vegetation.

Further analysis of time series data reinforces these conclusions, revealing that declines in NDVI closely coincide with extreme drought events measured by SPI6 and SPI12. This indicates that using long-term drought metrics is more effective for monitoring the impacts on vegetation, similar to what Rhee et al. (2010) found in their studies.

The results from the Mann-Whitney U test showed that while NDVI remains relatively stable during short droughts (like those measured by SPI1), significant declines occur during longer drought periods, especially with SPI12. This trend highlights how drought stress can progressively impact ecosystems over time. Additionally, cross-correlation analysis indicates that NDVI responses to moderate-duration droughts (SPI3 and SPI6) are delayed, peaking around 5 to 8 months after the drought ends. This delayed effect is consistent with findings from Wang et al. (2007), who also observed lagged responses in vegetation within dryland ecosystems.

5.3 Implications of Future extreme drought on the temporal NDVI distribution.

This subsection presents discussion of results from the analysis under both projected climate scenarios SSP245 and SSP585 using statistical methods.

5.3.1 Impacts under projected climate scenario SSP245.

Results from the Pearson moment correlation suggested no strong linear relationship between extreme drought and NDVI at all SPI time scales in the future under the SSP245 climate scenario. This may imply NDVI response may not be strongly influenced by linear drought patterns. The weak correlations may also reflect limitations of NDVI as a sole indicator of vegetation cover or the need for lag analysis to capture delayed vegetation responses, as suggested by studies such as Ji and Peters (2003) and Vicente-Serrano et al. (2013). However, times series results indicated a consistent correspondence between extreme drought and vegetation stress at SPI12. This may imply long term droughts have a clearer negative impact on vegetation.

Short term droughts although frequent may not always result in vegetation stress. Longer term droughts may be considered stronger predictors of vegetation decline. This suggests that the longer the SPI timescale the more consistent the negative NDVI response.

Basing the Mann –Whitney u test, statistically vegetation as measured by only NDVI does not consistently decline during extreme droughts. Although the plots suggested NDVI tends to dip during longer droughts (SPI6 and SPI12), the variability is high but not strong and significant. Therefore, there is no statistical evidence to support a strong relationship between NDVI distribution between drought periods or non-drought periods for all SPI time scales. This implies that predicting vegetation responses to changing climate conditions may become increasingly complex (Gao et al., 2012).

All these statistical analyses did not provide strong statistical evidence linking drought events to NDVI fluctuations, implying that other factors such as land management or temperature variations could be more influential under moderate climate change conditions. These findings align with previous research highlighting the increasing complexity of vegetation–drought interactions under future climate scenarios (Gao et al., 2012).

5.3.2 Impacts under projected climate scenario SSP585.

From the results based on the statistical analyses in this subsection, the Pearson moment correlation, depicted short term and seasonal droughts do not strongly impact vegetation conditions as detected through NDVI. This was evident by the weak correlations with no statistical support for a significant relationship. These findings are in line with previous studies that have noted variability in vegetation responses depending on drought duration and ecosystem type (Vicente-Serrano et al., 2013; Ji & Peters, 2003). The weak correlations might also reflect the lagged or non-linear responses of vegetation to drought, or the moderating influence of local land management practices, which are not captured in linear correlation analyses.

Mann Whitney U test results indicated p-values are well above 0.05 at all SPI timescales. This implies no statistically significant difference in NDVI between extreme drought and non-drought periods in the SSP585 climate scenario. Suggesting NDVI variability is not strongly distinguishable during extreme droughts even under a more extreme climate future SSP585. However, SPI3, which captures moderate-term drought conditions, demonstrated some statistical significance, suggesting that even under extreme climate change scenarios, monitoring moderate-term droughts remains useful for assessing vegetation health (Zhang et al., 2017).

The Mann-Whitney U test also revealed that SPI12 had the highest U statistic, but the relationship was not statistically significant, implying that other factors such as temperature variations, irrigation, and land use changes, unaccounted for in the current analysis may play a role in vegetation responses.

Time series analysis indicated that NDVI responses to longer-term droughts, particularly SPI6 and SPI12, were more pronounced compared to short-term droughts. This aligns with previous research emphasizing the importance of longer SPI durations for capturing the persistent effects of drought on vegetation (Zhang et al., 2017).

Cross-correlation analysis demonstrated that NDVI responded most strongly to SPI3 and SPI6 with a short lag of 0 to 3 months, supporting their relevance in early warning systems for drought. However, the low correlation coefficients highlight the limited predictive power of these measures. This suggests a need for more comprehensive drought indices or multi-variable approaches to improve the accuracy of vegetation response predictions under future high-emission conditions (Gao et al., 2012).

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

This chapter presents the conclusions and recommendations deduced from this academic research study.

6.1 Conclusions

This study investigated the relationship between extreme drought, as measured by the Standardized Precipitation Index (SPI), and vegetation cover, captured through the Normalized Difference Vegetation Index (NDVI), across past and projected future climate scenarios (SSP245 and SSP585). The findings contribute to a deeper understanding of drought and vegetation cover interactions in grassland ecosystems, with particular relevance for cattle keeping communities and agro-pastoral systems in Kiruhura District.

Extreme drought characteristics increased with increase in SPI timescale. The extreme drought analysis of trends at the different SPI timescales revealed short and midterm droughts were more frequent in the past and future. However, drought duration and severity appeared to increase with increase in SPI timescale in the past. In the future, extreme drought frequency at all SPI timescales was relatively higher compared to the past.

Grasslands were resilient to short-term extreme droughts but vulnerable to prolonged droughts. The results revealed that the strength and direction of the SPI and NDVI relationship is highly dependent on the SPI time scale. In the historical period, longer SPI timescales (SPI6 and SPI12) showed the strongest correlations with NDVI distribution over time, suggesting that extended moisture deficits have the most significant and detectable impacts on vegetation cover. This finding reinforces the suitability of mid to long-term drought indicators in ecological drought assessments and in the design of early warning and drought monitoring systems (Vicente-Serrano et al., 2012; Wang et al., 2014). Such dynamics underscore the ecological threshold beyond which grassland systems transition from resilience to vulnerability, with profound implications for livestock-based livelihoods in regions such as Uganda's cattle corridor (Nampala et al., 2015).

No detectable significant extreme drought impact on grasslands distribution in the future under both climate scenarios. Under future climate projections (SSP245 and SSP585), no statistically significant extreme drought NDVI relationship was detected under both projection pathways with no sensitivity responses even to all time lags probed. This suggests that tentatively, vegetation cover responses to extreme drought may become increasingly nonlinear, driven not only by precipitation anomalies but also by compound stressors such as rising temperatures, land-use changes, and intensified human pressures on ecosystems (IPCC, 2021). The reduced predictability of NDVI responses under future scenarios highlights the growing uncertainty in managing grassland systems under climate change.

6.2 Recommendations.

Based on the findings of this study, the following recommendations are proposed to enhance resilience of cattle keeping communities to the impacts of drought in the grasslands of Kiruhura District:

Drought monitoring and early warning systems in grassland-dominated regions such as Uganda's cattle corridor should prioritize mid- to long-term drought indicators (SPI6 and SPI12), as these timescales better capture cumulative moisture deficits that significantly affect grassland productivity and ecosystem functioning also demonstrated by (Vicente-Serrano et al., 2012; Wang et al., 2014).

Grassland management policies should emphasize adaptive strategies such as controlled stocking rates, pasture rotation, restoration of degraded grasslands, and protection of key dry-season grazing reservesto reduce vulnerability to prolonged and severe droughts also depicted by (Nampala et al., 2015).

Future drought impact assessments should move beyond precipitation-only indices and adopt integrated frameworks that combine SPI with temperature-based indices (e.g., SPEI), soil moisture, evapotranspiration, and land-use dynamics, especially under climate change scenarios based on the absence of statistically significant NDVI–drought relationships under both SSP245 and SSP585 (IPCC, 2021).

6.3 Limitations of the study

Limitations included; NDVI limitations including saturation and mixed pixels, reliance on SPI only without including soil moisture/ET, possible model bias in future precipitation, potential autocorrelation not fully accounted for, and limited ground truthing (Xuan et al., 2024; Saeidipour et al., 2019).

However, because of these study limitations, it would be inevitable to consider existing management regimes in place in the District including rangeland management practices, drought monitoring systems, and climate adaptation frameworks that influence grassland condition and drought response in resilience efforts. These regimes shape vegetation resilience by mediating grazing pressure, recovery capacity, and exposure to prolonged moisture stress. The weakening of NDVI–drought relationships under future climate scenarios suggests that current management approaches may be insufficient to address compound climatic and anthropogenic pressures, highlighting the need for adaptive and integrated management strategies.

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