CLIMATE VARIABILITY A DOMINANT DRIVER OF VEGETATION HEALTH DYNAMICS IN KAPCHORWA DISTRICT, UGANDA

BY

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DECLARATION

I affirm that this thesis on **climate variability a dominant driver of vegetation health dynamics in Kapchorwa district** is entirely my own work and has not been previously published or submitted for any other academic degree from any other institution.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

ABBREVIATIONS AND ACRONYMS

Coefficient of Variation (CV)

December-January-February (DJF)

Geographic Information System (GIS)

Global Positioning System (GPS)

Green House Gas (GHG)

Gross Domestic Product (GDP)

International Food Policy Research Institute (IFPRI)

June-July-August (JJA)

Mann-kendal Test (MK test)

March-April-May (MAM)

Maximum Value Composite (MVC)

Nanjing River Basin (NRB)

Near Infrared Radiation (NIR)

Normalized Difference Vegetation Index (NDVI)

Precipitation Concentration Index (PCI)

Red light Radiation (RED)

Relative Abundance (RA)

Rescaled range analysis (R/S)

September-October-November (SON)

Simpson's diversity index (SID)

Uganda National Meteorological Authority (UNMA)

Vegetation condition index (VCI)

World Meteorological Organization (WMO)

DEFINITION OF TERMS

Agroecological zone: a land resource mapping unit, defined in terms of climate, landform and soils, and/or land cover, and having a specific range of potentials and constraints for land use

Climate variability: refers to variations in the mean state and other climate statistics (standard deviations, the occurrence of extremes, etc.) on all temporal and spatial scales beyond those of individual weather events.

Climate change: long-term change in the average weather patterns

Ecotone: a transition area between two biological communities, where two communities meet and integrate.

Spatial and temporal: It describes a phenomenon in a certain location and time

Vegetation health indices: indicators of vegetation health namely NDVI

Weather: The state of the atmosphere at a given time and place, with respect to variables such as temperature, moisture, wind velocity, and barometric pressure.

ABSTRACT

Economic development, particularly in third world nations heavily reliant on agriculture, is under threat from climate change as a global phenomenon. While there have been some studies on its impact on vegetation productivity in other regions, there is a lack of research in African countries, specifically in Uganda's agricultural districts. This study aimed to evaluate the role of climate variability as a dominant factor in vegetation health in Kapchorwa district. To explore the relationships within the study, correlational research design with an integration of quantitative methods was employed. Secondary and primary climate data sets were used to determine the trends and variations in rainfall and temperature from 1989 to 2019. The Normalized Difference Vegetation Index (NDVI), Vegetation Relative Abundance, and relative abundance were employed as indicators of vegetation health, and their correlations with rainfall and temperature were examined. The results showed an increasing trend ($p>0.05$) in both maximum and minimum temperatures in Kapchorwa district over the 30-year period, with minimal variation. Rainfall also exhibited an upward trend ($p>0.05$) with high variability and relatively even distribution patterns. NDVI significantly increased from 1989 to 2019, with sporadic periods of drought in the earlier years. The district's vegetation diversity was moderate (0.47), with Poaceae (grass) being the most abundant vegetation type (57%), and Actinidiaceae (shrubs) the least abundant (46%). The strong correlation (72%) and regression coefficients (52%) indicated a significant impact of temperature on the diversity and abundance of vegetation, which are essential indicators of vegetation health. These findings emphasize that while Kapchorwa's vegetation health has generally benefited from the positive climatic trends, the diversity and distribution of vegetation types are essential considerations for sustainable management and conservation. The efforts of local governments and districts should focus on preserving the dominant species of grasses, trees, and shrubs, as they are essential for maintaining ecosystem stability. The preservation of native plant species and sustainable harvesting should be prioritized in local community conservation efforts to support and improve the current trend of healthy vegetation in the face of climate variability.

CHAPTER ONE: INTRODUCTION

1.1 Background

In modern times, climate variability presents a significant challenge for humanity, as the Earth's surface temperatures continue to rise (Nsubuga and Rautenbach, 2018a). Climate variability refers to fluctuations in climatic conditions from their long-term average in a given region (Dinse, 2010). These variations have profound consequences, particularly on ecological systems, with one of the most severe impacts being on vegetation health (Peterson *et al* 2014). Vulnerable populations in developing countries are especially ill-equipped to handle these impacts, which lead to decreased vegetation health and lower food productivity (Muwembe , 2017). Research has demonstrated that precipitation patterns in Africa have undergone significant changes, with projections indicating a potential 50% decrease in yields from rain-fed agriculture in the next decade (Odeny *et al* 2019). This reduction in productivity threatens to increase malnutrition for those who rely on subsistence farming and raises food insecurity for others who depend on market-purchased food (Jenkins et al 2021). The effects of climate variability have already caused food crises in countries such as Kenya, Uganda, Somalia, and Ethiopia (BBC, 2010a).

In East Africa, rising temperatures and changing precipitation patterns have led to more frequent and intense droughts, floods, heat waves, and landslides (Hartter *et al* 2012). In Uganda, however, limited research has been conducted to establish a clear link between climate variability and vegetation health (Kisembe *et al* 2019). While some studies have explored general rainfall and temperature patterns, they often fail to focus on specific regions or districts where climate interventions are necessary (Sabiiti *et al* 2016). The Intergovernmental Panel on Climate Change (IPCC) has warned that climate variability is accelerating faster than previously thought, yet research in Uganda has not fully addressed these changes (Jury, 2018a).

The alteration of climatic factors, especially precipitation and temperature, greatly impacts vegetation health, making it essential to investigate the relationship between these factors and vegetation well-being (Hamid *et al* 2021). Vegetation health refers to the overall condition and functioning of plant life in a specific area or ecosystem (Nyoike, 2000). It is measured through indicators such as the Normalized Difference Vegetation Index (NDVI), species diversity, and plant abundance (Yan *et al* 2017). Despite the importance of these indicators, many studies in Uganda have focused narrowly on vegetation productivity rather than incorporating the multi-faceted aspects of vegetation health (Mwaura & Okoboi, 2014a).

According to the Global Humanitarian Forum, Uganda is among the countries most vulnerable to climate variability (Odeny *et al* 2019). However, much of the research on climate variability in Uganda has focused on explaining trends and patterns of climatic factors, neglecting the crucial role vegetation plays in the ecosystem's survival (Nsubuga & Rautenbach, 2018a). As a result, the anticipated effects of increased rainfall variability, more frequent extreme weather events, and prolonged droughts on agriculture and food security are not thoroughly explored (Magrath, 2008).

Kapchorwa, a region in the eastern agro-ecological zone of Uganda, has experienced noticeable shifts in vegetation health over recent years (Aid *et al*., 2017). With climate variability affecting rainfall patterns, temperature, and soil moisture, there is growing concern that these fluctuations are significantly influencing vegetation dynamics in the region (Wortmann & Eledu, 1999). Despite an observed increase in food production, the health and sustainability of local vegetation remain vulnerable to the impacts of climate variability(Monaghan *et al*., 2012). This research seeks to understand the extent to which climate factors such as temperature variability, seasonal rainfall distribution, and extreme weather events contribute to changes in vegetation health. By analyzing a span of 30 years (1989 to 2019), this research offers an in-depth understanding of long-term climate trends in the Kapchorwa area (Pilesjo *et al*., 2021a). Climate variability is typically marked by gradual changes over time, making the examination of this extended period crucial for recognizing important trends and alterations in temperature and precipitation that could be overlooked in shorter intervals.

1.2 Problem statement

Kapchorwa District, located in eastern Uganda, has been experiencing significant impacts from climate change over the past few decades, with shifts in rainfall patterns and temperature fluctuations particularly evident between 1989 and 2019. The district, largely reliant on agriculture, has seen its population facing increasingly unpredictable weather conditions. Rainfall, once consistent and reliable, has become erratic, with prolonged droughts followed by intense, short rainy seasons leading to soil erosion and reduced soil fertility. Average annual temperatures have also risen, exacerbating moisture loss and putting stress on both crops and natural vegetation. Vegetation degradation in Kapchorwa has reached alarming levels due to these climate stresses coupled with human activities such as deforestation and overgrazing. It’s estimated that over 70% of Kapchorwa’s population depends directly on agriculture for their livelihoods, with maize, beans, and coffee being the primary crops. The increasingly unreliable rainfall and rising temperatures have severely impacted crop yields, reducing food security and economic stability for residents. Furthermore, declining vegetation cover has led to increased soil erosion, diminishing the land's capacity to support agricultural productivity in the future. Currently, Kapchorwa faces a challenging scenario where agricultural productivity is at risk, and the environment is under threat due to degradation. If the trend continues without intervention, the district could experience further loss of vegetation cover, reduced agricultural yields, and heightened food insecurity.

1.3 Objectives of study

1.3.1 General objectives

To assess the effect of climate variability on vegetation health in Kapchorwa district

1.3.2 Specific objectives

1. To determine the rainfall and temperature variation and trend in Kapchorwa district from 1989 to 2019.
2. To analyze the Normalized Difference Vegetation Index (NDVI) trends and variation in kapchorwa district from 1989 to 2019.
3. To determine the diversity and abundance of dominant plant species in kapchorwa district.

1.4 Null Hypothesis

1. There is no significant difference in the trends of rainfall and temperature in Kapchorwa district from 1989 to 2019.
2. There is no significant difference in the trend of vegetation health indices in kapchorwa district from 1989 to 2019.
3. There is no significant relationship between vegetation relative abundance, diversity and temperature in kapchorwa district.

1.5 Scope of study

Conducted in Kapchorwa district, the research aimed to analyze the climate and vegetation health dynamics over time and space. The study estimated changes in rainfall and temperature, examined trends in vegetation indices, and explored the connection between climate change and vegetation health from 1990 to 2019. The research spanned from December 2020 to May 2021 (6 months) and involved reviewing publications and journals from 2000 to 2020. A significant amount of current and up-to-date data and information was gathered from various sources.

1.6 Significance of study

Decision makers can utilize these research findings to effectively manage the impact of climate change on vegetation. The valuable information presented in this study is beneficial for both governmental and non-governmental institutions that have a vested interest in conducting vulnerability assessments of vegetation in relation to climate change. Additionally, the data collected in this study can serve as a reliable secondary source for future research and other related fields. Given the limited number of studies on climate change and its effects on vegetation in Uganda, this research has the potential to attract the attention of researchers from various fields. By identifying knowledge gaps, this study can inform future research directions and adaptive management strategies. Furthermore, this research is a valuable contribution to the national development policies and poverty reduction strategies of the Uganda government, which aims to elevate the country to a 'middle income' status by 2025. It promotes sustainable farming practices and the conservation of indigenous biodiversity resources, as well as the development of livelihoods from natural resources. This review also aligns with the goals of building a climate-resilient Green Economy, which prioritizes adaptation to climate change and the mitigation of greenhouse gas emissions. By enhancing the productivity of the agricultural sector and protecting and rehabilitating forests, this research supports the reduction of greenhouse gas emissions, while also improving food security and income for farmers and pastoralists.

1.7 Conceptual framework

Based on the theory proposed by (Sanctis et al 2011), this research explores the direct relationship between changes in vegetation greenness, biodiversity, relative abundance, and the variations in temperature and rainfall. The health of vegetation, as determined by its greenness, biodiversity, and relative abundance, is crucial for understanding the impacts of climate change on human life and ecosystems (Ritchie, 1986). The interconnection between climate and biodiversity is complex and cannot be ignored, as emphasized by the (IPCC-IPBES, 2020).

The distribution and composition of terrestrial ecosystems at both regional and global scales are highly influenced by climate (Wilcox, 2010). Vegetation, being a sensitive component of the ecosystem (Sintayehu, 2018a), undergoes dynamic changes in terms of both phenological metrics and land cover types (Bullock, 1997). These changes in vegetation are significant in the context of land-atmosphere interactions and can be measured using the Normalized Difference Vegetation Index (NDVI), which is positively correlated with productivity (T. F. Piao *et al* 2009).

The causes of vegetation dynamics are largely dependent on geographical conditions, such as climate constraints and human activities (Nkunzimana et al 2019). In East Africa, where the economy heavily relies on natural resource exploitation, these activities directly contribute to abnormal changes in climate (Sintayehu, 2018a). These changes, which deviate from the region's normal climatology, can be analyzed by studying long-term data spanning over thirty years (Cheng *et al 2018a).*

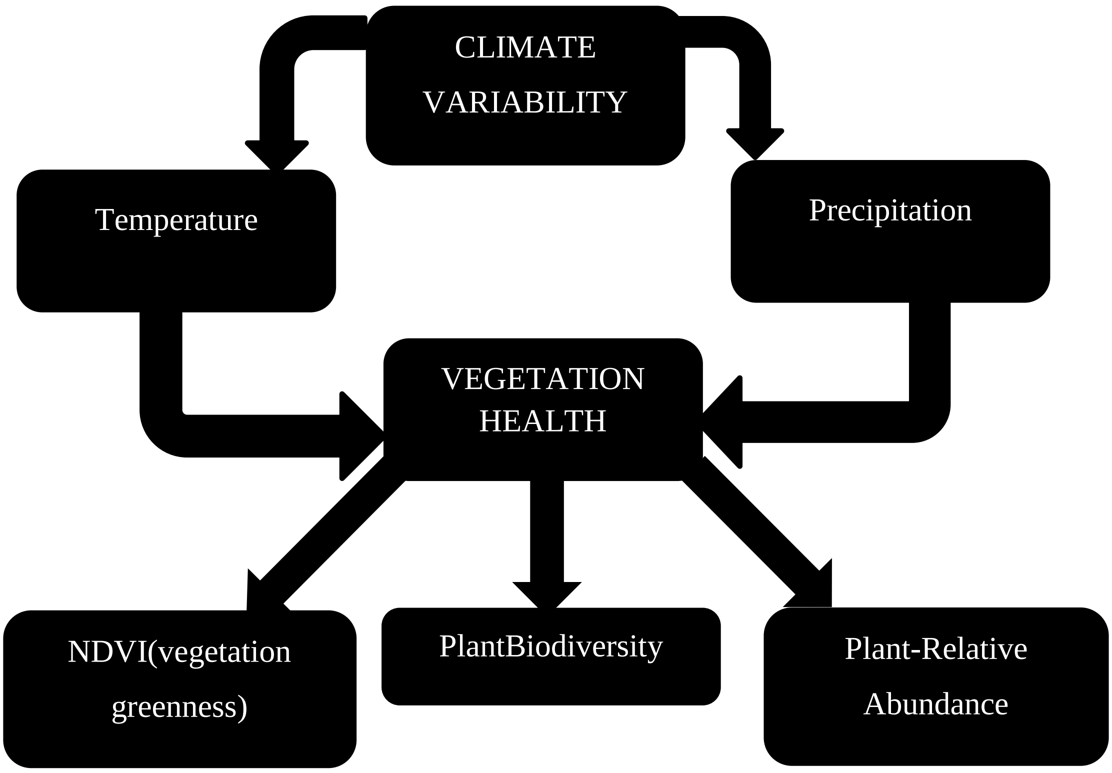


Figure 1.1: The relationship between climate variability and Vegetation Health

CHAPTER TWO: LITERATURE REVIEW

2.1 Climate variability and trends

Several studies have been conducted to examine changes in vegetation and their correlation with climate variability, with varying results depending on the location of the study (Tsai & Yang, 2016). For instance, Huang *et al*. (2016a) conducted a study focused on the upper and middle reaches of the Nanjing River Basin (NRB) to investigate inter-annual and seasonal fluctuations in vegetation coverage. The study utilized multi-temporal NDVI data and meteorological data from 1999 to 2010 to analyze potential causes for changes in vegetation. Through the combination of these datasets, the scientists were able to analyze the connection between changes in vegetation and fluctuations in climate within the NRB. Findings from the correlation and rescaled range (R/S) examinations revealed a minor rise in yearly NDVI and a noteworthy enhancement of 26.02% in the extent of vegetation in the designated region. However, in spring, there was a significant decrease of 13.33% in vegetation cover, while in autumn, there was a significant increase of 26.2%. According to Huang *et al.* (2016b), the activity of vegetation is expected to strengthen during summer and autumn, while the trend of decreasing in spring is likely to persist in the future. The annual NDVI showed significant positive associations with precipitation and relative humidity, but negative correlations with temperature, sunshine hours, and wind velocity. This could be attributed to the potential impact of these factors on increasing evapotranspiration and the risk of drought and cold damage to vegetation. The variations in annual NDVI were greatly influenced by summer temperature, relative humidity, and sunshine duration, while spring wind velocity also played a role. The seasonal NDVI showed a decrease with rising temperatures, but no correlation was found with precipitation. In each season, spring temperature, summer relative humidity, and autumn relative humidity were significant contributors to NDVI variations(Rabinowitz et al 1984a).

Huang et al (2016a) conducted additional research to examine the Regional Correlation between Precipitation and Vegetation. The main goals of this research were to examine the fluctuations in precipitation and precipitation anomalies over a period of time, observe the alterations in vegetation coverage and their distributions within the basin, and explore the influence of precipitation and precipitation anomalies on vegetation. The findings indicated a parallel geographic pattern between NDVI and precipitation, characterized by a decline from the southeast coastal area to the inland northwest region. Regions with low vegetation were predominantly found in dry and semi-arid zones, as well as heavily populated areas. In 61.6%

of the area, there was a positive correlation between vegetation coverage and consistent precipitation patterns, but a negative correlation was observed between vegetation coverage and precipitation anomalies (specifically, 62.7% for days without rain and 60.3% for days with heavy rain. Based on the clustering analysis, it was found that regions with plentiful vegetation tended to be situated in areas with high levels of precipitation or low anomalies, while areas with reduced vegetation were primarily observed in regions with low precipitation or high anomalies. Despite this, there were specific areas that did not follow the expected trend. This research emphasizes the significance of taking into account the spatial and temporal differences in climatic variables when examining data. The approach utilized was meticulous and methodical, enabling clear understanding.

In the year 2017, Yan and colleagues performed a research utilizing NDVI to evaluate the impact of climate change on the growth of vegetation in the interface area between the moist and dry regions of northern China spanning from 1982 to 2013.They investigated the influence of both climate and non-climate factors on vegetation growth in different eco-regions during this time period. The results showed that the climate in the region had become significantly warmer and slightly drier, leading to an overall increase in NDVI, although with varying levels of change across the study area. While cropland responded positively to the rise in temperature, the correlations between NDVI and climate factors were generally weaker. Using multiple regression models, it was determined that 60% of the NDVI increase was attributed to climate factors, while the remaining 40% was likely due to human activities. While some small areas showed a decrease in NDVI due to farming practices and crop rotations, the overall increase in NDVI in the Poaceae-crop transition zones was largely the result of human impact, possibly due to ecological restoration programs. A separate study by Kalisa *et al* (2019) assessed the impact of climate on vegetation dynamics in East Africa from 1982 to 2015, finding that NDVI demonstrated nonlinear responses to both climate and non-climate drivers. The analysis showed a stronger correlation between NDVI and precipitation compared to temperature.

Climate variability and trends have been a focal point of climate research, with numerous researchers employing diverse methodologies to measure and understand changes in climatic patterns. This literature review discusses the key methods used by various authors, highlighting their findings and contributions to the understanding of climate variability and trends.

Statistical approaches are among the most used methods to analyze long-term climate variability and trends. Researchers have employed various statistical techniques to identify trends in temperature, precipitation, and other climate variables.

The Mann-Kendall test and Sen's Slope Estimator are widely used nonparametric methods for trend analysis. For instance, Kalayci & Kahya, (2006) used these methods to detect trends in Turkish precipitation data and found a significant decreasing trend in some regions. Similarly, Dash et al (2009) applied these methods to Indian rainfall data and noted regional differences in trends, with some areas experiencing increases in precipitation, while others saw decreases.

Time series methods are often applied to assess both long-term trends and short-term variability. Chen & Chung, (2015) used time series decomposition to separate trends, seasonal components, and irregular components in global temperature data. They emphasized the importance of accounting for seasonality and interannual variability when analyzing climate trends.

Crop et al (2012) introduced the ARIMA model, which has since been applied in climate research for forecasting temperature and precipitation patterns. For example, Adler et al (2003) used ARIMA models to forecast monsoon precipitation trends in India and found that future projections indicated increased variability in monsoon rainfall, with potential implications for water resource management.

Remote sensing has become a critical tool for measuring climate variability, especially in regions where ground-based observations are scarce. Satellites provide valuable data on temperature, precipitation, and vegetation, allowing for a more comprehensive understanding of climate changes.

Gao et al (2017) used satellite-derived data to analyze global temperature trends. Their study confirmed that the Earth had warmed by approximately 0.8°C over the past century, with the rate of warming accelerating in recent decades. Satellite platforms such as MODIS and TRMM have also been employed to monitor precipitation variability, particularly in tropical regions, as demonstrated by *Mao et al (2012)*,who utilized TRMM data to assess rainfall variability over tropical and subtropical areas.

Remote sensing of vegetation through the Normalized Difference Vegetation Index (NDVI) has also been employed to assess climate impacts on ecosystems. *Bao et al (2015)* used

NDVI data to examine vegetation trends across Africa and found that vegetation cover was highly responsive to interannual climate variability, particularly changes in rainfall patterns.

Climate models are a vital tool for simulating future climate conditions and understanding the potential impacts of climate variability. Global Climate Models (GCMs) are commonly used for simulating large-scale climate systems and projecting future climate trends under different greenhouse gas emissions scenarios. (With & Change, 2015) employed GCMs to analyze projected future changes in temperature and precipitation. Their findings suggested that global temperatures could rise by 2-4°C by the end of the 21st century, depending on emissions levels. Osbahr et al (2011), in the IPCC's Fourth Assessment Report, also utilized GCMs to assess long-term climate projections, highlighting the potential for increased frequency of extreme weather events.

To capture finer spatial details, researchers have used Regional Climate Models (RCMs) to downscale GCM outputs. Renwick et al (2012) were among the first to demonstrate the utility of RCMs for understanding regional climate variability. They found that downscaling GCMs to regional models provided better resolution of local climate features, such as topography and land-use patterns, which are crucial for assessing climate variability at smaller scales.

2.2 Assessment of NDVI Trends and Variation

The Normalized Difference Vegetation Index (NDVI) is a widely used indicator for monitoring vegetation health, biomass productivity, and overall ecosystem functioning(Dutra et al 2018). It is derived from remote sensing data and is particularly useful for assessing the density and health of vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs)(Wang & Tenhunen, 2004). NDVI has been employed across a range of temporal and spatial scales to understand trends in vegetation health, the effects of climatic variations, land use changes, and human activities on natural ecosystems(Jiang et al 2006).

NDVI has proven to be a valuable tool in detecting temporal changes in vegetation health. For instance, Kalisa et al (2019) conducted an assessment on climate impact on vegetation dynamics in East Africa from 1982 to 2015.The NDVI trends showed a greening trend in many parts of the East Africa, particularly in the northern latitudes. This greening was attributed to longer growing seasons, primarily driven by climate change. Conversely, their study also found regions of "browning," particularly in areas suffering from deforestation, desertification, or prolonged droughts.

Similarly, Peterson *et al* (2014) used NDVI to study vegetation dynamics in semi-arid regions of Africa, concluding that NDVI trends are strongly influenced by rainfall variability. These authors emphasized that precipitation is the primary driver of vegetation productivity in arid and semi-arid regions, with clear evidence of a positive correlation between seasonal rainfall and NDVI values.

Bao et al (2015) highlighted the importance of NDVI in wildlife ecology, stating that changes in vegetation health, as measured by NDVI, could directly influence animal populations and their behaviors. The study noted that NDVI could serve as a proxy for habitat quality, which is critical for species conservation efforts. They stressed that spatial and temporal variations in NDVI help identify areas of habitat degradation and could aid in the design of conservation interventions.

Spatial variation in NDVI data has been instrumental in the assessment of ecosystem services, particularly in areas of agricultural expansion, deforestation, and urbanization. For instance,S. Piao et al (2006) investigated land-use change in China using NDVI and found that the rapid urbanization and agricultural intensification had a significant negative impact on natural vegetation cover. Their study showed declining NDVI values in urban and agricultural areas, signifying deteriorating vegetation health due to human encroachment.

In a different context, Gandhi et al (2015a) focused on Central Asia, where spatial NDVI patterns revealed the impacts of water scarcity and land-use practices on vegetation. The study noted that NDVI values were lower in areas affected by intensive irrigation practices, which led to soil salinization and desertification.

Climatic factors such as temperature, precipitation, and extreme weather events heavily influence NDVI variability. Mao et al (2012) explored NDVI variability in the Northeast China, where vegetation is highly sensitive to changes in precipitation patterns. The author found that both short-term and long-term NDVI variations could be linked to climatic fluctuations, particularly drought periods that resulted in lower NDVI values and decreased vegetation productivity.

In the tropics, Morton et al (2014) analyzed NDVI data in the Amazon rainforest and reported that drought-induced stress led to reductions in NDVI. They emphasized that the effects of drought on NDVI were more pronounced in areas where forest fragmentation occurred, suggesting that human disturbance exacerbates the impacts of climatic variability on vegetation health.

2.3 Assessment of Vegetation diversity and Abundance

Assessing vegetation abundance and diversity is crucial for understanding ecosystems, tracking environmental changes, and informing conservation efforts. Numerous methodologies have been developed, each offering unique insights depending on the research objectives and ecological context. This literature review outlines some commonly used methods in the assessment of vegetation abundance and diversity, citing key research studies.

Quadrat sampling is one of the oldest and most frequently employed methods for assessing vegetation abundance and diversity(Service et al 2009). In this method, a fixed-size plot (quadrat) is used to record all species within it. The data gathered from several quadrats are then used to estimate species richness, density, and cover in a broader area. This technique is simple yet effective for small-scale studies and is particularly valuable in grassland, savanna, and forest ecosystems (Dengler et al 2016a).

Byrnes et al (2014) developed a widely cited paper on this method, emphasizing its reliability in capturing spatial heterogeneity. However, the limitations of quadrat sampling, such as edge effects and time-consumption in large areas, have led to adaptations like nested quadrats, which improve detection of rare species (Soliveres et al 2014).

The line intercept method involves laying out a line of a predetermined length and recording all species that intercept or touch the line at different intervals (Silva et al 2017). This method is particularly useful in areas with dense vegetation, where it becomes difficult to apply quadrat sampling(T. F. Piao et al 2009). In a modification known as the point-intercept method, points are placed along the line, and the species present at these points are recorded.

Studies by Gobbett & Zerger,(2014) showed that line and point-intercept methods are effective in arid and semi-arid regions, where traditional quadrat methods may underestimate diversity due to patchy distribution. Point-intercept methods have been widely used in grassland and desert ecosystems, offering a non-destructive way to estimate cover, height, and species composition (Brotherton & Joyce, 2015a).

Recent advancements in remote sensing technologies have enabled large-scale assessments of vegetation abundance and diversity(Hou et al 2015). Remote sensing tools, such as satellite imagery and aerial drones, provide data on vegetation cover, biomass, and species distribution over large landscapes(Glenn et al 2010a). Different sensors, like LiDAR (Light Detection and Ranging) and multispectral/hyperspectral sensors, can capture structural complexity and even distinguish between species in some cases(Kamble et al 2013).

Balfour & Bond, (1993) demonstrated that remote sensing offers a viable complement to field-based techniques, especially in monitoring forest degradation and land cover changes. Singh, (2018) further emphasized the role of satellite-based remote sensing in assessing tropical biodiversity, where accessibility is often limited. Although effective for large-scale studies, the resolution and accuracy of remote sensing data still require validation through field-based methods (Lawley et al 2015).

The species-area curve is another well-known method used to assess vegetation diversity(Johnston, 2013). This method plots species richness against the area surveyed, helping researchers understand how species richness scales with area. It is particularly valuable in understanding biodiversity patterns and in making conservation decisions, such as determining reserve sizes (Lee et al 2013).

Arrhenius (1921) first formalized the species-area relationship, while Rosenzweig (1995) later explored its implications for biogeography and conservation biology. Species-area curves remain a fundamental tool in ecological studies, though their application can be limited by sampling effort and the ecological context (Guo & Rundel, 1997).

Diversity indices, such as the Shannon-Wiener Index and Simpson's Diversity Index, are often used to quantify species diversity (Scheiner & Rey-Benayas, 1994). These indices combine information on species richness (the number of species) with species evenness (the relative abundance of species) to provide a single value representing diversity (McClean et al 2005a).

(Suggitt et al 2019) extensively reviewed the use of these indices, emphasizing their ability to standardize comparisons across different ecosystems. The Shannon-Wiener Index, for example, is sensitive to both rare and common species, making it suitable for studies in diverse ecosystems, while Simpson's Index is more suited for systems where dominance is a key factor (Moradi & Oldeland, 2019).

CHAPTER THREE: MATERIALS AND METHOD

3.4 Study area

3.4.1 Location

Located in Eastern Uganda, Kapchorwa District lies between the coordinates of 1° 24’ 0” N and 34° 27’ 0” E. It shares borders with Kween District to the northeast and east, and Bulambuli District to the west and northwest. This district is comprised of 11 sub-counties and one municipality, which is divided into three divisions. The sub-counties include Amukol, Chema, Cheptarich, Gamogo, Kabeywa, Kapsinda, Kaptanya, Kaserem, Kawowo, Munarya, and Sipi. The divisions of Kapchorwa municipality are Central, Eastern (Kapchesombes/county and two parishes of Kaptanya s/county - Siron and Kirwoko), and Western (Tegeress/county and Kapteret s/county). With a total area of 517 square kilometers, the district is located 287 kilometers east of the capital city, Kampala.

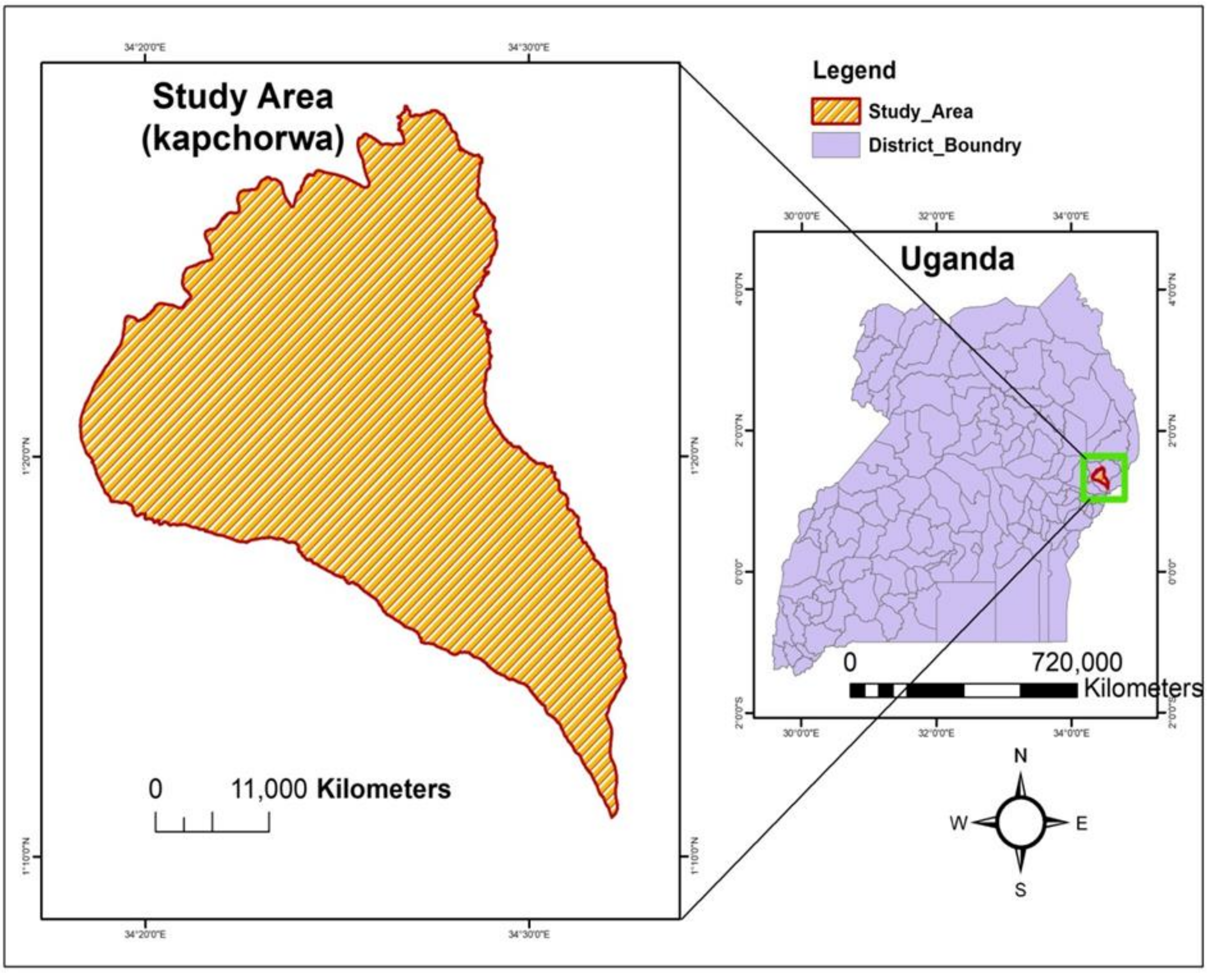


Figure 3. 1: Study area

3.4.2 Geomorphology

The topography of the district is mainly characterized by hilly terrain, with steep inclines and valleys. The main river is Sipi, with other smaller rivers and streams flowing northwards from Mt. Elgon. The district can be divided into three zones: lowlands, midlands, and highlands. The lowlands cover a significant portion of the district, specifically Kawowo and Kaserem sub-counties, spanning an area of approximately one third. The altitude in this area ranges from 1000m to 1300m above sea level, and the average land holding per household is 5 acres. The middle zone is characterized by high steep slopes and reliable rainfall, with an altitude of 1400m above sea level. The third zone is the high altitude, ranging from 1400m to 2300m. Mixed mountainous forests can be found at altitudes below 2500m, while the protected area of Mount Elgon National Park is mainly situated above this altitude. Bamboo and low canopy mountainous forests can be found between 2400m to 3500m, with moorland occupying altitudes above 3500m.

3.4.3 Soils and Geology

According to research done in 2010, Mt. Elgon is composed of prehistoric Mesozoic and Cainozoic rocks, consisting mainly of volcanic and sedimentary materials. These rocks, mostly composed of soda-rich agglomerates, lava, and tuff, were formed through extrusion. Despite their ancient origins, the rocks have also been influenced by volcanic intrusions, leading to the accumulation of sediment deposits in valleys that are rich in volcanic ash. As a result of weathering over time, the volcanic ash has been broken down, creating a variety of rock fragments scattered on the slopes and within the soil, ranging in size from small cobbles to large boulders. The soil found on the slopes of Mt. Elgon is primarily classified as Acrisols, Ferralsols, Nitisols, and Luvisols (as stated by the National Planning Authority in 2020). In the higher altitude forest belt, the soil is typically composed of brown to red-brown clay-loam and can reach depths of up to one meter. However, at elevations above 3000 meters, the soil consists primarily of shallow black humus, which is rich in organic matter. These soils are relatively young and fertile, with high levels of calcium, sodium, and potassium (according to the Government's findings in 2010).

3.4.4 Vegetation and Land use Stratification

Forests with a blend of mountains can be found at elevations below 2500 m. Between 2400 m and 3500 m, one can come across bamboo and low-lying canopy mountain forests. Moorland can be observed at altitudes above 3500 m. The open savannah to the North of the District has a low population density due to the occurrence of cattle rustling (Pilesjo et al 2021a).

3.4.5 Climate

The climate in the district is no longer reminiscent of the early 70s, when mist and clouds were a common occurrence during the rainy season (Bomuhangi et al 2016). This change in temperature and lack of mist could possibly be attributed to climate change. As a result, the district now experiences warmer temperatures. The average minimum temperature in Kapchorwa district ranges from 10 ℃ to 14 ℃, while the average maximum temperature ranges from 20 ℃ to 25 ℃ (Findings, 2010).

During the dry season, the north-east monsoon winds are particularly forceful, with the peak occurring between December and March (Government, 2011). These winds often lead to wind erosion and dusty conditions and can even cause simple cyclones. In some cases, the winds are strong enough to carry off roofs of buildings, as seen in 2014 when Tariate primary school in Kwoti, eastern division was affected (Republic, 2016). The impact of these winds is also felt in agriculture, as banana trees are often knocked down and their fruit destroyed. In fact, bananas are the most susceptible crop to wind damage in the district during this season (National Planning Authority, 2020).

The yearly average precipitation ranges from 920 mm to 1650 mm and is typically received from June to August. From December to February, the district encounters arid gusty weather, with sporadic storms occurring as well (Bomuhangi et al 2016)

3.5 Research method

The researcher employed a correlational research design, integrating quantitative methods to explore the relationships within the study. Through statistical analysis and graphical interpretation of NDVI (Normalized Difference Vegetation Index) data, the study examined connections between observed variables. The findings, derived from regression analysis, revealed the relationship between the dependent and independent variables, supported by comprehensive mathematical and statistical calculations.

3.6 Data types and sources

Continuous data type was used for rainfall and temperature measurements whereas Raster data type was used for aerial and satellite imagery. Secondary data was used including time series satellite imagery datasets obtained from earthexplorer.usgs.gov for Landsat 7 satellite, whereas climate data was obtained from the Uganda National Meteorological Authority (UNMA) in Entebbe.

3.7 Data collection and Processing

3.7.1 Climate Data

Data on rainfall and temperature for the Kapchorwa weather station was acquired from the Uganda National Meteorological Authority (UNMA) in Entebbe which was consolidated from the weather stations in Kapchorwa district. Monthly means of precipitation and temperatures (both minimum and maximum) were gathered for the period of January 1989 to December 2019. Additionally, temperature readings were taken on-site at each designated sampling point using a handheld thermometer (Figure 3.2). This data was utilized to determine the correlation between temperature and vegetation diversity. The GPS coordinates were obtained through a grid system and the actual sampling points were pinpointed using a GPS device on the ground.

The different variations in geographic effects were overcome by randomizing the selection of the sampling points through a grid-based approach. This technique considers diverse sites and eliminates bias.

3.7.2 Vegetation Data

Spatial and Temporal vegetation data were downloaded from earthexplorer.usgs.gov website using address/place search criteria. Date range from 1st January to 31st December was specified for each year set of data i.e., from 1989 to 2019.Landsat 7 satellite data images were downloaded for all the required years and imagery with the least cloud cover were selected for download. Band3 and Band4 of the images selected were finally downloaded to be used in the NDVI calculation. Downloaded satellite images of Band width 3&4 were uploaded into QGIS software as Raster layer. The Maximum Value Composite (MVC) method of the Geographic Information System (GIS) was used to synthesize the yearly NDVI data from the year 1989 to 2019. Minimum and Maximum NDVI values were recorded in excel sheet for analysis (Deng et al 2022).

3.7.3 Plant species Data

The collection of data on plant species in the district was accomplished by using a geographic information system (GIS)-based nonaligned block sampling design. This method involved plotting sampling points throughout the district map, as shown in Figure 3.3. the grid-based approach of GIS block sampling employs a randomized selection of sampling points, facilitating a comprehensive evaluation of parameters at multiple levels. This technique effectively mitigates sampling prejudices by considering diverse habitats with varying species. The sampling procedure was carried out on a digital map of Kapchorwa District, following a systematic stepwise process described as follows:

To begin, the map was divided into equal-sized grids in order to partition the study area and guarantee that samples were collected from all regions. A selection of 7 grids, encompassing over half of the district, was made to ensure that the sampling was representative.

In the second step, the grids chosen in the previous step were divided into even smaller sections. From these subsections, a total of 3 were randomly chosen with the assistance of a point generator tool in ArcGIS. Consequently, the total number of selected grids was amplified to 21.

In the third step, the grids from the previous step were further divided and two smaller grids were randomly chosen from each larger grid. This process resulted in a total of 42 sampling points, which were then utilized to create 30 m x 30 m plots for gathering data.

The final sampling points for the entire study area are depicted in Figure 3.2. These points were accurately pinpointed using a hand-held Global Positioning System (GPS) device by entering their coordinates. By using this data collection method, a thorough evaluation of plant species distribution was carried out as samples were gathered from different regions within the district.

Before implementing the afore mentioned procedure, the plot's dimensions were established using the species-area technique. This involved creating plots of various sizes and recording the number of species present (species richness) in each one. The larger plots encompassed the area of the smaller ones, with sizes of 100 m2, 400 m2, 900 m2, 1600 m2, and 3600 m2 being constructed. The recorded species richness for each plot was 5, 7, 12, 12, and 12, respectively. The optimal plot size is determined by a constant number of identified species as the plot size increases. According to this criterion, the 900 m2 plot was identified as the optimal size, falling within the recommended range of 400-2500 m2 as suggested by Sutherland.

To ensure the avoidance of repeating and overlooking specific species, the plots were fragmented into smaller sections, measuring 20 cm by 20 cm for Poaceae, 4 m by 4 m for Actini diaceae, and 30 m by 30 m for trees. This division streamlined the process of counting. The boundaries of the smaller units were designated using a lengthy cable. Every plant species within the designated plots and quadrats were distinguished and measured to assess the total range of diversity.

According to Singh (2018), vegetation encompasses a variety of plant species and their dominant forms of life, such as trees, Actinidiaceae, and Poaceae. In this particular study, the distinguishing factors used to classify these plants within the designated areas were their height, leaf structure, and stem structure. Trees are identified as having one primary stem and branching out, typically reaching heights of more than 3 meters when fully matured. In contrast, shrubs have multiple stems and are shorter in stature, ranging from 0.5 to 3 meters. Poaceae can be recognized by their leaves that sprout from nodes on the stem and encircle the stem, with an average height of less than 0.5 meters.

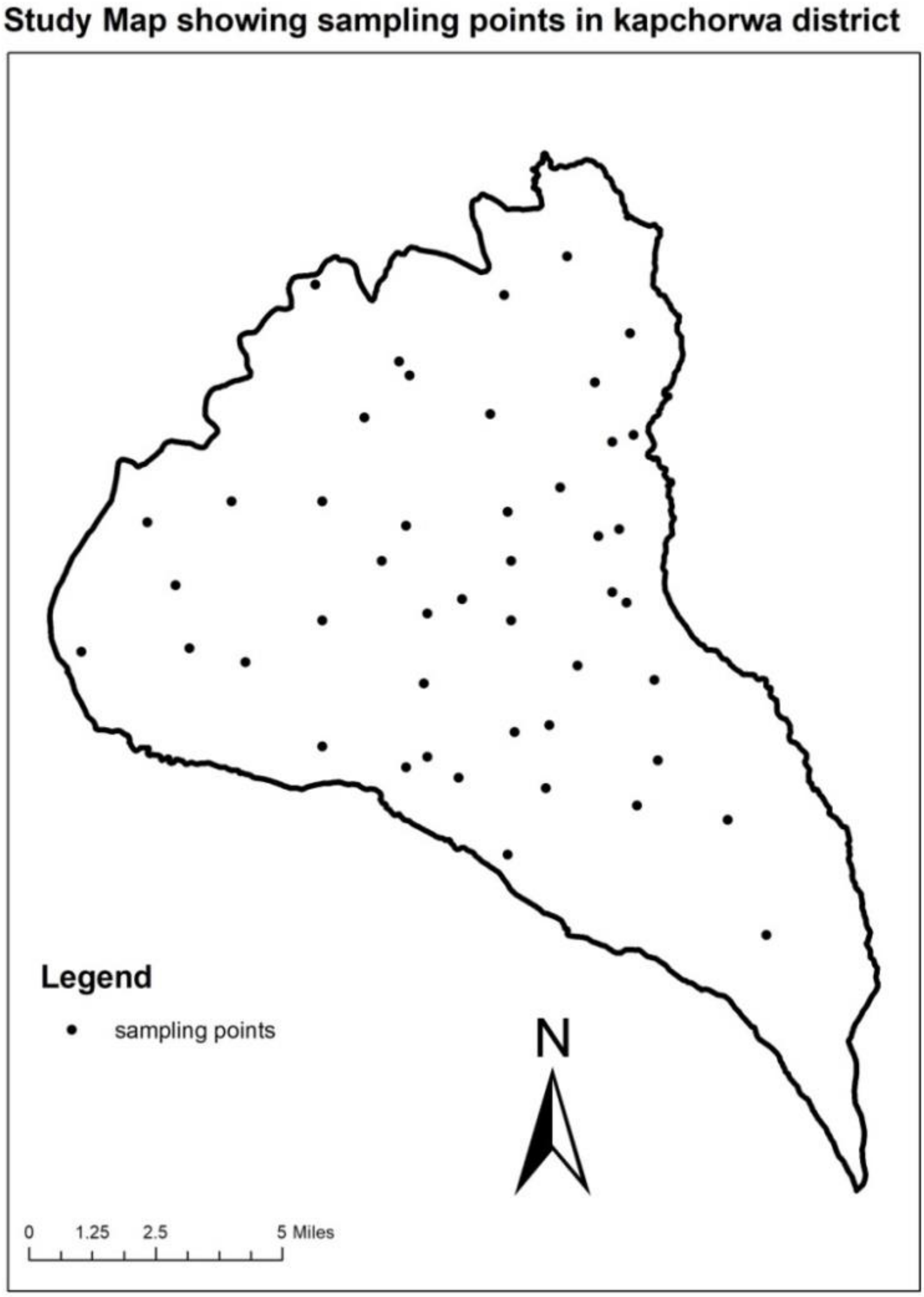


Figure 3. 2:Final sampling points

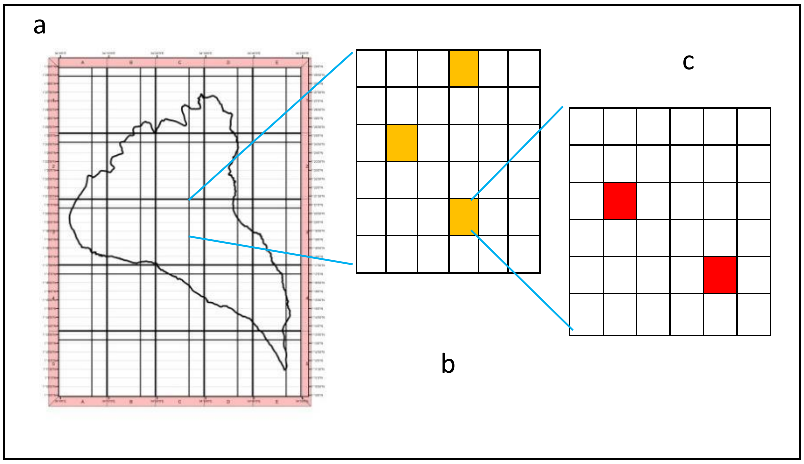


Figure 3. 3: GIS Block sampling Method.

Plate 3. 1: Plot and quadrat method.

3.8 Data analysis

Initially, the data on rainfall and temperature underwent normality testing to visually assess its alignment with the normal distribution test. It was imperative to establish if the data fulfilled the criteria for parametric or nonparametric statistical analysis approaches. Subsequently, nonparametric techniques were utilized for the assessment. Prior to performing trend analysis through the nonparametric Mann-Kendall test, the climatological and plant species data were inspected for autocorrelation to determine the necessity of Prewhitening. The use of autocorrelation, which determines the relationship between a time series and its previous and future values, can complicate the implementation of statistical tests by decreasing the number of independent observations(Haining & Li, 2019). As a result, this can result in the identification of significant patterns, regardless of their actual presence, and the opposite. To resolve this problem, the method of Prewhitening, which entails eliminating unwanted autocorrelations from time series data before conducting analysis, was carried out (Getis, 2010).

3.8.1 Rainfall and Temperature variation and Trend in Kapchorwa district from 1989 to 2019

The raw data on Temperature and Rainfall were entered into Excel sheet and the yearly and seasonal averages were calculated for the 30 years, whereas for precipitation annual and seasonal totals were calculated. Temperature was analyzed based on monthly averages for which annual means were calculated. The maximum and minimum temperature averages were analyzed both for the seasonal and yearly. R studio 4.3.0, SPSS statistic version 20, Microsoft excel, and XL Stat 2023 were the software used to analyze the data. The following indices and tests were conducted for analyzing the variations in rainfall and temperature within the study area.

3.8.1.1 Mann-Kendall Test

The Mann-Kendall (MK) test, which does not rely on specific parameters, is a prevalent and efficient statistical approach for identifying whether a time series exhibits a consistent increase or decrease trend. The reason this test is more desirable than other statistical methods for identifying trends in time series data is because it does not rely on the assumptions of normal distribution or linearity(Geary, 1954). Being a non-parametric test, it can evaluate trends in a time series without these limitations (Getis, 1991). Furthermore, it has a strong resistance to outliers and extreme values, making it a dependable option (Kendall 1975; Mann 1945; Poudel and Shaw 2016).The Mann-Kendall (MK) test, as employed by (Getis, 1991), is a valuable tool for determining the presence of a significant or non-significant trend in rainfall and temperature variability. It assesses both inter-annual variability (on an annual time scale) and intra-annual variability (on a seasonal scale, from season to season) of rainfall and temperature (Jury, 2018b). The null hypothesis (Ho) for this test assumes no trend, while the alternative hypothesis (H1), in a two-sided test, suggests the presence of a trend, either upward or downward. The Z score is calculated, and the confidence limits of the standard normal Z are determined. A positive (+) Z value indicates an increasing trend over time, while a negative (-) Z value suggests a decreasing trend (Surya Bhagavan 2016). As noted by Feng et al. (2016) and Longobardi and Villani (2010), the MK statistic S, variance statistic Var (δ), and related standard normal test statistic Z can be computed as follows:

$$S = \sum_{i=1}^{N-1} \sum\nolimits_{J=i+1}^{N} sgn(Xj - Xi)$$

If we let N represent the total number of data points and Xi and Xj represent the observations in a time series, then the value of Sgn (θ) can be determined by assuming that (Xj - Xi) is equal to θ.

$$Sgn = \begin{cases} +1 \ldots \theta > 0 \\ 0 \ldots \theta = 0 \\ -1 \ldots \theta < 0 \end{cases}$$

Under the hypothesis of independent and randomly distributed random variables, for large samples, when n ≥ 10 (source), the σ statistic is approximately normally distributed, with zero mean and variance.

$$\sigma^2 = \frac{n(n-1)(2n+5)}{18}$$

Therefore, the standardized normal deviate (Z-statistics) distribution will be then calculated as:

$$\begin{cases} Z = \dfrac{S-1}{\sqrt{Var(s)}}, if\ s > 0, \\ Z = 0, \quad if\ s = 0 \\ Z = \dfrac{s+1}{\sqrt{Var(s)}}, if\ s < 0, \end{cases}$$

When Z value exceeds either of the confidence limit lines, it shows a significant trend at a given significance level. Hence, Ho is rejected and in place H1 is accepted.

3.8.1.2 Sen’s Slope Estimator

The technique utilized for measuring the magnitude of trend in time series data is non-parametric. Compared to other estimators, it is considered to be more robust because it is less affected by extreme values (Chattopadhyay and Edwards 2016). Sen's Slope estimator is commonly employed for assessing the trend magnitude in hydro-meteorological time series (Jain and Kumar 2012). To obtain an estimate of the Slope bi, the Slopes of all data pairs are calculated using the following method.

$$b_i = \frac{X_{j-x_i}}{j-i}, i = 1,2,3 \dots, N, j > 1$$

Given: xj and xi represent data values at times j and i, where j > i. The Sen's estimator of the Slope is determined by finding the median of the N values of bi, where N represents the number of data points.

$$b = \begin{cases} b\frac{(N+1)}{2}, & if\ N\ is\ odd \\ 0.5\left(b\frac{N}{2} + b\frac{(N+2)}{2}\right), & if\ N\ is\ even \end{cases}$$

According to Chakraborty et al. (2013), when b is positive, there is an upward trend with increasing values over time, and when b is negative, there is a downward trend.

3.8.1.3 Precipitation Concentration Index (PCI)

The precipitation concentration index (PCI), as defined by Oliver, is a robust measure for assessing the temporal distribution of precipitation. It serves a similar purpose to the climate index (CI) and is commonly utilized to analyze seasonal variations in precipitation and examine the diversity of monthly rainfall patterns.

The method for calculating the PCI is outlined as follows: $PCI = 100 \times \frac{\sum_{i=1}^{12} p_i^2}{(\sum_{i=1}^{12} p_i)^2}$

where pi is the rainfall amount of month i, The annual Precipitation Concentration Index (PCI) measures the level of precipitation concentration within a year, with a range of 8.3 to 100. According to Oliver, a PCI value below 10 indicates a uniform distribution of precipitation throughout the year, while a value between 10 and 15 suggests moderate concentration. A PCI value of 16 to 20 indicates irregular distribution, and a value above 20 represents a significant irregular distribution of precipitation.

3.8.1.4 Coefficient of Variation (CV)

The CV, or Coefficient of Variation, is a statistical measure that quantifies the degree of deviation of individual data points from the mean. A higher CV value indicates a greater spatial variability, whereas a lower value indicates the opposite (Chakraborty et al 2013). The formula for calculating CV is as follows:

$$CV = \frac{\sigma}{X}$$

The coefficient of variation (CV) is represented by σ (standard deviation) over X (mean). A CV value below 20% indicates low variability, while a CV value between 20% and 30% suggests moderate variability, and a CV value above 30% indicates high variability in rainfall.

3.8.2 Assessment of vegetation indices trends and variation in kapchorwa district between 1989 to 2019

To evaluate the patterns and fluctuations in vegetation indices, we utilized the Man-Kendall nonparametric trend analysis method and the Sens slope estimator to determine the extent of change in these indices. The relevant mathematical equations for these methods were outlined in section 3.5.1.1.

3.8.2.1 NDVI analysis

The NDVI is an index that measures vegetation greenness. NDVI examines the difference/sum ratio of red and infrared radiation bands (NIR-RED)/ (NIR+ RED) (Dutra et al 2018).

Raster calculator under the spatial analysis tool in ArcGIS was used to generate NDVI index from the formula below.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

NDVI is Normalized Difference Vegetation Index

NIR is Near Infrared Radiation

RED refers to red light Radiation.

B4 is Band width 4: NIR.

B3 is Band width 3: RED.

Therefore, NDVI has no unit. Rather, it is an index value in which higher values (0.4 to 0.9) show lands covered by green, leafy vegetation and lower values (0 to 0.4) show lands where there is little or no vegetation. Negative values tend to indicate the presence of water, clouds or snow.(Jin et al 2019).Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow.

3.8.2.2 Vegetation condition index (VCI)

The VCI measures the present NDVI against the range of NDVI values recorded during the same time frame in previous years, providing a normalized index that reflects the percentage difference between the current NDVI maximum and the minimum NDVI value in the historical time series, in relation to the overall NDVI variability (Jiao et al 2016).

$$VCI = (\frac{NDVI_j - NDVI_{min}}{NDVI_{max} - NDVI_{min}}) \times 100$$

where NDVIj represents the current year NDVI

NDVI max denotes the multiyear maximum NDVI.

NDVI min represents the multiyear minimum NDVI.

Interpretation of the Vegetation Condition Index (VCI)

40 to 100% No drought,30 to 40% light drought,20 to 30% moderate drought,10 to 20% severe drought,0 to 10% Extreme drought.

3.8.3 Determination of diversity and abundance of dominant plant species in kapchorwa district and their relationship with temperature

3.8.3.1 Simpson’s diversity index, (SID)

The excel sheet was utilized to input the field data for species richness per sampling sight. The measurement of Simpson's index of diversity was chosen due to its nature as a dominance index, meaning it places more emphasis on common or dominant species. As a result, the presence of a few rare species with low representation will not significantly impact the overall diversity. The formula for Simpson's Diversity index is shown below,

$$D = 1 - \frac{n(n-1)}{N(N-1)}$$

Where, D is Simpson’s diversity index,

n is the number of individuals of one species

N is the total number of individuals of different species found

The index has a range of values (0 to 1) where: 0 is the lowest and towards 1 - the area is highly diverse in plant species. And these have linkages to climate change patterns in an area.

3.8.3.2 Relative abundance/species evenness

By using excel, the total count of a particular species in comparison to the overall number of species present in a specific region is determined. The total number of individuals belonging to each species category is computed and then divided by the sum of the total count of various species.

$$RA = \frac{TS}{TP} \times 100$$

Where RA is relative Abundance

TS is total number of species in an area.

TP is the total sum of the populations of all species in the area.

3.8.3.3 Regression analysis

The concept of regression analysis involves examining the correlation between dependent and independent variables, revealing how a change in one or more independent variables can affect the dependent variable due to various factors. This is represented by the formula Y=a+bX=E, where Y represents the dependent variable, X represents the independent variable, a is the intercept, b is the slope, and E is the residual. In the study, rainfall and temperature were the independent variables used to forecast changes in vegetation health, which served as the dependent variable.

The concept of regression analysis involves examining the correlation between dependent and independent variables, revealing how a change in one or more independent variables can affect the dependent variable due to numerous factors. This is represented by the formula $\boldsymbol{Y = a + bX = E}$ where Y represents the dependent variable, X represents the independent variable, a is the intercept, b is the slope, and E is the residual. In the study, rainfall and temperature were the independent variables used to forecast changes in vegetation health, which served as the dependent variable

3.8.3.4 Correlation analysis

The Pearson product moment correlation was applied to determine the degree of linear relationship between relative abundance, diversity index, temperature, and rainfall data, and was represented as r. This coefficient, r, ranged from +1 to -1. A value of 0 indicated no correlation between the variables. A positive value indicated a positive relationship, meaning an increase in one variable led to an increase in the other. A negative value indicated a negative relationship, meaning an increase in one variable resulted in a decrease in the other.

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

r_{xy} = Pearson r correlation coefficient between x and y

n = number of observations

x_i = value of x (for i th observation)

y_i = value of y (for i th observation)

CHAPTER FOUR: RESULTS

4.1 Rainfall and temperature Variation and trend in Kapchorwa district from 1989-2019

4.1.1 Rainfall

The total annual mean precipitation was 461.82 mm and standard deviation of 352.77 mm giving a coefficient of variation of 76.4 %. This signified a high variability in the rainfall totals across the years. The Precipitation concentration index showed a non-significant decreasing trend across the years and ranged from between 10 to 15, which indicated a moderate precipitation distribution across the years in Kapchorwa District tending to a normal distribution (Figure 4.2).The trend test showed an increasing significant trend (P=002) in total annual precipitation in Kapchorwa district from 1989 to 2019 (Table 4.1).Sens slope estimates an increase of 0.4 mm in rainfall per year (Table 4.1) and (Figure 4.1(a)).

The seasonal trends showed a significant increasing trend in the total precipitation for seasons March-April-May (MAM), September-October-November (SON) and December-January-February (DJF) and decreasing non-significant trend for the June-July-August (JJA) in Kapchorwa district. Sens slope estimated an increase in precipitation by 0.171 mm for the season MAM, 0.234 mm for the season SON and 0.064 mm for DJF (Table 4.1), (Figure 4.1b, c,d,e&f). All the seasons showed high variability in precipitation across the years with the highest being DJF (88.3%) and the lowest being JJA (55.9%). The season of MAM had the highest mean precipitation, followed by JJA (240.8 mm), SON (216.57 mm) and DJF (196.25 mm).

Table 4.1: Total annual and seasonal rainfall trend in Kapchorwa district from 1989 to 2019

Series\Test	Kendall's tau	p-value	Sen's slope	mean	CV %
total annual ppt	0.398	0.002	0.400	461.82	76.4
MAM	0.303	0.017	0.171	241.17	59.6
JJA	-0.075	0.563	-0.022	240.8	55.9
SON	0.428	0.001	0.234	216.57	66.4
DJF	0.252	0.049	0.064	196.25	88.3
PCI	-0.191	0.1347	-0.0311		

P<0.05 is significant.

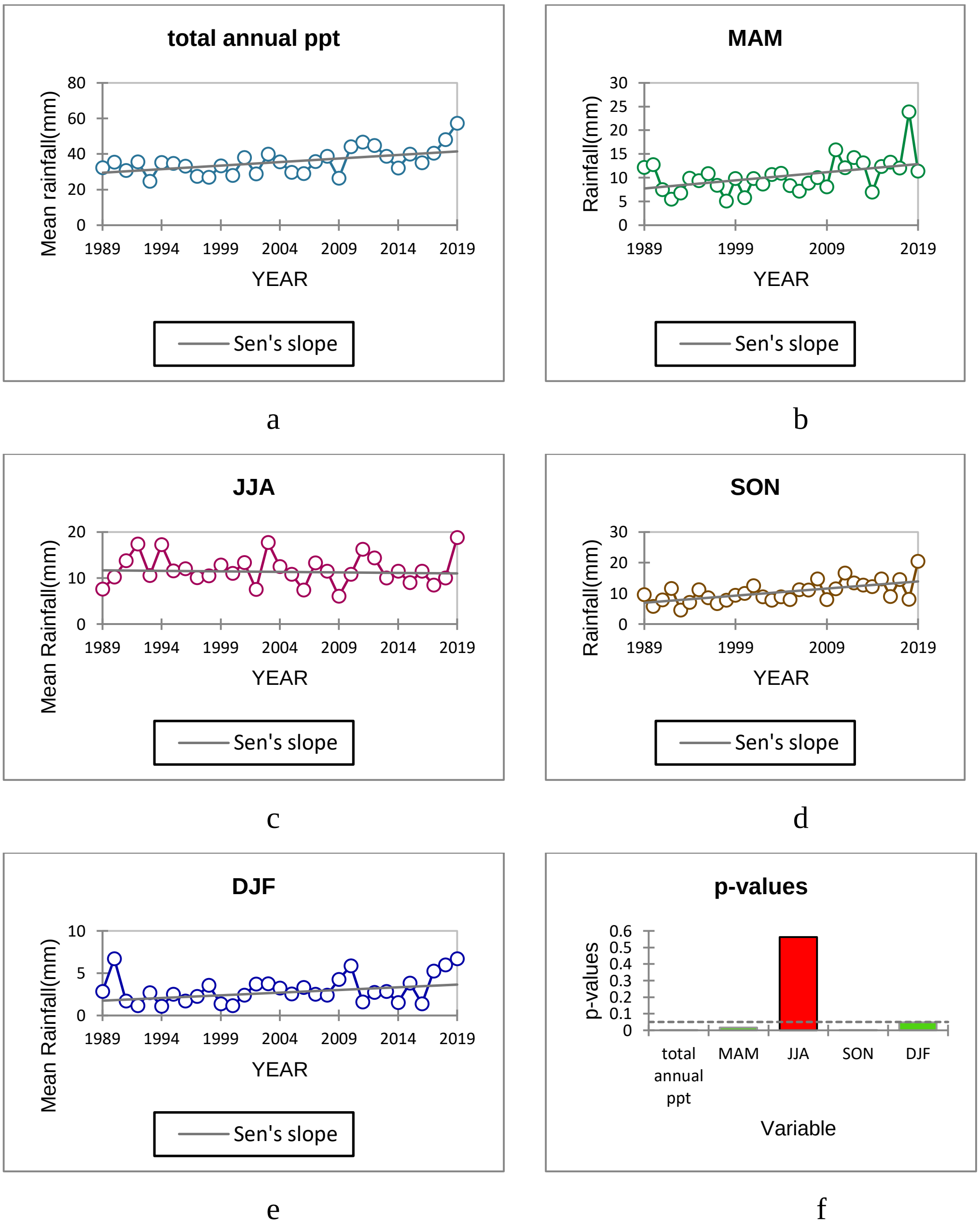


Figure 4. 1:Annual and seasonal rainfall trend for Kapchorwa district from 1989 to 2019

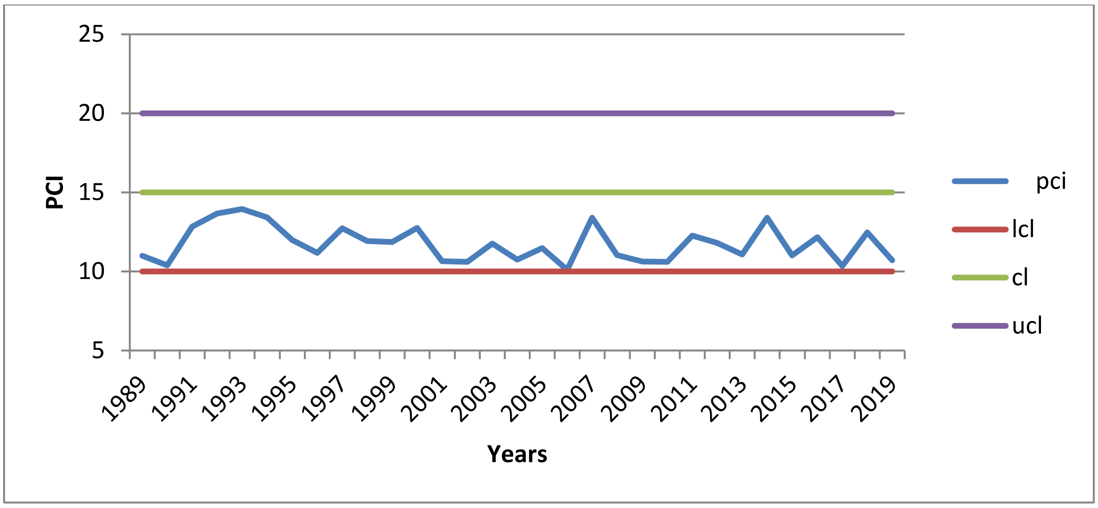


Figure 4. 2: Precipitation Concentration Index for Kapchorwa district from 1989 to 2019

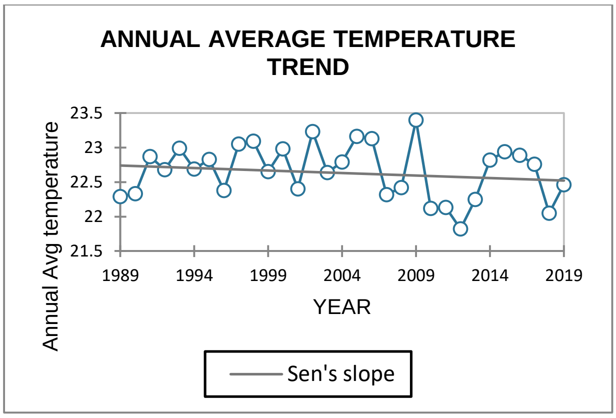
4.1.2 Temperature

The mean and seasonal temperatures showed a significant (P<0.05) decreasing trend for the period of 1989 to 2019 in kapchorwa district except for MAM which was not significant (Figure 4.3f). The season JJA (0.183) had a significant increasing trend (Table 4.2) & (Figure 4.3). The annual mean Temperature (22.66°C) was estimated to be decreasing at a rate of 0.007°C per year; the season of DJF had the highest mean temperature (23.86°C) expected to decrease at a significant rate of 0.002°C per year. The season of JJA had the smallest mean temperature (20.85 °C) estimated to be increasing at a significant rate of 0.016 °C/year. There was less variability in the annual mean temperature and across the seasons throughout the year with all means having a coefficient of variation of less than 20 % (Table 4.2).

Table 4. 2 Mean Temperature and seasonal temperature trend in Kapchorwa district from 1989 to 2019

Series\Test	Kendall's tau	p-value	Sen's slope	mean	SD	CV%
Temp Mean (°C)	-0.092	0.048	-0.007	22.66	0.39	1.72
MAM	-0.241	0.059	-0.034	23.85	0.81	3.41
JJA	0.183	0.015	0.016	20.85	0.65	3.12
SON	-0.189	0.014	-0.021	22.15	0.65	2.92
DJF	-0.026	0.009	-0.002	23.86	0.43	1.79

P<0.05



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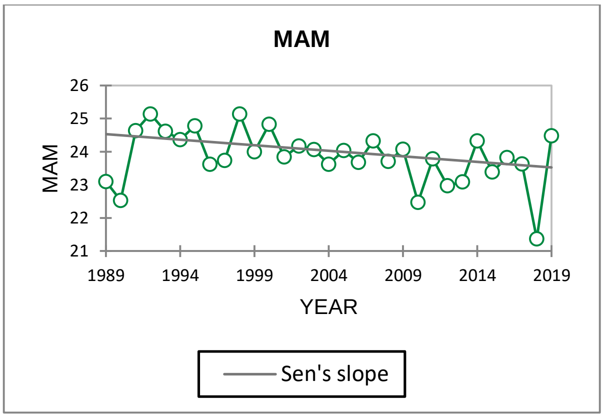

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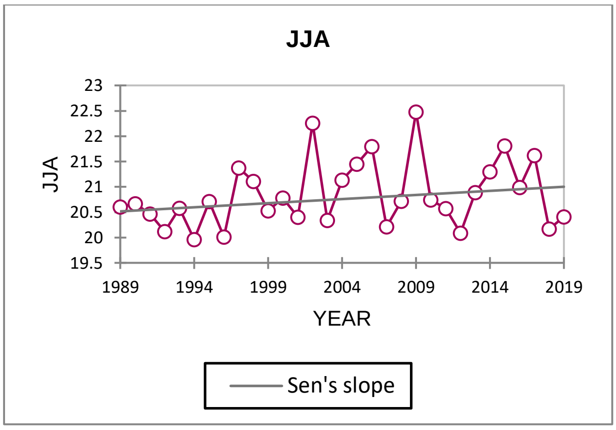

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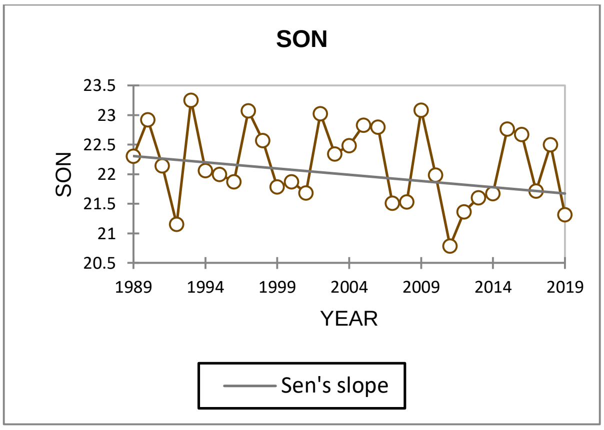

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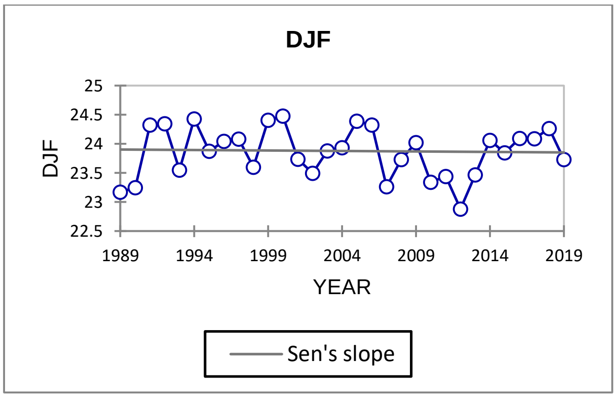

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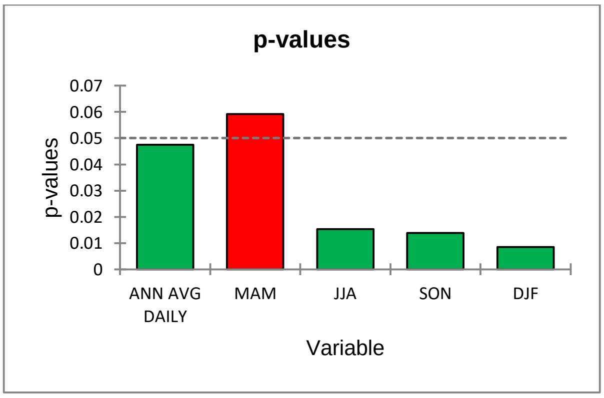


f

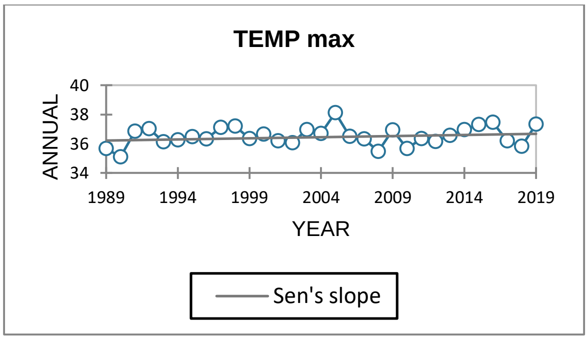
Figure 4. 3: Mean Temperature and seasonal temperature trend in Kapchorwa district from 1989 to 2019

There was an increasing significant trend for maximum Temperatures at an estimated rate of 0.015 ℃/year (Table 4.3) & (Figure 4.4a).The average maximum temperature for the 30 years showed a significant decreasing trend at a rate of 0.017 ℃/year in kapchorwa district (Figure 4.3b).The seasons of MAM and DJF showed a significant decreasing trend in their mean maximum temperatures at a rate of 0.033 and 0.010 ℃/year, whereas the trend was not significant for the seasons of JJA and SON (Table 4.3) & (Figure 4.4 c,d,e,f). The Maximum Temperature recorded for the 30 years was 36.53℃ with an average each year of 32.0 ℃. The season of MAM and DJF registered the highest max temperatures of 34.1 ℃ and 33.99 ℃ respectively whereas the seasons of JJA and SON registered the least maximum temperatures of 28.95 ℃ and 30.98 ℃ respectively. The coefficient of variation was less than 20% for both the annual maximum temperature and seasonal maximum temperature implying low variability of the temperatures across the years and the seasons.

Table 4.3: Maximum annual Temperature and Seasonal Maximum temperature trend in Kapchorwa district from 1989 to 2019

Series\Test	Kendall's tau	p-value	Sen's slope	mean	SD	CV%
Temp(max)	0.142	0.026	0.015	36.53	0.65	1.77
AVG max /Year	-0.170	0.019	-0.017	32.00	0.73	2.29
MAM	-0.183	0.015	-0.033	34.10	1.16	3.39
JJA	-0.024	0.087	-0.004	28.95	1.31	4.51
SON	-0.239	0.062	-0.043	30.98	1.23	3.97
DJF	-0.092	0.048	-0.010	33.99	0.59	1.74

P<0.05



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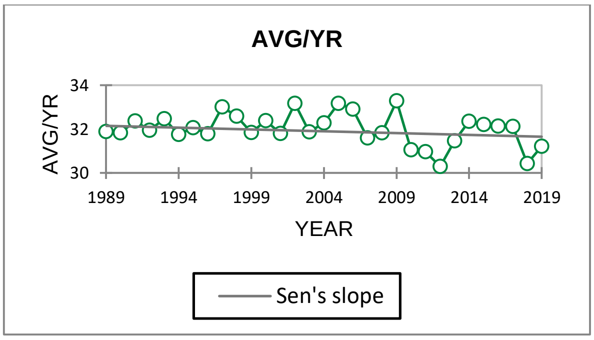

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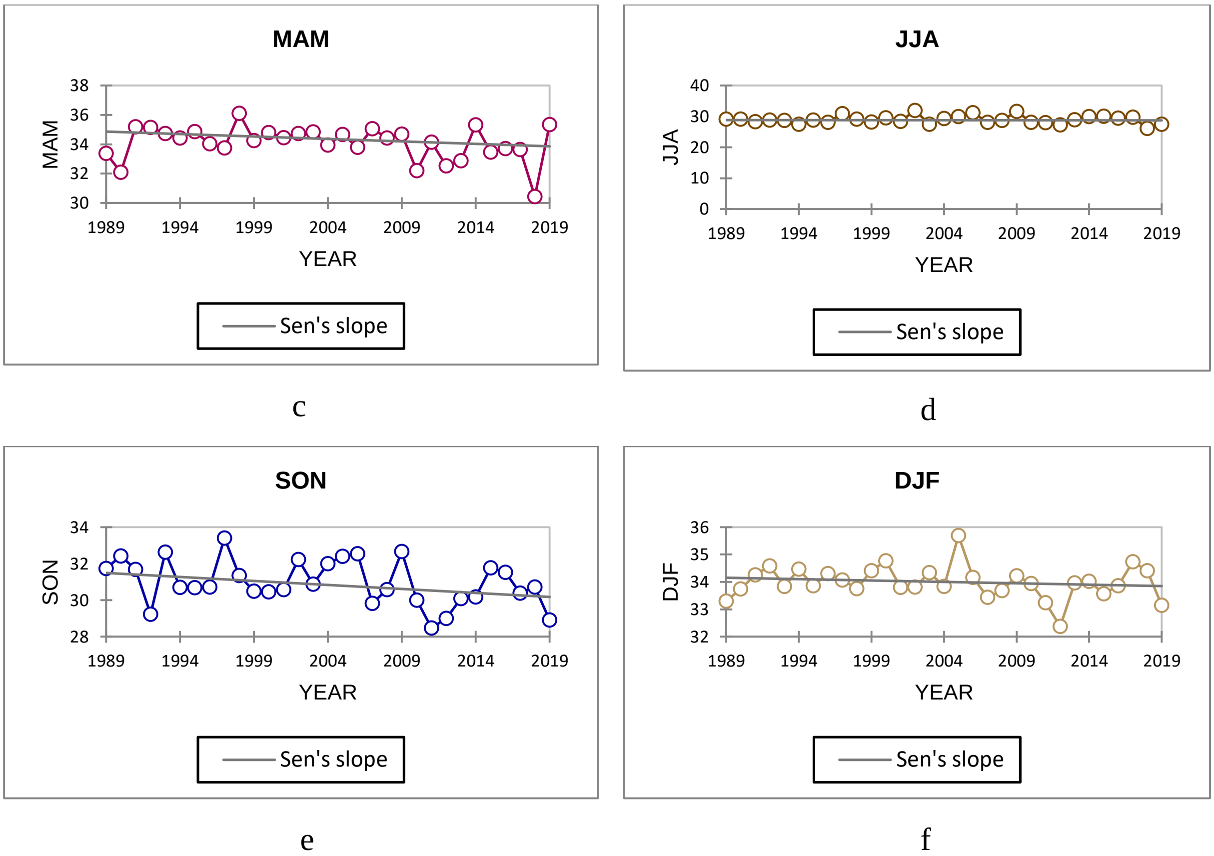


Figure 4.4: Maximum annual Temperature and seasonal maximum Temperature trend in Kapchorwa District from 1989 to 2019.

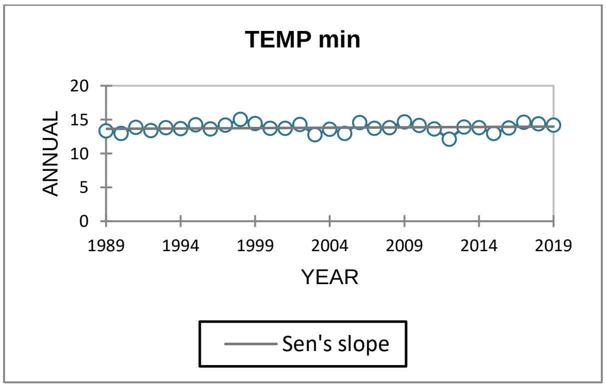
There was an increasing significant trend (P<0.05) for all minimum Temperatures and seasonal Temperatures. The minimum annual Temperature was estimated to increase at a rate of 0.012°C/year, whereas the average yearly minimum also increased at a rate of 0.012 °C/year. The seasonal minimum temperatures increased at a rate of 0.007, 0.016, 0.021, 0.002 °C/year respectively for MAM, JJA, SON, and DJF (Table 4.4) & (Figure 4.5). The coefficient of Variation (CV) was less than 20% for the annual minimum temperatures and across the seasons throughout the 30-year period in Kapchorwa District. This depicts less variability in the minimum temperatures across the years.

Table 4. 4 Minimum Annual and seasonal Temperature trend in Kapchorwa District from 1989 to 2019

Series\Test	Kendall's tau	p-value	Sen's slope	Mean	SD	CV%
Minimum Annual Temperature	0.136	0.029	0.012	13.81	0.63	4.53
Average yearly	0.222	0.008	0.012	15.25	0.30	1.94

Minimum						
MAM	0.112	0.039	0.007	16.14	0.34	2.08
JJA	0.235	0.007	0.016	14.88	0.43	2.93
SON	0.234	0.007	0.021	14.84	0.46	3.12
DJF	0.024	0.009	0.002	15.15	0.48	3.17

P<0.05



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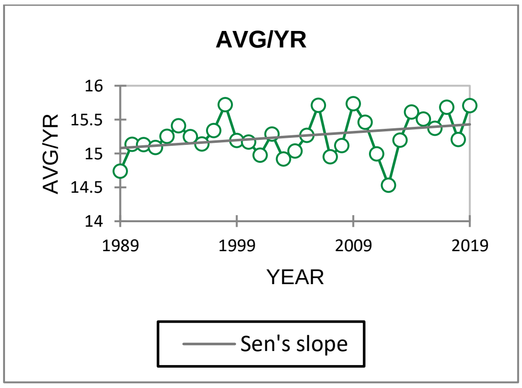

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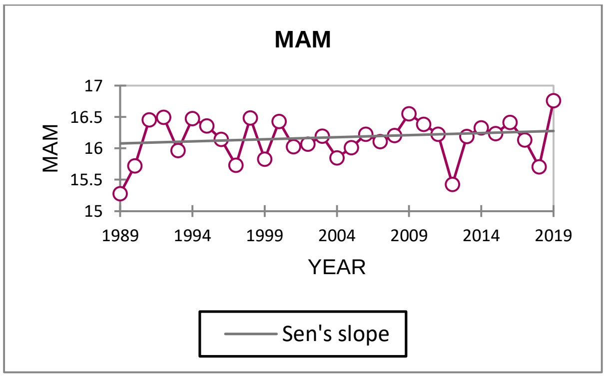

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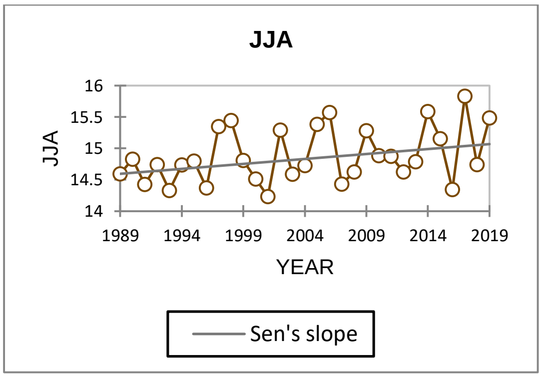

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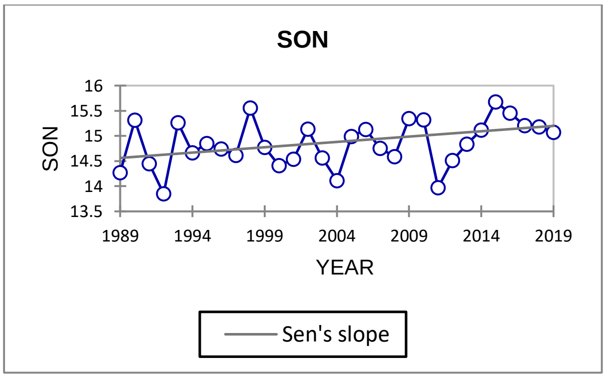

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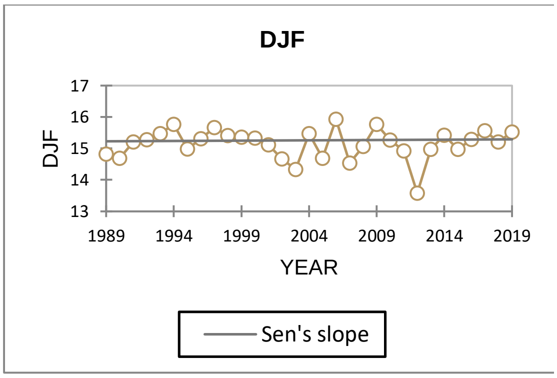

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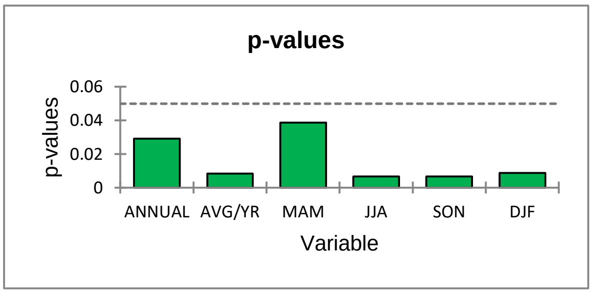

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Figure 4.5: Minimum Annual and seasonal Temperature trend in Kapchorwa District from 1989 to 2019

4.2 Assessment of vegetation indices trends and variation in kapchorwa district from 1989 - 2019.

The vegetation indices showed a positive significant trend ($P<0.05$) which implied that the vegetation in kapchorwa district became healthier from 1989 to 2019 (Figure 4.6). The increase in vegetation greenness was estimated at a rate of 0.006/year. The vegetation indices also had had low variability (15.67 %) across the years in kapchorwa district (Table 4.5).

Table 4. 5 Assessment of Vegetation indices trends and variation in Kapchorwa district from 1989 to 2019

	Kendalls Tau	P value	Sens slope	CV
NDVI	0.5046096	1e-04	0.006059	15.67%

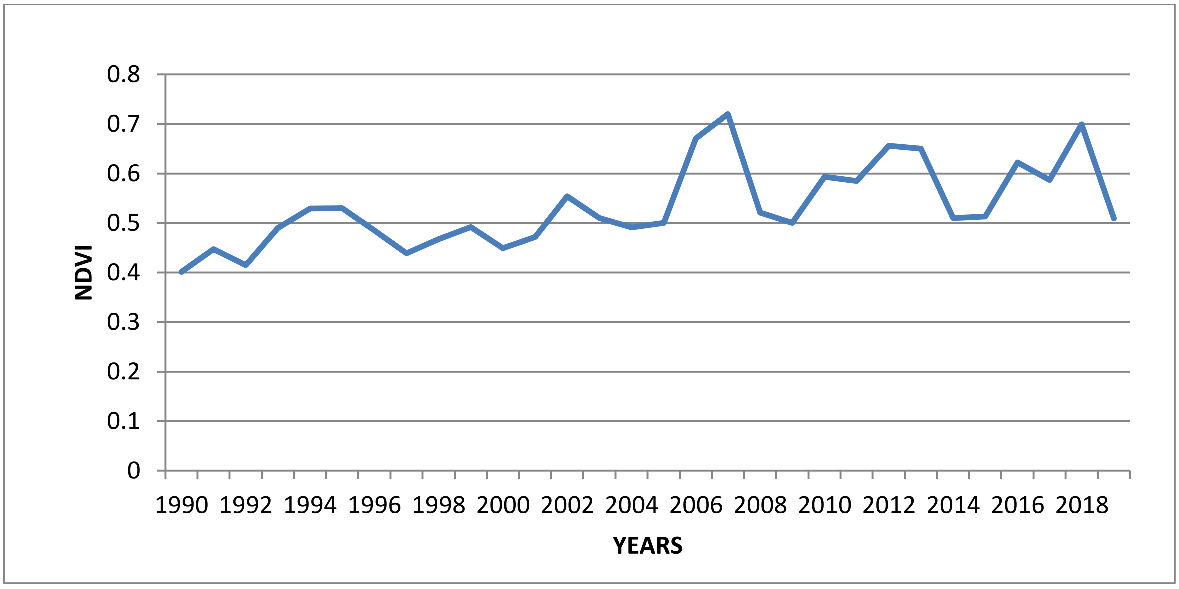

Figure 4. 6: NDVI trend across the years

NDVI analysis shows a general increase in the Vegetation cover and a decline in Barren land from 1989 to 2019 (Figure 4.7). Actinidiaceae and Poaceae had an overall increment of 193.33%, Sparse vegetation was at 100 %, and dense vegetation increased by 60.87 % from 1989 to 2019.Barren land decreased by 232 % from 1989 to 2019.From 1989 to 1999 there was no change in the barren land. Actinidiaceae and Poaceae increased by 66.7 %, sparse vegetation increased by 22.2 % and dense vegetation also increased by 29.4 % (Table 4.6). From 1999 to 2009, barren land declined by 56 %, Actinidiaceae and Poaceae declined by 8%, sparse vegetation increased by 27.3 % and dense vegetation cover increased by 29.4 % (Table 4.6). From 2009 to 2019, barren land further declined by 400 %, Actinidiaceae & Poaceae increased by 91.3 %, sparse vegetation increased by 28.6 % and Dense vegetation cover increased by 12.1 % (Table 4.6) & (Figure 4.7).

Table 4. 6 Assessment of Vegetation indices trends and variation in Kapchorwa district from 1989 to 2019

	NDVI				Percentage vegetation change			
vegetation type	1989	1999	2009	2019	1989 to 1999	1999 to 2009	2009 to 2019	1989 to 2019
barren land	-0.25	-0.25	-0.11	0.33	0.00%	-56.00%	-400.00%	-232.00%
Actinidiaceae &Poaceaees	0.15	0.25	0.23	0.44	66.7%	-8.0%	91.3%	193.33%
sparse vegetation	0.27	0.33	0.42	0.54	22.2%	27.3%	28.6%	100.00%
Dense Vegetation	0.46	0.51	0.66	0.74	10.9%	29.4%	12.1%	60.87%

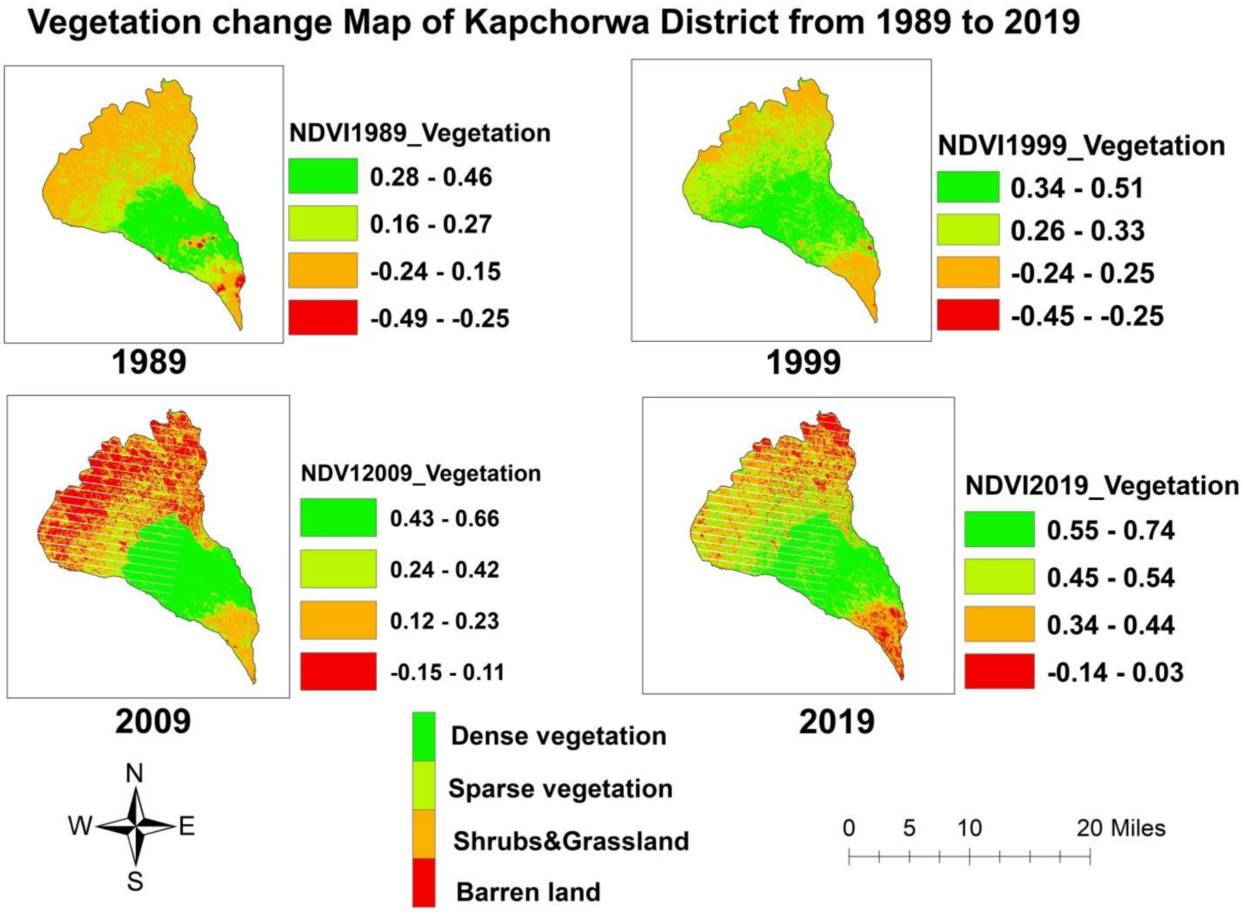

Figure 4. 7:Assessment of Vegetation indices trends and variation in Kapchorwa district from 1989 to 2019

The vegetation concentration index analysis suggests a significant increase in the vegetation concentration index across the years from 1989 to 2019 (Table 4.7). Areas with VCI less <10 % indicated areas experiencing extreme drought, VCI between 10 % and 20 % signified severe drought, VCI between 20% and 30% signified moderate drought, VCI between 30 % and 40 % signified light drought, and VCI between 40% and 100% signified no drought (Figure 4.8). In 1989 Kapchorwa experienced extreme, severe, moderate and no drought in some areas, whereas in 1999 it experienced severe and no drought in some areas. By 2009 it had experienced severe, light and no drought in some areas. In 2019 the area was experiencing some moderate drought but largely no drought in the entire area.

Table 4. 7: Vegetation Concentration Index changes from 1989 to 2019

	VCI			
Limits	1989	1999	2009	2019
Extreme Drought (0 to 10%)	5%	18%	11%	25%
Severe Drought (10 - 20 %)	15%	40%	32%	58%
Moderate Drought (20 - 30 %)	27%	58%	58%	80%
Light Drought (30 - 40 %)	45%	82%	82%	94%
No drought (40 - 100 %)	46%	83%	83%	95%

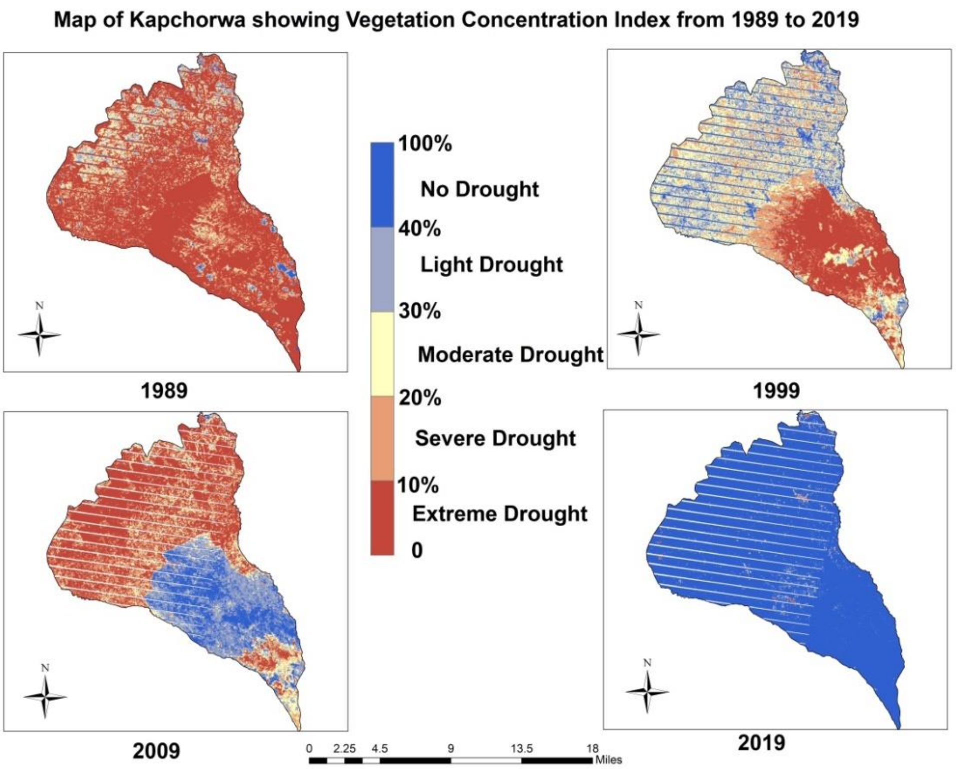

Figure 4. 8:Assessment of VCI trends and variation in Kapchorwa district from 1989 to 2019

4.3 Diversity and abundance of dominant plant species in kapchorwa district

The results showed that the most abundant vegetation type was Poaceae (grass) with a relative abundance index of 57 %, followed by Apocynaceae (trees) with 56 % and then Actinidiaceae (shrubs) with 46 % (Table 4.8). The relative abundance of Apocynaceae had the highest coefficient of variation (32 %) and followed by Actinidiaceae (29 %) and then Poaceae (25 %). Simpson's index of diversity was at 0.47 with a coefficient of variation of 30 % denoting moderate vegetation diversity in Kapchorwa .The mean temperature was 22.7 ℃ with a coefficient of variation of 10 % denoting less variability of the temperature at most of the sampling points. The high variation in vegetation diversity could be explained by the high variation in the relative abundance of the vegetation. The variation of relative abundance of the vegetation is because of other factors such as sunlight, soil quality, water availability and nutrient supply affect vegetation growth.

Table 4. 8 Sampling points, Relative Abundance, Temperature and Precipitation in Kapchorwa district

Parameter	sampling point (coordinate)		relative Abundance (RA)			Index of diversity (SID)
	Latitude	Longitude	Poaceae	Apocynaceae	Actinidiaceae	
	1.337	34.314	0.890	0.310	0.21	0.57
	1.380	34.357	0.760	0.220	0.31	0.62
	1.334	43.361	0.840	0.420	0.18	0.56
	1.374	34.333	0.740	0.290	0.25	0.44
	1.356	34.341	0.642	0.380	0.56	0.61
	1.338	34.345	0.746	0.541	0.45	0.59
	1.420	34.405	0.421	0.280	0.26	0.33
	1.442	34.381	0.723	0.410	0.31	0.73
	1.439	34.435	0.844	0.440	0.18	0.36
	1.405	34.431	0.542	0.668	0.28	0.56
	1.416	34.408	0.711	0.400	0.33	0.44
	1.404	34.395	0.671	0.450	0.25	0.81
	1.450	34.453	0.761	0.554	0.39	0.65
	1.428	34.471	0.641	0.480	0.51	0.56

	1.397	34.466	0.589	0.251	0.34	0.77
	1.413	34.486	0.655	0.610	0.43	0.55
	1.399	34.472	0.530	0.680	0.48	0.53
	1.414	34.461	0.546	0.560	0.37	0.49
	1.380	34.383	0.6	0.420	0.42	0.47
	1.373	34.407	0.613	0.570	0.46	0.51
	1.377	34.436	0.546	0.201	0.43	0.53
	1.363	34.400	0.440	0.610	0.49	0.56
	1.346	34.383	0.543	0.580	0.5	0.51
	1.328	34.412	0.561	0.650	0.53	0.5
	1.384	34.451	0.491	0.570	0.5	0.48
	1.372	34.468	0.533	0.620	0.46	0.211
	1.329	34.478	0.501	0.480	0.57	0.51
	1.354	34.466	0.431	0.660	0.48	0.4
	1.370	34.462	0.440	0.710	0.49	0.42
	1.351	34.470	0.410	0.489	0.43	0.46
	1.307	34.413	0.498	0.710	0.5	0.41
	1.310	34.383	0.520	0.680	0.62	0.35
	1.314	34.438	0.488	0.761	0.68	0.37
	1.279	34.436	0.398	0.640	0.53	0.3
	1.301	34.422	0.410	0.730	0.51	0.36
	1.304	34.407	0.566	0.690	0.6	0.32
	1.316	34.448	0.461	0.840	0.54	0.29
	1.298	34.447	0.391	0.870	0.55	0.44
	1.256	34.510	0.326	0.801	0.49	0.3
	1.289	34.499	0.470	0.790	0.55	0.25
	1.293	34.473	0.541	0.850	0.57	0.29
	1.306	34.479	0.301	0.820	0.61	0.24
Mean			57%	56%	44%	0.47
SD			14%	18%	13%	0.14
CV			25%	32%	29%	30%

Results showed a significant strong negative correlation for relative abundance of Apocynaceae and Actinidiaceae with temperature at -0.812 and -0.698 respectively (Table 4.9). This implied that as temperatures decreased, the abundance of Apocynaceae and Actinidiaceae increased (Figure 4.9). Only relative abundance of Poaceae had a significant strong positive correlation with Temperature at 0.754 (Figure 4.9). So, the abundance of Poaceae increased with increase in temperature and vice versa. Shannon's index of diversity had a strong positive correlation with temperature at 0.724 suggesting that diversity increased with increase in temperature and vice versa (Table 4.9 & Figure 4.10).

Regression analysis suggested that 66.2 % of the change in Relative abundance of Apocynaceae could be explained by the variation in temperature (Figure 4.9, Table 4.9). For Poaceae and Actinidiaceae, temperature variation could only explain 56.9 % and 48.6 % change in the relative abundance respectively. For diversity, 52.4 % of the changes could be explained by variation in temperature (Figure 4.10, Table 4.9).

Table 4. 9 Relationship between Temperature and Relative Abundance, Temperature and Shannon's Index of Diversity

		Temperature (°C)	
		correlation coefficient	R square
Shannon's index of diversity		.724**	0.524
Relative abundance	Apocynaceae	-.812**	0.664
	Poaceae	.754**	0.569
	Actinidiaceae	-.698**	0.486

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

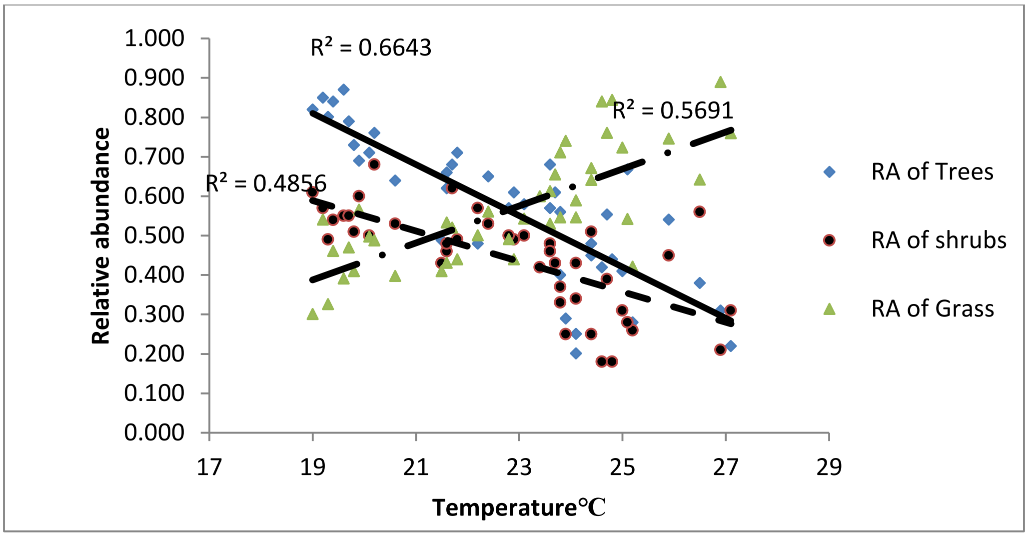

Figure 4. 9: Relationship between relative Abundance and temperature

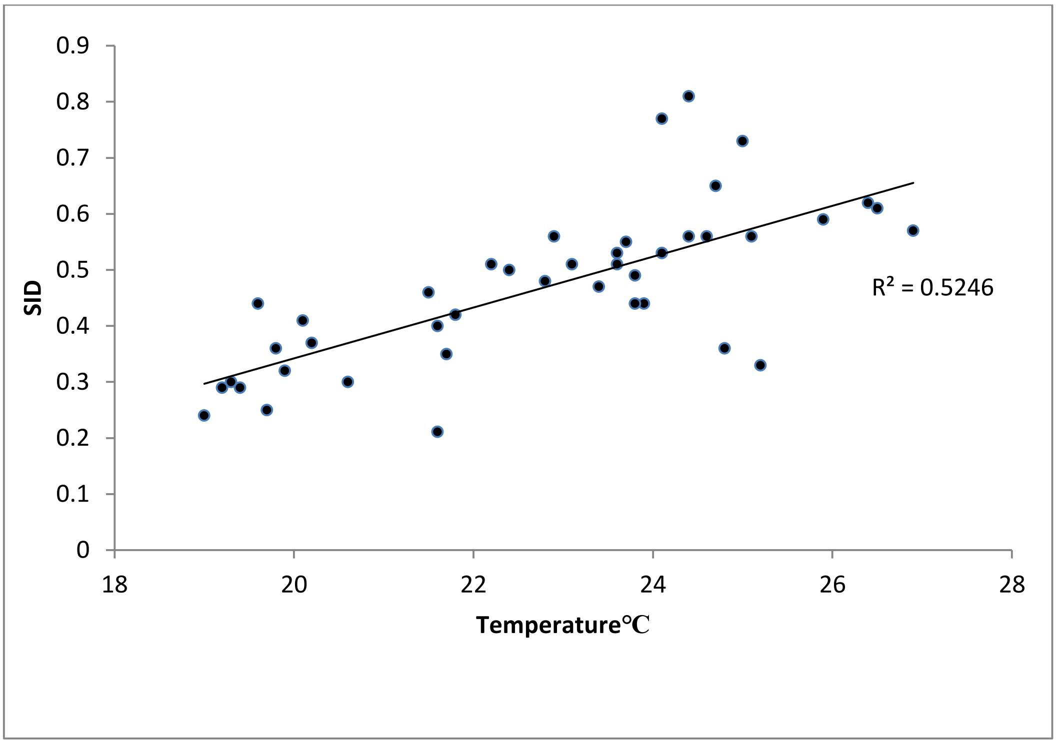

Figure 4.10: Relationship between Diversity index and Temperature

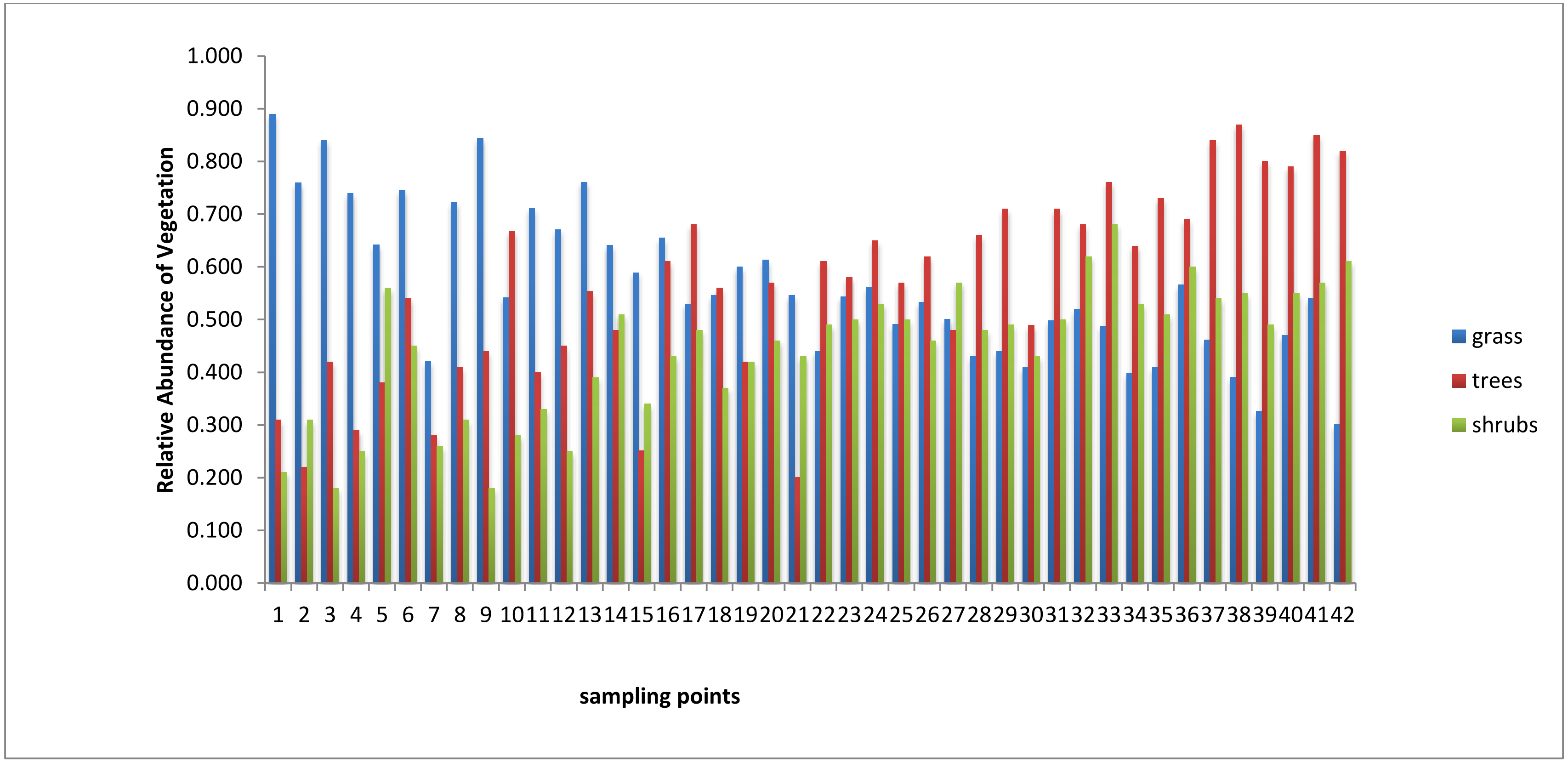

Figure 4. 11: Distribution of vegetation types in Kapchorwa District

CHAPTER FIVE: DISCUSSION

5.1 Rainfall and temperature Variation and trend for kapchorwa district from 1989-2019

5.1.1 Temperature

The observed significant positive trend in both maximum and minimum recorded temperatures in Kapchorwa District reflects substantial climate variability with potential implications for vegetation dynamics. Such trends suggest a consistent warming pattern, which often leads to shifts in vegetation composition, structure, and overall ecosystem dynamics. Low coefficients of variation and standard deviations in these temperature metrics indicate stable increases over time, potentially allowing less resilient plant species to be gradually replaced by more temperature-tolerant ones.

For instance, studies by IPCC, (2021) show that consistent increases in temperature, even at low variability, can lead to altered phenology in vegetation, such as earlier flowering or leafing times, which may disrupt local biodiversity. Similar findings by Nsubuga & Rautenbach, (2018a) highlight that temperature trends contribute to biome shifts, favoring species adapted to warmer conditions, potentially reducing diversity in cooler, highland ecosystems like Kapchorwa.

Additionally, Ali et al (2016) discusses how temperature trends can intensify evapotranspiration rates, which, coupled with stable temperature increases, can result in moisture stress. This stress can affect water availability for plants, further impacting vegetation structure. In the case of Kapchorwa, the consistent warming trend may necessitate adaptation strategies for local vegetation to ensure ecosystem stability and mitigate the risk of drought-related degradation (Alonso et al 2011).

This context of rising temperatures, as observed in the data, aligns with global patterns of climate-driven vegetation dynamics, reinforcing the need for monitoring and possible adaptation in Kapchorwa where temperature variability remains minimal but steadily increasing (Nsubuga & Rautenbach, 2018a).

The maximum mean temperatures increased at a rate of 0.015℃ per year implying that in the next one-decade maximum temperatures are expected to increase by 0.15℃ Table (4.3). This finding agrees with (IPCC-IPBES, 2020) which predicted that in the next decades global maximum temperatures will increase by 1.5℃. The increase in the maximum temperatures and the trends in seasonal maximum and minimum temperatures is a result of the global warming effect which has been confirmed by numerous studies worldwide (Hoegh-Guldberg et al, 2018). This therefore implies that kapchorwa is bound to experience hotter days and warmer nights in the future. The trend in the mean and seasonal temperatures is probably because of the temperature extremes in the area caused by the altitude effect. Highland areas such as the Elgon area, contributes to temperature stability because higher elevations generally experience cooler temperatures, while lower-lying areas have relatively warmer temperatures. This variation in altitude and the associated atmospheric conditions can contribute to low temperature variations within specific regions (Pickering et al 2008).

The district is expected to experience colder average temperatures in the years ahead at a projection decline of 0.07℃ in the next 10 years. The low variation in the temperatures is affected by the geographic location of Kapchorwa (Dekens et al 2013).Kapchorwa lies near the equator, where the angle of solar radiation is more direct and consistent throughout the year(Climate Investment Funds, 2010). This results in relatively stable temperatures with minimal seasonal variations compared to regions located farther away from the equator (Pilesjo et al 2021b).Alterations in land use, such as deforestation or conversion of natural landscapes into agricultural or urban areas, can affect local temperature patterns (Mwaura & Okoboi, 2014b).It is evident that a lot of land has been cleared for agriculture in Kapchorwa and others turned into urban centers (Pilesjo et al 2021b).This has an effect on the vegetation concentration which plays a role in regulating the temperature in a region or place (Wu et al 2015). The moderating effects of Lakes and Water Bodies helps to stabilize temperatures in the surrounding areas(Thomas, 2010).Kapchorwa is not far from river Manafwa and Lake Victoria which act as heat sinks, absorbing and releasing heat slowly.

5.1.2 Rainfall

The significant increasing trend in rainfall with high interannual variations in Kapchorwa District from 1989 to 2019 has critical implications for vegetation dynamics. Such variability, characterized by fluctuating periods of high and low rainfall, influences vegetation in multiple ways, often leading to changes in species composition, vegetation density, and ecosystem resilience.

Firstly, high rainfall variability is associated with shifts in plant growth cycles and productivity. Onyutha & Willems, (2017) notes that irregular rainfall can lead to periods of both water surplus and stress, which can create conditions that challenge water-sensitive species. In highland areas like Kapchorwa, this could mean a shift towards more resilient, drought- or flood-adaptive plant species, potentially reducing the diversity of more water-sensitive flora.

Additionally, the increased rainfall may accelerate soil erosion and nutrient leaching, especially on steep slopes like those in Kapchorwa. Orlove et al (2010) discusses how heavy rainfall events can lead to soil degradation, which affects vegetation growth by reducing soil fertility and destabilizing root structures. Consequently, native vegetation might struggle to adapt, favoring invasive or fast-growing species that can capitalize on disturbed soil and nutrient cycles, potentially altering the local biodiversity.

High variability in rainfall also affects the regeneration rates and succession stages of vegetation. Winkler et al (2017) explains that fluctuating precipitation impacts the establishment of seedlings, which are more sensitive to droughts or excessive moisture. In Kapchorwa, this could hinder regeneration rates for tree species and other perennial plants, slowing forest recovery and increasing vulnerability to landslides.

Furthermore, an increase in extreme rainfall events, as noted in research by IPCC, (2024) can stress ecosystems by disrupting local hydrological patterns, which may lead to waterlogging and create unfavourable growth conditions for certain species. In Kapchorwa, excessive rains may support aquatic or semi-aquatic vegetation in some areas, potentially reducing the abundance of non-adapted species and altering ecosystem dynamics over time.

The finding that the Precipitation Concentration Index (PCI) indicates a moderately uniform distribution of rainfall events in Kapchorwa suggests that rainfall is relatively consistent throughout the year. This has significant implications for vegetation dynamics in the region.

A moderately uniform distribution of rainfall can enhance plant growth and biodiversity, as various species can thrive with a reliable water supply. According to Shah et al (2024) consistent rainfall patterns support the establishment of diverse plant communities, which can lead to increased ecosystem stability and resilience. In Kapchorwa, this consistency may facilitate the growth of both native and agricultural species, enhancing food security for local communities.

However, while moderate rainfall distribution is beneficial, it may also pose challenges. For instance, if the rainfall is concentrated in certain months, it can lead to flooding and soil erosion, affecting root systems and plant health (Maity et al 2023) .Such conditions can stress vegetation, particularly during dry periods when water is scarce, impacting species composition and survival.

Additionally, the moderately uniform rainfall distribution may influence the competitive dynamics among plant species. Species that are better adapted to utilize water efficiently during periods of moderate supply may outcompete others, potentially leading to shifts in vegetation types (Ocen et al 2021). In Kapchorwa, this could result in a gradual change in the dominant species, impacting overall ecosystem services like carbon sequestration and habitat provision.

In summary, the moderately uniform distribution of rainfall in Kapchorwa, as indicated by the PCI, presents both opportunities and challenges for vegetation dynamics. While it supports diverse plant growth and agricultural productivity, it also necessitates careful management of water resources to mitigate risks of flooding and competition among species. Understanding these dynamics is crucial for developing sustainable land management practices in the region.

5.2 Assessment of vegetation indices trends and their variation in kapchorwa district between 1989 - 2019.

The increasing trend in the Normalized Difference Vegetation Index (NDVI) in Kapchorwa district from 1989 to 2019 is indicative of a positive shift in vegetation health over the three-decade period. NDVI is widely recognized as a reliable indicator of vegetation health and biomass, as it utilizes satellite data to assess the greenness and density of vegetation cover. An upward trend in NDVI suggests improved photosynthetic activity, which is often correlated with enhanced growth and vitality of plant life.

This trend could be attributed to various factors, including changes in land management practices, increased agricultural productivity, and reforestation efforts. For instance, studies have shown that sustainable agricultural practices and conservation efforts can lead to a rise in NDVI values, reflecting healthier and more resilient ecosystems. Authors like Joseph, (2002)have emphasized the role of agroforestry and sustainable land-use practices in enhancing vegetation cover and soil health, which can contribute to a higher NDVI.

Furthermore, climate-related factors such as changes in precipitation patterns and temperature can also impact vegetation health. Research by Ocen et al (2021) highlights the importance of climatic variables in shaping vegetation dynamics, suggesting that favourable climatic conditions during certain periods could have supported the increase in NDVI in Kapchorwa.

Additionally, socio-economic factors, such as population growth and land-use change, may have influenced vegetation trends. As communities adapt their agricultural practices and respond to market demands, there may be an increase in land dedicated to cultivation, which could enhance NDVI. However, it’s important to consider the potential for overexploitation and degradation if these practices are not managed sustainably, as discussed by Egeru et al (2019).

Rainfall can have a significant impact on NDVI values, particularly in areas where water availability is a limiting factor for vegetation growth (Huang et al 2016b). Rainfall plays a vital role in determining vegetation health by providing the necessary water for plant growth and supporting various physiological processes (Motohka et al 2010).This therefore justifies the increase in NDVI values from 1989 to 2019 implying that more Barren land is being cultivated due to the increase in rains. The moderate rainfall distribution in the district therefore suggests an explanation for the moderate variance in the NDVI of the district and the increase in the NDVI. This is because Kapchorwa district is an agricultural district and so availability of rain means an increase in crop agriculture (BBC, 2010b). Rainfall supplies plants with the water needed for photosynthesis, the process by which plants convert sunlight, carbon dioxide, and water into energy-rich carbohydrates (Glenn et al 2010b). Sustained and regular rainfall allows plants to maintain their metabolic activities, resulting in higher productivity and biomass accumulation (Cheng et al 2018b).

The increasing trend in the Vegetation Concentration Index suggests that the region experienced severe drought in the earlier years between 1989 and 1999.This is confirmed by (Nsubuga & Rautenbach, 2018c) who refers to the unusual rains recorded in 1961/62, 1997/98 and 2007 and severe drought that hit the country in 1993/94. A drought period refers to a prolonged period of abnormally low rainfall or precipitation in a specific region, resulting in water scarcity and a deficiency of moisture in the soil (Mwaura & Okoboi, 2014b). Droughts can vary in duration and severity, ranging from a few weeks to several years, and can have significant impacts on agriculture, ecosystems, and human populations (Dekens et al 2013). During a drought, the lack of precipitation leads to reduced water availability for various purposes, including drinking water, irrigation for crops, and industrial needs (Deng et al 2022). The scarcity of water can result in decreased crop yields, livestock losses, and increased food prices(Huang et al 2016c). In addition, droughts can cause water sources such as rivers, lakes, and reservoirs to shrink, affecting aquatic ecosystems and leading to ecological imbalances (Okonya et al 2013). The evidence of drought in the earlier years in the region can be further confirmed by the low NDVI Values in the earlier years between 1989 and 1999.

In summary, the increasing NDVI trend in Kapchorwa district from 1989 to 2019 reflects a general improvement in vegetation health, potentially driven by a combination of enhanced agricultural practices, climate conditions, and socio-economic changes.

5.3 Diversity and abundance of dominant plant species in kapchorwa district

The findings from the research in Kapchorwa District reveal a nuanced relationship between climate variability and vegetation health dynamics. The moderate diversity index of 0.47 indicates that while various vegetation types coexist, their representation is uneven. Grass species from the Poaceae family dominate the landscape, comprising an abundance index of 57%. This dominance may be reflective of climate conditions that favor grass growth, such as increased rainfall or temperature variations that enhance their competitive advantage over trees and shrubs. The second and third most abundant vegetation types, trees (Apocynaceae) and shrubs (Actinidiaceae), with abundance indices of 56% and 47% respectively, further illustrate this trend but suggest that these groups are less resilient to the prevailing climatic fluctuations.

Climate variability significantly influences the dynamics of vegetation health, diversity, and abundance by altering growth conditions, resource availability, and species interactions. According to authors such as Soliveres et al (2014), changes in climate can lead to shifts in species distributions and community compositions, affecting overall biodiversity. In the context of Kapchorwa, the prevailing climate conditions may have favored the proliferation of grass species while imposing stress on tree and shrub populations. This phenomenon underscores the importance of considering climate variability in ecological studies, as it acts as a critical driver in shaping vegetation patterns. Moreover, the findings are consistent with research by other scholars, such as Cadotte et al (2010), who highlight the sensitivity of certain species to climatic changes, which can lead to altered vegetation dynamics over time.

The strong correlation and regression coefficients suggest that temperature has a direct impact on the abundance and diversity of vegetation which has a direct link to vegetation health and productivity (Sintayehu, 2018b). A similar study was done by (Bellard et al 2012a) who found out that NDVI was significantly correlated with diversity. NDVI was employed as a substitute for the lack of long-term plant diversity data in his research. It should be emphasized that temperature has a major impact on the variety of crops found in a specific area, as stated by (Bellard et al (2012). This is because different crops have specific temperature requirements for optimal growth and development (Dengler et al 2016b).

Apocynaceae and Actinidiaceae are more abundant in areas of lower temperatures due to several factors. These factors include adaptations to colder climates, the availability of water resources, and competition with other plant species (Paruelo & Lauenroth, 1996). However, it is important to note that the abundance of Apocynaceae and Actinidiaceae is influenced by a combination of factors and can vary depending on specific local conditions (Sykes, 2009).Here are some explanations for the greater abundance of Apocynaceae and Actinidiaceae in colder areas. Adaptations to cold climates: Apocynaceae and Actinidiaceae in colder regions have evolved specific adaptations to withstand low temperatures. These adaptations include features like deep root systems, insulating bark, and the ability to enter dormancy during winter months. These adaptations allow Apocynaceae and Actinidiaceae to survive and thrive in colder environments (Dharani, 2011). Availability of water resources: Lower temperatures in colder areas often result in increased precipitation in the form of rain or snow. Adequate water availability is crucial for the growth and survival of Apocynaceae and Actinidiaceae. Areas with higher precipitation provide a consistent water supply, supporting the growth of vegetation (Tsai & Yang, 2016). Reduced competition: Colder environments may have fewer plant species compared to warmer regions, reducing competition for resources such as sunlight, water, and nutrients. This reduced competition allows Apocynaceae and Actinidiaceae to occupy available niches and establish themselves more abundantly (McClean et al 2005b). Soil characteristics: Cold regions often have soils that are rich in organic matter and nutrients due to slower decomposition rates. These nutrient-rich soils provide favorable conditions for the growth and development of Apocynaceae and Actinidiaceae (Kosmas et al 2000).

The results also showed that the most dominant vegetation type was Poaceae followed by Apocynaceae and Actinidiaceae respectively. Poaceae is often considered a dominant species in many ecosystems due to several key factors. Poaceae have evolved and adapted to a wide range of environmental conditions, allowing them to thrive in various habitats such as prairies, savannas, meadows, and even disturbed areas (Young & Young, 1983). They can withstand extreme temperatures, drought, and grazing pressure. Poaceae are known for their ability to grow quickly and efficiently. They have an extensive root system that enables them to absorb nutrients and water efficiently from the soil, giving them a competitive advantage over other plants (Rabinowitz et al 1984b). Poaceae employ effective reproductive strategies (de Jong & Klinkhamer, 2005). They often produce large quantities of lightweight seeds that are easily dispersed by wind, water, or animals. This helps them colonize new areas and establish themselves rapidly. Poaceae can recover and regrow rapidly after disturbances such as mowing, trampling, or even human activities. Their ability to adapt and persist makes them highly resilient in the face of changing environmental conditions (Brotherton & Joyce, 2015b).

The high variation in vegetation diversity could be explained by the high variation in the relative abundance of the vegetation. The variation of relative abundance of the vegetation is because of other factors that affect vegetation growth such as sunlight, soil quality, water availability and nutrient supply (Duchesne et al 2018). It is important to note that human activities possibly plays an important role in the variation in vegetation diversity. Activities such as farming, and urbanization require vegetation to be cleared from land leading to reduction in vegetation cover. The results also suggest that Poaceae shrive in areas of higher temperatures whereas Apocynaceae and Actinidiaceae shrive in areas of lower temperatures that is why the larger part of the mountainous area of the district is covered by forest. These mountainous areas have relatively cooler temperatures than the low-lying fields. (Sintayehu, 2018b) admits that many species shift their geographic ranges in response to rapid changes in temperature and precipitation regimes, generally pole ward, toward higher elevations.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

In conclusion, this study has shown that climate variability, specifically temperature and rainfall trend, plays a dominant role in driving vegetation health dynamics in Kapchorwa District. Over the past three decades (1989–2019), there has been a significant positive trend in both maximum and minimum mean recorded temperatures, as well as an increasing trend in mean annual rainfall with notable interannual variations. These climate factors have corresponded with an observed positive trend in vegetation health, as evidenced by the increasing Normalized Difference Vegetation Index (NDVI) values. The NDVI trend suggests that overall vegetation health in the district has improved over time, potentially due to favourable climatic conditions.

Moreover, the study highlights moderate diversity in vegetation types, with grass (Poaceae) as the most abundant vegetation, followed by trees (Apocynaceae) and shrubs (Actinidiaceae), showcasing a balanced yet varied vegetation structure in the area. These findings emphasize that while Kapchorwa's vegetation health has generally benefited from the positive climatic trends, the diversity and distribution of vegetation types are essential considerations for sustainable management and conservation. The study underscores the importance of ongoing monitoring of climate-vegetation interactions, which are likely to have significant implications for ecosystem stability and agricultural productivity in the face of future climate variability.

6.2 Recommendations

Based on the findings of this study, several recommendations are put forth to guide future research and policy development on vegetation health dynamics in the context of climate variability.

Given the significant positive trends in both maximum and minimum recorded temperatures over the three-decade period, it is recommended to monitor temperature changes and analyze their implications on specific vegetation types, especially those sensitive to temperature fluctuations. This ongoing monitoring would provide more localized insights into the vegetation's resilience or susceptibility to temperature shifts and help anticipate potential adaptations or conservation strategies.

The study highlighted a significant increase in rainfall with high interannual variability, suggesting the need for adaptive water management practices and climate-smart agriculture in Kapchorwa District. Establishing early warning systems and promoting soil moisture conservation techniques could mitigate potential negative effects of rainfall variability, thereby supporting sustainable vegetation health.

Accessibility of climate data and coverage remains a challenge to many researchers who must go an extra mile to pay for the data and most times are given an incomplete set of data. This problem needs to be addressed by the concerned Authorities to ease research. This concern is not only tied to Uganda but several African countries where similar research on climate has been carried out (Dorward et al 2020b). Climate data from the meteorological centres should be made available and easy to access.

Further research should be conducted to explore additional factors that could potentially impact the health of vegetation, such as soil moisture, mineral content, and the geographical and geological characteristics of an area. While this study focused on using NDVI, vegetation abundance, and diversity as indicators of vegetation health, it is also important to consider other indicators such as growth, productivity, and biomass density.

Finally, the upward trend in NDVI reflects improved vegetation health, which, along with the moderate vegetation diversity, underscores the importance of biodiversity conservation measures. Efforts should be made to preserve the dominant grass, tree, and shrub species, which play crucial roles in ecosystem stability. Conservation practices, such as promoting native plant species and sustainable harvesting, should be prioritized to maintain and enhance this positive vegetation health trend amidst climate variability. Together, these recommendations aim to strengthen the resilience of Kapchorwa District's vegetation to ongoing climatic shifts.

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APPENDIX 1:Dorminant Vegetation types

VEGETATION TYPE	APOCYNACEAE	ACTINIDIACEAE	POACEAEES
SPECIES name	Funtumia Africana(Apocynaceae). False rubber	Actinidia Chinensis kiwi(Actinidiaceae)	Barnyard Poaceae Echinochloa crus-gall(Poaceae)
			

Plate 3. 2:Common vegetation types

APPENDIX 2 :Temperature Raw Data

NASA/POWER CERES/MERRA2 Native Resolution Monthly and Annual
Dates (month/day/year): 01/01/1989 through 12/31/2019
Location: Latitude 1.3268 Longitude 34.4511
Elevation from MERRA-2: Average for 0.5 x 0.625 degree lat/lon region = 1430.67 meters

PARAMETER	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANN
TS	1989	23.89	25.51	27.43	23.91	22.36	22.18	20.9	21.76	23.41	23.13	23.92	24.58	23.57
TS	1990	24.55	25.83	25.23	22.93	23	22.13	21.14	21.47	23.68	24.51	24.68	23.86	23.57
TS	1991	25.94	28.6	28.43	26.8	24.23	22.15	20.55	20.92	22.86	23.15	23.35	23.92	24.21
TS	1992	26.32	28.51	28.99	26.92	25.44	21.32	20.21	20.68	21.38	21.78	22.18	23.49	23.92
TS	1993	23.67	26.23	28.04	28.05	23.48	21.44	20.92	21.92	24.04	25.87	24.54	25.55	24.47
TS	1994	27.62	27.61	28.74	26.84	22.91	21.14	19.83	20.42	22.34	23.59	23.1	23.4	23.94
TS	1995	26	26.73	27.3	28.23	24.5	22.34	20.27	21.58	22.62	23.57	22.8	23.87	24.13
TS	1996	25.36	27.29	26.84	26.1	22.76	20.27	20.56	21.09	21.79	23.4	23.47	24.52	23.61
TS	1997	26.58	27.55	28.57	22.87	24.52	23.51	21.62	21.98	26.48	24.05	22.92	23.25	24.48
TS	1998	23.67	26.08	29.01	27.71	23.86	22.87	21.34	22.12	23.93	23.79	23.81	25.45	24.45
TS	1999	26.27	27.9	27.39	26.73	23.08	22.21	20.03	21.4	23.01	22.3	22.85	23.98	23.9
TS	2000	26.25	27.76	28.39	27.4	24.01	22.65	21.39	20.84	22.79	22.56	23.19	24.53	24.3
TS	2001	24.47	27.22	26.3	25.83	23.87	21.12	20.96	20.98	22.91	22.77	21.84	23.73	23.48
TS	2002	24.12	26.88	26.87	26.38	23.88	23.51	24.51	22.51	24.79	24.29	23.82	23.62	24.58
TS	2003	24.94	28.3	28.11	25.15	23.03	21.19	20.62	20.53	22.12	23.36	23.58	22.67	23.6
TS	2004	25.12	26.74	27.29	24.06	23.33	21.96	21.99	21.57	23.17	23.93	23.36	24.15	23.88
TS	2005	25.15	27.04	27.44	26.31	22.59	23.01	21.55	22.44	22.93	24.65	24.24	25.49	24.38
TS	2006	26.86	28.01	26.83	24.93	23.99	23.27	22.8	22.76	24.2	25.06	22.8	22.82	24.51
TS	2007	24.52	25.29	27.1	26.52	24.08	21.01	20.53	20.59	20.57	22.4	23.42	23.89	23.31

TS	2008	25.78	25.62	25.9	25.19	24.29	21.94	20.83	21.55	22.58	22.3	21.62	23.87	23.45
TS	2009	25.62	26.94	28.41	25.1	23.19	24.75	22.65	23.72	24.93	23.72	24.48	24.1	24.78
TS	2010	24.23	25.33	23.96	24.06	21.89	21.48	20.86	21.19	21.76	23	23.37	24.15	22.92
TS	2011	25.91	27.04	26.48	26.08	22.9	20.81	21.56	20.44	20.79	21.95	20.65	21.12	22.95
TS	2012	23.3	25.38	27.14	23.46	21.53	20.67	20.09	20.4	21.26	22.18	22.16	22.94	22.54
TS	2013	24.57	26.5	27.46	23.02	22.39	22.03	21.69	21.42	22.33	22.26	22.33	22.96	23.23
TS	2014	25.93	27.08	27.21	27.3	23.73	23.02	22.41	21.19	22.47	22.31	22.6	23.51	24.05
TS	2015	24.9	27.98	27.8	23.29	22.86	21.5	22.75	23.83	24.74	24.51	22.12	22.71	24.06
TS	2016	24.35	26.81	28.36	24.22	22.25	21.95	21.02	21.88	23.77	23.9	23.61	24.84	23.9
TS	2017	26.45	26.02	25.91	25.4	22.9	23.69	21.52	22.41	22.43	22.79	22.23	24.09	23.8
TS	2018	25.59	28.16	23.23	21.74	20.94	20.16	20.32	20.99	23.16	22.87	23.74	23.58	22.84
TS	2019	25.4	27.76	27.44	26.58	23.3	20.92	20.46	20.97	21.83	21.76	21.83	21.29	23.26

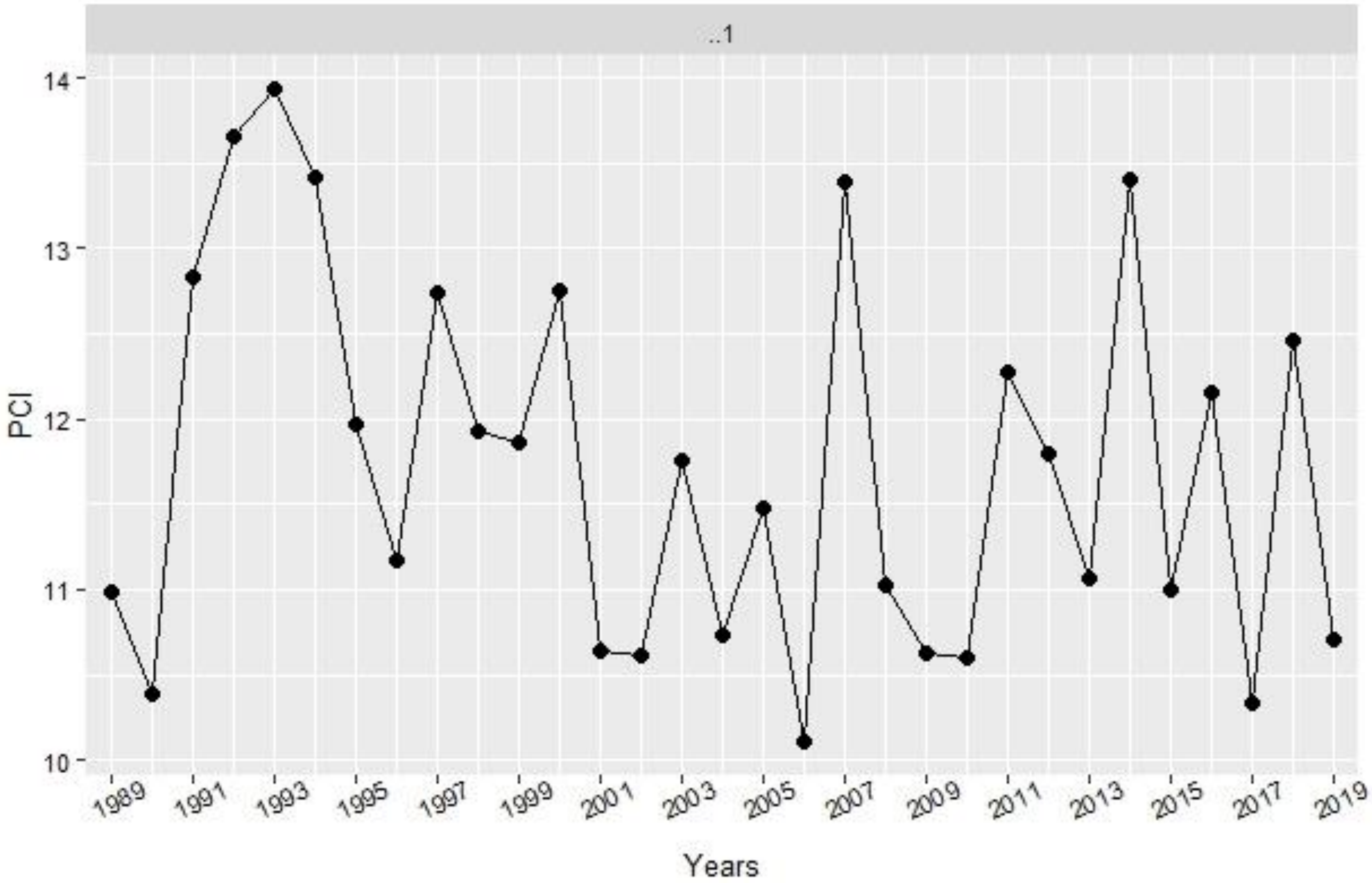
APPENDIX 3: Rainfall Raw Data & Precipitation concentration Index

NASA/POWER CERES/MERRA2 Native Resolution Monthly and Annual
Dates (month/day/year): 01/01/1989 through 12/31/2019
Location: Latitude 1.3466 Longitude 34.4323
Elevation from MERRA-2: Average for 0.5 x 0.625 degree lat/lon region = 1430.67 meters
The value for missing source data that cannot be computed or is outside of the sources availability range: -999
Parameter(s):
PRECTOTCORR MERRA-2 Precipitation Corrected (mm/day)
PRECTOTCORR_SUM MERRA-2 Precipitation Corrected Sum (mm)
-END HEADER-

PARAMETER	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
PRECTOTCORR	1989	0.19	0.42	2.22	4.31	5.63	1.47	3.18	2.96	3.25	4.13	2.21	2.22
PRECTOTCORR	1990	0.87	4.43	3.24	5.67	3.85	1.88	3.49	4.8	1.99	2.37	1.38	1.43
PRECTOTCORR	1991	0.81	0.12	1.19	1.14	5.13	3.2	5.11	5.41	1.74	4.39	1.72	0.77
PRECTOTCORR	1992	0.2	0.19	0.36	2.79	2.34	5.79	6.37	5.2	4.59	5.97	1.01	0.78
PRECTOTCORR	1993	1.7	0.2	0.38	0.65	5.71	4.91	2.77	2.86	1.59	1.09	1.87	0.81
PRECTOTCORR	1994	0.03	0.29	0.95	2.88	6.04	4.48	5.9	6.83	2.13	1.45	3.47	0.78
PRECTOTCORR	1995	0.33	1.05	1.29	1.96	6.08	2.78	6.59	2.16	4.28	3.33	3.62	1.12
PRECTOTCORR	1996	0.46	0.97	2.7	2.9	5.23	4.39	2.88	4.77	4.34	2.51	1.71	0.27
PRECTOTCORR	1997	0.09	0	2.29	5.38	0.69	2.55	3.56	3.93	0.17	3.34	3.19	2.17
PRECTOTCORR	1998	2.19	1.11	0.18	0.99	3.89	1.83	4.95	3.7	1.65	3.76	2.36	0.28
PRECTOTCORR	1999	0.82	0.02	1.44	3.33	5.06	3.48	5.61	3.7	2.89	4.92	1.53	0.55
PRECTOTCORR	2000	0.13	0.21	0.47	1.6	3.71	2.72	2.99	5.31	3.62	4.69	1.7	0.83
PRECTOTCORR	2001	1.53	0.4	2.47	2.29	5.03	3.92	5.32	4.1	4.05	5.24	3.17	0.49
PRECTOTCORR	2002	0.92	0.44	2.08	2.43	4.13	2.08	1.05	4.42	2.09	4.3	2.45	2.37
PRECTOTCORR	2003	1.11	0.21	1.21	5.18	4.3	4.88	4.74	8.09	3.12	3	1.61	2.45
PRECTOTCORR	2004	1.47	0.48	1.58	5.78	3.54	3.33	3.62	5.54	3.97	2.76	2.12	1.3
PRECTOTCORR	2005	1.53	0.93	1.07	2.7	4.55	1.81	5.15	3.87	3.87	2.59	1.52	0.09
PRECTOTCORR	2006	0.32	0.92	1.5	3.12	2.51	1.95	3.03	2.39	3.71	3.02	4.46	2.08
PRECTOTCORR	2007	0.6	1.3	0.57	2.58	5.67	3.36	5.34	4.58	7.86	2.58	0.69	0.63

PRECTOTCORR	2008	0.32	2.03	2.74	2.28	4.98	3.17	3.48	4.84	5.76	5.85	3.13	0.05
PRECTOTCORR	2009	0.65	0.46	1.21	2.84	4.04	1.2	1.84	3.04	3.83	2.49	1.64	3.17
PRECTOTCORR	2010	1.13	3.87	2.77	5.24	7.84	2.91	3.12	4.8	5.59	3.93	1.95	0.87
PRECTOTCORR	2011	0.26	0.36	2.6	2.38	7.12	4.64	2.92	8.66	4.97	4.42	7.26	0.99
PRECTOTCORR	2012	0.01	0.3	0.75	7.71	5.8	5.09	3.76	5.48	6.56	3.46	3.37	2.44
PRECTOTCORR	2013	0.61	0.24	2.67	5.2	5.25	1.71	2.85	5.45	5.51	4.69	2.45	2.01
PRECTOTCORR	2014	0.16	0.32	1.24	0.65	5.07	2.38	3.4	5.67	4.08	6.37	1.76	1.06
PRECTOTCORR	2015	0.02	0.48	1.58	5.24	5.55	4.03	2.18	2.76	4.07	4.56	6.09	3.33
PRECTOTCORR	2016	0.93	0.19	1.71	7.18	4.35	5.03	2.78	3.65	3.81	3.16	1.98	0.26
PRECTOTCORR	2017	1.42	3.66	3.66	2.88	5.49	2.03	3.12	3.34	6.4	5	3.14	0.19
PRECTOTCORR	2018	0.25	2.9	5.19	11.4	7.31	4.61	2.3	3.07	2.71	3.82	1.59	2.85
PRECTOTCORR	2019	0.36	1.22	1.26	5.54	4.56	7.01	4.27	7.47	6.23	9	5.23	5.14
	Mean	**0.69**	**0.96**	**1.76**	**3.75**	**4.85**	**3.37**	**3.80**	**4.61**	**3.88**	**3.94**	**2.63**	**1.41**
	SD	**0.58**	**1.18**	**1.10**	**2.34**	**1.45**	**1.44**	**1.37**	**1.60**	**1.71**	**1.58**	**1.48**	**1.18**
	CV	84.05%	124%	62.7%	62%	29.9%	43%	36%	34.8%	44.1%	40.0%	56.4%	83.42%

	year	PCI (precipitation concentration index)
1	1989	10.99027
2	1990	10.38428
3	1991	12.83174
4	1992	13.65367
5	1993	13.93709
6	1994	13.42151
7	1995	11.97455
8	1996	11.17510
9	1997	12.73939
10	1998	11.92444
11	1999	11.86033
12	2000	12.75035
13	2001	10.64361
14	2002	10.61141
15	2003	11.75381
16	2004	10.74007
17	2005	11.47939
18	2006	10.10377
19	2007	13.39332
20	2008	11.02437
21	2009	10.63245
22	2010	10.59702
23	2011	12.27327
24	2012	11.80186
25	2013	11.07190
26	2014	13.40186
27	2015	11.00631
28	2016	12.15397
29	2017	10.33555
30	2018	12.45809
31	2019	10.70794



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PCI
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2019
Years

APPENDIX 4: Sampling Points, temperature, RA, NDVI& Altitude

sampling points	**Latitude**	**Longitude**	RA	Altitude(m)	temp
1	1.33700000	34.31400000	0.890	1461	26.9
	1.38000000	34.35700000	0.760	1426	26.4
	1.33400000	43.36100000	0.840	1403	24.6
	1.37400000	34.33300000	0.740	1546	23.9
	1.35600000	34.34100000	0.768	1432	26.5
	1.33800000	34.34500000	0.746	1598	25.9
2	1.42000000	34.40500000	0.701	1640	25.2
	1.44200000	34.38100000	0.723	1659	25
	1.43900000	34.43500000	0.844	1599	24.8
	1.40500000	34.43100000	0.732	1632	25.1
	1.41600000	34.40800000	0.711	1646	23.8
	1.40400000	34.39500000	0.671	1638	24.4
3	1.45000000	34.45300000	0.761	1669	24.7
	1.42800000	34.47100000	0.641	1664	24.4
	1.39700000	34.46600000	0.589	1671	24.1
	1.41300000	34.48600000	0.655	1676	23.7
	1.39900000	34.47200000	0.530	1690	23.6
	1.41400000	34.46100000	0.546	1728	23.8
4	1.38000000	34.38300000	0.6	1741	23.4
	1.37300000	34.40700000	0.613	1758	23.6
	1.37700000	34.43600000	0.546	1736	24.1
	1.36300000	34.40000000	0.440	1771	22.9
	1.34600000	34.38300000	0.543	1786	23.1
	1.32800000	34.41200000	0.561	1823	22.4
5	1.38400000	34.45100000	0.491	1876	22.8
	1.37200000	34.46800000	0.533	1883	21.6
	1.32900000	34.47800000	0.501	1856	22.2
	1.35400000	34.46600000	0.431	1820	21.6
	1.37000000	34.46200000	0.440	1800	21.8
	1.35100000	34.47000000	0.410	1871	21.5
6	1.30700000	34.41300000	0.498	1844	20.1
	1.31000000	34.38300000	0.520	1807	21.7
	1.31400000	34.43800000	0.488	1961	20.2
	1.27900000	34.43600000	0.398	1933	20.6
	1.30100000	34.42200000	0.410	1954	19.8
	1.30400000	34.40700000	0.566	1986	19.9
7	1.31600000	34.44800000	0.461	2100	19.4
	1.29800000	34.44700000	0.391	2250	19.6
	1.25600000	34.51000000	0.326	2296	19.3
	1.28900000	34.49900000	0.470	2201	19.7
	1.29300000	34.47300000	0.541	2210	19.2
	1.30600000	34.47900000	0.301	2300	19

Plate 3. 3:Some of the sampling points and equipment

year	Avg Rf/yr	Max AvgNDVI/yr
1990	155.0	0.401
1991	148.3	0.447
1992	261.1	0.415
1993	206.4	0.49
1994	198.6	0.529
1995	154.5	0.53
1996	152.3	0.485
1997	224.0	0.439
1998	230.8	0.467
1999	129.0	0.492
2000	189.3	0.449
2001	157.0	0.472
2002	127.3	0.554
2003	162.9	0.510
2004	139.1	0.491
2005	216.2	0.500
2006	201.0	0.510
2007	377.0	0.513
2008	182.8	0.479
2009	138.0	0.500
2010	168.0	0.593
2011	178.0	0.585
2012	198.1	0.656
2013	212.0	0.780
2014	178.3	0.859
2015	183.4	0.878
2016	151.2	0.489
2017	183.2	0.493
2018	195.9	0.457
2019	213.1	0.509