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DIRECTORATE OF RESEARCH AND

GRADUATE TRAINING

INVESTIGATING CHANGES IN CLIMATIC DRY CONDITIONS ACROSS THE WATER MANAGEMENT ZONES IN UGANDA

BY

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DECLARATION

I, Kerudong Acayerach Paskwale, hereby declare that this submission is my work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree of the University or other institute of higher learning, except where due acknowledgement has been made in the text and reference list.

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APPROVAL

The undersigned certifies as a sole supervisor that he has read and hereby recommends for acceptance by Kyambogo University, a research dissertation titled: "Investigating changes in climatic dry conditions across the water management zones in Uganda", in fulfillment of the requirements for the award of Master of Science in Water and Sanitation Engineering Degree of Kyambogo University (KyU).

Dr. Charles Onyutha

Sign: ....

Date: ....30th August, 2022....

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DEDICATION

This report is dedicated to my late parents, John Kerudong and Akech Ventorinah. And in a more special way, to my lovely wife, Mrs. Flavia Kerudong, and children, Munguleng Michael Acayerach, Amaru Alma Akech and Afoyumungu Abigail Alice.

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AMO	Atlantic Multi-decadal Oscillation
ASA	Autocorrelation Spectral Analysis
AWMZ	Albert Water Management Zone
BADC	British Atmospheric Data Centre
CI	Confidence Interval
CMIP5	Coupled Model Inter-comparison Project
CMP	Catchment Management Plan
CSD	Cumulative Sum of rank Difference
CSFR	Climate Forecast System Reanalysis
CV	Coefficient of Variation
EOF	Empirical Orthogonal Function
ETCCDI	Expert Team on Climate Change and Detection Indices
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product

GMST	Global Mean Surface air Temperature
IOD	Indian Ocean Dipole
IPCC	Intergovernmental Panel on Climate Change
IWRM	Integrated Water Resources Management
KWMZ	Kyoga Water Management Zone
MBE	Mean Bias Error
NAIM	Non parametric Anomaly Indicator Method
NCAR	National Centre for Atmospheric Research
NCEP	National Centre for Environmental Prediction
NDP	National Development Plan
NOAA	National Oceanic and Atmospheric Administration
NPA	National Planning Authority
PC	Principle Component
PET	Potential Evapotranspiration
PGF	Princeton Global Forcings
PRCTOT	Annual Total Precipitation

QBO	Quasi Biennial Oscillation
RMSE	Root Mean Squared Error
SDG	Sustainable Development Goal
SDII	Simple Daily Intensity Index
SMR	Spearman’s Rho
SPI	Standard Precipitation Index
SQMK	Sequential Mann-Kendal
SST	Sea Surface Temperature
TRMM	Tropical Rainfall Measuring Mission
UNDP	United Nations Development Programme
UNMA	Uganda National Meteorological Association
UNWMZ	Upper Nile Water Management Zone
VWMZ	Victoria Water Management Zone
WMO	World Meteorological Organization
WMZ	Water Management Zone
WRM	Water Resources Management

OPERATIONAL DEFINITIONS

CDD1	Maximum consecutive dry days with rainfall <1mm
CDD5	Maximum consecutive dry days with rainfall <5mm
CDPET10	Maximum number of consecutive days with potential evapotranspiration (PET) >10mm
CDPET5	Maximum number of consecutive days with PET >5mm
NDD1	Number of dry days with rainfall < 1mm
NDD5	Number of dry days with rainfall < 5mm
NDPET10	Number of days with PET >10mm
NDPET5	Number of days with PET >5mm
SPETD10	Sum of PET for days with PET >10mm
SPETD5	Sum of PET for days with PET >5mm
Climate index	Is a simply computed value used to describe and characterize changes and status of a geophysical system for instance global circulation pattern (AMO, IOD, QBO, Nino3)

Extreme climatic indices: Extreme values extracted from daily precipitation to characterize dry conditions.

ABSTRACT

Prolonged insufficient precipitation associated with evapotranspiration affects society in various ways such as wilting of crops. Studies with comprehensive analyses of climatic droughts while considering hydro-climatic differences among the various Water Management Zones (WMZs) in Uganda are inadequate. This study addressed this, by extracting extreme climatic indices (ECI) from precipitation and potential evapotranspiration (PET), characterizing climatic drought across the WMZs and analyzing connection of variability in the indices to large-scale ocean-atmosphere conditions from 1979 to 2013. Examples of the extracted ECIs included number of dry days (NDD), number of consecutive dry days, and sum of PET, above a defined threshold. The long term statistics of the extreme climatic conditions showed Kyoga and Victoria as the driest and wettest WMZs in Uganda. The extent and severity of drought were found to depend on the threshold for extracting the ECIs. Furthermore, the severity of the drought was found to be disproportionate across the country with the Kyoga and Victoria WMZs being the most and least severely affected by the impacts of climatic drought. Generally, all WMZs exhibited decreasing trends in the NDD over the study period, indicating that the country was becoming wetter recently. Across the country, the Indian Ocean Dipole (IOD) was negatively correlated with variability of a number of ECIs of both precipitation and PET. However, correlation between Quasi Biennial Oscillation (QBO) and variability of several ECIs was generally positive ($p<0.05$).

Key words: Drought, Climatic Indices, Evapotranspiration, Variability, Trend

CHAPTER ONE: INTRODUCTION

1.1 Background

Extreme rainfall that is associated with flood and drought tends to have substantial impact on the way community lives (Gudoshava et al., 2020; Shilenje et al., 2019) in various parts of the world. Drought is considered a sustained period with dry climatic condition, marked by scarcity of water (Crossman, 2018) that tends to occur globally, with negative impact on environmental systems and socio-economic condition of a country and in extreme cases, results in to death (Jedd et al., 2021; Kyatengerwa et al., 2020; Eslamian et al., 2017; Meza et al., 2020; Mfitumukiza et al., 2017). The severity further extends to limited grazing land thus reducing availability of fodder for cattle (Lwasa, 2018) as livestock productivity reduces. While droughts are driven largely by rainfall deficit, its impact can broadly be categorized as meteorological, hydrological, agricultural and socioeconomic droughts (Choi *et al.*, 2013) respectively.

Rojas, (2020) and Dai, (2013) study findings established positive drought intensity around the world in some seasons. This was linked to 21st century and was attributed to reduced precipitation and/or increased evapotranspiration. The global rise in temperature by 0.91°C in the past 100 years (Tignor and Allen, 2013), continues to impact on global warming, agricultural and forestry production. For example, Lewis et al., (2011) and Yang et al., (2018) study finding showed severe drought experience in more than half of the Amazon that caused increase in tree mortality and reduced tree growth.

The drought episodes were greatly associated with high spatio-temporal variability in rainfall distribution over the past few decades across the Sub-Saharan Africa (Owusu and Waylen, 2013; Bibi et al., 2014). This variability influences precipitation deficit and evapotranspiration across the country (Ssentongo et al., 2018), that directly contribute to the dry condition. Though it is well known that drought is more associated with aridity, studies conducted for example by Tánago et al. (2016) indicates devastating vulnerability, due to the impact of drought in some tropical areas of the world. In their study, Ayana et al. (2016) indicated an increase in the duration of drought and the areas impacted in the last two decades, within the East Africa region.

Uganda in particular, experiences a bi-modal rainfall season per year in most parts with largely varied tropical climate given its location in the equatorial region (Nsubuga and Rautenbach, 2018; Nsubuga et al., 2017). The variation is associated with droughts episodes which are disproportionate across the various regions of Uganda. It is because of the differences in the distributions of climatic variables, such as precipitation. According to Egeru et al., (2014), Karamoja region (north east) has a uni-modal regime and experience long dry spell that varies in space. Similarly, Aswa basin is dry and more susceptible to severe condition compared to Lake Kyoga basin (Byakatonda et al., 2021). However, Demissie et al. (2019) projected a decrease of about 3-5 days in the longest consecutive dry days (CDD) across most parts of the study area except, the southern area (slight increase in CDD in the long rain season). Due to this projection, Zinyengere et al. (2016) estimated an economic loss in the country of about US$ 1.5 billion by 2050.

The United Nations, Sustainable Development Goal (SDG) thirteen, identifies with measurers to address climate change and its impact through reduction of global average temperature (UNDP-SDG, 2015). Two of the several targets under this goal, promotes strategies for effective climate change planning and management, and adaptive capacity to potential hazards related to climate and natural disasters. Uganda in its National Development Plan (NDP) III, vision 2040 (National Planning Authority, 2020), recognizes the contribution of effective management of climate and natural resources issues to address disaster challenges for improvement of household income and sustainable livelihood. Consequently, strategic responses by government have been developed for adaptation and mitigation against adverse impact of changing climate. In addition, Uganda also adopted the Integrated Water Resources Management (IWRM) strategy, which is being implemented by using the catchment-based approach (Ministry of Water and Environment, 2014). Under this framework, various Catchment Management Plans (CMPs) have been developed to address changes in the climatic variables and depends mainly on the level of hydro-climatic information available, prior to the plan preparation.

However, the current information on dry climatic conditions is insufficient to explain in particular, the changes in dry climatic conditions related to evapotranspiration. Several studies (Byakatonda et al., 2021; Byakatonda et al., 2018) have characterized climate drought based on standard precipitation and evaporation index (SPEI) (McKee et al., 1993), drought severity index (DSI) (PaiMazumder et al., 2013), Palmer drought severity index (PDSI) (Palmer, 1965) and Standardized precipitation and evapotranspiration index (SPEI) (Vicente-Serrano et al., 2010). To precisely determine water balance, both precipitation and PET should be combined as key factors in drought analysis. Though SPI is the most commonly used index, Anshuka et al., (2019) recommended drought analysis using other indices due to its inability to characterize drought events effectively (Wu et al., 2007). Notably, the East African region has been the focus for various drought studies in recent years (Haile et al., 2019). Much of these studies did not consider this important climatic variable (evapotranspiration). For predictive planning of water resources management, it is important to have good understanding of the historical trend and variability of climatic indices on precipitation and evapotranspiration that explains dry condition. This study aimed to investigate changes in dry condition across the four WMZs in Uganda, which cover Lake Albert, Kyoga, Victoria and Albert Nile basins.

1.2 Problem statement

Several parts of the world continued to show increase in variability of drought frequency and severity (Mukasa et al., 2020). On average, about 10% of Ugandans experience water scarcity annually and are likely to be more during the dry year (World Bank, 2019). It is estimated that about US$ 1.5 billion economic losses will be incurred by 2050, as a result of the changing climatic variable impact (Zinyengere et al., 2016).

The impacts of drought on livelihood are disproportionate among the regions of Uganda. Global Facility for Disaster Reduction and Recovery, GFDRR (2017), reported close to 24 million people suffered from the impact of drought between 2004 and 2013. It estimated that $1.2 billion (about 7.5% of Uganda’s 2010 Gross Domestic Product (GDP)) loss and damage was incurred in 2010 and 2011 respectively. Uganda losses on average, $20 million in agriculture annually and in 2017 more than 1 million people needed food assistance (World Bank, 2019). Drought occurrence impacts agricultural, energy productivity and economic growth.

Several studies were conducted on drought in Uganda, for instance by Demissie et al. (2019); Mukasa et al. (2020) and Twongyirwe et al. (2019). However, these studies conducted earlier did not consider extreme precipitation and evapotranspiration indices to analyze drought. Furthermore, they left out the variance in the hydro-climate of the four WMZs in Uganda. There is the need to address the research gap on drought, considering the entire country, which has compelled the undertaking of this research.

1.3 Objectives of the study

1.3.1 Main objective

The main objective of this study was to investigate the changes in climatic dry conditions across the WMZs in Uganda.

1.3.2 Specific objectives

The specific objectives of this study included;

a) Characterizing climatic dry conditions across the WMZs;

b) Determining significance of changes in the extreme climatic indices;

c) Analyzing multi-decadal co-variability in extreme climatic indices with changes in large- scale ocean-atmosphere conditions.

1.4 Research questions

a) What are the characteristics of dry climatic conditions across the WMZs?

b) What is the significance of changes in the extreme climatic indices?

c) What is the relationship between multi-decadal co-variability in extreme climatic indices with changes in large- scale ocean-atmosphere conditions?

1.5 Research justification

Investigation of the changes in climatic dry condition across the four WMZs in Uganda, especially understanding the trend and variability of climatic variable like rainfall and PET, will guide the planning for the water catchments within these zones and decisions in water resources management (WRM). This planning process recognizes the need for accurate information on the dry state of the zones in terms of space and time, which is lacking in this case.

The increasing threats from global warming and continuous anthropogenic activities are clearly visible in these WMZs. Therefore, this research is vital in informing policy makers at national and local level on strategy for sustainable adaptation to the changes in climatic dry conditions. Implementers, such as water resources planners, engineers and climate experts will find this information useful in their routine applications.

1.6 Significance

Knowledge of the characteristics of climatic condition is vital for planning for climate adaptation and resilient coping mechanisms of communities. In addition, such information is helpful in guiding the catchment planning processes in the water management zones.

Maps showing the correlation between different climatic indices and large-scale ocean-atmosphere conditions generated are considered vital for the weather prediction, especially to the meteorological operation of Uganda, as such critical decision is supported to guide the Country's climate and productive weather sectors.

The research is important to policy makers and regulatory bodies in the water and meteorological sector, with an improved understanding of the dynamic of the changes in climatic dry conditions across the WMZs in Uganda. It also supports the development of a strategy for climate adaptation measures for sustainable community livelihood.

The research will provide knowledge to learners at post graduate and undergraduate level. The recommendation offers opportunity for further research areas, hence contributing to further academic fields.

1.7 Scope of the study

1.7.1 Time scope

This research was conducted from August 2019 to June 2021.

1.7.2 Geographical scope

The study was limited to the four WMZs of Uganda, located in the East Africa region.

1.7.3 Content scope

This research focused on analyzing trend and variability of the climate indices, characterization of the climatic condition and correlation between the large-scale ocean-atmosphere conditions with the indices. Validation of the reanalysis data was also carried out with station data, obtained from the study area. The research focused on analysis of the correlation between climate indices and variability in drought indicators.

1.7.4 Financial scope

The finances used, was limited to the cost of acquiring data required for validation, stationery and printing services, transport and related logistics only. About five million Uganda shilling was used to facilitate this financial demand.

1.8 Conceptual framework

The increase or decrease in precipitation and evapotranspiration (independent variables) as a result of influence from the sea surface temperature, sea level pressure (moderating factors), will cause changes in the trends and variability (dependent variables). Figure 1.1 shows the conceptual framework depending on the variables.

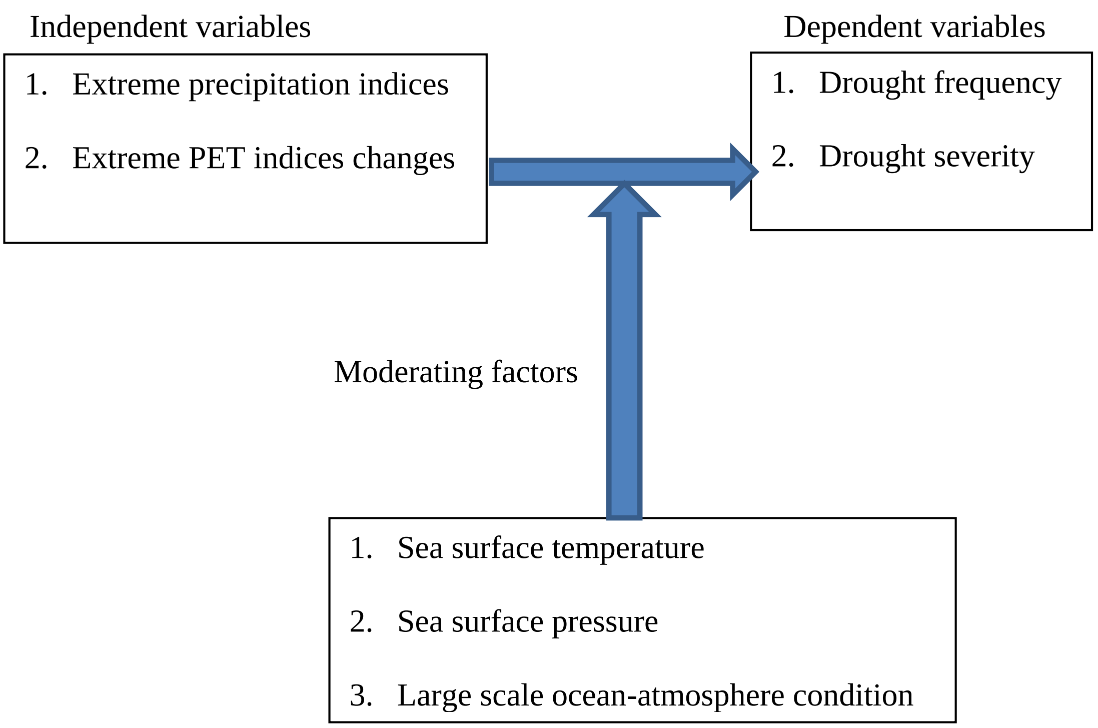

Figure 1.1: Conceptual framework

1.9 Chapter summary

This chapter introduces the research area together with the justification for conducting the study and a review of the changes in climatic dry condition across the WMZs in Uganda. Research questions were formulated to provide framework on the changes in climatic dry condition. The chapter also describes the purpose and specific objectives of the study including the scope. Further, linkages between rainfall and evapotranspiration trends and variability were presented. This understanding guides the literature search and limit of data acquisition in order to concentrate on information that is useful to attainment of the research objectives.

CHAPTERTWO: LITERATURE REVIEW

2.1 Introduction

Drought can be taken as “a period of abnormally dry weather, sufficiently prolonged for the lack of precipitation, to cause a serious hydrological imbalance” (IPCC, 2007). Drought is more pronounced during precipitation deficit and could be worsened by evapotranspiration. The key drivers of drought conditions in the WMZs are mainly changes in climatic variables and land cover. Change in this case referred to understanding trend and variability of the climatic condition (Mubialiwo et al., 2021).

The goal of this chapter was to evaluate the different methods of conducting trend, variability and correlation analysis to investigate change in dry condition. Assessment of the advantages and limitations of methods, to inform selection of appropriate approaches and models for application were reviewed alongside other methods. Further, review of the methods of dispersion, to characterize climatic conditions, were equally done in this chapter.

2.2 Trends

Trend analysis helps in understanding the changes in temperature, rainfall, river flow of a catchment (Adarsh and Reddy, 2015). It looks at both the slope and direction of the changes in variables over time. This is important because, the predictability of the likelihood of future occurrence in changes in climatic condition can be easily derived. Such certainty further guides planning process in management of catchment water resources (Onyutha, et al., 2021).

2.2.1 Trend magnitude

According to Onyutha (2018), trend magnitude indicates the amount variables changes linearly over a specific time of observed data. Trend magnitude is also known as trend slope.

The trend magnitude (*m*) is can be given by (Theil, 1950) and (Sen, 1968)

$$m_i = \text{Median}\left(\frac{x_j - x_i}{j - i}\right), \text{for } i = 1,2, \dots \dots \dots ., n \tag{2.1}$$

where n is the sample size, while x_j and x_i are data values at time j and i ($j > i$). From equation (1), the significance of m_i is tested, for a no trend, H_0, $m_i = 0$ and alternative, H_1, $m_i \neq 0$ at selected α, adopted as shown by Onyutha (2016c). The estimate of trend slope using Sen's slope is robust (Onyutha, 2016a) and unbiased (Pechlivanidis et al., 2017).

2.2.2 Trend direction

Trend direction indicates the dependence of a variable on time, which can take either positive or negative pattern (Onyutha, 2017). This can be determined in terms of the significance of the non-zero slope at a selected significance level, α_s%. Various non-parametric methods are used to detect trend including the Mann-Kendall (MK) (Mann, 1945, Kendall, 1975), Spearman's Rho (SMR) (Spearman, 1961; Lehmann and D'Abrera, 1975; Sneyers, 1991), the Cumulative Sum of rank Difference (CSD) test (Onyutha, 2016a, c, e).

2.2.3 Significance of trend

The need for significance assessment of trend is because some factors such as noise, affect the sample variation (Onyutha, 2017) in terms of CV. In order to check if a linear increase or decrease is significant, trend tests are carried out by both parametric and non-parametric methods.

2.2.4 Methods for trend analyses

Several methods are used to analyze trends, and include both parametric and non-parametric methods. Non parametric method is normally desired because they deal with ranks of data (Ahmad et al. 2017). However, it can be biased by the effect of autocorrelation. Examples of this method include, MK test (Mann, 1945 and Kendall, 1975), SMR test, CSD test, Theil and Sen's slope method, Sequential Mann-Kendall test (SQMK). While parametric methods suppose a fundamental distribution (generally normal) for the variables of interest. Example of parametric method include Simple Linear Regression test and Regression analysis, Buisehand range test (Buishand, 1982).

2.2.4.1 Mann – Kendall test

The rank based MK test is determines temporary trend in hydro-meteorological data. Among the various methods for trend detection, the MK test is the most commonly applied. This is because it makes use of ranks which is not affected by the requirement of normal distribution (Onyutha, 2016b) and breaks in data due to inhomogeneity do not largely raise its sensitivity (Hossein and Hosseinzadeh, 2011). However, this method may not necessarily be ideal for detecting trend at all times due to serial correlation that it does not consider, (Abeysingha et al., 2016).

The MK test statistic S is given by;

$$\mathrm{S} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right) \tag{2.2}$$

where n, x_j and x_i are as defined for Eq (2.1), and

$$\operatorname{sgn}(\delta) = \begin{cases} 1 \text{ if } \delta > 0 \\ 0 \text{ if } \delta = 0 \\ -1 \text{ if } \delta < 0 \end{cases} \tag{2.3}$$

where $\delta = (x_j - x_i)$

For large samples, where $n > 10$, normal distribution for sampling of S is considered with mean equal zero and variance (Kendall, 1955), given as in equation 2.4.

$$\mathrm{Var}\ (\mathrm{S}) = \frac{n(n-1)(2n+5) - \sum_{k=1}^{tn} t_k(\mathrm{t_k}-1)(2\mathrm{t_k}+5)}{18} \tag{2.4}$$

where tn is the number of tied groups and t_k refers to the number of data points in the k^{th} tied group.

The strength of relationship between variables is measured using Kendall's rank correlation Statistic Z, defined using equation 2.5:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \dfrac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S < 0 \end{cases} \tag{2.5}$$

If the value of $|Z| > Z\alpha/2$, then the null hypothesis of no trend is rejected at α level of significance in a two sided test (i.e. the trend is significant). Positive and negative Z values indicate increasing and decreasing trends, respectively.

2.2.4.2 Spearman's rho test (SMR)

Gauthier, (2001) considered this method as robust and simple test method to use, which does not need any distribution of samples and yet not altered by a few abnormal values. When using the SMR method, for a sample size n greater than 30, Spearman's, r_s statistics will be normal (Sabzevari et al., 2015) and the z statistics is defined by equation 2.6 below.

$$z = r_s\sqrt{n-1} \tag{2.6}$$

The increase and decrease in trend will be indicated by the positive and negative value of z. With |z| value greater than 1.96 as a threshold for 95% Confidence Interval (C.I), the H_0 is rejected, meaning a significant trend is achieved.

2.2.4.3 Linear Regression

This method uses a straight line to fit distribution and test in order to determine if the slope is zero or not. Considering a straight line of the nature $y = \mathrm{a} + \mathrm{b}x,$ the test statistic *t* is calculated and can be tested using student's *t*-test.

Linear regression is normally applied when establishing a relationship between two variables. An increase in trend is usually shown by positive value of the slope and a decrease is indicated by a negative value. The advantage of this method as indicated by Hirsch et al., (1991) is that the test analyzes both slope and intercept.

2.2.4.4 CSD test

CSD test (Onyutha, 2016a,b,c,d) is based on ranks of data. It employs both statistical and graphical analysis of changes in a data set. When you consider dataset X of sample size n, a_i (difference between the exceedance and non-exceedance counts of data points in X) is obtained as a new time series, which replicates X. The CSD statistic K is computed using Onyutha (2016c). To detect long term trend, the trend statistics K, is computed using the equation 2.7 below.

$$\mathrm{K} = \frac{6}{(\mathrm{n}^3 - \mathrm{n})} \sum_{\mathrm{i}=1}^{\mathrm{n}-1} \sum_{\mathrm{j}=1}^{\mathrm{i}} a_{\mathrm{i}} \tag{2.7}$$

where; a_i is based on X and it is computed using (Onyutha, 2016a,b,c)

$$a_i = 2\sum_{j=1}^{n} sgn_1\left(y_j - x_i\right) - \left(n - \sum_{j=1}^{n} sgn_2\left(y_j - x_i\right)\right) \text{ for } i = 1,2,\ldots\ldots,n \quad (2.8)$$

where,

$$sgn_1\left(y_j - x_i\right) = \begin{cases} 1 \text{ if } \left(y_j - x_i\right) > 0 \\ 0 \text{ if } \left(y_j - x_i\right) \leq 0 \end{cases} \quad (2.9)$$

$$sgn_2\left(y_j - x_i\right) = \begin{cases} 1 \text{ if } \left(y_j - x_i\right) = 0 \\ 0 \text{ if } \left(y_j - x_i\right) < 0 \text{ or } \left(y_j - x_i\right) > 0 \end{cases} \quad (2.10)$$

Rank difference a_i is useful in detecting both trend and variability (Onyutha, 2018).

For an increase and decrease in trends, *K* values are reflected in positive and negative, respectively. *K* is normally distributed with mean of zero and variance (V_K) given by (Onyutha, 2016c,d)

$$V_K = \frac{1}{n-1}\left(1 - \frac{10}{17}b^2 - \frac{7}{17}b\right) \quad (2.11)$$

where $sgn_2(y_j - x_i)$ is defined in equation (2.10) and *b* in equation (2.12) below is the measure of ties in the data such that Onyutha, (2016b);

$$b = \frac{-1}{n^2 - n}\left(n - \sum_{i=1}^{n}\sum_{j=1}^{n} sgn_2(y_j - x_i)\right) \quad (2.12)$$

The standardized statistics of the CSD test (Z_{CSD}) is given by equation (2.13). Let $Z\alpha/_2$ denote the standard normal variate at the significance level α%. The H_0 (no trend) is accepted if $|Z| < Z\alpha/_2$, otherwise the H_0 is rejected. The Z_{CSD} is given by

$$Z_{\mathrm{CSD}} = \frac{K}{\sqrt{\beta \times V_K}} \tag{2.13}$$

Where the term β corrects V_K from the effect of persistence in the data. The details of β can be obtained from Onyutha (2016d).

2.2.5 Past studies in Uganda on climatic trends

The MK was applied in several studies in Uganda; for instance in Onyutha et al., (2016); Mubiru et al., (2018); Nsubuga et al., (2013); Kilama Luwa et al., (2021); Owoyesigire et al., (2016); Iwadra et al., (2020); Mugume et al., (2016); Ojara et al., (2020); Mubialiwo et al., (2021) and Mubialiwo et al., (2020).

In Uganda, Mubiru et al. (2018) studied climate trends based on historical rainfall and temperature data from 1938-2012 and used the GenStat Discovery Version 3. The study fitted the trend lines using the linear regression models with GenStat statistical package. The finding established a decline in average annual rainfall trend and normal trend for Hoima and Rakai respectively, from three stations in Uganda.

Nsubuga et al. (2013), analyzed rainfall trend and variability in the mid-twentieth century over south western Uganda using both the MK test and linear regression method. They applied the test at 5% significance level to annual rainfall. The result showed 63% of the stations had a negative trend with 32% being significant.

The MK test was used by Kilama Luwa et al.(2021) in detection of both trends and variability in climate and hydrological series dataset in the Sipi sub-catchment on the slope of Mount Elgon, Uganda. This study used observed rainfall and temperature data from 1981 to 2015, got from the Uganda National and Meteorological Authority (UNMA). The mean, standard deviation (SD) and coefficient of variation (CV) were first analyzed to characterize rainfall and temperature data over the catchment. The MK test was then applied, based on the H_0 (no trend). The trend analysis result revealed an increase in the annual minimum and mean temperature, with direct influence on the evapotranspiration trend. The study also found no significant trend in the rainfall. However, the study recommended more meteorological stations in the catchment to address the limitation in data availability.

Mugume et al. (2016) study on patterns of decadal rainfall variation over a selected region in Lake Victoria basin, Uganda, applied MK trend test to determine intra-seasonal variability using the March-May season. The result showed that trend of the light rain days was increasing with 74% accounting for 2-4 consecutive dry days (CDD), though the trends were all insignificant.

Owoyesigire, Mpairwe and Peden, (2016) study, used MK test to analyze trends in rainfall and temperature. Daily time series data on rainfall and temperature was got from UNMA, covering the period 1961 to 2013. The finding showed a continuous rise in maximum and minimum temperature in Mbarara, Soroti and Masindi stations.

Consecutive dry days (CDD) a measure of extremely dry days with rainfall less than 1mm, indicated a weak declining trend in areas of Mbarara and a significant decrease in the Masindi area. However, there was a strong significant trend in CDD in the Soroti region.

Iwadra et al. (2020) investigated future changes in onset and cessation of rain over the Aswa catchment in Uganda. The study analyzed trends of wet and dry condition using data (2000 – 2016) obtained from Tropical Rainfall Measuring Mission (TRMM) based on a non-parametric Mann – Kendall test. The trend result established a positive simulated future annual rainfall over the Aswa catchment. The classification of standard precipitation index (SPI) based on moderate, severe and extreme condition indicated a declining trend in to the future over the catchment, for all the selected station.

Onyutha, (2016b) analyzed trends in rainfall across Uganda and he used the CSD method. He used daily rainfall data from Princeton Global Forcing (PGFs) (Kalnay et al., 1996) for the period from 1948-2008. The result showed a positive increase in long term rainfall in the southern part of VWMZ, mainly around L. Victoria and south eastern KWMZ. This explains a decrease in dry conditions around these areas. A large part of UNWMZ especially West Nile region was generally characterized with a decline in rainfall, which describes an increase in drought episodes. In the south western Uganda, the extreme rainfall events were characterized by both increase and decrease.

In a study to understand trends in length of dry spells across the Lake Kyoga basin, Ojara et al. (2020) applied the MK test. The study used historical daily observed rainfall data from nine UNMA stations that covered a period from 1963-2017. The study used the direct approach to determine the longest consecutive dry days and defined it as days with rainfall less than 0.85mm (Stern et al., 1982; Barron et al., 2003). The spatial distribution of the longest dry spell was interpolated to raster surface using ArcGIS10.3 software by Kriging interpolation method. The result showed an increase in the maximum dry spell during the March, April and May (MAM) rainy season in five out of the nine stations.

Mubialiwo et al., (2021) analyzed changes in precipitation and evapotranspiration in two catchments of the northeastern part of Uganda. In this study, they adopted the CSD method to test the significance of trend slopes. Mubialiwo et al., (2020) also applied the CSD method while making use of the PGF data. The result by Mubialiwo et al., (2020) showed a positive significant trend in the annual evapotranspiration over the catchment.

2.3 Other studies on trends in the hydro-climate of East Africa

Various studies in East Africa conducted trend analysis using different methods, these include; Langat et al., (2017); Fikru et al., (2017); Ongoma et al., (2019); Ayugi et al. (2020); Ongoma et al. (2018); Rowell et al. (2015); Shiferaw et al. (2014); Gitau et al. (2018) and Cattani et al. (2018).

Over the equatorial East Africa, Gitau et al. (2018) analyzed trends of intra-seasonal descriptors of wet and dry spell from 1962 - 2012 and used a rank based MK test to determine the significance. The statistical test on dry spell descriptors, such as dry days showed increasing trend at both seasonal and monthly time scale. The overall summary of finding was that there were certain locations that have a consistent significance trend signal, which appears at both seasonal and monthly timescale. In the case of Uganda, the study also found the shorter wet spell and longer dry spell throughout the season.

Cattani et al. (2018) applied a non-parametric MK test to analyze the trend of the ETCCDI index time series in evaluation of the presence of significant trends on annual and seasonal scales. The result shows that most area of East Africa is characterized by the shortest dry periods (CDD index), no longer than 40 consecutive days, with standard deviation ranging from 20 – 40%. Generally, the study established that a higher percent standard deviation was associated with the lower ensemble mean values. The result also showed a significant trend in CDD index, with indication of increase around Lake Victoria region.

Ongoma et al., (2019) and Ongoma and Chen (2017) applied the MK test to detect trends in time series of rainfall across East Africa. The result indicated reducing trends in all the extreme rainfall indices (total precipitation, R$\geq 10mm, R \geq 20mm$) over Uganda for the period from 1980 to 2010, mainly attributed to the decrease in rainfall over the region.

2.4 Variability

The World Meteorological Organization (WMO) (2019) defined climate variability as "the changes in the mean state and other statistics of the climate on all temporal and spatial scales, beyond individual weather event". It is used to check alteration of climatic statistics over the time span (e.g. a month, season or year). Variability can be classified as a combination of preferred spatial patterns, for example as modes of climate variability (Wodaje et al., 2016).(Gonzales Amaya, Villazon and Willems, 2018)(Gonzales Amaya, Villazon and Willems, 2018)

2.4.1 Methods for variability analyses

Different methods are available and used in the analysis of variability. These include; Non-parametric Anomaly Indicator Method (NAIM), Quantile Perturbation Method (QPM), Empirical Orthogonal Function (EOF), Auto correlation Spectral Analyses (ASA), the use of Coefficient of Variation (CV), Standard deviation (SD).

2.4.1.1 EOF

The EOF uses the principle analysis component to group time series data. The idea it to extract dominant coherent variations. The problem with the use of EOF may arise, if the structure of the data is interpreted as taking individual dynamical, kinematic, or statistical meaning. Several studies applied EOF methods in their variability analysis. These include, Onyutha and Willems (2017) and Onyutha (2016a).

Onyutha and Willems (2017) applied EOF to analyze rainfall variation in the River Nile basin. The EOF analysis in this study considered space and time as the structure and sampling dimensions, respectively. The complementary sets of structures produced are EOF's and Principle Components (PC), as the structure dimension and time dimension. Both PC's and EOF's are orthogonal in their dimensions. The maximum amount of variance was used to explain the orthogonality (i.e. the lack of correlation in time) that makes the PC's very efficient and suitable for analysis of the variability. To consider the rotation of eigenvectors, the Varimax method was adopted to preserve the orthogonality. It also, provides more physically explainable variability patterns than other methods. The results showed that the variation in EOF loading across the study area suggested differences in variability driving forces at a regional scale.

2.4.1.2 Coefficient of variation (CV)

CV is the ratio of the SD to mean. While analyzing variability, Wei et al., (2016) emphasized the use of CV for its scale invariant properties, compared to the standard deviation or variance. CV is computed from equation 2.14 below.

$$\mathrm{CV} = \frac{\mathrm{SD}}{\overline{\mathrm{X}}} \times 100\% \tag{2.14}$$

Where, SD is standard deviation and $\overline{\mathrm{X}}$ is the sample mean. A result with a greater value of CV indicates larger spatial variability, and vice versa. Key argument advanced for applying CV is that it compares well across different quantities and the measured level of variability does not change in response to a change in the units of measurement. The disadvantage of the Coefficient of Variation (CV) is that its limited to data with non-zero mean, thus standard deviation became a better metric.

2.4.1.3 Autocorrelation Spectral Analyses (ASA)

According to Broersen (2006), between two observations, x_n and x_{n+k} the covariance is given by the equation 2.15.

$$r(k) = \mathrm{cov}(x_n, x_{n+k}) = E[(x_n - \mu)(x_{n+k} - \mu)]\ \forall k \qquad (2.15)$$

The equation above is called the auto covariance function of x_n that measures covariance between pairs at a distance or lag k, for all values of k, making it a function of lag k. The long r(k) function indicates slow data variation and short r(k) indicates no correlation (Broersen, 2006).

2.4.1.4 Quantile Perturbation Method (QPM)

The QPM (Ntegeka and Willems, 2008) can be applied to investigate historical changes in ranked extremes. The method combines frequency and perturbation in extremes (Nyeko-Ogiramoi et al., 2013).

2.4.1.5 CSD

The CSD method produced by Onyutha (2016a, b, c, d) considered two ways of testing for variability, the application of variability statistics and analyses of sub-trends in terms of graphs. Graphical identification of the significance of sub-trends may be subjective. Thus, there is a need for a statistical CSD test for conclusiveness (Onyutha, 2016c). The advantage of CSD method is that it is rank-based.

Statistically, the rank difference, a_i in equation 2.8 can be used to detect both trend and variability (Onyutha, 2018). Assessment of variability can be done by testing the null hypothesis H_0(natural randomness) as presented in the following procedure.

Consider β as the number of times when $a_{i-1} > 0$ and $a_i < 0$ for $2 \leq i \leq n$; γ as the number of times when $a_{i-1} < 0$ and $a_i > 0$ for $2 \leq i \leq n$ and let's take $\delta = \beta + \gamma$ (Onyutha, 2018). The distribution of δ is almost normal with the mean and variance given by $[2^{-1} \times (n-1)]$ and $[4^{-1} \times (n-1)]$, respectively. If the probability (p) value is computed using the z statistics given by $[(n-1)^{-0.5} \times |(1-n+2\delta)|]$ is less than or equal to α, the H_0 is rejected; otherwise H_0 is not rejected (Onyutha, 2018).

2.4.2 Relevant past studies on variability

Several studies analyzed variability in climatic conditions across Uganda. These include; Nyeko-Ogiramoi et al., (2013); Onyuth (2016a); Onyutha et al., (2020); Mubialiwo et al., (2020); Mubialiwo et al., (2021); Kilama Luwa et al. (2021); Onyutha (2015); Onyutha (2018); Egeru et al. (2014) and Nsubuga et al. (2013).

In Nyeko-Ogiramoi et al., (2013), QPM was used to address the concern of the driver(s) which influence variability in hydro-meteorological extremes on selected climate indices. The result indicated that AMO resonate negatively with extremes in rainfall within the L. Victoria basin. The trends of the IOD anomalies indicated strong correlation between rainfall extremes.

In Egeru et al. (2014), climate variability was determined using CV. The result showed the region had high spatial variation in rainfall, estimated at 35%, with both extreme dryness and wetness across the region.

Study conducted by Kilama Luwa et al. (2021) on variability and trends of rainfall, temperature (1981-2015) and river flow (1998-2015) in Sipi sub catchment on the slopes of Mount Elgon in Uganda, assessed variability using the coefficient of variation. Observed rainfall and temperature data was obtained from UNMA. The result indicated an increase in extreme dry events in the post 2000 years compared to pre 2000 period. This seems to indicate that the sub catchment has become prone to the extreme dry condition in the recent years, compared to the past and projects a future with high risk to livelihood.

Mubialiwo et al. (2020) studied variability using non-parametric method that was based on the CSD approach. A gridded (0.25° × 0.25°) Princeton Global Forcing (PGF) data from 1948-2016 was used for its high spatial and temporal resolution. The spatiotemporal variability of rainfall was explained in terms of oscillation highs (OHs), indicating a variable being higher than the long term mean and oscillation lows (OLs), for a variable below the long term mean. The result showed that the entire catchment experienced both insignificant OH and OL with weak frequency fluctuations at the annual level. Similarly, evapotranspiration indicated significant OH in the north and southeast of the catchment.

Nsubuga et al. (2013) analyzed mid twentieth century rainfall trends and variability over southwestern Uganda, specifically AWMZ and VWMZ. Monthly observed rainfall data recorded at 58 stations were obtained from Uganda's Meteorology Department covering 1943-1977. Linear regression method was applied to estimate a value of a function between two unknowns. The study established inter-annual variability of each station using the mean of CV. The result indicated that rainfall did not vary greatly from one year to another with an average of 19%. According to De Luis et al. (2000) and Türkeş (1996) study, areas with CV higher than 30% is likely to have frequent and severe drought and flood.

Mubialiwo et al. (2021) analyzed trends in precipitation over catchments within the KWMZ. The study obtained PGF long term gridded daily precipitation, minimum and maximum temperature data (1948-2016) of high resolution (0.25° × 0.25°) over Lokok and Lokere catchments. Variability was analyzed using the CSD approach. The result showed that the catchments were characteristically different with insignificant variation in time considering the annual time scale. There was significant OL in the northern part, while the rest of the catchments experienced both OL and OH in the June, July and August (JJA) season. The study applied un calibrated empirical Hargreaves method to approximate PET which could have biased the result and thus, recommended use of more than one method in the estimation of PET in a future study.

Onyutha (2016a) applied EOF to daily rainfall extracted from high resolution (0.5° × 0.5°) gridded PGF, covering the period 1948-2008. PGF data has been used in various studies (Zeng and Cai, 2016 and Hoell et al., 2015). The result showed OH in the mid, 1950's, late 1960's, 1990's and early 2000's, while the period around 1970 and late 1980's exhibited OL in terms of temporal variability. Spatially, areas around Lake Victoria, southwestern Uganda and south of KWMZ exhibited positive variation, while areas around Lake Albert and north eastern Uganda, showed negative variation. The study recommended an update of this finding in future using long term observed data when available or if the bias in the rainfall reanalysis datasets reduces tremendously.

Onyutha et al., (2020) computed precipitation variability in terms of sub-trends based standardized trend statistics using CSD approach (Onyutha, 2018). The study used monthly gridded (0.3° × 0.3°) precipitation data of CenTrend v1.0 over the selected period 1961-2015 and daily minimum(T_{min}) and maximum (T_{max}) gridded (0.5° × 0.5°) temperature PGF data that covered the period from 1948-2008, but used 1961 to 2008 for this study. Observed daily and monthly rainfall data from 1961 to 2000 was obtained from UNMA for Bugaya and Ivukula stations. The result showed both precipitation and PET exhibited negative and positive sub-trends in a temporally clustered way. PET varied positively in the early 1960s and 1990s, while a decrease was noted in precipitation over the same period.

Onyutha (2015) determined temporal variability through the nonparametric aggregation of rescaled series in terms of the difference between the exceedance and non exceedance of the data counts based on non-parametric anomaly indicator. Monthly rainfall data covering the period 1901 to 2011 was obtained from the British

Atmospheric Data Centre (BADC). The finding indicated Uganda with above average rainfall in the 1960s to early 1980s, with a significant jump in the Lake Victoria basin in terms of temporal variability.

Ongoma et al. (2016) applied Sequential Mann Kendall to show variability in total precipitation over Uganda and Kenya. The indices considered are wet days($R \geq 1\text{mm}$), annual total precipitation in wet days (PRCPTOT), simple daily intensity index (SDII), heavy precipitation days($R \geq 10\text{mm}$), very heavy precipitation days ($R \geq 20\text{mm}$) and severe precipitation($R \geq 50\text{mm}$). Daily rainfall data was used in the computation of the indices. For Uganda, 12 stations data was obtained from UNMA for the period 1980-2010. The result showed generally an increase in the number of wet days over Uganda. This increase however, was found to be insignificant at 5% significant level in all the stations. The research further established a reduction in a number of heavy rainy days, explaining a possible increase in dry condition across the area. The study recommended undertaking similar research, while utilizing long term observed data to avoid generalization of the outcome of the result found here.

2.5 Computation of potential evapotranspiration

Various methods are used to estimate PET. These include, FAO Penman Monteith (Allen et al., 1998), based on energy mass balance; Thornthwaite (Thornthwaite, 1948); Hamon (Hamon, 1963); Hargreaves-Samani (Hargreaves, 1975; Hargreaves and Samani, 1982; Hargreaves and Samani, 1985) temperature based; empirical methods such as Priestley-Tylor (Priestley and Taylor, 1972); Turc (Turc, 1961) and

Makkink (Makkink, 1957), based on radiation; artificial neural networks (Penman, 1948). Mathematical detail in regards to these methods, refer to Jensen, Burman and Allen (1990); Wright (1985); Federer, Vörösmarty and Fekete (1996); Vörösmarty, Federer and Schloss (1998) and Lu (2002) or citations in the original method.

While FAO Penman-Monteith is widely used to evaluate PET, it requires a lot of variables such as wind speed, solar radiation, relative humidity and many more. Conversely, the Hargreaves method uses only minimum and maximum temperature in the estimation of PET. This makes it easy to use in areas with less data on climate elements and less affected with data from arid or semiarid, un irrigated area than Penman-Monteith method (Hargreaves and Allen, 2003).

In a study on implications of PET methods for stream flow estimations under changing climatic conditions, Seong, Sridhar and Billah (2018) compared five various methods to estimate PET. These included Hamon (Hamon, 1963); Hargreaves (Hargraves and Samani, 1982); Thornthwaite (Thornthwaite, 1948); Priestley-Taylor (Priestley and Taylor, 1972) and Penman-Montieth (Allen et al., 1998). The result established that Hargreaves and Penman-Monteith derived similar values in terms of PET when applied to the Susquehanna watershed across Pennsylvania, New York and Maryland States.

2.6 Validation of datasets

Due to scarcity of data as a result of few meteorological stations, reanalysis data provides opportunity for easy access of daily time scale at each location (Mubialiwo et al., 2020). However, this reanalysis data may not be accurate. For deeper insight in to reliability of analysis based on reanalysis data, there is need for validation of result. Data from a particular ground station is picked and compared with reanalysis data from the same location to determine accuracy of results.

Several studies conducted validation of reanalysis and/or satellite precipitation in Uganda. These include; Mubialiwo et al. (2021); Mubialiwo et al. (2020); Ongoma and Chen (2017); Ongoma et al. (2018); Ongoma et al. (2019) and Ayugi et al. (2020).

Various methods have been used to validate satellite based reanalysis data with observed ground data. For instance Mubialiwo et al. (2021) used correlation coefficient and presented result both statistically and graphically. The H_0 (no correlation) test was applied to test for significance level α of 5%.

Several methods tend to be used for evaluating performance of satellite data such root mean squared error (RMSE), percentage (PBIAS), correlation coefficient (*r*), standard deviation, and model estimation bias (BIAS). One example of a study which applied this methods is Ongoma et al. (2019).

Furthermore, to quantitatively evaluate the data quality of different precipitation products, Wang et al. *(*2020) used statistical evaluation to compare the model's performance amongst reanalysis and simulated precipitation. These methods included correlation coefficient (CC), mean bias error (MBE), and root mean square difference (RMSD).

Other studies on validation of reanalysis data set includes Ayugi et al. (2020) who employed three statistical evaluation techniques to compare model's performance over East Africa. They included CC, RMSD and MBE. The equations for these metrics are shown in equation 2.16.

$$\mathrm{MBE} = \frac{I}{n}\sum_{k-1}^{n}(M_i - O_i) \qquad (2.16)$$

Where *M* and *O* are reanalysis and observed values, respectively.

2.6.1 Methods of quantifying mismatch among datasets

2.6.1.1 Root Mean Squared Error (RMSE)

RMSE is expressed as

$$R\mathrm{SME} = \sqrt{\frac{1}{N}\sum_{k-1}^{N}(M_i - O_i)^2} \qquad (2.17)$$

2.6.1.2 Pearson product-moment correlation coefficient

The formula for *r* can be given by.

$$r = \frac{\sum_{k=1}^{n}(O_i - \bar{O}_1)(M_i - \bar{M}_1)}{\sqrt{\sum_{k-1}^{n}(O_i - \bar{O}_1)^2 \sum_{k-1}^{n}(M_i - \bar{M}_1)^2}} \qquad (2.18)$$

Where R and O are reanalysis and observed values, respectively. i refers to the reanalysis and observed pairs, n is the number of observations of the rainfall.

2.6.1.3 PBIAS

According to Gupta et al., (1999), PBIAS, also termed relative bias (RE) is given by

$$PBAIS(\%) = \frac{\sum_{i=1}^{n}(R_i - O_i)}{\sum_{i=1}^{n} O_i} 100\% \tag{2.19}$$

2.6.1.4 Standard deviation

The standard deviation summarizes the probable distribution in terms of space, which is important in identifying regions with varying variable uncertainty, especially when predicting weather. Variability is important to understand changes in water resources (Nsubuga et al., 2013). The greater the variability, the more expensive and difficult management of water resources becomes.

2.7 Past studies on drought in Uganda

Drought is tends to affect sensitive sectors of the economy, such as production (Najjuma et al., 2021). Several studies have been conducted in Uganda on drought. Some of these studies include; Najjuma et al. (2021); Nakalembe (2018); Mukasa (2020); Twongyirwe et al. (2019); Iwadra et al. (2020); Epule et al.(2017); Nsobya (2019); Lwasa (2018); Bernard et al. (2013): Damalie et al., (2017); Mfitumukiza, Barasa and Ntale (2017); Nkuba et al. (2020); Alex, Jesse and Neoline (2019); Hassan (2019); Kalisa et al. (2020); Jury (2018) and Hao et al. (2021).

For instance, Nakalembe (2018) characterized agricultural drought in the Karamoja using the historical rainfall data (1960-2012) from UNMA to compute SPI at 1, 3, 6, 9 and 12 month time scale. The challenge with use of SPI in the Karamoja region was limited climatic data from the stations. However, the result found out that 1965 was the year the region experienced the worst drought. The study then recommended a continuous assessment of drought while providing detail in order to regulate dissemination of inaccurate information.

Kalisa et al. (2020) analyzed drought using precipitation data set from Climate Research Unit (CRU). The study adopted Haroon, Zhang and Yao (2016) method to compute standardized precipitation index SPI (McKee, Doesken and Kleist, 1993),. The SPI-12 showed a dry spell over the Country from 1920 to 2004 and a much wetter period over the last one and half decade, with considerable decrease in dry and wet period at longer timescale.

Jury (2018) in a study on warm spells on the East African plateau and impacts in the White Nile basin, which included Uganda, used daily maximum temperature reanalysis data from Berkeley and the European Centre for Medium – Range Weather Forecasts (ECMWF). The result indicated a decrease in rainfall-evapotranspiration ratio from $> 100\%$ to $\sim 70\%$ during the study period (2004-2007) with water deficit in the same period. Though the study projected an increase in maximum temperature to $+2℃$ by end of the 21st century, the length of the dry season was expected to reduce.

Hao et al. (2021) used Global Land Data Assimilation System Noah Land Surface Model L4 monthly $0.25° \times 0.25°$ Version 2.1 (GLDAS_NOAH025_M_V2.1) and TRMM for computation of PET and subsequently SPEI respectively. The study estimated SPEI and vegetation condition index (VCI) in assessment of the dry climatic condition on an annual spatial distribution. The finding of an average annual SPEI distribution indicated a very moderate drought behavior in the basin during the study period (2003 -2016).

Najjuma et al. (2021) used Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS) rainfall and Regional Atmospheric Climate Model (RACMO22T) data to analyzed drought in Mubende and Bukomansimbi districts. The historical rainfall observation was provided by CHIRPS with a blend from ground station data (Funk *et al.*, 2015). The observed rainfall data for both districts were obtained for a period of 38 years (1981-2018). The projected monthly rainfall data set was obtained from the model output of version 2.2 of the RACMO22T (Meijgaard et al., 2008), considered a very skillful model over Uganda (Kisembe et al., 2019). The study categorized drought events using a 12-month SPI, based on statistics described by McKee, Doesken and Kleist (1993). The result showed extreme severe drought events from 2004 to 2008 with generally, a slight increase in drought trend in both Bukamansimbi (severe drought, SPI = -1.76 in 2021) and Mubende (extreme drought events, SPI = -2.66in 2026) districts.

Kyatengerwa, Kim and Choi (2020) applied climate reanalysis data (1984 - 2017) from NASA World Wide Energy Resource (POWER) project system to analyze drought across Uganda. The study computed Standardized Evapotranspiration Deficit Index (SEDI) and SPI (for comparison with SEDI) to identify and analyze drought using five time scales (1, 3, 6, 9 and 12 months). The result showed that the central and north western Uganda was likely to become drier, while the north east and south west could become wetter. Notably, areas with negative trend constituted 75% of the Country. Nsubuga et al. (2013) demonstrated that a significant decrease in rainfall was associated with an increase in inter-annual variability within the “dry corridor” of Uganda.

2.7.1 Methods for analysis of drought index

2.7.1.1 Standard Precipitation Index (SPI)

The SPI (McKee et., 1993) it is a tool used for drought monitoring which is based only on rainfall data (Haroon et al., 2016). The index which can have both positive and negative values as a measure of wet and dry conditions, have been statistically described by McKee et al. (1993b) as a deviation from the mean value, normalized by the standard deviation of the entire range of data records. The negative values are normally the focus since they represent the drought events. The weakness of SPI is that precipitation is the only input data and values based on this climatic variable in long-term may change (McKee et., 1993).

2.7.1.2 Standard Precipitation and Evapotranspiration Index (SPEI)

The SPEI is computed using the precipitation and PET to delineate the phases of the anomaly of dry and wet conditions by normalizing the alteration among precipitation (water supply) and evapotranspiration (demand) (Ayugi et al., 2020). Both SPEI and SPI (McKee et al., 1993) are similar, except the SPEI includes PET and employs various schemes to derive the PET. Similar to SPI, a negative value indicate dry condition, while a positive value depict wet condition. For example, the drought events are divided in to four main classes, as; extreme (SPEI≤ -2.00), severe (-1.50 SPEI > SPEI > -1.99), moderate (-1.00 > SPEI > 1.49), and mild (0 > SPEI > -0.99). Similarly, wet events with the same but positive values.

2.7.1.3 Palmer Drought Severity Index (PDSI

PDSI is one of the most used drought indices for monitoring and studying the surface areal extent of drought severity (Yihdego et al., 2019). This index was developed by Wayne Palmer (Palmer, 1965) and it is calculated using precipitation, temperature and soil moisture data. It was largely designed as an agricultural drought index to measure moisture content using water balance equation. PDSI uses temperature, precipitation and soil moisture in its computation.

2.7.1.4 Other methods for analysis of drought indices

Over the years several methods have been developed to analyze drought. Detail of each methods highlighted can be obtained from the references as cited; Drought Severity Index (DSI) (Mu et al., 2013); SNIPE, PALMER. Several studies have indicated that no single drought index (DI) can precisely and comprehensively represent and/or evaluate dry situation (Yihdego et al., 2019). To address this, various studies recommend use of different methods and approaches.

2.8 Chapter summary

The discussion in this chapter draws on the findings of previous studies undertaken in the same field. Review of trends and variability in precipitation and evapotranspiration, as factors that influence change in climatic condition were all investigated under different studies.

CHAPTER THREE: MATERIALS AND METHODS

3.1 Introduction

This chapter provided the context for the study methodology and guidance on the study area, the kind of data that were required for the completion of research and the selection of methods for data analysis.

3.2 Study area and data

3.2.1 Study area

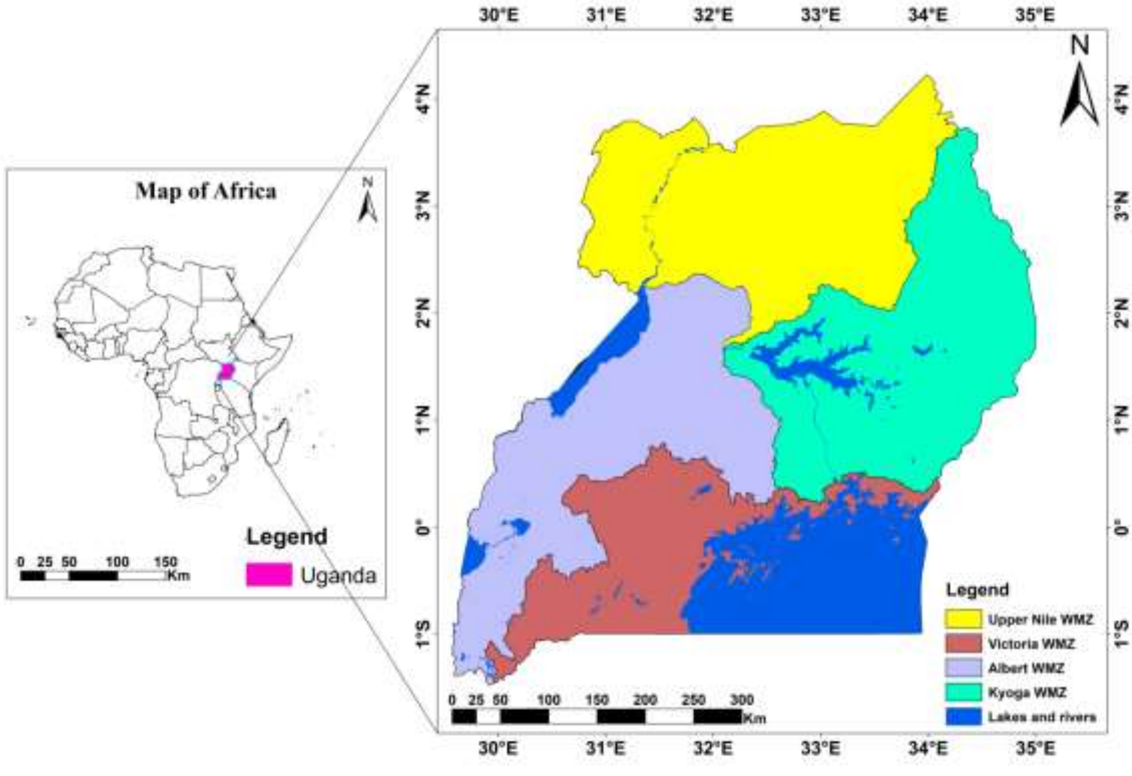

Figure 3.1: Study area map showing the four Water Management Zones of Uganda

Figure 3.1 shows Uganda's location with a total surface area covering 236040 km^2. Hydrologically, the country was delineated in to four WMZs, which include Albert, Victoria, Kyoga and Upper Nile WMZs. Salient features of Uganda's hydrology include the freshwater lakes and rivers with warm tropical climate. The present study was to investigate the changes in climatic dry conditions focused on the four WMZs in Uganda.

3.2.2 Sources of data used in the study

Datasets were got from various. Observed data from selected stations across the WMZs were obtained from Uganda UNMA, for the purpose of the validation exercise.

Table 3. 1: Observed station locations across the WMZs

SNo	Station Name	Station No.	Coordinates (degree)	
			Longitude	Latitude
1	Wadelai Station	873310150	31.40	2.73
2	Gulu Station	87320000	32.28	2.78
3	Masindi Station	88310030	31.72	1.68
4	Kassanda Station	89310080	31.68	0.45
5	Serere Station	88330040	33.45	1.52
6	Soroti Station	88330060	33.62	1.72
7	Masaka Forest Station	90310040	31.73	-0.33
8	Nkozi Experimental Farm Station	90320010	32.02	0.02

3.2.2.1 Precipitation

Gridded high resolution (0.3° x 0.3°) Climate Forecast System Reanalysis (CSFR) precipitation and temperature daily time series data were used in this research study. The gridded data from 437 locations spanned over a period covering the year 1979 – 2013 and was downloaded from https://globalweather.tamu.edu/data/cfsr/.

3.2.2.2 Temperature

Mean daily minimum (T_{min}) and maximum (T_{max}) temperature data from 1979-2013 was obtained from CSFR high resolution (0.3° × 0.3°). This was used in the computation of PET.

3.2.2.3 Potential evapotranspiration (PET)

The study computed PET_0 from T_{min} and T_{max} (1979-2013) using Hargreaves (Hargreaves, 1975; Hargraves and Samani, 1982; Hargreaves and Samani, 1985) method, as presented in the equations 3.1 and 3.2 below.

$$PET = 0.0023R_a[T_{max} + 17.8]T_r^{0.5} \tag{3.1}$$

$$T_r = T_{max} - T_{min} \tag{3.2}$$

Where;

T_{max} = Mean daily maximum temperature (°C)

T_{min} = Mean daily minimum temperature (°C)

T_r = Mean maximum daily temperature minus mean minimum daily temperature, equation 3.2

Ra = Extraterrestrial radiation, which is given by the equation 3.3 below;

$$R_a = 15.392 d_r (w_s sin\emptyset sin\alpha + cos\emptyset cos\alpha sin w_s) \quad (3.3)$$

Where,

R_a = is the water equivalent of extraterrestrial radiation [$mmday^{-1}$]

d_r = the relative distance between the earth and the sun

w_s = the sunset hour angle (radians)

$\emptyset$ = the latitude (rad) of site (+ for Northern Hemisphere, - for Southern Hemisphere)

$\alpha =$ Solar declination angle (rad)

3.2.3 Climate indices

Large-scale ocean-atmosphere condition data (AMO, IOD, Nino3 and QBO) were considered for attribution.

3.2.3.1 Atlantic Multi-decal Oscillation (AMO)

The AMO index is the area weighted average Sea Surface Temperature (SST) of the Atlantic Ocean from latitude 0°N to 70°N (Douglass, 2018). The AMO index values are monthly values of the area weighted SST from the equator to 70°N. The data range from 1856 to the present (Douglass, 2018). The AMO index was downloaded from National Oceanic and Atmospheric Administration (NOAA) (refer to https://www.esrl.noaa.gov/psd/data/timeseries/AMO/) (accessed: 20th February, 2021).

3.2.3.2 Indian Ocean Dipole (IOD)

The IOD index is the climate mode associated with the state of Sea Surface Temperature (SST) over western equatorial and southeastern Indian Ocean. The 1997 IOD mode was greatly associated with severe flood in Eastern Africa and droughts over Indonesia (Li et al., 2003). The observed monthly SST fields covered the tropical IOD (30°S - 30°N, 40° - 110°E) and climatological fields elsewhere. The monthly time series data in this case was accessed online via website of National Oceanic and Atmospheric Administration (NOAA) from 1979 to 2013 via, http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.ERSST/.version4/.IOD/.C 1961-2015/.iod/index.html (20th February, 2021).

3.2.3.3 Niño3

The Niño3 index is a large climate index defined as average Sea Surface Temperature (SST) over the Pacific Ocean. The data were obtained online from http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Nino3/index.html(accessed: 20th February, 2021).

3.2.3.4 Quasi-Biennial Oscillation (QBO)

The Quasi – Biennial Oscillation (QBO) is a meteorological term to specify the equatorial stratospheric oscillation (Maruyama, 1997). The region of the stratosphere is between 17km to nearly 60km over the equator and the QBO is more dominant in the lower tropical stratosphere close to the equator (Baldwin et al., 2001). The QBO was downloaded via https://www.daculaweather.com/4_qbo_index.php (accessed: 20th February, 2021) and covered the period from 1979 – 2013.

3.2.4 Extreme climatic indices

The extreme climatic indices selected for investigation of dry condition across the WMZ's included those of rainfall and evapotranspiration. The rainfall indices considered were NDD1, NDD5, CDD1 and CDD5, while PET indices included, NDPET5, NDPET10, CDPET5, CDPET10, SPETD5 and SPETD10.

NDD and CDD per annum were extracted for rainfall less than 1mm (NDD1 and CDD1) and 5mm (NDD5 and CDD5). NDD1 and NDD5 explain a characteristic condition of extreme dryness. Similarly, CDD explain an accumulated precipitation of less than a given threshold (1mm and 5mm) over a specified period. It is a good index that indicates a risk of inadequate water supply especially in an irrigation area. In this case, an annual time scope was considered for all the rainfall and PET indices. The lower thresholds (1 and 5 mm/d) were selected to characterize dryness over the catchment in a defined period of time. This is because dry condition reduces water availability for crop yields for instance and other demand in the catchment.

The PET indices (NDPET, CDPET and SPETD) indicate the dominant loss of water within a particular catchment and describe the limitation of water availability. In this case, a predetermined threshold $(PET < 5\, mm/d\ and\ 10\, mm/d)$ was set for each indices.

3.3 Research design

The study used a quantitative method in investigating changes in climatic dry condition across the WMZs. Analysis adopted a descriptive approach to establish the relationship between multi-decadal co-variability in extreme climatic indices with changes in large- scale ocean-atmosphere conditions. In the detection of changes in the extreme climatic indices and characterization of climatic conditions, the study used both statistical and graphical techniques to analyze changes in trend and variability as described in Figure 3.2.

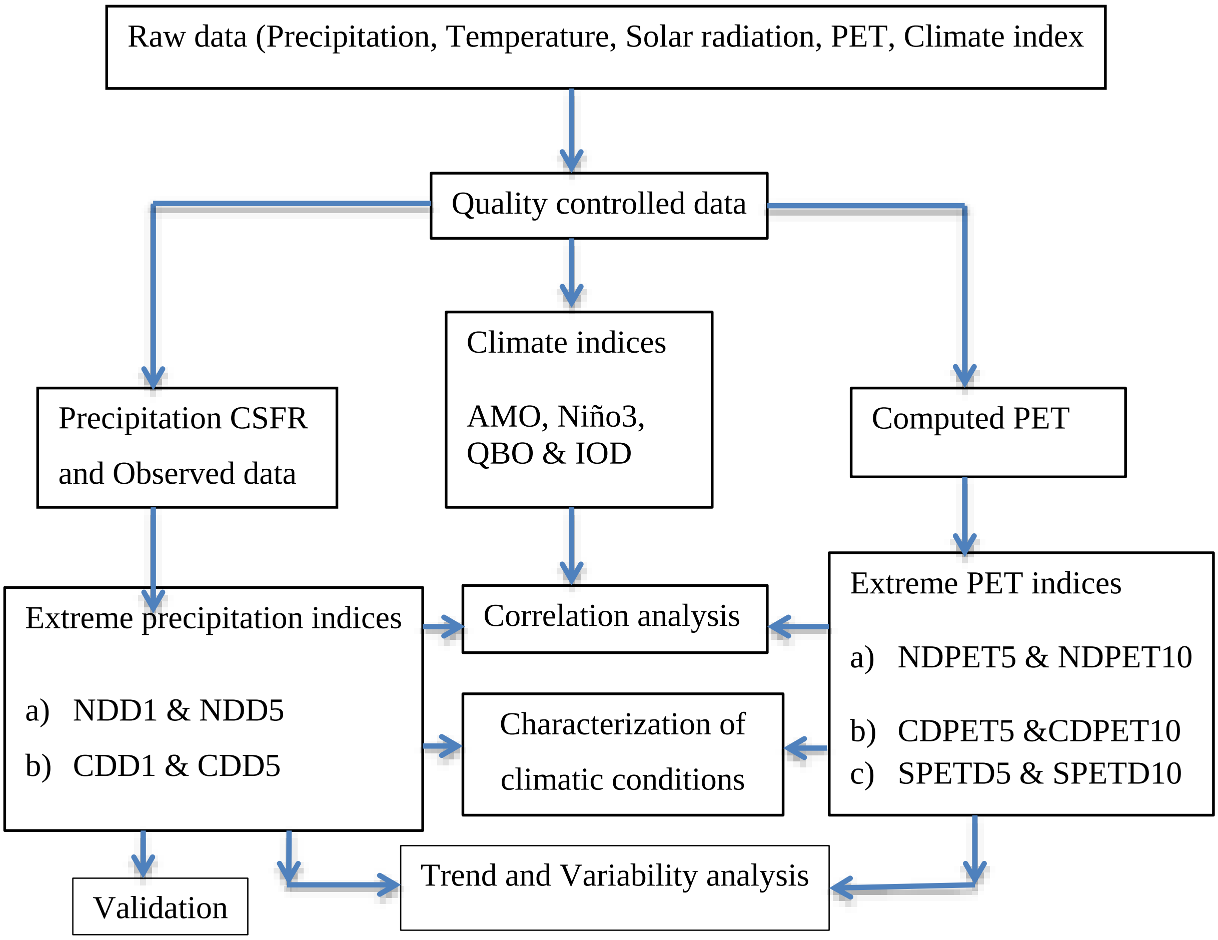

Figure 3.2: Methodological framework

3.4 Research Approach

The study used quantitative research approach to analyze the changes in climatic indices in terms of trend direction and slope and the variability across the WMZs. Correlation of large-scale ocean-atmosphere condition with the indices was also considered in this approach.

3.5 Methods

3.5.1 Analysis of trend

Trend slope (m) was computed using Theil, (1950) and Sen, (1968). The significance of m was assessed by testing the H_0 (no trend) using CSD method (Onyutha, 2021). For a given dataset X of sample size n, X was re-scaled into series d_x (equation 3.4) in terms of

$$d_{x,j} = n - w_{x,j} - 2t_{x,i} \text{ for } 1 \leq i \leq n \quad (3.4)$$

where, $t_{x,i}$ denotes the number of times the i^{th} observation exceeds other data points in X . In the same line, $w_{x,i}$ refers to number of times the i^{th} data point appears within X. The trend statistic T was computed using equation 3.5 below.

$$T = \sum_{j=1}^{n} \sum_{i=1}^{j} e_{x,i} \quad (3.5)$$

The mean of T is zero and for large n the distribution of T is approximately normal with the variance of T given by Onyutha, (2021) in equation 3.6 below.

$$V\left(T\right)=\frac{n\left(n^{2}-1\right)}{12}. \qquad (3.6)$$

For data which follow the fractional Gaussian noise, $V(T)$ taking into account the correction from the effect of persistence, can be denoted as $V^{c}\left(T\right)$ such that the computation is performed using equation 3.7.

$$V^{c}\left(T\right)=V\left(T\right)\times\gamma\times n^{\eta} \qquad (3.7)$$

Where, γ and η are computed using equation 3.8 and 3.9 below;

$$\gamma=1.4784H_{Est}^{4}+0.5094H_{Est}^{3}-3.9455H_{Est}^{2}+0.8312H_{Est}+1.4174 \qquad (3.8)$$

$$\eta=-0.4512H_{Est}^{4}-0.4057H_{Est}^{3}+1.9193H_{Est}^{2}+4.237H_{Est}-0.6144 \qquad (3.9)$$

and H_{Est} is the sample scaling. The standardized test statistic Z is given by Onyutha (2021) in equation 3.10 below.

$$Z=\frac{T}{\sqrt{V^{c}\left(T\right)}} \qquad (3.10)$$

Consider $Z_{\alpha/2}$ as the standard normal variate at the selected α. The H_0 (no trend) is rejected for $\left|Z\right|>\left|Z_{\alpha/2}\right|$. Otherwise the H_0 is not rejected at α. In this study, α was taken as 0.05. This method can be found implemented in a tool called CSD-VAT (Onyutha, 2021) which is available via https://sites.google.com/site/conyutha/tools-to-download (accessed: 25th April, 2021). The trend test was applied to the extreme climatic index at each grid point. A result of the trends across the various WMZs was obtained through spatial interpolation in ArcGIS 10.1 version.

3.5.2 Variability analysis

Variability was analyzed by testing the H_0 (natural randomness) in each extreme climatic index. For dataset *X*, with a subset *x* from the a^{th} to the b^{th} value of *X*, a standardized trend statistic Z based on time slice moved from the beginning to the end of the series was computed in an overlapping way. For a selected *t*, i considered another term $\phi = 0.5\times(t+1)$ and $\phi = 0.5\times t$ in cases where *t* is odd and even, respectively. Sub-trends were computed using in equation 3.11 below.

$$Z_j^{(t)} = f\left(x \subset X \mid x_a \le x \le x_b\right) \quad \text{for } j = 1,\ 2,\ ....,\ n \tag{3.11}$$

Where;

Z_j is the j^{th} value of *Z*, and the terms *a* and *b* are all based on *j* and can be given by equation 3.12 below.

$$\left.\begin{array}{l} \text{if } j < \phi, \quad a = 1, \ \ b = t + j - \phi - 1 \\ \text{if } j \ge \phi \text{ and } j \le (n-\phi), \quad a = j - \phi + 1, \ \ b = j + \phi \\ \text{if } j > (n-\phi) \text{ and } j \le n, \ \ a = j - \phi + 1, \ \ b = n \end{array}\right\} \tag{3.12}$$

To test the H_0 (natural randomness), $100(1-\alpha)\%$ confidence interval limits (CILs) on the variability was constructed using $\pm Z_{\alpha/2}$ after plotting Z_j against the corresponding j^{th} data year. The H_0 (natural randomness) was rejected for values of Z outside the CILs. Otherwise, the H_0 (natural randomness) was not rejected.

3.5.3 Correlation analysis

The relationship between variation in large-scale ocean-atmosphere indicators (AMO, Niño 3, IOD, and QBO) and the extracted extreme precipitation and PET indices included NDD1, NDD5, CDD1, CDD5, NDPET5, NDPET10, CDPET5, CDPET10, SPETD5 and SPETD10 were obtained using correlation analysis. The indices were extracted from the daily time series and converted on annual basis. The large-scale Ocean-atmosphere condition represented by the climate indices (AMO, IOD, Niño3 and QBO) were obtained online and converted also into annual time series for the equivalent study period of 35 years.

Computation of sub-trends was executed using 35-year time scale from precipitation and PET. The H_0 (no correlation) was tested for coefficient of correlation and if the computed value was outside the critical value of the Pearson correlation, the H_0 (no correlation) was not rejected at the selected α; otherwise, the H_0 (no correlation) was rejected. A two-tailed hypothesis test was used with a critical correlation value at α = 0.05 as 0.27.

3.5.4 Characterization of climatic condition

In this study, the annual mean and standard deviation of the extracted rainfall and evapotranspiration indices were selected to characterize climatic condition based on the extreme climatic indices through spatial interpolation in ArcGIS 10.1 version. The mean and standard deviation were computed based on the long term precipitation and temperature (for calculation of PET) obtained from gridded CFSR high resolution data records. In doing so, i was able to understand the characteristic dryness of areas and their distribution across the WMZs.

3.5.5 Extraction of extreme climatic indices

This was achieved through identification of indices for precipitation and evapotranspiration that included NDD1, NDD5, CDD1, CDD5, NDPET5, NDPET10, CDPET5, CDPET10, SPETD5 and SPETD10. The extraction of these indices from 35 years data series were executed using MATLAB software. The indices extracted were to diagnose the dry condition of the WMZs in Uganda.

Table 3.2: Considered indices

S/N	Extreme precipitation and PET indices	Notation
1.	Maximum consecutive dry days with rainfall <1mm	CDD1
2.	Maximum consecutive dry days with rainfall <5mm	CDD5
3.	Number of dry days with rainfall < 1mm	NDD1
4.	Number of dry days with rainfall < 5mm	NDD5
5.	Number of days with potential evapotranspiration >5mm	NDPET5

S/N	Extreme precipitation and PET indices	Notation
6.	Number of days with potential evapotranspiration >10mm	NDPET10
7.	Maximum number of consecutive days with PET >5mm	CDPET5
8.	Maximum number of consecutive days with PET >10mm	CDPET10
9.	Sum of PET for days with PET >5mm	SPETD5
10.	Sum of PET for days with PET >10mm	SPETD10

3.6 Validation of extreme precipitation indices

Extreme precipitation indices extracted from the high resolution gridded CFSR daily data was validated (using data from eight stations) with those obtained from ground based dataset. This was executed using the method applied in recent studies by Mubialiwo et al., (2021), Ngoma et al. (2021) and Onyutha et al. (2021). Due to the missing daily records in some stations during 1979-2013, the validation periods were reduced to cover the period from 1979 to 2009 for all stations. Two methods of RSME and Pearson product-moment correlation coefficient (r) in equations 2.17 and 2.18, respectively, were used to validate the two datasets.

Many research studies employed these metrics to evaluate performance of time series datasets of climate variables (Ayugi et al., 2020; Ngoma et al., 2021). The similarities of the two datasets were statistically compared.

3.7 Ethics

The research was conducted with strict observance of the University guidelines. Data acquisition followed the required procedure of the source providers and recognition of authors as referenced in this report eliminated plagiarism.

3.8 Chapter summary

This chapter presented the geographical extent of the study area including data sources for the study, methods and analytical tools. Different methods and techniques for data collection and analysis were used. The next chapter presents the results based on analysis conducted using methods identified in this chapter.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Introduction

The results from the research are presented under this chapter, in line with set specific objectives. Results are also discussed in this section.

4.2 Characteristics of extreme climatic conditions

4.2.1 Long – term mean climatic conditions

Figure 4.1 indicates the annual mean of the extreme climatic indices across the four WMZs. NDD1 showed high long term mean in the north east (Karamoja) of the country, a region known for its aridity and North West of AWMZ (Figure 4.1a). Similarly, as the threshold was increased from 1mm to 5mm, the spatial area with high mean values of NDD5 also increased, covering the Albertine rift and north eastern region (Figure 4.1b). Karamoja and north east of the study area showed high mean of both CDD1 and CDD5 (Figure 4.1c, d). However, areas around Mt Rwenzori, Mt Elgon, Mt Mufumbira and south of Lake Kyoga showed low mean for both NDD1 and NDD5 respectively (Figure 4.1a, b). Low mean values for both CDD1 and CDD5 concentrated more to the east of AWMZ, southern KWMZ, north east of VWMZ, and Mt Rwenzori region (Figure 4.1c, d). Nearly the entire country exhibited high mean values for NDPET5 (Figure 4.1e), except for Lake Victoria, that showed low mean for both NDPET5 and NDPET10 (Figure 4.1e, f). The low mean value of NDPET in L. Victoria was attributed to lack of contribution from land surface evaporation and plant transpiration. With increased threshold from 5mm to

10mm (Figure 4.1f), the area having high mean values of NDPET10 were confined to northern part of Mt Elgon and Albertine rift. Similarly, Figure 4.1g & h, indicated Karamoja and Albertine rift region as having the highest mean for both CDPET5 and CDPET10. As in (Figure 4.1e, f), Lake Victoria showed low mean values of CDPET (Figure 4.1g, h). High mean values for SPETD5, were observed in Albertine rift up to west Nile, north east of the country (Figure 4.1i). Generally, KWMZ exhibited the highest mean values of NDD1, NDD5, CDD5, NDPET10, CDPET5, CDPET10, SPETD5 and SPETD10 followed by UNWMZ (Table 4.1). This shows that KWMZ is characteristically, drier than all the other WMZs. This result agrees with Onyutha, et al., (2021) study, that showed UNWMZ and KWMZ were characterized with high PET, especially in the north eastern part of the KWMZ. With such result, scarcity of water could be a threat to agricultural productivity. Sustainable measures are required to conserve water for various use in the WMZs. VWMZ showed lowest long term average values of NDD1, CDD1, NDPET5, CDPET5, CDPET10, SPETD5 and SPETD10 (Table 4.1).

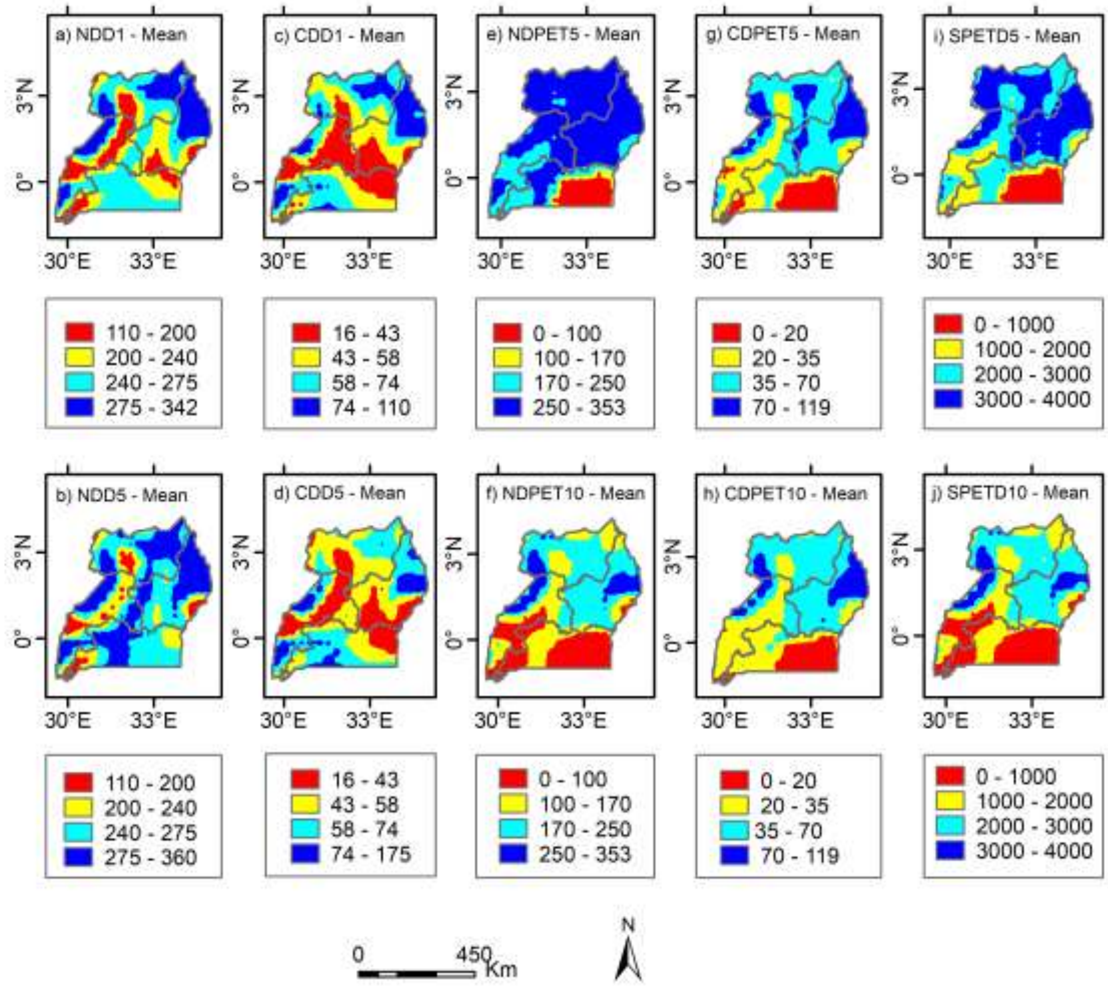

Figure 4.1: Mean a) NDD1, b) NDD5, c) CDD1, d) CDD5, e) NDPET5, f) NDPET10, g) CDPET5, h) CDPET10, i) SPETD5, j) SPETD10.

Table 4.1: Average values of extreme climatic indices across the four WMZs.

WMZ	NDD1 (days/yr)	NDD5 (days/yr)	CDD1 (days/yr)	CDD5 (days/yr)	NDPET5 (days/yr)	NDPET10 (days/yr)	CDPET5 (days/yr)	CDPET10 (days/yr)	SPETD5 (mm/yr)	SPETD10 (mm/yr)
AWMZ	237	**94**	52	94	298	72	55	9	2540	851
KWMZ	**254**	**317**	59	**95**	323	**95**	**74**	**13**	**2878**	**1116**
UNWMZ	253	312	**61**	**92**	**326**	90	67	12	2850	1059
VWMZ	**233**	307	**49**	94	**179**	**24**	**28**	**4**	**1402**	**263**

Bold values indicate the highest and lowest mean across the WMZs.

4.2.2 Long – term mean of spatial variation

Figure 4.2 shows annual standard deviation of the extreme climatic indices across the four WMZs. High spatial variation around long term mean of NDD1 was noticed in central and southern part of the country (Figure 4.2a). This presents a situation of uncertainty in predictive planning for water resources management. Coincidentally, this area exhibited low mean values (Figure 4.1a). However, Karamoja, Lake Victoria and Albertine rift region showed low deviation (Figure 4.2a, b). This is because of the influence of single PET (evaporation) variable contributing to changes in PET indices due to less vegetated land and open water surfaces in the region. Low deviation was noticeable in the north and central part of the country, with the south projecting high values for both CDD1 and CDD5 (Figure 4.2c, d) respectively. There were low standard deviations in NDPET5 values for UNWMZ, KWMZ and L. Victoria (Figure 4.2e). Noticeably, higher standard deviation around Mt. Elgon and Albertine rift region were observed, with increase in threshold from 5 to 10 (Figure 4.2f). Almost the entire country, except L. Victoria, exhibited higher standard deviation values of CDPET5 (Figure 4.2g). This contrasted with Figure 4.2h, when the threshold was increased from 5 to 10, where the entire study area showed low deviation. The highest deviation of SPETD5 values (Figure 4.2i) was confined to the north of Lake Albert and south western Uganda. With the increase in the threshold from 5 to 10, Karamoja and Albertine rift region exhibited higher deviation and Lake Victoria, the lowest standard deviation (Figure 4.2j).

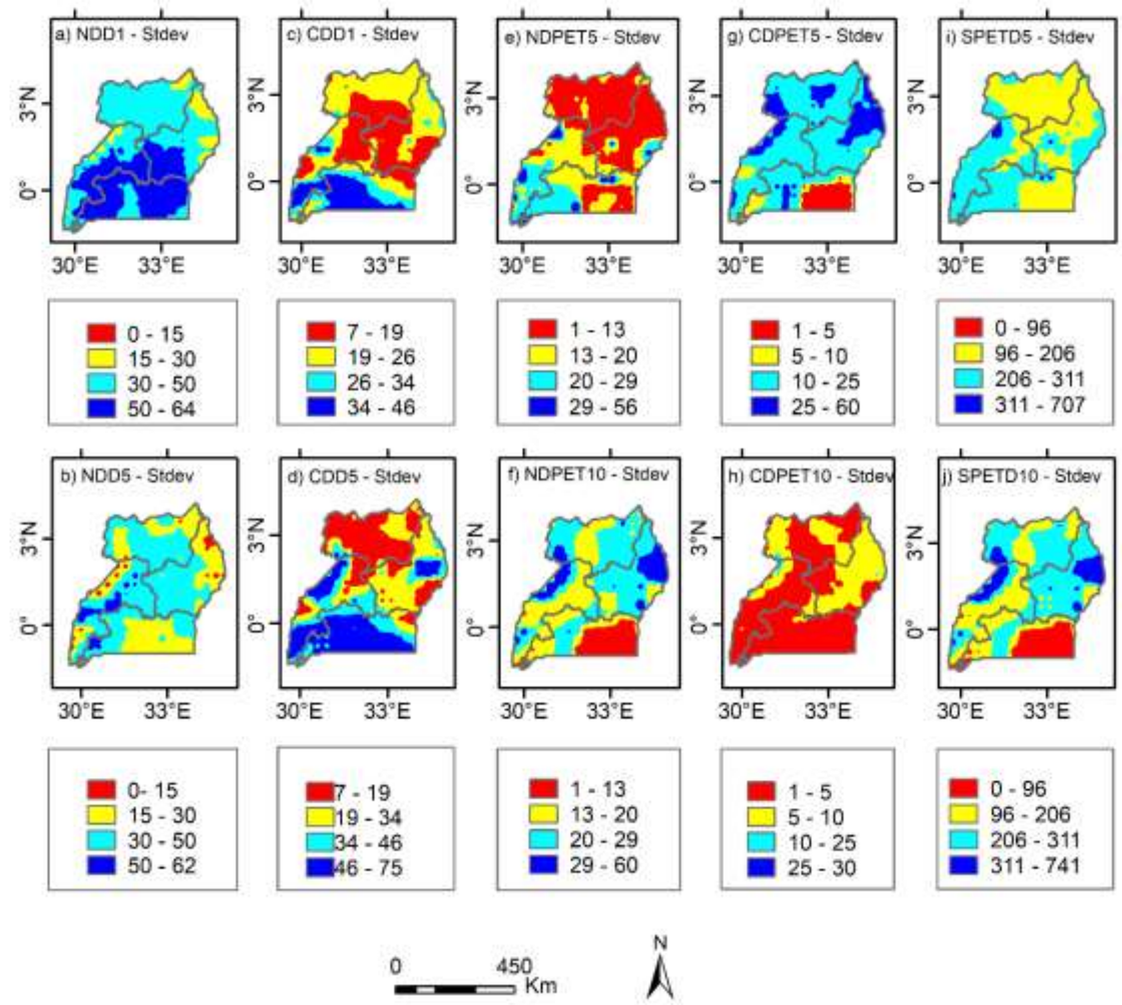

Figure 4.2: Standard deviation (Stdev) a) NDD1, b) NDD5, c) CDD1, d) CDD5, e) NDPET5, f) NDPET10, g) CDPET5, h) CDPET10, i) SPETD5, j) SPETD10.

Climatic indices for rainfall (NDD1, CDD1 and CDD5) are highly varied in VWMZ, except for NDD5 (AWMZ) and this is contrary to PET indices (Table 4.2). UNWMZ exhibited the lowest variability in precipitation indices under study and SPETD5 (Table 4.2). Generally, KWMZ showed high variability in PET indices (Table 4.2).

Table 4.2: Average standard deviation of extreme climatic indices across the WMZs.

WMZs	**NDD1 (days/year)**	**NDD5 (days/year)**	**CDD1 (days/year)**	**CDD5 (days/year)**	**NDPET5 (days/year)**	**NDPET10 (days/year)**	**CDPET5 (days/year)**	**CDPET10 (days/year)**	**SPETD5 (mm/year)**	**SPETD10 (mm/year)**
AWMZ	47	**38**	23	40	**19**	18	19	4	**229**	220
KWMZ	42	32	**20**	32	12	**22**	**23**	**6**	184	**265**
UNWMZ	**39**	**31**	**20**	**26**	**10**	19	22	5	**162**	235
VWMZ	**52**	33	**30**	**45**	18	**10**	**12**	**2**	177	**109**

Bold values indicate both high and low average standard deviations across the WMZs.

4.2.3 Trends

Figure 4.3 indicates statistical annual trend slope of the extreme climatic indices across the four WMZs. Positive trend in both NDD1 and NDD5 were observed in the Karamoja and Albertine rift region, and the area expanse increased as the threshold was increased from 1mm to 5mm (Figure 4.3a, b). Similarly, CDD1 and CDD5 showed positive trend variation in UNWMZ as the threshold was increased (Figure 4.3c, d). This result compares well with Egeru et al., (2017) study in Agago sub catchment within UNWMZ, that established increasing drought severity in the recent past (after 1990s) despite low intensity. However, the remaining study area showed negative trend. Much of central part of the country and south east of KWMZ experienced positive trend compared to the rest of the country that exhibited negative trend (Figure 4.3c). With increased threshold from 5mm to 10mm (Figure 4.3d), area with positive trend was reduced to south east of KWMZ and North West of the country. Both NDPET5 and NDPET10 showed positive trend in south east of KWMZ, north east and negative trend for the remaining study area (Figure 4.3e, f). Generally, KWMZ experienced a decline in rainfall indices, though a positive trend in PET indices with higher threshold (Table 4.3). The extreme rainfall indices result agreed Obubu et al., (2021) study, that showed that the zone was climatically wetter (1981-2010). Though this finding agrees with rainfall indices, the contrary result of PET indices, contradicts the wet condition indicated in Obubu et al., (2021), though this can be attributed by increase in maximum temperature as per previous study (Obubu *et al.*, 2021). However, study by Onyutha et al., (2020) showed reduction in precipitation (1960-2000) in KWMZ, which can be linked to the positive trend in extreme PET indices. CDPET5 (Figure 4.3g) generally exhibited positive trend in the entire study area. With further increase in the threshold from 5mm to 10mm, VWMZ and AWMZ showed negative trend in CDPET10 (Figure 4.3h). Almost, half of the country in the western direction showed negative trend in SPETD5 (Figure 4.3i) and positive trend in the eastern direction. The spatial extent of positive trend increased westward when the threshold was increased from 5mm to 10mm (Figure 4.3j) respectively.

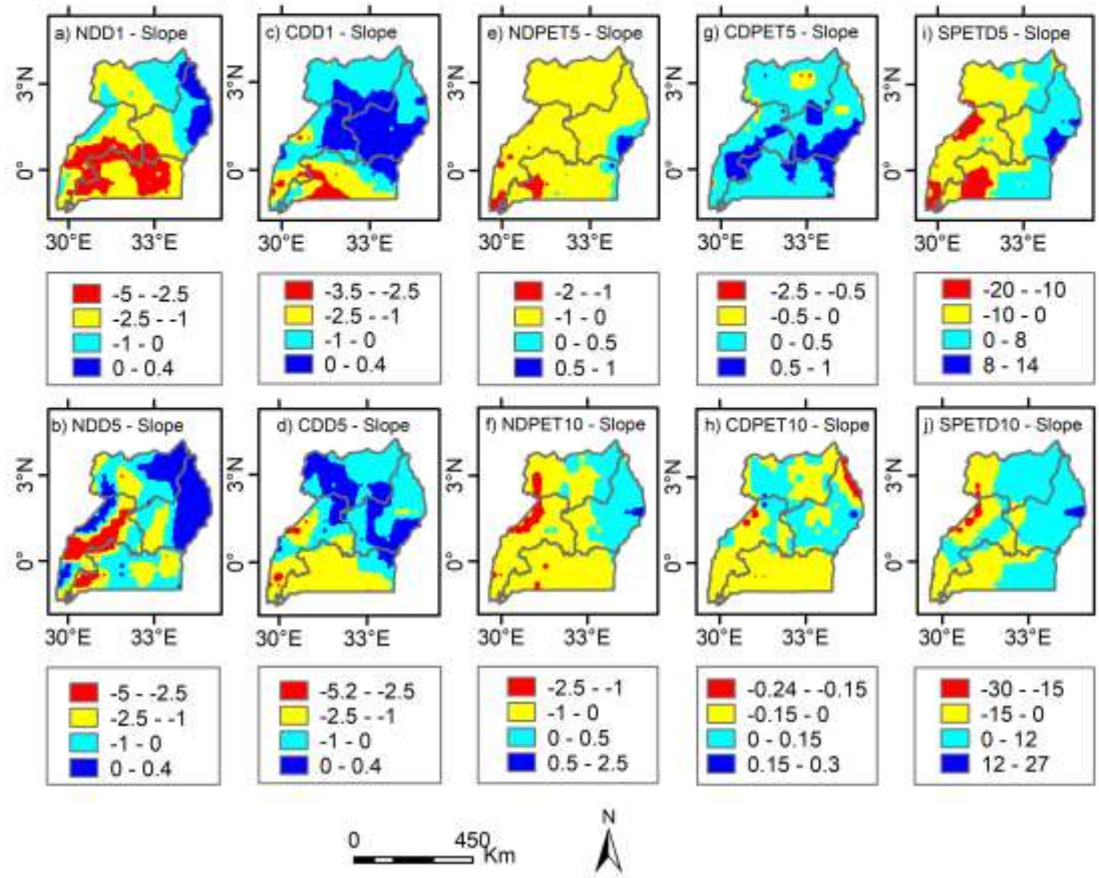

Figure 4.3: Trend Slope a) NDD1, b) NDD5, c) CDD1, d) CDD5, e) NDPET5, f) NDPET10, g) CDPET5, h) CDPET10, i) SPETD5, j) SPETD10.

Table 4.3: Average trend slope of climatic indices in each WMZ.

WMZs	NDD1 (day/year)	NDD5 (day/year)	CDD1 (day/year)	CDD5 (day/year)	NDPET5 (day/year)	NDPET10 (day/year)	CDPET5 (day/year)	CDPET10 (day/year)	SPETD5 (mm/year)	SPETD10 (mm/year)
AWMZ	**-3.35**	**-2.26**	-1.15	**-2.41**	-0.88	-0.42	-0.22	0.01	**-8.54**	**-4.93**
VWMZ	**-3.76**	**-2.02**	-1.69	**-2.85**	-0.57	-0.27	-0.12	-0.01	**-6.34**	**-2.89**
UNWMZ	**-2.22**	-1.45	-0.96	-1.24	-0.57	-0.12	-0.57	0.03	**-4.59**	-1.25
KWMZ	**-2.01**	-1.16	-0.56	-1.33	-0.21	0.36	-0.21	0.03	0.2	**4.33**

The bold values indicate that the trend was significant.

Figure 4.4 shows statistical annual trend direction of extreme climatic indices across the WMZs and the $Z_{\alpha/2}$ (1.95) value for significance ($p < 0.05$) of the trend was selected at α = 0.05. Figure 4.4a – e exhibited negative trend direction for all the extreme rainfall indices and NDPET5. In this case, the indices explain the spatial variation in drought severity, which was significant($p = 0.05$) in UNWMZ (Table 4.4). This finding agrees with Kalisa et al., (2020) on decreasing drought in northern Uganda, which is part of UNWMZ. With increased threshold in PET indices, from 5mm to 10mm, UNWMZ and KWMZ showed an increase in spatial extent of positive trend (Figure 4.4f, g, h, I, j). This increase indicates that the regions moisture condition increased in AWMZ and VWMZ more than other zones, though with insignificant magnitude (Table 4.4). The loss in moisture is associated with drought episode.

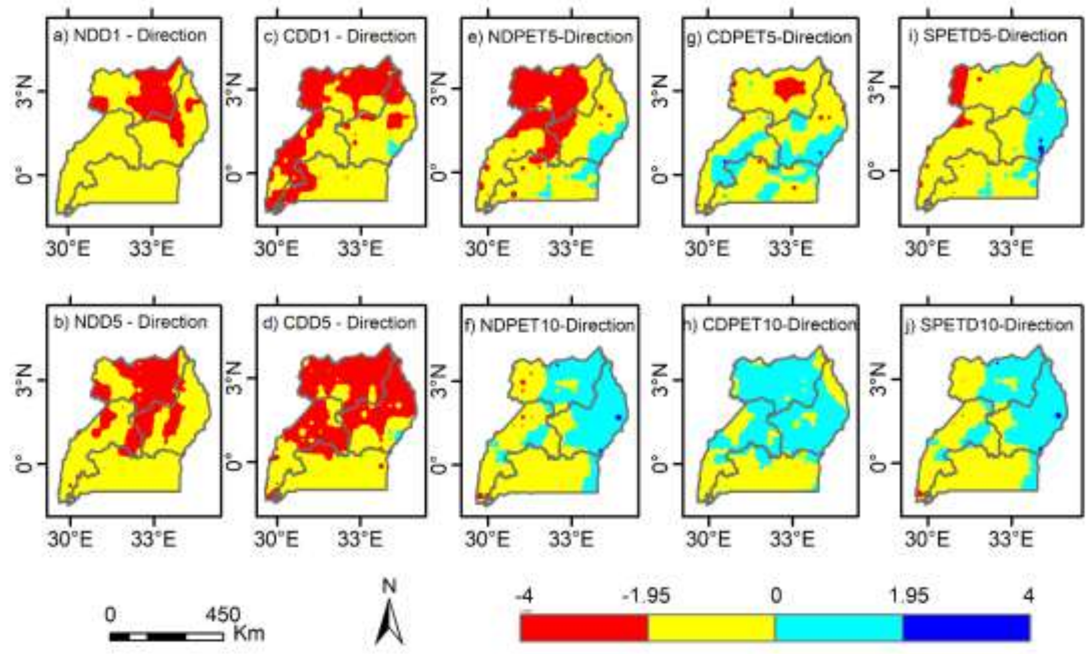

Figure 4.4: Trend directions a) NDD1, b) NDD5, c) CDD1, d) CDD5, e) NDPET5, f) NDPET10, g) CDPET5, h) CDPET10, i) SPETD5, j) SPETD10.

Generally, all the climatic indices showed negative trend across the four WMZs, except for NDPET10 (KWMZ), CDPET10 (AWMZ, KWMZ and UNWMZ), SPETD5 and SPETD10 (KWMZ) (Table 4.4). With Z value standardized at 1.95, UNWMZ exhibited significant ($p < 0.05$), negative trend in all the rainfall indices and NDPET5 (Table 4.4). Related to this, the study exhibited significant ($p < 0.05$) negative trend in AWMZ and KWMZ (Table 4.4).

Table 4.4: Average trend direction of the extreme climatic indices across the WMZs.

WMZ	**NDD1 (Z)**	**NDD5 (Z)**	**CDD1 (Z)**	**CDD5 (Z)**	**NDPET5 (Z)**	**NDPET10 (Z)**	**CDPET5 (Z)**	**CDPET10 (Z)**	**SPETD5 (Z)**	**SPETD10 (Z)**
AWMZ	-1.60	-1.83	-1.84	**-2.03**	-1.84	-0.72	-0.30	0.11	-1.48	-0.65
KWMZ	-1.64	-1.74	-1.50	**-1.97**	-1.06	0.61	-0.34	0.45	0.05	0.63
UNWMZ	**-2.00**	**-2.10**	**-2.02**	**-2.28**	**-2.20**	-0.08	-1.28	0.53	-1.08	-0.02
VWMZ	-1.50	-1.56	-1.77	-1.64	-1.01	-0.64	-0.32	-0.26	-0.92	-0.62

4.2.4 Variability

Figure 4.5 shows annual variability of extreme climatic indices (both rainfall and PET) across the VWMZ. Considering the periods at the beginning and end of the data (Table 4.5), the entire VWMZ was characterized by mainly positive and negative sub-trends. In this case, H_0 (natural randomness) was rejected ($p < 0.05$) for CDD1, CDD5, NDD1, NDD5 (Figure 4.5a-d) with significant oscillation low (OL). Both CDPET5 and CDPET10 (Figure 4.5e, f) were characterized by weak amplitude of the oscillation in a temporal pattern. This provides certainty in defining predictive measures on coping mechanism to cumulative impact of loss of moisture. However, this finding does not agree with previous study by Najjuma et al., (2021) that showed extreme and severe drought variation from 2004 to 2008 in Mubende and Bukomansimbi Districts within VWMZ. This is simply because of the small area considered under this study with very short time window that may not infer relatively on VWMZ. In this case, the H_0 (natural randomness) was not rejected($p < 0.05$), for the extreme PET indices CDPET5, CDPET10, NDPET5, NDPET10, SPETD5, AND SPETD10 (Figure 4.5e-j). The compiled oscillation lows and highs in the extreme climatic indices averaged over the Victoria WMZ can be found in Table 4.5.

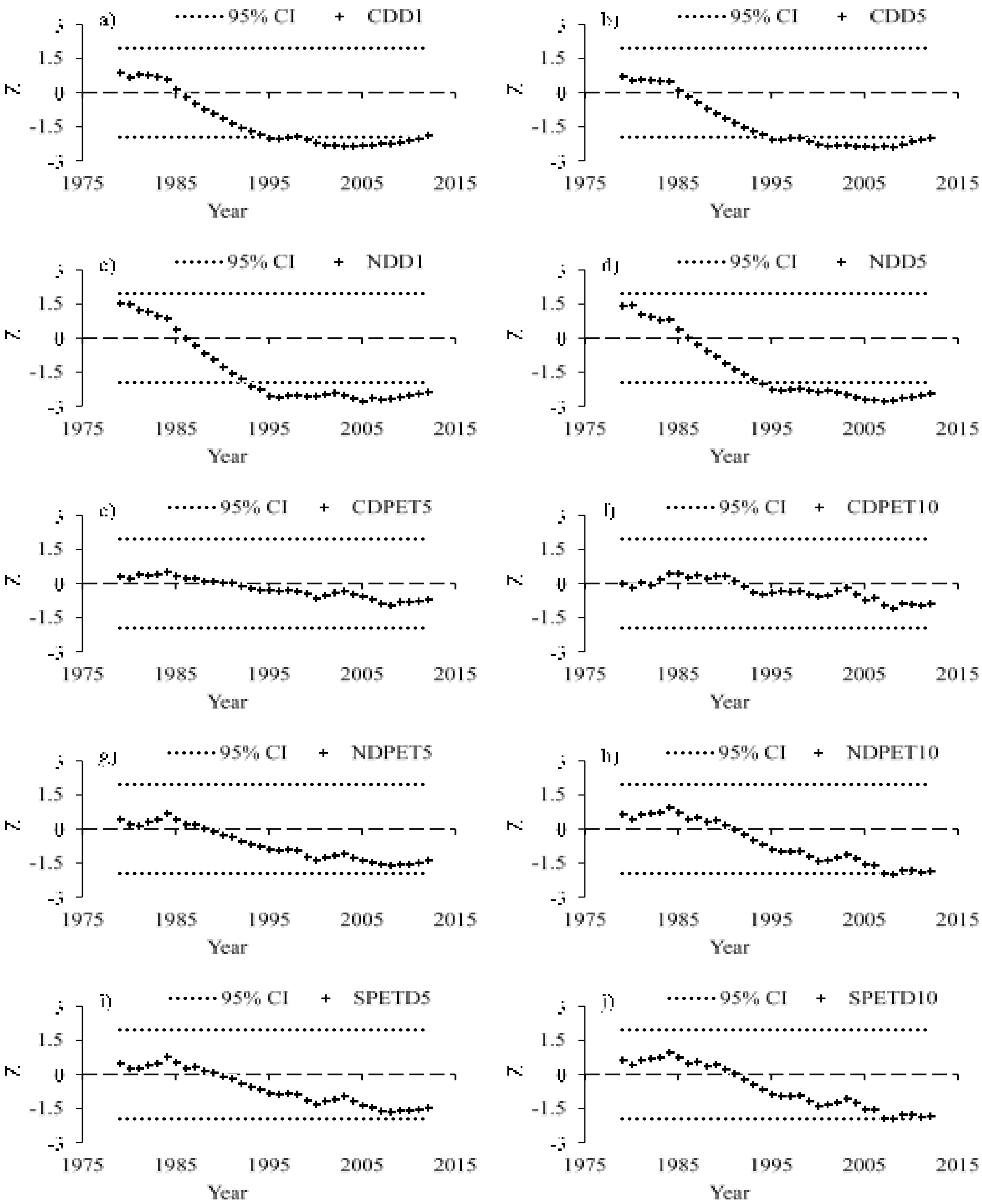

Figure 4.5: Variability in climatic indices in VWMZ a) CDD1, b) CDD5, c) NDD1, d) NDD5, e) CDPET5, f) CDPET10, g) NDPET5, h) NDPET10, i) SPETD5, j) SPETD10 annual time scale.

Table 4.5: Variability of climatic indices in VWMZ.

Extreme climatic indices	Period	
	Positive sub trend	**Negative sub trend**
CDD1	1979-1985	1986-2013
CDD5	1979-1985	1986-2013
NDD1	1979-1986	1987-2013
NDD5	1979-1986	1987-2013
CDPET5	1979-1991	1992-2013
CDPET10	1979-1991	1992-2013
NDPET5	1979-1989	1990-2013
NDPET10	1979-1991	1992-2013
SPETD5	1979-1989	1990-2013
SPETD10	1979-1991	1992-2013

Figure 4.6 shows annual variability of extreme climatic indices across the AWMZ (Figure 4.6). Given the selection of α as 0.05, the $Z\alpha/_2 = 1.95$ and the entire period of data was characterized by both high and low oscillations, respectively (Table 4.1). For instance, NDD1 showed positive and negative sub-trends from 1979 to 1985 and 1986 to 2013, respectively (Figure 4.6c). Considering the oscillation low, H_0 (natural randomness) was rejected ($p < 0.05$) for NDD1 and NDD5 (Figure 4.6c, d) with significant decline from 1986 to 2013 (Figure 4.6c, d). The H_0 (natural randomness) was not rejected ($p > 0.05$) for the remaining extreme climatic indices including CDD1, CDD5, CDPET5, CDPET10, NDPET5, NDPET10, SPETD5, and SPETD10

(Figure 4.6a, b and e-j). This shows that the variability around the long term mean of these indices except for NDD1 and NDD5 is weak, as such, it is less difficult to manage the drought scenarios since the extreme can be easily predictable. Table 4.6 shows the epochs of both negative and positive sub-trends of the extreme climatic indices averaged over the AWMZ.

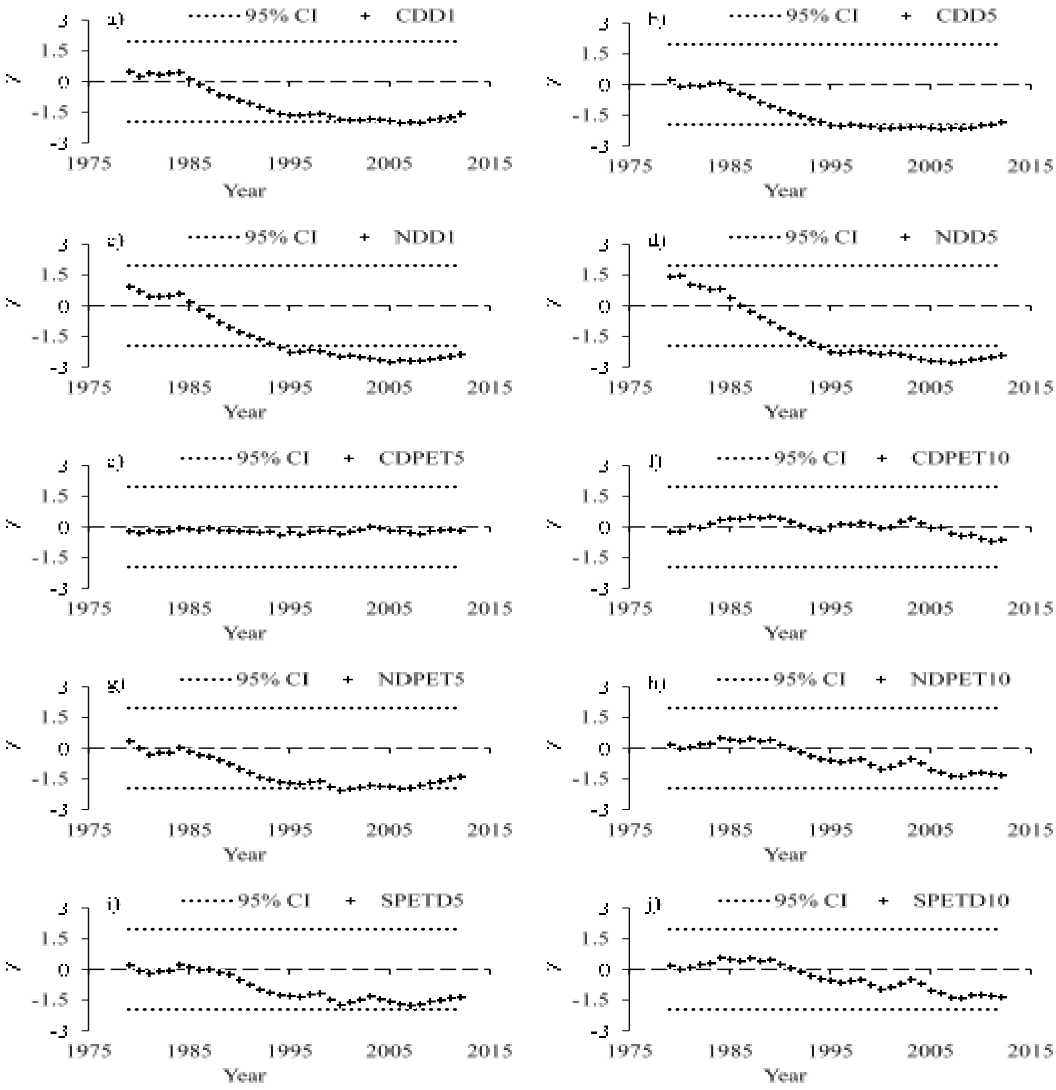

Figure 4.6: Variability in climatic indices in AWMZ a) CDD1, b) CDD5, c) NDD1, d) NDD5, e) CDPET5, f) CDPET10, g) NDPET5, h) NDPET10, i) SPETD5, j) SPETD10 annual time scale.

Table 4.6: Variability of climatic indices in AWMZ.

Extreme climatic indices	Period	
	Positive sub trend	**Negative sub trend**
CDD1	1979-1985	1986-2013
CDD5	1979-1984	1985-2013
NDD1	1979-1985	1986-2013
NDD5	1979-1986	1987-2013
CDPET5		**1979-2013**
CDPET10	1981-2006	1979-1980, 2007-2013
NDPET5	1979-1980	1981-2013,
NDPET10	1979-1991	1992-2013
SPETD5	1979-1987	1988-2013
SPETD10	1979-1992	1993-2013

Figure 4.7 shows annual variability of extreme climatic indices across the KWMZ. The variation in the amplitude of extreme PET indices was mainly positive for CDPET10, NDPET10 and SPETD10 (Figure 4.7f, h, j). The increased loss of moisture evident during this period, contribute to climatic dry condition. Onyutha et al., (2020) study, draws similarity with this result, where there was observed decrease in annual precipitation from 1961 to 2000. The temporal variation for the

period after 2000, Table 4.7 further indicate positive sub-trend in these indices up to 2013. Generally, the periods from the beginning and end of the showed both positive and negative sub-trends. For instance, NDD1 exhibited positive and negative sub-trends from 1979 to 1986 and 1987 to 2013, respectively (Figure 4.7c). Following this oscillation, H_0 (natural randomness) was rejected ($p < 0.05$) for NDD1 and NDD5 (Figure 4.7c, d). Relatedly, H_0 (natural randomness) was not rejected ($p > 0.05$) for the remaining extreme climatic indices including CDD1, CDD5, CDPET5, CDPET10, NDPET5, NDPET10, SPETD5 and SPETD10 (Figure 4.7a, b and e-j). Table 4.7 shows epochs over the study period where positive and negative sub-trends occurred in the extreme climatic indices averaged over the KWMZ.

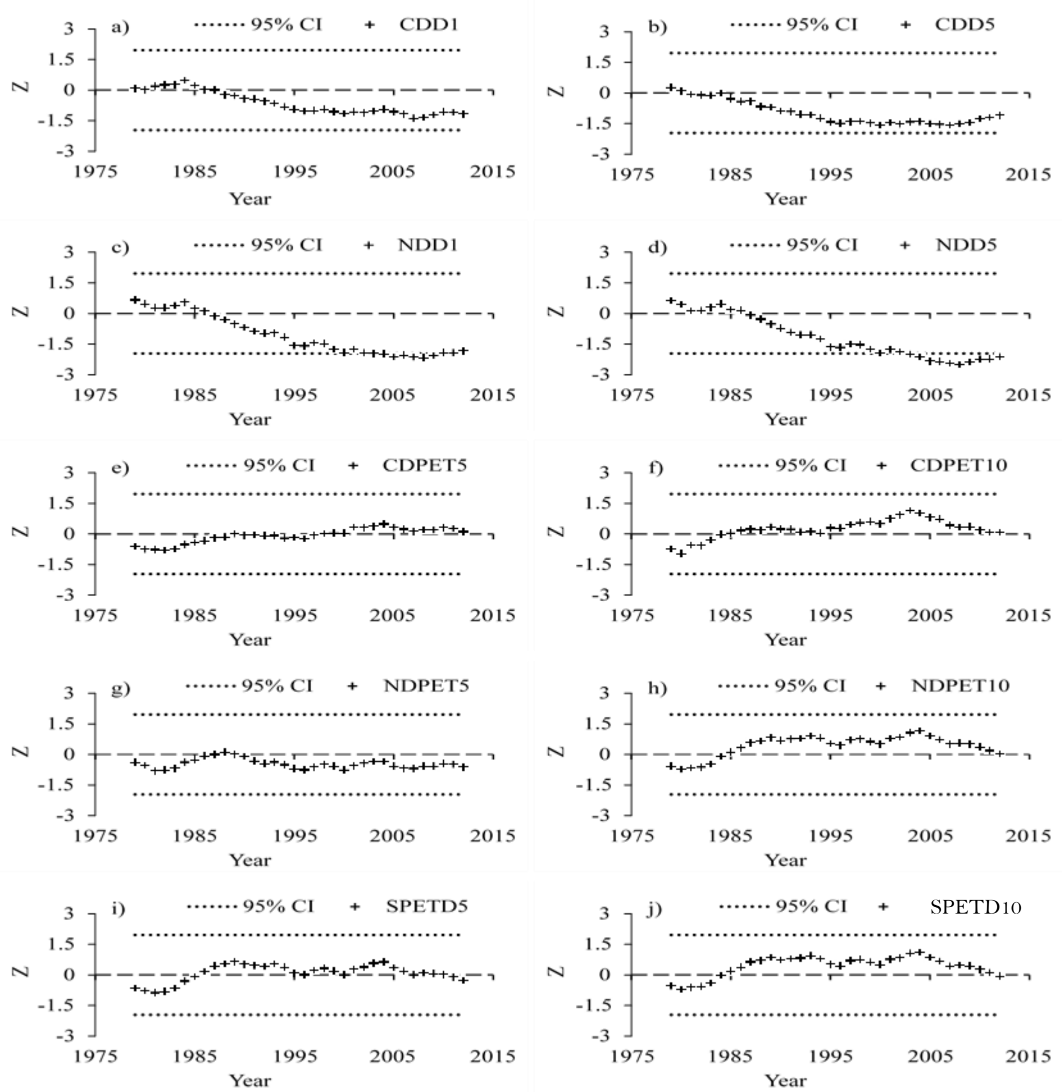

Figure 4.7: Variability in climatic indices in KWMZ a) CDD1, b) CDD5, c) NDD1, d) NDD5, e) CDPET5, f) CDPET10, g) NDPET5, h) NDPET10, i) SPETD5, j) SPETD10 annual time scale.

Table 4.7: Variability of climatic indices in KWMZ.

Extreme climatic indices	Period	
	Positive sub trend	**Negative sub trend**
CDD1	1979-1987	1988-2013
CDD5	1979-1984	1985-2013
NDD1	1979-1986	1987-2013
NDD5	1979-1986	1987-2013
CDPET5	2000-2013	1979-1999
CDPET10	1985-2013	1979-1984
NDPET5		**1979-2013**
NDPET10	1985-2013	1979-1984
SPETD5	1986-2010	1979-1985, 2011-2013
SPETD10	1985-2013	1979-1984

Figure 4.8 shows annual variability of extreme climatic indices across Upper Nile WMZ. The periods at the beginning and end of the data for both rainfall and PET indices were characterized by negative sub-trend in almost the entire zone, except for CDPET10 (1984-2010), NDPET10 (1986-1993, 1996-2000) and SPETD10 (1985-1994, 1997-2006) were positive sub-trend was observed (Table 4.8). For instance, NDPET5 exhibited negative sub-trends over the entire period 1979-2013 (Figure 4.8g). Considering this variability, H_0 (natural randomness) was rejected ($p < 0.05$) for NDD1 and NDD5 (Figure 4.8c, d). Similarly, H_0 was not rejected ($p > 0.05$) for the remaining extreme climatic indices including CDD1, CDD5, CDPET5,

CDPET10, NDPET5, NDPET10, SPETD5, and SPETD10 (Figure 4.8a, b and e-j). This result shows that the region have been wetter in recent years than before. Table 4.8 shows epochs of oscillation lows and highs of the extreme climatic indices averaged over the UNWMZ.

Table 4.8: Variability of climatic indices in UNWMZ.

Extreme climatic indices	**Period**	
	Positive sub trend	**Negative sub trend**
CDD1	Nil	**1979-2013**
CDD5	Nil	**1979-2013**
NDD1	Nil	**1979-2013**
NDD5	Nil	**1979-2013**
CDPET5	Nil	**1979-2013**
CDPET10	1984-2010	1979-1983, 2011-2013
NDPET5	Nil	**1979-2013**
NDPET10	1986-1993, 1996-2005	1979-1985, 1994-1995, 2006-2013
SPETD5	Nil	**1979-2013**
SPETD10	1985-1994, 1997-2006	1979-1984,1995-1996, 2007-2013

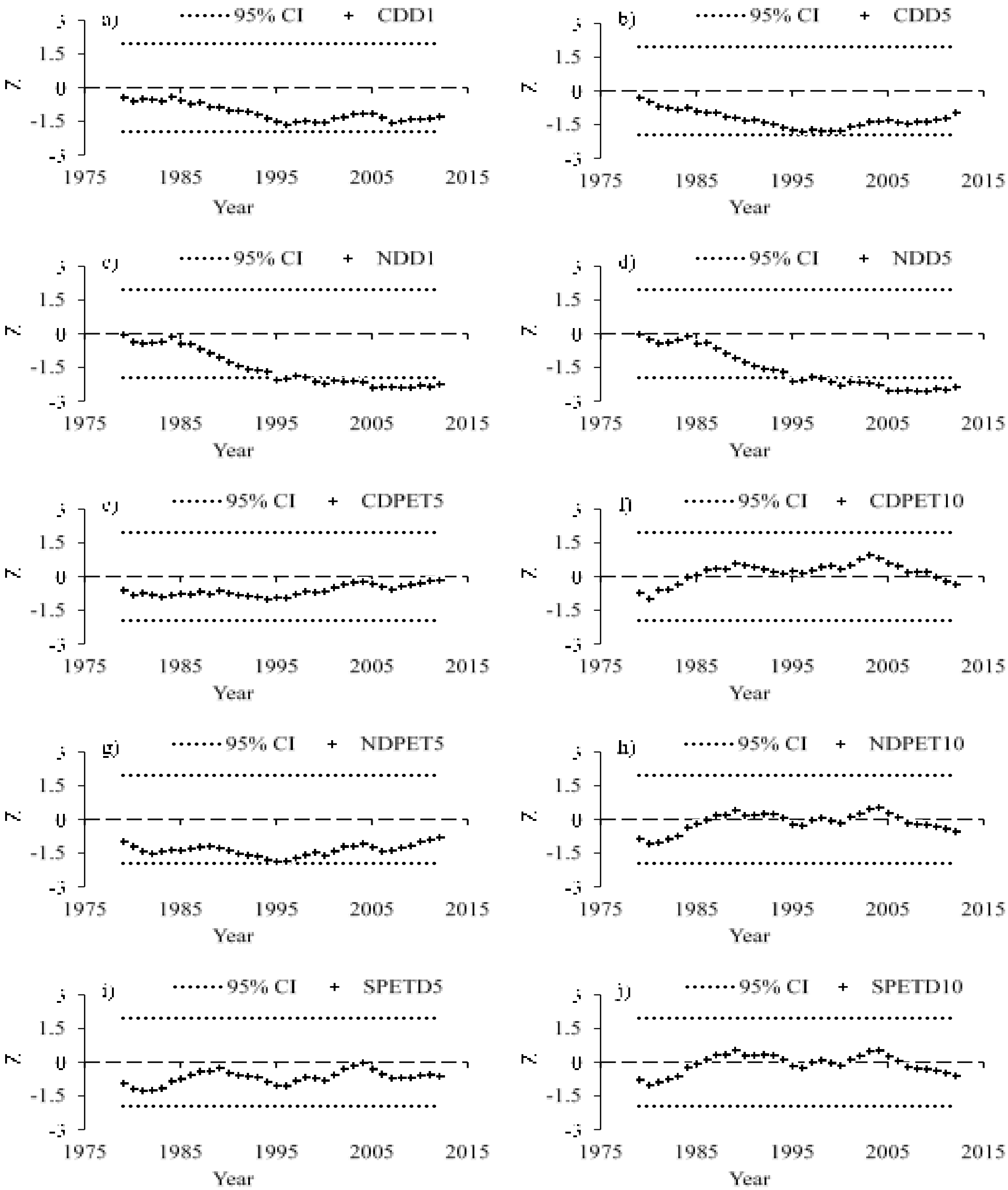

Figure 4.8: Variability in climatic indices in UNWMZ a) CDD1, b) CDD5, c) NDD1, d) NDD5, e) CDPET5, f) CDPET10, g) NDPET5, h) NDPET10, i) SPETD5, j) SPETD10 annual time scale.

4.3 Correlation analysis

Figure 4.9 shows linkages of rainfall climatic indices (NDD1 and NDD5) with large-scale ocean-atmosphere conditions. The legend in Figure 4.9 was standardized to indicate significance to different levels, with critical correlation value at $\alpha = 0.05$, as 0.27. AMO negatively correlated with both NDD1 (Figure 4.9a) and NDD5 (Figure 4.9e), almost across entire country, except in the northeastern. However, the correlation was significant over VWMZ (for NDD1) and southernmost part of the Albert WMZ (Table 4.9). Noticeably, the area with correlation ranging from -0.27 to zero is larger for NDD1 than that of NDD5 (Figure 4.9a, e). This is because of the increase in the threshold from 1mm to 5mm. In other words, increasing precipitation threshold from 1mm to 5mm led to a decrease in the area with dry conditions. Thus, AMO is more correlated with wet than dry condition. Generally, IOD showed significant ($p < 0.05$) negative correlation with both NDD1 and NDD5 in all the WMZs (Table 4.9). Similarly, QBO showed significant ($p < 0.05$) positive correlation with NDD1 and NDD5 across the four WMZs (Table 4.9). However, the variation in NDD1 and NDD5 across the country positively correlated with both Niño3 and QBO (Figure 4.9c-d, g-h).

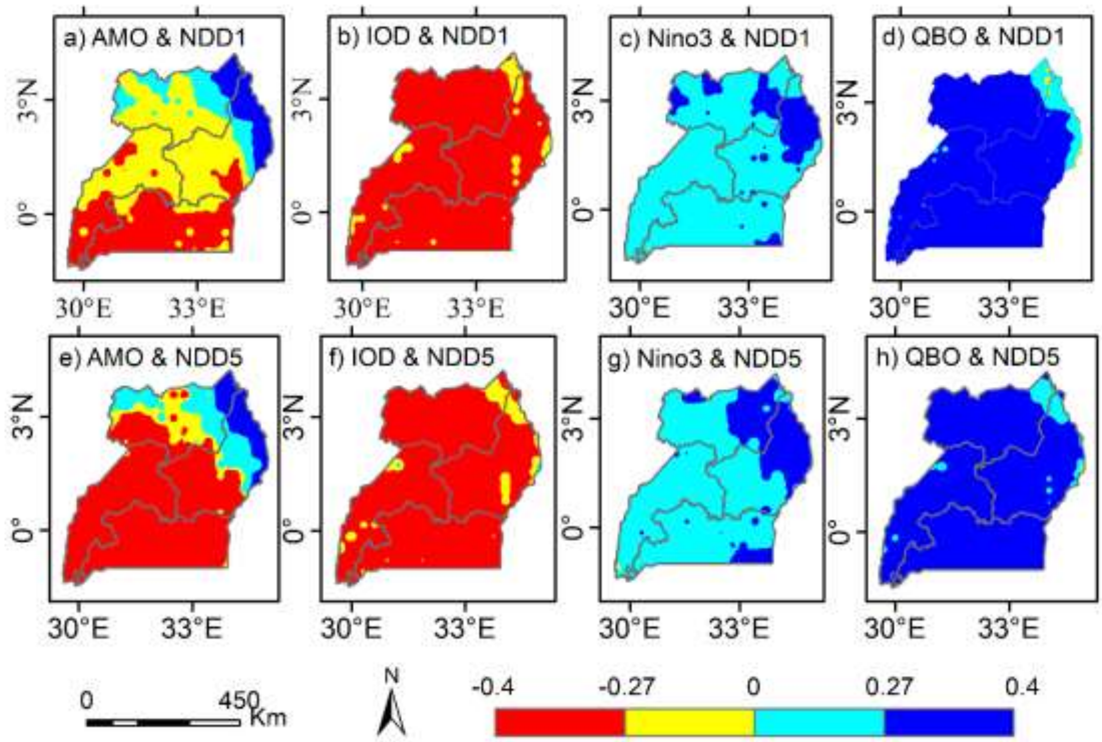

Figure 4.9: Correlation between a) AMO and NDD1, b) IOD and NDD1, c) Niño3 and NDD1, d) QBO and NDD1, e) AMO and NDD5, f) IOD and NDD5, g) Niño3 and NDD5, h) QBO and NDD5.

Table 4.9: Average correlation of NDD1, NDD5 and large-scale ocean-atmosphere conditions across the WMZs.

WMZs	Extreme rainfall indices	AMO	IOD	QBO	Niño3
AWMZ	NDD1	-0.26	**-0.52**	**0.56**	0.17
	NDD5	-0.24	**-0.53**	**0.56**	0.17
VWMZ	NDD1	**-0.33**	**-0.49**	**0.55**	0.19
	NDD5	-0.27	**-0.51**	**0.55**	0.20
KWMZ	NDD1	0.01	**-0.46**	**0.48**	0.25
	NDD5	-0.01	**-0.46**	**0.49**	0.26
UNWMZ	NDD1	0.03	**-0.55**	**0.56**	0.23
	NDD5	0.01	**-0.53**	**0.56**	0.25

Figure 4.10 shows how the climatic indices (CDD1 and CDD5) are correlated with large-scale ocean-atmosphere conditions with critical correlation value computed as 0.27, at $\alpha = 0.05$. Both AMO and IOD negatively correlated with CDD1 and CDD5 in almost all the four WMZs across the entire country (Figure 4.10a, b, e, f), except in the northeastern (Figure 4.10a, b, e, f) part of the country. However, there was significant ($p < 0.05$) negative correlation over VWMZ, for both CDD1 and CDD5 (AMO and IOD); AWMZ for CDD1 and CDD5 (AMO) and CDD5 (IOD); similarly, KWMZ and UWMZ for CDD5 (Table 4.10). Unlike AMO and IOD, Niño3 and QBO positively correlated with CDD1 and CDD5 in the almost all parts of the country (Figure 4.10c, d, g, h). The correlation was significant ($p < 0.05$) between QBO and both CDD1 and CDD5 in AWMZ, CDD1 (VWMZ), CDD5 (KWMZ) and CDD1 (UNWMZ) western part of UNMWZ and KWMZ. It is evident that variations in large scale ocean atmosphere state influenced by QBO, significantly increased

CDD1 and CDD5 in all the zones. This is similar with NDD1 and NDD5 in Table 4.9 above. Therefore, the zones dryness is partly attributed by changes in QBO in all the WMZs. Also observed was that, the area with correlation ranging from 0 to 0.27 was larger between Nino3, CDD1 and CDD5 (Figure 4.10c, g) in AWMZ and VWMZ respectively. QBO also correlated strongly with CDD1 and CDD5 in AWMZ, VWMZ and west Nile with values ranging from 0.27 to 0.4 (Figure 4.10d, h). However, Karamoja and Mount Elgon areas showed negative correlation of CDD1 with QBO (Figure 4.10d). When the threshold was increased from 1mm to 5mm, a change was observed in the same areas to positive (Figure 4.10h). In other words, increasing precipitation threshold from 1mm to 5mm leads to increase in the area with dry conditions. Thus, QBO is more correlated with dry than wet condition (Figure 4.10d, h), while Nino3 with wet than dry condition (Figure 4.10c, g).

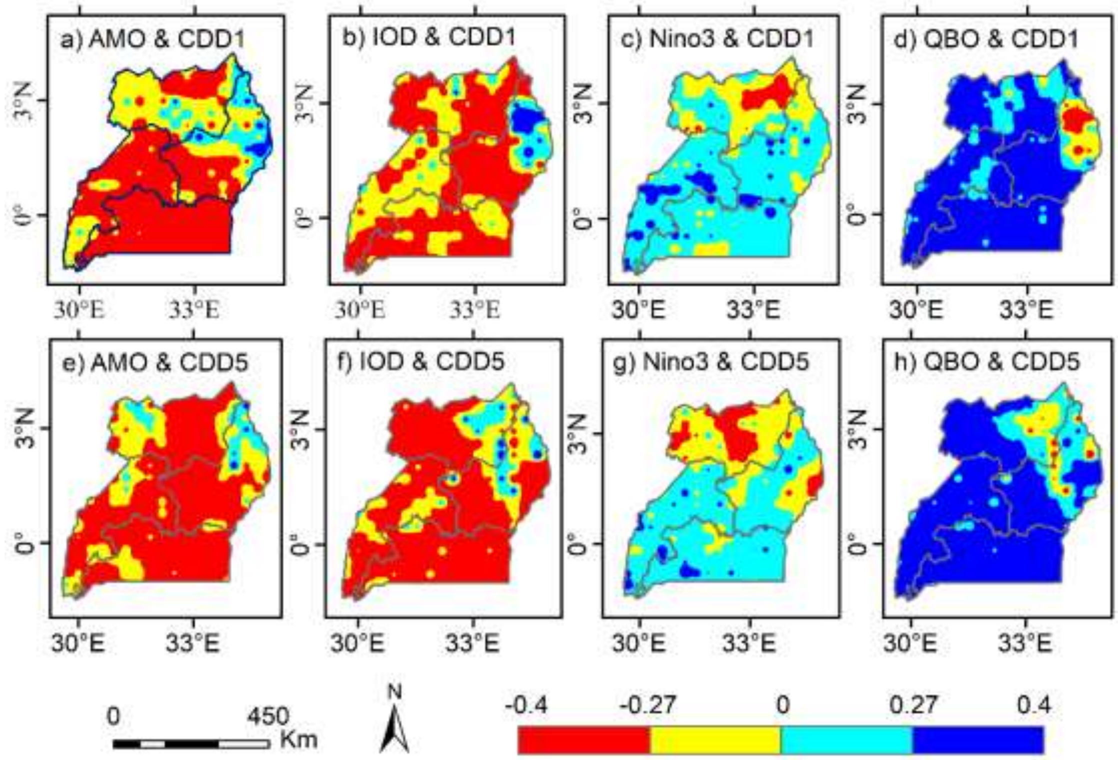

Figure 4.10: Correlation between a) AMO and CDD1, b) IOD and CDD1, c) Niño3 and CDD1 d) QBO and CDD1, e) AMO and CDD5, f) IOD and CDD5, g) Niño3 and CDD5, h) QBO and CDD5.

QBO positively correlated with CDD1 and CDD5 across all the WMZs and more significantly in AWMZ, VWMZ (CDD1), KWMZ (CDD5) and UNWMZ (CDD1) (Table 4.10).

Table 4.10: Average correlation of CDD1, CDD5 and large-scale ocean-atmosphere condition across the WMZs

WMZs	**Extreme rainfall indices**	**AMO**	**IOD**	**QBO**	**Niño3**
AWMZ	CDD1	**-0.34**	-0.24	**0.38**	0.19
	CDD5	**-0.33**	**-0.34**	**0.45**	0.12
VWMZ	CDD1	**-0.44**	**-0.29**	**0.42**	0.12
	CDD5	**-0.39**	**-0.40**	0.25	0.14
KWMZ	CDD1	-0.13	-0.19	0.23	0.10
	CDD5	**-0.30**	**-0.28**	**0.29**	0.01
UNWMZ	CDD1	-0.19	**-0.35**	**0.33**	-0.07
	CDD5	**-0.37**	**-0.30**	0.25	-0.20

Figure 4.11 shows linkages of climatic indices (NDPET5 and NDPET10) with large-scale ocean-atmosphere conditions, with critical correlation value computed as 0.27, at α = 0.05. IOD exhibited significant ($p < 0.05$) negative correlation with both NDPET5 and NDPET10 across almost the entire WMZs, except in KWMZ (NDPET10) (Table 4.11). Similarly, like for IOD, AMO was negatively correlated with NDPET5 in AWMZ (Figure 4.11a). However, with the increase in threshold from 5mm to 10mm, the area under UNWMZ and KWMZ showed a change in correlation range from 0 to 0.27 and above (Figure 4.11a, e). Consequently, the result exhibited significant ($\mathrm{p} < 0.05$) positive relationship between AMO and NDPET10 (Figure 4.11a, e). In other words, increasing PET threshold from 5mm to 10mm led to an increase in the area with dry conditions. This showed that, AMO was more correlated with dry than wet condition. Variation in number of days with PET greater than 5mm and 10mm across the country was positive with QBO, except for areas

around Mount Elgon and further north (Figure 4.11d, h). Correlation was significant ($P < 0.05$) between both NDPET5 and NDPET10 with QBO in AWMZ and VWMZ (Table 4.11). Niño3 exhibited insignificant correlation with range from -0.27 to 0.27 (Figure 4.11c, g).

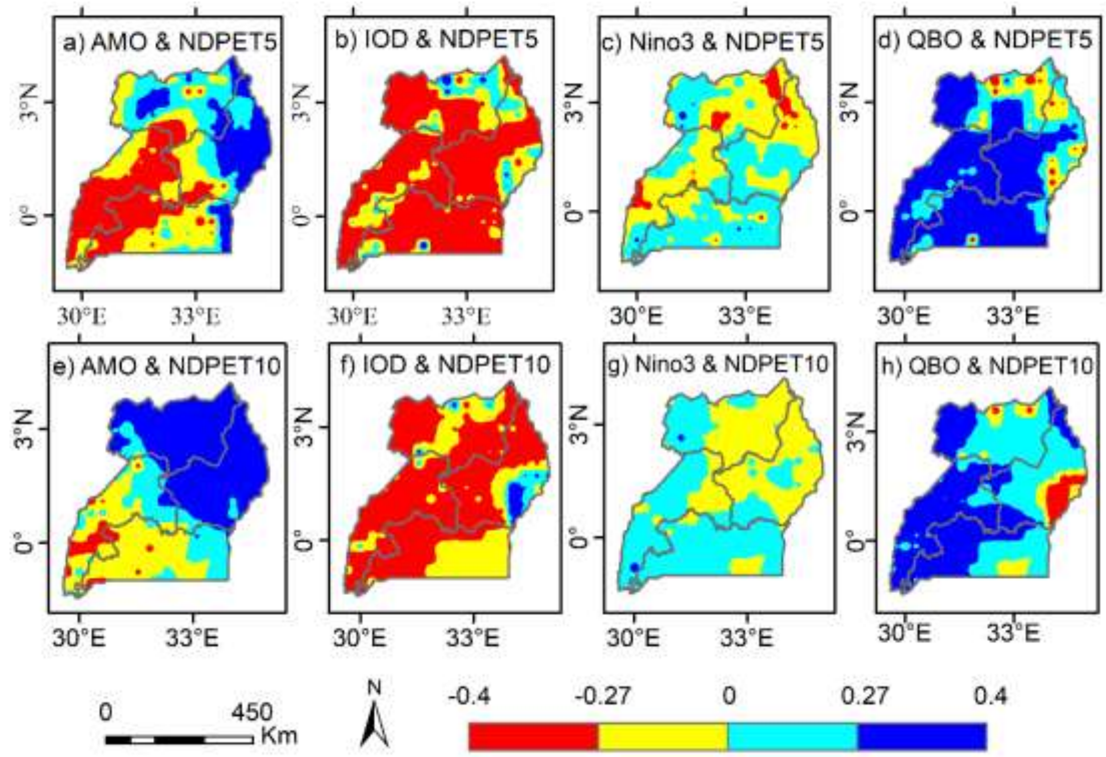

Figure 4.11: Correlation between a) AMO and NDPET5, b) IOD and NDPET5, c) Niño3 and NDPET5, d) QBO and NDPET5, e) AMO and NDPET10, f) IOD and NDPET10, g) Niño3 and NDPET10, h) QBO and NDPET10.

Table 4.11: Average correlation of NDPET5, NDPET10 and large-scale ocean-atmosphere condition across the WMZs.

WMZs	Extreme PET indices	AMO	IOD	QBO	Niño3
AWMZ	NDPET5	**-0.43**	**-0.42**	**0.46**	-0.06
	NDPET10	-0.04	**-0.46**	**0.44**	0.07
VWMZ	NDPET5	-0.18	**-0.42**	**0.44**	0.06
	NDPET10	-0.06	**-0.32**	**0.32**	0.07
KWMZ	NDPET5	0.16	**-0.36**	0.26	-0.04
	NDPET10	**0.47**	-0.25	0.09	-0.03
UNWMZ	NDPET5	0.07	**-0.30**	0.22	-0.06
	NDPET10	**0.43**	**-0.32**	0.19	-0.01

Figure 4.12 shows linkages of climatic indices (CDPET5 and CDPET10) with large-scale ocean-atmosphere conditions, with critical correlation value computed as 0.27 at α = 0.05 (Figure 4.12). Correlation between both AMO and IOD was negatively significant ($p < 0.05$) with CDPET5 in all the WMZs, and CDPET10 in KWMZ and UNWMZ (Table 4.12). IOD was negatively correlated with CDPET5 almost across entire country (Figure 4.12b). An increase in threshold from 5mm to 10mm in in Figure 4.12a, e, the area with critical values from 0 to 0.27 and above increased significantly (Table 4.12). This shows that AMO is more correlated with dry than wet condition. Niño3 insignificantly correlated with CDPET5 and CDPET10 in all the WMZs (Table 4.12). However, the correlation was positive over AWMZ, VWMZ and southwest KWMZ (Figure 4.12 c). QBO showed significant ($p < 0.05$) positive correlation with CDPET5 in AWMZ, VWMZ and KWMZ, and insignificant for UNWMZ (Table 4.12).

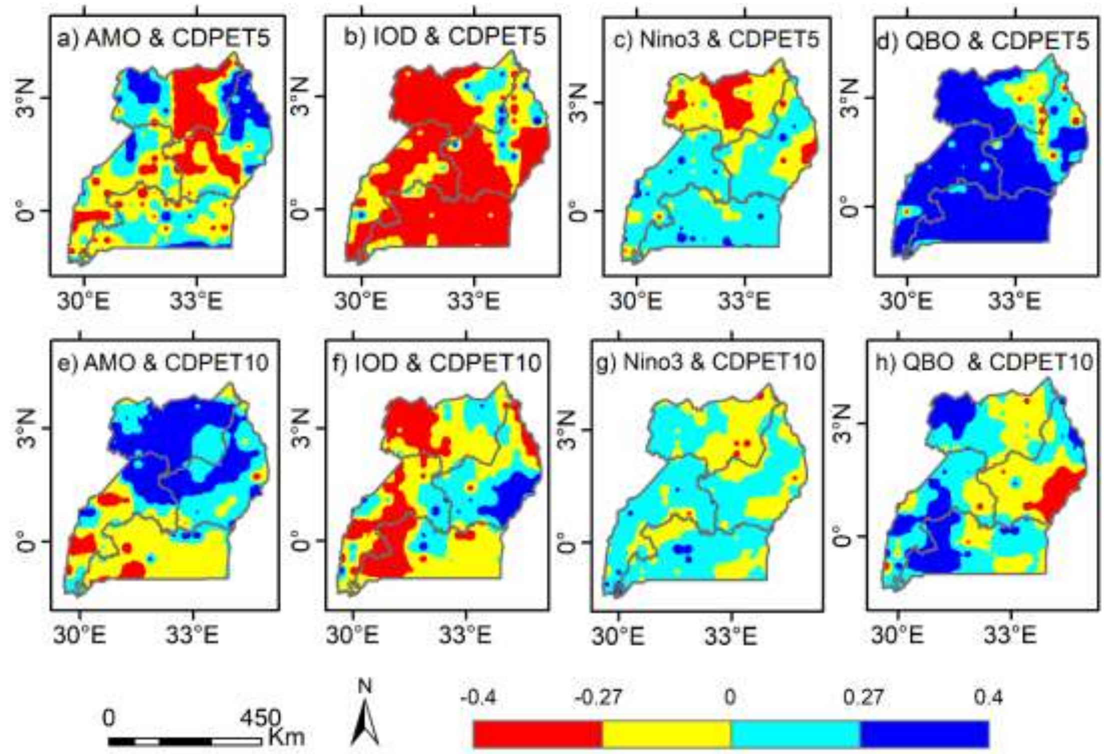

Figure 4.12: Correlation between a) AMO and CDPET5, b) IOD and CDPET5, c) Niño3 and CDPET5, d) QBO and CDPET5, e) AMO and CDPET10, f) IOD and CDPET10, g) Niño3 and CDPET10, h) QBO and CDPET10.

Table 4.12: Average correlation of CDPET5, CDPET10 and large-scale ocean-atmosphere condition across the WMZs.

WMZs	Extreme PET indices	AMO	IOD	QBO	Niño3
AWMZ	CDPET5	**-0.37**	**-0.32**	**0.42**	0.09
	CDPET10	0.16	-0.14	0.13	0.08
VWMZ	CDPET5	**-0.33**	**-0.39**	**0.48**	0.14
	CDPET10	0.05	-0.14	0.14	0.04
KWMZ	CDPET5	**-0.30**	**-0.28**	**0.29**	0.01
	CDPET10	**0.29**	0.10	-0.12	0.02
UNWMZ	CDPET5	**-0.37**	**-0.30**	0.25	-0.20
	CDPET10	**0.39**	-0.19	0.10	-0.03

Figure 4.13 shows linkages of climatic indices (SPETD5 and SPETD10) with large-scale ocean-atmosphere conditions with critical correlation value selected as 0.27 at α = 0.05. The tropical climate are influenced by thermodynamic variables such as Sea Surface Temperature (SST) and moisture fluxes (Lau and Nath, 1994). The atmosphere and ocean condition to a large extent changes due to these variables, with a positive or negative feedback (Xue et al., 2020). The feedback covers wide region and basin scale level impacting on the ocean atmosphere condition in terms of IOD, AMO variables (Hrudya, Varikoden and Vishnu, 2021). In this case both AMO (KWMZ and UNWMZ) and QBO (AWMZ and VWMZ) showed significant ($\mathbf{p < 0.05}$) positive correlation with SPETD5 and SPETD10 respectively Table 4.13). IOD correlated negatively with both SPETD5 and SPETD10 in all the WMZs (Figure 4.13). It was significant ($\mathbf{p < 0.05}$) in AWMZ, VWMZ, UNWMZ and KWMZ (SPETD5) (Table 4.13). Noticeably, the area with correlation ranging from

-0.4 to zero was larger for SPETD5 than that of SPETD10 (Figure 4.13a, e). This is because of the increase in the threshold from 5 mm to 10 mm. This means, increasing PET threshold from 5mm to 10mm led to an increase in the area with positive correlation (Figure 4.13a, e). Thus, AMO is more correlated with dry than wet condition. Niño3 exhibited both negative and positive correlation in the range of -0.27 to 0.27 across the four WMZs in the country (Figure 4.13c, g).

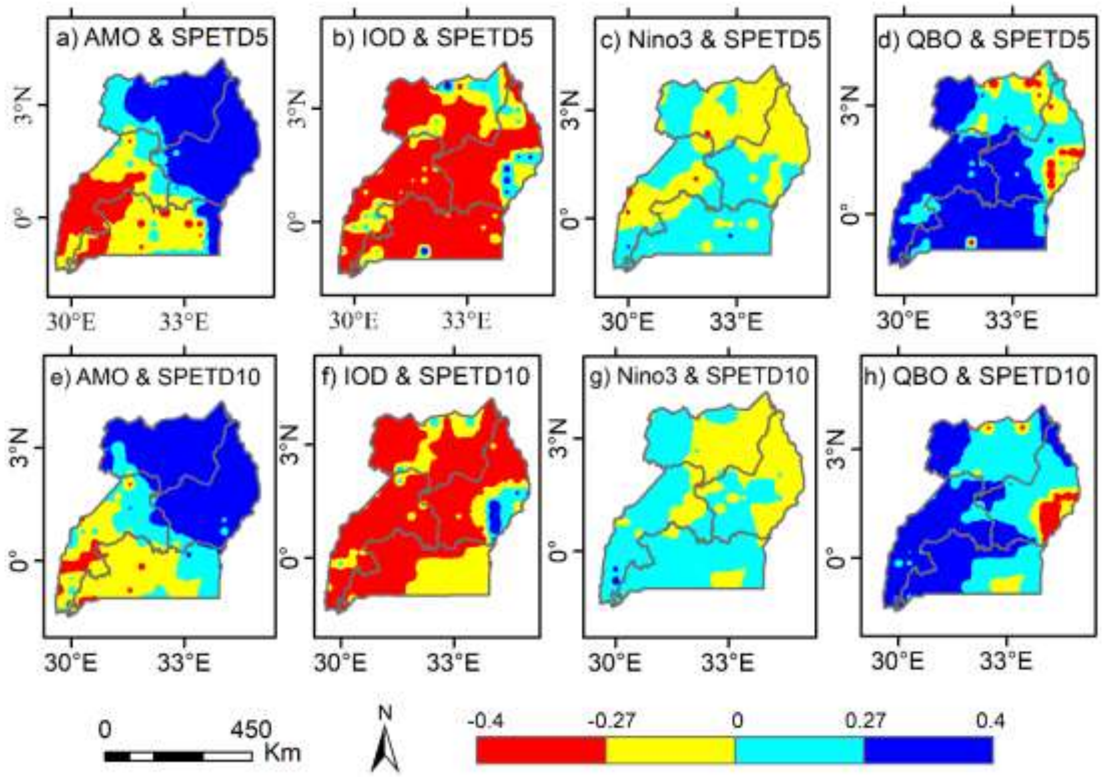

Figure 4.13: Correlation between a) AMO and SPETD5, b) IOD and SPETD5, c) Niño3 and SPETD5, d) QBO and SPETD5, e) AMO and SPETD10, f) IOD and SPETD10, g) Niño3 and SPETD5, h) QBO and SPETD10.

Table 4.13: Average correlation of SPETD5, SPETD10 and large-scale ocean-atmosphere condition across the WMZs.

WMZ	Extreme PET indices	AMO	IOD	QBO	Niño3
AWMZ	SPETD5	-0.25	**-0.43**	**0.44**	-0.02
	SPETD10	-0.01	**-0.46**	**0.44**	0.08
VWMZ	SPETD5	-0.12	**-0.45**	**0.47**	0.08
	SPETD10	-0.05	**-0.32**	**0.32**	0.07
KWMZ	SPETD5	**0.42**	**-0.31**	0.16	-0.03
	SPETD10	**0.47**	-0.27	0.11	-0.02
UNWMZ	SPETD5	**0.34**	**-0.31**	0.17	-0.04
	SPETD10	**0.43**	**-0.36**	0.22	-0.01

4.4 Validation of dataset

This result demonstrated that CFSR can reliably reproduce precipitation indices extracted from the rainfall climatology over the WMZs. This was noted for Kasanda, Masaka Forest and Nkozi stations, and Gulu station for NDD1, where there was strong agreement. However, despite the reliability of CSFR in reproducing the extreme rainfall indices in some stations, there was contrary performance in Wadelai (low correlation), Gulu (for NDD5, CDD1 and CDD5), Masindi, Soroti and Serere stations. There is need for further investigations in these stations. Generally, the CFSR can be used as an alternative to observed, especially, in areas known for ground-based data scarcity for timely investigation of dry climatic conditions.

Table 4.15 presents a summary of statistical metrics of results obtained from the validation analysis of gridded CFSR and observed station datasets based on daily distribution covering a period from 1979 to 2009.

Table 4.14: Correlation coefficient values between observed rainfall indices at selected stations and gridded CFSR.

S/No.	Station name	From	To	Location		Correlation for various rainfall Indices			
				Long.	Lat.	NDD1	NDD5	CDD1	CDD5
1	Wadelai WDD - Gulu	1979	2009	31.40	2.73	0.38	0.38	0.28	0.24
2	Gulu Met. Station - Gulu	1979	2009	32.28	2.78	**0.53**	-0.01	0.41	0.22
3	Masindi Met. Station	1979	2009	31.72	1.68	-0.01	-0.07	-0.02	0.14
4	Kassanda - Mubende	1979	2009	31.68	0.45	**0.96**	**0.96**	**0.96**	**0.96**
5	Serere Agric. Station - Soroti	1979	2009	33.45	1.52	0.30	0.27	0.24	0.05
6	Soroti Met. Station - Soroti	1979	2009	33.62	1.72	0.31	-0.01	0.14	-0.23
7	Masaka Forest - Masaka	1979	2009	31.73	-0.33	**0.91**	**0.98**	**0.95**	**0.87**
8	Nkozi Experimental Farm - Mpigi	1979	2009	32.02	0.02	**0.99**	**0.79**	**0.94**	**0.92**

Note: values in bold shows H_0 (no correlation) was rejected($p < 0.05$).

Table 4.15: RMSE values between observed and gridded CFSR Climate indices.

S/No.	Station name	From	To	Location		RMSE for various rainfall Indices			
				Long.	Lat.	NDD1	NDD5	CDD1	CDD5
1	Wadelai WDD - Gulu	1979	2009	31.40	2.73	107.01	75.03	72.91	83.46
2	Gulu Met. Station - Gulu	1979	2009	32.28	2.78	144.68	109.26	22.07	48.38
3	Masindi Met. Station	1979	2009	31.72	1.68	126.74	80.04	29.28	47.98
4	Kassanda - Mubende	1979	2009	31.68	0.45	0.00	0.00	0.00	0.00
5	Serere Agric. Station - Soroti	1979	2009	33.45	1.52	82.13	66.15	47.37	99.54
6	Soroti Met. Station - Soroti	1979	2009	33.62	1.72	79.36	83.70	71.09	141.92
7	Masaka Forest - Masaka	1979	2009	31.73	-0.33	0.63	1.26	0.00	0.00
8	Nkozi Experimental Farm - Mpigi	1979	2009	32.02	0.02	9.02	18.45	21.19	35.99

4.5 Chapter summary

This results of the research objectives where presented under this chapter. The findings were categorized based on the set out objectives. This was done using maps, tables and graphs. Further discussion was conducted to logically interpret results that informed conclusions and appropriate recommendations for future actions.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In conducting this research, changes in climatic dry condition in the four WMZs in Uganda was investigated. Gridded daily CFSR dataset was used to conduct analysis of extreme rainfall and PET indices, with conclusion from finding drawn as below.

i) What are the characteristics of dry climatic conditions across the WMZs

In characterizing the climatic dry conditions across the WMZs, data obtained on rainfall indices (1979 – 2013) indicated that KWMZ had the highest annual average NDD1, NDD5, CDD5, NDPET10, CDPET5, CDPET10, SPETD5 and SPETD10. This means KWMZ was climatically drier than all the other three WMZs, followed by UNWMZ. Similarly, VWMZ showed the lowest average number of NDD1, CDD1, NDPET5, NDPET10, CDPET5, CDPET10, SPETD5 and SPWTD10, implying that VWMZ was climatically wetter than all the WMZs followed by AWMZ, during the study period (1979 - 2013). Hence, KWMZ was the most affected zone with meteorological drought and VWMZ being the least affected.

Generally, the long term average annual trend magnitude of rainfall and PET extreme climatic indices in all the four WMZs exhibited a decline an indication that the WMZs were influenced by rainfall of higher magnitude than 1mm over the study period. However, in specific regions within the WMZs, there was variability in the trends observed. For example, the Karamoja, Albertine rift and north east of

UNWMZ areas exhibited increased trend in the number of dry days that signified positive change in severity of the dry condition.

ii) What is the significance of changes in the extreme climatic indices

There was a significant ($p<0.05$) decline in sum of PET indices, except in KWMZ where a positive trend was significantly observed in sum of PET >10mm/day. Similarly, SPETD10 exhibited significant change, except in UNWMZ. Generally, the rest of the climatic indices of both rainfall and PET exhibited insignificant changes across the four WMZs over the period from 1979 to 2013 with a wetter condition.

iii) What is the relationship between multi-decadal co-variability in extreme climatic indices with changes in large- scale ocean-atmosphere conditions

QBO (IOD) exhibited significant ($p < 0.05$) positive (negative) correlation in all the four WMZs, between NDD1 and NDD5, while AMO (negative) with NDD1 in VWMZ. Niño3 (AMO) showed insignificant positive (negative) correlation across the entire WMZs. The finding showed that as QBO increased, it influenced positive change on the meteorological drought indicators in all the WMZs in Uganda and therefore contributed to drought episodes during the study period.

There was significant ($p < 0.05$) negative correlation in AWMZ and VWMZ between AMO and (CDD1 and CDD5). In KWMZ and UNWMZ, the significance was with CDD5 only. Similarly, IOD exhibited significant ($p < 0.05$) negative correlation in VWMZ and UNWMZ, and only with CDD5 in AWMZ and KWMZ. QBO had significant ($P < 0.05$) positive correlation in AWMZ and VWMZ with

CDD1, UNWMZ (CDD1) and KWMZ (CDD5) respectively. There was no significant linear correlation between Niño3 and extreme rainfall index in all the WMZs.

NDPET5 and NDPET10 showed significant $(p < 0.05)$ positive correlation with QBO in AWMZ and VWMZ. Similarly, AMO and NDPET10 in KWMZ and UNWMZ, respectively. IOD showed significant $(p < 0.05)$ negative correlation in all the WMZs, except for NDPET10 in KWMZ. Niño3 exhibited insignificant correlation across the entire four WMZs.

AMO and IOD exhibited significant $(p < 0.05)$ negative correlation with CDPET5 in all the WMZ. Similarly a significant $(p < 0.05)$ positive correlation between AMO and CDPET10 was exhibited in KWMZ and UNWMZ. QBO showed significant $(p < 005)$ positive correlation with CDPET5 in AWMZ, VWMZ and UNWMZ respectively. There was no significant correlation with Niño3 in all the WMZs.

SPETD5 and SPETD10 showed significant $(p < 0.05)$ positive correlation with both AMO (KWMZ and UNWMZ) and QBO (AWMZ and VWMZ). This means AMO influences KWMZ and UNWMZ, while QBO influences AWMZ and VWMZ. IOD had significant $(p < 0.05)$ negative correlation in all the WMZs, except for SPETD10 in KWMZ which was not significant. There was no correlation with Niño3 in the entire WMZs. With all these information providing knowledge of the drivers of variability in rainfall and PET indices, dry climatic condition can be easily predicted.

5.2 Relevance of the findings

- Analysis of variability in rainfall and evapotranspiration indices provides an opportunity to characterize changes in climatic dry conditions across the WMZs.
- Based on the linkages between the variation in dry climatic conditions and climatic indices (AMO, Nino3, IOD, QBO), it is possible to predict future scenario of drought, for reliable adaptation to the impact of changes of climate on hydro-climate.

5.3 Recommendations

This research recommends that, further studies in the future across the WMZs should focus on the following;

a) The predictive potential of changes in drought indices on a seasonal river system.
b) Analysis of the impact of variability in PET0 to catchment water losses across the WMZs.
c) Correlation in seasonal variation in temperature on extreme rainfall episodes.

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