ANALYSIS OF STREAM FLOW REGIME CHANGES IN SOUTH RUKURU RIVER IN THE NORTHERN REGION OF MALAWI

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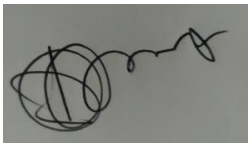
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ABSTRACT

The study examined the changes in the South Rukuru River's stream flow regime over the past three decades in Malawi. It aimed to determine rainfall and streamflow trends, examine their relationship, and assess the impact of land use modifications on streamflow patterns. The research uses historical climate data, streamflow records, and Landsat satellite imagery for land cover analysis. Statistical methods like Mann-Kendall test, Sens estimator, Pettitt test, and Pearson correlation were used to analyze trend analysis. The research project discovered that there was a statistically insignificant decreasing pattern in yearly rainfall over the watershed's both dry and wet seasons over the 30-year period from 1992 to 2022. Overall, the average yearly streamflow and the summertime streamflow showcased a non-significant declining pattern in accordance to the Mann-Kendall test, whilst the moist-season streamflow revealed a non-significant growing trend. The study concluded that addressing these hydrological changes requires integrated water resource management strategies considering climate variability and human activities. Future research should focus on developing predictive models to better understand these changes and guide sustainable water resource management. This research contributes to hydrological science advancement and supports climate change adaptation and sustainable development in the region.

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ACRONYMS/ABBREVIATIONS

SDGs	Sustainable Development Goals
CV	Coefficient of Variation
ENSO	El Nino Southern Oscillation System
IOD	Indian Ocean Dipole
LULC	Land use Land Cover
DEM	Digital Elevation Model
LCCS	Land Cover Classification System
GIS	Geo-Information Systems
ITCZ	Inter-Tropical Convergence Zone

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1. INTRODUCTION

1.1. Background

Stream flow regime changes refer to the variations in the magnitude, frequency, and duration of stream flows, which can have significant impacts on the ecological, social, and economic systems that depend on these flows (Seyfried & Fang, 2017). Global studies have shown that changes in stream flow regimes are occurring due to a variety of factors, including climate change, land use changes, and human activities such as dam construction, urbanization, agriculture and water diversion which can have significant impacts on stream flow regimes, with far-reaching consequences for freshwater ecosystems, water resources management, and human societies. These specifically result into alterations to aquatic habitats, changes in water quality, and impacts on human communities that rely on these streams for water supply, agriculture, and other purposes (Wernersson & Hjerpe, 2017). Studies have shown that changes in stream flow regimes are not limited to specific regions, but are occurring globally. For example, a study published in the journal Nature found that stream flows in the western United States have decreased by up to 20% over the past century due to changes in precipitation patterns and increased water demand (Seyfried & Fang, 2017). Similarly, a study in the journal Environmental Research Letters found that stream flows in Europe have decreased by up to 15% over the past 50 years due to changes in climate and land use (Wernersson & Hjerpe, 2017).

In Malawi, stream flow regimes are also facing changes due to a variety of factors, including climate change, deforestation, and human activities such as dam construction and water diversion. For example, a study published in the journal Hydrology and Earth System Sciences found that stream flows in the Shire River basin in Malawi have decreased by up to 30% over the past 50 years due to changes in precipitation patterns and increased water demand (Chimango & Mwakasango, 2018). The significance of carrying out studies on stream flow regime changes in Malawi is highlighted by the country's commitment to achieving Sustainable Development Goals (SDGs) and policy formulation. According to United Nations (2015), it aids in effective water resource management, climate action, and ecosystem

protection. Sustainable Development Goal number 6 which emphasize the importance of ensuring the availability and sustainable management of water and sanitation for all (Adams & Smiley, 2018). Malawi's Vision 2063 also emphasizes the importance of sustainable development and the need to protect the country's water resources. Environmentally friendly practices that promote sustainability include proper waste disposal, treatment, and recycling; controlling air and water pollution; and using water resources wisely in light of anticipated rises in demand and consumption. It also forms Integrated Water Resource Management, climate adaptation, and environmental conservation policies. Stream flow analysis also aids in infrastructure planning, hydropower development, and international water treaties. The National Water Policy and Climate Change Management Act emphasize integrated water resource management. Analyzing stream flow regime changes can inform decisions on water allocation, infrastructure development, and environmental protection. Despite the importance of stream flow regime changes in Malawi, there are significant gaps in the understanding of these changes and their impacts. For example, there is limited data on the magnitude and frequency of stream flows in many parts of the country, and there is a lack of information on the impacts of stream flow regime changes on ecological and human systems.

The specific study area of this research, the South Rukuru River, is located in the Northern Region of Malawi and is an important source of water for irrigation, domestic use, and other purposes. It is characterized by a subtropical highland climate with two distinct seasons: a rainy season from November to March and a dry season from April to October. The river originates from the Nyika Plateau and flows through a series of valleys and plains before entering Lake Malawi. The catchment area of the South Rukuru River covers approximately 4,000 square kilometers, and the river is approximately 150 kilometers long (Mwakasungula et al., 2015). However, there is limited information on the stream flow regime of the South Rukuru River, and there is a need for more research on the impacts of stream flow regime changes on this system. Therefore, there is a need to understand the changes in the stream flow regime of the South Rukuru River and their impacts on water resources in the region. This study was aimed to analyze the changes in the stream flow regime of the South Rukuru River and it assessed their impacts on water resources in the region.

Specifically, the study investigated the effects of human activities and climate change on the stream flow regime of the South Rukuru River and it evaluated the potential impacts of these changes on water resources in the region.

1.2. Problem Statement

The South Rukuru River is an important water resource in the Northern Region of Malawi, supporting a variety of ecosystems and providing water for irrigation, drinking, and other domestic uses. However, there is limited information on the stream flow regime of the river, and it is essential to understand the changes that are occurring to effectively manage the resource. Additionally, the region is experiencing changes in land use and climate, which may be affecting the river's flow regime, and this study aims to investigate these factors. There have been some studies on the hydrology of the South Rukuru River, but these have been limited in scope and have not fully addressed the changes in the stream flow regime. For example, a study by Mwakasungula et al. (2015) analyzed the hydrological characteristics of the river, but did not investigate changes in the flow regime. Another study by Chimango et al. (2018) examined the impact of land use changes on the river's water quality, but did not consider the flow regime. Therefore, this study was aimed to provide a more comprehensive understanding of the changes in the stream flow regime of the South Rukuru River.

The existing studies on the South Rukuru River have focused primarily on hydrological characteristics such as temperature, groundwater and rain which play a role in Earth's water cycle. They also shape landscapes, ecosystems, and climate patterns, influencing climate patterns, shaping landscapes, and sustaining life. The existing studies also focused on water quality which is the physical, biological, and chemical characteristics of water, which determine its suitability for various uses and its impact on human health and the environment. Those previous studies had limited information on the stream flow regime and this study was aimed to address the following research gaps by trying to investigate the changes in the stream flow regime of the South Rukuru River over time, identify the factors responsible for the changes in the stream flow regime and assess the impact of the changes in the stream flow regime on the local ecosystems and communities.

1.3. Study Objectives

1. To determine the rainfall and streamflow trends of the South Rukuru River over the past 30 years (1990-2020).
2. To examine the relationship between rainfall and streamflow
3. To investigate land use modifications in stream flow regime alterations.

1.3.1. Research Questions

a. Why have stream flow regime changes occurred?
b. How have they affected flow volumes and timing of peak flows in the South Rukuru River?
c. What are the main drivers behind these changes, and how have they evolved over time?
d. When did these alterations begin, and are there any discernible trends or patterns in their occurrence?
e. Where within the South Rukuru River basin are these changes most pronounced, and what are the localized impacts?

1.4. Significance

The analysis of stream flow regime changes in the South Rukuru River within the Northern Region of Malawi holds significant importance on multiple fronts.

This research project contributes to the advancement of scientific understanding in the field of hydrology and climate change adaptation. By comprehensively studying the drivers and patterns of stream flow regime changes in this specific river system, it provides valuable insights into the complex dynamics of hydrological alterations in a changing climate, thereby filling a critical knowledge gap.

The technical contributions of this research lie in the development of data-driven models and hydrological assessments that can be used as tools for predicting and managing stream flow regime changes. The data generated through this research can assist water resource managers and policymakers in making informed decisions about water allocation, flood mitigation, and sustainable land use practices. These technical contributions align with SDG 6 (Clean Water and Sanitation) and SDG 13 (Climate

Action) by promoting evidence-based approaches to safeguard water resources and adapt to climate-induced challenges.

2. LITERATURE REVIEW

2.1. Introduction

This Chapter aims at providing an overview of the current knowledge in the field of hydrology, with a specific focus on analysing stream flow regime changes. It seeks to give an overview on the determination of the rainfall and stream flow trends of the South Rukuru River over the past 30 years, investigate the land use modifications in stream flow regime alterations, and evaluate the effects of the changes in stream flow regime on local communities and agriculture.

2.2. Stream flow variability

Stream flow regime refers to the temporal patterns and variability of water discharge in a river over different time scales, including daily, seasonal, and inter annual variations. It is influenced by various factors such as precipitation patterns, land use changes, climate variability, and anthropogenic activities. Several factors contribute to stream flow variability in the Southern Rukuru River. Climate change is a significant driver, impacting precipitation patterns and evapotranspiration rates, thereby influencing stream flow dynamics. Land use changes, such as deforestation, urbanization, and agricultural practices, do alter surface runoff and infiltration rates, leading to changes in stream flow regimes. Additionally, water abstraction for irrigation and domestic use further accelerates stream flow variability. Changes in the stream flow regime of the Southern Rukuru River have significant impacts on both natural ecosystems and human communities. Alterations in water availability affects aquatic habitats, biodiversity, and ecosystem services provided by the river. Furthermore, variations in stream flow patterns impact water supply reliability for agriculture and domestic use, posing challenges for water resource management (Chirwa, 2016).

2.3. Rainfall and Stream flow Trends

Studies have shown varying trends in rainfall patterns in the Southern Rukuru region. Some research indicates an increase in total annual rainfall over the past few decades, attributed to climate change and variability. On the other hand, studies done by Chimango & Mwakasango and Mwakasungula et al., suggested a decrease in seasonal rainfall distribution, leading to more intense and sporadic rainfall events. These

contrasting trends highlight the complexity of rainfall patterns in the region and hence the need for further investigation. The South Rukuru River basin experiences a tropical climate with high rainfall variability, with an average annual rainfall of 1,200 mm to 1,800 mm (Mwakasungula et al., 2015). The rainfall trend over the past 30 years has shown a decreasing pattern, with a significant decrease of 10% to 20% in the annual rainfall (Mwale, 2018). This decrease in rainfall has been attributed to climate change, particularly the warming of the Indian Ocean and the changing patterns of the Intertropical Convergence Zone (ITCZ) (Chirwa, 2016).

The stream flow trend of the South Rukuru River has also shown a decreasing pattern over the past 30 years, with a significant decrease of 20% to 30% in the monthly stream flow (Mwale, 2018). This decrease in stream flow has been attributed to the decrease in rainfall, as well as the increase in evapotranspiration due to rising temperatures. The changes in rainfall patterns have direct implications for stream flow regimes in the Southern Rukuru River. Research by Mwale (2018) has indicated alterations in stream flow characteristics, including changes in flow volumes, peak flows, and low-flow periods. These changes can impact water availability for irrigation, domestic use, and ecosystem health within the basin. Understanding these impacts is essential for developing adaptive strategies to mitigate potential water resource challenges (Mwale, 2018).

2.4. Land Use Modification

The impact of land use and land cover changes on streamflow regime is a crucial aspect to consider in the analysis of streamflow alterations in the South Rukuru River in the Northern Region of Malawi. Land use refers to the human activities and practices that occur on a particular piece of land, while land cover refers to the physical characteristics of the land surface, such as vegetation, water bodies, and bare soil. Land use modifications have significant effects on the streamflow regime. The South Rukuru River basin has experienced significant deforestation and land degradation over the past 30 years, particularly in the upper catchment areas (Mwale, 2018). This deforestation and land degradation have been attributed to the expansion of agricultural activities, such as tobacco and cotton farming, as well as the extraction of timber and charcoal (Mwakasango, Chidya, & Mwapasa, 2017).

Agricultural activities in the South Rukuru River basin have increased significantly over the past 30 years, with the main crops being tobacco, cotton, and maize (Mwakasango, Chidya, & Mwapasa, 2017). These agricultural activities have been attributed to the increasing population and the demand for food, as well as the expansion of the agricultural sector in Malawi. Other studies investigated the direct impacts of land use modifications on stream flow regimes in the river basin. The research done by (Chirwa, 2016) utilized remote sensing data and hydrological modelling to assess how changes in land cover, particularly deforestation for agriculture and urbanization, have influenced stream flow characteristics. The results demonstrated a clear correlation between land use modifications and alterations in stream flow regimes, with significant implications for water resource management and ecosystem health. Hence, using proposed integrated watershed management approaches that focus on sustainable land use practices, reforestation efforts, and community engagement to restore natural hydrological processes in the Southern Rukuru River basin can minimize the impacts. Also, by promoting sustainable land management practices and enhancing ecosystem resilience, these strategies aim to mitigate the adverse impacts of land use modifications on stream flow regimes and ensure long-term water resource sustainability (Mwale, 2018).

2.5. Current Knowledge

To gain a comprehensive understanding of stream flow regime changes in the South Rukuru River, related knowledge from neighboring regions or similar river systems is essentially considered. Studies conducted on other rivers in Malawi or nearby countries provide valuable insights into potential drivers and impacts of stream flow regime changes. For example, research by Kumwenda et al. (2019) on the Bua River in Malawi highlighted the influence of climate change and land use changes on its flow regime. Similarly, studies on the Zambezi River in neighboring countries, such as Mozambique and Zambia, examined the impacts of hydropower development on stream flow regimes. Several studies have investigated streamflow trends in the South Rukuru River. A study by Mwakasango et al. (2016) found that the river's streamflow increases during the wet season and decreases during the dry season, over the past 30 years. The study attributed the changes to land use modifications and climate

change. Another study by Chimango et al. (2019) found that the river's streamflow has become more variable over the past 30 years, with increased extreme events such as floods and droughts. The study suggested that the changes were linked to climate change and land use modifications. Overall, the current knowledge on streamflow trends in the South Rukuru River suggests that the river's flow is influenced by a combination of factors, including rainfall, land use, water abstraction, and climate change.

To analyze streamflow regime changes, various methodologies are employed to identify where alterations occur and understand their underlying causes. One commonly approaches used is the trend analysis, which involves examining long-term data to identify patterns and trends in rainfall and streamflow. Statistical techniques such as linear regression or Mann-Kendall tests is also applied to detect significant trends over time. Remote sensing techniques are used as well to analyze land use and land cover changes. Satellite imagery provided information on vegetation cover, urban expansion, and deforestation rates over time. By comparing historical and current images, researchers can quantify changes in land cover and relate them to streamflow alterations. For the specific study on the South Rukuru River, the methodologies adopted included a combination of field measurements and analysis of historical climate and land use data. Field measurements could involve collecting streamflow data at various locations along the river to assess flow characteristics. Additionally, historical climate data from meteorological stations and satellite imagery was analyzed to understand rainfall patterns and land cover changes in the study area.

By synthesizing and analyzing existing literature on stream flow regime changes in similar contexts, researchers can develop a more robust theoretical framework for studying the South Rukuru River's flow dynamics.

3. METHODOLOGY

3.1. Introduction

This study investigates stream flow regime changes in the South Rukuru River, Northern Malawi, using a quantitative approach. Data was collected from the Malawi Meteorological Services and Water Resources Department over a 30-year period. Statistical software packages and Landsat imagery were used for analysis. It also includes remote sensing techniques for land use and cover changes.

3.2. Study Area

This study was carried out in the South Rukuru River which is located in the Northern Region of Malawi. The South Rukuru rises in southern Mzimba District, and flows roughly north-northeast to empty into Lake Malawi. Its watershed mostly lies in the Mzimba Plain. Its tributaries drain the western slopes of the Viphya Mountains. To the east, a low divide which forms the Malawi-Zambia border separates the South Rukuru's watershed from that of Luangwa River in Zambia. The lower valley of the river separates the northern end of the Viphya Range from the Nyika Plateau to the north. The catchment area of the South Rukuru River covers approximately 4,000 square kilometres, and the river is approximately 150 kilometres long. Below is figure 1 which contains map of the study area.

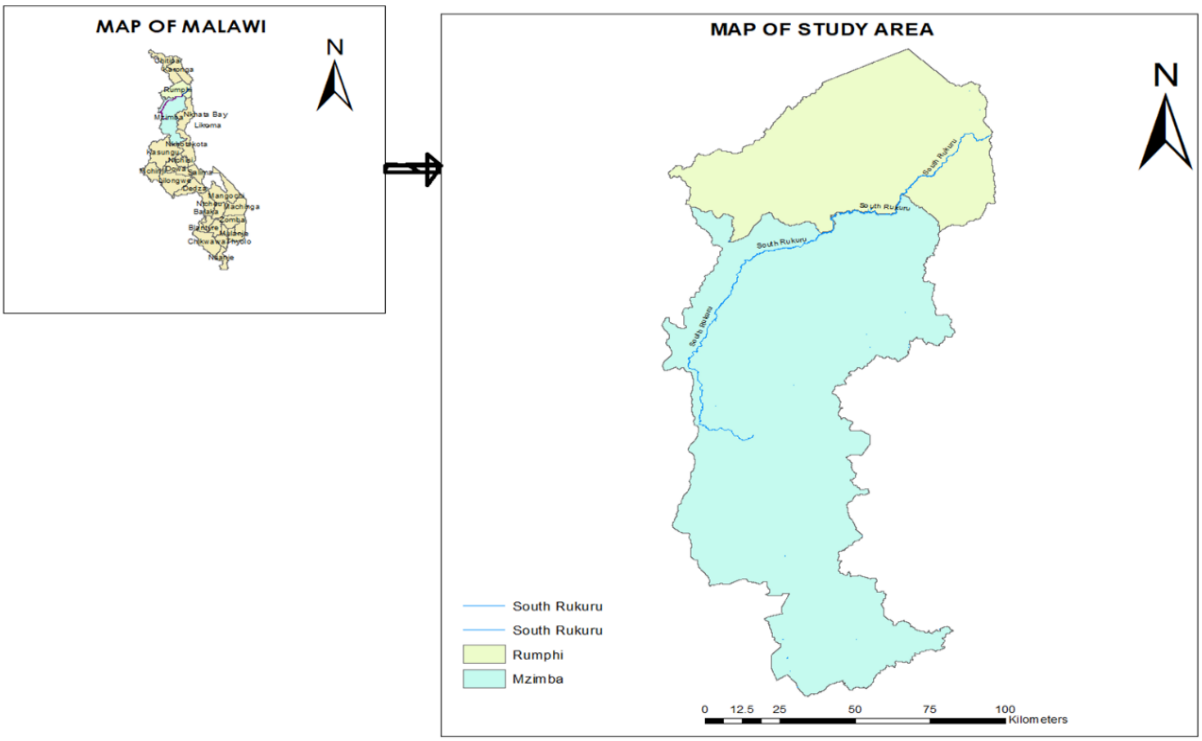


Figure 1: Map of the study area

3.3. Research Design

The study was a quantitative research approach, it involves collecting and processing numerical data by utilizing statistical measures and trend analysis to quantify and understand variations in streamflow patterns. The Conceptual framework is presented in figure 2 below.

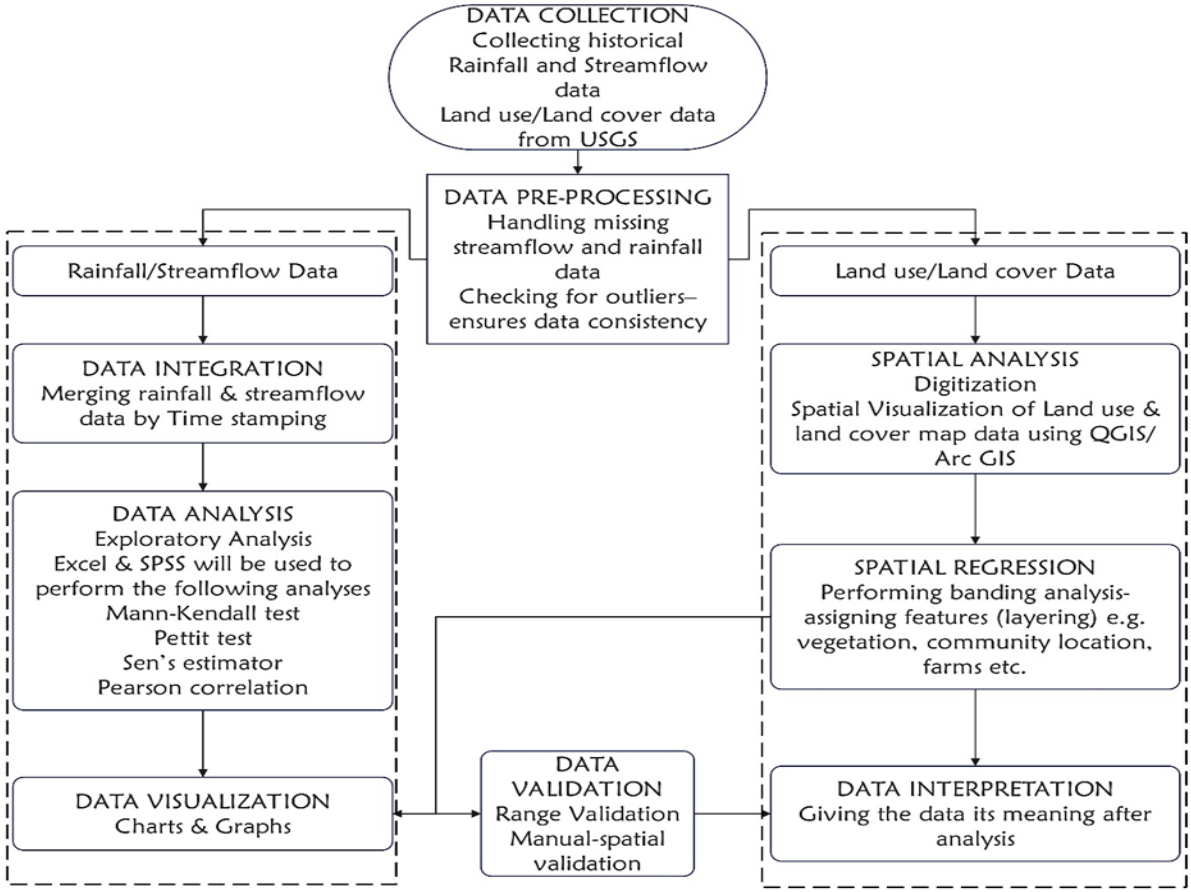


Figure 2: Conceptual framework

3.4. Data Collection

- It involved gathering historical records of rainfall and streamflow measurements for a period of 30 years from the Malawi Meteorological Services and Water Resources Department. Records, including daily, monthly, or annual data, was collected to achieve the first objective of this study.
- The study used imagery from two Landsat missions, Landsat 5 and Landsat 8, covering the period from 1993 to 2022 with different sensors and spectral resolutions.
- Cloud-free data from the Landsat Thematic Mapper (1993, 2002) and Landsat Operational Land Imager (2013 and 2022) were sourced from the USGS (https://www.usgs.gov).
- Landsat imagery was selected for its free access, optimal ground resolution, and spectral bands, making it effective for tracking land use changes.

- Landsat 5 was used for 2002 instead of Landsat 7 to avoid the scan line error in Landsat 7, which could compromise the classification output and analysis.

3.5. Methodology Matrix

Table 1 Methodology matrix

Objectives	Variables	Data Collection	Data Analysis
Determining the rainfall and streamflow trends of the South Rukuru River over the past 30 years.	✓ Rainfall ✓ Stream flow	Data acquisition. Historical data from the Malawi Meteorological Services and Water Resources Department.	Used Excel, R studio, STATA & SPSS for trend analysis ❖ Mann-Kendall test ❖ Pettit test ❖ Sen's estimator
To examine the relationship between rainfall and streamflow	✓ Streamflow ✓ Rainfall	Used secondary data obtained from the Malawi Meteorological Services and Water Resources Department	Used excel/SPSS for analysis. ❖ Pearson correlation was used to determine the relationship
Investigating the land use modifications in stream flow regime alterations	✓ Land use ✓ Land cover	Landsat data was downloaded from USGS website	Used Arc GIS/QGIS to integrate & visualize land use and land cover changes

3.6. Checking for Missing Data/Outliers

Missing streamflow data values and outliers were identified and handled using various ways.

3.6.1. Identifying Missing Data

1. Data inspection: Visual inspection of the data was done to identify missing values. Gaps or inconsistencies were looked at in the data series. This method was simple and effective when dealing with small datasets.
2. Descriptive statistics: Calculating descriptive statistics such as mean, median, and standard deviation helped to identify missing values. If the calculated statistics didn't make sense or are significantly different from expected values, it indicated missing data.
3. Data import verification: When importing data from external sources, it was essential to verify that all data points have been successfully imported into the excel data sheet for analysis. This was done by comparing the imported data with the original source or by checking the import log file.

3.6.2. Handling Missing Data

1. Data imputation: Imputation is the process of replacing missing values with estimated values. There were several methods for data imputation, including mean imputation, regression imputation, and multiple imputation. The choice of method depended on the nature of the missing data and the available data.
2. Deletion: In some cases, it was appropriate to delete the entire record containing missing data. However, this method was used with caution, as it can lead to a loss of valuable information and may introduce bias in the analysis.
3. Interpolation: A technique used to estimate missing values based on the values of neighbouring data points. This method was particularly useful for spatial data, such as streamflow data, where nearby measurements provide useful information for estimating missing values.

3.6.3. Identifying Outliers

1. Data inspection: Visual inspection of the data helped to identify outliers. Scatter plots or box plot were used to identify any unusual values.
2. Statistical tests: There were several statistical tests available for identifying outliers but in this study the Z-score test was used. This test helped to determine whether a data point was an outlier based on its distance from other data points.
3. Data transformations: In some cases, outliers may be a result of non-linear relationships between variables. Data transformations, such as logarithmic or square root transformations have helped to identify and remove outliers by linearizing the relationship between variables.

3.6.4. Handling Outliers

1. Data validation: Outliers were caused by errors in data collection or measurement. Data was validated and investigated for the possibility of errors before removing outliers.
2. Data exclusion: If outliers were determined to be genuine and not caused by errors, they were removed from the analysis. However, this method was used with caution, as it led to a loss of valuable information and may introduce bias in the analysis.
3. Data transformation: In some cases, outliers were addressed by transforming the data. For example, using a logarithmic or square root transformation helped to reduce the influence of outliers on the analysis.

3.7. Data Analysis

Historical data on stream flow and rainfall patterns was subjected to rigorous analysis using advanced statistical software packages, including SPSS, R studio, STATA and XLSTAT. To provide a comprehensive understanding of the data, descriptive statistics, such as means and standard deviations, were employed to summarize key aspects. Additionally, inferential statistical methods, such as regression analysis, comparative analysis, and t-tests, were utilized to unearth meaningful relationships between stream flow characteristics and explanatory variables, such as land use practices and human settlement patterns. This multifaceted approach allowed for a thorough examination of the data and the identification of significant correlations and trends.

3.7.1 Data analysis methods

3.7.1. Trend test

Mann Kendal Trend Test

The non-parametric test based on the Mann–Kendall rank correlation coefficient had been used in this study (Mann, 1945; Kendall, 1975); the method has been widely and commonly used to assess the significance of trends in hydro meteorological time-series. The main reason for using non-parametric statistical tests was that, compared with parametric statistical tests, the factors were thought to be more suitable for non-

normally distributed data, which were frequently encountered in hydro-meteorological time series (Fooladi et al., 2021).

Equation 1: Mann Kendal trend test equations

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k)$$

Where x1, x2; ..., xn represent 'n' data points, xj represents the data point at time j. A rising trend is indicated by a positive value of "S," whereas a falling trend is shown by a negative number.

$$sgn(x_j - x_k) = \begin{cases} 1, & \text{if } x_j - x_k > 0 \\ 0, & \text{if } x_j - x_k = 0 \\ -1, & \text{if } x_j - x_k < 0 \end{cases}$$

When n is greater than or equal to 10, it is assumed that the test statistic S is approximately normally distributed with the mean E(S) = 0, and its variance is

$$Var(S) = \frac{1}{18}\left[N(N-1)(2N+5) - \sum_{i=0}^{m} t_i \ (t_i - 1)(2t_i + 5]\right.$$

Where t_i is the number of data points in the ith group, n is the number of data points, and m is the number of tied groups (a tied group is a collection of sample data with the same value).

The standardized test statistic Z is computed as follows:

$$Z = \begin{cases} \frac{S-1}{[VAR(S)]^{1/2}}, & \text{if S} > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{[VAR(S)]^{1/2}}, & \text{if } S < 0 \end{cases}$$

The MK test was utilized to examine the rainfall and streamflow in the monthly, yearly, and seasonal series at a significance level of 5%.

Pettit Test

The Pettitt test is a statistical test used to detect a change point (or breakpoint) in a time series data. It's a non-parametric test, which means it doesn't require normality or equal variances (Ferrari et al., 2023). The test is commonly used in climate science, hydrology, and other fields to identify significant changes or trends in data. It tests

for a change point in a time series data, where the distribution of the data changes significantly (Messer, 2022). It calculates a statistic (called the Pettitt statistic) that measures the difference between the two segments of the data (before and after the potential change point) and it provides a p-value, which indicates the probability of observing the change point by chance (Prabuchandran et al., 2022).

The test starts by ranking the data from smallest to largest. It then calculates the Pettitt statistic (U) as the maximum difference between the sums of the ranks before and after each potential change point (Fooladi et al., 2021; Yangouliba et al., 2022). Then the test statistic (U) is compared to a critical value from a standard distribution (usually the standard normal distribution). If the test statistic (U) exceeds the critical value, the null hypothesis (no change point) is rejected, indicating a significant change point (Ferrari et al., 2023). Using the following formula, the alternative hypothesis of a change point in the data series is pitted against the null hypothesis of the test, which is the absence of a change point.

Equation 2: The Pettitt test equations

KN = max|Ut.N|

$$U_{t,N} = \sum_{i=1}^{t} \sum_{j=i+1}^{N} sgn(x_i - x_j) \text{ fort} = 1, 2, \cdots\cdots, \text{N}$$

The null hypothesis's test statistic is KN.Ut,N, verifies whether or not the two data series (xi..... xt and xi + 1.....,xN) belong in the same category.

Then, the following formula can be used to get the approximate significance probability, p (t), of a change point.

$$\cong 2 * \exp\left[\frac{-6K_N{}^2}{N^3 + N^2}\right]$$

P stands for the change point's probability at the 5% significant level. A substantial change in the time series, both upward and downward, was indicated by a p value > 0.05.

Sen's Slope (Estimator)

Sen's estimator, or Sen's slope estimator, is a non-parametric method used to determine the slope of a trend line in time series data, known for its robustness to outliers (Truong et al., 2020; Yu et al., 2023). It calculates the median slope from all pairs of data points, making it a reliable measure for detecting trends without assuming a specific data distribution. This estimator is widely used in environmental and climate studies to analyze long-term trends, such as pollutant levels, streamflow, or temperature changes (Yu et al., 2023). Its robustness and non-parametric nature make it Sen, It is calculated using the formula below.

Equation 3: Sen's Slope equations

$$\text{where } T_i = \frac{x_{j-x_k}}{j-k} \text{fori} = 1, 2, 3 \cdots .\text{N}$$

For data values at times j and k (j < k), denoted by the variables xj and xk. Sen's estimator of slope is the median of these N values of Ti, and it is computed as

$$\cong 2 * \exp\left[\frac{-6{K_N}^2}{N^3 + N^2}\right]$$

In the rainfall and streamflow data series, a positive value of b denotes an increasing trend while a negative value denotes a decreasing trend.

Pearson Correlation Coefficient

The Pearson correlation coefficient, often denoted as "r," is a statistical measure that quantifies the strength and direction of the linear relationship between two variables (Harisuseno, 2020). It ranges from -1 to 1, where a value of 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship (Panditharathne et al., 2023). It's calculated by dividing the covariance of the two variables by the product of their standard deviations. Pearson's r is widely used in various fields such as economics, psychology,

and biology to assess the degree of association between variables, aiding in understanding patterns and making predictions. However, it's important to note that Pearson's r only captures linear relationships and may not accurately represent nonlinear associations (Panditharathne et al., 2023). Additionally, correlation does not imply causation, so careful interpretation and consideration of other factors are crucial. It is calculated using the following equation.

Equation 4: Pearson Correlation Coefficient Equations

$$r = \frac{\sum_{i=1}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Where N is the total number of elements being studied, and x and y are the variable values. The values of "r" range from 1 to 1. Negative numbers demonstrate the opposite relationship between the two variables, whereas positive values near 1 suggest a significant correlation.

Sgn (xi, xj;) can be computed as follows:

$$sgn(x_j - x_k) = \begin{cases} 1, & \text{if } x_j - x_k > 0 \\ 0, & \text{if } x_j - x_k = 0 \\ -1, & \text{if } x_j - x_k < 0 \end{cases}$$

3.8. Ethical consideration and limitations

The study necessitates thorough ethical considerations to ensure responsible conduct and respect for all stakeholders' rights and well-being. It will include:

a. **Informed Consent**: Obtaining informed consent from all individuals or communities affected by the research is essential. The research clearly explained the purpose, potential risks, and benefits of the study to participants, ensuring they have a comprehensive understanding before agreeing to participate.

b. **Environmental Justice**: The research considered issues of environmental justice, particularly in relation to vulnerable communities who may be disproportionately affected by stream flow regime changes.

c. **Data Privacy and Confidentiality**: The Research ensured that any personal information collected during the study is kept confidential and used only for the intended research purposes.

4. RESULTS AND DISCUSSION

4.1. Introduction

The study analyzes rainfall and streamflow trends in the South Rukuru River catchment, revealing significant variability across months and seasons. It also examines the relationship between rainfall and streamflow, providing insights into the river's hydrological behaviour and the effects of climatic and anthropogenic factors on its flow regime.

4.2. Rainfall

The following section will display and discuss the results from the analysis of rainfall in South Rukuru River catchment.

4.2.1. Mean, Standard Deviation and the Coefficient of Variation

The mean, also known as the average, is a measure of central tendency that represents the typical value in a dataset and the standard deviation is a measure of dispersion or variability in a dataset (Gentilucci et al., 2023). A higher standard deviation suggests that the rainfall amounts vary significantly from the average, while a lower standard deviation implies that most values are close to the mean. The coefficient of variation (CV) is a relative measure of variability that expresses the standard deviation as a percentage of the mean (Gentilucci et al., 2023). It allows for comparison of variability between datasets with different units or scales. A higher CV indicates greater relative variability compared to the mean, while a lower CV suggests more consistency in rainfall patterns.

The results of mean, standard deviation and coefficient of variation are presented in the table 2.

Table 2: Mean, standard deviation and coefficient of variation of rainfall

Variable	Mean	Std. Deviation	Coefficient Of Variation (%)	Interpretation
Jan	209.735	135.069	64.4	High Variability
Feb	133.491	73.124	54.8	Moderate High Variability
Mar	112.882	104.016	92.1	Extremely High Variability
Apr	43.17	30.46	70.6	High Variability
May	3.62	5.289	146.1	Extremely High Variability
Jun	1.425	1.922	134.9	Extremely High Variability
Jul	13.144	23.642	179.9	Extremely High Variability
Aug	0.127	0.216	170.4	Extremely High Variability
Sep	1.727	2.854	165.2	Extremely High Variability
Oct	4.378	6.473	147.9	Extremely High Variability
Nov	48.719	43.285	88.8	High Variability
Dec	187.022	166.249	88.9	High Variability
ANNUAL TOTAL	759.442	322.35	42.4	Moderate High Variability
WET SEASON (NOV-APRIL)	735.02	326.859	44.5	Moderate High Variability
DRY SEASON (MAY-OCTOBER)	24.421	26.088	106.8	Extremely High Variability

The highest average rainfall occurred in January (209.735 mm), indicating it is the wettest month, while the lowest is in August (0.127 mm), suggesting it is the driest month. January has the highest SD (135.069 mm), which means there's was wide range in the amount of rainfall from year to year during this month. Conversely, August had the lowest SD (0.216 mm), indicating very little variation in rainfall. May

had a high CV of 146.1%, which means the rainfall was highly variable relative to its low mean. In contrast, February has a lower CV of 54.8%, indicating less relative variability despite having a higher mean rainfall than May. January, February, April, November, and December had high variability. March, May, June, July, August, September, and October had most high variability, with July and August being the most variable months. The wet season had a total mean rainfall of 735.02 mm with a CV of 44.5%, placing it in the moderate variability category. This suggests that while the wet season is expectedly rainier, its rainfall is not as unpredictable as some individual months. The dry season had a significantly lower mean rainfall of 24.421 mm but a higher CV of 106.8%, categorizing it as most highly variable. This indicates that the dry season experiences less rainfall overall, but the amount it does receive varies greatly. The annual total mean rainfall is 759.442 mm with a CV of 42.4%, which falls into the moderate variability category. This suggests that while there is some year-to-year variation in total rainfall, it is not as extreme as the variability seen within certain months or seasons.

4.2.2. Trend analysis and change point detection

Mann Kendal test results are presented in the Table 3 below, illustrating the Kendall's tau, S value which is the statistical summary, computed p-value, and trend. A positive value of 'S' indicates rising trend, whereas a negative value indicates a decreasing trend.

Table 3: Mann Kendal test results for rainfall

Month	Kendall's tau	S	p-value	Trend
January	0.363	169	0.004	Increasing
February	0.527	245	3.367	Increasing
March	0.213	99	0.095	Increasing
April	-0.032	-15	0.811	Decreasing
May	-0.318	-135	0.017	Decreasing
June	-0.264	-110	0.051	Decreasing
July	-0.461	-201	0.000	Decreasing
August	-0.512	-189	0.000	Decreasing
September	-0.524	-205	0.000	Decreasing
October	1.358	6	0.931	Increasing
November	-0.312	-145	0.014	Decreasing
December	1.505	7	0.918	Increasing
Annual Total	0.222	103	0.083	Increasing
Wet Season (Nov-April)	0.260	121	0.041	Increasing
Dry Season (May-Oct)	-0.295	-136	0.021	Decreasing

January, February, and March show positive Kendall's tau values of 0.363, 0.527, and 0.213 respectively. The positive values indicate an increasing trend in rainfall. Importantly, the p-values for these months are below 0.1, with January and February being statistically significant ($p < 0.05$). This confirms that the increasing trend in rainfall for these months is not likely due to random chance but is a reliable pattern. Annual Total and Wet Season (November-April) also exhibit positive trends, with Kendall's tau values of 0.222 and 0.260. The p-values are 0.083 and 0.041 respectively. Although the trends are mild, the p-values indicate that the trends for

the Wet Season and Annual Total rainfall are statistically significant, reinforcing the observation of a general increase in rainfall during these periods.

October and December show unusually high positive Kendall's tau values of 1.358 and 1.505. However, the p-values for these months are very high (0.931 and 0.918), indicating that the observed trends are not statistically significant. This suggests that the apparent increases in rainfall during these months are likely due to random variation rather than a true underlying trend.

April through September show negative Kendall's tau values, indicating a decreasing trend in rainfall. For May, July, August, and September, the p-values are below 0.05, making these decreasing trends statistically significant. This indicates that rainfall during these months has a consistent pattern of decline. The Dry Season (May-October) also shows a negative trend with a Kendall's tau value of -0.295 and a p-value of 0.021. This confirms a statistically significant decreasing trend in rainfall during the Dry Season, suggesting a broader pattern of reduced rainfall during these months.

The data indicates a complex pattern of changes in rainfall distribution over the year. There is a notable increase in rainfall during the early months of the year and the Wet Season, suggesting that the region might be experiencing wetter conditions during these periods. Conversely, the decrease in rainfall from April to September and during the Dry Season points to drier conditions during these months. The lack of statistical significance in the high positive tau values for October and December suggests caution in interpreting these particular months, as the observed trends may not reflect actual long-term changes but rather short-term fluctuations or anomalies.

Table 4 below presents the Sen's slope results.

Table 4 Sen's slope

Month	Sen's Slope
January	7.237
February	4.985
March	1.935
April	-0.101
May	-0.09
June	-0.033
July	-0.458
August	-0.003
September	-0.095
October	0
November	-1.95
December	0.339
Annual	10.151
Wet (Nov-April)	11.5
Dry (May-Oct)	-0.924

January shows the highest positive slope of 7.237, indicating a strong upward trend in rainfall, meaning that rainfall was increasing at a relatively rapid rate. February and March also show significant positive slopes of 4.985 and 1.935, supporting an increasing trend. December has a smaller positive slope of 0.339, suggesting a slight increase in rainfall. The positive slopes in January, February, and March indicate a significant increase in rainfall, possibly due to shifts in weather patterns or climate change. December's smaller increase suggests a less pronounced but still upward trend. These changes may reflect seasonal variations influenced by larger climatic factors. April through September show negative slopes, with July having the most pronounced decrease -0.458 suggesting that rainfall was decreasing at a moderate rate. November also shows a notable negative slope of -1.95, indicating a significant

decreasing trend in rainfall. October has a slope of 0, indicating no change in the trend for this month. The wet season (November-April) shows an increasing trend with a Kendall's tau of 0.260 and a Sen's Slope of 11.5, indicating not only more frequent rainfall events but also a significant increase in the amount of rainfall. Conversely, the Dry season (May-October) shows a decreasing trend with a Kendall's tau of -0.295 and a Sen's Slope of -0.924, suggesting less frequent and lower amounts of rainfall. A statistical significance of 5% is observed for both the wet and dry seasons. The conclusion of the studies is still significant even at a 10% level. The acceptance of a 10% significance level in the study ensured that potentially meaningful trends are not overlooked. Given the high variability and the critical implications of rainfall trends, a 10% level was justified. This approach aligned with the broader practices in environmental science, where the cost of failing to detect a real change could outweigh the cost of a false positive.

Using a 10% significance level strikes a balance between Type I errors (false positives) and Type II errors (false negatives). In climate studies, missing a real trend (Type II error) can be as detrimental as falsely identifying a trend.

The p-values of 0.083 and 0.041 indicate a significant increasing trend at both the 10% and 5% levels, respectively. This reinforces the reliability of the observed trends. For instance, Wilks (2006) discusses the application of different significance levels in atmospheric sciences, emphasizing the importance of context and the consequences of Type II errors (failing to detect a true effect) in environmental research.

4.2.3. Annual Total Rainfall in Rumphi District

The annual total rainfall of Rumphi District is approximately 1200-1800 millimeters per year based on historical weather data collected by the Meteorological Department or National Meteorological Service of Malawi. Annual rainfall data refers to the total amount of rainfall recorded in a year, usually from January to December. Analyzing the annual total rainfall data has provided us with insights into the typical identification of long-term trends that is increase or decrease in rainfall over the years, year-to-year changes in rainfall amounts and as well periodic patterns,

such as wet and dry cycles in Rumphi District, observed over the past period of 31 years that is between 1992 and 2022.

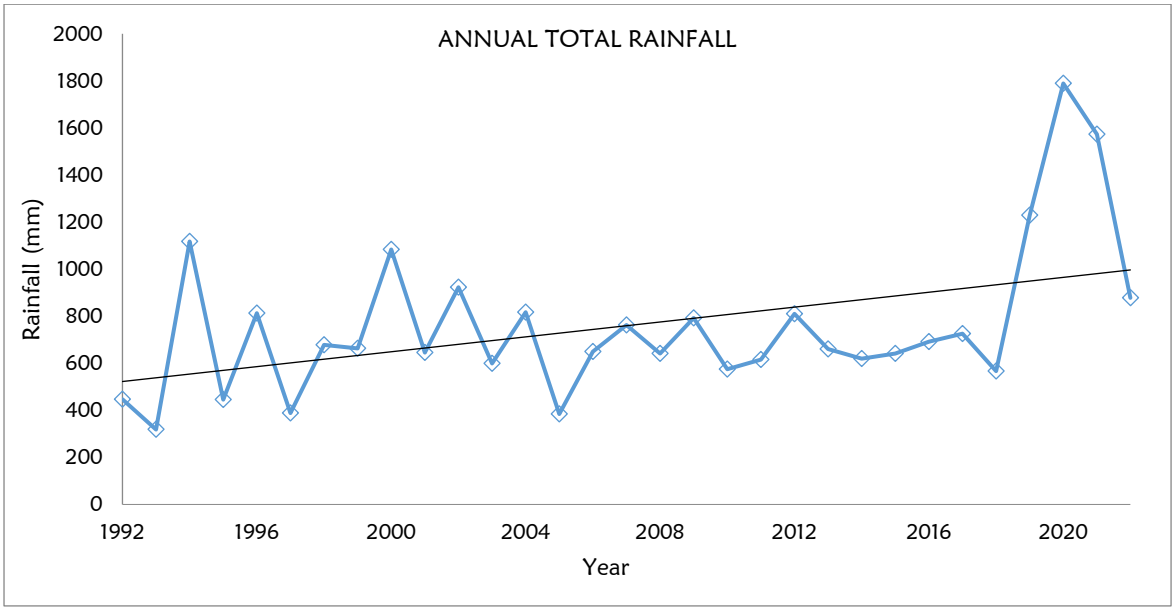


Figure 3: The annual rainfall distribution

The graph 3 above indicates variability in annual rainfall with some years experiencing higher totals than others. There is a noticeable upward spike in rainfall around the year 2020, which could suggest an anomalous increase in precipitation that year. This could be due to various factors, including climatic events like El Niño or La Niña, or it could be indicative of a broader trend related to climate change (Mwale, 2018). The overall pattern does not show a consistent increase or decrease but rather significant fluctuations from year to year. This suggests that while there may be underlying trends, annual rainfall is subject to a variety of influencing factors, making it inherently variable. The significant year-to-year fluctuations in annual rainfall observed in the South Rukuru River catchment are consistent with broader hydrological research, which attributes such variability to a complex interplay of climatic factors. Atmospheric circulation patterns, oceanic phenomena like El Niño and La Niña, and regional geographic features influence rainfall patterns, leading to altered precipitation trends as noted by the IPCC (2014). In sub-Saharan Africa, the Intertropical Convergence Zone (ITCZ) drives this variability, shifting seasonally and interannually to affect local precipitation (Nicholson, 2018). These factors make it

difficult to discern clear trends over shorter timescales, highlighting the inherent variability in rainfall.

4.2.4. Wet Season in Rumphi District (Nov-April)

A graph in figure 4 shows wet season rainfall distribution which is between the month of November and April for the past three decades, between 1992 and 2022.

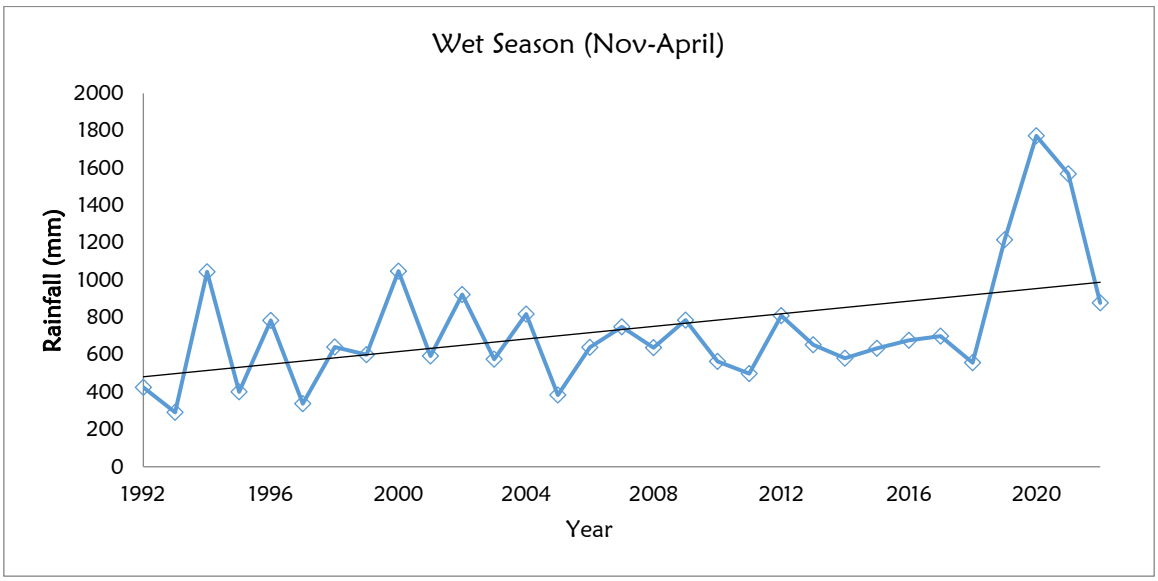


Figure 4: Wet season rainfall distribution

The wet season in Rumphi District typically spans from November 25 to April 16, lasting for about 4.7 months (Mwakasungula et al., 2015).

During this period, there is an increase in precipitation, with January being the month with the most rain, experiencing an average percentage of 39% at an average of 23.2 wet days and 9.1 inches of rainfall compared to the dry season (Mwakasungula et al., 2015). This season is characterized by higher humidity levels and more frequent rainy days. The wettest months fall within the range of November 11 to June 3, covering approximately 6.8 months. The wet season brings about a significant change in weather patterns, with an increase in cloud cover and precipitation. The region receives a substantial amount of rainfall during this period, contributing to the tropical wet savanna climate experienced in Rumphi District (Mwakasungula et al., 2015)

4.2.5. Dry Season in Rumphi District (May-Oct)

The dry season in Rumphi District typically spans from April 16 to November 25, lasting for about 7.3 months. During this period, the region experiences significantly

fewer wet days compared to the wetter season (Mwale, 2018). Figure 5 shows dry season rainfall distribution for the month of May and October for the past 31 years (1992-2022).

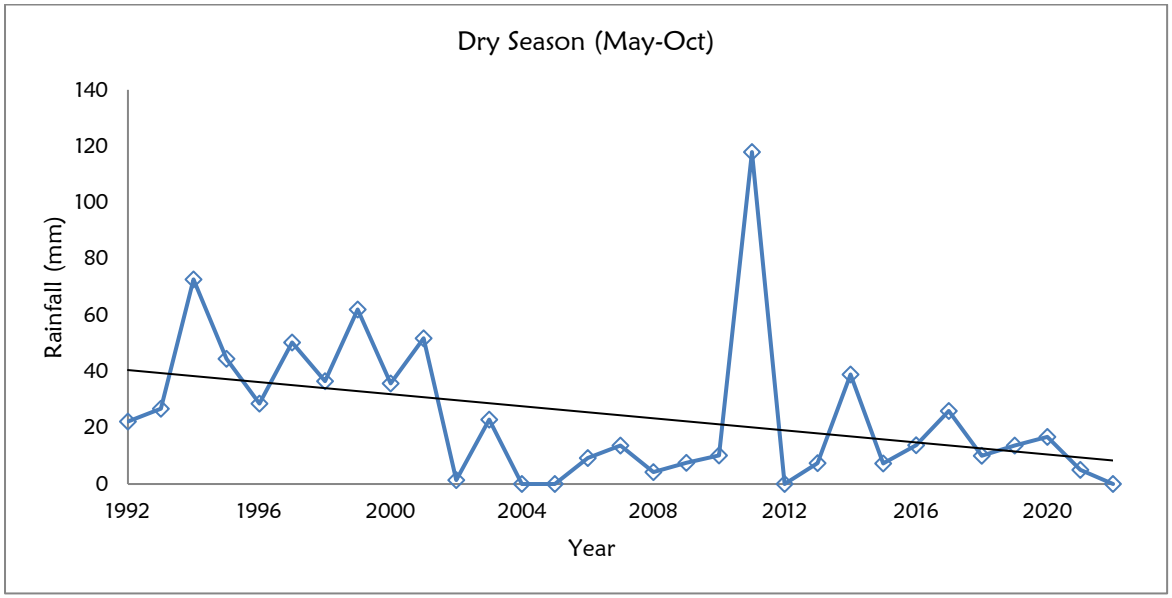


Figure 5: Dry Season rainfall distribution

The trend line suggests a slight decrease in rainfall over the three-decade period. Starting from around 60 mm in 1994, it declines to just below the mark by 2022. There is considerable year-to-year fluctuation, with some years experiencing much higher or lower rainfall than the average. Notably, there is a significant peak around 2011, where rainfall was almost 120 mm, which is an outlier compared to other years. The fluctuations indicate high variability in dry season rainfall, which is consistent with the high coefficient of variation (CV) noted in the earlier data provided. The dry season is characterized by lower precipitation levels, with August being one of the driest months, having only 0.6 days of wet weather and minimal rainfall of 0.04 inches. The least rainy period falls between June and October (Mwale, 2018), with August recording the lowest amount of rainfall at just 0.1 inches. This contrasts sharply with the wetter season, particularly January, which experiences more frequent and heavier rainfall.

4.2.6. Monthly Total Rainfall

Monthly total rainfall in Rumphi District exhibits significant seasonal variation, with the wetter season lasting approximately 4.7 months from November to April with a

total rainfall of 22,785.6 mm received over the past three decades, during which an average of 39% of days experience some precipitation (Chirwa, 2016). The figure 6 shows Monthly total rainfall distribution.

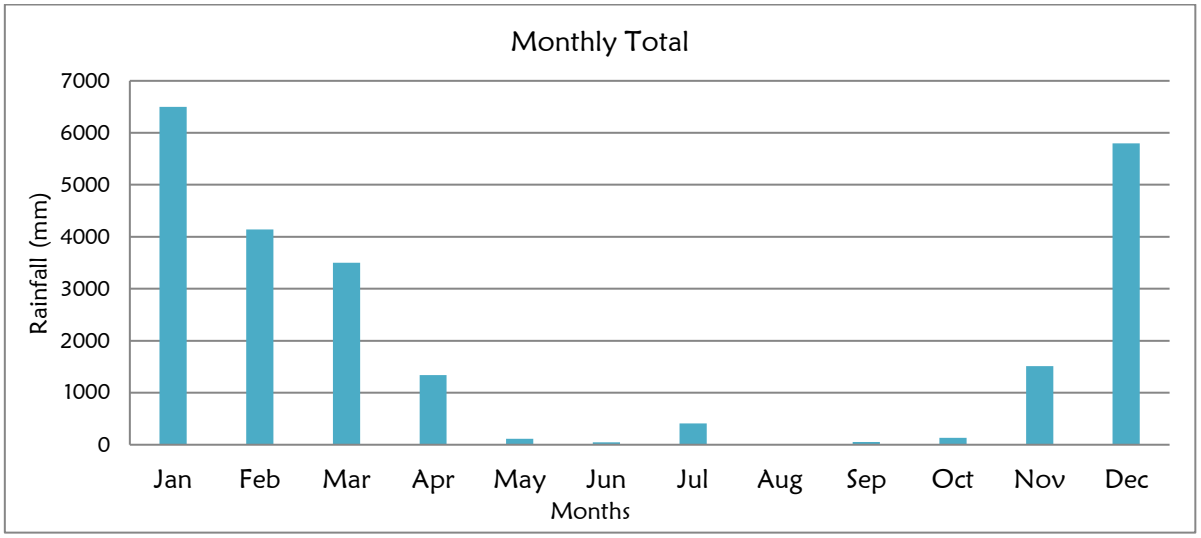


Figure 6: Monthly total rainfall distribution

The figure 6 above shows graph which started with an extraordinary peak in January, indicating the highest rainfall of the year, which is 6500 mm. This suggested that January is likely part of a wet season, possibly influenced by monsoonal patterns or other climatic factors that bring about heavy precipitation. February and March also showed significant rainfall, with February's totals around 4000 mm and March just 3500 mm. The declining trend from January to March suggests a gradual transition from the wettest conditions towards a drier period. There was a notable drop in April, with rainfall slightly above 1000 mm. This could mark the end of the wet season or a shift in weather patterns leading to reduced precipitation. May to October show a marked dry spell, with rainfall amounts hovering close to the bottom of the graph. The consistent low values indicated a prolonged dry season, which could have implications for water availability. A slight uptick in rainfall occurs in November, remaining below 1000 mm. This could be the onset of the wet season or pre-monsoon showers beginning to increase the moisture levels. December ends with a sharp rise in rainfall, comparable to January's high levels. This resurgence of heavy precipitation could be part of the wet season's return, completing a cyclical pattern observed in the graph. The graph clearly illustrates a bimodal rainfall

distribution, with two distinct wet seasons separated by a prolonged dry period. Such patterns are often observed in tropical climates, where the interplay of ocean currents, wind patterns, and geographical features can lead to significant seasonal variations in rainfall.

4.2.7. Change Point Detection

Change point detection is carried out using a Pettitt Homogeneity Test (Gedda et al., 2023). A significant result (p-value < 0.05) indicated a change point in the data, which represented a shift in the mean, variance, or distribution. The change point was estimated at the point where the Pettitt statistic (U) was the maximum. (Ferrari et al., 2023)

4.2.7.1. Change point detection for the monthly rainfall

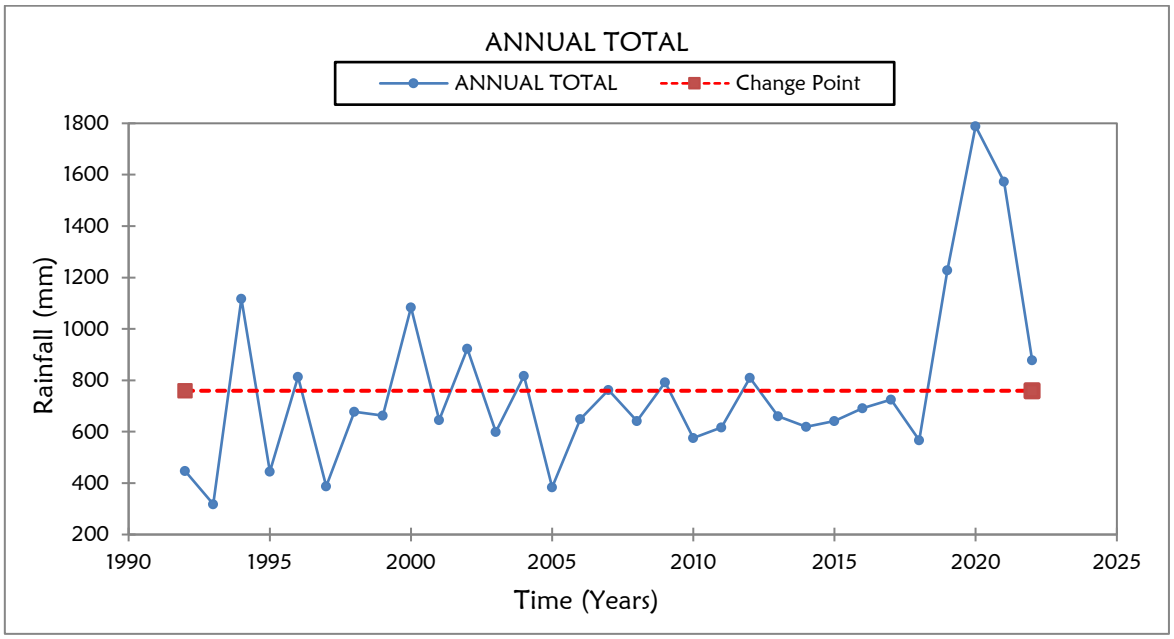
Multiple change points are detected in the monthly rainfall data, indicating significant changes in rainfall patterns over time. The change points are identified in the following months, April 1992 (67.6 mm), October 1998 (5.6 mm), January 2003 (188.7 mm), and July 2010 (0.4 mm). After April 1992, the pattern changed, with a more pronounced increasing trend from January to May, followed by a sharp decrease in June and July, and a relatively constant trend from August to December. The change in October 1998 marked a shift towards a more erratic rainfall pattern, with increased variability and unpredictability. The change in January 2003 indicated a return to a more consistent pattern, with an increasing trend from January to March and a decreasing trend from April to December. The final change in July 2010 marked a significant decrease in rainfall amounts, potentially indicating a drought or dry spell (Mwale, 2018).

4.2.7.2. Change point detection for the annual and seasonal rainfall

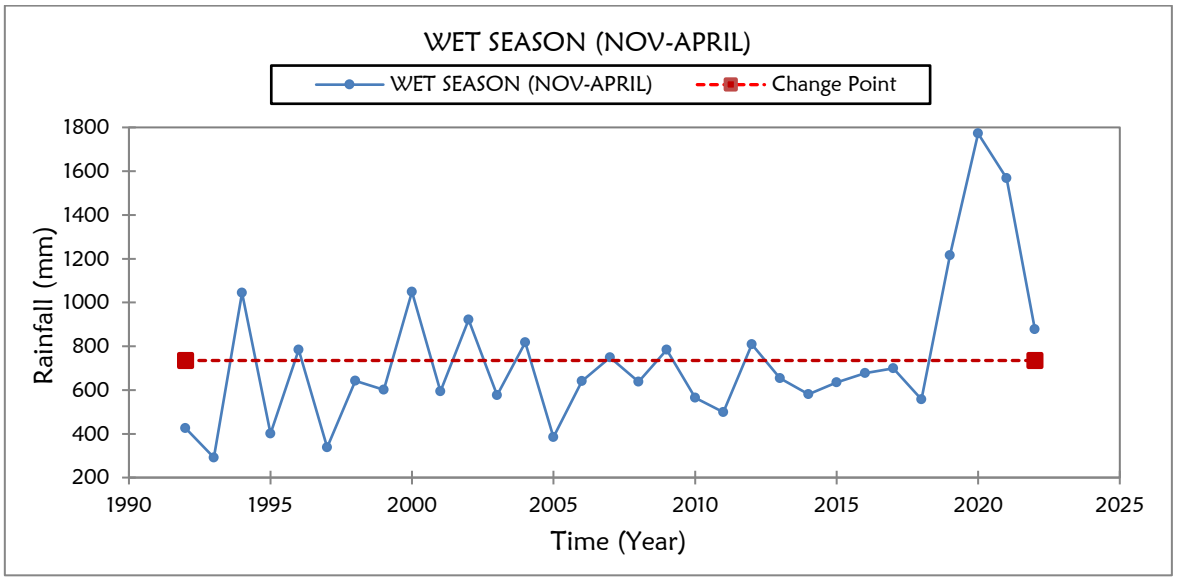
The change points detected in annual and seasonal rainfall data suggest that the Rumphi catchment has experienced significant changes in rainfall patterns over the past few decades. No significant change point is detected in annual total rainfall during the whole period of 31 years, indicating a no shift in the annual rainfall pattern and the wet season rainfall pattern. Change points were detected in different seasons namely the dry season (May to October) where a significant increase in rainfall is

detected in 2011. This change point may be attributed to climate change for example, shifts in the Indian Ocean Dipole (IOD) or the El Niño-Southern Oscillation (ENSO) cycles, which affected rainfall patterns in the region potentially accelerating drought conditions or causing the wet season to start earlier or end later than usual, land use changes, or other environmental factors (Mwale, 2018). Figure 7 are the illustrations for the changes in the annual and seasonal rainfall distribution.

a. Pettitt homogeneity test for annual total rainfall



b. Pettitt homogeneity test for wet season rainfall (Nov-April)



c. Pettitt homogeneity test for dry season rainfall (May-Oct)

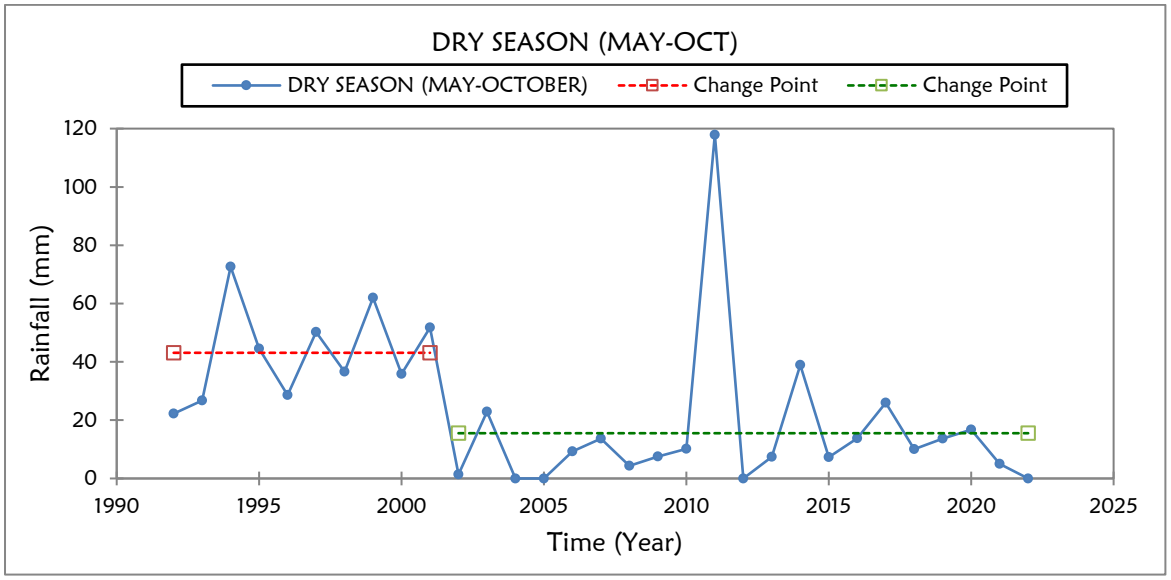


Figure 7: Pettitt homogeneity test for (a) annual total rainfall, (b) wet season (Nov-April) and (c) dry season (May-Oct)

The early 1990s show rainfall amounts generally below 20 mm, indicating a drier period during the dry season. Leading up to 2011, there is a significant increase in rainfall, with the peak reaching close to 120 mm. This suggests an unusually wet period for the dry season, which is well above the average for the preceding years. After the peak in 2011, there is a sharp decline in rainfall, with amounts dropping below 0 mm, which aligns with the lower end of the y-axis scale. This indicates a return to drier conditions. The subsequent years show rainfall amounts fluctuating mostly between 20 mm and 60 mm, with occasional dips below 20 mm. This suggests a stabilization of the dry season's rainfall at a lower level than the peak observed in 2011. The change points marked on the graph correspond to years where the actual rainfall diverges significantly from the expected or average values. These points are crucial in identifying shifts in the rainfall trend. The average or expected rainfall, indicated by the dashed red line, seems to hover around the 40 mm mark on the y-axis. The actual rainfall intersects this line at several points, indicating years where rainfall matched the expected amounts. The overall trend from a peak around 2011 to lower levels in subsequent years suggests a long-term decrease in rainfall during the dry season. This is evident from the consistent positioning of the blue line towards the lower end of the y-axis in the latter part of the graph.

4.3. Streamflow

The Mlowe gauging station recorded its highest mean annual streamflow between 1992 and 2022 at 239.7 m3/s, while the lowest mean annual streamflow during the same period was 11.1 m3/s. The river's overall mean annual streamflow stands at 105.39 m3/s, accompanied by a coefficient of variation of 33.36%. Additionally, the wet season observed a mean streamflow of 178.2 m3/s, whereas the dry season recorded a mean streamflow of 32.6 m3/s.

4.3.1. Annual and seasonal streamflow trend

The table 5 below presents the results of the Mann-Kendall test for annual and seasonal streamflow, where a positive 'S' value signifies an increasing trend. The other table displays the results of the Sen's slope test, with positive values indicating an increasing trend and negative values indicating a decreasing trend (Bey et al., 2024; Gudmundsson & Seneviratne, 2015).

Summary of Mann Kendall test results for monthly and seasonals streamflow data from 1992 to 2022 is described in the table 5 below.

Table 5: Mann Kendal test results for streamflow

Month	Kendall's tau	S	p-value	Trend
January	0.617	287	1.168	Increasing
February	0.634	295	5.825	Increasing
March	0.626	291	8.267	Increasing
April	0.609	283	1.643	Increasing
May	0.574	267	6.153	Increasing
June	0.591	275	3.208	Increasing
July	0.617	287	1.168	Increasing
August	0.471	219	0.000	Increasing
September	0.389	181	0.002	Increasing
October	0.497	231	9.261	Increasing
November	0.574	267	6.153	Increasing
December	0.505	235	6.974	Increasing
Annual Average	0.686	319	6.486	Increasing
Wet Season	0.695	323	4.429	Increasing
Dry Season	0.583	271	4.453	Increasing

Sen's Slope test results for monthly, annual and seasonal streamflow data from 1992 to 2022 are shown in table 6 below.

Table 6: Sen's Slope test results for streamflow

MONTH	SEN'S ESTIMATOR
JANUARY	13.732
FEBRUARY	18.345
MARCH	17.453
APRIL	10.642
MAY	3.436
JUNE	1.364
JULY	0.699
AUGUST	0.363
SEPTEMBER	0.212
OCTOBER	0.316
NOVEMBER	0.562
DECEMBER	5.948
ANNUAL	6.649
WET SEASON	12.385
DRY SEASON	1.117

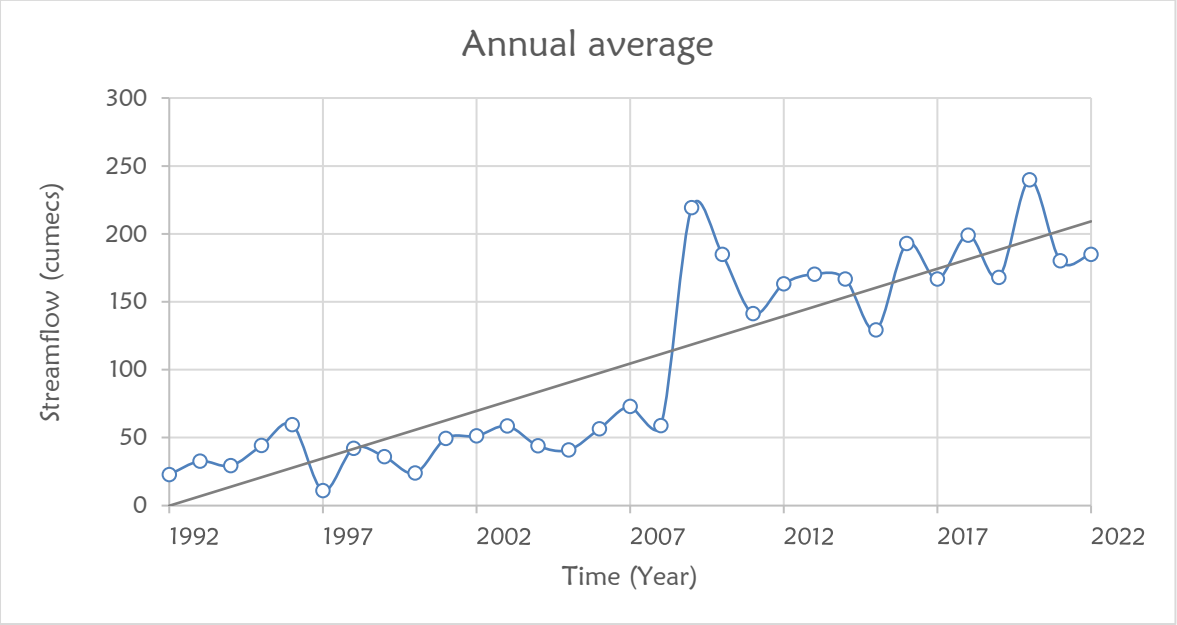
The results of the Mann-Kendall trend test for monthly, seasonal, and annual streamflow, showing that all periods exhibit increasing trends. Kendall's tau values range from 0.389 (September) to 0.695 (wet season), indicating consistent positive trends across all months, seasons, and the annual average. Significant increases are particularly evident in August (tau = 0.471, p = 0.000) and September (tau = 0.389, p = 0.002). Other notable increases include February (tau = 0.634, p = 5.825) and the annual average (tau = 0.686, p = 6.486). Both the wet (tau = 0.695, p = 4.429) and dry seasons (tau = 0.583, p = 4.453) also show significant increasing trends, demonstrating a pervasive upward trend in streamflow across the entire year.

The Sen's estimator for streamflow trends across different months, the annual total, and seasonal periods. The values indicate the magnitude of the trend in each period. January through March show substantial increases, with Sen's estimators of 13.73194, 18.34502, and 17.45335, respectively. April also has a notable positive trend of

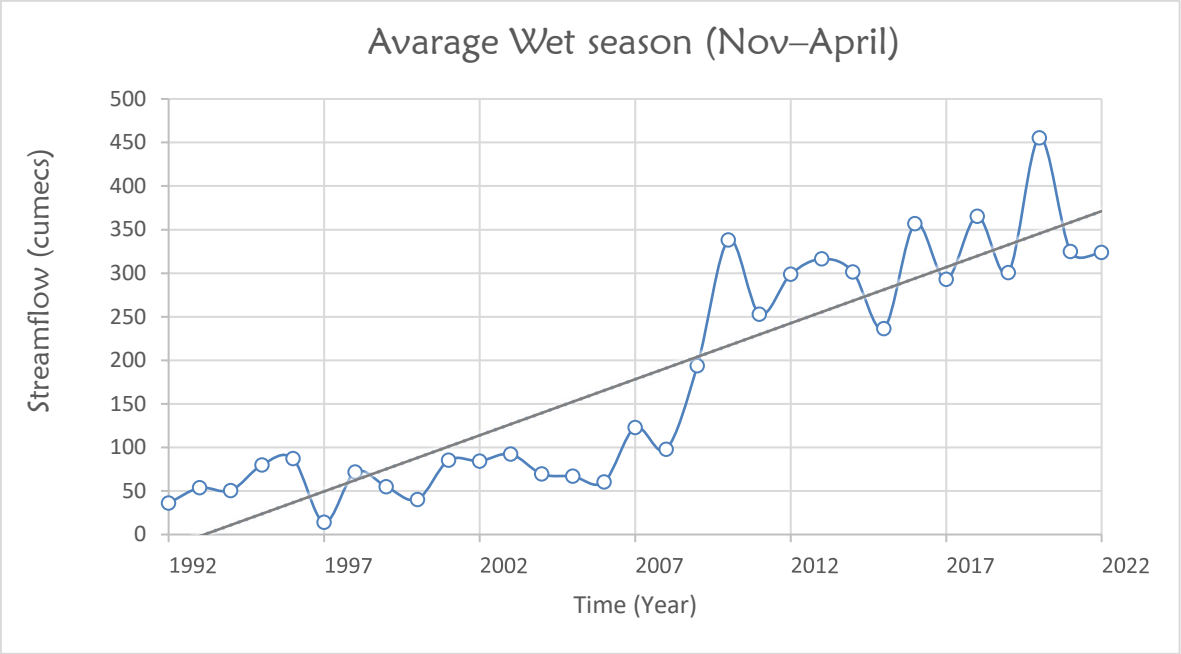
10.6422. The remaining months from May to November exhibit smaller increases, ranging from 0.2115739 in September to 5.948397 in December, with July and August having the smallest values at 0.6991114 and 0.3625399, respectively. The annual trend is 6.649177, reflecting an overall moderate increase. Seasonally, the wet season (November to April) shows a significant upward trend with an estimator of 12.38473, while the dry season (May to October) has a modest increase of 1.117024.

The Mann-Kendall test identifies the presence and significance of trends, showing significant increasing trends for all months, seasons, and the annual average with positive Kendall's tau values and low p-values. Sen's slope quantifies the magnitude of these trends, indicating specific rates of increase. For example, January has a high positive Kendall's tau of 0.617 and a Sen's slope of 13.731 units per year, reflecting a strong increasing trend. Similarly, the wet season shows a substantial increase with a tau of 0.695 and a Sen's slope of 12.38473. The consistency between higher Kendall's tau values and larger Sen's slope estimates demonstrates a robust relationship, indicating significant and quantifiable increases in streamflow across most periods

a. Annual average streamflow distribution



b. Average wet season streamflow distribution (November-April)



c. Average dry season streamflow distribution (May-October)

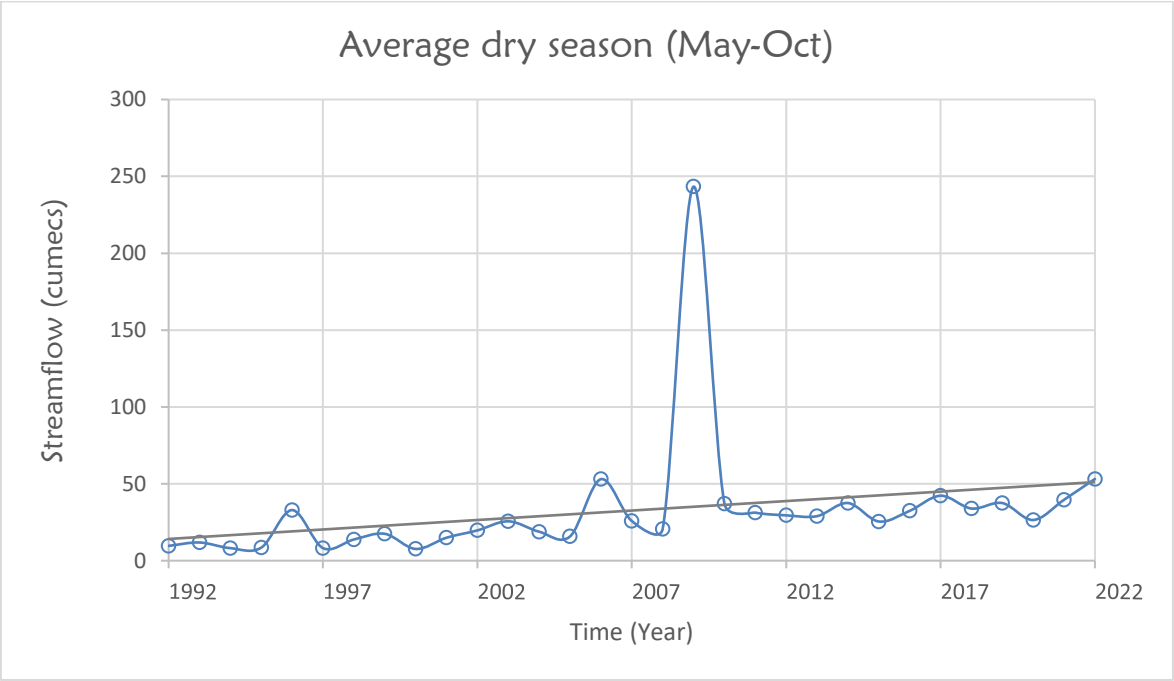


Figure 8: Illustrating (a) annual average streamflow, (b) wet season streamflow (Nov-April) and (c) dry season streamflow (May-Oct)

4.3.2. Monthly streamflow trend

The Mann-Kendall test results reveal varying monthly streamflow trends, with some months showing significant increases while others display non-significant trends. For instance, January, February, March, and April exhibit significant increasing trends

according to the Mann-Kendall test, with Kendall's tau values of 0.617, 0.634, 0.626, and 0.609, respectively. Similarly, Sen's slope analysis supports these findings, demonstrating substantial positive trends in these months, with values of 13.73194, 18.34502, 17.45335, and 10.6422, respectively. However, May through September show decreasing trends, significant in July, August, and September, with Kendall's tau values of -0.461, -0.512, and -0.524, respectively, and corresponding Sen's slope values of 0.6991114, 0.3625399, and 0.2115739. Meanwhile, October, November, and December portray increasing trends, with November and December displaying significant increases, as validated by both the Mann-Kendall and Sen's slope analyses, with Kendall's tau values of 0.574 and 0.505, and Sen's slope values of 0.5619167 and 5.948397, respectively.

4.3.3. Change point detection of annual streamflow

The results of Pettitt's test for the annual average streamflow indicate a significant change point around the year 2009. Before 2009, the annual average streamflow values fluctuated between 11.1 (1997) and 73.1 (2007). However, starting in 2009, there is a noticeable and substantial increase in streamflow values, with the annual average jumping from 58.7 in 2008 to 219.2 in 2009. This marked change point is followed by consistently higher streamflow values, such as 184.8 in 2010, 163.3 in 2012, 192.9 in 2016, and reaching a peak of 239.7 in 2020. The change point detection suggests a significant upward shift in the streamflow regime starting from 2009, highlighting a marked increase in the annual average streamflow in the subsequent years.

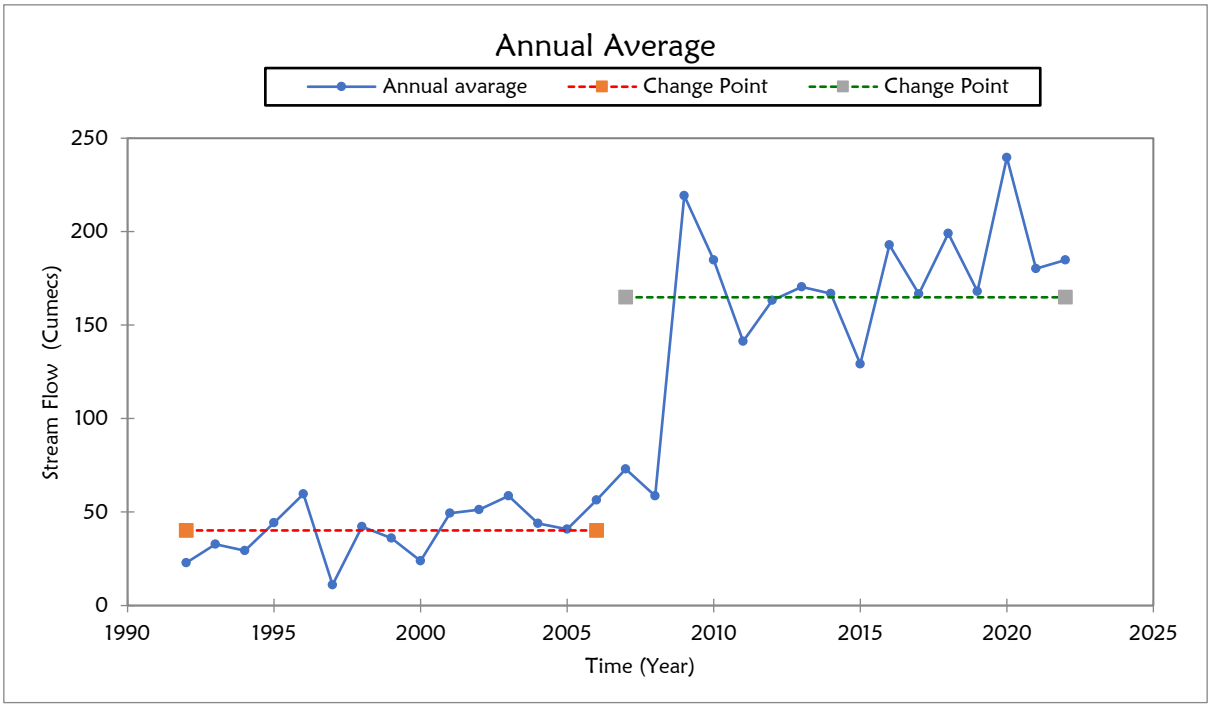


Figure 9: A graph of change point for annual average streamflow

4.3.3.1. Change point detection for wet season streamflow

The results of Pettitt's test for the average wet season streamflow (November to April) indicate a significant change point around the year 2009. Before 2009, the streamflow values were generally lower, with averages ranging from 13.9 in 1997 to 122.8 in 2007. However, starting in 2009, there is a noticeable and substantial increase in the wet season streamflow, with the average rising sharply to 193.8 in 2009. This upward shift continues, with significantly higher values in the following years, including 338.0 in 2010, 298.6 in 2012, 356.9 in 2016, and reaching a peak of 455.4 in 2020. The significant increase in wet season streamflow values since 2009 is attributed to climate change, which causes increase in rainfall and more extreme weather events. Human activities, such as changes in land use and water management practices, and natural climate variability also contributed to higher runoff and streamflow. The change point detection highlights a marked increase in the wet season streamflow from 2009 onwards, indicating a significant upward shift in the hydrological regime during this period.

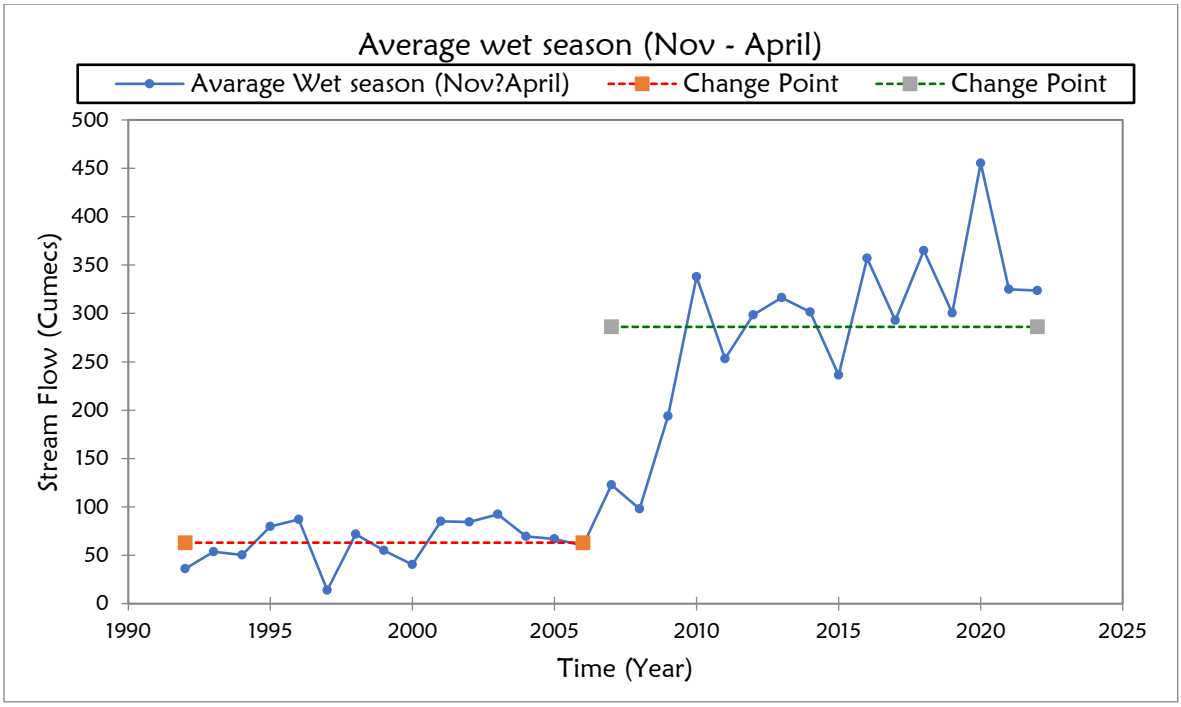


Figure 10: A graph of change point detection for wet season streamflow

4.3.3.2. Change point detection for average dry season streamflow

The results of Pettitt's test for the average dry season streamflow (May to October) reveal a significant change point around the year 2009. Prior to 2009, the streamflow values were generally low, with averages ranging from 7.6 in 2000 to 53.0 in 2006. In 2009, there is a dramatic increase, with the average streamflow surging to 243.3. Following this change point, the dry season streamflow values remain consistently higher, with averages such as 37.1 in 2010, 37.5 in 2014, 42.3 in 2017, and 53.2 in 2022. This shift indicates a marked increase in streamflow during the dry season from 2009 onwards, reflecting a significant upward trend in the hydrological patterns for this period.

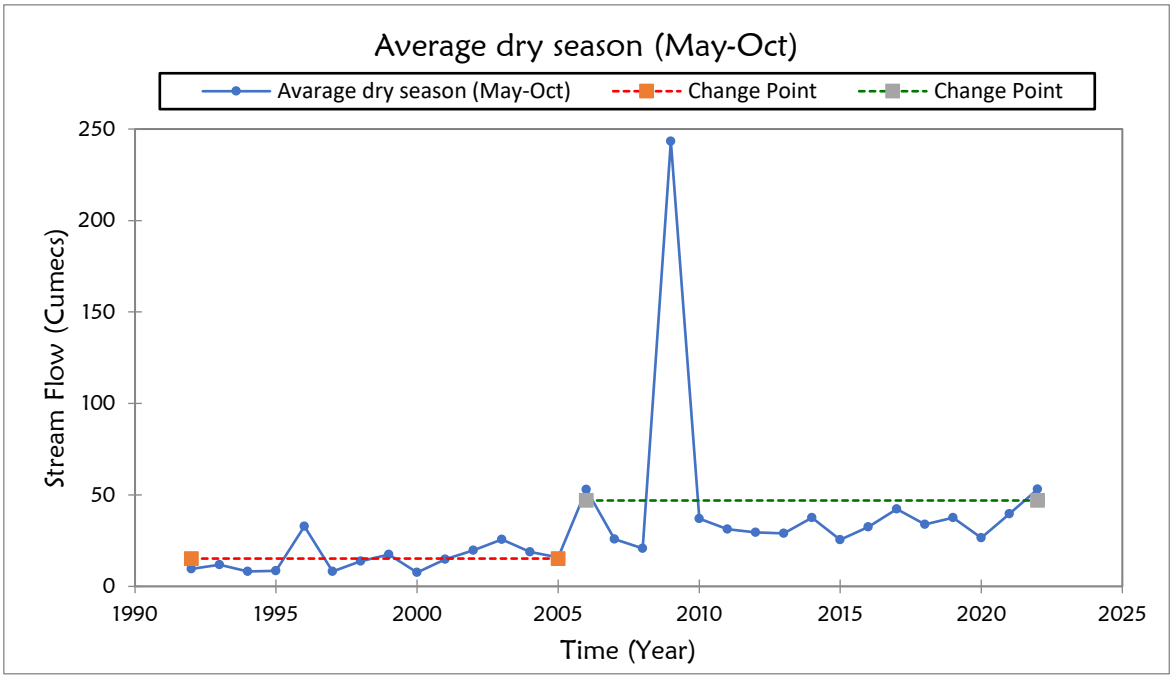


Figure 11: A graph of change point detection for average dry season streamflow

4.4. Rainfall-Streamflow Relationship

The relationship between rainfall and streamflow has helped researchers to understand the water dynamics within a catchment. Rainfall is a primary driver of streamflow as it directly influences the amount of water entering the river system(Ahn & Merwade, 2014). In the case of the South Rukuru catchment, the rainfall received in the area has a direct impact on the streamflow of rivers flowing through it. To examine the linear relationship between rainfall and streamflow in the South Rukuru catchment over the past three decades, from 1992 to 2022, Pearson correlation analysis was performed to calculate the correlation coefficient (r) and coefficient of determination (r^2). This helped to quantify the strength and significance of the relationship between two variables, in this case, rainfall and streamflow whereas a positive correlation indicated that as rainfall increases, streamflow also increases, while a negative correlation implied an inverse relationship (Fang & Shen, 2017). Below is table 7 showing the correlation analysis.

Table 7: The correlation analysis table

Very strong correlation	Strong correlation	Strong moderate correlation	Moderate correlation	Weak correlation
0.8-1.0	0.6-0.8	0.4-0.6	0.2-0.4	0-0.2

Cited from YuHui & RuoRong (2019)

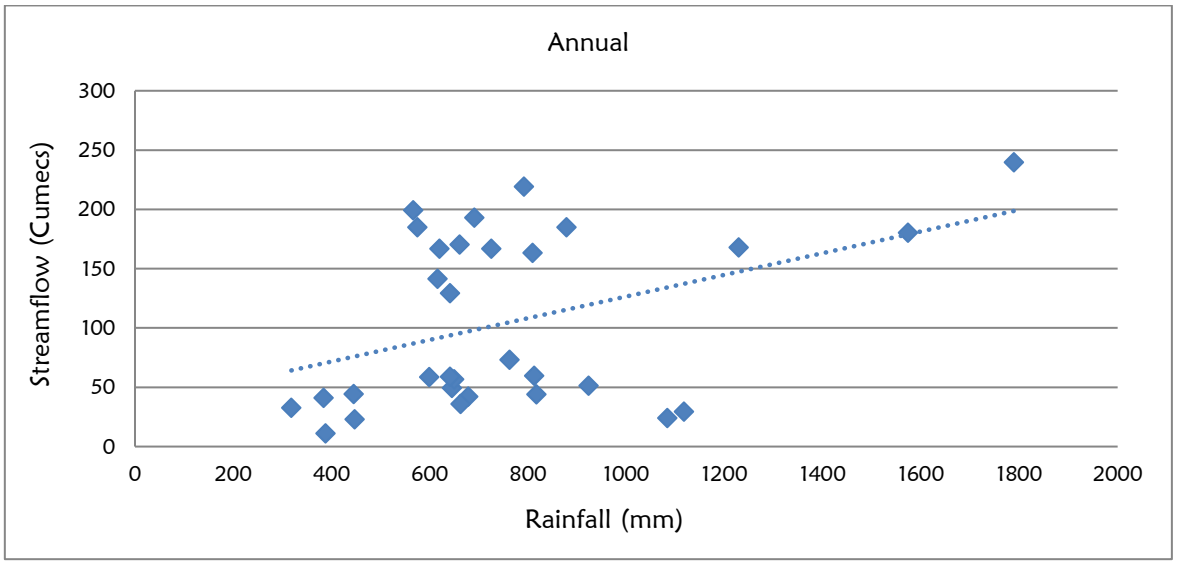
Table 8: Monthly, annually and seasonal values for rainfall-streamflow relationship

Month	Correlation value	P-value
January	0.548	0.001
February	0.605	0.000
March	0.542	0.002
April	0.258	0.161
May	0.314	0.085
June	-0.242	0.191
July	-0.186	0.317
August	-0.148	0.428
September	-0.136	0.465
October	-0.108	0.563
November	-0.002	0.991
December	0.130	0.487
Annual	0.408	0.023
Wet Season (Nov-April)	0.440	0.013
Dry Season (May-October)	-0.213	0.249

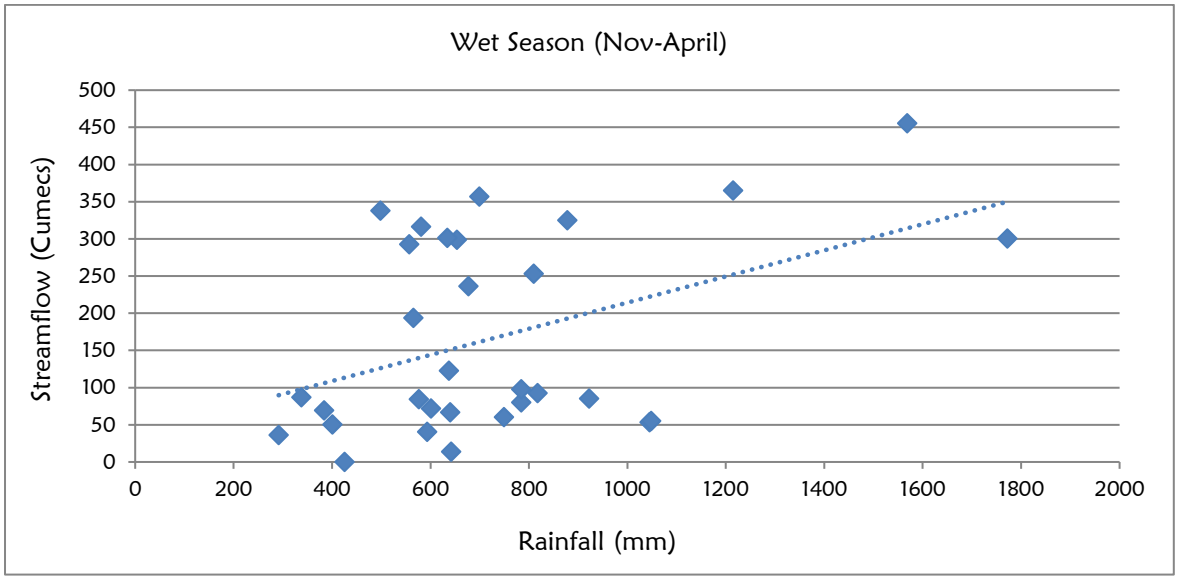
January to March show a strong positive correlation of 0.542 to 0.605, with very low p-values of 0.000 to 0.002, indicating a statistically significant relationship

where higher rainfall likely leads to increased streamflow. December and annual figures also show a positive correlation of 0.130 and 0.408 respectively, but with a higher p-value for December of 0.487, suggesting that the correlation is not statistically significant for that month (Gentilucci et al., 2023). The wet season has a moderate positive correlation of 0.440 with a low p-value of 0.013, indicating a significant relationship during this period. June to November and the dry season show negative correlation values, suggesting that higher rainfall might be associated with lower streamflow, although this is not a strong relationship. The p-values for these months and the dry season ranging from 0.191 to 0.991 are above the typical significance level of 0.05, indicating that the negative correlations are not statistically significant. April and May show a weak positive correlation of 0.258 and 0.314 respectively, but the p-values of 0.161 and 0.085 suggest that these correlations are not statistically significant. October and November have very low or no correlation (-0.108 and -0.002), with high p-values of 0.563 and 0.991, indicating no significant relationship between rainfall and streamflow during these months. The data suggests a significant positive correlation between rainfall and streamflow during the wet season, particularly from January to March. Conversely, there is no significant correlation during the dry season, with some months even showing a negative but non-significant relationship. The figure 12 are graphs showing annual correlation, wet season correlation and dry season correlation.

a. Annual correlation



b. Wet season correlation (November-April)



c. Dry season correlation (May-October)

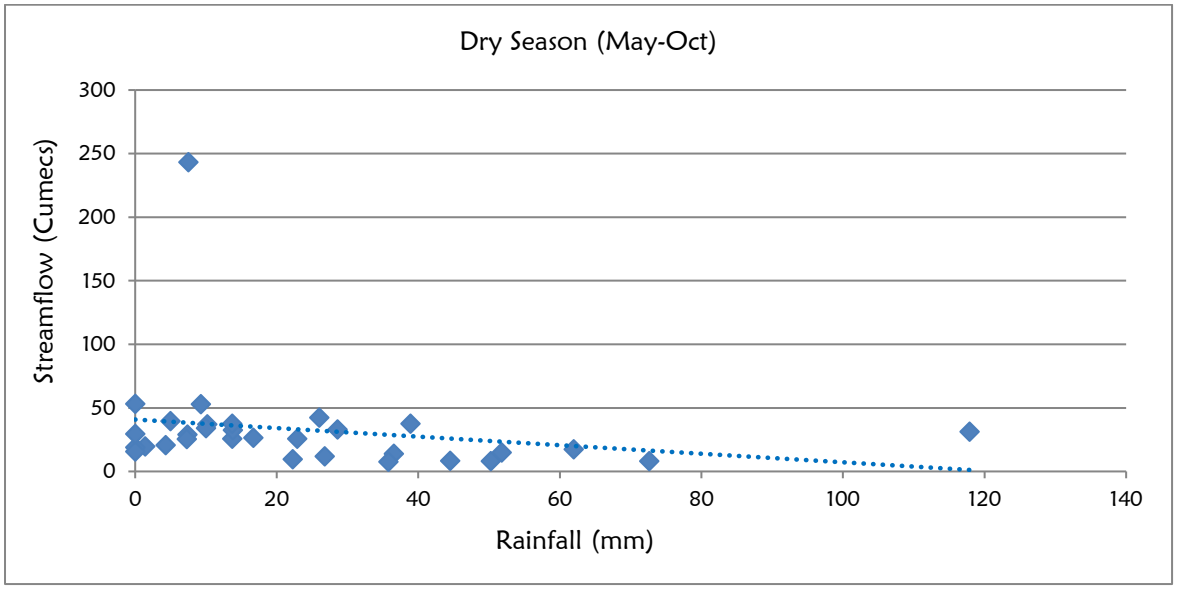


Figure 12: Illustrations showing (a) annual correlation, (b) wet season correlation (Nov-April) and (c) dry season correlation (May-Oct)

The figure 12 show that there is a substantial positive correlation between monthly streamflow and rainfall. This indicates that streamflow variations are significantly influenced by rainfall, meaning that an increase in rainfall causes a corresponding rise in streamflow (Fortesa et al., 2021). Similarly, during the yearly and wet season, there is a positive strong moderate linear association in the watershed. This makes it abundantly evident that variations in rainfall over this time frame impact the decline in streamflow. In contrast, during the dry season, there is a slight negative linear relationship between streamflow and rainfall.

4.5. Land Use and Land Cover Classification in the South Rukuru Catchment

Using remote sensing methods and geographic information systems (GIS), the Rumphi District's land use and cover (LULC) was classified from 1993 to 2022. Classifying the land into classes like range land, bare land, water bodies, and forest cover required the analysis of satellite imagery from three different time periods: 1993–2002, 2002–2013, and 2013–2022. Accurate classification of the land cover types was achieved through the use of supervised classification methods. Figure 13 shows land use/land cover map of South Rukuru Catchment.

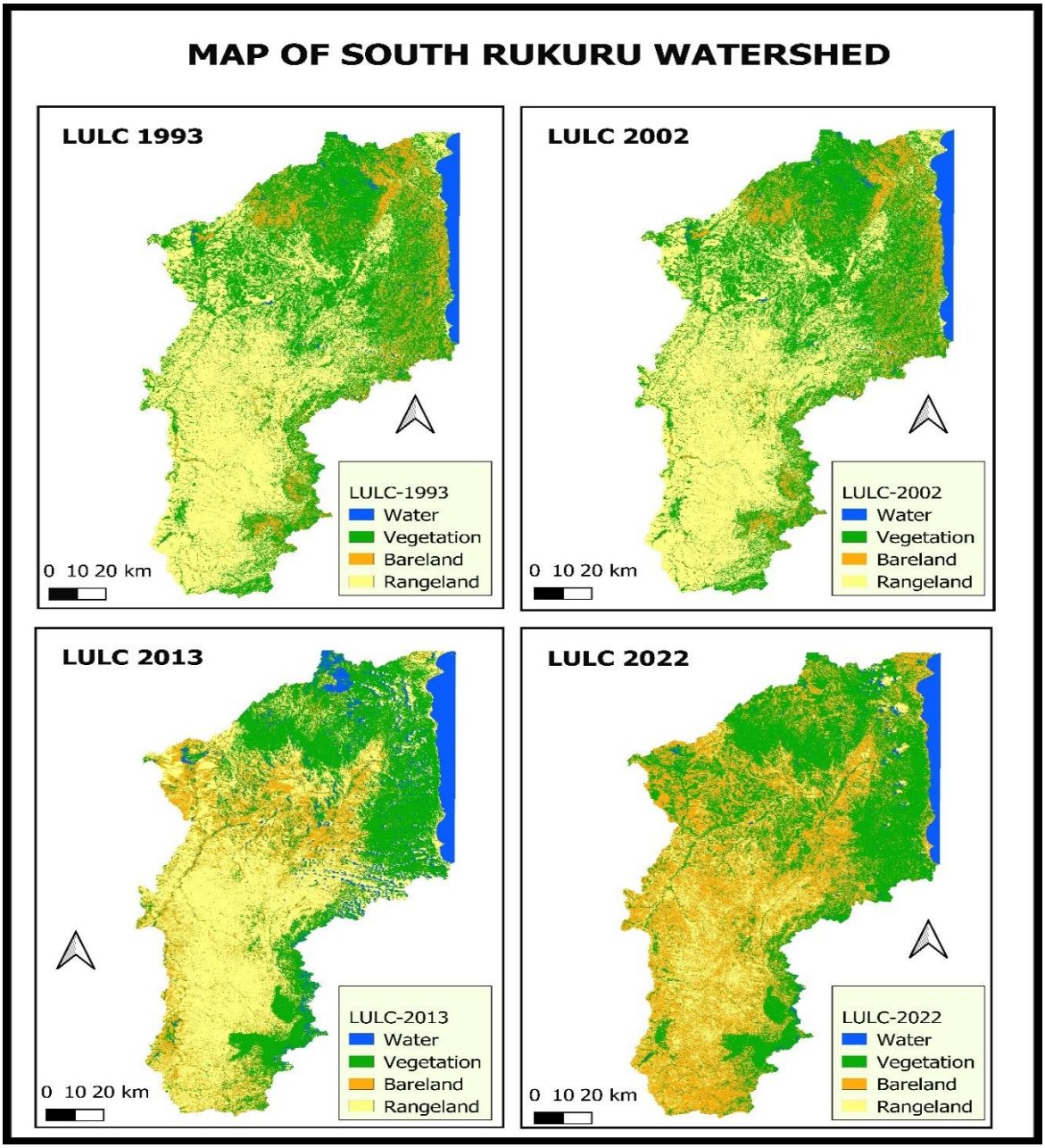


Figure 13: Land use/land cover map of South Rukuru Catchment

A display of land cover and land cover maps created from the 1993 and 2022 Landsat DEM images for the South Rukuru watershed accompanies the findings of the land cover categorization. The features of each categorized land cover class according to the LCCS classification system are then described. Relevant data that illustrates the geographic ranges and distributions of every classed land cover type have been emphasized. An explanation of the accuracy assessment results concludes this section.

Table 9: Areas of Land use/Land cover types

Area (km^2)/ LULC change	1993	2002	2013	2022
	km^2	km^2	km^2	km^2
Water	1127.299	526.5981	458.3628	491.5341
Vegetation	5833.562	5777.899	4818.681	2650.609
Bare land	1564.111	2605.529	3228.896	5983.113
Range land	8212.914	6717.128	5997.606	2207.508

The area covered by water has decreased significantly from 1127.299 km^2 in 1993 to 491.5341 km^2 in 2022. This suggests a loss of water reservoirs over the years, which could be due to factors like droughts, climate change, or human activities such as water diversion during construction activities (roads and dams etc.) (Harisuseno, 2020). There has been a dramatic decrease in vegetation cover, from 5833.562 km^2 in 1993 to 2650.609 km^2 in 2022. This could indicate deforestation, changes in land use for agriculture or urban development, or possibly the impact of climate change on vegetation patterns. Particularly, the area of bare land has increased almost fourfold, from 1564.111 km^2 in 1993 to 5983.113 km^2 in 2022. This increase could be a result of soil erosion, loss of vegetative cover, or the expansion of urban/rural areas (Mwale, 2018). The range land, which often includes natural pastures or grazing areas, has decreased from 8212.914 km^2 in 1993 to 2207.508 km^2 in 2022. This significant reduction could be attributed to overgrazing, conversion to agricultural land, or urban/rural expansion (Chimango & Mwakasango, 2018). The figure 14 Illustrate the land cover and land use types for year 1993.

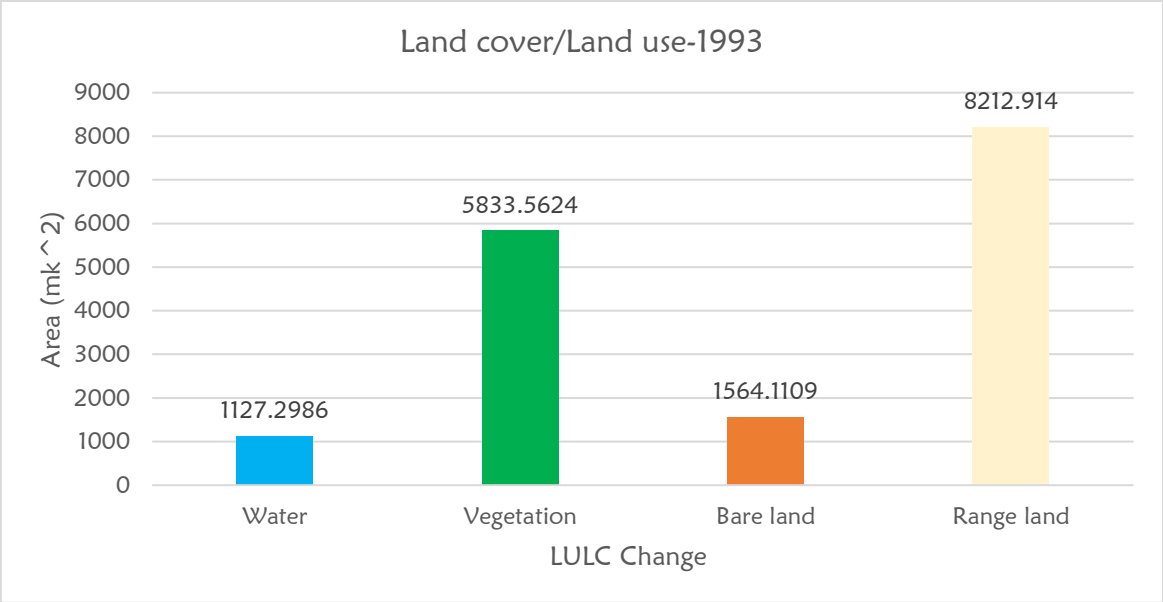


Figure 14*: Illustration of Land cover and Land use types for year 1993*

4.5.1. Spatial distribution of land cover classes in 1993

The distribution consists of large savanna shrub regions, comprising 5833.56 square kilometers or 35% of the total, are classified as being mostly found in the lower escarpments and mountains. Savanna shrubs are found on open grasslands and among scattered trees and bush thickets that are no taller than fifteen meters. The majority, or 8212.91 square kilometers, or 49% of the entire research area, were range lands, which are also utilized as grazing grounds following crop harvest. A second class included of bare ground that covered up to 1564.11 square kilometers, or 9% of the study area, and a class consisting of water that covered 1127 square kilometers, or 7% of the total land area in the South Rukuru watershed. The figure 15 shows the land cover and land use types for year 2002.

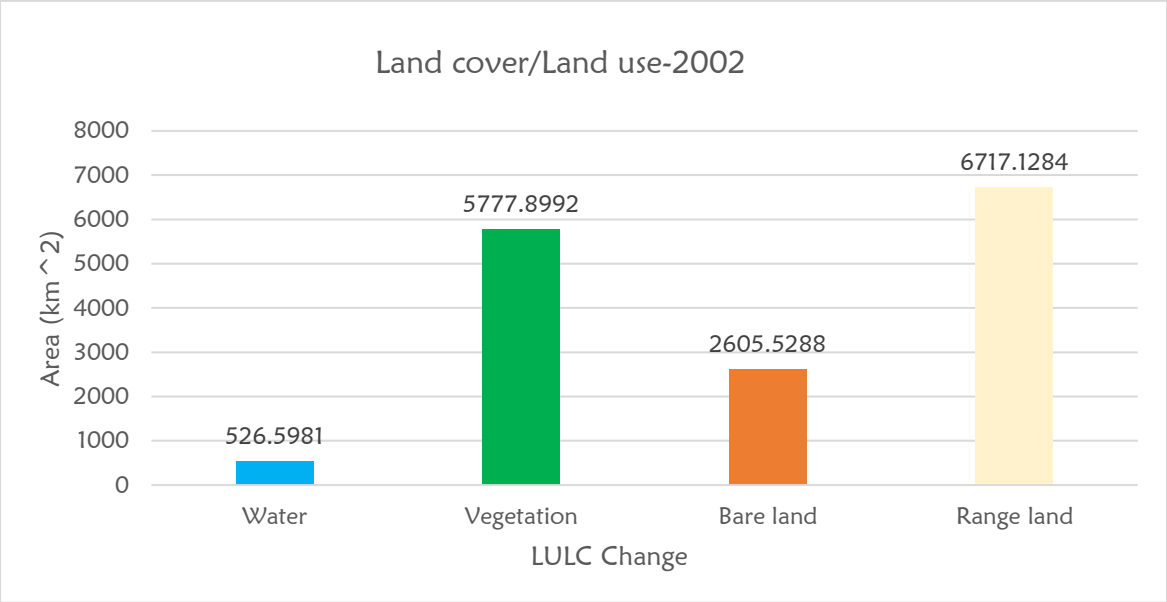


Figure 15: Illustration of Land cover and Land use types for year 2002

4.5.2. Spatial distribution of land cover classes 2002

As seen in the accompanying image, the extent of land surface feature coverage for 2002 was quite different. Range land accounted for the greatest portion of the land surface, including around 6717.12 square kilometers, or 43%, of all land cover types. Vegetation comes in at number two with 5777.89 square kilometers, or 37% of the total area. With 2605.52 square kilometers of barren ground covering it, the third biggest section represents 17% of the whole watershed area. Water made up the smallest component, accounting for 526.59 square kilometers or 3% of the land area. The figure 16 shows the land cover and land use types for year 20013.

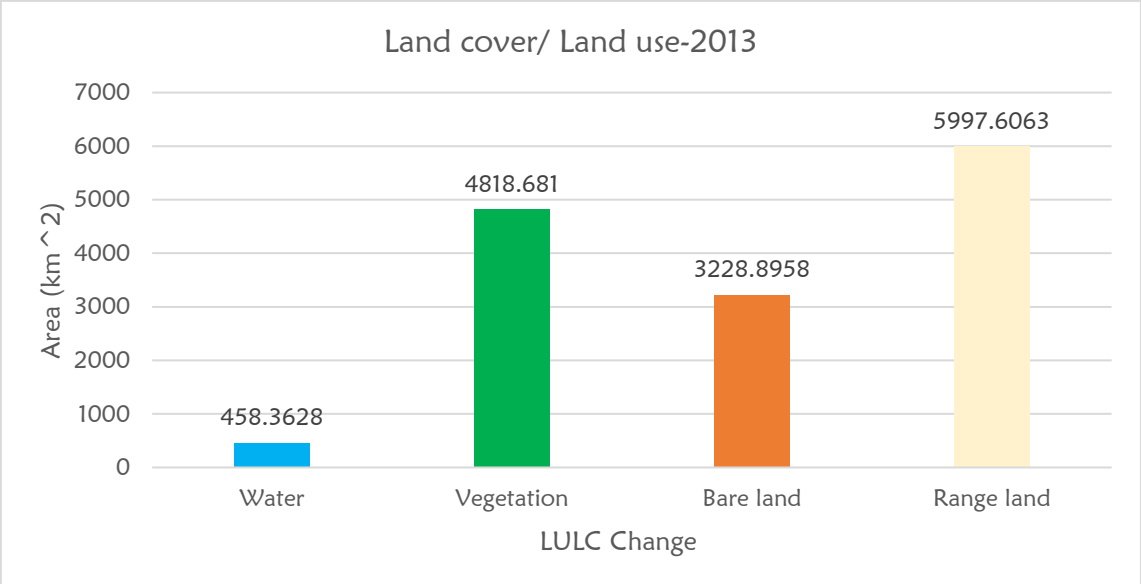


Figure 16: Illustration of Land cover and Land use types for year 2013

4.5.3. Spatial distribution of land cover classes 2013

As seen in the following picture, there was a modest variation in the coverage of land surface characteristics in 2013. Range land represented (42%) of the land surface, with the biggest extents of all the land cover classifications, measuring around 5997.60 square kilometers. With a total area of 4818.68 square kilometers, or 33%, vegetation is the second major category. With 3228.89 square kilometers, or 22% of the entire watershed area, barren land makes up the third biggest sector. Water accounted for 458.36 square kilometers, or 3% of the land area, making it the smallest category. The figure 17 shows the land cover and land use types for year 20022.

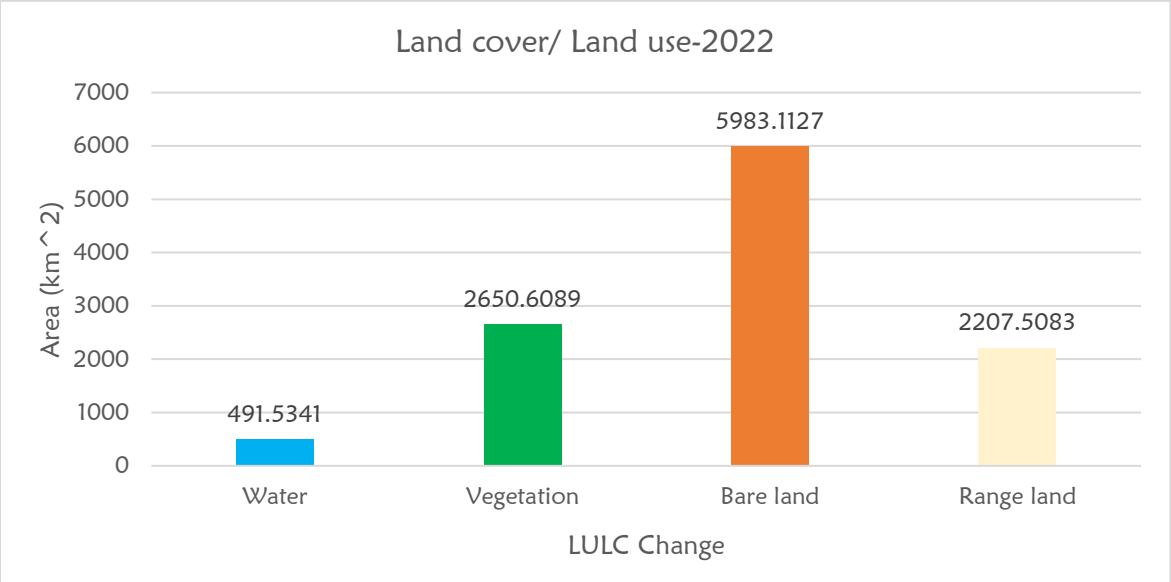
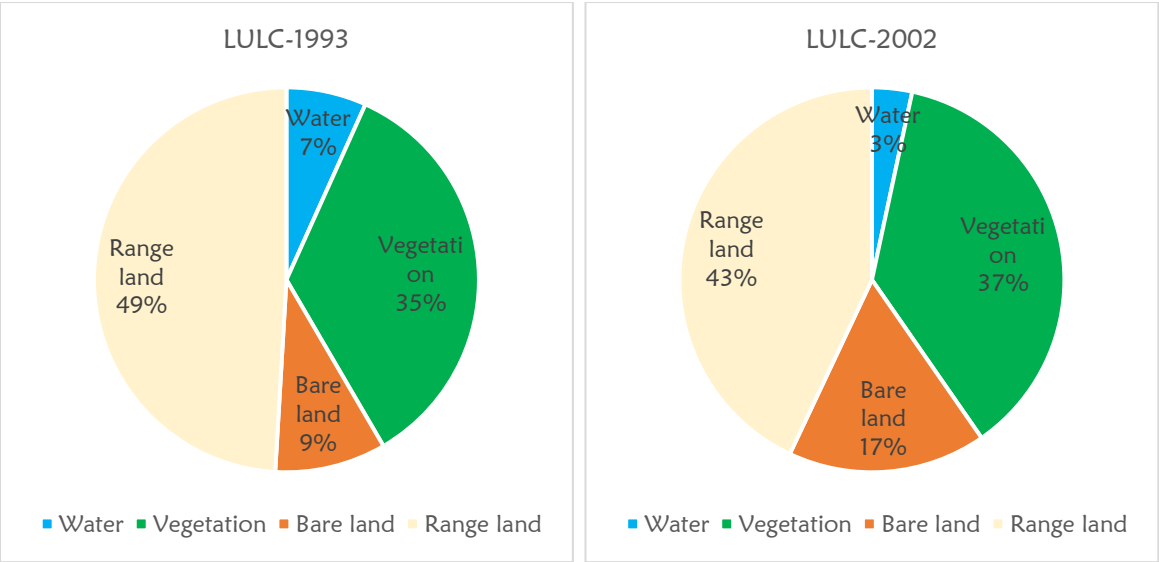


Figure 17: Illustration of Land cover and Land use types for year 2022

4.5.4. Spatial distribution of land cover classes 2022

The graph above illustrates how much of a difference there was in the extent of coverage of land surface characteristics in 2022. Bare land constituted the biggest land cover type, with around 5983.11 square kilometers, or 53% of the total land area. Vegetation comes in at number two, accounting for 2650.60 square kilometres or 23% of the total. Range lands, at 2207.50 square kilometers (20%) of the overall watershed area, make up the third biggest part. Water made up the smallest component, accounting for 491.53 square kilometers or 4% of the land area. Figure 18 is the Illustration of Land cover and Land use types for year 1993, 2002, 2013 and 2022 expressed as percentage



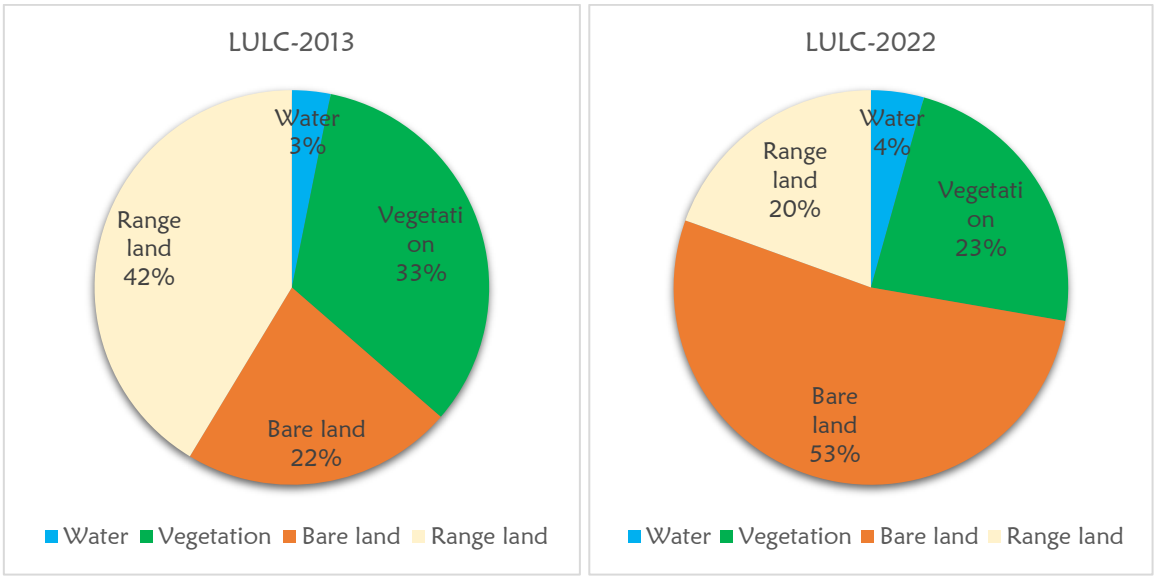


Figure 19: Illustration of Land cover and Land use types for year 1993, 2002, 2013 and 2022 expressed as percentage

One of the prominent findings is the significant decrease in forest cover over the years. Deforestation has been a major issue in South Rukuru Catchment, driven by factors such as logging, agriculture expansion, and charcoal production (Chirwa, 2016). The loss of forest cover has led to environmental degradation, loss of biodiversity, and increased vulnerability to climate change. Another notable trend is the expansion of agricultural lands in the district. As the population grows and demands for food increase, more land has been converted for farming purposes as shown in by the decrease in range land (Mwakasungula et al., 2015). This expansion has often encroached upon forested areas, leading to further deforestation hence increasing the percentages of having more bare land. Urban areas in the watershed have also witnessed growth during this period. The increase in urbanization is associated with population growth, economic development, and new infrastructure projects (Chirwa, 2016). Urban sprawl has resulted in the conversion of agricultural lands and natural habitats into built-up areas even though settlement has not been illustrated on the map because the satellite's resolutions. The presence of bare land or areas devoid of vegetation were identified during the classification process. Bare land was attributed to activities like deforestation, mining, soil erosion, or natural disturbances (Chimango & Mwakasango, 2018).

4.6. Land use/Land cover and Streamflow relationship

There is a comprehensive analysis of the streamflow regime changes in the South Rukuru River in Malawi, emphasizing the interplay between streamflow, rainfall, and land use changes. The study highlights significant variability in both streamflow and rainfall throughout the year. This high variability, particularly during certain months, poses challenges for water resource management in the region. Such variability affects water availability for agriculture, domestic use, and ecosystem health, necessitating adaptive management strategies to ensure sustainable water use (Huang et al., 2021). A strong positive correlation between streamflow and rainfall is evident, indicating that changes in rainfall directly influence streamflow patterns, especially during the wet season. Increased rainfall results in higher streamflow levels, while a more complex, often negative relationship is observed during the dry season (Yürekli, 2015). This correlation underscores the critical role of rainfall in driving streamflow dynamics and the need for integrated water resource management approaches that consider seasonal variations in precipitation. Remote sensing and GIS techniques classified land use and land cover (LULC) in the South Rukuru catchment, analyzing changes from 1993 to 2022. This analysis reveals significant changes in land cover types such as range land, bare land, water bodies, and forest cover. Notably, there has been a substantial increase in bare land and a decrease in vegetation cover over the years. For instance, bare land increased from 1,564 km² in 1993 to 5,983 km² in 2022, while vegetation cover decreased from 5,834 km² to 2,651 km² over the same period. These changes in land use are closely linked to streamflow variations. Deforestation, urbanization, and agricultural expansion can significantly alter hydrological processes, affecting the infiltration of rainfall, surface runoff, and overall water availability (Raziei, 2018). The study's findings suggest that human activities leading to land cover changes have contributed to the observed streamflow alterations in the South Rukuru River. For example, the shift in land use from vegetated areas to bare land increases surface runoff, reducing the soil's ability to absorb water, thus leading to higher streamflow during the wet season and lower base flows during the dry season (Mwale, 2018). The change point detection methods identified significant shifts in streamflow patterns, pinpointing a major

change around 2009. This change is marked by a substantial increase in annual and seasonal streamflow values, likely influenced by a combination of climate change and land use modifications. The increase in streamflow post 2009 aligns with the period of significant land use change, indicating a potential causal relationship between land cover alterations and streamflow dynamics.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

Analysing changes in the stream flow regime in the South Rukuru River during a 30-year period in Malawi's Northern Region was the primary goal of the study. The South Rukuru River's streamflow and monthly, seasonal, and yearly rainfall trends were examined using the Mann-Kendall, Sen's slope, and Pettitt tests. The research project discovered that there was a statistically insignificant decreasing pattern in yearly rainfall over the watershed's both dry and wet seasons over the 30-year period from 1992 to 2022. All months except April, June, and October revealed non-significant reductions in monthly precipitation. Overall, the average yearly streamflow and the summertime streamflow showcased a non-significant declining pattern in accordance to the Mann-Kendall test, whilst the moist-season streamflow revealed a non-significant growing trend. Sen's slope assessment confirmed these inferences by displaying declining patterns as well. Whereas periodic streamflow patterns shifted the variations were generally non-significant and diminishing.

Both streamflow and precipitation had distinctive phases of change all throughout the duration of the 30-year time span, according to the Pettitt test. Significant transition points in streamflow started showing up in 2009, suggesting increasing patterns with respect to that direction. The Pettitt test additionally highlighted the points at which the average yearly rainfall, annual streamflow, and rainy season streamflow varied. Significant additional knowledge regarding the hydro-meteorological shifts occurring in the South Rukuru river basin area has been provided by these investigations. The unpredictable trends detected in the hydrometeorological characteristics may be attributable to human-induced changes, such as modifications in land use and vegetation diversity between 1992 and 2022, or to alterations in the climate. Employing the correlation coefficient calculated by the Pearson approach, the association connecting streamflow and rainfall was investigated and the findings demonstrated an exponential correlation among the two. The monthly statistics displayed an extensive relationship that was linear, whereas both the annual and seasonally statistics demonstrated an inconsistent

association. This indicates that the fluctuations in streamflow in the South Rukuru basin could possibly have been attributed to a number of different reasons, particularly activity by humans. The efficient management of the watershed geographical area is dependent upon this essential knowledge related to patterns in precipitation and streamflow.

5.2. Recommendations

i. Land use planning

Develop and enforce land use planning policies that promote sustainable land management practices to minimize the adverse effects on stream flow regimes. This may include regulations on deforestation, urban expansion, and agricultural practices that contribute to changes in surface runoff and infiltration rates.

ii. Climate change adaptation

Incorporate climate change adaptation strategies into water resource management plans to address the impact of changing precipitation patterns and temperature on stream flow dynamics. This may involve implementing measures to mitigate the effects of climate change on water availability and quality.

iii. Community engagement

Engage local communities in conservation efforts and sustainable land use practices to protect water resources in the South Rukuru River basin. Community participation and awareness programs can help foster a sense of ownership and responsibility towards preserving the river ecosystem.

iv. Capacity building

Provide training and capacity-building programs for local stakeholders, including farmers, landowners, and water resource managers, on sustainable land management practices and water conservation techniques. Empowering communities with knowledge and skills can contribute to long-term water resource sustainability.

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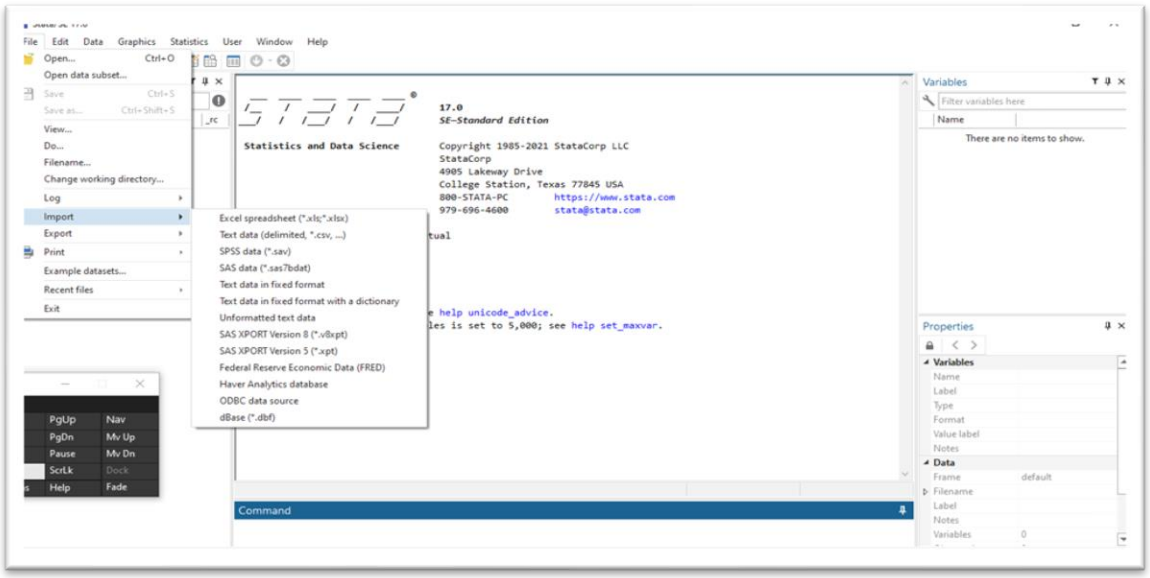
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APPENDICES

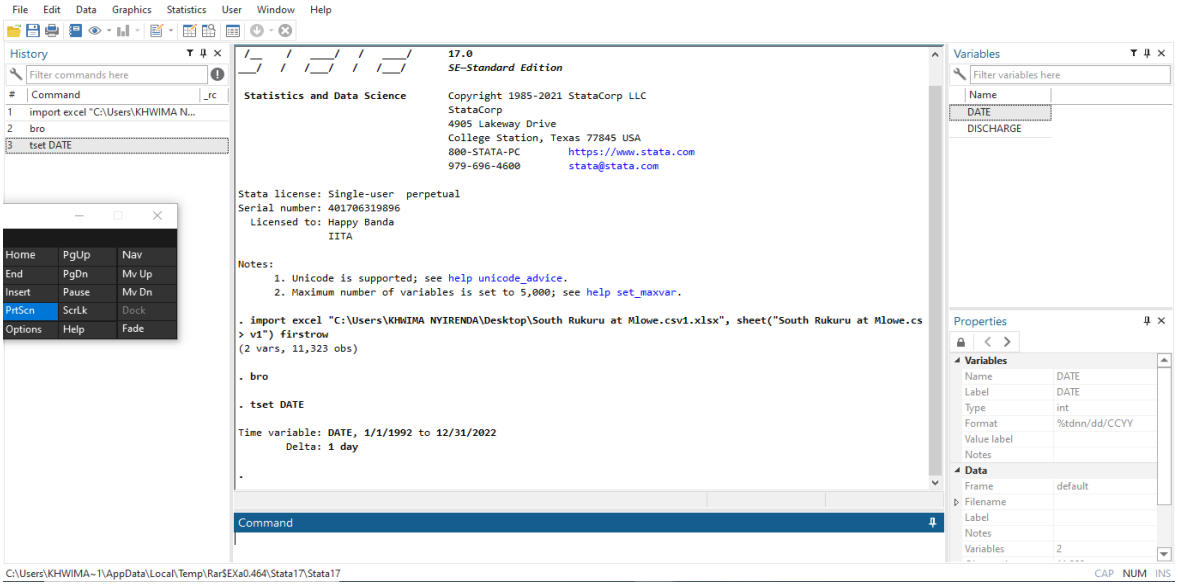
Processes and steps that were followed to do data analysis

Performing Multiple Imputation using STATA

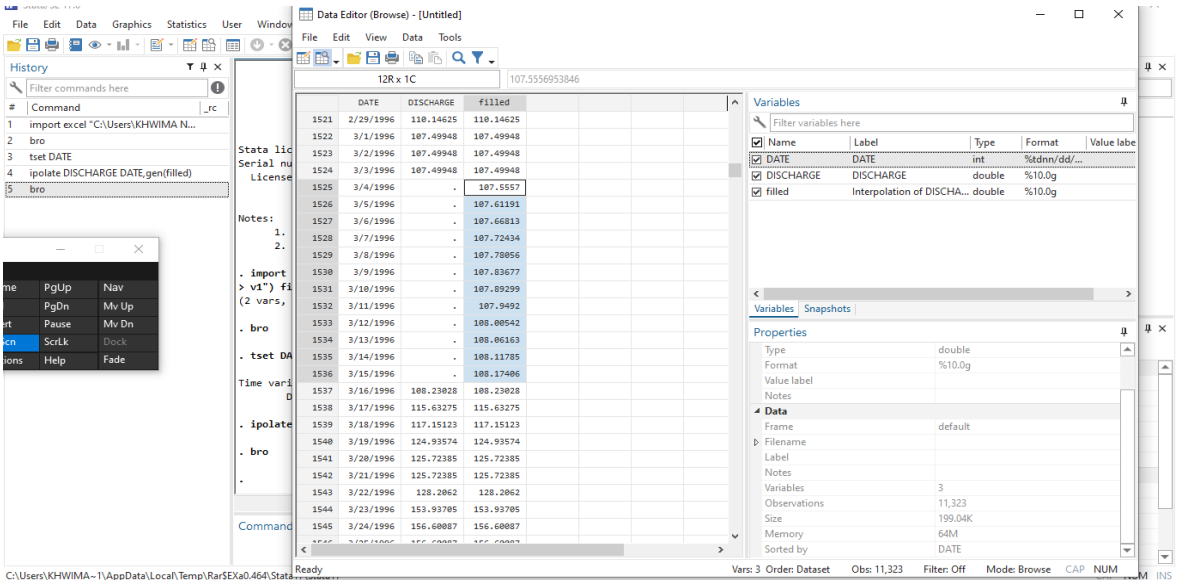
Firstly, streamflow data was prepared to ensure that it is in a suitable format for imputation and later imported into Stata application with variables columns already set because streamflow data should be in numeric not strings. Below is the illustration



After importing data, a set of commands e.g. “bro” were used to browse the prepared streamflow data with the missing values. Thereafter, commands like “tset Date” were also used to mark a demarcation on the date within the streamflow data time frame that is, the first of January in 1992 up to the thirty first of December 2022. Below is the illustration.



Finally, a multiple imputation was performed on the imported streamflow data in order to generate multiples of the missing values. To do this, commands like "ipolate Date Discharge, gen (Filled)" was used to compute the missing dataset. After that the data was exported in an excel format for further analysis. Below is the illustration of the original data before and after imputation.

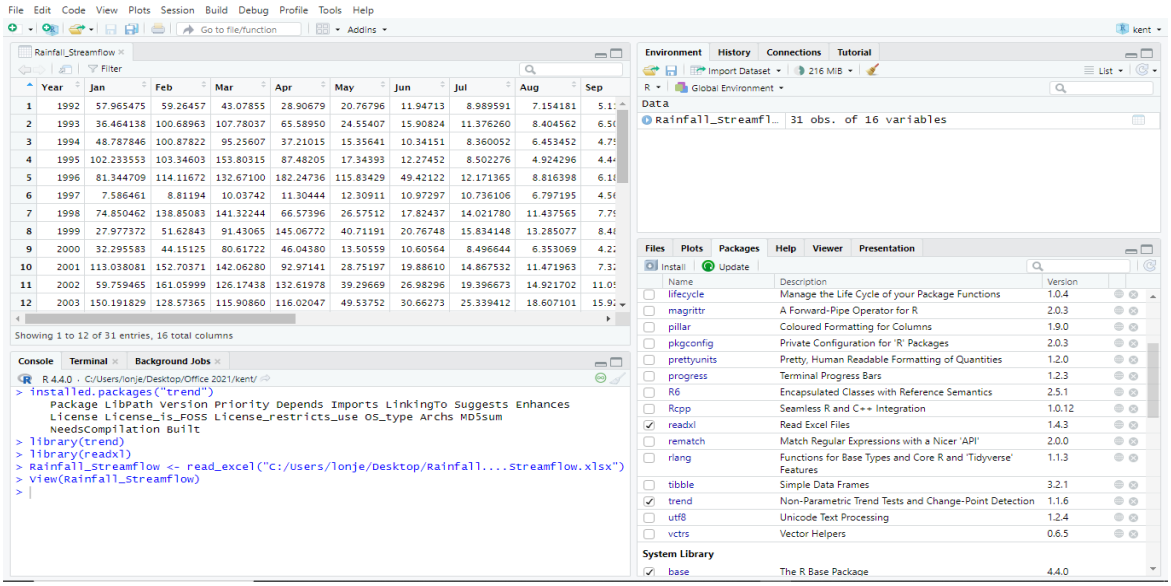


Stata software was used to calculate streamflow data because multiple imputations in SPSS did not work on all the missing data values such that there were many unfilled spots due to unavailability of most of the data for many days and months. Though this been the case, multiple imputation in SPSS was used fill all the missing rainfall values data without leaving any gaps because missing data was small compared to that of streamflow.

Mann Kendall Test and Sen's Slope using R Studio

Firstly, a "trend" package was installed and loaded. This is because the "trend" package in R provides functions for calculating the Mann-Kendall test and Sen's slope, which are essential for analyzing time series data. It was done after opening R Studio and typing install.packages ("trend") to install the package followed by typing library (trend) to load the packages.

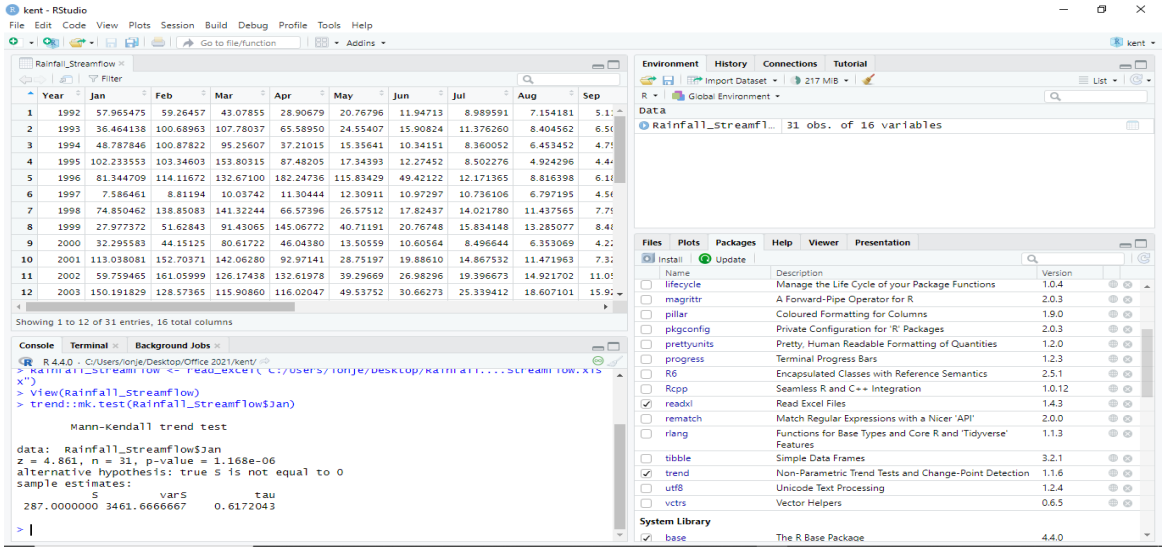
After completing the process of installing packages, load the dataset into R Studio to perform the analysis. This is done by importing the dataset with a specified file format e.g. Excel or CSV. Below is an illustration in the bottom left window.



Then convert the data to a time series because the Mann-Kendall test and Sen's slope require time series data. This is done by typing data file name_ts<- ts (data file name $variable, start = data file name$year, frequency = 1) to convert the data to a time series.

Perform the Mann-Kendall test which is a non-parametric test used to detect trends in time series data. This is done by typing mk.test(data file name_ts) to perform the Mann-Kendall test on the given time series data.

A visual of R Studio with the command `mk.test(your_ts)` and the output showing the test statistic (Tau), p-value, and other information in the bottom left window.

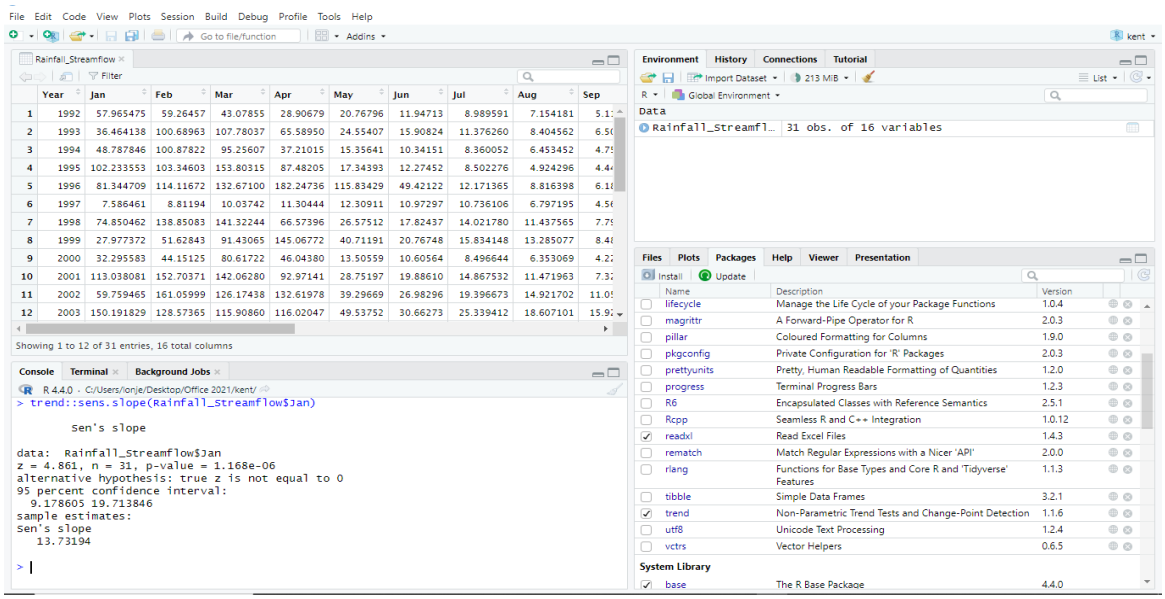


Finally extract the test statistic (Tau) and p-value because they are important indicators of the trend in the data. This was done by copying the values direct from the interface

After calculating the Kendall's Tau test, Sen's slope was estimated as well. This is a non-parametric method used to estimate the slope of the trend in time series data.

The same steps were carried out to determine sens slope. It was done by typing 'sens.slope (data file name_ts)' to perform Sen's slope estimation on the time series data.

A visual of R Studio with the commands and the output, showing the slope estimate and confidence interval in the bottom left window.



Finally, slope estimate and confidence interval were extracted by copying the values into an excel file sheet. The slope estimate and confidence interval are important indicators of the trend in the data.