

**SPATIAL VARIATION OF HISTORICAL AND FUTURE SEASONAL RAINFALL
TRENDS IN THE LUVUVHU RIVER CATCHMENT, LIMPOPO PROVINCE, SOUTH
AFRICA**

By

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ABSTRACT

This study focused on determining the spatial variation of historic and future seasonal rainfall trends in the Luvuvhu River Catchment. Trend analysis studies hold considerable scientific and practical importance in assessing hydrological hazards and soil erosion monitoring. Rainfall trends are a valuable tool for assessing the impacts of climate change and offering guidance on how to mitigate its negative effects on agriculture. Rainfall in the Luvuvhu River Catchment exhibits significant variability. Alterations in precipitation patterns and trends can lead to an increase in the frequency of extreme events such as drought and floods. Rainfall data was sourced from the Department of Water and Sanitation, South African Weather Services and the Coupled Model Intercomparison Project six. The Innovative Trend Analysis (ITA) and Auto-regressive Moving Average (ARIMA) were used to compute historical and future seasonal rainfall trends for a period of about 135 years from 1950 to 2085. The standard deviation, coefficient of variation, seasonality index and kriging were used to determine spatial variations. The ITA and ARIMA results showed dominantly decreasing trends during summer and all other seasons for both historical and future rainfall data. The results from the ITA method are in agreement with the results of the ARIMA method. The homogeneity test using the Standard Normal Homogeneity Test and the Pettit test was done for the rainfall data. The Standardised Precipitation Index (SPI) was used to check the possible causes of the changes during dry and wet seasons. The historic results of the standard deviation range from 11 in winter to 463 in summer, the coefficient of variation from 0.401 to 1.037 and the seasonality index from 0.02 in winter to 2.358 in summer. The future results indicate that the standard deviation ranges from 2 in winter to 86 in summer, the coefficient of variation from 0.286 to 4.120 and the seasonality index from 0.09 in winter to 3.950 in summer. The kriging results show high variability in the north east side of the catchment where stations such as the Pafuri and Punda Maria are situated for both the historic future seasonal trends. The breaks or changes from the homogeneity tests occurred in the years 1962, 1975, 1979, 1982, 1986, 1987, 1996, 2005, 2008 and 2012. The results of the two methods compared fairly well. The SPI results indicated that causes of changes were indicated by breaks periods of flooding and periods of drought on the data that occurred in the years 1975, 2000, 1990, 2046, 2036, 2076, 2043 and 2073. Trend analysis and forecasting for the catchment using satellite data is recommended in order to compare the results of the current study and other studies that have been done in the catchment. The results in this study indicate that there is a dominant decreasing trend in the catchment, it is therefore recommended that a plan be developed for efficient and sustainable water use, localized climate adaptation strategies be developed and further research be done expanding on the current study.

Keywords: climate change, extreme events, homogeneity test, seasonal rainfall trends, spatial variation

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Rainfall is one of the most important fundamental physical variables in the climate as it determines the environmental conditions of a certain catchment. It also determines the amount of water available to satisfy various demands, including agriculture, industrial use, domestic water supply, and hydroelectric power generation (Lal et al., 2010). Furthermore, rainfall is an influential weather variable as it affects the spatial and temporal distribution of water in the catchment. Chabalala et al. (2019) noted that some of the latest studies indicated that rainfall plays a crucial role in water resources management and planning as well as flood control and flood frequency in any catchment.

Variability of rainfall can be defined as the variation of rainfall patterns and volume across different locations and seasons. It can be described by the seasonal rainfall cycles, the amount of rainfall, the beginning, end and the duration of the rainfall event (Segele and Lamb, 2005). According to Alahacoon et al. (2021) the natural causes of variability in rainfall in Africa are usually attributed to the El Niño-Southern , La Niña-Southern Oscillation (ENSO) and Indian Ocean Depot (IOD) . Moreover, the variation is usually influenced by elevation, land use, temperature, amongst others. Fields such as agriculture and engineering are particularly dependent on understanding this variability, given its significant implications for their practices. The analysis of rainfall variability is therefore essential for effective water resource management and for the assessment of climate variability.

Seasonal Rainfall trends can be decreasing or increasing and can also be characterised by wet or dry seasons. Analysis of rainfall trends has been utilised by climatologists and hydrologists for many years, and recently, it has been chiefly used to trace the magnitude and impact of climatic variability and change due to natural and anthropogenic influences across the globe (Change, 2001). These global climate changes may affect long-term rainfall trends influencing water availability and increasing the likelihood of drought and floods (Pal et al., 2017). The study done by Odiyo et al. (2015) reported that at the Luvuvhu River Catchment (LRC), there have been numerous devastating floods and droughts causing widespread negative impacts on agriculture and rural communities.

A comprehensive analysis of rainfall trends is essential, as the findings from this research play a pivotal role in effective climate risk management, the preservation of agricultural productivity, and informed decision-making in water resource management. These insights are critical not

only for addressing immediate challenges in the short term but also for crafting sustainable strategies that will benefit future generations in the long run.

1.2 STATEMENT OF THE PROBLEM

Changes in climate globally may influence long-term rainfall patterns causing impacts on the water availability, coupled with more frequent droughts and floods (Pal et al., 2017). Li et al. (2011) mentioned that changes in precipitation characteristics and trends can lead to increased frequency of extreme events such as droughts and floods. Mashinye (2018) and Odiyo et al. (2020) indicated that rainfall in the LRC is highly variable and is characterized by extreme events, which are worsened by climate change. According to Botai et al. (2018) climate change in South Africa has implications on the water resources because of prolonged dry spells.

Climate variability and change pose significant threats to developing countries, particularly to the people of Africa. This is because the rise in temperature impacts all key components of the hydrological systems, leading to increased evapotranspiration, shorter growing seasons, soil drying, higher pests and disease pressures, shifts in suitable areas for crop and livestock production and other agricultural challenges (Lobell et al., 2008). Scientists project that variation in rainfall trends will continue to accelerate, hence the risk to human health, forest, agriculture, fresh water supplies coastline and other natural resources that are important for the quality of life, environment and the economy of the country. This is because the climate is tied to many systems; therefore, changes in climate causes changes in the ecosystem.

The LRC is located in the region that is highly dependent on various land uses including, commercial forestry (4%), commercial dry land agriculture (10%), commercial irrigation agriculture (3%), range land (50%), conservation areas (30%), urban areas (3%) and small scale irrigation schemes, such as the Dzindi irrigation scheme which utilises runoff river water (State of the River Report, 2001). However these land use activities are increasingly being threatened by rainfall variability, which scientists project that it will continue to accelerate. Supporting this, Shongwe et al. (2009) indicated that such variations are intensifying over time.

Seasonal rainfall in the LRC show spatial and temporal variability which has an impact on the water resource. A number of studies done in the catchment did not integrate both historical and future seasonal trends. This gap limits the ability of decision makers to implement adaptation strategies. This study seeks to address the problem by analyzing both historical and future seasonal trends using rainfall dataset and geostatistical techniques while providing insight for sustainable resource management.

1.3 MOTIVATION

One of the main constituents of the hydrological cycle, which affects both the surface and subsurface water resources, is rainfall. Studying and understanding the patterns, trends, changes, and properties of rainfall in both time and space is of importance in the characterisation of the earth systems and in the models of water resources management, surface hydrology and ecology (Kaptué et al., 2015). These studies also provide a scientific basis for modelling water resource allocation among competing users in the catchment. They help derive mitigation measures and evaluate ecosystem resilience against rainfall variability.

Understanding the seasonal and inter-annual variability of rainfall, as well as its spatial and temporal changes in a changing climate, is essential for evaluating climate-induced impacts and recommending effective future water resource management strategies (Wagesho et al., 2013). In order to develop comprehensive climate scenarios, it is essential to analyse rainfall trends across diverse spatial and temporal scales. The application of these strategies in specific locations can address issues related to flooding and drought, as well as manage water availability more effectively (Tolosa and Tolossa, 2021). It is also important to have information about the seasonal rainfall trends in order to make informed decisions on management of water resources and strategies for prevention or reduction of the impacts of extreme events.

Spatial variation of rainfall has had a significant impact on the natural flow regime of rivers and dams. Regardless of the positive or negative variation impacts, there is a need to compute the trends of rainfall seasonally. This study provides vital information about the possibility of future changes in rainfall which will allow for better water resources management in the catchment.

Mashinye (2018) studied long-term seasonal and annual changes in rainfall duration and magnitude in the LRC; the focus was mostly on the seasonal and annual long-term changes; the trends were also analysed based on historical data. Odiyo et al. (2015) studied long-term changes and variability in rainfall and streamflow and their impact on available water resources. Mazibuko et al. (2021) investigated the effects that climate changes have on different land uses in the LRC, and Tshililo et al. (2021) also studied the rainy season characteristics in the LRC. The approaches that will be used in this study will differ from the one used by Mashinye (2018). In this study the stochastic and data-driven approaches will be used for analysing the spatial variation of seasonal rainfall. Rathnayake (2019) notes that literature presents several methods for identifying rainfall trends, but the two widely used and simplest tests in trend analysis are non-parametric tests and graphical (for example, linear regression) trend analysis. The Mann-Kendall (MK) trend test is widely recognized as the most utilised method for trend analysis (Wang et al., 2020). However, given the uncertainty of rainfall

events and its stochastic nature, Hyndman and Athanasopoulos (2018) indicated that forecasting with stochastic trends is safer particularly for longer forecasting horizon, as prediction intervals account for greater uncertainty in future changes. Stochastic trends are said to be user-friendly and yield more reliable results than non-stationary results.

The LRC has a number of land use activities that help sustain the surrounding communities, agriculture being the most dominant and depends on rainfall. This study of spatial variation of historical and future rainfall trends provides a knowledge base for improved management of agriculture, irrigation and other water-related activities in the catchment. Furthermore, understanding the variations in rainfall, both spatially and temporally, is essential for planning crop cultivation, designing water storage systems and planning drainage channels to mitigate floods and droughts.

Roffe et al. (2021) indicate that in South Africa, the majority of research has concentrated on the impact of large-scale climate system changes on overall rainfall totals. However, there has been comparatively little investigation into the resulting changes in rainfall seasonality, including the timing of rainfall and the beginning and end of the wet season. This study contributes to addressing the problem and research gaps on seasonal rainfall trends. The LRC is characterized by year-to-year changes in rainfall, and due to that, it is important to always update the rainfall trends and variability of the catchment.

1.4 RESEARCH OBJECTIVES

1.4.1 Main objective

To determine the spatial variation of historical and future seasonal rainfall trends of the Luvuvhu River Catchment.

1.4.2 Specific objectives

- To compute historical and future seasonal rainfall trends from 1950 to 2085.
- To determine the spatial variation of historical and future rainfall trends from 1950 to 2085.
- To investigate the possible causes of rainfall trends from 1950 to 2085.

1.5 RESEARCH QUESTIONS

- What are the differences between the historical and future seasonal trends?

- Which trends are dominant in the study area?
- What causes the changes in the rainfall trends?
-

1.6 CHARACTERISTICS OF THE STUDY AREA

1.6.1 Location

The LRC is situated in South Africa's Limpopo Province specifically in the Luvuvhu/Letaba Water Management Area. The LRC lies between latitudes $22^{\circ}17'33.57''\text{S}$ and $23^{\circ}17'57.31''\text{S}$ and longitudes $29^{\circ}49'46.16''\text{E}$ and $31^{\circ}23'32.02''\text{E}$. It has a catchment area of 5941 km^2 ; the catchment covers all the A91 and A92 quaternary catchments. The Luvuvhu River rises as a steep mountain stream in the south-easterly slopes of the Soutpansberg Mountains flowing for about 200 km through a diverse range of landscapes before it joins the Limpopo River near Pafuri in the Kruger National Park (KNP). The catchment forms part of the larger Limpopo system, which extends into Mozambique. *Figure 1-1 Location of the Study Area* show the map of the study area with the dams, town and rivers.

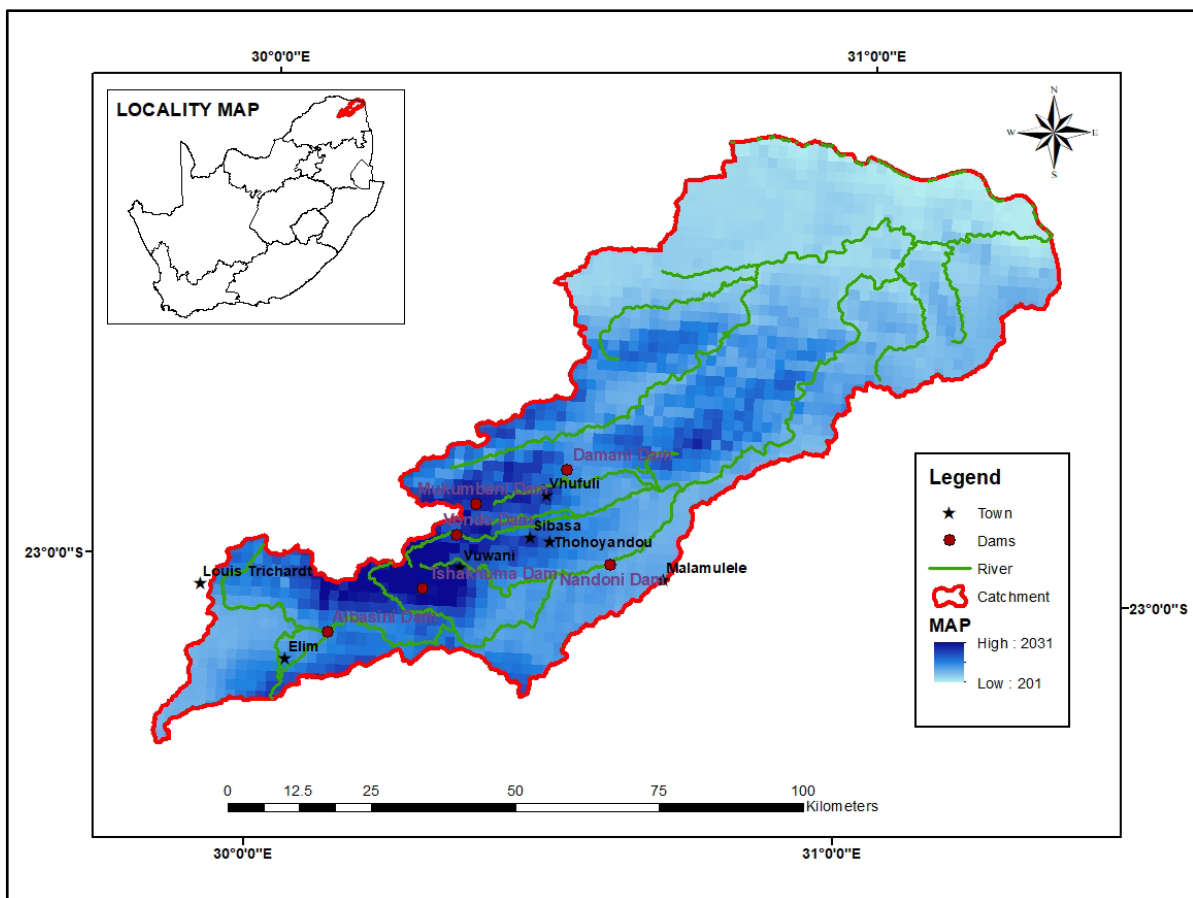


Figure 1-1: Location of the Study Area

1.6.2 Hydrology

The LRC is situated in the summer rainfall region with an estimated mean annual precipitation (MAP) of 608 mm, a mean annual runoff of $520 \times 10^6 \text{ m}^3$ with a mean annual evaporation of 1 678 mm, respectively (Report, 2001). The lower regions surrounding the KNP receive minimal rainfall, whereas the upper reaches where the Soutpansberg Mountains are located receive the most (see *Figure 1-1*). October through April is the rainy season, with dry season conditions prevailing from May through September. Rainfall surpasses 1,000 mm/a in the upper portion of the watershed and drops to less than 200 mm/a in the east-northeast direction, with a higher potential for evaporation (Mathivha et al., 2021).

The Luvuvhu River catchment contains several dams, including Nandoni, Albasini, Mambedi, Tshakhuma, Damani, Vondo, and Phiphidi Dams. Phiphidi and Vondo Dams are located on the Mutshindudi River. The river's tributaries include Sterkstroom, Latonyanda, Dzindi, Mukhase, Mbwedi, Mutale, and Mutshindudi. The Luvuvhu River and all its tributaries that originate in the Soutpansberg mountain range are perennial, as reported in the (Report, 2001).

1.6.3 Topography

Topography of the LRC is characterised by deep valleys that run parallel to the river channel throughout the sub basin, floodplains in the northeast that are low-lying and mountainous highlands (Forestry, 2004). The highest elevations in the Soutpansberg mountains are about 1587 metres above sea level (m.a.s.l.) with the lowest elevation at about 200 m.a.s.l at the Pafuri floodplain near the Limpopo River confluence. The elevation decreases gently through the steeply-incised Luvuvhu before reaching the upper reaches of the catchment (Report, 2001, Affairs, 2012). The topography strongly influences the rainfall distribution in the catchment; with the highest rainfall occurring on the Soutpansberg mountains and the lowest in the east of the catchment along the KNP (Tshililo et al., 2021).

1.6.4 Land use

Land use activities in the LRC include forestry, agriculture and settlements. The activities are sub-divided as follows: the upper reaches of the Luvuvhu and Lotonyanda rivers have commercial forestry at 4 %, commercial dry land agriculture at 10%, commercial irrigation agriculture at 3%, range land at 50%, conservation areas at 30% and urban areas at 3% (Odiyo et al., 2015). The upper reaches of the Luvuvhu and Latonyanda Rivers are covered with forestry plantations, which gradually decrease as they approach the Albasini Dam. Plantations of exotic pine and eucalyptus trees dominate the land cover in the southern highlands of the

LRC. Subsistence agriculture constitutes approximately one-third of the overall agricultural sector. Forests send back more energy back to the atmosphere in the form of evapotranspiration and this contributes to changes in rainfall (Change, 2001). According to Touseef et al. (2020) in the urban areas precipitation patterns are influenced by changes in vegetation cover and surface albedo.

CHAPTER 2: LITERATURE REVIEW

2.1 RAINFALL TRENDS ANALYSIS

A trend is defined as change or a development in a general direction. According to Webber and Hawkins (1980) a trend is defined as the overall direction of a series over an extended period or as a long-term change in the dependent variable across a significant time frame. Nyatuame et al. (2014) defined trends as long-term movements reflecting growth or decline in a time series, influenced by natural, human, and economic processes. Rainfall trends can therefore be defined as the movement, directions and patterns which rainfall takes.

Visser et al. (2015) indicated that trend analysis is carried out in order to predict the future using past observations. When trends are analysed one can note the events that have occurred, when they occurred, their severity and the duration of the events, for this reason, trend analysis is done. According to Joshi et al. (2019) rainfall trends are a crucial instrument for evaluating the consequences of climate change and offering guidance on how to mitigate its negative effects on agriculture. This is because changes in rainfall detected through analysing trends can indicate if there are climate changes. Trend analysis offers scientific information for more effective modelling, prediction and control of the problem (Mohorji et al., 2017) Results from trend analysis studies play a crucial role in scientific and practical monitoring of hydrological hazard and soil erosion.

In most parts of Southern Africa decreasing trends have been previously reported (Nenwiini and Kabanda, 2013); Marumbwa et al. (2021); Gyamfi et al. (2016)). These decreases in rainfall have been attributed to the influence of El Niño and shifts in atmospheric circulation processes (Mugiyo et al., 2023). It is important to note that rainfall in Southern Africa is usually caused by both the El Niño-Southern and La Niña-Southern Oscillations. El Niño-Southern Oscillation is associated with a rise in temperature and a decrease in rainfall or drought while the La Niña-Southern Oscillation is associated with low temperature and an increase in rainfall or floods (Du Plessis and Kibii, 2021). Kruger (1999) indicated that extreme events of rainfall usually occur when there is above normal or below normal rainfall, that is when there is a La Niña and EL Nino. These below normal (dryness) and above normal (wetness) are determined by cyclic fluctuations of sea surface temperature.

A trend refers to a long term change over time in data which is often influenced by natural or human factors. In the context of rainfall, trend help to identify patterns and shifts in rainfall which are important to predict future conditions. Trend analysis is used to assess the timing, intensity, duration, patterns of past and future events. Studies have shown that trend analysis

is important due to its role in monitoring extreme events and guiding the strategies needed for adaptation. In South Africa, a number of studies have indicated that there are decreasing trends attributed to the atmospheric phenomenon.

2.2 STUDIES DONE ON RAINFALL TRENDS

Kruger and Nxumalo (2017) studied the rainfall trends in South Africa with the aim to revise the analysis of past rainfall trends that have been done previously, by using longer records. For the analysis of trends in the study, sixty (60) district rainfall and ninety-four (94) individual rainfall stations datasets were used. South African Weather Services (SAWS) divided South Africa into 94 districts based on maximum rainfall and the seasons. Districts rainfall datasets is an average rainfall from different individual stations in a region while individual stations has data from one station at a specific location. The study results showed a rise in rainfall at the majority of rainfall stations in the southern interior of South Africa, with the far northern and north- eastern parts indicating a decrease in rainfall. For seasonal trends in rainfall, summer rains have shown an increase, particularly with annual increases noted in the south and central interior regions. However, for much of the country, no clear historical patterns in annual total rainfall were observed during the autumn, winter, or spring seasons. This suggests that while summer rainfall may be becoming more abundant, the other seasons remain relatively stable without significant trends. Some findings from earlier research indicated noticeable differences, and certain trend results were found to be clearly distinct from those reported in previous studies. This variation highlights the complexities and evolving understanding of rainfall patterns and their underlying factors. It suggests that while some trends may remain consistent over time, others may shift significantly due to changing environmental conditions, urbanisation, or other influences. As such, ongoing analysis is essential to refine our understanding of these trends and their implications for climate change and ecosystem dynamics.

Gyamfi et al. (2016) researched the historical analysis of rainfall trends in the Olifants Basin in South Africa. The Mann Kendall and a set of homogeneity test trend methods were applied to the records of 13 historical rainfall stations. This was done in order to detect changes in rainfall patterns under a changing climate. It was revealed that the basin is experiencing a negligible tendency of decreasing rainfall trends with a MAP of 644 mm. Furthermore, it was noted that seasonal and inter-annual variability predominate and that rainfall in the basin varies spatiotemporally, with a coefficient of variation of 24% indicating moderate variation.

According to Morishima and Akasaka (2010) there is seasonality in the spatial and temporal structures of trends in rainfall from 1979 to 2007 in southern Africa. The relationship between the seasonal trend and the interannual variation of the seasonal march of rainfall was clarified using the empirical orthogonal function (EOF) analysis method. The results of the study indicated that there is strong seasonality, and their seasonal marches modulated after 1987 and 1995, respectively.

The variability and trends of rainfall, precipitation, and discharges over the Zambezi River basin were reviewed by Banze et al. (2018). They also examined the likely changes in runoff in response to variations in precipitation and air temperature over southern Africa (namely, Namibia, Mozambique, Zimbabwe, Zambia, Botswana, and South Africa) and the Zambezi River in particular. After reviewing the key findings of numerous studies and reports, it was determined that the large degree of natural variability in rainfall can make it challenging to separate the specifics of climate change trends and projections for southern Africa. The study also revealed that rainfall trends in southern Africa have been observed over the last century. They further indicated that a considerable warming trend is anticipated in the Zambezi basin and that rainfall will decline and become shorter and more erratic, leading to longer droughts and more severe floods.

Banda et al. (2021) analysed both long- and short-term trends in stream discharge, temperature, and rainfall data in the Rietspruit sub-basin of South Africa. Prior to conducting trend tests, the data underwent homogeneity testing. The latter study, then applied the Mann-Kendall test and Sen's slope estimator to assess the trends. During the observed time steps, the study showed a mix of upward and downward trends in both temperature and rainfall data. Furthermore, in the annual rainfall data, no statistically significant monotonic trends were found, although non-significant downward trends were more prevalent. However, In the months of April, August, September, and November, significant decreasing trends in rainfall were observed during periods of low rainfall and dry conditions.

Hussain et al. (2015) studied rainfall trends by using the Mann-Kendall test and Sen's slope estimates: in the Chakwal rain gauge, Barani area, Northern Punjab province, Pakistan. The study was done because rainfall in the study area is erratic and unpredictable. The nonparametric analysis using the Mann-Kendall test and Sen's Slope Estimator was applied to the daily rainfall data from 1977 to 2013 to analyse the trends and to estimate the trend's magnitude. The results indicate a predominantly increasing trend in both the annual and seasonal scales. While the overall seasons displayed a decreasing trend, seven individual months (January, February, May, June, July, August, and September) exhibited an upward trend, whereas the remaining five months (March, April, October, November, and December)

showed a downward trend. Additionally, both the total annual rainfall and monsoon seasons revealed a significant positive increase, with confidence levels of 99% and 95%, respectively.

Mzava et al. (2020) studied the characterisation of past and future trends and frequency of extreme rainfall in urban catchments. The research examined the patterns and frequency of annual, seasonal, and extreme rainfall by utilizing data from four essential ground-based weather stations in conjunction with Regional Climate Models (RCM) data. The analysis of rainfall variability and trends was conducted using the Mann-Kendall test and Sen's slope estimator. The findings indicated a notable increase in both annual and seasonal maximum rainfall, as well as an escalation in extreme rainfall events projected for the future under the RCP4.5 carbon dioxide (CO₂) concentration scenario.

Abiy et al. (2019) investigated rainfall trends and variability in southeast Florida, utilising linear regression and Mann-Kendal trend tests to determine whether rainfall monotonic trends were present. During most months of the wet season, the total rainfall increased significantly. In October a decrease in rainfall, which led to a decrease in the length of the wet season was observed. The wet season and total annual rainfall have suddenly increased since 1990. With the exception of the frequency of sporadic dry periods, the Standardised Precipitation Index (SPI) research has shown that the current rainfall regime has been characterised by prolonged wetness since 1995.

The study by Yadav et al. (2014) was mainly concerned with the changes in rainfall and temperature trends in all thirteen districts of the state Uttarakhand in India. Daily rainfall data for the years 1971 to 2011 (40 years) and the lowest and highest temperature data for the years 1971 to 2007 (36 years) were processed in order to find the rainfall trends, slope and variability using the Mann-Kendall and the Sen's Slope Estimator. The results of the study showed that there were increasing trends of precipitation and temperature in some months and decreasing trends in some other months for all thirteen districts of Uttarakhand.

Mashinye (2018) studied long-term seasonal and annual changes in rainfall duration and magnitude in the LRC where trends were also analysed using linear regression, quantile regression and the Mann-Kendall test methods. The study was motivated by the year-to-year changes in rainfall. The study revealed that there were dominant decreasing trends in annual and seasonal rainfall. The recommendation was made to analyse trends further using additional methods and to enhance and update the information base.

To provide evidence of climate change in the Volta region, a statistical analysis of rainfall trends was conducted in the region (Nyatuame et al., 2014). Rainfall data from 1981 to 2011 (a span of 30 years) was used to analyse trends. Parametric trend estimation was conducted,

utilizing graphs to illustrate the changing trends over the months and years in the various zones. Statistical analyses were also performed to assess significant differences among the three zones and within the months and years studied. The results of the study showed significant differences among the three zones: the northern zone had the highest precipitation, followed by the middle zone and lastly, the coastal zone. However, the rainfall trends within these zones were oscillatory. Additionally, the linear regression analysis indicated both upward and downward trends in the data during certain months and years within the mentioned zones.

Joshi et al. (2019) assert that since rainfall is one of the most important climatic variables, it is crucial to investigate its long-term behaviour throughout space using several time series (annually, seasonally, monthly, and weekly). Nine distinct stations were chosen to conduct trend analysis in the Solapur area, where agriculture is the primary industry. The monotonic trend was identified using the non-parametric Mann-Kendall test, and the trend's size was calculated using Sen's Slope estimation technique. According to the findings, there was a statistically significant decline in monthly, seasonal, and yearly rainfall. Additionally, the majority of the time series examined in various Solapur district locations demonstrated a noticeably declining trend in rainfall

Anand and Karunanidhi (2020) used GIS methods and statistical tools to identify the long-term spatial and temporal distribution of rainfall in the Lower Bhavani basin. Data from twenty-two rain gauges were used for the period 1983-2015 (33 years). The Mann-Kendall Test was applied to estimate whether the trends were monotonic increasing and decreasing over time on a monthly basis. In the months of October, it was noted that the positive trend existed over ten rain gauge stations in the upper northern part of the basin. In the southern part of the basin, during the month of January, six rain gauging stations showed negative trends. The results illustrated that the topography, agriculture productivity, and groundwater management across the basin are influenced by the spatial distribution of rainfall and trend pattern.

Borse and Agnihotri (2017) conducted a study to determine the changing trends of rainfall of a river basin in the Surat district. In the study, two main categories were explored, namely, the parametric and non-parametric trends analysis methods. Parametric trends were analysed by the graphical procedure and by fitting the line on the data while non-parametric trends were analysed by Mann-Kendall method and Sen's Method. Data from thirty-six rainfall stations with an average precipitation of 102 years were used for trend analysis. Generalized Mat Lab coding was applied for the trend analysis and coding was validated using standards. The results indicated that the Surat district's rainfall pattern was declining.

Patle and Libang (2014) analysed the effects of climate change on rainfall trends in four districts of Arunachal Pradesh, located in the northeastern region of India. They used the nonparametric Mann-Kendall test at a 5% significance level to detect annual and seasonal

trends. The results indicated a decreasing trend in annual mean rainfall in the East Siang, Upper Siang, and Lower Dibang Valley districts, while no significant trend was observed in the West Siang district over the period from 1971 to 2007. Additionally, a decreasing trend in rainfall was recorded during the post-monsoon season, with slope magnitudes of 3.01 mm/year for East Siang, 3.32 mm/year for Upper Siang, and 3.95 mm/year for Lower Dibang Valley.

Nyatuame and Agodzo (2018) used the Autoregressive Integrated Moving Average (ARIMA) model to estimate the Tordzi watershed's maximum temperature and yearly rainfall. The purpose of the study was to support and enhance the future planning efforts of those in charge of making decisions and protecting people and property. The augmented Dickey–Fuller (ADF), Mann–Kendall, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were used to test for stationarity. The numerous analysis' findings showed that the models were sufficient and could support projections for future water planning. The study's findings also showed that, throughout the majority of the watershed, rainfall is expected to decline somewhat and fluctuate until 2024.

Pazvakawambwa (2017) modelled monthly rainfall in Windhoek from 1891 to 2011 using time-series forecasting techniques to aid in planning for future events. The analysis employed the ARIMA model. The forecast values indicated that for the 2046/47 period, the point estimates for monthly rainfall during the winter season are approximately 15 mm (with June at 14.5 mm, July at 14.5 mm, and August at 14.3 mm), which may be higher than anticipated. The results showed that, based on the ARIMA modelling of the rainfall data, despite seasonal and irregular fluctuations, the mean monthly rainfall levels did not demonstrate a significant upward or downward trend over the century.

Merabtene et al. (2016) investigated the possible effects of climate change on the long-term rainfall trends over Sharjah City in the United Arab Emirates. Using parametric and nonparametric statistical measures, such as Mann-Kendall trend analysis, Mann-Kendall seasonal trend, and monotonic linear regression trend analysis, both with and without considering serial correlation powered by Sen's slope and 10-year moving average, long-term and short-term rainfall trends were assessed. The findings indicated that all methods analysed were consistent, suggesting that linear regression for trend analysis produces similarly effective results, even though non-parametric methods are generally preferred. Overall, study found that the annual rainfall trend in Sharjah City has been consistently decreasing over time. The results suggest that to achieve sustainability in the catchment, it is essential to implement strategies for water resource preparedness, development, and management in light of a changing climate.

Praveen et al. (2020) used data from 1901 to 2015 (114 years) to analyse and estimate long-term spatiotemporal variations in rainfall across India at the meteorological divisional level. The study's findings have some implications for the management of water resources because it was driven by the region's limited supply of water resources and growing future water demand. The MK test and Sen's Innovative Trend Analysis were used to analyse rainfall trends, while the Pettitt test was employed to identify any abrupt shifts within the time frame. To predict India's rainfall over the next 15 years, the Artificial Neural Network-Multilayer Perceptron (ANN-MLP) method was utilised. The rainfall trend pattern was mapped across the entire country using geo-statistical techniques such as Kriging in the ArcGIS environment. The results show that most divisions experienced a significant decline in rainfall trends. Furthermore, change was detected after the year 1960 for most of the stations. The rainfall forecast for the next 15 years across all meteorological divisions shows a notable declining trend in rainfall.

Bouklikha et al. (2021) performed a study investigating the annual, monthly and seasonal rainfall trends in the Tafna watershed in Algeria. The study's objective was to use the innovative trend analysis (ITA) method to find long-term (46 years) regional and temporal patterns in annual, seasonal, and monthly precipitation. From 1970 to 2016 (46 years), monthly rainfall data from 17 stations was used. The method categorises trends into three levels: "low," "medium," and "high." The study found that all stations (100%) observed a downward trend in monthly rainfall during February, March, April, and May. This trend is observed at most stations during the months of June, July, and December, affecting 58% of the stations. The seasonal study indicates a declining trend in winter and spring. Additionally, 59% of the stations located in the northern, western, and central regions of Tafna are experiencing a decrease in yearly rainfall.

According to Yang et al. (2020) spatial differences in precipitation trends suggest that water resource managers should take steps to adjust to various regions in light of global warming. Yang et al. (2020) employed the Innovative Trend Analysis (ITA) method, utilizing daily rainfall data collected from 26 stations, to examine the regional and temporal variations in annual and seasonal precipitation of different intensities in Ningxia, China, over a period of 57 years, from 1961 to 2018. The findings reveal that annual precipitation decreases in the southern mountainous region while it increases in the northern plains. Low-intensity precipitation exhibits an upward trend, whereas high-intensity precipitation displays a downward trend. The analysis highlighted that variations and trends in extreme precipitation are more pronounced, with contributions from different types of extreme precipitation differing by season. The study

aimed to address extreme events like floods and droughts while also providing support for water resource planning.

Botai et al. (2018) used the Tropical Rainfall Measuring Mission (TRMM) 3B42 version 7 satellite precipitation data sets covering 1998 to 2015 (17 years) to examine the spatial-temporal variability and trends of precipitation concentration throughout South Africa. The annual, seasonal, and supra-seasonal spatial distributions as well as the variability of temporal precipitation contrasts were estimated using the precipitation concentration index (PCI). The results from the study show that precipitation concentration across South Africa exhibits noticeable spatial-temporal variability that there is observable spatial-temporal variability in precipitation concentration throughout South Africa. At annual timeframes, the precipitation distribution varies from reasonably uniform (mostly in South Africa's central and southern interior) to extremely variable (particularly in the country's northeast and west). According to PCI classification standards on seasonal timeframes, the distribution of precipitation is constant from December to February, moderate from March to May and September to November, and extremely variable from June to August.

A number of the studies reviewed used the MK and the Sen slope estimator methods to determine the trends, for example studies done by (Praveen et al. (2020), Yadav et al. (2014), Borse and Agnihotri (2017), Bouklikha et al. (2021) and Yang et al. (2020)) analysed trends using the ITA methods. While Nyatuame and Agodzo (2018) and Pazvakawambwa (2017) used the ARIMA model. Only one study where ANN was used was reviewed. This indicates that most studies do not use the ANN for trend analysis. That can be attributed to the complexity of the model and the availability of the model. The Regression model is also not mostly used due to the fact that it is too simple and the accuracy could also be questionable. Accurate estimation of spatial distribution and trends of rainfall is complicated, especially in mountainous areas where precipitation patterns may be influenced by topography (Buytaert et al., 2006). Most of the methods have not been explored in South Africa.

Most studies conducted, especially in Southern Africa, prioritize addressing data quality issues first. This may be due to the reported deterioration of monitoring weather stations in South Africa. The other issue is also because of the gaps in the data record, data needs to be patched first before it can be used. Most of the gauging stations have missing data due to vandalism of stations and wrong recording. In the study done by Mashinye (2018) data quality controls were done, where the data was also patched first before it could be used. The data is usually not consistent and comprehensive.

The impacts of climate change, the impacts on farmers and the impacts on the water resources or hydrology are usually addressed when the rainfall trend analysis is done. Praveen et al. (2020) did a study motivated by the fact that there is limited availability of water resources and an increase in the future water demand in the area. Rainfall patterns are also studied. Studies also use more than one method to analyse the trends; this is in order for one to compare the results of the methods used, which gives confidence to the analyst if the methods are in agreement. Some methods are also used hand in hand. For example, Yadav et al. (2014) used both the MK and the Sen slope estimator to detect and analyse the trends.

Odiyo et al. (2015) conducted a study at the LRC investigating long-term changes and variability in daily rainfall and streamflow. The linear regression and MK methods were used to compute the trends for a period of 86 years (1920-2006). Daily rainfall data from six rainfall stations was used. Of all the stations, only two showed increasing trends while the others show decreasing trends.

A number of studies done on trend analysis usually cover the whole of South Africa and beyond, while a few studies have done this at the LRC. Kruger and Nxumalo (2017) and Gyamfi et al. (2016) examine long-term rainfall patterns across South Africa not catchment based. Odiyo et al. (2015) and Mashinye (2018) did studies that are catchment based at the LRC using the linear regression and MK methods while analysing historical data with future climate scenarios not taken into consideration. Odiyo et al. (2015) only used six rainfall stations, hence a huge part of the catchment was not covered. Mzava et al. (2020) and Praveen et al. (2020) showed that it is important to include future climate scenarios and spatiotemporal analyses, this are often conducted in broader scales. This indicates that there is a greater need for research such as the current that integrates historic and future rainfall while using the ARIMA and ITA methods at a catchment level while using longer record length and more rainfall stations around the catchment.

2.3 METHODS USED IN TREND ANALYSIS

A number of methods are used in trend analysis and they are grouped into different classes or methods. Rathnayake (2019) did a study where the statistical and the graphical methods were compared. A comparison of statistical and graphical trend analysis methods for two Sri Lankan tropical catchments was revealed in the paper. The findings show that both trend analysis approaches when used to determine rainfall patterns for various time steps, such as yearly, seasonal, and monthly rainfalls, generally yield results that are equivalent. Four groups will be discussed in this section.

2.3.1 Exploratory data analysis

In this group, visual inspection and expert judgment of patterns are employed. Trends in this group are simple low-pass filters (Visser et al., 2015). Methods in this group are easy and simple to use. Exploratory data analysis methods help one gather insight into the trend and also gives one a feel for the data used. The disadvantage of these methods is that there can be errors of judgement. There are four categories in this group, namely the univariate non-graphical, univariate graphical, multivariate non-graphical and multivariate graphical. The univariate non graphical involves the analysis or evaluation of a single variable without using a graphical technique, for example, mean, variance, quartiles. In the univariate graphical a single variable is assessed, for example, histograms. To check the relationship between a number of variables without using a graph, the multivariate non graphical technique is used, for example, correlation coefficients. Lastly the multivariate graphic helps one visualize relationships between multiple variables by means of a plot, for example, scatter plots. Methods used in this group are open-ended and allow one to identify and analyse trends (Coursera, 2024).

2.3.2 Parametric methods

In this group, the methods are used when the type of distribution of the data is known. This model gives a precise description of a trend shape and the relations to external variables. This group comprises mainly graphical methods. Below are a few examples that fall under this group.

- **Method of semi averages**

In terms of time, the data is split into two equal sections. Following the division of the data into two sections, the arithmetic mean (average) of each section is calculated, yielding two points. Every point is plotted against each part's mid-year. The trend line is then created by joining these two points with a straight line. To obtain intermediate values or forecast future values, the line can be extended either upward or downward.

The semi-averages method is simple, easy, and quick to use and understand. It is based on a mathematical model, hence it gives a better approximation to the trends. The other advantage of the method is that it smooths out seasonal variations (Aslam, 2023). It also does not require extensive calculations. The method gives the same trendline (Almazroui and Şen (2020); Borse and Agnihotri (2017)).

The disadvantage of the semi averages is that it assumes a linear relationship for data, hence it is used when the trend is linear. This might not usually be the case. It uses averages and they are affected by extreme values. Aslam (2023) indicated that the method is rough and objective. Studies on rainfall trends analysis using the method of semi-averages are limited. This could be due to its assumption and the fact that trends are determined using time series data and often involves a large amount of information. Borse and Agnihotri (2017) used the method when studying the rainfall trend analysis of the Godavari, in India. Ajadi et al 2017 also used the semi-average method to find the trends; the results indicate that the data gives an upward trend.

- **Linear Regression**

A simple plot against two variables is created in order to have a general idea of the trend. These methods do not involve any complex mathematical techniques. The advantages of linear regression are that it is very simple to use, understand and master, a linear relationship is assumed and it is very easy to interpret the results thereof (James et al., 2023).

The linear relationship assumption limits this method to linear datasets only, as it struggles to accommodate more complex data. The model is very sensitive to outliers which can lead to incorrect estimation if the outliers are not dealt with (Kowalskie, 2025).

A simple linear regression equation (equation 2-1) is provided below:

$$Y = a + bx \quad 2-2$$

Where Y is the dependent variable, b is the slope, a is the intercept and x is the independent variable

A study done by Brook and Mametse (1970) used Linear regression to analyse rainfall trends in South Africa, and the results show distinctive positive and negative rainfall trend, while some parts of the country experienced a decrease in rainfall and others a decrease in rainfall. Mashinye (2018) also used Linear regression along with other methods to determine trends in the LRC. The results of the method generally indicated dominant decreasing trends.

2.3.3 Non-parametric methods

Non-parametric methods are used when the distribution of the data is unknown. The shapes of the trend in this group are data-driven since the models in this group do not have a predefined functional relation. Non-parametric tests have the extra power to detect trends with

seasonal variations. Models in this group are the most popularly used in trend analysis. Examples of non-parametric methods are discussed below.

- **Mann-Kendall**

The MK test is a widely used method for trend analysis due to its simplicity and the fact that it does not require data to be normally distributed. However, one of its drawbacks is its low sensitivity to abrupt changes, especially in inhomogeneous time series (Shikwambana et al., 2021).

The MK test operates under two main hypotheses: the null hypothesis (H0) posits that there is no trend, meaning the data is independent and randomly ordered, while the alternative hypothesis (H1) asserts that there is a trend in the data.

Several studies have shown that non-parametric statistical techniques, such as the MK test, have limitations. These include the presence of serial correlation within the datasets, non-linearity, and, notably, sample size, which can significantly influence the results. (Kendall, 1948) developed and added the presence of correlation. The MK test uses the following statistics as shown in equation 2-3 and 2-4 :

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad 2-5$$

$$\text{sign}(x_j - x_i) = \begin{cases} +1, & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1, & \text{if } (x_j - x_i) < 0 \end{cases} \quad 2-6$$

Where n is the length of the sample, x_j and x_i are the variable values in years j,i.

If n is bigger than 10, statistics S approximates to normal distribution. If the mean of S is 0, the variance of S can be acquired as shown in equation 2-7:

$$\begin{aligned} \text{var}(S) \\ = \frac{n(n-1)(2n+5)}{18} \end{aligned} \quad 2-8$$

then the test statistics Z is computed as follows (equation 2-9):

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}}, & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{var}(S)}}, & \text{if } S < 0 \end{cases} \quad 2-10$$

Z is used to measure the significance of trends. When $Z > 0$ it indicates a positive trend. A positive value of S indicates an upward trend and vice versa.

- **Sen's Slope Estimator**

The Sen's slope test estimates the true slope of an existing trend, such as amount of change per year, using the median or weighted mean. It also determines the strength of the trend without adhering to any specific probability distribution. This method is usually used in conjunction with the MK test. The Sen's slope estimator test demonstrates significant resistance to outliers (Rathnayake, 2019). The other benefit of this test is that it is distribution-free and remains unaffected by seasonal fluctuations. This test's additional benefit is that it is independent of dispersion and unaffected by seasonal variations. This method entails ranking the gathered data, creating a scatter plot, and then figuring out the data's median. The type of trend is determined based on the data's median. When Sen's slope is positive, the time series shows an upward or increasing trend; when it is negative, the trend is downward or falling (Panda and Sahu, 2019). The following equations (2-11 and 2-12 developed by (Sen, 1968)) are used for the calculations:

$$Q_{jk} = \frac{y_j - y_k}{j - k}, \quad 2-13$$

Where Q_{jk} is the Sean slope, k and j represent the time, y_j and y_k are data values at times j and k.

The median of the Sean slope is given by:

$$Q_{med} = \left\{ m \left(n + \frac{1}{2} \right), \quad \text{for } n \text{ is odd} \quad \frac{1}{2} \left(m_{(n/2)} \right) \right. \\ \left. + m \left(n + \frac{2}{2} \right), \quad \text{for } n \text{ is even} \right\} \quad 2-14$$

Where:

Q_{med} , is the median slope, m denotes the number of distinct pairs of data points, n is the total number of data points

Nenwiini and Kabanda (2013) examined the trends and variability in rainfall within the Vhembe region of South Africa using Mann-Kendall trend analysis and Sen's slope estimator. The Sen's slope estimates ranged from -3.95 to -18.3 mm per year in the humid zone and from -1.623 to -4.395 mm per year in the semi-arid zone for stations that displayed significant trends. Notably, no station in the semi-arid zone exhibited a positive value for Sen's estimator. Overall,

the trends in the semi-arid zone were predominantly downward and statistically significant, while in the humid zone, only one-third of the stations showed significant downward trends with a confidence level exceeding 95%. Additionally, a significant negative trend emerged across nearly all zones starting in the mid-1990s.

In a related study, Chanzi et al. (2023) applied the Mann-Kendall and Sen slope estimator methods to analyse trends in rainfall and temperature at the Killombero Basin in Tanzania. This investigation focused on both historical and projected trends in rainfall and temperature. The findings from the Sen slope indicator indicated a variation in trends across the stations, with decreasing trends being the most common.

- **Innovative Trend Analysis (ITA)**

The ITA method introduced by Şen (2012) is a high visual capability model which gives stable results even when there is an autocorrelation effect in the given time series (Alashan, 2018). This method involves splitting the original series into two segments and analyzing the differences between them to identify the trend (Elouissi et al., 2016). The procedure is to divide the time series into two equal parts, arrange the two equal parts into ascending order, plot the first half on the x-axis and the second half on the y-axis, obtain a scatter plot and construct a 1:1 line to divide the plot and after that the trend interpretations will be possible. The interpretations provided by (Şen, 2014) are that if the points fall in a straight line that is nearly parallel to the diagonal, the trend in the data is increasing or decreasing; If the points do not align along a straight line parallel to the diagonal, the data demonstrates a non-monotonic trend, which may be either increasing or decreasing depending on the relative position of the points to the diagonal. Furthermore, the distance between the diagonal and the line created by the scatter points reflects the strength of the trend: a greater distance indicates a stronger trend.

The advantages of the ITA include its simplicity and effectiveness, its ability to produce strong and robust results with minimal error, and its insensitivity to serial correlation. Consequently, the ITA does not require assumptions such as non-linearity, universal applicability, hypothesis testing, seasonal periods, serial correlation, or sample sizes like other parametric and non-parametric statistical tests. This provides it with a significant advantage over those methods. The ITA index has shown strong agreement with other statistical techniques, indicating that it is a practical and efficient method for conducting trend analysis (Wu and Qian, 2017). Some studies suggest that certain unidentified trends found using the MK test can be recognized through the ITA method, which also identifies significant hidden sub-trends within a graph. The equation (equation 2-15) below can be used for ITA calculations:

$$S = \frac{(m_2 - m_1)}{\frac{n}{2}},$$

2-16

Where m_1 and m_2 are arithmetic mean, n is the data number

The study done by Rao et al. (2023) in the Kadiri watershed division of India used the ITA method to assess the temporal trends of annual rainfall in different seasons from 1982 to 2020 (38 years). The long-term annual analysis shows a positive trend in the higher cluster, a negative trend in the bottom cluster and a positive or no trend in the middle cluster. Rao et al. (2023) further indicated that, ITA is a highly effective tool in determining rainfall patterns and overcoming issues such as normality of distribution and data length. Singh et al. (2021) indicated that ITA is capable of identifying hidden trends that can be missed by traditional methods such as the MK and linear regression. The ITA method was performed to determine the seasonal and annual trends in different meteorological regions in India from 1901 to 2019 (118 years). Seenu and Jayakumar (2021) analysed monthly, seasonal and annual rainfall trends from 1961 to 2018 (57 years) in Kondaveeti Vagu India using the MK and the ITA techniques. The results of the MK and ITA were in agreement, and it was observed that the ITA method detects trends more effectively than the MK.

2.3.4 Stochastic methods for trend analysis

According to Visser et al. (2015) stochastic trends are trends whose behaviour is assumed to arise from underlying noise processes. Stochastic trends have significantly wider prediction intervals due to the non-stationary nature of the errors. These trends can vary over time, and the estimated growth represents only the average growth observed during the historical period, rather than the growth rate that will occur in the future (Hyndman and Athanasopoulos, 2018). Studies show that the prediction of intervals allow for greater uncertainty in future growth, hence it is more reliable to forecast using stochastic models. The examples are discussed below.

- **Auto-regressive Moving Average (ARIMA)**

Nyatuame and Agodzo (2018) indicated that The ARIMA model is a linear statistical method used for modelling time series data and forecasting rainfall, making future predictions more accessible. It integrates an autoregressive (AR) process with a moving average (MA) process, specifically designed for non-stationary data series (Mahsin et al., 2012). This model accounts for autocorrelation in the water demand time series by utilizing values from previous periods, such as days, weeks, months, or years, as independent variables to forecast future values. The model is highly accurate and reliable. It performs better on short-term forecast and can model non-stationary time series. The disadvantages of the model are that the

parameters(p,d,q) need to be manually defined, it is difficult to predict turning points, computationally expensive, and the model cannot be used for seasonal time series. The ARIMA model was developed by Jenkins and Box in 1976. The general ARIMA (p,d,q) model can be presented as shown in equations 2-17 and 2-18 (Box et al., 2015):

$$U_t = \phi_p U_{t-1} + \phi_2 U_{t-2} + \dots + \phi_p U_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad 2-19$$

$$U_t = X_t - X_{t-d_t} \quad 2-20$$

Where:

ϕ_p is the autoregressive parameter, ε_t is the residual or white noise, ϕ_p is moving average parameter, U_t is the d^{th} difference of the dependent variable

(Twumasi et al., 2021) studied the timeseries analysis on selected stations in Louisiana state in the United States of America using the ARIMA approach from 1950 to 2020 (70 years). The study results showed a long-term linear increase in precipitation at all stations, except for New Orleans, which exhibited a decreasing trend. Additionally, the models that were identified as suitable and found to provide a good fit for modeling precipitation data include: Baton Rouge (ARIMA (0,1,1) (0,0,2)12), Abbeville (ARMA (0,0,1) (0,0,2)12), Monroe Regional (ARMA (0,0,1) (0,0,0)12), New Orleans Airport (ARMA (1,0,0) (0,0,2)12), Alexandria (ARMA (1,0,1) (0,0,0)12), Logansport (ARIMA (0,1,2) (0,0,0)12), New Orleans Audubon (ARMA (1,0,0) (0,0,0)12), and Lake Charles Airport (ARMA (2,0,2) (0,0,0)12). Ali (2013) studied the time behavior of monthly rainfall data set of the Baghdad meteorological station in Iran. Significant seasonality and increasing trends were found, hence the seasonal ARIMA model (2,1,3) (0,1,1) was found to provide a better fit and also show similar rainfall trends.

- **Artificial Neural Network (ANN)**

The ANN is a non-linear black box which reflects the behaviour of human brain allowing the computer programs to recognise patterns and solve problems. It mimics the nervous system by formulating a complex set of regression equations. According to Foroumadi et al. (2021), ANNs are dynamic systems that transfer knowledge or rules from data to a network structure through the processing of empirical data. The ANN model operates using a feed-forward multilayer perceptron structure that includes an input layer, one or more hidden layers, and an output layer. The multi-layer perceptron (MLP) with two hidden layers is widely used for predicting and forecasting complex hydrological and climatic phenomena. Some advantages

of ANNs are their strong performance and ability to manage large, complex data sets (Praveen et al., 2020). ANNs have been and are still being used in a number of disciplines due to their ease of use, fast results and the production of more accurate results with low margins of errors Ceribasi et al. (2017) ANNs are computationally expensive and difficult to use, they take time and are not suitable for studies wherein a simple and easy-to-use and functionally compact approximation is the objective (Teegavarapu and Chandramouli, 2005).

The ANNs are predominantly utilized for forecasting and predicting future rainfall trends. In their 2016 study, Amoo and Dzwauro (2016) explored trend analysis and the effectiveness of ANN in rainfall prediction. The aim of their research was to evaluate the capability of ANN to forecast future rainfall trends in the Mkomazi Basin, South Africa. They implemented a backpropagation neural network approach to create a predictive model for these trends. Finally, they compared the accuracy of the ANN model with that of the linear regression method.

A variety of statistical approaches have been used to analyze rainfall trends including exploratory, parametric, non-parametric and stochastic methods. Exploratory techniques are useful in virtualizing rainfall patterns but does not give you confidence in trend detection especially in a highly variable catchment such as the LRC. Parametric methods can give misleading results. The MK and Sen slope estimator have been used widely and have yielded good results, with studies such as those done by Dagada (2017), Mashinye (2018) and (Odiyo et al., 2015) using those methods at the LRC. (Nyatuame and Agodzo, 2018) and Pazvakawambwa (2017) show that the ARIMA model is effective in trend analysis yet a few studies in South Africa or even at LRC have used it in the context of seasonal rainfall analysis. Though the ITA method is gaining more popularity due to its advantages, there is still limited studies that have been done in South Africa and no study has been done at the LRC. The combined use of the ARIMA and ITA methods allows for the detection of complex rainfall trends allowing for a more comprehensive understanding of rainfall trends and variability at the catchment.

2.4 RAINFALL VARIABILITY

The degree to which rainfall levels fluctuate over time within a region is known as rainfall variability. Geographical considerations and seasonal atmospheric phenomena are the causes of rainfall variations (Sanjeevaiah et al., 2021). Variability of rainfall can be used to characterize the area of a region. Alemayehu et al. (2020) emphasized the importance of understanding rainfall variation over time and space for sustainable water resource management and agricultural productivity.

(Alemayehu et al., 2020) conducted an in-depth study on the seasonality, variability, and spatial distribution of rainfall in the Amhara region. They analysed time series rainfall data spanning from 1981 to 2017, obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). The researchers employed various metrics, including the coefficient of variation, precipitation concentration index (PCI), seasonality index (SI), and standardised anomaly index (SAI), to evaluate rainfall seasonality and variability.

The study's findings indicated that the region has experienced extreme weather events, such as droughts and floods, as a consequence of rainfall variability over the years. The SAI results demonstrated that there was inter-annual variability in rainfall, with negative anomalies occurring in 40.54% of the years studied and positive anomalies in 59.46%.

Geo-statistical methods such as the ordinary kriging, precipitation concentration index, global polynomial interpolation, spatial autocorrelation were used to study the rainfall trends variability spatially (Javari, 2017). Results show weak, moderate, and strong seasonal and annual spatial variability. This was predicted by relative nugget effect (RNE) predicted from variograms. Furthermore, during the study period, the monthly rainfall variability decreased significantly in eastern and central Iran, while in the northern and western regions of the country, it increased. Monthly rainfall variability patterns were both spatially random and statistically significant.

Bojago (2024) did a study to establish the changes in rainfall from 1987 to 2021 (34 years). The variation in rainfall was analysed using standard statistical methods, including the mean, coefficient of variation, precipitation concentration index (PCI), and standardised anomaly index (SAI). The findings revealed that none of the years studied were categorised as exceptionally wet. Notably, the years 1996 and 1997 represented 5.71% of the total for severe wet years, while 1987, 2006, and 2020 accounted for 8.57% of moderately wet years. Additionally, the variability in the coefficient of variation (CV) of mean annual rainfall for each zone was evaluated using ordinary kriging. The northeast highland region showed a CV of 31.63% in rainfall distribution, whereas the southwest lowland region exhibited a CV of 24.22%, along with a reduction in rainfall amounts.

Kumar et al. (2023) employed the coefficient of variation (CV) and standardised anomaly index (SAI) to assess the spatiotemporal rainfall variability and trend analysis across all West Bengal districts throughout the 41-year period from 1980 to 2021. West Bengal's central district stations have higher CV values, according to the outcome analysis. Harka et al. (2021) investigated the Upper Wabe Shebelle River Basin in Ethiopia's spatial distribution, temporal

rainfall variability, and trend analysis from 1989 to 2018 (29 years) The rainfall variability was examined using the CV, PCI, and SAI methodologies. It was discovered that the yearly and seasonal rainfall had a heterogeneous spatial distribution. The CV displayed moderate to high variability across the research area, while the Bega and Belg season rains displayed high and above-limit variability. During the Kiremt, Bega, and Belg seasons, the negative SAI values were 54.6%, 53.3%, 60%, and 58.6%, respectively. Overall, the dry season is evident in the majority of the studied region. Additionally, it was observed that during the study period, the spatial distribution of SAI in the studied area varied between drier and wetter years.

To illustrate the spatial trends of rainfall and temperature, the inverse distance weighting spatial analysis tool was utilized. The results revealed spatial variation in the decadal, annual, and seasonal distributions of rainfall. The coefficient of variation also revealed that there is variation in rainfall. This was noted in the study done by Mekonen and Berlie (2020) where the spatial variability of rainfall was examined.

Literature show that variability studies have been done across the world using statistical and geo-spatial methods. Furthermore, these studies demonstrate that rainfall variability plays an important role in hydrology and agricultural planning. A number of studies on rainfall variability were done in the LRC such as that done by Odiyo et al. (2015) and Dagada (2017). These studies rely on a few rainfall stations and does not integrate both the statistical and geospatial tools to capture both the magnitude and spatial distribution of rainfall variability at a seasonal scale. This research fill the gap by combining spatial statistical methods with innovative trend analysis methods to investigate rainfall variability seasonally.

2.4.1 Methods used in rainfall spatial variability

- **Mean**

The mean gives an average of the given data set. The mean is a good representative of data and is easy and fast to calculate. The disadvantage of the mean is that it is sensitive to outliers, cannot be determined by inspections, cannot be located graphically and cannot be estimated for nominal or percentage data (Manikandan, 2011). The mean can be estimated as shown in equation 2-21 :

$$\mu = \frac{\sum x_i}{N}, \quad 2-22$$

Where μ is the mean, x_i is each individual value and N is the sample size

- **Standard deviation (SD)**

The standard deviation (SD) measures the distribution of values in a data set related to its mean. It provides a clear picture of data distribution in an observation. It also serves as a shield against the effects of extreme values or outliers in quantifiable observation. The SD is not easily affected by extreme values and it is the best measure of dispersion. The limitation of the method is that it assumes a normal distribution pattern, does not give you a full range of data, and does not exactly measure the actual distance of each observation (Lee et al., 2015). The formula to calculate the SD can be seen in equation 2-23:

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}, \quad 2-24$$

Where

σ is the standard deviation, N is the sample size, μ is the mean, x_i is each individual value

- **Coefficient of variation (CV)**

A standard deviation's size in proportion to its mean is shown by the CV, a relative measure of variability. You can compare the variability of different groups and attributes using this standardised, unitless metric (Abdi, 2010). It is also known as the relative standard deviation (RSD). The relative standard deviation (RSD) is another name for it. The relative distribution of data points around the mean is measured by the CV. The CV's unit lessness, which allows it to be applied to any given quantifiable observation, is one of its major advantages. This makes it possible to compare how much two distinct data sets vary from one another (Achite et al., 2021). A higher value of CV indicates higher/larger rainfall variability. CV less than 1 is considered less variable, and CV greater than 1 is considered highly variable. The disadvantages of the CV are that when the mean is 0, the CV is infinity, it is sensitive to small mean values, cannot be used to calculate the confidence interval of the mean, and cannot calculate logarithm values. The CV can be calculated as indicated in equation 2-25.

$$CV = \frac{\sigma}{\mu}, \quad 2-26$$

Where μ is the mean, σ is the standard deviation

- **Standardised anomaly index (SAI)**

The SAI is used to analyse trend patterns and identify dry and wet years in the record (Bekele et al., 2017). The SAI accepts monthly, seasonal and annual rainfall data timestep. Its advantages are that it is simple to use and uses a variable time scale. Its drawback is that it relies solely on precipitation data, which limits its capability to identify areas more prone to

drought. Additionally, the accuracy of these calculations depends on the quality of the data (Katz and Glantz, 1986). A drought period is indicated by the negative value of SAI, while the positive ones indicate a wet period. The SAI has been used in several studies for determining the variability of rainfall. Studies such as one done by Kumar et al. (2023) and Harka et al. (2021) investigated rainfall variability using the SAI technique. The results of these studies are discussed under rainfall variability section. The SAI used by Kraus (1977) can be computed using equation 2-27 below :

$$I_t = \frac{1}{N} \sum_{i=1}^N (R_{it} - \mu_i) / \sigma_i \quad 2-28$$

Where I_t is the SAI, N is the number of station, R_{it} is the total rainfall at a station, μ is the mean, σ is the standard deviation

- **Precipitation concentration index (PCI)**

The PCI is an index used to illustrate the distribution of monthly rainfall data. Gocic and Trajkovic (2013) indicated that the PCI can potentially be utilised as a drought and flood indicator. The relative distribution of precipitation patterns can be quantified using the PCI (Petković et al., 2017). The PCI is more comparable across regions with varying climates and is not complicated. The method's shortcomings include its inability to account for evapotranspiration, its sensitivity to data quantity and reliability due to its use of 30- to 50-year records, and its failure to take into account precipitation intensity and its possible effects on runoff, streamflow, and water availability (Botai et al., 2025). Oliver (1980) states that a PCI value of less than 10 indicates a uniform monthly rainfall distribution, a value between 11 and 16 indicates a moderate concentration of rainfall, a value between 16 and 20 indicates an irregular monthly rainfall distribution, and a value of 20 or higher indicates a very high concentration of rainfall distribution.

. The PCI is calculated as follows (equation 2-15) :

$$PCI = \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2} \quad 2-15$$

Where P_i is the total precipitation amount in month, i is the month

- **Seasonality index (SI)**

The SI is an average that is used to compare an actual observation to what it would be in the absence of seasonal variation. The SI method requires a few data points for calculation and it is simple to use. The method requires data to be regionalized based on the Thiessen method. At least a period of 30 years of rainfall data is required to describe the prevailing rainfall seasonality index of an area. When using the mean rainfall data, the method does not

consider year-to-year variation (Sharma and Singh, 2019). The formula (equation 2-296) used to compute the seasonal index is shown :

$$\overline{SI} = \frac{1}{\bar{R}} \sum_{n=1}^{12} \left| X_n - \frac{\bar{R}}{12} \right| \quad 2-306$$

Where X_n is the mean rainfall of month n, $\bar{R}$ is the mean annual rainfall. There are SI class values and the associated rainfall regime (see Table 2-1)

Table 2-1: SI class and rainfall regime

SI	Rainfall regime
<0.19	Rainfall throughout the year
0.20-0.39	Rainfall throughout the year but with a definite wetter season
0.4- 0.59	Seasonal with a short dry season
0.60- 0.79	Seasonal
0.80- 0.99	Seasonal with a long dry season
1.0-1.19	Extremely seasonal, most rainfall in <3 months

- **Inverse distance weighted (IDW)**

IDW interpolates a raster surface based on points. The best results are achieved when the sampling density is adequate to capture the local variation being simulated. If the input points are sparse or unevenly distributed, the resulting surface may not accurately reflect the desired outcome (Watson, 1985). The other disadvantage of using the IDW method is that there are errors in the computing times when processing large data sets (Maleika, 2020). The method is also sensitive to outliers (Li et al., 2018). The IDW method calculates an average value for unsampled locations by using values from nearby sampled points, with the weights determined by the distance between the points. These weights can be adjusted using the IDW power coefficient (ESRI) IDW is expressed as in equation 2-17 :

$$\hat{Z}_j = \frac{\sum_i Z_i / d_{ij}^n}{\sum_i 1 / d_{ij}^n} \quad 2-17$$

Where $\hat{Z}_j$ is the estimated value for the prediction point, Z_i is the measured value for sample point, d_{ij} is the Euclidean distance between sample point and prediction point, n is a power parameter

- **Kriging**

Kriging is a sophisticated geostatistical method that creates an estimated surface from a dispersed set of points with z-values. In this method points are interpolated from a raster

surface. Kriging is based on statistical models. These techniques provide some measure of accuracy in the prediction. Kriging is predicated on the idea that spatial correlation, which can be utilised to explain surface variation, is reflected in the direction or distance between sample points (ESRI). The optimal linear unbiased estimator is referred to as Kriging. The method's drawbacks include its restricted applicability in cases where there are few sampled observations, the data's limited spatial breadth, and the absence of spatial correlation (Health). The general formula for Kriging is shown in equation 2-31 below:

$$\hat{Z}(S_0) = \sum_{i=1}^N \lambda_i Z(S_i) \quad 2-32$$

Where $Z(S_i)$ is the measured value at the i th location, λ_i is an unknown weight for the measured value at the i th location, S_0 is the prediction location, N is the number of measured values

Existing studies mostly use metrics such as the mean, SD, CV, SAI and PCI to assess rainfall variability such as that done by Alemayehu et al. (2020) and Kumar et al. (2023). Those studies use those metrics in isolation. This study adopts an integrated approach by using the mean, CV, SD, SAI and the kriging interpolation to be able to assess both the temporal variability and spatial distribution of seasonal rainfall. Kriging provides a statistical spatial interpolation with error estimation making it better suited to determine rainfall variability in data sparse region such as that of the LRC. This study addresses the lack of spatial precision or seasonal resolution gap that has been left by previous studies.

A comprehensive analysis of rainfall trends is essential, as the findings from this research play a pivotal role in effective climate risk management, the preservation of agricultural productivity, and informed decision-making in water resource management. These insights are critical not only for addressing immediate challenges in the short term but also for crafting sustainable strategies that will benefit future generations in the long run.

CHAPTER 3: METHODOLOGY

The following diagram (*Figure 3-1*) show the sequence of flow in methods for ease of reference. In order to be able to achieve the first specific objective which was to analyse historic and future trend, data had to be obtained and analysed. .

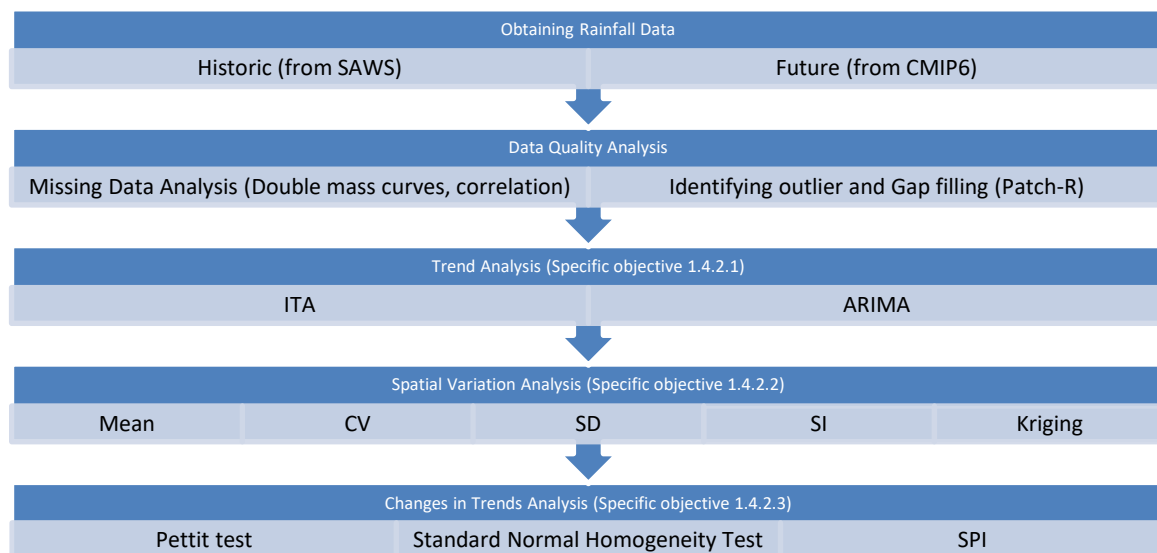


Figure 3-1: General outline of methodology

3.1 DATA COLLECTION

The rainfall data utilized in this study was for both historical and future periods. For historical data, rainfall gauging stations in the vicinity of LRC were checked and data was collected from those stations. Historical rainfall data was sourced from the Department of Water and Sanitation (DWS) and from the SAWS for the period 1950-2021.

Future rainfall data utilised in this study encompasses two time periods: a 30-year near future period from 2025 to 2054 and a 30-year far future period from 2055 to 2085. The data was sourced from CMIP6 (Coupled Model Intercomparison Project Phase 6) dataset under the Representative Concentration Pathway (RCP 8.5) scenarios.

3.2 DATA ANALYSIS

3.2.1 Data quality control

The quality of the data was evaluated using Double Mass Curves, linear regression, and correlation analysis. According to Merabtene et al. (2016) a strong correlation between the data sets from

rainfall stations can serve as a reliable indicator for validating data consistency. The single mass plot and the Qsum plot were used for the initial screening of the gauges. Data for each station was assessed. This was done so that the outliers (values that are very low or very high and do not correspond with the values of the nearby gauges) are flagged and patched or corrected. This is done using the Rain-IMS program. The program has features that help identify outliers, such as extreme weather events. The values were flagged based on the following:

- Periods of no record, i.e. no rainfall data.
- High or very low values were periods of flooding or drought were not recorded.
- Monthly values greater than three times the monthly average.
- Annual values greater than twice the annual average.
- Annual values less than half the annual average.
- Values that repeat more than three times.

A threshold of <10% was used to decide on which stations to use on trend analysis, due to the fact that literature indicate that rainfall stations with such a threshold are still acceptable or usable. Data with more than 15% missing monthly rainfall were excluded while stations with < 10% were patched using the Patch R program.

3.2.2 Computation of historical and future seasonal rainfall trends

The main and specific objective 1.4.2.1 was to determine the historic and future seasonal rainfall trends. The ITA and ARIMA methods were used to analyse the trends. These methods were used as they are simple to use, fast and effective, and they produce more reliable results. In a number of studies the MK is used for trend analysis. In this study, methods that are not usually used were chosen to see how they perform, and also, in the study area, trends have been analysed using the MK method. The ITA method is particularly suitable for climate datasets that are often non-linear or exhibit outliers. The ARIMA was run on MATLAB R2019a to get the rainfall trends. The ITA was done on Microsoft Excel. According to (Kruger, 2004), South Africa can generally be divided into 4 rainfall seasonal zones. Data was analysed according to seasons that is, summer (December, January and February), autumn (March, April and May), winter (June, July and August) and spring (September, October and November).

In order to run the ARIMA model, one needs to first determine the stationarity of the data, whether the data is stationary or non-stationary. If the data is non-stationary differentiation should be done before the model can be determined. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity was used. The KPSS test has two hypothesis; one is the null hypothesis, which is that the trend is stationary, and the alternative hypothesis which is that

the series has a unit root, meaning that the data series is not stationary. Furthermore, a suitable model was developed based on the AIC value obtained. The AIC number is a number used to determine which model is best for given datasets. The lower the AIC score the better.

3.2.3 Determination of the spatial variation of historical and future rainfall trends

The specific objective 1.4.2.2 was to determine spatial variation of historic and future seasonal trends. This was achieved by using the Mean, SD, CV, SI and kriging methods. The formulas for these methods are presented in 2.4.1. The mean, SD, CV, and SI were calculated on Microsoft Excel. Kriging was used to create maps for spatial variation of rainfall in ArcGIS. The results of the seasonal average rainfall trend analysis and CV were utilised in the Kriging process.

3.2.4 Investigation of the possible causes of rainfall trends

The possible causes of rainfall trends was the specific objective 1.4.2.3. The homogeneity test using the Standard Normal Homogeneity Test (SNHT) and the Pettitt test was done in order to detect the change in the trends. Alexandersson (1986) developed the SNHT to detect a change in a series of rainfall data. Pettitt's test is a nonparametric test adapted from the rank-based Mann-Whitney test. It does not require any assumptions about the data distribution and enables the identification of the time when the shift happens. The SNHT and Pettitt test show the homogeneity and where the break or changes on the record occur. Kang and Yusof (2012) provided the SNHT equation (3-1) while Pettitt (1979) indicated the Pettitt test equation (3-2) as below. According to Kang and Yusof (2012) the SNHT, statistics can be obtained as follows:

$$T_y = y\bar{z}_1 + (n - y)\bar{z}_2, y = 1, 2, \dots, n \quad 3-3$$

$$\text{Where : } \bar{z}_1 = \frac{1}{y} \sum_{i=1}^y \frac{(Y_i - \bar{Y})}{S} \text{ and } \bar{z}_2 = \frac{1}{n-y} \sum_{i=y+1}^n \frac{(Y_i - \bar{Y})}{S}, \quad 3-4$$

S is the standard deviation, $\bar{Y}$ is the mean

The Pettitt test is a non-parametric rank test based on r_i of the Y_i and ignores the normality of series:

$$X_y = 2 \sum_{i=1}^y r_i - y(n + 1), y = 1, 2, \dots, n \quad 3-5$$

The break occurs in year k when $X_k = \max |X_y|$, the value is then compared with the Pettitt values from Pettitt (1979). The two methods were run on R Studio.

To further investigate the possible causes the 3 months SPI was computed using the SPI generator software. The SPI was developed by McKee et al. (1993) to measure how far the precipitation for a given period deviated from the mean. The SPI was used in this study because it is simple to use, and it assess both the dry and wet conditions. Positive SPI values indicate wet conditions while negative values signify dry conditions. The results obtained from the tests above were used with those from the SPI in order to be able to conclude the causes of changes in rainfall trends. The data from the 3 months SPI was compared, to see if the break occurred where there are changes and in a period of extremely wet or extremely dry season associated with ENSO events. It is important to note that the above techniques do not directly pinpoint the causes of rainfall trends, but they were used as indicators in order to infer possible causes.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 DATA QUALITY CONTROL RESULTS

About 56 rainfall stations in and around the study area were identified (see *Figure 4-1*). Only 15 rainfall gauging stations were used. The stations were used because they have sufficient data with a record length of more than 50 years, with the exception of the 0728011 and 0812567, which are located in the lower reaches of the catchment that had shorter records. The two stations were used in order to get a picture of the trends in the lower reaches of the catchment since there aren't any stations in that vicinity. A number of studies indicate that stations should be at least 30 years or more in order to produce reliable results and also to be satisfactory.

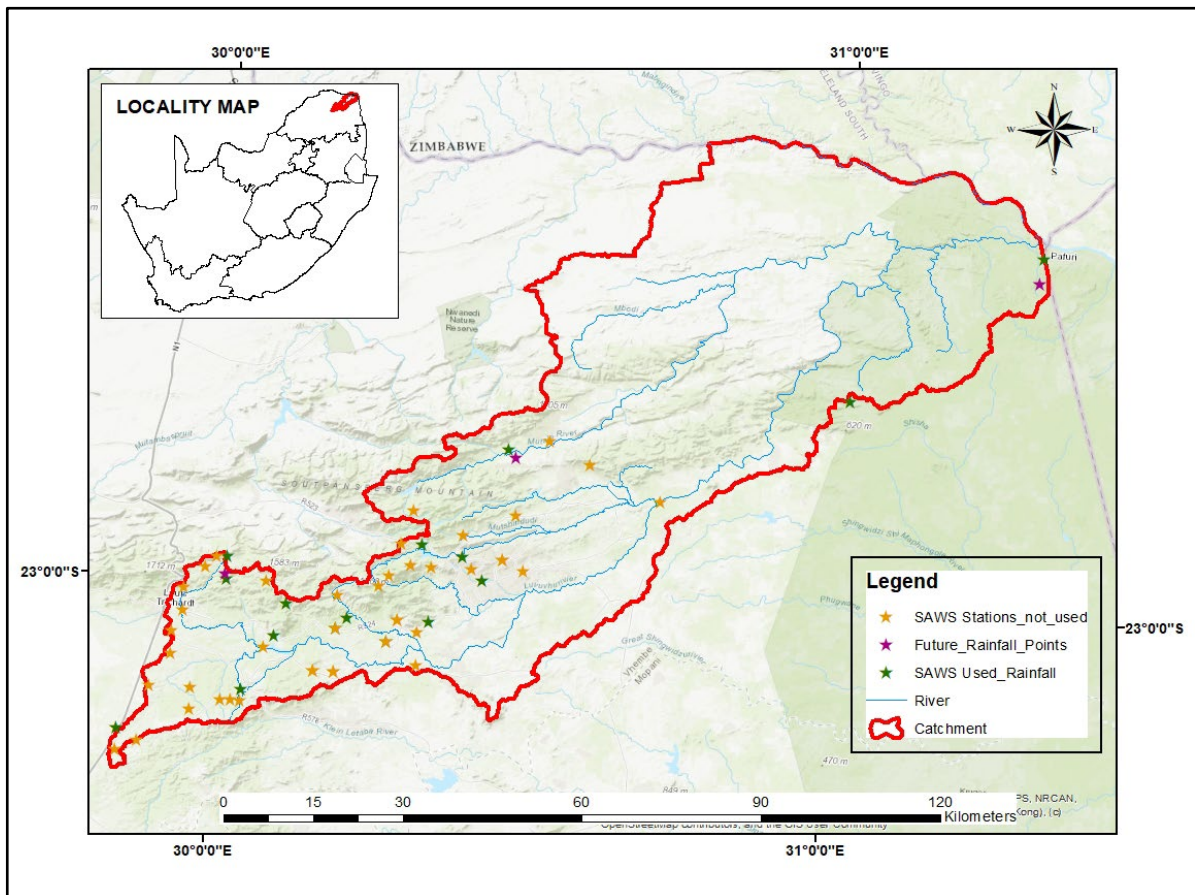


Figure 4-1: Rainfall stations in the LRC

For historic analysis, the gauges used showed stationarity, meaning that the data is continuous (see *Figure 4-2*, *Figure 4-3* and *Figure 4-4*). The MAPs of all rain gauges compare well ranging from about 300 to 1430 mm. Stations with missing values less than 10% were chosen. All the selected rainfall stations with missing values were patched.

Table 4-1: Data Quality Controls Results

Rainfall Station Number	Name	Location		Record Length (Years)		MAP (mm)	R ²
		Lat	Long	Start	End		
0723182 W	Shefeera	-23° 2'	30° 7'	1949	2021	1424	0.985
0722614 W	Zwartrandjes	-23° 14'	29° 52'	1979	2021	508	1.000
0766827 W	Rambuda	-22° 47'	30° 51'	1952	2014	765	0.996
0812567 W	Pafuri	-22° 27'	31° 19'	1979	1999	337	0.965
0723070 W	ElimHosp	-23° 9'	30° 3'	1949	2021	733	0.99
0723155 W	Goedehoop	-23° 4'	30° 8'	1949	2021	910	0.992
0723334 W	Nooitgedacht	-23° 4'	30° 12'	1949	2022	997	0.991
0723363 W	Klein Australie	-23° 3'	30° 13'	1949	2022	1126	0.997
0723485 W	Levubu	-23° 6'	30° 17'	1979	2022	876	0.999
0723603 W	Tsianda	-23° 3'	30° 21'	1952	2021	928	0.99
0766596 W	VondoBos	-22° 56'	30° 20'	1962	2021	1284	0.999
0766030 W	RoodewalBos	-23° 1'	30° 1'	1949	2021	862	0.991
0768011 W	PundaMaria	-22° 41'	31° 1'	1979	1994	478	0.998
0766717 W	Phiphidi	-22° 57'	30° 24'	1985	2021	1338	0.998
0766779 W	Palmaryville	-22° 59'	30° 26'	1949	2022	884	0.994

The DM curves showed stationarity with the curves being straight and the R^2 of all the stations were greater than 0.96, as in *Table 4-1: Data Quality Controls Results*. The DM curves have a consistent slope over the entire time period, that is the curves show a straight line which indicate stationarity (see *Figure 4-2, Figure 4-3 and Figure 4-4*). For future data, DM curves also had an R^2 greater than 0.99; consistent slope (see *Figure 4-5*) all the stations had a R^2 of 0.999 (*Table 4-2*). The greater R^2 in the catchment shows that there is a good correlation between the rainfall data of the stations, hence a good, consistent, linear relationship between the stations. The catchment seems to have the same pattern of rainfall. Studies done in the LRC, such as those by Nkuna and Odiyo (2011) and Mashinye (2018) show that the DM curves have an R^2 greater than 0.9, which is comparable to what has been obtained in this study. The figures below show the DM curves for all the stations used.

Table 4-2: List of rainfall stations used for future analysis

Name	SAWS Station close by	Location		Record Length (Years)		R ²
		Lat	Long	Start	End	
Station 01	Shefeera	-22° 3'	31° 18'	2025	2085	0.999
Station 02	Rambuda	-22° 42'	30° 36'	2025	2085	0.999
Station 03	Pafuri	-22° 48'	30° 48'	2025	2085	0.999

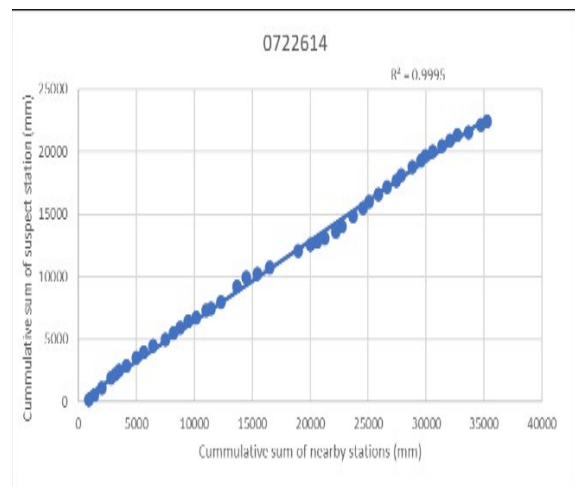
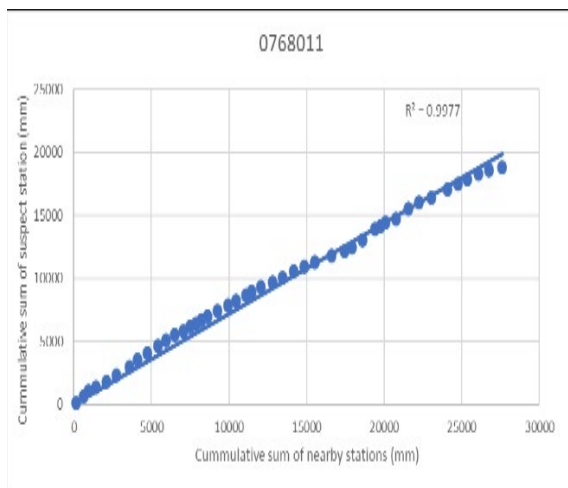
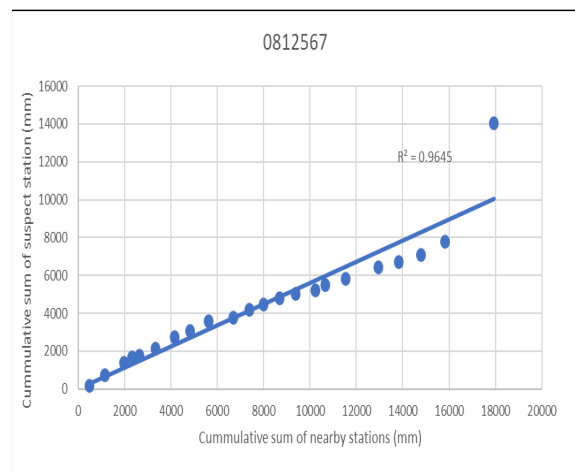
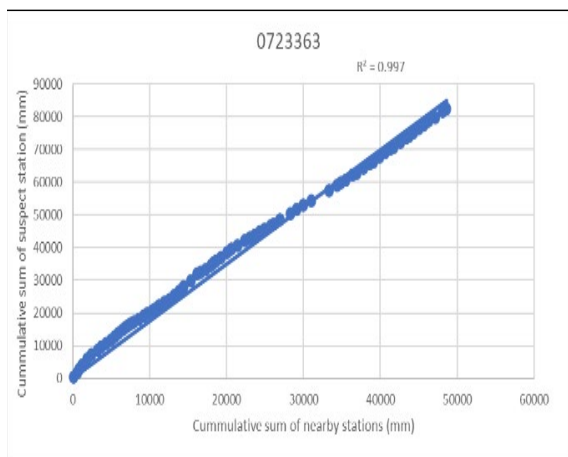
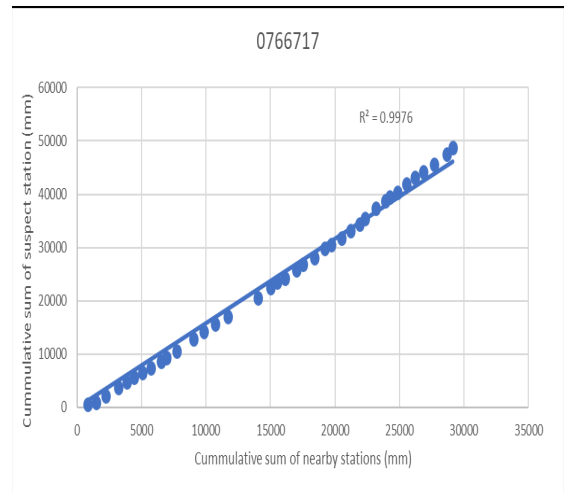
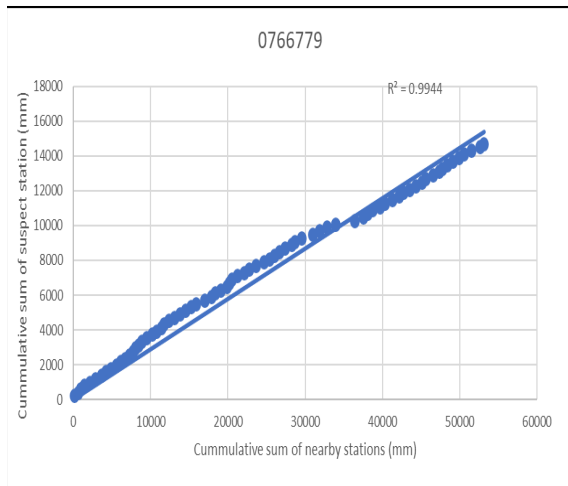


Figure 4-2: DM curves for stations Palmaryville, Phiphidi, Klein Australie, Pafuri, Punda Maria and Zwartrandjes

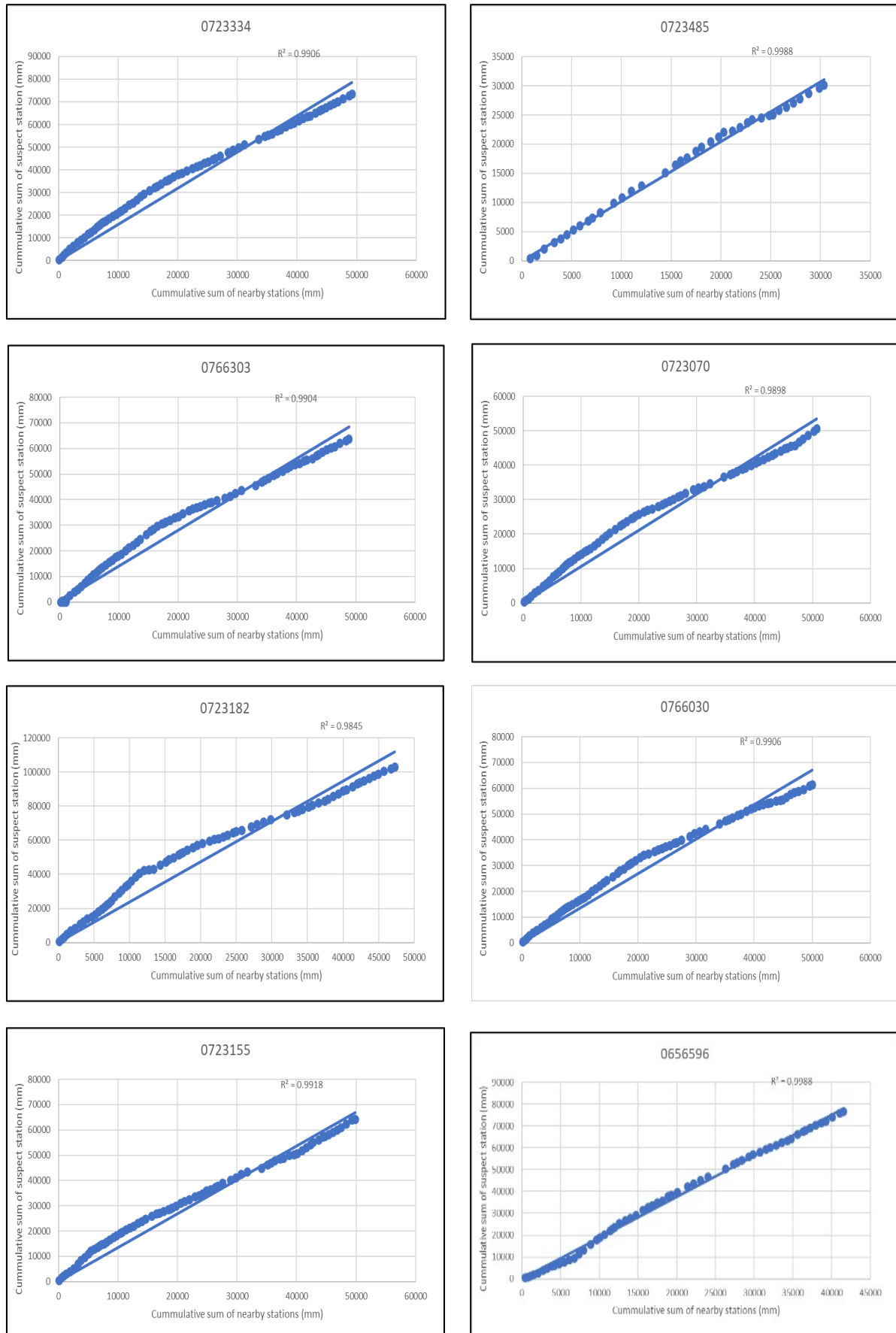


Figure 4-3: DM curves for stations Noitgedacht, Levubu, Tsianda, Elim Hosp, Goedehoop, Vondo Bos, Shefera and Roodewal Bos



Figure 4-4: DM curve for Rambuda station

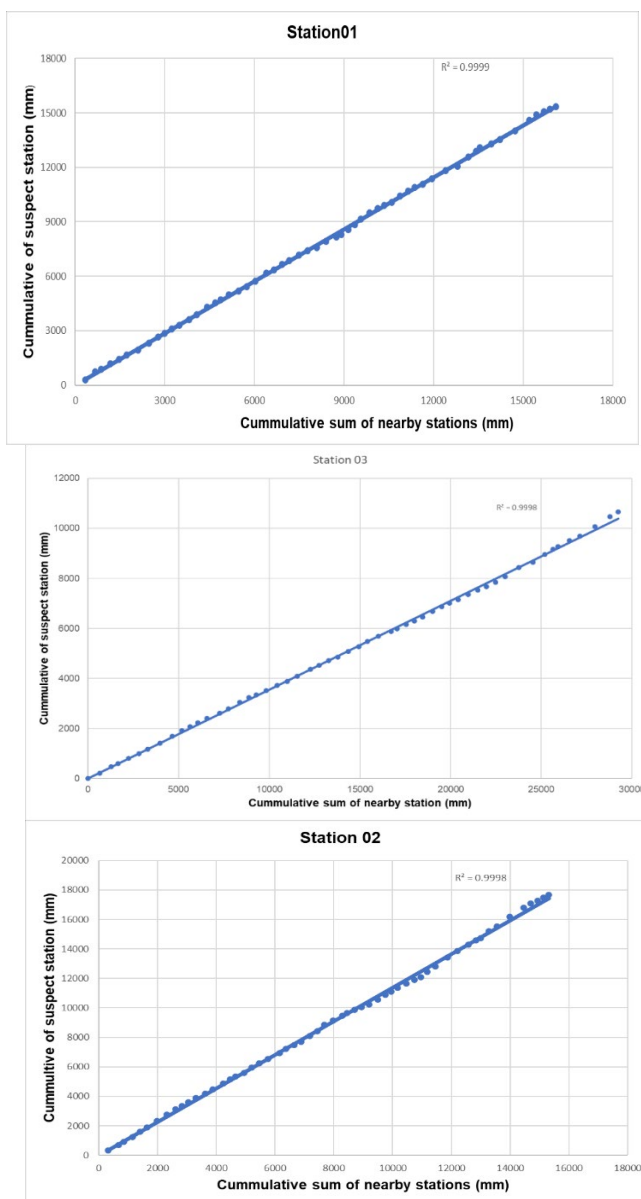


Figure 4-5: Future Data DM Curves

4.2 RESULTS OF HISTORIC SEASONAL TREND ANALYSIS

Trend Analysis results based on a plot

Figure 4-6 shows the plot of average seasonal rainfall trends of the selected stations in the study area. Summer had the highest rainfall, and winter had the lowest. Vondo, Roodewal-Bos, Shefeera, Klein-Australie Bos and Pafuri stations show similarities, with Autumn having the second highest average seasonal rainfall, followed by spring. These stations are on the same escarpment, part of the upper boundary of the catchment except for the Pafuri stations. The highest rainfall of the catchment is found on that side of the catchment, that is the upper boundary of the catchment. Tshililo et al. (2021) indicated that seasonal rainfall starts early in the semi-arid regions of the catchment, leading to long rainy seasons and high seasonal rainfall amount. The Levubu, Phiphidi, Palmaryville, Tsianda, Nooitgedacht, Goedeheop-Bos, Elim hosp, Rambuda, Zwartrandjes and Punda Maria stations have spring as the second highest followed, by Autumn. Phiphidi station receives the highest average seasonal rainfall in summer, totaling approximately 880 mm. Zwartrandjes and Punda Maria stations have the lowest average rainfall of about 12 mm occurring in winter. The LRC is characterised by summer rainfall, hence the high rainfall pattern that is observed in summer. This is supported by (Singo et al., 2018) where it was indicated that the catchment receives wet summers with the highest rainfall in January and February; hence summer has the highest mean seasonal rainfall.

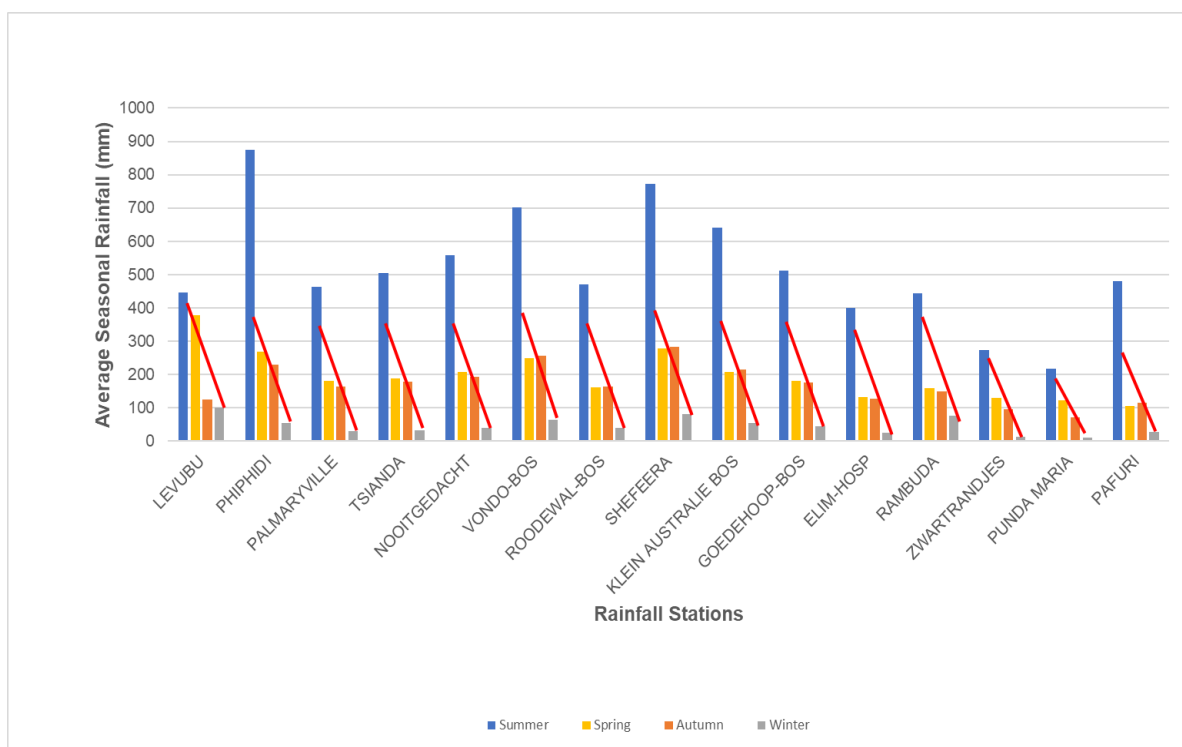


Figure 4-6: Historical average seasonal rainfall trends at all the stations

Trend analysis results based on ITA

The seasonal ITA at the fifteen rainfall stations showed that in most stations there is a decreasing trend (*Table 4-2*). In summer, Phiphidi, Nootitgedacht, Vondo Bos, Klein Australie, Goedeheop Bos, Zwartrandjes and Punda Maria stations show an increasing trend, and the Levubu, Palmaryville, Tsianda, Roodewal Bos, Shefeera, ElimHosp, Rambuda and Pafuri stations show decreasing trends. In autumn, Vondo Bos, Klein Australie, Goedeheop Bos, and Punda Maria stations show increasing trends, and Levubu, Phiphidi, Palmaryville Tsianda, Nootitgedacht Roodewal Bos, Shefeera ElimHosp, Rambuda Zwartrandjes and Pafuri stations show increasing trends. In winter, five stations, namely; Nootitgedacht, Vondo Bos, Klein Australie, Goedeheop Bos, Rambuda and Punda Maria show an increasing trend, and Levubu, Phiphidi, Palmaryville Tsianda, Roodewal Bos, Shefeera ElimHosp, Zwartrandjes and Pafuri show decreasing trends. In spring, Klein Australie, Goedeheop Bos, Rambuda, Zwartrandjes and Punda Maria stations show increasing trends, and Levubu, Phiphidi, Palmaryville Tsianda, Nootitgedacht, Vondo Bos, Roodewal Bos, Shefeera, ElimHosp and Pafuri stations show decreasing trends. Mashinye (2018) indicated that at Levubu, Shefeera, Nootitgedacht and Palmaryville the trends are decreasing which are in agreement with what has been found in this study. Klein Australie and Vondo-Bos show an increasing trend, which is also the case in this study. The stations in the upper boundary have similarities and differences; this is because some stations show decreasing trends while others show increasing trends for almost all the seasons.

Table 4-2: Historical Seasonal ITA Results

Station Name	Seasonal Trends				Trend slope			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Levubu	Decreasing	Decreasing	Decreasing	Decreasing	-0.305	-0.513	-0.442	-0.278
Phiphidi	Increasing	Decreasing	Decreasing	Decreasing	0.061	-0.235	-0.308	-0.257
Palmaryville	Decreasing	Decreasing	Decreasing	Decreasing	-0.118	-0.243	-0.024	-0.225
Tsianda	Decreasing	Decreasing	Decreasing	Decreasing	-0.131	-0.264	-0.024	-0.200
Nootitgedacht	Increasing	Decreasing	Increasing	Decreasing	0.019	-0.039	0.040	-0.164
Vondo-Bos	Increasing	Increasing	Increasing	Decreasing	0.158	0.008	0.083	-0.058
Roodewal-Bos	Decreasing	Decreasing	Decreasing	Decreasing	-0.124	-0.112	-0.049	-0.226
Shefeera	Decreasing	Decreasing	Decreasing	Decreasing	-0.121	-0.176	-0.179	-0.390
Klein Australie	Increasing	Increasing	Increasing	Increasing	0.142	0.123	0.076	0.014
Goedeheop Bos	Increasing	Increasing	Increasing	Increasing	0.154	0.084	0.051	0.041
Elim-Hosp	Decreasing	Decreasing	Decreasing	Decreasing	-0.010	-0.125	0.000	-0.209
Rambuda	Decreasing	Decreasing	Increasing	Increasing	-0.198	-0.107	0.143	0.189
Zwartrandjes	Increasing	Decreasing	Decreasing	Increasing	0.098	-0.087	-0.081	0.121
Punda Maria	Increasing	Increasing	Increasing	Increasing	0.120	0.045	0.123	0.377
Pafuri	Decreasing	Decreasing	Decreasing	Decreasing	-0.188	-0.081	-0.009	-0.133

Summer

Levubu, Shefeera, Roodewa Bos, Palmaryville, Tsianda, Nooitgedacht, , Elim hosp, Rambuda, and Pafuri stations show a decreasing trend during the summer season. The decreasing trends are further indicated by a negative slope in those stations. Goedehoop-Bos, Punda Maria, Vondo, Klein Australie and Zwartrandjes rainfall stations show increasing trends, with a positive slope. When Odiyo *et al.* (2019) did a study investigating hydrological hazard in the Vhembe district where the LRC is located, negative trend outcomes were observed in summer rainfall records at Shefeera, Tsianda, Nooitgedacht, Rambuda, and Zwartrandjes, with Palmaryville and Rambuda showing significant trends at the 95% confidence interval. The study supports the results in the current study. (*Figure 4-7, Figure 4-8, Figure 4-9, and Figure 4-10*) show all the summer ITA trends.

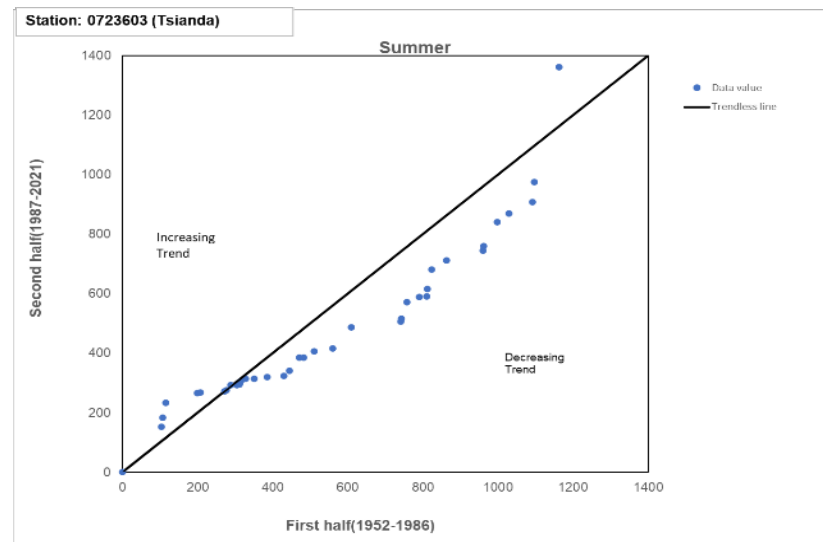
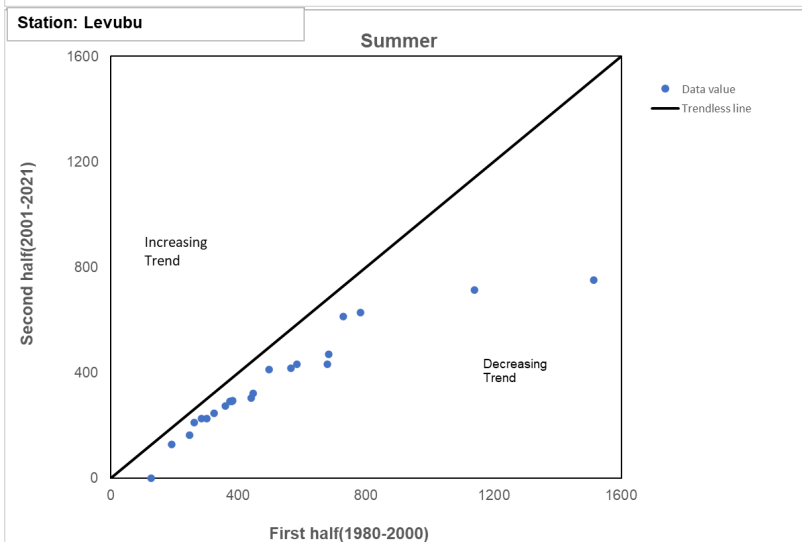
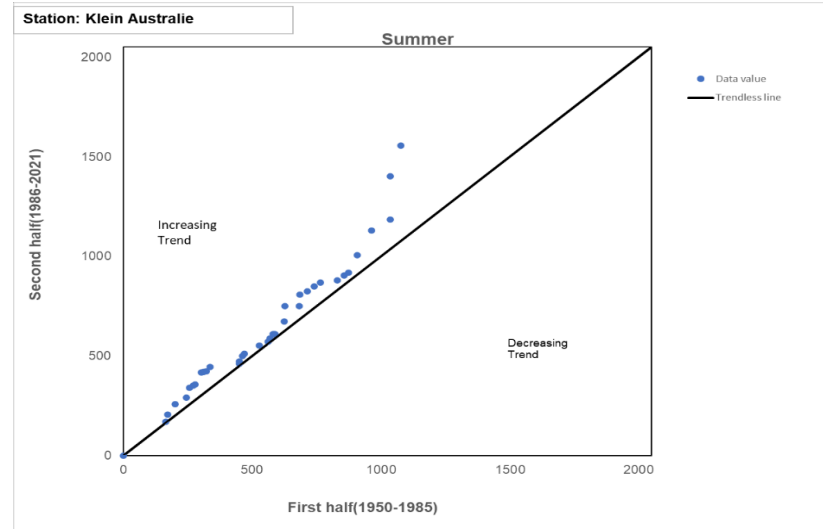
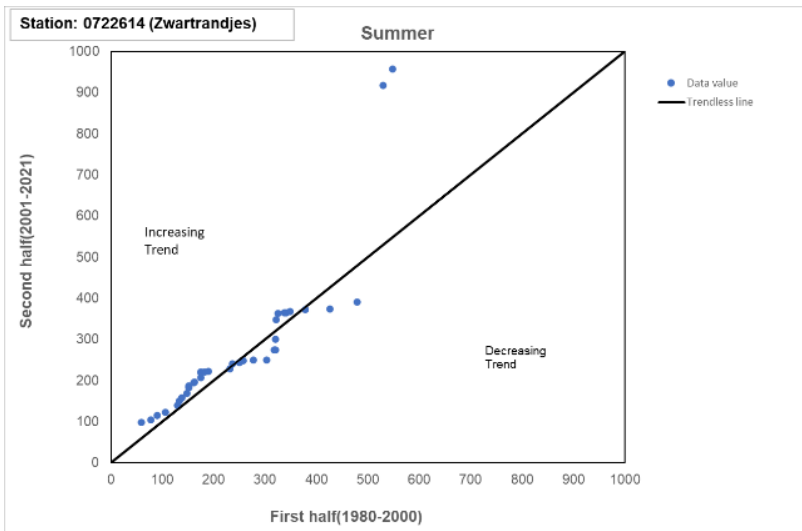


Figure 4-7: Summer ITA results for Zwartrandjes, Levubu, Tsianda and Klein Australie

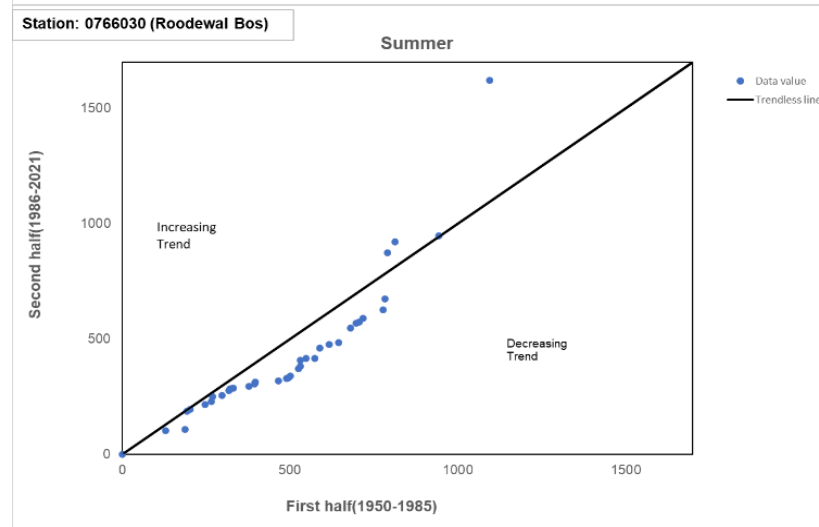
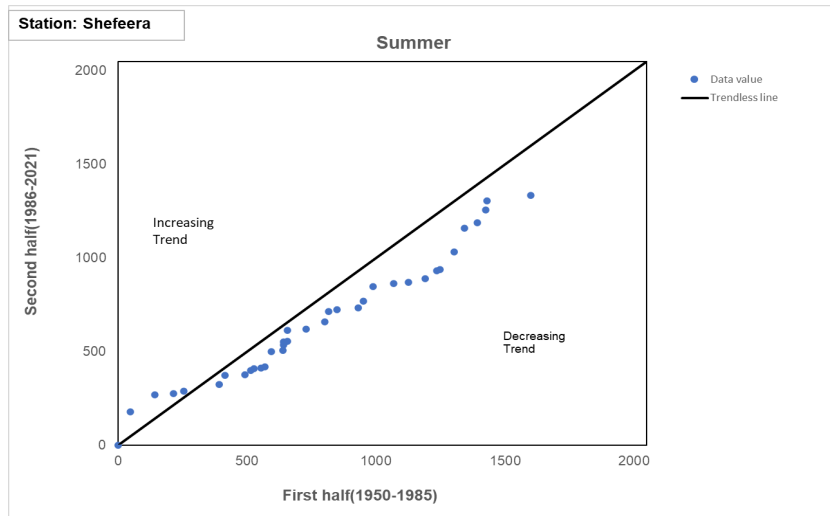
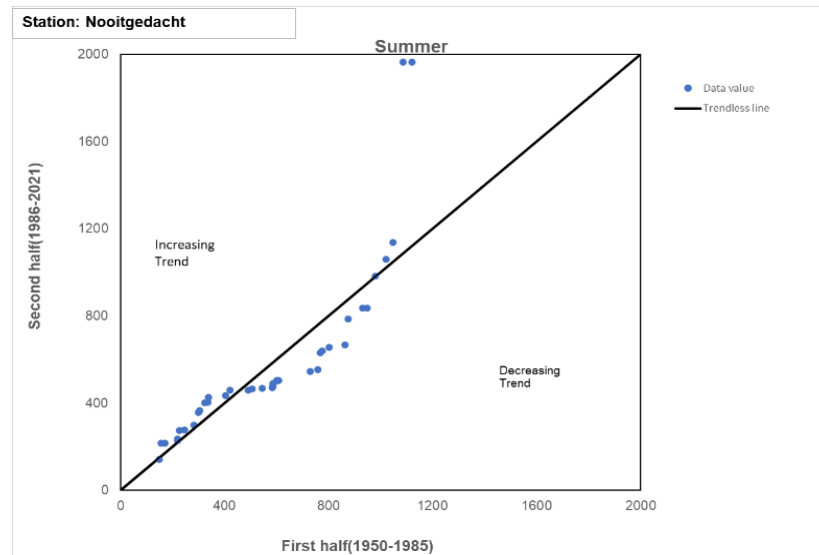
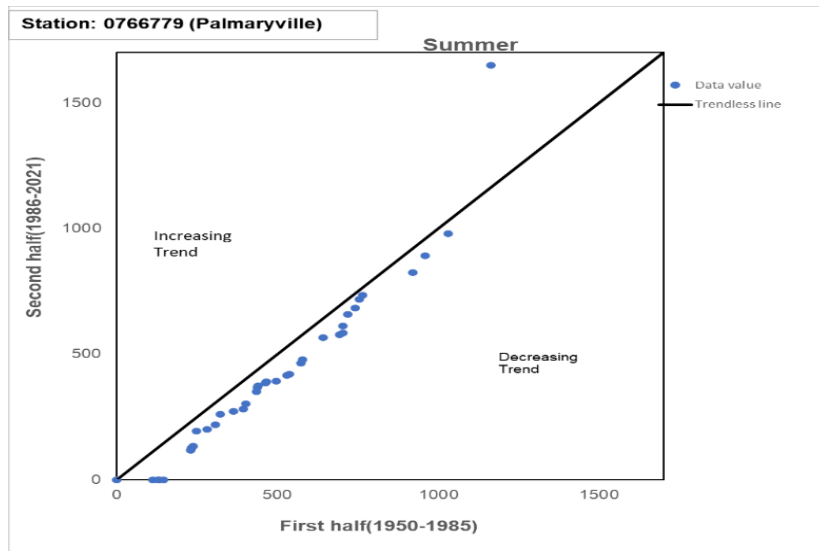


Figure 4-8: Summer ITA results for Palmaryville, Shefeera, Noitgedacht and RoodewalBos

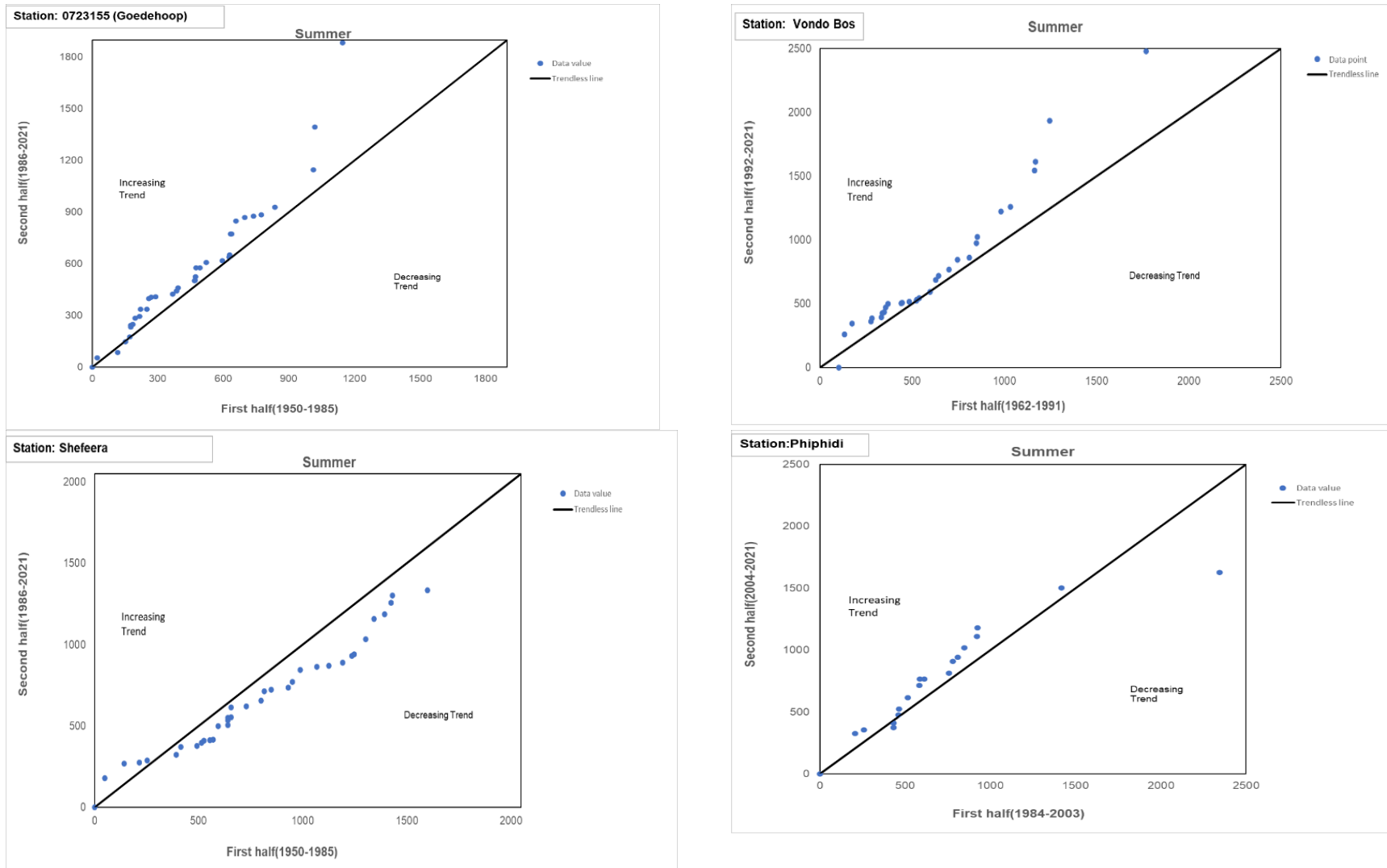


Figure 4-9: Summer ITA results for Goedeheop Bos, Shefeera, Vondo Bos and Phiphidi

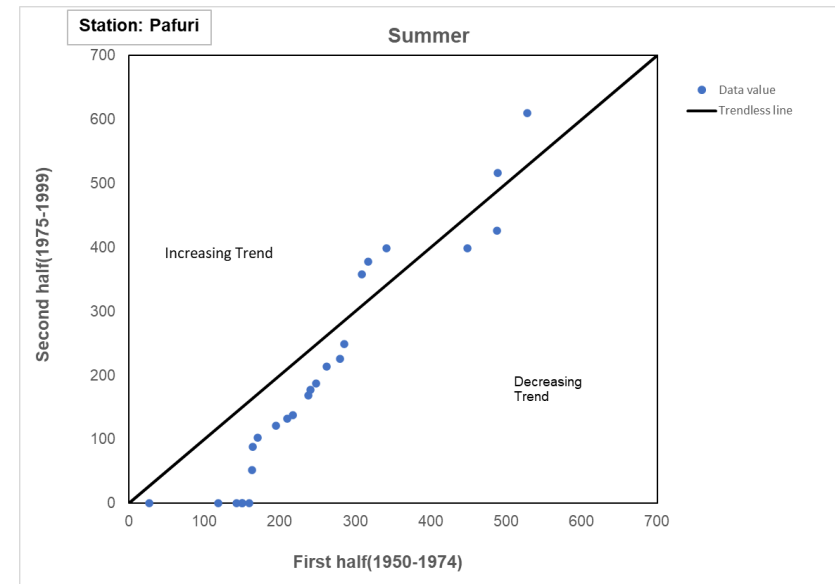
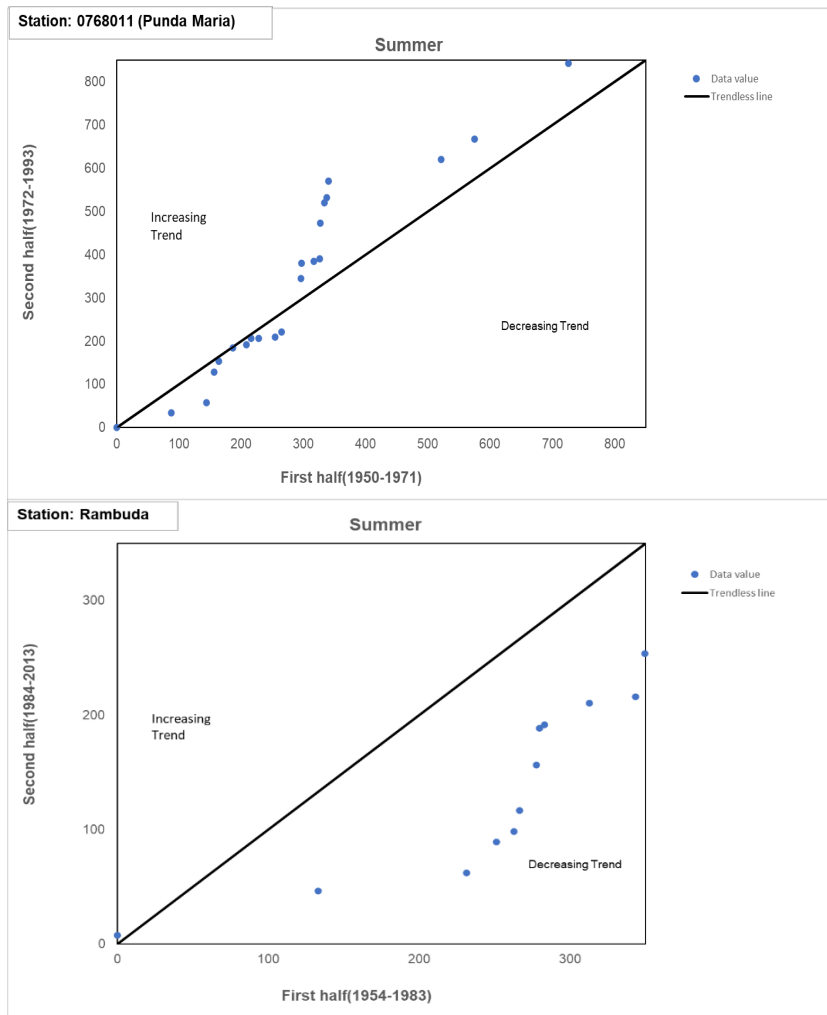


Figure 4-10: Summer ITA Results for Punda Maria, Rambuda and Pafuri

Autumn

Autumn shows a more mixed trend pattern, though predominantly negative with decreasing trends spatially distributed across the catchment. Stations such as Levubu (-0.513), Palmaryville (-0.243), Tsianda (-0.264), and Shefeera (-0.176) demonstrate moderate to strong declines, indicating a potential shortening of the rainfall period after summer. The strongest decreasing trend is observed at Levubu, possibly due to its elevation and land cover interactions.

However, stations including Vondo-Bos (0.008), Goedehoop Bos (0.084), Klein Australie (0.123), and Punda Maria (0.045) show slight positive trends. Though these increases are relatively small in magnitude, they may reflect slight shifts in seasonal rainfall distribution toward later months in some locations

Figure 4-11, Figure 4-12, Figure 4-13, and Figure 4-14 indicate the ITA graph for the autumn season for all the stations in the LRC.

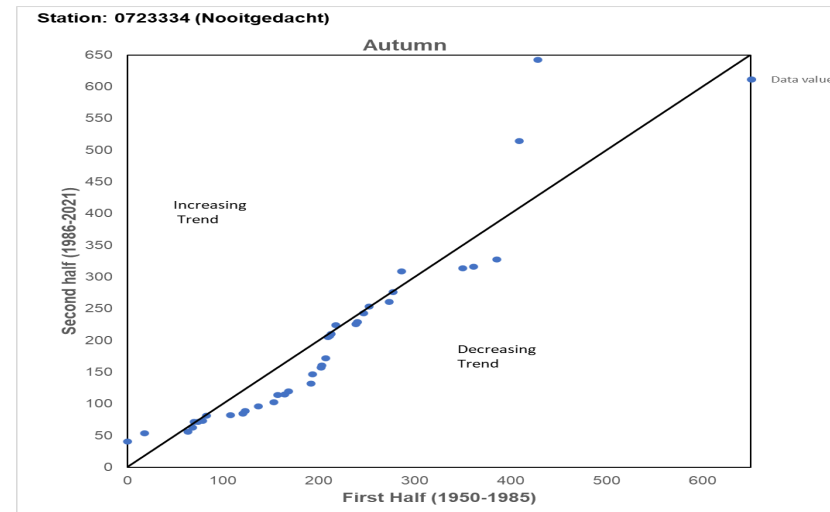
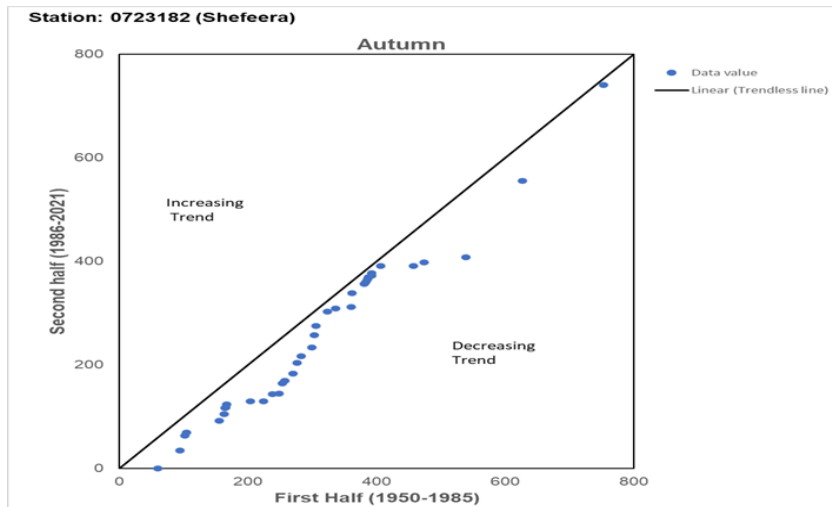
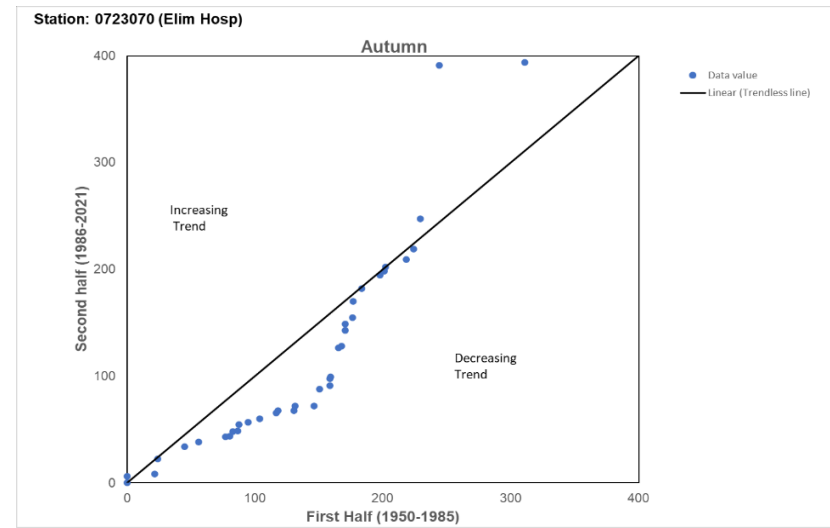
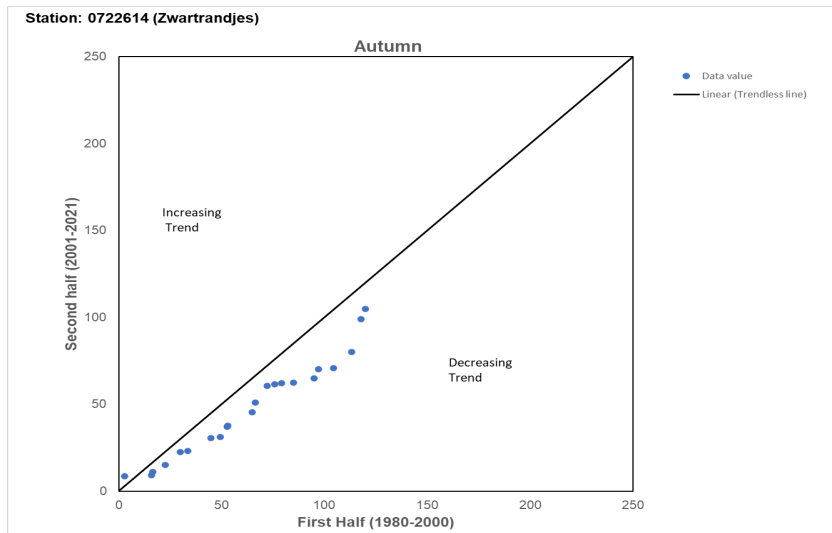


Figure 4-11 : Autumn ITA results for Zwartrandjes, Elim Hosp, Shefeera and Nooitgedacht

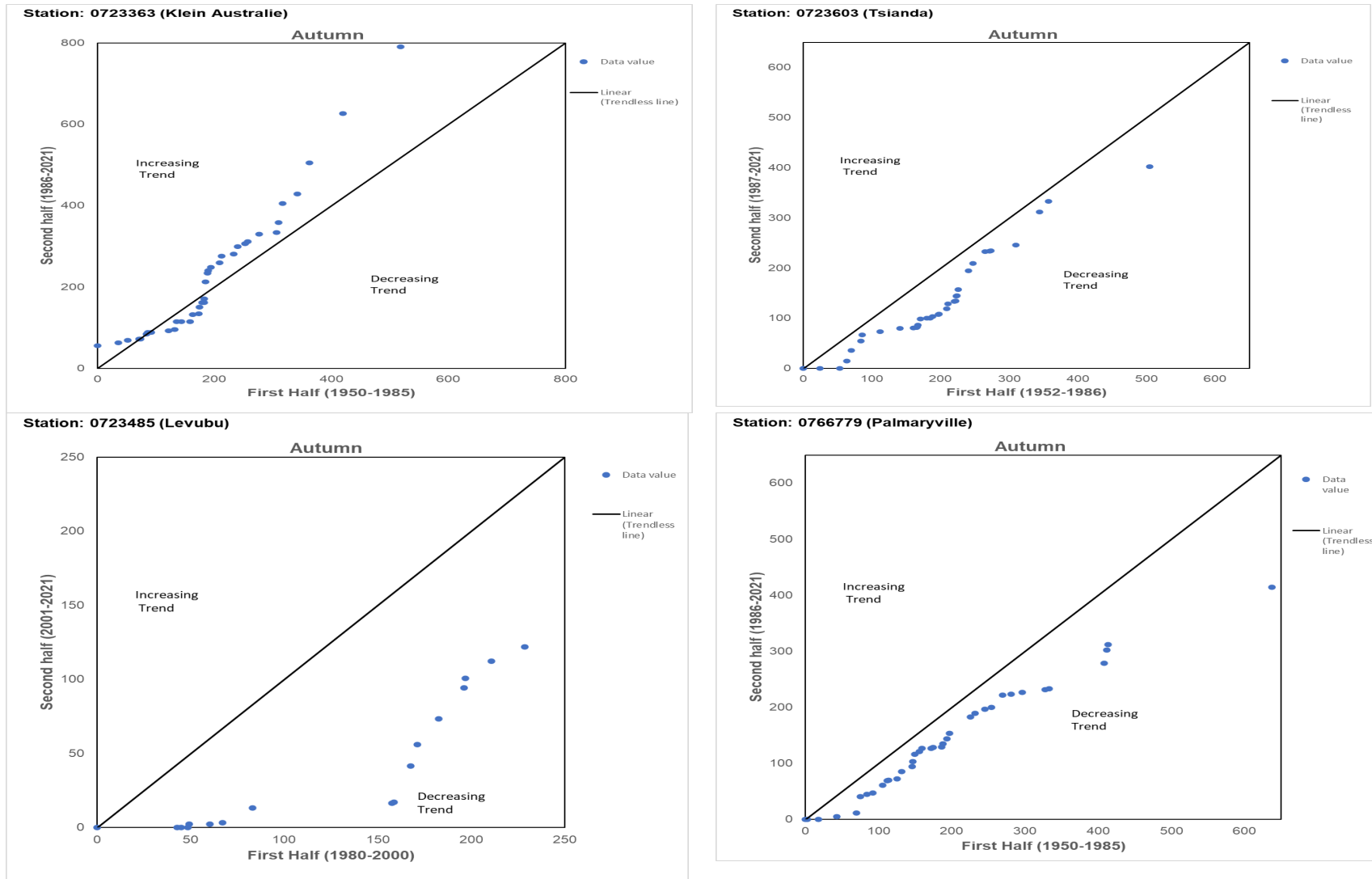


Figure 4-12: Autumn ITA results for Klein Australie, Levubu, Tsianda and Palmaryville

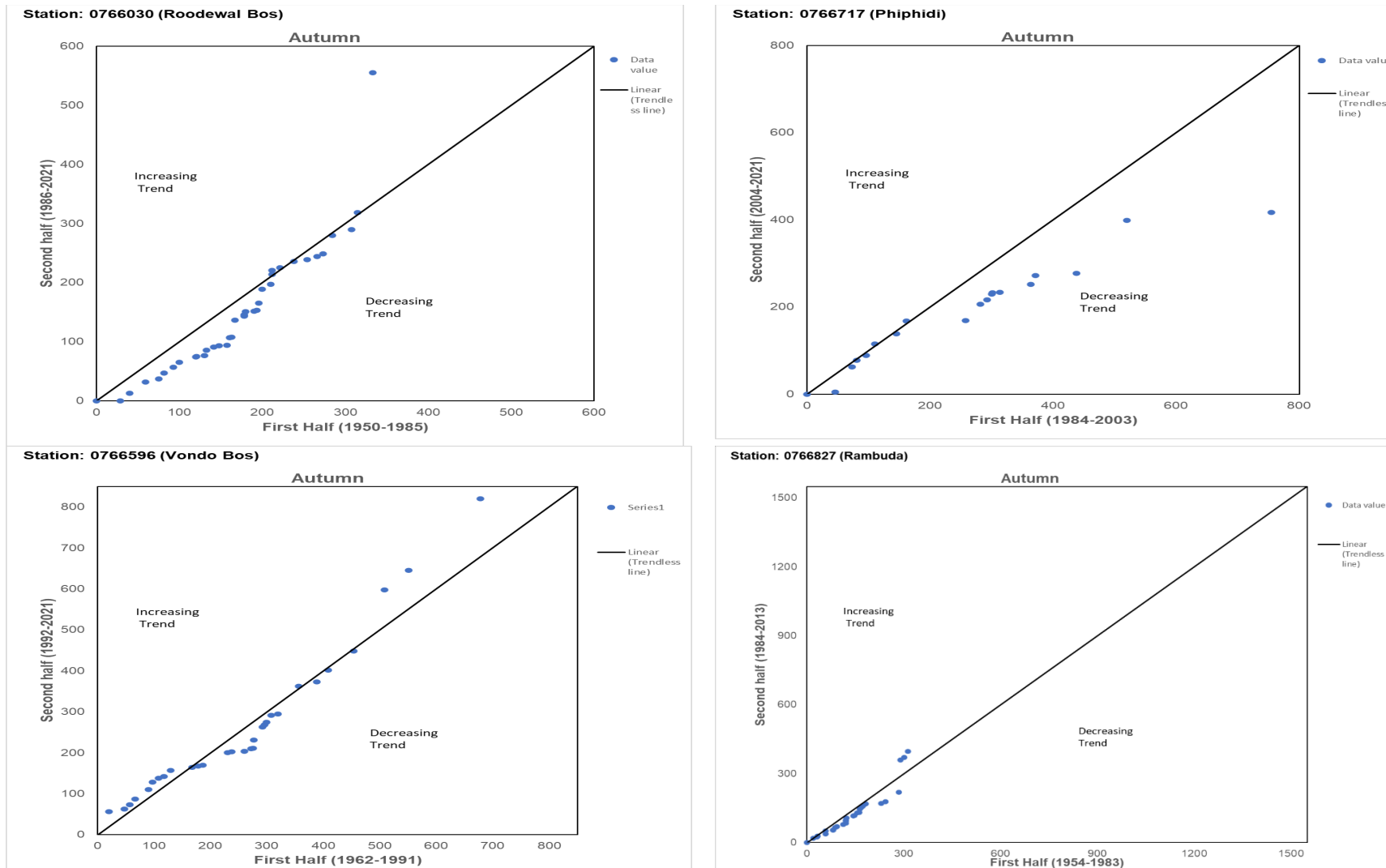


Figure 4-13: Autumn ITA results for Roodewal Bos, Vondo Bos, Phiphidi and Rambuda

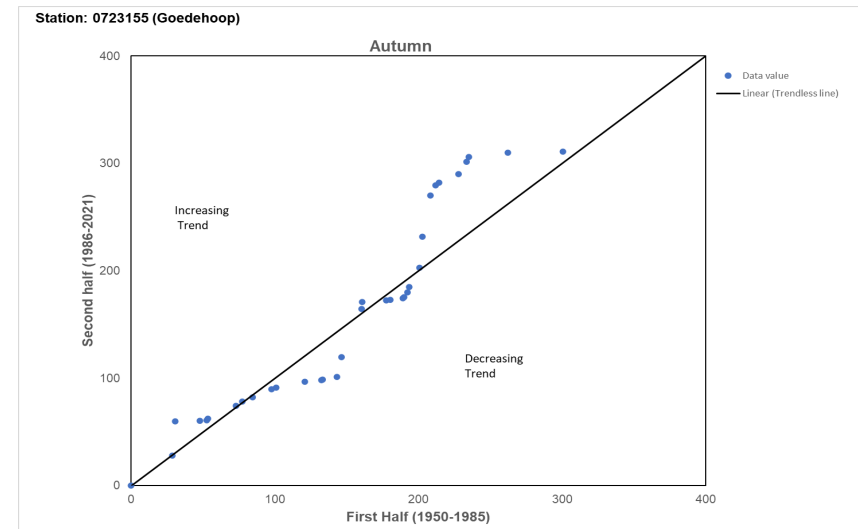
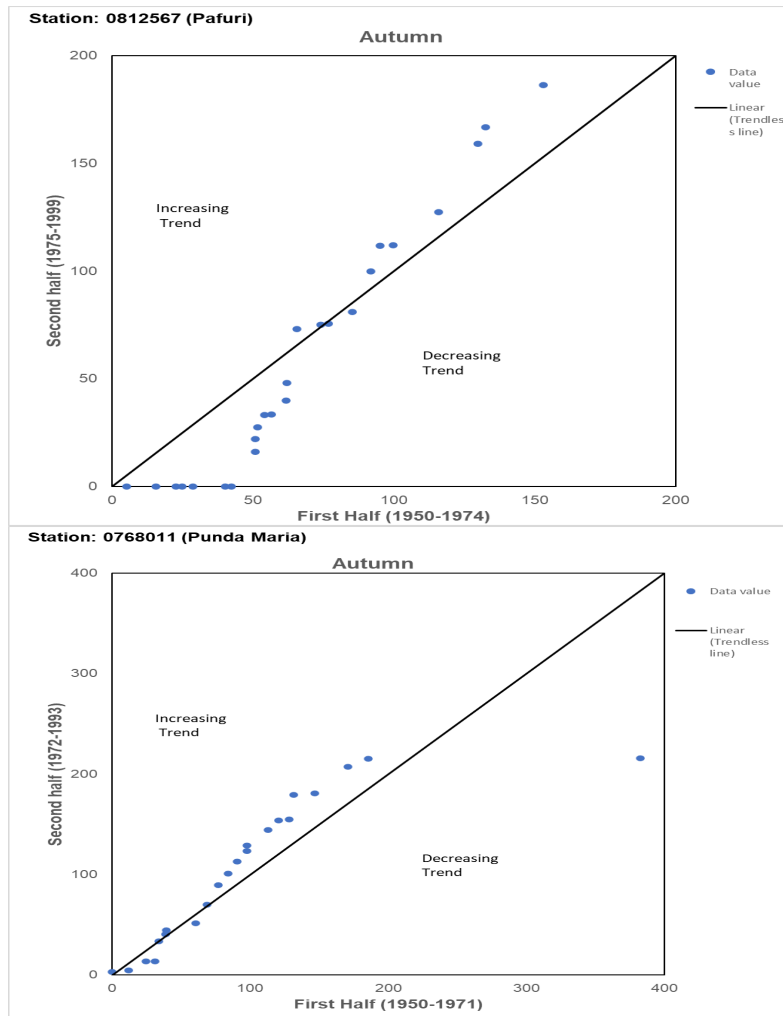


Figure 4-14: Autumn ITA results for Punda maria, Goedehop and Pafuri

Winter

Figure 4-15, Figure 4-16, Figure 4-17, and Figure 4-18 show the winter season ITA graph. In winter, at the stations displaying data points on both the increasing and decreasing halves of the graph, the slope of the trend was analysed to determine whether it was rising or falling. If the slope was negative the trend was classified as decreasing and if it was positive, the trend of the station was classified as increasing. Winter trends are generally negative but less consistent, with most stations showing only minor declines (for instance, Levubu: -0.442, Roodewal-Bos: -0.049, Zwartrandjes: -0.081). These small declines may indicate marginal drying, though not yet at a statistically alarming rate. Notably, Punda Maria (0.123), Rambuda (0.143), and Vondo-Bos (0.083) show increasing winter rainfall trends, which could indicate seasonal extension or unseasonal rainfall events which can be potentially linked to broader climate anomalies or regional circulation shifts.

The spring season graphs are depicted in *Figure 4-19, Figure 4-20, Figure 4-21, and Figure 4-22*. Spring rainfall is overwhelmingly decreasing across the catchment especially at Levubu (-0.278), Shefeera (-0.390), and Palmaryville (-0.225). This is supported by the projections in a study done by Schulze et al. (2023) which suggest widespread spring drying across southern Africa and a delayed onset of the rainy season. Increasing trends are seen at Rambuda (0.189), Zwartrandjes (0.121), and Punda Maria (0.377).

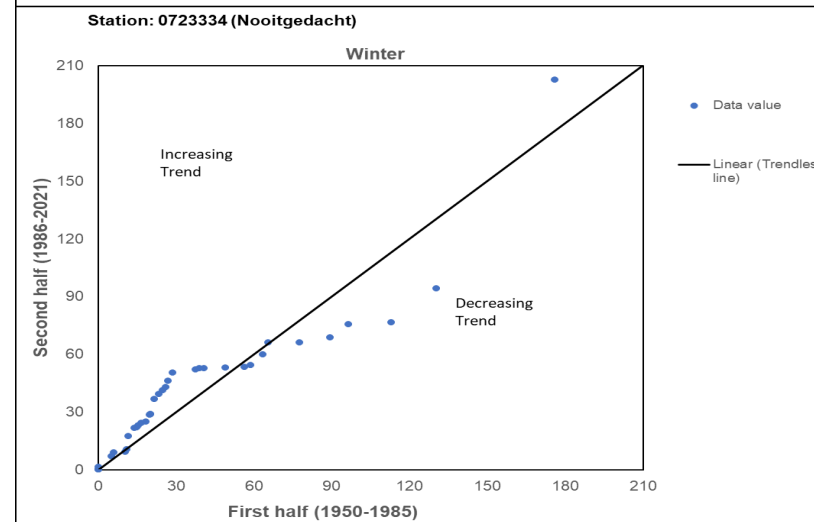
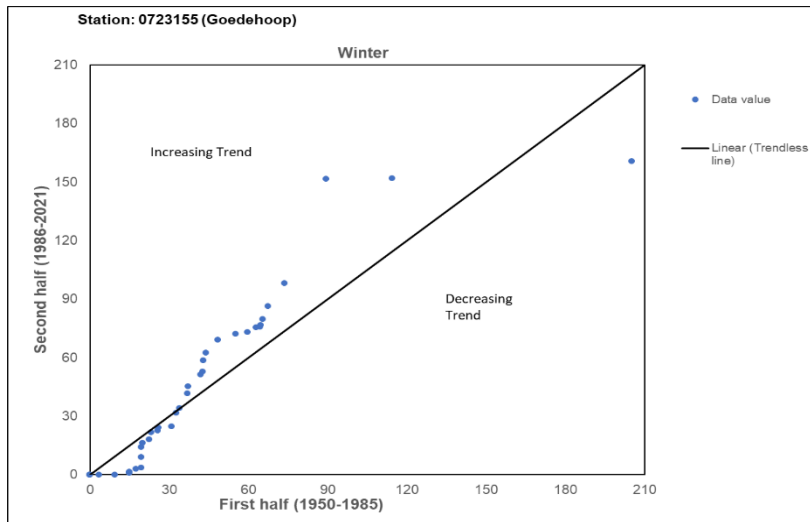
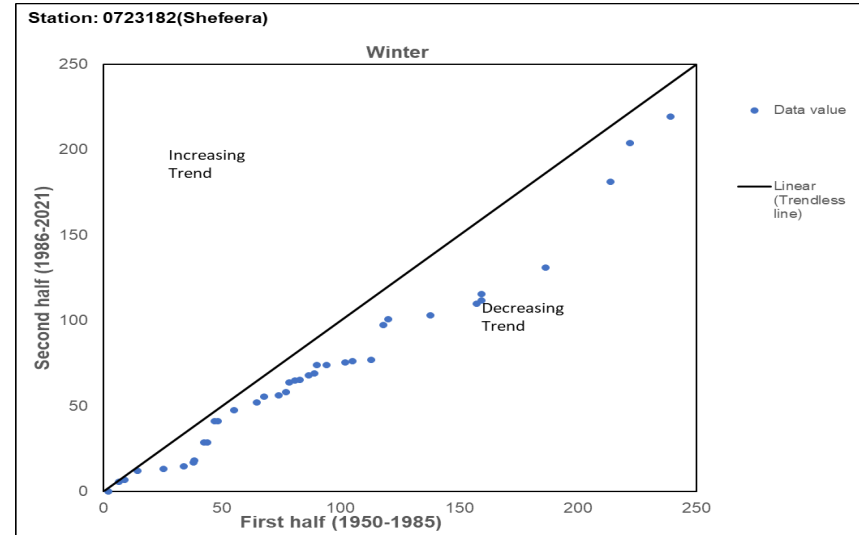
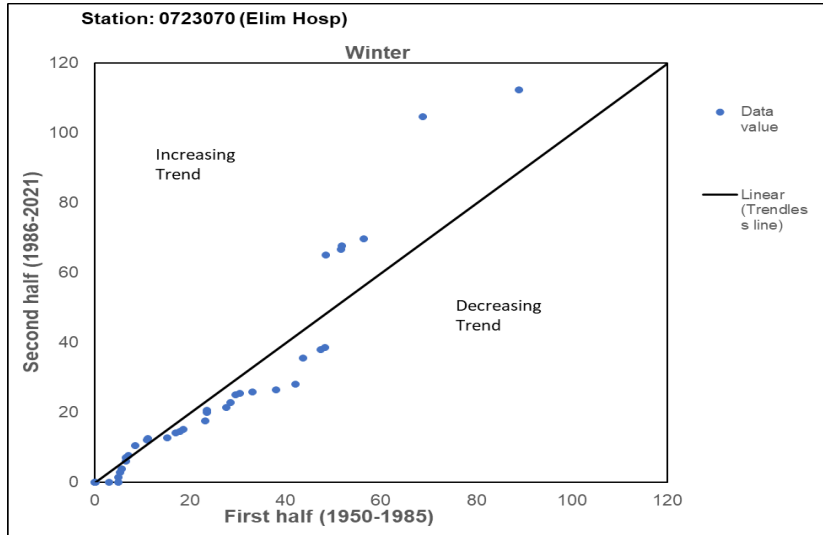


Figure 4-15: Winter ITA results for Elim Hosp, Shefeera, Goedehoop Bos and Nooitgedacht

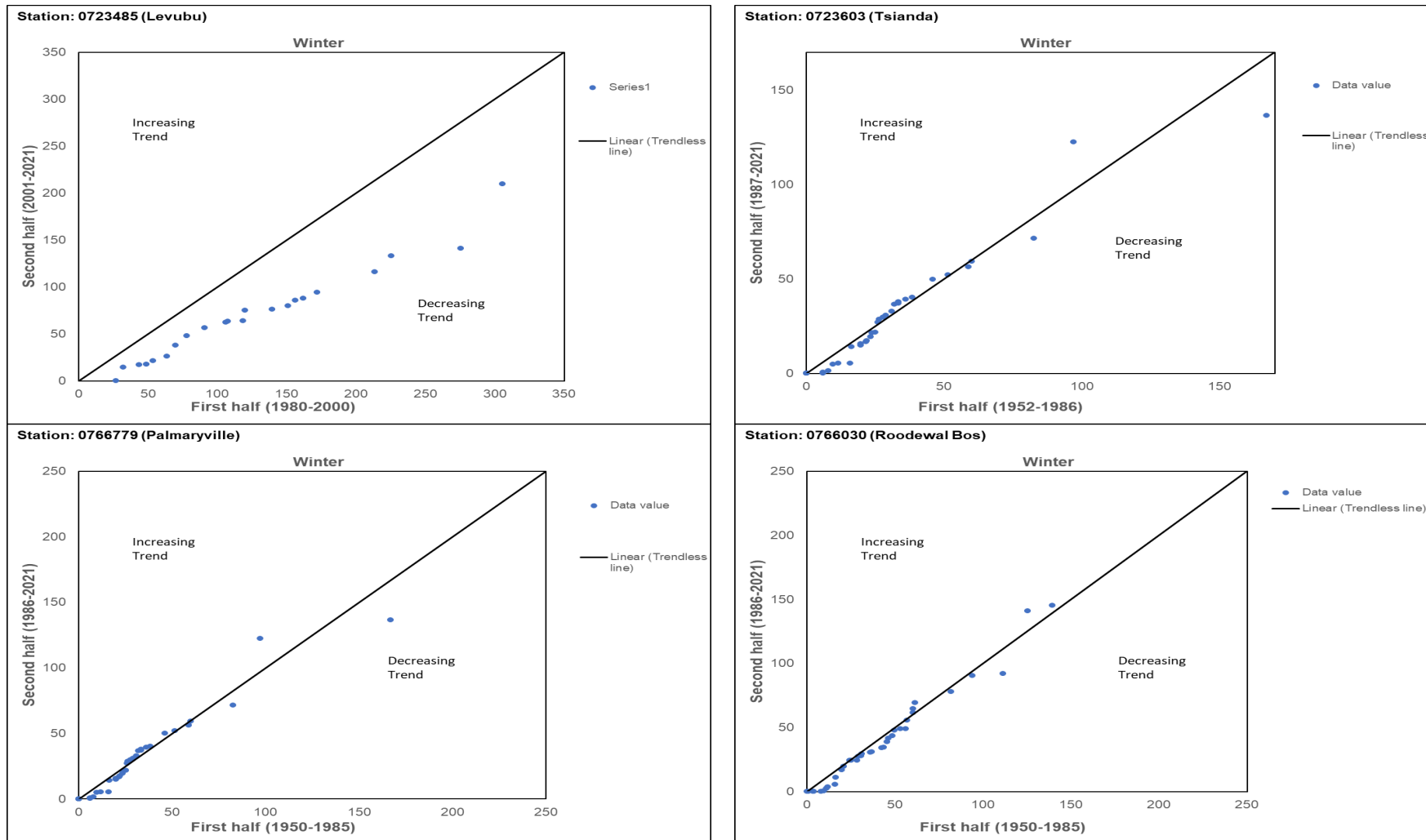


Figure 4-16: Winter ITA results for Levubu, Palmaryville, Tsianda and RoodewalBos

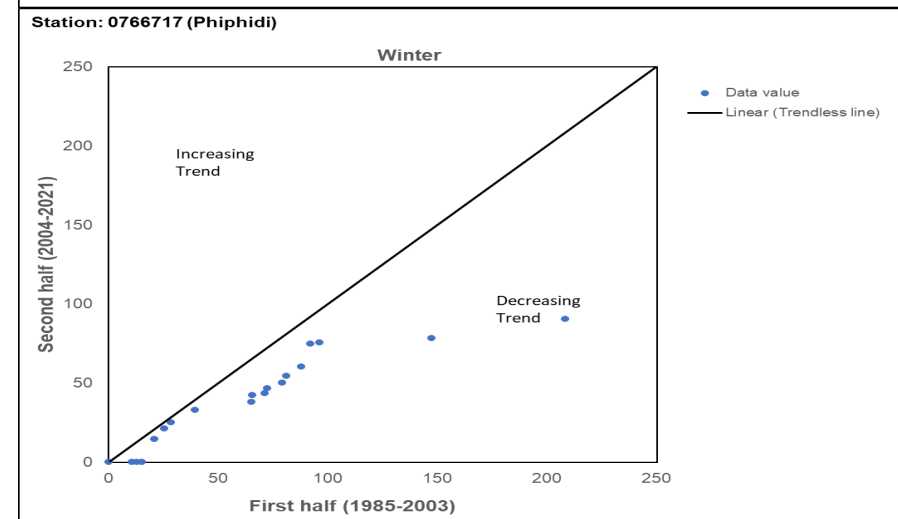
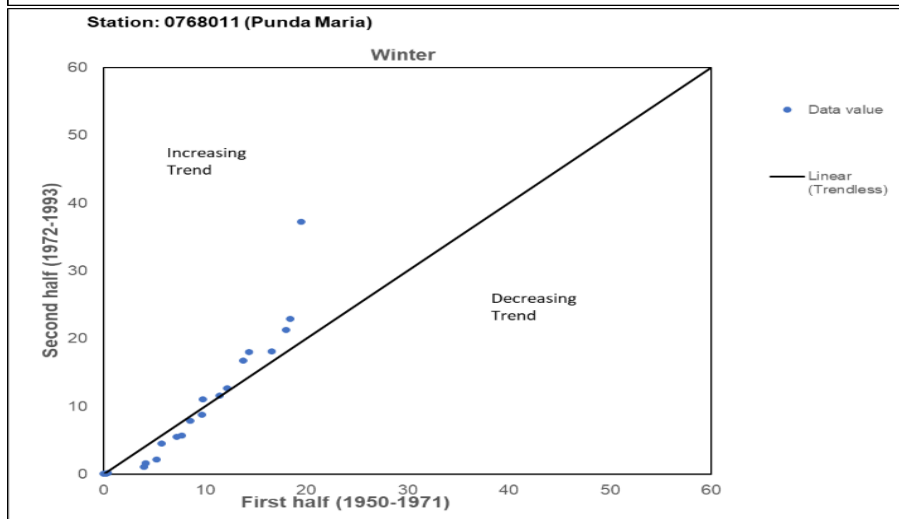
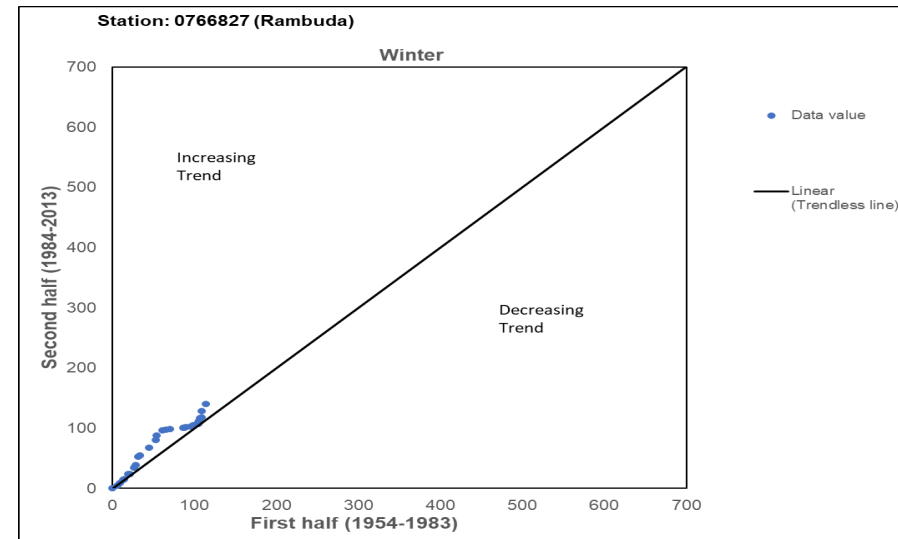
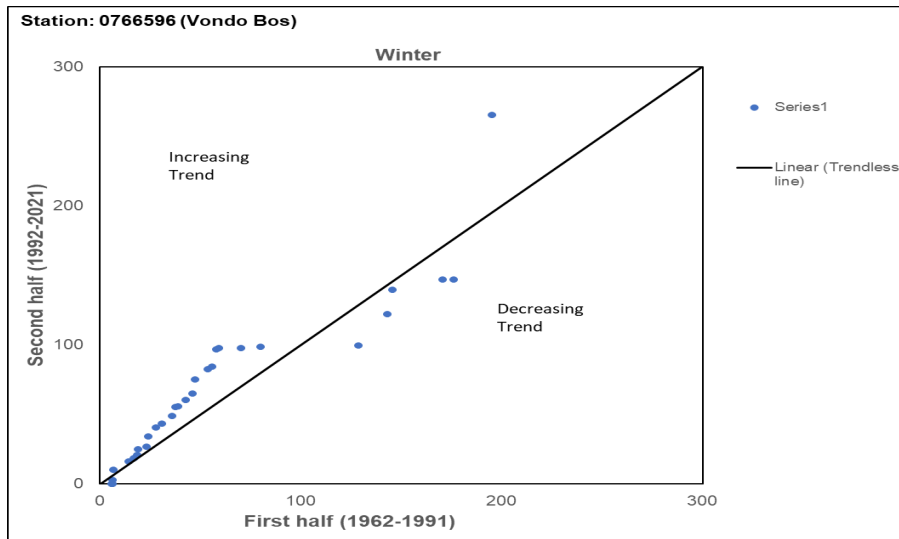


Figure 4-17: Winter ITA results for Vondo Bos, Rambuda, Punda maria and Phiphidi

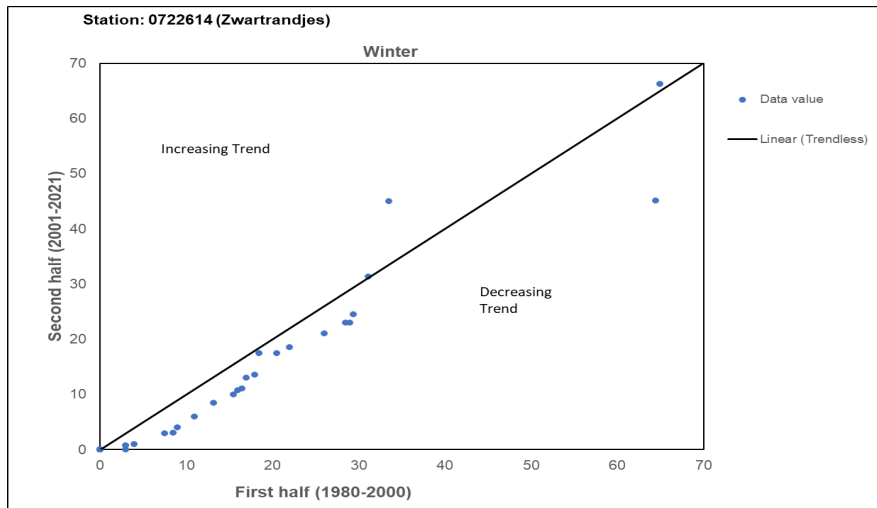
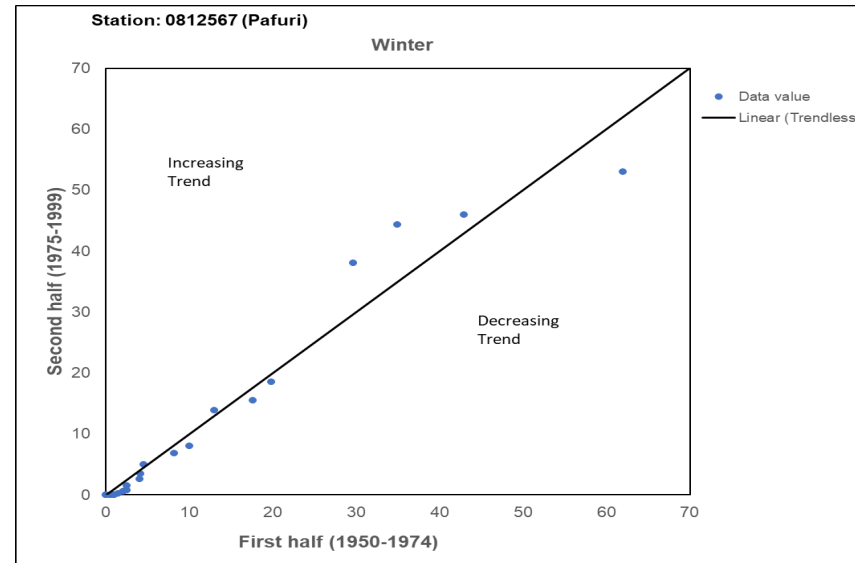
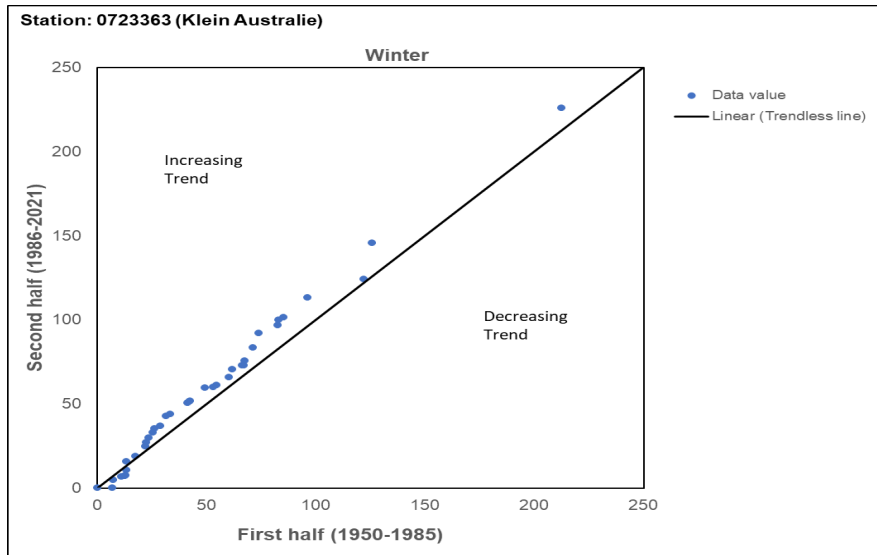


Figure 4-18: Winter ITA results for Klein Australie, Pafuri and Zwartrandjes

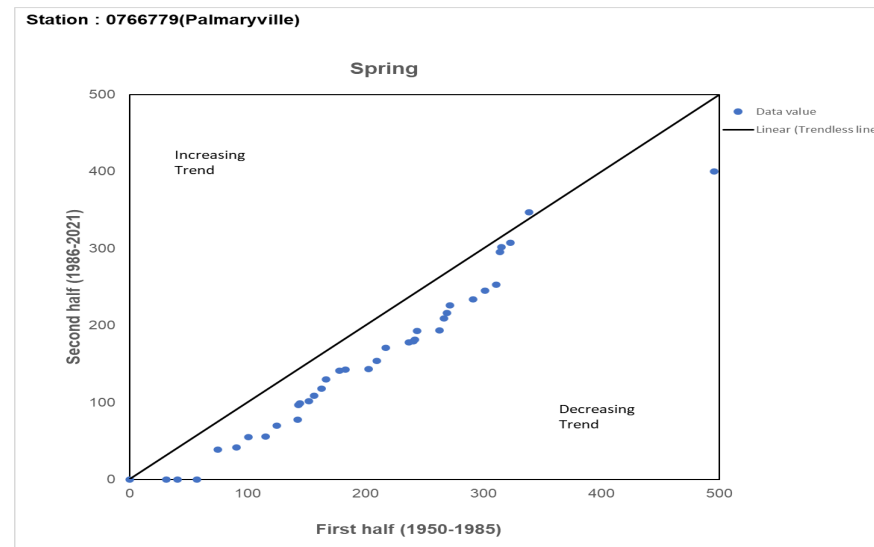
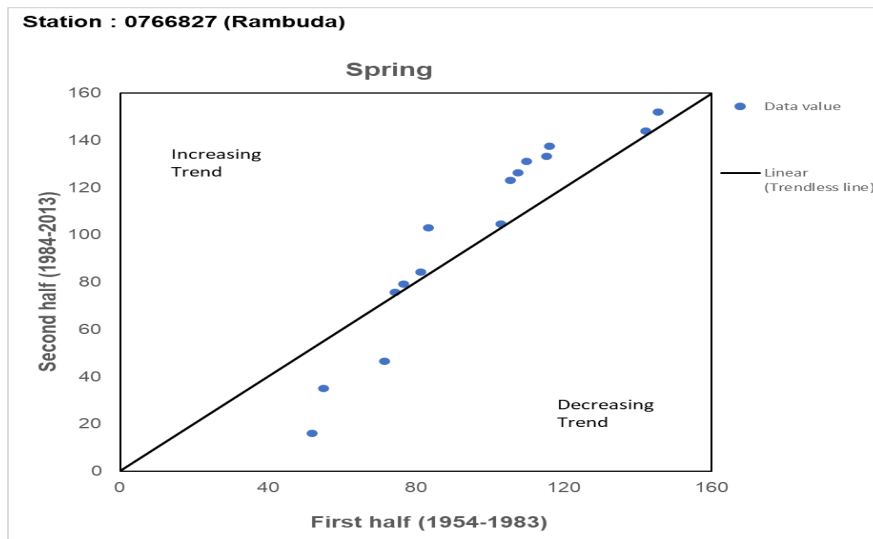
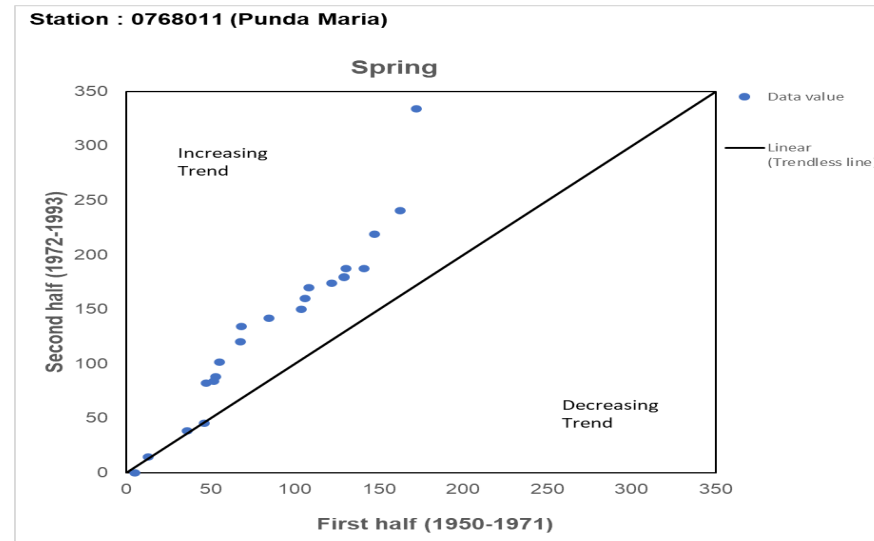
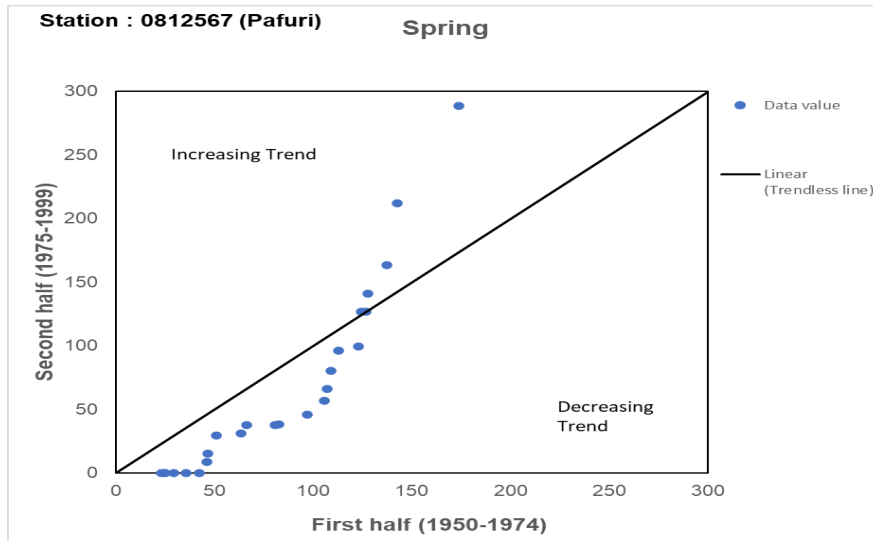


Figure 4-19: Spring ITA results for Pafuri, Rambuda, Palmmaryville and Punda maria

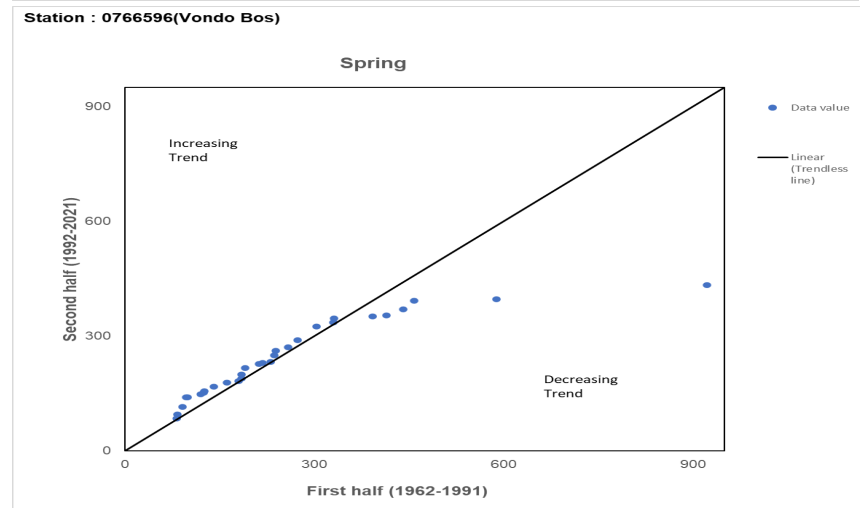
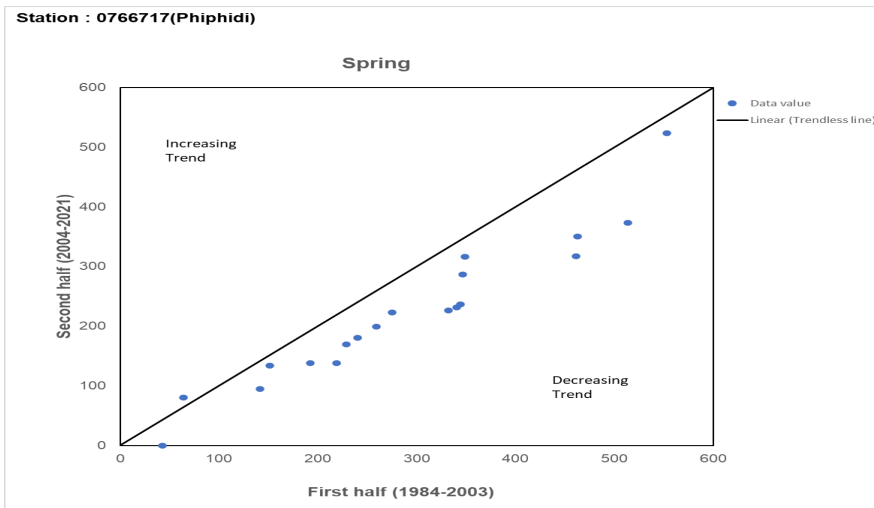
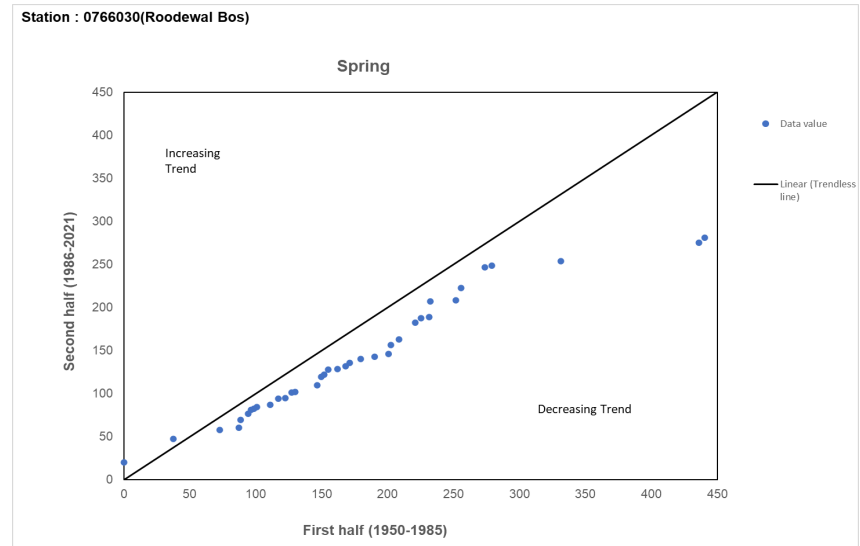
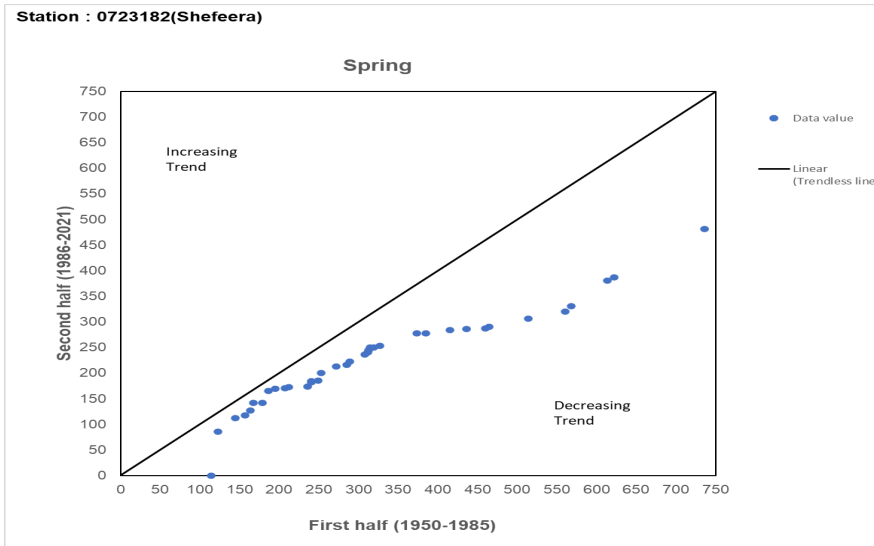


Figure 4-20: Spring ITA results for Phiphidi, Shefeera, Roodewal Bos and Vondo Bos

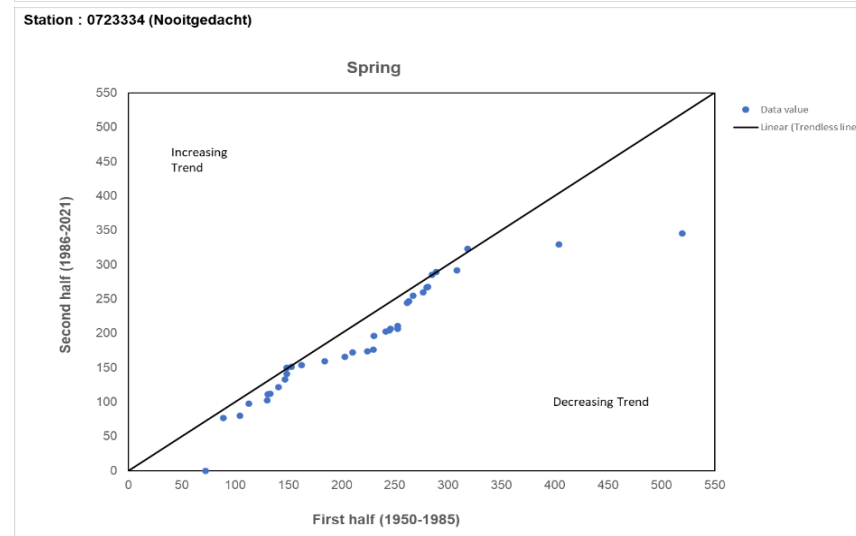
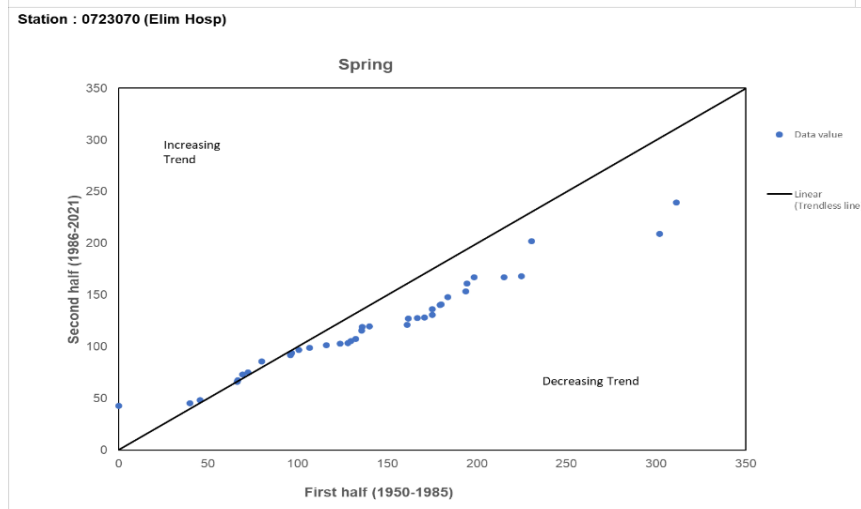
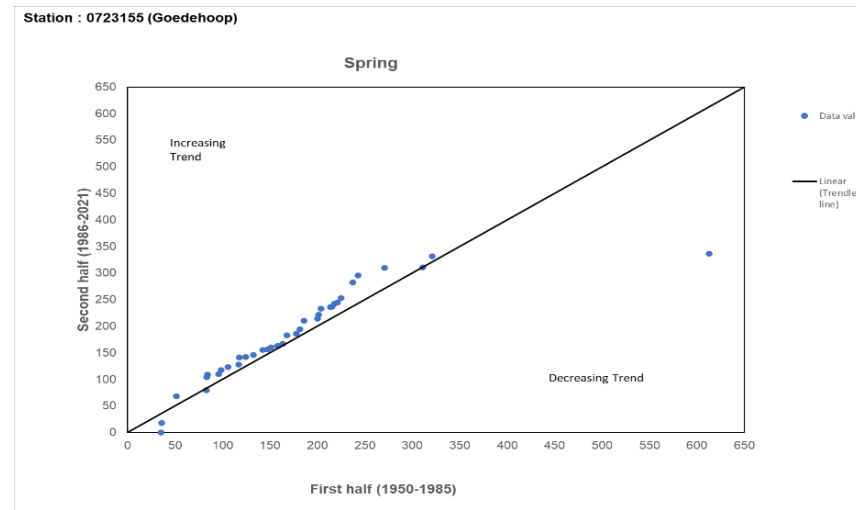
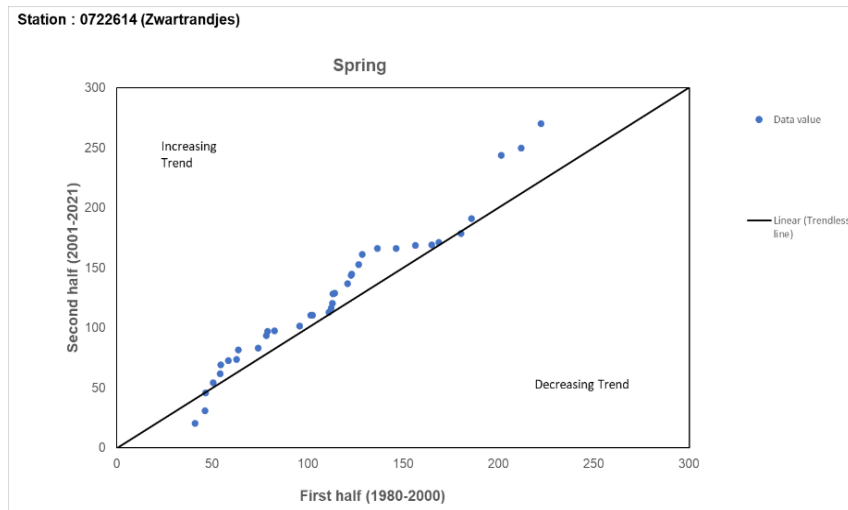


Figure 4-21: Spring ITA results for Zwartrandjes, Elim Hosp, Goedeheop Bos and Nooitgedacht

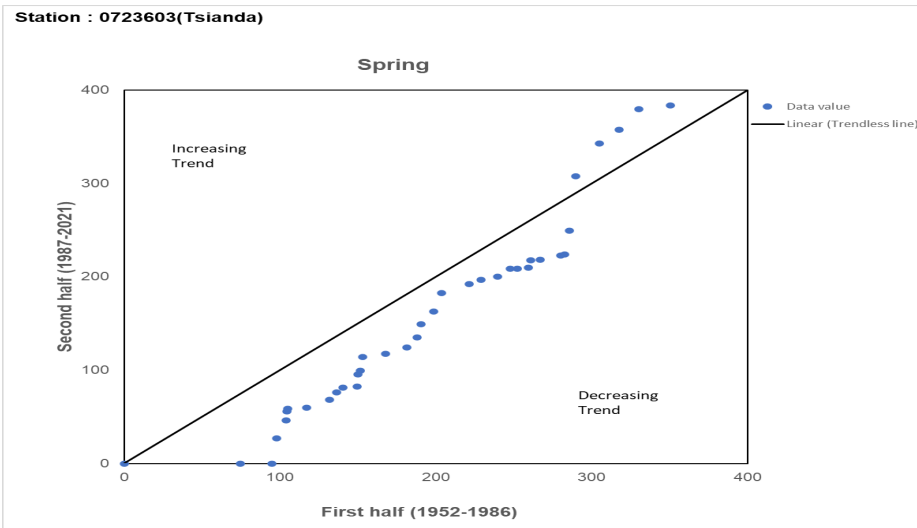
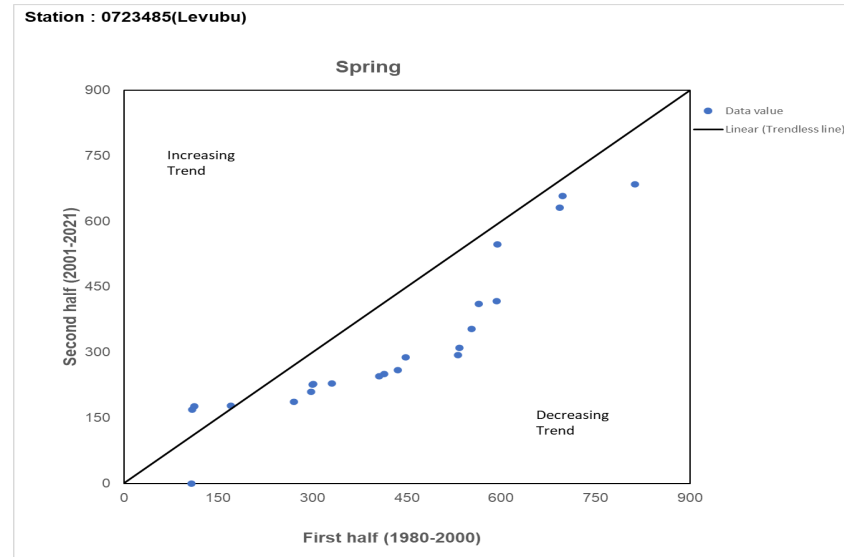
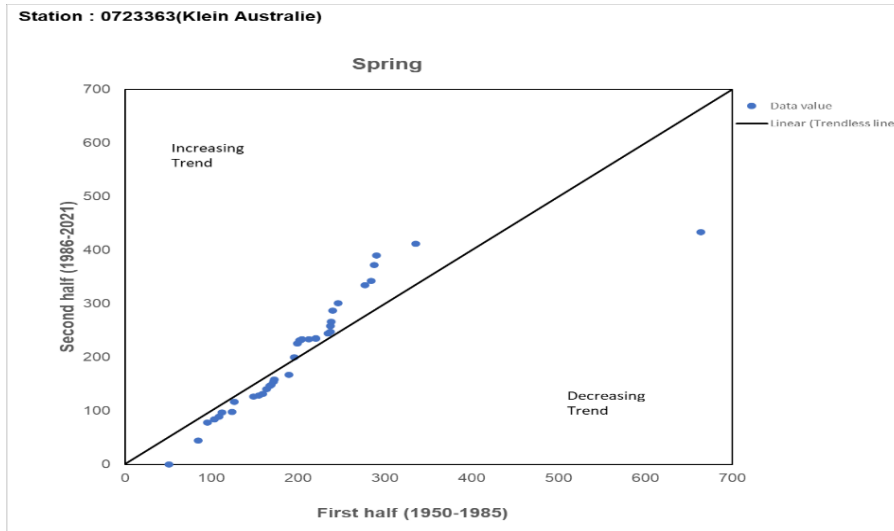


Figure 4-22: Spring ITA results for Klein Australie, Tsianda and Levubu

Trend analysis results based on the ARIMA model

The seasonal ARIMA model was determined in order to get trends for each station. Prior to model fitting, the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) test confirmed that all the time series were stationary at level, which is a prerequisite for the SARIMA model application. The dominant model estimated for the stations was $(2,0,1)(2,0,1)_{12}$, which captures both short-term dependencies and seasonal dynamics with a 12-month cycle.

This model was found to have the lowest Akaike information criteria (AIC). The AIC number is a number used to determine which model is best for given datasets. The lower the AIC score the better. Overall the data is dominated by decreasing trends. *Figure 4-23 to Figure 4-53* indicate the seasonal ARIMA results in all the seasons.

Summer

In summer, data for all the stations in summer was stationary. The seasonal ARIMA model was determined in order to get trends for each station. The model estimated for all the stations was $(2,0,1)(2,0,1)_{12}$. This model was found to have the lowest Akaike information criteria (AIC). The highest AIC was 1160.5 at Sheefera and the lowest 629.8 at Punda Maria. Tsianda, (See *Table 4-3*). The low AIC indicates that the model fits the data well and the model has captured the trend well. the high AIC at Shefeera (AIC = 1160.53) and Klein Australie (AIC = 1157.56) showed more variability, suggesting more complex rainfall behavior in those areas.

Table 4-3: Historical Summer Results from the ARIMA model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Levubu	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	647
Phiphidi	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	630
Palmaryville	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1075
Tsianda	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	1031
Nooitgedacht	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	1110
Vondo-Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	957
Roodewal-Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1076
Shefeera	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1161
Klein Australie	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	1158
Goedehoop Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1104
Elim-Hosp	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	1060
Rambuda	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	926
Zwartrandjes	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	998
Punda Maria	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	630
Pafuri	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	698

Decreasing trends were exhibited at Levubu, Phiphidi, Palmaryville, Roodewal-Bos, Shefeera, Pafuri, Punda Maria, Zwartrandjes, Rambuda and Goedeheop-Bos stations in summer. Decreasing trends were observed at the majority of stations, including Levubu, Phiphidi, Palmaryville, Roodewal-Bos, Shefeera, Goedeheop Bos, Rambuda, Zwartrandjes, Punda Maria, and Pafuri. A decreasing trend in summer can indicate water shortages. When there is less rainfall it can affect the agricultural sector in the LRC that depends on the rainfall for production. Increasing trends were found at Tsianda, Nooitgedacht, Vondo-Bos, Klein Australie, and Elim-Hosp, indicating potential localized intensification of summer rainfall.

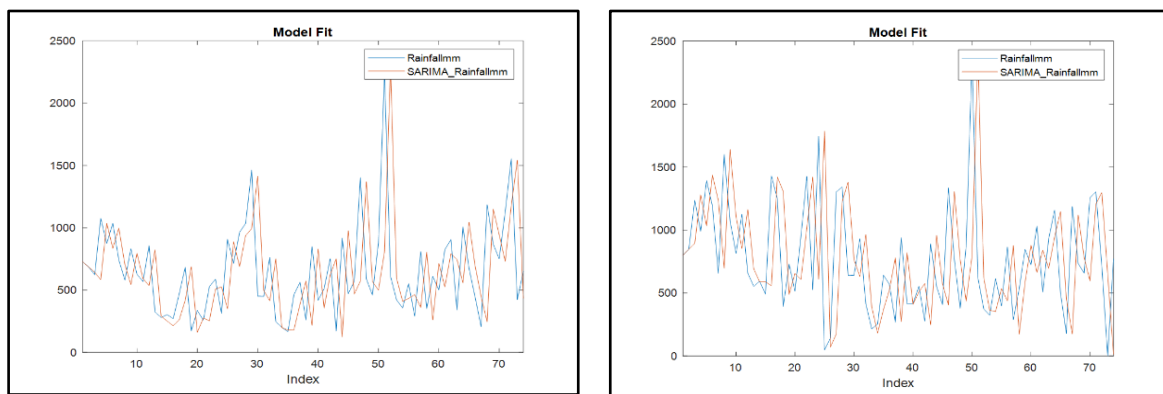


Figure 4-23: Klein Australie and Shefeera summer SARIMA

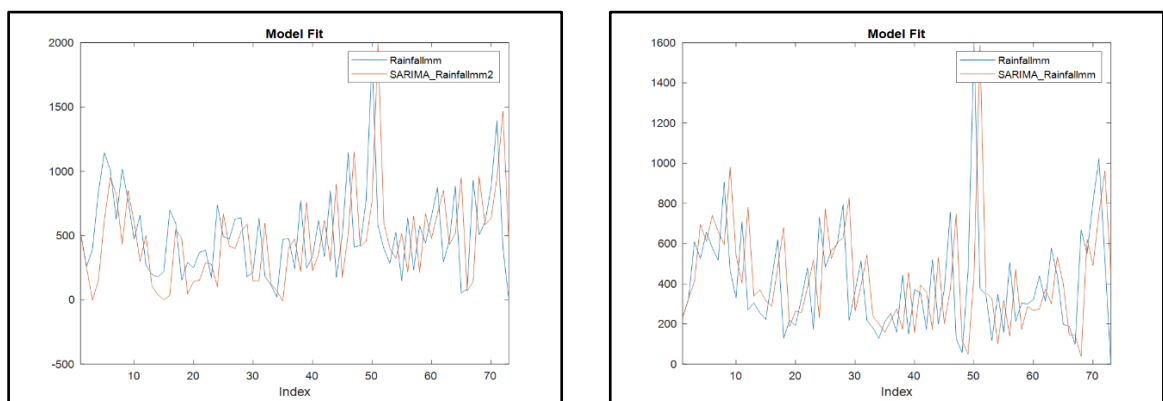


Figure 4-24: Goedeheop and Elim summer SARIMA

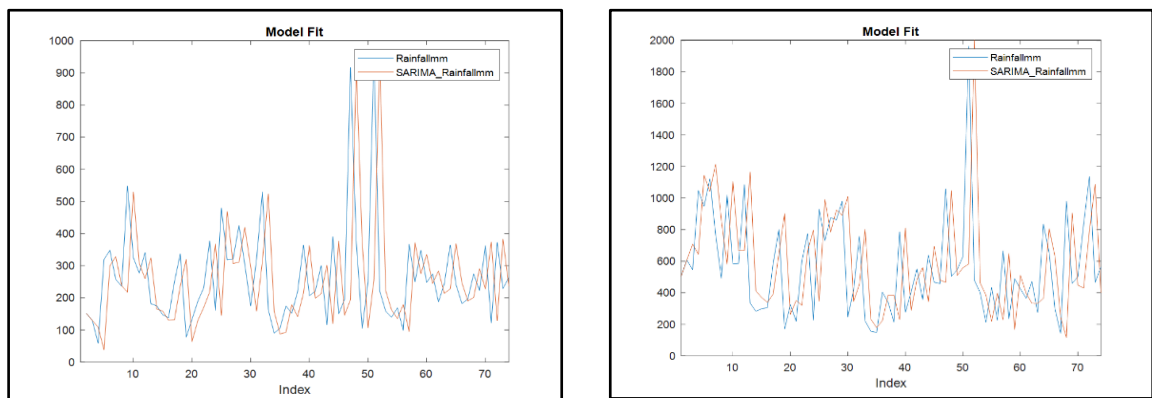


Figure 4-25: Zwartrandjes and Nooitgedacht summer SARIMA

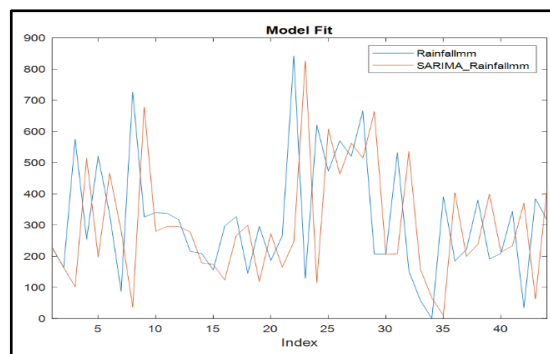
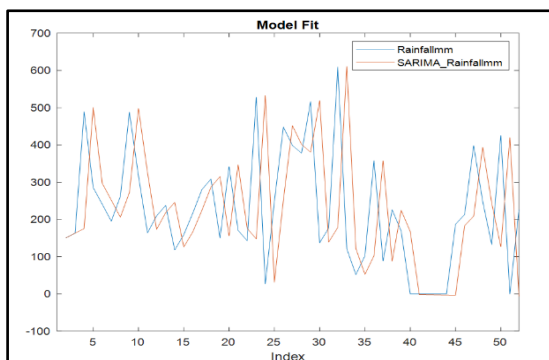


Figure 4-26: Pafuri and Punda Maria summer SARIMA

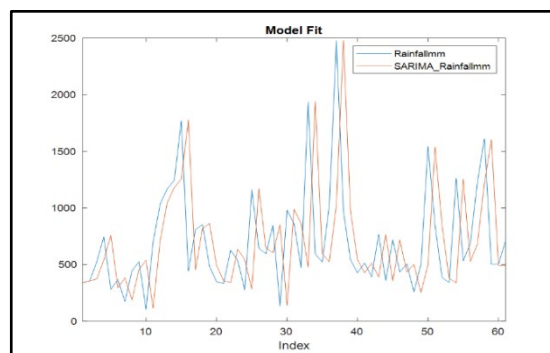
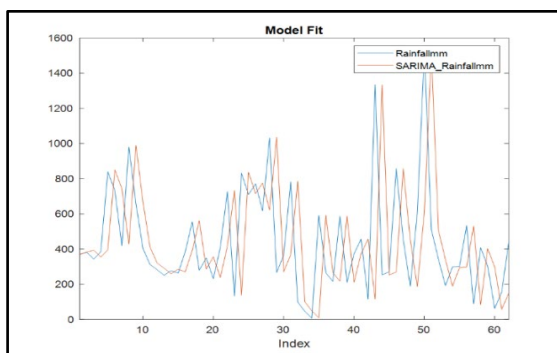


Figure 4-27: Rambuda and Vondo summer SARIMA

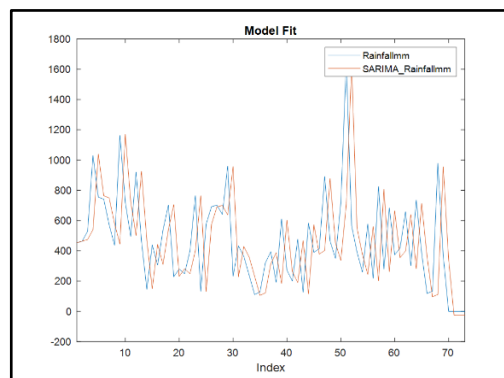
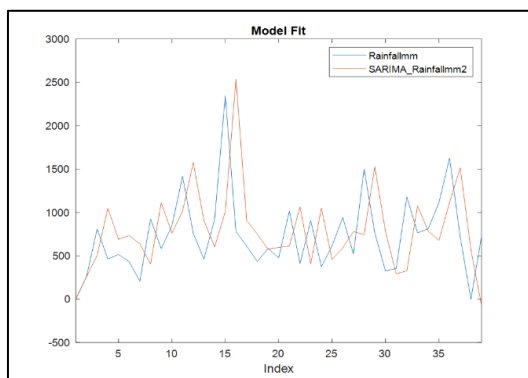


Figure 4-28: Phiphidi and Roodewal Bos summer SARIMA

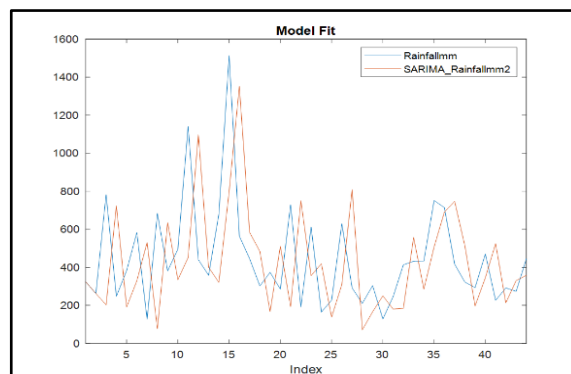
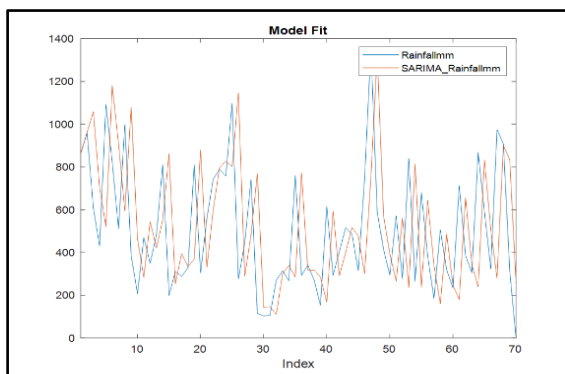


Figure 4-29: Tsianda and Levubu summer SARIMA

Autumn

In Autumn, data at Punda Maria was non-stationary and a differentiation ($d=1$) was estimated for the station. The model estimated for Punda Maria was $(2,1,1)(2,1,1)_{12}$ with a AIC of 523.2 and a decreasing trend. This suggest a shift in seasonal rainfall variability Model $(2,0,1)(2,0,1)_{12}$ was estimated for Levubu, Phiphidi, Palmaryville, Roodewal-Bos, Shefeera, Pafuri, Zwartdrandjes, Rambuda, Goedeheop-Bos, Tsianda, Noitgedacht, Vondo-Bos, Klein Australie and Elim-Hosp. The model shows the lowest AIC at all the stations with the lowest AIC at 523. *Table 4-4* show all the information.

Table 4-4: Historical Autumn Results from the ARIMA model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Levubu	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	570
Phiphidi	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	546
Palmaryville	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	955
Tsianda	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	930
Nooitgedacht	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	985
Vondo-Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	829
Roodewal-Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	936
Shefeera	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1021
Klein Australie	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1003
Goedeheop Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	959
Elim-Hosp	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	916
Rambuda	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	807
Zwartdrandjes	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	888
Punda Maria	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	523
Pafuri	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	561

Elim-Hosp shows an increasing trend while all the other stations show decreasing trends. LRC seems to be prone to dry autumn due to the decreasing trends presented. This broad reduction in rainfall in the post-summer season suggests a shortening of the rainy season, which can impact groundwater recharge and late-season crops. Overall, the autumn season appears to be drying, reinforcing projections of a contracting rainy season window in southern Africa. *Figure 4-30, Figure 4-31, Figure 4-32, Figure 4-33, Figure 4-34, Figure 4-35 and Figure 4-36* show the autumn trends results from the SARIMA.

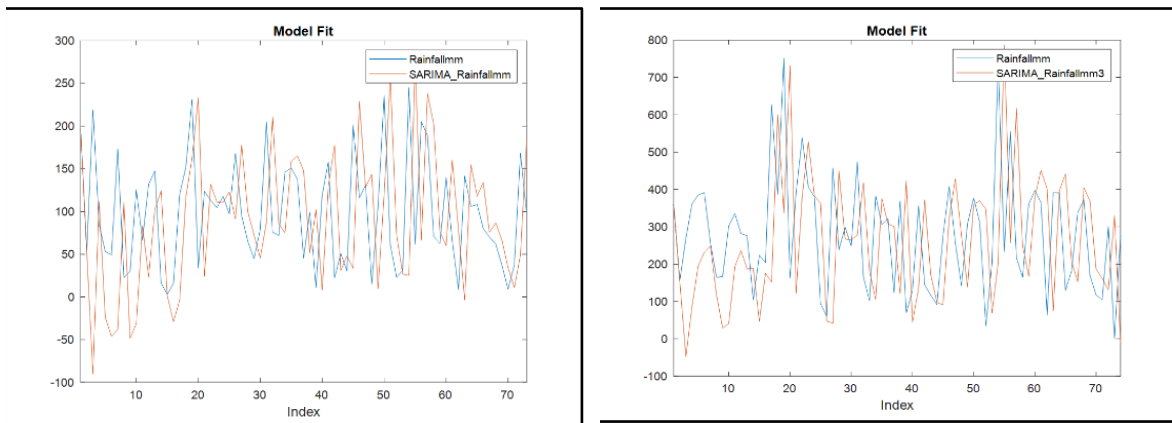


Figure 4-30: Zwartrandjes and Shefeera autumn SARIMA

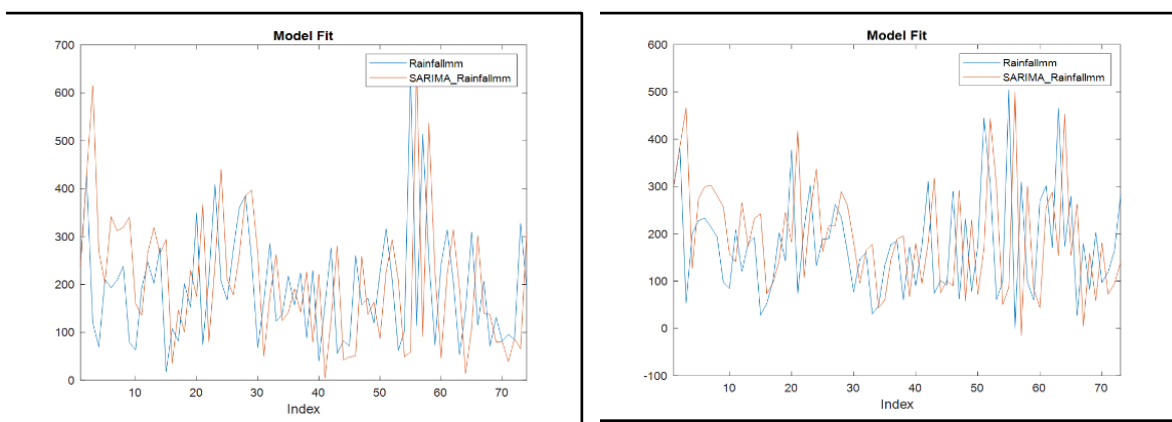


Figure 4-31: Nooitgedacht and Goedehoop autumn SARIMA

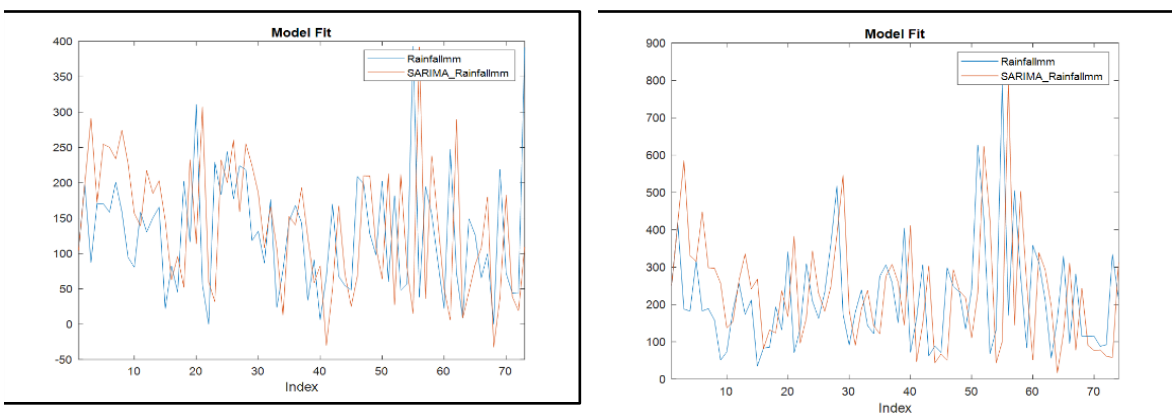


Figure 4-32: Elim and Klein Australie autumn SARIMA

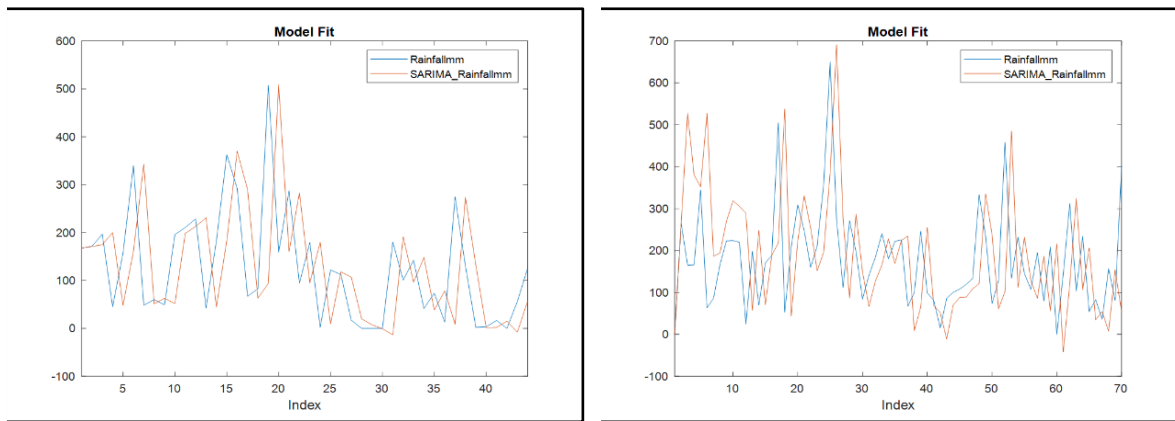


Figure 4-33: Levubu and Tsianda autumn SARIMA

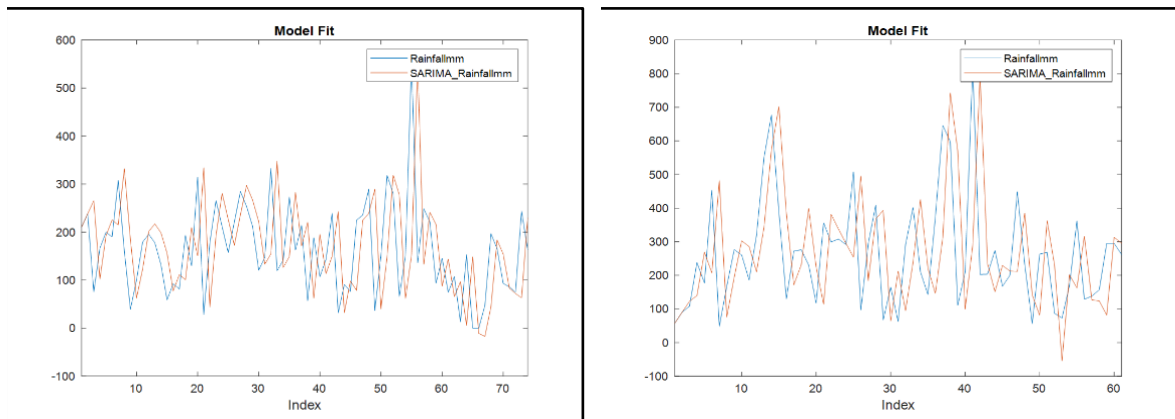


Figure 4-34: Roodewal Bos and Vondo autumn SARIMA

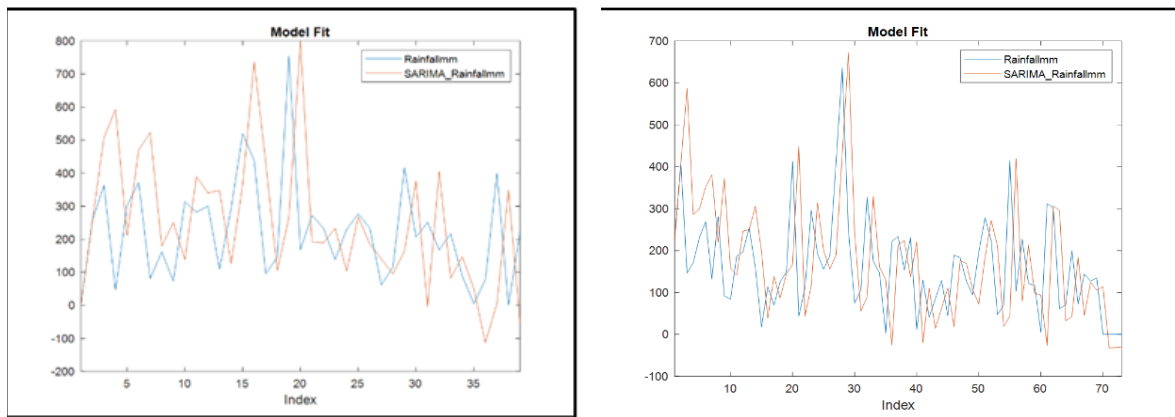


Figure 4-35: Phiphidi and Palmaryville autumn SARIMA

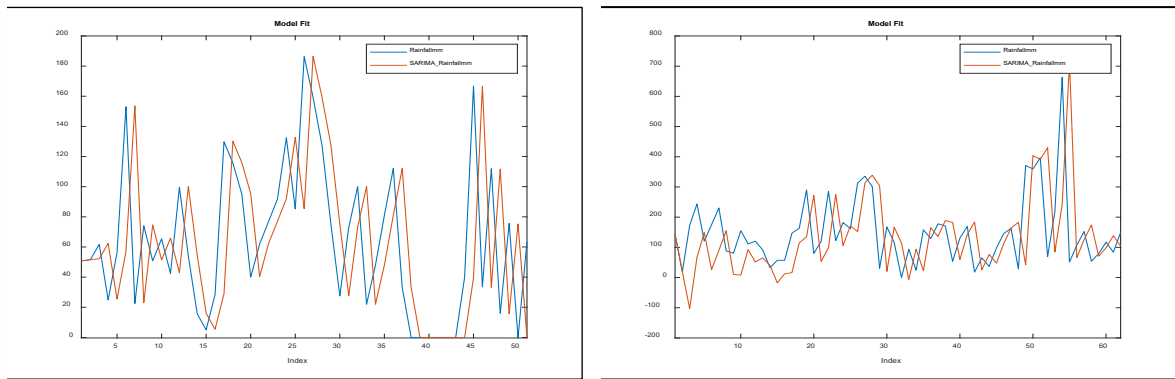


Figure 4-36: Pafuri and Rambuda autumn SARIMA

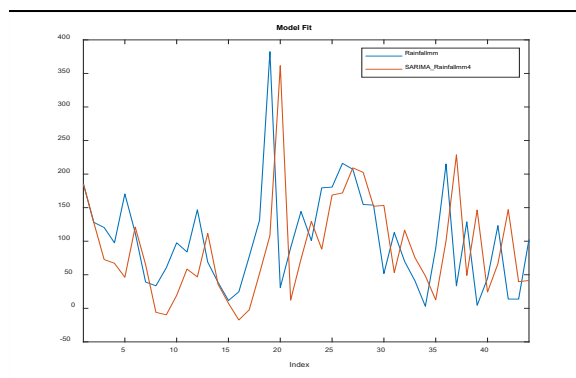


Figure 4-37: Pafuri autumn SARIMA

Winter

Show the output from the SARIMA model (Table 4-5). Data from Levubu, Vondo-Bos and Klein Australie show non-stationarity while data at the rest of the stations are stationary. A differentiation ($d=1$) was estimated for the three stations, with model $(2,1,1)(2,1,1)_{12}$. An increasing trend was seen at Pafuri station with AIC of 468.5 mm. At Levubu, Phiphidi, Palmaryville, Roodewal-Bos, Shefeera, Punda Maria, Zwartrandjes, Rambuda, Goedeheop-Bos, Tsianda, Noitgedacht, Vondo-Bos, Klein Australie and Elim-Hosp the trends were all decreasing with model $(2,0,1)(2,0,1)_{12}$ estimated with the lowest AIC at all those stations. Punda Maria has the lowest AIC of 374 mm, followed by Phiphidi at 446.8 mm, Levubu at 458.9 mm, Zwartrandjes at 673, Rambuda at 680 mm, Vondo-Bos at 688.8, Elim-Hosp at 738, Tsianda at 744.7 mm, Palmaryville at 775, Roodewal-Bos at 791.7 mm, Nooitgedacht at 805 mm, Goedeheop Bos at 809.5 mm, Klein Australie at 809.9 mm and Sheefera at 884 mm. The low AIC in the catchment indicates that the model fits the data better. The catchment receives very little or no rain during the winter season.

Table 4-5: Historical Winter Results from the ARIMA model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Levubu	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	459
Phiphidi	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	447
Palmaryville	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	775
Tsianda	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	745
Nooitgedacht	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	805
Vondo-Bos	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	689
Roodewal-Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	792
Shefeera	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	884
Klein Australie	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	810
Goedehoop Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	809
Elim-Hosp	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	738
Rambuda	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	680
Zwartrandjes	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	673
Punda Maria	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	374
Pafuri	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	468

Figure 4-38, Figure 4-39, Figure 4-40, Figure 4-41, Figure 4-42, Figure 4-43, Figure 4-44 and Figure 4-45 show the graphs indicating the trends of rainfall for each station from the SARIMA. The decreasing trend in winter is expected since the catchment is a summer rainfall region. The ecosystem is mostly affected by the decreasing trends of rainfall since they cannot be properly replenished. On the other hand, rainfall in winter usually helps to grow forests.

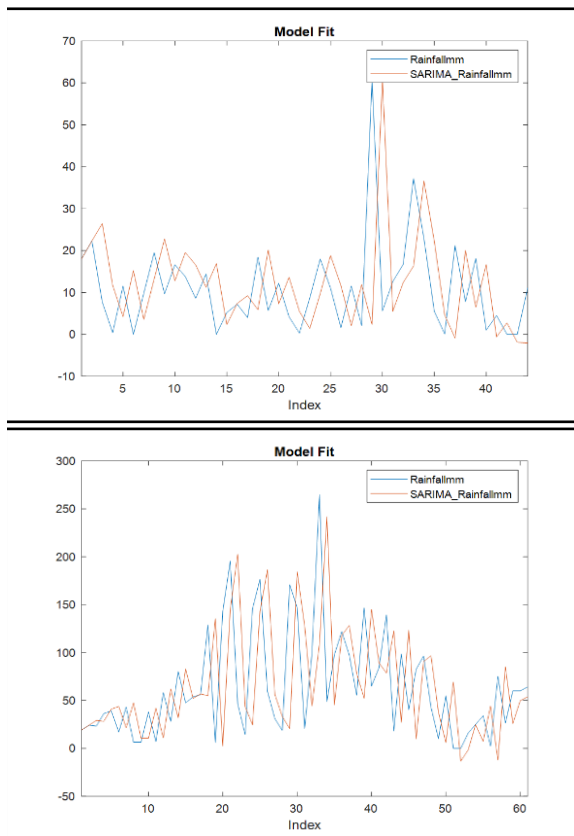


Figure 4-38: Punda Maria and Vondo winter SARIMA

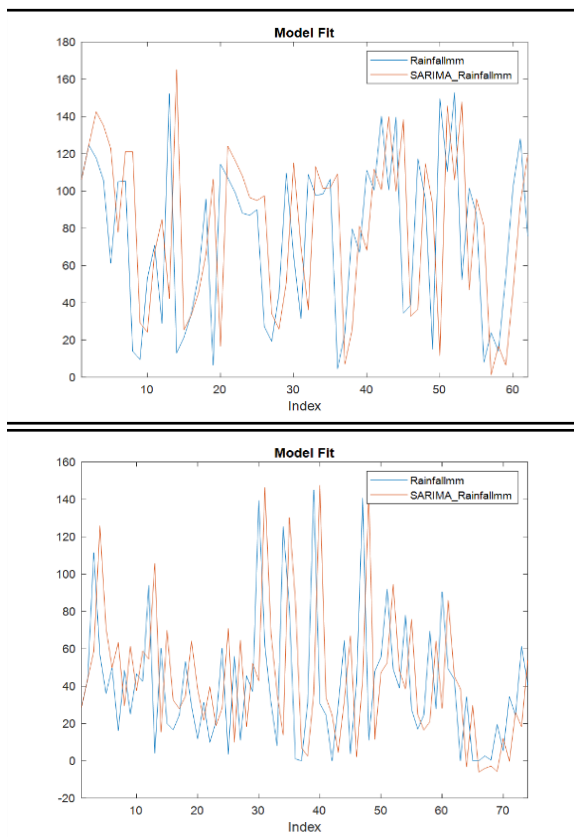


Figure 4-39: Rambuda and Roodewal Bos winter SARIMA

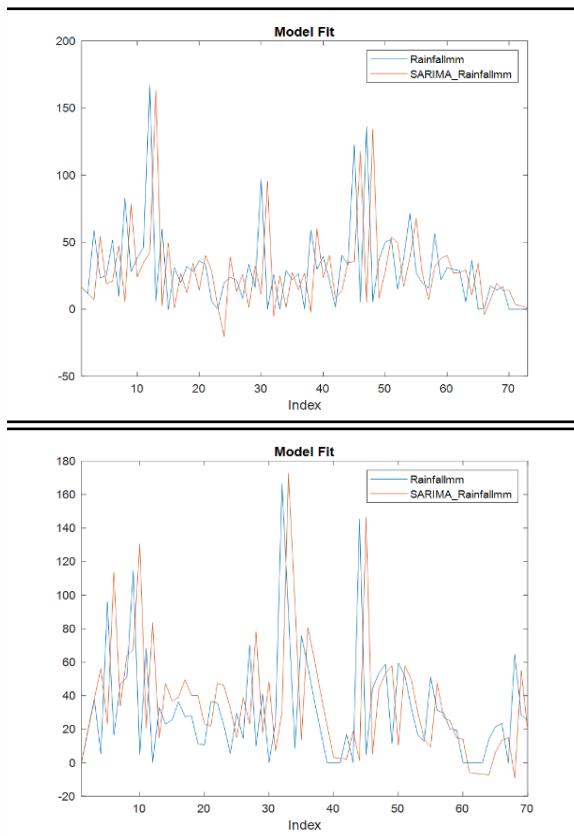


Figure 4-40: Palmaryville and Tsianda winter SARIMA

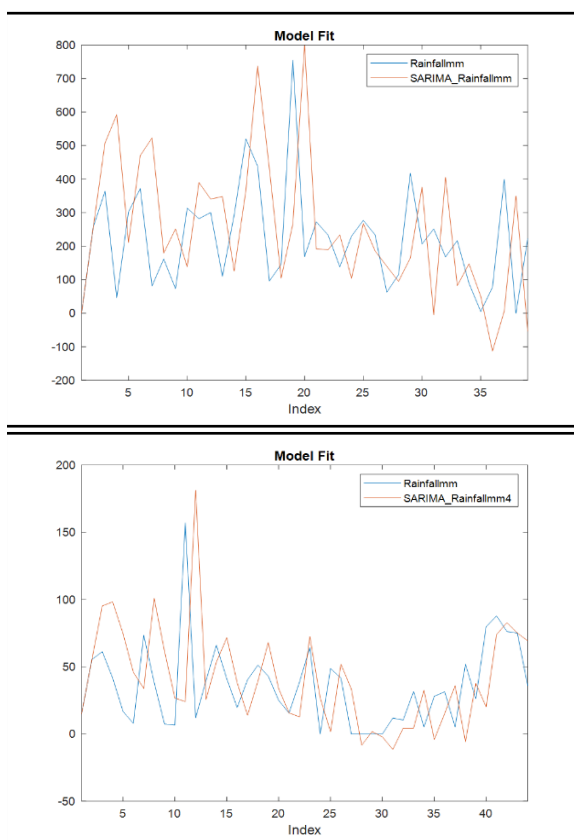


Figure 4-41: Phiphidi and Levubu winter SARIMA

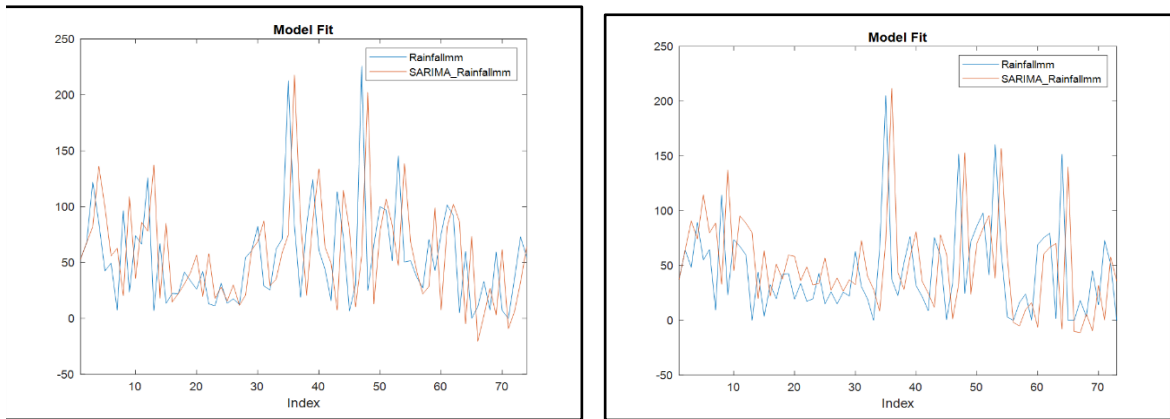


Figure 4-42: Klein Australia and Goedehoop winter SARIMA

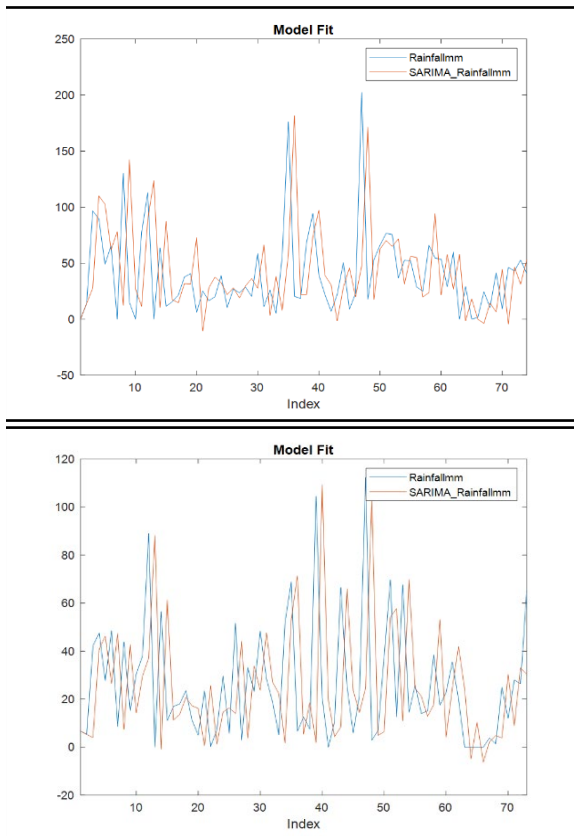


Figure 4-43: Nooitgedacht and Elim Hosp winter SARIMA

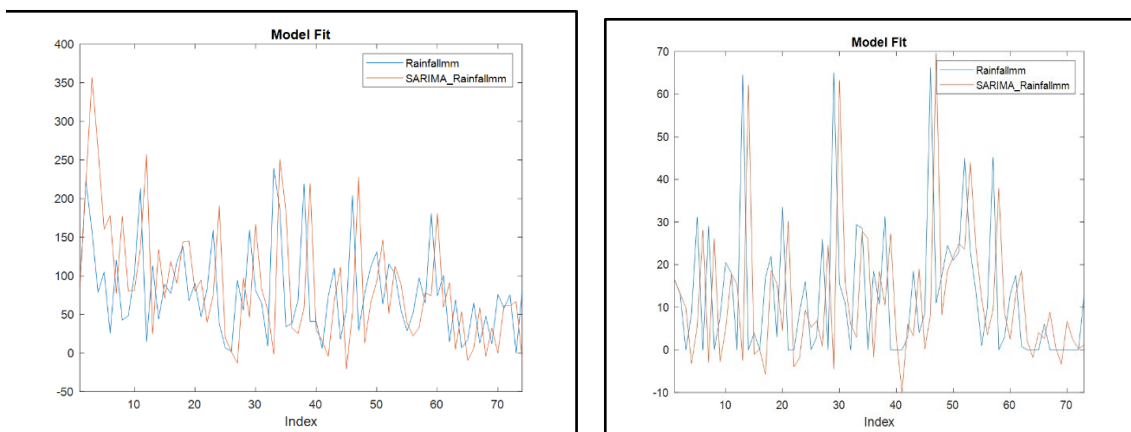


Figure 4-44: Shefeera and Zwartrandjes winter SARIMA

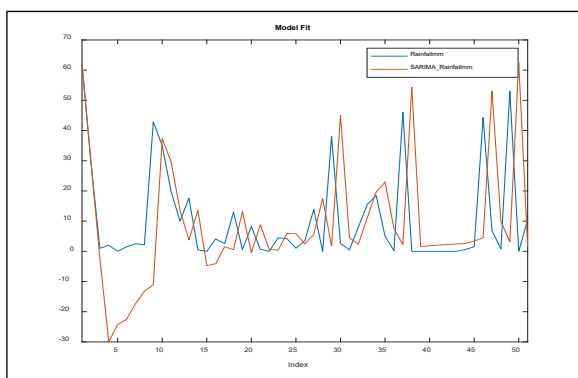


Figure 4-45: Pafuri winter SARIMA

Spring

In spring, at Phiphidi, Tsianda, Vondo-Bos, Roodewal-Bos, Klein Australie, Punda Maria and Pafuri data show non-stationarity this can be indicating significant interannual variability and possibly increasing climate unpredictability. A differentiation ($d=1$) was estimated for the stations with the model $(2,1,1)(2,1,1)_{12}$ with the lowest AIC of 514.7 mm at Phiphidi. The model estimated at Levubu was $(2,0,1)(2,0,3)_{12}$ with the lowest AIC of 552.3 mm and at the rest of the stations, the model estimated was $(2,0,1)(2,0,1)_{12}$. *Table 4-6* indicates the results from the ARIMA model.

Table 4-6: Historical Spring Results from the ARIMA model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Levubu	Stationary	$(2,0,1)(2,0,3)_{12}$	Decreasing	552
Phiphidi	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	515
Palmaryville	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	933
Tsianda	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	847
Nooitgedacht	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	913
Vondo-Bos	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	800
Roodewal-Bos	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	893
Shefeera	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	884
Klein Australie	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	906
Goedehoop Bos	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	928
Elim-Hosp	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	1060
Rambuda	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	753
Zwartrandjes	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	861
Punda Maria	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	517
Pafuri	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	574

The spring season graphs are depicted in *Figure 4-46* to *Figure 4-53*. Except for Rambuda station, all the stations have decreasing trends. The decreasing trend may affect the food security of the catchment

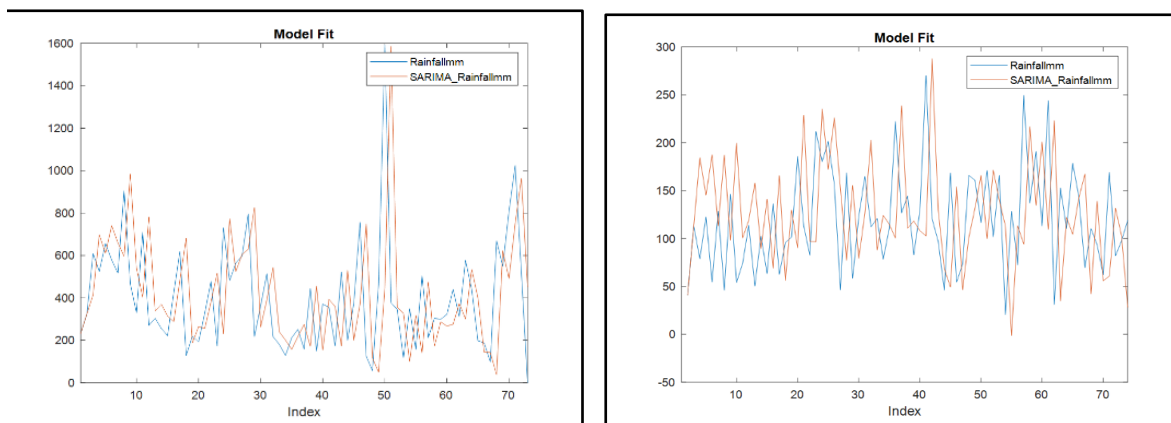


Figure 4-46: Elim Hosp and Zwartrandjes spring SARIMA

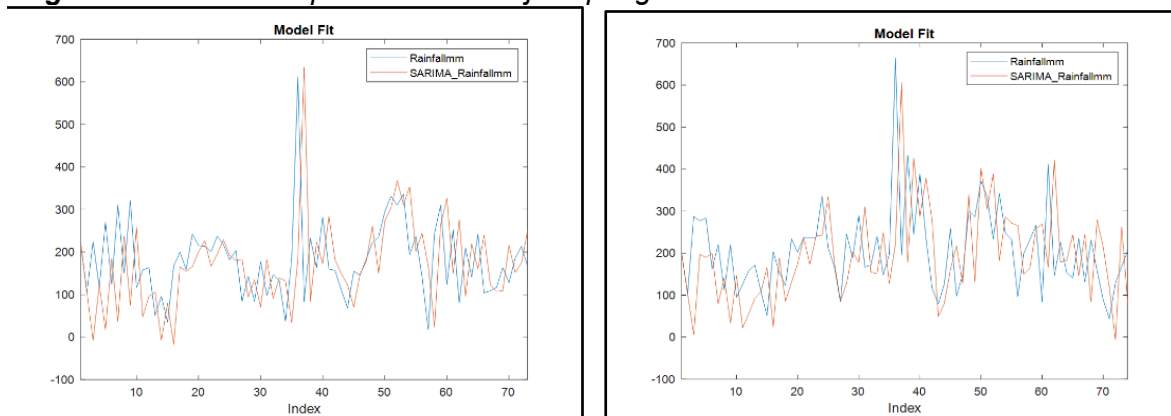


Figure 4-47: Goedehoop and Klein Australie spring SARIMA

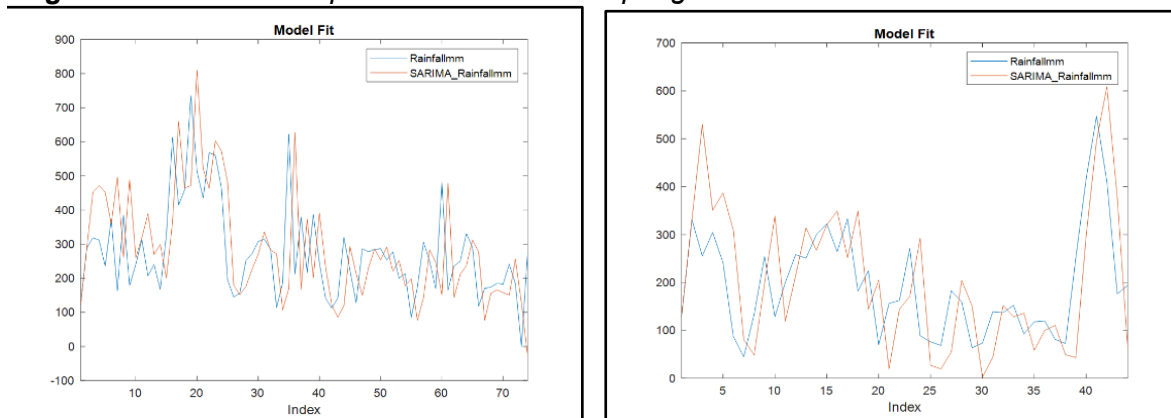


Figure 4-48: Shefeera and Levubu spring SARIMA

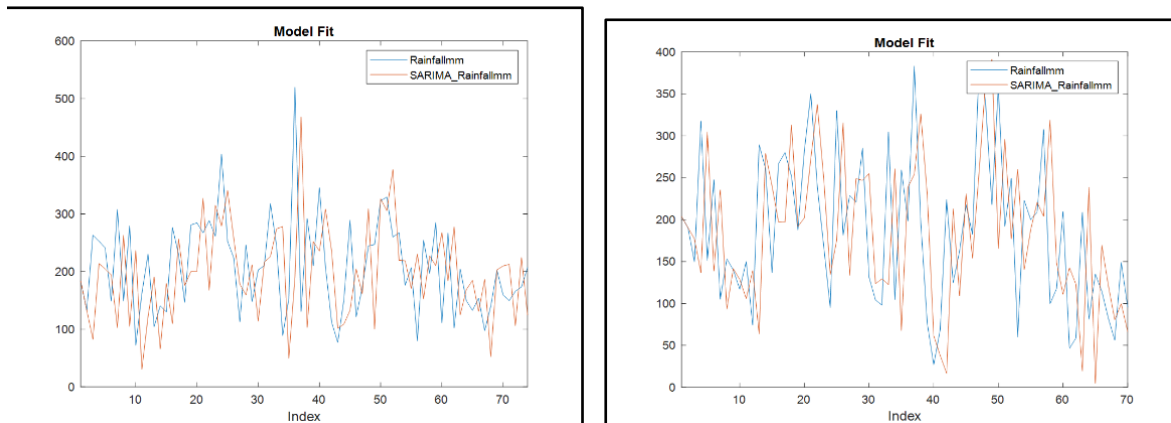


Figure 4-49: Nooitgedacht and Tsianda Spring SARIMA

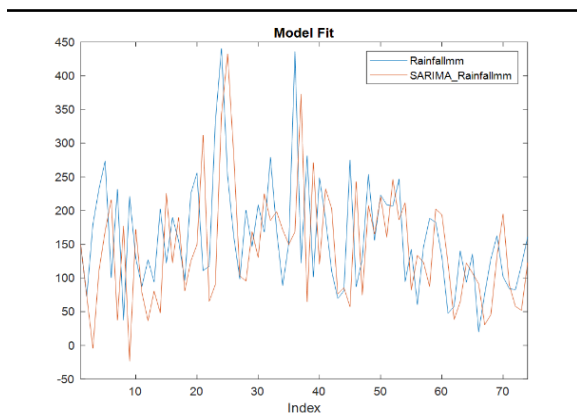


Figure 4-50: Roodewal Bos and Rambuda spring SARIMA

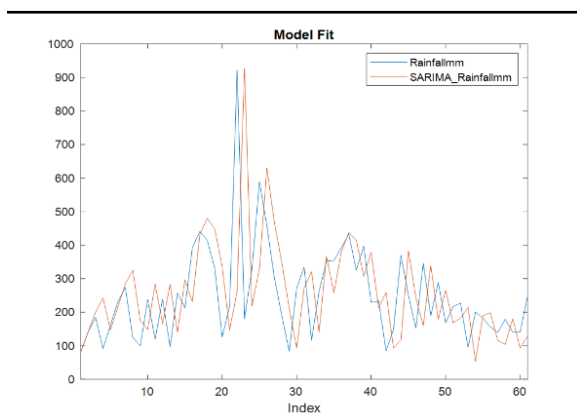
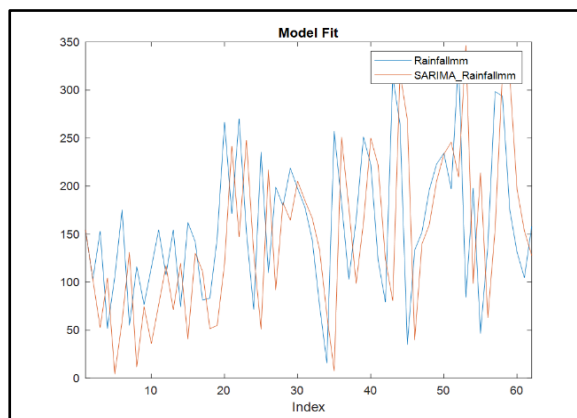


Figure 4-51: Vondo and Punda Maria spring SARIMA

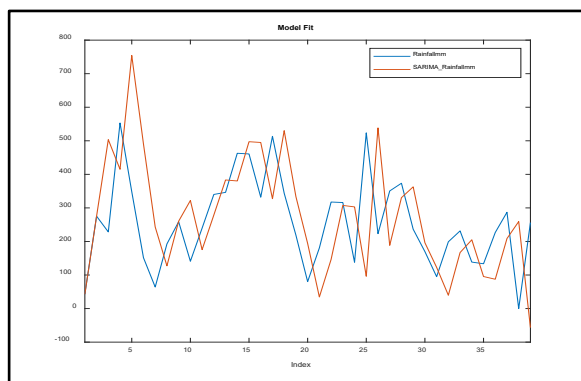
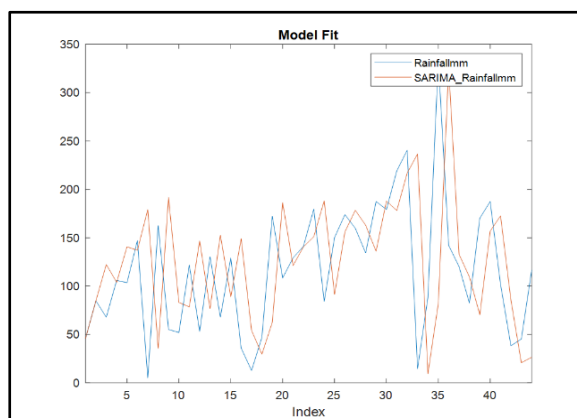


Figure 4-52: Phiphidi and Pafuri spring SARIMA

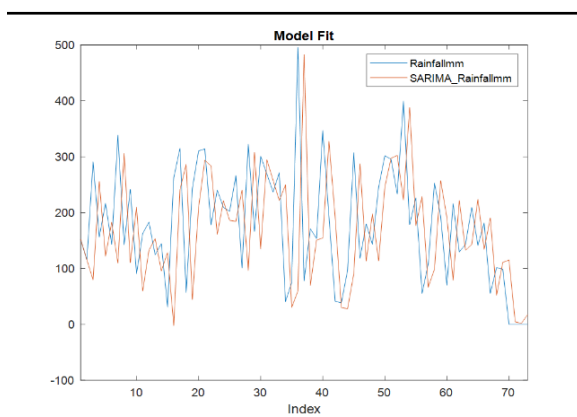
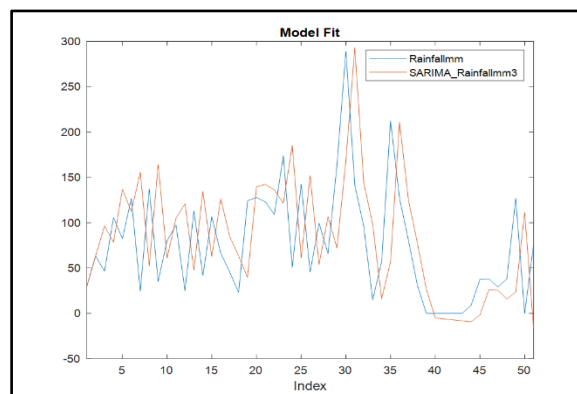


Figure 4-53: Palmaryville Spring SARIMA

4.3 RESULTS OF FUTURE SEASONAL TRENDS

Figure 4-54 show the graphical presentation of future seasonal trends from the three locations in the catchment. Station 03 has the highest rainfall of about 270 mm , followed by station 02 with 174 mm, and station 01 with 163 mm in summer. Spring experiences the second highest rainfall with station 01 having 180 mm, station 02 having 102 mm and station 03 at 77 mm. The autumn month has the third highest average, with station 03 at 59 mm, station 02 at 29 mm and station 01 at 27 mm. Winter has the lowest average, with station 03 having 38 mm, station 02 at 13 mm and station 01 at 6 mm, respectively. In summer, rainfall is the highest, followed by spring, autumn, and winter. All these stations show the same trend even though they are located in different regions of the LRC. The upper reaches of the catchment show low rainfall as expected. The same trend is also exhibited by the stations of historical data. This indicates that the historical and the future trends are the same. The decreasing trend in the future is worrying since it may alleviate food and water scarcity, affect the crops and livestock, cause heatwaves and increase the risk of waterborne diseases. Drought is more likely to occur within the catchment since there are decreasing trends.

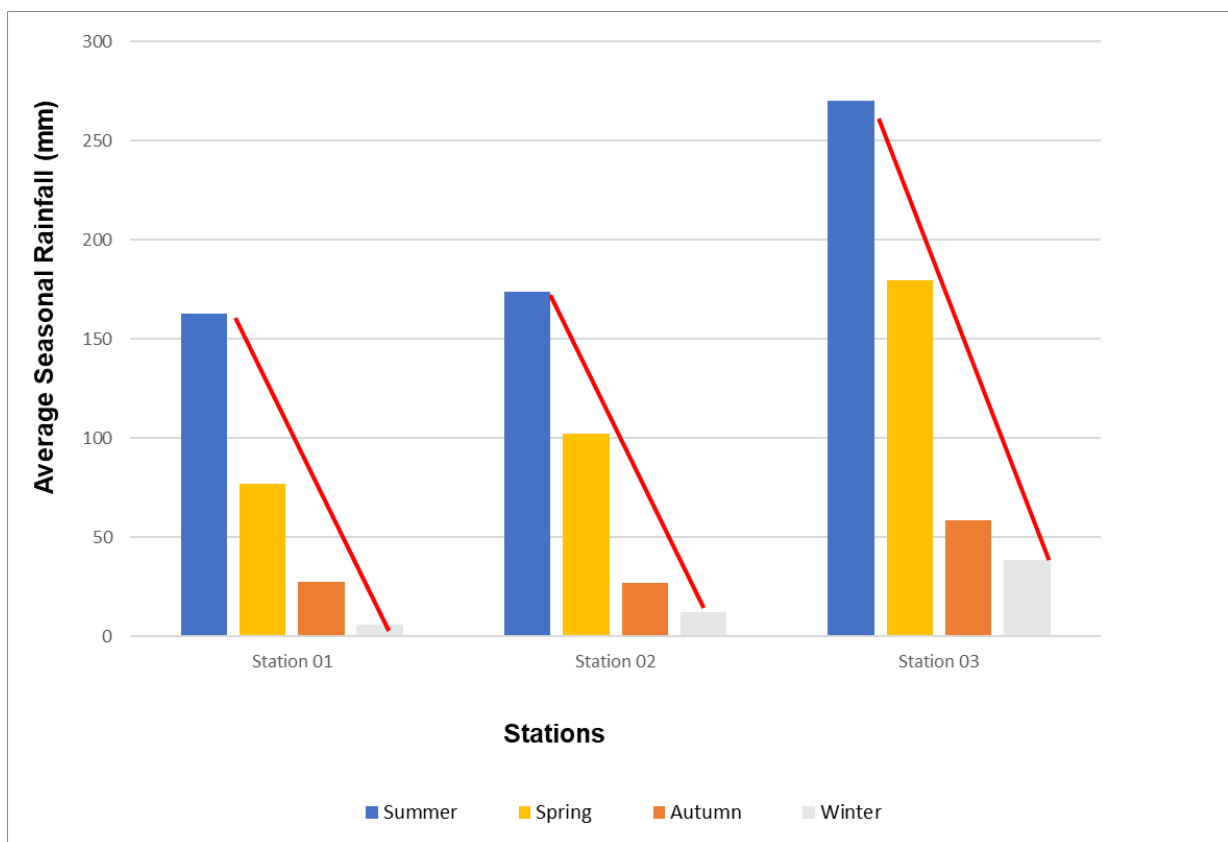


Figure 4-54: Future seasonal rainfall trends at all stations

For future seasonal ITA , winter shows increasing trends for all stations. Autumn shows a decreasing trend for all the stations. In spring, station 01 and station 03 show an increasing trend, while station 02 show a decreasing trend. Summer shows an increasing trend for station 01 and station 02, respectively, while station 03 shows a decreasing trend. All the results for all the stations are presented in *Table 4-7*.

Table 4-7: Future Seasonal ITA Results

Station Name	Seasons			
	Summer	Autumn	Winter	Spring
Station 01	Increasing Trend	Decreasing Trend	Increasing Trend	Increasing Trend
Station 02	Increasing Trend	Decreasing Trend	Increasing Trend	Decreasing Trend
Station 03	Decreasing Trend	Decreasing Trend	Increasing Trend	Increasing Trend

When using the ITA method, the slope of a trend can also be used to indicate if the trend is decreasing or increasing. A positive slope indicates an increasing slope, while a negative slope indicate a decreasing trend. *Table 4-8* indicates the decreasing trend in autumn for all the stations, increasing trend in winter for all the stations, and increasing trends in spring and summer for the two stations.

Table 4-8: Future seasonal slopes from ITA methods

Station Name	Seasons			
	Summer	Autumn	Winter	Spring
Station 01	0.079	-0.358	0.196	0.051
Station 02	0.091	-0.473	0.097	-0.055
Station 03	-0.023	-0.449	0.272	0.057

The graphs (*Figure 4-55*) below show that more points are on the increasing side indicating an increasing trend. Station 01 and Station 02 show an increasing trend in summer rainfall, suggesting potential enhancement of peak season precipitation in future periods. This may benefit agriculture and recharge systems. Station 03, however, exhibits a decreasing trend, indicating possible future drying during the summer, which could lead to water stress..

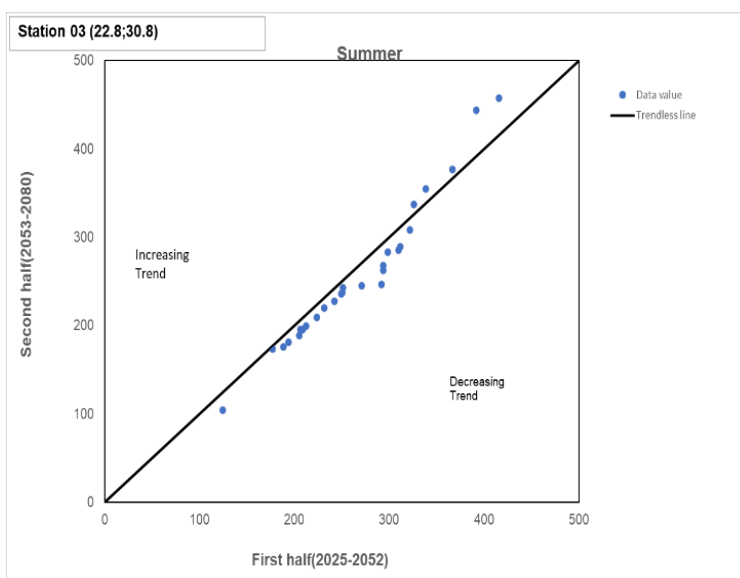
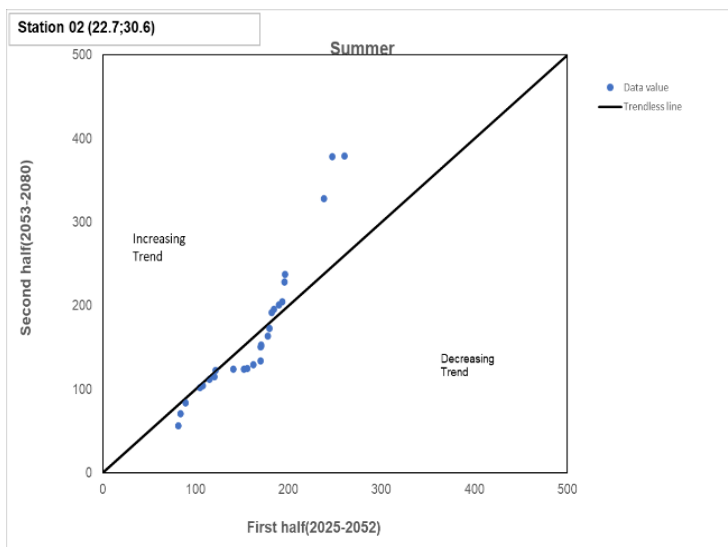
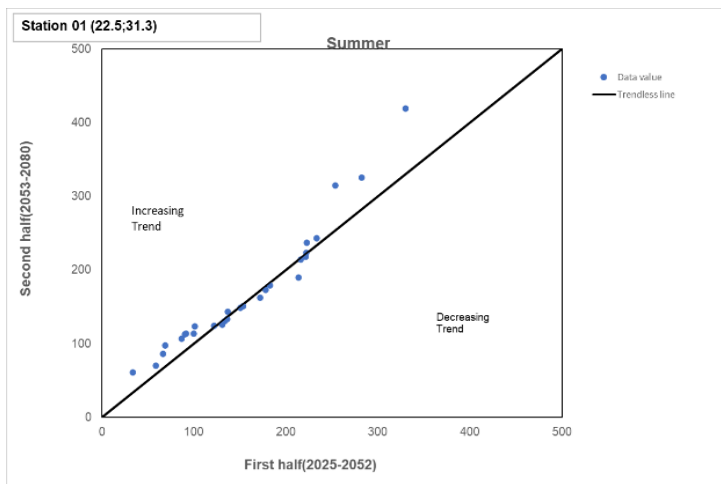


Figure 4-55: Future summer ITA Results for stations 01,02 and 03

All three stations in *Figure 4-56* indicate a decreasing trend in autumn rainfall, suggesting a contraction of the post-summer wet period. This can result in farmers being limited to late

planting and harvesting and the reduction of soil moisture that could be carried over to the dry season. This is supported by a study done by Schulze et al. (2023).

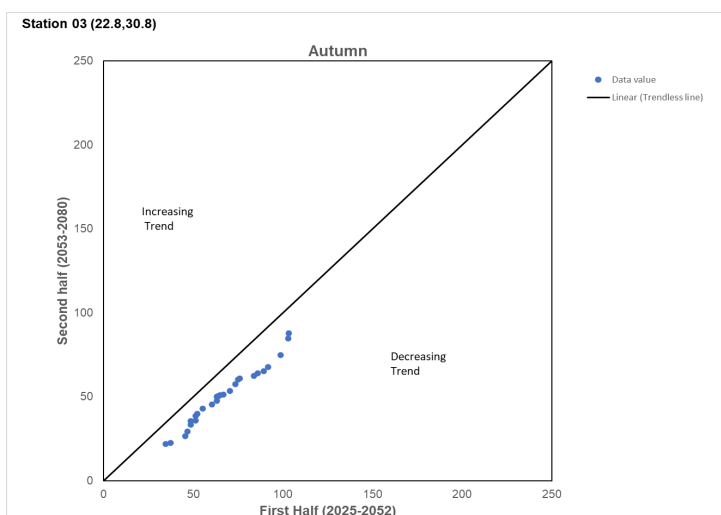
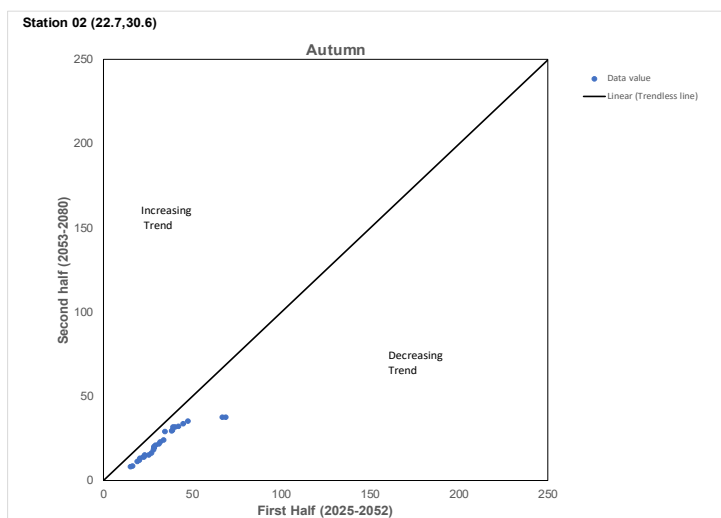
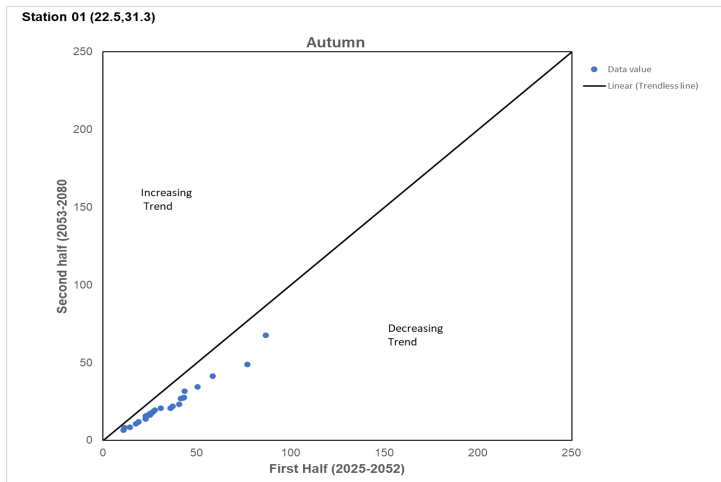


Figure 4-56: Future autumn ITA Results for stations 01, 02 and 03

Figure 4-57 show the leaning towards the left of the seasonal rainfall in the LRC, indicating an increasing trend. It is interesting that all the stations show an increase in winter while LRC is known to be dry in winter, hence a summer rainfall region, receiving its rainfall in summer.

The reason for this could possibly be because of the delayed rainy season withdrawal and also events that occur out of season happening more frequently.

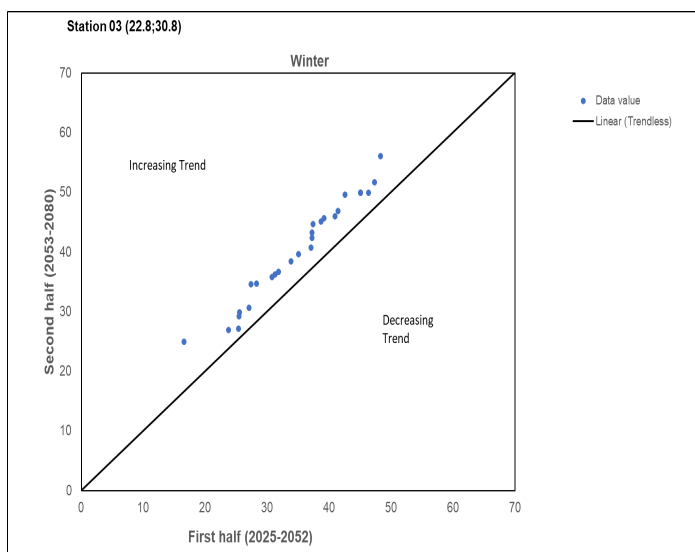
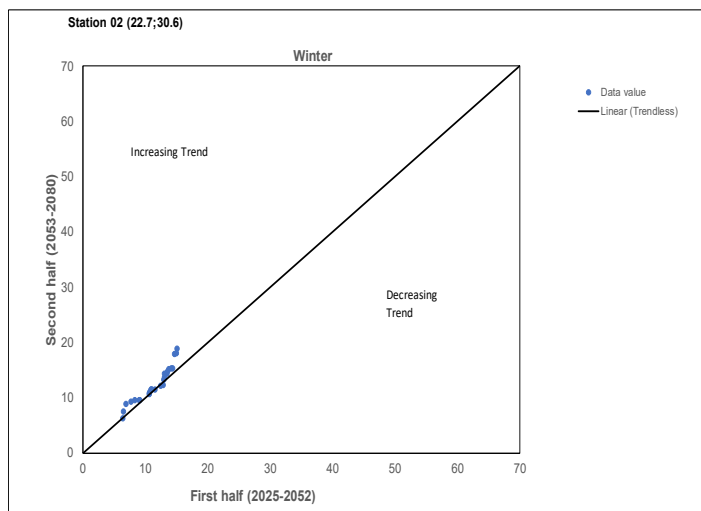
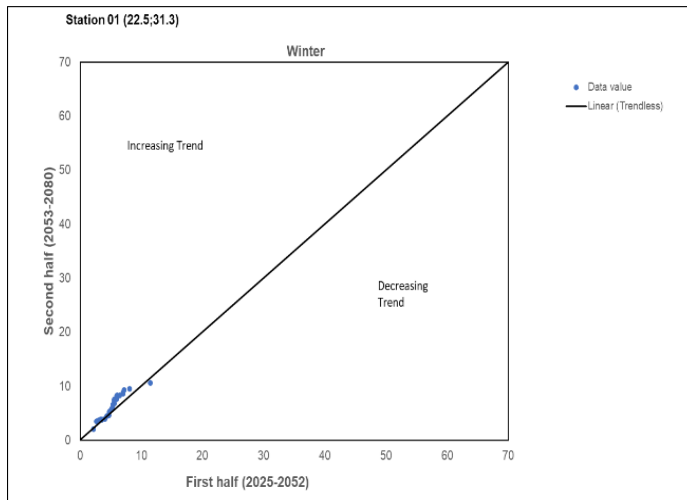


Figure 4-57: Future winter ITA Results for stations 01, 02 and 03

For spring, Station 01 and Station 03 show increasing trends, potentially signaling a gradual advancement of the rainfall onset, which could extend the growing season and provide early

moisture for germination. Station 02 presents a decreasing trend, which may indicate a delayed or weakened start to the rainy season in that specific area. This is indicated in *Figure 4-58*.

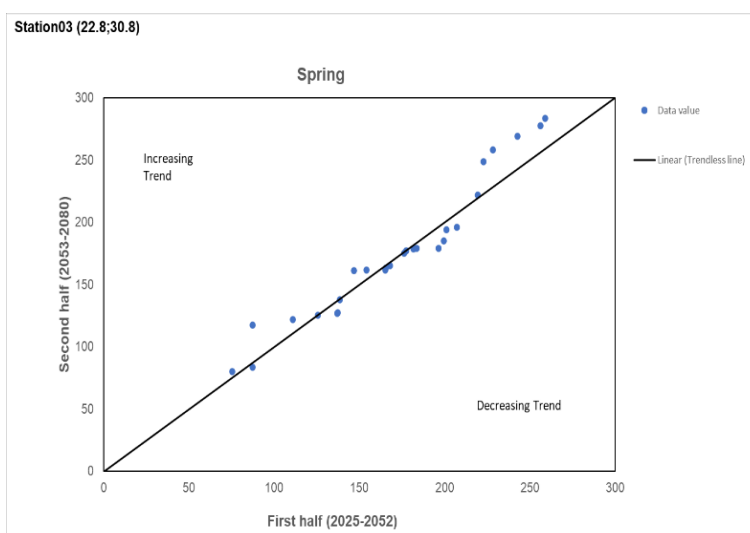
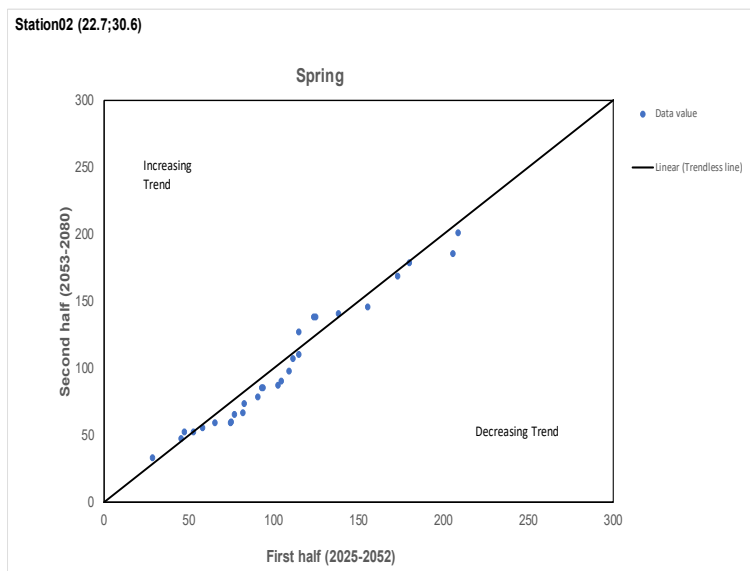
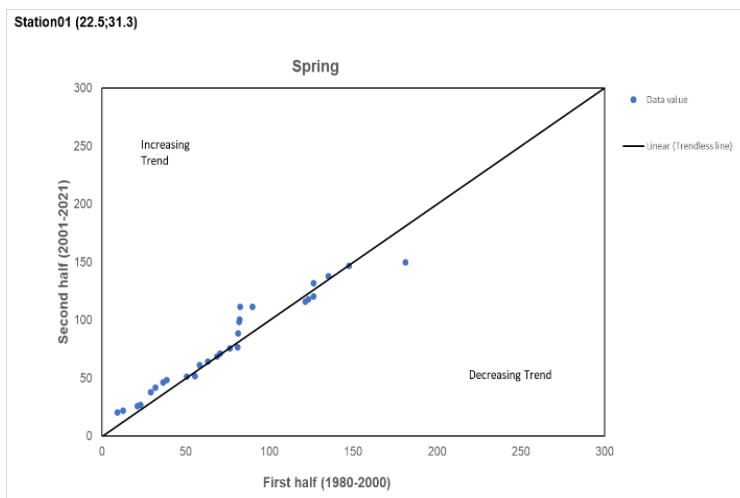


Figure 4-58: Future spring ITA Results for stations 01, 02 and 03

Future seasonal rainfall trends using the ARIMA model were done according to seasons. In summer, the trends were all stationary with the AIC values ranging from 680 to 831. The model $(2,0,1)(2,0,1)_{12}$ was used because of the low AIC in all the three stations. For station 01, the trends were increasing, and for station 02 and 03, the trends were decreasing. *Table 4-9* summarizes the summer results.

Table 4-9: Future Summer Results from the ARIMA Model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Station 01	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	763
Station 02	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	679.
Station 03	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	831

In autumn, station 02 shows non-stationarity with a decreasing trend, an AIC of 497, a model $(2,1,1)(2,1,1)_{12}$. Station 01 and station 02 both show stationarity, decreasing trends, AIC of 595 and 613, respectively (see *Table 4-10*).

Table 4-10: Future Autumn Results from the ARIMA Model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Station 01	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	595
Station 02	Non-Stationary	$(2,1,1)(2,1,1)_{12}$	Decreasing	497
Station 03	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	612

Table 4-11 shows that in winter, in all the stations, the trends are stationary with model $(2,0,1)(2,0,1)_{12}$ fitting the data best. Stations 02 and 03 show increasing trends with AIC of 297 and 424 mm, respectively. Station 01 shows a decreasing trend with an AIC of 519 mm.

Table 4-11: Future Winter Results from the ARIMA Model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Station 01	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	518
Station 02	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	296
Station 03	Stationary	$(2,0,1)(2,0,1)_{12}$	Increasing	424

In spring, all the stations show stationarity and a decreasing trend. Model $(2,0,1)(2,0,3)_{12}$ fitted data best for Station 01 with an AIC of 716 mm. For Station 02 and Station 03, model $(2,0,1)(2,0,1)_{12}$ was used with AIC of 611 mm and 752 mm, respectively. *Table 4-12* summarises the results.

Table 4-12: Future Spring Results from the ARIMA Model

Station Name	Stationarity (KPSS)	Model (SARIMA)	Trends	AIC
Station 01	Stationary	$(2,0,1)(2,0,3)_{12}$	Decreasing	715
Station 02	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	610
Station 03	Stationary	$(2,0,1)(2,0,1)_{12}$	Decreasing	751

For summer, *Figure 4-59*, *Figure 4-60*, and *Figure 4-61* indicates decreasing and increasing trends. Station 01 shows a decreasing summer rainfall trend while station 02 shows an increasing rainfall future trend. The decrease aligns with what has been projected in Southern Africa where it is indicated that there might be a decrease in summer rainfall. This will affect negatively water availability. This difference in results when the same model is used might imply spatial heterogeneity.

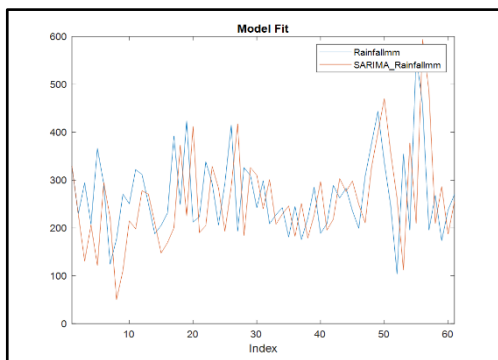


Figure 4-59: Station 01 Summer SARIMA

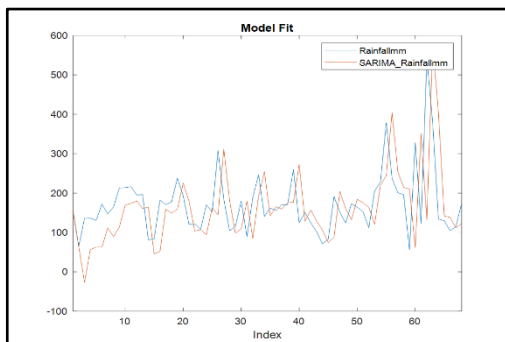


Figure 4-60: Station 02 Summer SARIMA

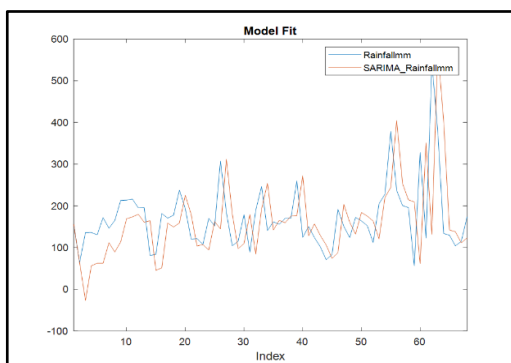


Figure 4-61: Station 03 Summer SARIMA

In *Figure 4-62*, *Figure 4-63*, and *Figure 4-64* the graphical results of the seasonal ARIMA model in the autumn season are presented. All the stations in autumn season for future analysis show a decreasing trend. This could lead to the shortening of the rainfall season.

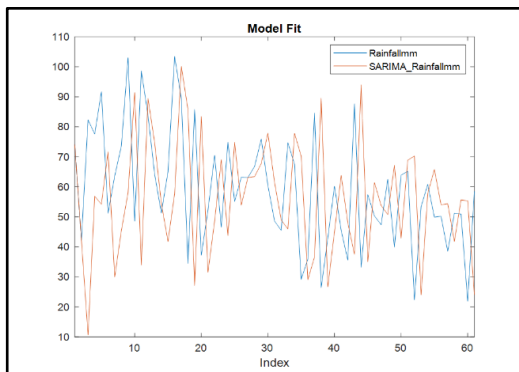


Figure 4-62: Station 01 Autumn SARIMA

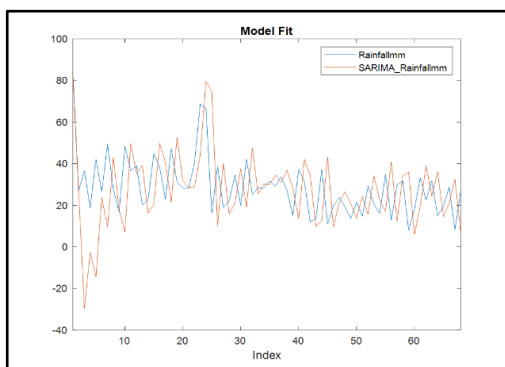


Figure 4-63: Station 02 Autumn SARIMA

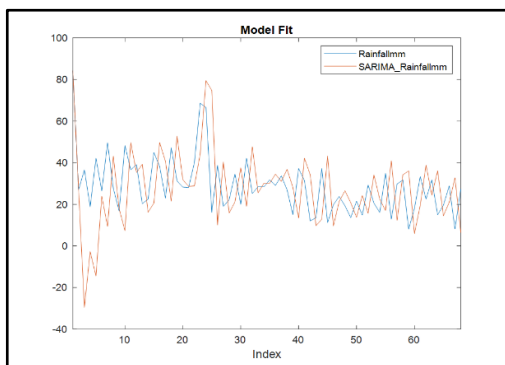


Figure 4-64: Station 03 Autumn SARIMA

In *Figure 4-65*, *Figure 4-66*, and *Figure 4-67* the graphical results of the seasonal ARIMA model in the winter season are presented. Station 01 indicate a decreasing trend while station 02 and 03 indicate an increasing trend. This was seen to also be the case for the results found from the ITA method hence supporting the results of the ARIMA.

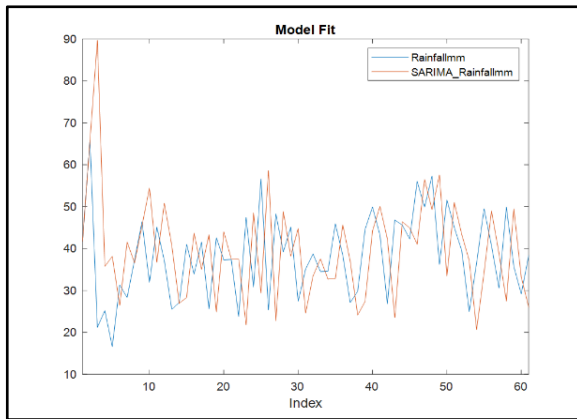


Figure 4-65: Station 01 Winter SARIMA

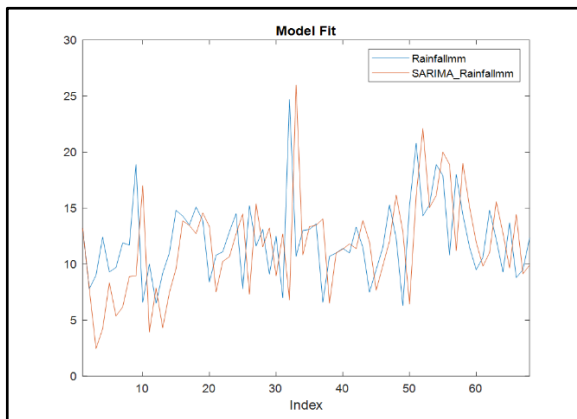


Figure 4-66: Station 02 Winter SARIMA

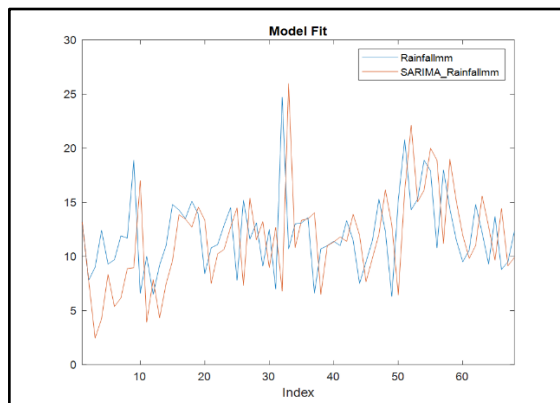


Figure 4-67: Station 03 Winter SARIMA

In *Figure 4-68*, *Figure 4-69* and *Figure 4-70* the graphical results of the seasonal ARIMA model in the future spring season are presented. For spring, future rainfall trends are decreasing for all the stations. These could have an impact on the agriculture of the LRC in future.

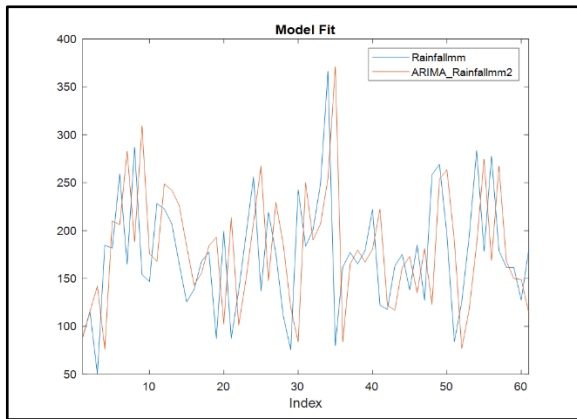


Figure 4-68: Station 01 Spring SARIMA

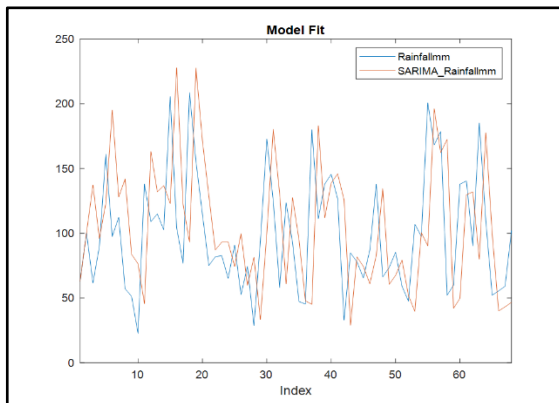


Figure 4-69: Station 02 Spring SARIMA

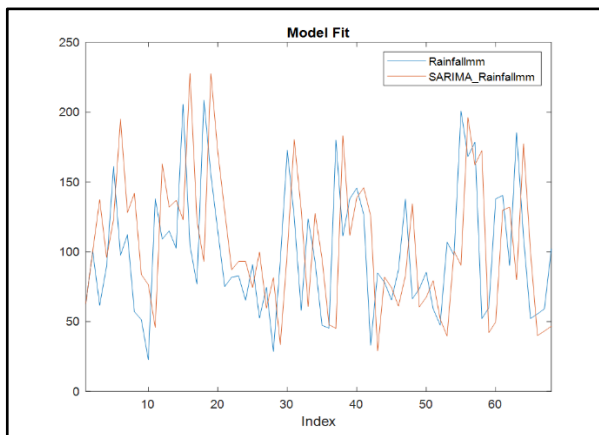


Figure 4-70: Station 03 Spring SARIMA

The comprehensive analysis of rainfall trends across seasonal, temporal, and spatial scales has revealed significant patterns of climatic variability and change in the study area. Both ITA and SARIMA modeling consistently indicate declining rainfall trends during the autumn and spring seasons across the majority of stations, suggesting a shortening of the traditional rainy season and a potential shift in seasonal rainfall start and end.

From the results, the good model performance (SARIMA) across all seasons and stations, as indicated by low AIC values, strengthens the reliability of these projections. The ITA results confirmed the heterogeneity of future rainfall behavior, with varying trends across both space and season. The results from the trend analysis may call for a need to have proper water management in the LRC , agricultural plans and calenderer due to the shifting times and seasons and policy frameworks that will adopt to policies in line to what was revealed from the current analysis.

4.4 COMPARISON OF METHOD RESULTS

The results of the ARIMA and the ITA methods compare well to each other. The stations show similar seasonal trends. In summer, all the stations show similar trends except for Phiphidi, Tsianda, Goedeheop, Zwartrandjes and Pafuri. Vondo and Goedeheop differ from the other stations in Spring, while Vondo, Klein Australie, Goedeheop and Rambuda differ in Winter. In Autumn, Vondo, Klein Australie, Goedeheop, Elim Hosp and Pafuri differ from other stations. Overall, in all the seasons, there is a decreasing trend in the catchment; it's only a few instances where the trends were increasing. The use of ITA alongside SARIMA provides a more robust understanding of rainfall dynamics under historic and future climate scenarios reinforcing the need for targeted adaptation strategies tailored to specific stations and seasons. It can therefore be concluded that the two methods produce comparable results.

4.5 THE RESULTS OF THE SPATIAL VARIATION OF HISTORICAL AND FUTURE RAINFALL TRENDS

The results of spatial variation are presented in *Tables 4-14, Table 4-15 and Table 4-16*. The results of the five parameters are in agreement with each other. The mean is the highest in summer and at the lowest in winter seasons. In winter the results of the mean, SD and SI are at the lowest as compared to the other seasons. The CV is the highest in winter and lowest in spring. In general, Pafuri, Punda Maria, Tsianda, Palmaryville show higher variability. Mazibuko et al. (2021) indicated that high rainfall variability in the catchment is experienced in the north- eastern parts, which supports the results from the current study. Mazibuko et al. (2021) further indicated that the variability in the LRC is induced by the ENSO phenomenon. Variability is also noticed within the seasons; there is high variability in winter, followed by autumn , spring and summer. This is due to the fact that most of the rainfall in the catchment is experienced in summer. The stations selected for future analysis show similarities in characteristics and variability with those used for historic analysis that are located in close proximity to each other. The high variability in the eastern parts of the catchment ,particularly the lower reaches, leads to increased occurrences of drought and floods in these areas.

Mean

Across all stations, the summer season consistently recorded the highest mean rainfall, ranging from as low as 227 mm at Pafuri to as high as 782 mm at Shefeera. This confirms that the LRC lies predominantly within a summer rainfall region, with the rainy season peaking between November and March. The spring and autumn seasons display moderate rainfall amounts, while winter rainfall is minimal, with many stations recording winter means below 50 mm for example., Palmaryville; 30 mm; Pafuri; 9 mm. This indicates a strongly seasonal rainfall regime, where over 60–70% of annual precipitation is concentrated in the summer months

SD

A high standard deviation shows that there is higher variability. Variability is higher in the upper reaches of the catchment and lower at the lower reaches of the catchment where the Pafuri station is located. The standard deviation is the highest in summer and at the lowest in winter. Phiphidi, Palmaryville, Shefeera, Rambuda, Goedehoop-Bos, Noitgedacht, Vondo-Bos, and Klein Australie have the SD above 300, while Levubu, Tsianda, Roodewal-Bos, and Elim-Hosp, SD between 200 to 300, Punda Maria, Zwartrandjes and Pafuri with the lowest SD that is less than 200 in summer. In winter, SD ranges from 11 to 57 with 11 at Pafuri and 57 at Shefeera. In Spring, the SD ranges from 61 to 143, with 61 at Pafuri. Vondo has the highest SD value in Autumn of 164, with Pafuri at the lowest of 49. the SD greater than 100 indicate that there very high variability while over 200 signifies extreme variability. The results indicate that the LRC is prone to extreme events, with very dry and very low rainfall.

CV

The CV ranges from 0.5 to 1.5 in all seasons. In summer, Roodewal Bos and Shefeera, have a CV of approximately 0.5 which is the lowest in Summer, while Tsianda, Zwartrandjes, Noitgedacht, Goedehoop, Elim-Hosp, Palmaryville Punda Maria Levubu, Phiphidi Vondo and Klein Australie the CV was approximately 0.6, Pafuri and Rambuda have a CV of approximately 0.7 which is the highest for summer. In autumn, the CV ranges from 0.5 to 0.9. Levubu with the highest CV of 0.9, followed by Pafuri and Rambuda, both with a CV of 0.8. Punda Maria, Palmaryville, Phiphidi, Klein Australie, and Tsianda have a CV of 0.7. Meanwhile, Zwartrandjes, Roodewal Bos Vondo, Noitgedacht, Goedehoop and Elim-Hosp each have a CV of 0.6. Shefeera has the lowest CV of 0.5.

In winter, variability values ranges from 0.6 to 1.5, indicating high variability. Pafuri has the highest CV at 1.5 and 0.6 at Rambuda station. Winter has the highest variability. Spring has variability, ranging from 0.4 to 0.8. Pafuri has a CV of 0.8 which is the highest in spring and a CV of 0.4 at Nooitgedacht and Elim-Hosp. Winter has the highest values of variability in the LRC, followed by Autumn, Spring and Summer with the lowest. In the future, the CV ranges from 0.3 to 0.6 in summer, 0.3 to 4.1 in autumn, 0.4 to 3.0 in winter and 0.5 to 3.1 in spring. High variability is indicated in Autumn. The high CV in winter (for example, Zwartrandjes: 1.243; Palmaryville: 1.029; Pafuri: 1.528) indicate the low rainfall in the season which makes winter unreliable for water dependent activities. The lower CV values in summer and autumn indicating stable and predictable seasons

SI

To determine the SI, the mean rainfall of each season was divided by the annual mean. In the LRC, the SI is the highest in summer showing that the area is highly seasonal, ranging from 0.7 to 2.4. Winter has the lowest SI, ranging from 0.0 to 0.2, indicating that there is no rainfall throughout the season with wetter days. In autumn the SI ranges from 0.2 to 0.8, Spring 0.2 to 1.0. Rambuda and Pafuri have the lowest at 0.003, while Elim-Hosp has the highest value at 2.4. The high SI of above 2 indicate the dominance of the summer rainfall. Moderate SI values in autumn and spring at higher-rainfall stations such as Shefeera and, Levubu suggest some spatial variability in the transition months, possibly influenced by topography and local microclimates

The spatial variation results indicate that there is variability in the catchment which differs by location. Rainfall in the LRC is highly seasonal with autumn and spring serving as transitional periods, and winter contributing minimally and summer contributing the most rainfall. Stations in the western and north eastern side of the catchment show high variability. The high CV and low SI in autumn, winter and spring seasons suggest increasing vulnerability to dry spells, droughts, and water insecurity in those seasons.

Table 4-13: Historical results of spatial variation parameters

Parameters	Zwartrandjes				Elim Hosp				Goedehoop				Shefeera				Nooitgedacht			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Mean	264	98	13	119	407	125	25	133	518	176	45	182	782	283	81	279	565	190	41	208
Standard Deviation	156	64	16	55	254	78	25	57	332	108	41	91	427	151	57	134	321	116	38	83
Coefficient of Variance	0.592	0.649	1.243	0.459	0.625	0.624	0.964	0.428	0.640	0.613	0.905	0.499	0.546	0.536	0.710	0.481	0.567	0.609	0.944	0.401
Seasonality Index	2.137	0.793	0.104	0.966	2.358	0.722	0.148	0.772	2.251	0.763	0.196	0.790	2.196	0.794	0.227	0.783	2.252	0.757	0.162	0.828

Table 4-14: Historical results of spatial variation parameters

Parameters	Klein Australie				Levubu				Tsianda				Roodewal Bos				Vondo			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Mean	653	214	54	208	445	126	36	194	505	179	32	187	478	162	40	161	716	265	65	251
Standard Deviation	367	139	45	101	268	116	32	112	285	119	33	89	263	95	35	83	462	164	56	143
Coefficient of Variance	0.561	0.653	0.818	0.486	0.602	0.920	0.877	0.578	0.564	0.664	1.037	0.475	0.549	0.588	0.866	0.514	0.645	0.618	0.867	0.569
Seasonality Index	2.314	0.757	0.193	0.736	2.224	0.629	0.180	0.968	2.237	0.792	0.142	0.830	2.272	0.770	0.191	0.767	2.230	0.826	0.202	0.783

Table 4-15: Historical results of spatial variation parameters

Parameters	Phiphidi				Palmaryville				Rambuda				Punda Maria				Pafuri			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Mean	751	229	53	262	470	163	30	180	444	149	75	158	319	101	11	118	227	64	9	77
Standard Deviation	447	155	43	132	301	119	31	104	303	116	43	74	193	75	11	67	156	49	14	61
Coefficient of Variance	0.595	0.676	0.818	0.505	0.639	0.730	1.029	0.576	0.683	0.776	0.575	0.470	0.605	0.746	1.037	0.570	0.689	0.775	1.528	0.797
Seasonality Index	2.338	0.713	0.165	0.816	1.466	0.507	0.095	0.561	1.383	0.465	0.235	0.492	0.993	0.314	0.034	0.368	0.707	0.199	0.029	0.240

Future variability results (*Table 4-17*) indicate that the SD results are the lowest in winter and highest in summer ranging from 2 to 86. The CV ranges from 0.286 to 4.120. The SI ranges from 0.090 to 3.950 in station 03. High variability is seen in the lower reaches of the catchment. Results indicate a significant variability during seasons, especially in summer. There is moderate variability in summer for station 01 and station 02 with extreme variability observed in station 03 for autumn, this can indicate there will be a major problem in the future when it comes to rainfall reliability during those seasons. Moreover, high variability can lead to shift in seasonal patterns.

Table 4-16: Future results of spatial variation parameters

Parameters	Station 01				Station 02				Station 03			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
Mean	165	28	6	78	175	28	12	103	271	59	38	181
Standard Deviation	78	17	2	42	85	12	4	46	86	20	9	59
Coefficient of Variance	0.590	0.384	0.537	0.472	0.447	0.286	0.451	0.486	0.336	4.120	3.049	3.129
Seasonality Index	2.402	0.411	0.090	1.134	2.555	0.403	0.181	1.501	3.950	0.864	0.562	2.636

Kriging

To investigate the spatial variation of the seasonal rainfall, the kriging method on ArcGIS was utilised. Seasonal rainfall ranges from 82 mm to 220 mm in autumn, with the highest rainfall occurring in the upper reaches of the catchment. At the lower reaches rainfall is the lowest. Stations such as Shefeera, Vondo, Klein Australie and Phiphidi are located in the area with the highest rainfall while the lowest rainfall is found in Pafuri. The low rainfall in winter may be due to the El Nino which is associated with dry conditions. The changes in atmospheric circulation can also affect the amount of rainfall in a catchment, resulting in varying rainfall occurring in the same catchment in different seasons. The study done by Odiyo et al. (2015) shows that there is increased variability in the catchment. According to Tshililo et al. (2021) rainfall in the catchment is influenced by topography, hence the high rainfall in the upper reaches of the catchment, leading to spatial variation of rainfall. Furthermore there is a spatial variation in rainy seasons across the catchment between dry and wet areas.

The Kriging map generated using seasonal mean rainfall data for summer reveals notable spatial variability across the study area. A clear rainfall gradient is seen from north to south in the map below (*Figure 4-71*). High rainfall regions can be seen on the south west of the catchment with low rainfall seen in the north eastern side during the summer season. Rainfall in summer ranges from 270 mm to 640 mm, varying from the upper reaches to the lower reaches. This pattern suggests that the lower parts of the region receive significantly more rainfall during the summer months, possibly influenced by topography. The interpolation highlights zones of high rainfall concentration in the lower reaches, which could be critical for flood risk assessments, agricultural planning, and water resource management during the wet season. The low rainfall in the upper reaches might potential vulnerability to seasonal water shortages. The Kriging technique effectively captures these spatial dynamics, offering a continuous surface that supports better understanding of summer rainfall distribution.

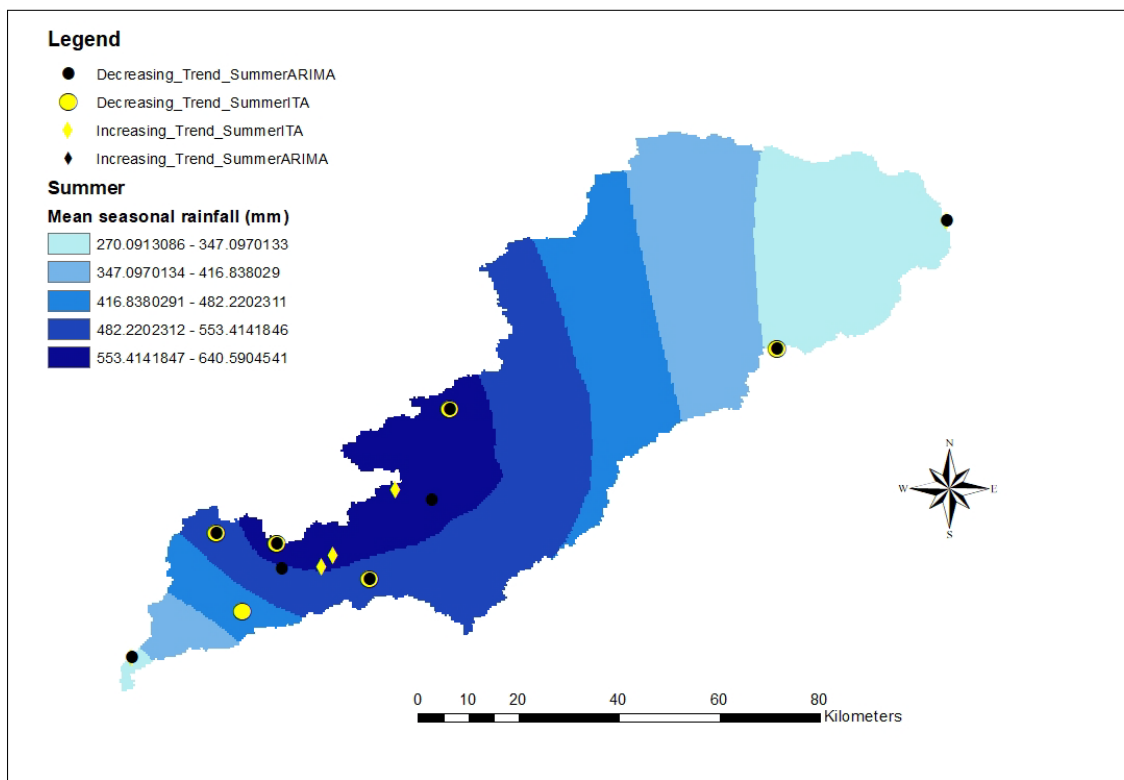


Figure 4-71: Summer Kriging Map

The Kriging map for autumn seasonal mean rainfall shows a clear spatial variation across the study area (*Figure 4-72*), with rainfall amounts ranging from 82 mm to 218 mm. Similar to the summer pattern, rainfall increases from the upper reaches toward the lower reaches, indicating a persistent spatial gradient likely driven by topographic influences. A mixture of both decreasing and increasing trends in the same area show the high spatial variation experienced in the area, showing that there should be different measures taken for each station or area rather than just for the whole catchment.

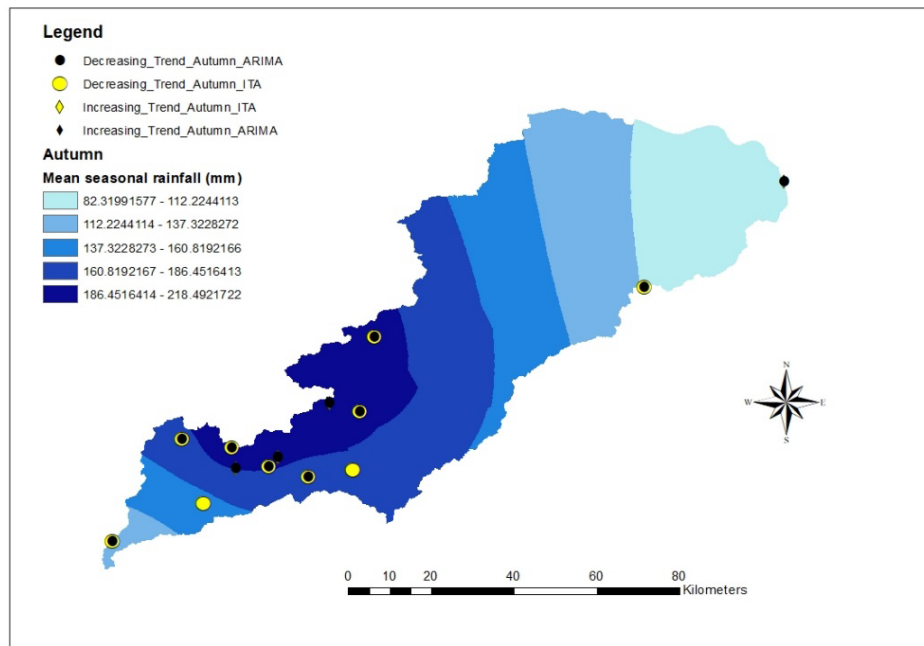


Figure 4-72:Autumn Kriging Map

Winter has the lowest rainfall, ranging from 16 mm to 59 mm. The spatial variability in winter differs from that in other seasons (*Figure 4-73*). There is high variability in this season. The catchment receives less rainfall during the winter seasons due to the fact that the area is characterised by summer rainfall. The low rainfall in winter in the area is attributed to the El Nina. This irregular distribution may be attributed to localized weather patterns. The winter season's minimal and uneven rainfall further emphasizes the region's dependence on summer rains for agriculture and water supply.

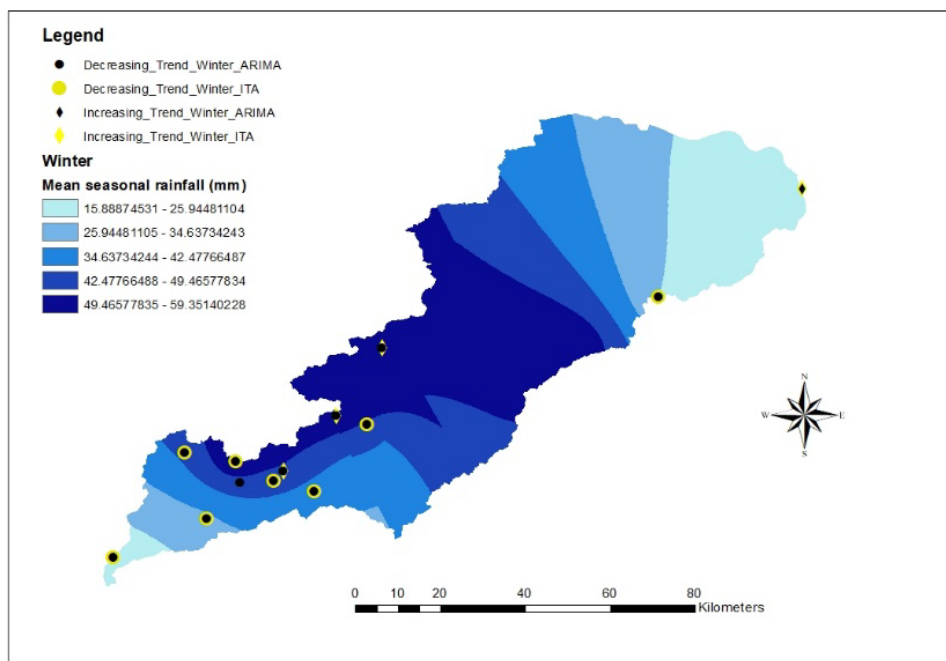


Figure 4-73: Winter Kriging Map

Rainfall in spring ranges from 86 mm to 235 mm, with the lowest rainfall at the upper reaches of the catchment. Rainfall varies from Pafuri to Zwartrandjes (*Figure 4-74*). The results for the spring kriging indicates the same gradient as those of the other seasons.

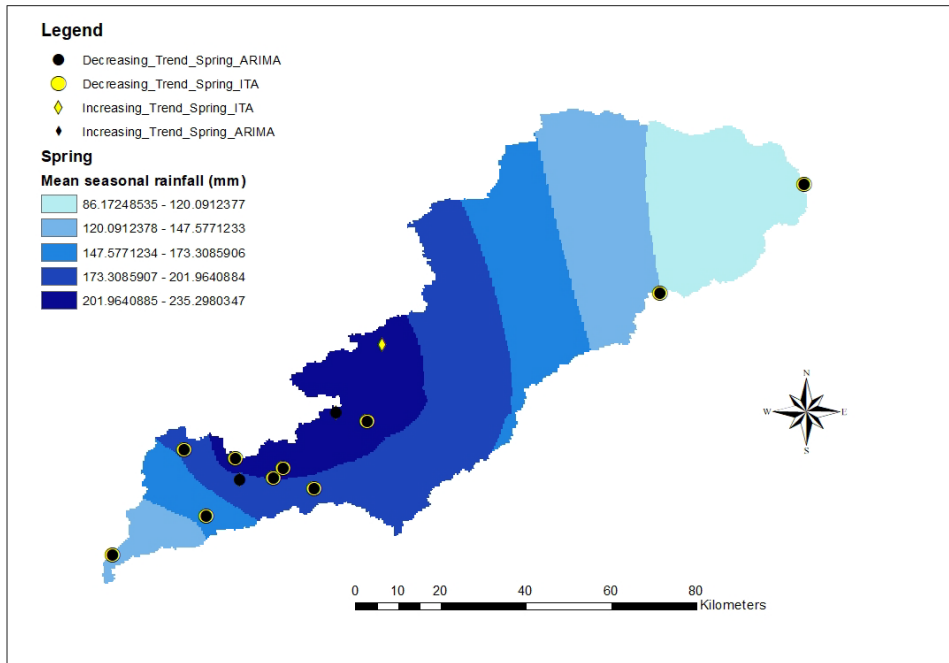


Figure 4-74: Spring Kriging Map

Future maps were also developed to check the spatial distribution of the seasonal rainfall. There is high variability in future rainfall trends depicted by the maps below for the summer, autumn and winter seasons. The maps show areas of high and low rainfall. The areas with darker blue are characterized by high rainfall in the catchment, with dryer areas depicted by lighter blue. There is a clear gradient in rainfall, with summer and spring experiencing the highest rainfall in the catchment. Summer is the highest rainfall season with rainfall ranging from 162 mm to 270 mm, making it the wettest season. Winter was seen to be the driest season with rainfall ranging from 6 mm to about 40 mm. Autumn shows a transitional rainfall pattern with totals ranging from 25 mm to 58 mm. The kriging results captures the magnitude and spatial distribution but uncertainties could result when only a few stations are used. At LRC future rainfall indicate higher variability (see *Figure 4-75*).

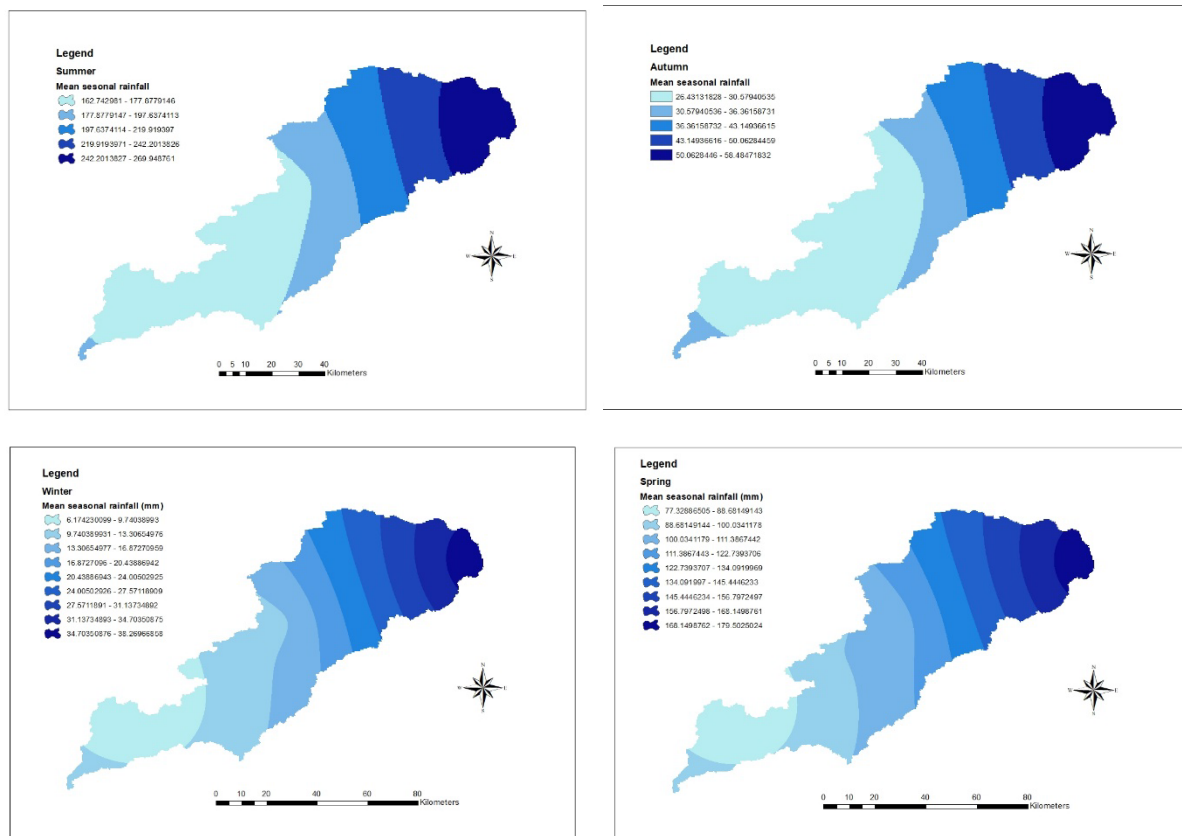


Figure 4-75: Future Spatial variation for seasonal rainfall

The results of the CV were further utilised to generate maps that show the distribution of rainfall station and variability in the catchment. The latter is shown in *Figure 4-76*. High variability can be seen at the lower reaches of the catchment for all the seasons. In the upper reaches of the catchment where rainfall usually starts, in the mountainous area, variability is low in comparison to the upper reaches. These lower regions may be more susceptible to localized and erratic rainfall events, possibly due to variable land use changes, which contribute to inconsistent precipitation patterns over time. The reduced variability in the mountainous areas, that is the upper reaches of the catchment might be due to more consistent orographic rainfall processes, which create more stable seasonal precipitation patterns. High variability is observed in winter which can be attributed to the generally low and irregular nature of winter rainfall in the region, followed by autumn (which could be due to transition in seasons), spring and then summer with the lowest indicating that rainfall is evenly distributed during this season.

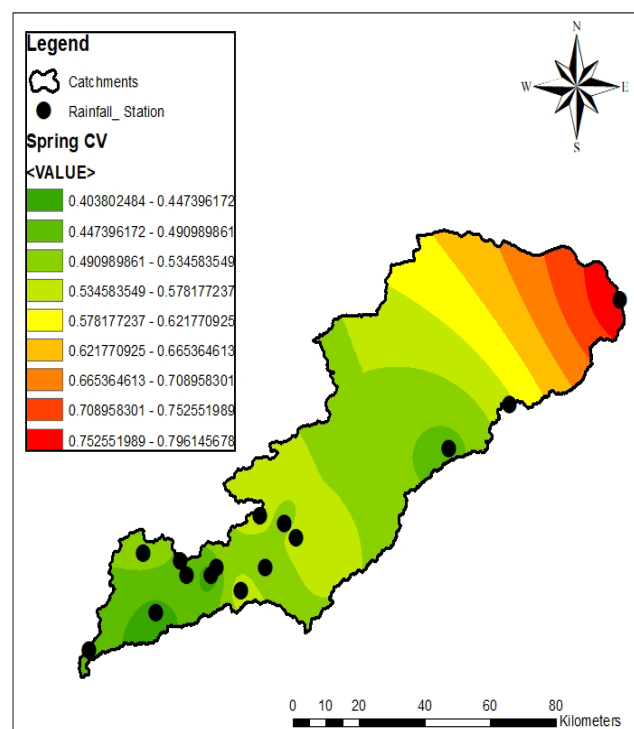
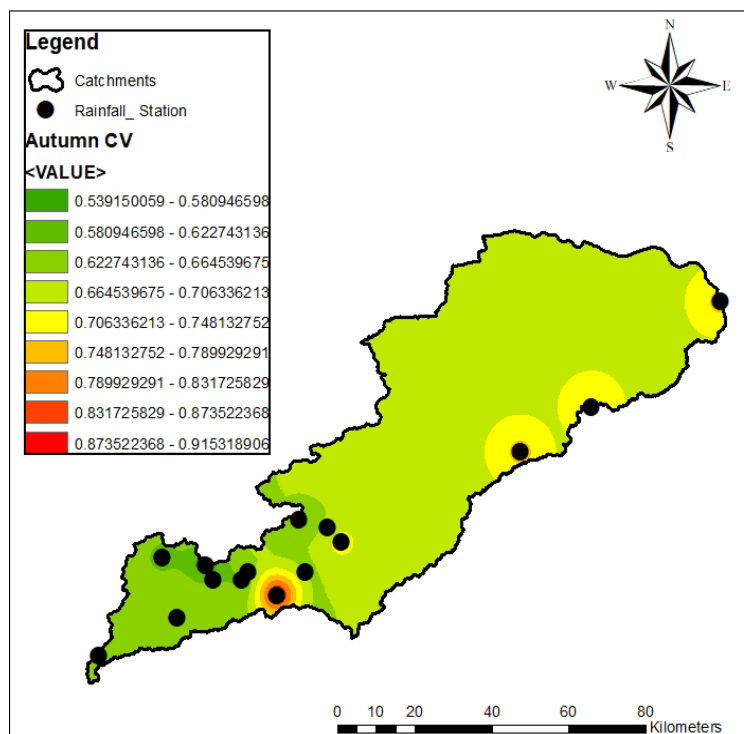
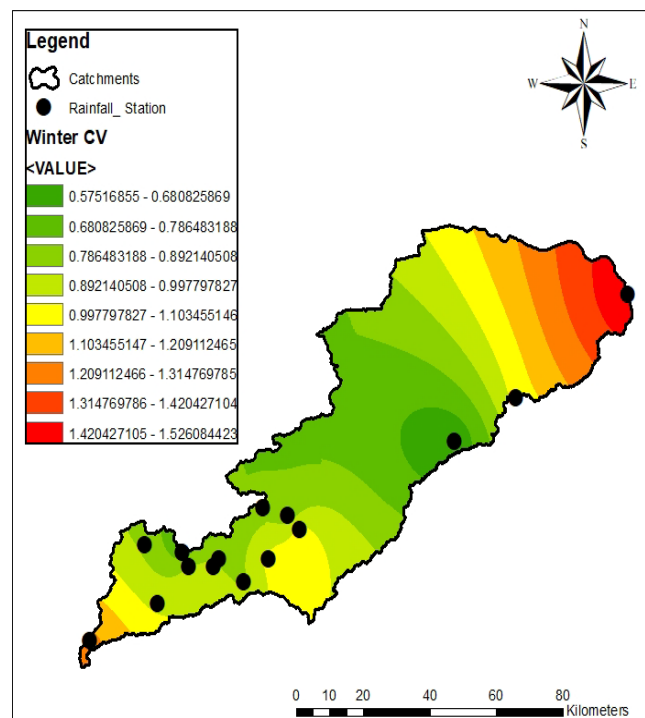
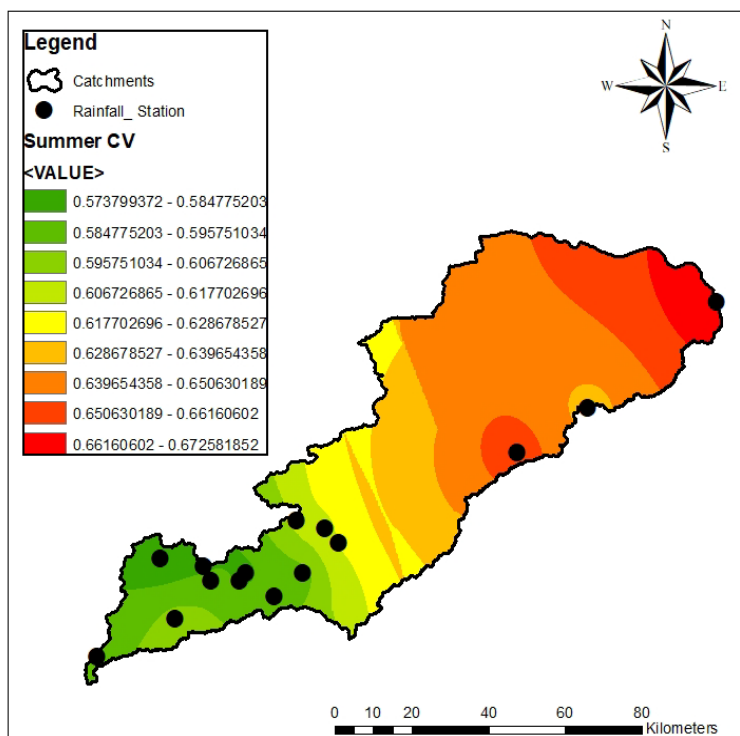


Figure 4-76: Spatial variation of CV for seasonal rainfall

4.6 INVESTIGATION OF THE CAUSES OF THE CHANGES IN RAINFALL TRENDS RESULTS

Two homogeneity testing methods were used to check the break in the record. *Table 4-18* show the results of homogeneity test. The results of the two methods show breaks at the same time and at other instances at different times. Overall, the results of the methods are in agreement to each other. In 1979, there was a break at Zwartrandjes, Elim-Hosp, Pafuri and Nooitgedacht. At Vondo and Shefeera the break occurred in 1975. In 1986/87, a break occurred at Phiphidi, Levubu and Palmaryville. In Roodewal-Bos and Tsianda the break occurred in 1982. In 1962/63, the break occurred at Goedeheop and Punda maria. The location of the stations appears to influence the timing of the break. Stations located close to each other turn to have a break at the same time. The breakpoints occur at the time after a high rainfall event, indicating a wet period. The results indicate that the change might have been caused by a flood event since the change occurred after the event. At Elim-Hosp, Rambuda, and Roodewal, the Pettit and SNHT tests give different results.

Table 4-17: Homogeneity Tests Results

Station	Standard Normal Homogeneity			Pettit		
	Num	Break	P value	Num	Break	P value
Zwartrandjes	31	1979	0.0000	31	1979	0.0000
Vondo	27	1975	0.0450	27	1975	0.0000
Tsianda	34	1982	0.8200	34	1982	0.3370
Shefeera	27	1975	0.0480	27	1975	0.0265
Roodewal Bos	60	2008	0.0108	34	1982	0.1540
Rambuda	63	2005	0.0000	32	1985	0.0007
Punda Maria	64	2012	0.8150	13	1961	0.8990
Phiphidi	39	1987	0.0000	37	1985	0.0000
Palmaryville	38	1986	0.0000	38	1986	0.0000
Pafuri	31	1979	0.4470	31	1979	0.0035
Nooitgedacht	31	1979	0.5760	31	1979	0.2070
Levubu	38	1986	0.0000	37	1985	0.0000
Klein Australie	48	1996	0.2980	48	1996	0.3440
Goedeheop	12	1962	0.2460	13	1963	0.0735
Elim Hosp	31	1979	0.6360	34	1982	0.2190

Figure 4-77 to Figure 4-84 present the output from the SPI software indicating when the wet or dry periods occurred by using historic data. To further investigate the cause of changes trends and to present the changes occurring in rainfall patterns or trends, the three months SPI was analysed. A 3-month SPI shows short- and medium-term moisture conditions, offering a seasonal estimate of precipitation. The wet period or season in the record was identified in the years 1999/2000, 1984/85, 1987/88, 1980/81 and 2008/2009. The

years 1964/65, 1973/74, 1997/98 and 2015/16 were identified as the dry periods. The wet periods identified are in agreement with the results from the homogeneity test, where before or after an event, a change or breakpoint is identified. A study done by Mazibuko (2020) indicated that 1982/83, 1991/92, 1997/98 and 2015/16 were identified as the driest El Niño seasons while the wetter seasons were recorded in 1988/89, 1998/99, 1999/00, 2007/08 and 2010/11, furthermore the study concluded that the ENSO phenomenon is associated with rainfall variability in the LRC. The years recorded as La Niña seasons and El Niño seasons were also identified in the current study. The graphs below indicate the SPI values for each station. The wet and dry seasons classified show wet and dry seasons in different years; this indicate that there is spatial variability.

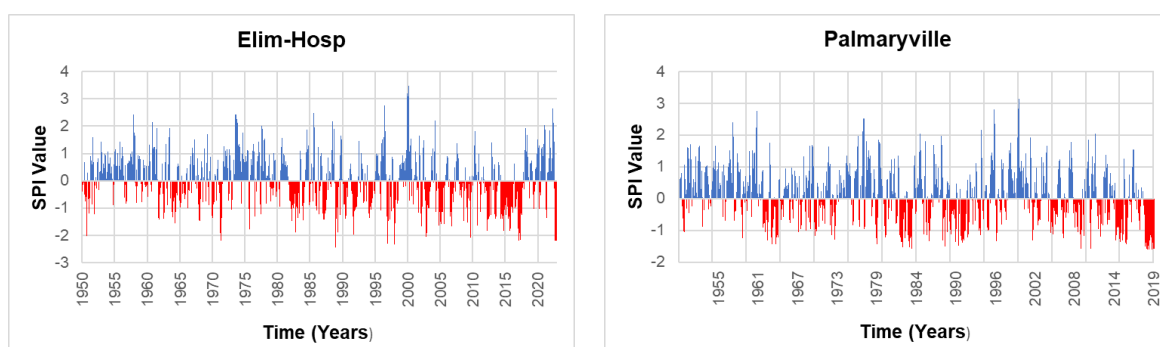


Figure 4-77: Historical SPI Results for Elim-Hosp and Palmaryville

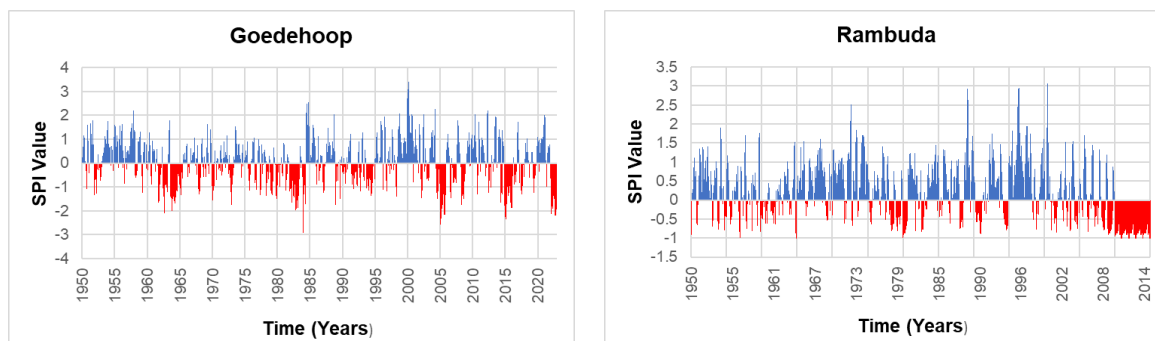


Figure 4-78: Historical SPI Results for Goedeheop and Rambuda

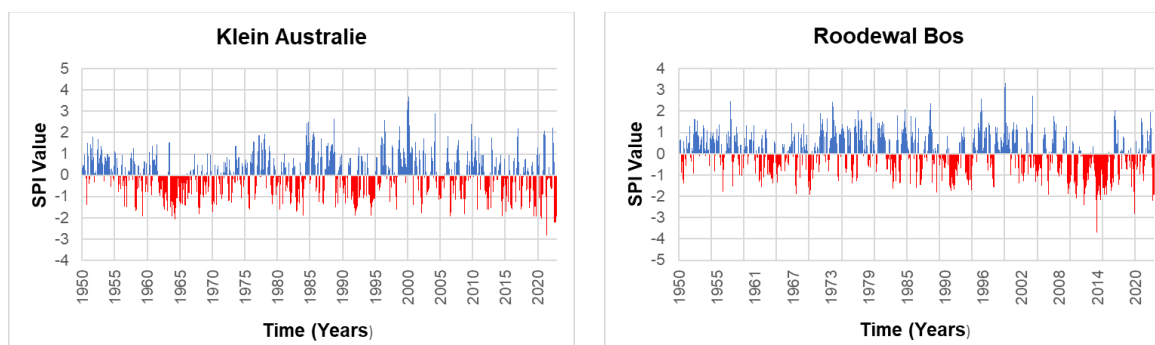


Figure 4-79: Historical SPI Results for Klein Australie and Roodewal-Bos

]

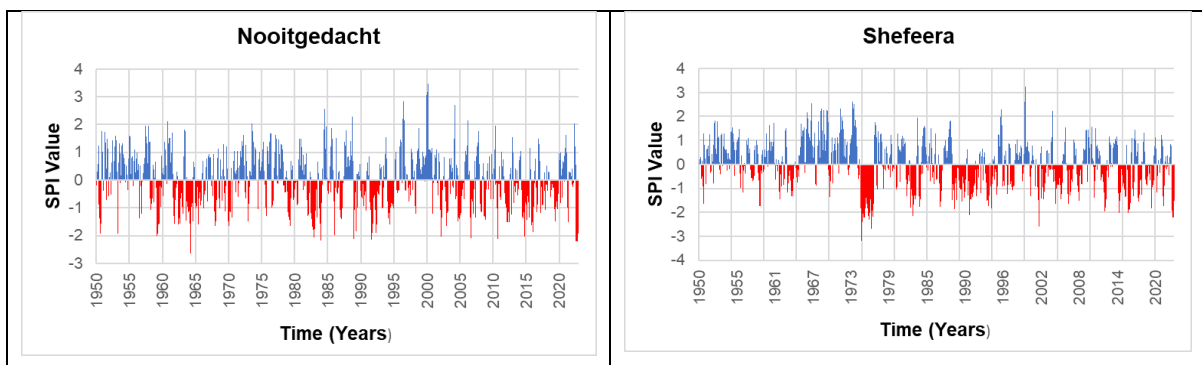


Figure 4-80: Historical SPI Results for Noitgedacht and Shefeera

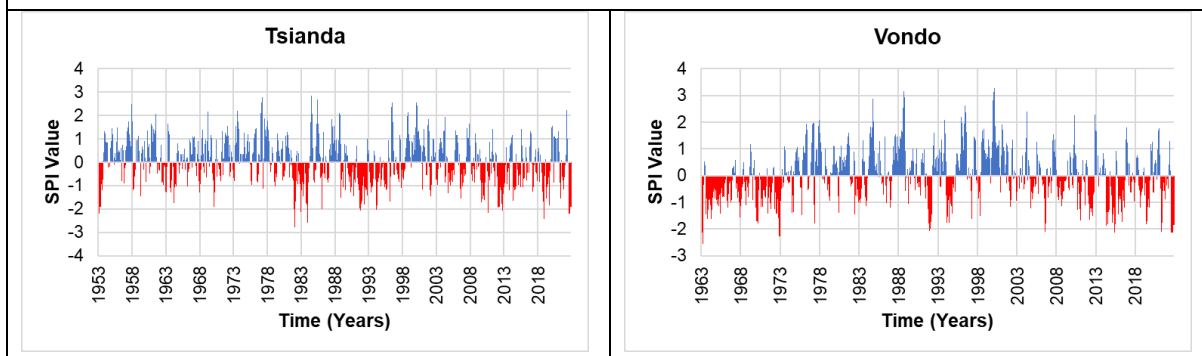


Figure 4-81: Historical SPI Results for Tsianda and Vondo

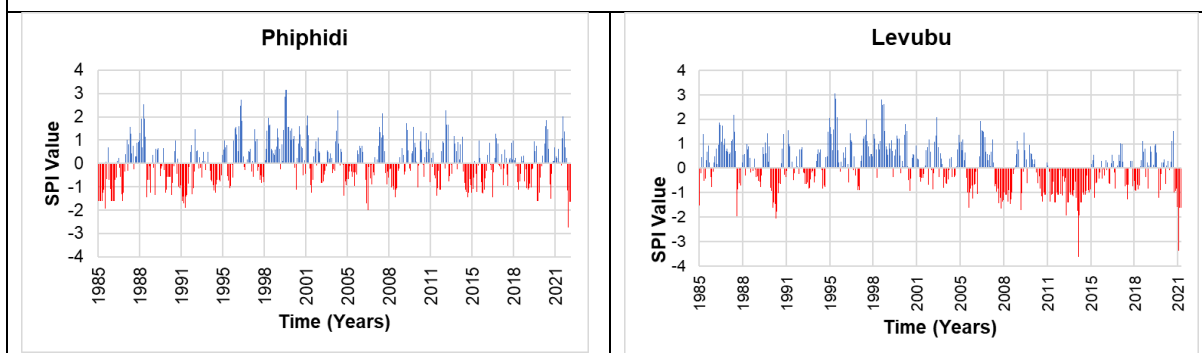


Figure 4-82: Historical SPI Results for Phiphidi and Levubu

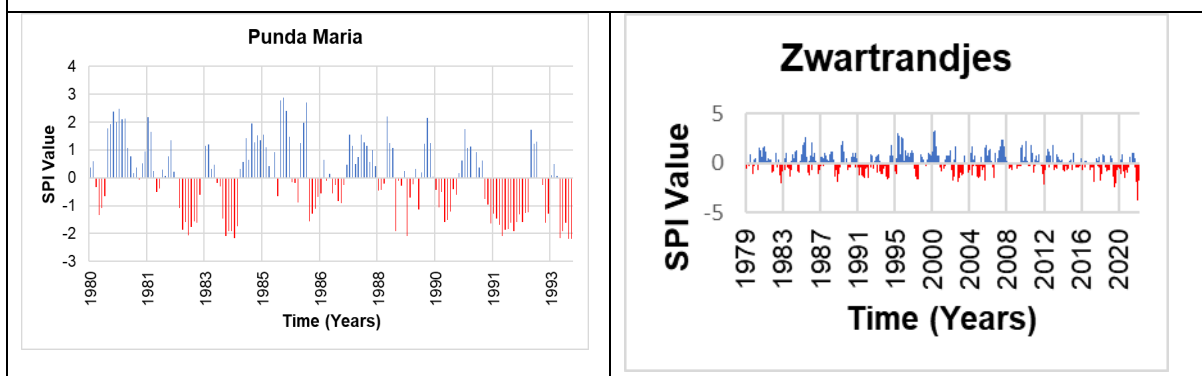


Figure 4-83: Historical SPI Results for Punda Maria and Zwartrandjes

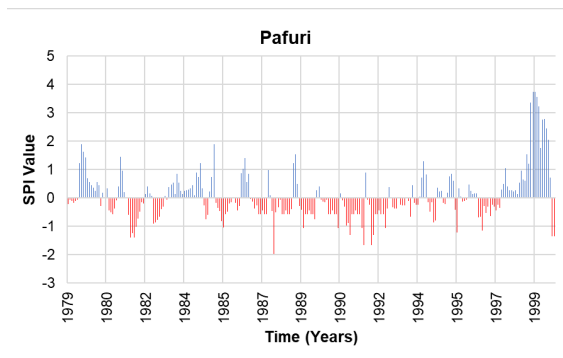


Figure 4-84: Historical SPI Results for Pafuri

Figure 4-85 show future wet and dry period that are likely to occur in the LRC In the future, in stations 01 and 02, wet periods are observed in 2046/47, 2036/37 and 2075/76, whereas in station three, they are in 2038/39 and 2076/77. 2043 and 2073 indicate dry periods in the catchment. The decrease in future rainfall will have negative implications on agriculture and water supply and it will also result in a shift in rainfall seasons.

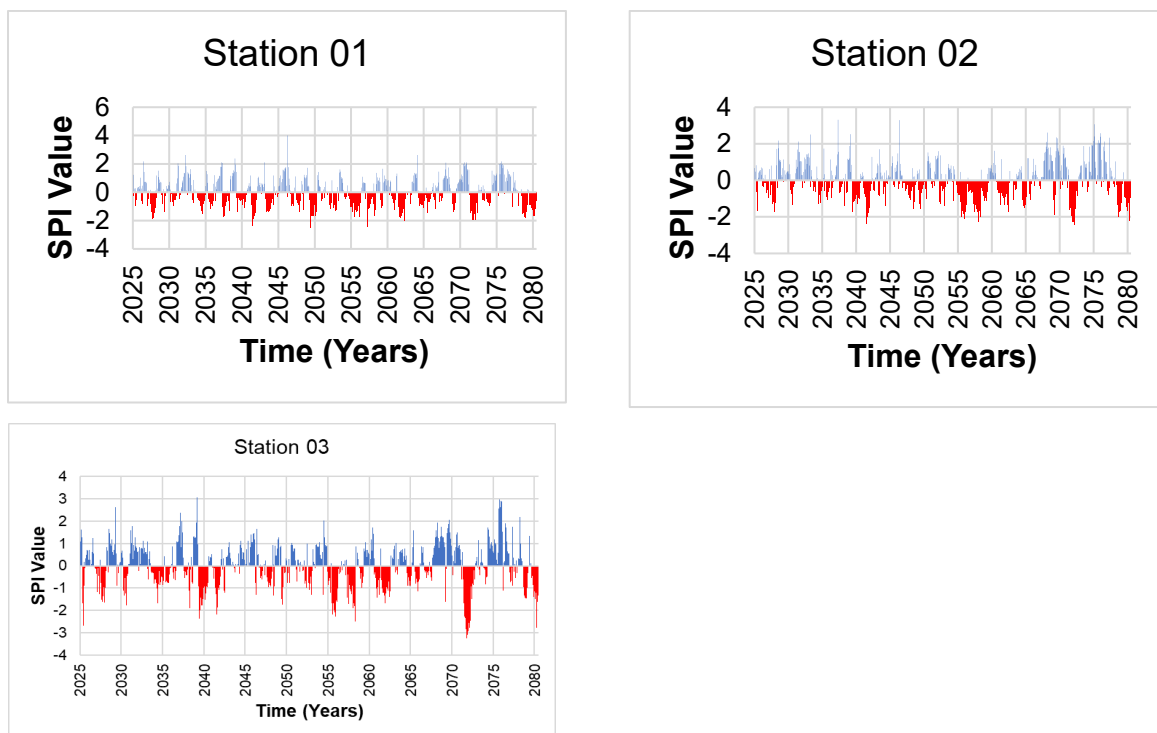


Figure 4-85: Future SPI Results for Station 01, 02 and 03

5 CHAPTER 5: CONCLUSIONS AND RECOMMENDATION

5.1 CONCLUSIONS

The primary objective of the study was to determine the spatial variation of historical and future seasonal rainfall trends in the Luvuvhu River Catchment. This objective was achieved through three specific objectives. The first specific objective was to determine both historical and future seasonal trends. Historical trends were analysed using past rainfall data while, future trends were analysed using future data from CMIP6 dataset. To identify these trends, graphical methods, the ITA (Innovative Trend Analysis) and ARIMA (Autoregressive Integrated Moving Average) techniques were employed. The methods provided insight into both linear and non-linear rainfall patterns. The analysis revealed that both increasing and decreasing rainfall trends were observed across different stations and seasons., with decreasing trends being prevalent during the summer season, as well as in all the other seasons, for both historical and future rainfall data.

To determine the spatial variation of historical and future rainfall trends, methods such as the mean, standard deviation, variation, and kriging for both historical and projected rainfall data were employed. The results indicate significant spatial variation in the trends. . Rainfall levels fluctuate from the upper reaches of the catchment to the lower reaches, with higher rainfall observed in the upper regions. The spatial heterogeneity in the catchment may indicate that rainfall variability is strongly influenced by the topography. There is very low rainfall during the winter months, while the summer months experience more considerable precipitation.

The causes of rainfall trends were investigated. The SNHT and Pettit methods were used to determine when the changes occur. The breaks or changes occurred in the years 1962, 1975, 1979, 1982, 1986, 1987, 1996, 2005, 2008 and 2012. The results of the two methods compare fairly well. The SPI was used to identify the potential causes and implications of the observed trends particularly for wet and dry spells. The changes were shown in the following years 1962, 1975, 1979, 1985, 1986 respectively. The causes of changes were indicated by breaks periods of flooding and periods of drought in the data that occurred in the following years, 1975, 2000, and 1990. The year 2000 summer season was seen to be extremely wet. For future results changes were seen in 2046, 2036, 2038, 2076, 2077 for extremely wet seasons and 2043 and 2073 for dry periods.

Overall, the results from this study indicate that there are dominantly decreasing historical and future trends in the LRC, with the frequency of wet and dry periods. The events were seen in

the historical and future trends. This indicates that there is a risk of drought and flooding in the LRC, which can affect the availability of water. Furthermore, this also indicates spatial climatic variability in the LRC, which could lead to major implications on the water resources and agricultural sector, resulting in a food security threat. The spatially differentiated rainfall trends and the future changes revealed in the study necessitate a need for climate adaptation strategies that are localized.

5.2 RECOMMENDATIONS

Data analysis in the lower reaches of the catchment was challenging and compromised. This is due to the fact that there are only a few rainfall gauging stations located in that part of the catchment and the data available is not sufficient.

The following are recommended:

- where possible rainfall gauges be installed in the lower reaches of the catchment to monitor and record rainfall.
- trend analysis and forecasting for the catchment using satellite data in order to compare the results of the current study and other studies that have been done in the catchment.
- the results of this study indicate that there is a dominant decreasing trend in the catchment; it is therefore recommended that a plan be developed for efficient and sustainable water use in the catchment.
- the results of the trend analysis are likely to be biased due to the time periods and breaks used for historic and future rainfall data records further future investigations are recommended

REFERENCES

- Abdi, H. 2010. Coefficient of variation. *Encyclopedia of research design*, 1, 169-171. <https://doi.org/10.1371/journal.pone.0212008>
- Abiy, A. Z., Melesse, A. M., Abtew, W. & Whitman, D. 2019. Rainfall trend and variability in Southeast Florida: Implications for freshwater availability in the Everglades. *PLoS One*, 14, e0212008. <https://doi.org/10.1371/journal.pone.0212008>
- Achite, M., Caloiero, T., Wałęga, A., Krakauer, N. & Hartani, T. 2021. Analysis of the spatiotemporal annual rainfall variability in the Wadi Cheliff Basin (Algeria) over the period 1970 to 2018. *Water*, 13, 1477. <https://doi.org/10.3390/w13111477>
- Affairs, D. O. W. 2012. Development of a Reconciliation Strategy for the Luvuvhu And Letaba Water Supply System: Literature Review Report. In: Affairs, D. O. W. (ed.). Pretoria: Department of Water Affairs
- Alahacoon, N., Edirisinghe, M., Simwanda, M., Perera, E., Nyirenda, V. R. & Ranagalage, M. 2021. Rainfall variability and trends over the African continent using TAMSAT data (1983–2020): Towards climate change resilience and adaptation. *Remote Sensing*, 14, 96.. <https://doi.org/10.3390/rs14010096>
- Alashan, S. 2018. Data analysis in nonstationary state. *Water Resources Management*, 32, 2277-2286. <https://doi.org/10.1007/s11269-018-1928-2>
- Alemayehu, A., Maru, M., Bewket, W. & Assen, M. 2020. Spatiotemporal variability and trends in rainfall and temperature in Alwero watershed, western Ethiopia. *Environmental Systems Research*, 9, 1-15. <https://doi.org/10.1186/s40068-020-00184-3>
- Ali, S. 2013. Time series analysis of Baghdad rainfall using ARIMA method. *Iraqi Journal of Science*, 54, 1136-1142
- Almazroui, M. & Şen, Z. 2020. Trend analyses methodologies in hydro-meteorological records. *Earth Systems and Environment*, 4, 713-738. <https://doi.org/10.1007/s41748-020-00190-6>

- Amoo, O. T. & Dzwauro, B. 2016. Trend analysis and artificial neural networks forecasting for rainfall prediction. *Environmental economics*, 149-160
- Anand, B. & Karunanidhi, D. 2020. Long term spatial and temporal rainfall trend analysis using GIS and statistical methods in Lower Bhavani basin, Tamil Nadu, India.
- Aslam, M. 2023. Time series data analysis under indeterminacy. *Journal of Big Data*, 10, 126. <https://doi.org/10.1186/s40537-023-00806-4>
- Banda, V. D., Dzwauro, R. B., Singh, S. K. & Kanyerere, T. 2021. Trend analysis of selected hydro-meteorological variables for the Rietspruit sub-basin, South Africa. *Journal of Water and Climate Change*, 12, 3099-3123. <https://doi.org/10.2166/wcc.2021.260>
- Banze, F., Guo, J. & Xiaotao, S. 2018. Variability and trends of rainfall, precipitation and discharges over zambezi river basin, southern africa: review. *International Journal of Hydrology*, 2, 132-135. DOI: 10.15406/ijh.2018.02.00062
- Bekele, D., Alamirew, T., Kebede, A., Zeleke, G. & Melese, A. M. 2017. Analysis of rainfall trend and variability for agricultural water management in Awash River Basin, Ethiopia. *Journal of Water and Climate Change*, 8, 127-141. <https://doi.org/10.2166/wcc.2016.044>
- Bojago, E. 2024. Spatio-temporal rainfall variability and trends using a Kriging-interpolation and Innovative trend analysis approach: the case of Wolaita zone, south Ethiopia. *Discover Sustainability*, 5, 495. <https://doi.org/10.1007/s43621-024-00685-6>
- Borse, K. & Agnihotri, P. G. 2017. Study of rainfall trend analysis of upper Godavari basin: a case study. *Hydro-2017 International April*, 2018, 149-159
- Botai, C. M., Botai, J. O. & Adeola, A. M. 2018. Spatial distribution of temporal precipitation contrasts in South Africa. *South African Journal of Science*, 114, 70-78. <https://doi.org/10.17159/sajs.2018/20170391>
- Botai, C. M., Botai, J. O., Mukhawana, M. B., De Wit, J., Masilela, N. S., Zwane, N. & Tazvinga, H. 2025. Evaluation of Rainfall Distribution Based on the Precipitation Concentration Index: A Case Study over the Selected Summer Rainfall Regions of South Africa. *Hydrology*, 12, 136. <https://doi.org/10.3390/hydrology12060136>

- Bouklikha, A., Habi, M., Elouissi, A. & Hamoudi, S. 2021. Annual, seasonal and monthly rainfall trend analysis in the Tafna watershed, Algeria. *Applied Water Science*, 11, 1-21. <https://doi.org/10.1007/s13201-021-01404-6>
- Box, G. E., Jenkins, G. M., Reinsel, G. C. & Ljung, G. M. 2015. *Time series analysis: forecasting and control*, John Wiley & Sons.
- Brook, G. & Mametse, M. 1970. Rainfall trend patterns in South Africa. *South African Geographical Journal*, 52, 134-138
- Buytaert, W., Celleri, R., Willems, P., De Bievre, B. & Wyseure, G. 2006. Spatial and temporal rainfall variability in mountainous areas: A case study from the south Ecuadorian Andes. *Journal of hydrology*, 329, 413-421. <https://doi.org/10.1016/j.jhydrol.2006.02.031>
- Ceribasi, G., Dogan, E., Akkaya, U. & Kocamaz, U. 2017. Application of trend analysis and artificial neural networks methods: The case of Sakarya River. *Scientia Iranica*, 24, 993-999. [10.24200/sci.2017.4082](https://doi.org/10.24200/sci.2017.4082)
- Chabalala, D. T., Ndambuki, J. M., Salim, R. W. & Rwanga, S. S. Impact of climate change on the rainfall pattern of Klip River catchment in Ladysmith, KwaZulu Natal, South Africa. IOP Conference Series: Materials Science and Engineering, 2019. IOP Publishing, 012088.
- Change, I. P. O. C. 2001. Climate change 2007: Impacts, adaptation and vulnerability. *Genebra, Suíça*,
- Chanzi, G., Bushesha, M., Munishi, S. & Karia, A. 2023. Application of Mann Kendal Sen's Slope Estimator in Trend Analysis of Historical And Future Precipitation and Temperature in the Kilombero River Basin. *Huria: Journal of the Open University of Tanzania*, 30, 127-150
- Coursera. 2024. *What Is Exploratory Data Analysis?* [Online]. <https://www.coursera.org>: Coursera. Available: <https://www.coursera.org/articles/exploratory-data-analysis> [Accessed 2024].
- Dagada, K. 2017. *Influence of climate change on flood and drought cycles and implications on rainy season characteristics in Luvuvhu River Catchment*.

- Du Plessis, J. & Kibii, J. 2021. Applicability of CHIRPS-based satellite rainfall estimates for South Africa. *Journal of the South African Institution of Civil Engineering*, 63, 43-54. <https://doi.org/10.17159/2309-8775/2021/v63n3a4>
- Elouissi, A., Şen, Z. & Habi, M. 2016. Algerian rainfall innovative trend analysis and its implications to Macta watershed. *Arabian Journal of Geosciences*, 9, 1-12. <https://doi.org/10.1007/s12517-016-2325-x>
- Esri. *Kriging* [Online]. Available: <http://webhelp.esri.com> [Accessed 2023].
- Forestry, D. O. W. a. A. 2004. Luvuvhu/Letaba 558 Water Management Area: Internal Strategic Perspective. . *Luvuvhu/Letaba 558 Water Management Area: Internal Strategic Perspective*. Pretoria: Department of Water and Sanitation
- Foroumandi, E., Nourani, V. & Sharghi, E. 2021. Climate change or regional human impacts? Remote sensing tools, artificial neural networks, and wavelet approaches aim to solve the problem. *Hydrology Research*, 52, 176-195. <https://doi.org/10.2166/nh.2020.112>
- Gocic, M. & Trajkovic, S. 2013. Analysis of changes in meteorological variables using Mann-Kendall and Sen's slope estimator statistical tests in Serbia. *Global and planetary change*, 100, 172-182. <https://doi.org/10.1016/j.gloplacha.2012.10.014>
- Gyamfi, C., Ndambuki, J. & Salim, R. 2016. A historical analysis of rainfall trend in the Olifants Basin in South Africa. *Earth Sci. Res*, 5, 129-142. doi:10.5539/esr.v5n1p129
- Harka, A. E., Jilo, N. B. & Behulu, F. 2021. Spatial-temporal rainfall trend and variability assessment in the Upper Wabe Shebelle River Basin, Ethiopia: Application of innovative trend analysis method. *Journal of Hydrology: Regional Studies*, 37, 100915. <https://doi.org/10.1016/j.ejrh.2021.100915>
- Health, P. *Kriging Interpolation* [Online]. Available: <https://www.publichealth.columbia.edu/research/population-health-methods/kriging-interpolation> [Accessed 2023].
- Hussain, F., Nabi, G. & Boota, M. W. 2015. Rainfall Trend Analysis by using the Mann-Kendal test & Sen's slope estimates: A case study of District Chakwal rain gauge, Barani area, Northern Punjab Province, PAKISTAN. *Science International*, 27

- Hyndman, R. J. & Athanasopoulos, G. 2018. *Forecasting: principles and practice*, OTexts.
- James, G., Witten, D., Hastie, T., Tibshirani, R. & Taylor, J. 2023. *Linear regression. An introduction to statistical learning: With applications in python*. Springer.
- Javari, M. 2017. Spatial variability of rainfall trends in Iran. *Arabian Journal of Geosciences*, 10, 78. <https://doi.org/10.1007/s12517-017-2857-8>
- Joshi, J., Upadhye, S. & More, D. 2019. Long Term Rainfall Trend Analysis of Different Time Series in Solapur District of Maharashtra, India. *Int. J. Curr. Microbiol. App. Sci*, 8, 2359-2367. <https://doi.org/10.20546/ijcmas.2019.812.278>
- Kang, H. M. & Yusof, F. 2012. Homogeneity tests on daily rainfall series. *Int. J. Contemp. Math. Sciences*, 7, 9-22
- Kaptué, A. T., Hanan, N. P., Prihodko, L. & Ramirez, J. A. 2015. Spatial and temporal characteristics of rainfall in a frica: S ummary statistics for temporal downscaling. *Water Resources Research*, 51, 2668-2679. <https://doi.org/10.1002/2014WR015918>
- Katz, R. W. & Glantz, M. H. 1986. Anatomy of a rainfall index. *Monthly Weather Review*, 114, 764-771. [https://doi.org/10.1175/1520-0493\(1986\)114<0764:AOARI>2.0.CO;2](https://doi.org/10.1175/1520-0493(1986)114<0764:AOARI>2.0.CO;2)
- Kendall, M. G. 1948. Rank correlation methods.
- Kowalskie, A. 2025. The Impact of Outliers on Linear Regression Models: Detection and Correction Strategies. *OTS Canadian Journal*, 4, 108-118. <https://doi.org/10.58840/fzbcv732>
- Kraus, E. 1977. Subtropical droughts and cross-equatorial energy transports. *Monthly weather review*, 105, 1009-1018. [https://doi.org/10.1175/1520-0493\(1977\)105<1009:SDACEE>2.0.CO;2](https://doi.org/10.1175/1520-0493(1977)105<1009:SDACEE>2.0.CO;2)
- Kruger, A. 1999. The influence of the decadal-scale variability of summer rainfall on the impact of El Niño and La Niña events in South Africa. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 19, 59-68. [https://doi.org/10.1002/\(SICI\)1097-0088\(199901\)19:1<59::AID-JOC347>3.0.CO;2-B](https://doi.org/10.1002/(SICI)1097-0088(199901)19:1<59::AID-JOC347>3.0.CO;2-B)
- Kruger, A. 2004. *Climate of South Africa: climate regions*, South African Weather Service.

- Kruger, A. & Nxumalo, M. 2017. Historical rainfall trends in South Africa: 1921–2015. *Water Sa*, 43, 285-297
- Kumar, A., Sankalp, S. & Remesan, R. 2023. Spatiotemporal rainfall variability and trend analysis over all the districts of West Bengal during 1980–2021. *Developments in Environmental Science*, 14, 1-15.<https://doi.org/10.1016/B978-0-443-18640-0.00004-3>
- Lal, A. W., Wang, N., Moustafa, M. & Brown, M. 2010. Mass residuals in implicit finite volume models for overland and groundwater flow. *Journal of Hydrology*, 384, 26-32.<https://doi.org/10.1016/j.jhydrol.2010.01.003>
- Lee, D. K., In, J. & Lee, S. 2015. Standard deviation and standard error of the mean. *Korean journal of anesthesiology*, 68, 220-223.<https://doi.org/10.4097/kjae.2015.68.3.220>
- Li, X., Jiang, F., Li, L. & Wang, G. 2011. Spatial and temporal variability of precipitation concentration index, concentration degree and concentration period in Xinjiang, China. *International Journal of Climatology*, 31, 1679-1693.DOI: 10.1002/joc.2181
- Li, Z., Wang, K., Ma, H. & Wu, Y. An adjusted inverse distance weighted spatial interpolation method. 2018 3rd International Conference on Communications, Information Management and Network Security (CIMNS 2018), 2018. Atlantis Press, 128-132.
- Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P. & Naylor, R. L. 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science*, 319, 607-610
- Mahsin, M., Akhter, Y. & Begum, M. 2012. Modeling rainfall in Dhaka division of Bangladesh using time series analysis. *Journal of mathematical modelling and application*, 1, 67-73
- Maleika, W. 2020. Inverse distance weighting method optimization in the process of digital terrain model creation based on data collected from a multibeam echosounder. *Applied Geomatics*, 12, 397-407.<https://doi.org/10.1007/s12518-020-00307-6>
- Manikandan, S. 2011. Measures of central tendency: The mean. *Journal of pharmacology & pharmacotherapeutics*, 2, 140.10.4103/0976-500X.81920

- Marumbwa, F. M., Cho, M. A. & Chirwa, P. W. 2021. Geospatial analysis of meteorological drought impact on Southern Africa biomes. *International Journal of Remote Sensing*, 42, 2155-2173. <https://doi.org/10.1080/01431161.2020.1851799>
- Mashinye, M. D. 2018. *Long term seasonal and annual changes in rainfall duration and magnitude in Luvuvhu River Catchment, South Africa.*
- Mathivha, F., Nkosi, M. & Mutoti, M. 2021. Evaluating the relationship between hydrological extremes and groundwater in Luvuvhu River Catchment, South Africa. *Journal of Hydrology: Regional Studies*, 37, 100897. <https://doi.org/10.1016/j.ejrh.2021.100897>
- Mazibuko, S., Mukwada, G. & Moeletsi, M. 2021. Assessing the frequency of drought/flood severity in the Luvuvhu River catchment, Limpopo Province, South Africa. *Water SA*, 47, 172-184
- Mckee, T. B., Doesken, N. J. & Kleist, J. The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology, 1993. California, 179-183.
- Mekonen, A. A. & Berlie, A. B. 2020. Spatiotemporal variability and trends of rainfall and temperature in the Northeastern Highlands of Ethiopia. *Modeling Earth Systems and Environment*, 6, 285-300. <https://doi.org/10.1007/s40808-019-00678-9>
- Merabtene, T., Siddique, M. & Shanableh, A. 2016. Assessment of seasonal and annual rainfall trends and variability in Sharjah City, UAE. *Advances in Meteorology*, 2016, 6206238. <https://doi.org/10.1155/2016/6206238>
- Mohorji, A. M., Şen, Z. & Almazroui, M. 2017. Trend analyses revision and global monthly temperature innovative multi-duration analysis. *Earth Systems and Environment*, 1, 1-13. <https://doi.org/10.1007/s41748-017-0014-x>
- Morishima, W. & Akasaka, I. 2010. Seasonal trends of rainfall and surface temperature over southern Africa. *African Study Monographs. Supplementary Issue.*, 40, 67-76. <https://doi.org/10.14989/96297>
- Mugiyo, H., Magadzire, T., Choruma, D. J., Chimonyo, V. G. P., Manzou, R., Jiri, O. & Mabhaudhi, T. 2023. El niño's effects on southern african agriculture in 2023/24 and

- anticipatory action strategies to reduce the impacts in zimbabwe. *Atmosphere*, 14, 1692. <https://doi.org/10.3390/atmos14111692>
- Mzava, P., Valimba, P. & Nobert, J. 2020. Characterizing past and future trend and frequency of extreme rainfall in urban catchments: a case study. *h2oj*, 3, 288-305. <https://doi.org/10.2166/h2oj.2020.009>
- Nenwiini, S. & Kabanda, T. A. 2013. Trends and variability assessment of rainfall in Vhembe South Africa.
- Nkuna, T. & Odiyo, J. O. 2011. Filling of missing rainfall data in Luvuvhu River Catchment using artificial neural networks. *Physics and Chemistry of the Earth, Parts A/B/C*, 36, 830-835
- Nyatuame, M. & Agodzo, S. K. 2018. Stochastic ARIMA model for annual rainfall and maximum temperature forecasting over Tordzie watershed in Ghana. *Journal of water and land development*. DOI: 10.2478/jwld-2018-0032.
- Nyatuame, M., Owusu-Gyimah, V. & Ampiaaw, F. 2014. Statistical analysis of rainfall trend for Volta region in Ghana. *International Journal of Atmospheric Sciences*, 2014, 203245. <https://doi.org/10.1155/2014/203245>.
- Odiyo, J., Makungo, R., Nkuna, T. & Chikoore, H. 2020. Hydrological Modelling of Climate Change Impacts for Development of Adaptation Strategies: the Case of Luvuvhu River Catchment, Limpopo, South Africa. *Water Research Commission, Pretoria, South Africa*,
- Odiyo, J. O., Makungo, R. & Nkuna, T. R. 2015. Long-term changes and variability in rainfall and streamflow in Luvuvhu River Catchment, South Africa. *South African Journal of Science*, 111, 1-9. <https://dx.doi.org/10.17159/SAIS2015/20140169>.
- Oliver, J. E. 1980. Monthly precipitation distribution: a comparative index. *The Professional Geographer*, 32, 300-309. <https://doi.org/10.1111/j.0033-0124.1980.00300.x>
- Pal, A. B., Khare, D., Mishra, P. K. & Singh, L. 2017. Trend analysis of rainfall, temperature and runoff data: a case study of Rangoon watershed in Nepal. *Int. J. Stud. Res. Technol. Manag*, 5, 21-38

- Panda, A. & Sahu, N. 2019. Trend analysis of seasonal rainfall and temperature pattern in Kalahandi, Bolangir and Koraput districts of Odisha, India. *Atmospheric Science Letters*, 20, e932. <https://doi.org/10.1002/asl.932>
- Patle, G. & Libang, A. 2014. Trend analysis of annual and seasonal rainfall to climate variability in North-East region of India. *Journal of Applied and Natural Science*, 6, 480
- Pazvakawambwa, G. T. 2017. A time-series forecasting model for Windhoek Rainfall, Namibia.
- Petković, D., Gocic, M., Trajkovic, S., Milovančević, M. & Šević, D. 2017. Precipitation concentration index management by adaptive neuro-fuzzy methodology. *Climatic Change*, 141, 655-669. <https://doi.org/10.1007/s10584-017-1907-2>
- Pettitt, A. 1979. Testing for bivariate normality using the empirical distribution function. *Communications in Statistics-Theory and Methods*, 8, 699-712. <https://doi.org/10.1080/03610927908827793>
- Praveen, B., Talukdar, S., Shahfahad, Mahato, S., Mondal, J., Sharma, P., Islam, A. R. M. T. & Rahman, A. 2020. Analyzing trend and forecasting of rainfall changes in India using non-parametrical and machine learning approaches. *Scientific reports*, 10, 10342
- Rao, B. M., Mani, A., Devi, B. S., Vishnuvardhan, S. & Rao, C. S. 2023. Innovative Trend Analysis (ITA) of Rainfall for Kadiri Watershed Area.
- Rathnayake, U. 2019. Comparison of statistical methods to graphical methods in rainfall trend analysis: case studies from tropical catchments. *Advances in Meteorology*, 2019, 8603586. <https://doi.org/10.1155/2019/8603586>
- Report, S. O. R. 2001. South African River Health Programme Letaba and 741 Luvuvhu River Systems. . In: Report., S. O. R. (ed.). Pretoria: Water Research Commission
- Roffe, S. J., Fitchett, J. M. & Curtis, C. J. 2021. Investigating changes in rainfall seasonality across South Africa: 1987–2016. *International Journal of Climatology*, 41, E2031-E2050. <https://doi.org/10.1002/joc.6830>

- Sanjeevaiah, S. H., Rudrappa, K. S., Lakshminarasappa, M. T., Huggi, L., Hanumanthaiah, M. M., Venkatappa, S. D., Lingegowda, N. & Sreeman, S. M. 2021. Understanding the temporal variability of rainfall for estimating agro-climatic onset of cropping season over south interior Karnataka, India. *Agronomy*, 11, 1135. <https://doi.org/10.3390/agronomy11061135>
- Schulze, R., Schütte, S., Gwena, K. & Nxumalo, N. 2023. A National Assessment of Potential Climate Change Impacts on the Hydrological Yield of Different Hydro-Climatic Zones of South Africa. WRC Report
- Seenu, P. & Jayakumar, K. 2021. Comparative study of innovative trend analysis technique with Mann-Kendall tests for extreme rainfall. *Arab J Geosci* 14 (7). <https://doi.org/10.1007/s12517-021-06906-w>
- Segele, Z. T. & Lamb, P. J. 2005. Characterization and variability of Kiremt rainy season over Ethiopia. *Meteorology and Atmospheric Physics*, 89, 153-180. <https://doi.org/10.1007/s00703-005-0127-x>
- Sen, P. K. 1968. Estimates of the regression coefficient based on Kendall's tau. *Journal of the American statistical association*, 63, 1379-1389
- Şen, Z. 2012. Innovative trend analysis methodology. *Journal of Hydrologic Engineering*, 17, 1042-1046. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0000556](https://doi.org/10.1061/(ASCE)HE.1943-5584.0000556)
- Şen, Z. 2014. Trend identification simulation and application. *Journal of Hydrologic Engineering*, 19, 635-642. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.000081](https://doi.org/10.1061/(ASCE)HE.1943-5584.000081)
- Sharma, S. & Singh, P. K. 2019. Spatial trends in rainfall seasonality: a case study in Jharkhand, India. *Weather*, 74, 31-39. <https://doi.org/10.1002/wea.3231>
- Shikwambana, L., Kganyago, M. & Mhangara, P. 2021. Temporal analysis of changes in anthropogenic emissions and urban heat islands during COVID-19 restrictions in Gauteng province, South Africa. *Aerosol and Air Quality Research*, 21, 200437. DOI <https://doi.org/10.4209/aaqr.200437>
- Shongwe, M. E., Van Oldenborgh, G., Van Den Hurk, B., De Boer, B., Coelho, C. & Van Aalst, M. 2009. Projected changes in mean and extreme precipitation in Africa under

- global warming. Part I: Southern Africa. *Journal of climate*, 22, 3819-3837. <https://doi.org/10.1175/2009JCLI2317.1>
- Singh, R., Sah, S., Das, B., Potekar, S., Chaudhary, A. & Pathak, H. 2021. Innovative trend analysis of spatio-temporal variations of rainfall in India during 1901–2019. *Theoretical and Applied Climatology*, 145, 821-838. <https://doi.org/10.1007/s00704-021-03657-2>
- Singo, L. R., Kundu, P. M. & Odiyo, J. O. 2018. Application of GIS and Remote Sensing techniques to evaluate the impact of land cover and land use changes on the hydrology and water resources of Luvuvhu River Catchment in Limpopo Province, South Africa.
- Teegavarapu, R. S. & Chandramouli, V. 2005. Improved weighting methods, deterministic and stochastic data-driven models for estimation of missing precipitation records. *Journal of hydrology*, 312, 191-206. <https://doi.org/10.1016/j.jhydrol.2005.02.015>
- Tolosa, A. & Tolossa, T. 2021. Recent and Future Trend Analysis of Inter-Seasonal to Seasonal Rainfall and Temperature to Climate Change and Variability in Dire Dawa city Administration, Ethiopia. *Environ Pollut Climate Change*, 5, 1-20
- Touseef, M., Chen, L., Yang, K. & Chen, Y. 2020. Long-Term Rainfall Trends and Future Projections over Xijiang River Basin, China. *Advances in Meteorology*, 2020, 1-18. [10.1155/2020/6852148](https://doi.org/10.1155/2020/6852148)
- Tshililo, F. P., Savage, M. J. & Moeletsi, M. E. 2021. Rainy season characteristics for the Luvuvhu River catchment, South Africa. *Water SA*, 47, 480–487
- Twumasi, Y. A., Annan, J. B., Merem, E. C., Namwamba, J. B., Ayala-Silva, T., Ning, Z. H., Asare-Ansah, A. B., Oppong, J., Frimpong, D. B. & Loh, P. M. 2021. Time series analysis on selected rainfall stations data in Louisiana using ARIMA approach. *Open Journal of Statistics*, 11, 655-672. [10.4236/ojs.2021.115039](https://doi.org/10.4236/ojs.2021.115039)
- Visser, H., Dangendorf, S. & Petersen, A. C. 2015. A review of trend models applied to sea level data with reference to the “acceleration-deceleration debate”. *Journal of Geophysical Research: Oceans*, 120, 3873-3895. <https://doi.org/10.1002/2015JC010716>

- Wagesho, N., Goel, N. K. & Jain, M. K. 2013. Temporal and spatial variability of annual and seasonal rainfall over Ethiopia. *Hydrological Sciences Journal*, 58, 354-373. <https://doi.org/10.1080/02626667.2012.754543>
- Wang, Y., Xu, Y., Tabari, H., Wang, J., Wang, Q., Song, S. & Hu, Z. 2020. Innovative trend analysis of annual and seasonal rainfall in the Yangtze River Delta, eastern China. *Atmospheric Research*, 231, 104673. <https://doi.org/10.1016/j.atmosres.2019.104673>
- Watson, D. F. 1985. A refinement of inverse distance weighted interpolation. *Geoprocessing*, 2, 315-327
- Webber, J. & Hawkins, C. 1980. Statistical analysis application to business and economics. Harper and Row, New York
- Wu, H. & Qian, H. 2017. Innovative trend analysis of annual and seasonal rainfall and extreme values in Shaanxi, China, since the 1950s. *International Journal of Climatology*, 37, 2582-2592
- Yadav, R., Tripathi, S., Pranuthi, G. & Dubey, S. 2014. Trend analysis by Mann-Kendall test for precipitation and temperature for thirteen districts of Uttarakhand. *Journal of Agrometeorology*, 16, 164-171
- Yang, H., Xiao, H., Guo, C., Sun, Y. & Gao, R. 2020. Innovative trend analysis of annual and seasonal precipitation in Ningxia, China. *Atmospheric and Oceanic Science Letters*, 13, 308-315. <https://doi.org/10.1080/16742834.2020.1752616>