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SCHOOL OF ENVIRONMENTAL SCIENCES

DEPARTMENT OF HYDROLOGY AND WATER RESOURCES

LONG TERM SEASONAL AND ANNUAL CHANGES IN RAINFALL DURATION AND MAGNITUDE IN LUVUVHU RIVER CATCHMENT, SOUTH AFRICA

BY

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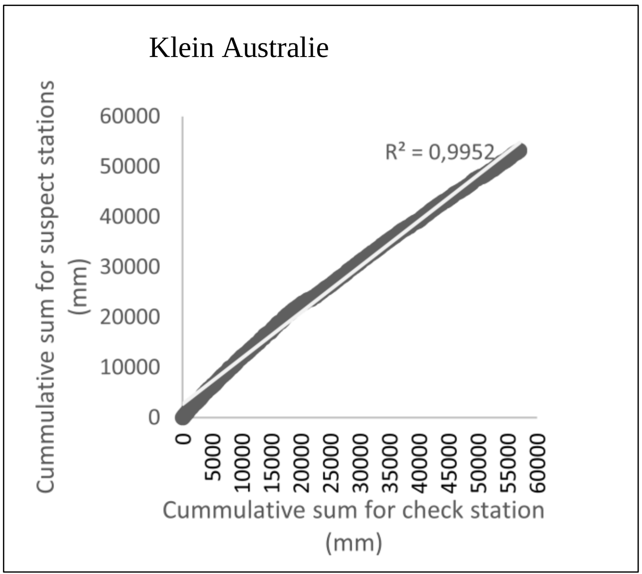
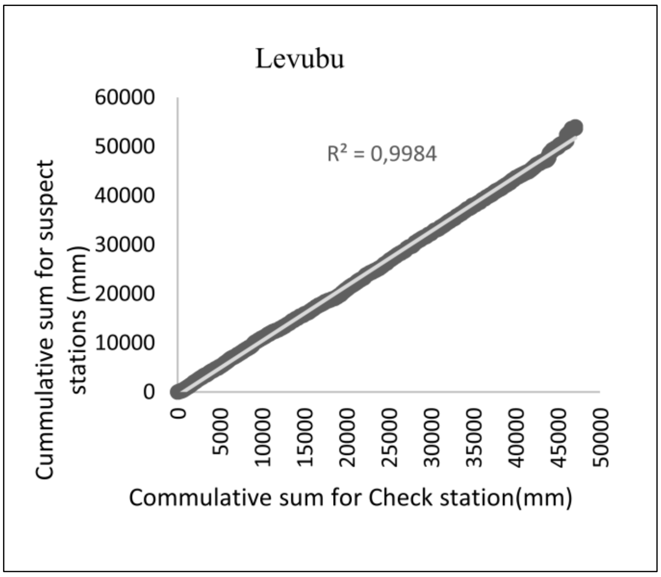
A dissertation submitted to the Department of Hydrology and Water Resources in fulfilment of the requirements for the Master of Earth Sciences Degree in Hydrology and Water Resources (MESHWR)

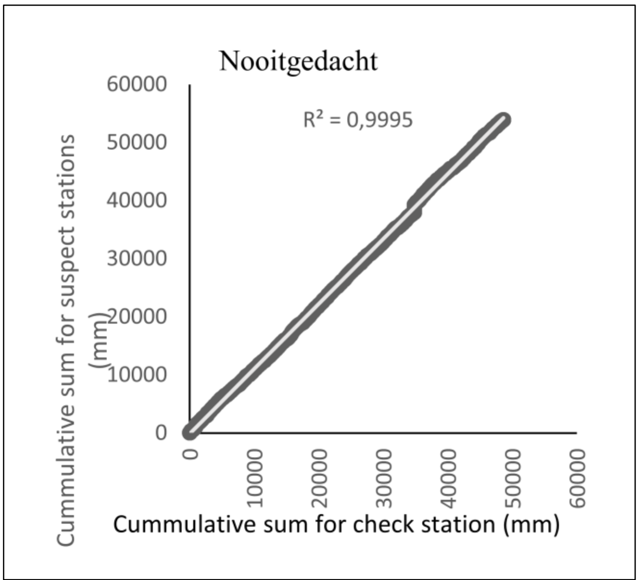
FEBRUARY 2018

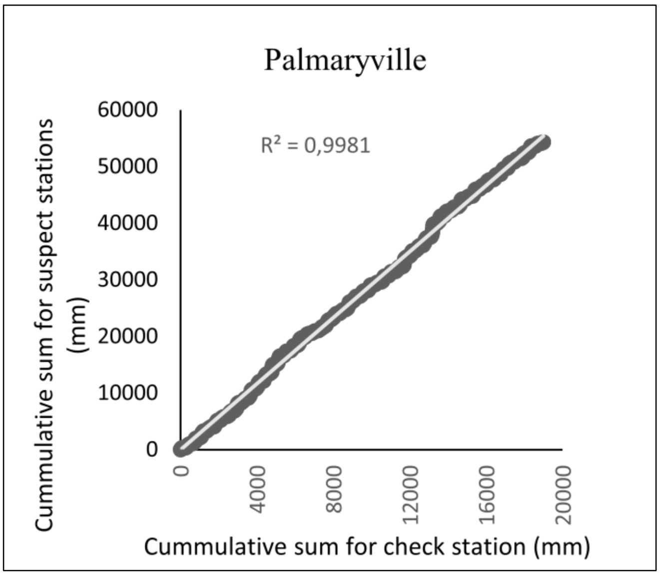
APPENDICES

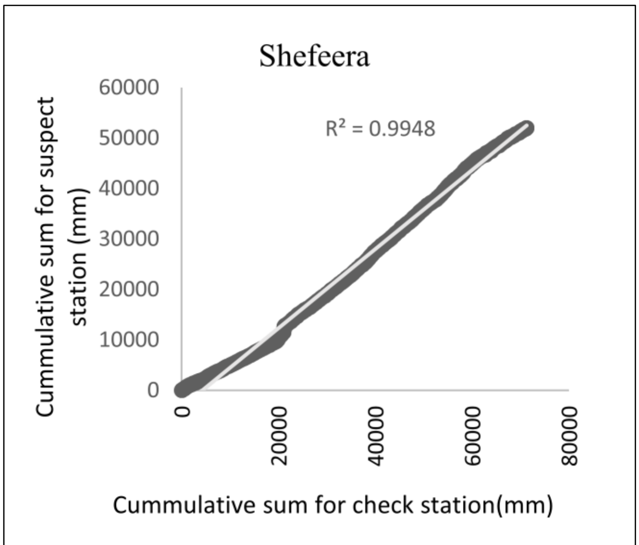
Appendix A: Double mass results for Klein Australie, Levubu, Nooitgedacht, Palmaryville, Shefeera and Vondo Bos stations.

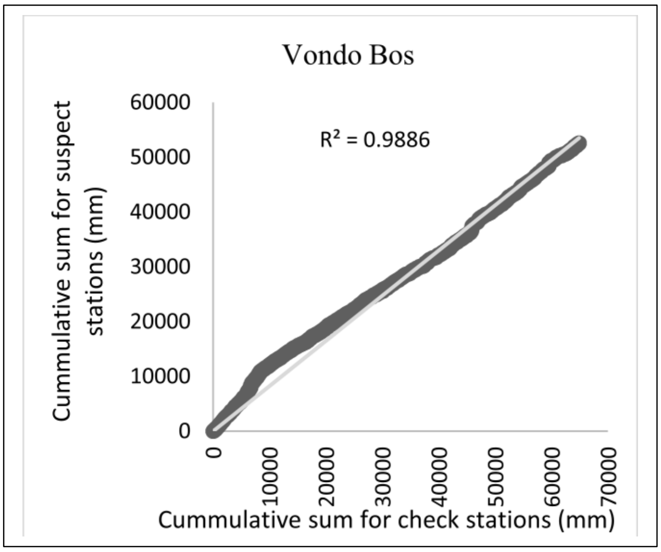


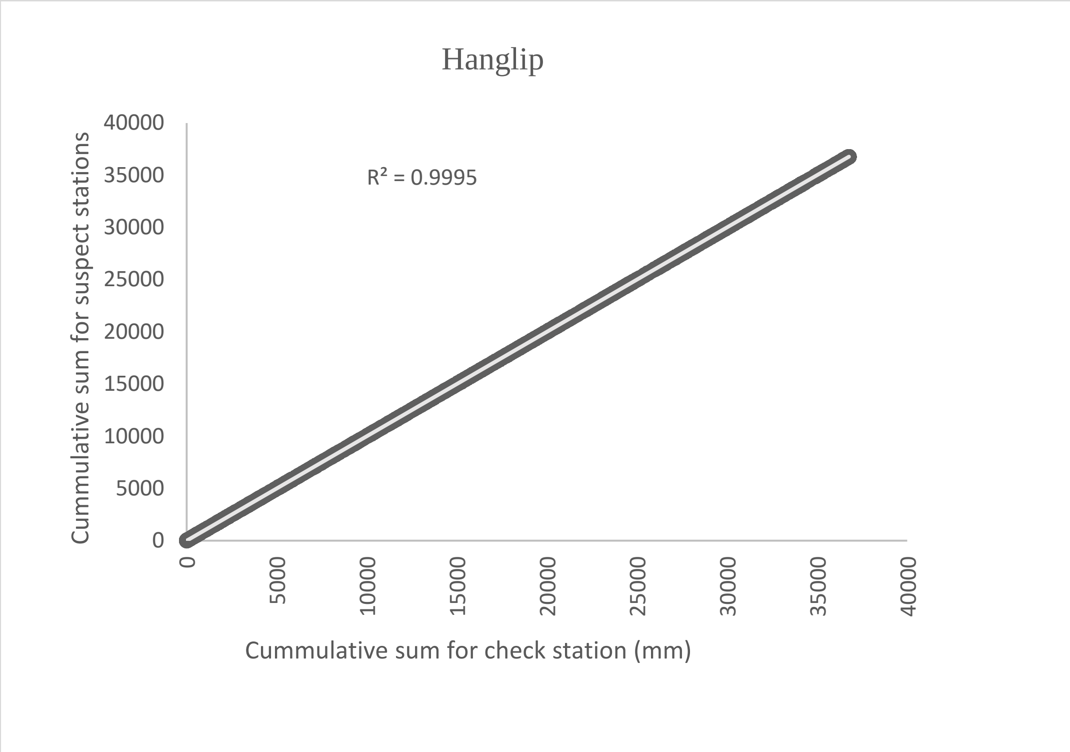











Hanglip
R² = 0.9995
Cummulative sum for suspect stations
40000
35000
30000
25000
20000
15000
10000
5000
0
0
5000
10000
15000
20000
25000
30000
35000
40000
Cummulative sum for check station (mm)

Declaration

I Mashinye Mosedi Deseree (student number 11564666) declare that this dissertation for the award of Master of Earth Sciences Degree in Hydrology and Water Resources (MESc HWR), at the university of Venda has not previously been submitted by me or any other person for a degree at this or any other institution, and that all the reference materials contained in it have been duly acknowledged.

Signature .... Date ....

Abstract

This study was aimed at investigating the long term seasonal and annual changes in rainfall duration and magnitude at Luvuvhu River Catchment (LRC). Rainfall in this catchment is highly variable and is characterised of extreme events which shift runoff process, affect the timing and magnitude of floods and drought, and alter groundwater recharge. This study was motivated by the year to year changes of rainfall which have some effects on the availability of water resources. Computed long term total seasonal, annual rainfall and total number of seasonal rainy days were used to identify trends for the period of 51 years (1965- 2015), using Mann Kendal (MK), linear regression (LR) and quantile regression methods. The MK, LR and quantile regression methods have indicated dominance of decreasing trends of the annual, seasonal rainfall and duration of seasonal rainfall although they were not statistically significant. However, statistical significant decreasing trends in duration of seasonal rainfall were identified by MK and LR at Matiwa, Palmaryville, Levubu, and Entabeni Bos stations only. Quantile regression identified the statistically significant decreasing trends on 0.2, 0.5 and 0.7 quantiles only in the Palmaryville, Levubu and Entabeni Bos, respectively. Stations with non-statistically significant decreasing trends of annual and seasonal rainfall had magnitude of change ranging from 0.12 to 12.31 and 0.54 to 6.72 mm, respectively. Stations with non-statistically increasing trends of annual and seasonal rainfall magnitude had positive magnitude of change ranging from 1.51 to 6.78 and 2.05 to 6.51 mm, respectively. The Study recommended further studies using other approaches to determine the duration of rainfall to improve, update and compare the results obtained in the current study. Continuous monitoring and installation of rain gauges are recommended on the lower reaches of the catchment for the findings to be of complete picture for the whole catchment and to also minimize the rainfall gaps in the stations. Water resources should be used in a sustainable way to avoid water crisis risk in the next generations.

Dedication

This study is dedicated to my late Father who continuously encouraged me to further my studies, in addition to motivating me about the importance of education and believing in me.

Acknowledgments

I would like to thank God Almighty for giving me strength, knowledge, ability and opportunity to undertake this study, without His grace this study would have not been possible.

I would also like to acknowledge the National Research Foundation (NRF) for funding my study. South African Weather Services is acknowledged for providing rainfall data used in this study. I would like to express my sincere thanks to the following:

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- Co-supervisor Ms Makungo R. for her wonderful perseverance, the care she has shown about my work, her extra ordinary human qualities, for promptly responding to my queries, and for not giving up on me when I encountered difficulties in this study.
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- My family for the unconditional love, financial and emotional support that they have shown throughout my study, without them I would have not come this far.

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Abbreviations

ANN	Artificial Neural Network
CUSUM	Cummulative Sum Charts
DMA	Double Mass Analysis
ENSO	El Nino-Southern Oscillation
GP	Genetic Programming
ITCZ	Inter Convergence Zone
KNP	Kruger National Park
LR	Linear Regression
LRC	Luvuvhu River Catchment
MK	Mann Kendall
NAO	North Atlantic Oscillation
SA	South Africa
SAS	Statistical Analysis Software
SAWS	South African Weather Services
SR	Spearson Rho
WMO	World Meteorological Organisation

CHAPTER 1: INTRODUCTION

1.1 Background

South Africa (SA) is a water stressed country, prone to erratic and unpredictable extremes such as floods and drought that reduce land to a dry and arid wasteland (Marete, 2003). According to UNESCO as quoted by Dennis and Nell (2002), 90 % of the total area of SA is arid and semi-arid. Therefore, water resources in SA are limited, making them critically important for the sustainable economic and social development of the country. On average, SA receives mean annual rainfall of less than 500 mm, in comparison with the annual world average of 860 mm. It experiences 80% predominantly summer rainfall, 10% winter rainfall and less than 10% rainfall throughout the year (Tadross and Johnston, 2012).

Rainfall is a renewable resource which is highly variable in space and time and is subject to depletion or enhancement due to both natural and anthropogenic causes (Abaje, 2010). The South African Climate Change Response Strategy (DEAT, 2004) states that SA's rainfall is already variable in spatial distribution and unpredictable, both within and between years. Changes in the hydrologic cycle due to an increase in greenhouse gases are projected to cause variations in intensity, duration, and frequency of precipitation events (Mirhosseini *et al.*, 2012). Climate is, with particular reference to rainfall, known to be changing world wide and there has been growing concern about the direct effects of these changes on settlement and infrastructure (Chaponniere and Smakhtin, 2006). While there is uncertainty on the magnitude of climate change impacts on rainfall in southern Africa (Christensen *et al.*, 2007), the IPCC (2007) suggests that climate change will decrease rainfall.

According to Jain and Kumar (2012), understanding rainfall variability is crucial and necessary, in order to appreciate the impacts of climate change. This is also a basic important requirement for the planning and management of water resources. Thus, this study seeks to find out the long term changes in seasonal and annual rainfall duration and magnitude in Luvuvhu River Catchment (LRC) so that drought/floods mitigation can be planned after understanding the behaviour of the rainfall. Rainfall is a fundamental requirement in a wide variety of human activities and water projects design.

1.2 Statement of the research problem

Over the last century, SA has suffered from dramatic changes in rainfall characterised by severe drought and wet spells. Warburton and Schulze (2005) reported that, over the latter half of the 20^{th} century, median annual rainfall has decreased, markedly over the Limpopo and into the border of SA with Botswana. This variability of rainfall has affected the agricultural industry, water reserves and gross national product (Jury, 2002). Prudhomme and Ragab (2002) reported that vegetation patterns and growth rates may be directly affected by shifts in precipitation amount and distribution, which will, in turn, affect agriculture and natural ecosystems. According to Glantz and Kartz (1987) and Tarhule and Woo (1997), droughts, rainfall changes and water scarcity constitute the major constraints to the attainment of self-sufficiency in food production and development of regions. This is because a deficiency in precipitation can possibly lead to a depletion of stream discharge and reservoir storage, which would, in turn, affect sectors such as the public utilities (power and water supply) sector (Tarhule, 1997).

Rainfall in LRC is highly variable and is characterized of extreme events. This affect the timing and magnitude of floods and droughts, shift runoff processes, as well as alter groundwater recharge rates. According to David and Frederick (1997), decreased precipitation will deprive us of water resources, resulting in water tables and water levels in reservoirs falling and wetlands and rivers becoming empty. The recharge of the aquifer depends on aquifer type. Recharge is closely linked to high and persistent rains. Some of the aquifers are more responsive to rainfall while others, such as deep aquifers, are slow to respond and require consistent rain over a long period of time (Visser, 2004). Depletion of groundwater may result in poor water quality from saline or contaminants on the land surface. According to DWAF (2003), groundwater is the only dependable source of water for many users in this catchment. The water is used for domestic, for stock watering, game watering and irrigation. In total, 15% of the yield from local resources is from groundwater. Reduction in rainfall and recharge in LRC impacts negatively on availability of groundwater for game watering in Kruger National Park (KNP), which has serious impact on tourism and economy if the animals die or migrate.

Kirchener *et al.* (1991) reported that, before any recharge takes place, rainfall and soil moisture thresholds must be exceeded. The bulk of the recharge takes place in the years in which the average annual precipitation is exceeded and during periods of high rainfall intensity. It stands to reason, therefore, that the areas under LRC which are dependent on groundwater will be most vulnerable to decreases in rainfall or variability. According to Gowing *et al*. (2004), it is estimated that some 624907 people, including the populations of Thohoyandou, Louis Trichardt and Malamulele, depend on the Luvuvhu River for their water needs. The changes in the rainfall duration and magnitude may affect these mentioned communities.

Rainfall is a major factor for the planning and management of irrigation projects, as well as agricultural production. Thus, rainfall change especially the reduction of annual rainfall, may have a great effect on the effectiveness and accuracy of the planning of irrigation projects. The LRC has an extensive area which is under rain-fed cultivation of vegetables, citrus fruits, variety of tropical foods and nuts. Regular rain pattern is vital for healthy plants, while too much or too little rainfall can be harmful, even devastating to crops because certain areas may not be climatically suitable for production of specific species (as different species have different climatic constrains such as mean rainfall).

1.3 Motivation

LRC is one of the regions in SA which has been severely affected by floods. Floods caused enormous damage to both property and life and impacted negatively on fauna and flora. Over the years, the catchment experienced floods resulting from heavy rainfall associated with the Intertropical Convergence Zone (ITCZ) (Odiyo *et al.*, 2015). The current study is motivated by the year to year changes of rainfall in the study area, which have some effect on the availability of water resources. According to Davis (2010), about 8 % reduction in rainfall would result in a 31 % reduction in surface run-off. In addition climate change is expected to exacerbate the poor state of major rivers in SA (Davis, 2010). Changes in rainfall have important implications for the hydrological cycle and water resources as rainfall is the main driver of variability in the water balance, upon which human and environment depend (Warburton and Schulze, 2005).

Kabanda and Nenwiini (2013) analysed trends and variability of rainfall in Vhembe District where LRC is found. However, the study focused on the rainfall magnitude and not on the rainfall duration. Moreover the findings of the latter study may not apply to LRC since rainfall is highly variable within local settings. Odiyo *et al.* (2015) investigated the long-term changes and variability in rainfall. The study focused on annual rainfall and seasonal rainfall. However changes in duration of rainfall was not included. In addition, the magnitude of the change of the rainfall was not estimated. The study also did not apply the quantile regression method. This method is able to determine changes along the whole range of quantiles (low, median and high) and this will aid in identifying changes in low, median and high rainfall events than to identify trends on the average mean of the variable. Furthermore, Aguilar *et al*. (2009) pointed that a study that examines possible changes over time of rainfall during years with low and high rainfall will contribute towards the development of appropriate adaptation measures for such changes.

Application of quantile regression in this study enabled identification of heteroscedastic changes (which have different values of the slope coefficient for different quantiles), and thus it is more informative as compared to LR and MK that only identifies monotonic trends. These methods were used together in this study to complement each other. Furthermore, using more than one method for trend analysis improves on the reasonableness of the results (Nkuna and Odiyo, 2011).

The changes in rainfall duration and magnitude of annual rainfall will directly affect the availability of water. Therefore, it is important to know whether there will be a reduction/increase in rainfall magnitude and duration of rainfall so that the information can be used for adjusting the planning and management of irrigation projects in this catchment and water resources related issues. This approach is in agreement with Lumsden *et al.* (2009), that recommended that changes in the seasonal distribution of rainfall should be examined in support of efforts to adapt climate change in the Southern African region. The results of this study will be useful in inculcating the need to conserve water and, thus, help the community to use water efficiently and in a sustainable way.

1.4 Research objectives

1.4.1 Main objective

- The main objective of the study is to investigate the long term seasonal and annual changes in rainfall duration and magnitude

1.4.2 The specific objectives

- To compute the long term seasonal and annual rainfall and identify the trends
- To compute total number of seasonal rainy days and identify changes in the duration of seasonal rainfall
- To identify trends on annual, seasonal rainfall and duration of seasonal rainfall for low, median and high quantiles
- To determine the magnitude of change for seasonal and annual rainfall
- To assess the significance of trends for seasonal, annual rainfall and duration of seasonal rainfall.

1.5 Research questions

- What are the changes in seasonal and annual rainfall magnitude?
- What are the changes in duration of seasonal rainfall?
- What is the range of magnitude of change for seasonal and annual rainfall magnitude?
- What are the significance of change in annual, seasonal rainfall magnitude and duration of seasonal rainfall?

1.6 Description of the study area

LRC is located in the Luvuvhu/Letaba Water Management Area in the north eastern part of SA (Limpopo Province). It forms part of the Limpopo River Basin, which is an international water course shared by SA, Botswana, Zimbabwe and Mozambique. It covers a total area of 5 941 km^2 and is located between the longitudes 29°49'46.16"E and 31°23'32.02"E and latitudes 22°17'33.57"S and 23°17'57.31"S (Figure 1.1). The catchment forms part of the larger Limpopo system, which runs downstream into Mozambique and is drained by the Luvuvhu River and its major tributaries: the Dzindi, Latonyada, Mutale, Mutshindudi and Mbwedi Rivers.

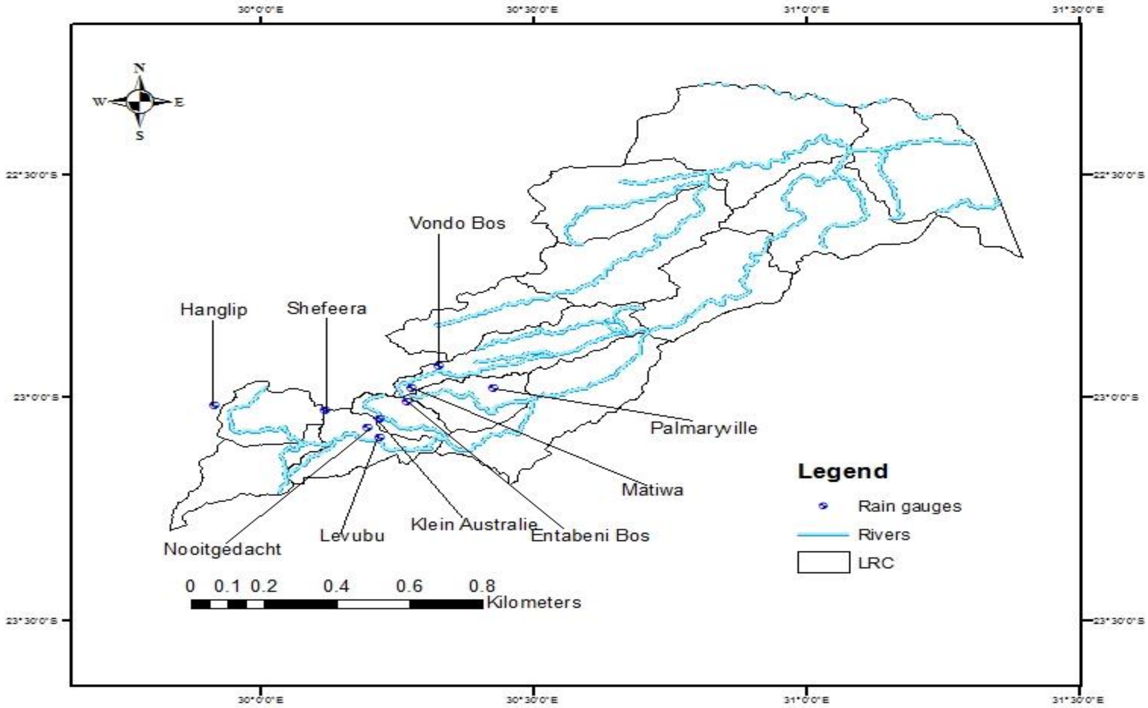


Figure 1.1: Map of the study area

1.6.1 Hydrology

The catchment generally has a hot humid climate with predominantly summer rainfall. The rainfall is largely influenced by the topography. The mean annual rainfall is 608 mm, while the mean annual runoff (MAR) is 520 x 10^6 m^3. The area receives one cycle of rainfall that extends from October of the previous year and ends in April of the following year. The dry season runs from May to September. The peak rainfall months are January and February and the highest rainfall occurs in the upper reaches of the catchment where the Soutpansberg Mountains are found, while little rainfall is experienced in the lower reaches around KNP. Mean annual evaporation (MAE) show high spatial and temporal variation and lowest evaporation over the Soutpansberg mountain range and lowest rainfall with highest evaporation to the KNP (Le Roux *et al.*, 2004).

Dams in the LRC include Albasini, Nandoni, Mambedi, Tshakhuma, Damani, Vondo and Phiphidi. The latter two lie in the Mutshindudi River. Nandoni Dam is in the middle section of Luvuvhu River, east of the confluence with Dzindi tributary. The upper Luvuvhu, Sterkstroom, Latonyanda, Dzindi, Mukhase, Mbwedi and Mutshindudi are steep, narrow rivers dominated by cobble riffles. Rivers in this catchment are perennial (State of the River Report, 2001).

1.6.2 Topography

Topography varies from 200-1500 m and it greatly influences rainfall and runoff distribution in the catchment (State of the River Report, 2001). It is marked by the northern extremity of the Drakensberg range and the eastern Soutpansberg, which both extend to the western parts of the water management area, and the characteristic wide expanse of the Lowveld to the east of the escarpment (DWAF, 2003).

1.6.3 Temperature

Temperatures range from a high average of 21°C in the upper catchments, to a very high average of 25°C in the KNP. Frost rarely occurs. High and low temperatures occur in the months of January and July, respectively (DWAF, 2004).

1.6.4 Geology

The geology of LRC is varied and complex. It consists mainly of sedimentary, metamorphic and igneous rocks in the south. High quality coal deposits are found near Tshikondeni and in the northern part of the KNP (DWA, 2012). With the exception of sandy aquifers in the Limpopo River valley, minerals found in the study area, include complex flake granite, ironstone, marble, fireclay, surficial limestone, magnesium and barile mineralisation (Singo, 2008).

CHAPTER TWO: LITERATURE REVIEW

2.1 Preamble

The literature review focused on local, national, regional and global studies on long-term changes is seasonal and annual rainfall. Literature also reviewed methods used to detect trends, and their advantages and how those methods applied. This literature review aided in choosing methods to be used, to achieve the objectives of the study.

2.2 Long term changes in seasonal and annual rainfall

According to Warburton and Schulze (2005), changes in rainfall have important implications for the hydrological cycle and water resources, as rainfall is the main driver of variability in the water balance, upon which humans and the environment depend. Many climate change models predict a 5 to 15% decrease in seasonal rainfall in southern Africa (IPCC, 2001). Hulme *et al*. (1999) predicted a 5 to 10% reduction in rainfall and Mazvimavi (2011) projected a 3 to 23% decrease in rainfall under climate change in southern Africa. This was in agreement with studies done by Hulme *et al.* (2001) and Arnell *et al*. (2003), which predicted that in future the region will be characterised by below-normal rainfalls and frequent droughts.

Rossel (2011) analysed total rainfall, seasonal changes, rainfall variability and rainy days computed from daily rainfall data of seven stations in the central highlands of Ethopia during the period 1987-2007. Rainfall results showed an increase in the annual rainfall and also in Kiremt (long rainy season). The Belg (the short rainy period) rainfall had, however, declined during the 30 year period that was analysed. High rainfall variability, more extreme rainfall during the start of the Kiremt season and more rainy days during the Kiremt season were found.

In SA, Hewitson and Crane (2005), using 50 years of data (1950–1999), reported that rainfall increases in regions where orography plays a strong role, and also increases in late summer dry spell duration for much of the summer rainfall region. Kane (2009) showed that annual rainfall had considerable year-to-year fluctuations (50–200% of the mean), while 5-year running means showed long-term fluctuations (75–150% of the mean). These studies suggested that annual rainfall has not had a clear tendency in the last 20 or 30 years. However, most concur that dry periods in southern Africa have become longer and more intense (Jewitt *et al.*, 2013).

Lynch *et al*. (2001) noted a gradual increase in annual rainfall in the Potchefstroom area from 1925 to 1998, while Du Plessis and Van Wageningen (2007) noted a reduction in annual rainfall (with an accompanying increase in rainfall intensity) at Table Mountain, Cape Town over the latter half of the 20th century. Mackellar *et al.* (2007) reported both wetting (central coastal belt, north-eastern areas) and drying (escarpment) over the Namaqualand region during the latter half of the 20th century. At national level, Richard *et al.* (2001) and Fauchereau *et al.* (2003) noted that there was no overall wetting or drying, but an increase in inter-annual rainfall variability during the 20th century.

Unganai (1996) fitted a linear regression model to annual areal average rainfall of Zimbabwe and concluded that annual rainfall had declined by 10% between 1900 and 1994. Makarau (1995) made similar conclusion. Morishima and Akasaka (2010) analysed rainfall data for the 1979-2007 period for southern Africa and concluded that annual rainfall has decreased over the African continent from the equator to 20ºS, as well as in Madagascar, resulting in a shorter and weaker rainy season in southern Africa, with rainfall in Angola, Zambia, and Namibia tending to decrease from December to March. Ngongondo *et al.* (2011), using data from 42 rainfall stations, noted that most stations revealed statistically non-significant decreasing rainfall trends for annual, seasonal, monthly and individual months from March to December at the 5% significance level.

2.3 Rainfall variability and trends

Rainfall variability refers to the variation in the mean state and other statistics (such as standard variation, the occurrence of extreme, amongst others) of rainfall on all spatial and temporal scales beyond that of individual precipitation events (Odjugo, 2010). The latter study noted that, like climate change, variability maybe due to interior or external variables, example includes greenhouse emission, ENSO, and NAO (North Atlantic Oscillation).

Rainfall variability in SA is caused by changes in frequency, duration and large scale weather systems that are responsible for the number of days with significant rainfall rather than the number of days or the length of the rainy season (Harrison, 1983). The main weather systems that are responsible for rainfall over SA are tropical temperate troughs and their associated cloud bands; the tropical lows or easterly troughs; the cut off lows or deep west-coast troughs and tropical cyclones (Alexander and Van Heerden, 1991).

High rainfall amounts over central parts of SA are associated with a trough axis over Namibia, Botswana and central Africa. It was also revealed that rainfall variations in southern Africa are associated with the interaction of easterly disturbances from the tropics and temperate westerly disturbances. For example, Lindesay and Jury (1991) found that interactions between tropical easterly waves from the south-west Indian Ocean and the mid-latitude westerly wave disturbance resulted in the floods of February 1988 over SA.

There are many different ways in which change in hydro meteorological series can take place. A change can occur abruptly (step change) or gradually (trend) or it may take a more complex form. Trends may be spatial or temporal and they can take various forms, including steady increases or decreases or a steep increase or decrease at a point in time or space (Pashiardis, 2009). Longobardi and Villani (2009) defined trend as a significant change over time exhibited by a random variable, detectable by statistical parametric and non-parametric procedures. Significant change is a trend that does not vary a lot if one adds or removes only a few points from the time series. A non-significant trend is a trend that will certainly disappear if one adds one or two points that go against a trend (Pashiardis, 2009).

Rainfall trends are characterised by more severe droughts in the southwest of Southern Africa and enhanced rainfall farther north in Zambia, Malawi, and northern Mozambique (Shongwe *et al.*, 2009). New *et al.* (2006) reported a spatially coherent increase in consecutive dry days over much of southern Africa in the last decades of the twentieth century. However, an analysis of observed rainfall trends for Zimbabwe (1933 - 2000) by Mazvimavi (2010) showed that there was no statistically significant rainfall reduction in Zimbabwe. Modest downward trends in rainfall are found in Botswana, Zimbabwe and western South Africa (Abdrabo *et al.*, 2014). Apart from changes in total or mean summer rainfall, certain intra-seasonal characteristics of seasonal rainfall, such as onset, duration, dry spell frequencies, rainfall intensity, as well as delay of rainfall onset, have changed (Tadross *et al.*, 2005; Thomas *et al.*, 2007). Moeletsi *et al*. (2016) noted eight agricultural seasons in the years 1983/84, 1988/89, 1991/92 1993/94, 2001/02, 2002/03, 2004/05 and 2014/15 at LRC, subjected to extreme widespread droughts. The study further indicated no trend for all the various dry spells length (short, medium and long dry spell) except for Thohoyandou and Sigonde rainfall station with decreasing trend and weak increasing trend in long dry spells, respectively.

Chamaillé-Jammes *et al.* (2007) and Joubert *et al.* (1996) concluded that rainfall in southern Africa showed no consistent or statistically significant trends across the region, but also noted a decrease of regionally-averaged total rainfall (but this is not statistically significant). Nicholson (2000, 2001) found a shift from relatively wet conditions of the 1920s - 1950s to dry conditions from the 1970s onward. For the northernmost part of southern Africa, including Zimbabwe, an increase in rainfall in the 1970s of 6% followed by a reduction of 5% in the 1980s was experienced (Nicholson, 2001).

Scientific evidence points to a future of an increased inter-annual variability, with extremely wet periods and more intense droughts in different countries (DEA, 2013). Besides volumes, rainfall patterns are also expected to change in intensity and frequency, resulting in more extreme events and longer periods between rainfalls (Christensen *et al.*, 2007). In almost all hydrological zones of SA, there has been a reduction in rainfall for the autumn months. Annual rainfall has not changed significantly, but an overall reduction in the number of rainy days is noted. Significant reductions in rainfall are plausible over Limpopo in the near future, with the pattern of drying projected to increase over time (DEA, 2013).

A study by Kabanda and Nenwiini (2013) observed non-significant (downward) trends (95 % to 99% confidence level) over Vhembe District of Limpopo Province. Generally, changes in rainfall characteristics were mostly observed from the mid-1990s. The study by Odiyo *et al.* (2015) concluded that the rainfall stations at LRC, which is found in the northern eastern part of SA, showed increasing trends in 5 and 10 year mean rainfall except for one station. The latter study explained that this may be due to its location in a remote mountainous area which has a different hydrologic behaviour.

Easterling *et al.* (2000) indicated a tendency for increased extreme precipitation in the south western and eastern parts of SA during most of the 20th century. This was supported by Groisman *et al*. (2005), who showed a significant increase in the annual frequency of very heavy rainfall events over eastern SA from 1906-1997. Furthermore, Mason *et al*. (1999) demonstrated increases in the intensity of high rainfall events over much of SA in the 1961-1990 periods compared to 1931-1960. Kruger (2006) showed increases in extreme rainfall indices over the southern Free State and parts of the Eastern Cape from 1910-2004. New *et al*.

(2006) also showed some evidence of increased rainfall extremes over parts of southern Africa for the 1961-2000 period. Smakhtina (1998) reported that the Eastern Cape Province of SA experienced an increase in heavy rainfall events and in the mean rainfall amount per rain-day associated with reduction of the number of the rainy days since the beginning of the century.

Nel (2009) demonstrated a shift in seasonality for stations in the KwaZulu-Natal (KZN) Drakensberg for 1955-2000; the mean annual precipitation (MAP) showed no significant trend, but an increase in summer rainfall was accompanied by decreased autumn and winter rainfall, resulting in a shorter wet season and a more pronounced seasonal cycle. This was consistent with results for north-west KZN, where an increase in early-season rainfall was observed along with a decrease in late-season rainfall between 1950 and 2000 (Thomas *et al*., 2007). Seasonal shifts were also observed by Thomas *et al.* (2007) in Limpopo for the same period, where there was a tendency for a late seasonal rainfall onset accompanied by increased dry spells and fewer rain days. Increased dry spell duration was also evident for much of the Free State and Eastern Cape, and decreases in wet spell duration were observed for parts of the Eastern Cape and the north eastern parts of SA in the period 1910-2004 (Kruger, 2006).

2.4 Data quality control

Data quality control is essential for determining the reliability of the data and also for eliminating errors that may affect the final results. Data quality control relies primarily on checking for outliers (e.g. implausible rainfall values) by comparison with past observation or with data from neighbouring stations (Bonaccorso *et al.*, 2008).

Studies of precipitation change are typically complicated by factors such as missing data, seasonal and other short-term fluctuations (climate variability) and by lack of homogeneity data. This is why data quality control is essential.

After acquiring a set of rainfall data, it is necessary to first verify the data before using it for analysis or design. The data set should be checked for consistency and for missing data. If there are missing data, they should be replaced, if possible; if they are inconsistent data they should be adjusted. The possible causes of missing data/homogeneity may be due to equipment malfunctioning or faulty data acquisition procedures among others.

2.4.1 Patching of rainfall missing data

A number of methods are adopted in patching missing data depending on the length of the gaps, availability of hydro-meteorological data from neighbouring stations, the season of missing values, the climatic region under consideration, the knowledge and expertise of the person responsible for correcting data, length of existing data record, the importance of prediction and, hence, consideration of the performance of the model to be used for infilling (Gyau-Boake and Schultz, 1994; Khalil *et al*., 1998; Rees, 2008).

Arithmetic mean

In this method, data from surrounding gauges are used to estimate the missing data. This method assumes equal weights from all nearby rain gauge stations and uses the mean of the precipitation records as estimates (Tabios and Salas, 1985). The rainfall depth for the station missing data is simply estimated as

$$p_m = \frac{1}{n}\left[\sum_{i=1}^{n} p_i\right] \qquad 2.1$$

Where p_m = Estimate of rain depth at the missing data location (mm)

p_i = Rain depth observed at gauge $_i$ (mm)

n = Number of rain gauge

The advantage of this method is that it is simple and it permits the solution of any system of equations and no special tool is needed to use it. The disadvantage of this method is that it can only be used if the normal annual precipitation at each of the index stations is within 10 percent of the station with the missing data.

Normal ratio method

Unlike the arithmetic mean, the normal ratio method takes account of the normal ratio between annual rainfalls depth measured by the rain gauge which failed and all of the rain gauges in the network. This method is used if any surrounding gauges have normal annual precipitation exceeding 10% of the considered gauge. This weighs the effect of each surrounding station (Caldera *et al.* 2016).

$$p_m = \frac{1}{n}\left[\sum_{i=1}^{n}\left(\frac{N_m}{N_I}\right)p_i\right] \qquad 2.2$$

Where p_m = Estimate of rain depth at missing data location (mm)

N_m = Average annual rain at rain gauge for which data are missing (mm)

N_i = Average annual rain at gauge *i* (mm)

Pi = Precipitation depth at gauge *i* (mm)

The disadvantage of this method is that one needs to know the average annual rain gauge amounts measured by each of the gauges in order to use this method.

Reciprocal inverse weighting factor

This method differs, once more with previous methods, in that it takes into account the distances between the missing data gauge and the four nearest gauges in each quadrant surrounding the gauge. In this method, weights for each sample are inversely proportional to its distance from the point being estimated (Lam, 1983). Simanton and Osborn (1980) used the inverse weighting method to estimate missing rainfall data.

Procedure

- divide area around gauge of interest into four quadrants
- using records at nearest station in each quadrant compute missing precipitation amount

$$p_m = \frac{1}{\sum_{i=1}^{4}\frac{1}{X_i}}\left(\sum_{i=1}^{4}\frac{p_i}{X_i^2}\right) \qquad 2.3$$

Where p_m = Estimate of rain depth at the missing data location (mm)

P_i = Rainfall recorded by gauge *i* (mm)

X_i = Distance from gauge *i* to missing data (km)

The shortcoming of this method is that it can never yield a point estimate greater than the largest amount observed or less than the smallest.

Aerial Precipitation Ratio (APR) method

This method was developed based on the spatial distribution of daily rainfall without taking into account the historical recurrence (De Silva *et al.*, 2007). The method leads the extension of point rainfall records to Thiessen Polygon areas. The APR method assumes that the contribution of rainfall from surrounding stations is proportional to the aerial contribution of each sub catchment (Thiessen polygon area claimed by each station without considering the missing gauge), when the station of missing values is excluded (De Silva, 1997).

The formula of the method can be given as follows:

$$P_x = \frac{\sum_{i=1}^{n}\left[\left(A_j - A_i\right)p_i\right]}{\sum_{i=1}^{n}\left(A_j - A_i\right)} \qquad 2.4$$

$\sum_{i=1}^{n}\left(A_j - A_i\right)$=Thiessen polygon area for the station with missing values

A_i =Thiessen polygon area when station with missing values is included

A_j= Thiessen polygon area when a station with missing values is excluded

P_i = Annual precipitation of surrounding stations

P_x = Estimate of the monthly rainfall for the stations with missing observation.

De Silva *et al.* (2007) studied the arithmetic mean, normal ratio and inverse distance weighting methods besides proposing areal precipitation ratio method for selected rain gauge stations in agro-ecological zones of Sri Lanka for daily records. The results indicated that different methods are appropriate for different zones of location of rain gauges. Bennett *et al.* (2007) preferred arithmetic mean, normal ratio and inverse distance weighting methods as such it is difficult for one to compare these simple methods and computationally expensive methods and make a judicious choice to select an appropriate method for a given basin.

Regression methods

Makhuvha *et al.* (1997) introduced and theoretically developed six methods of patching rainfall data based on multiple linear regression. The first three methods namely Method A: (The T_p criterion using all subset selections); Method B: (The J_p criterion using all subset selection) and Method C: (The T_p criterion using forward selection), were best subset selection methods employing three different strategies to yield the best patch when allowing for the missing data in the control. Pseudo-EM Version 1, Pseudo-EM Version 2 and EM algorithms are iterative methods which estimate the parameter of the regression model and the missing data in the target and control in a recursive way. The procedure for all these six methods is well explained in Makhuvha *et al.* (1997).

Pegram (1997) used multiple linear regression to estimate missing rainfall data. Lynch (2004) used the regression method to patch and extend daily rainfall data in SA. Its advantage is that predictions can still be made when the control data is also missing, but extensive computations are required for these calculations. If the method has to be applied on a routine basis to a large number of records, then the computing can be substantial and burdensome to the extent that it may not be worthwhile doing. Villazon and Willems (2010) considered the application of linear and multiple linear regression models for patching monthly missing rainfall in the Pirai River Basin, a tributary of the Amazon River.

Genetic Programming (GP)

GP is applied for modelling rainfall infilling by developing individual models for each month or day. The concept of GP is borrowed from the process of evolution occurring in nature, in which the species survive as per the principle of 'survival of the fittest'. GP is similar to more widely known genetic algorithms (GA), but, unlike GA, its solution is a computer programme or an equation against a set of numbers in the GA.

The algorithm considers an initial population of randomly generated programmes (equations), derived from the random combination of input variables, random numbers and functions, which include arithmetic operators (plus, minus, multiply, divide), mathematical functions (sin, cos, exp, log), logical/ comparison functions, which have to be appropriately chosen based on some understanding of the process, and the fitness (a measure of how well the problem will be solved) of the evolved programmes are evaluated. Individual programs that best fit the data are then selected from the initial population. The main operators used in evolutionary algorithm, such as GP, are crossover and mutation. Up to three stations in the neighbourhood of the station with missing data and which are believed to affect the rainfall in the missing station, are identified. The selection of the stations should be based purely on the proximity to the missing station; stations from same land use are adopted.

Monthly models are constructed using the Disciplus tool. GP is implemented to identify the importance of the given input variable in the modelling process. Consequently, the variable which performs poorly is removed in the subsequent trial to improve the modelling results. The patching or infilling performance is evaluated using the two criteria, the root-mean square error (RMSE) and the correlation co-efficient (CC).

Jeselia *et al.* (2015) have used the GP method to infill missing monthly data in the agricultural region of the Yarra Catchment in Australia and they found that GP is able to detect the subtle nonlinear effect superimposed over the linear behaviour. The advantage of GP is that it has the ability to evolve mathematical modes which can be compared with other models (Jeselia *et al.*, 2015). It also has almost good modelling accuracy or even more when compared to artificial neural network in many studies. GP can iteratively generate new values until they reach a certain level of acceptance as per the selected criterion, and thus it is good for the retrieval of missing values (Deo and Karla, 2007).

Artificial Neural Networks (ANN)

ANNs are methods developed for automatic quality control of the data that makes it possible to perform a preliminary analysis of the acquired information aimed at identifying potential anomalies in the observation. ANN has been applied to patch missing rainfall data. Nkuna and Odiyo (2011) have patched rainfall missing data with the aid of ANN using a radial basis function. Ilunga and Stephenson (2005) also used ANN to infill missing hydrological data in South Africa. Their study used feed forward back propagation algorithm to estimate missing data in the Eastern Cape Province of South Africa. According to Bennet *et al.* (2001), ANN requires training and data that is based on past relationships. This may result in over fitting. Ilunga (2010) also used the ANN method to patch the total rainfall missing data for the stations around SA. Missing values were patched by using standard Back Propagation (BP) techniques and generalised BP techniques, wherein the study indicated that the generalised BP techniques performed slightly better than the standard BP technique.

Artificial neural networks are able to generalise the relationships from a small subset of data while remaining relatively robust in the presence of noise or missing inputs (Ilunga and Stephenson, 2005). Nkuna and Odiyo (2011) noted that ANN are capable of identifying complex non-linear relationships between inputs and outputs.

According to Jeselina *et al*. (2015), although many approaches have been reported in the patching of missing rainfall information, it is generally believed that no single method can be considered best universally. The choice of a particular approach should account for both topographic and orographic effects of rainfall. For these reasons, the method suitable for this study will be chosen, in order to fill in the missing data.

2.4.2 Homogeneity or consistency of hydrological data

Consistency refers to accuracy and uniformity of the data. The consistency in data is demonstrated by a linear slope of the double mass curve. Inconsistency in data is demonstrated by a distinct change in the slope of the double mass curve. This does not imply that either period is incorrect –only that it is inconsistent. Homogeneity is meant to understand that the time-series follow similar temporal variations, with a pseudo-proportional increase or decrease of the precipitation at all stations included in the region. If a region is homogenous, the analysis done using the regional index will also be valid for all the stations included in the region (Pashiardis, 2009).

Double mass analysis (DMA) is a technique commonly employed to determine corrections to hydro meteorological data, and to account for changes in data collection procedures or other local conditions. The changes may result from a variety of things including changes in instrumentation, changes in observation procedures, or changes in gauge location or surrounding conditions. If climate variation affects hydrological measurements at two closely located stations in a similar way, a double mass analysis of those stations should plot as almost straight line. Non-linearity or bends are indications of changed conditions in (at least) one of the stations. Such changes may originate from poor worsened measurement accuracy or from changed catchment conditions.

DMA tests the consistency of the record at a station by comparing its accumulated annual or seasonal precipitation with concurrent accumulated values of mean precipitation for a group of surrounding stations (Linsley, 1988). The data can be made consistent by adjusting so that there is no break in the resulting double mass curve. The existence of a discontinuity in the double mass plot does not itself indicate which part of the curve should be adjusted (before or after). It is the usual practice to adjust the earlier part of the record so that the entire record is consistent with the present and continuity record. There may be circumstances, however, when the adjustment is made in the later part, where an errenous source of the consistency is known or where the record has been discontinued.

2.5 Statistical methods to detect changes in rainfall data

Time series consist of trends, seasonal variation or seasonality, cyclical variation or repetitive trends, and irregular activity (Kvanli *et al.*, 1996). The purpose of trend testing is to determine if the values of a random variable generally increases or decreases over some period of time in statistical terms (Helsel and Hirsch, 1992). In some cases, the detection of trends may be complicated by the over-laying of long- and short-term trends, cyclical effects such as seasonal or weekly systematic variations, autocorrelations, or impulses or jumps from interventions or procedural changes (Hart, 2008). According to Sahoo and Smith (2009), detecting past trends, changes and variability in the times series of hydro-climatic variable is very important in understanding the potential impact of future changes in the region.

In order to carry out some of the statistical tests, the null and the alternative hypotheses are defined. These are actually statements that describe what the test is investigating. To compare the null and alternative hypotheses, a test statistic is selected and then its significance is evaluated based on the available evidence. Robson and Kundzewicz (2004) defined test statistic as a simple numerical value that is calculated from the data series that are being tested. It is selected so that it highlights the difference between the two hypotheses. Significance level measures whether the test statistic is very different from the range of values that would typically occur under the null hypothesis.

2.5.1 The least square method

The least square method is a common method to test trends in time series (Yu, 2007). For the linear regression (Equation 2.5) the slope *b* can be used as the indicator to test the trend. Dejuan *et al.* (2012) used the least square method, the Man Kendall test, to detect the trends in seasonal precipitation data series in Beinjing.

$$x = a + bt + \varepsilon \qquad 2.5$$

$$b = \frac{n\sum_{i=1}^{n} x_i t_i - \left[\sum_{i=1}^{n} x_i\right] - \left[\sum_{i=1}^{n} t_i\right]}{\sum_{i=1}^{n} t_i^{\,2} - \left[\sum_{i-1}^{n} t_i\right]^2} \qquad 2.6$$

Where x_i is a climatic factor

t_i is the time

n is the length of the sequence

As the value of *b* may be impacted by small scale fluctuations, it needs to be of significant results. Assuming that the time series X_i can be fitted by linear Equation 2.5, and the error standard complies with the standard normal distribution, the sum of deviation of variable is expressed as follows:

$$L_{xx} = \sum_{i=1}^{n}(x_i - \bar{x})^2 = \sum_{i=1}^{n}(x_i - \tilde{x})^2 + \sum_{i=1}^{n}(\tilde{x} - \bar{x})^2 = Q + U \qquad 2.7$$

Where

$$U = \sum_{i=1}^{n} (\tilde{x} - \bar{x})^2 = b^2 \sum_{i=1}^{n} (t_i - \bar{t})^2$$

And

$$Q = L_{xx} - U$$

U is the sum of deviation square between return values and the measured mean values called the regression sum of squares. *Q* is the difference between sum of deviation of the variable and regression sum of squares, called error sum of square or residual sum of squares. If the null hypothesis H_0: b=0 is true, for or given confidence level α, assuming the rejection of the constructor of the statistic Equation *2.8* is$W = \{f > f_\alpha(1, n-2)\}$.

F test is used to detect the significance of the trends in all meteorological parameters and is calculated as follows:

$$f = \frac{U}{\frac{Q}{n-2}} \sim f(1, n-2) \qquad 2.8$$

2.5.2 Quantile regression model

Quantile regression model, which was developed by Koenker and Bassett (1978), is a statistical method to estimate the conditional quantiles of a response variable distribution in the linear model and provides a more complete view of relationships between variables. Quantile regression model is capable of identifying changes over time of any percentile values of hydrologic and climate variables. Widespread applications of this method have been observed in economics, biology, ecology, and finances (Yu *et al.*, 2003). However this method has recently emerged in climatological research. Charmaile-Jammes *et al.* (2007) and Mazvimavi (2010) employed the quantile regression to detect changes of annual rainfall over time in Zimbabwe. Villarini *et al.* (2011) used the quantile regression to investigate the temporal and spatial variation of rainfall in the Midwest of the United States. The procedure for this method is also explained in Huang and Shiau (2015). Computations are performed by using a function called quantreg. Quantile regression has the desirable attribute of being able to describe responses of both homoscedastic and heteroschedastic variables (Mazvimavi, 2010). This method provides a more complete picture for the conditional distribution of the dependent variable given the independent variable when both lower and upper or all quantiles are of interest, so it is especially useful in applications where extremes are more important (Lee *et* *al.*, 2012). It is useful for detecting trends in extremes hidden in non-significant mean effects or changes in median conditions in extreme stochastic environments (Chamaillé-Jammes *et al.*, 2007).

2.5.3 Cumulative sum charts (CUSUM)

This is a rank-based test in which successive observations are compared with the median of the series. The test statistic is the maximum Cumulative Sum (CUSUM) of the signs of the difference from the median (i.e. the CUSUM of a series of values of +1 or –1) starting from the beginning of the series. This procedure was implemented by Wayne (2000) for performing a change-point analysis. CUSUM is a technique used to determine an average value for sub groused and to determine the expected variability about the mean. CUSUM charts are used to perform change point analysis and detection. Change point analysis is an analysis used to determine whether a change has taken place or not. Ahmed and Mahmoud (2006) used the cumulative sum charts and bootstrapping to find changes in the total rainfall and number of rainy days at Ahman Airport meteorological station in Jordan during the period 1922-2003.

The CUSUM change statistic (V_k) as defined by Inclan and Tiao (1994) is as follows:

$$V_k = \sum_{i=1}^{k} \operatorname{sgn}\left(x_i - x_{median}\right) \qquad 2.9$$

Where

K= 1, 2, 3……………...*n*

$$\operatorname{sgn}(x) = \begin{matrix} 1 & if & \theta > 0 \\ 0 & if & \theta = 0 \\ -1 & if & \theta < 0 \end{matrix}$$

x_{median} is the median of x data

The types of tests used to evaluate an out-of-control condition in the CUSUM are the run-sum and the V-mask. The V-mask standardizes the deviations from the mean, or target value, and plots the deviations from this value. If the process remains in control, then the deviations will scatter around the target. On the Cusum chart, this will produce a straight line or a random shift around the target with a mean of zero. A sudden change in the direction of the CUSUM indicates a sudden shift in the average. The period where the CUSUM chart follows a relatively straight path indicates a period where the average does not change. Most of the values added to the CUSUM will be positive and the sum will steadily increase. A segment of the CUSUM chart with an upward slope indicates a period where the values tend to be above the overall average. Likewise, a segment with a downward slope indicates a period of time where the values tend to be below the overall average.

The confidence level can be determined by performing the bootstrap analysis. The procedure for the bootsrap analysis is well explained in Ahmed and Mahmoud (2006). Before performing the bootstrap analysis, the magnitude of the change (S_{diff}) should be determined as follows:

$$S_{diff} = S_{\max} - S_{\min} \tag{2.10}$$

Where $S_{\max} = \max_{1=0......n} S_i$

$$S_{\min} = \min_{1.=0......n} S_i$$

Then Let x be the number of bootstraps for which $S^0_{diff} < S_{diff}$ then the confidence level (C L) at which a change point occurs is :

$$CL = 100\frac{x}{n}\% \tag{2.11}$$

To estimate the location of the change point, define *m* such that:

$$|s_m| = \max_{i=0,...n} |s_i| \tag{2.12}$$

S_m is the point noted furthest from zero in the CUSUM chart. The point estimates the last point before the occurrence of the change point. The point *m*+1 estimates the first point after the change. Another estimator that can be used to estimate when the change occurred is the mean square error estimator.

$$\text{MSE }(m) = \sum_{i=1}^{m}(x_1 - \overline{X})^2 + \sum_{i=m+1}^{n}(x_1 - x_2)^2 \tag{2.13}$$

Where $\overline{X_1} = \frac{\sum_{i=1}^{m} x_i}{m}$ and $\overline{X_2} = \frac{\sum_{i=m+1}^{n} x_i}{n-m}$

The MSE error estimator is based on the idea of splitting the data into two segments 1 to *m* and *m+1* to *n,* estimating the average of each segment, and then seeing how well the data fits the two estimated averages. The value *m* that minimises MSE (*m)* is the best estimator of the last point before the change. As before, the point *m*+1 estimates the first point after the change.

The CUSUM Chart is very powerful at detecting smaller sustained changes and it better characterises such changes including detection of multiple changes well. It reduces the number of false detections by controlling the change-wise error rate. It is robust to outliers and can be made even more robust by performing a change-point analysis on the ranks. It is more flexible. The same procedure works for all types of data including attribute data, individual values, counts, averages and standard deviations. Furthermore, a change-point analysis can be performed on ill-behaved data like particle counts and complaint data, which do not follow any of the traditional control charting distributions and may contain numerous outliers. It is simpler to use and interpret, especially for large data sets and when multiple changes have occurred.

Despite its numerous advantages, it has some shortcomings. First, it does not detect isolated abnormal points. Change-point analysis should be supplemented with a Shewhart control chart when such points are of concern. Box and Luceño (1997) demonstrate that Shewhart control charts are optimal at detecting isolated abnormal points, while CUSUM charts are optimal at detecting shifts of the mean. If one is concerned with both types of changes, both procedures can be used to complement each other. It is also difficult to find the magnitude of change using this method, no procedure is shown on how to find the magnitude of change. It is more suitable when a person needs to understand the variability of the hydrological time series.

2.5.4 Mann Kendal (MK) test

The Mann Kendall (MK) test is a statistical test widely used for the analysis of trend in climatologic and in hydrologic time series. Any data reported as non-detects are included by assigning them a common value that is smaller than the smallest measured value in the data set. According to this test, the null hypothesis H_0 assumes that there is no trend (the data is independent and randomly ordered) and this is tested against the alternative hypothesis H_a, which assumes that there is a trend.

The computational procedure for the MK test considers the time series of *n* data points and X_i and X_j as two subsets of data where $i = 1,2,3, \ldots, n-1$ and $j = i+1, i+2, i+3, \ldots, n$. The data values are evaluated as an ordered time series. Each data value is compared with all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time period, the statistic *S* is incremented by 1. However, if the data value from a later time period is lower than a data value sampled earlier, *S* is decremented by 1. The net result of all such increments and decrements yields the final value of *S*.

The MK Statistic, as explained by Karmeshu (2012), is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(X_j - X_i) \qquad 2.14$$

Where $Sign\ (X_j - X_i) = \begin{cases} 1 & if \quad (X_j - X_i) > 0 \\ 0 & if \quad (X_j - X_i) = 0 \\ -1 & if \quad (X_j - X_i) < 0 \end{cases}$

Where

X_j and X_i are the variable values in years *j* and *i*, *j* > *i*, respectively.

If n < 10, the value of |*S*| is compared directly to the theoretical distribution of *S* derived by Mann and Kendall. At certain probability level H_0 is rejected in favour of H_1 if the absolute value of *S* equals or exceeds a specified value $S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest *S* which has the probability less than α/2 to appear in case of no trend. A positive (negative) value of *S* indicates an upward (downward) trend. However, to statistically quantify the significance of the trend, it is necessary to compute the probability (*p* -value) associated with S and the sample size n. For n ≥ 10, the statistic S is approximately normally distributed with the mean and variance as follows:

$E(S) = 0$

The variance of the *S* statistic is defined by: 2.15

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum t_i(i)\,(i-1)(2i+5)}{18} \quad 2.16$$

In which t_i denotes the number of ties to extent *i*. The summation term in the numerator is used only if the data series contains tied values. The standard test statistic Z_s is calculated as follows:

$$Z_S = \begin{Bmatrix} \frac{S-1}{\sigma} & for & S > 0 \\ 0 & for & S = 0 \\ \frac{S+1}{\sigma} & for & S < 0 \end{Bmatrix} \quad 2.17$$

The test statistic Z_s is used as a measure of significance of trend. In fact, this test statistic is used to test the null hypothesis, H_0. If $|Zs|$ is greater than $Z\alpha/2$, where α represents the chosen significance level (e.g.: 5% with $Z_{0.025} = 1.96$), then the null hypothesis is invalid implying that the trend is significant.

Khambhammettu (2005) has reported that when deciding on a probability level the significance will be (95% typically). The trend is said to be decreasing if Z is negative and the computed probability is greater than the level of significance. Trend is said to be increasing if the Z is positive and the computed probability is greater than the level of significance. If the computed probability is less than the level of significance, there is no trend.

Kendall's tau

In time series analysis, it is essential to consider autocorrelation or serial correlation, which is defined as the correlation of a variable with itself over successive time intervals, prior to testing for trends. Autocorrelation increases the chances of detecting significant trends even if they are absent and vice versa.

This statistic can also be obtained when running the MK test. It is a measure of correlation and, therefore, measures the strength of the relationship between the two variables. Kendall's tau is carried out on the ranks of the data. That is, for each separate variable, the values are arranged in an orderly manner and numbered, 1 for the lowest value, 2 for the next lowest and so on. In common with other measures of correlation, Kendall's tau will take values between - 1 and +1, with a positive correlation, indicating that the ranks of both variables increase together whilst a negative correlation indicates that, as the rank of one variable increases, the other decreases. One of the softwares used for performing the statistical MK test is Addinsoft's XLSTAT. The null hypothesis is tested at 95% confidence level. The linear trend lines for each state can be plotted using Microsoft Excel, in order to compare the results obtained from the MK test.

In order to consider the effect of autocorrelation, Hamed and Rao (1998) suggest a modified MK test, which calculates the autocorrelation between the ranks of the data after removing the apparent trend. The adjusted variance is given by:

$$Var[S] = \frac{1}{18}[N(N-1)(2N+5)]\frac{N}{NS^*} \qquad 2.18$$

Where

$$\frac{N}{NS^*} = 1 + \frac{2}{N\big(N-1(N-2)\big)}\sum_{i=1}^{p}(N-i)\,(N-i-1)(N-i-2)p_s(i)$$

N is the number of observations in the sample, *NS** is the effective number of observations to account for autocorrelation in the data, *ps (i)* is the autocorrelation between ranks of the observations for lag *i*, and *p* is the maximum time lag under consideration.

The rank-based non-parametric MK statistical test has been commonly used to assess the significance of trends in hydro-meteorological time series such as water quality, streamflow, temperature and precipitation. Many Previous studies have used the M-K test for detecting trends in hydrological and hydro meteorological time series (Hamed, 2008; Kabanda and Nenwiini, 2013).

The MK trend test is less affected by outliers because its statistic is based on the sign differences, not directly on the values of the random value (Bayazit and Bihrat, 2003). In the Mann-Kendall test missing values are allowed and the data need not conform to any particular distribution. It is commonly used with the Sen Slope estimator, in order to find and identify the magnitude of the change and the trends of the variable. Previous studies, such as Kundu *et al*. (2012), Kabanda and Nenwiini (2013) and Begum and Rahman (2013), used a combination of these two methods to detect the trends. These two methods may be useful in achieving the specific objectives of the current study. According to Adamwoski *et al.* (2014), MK trend test has been found to be an excellent tool for trend detection and many researchers have used this test to assess the significance of the trends in hydro-climatic data such as that of temperature and precipitation.

2.5.5 Sen's slope estimator

The Sen's slope method is used to determine the magnitude of the trend. The Sen's slope method gives a robust estimation of the trend (Yue *et al.*, 2002). According to Salmi *et al.* (2002) in cases where important significant trends are observed, this method gives high levels of significance with a narrow angle between the confidence lines. The Sen's method is not greatly affected by gross data errors or outliers, and also it can be computed when data are missing. The method requires a time series of equally spaced data. It then proceeds by calculating the slope as a change in measurement per change in time.

According to Theil (1950), if a trend is present in a time series, the true slope of the trend is estimated using a simple non-procedure, which is given by:

$$Q' = \frac{X_{t'} - X_t}{t' - t} \qquad 2.19$$

Where,

Q'= is Sen Estimator of slope between data point x_t and $x_{t'}$

$x_{t'}$ = data measurement at time t'

x_t = data measurement at time t

$$Qmed = \begin{Bmatrix} Q'\left(\frac{N+1}{2}\right) & if & N\ is\ Odd \\ Q'\left(\frac{N}{2}\right) + Q'\left(\frac{N+2}{2}\right) & if & N\ is\ Even \end{Bmatrix}$$

Where *N* is the number of calculated slopes.

2.5.6 Student's t test

This is the parametric test that considers the linear regression of the variable Y and on time X. The regression correlation coefficient β (or the Pearson correlation coefficient) is the interpolated regression line slope coefficient computed from data. The student-test (Hald, 1952; Panofsky and Brier, 1968) assesses whether the means of two groups are not statistically different from each other. It can be performed for both homogeneous (omoscedastic case) or nonhomogeneous (eteroschedastic case) sample variance.

In the eteroschedastic case (walch test) if n_1 and n_2 are the sample size and s_1 and s_2 are the sample variance, the degree of freedom (v) is always smaller than in the omoschedastic case.

$$v = \frac{\left[\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right]}{\frac{\left(\frac{S_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{S_2^2}{n_2}\right)^2}{n_2 - 1}} \qquad 2.20$$

This would entail that, for a given significance level, the critical region of the Welch test is wider than that corresponding to the Student's test and, consequently, that the null hypothesis (H0: $\mu 1 = \mu 2$) is rejected for a smaller number of gauged stations. The omoschedastic test then represents the more conservative case, and therefore has been selected to assess data homogeneity. If the variances in the two samples are assumed to be equal, the t -test statistic, which has a Student's distribution, is defined as:

$$t_{n_1 n_2} = \frac{\overline{X}_1 - \overline{X}_2}{S} \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \qquad 2.21$$

Where n_1 and n_2 are the sample sizes, $\overline{X_1}$ and $\overline{X_2}$ are the respective sample means and S is the sample variance, calculated as:

$$S = \sqrt{\frac{n_1 s_1^2 + n_2 s_2^2}{n_1 + n_2 - 2}} \qquad 2.22$$

If the calculated t value is above the threshold chosen for statistical significance (usually the 0.05 level), then the null hypothesis, H0 ($\mu_1 = \mu_2$), that the two groups do not differ is rejected in favour of an alternative hypothesis, which states that the groups do differ (Ha:$\mu_1 = \mu_2$). The critical region for a given significance level α is $|t_{n1,n2}| \geq t(\alpha/2,\upsilon)$ (two-tailed test), where υ is the degree of freedom, which is $\upsilon = n_1 + n_2 - 2$ for equal variances.

The *t*-test is applied supposing that each year of the monitored period could represent a potential changing point, thereby breaking the sample series into two subset series, whose size is n_1 and n_2 (with $n_1 + n_2$ equal to the total sample size) and calculating whether, for a given confidence level, differences between the sub-set series are significant or not.

The student t-test is a parametric test, it assumes that the random variables are normally distributed and homoscedastic and is based on linear regression and therefore checks only for a linear trend. In general, the student t parametric test, when compared to non-parametric test, is more powerful for given *n* when the variable is normally distributed but much less powerful when it is not (Hirsch *et al.*, 1991). Thus this method is not suitable for this study because it focuses only on the linear trends.

2.5.7 Spearson Rho (SR)

SR is a rank-based test that determines whether the correlation between two variables is significant. In trend analysis, one variable is taken as the time itself (years) and the other as the corresponding time series data. Given a sample data set $\{x_i = 1, 2 \ldots\ldots n\}$, the null hypothesis H_0 of the SR test against trend test is that all the x_i are independent and identically distributed, the alternative hypothesis is that x_i increases or decreases with ***i*,** and that means the trend exist.

The test statistic is given by:

$$D = \frac{6\sum_{i=1}^{n}\left[R(x_i)-1\right]^2}{n(n^2-1)} \qquad 2.23$$

Where R_{xi} is the rank of the i^{th} observation, x_i is the sample size n

Under the null hypothesis, the distribution of D is asymptotically normal with the mean and variance as described in Lehman (1975) and Sneyer (1990):

$E(D) = 0$

$V(D) = \frac{1}{n-1}$ 2.24

V= Variance

D= The test statistic

E= The mean

The P-value of the SR statistics (d) of the observed sample data is estimated using the normal commutative distribution function (CDF) as its statics are approximately normally distributed with a mean of zero and variance of V (D) for the SR statistic using the following standardization.

$Z_{SR} \frac{D}{\sqrt{V(D)}}$ 2.25

The standardised Z follows the standard normal distribution Z~ 0.1. The *p*–value (probability value) of sample data can be estimated using the normal distribution function (CDF)

$P = 0.5 - \boldsymbol{\Phi}(|\boldsymbol{z}|)$ ($Z=Z_{SR}$) 2.26

If the P-value is small enough, the trend is quite unlikely to be caused by the random sampling. At the significance level of 0.05, if $p \leq 0.05$, then the existing trend is considered to be statistically significant.

Yue *et al*. (2002) investigated the power of M K over SR and the results indicated that the two tests have similar powers for detecting trend in highly skewed time series. However, reviewed literature did not show that the SR method can be implemented with Sen S estimator to determine the magnitude of the trend.

2.5.8 Seasonal Kendall Analysis

The Seasonal Kendall is a non-parametric method of detecting trends in groundwater data series as well as hydrological data series. It is one of the most commonly used tests for trend in environmental sciences (Helsel and Hirsch, 2002). It is a version of the Mann-Kendall test that allows for seasonality in the data (Hirsch *et al*., 1982).

According to Hipel and McLeod (1994) and McLeod *et al.* (1990), the Seasonal-Mann-Kendall trend test is a test for monotonic trend in a time series with seasonal variation. Hirsch *et al.* (1982) developed this test by computing the Kendall score separately for each month. The separate monthly scores are summed up to obtain the test statistic. The variance of the test statistic is obtained by summing up the variances of the Kendall score statistic for each month. The normal approximation may then be used to evaluate the significance level. In this test, the null hypothesis is that the time series is of the form:

$$Zt = \mu m + et \tag{2.27}$$

where *et* is white noise error, *µm* represents the mean for period *m* and z_t is Kendal statistics

The *T* coefficient is defined by:

$$T = \frac{\sum_{i=1}^{s} S_i}{\sum_{i=1}^{s} D_i} \tag{2.28}$$

Where S_i; D_i; $i = 1, \ldots, s$ denote the Kendall scores and denominators for the *i*-th season and *s* is the seasonal period (Hipel and McLeod, 1994) and (McLeod *et al*., 1990).

2.5.9 Linear regression (LR)

LR is a method of modelling data to show a decreasing or increasing trend in the form of a graph. Regression refers to the fact that, although observed data are changing, they tend to move backwards towards their mean. Linear refers to the type of equation used in the models. Higgins (2005) defined linear regression as a model that uses the fact that there is a statistically significant correlation between two variables to allow one to make predictions about one variable based on the knowledge of the other. This method gives a clear interpretation of the slope direction on the graph for the time series data sets. LR is a parametric test that assumes that data are normally distributed and that the errors (deviations from the trend) are independent and follow the same normal distribution with a zero mean.

Where temporal or spatial patterns are strong, simple procedures such as time plots or linear regression over time can reveal trends (Hart, 2008). Robson and Kundzewicz (2000) showed that it is one of the most common tests for trend and, in its basic form, assumes that data are normally distributed. It is on more complex situation where sophisticated statistical models and procedures may be needed.

Zou *et al.* (2003) explained that the main goal of linear regression is to fit a straight line through the data that predicts Y based on X. LR should not be done unless the correlation coefficient is statistically significant and, for it to work there is need to have a linear relationship between the variables (Higgins, 2005). Makarau (1995) and Unganai (1996) in their investigation of the possible decline of rainfall in Zimbabwe used linear regression, which reflects changes around the mean value.

LR is the first analysis to be used extensively, the reason being that models which depend linearly on their unknown parameter are easier to fit than models which are non-linearly related to their parameter, and also because the statistical properties of the resulting estimator are easier to determine. The least square is the common estimation technique for linear regression. It is conceptually simple and computationally straightforward. Kamershu (2012) used LR to plot the linear trend line in Microsoft Excel to complement the results obtained using the MK test since the results are in digit form and the linear regression will be graphical. This method only provides information about the trend of the average value regarding the dependent variable for every value of the independent variable.

2.5.10 Worsley likelihood ratio test

The ratio test developed by Worsley (1979) gives the jump in between the time series and this indicates the initiation of change. This method tests whether the means in two parts of a record are different (for an unknown time of change). The test assumes that data are normally distributed; this is an unlikely scenario for hydrological data. The Worsley likelihood ratio test is similar to Student's *t* test, but is suitable for use when the change-point time is unknown. Normal scores tests are likely to give slightly improved power for detection of change relative to equivalent rank-based tests. The Worsley likelihood ratio test is defined as:

$$W = \frac{(n-2)^{0.5} V}{(1-V^2)^{0.5}} \quad . \qquad 2.29$$

Where $V = Max|Z_w|$

$$Z_w = [k(n-1)]^{0.5} \times SS$$

$$Z_w = \frac{Z_U}{dx}$$

n = number of observation

k = weight assigned to SS

Z_W = Worsely statistic

Z_u =test quotient

V = any convenient statistic

The critical test statistic value for various significance levels for all selected observation are 2.869, 3.159 and 3.79 at 90, 95 and 99% probability levels, respectively.

2.6 Determining rainfall duration and its changes

Duration of rainfall can be defined as the length of time over which the rainfall has occurred in one year, one month days, hour or minutes. It can also be defined as the period of time in which rain is measured. The length of the rainy season is calculated by subtracting the starting date of the rain in Julian days from 365 (366 for leap years) and adding the number of Julian days for the end of the rains if the start of the season is before 31 December. If the start of rain/season is in January onwards, the rainy season length is obtained by subtracting the start date of rains (Julian days) from the end date of rains (Julian days) (Moeletsi *et al*., 2011).

Moeletsi *et al*. (2010) determined the duration of rainy seasons firstly by determining the onset and cessation of the rainy season. Onset was defined as the first day of the season in which 25 mm or more rainfall was accumulated during the previous 10 days, thereafter accumulating more than 20 mm rainfall in the subsequent 20 days. This was used to determine the beginning of the rainy season in most semi-arid areas of SA. Cessation was defined as the end of the rainy season and was obtained by getting the last day in which cumulated rainfall of 25 mm over ten days occurred. The length of the rainy season (duration of the rainy season) was defined as the difference between cessation date and onset date on the same rainy season.

Ilesanmi (1972) determined the onset and cessation of the growing season by first deriving the percentage mean annual rainfall that occurs for each 5 day interval and followed by accumulating the percentages of the 5-day periods. When the cumulative percentage is plotted against time through the year, the first point of maximum positive curvative of the graph corresponds to the time of rainfall onset, and the last point of maximum negative curvature corresponds to the rainfall cessation. The study further noted that the point of onset on the graph corresponds to the time when an accumulated 7–8% of the annual rainfall totals have been obtained, whereas that of rainfall cessation is 90%.

Gong *et al.* (2004) determined the duration of the rainy season by counting the number of rainy days in the rainy season (May – Sep) from 1956 to 2000 for each year and for each station (30 stations) in the semi-arid region, in northern China. The day when the amount of precipitation was $\geq$ 0.1 mm was regarded as a rainy day (Gong *et al.*, 2004). Gong *et al.* (2004) then calculated the changes in the number of rainy days from averaging the mean values for all the stations.

In Zimbabwe, two criterions are used in coming up with the onset of the rainy season. The first criterion determines the onset of the rainy season following cumulative rainfall exceeding 25 mm occurring during a maximum time span of 7 days (Raes *et al.*, 2004). The other criterion determines the onset of the rainy season following cumulative rainfall exceeding 40 mm, but having been received in a maximum of 15 days. The cessation of the rainy season is normally determined as the first dry day after mid – February in a period of 14 days, whose cumulative rainfall total is less than 40 mm. In this criterion, a dry day is considered to be one with less than 0.3 mm of total rainfall.

Ngongondo *et al.* (2014) found that onset and cessation of rainfall over Malawi shifted to later dates, but without major changes in the length of the growing season. The results suggested that the growing season in most parts of Malawi starts in the middle or late December, although some stations experience an earlier start in November. It was discovered that rainfall cessation at most stations changed to the end of April or early May.

Mackellar *et al.* (2014) showed statistical significant decreases in rainfall and the number of rainy days over the central and north eastern parts of the SA in autumn months and that there were significant increases in the number of rainy days around the southern Drakensberg in spring and summer. An increased dry spell duration was evident for much of the Free State and Eastern Cape, and decreases in the wet spell duration were observed for parts of the Eastern Cape and the north eastern parts of SA during 1910–2004 (Kruger, 2006).

Dagada (2017) noted that mean duration of rainfall varied from 102 to 128 days in Luvhuvu River Catchment of South Africa. Mean onset of rainfall varying from day 255 to 297 of the Julian calendar and cessation of rainfall for most hydrological years being higher than the mean days of 88, 83 and 86 days.

CHAPTER THREE: METHODOLOGY

3.1 Preamble

This chapter presents the types of data used in this study, and where the data was collected. It also describes data analyses methods that were employed to achieve the objectives of the study.

3.2 Data collection

Historical rainfall data for hydrological years 1965- 2015 (51 years period) for 9 stations (Table 3.1 and Figure 3.1) was obtained from South African Weather Services (SAWS) and Lynch (2004) database. Stations were selected based on availability of long-term rainfall data that exceeded 30 years period and also considering stations with minimal or no gaps. For Lynch (2004) database, stations with 90 % or more, reliable data were considered and for SAWS data, stations that had less than 10 days of missing rainfall data in a month were considered. Fifty years period was chosen because, according to WMO (1976) at least 30 years or longer is ideal for climate change of significance to take place. Kabanda (2004) stated that the longer the period, the more complete the picture obtainable of the climate of the station. The stations used in the current study were within the upper reaches of the catchment because of lack of data at the lower reaches of the catchment.

The data were analysed based on the hydrological years, meaning that a hydrological year started from October of the current year and proceeded to September of the following year. At seasonal scale, the season started from October of the current year and proceeded to March the following year. For example, the hydrological year 1965 covers the period from October 1965 to September 1966 for annual time scale while the seasonal time scale covers October 1965 to March 1966.

Table 3.1: Stations used in the study

Name of station	Longitude(º)	Lattitude(º)	Altitude(m)
Hanglip	29.92	-23.02	1036
Nooitgedacht	30.2	-23.07	762
Palmaryville	30.43	-22.98	610
Shefeera	30.12	-23.03	1214
Levubu	30.22	-23.09	706
Klein Australie	30.22	-23.05	702
Matiwa	30.28	-22.98	1311
Vondo Bos	30.33	-22.93	1130
Entabeni Bos	30.27	-23.01	1376

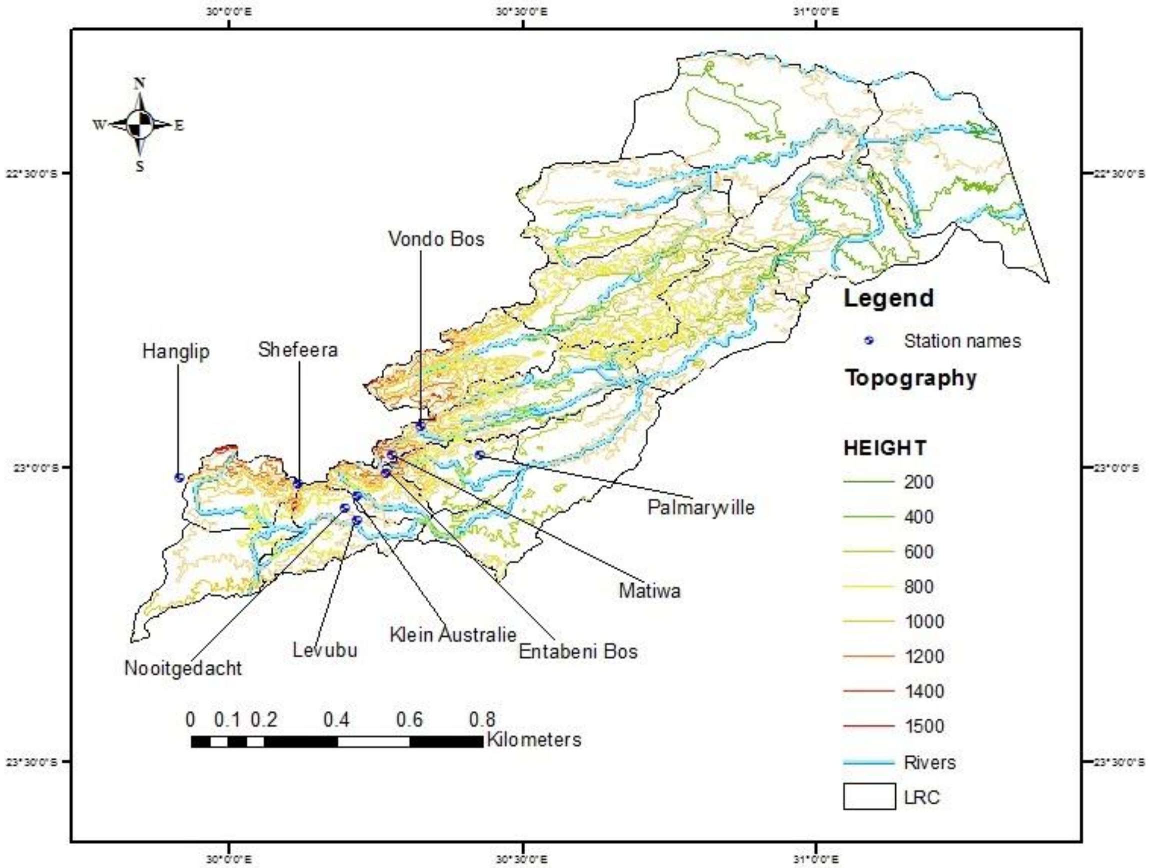


Figure 3.1: Topography of the study area

3.3 Data analysis methods

3.3.1 Data quality control

Arithmetic mean method was used to patch missing daily rainfall data because of its convenience, simplicity and also because it permits the solution of any system of equations. DMA was used to check the consistency and homogeneity of daily rainfall data. Coefficient of determination (R^2) was used to show how strong the correlation and relationship between the surrounding stations and check station is and hence confirm consistency of rainfall data.

3.4 Detecting trends

Total annual rainfall for each hydrological year, total seasonal rainfall, and total number of seasonal rainy days (rainfall duration) were computed from daily rainfall for each station.

These constituted long term annual and seasonal rainfall, and seasonal rainy days. The same approach used by Moeletsi *et al*. (2010) which is described in subsection 2.6, was used to determine the duration of seasonal rainfall (number of rainy days). The computed total annual and seasonal rainfall magnitude and seasonal rainy days were used to detect the trends.

3.4.1 Linear regression

The linear regression method was used to detect trends, for long term annual and seasonal rainfall magnitude, and duration of seasonal rainfall.

$$Y = a + bX \qquad 3.1$$

In this study, Y variable in Equation 3.1 is rainfall magnitude (mm) or rainfall duration (rainy days) and independent variable X is the year of record. The slope of regression showed the direction of trend. The decreasing (increasing) trends was shown by the negative (positive) sign of the slope of regression, respectively. The significance of the trend was shown by the probability value (p-value) of which it was estimated during the computations using linear regression functions of the Data Analysis ToolPak of Microsoft Excel software.

3.4.2 Quantile regression model

Quantile regression model was also used to identify the presence of trends for selected quantiles (0.1, 0.2, 0.5, 0.7 and 0.9) for long term annual, and seasonal rainfall magnitude, and duration of seasonal rainfall. Huang and Shiau (2015) had shown that changes of rainfall regime may not equally affect all the percentile values of rainfall. Thus, it is necessary to examine the changes in various quantiles levels than to detect changes in specific quantiles such as 0.9 and 0.1 only as done by Xuan *et al*. (2017) and Chamaile-Jammes *et al.* (2007). Such separate quantiles do not reveal changes in entire distribution of the variable (rainfall). This was the basis for selecting the quantiles 0.1, 0.2, 0.5, 0.7 and 0.9 to detect trends in different distribution of rainfall. Quantiles 0.1 and 0.2, and 0.5, and 0.7 and 0.9 were considered to represent low, median and high rainfall events, respectively. Quantile regression model (Equation 3.2) was computed using quantreg function in Statistical Analysis Software (SAS).

$$Y = \beta(\theta)_0 + \beta(\theta)_1 X + \xi \qquad 3.2$$

From Equation 3.2 random variable Y represented rainfall magnitude or duration of seasonal rainfall and X represented the record of the study (years). Slope coefficient $\beta(\theta)_1$ was used to determine the direction of the trend following Mazvimavi (2010). If the slope coefficient was negative (positive) and significantly different from zero (measured by *p*-value) it meant that the θ th quantile of rainfall magnitude or duration of seasonal rainfall was decreasing (increasing). The linear trend line on the graph was also used to determine the direction of the trend. In cases where the trend line was not clear or showing the constant line in the graph, the sign on the slope co-efficient was helpful in giving a clear direction of the trend. The significance of the trend was measured by the *p*-value which is the two-tailed probability computed using *t* distribution following Yankovsky (2015). It is the probability of observing a greater absolute val0ue of *t* under the null hypothesis. If *p*-value was less than α of 0.05, the conclusion was that the trend was statistically significant and non-statistically significant if the *p*-value was greater than α of 0.05. The slope coefficients and *p*-values for these coefficients were estimated by the software.

3.4.3. Mann Kendall test

MK method was used to detect trends in seasonal, annual and the duration of seasonal rainfall using the XLSTAT software. In this study two hypothesis were tested in order to see if the trend exists or not. The first hypothesis was called the null hypothesis (there is no trend in the time series) and was referred to as H_0 which was opposed to hypothesis called the alternative hypothesis (the trend exists), referred to as H_a. The statistical test produces *p*-value, which is the probability of obtaining the data or more extreme data under the null hypothesis. It actually helped in determining the significance of the trend. If *p*-value was lower than α of 0.05, the null hypothesis was rejected and the alternative hypothesis accepted. The trend was therefore referred to as statistically significant. If *p*-value was greater than α, it meant that the statistical test was not "strong" enough to lead to a *p*-value lower than alpha then the trend was not statistically significant. The MK Statistic estimated by the software was used to indicate the direction of the trend. The negative (positive) sign was implying that the trend is decreasing (increasing). The Sen's slope estimator was also estimated during the computation by the software. This was used to determine the magnitude of the trends in the time series.

3.4.4. Reasons for using three trend detection methods

MK and LR methods are widely used together to identify possible trends of hydrologic and climate series. In this study LR was used to give a clear interpretation of direction of the monotonic trend on the graph. MK method has been found to be an excellent tool for trend detection and many studies have used this test to assess the trends in hydro-climatic time series. In the process of computing MK the XLSTAT software is able to estimate the Sen's slope, and the significance of the trend, thus it is able to give the magnitude of change and the significance of the trend. MK was then applied in this study for these purposes. MK and LR methods identify monotonic trends only. The quantile regression method is known to identify changes, over time, of any percentile values of hydrologic and climate variables. It enables determination of trends along the whole range of quantile values from 0 to 1 of dependent variable distributions. This means that it can be able to identify heteroscedastic changes (which have different values of the slope coefficient, $\beta\ (\theta)_1$ for different quantile values), and that is more informative as compared to LR and MK that only identifies monotonic trends. It was therefore used to identify such changes. These methods were used together in this study to complement each other. Furthermore, using more than one method for trend analysis as stated earlier, improves on the reasonableness of the results (Nkuna and Odiyo, 2011).

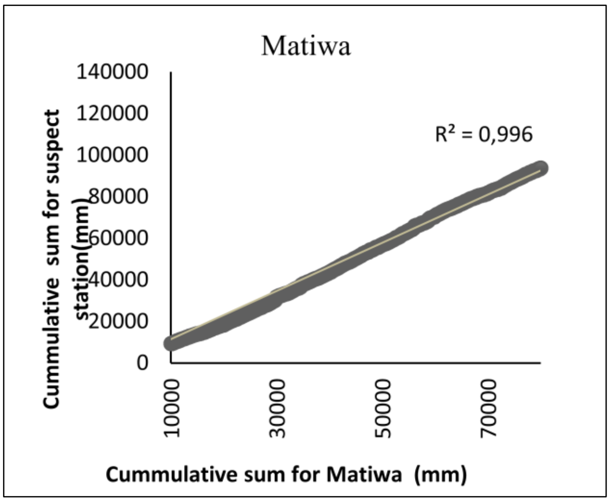
CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Preamble

This chapter presents the results of rainfall data analyses in detail at the area of study. Long term seasonal and annual rainfall magnitude and seasonal rainy days were used for identifying changes in seasonal and annual rainfall magnitude, and duration of seasonal rainfall.

4.2 Data quality control

Figure 4.1 gives DMA results for Matiwa and Entabeni Bos stations. The rest of the DMA results are presented in Appendix A. According to Lombaard *et al*. (2015), the mass plot for a station with no errors should form approximately straight line and this indicates stationary data. This shows that rainfall data for all stations in the study area is consistent since the DMA curves are approximately straight lines. R^2 values for Matiwa and Entabeni Bos are 0.996 and 0.9988, respectively. R^2 values in Appendix A range from 0.9986 to 0.9995 indicating the strong linear relationship between check station and other surrounding stations. A value of R^2 near 0 means a very weak linear relationship whereas a value near 1 indicates a strong relationship between the two variables (Moore et *al*., 2009). Nkuna and Odiyo (2011) have shown that R^2 values for DMA results in LRC were above 0.996. This is comparable with the values obtained in the current study. This shows that the data is homogenous and consistent.



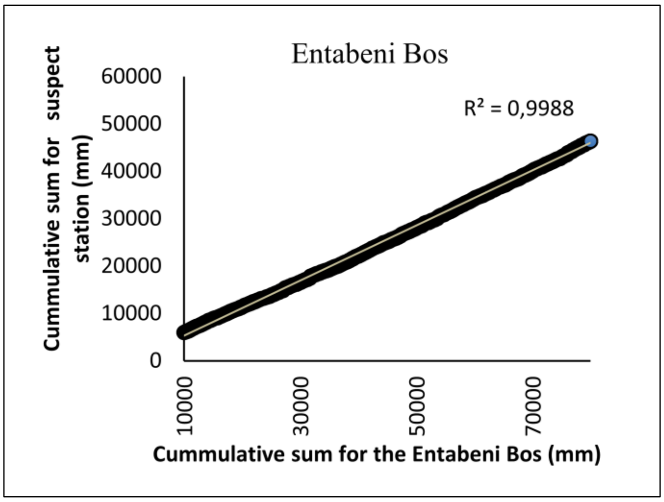


Figure 4.1: DMA for Matiwa and Entabeni Bos stations

4.3 Trends analysis based on MK method

Table 4.1 gives the MK results for annual rainfall magnitude for all 9 stations in the study area. Levubu, Matiwa, Nooitgedacht, Shefeera and Palmaryville stations had negative MK statistics and *p*-value greater than α=0.05. This showed non-statistically significant decreasing trends of annual rainfall magnitude in these stations. Entabeni Bos had negative MK statistic and *p*-value less than α =0.05, implying statistically significant decreasing trend of annual rainfall magnitude in this station. Hanglip and Vondo Bos had positive MK statistic and *p*-value greater than α= 0.05 indicating non-statistically significant increasing trend of annual rainfall magnitude. Klein Australie had positive MK statistic and *p*-value less than α= 0.05 indicating significantly increasing trend of annual rainfall magnitude. The results showed that decreasing trends of annual rainfall magnitude were dominant in 5 stations, and were not statistically significant. Hanglip, Vondo Bos and Klein Australie stations had increasing trends with only Klein Australie having statistically significant trends.

Table 4.1: MK results of annual rainfall for all 9 stations

Station name	MK statistic	*p*-value	Sen's slope (mm)	Direction of the trend	Significance
Klein Australie	256.00	0.03	6.78	Increasing	S
Hanglip	43.00	0.72	1.51	Increasing	NS
Vondo Bos	177.00	0.14	5.53	Increasing	NS
Entabeni Bos	-251.00	0.04	-12.31	Decreasing	S
Levubu	-205.00	0.09	-6.37	Decreasing	NS
Matiwa	-128.00	0.28	-6.88	Decreasing	NS
Nooitgedacht	-3.00	0.98	-0.12	Decreasing	NS
Shefeera	-225.00	0.06	-9.69	Decreasing	NS
Palmaryville	-105.00	0.38	-3.20	Decreasing	NS

Legend: S = significant; NS = not significant

From Table 4.1, the negative and positive signs on the Sen's Slope results show the direction of the magnitude of change. The magnitude of change of annual rainfall for the stations with increasing trends (+ sign) and decreasing trends (- sign) ranged from 1.51 and 6.78 mm, and -12.31 to -0.12 mm, respectively. This implies that annual rainfall has increased within the range of 1.51 and 6.78 mm for stations with increasing trends. Similarly, annual rainfall has decreased within the range of 0.12 to 12.31 mm for stations with decreasing trends. The results showed magnitude of change for decreasing trends of annual rainfall ranging from 0.12 to 12.31 mm.

Table 4.2 gives the MK results for seasonal rainfall magnitude in all 9 stations. Entabeni Bos, Levubu, Matiwa, Nooitgedacht, Shefeera and Palmaryville had negative MK statistics and *p*-values greater than α= 0.05, thus there were decreasing trends in seasonal rainfall magnitude that were not statistically significant. Hanglip and Vondo Bos had positive MK statistics with *p*-values greater than α=0.05, and Klein Australie station had positive MK statistic and *p*-value less than α=0.05. This implied statistically significant increasing trends of seasonal rainfall magnitude at Klein Australie and non-statistically significant increasing trends at Hanglip and Vondo Bos stations. The results showed general decreasing trends in long term seasonal rainfall magnitude in six stations.

Table 4.2: MK results for seasonal rainfall of all 9 stations.

Station name	MK statistics	*p*-value	Sens'slope (mm)	Direction of the trend	Significance
Hanglip	79.00	0.509	2.05	Increasing	NS
Klein Australie	243.00	0.042	6.51	Increasing	S
Vondo Bos	161.00	0.178	5.94	Increasing	NS
Entabeni Bos	-139.00	0.248	-6.72	Decreasing	NS
Levubu	-160.00	0.181	-5.52	Decreasing	NS
Matiwa	-77.00	0.52	-3.72	Decreasing	NS
Nooitgedacht	-116.00	0.336	-0.54	Decreasing	NS
Shefeera	-141.00	0.238	-6.00	Decreasing	NS
Palmaryville	-147.00	0.38	-4.25	Decreasing	NS

Legend: S=significant; NS =Not significant

The magnitude of change for seasonal rainfall for stations with decreasing and increasing trends based on Sen's slope results ranged from 0.54 to 6.72 mm and 2.05 to 6.51 mm, respectively (Table 4.2). This showed that seasonal rainfall has decreased and increased within the range of 0.54 and 6.72 mm and 2.05 to 6.51 mm, respectively. Thus, there is increasing and decreasing trends in both annual and seasonal rainfall magnitude but with decreasing trends dominating in both cases and mostly with the trends being statistically non-significant. Kabanda and Nenwiini (2013) noted that most stations in Vhembe district showed non-statistical significant change of rainfall with Sen's slope estimates varying between -3.95 and -18.3. The latter study further showed that Entabeni Bos, Levubu and Matiwa had the Sen's slope values of 12.52, 5.61 and 5.54, respectively, which are comparable to those of the current study.

Table 4.3 shows MK results for duration of seasonal rainfall in all 9 stations. Levubu, Matiwa, Palmaryville, Entabeni Bos, Shefeera and Nooitgedacht had negative MK statistics indicating decreasing duration of seasonal rainfall. Levubu, Matiwa, Palmaryville and Entabeni Bos had *p*-value less than or equal to α=0.05 indicating statistically significant decreasing trends in duration of seasonal rainfall in these stations. Shefeera and Nooitgedacht stations had *p*-value greater than α= 0.05 indicating non-statistically significant decreasing trends of duration of seasonal rainfall in these stations. Hanglip, Vondo Bos and Klein Australie had positive MK statistics and *p*-value greater than α=0.05 indicating non-statistically increasing trends in the duration of seasonal rainfall at Hanglip, Vondo Bos and Klein Australie stations. The results showed dominant decreasing trends on the long term duration of seasonal rainfall in six stations (Entabeni Bos, Levubu, Matiwa, Palmaryville Nooitgedacht and Shefeera), which were statistically significant for the first four stations and not-statistically significant for the last 2 stations. In general, it can be concluded that the duration of the seasonal rainfall just like the magnitude is showing increase and decrease in trends but with decreasing trends dominating. It is important to note that the increasing trends in this case are all statistically non-significant, while the decreasing trends are mostly statistically significant.

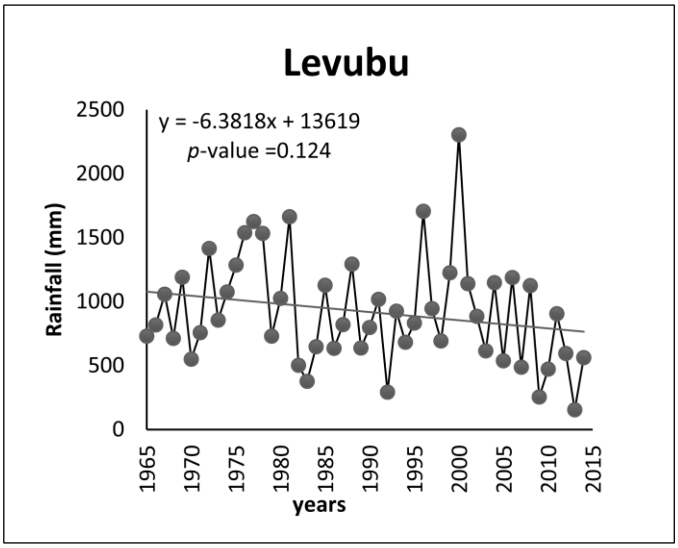
The magnitude of change based on Sen's slope results of the duration of seasonal rainfall for stations with non-statistically significant increasing trends ranged from 0.08- 0.17. This implies that the long term duration of rainfall had increased by less than half a day in these stations, although the change is not statistically significant. The stations with statistically significant decreasing trends had magnitude of change ranging from -0.28 to -0.80. This implies that the duration of seasonal rainfall mostly decreased by almost a day in these stations. The results show dominant increasing trends in both magnitude of change and duration of rainfall.

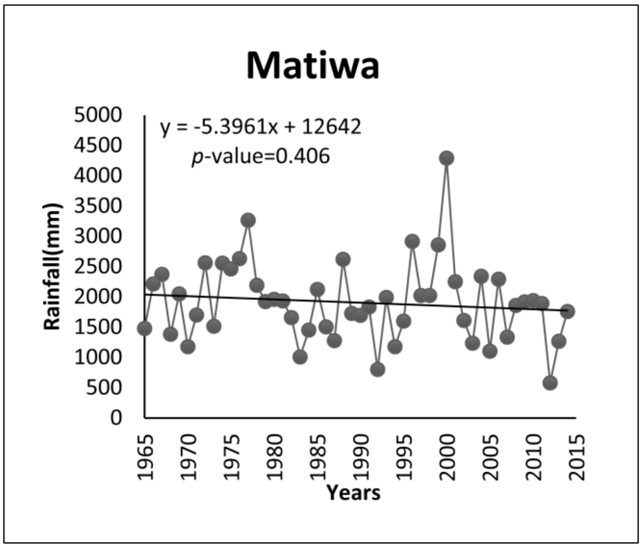
Table 4.3: MK results for long term duration of seasonal rainfall in all 9 stations

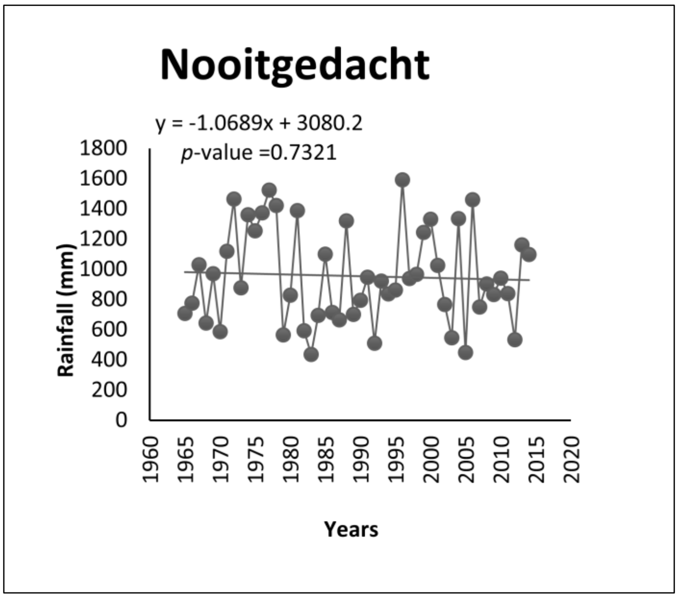
Station name	MK statistic	*p*-value	Sen's slope(days)	Direction of the trend	Significance
Hanglip	41	0.73	0.08	Increasing	NS
Vondo Bos	36	0.76	0.07	Increasing	NS
Klein Australie	65	0.59	0.17	Increasing	NS
Shefeera	-225	0.06	-0.02	Decreasing	NS
Nooitgedacht	-116	0.34	-0.25	Decreasing	NS
Entabeni Bos	-334	0.01	-0.66	Decreasing	S
Levubu	-275	0.02	-0.72	Decreasing	S
Matiwa	-236	0.05	-0.28	Decreasing	S
Palmaryville	-308	0.01	-0.80	Decreasing	S

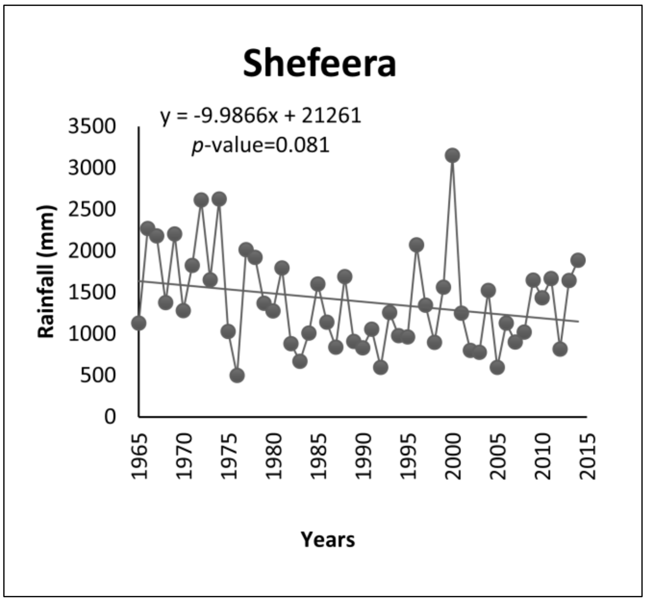
4.4 Trends analysis based on linear regression (LR) method

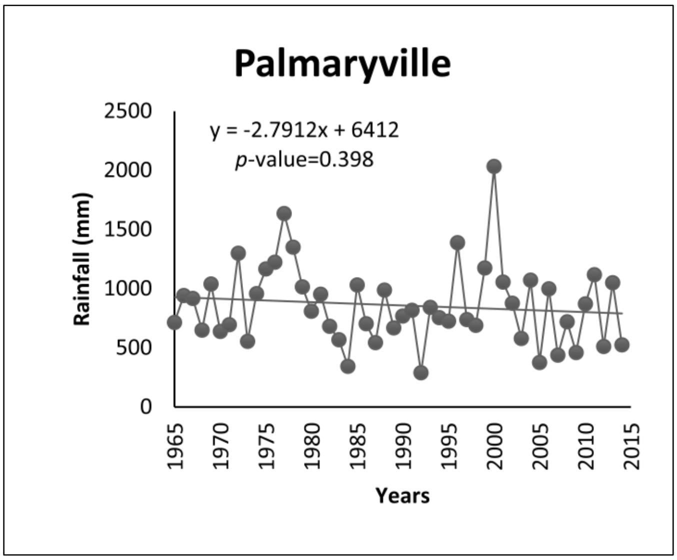
Figures 4.2 and 4.3 give the linear regression results for annual rainfall magnitude for all 9 stations in the study area. In Figure 4.2, Levubu, Matiwa, Nooitgedacht, Shefeera, Palmaryville Entabeni Bos, had decreasing slopes of regression (shown by the negative sign in the regression equation) and *p*-value greater than $\alpha = 0.05$. This showed non-statistically significant decreasing trends of annual rainfall magnitude in these stations. Hanglip, Klein Australie and Vondo Bos had positive slope of regression and *p*-value greater than $\alpha=0.05$. This showed non-statistically significant increasing trends in the annual rainfall magnitude. The results showed that decreasing trends in long term annual rainfall magnitude were dominant though they were not statistically significant.


Levubu
y = -6.3818x + 13619
p-value =0.124
Rainfall (mm)
years


Matiwa
y = -5.3961x + 12642
p-value=0.406
Rainfall(mm)
Years


Nooitgedacht
y = -1.0689x + 3080.2
p-value =0.7321
Rainfall (mm)
Years


Shefeera
y = -9.9866x + 21261
p-value=0.081
Rainfall (mm)
Years


Palmaryville
y = -2.7912x + 6412
p-value=0.398
Rainfall (mm)
Years

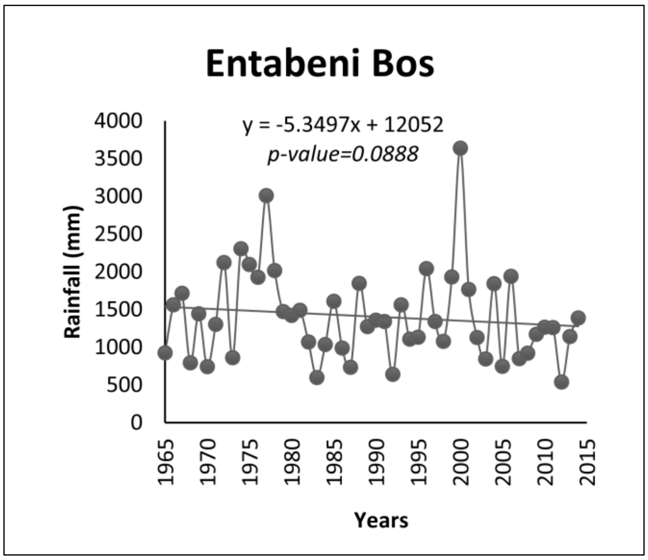

Entabeni Bos
y = -5.3497x + 12052
p-value=0.0888
Rainfall (mm)
Years

Figure 4.2: LR results for annual rainfall magnitude for Levubu, Matiwa, Nooitgedacht, Shefeera, Palmaryville and Entabeni Bos stations

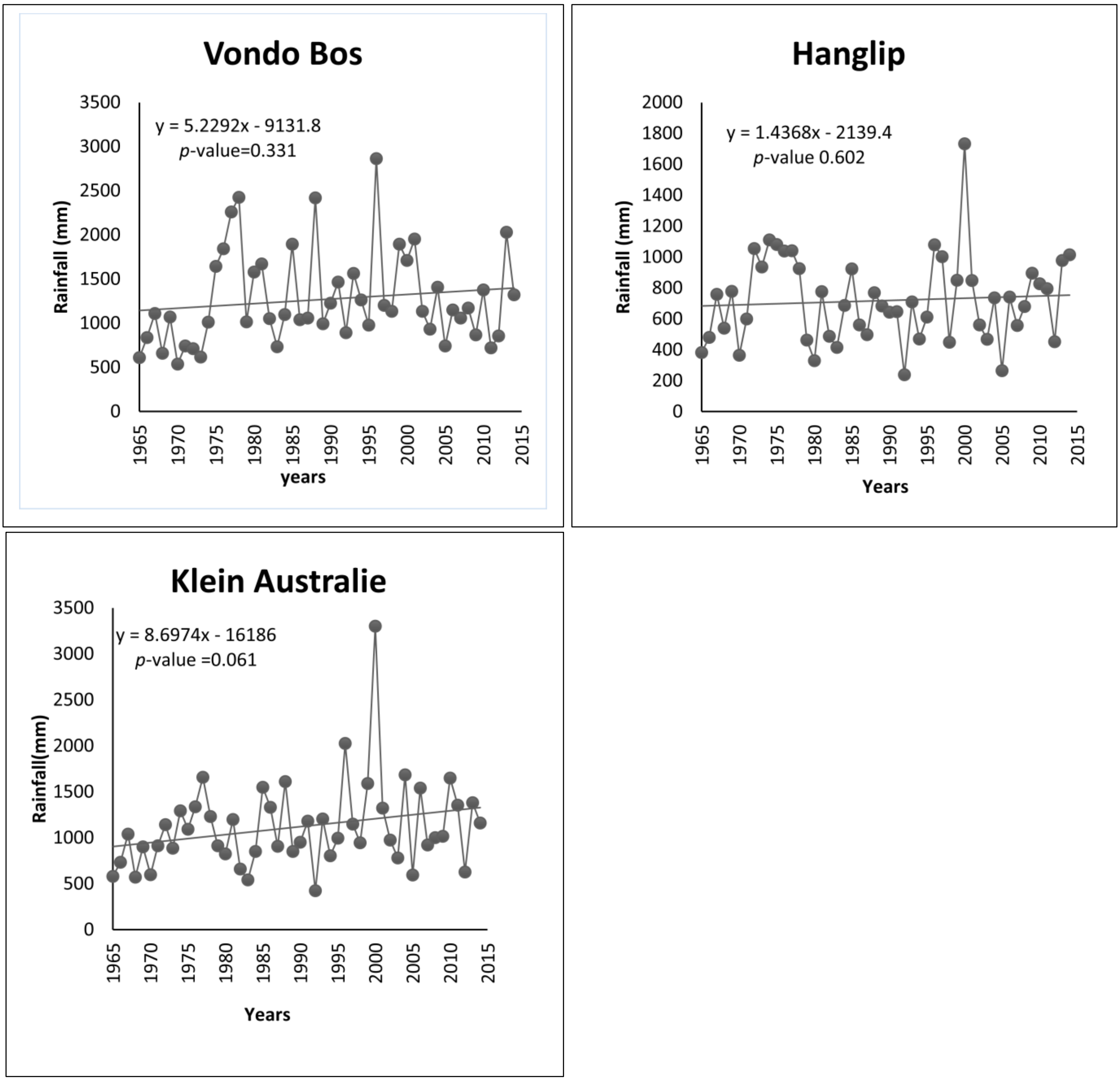


Figure 4.3: LR results for annual rainfall magnitude for Vondo Bos, Hanglip and Klein Australie stations

Figures 4.4 and 4.5 show the LR results for seasonal rainfall magnitude of all 9 stations. Entabeni Bos, Levubu, Matiwa, Nooitgedacht, Shefeera and Palmaryville rainfall stations had negative slopes of regression and *p*-value greater than α= 0.05. This showed non- statistically decreasing trends of seasonal rainfall magnitude in these stations. Hanglip, Klein Australie and Vondo Bos rainfall stations had positive slopes of regression and *p*-value greater than α=0.05. This showed non-statistically increasing trends of seasonal rainfall magnitude in these stations. Though, the results show both increasing and decreasing trends of long term seasonal rainfall magnitude, decreasing trends are dominating and all stations exhibit non-statistical significance.

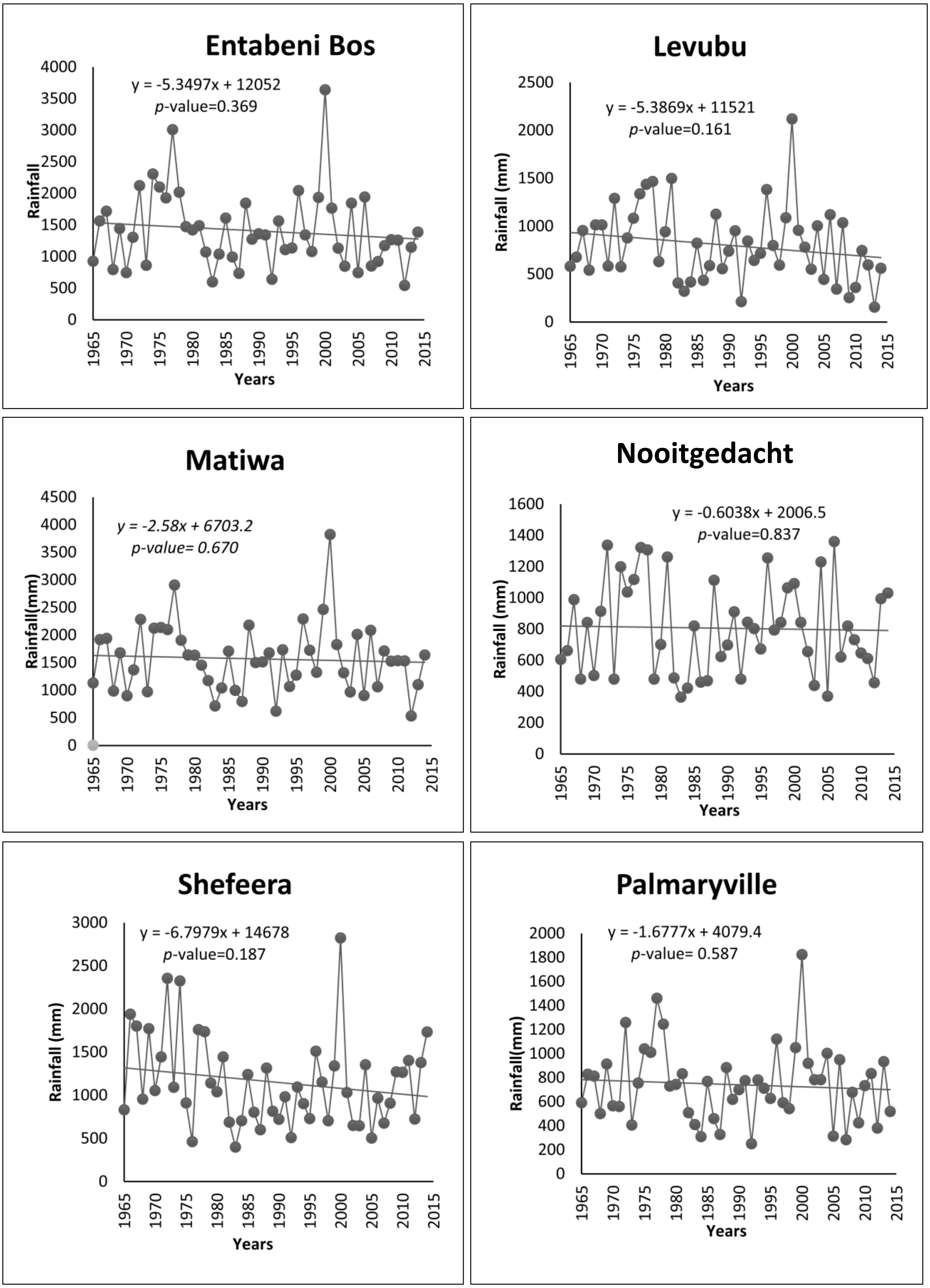


Figure 4.4: LR results for seasonal rainfall magnitude for Entabeni Bos, Levubu, Matiwa, Nooitgedacht, Shefeera and Palmaryville stations

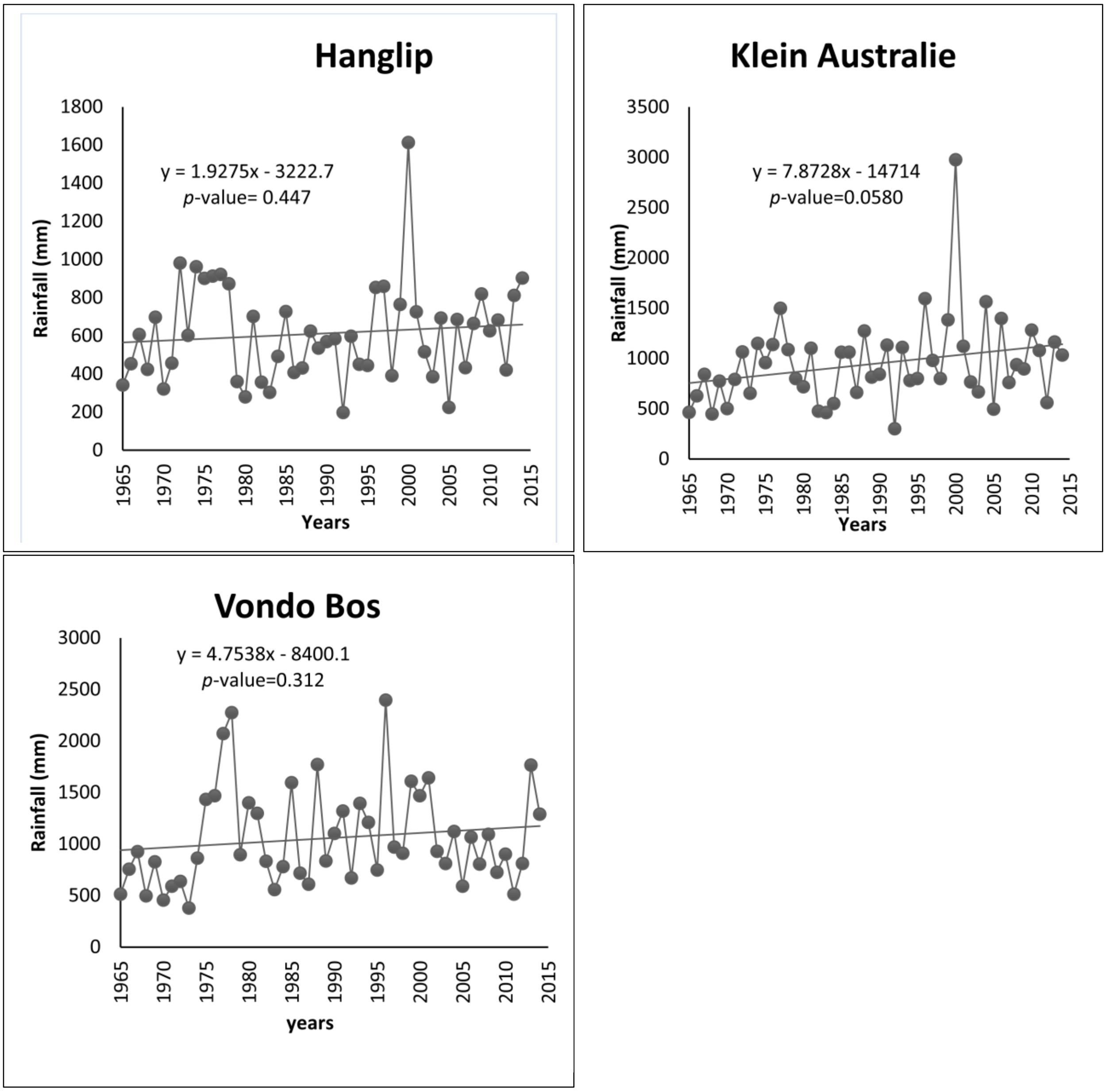


Figure 4.5: LR results for seasonal rainfall magnitude for Hanglip, Klein Australie and Vondo Bos stations

Figures 4.6 and 4.7 show the LR results for duration of seasonal rainfall for all 9 stations in the area of study. Entabeni Bos, Levubu, Matiwa and Palmaryville had negative slopes of regression and *p*-values less than α=0.05. This showed statistically significant decreasing trends of duration of seasonal rainfall in the stations. Hanglip, Nooitgedacht and Klein Australie stations had negative slopes of regression and *p*-values greater than α=0.05. This implied non-statistically significant decreasing trends on duration of seasonal rainfall. Shefeera and Vondo Bos had positive slopes of regression and *p*-values greater than α =0.05 indicating non-statistically significant increasing trends in the duration of seasonal rainfall magnitude in these stations. The results showed decrease and increase in trends, with decreasing trends in the long-term duration of seasonal rainfall in 7 stations (Entabeni Bos, Levubu, Matiwa, Palmaryville, Hanglip, Nooitgedacht and Klein Australie) dominating with the four stations being statistically significant and the last three are non-statistically significant.

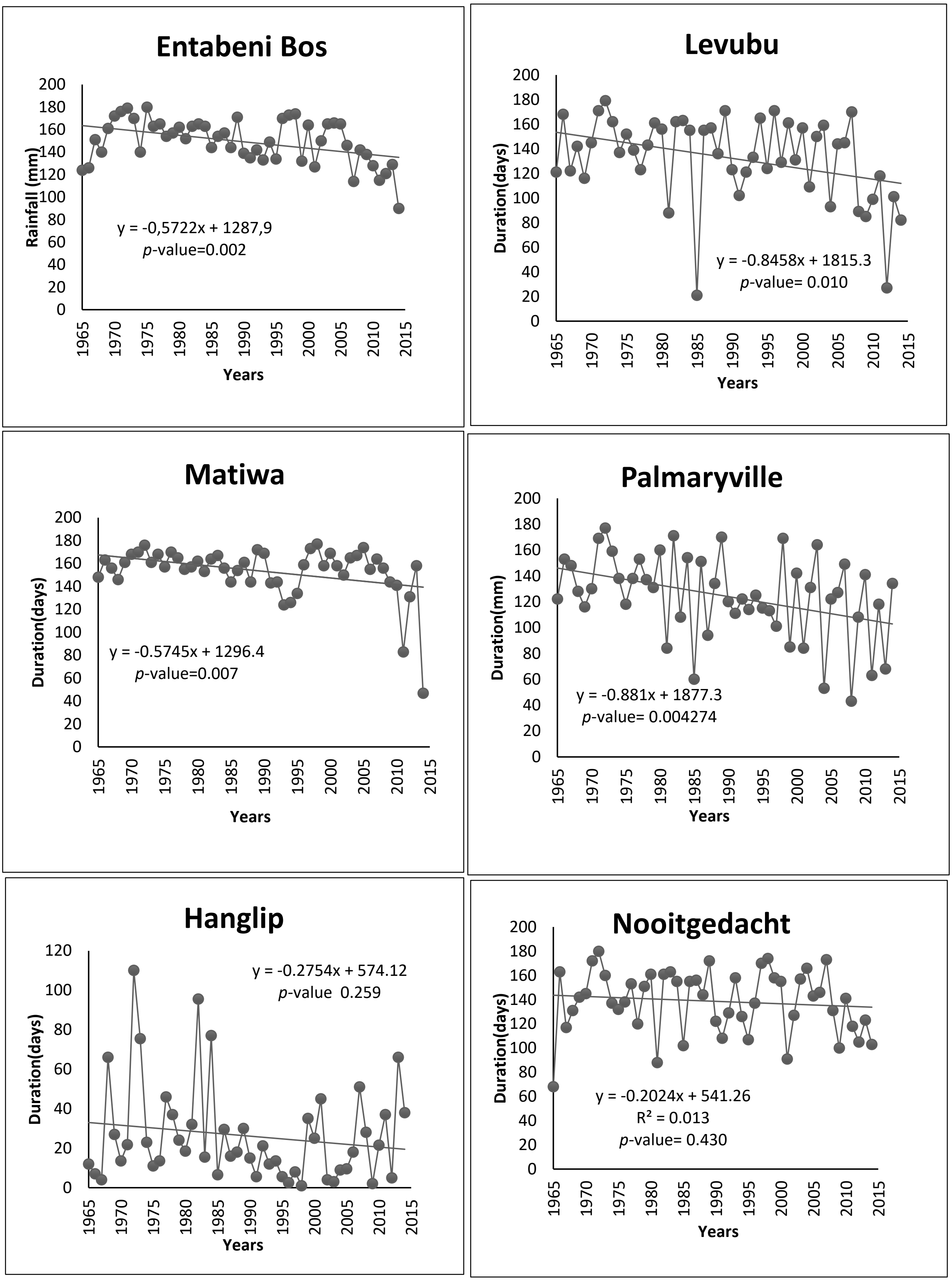


Figure 4.6: LR results for duration of seasonal rainfall for Entabeni Bos, Levubu, Matiwa, Palmaryville, Hanglip and Nooitgedacht stations.

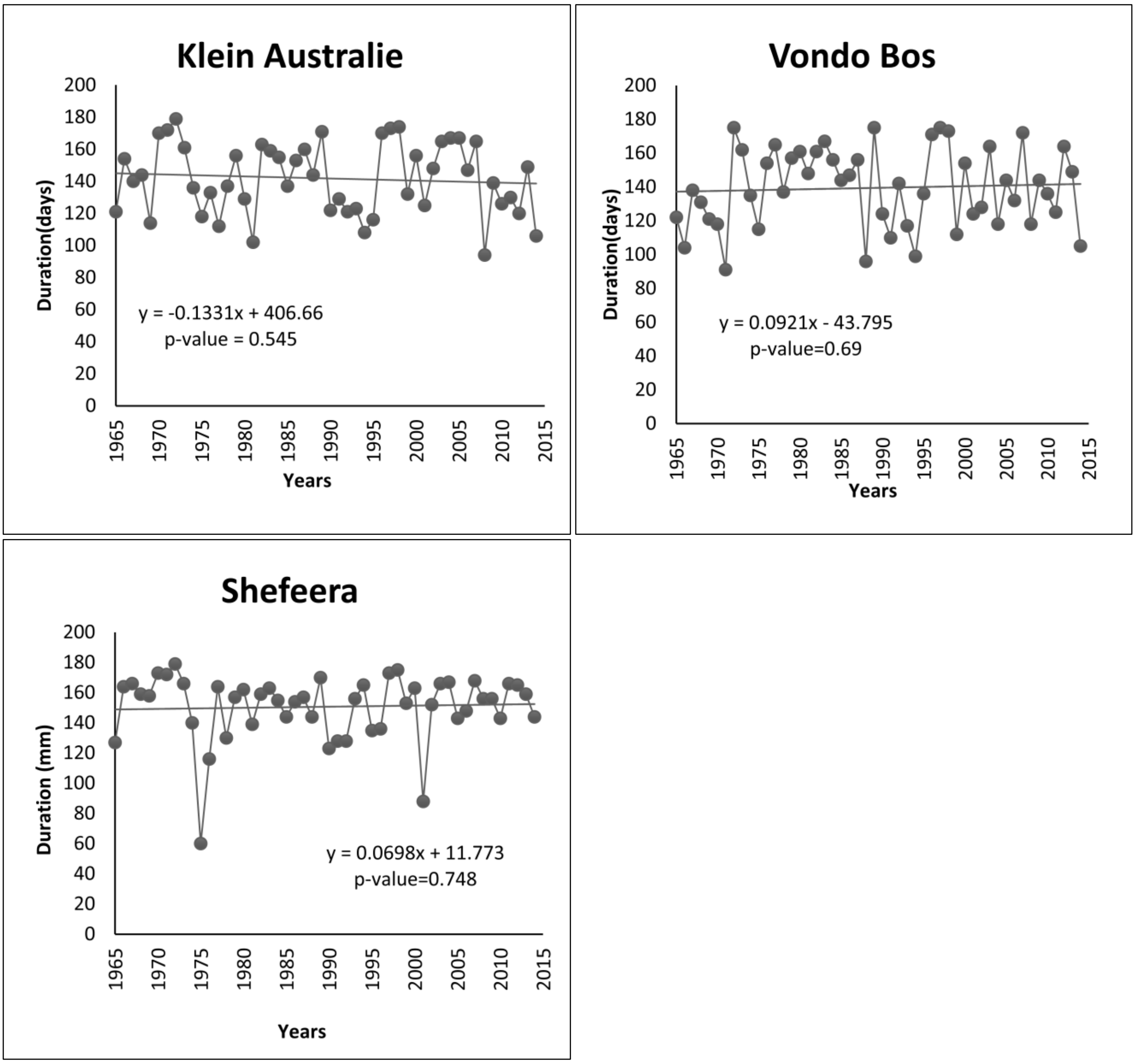


Figure 4.7: LR results for duration of seasonal rainfall for Klein Australie, Vondo Bos and Shefeera stations.

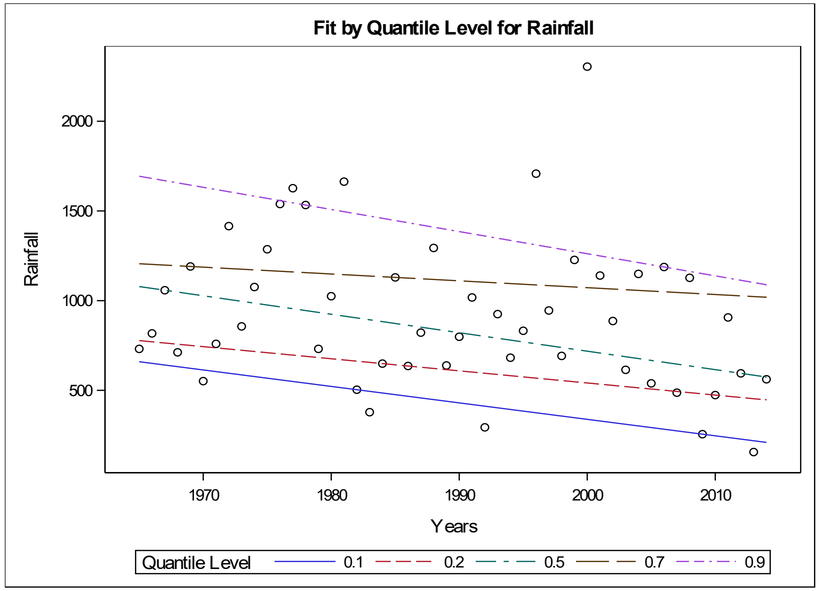
4.4 Trends analysis based on quantile regression model

Figures 4.8 to 4.10 and Table 4.4 give the quantile regression results of annual rainfall magnitude for all 9 stations in the area of study. The dotted lines in Figures 4.8 to 4.10 show regression for annual rainfall quantiles 0.9, 0.7, 0.5, 0.2 and 0.1 representing 90th, 70th, 50th 20th and 10th percentiles, respectively. Levubu, Palmaryville, Shefeera had negative slope coefficients and regression lines, and *p*-values greater than α=0.05 in all quantiles (Figure 4.8 and Table 4.4) This showed non-statistically significant decreasing trends in all quantiles of annual rainfall magnitude in these stations. Entabeni Bos, Nooitgedacht and Matiwa had *p*-values greater than α =0.05 and negative slope coefficients and regression lines in most quantiles. The latter three stations had *p*-values greater than α=0.05 and positive slope coefficients and regression lines in quantiles 0.1, 0.2 and 0.9, respectively. This implied non-statistical significant decreasing trends in most quantiles of annual rainfall magnitude and non-statistically significant increasing trends on 0.1, 0.2 and 0.9 quantiles of annual rainfall magnitude in these stations.

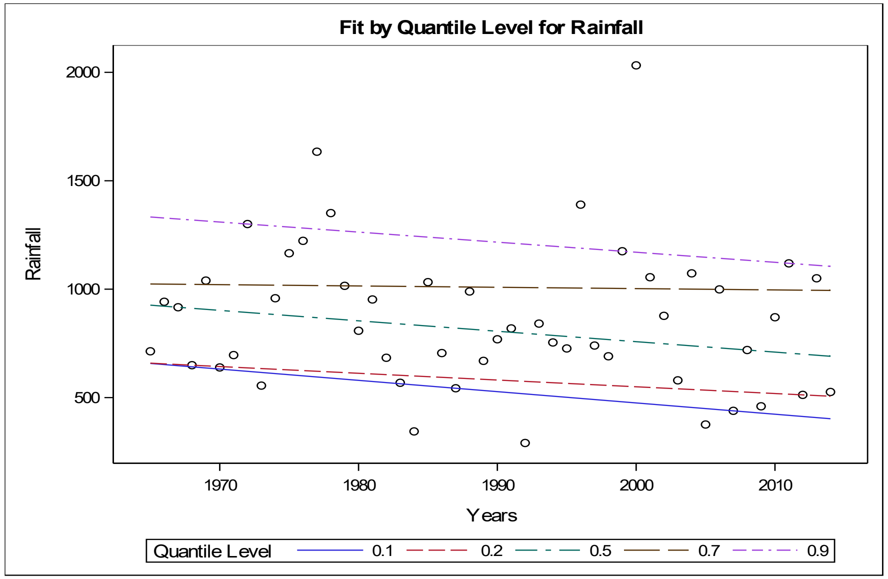
Klein Australie had positive slope coefficients and regression lines, and *p*-values greater than α=0.05 showing non-statistically significant increasing trends in all quantiles of annual rainfall magnitude. Vondo Bos and Hanglip had *p*-values greater than α=0.05 and positive slope coefficients, and regression lines in most quantiles. The two latter stations had *p*-values greater than α=0.05 and negative slope coefficients and regression lines in 0.7, and 0.7 and 0.9 quantiles, respectively. This showed non-statistically significant increasing trends in most quantiles of annual rainfall magnitude except for quantile 0.7 and 0.9 quantiles of annual rainfall magnitude these stations, respectively.

The results showed that six stations (Levubu, Palmaryville, Shefeera, Entabeni Bos, Nooitgedacht and Matiwa) had dominant non-statistically significant decreasing trends in either all or most quantiles of annual rainfall magnitude. Entabeni Bos and Nooitgedacht had non-statistically significant decreasing trends in most quantiles and had non-statistically significant increasing trends on the low rainfall events. Matiwa had non-statistically significant increasing trends on high rainfall events. Klein Australie, Vondo Bos and Hanglip were dominated by non-statistically significant increasing trends, though Vondo Bos and Hanglip had an exception of showing non-statistically significant decreasing trends on quantile 0.7 and 0.9 (corresponding to high rainfall event).

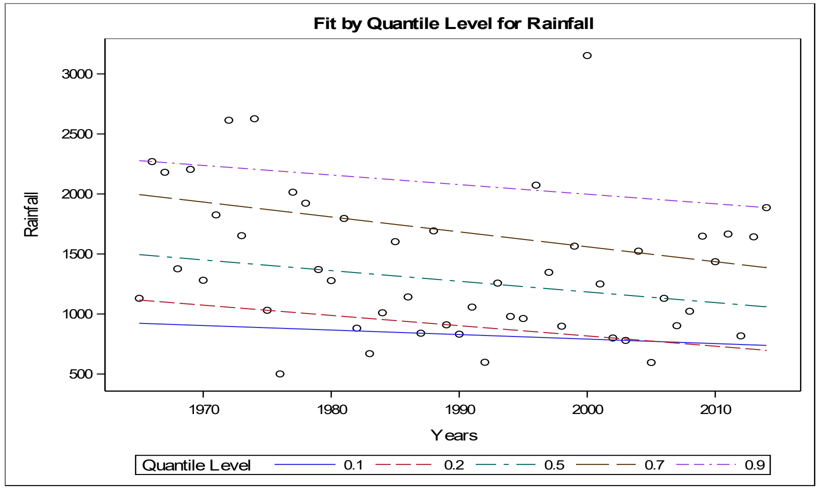
Levubu



Palmaryville



Shefeera



Nooitgedacht

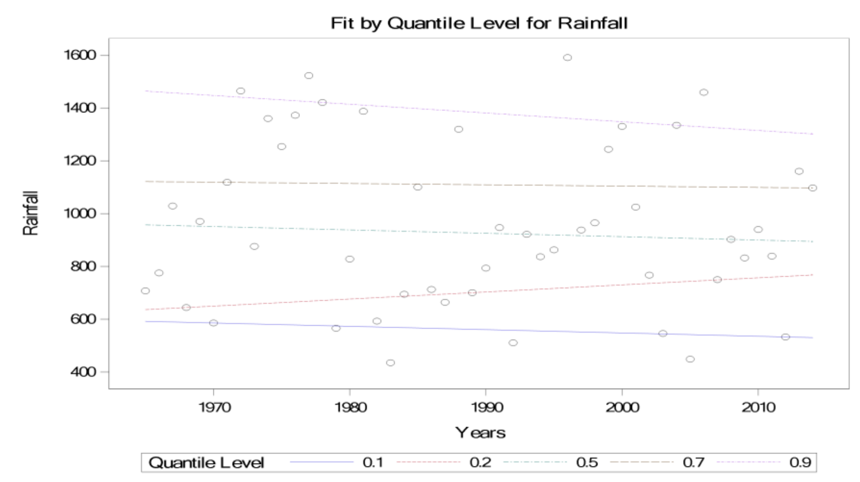
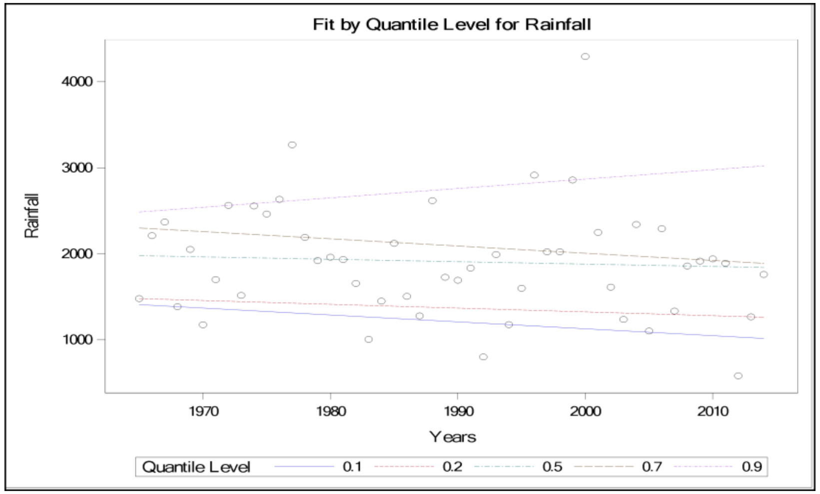
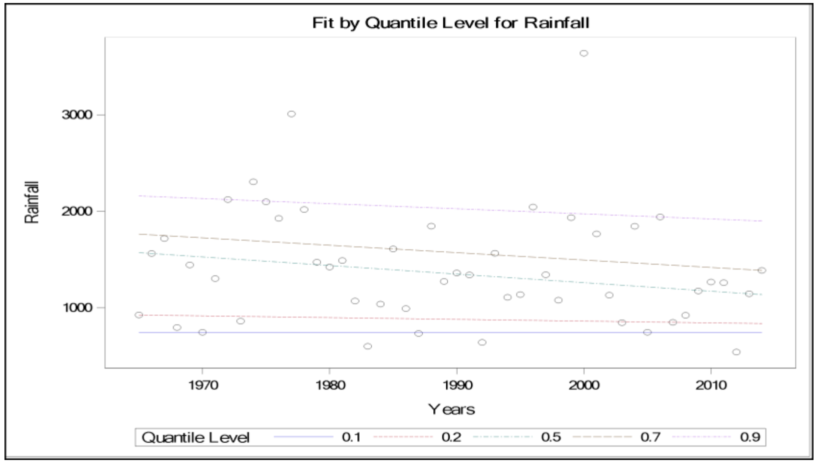


Figure 4.8: Quantile regression results for annual rainfall magnitude for stations: Levubu, Palmaryville, Shefeera and Nooitgedacht

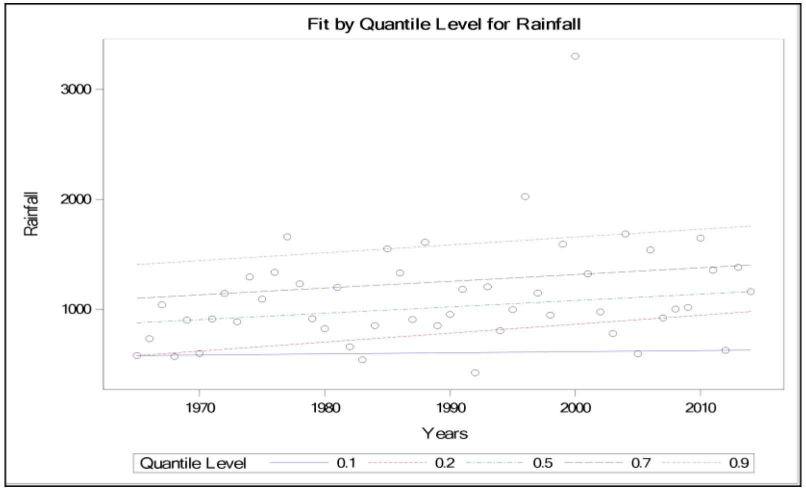
Matiwa



Entabeni Bos



Klein Australie



Vondo Bos

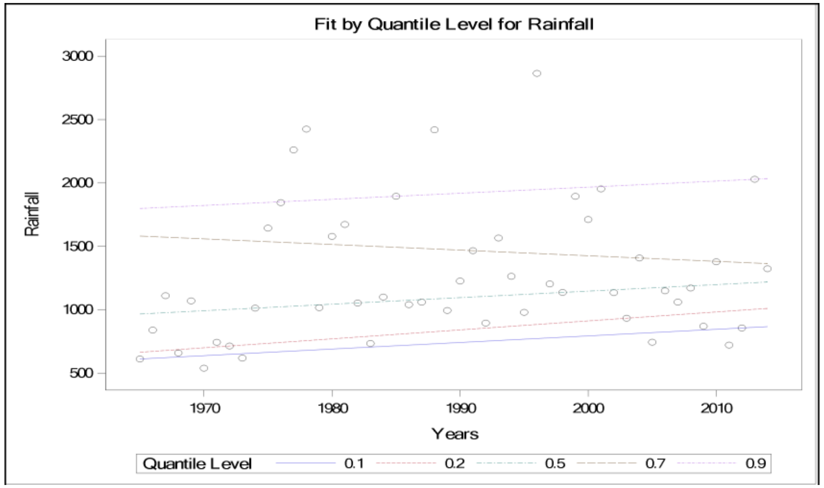


Figure 4.9: Quantile regression results for annual rainfall magnitute for Matiwa, Entabeni Bos, Klein Australie and Vondo Bos stations

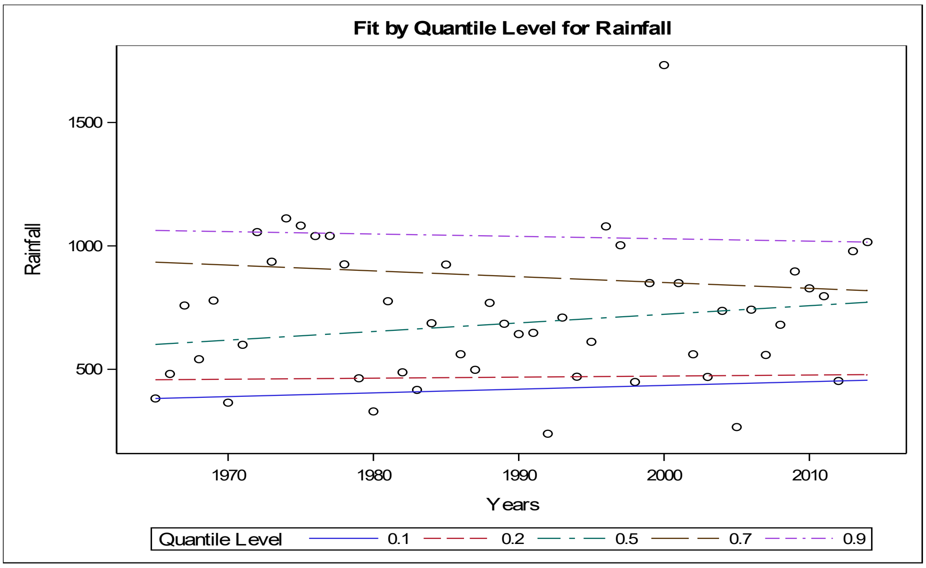


Figure 4.10: Quantile regression results for annual rainfall for Hanglip station

Table 4.4: *p*-values and slope coefficients for annual rainfall

Quantile		**Levubu**	**Palmaryville**	**Shefeera**	**Entabeni Bos**	**Nooitgedacht**	**Matiwa**	**Klein Australie**	**Vondo Bos**	**Hanglip**
0.1	*p*-value	0.12	0.39	0.83	1.00	0.79	0.55	0.91	0.06	0.85
	Slope coefficient	-9.18	-5.21	-3.76	0.01	-1.26	-8.02	1.01	5.20	1.51
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.2	*p*-value	0.06	0.24	0.20	0.79	0.51	0.51	0.06	0.10	0.93
	Slope coefficient	-6.75	-3.11	-8.54	-1.82	2.68	-4.41	8.14	7.07	0.43
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.5	*p*-value	0.12	0.30	0.37	0.13	0.77	0.74	0.23	0.43	0.40
	Slope coefficient	-10.29	-4.81	-8.88	-8.88	-1.28	-2.72	5.79	5.15	3.48
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.7	*p*-value	0.64	0.90	0.17	0.44	0.94	0.19	0.32	0.77	0.44
	Slope coefficient	-3.81	-0.61	-0.61	-7.67	-0.49	-8.18	6.16	-4.43	-2.36
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.9	*p*-value	0.85	0.72	0.59	0.85	0.79	0.70	0.76	0.87	0.85
	Slope coefficient	-12.34	-4.64	-4.64	-5.30	-3.31	10.93	7.14	4.80	-0.96
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS

Figures 4.11 to 4.13 and Table 4.5 give the quantile regression results of seasonal rainfall magnitude in the area of study. Levubu station had negative slope co-efficients and regression lines, and *p*-values greater than α=0.05 in all quantiles of seasonal rainfall magnitude indicating non- statistically significant decreasing trends. Entabeni Bos, Shefeera, Matiwa, Palmaryville and Nooitgedacht had negative slope coefficients and regression lines, in most quantiles with *p*-values greater than α=0.05. Entabeni Bos and Shefeera, and Matiwa had *p*-values greater than α=0.05 and positive slope coefficients and regression lines, for quantiles 0.1, and 0.1 and 0.2, respectively. Palmaryville and Nooitgedacht had positive slope coefficients and regression lines, and *p*-values greater than α=0.05 at quantile 0.7. The results showed non-statistically decreasing trends in most quantiles of seasonal rainfall magnitude and non-statistically increasing trends in 0.1, 0.2 and 0.7 quantiles of seasonal rainfall magnitude, respectively,for the stations discussed above. Klein Australie had positive slope co-efficients and *p*-values greater than α=0.05 in all quantiles indicating non-statistically increasing trends. Vondo Bos and Hanglip had *p*-values greater than α=0.05 and positive slope co-efficients in most quantiles, and had negative slope co-efficients and *p*-values greater than α=0.05 in 0.7 and 0.9 quantiles, respectively. This shows that the two stations had non-statistically increasing trends in most quantiles of seasonal rainfall magnitude except in quantiles 0.7 and 0.9, which showed non-statistically significant decreasing trends.

The results showed dominant decreasing trends that were not statistically significant in most quantiles for seasonal rainfall magnitude at six stations (Levubu, Entabeni Bos, Matiwa, Nooitgedacht, Palmaryville and Shefeera), with Entabeni Bos, Matiwa and Shefeera showing non-statistically increasing trends on the low rainfall events (0.1 and 0.2 quantiles), Palmaryville and Nooitgedacht showing non-statistically increasing trends on high rainfall event (quantile 0.7). Klein Australie, Vondo Bos and Hanglip showed dominant non-statistically increasing trends in most quantiles of seasonal rainfall magnitude, with Vondo Bos and Hanglip showing non-statistically decreasing trends on quantiles 0.7 and 0.9, respectively.

Levubu Entabeni Bos

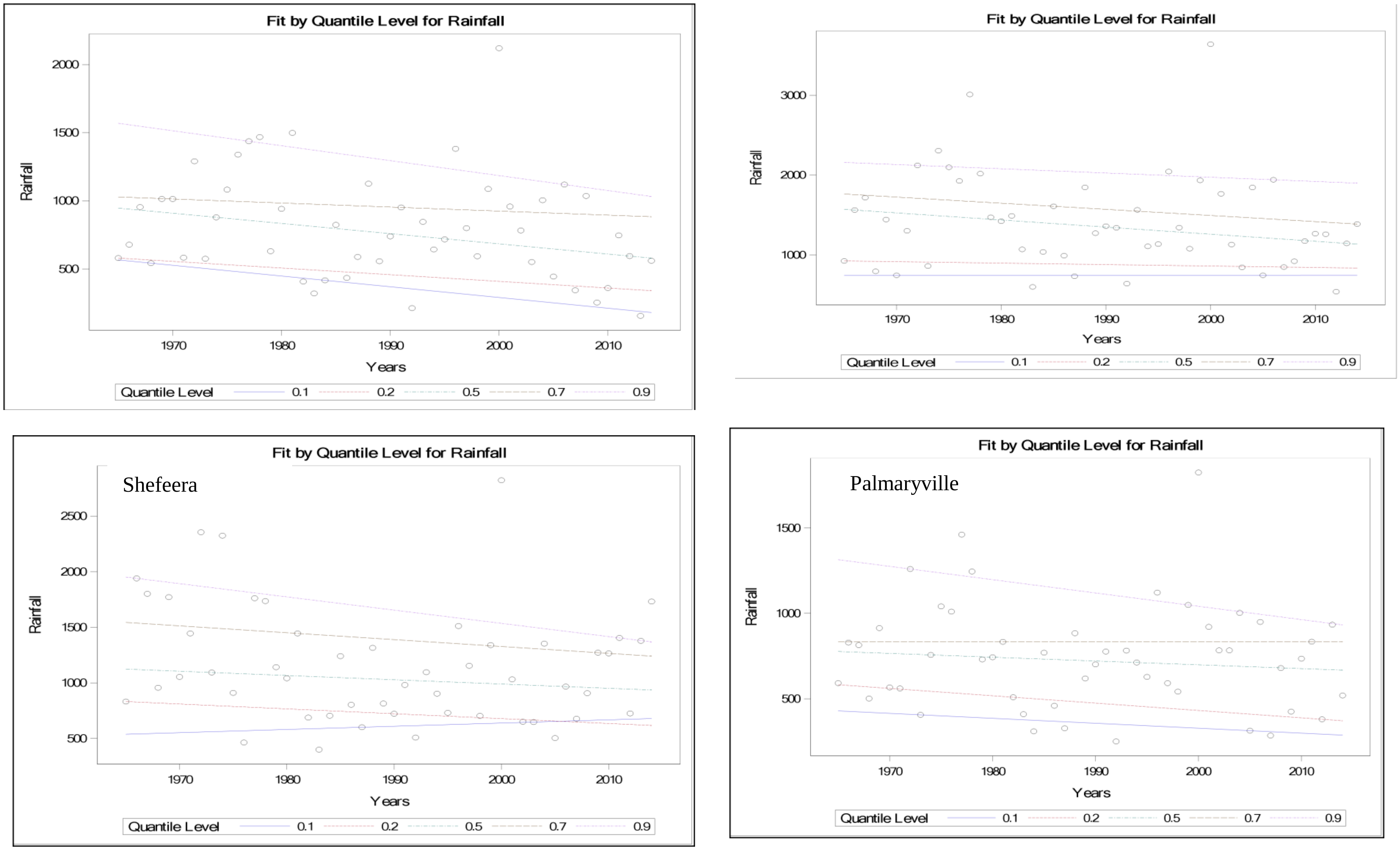
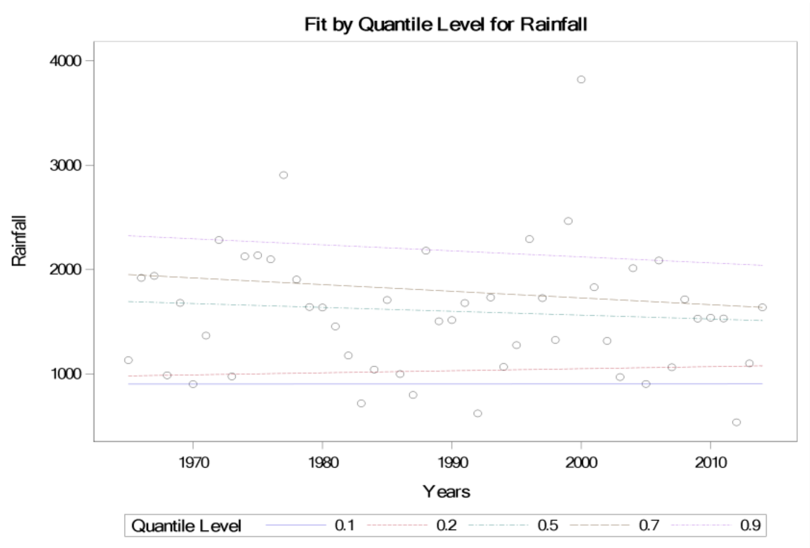
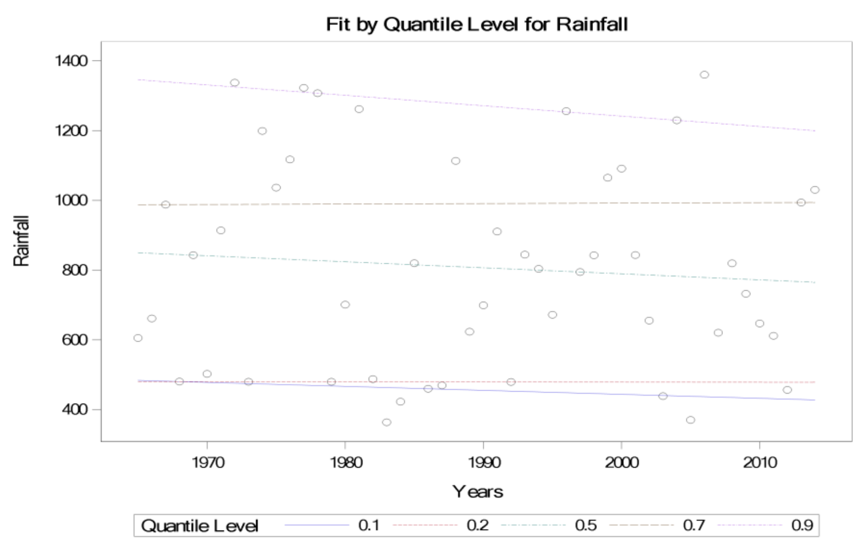


Figure 4.11: Quantile regression results of seasonal rainfall for Levubu, Entabeni Bos, Shefeera and Palmaryville stations

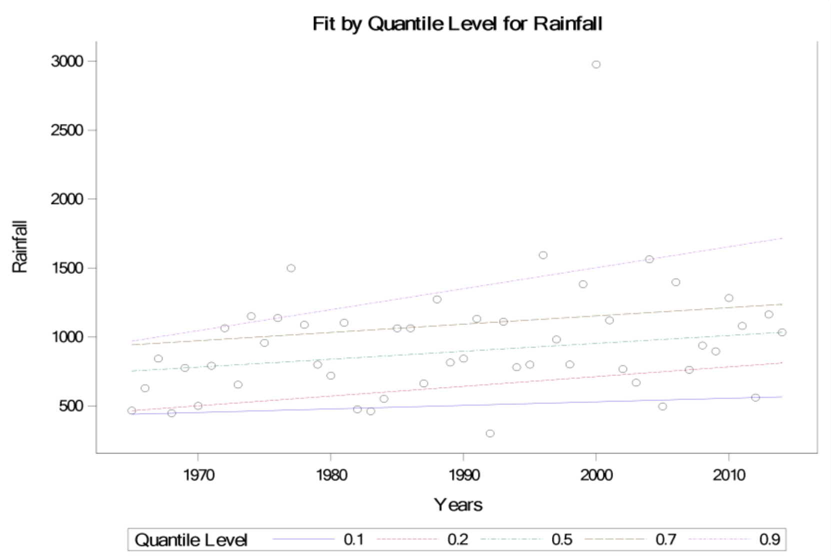
Matiwa



Nooitgedacht



Klein Australie



Vondo Bos

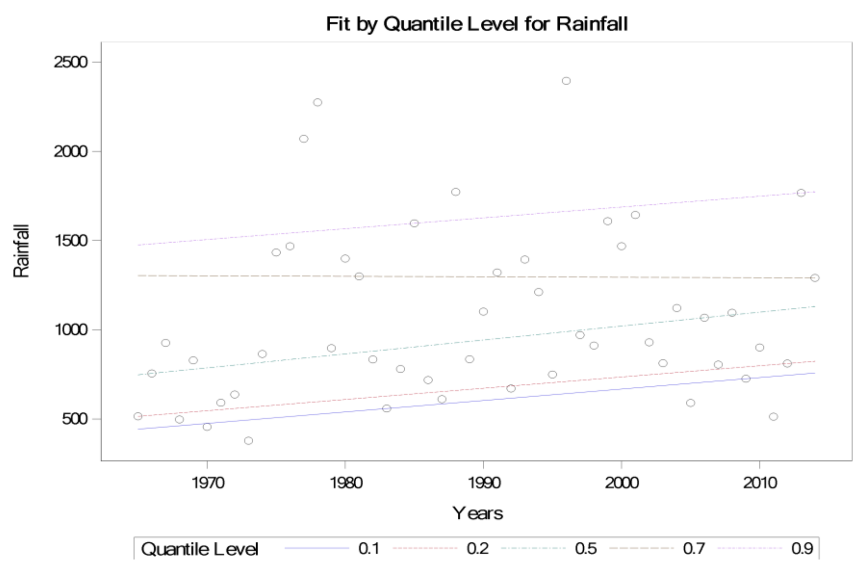


Figure 4.12: Quantile regression results of seasonal rainfall for Matiwa, Nooitgdacht, Klein australie and Vondo Bos stations

Hanglip

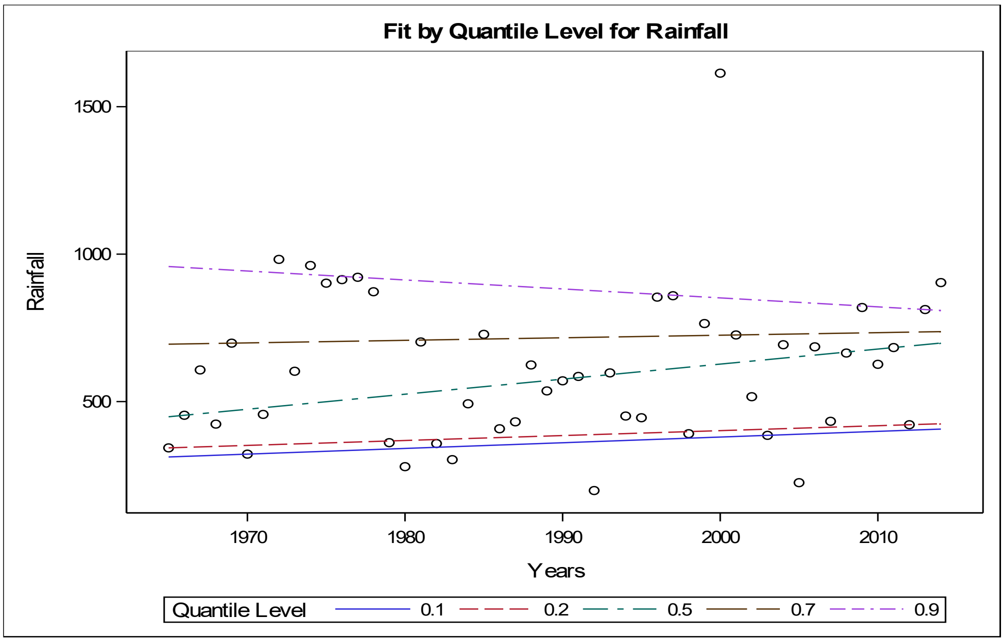


Figure 4.13: Quantile regression results for seasonal rainfall for Hanglip station.

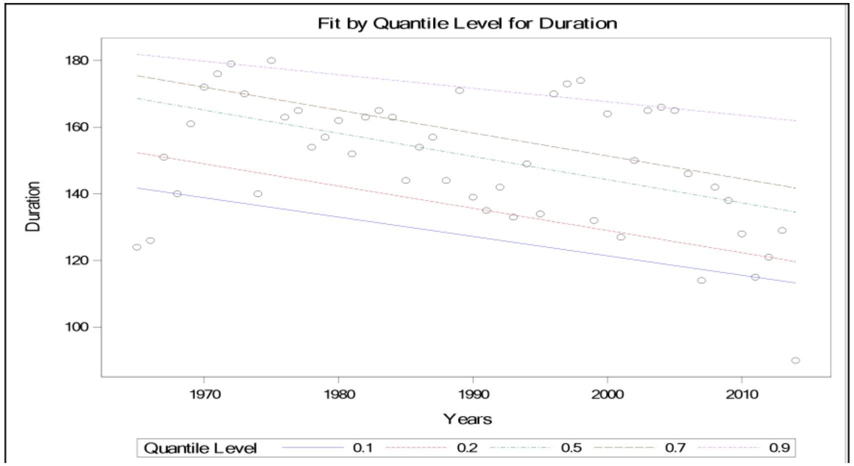
Table 4.5: *p*-values and slope coefficients for the seasonal rainfall magnitude for different quantiles of all 9 stations

Quantile		Levubu	Entabeni Bos	Shefeera	Matiwa	Palmaryville	Nooitgedacht	Klein Australie	Vondo Bos	Hanglip
0.1	P-value	0.10	1.00	0.78	1.00	0.46	0.73	0.76	0.06	0.62
	Slope coefficient	-7.88	0.01	2.89	0.05	-2.89	-1.14	2.58	6.42	1.93
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.2	P-value	0.15	0.79	0.45	0.76	0.22	0.99	0.09	0.09	0.57
	Slope coefficient	-4.88	-1.82	-4.33	1.97	-4.30	-0.05	7.05	6.30	1.67
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.5	P-value	0.15	0.13	0.66	0.62	0.54	0.73	0.17	0.23	0.10
	Slope coefficient	-7.48	-8.88	-3.84	-3.72	-2.23	-1.73	5.73	7.81	5.10
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.7	P-value	0.67	0.45	0.49	0.33	1.00	0.98	0.29	0.98	0.83
	Slope coefficient	-2.96	-7.67	-6.19	-6.41	0.03	0.13	6.00	-2.67	0.87
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.9	P-value	0.73	0.83	0.39	0.80	0.76	0.72	0.61	0.80	0.78
	Slope coefficient	-10.97	-5.30	-11.91	-0.80	-7.79	-2.95	15.21	6.08	-3.04
	Significance	NS	NS	NS	NS	NS	NS	NS	NS	NS

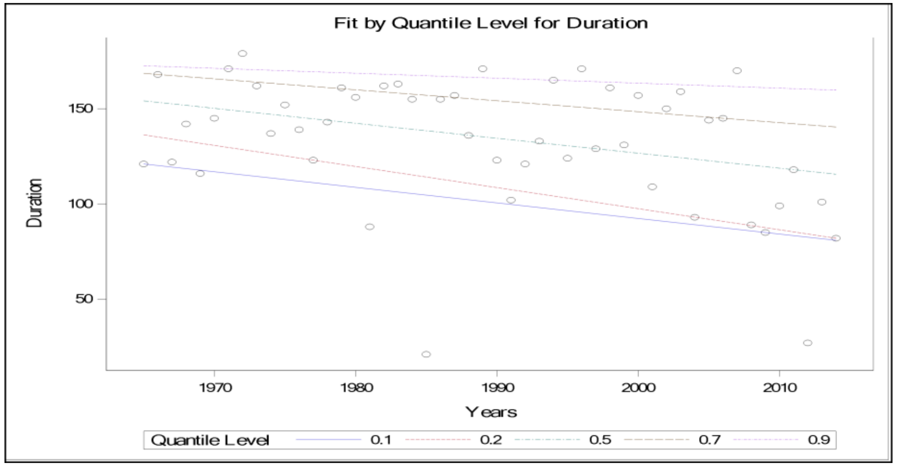
Figures 4.14 to 4.16 and Table 4.6 give the quantile regression results for duration of seasonal rainfall. The plotted lines show regression for duration of seasonal rainfall quantiles 0.9, 0.7, 0.5, 0.2 and 0.1 and the period of the study. Levubu, Entabeni Bos and Palmaryville stations had negative regression lines and slope of coefficients, in all quantiles. Entabeni Bos had *p*-values less than or equal to α=0.05 at quantiles 0.2, 0.5 and 0.7, Levubu and Palmaryville had *p*-values less than α=0.05 at 0.2 quantile only, indicating statistically significant decreasing trends. Nooitgedacht, Klein Australie, Shefeera, Matiwa and Hanglip stations had negative slope of coefficients in most quantiles and *p*-value greater than α=0.05 in all quantiles. Nooitgedacht, Klein Australie, Hanglip, Matiwa and Shefeera had positive slope of coefficients and *p*-values greater than α=0.05 at 0.1, 0.2, 0.7, 0.9 and, 0.1 and 0.2 quantiles, respectively. This showed non-significant decreasing trends in duration of seasonal rainfall in most quantiles for most of the stations. Vondo Bos had positive slope co-efficients and *p*-values greater than α=0.05 in all quantiles except for 0.7 quantile which had negative slope co-efficient with *p*-value greater than α=0.05. This showed dominance of non-statistically increasing trends of duration for seasonal rainfall in this particular rainfall station.

The results showed dominant non-statistically significant decreasing trends of duration of seasonal rainfall magnitude in 8 stations (Levubu, Entabeni Bos, Palamryville, Nooitgetdat, Klein Australie, Shefeera, Matiwa and Hanglip). Klein Australie, Nooitgedacht and Shefeera had increasing trends in the low quantile for duration of seasonal rainfall event. Hanglip and Matiwa showed non-statistically increasing trends in high quantile for duration of seasonal rainfall event. Vondo Bos was dominated by non-statistically increasing trends in most quantiles for duration of seasonal rainfall except in some of the events with high duration of seasonal rainfall.

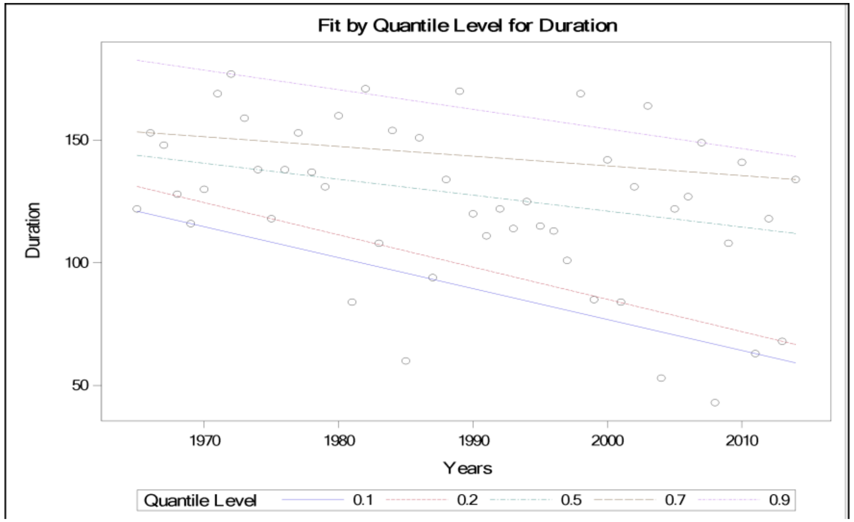
Entabeni Bos



Levubu



Palmaryville



Klein Australie

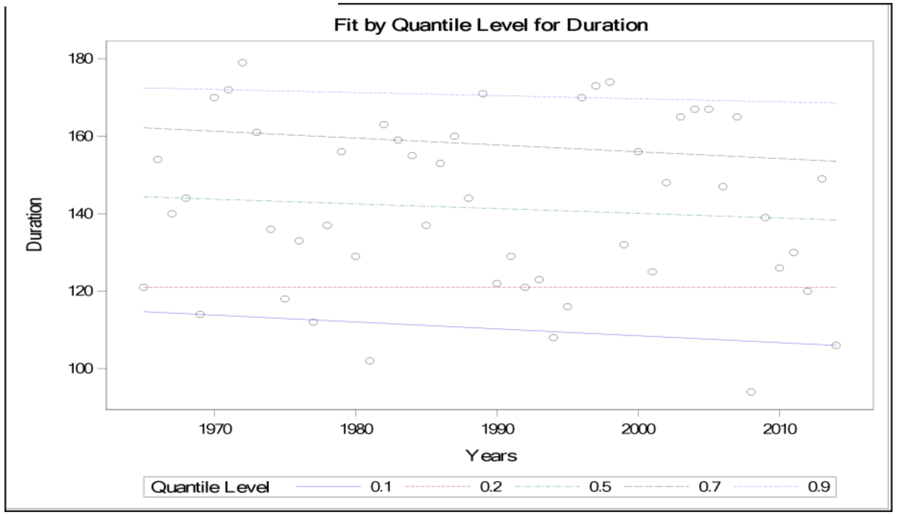


Figure 4.14: Quantile regression results of duration of seasonal rainfall for Entabeni Bos, Levubu, Palmaryville and Klein Australie stations

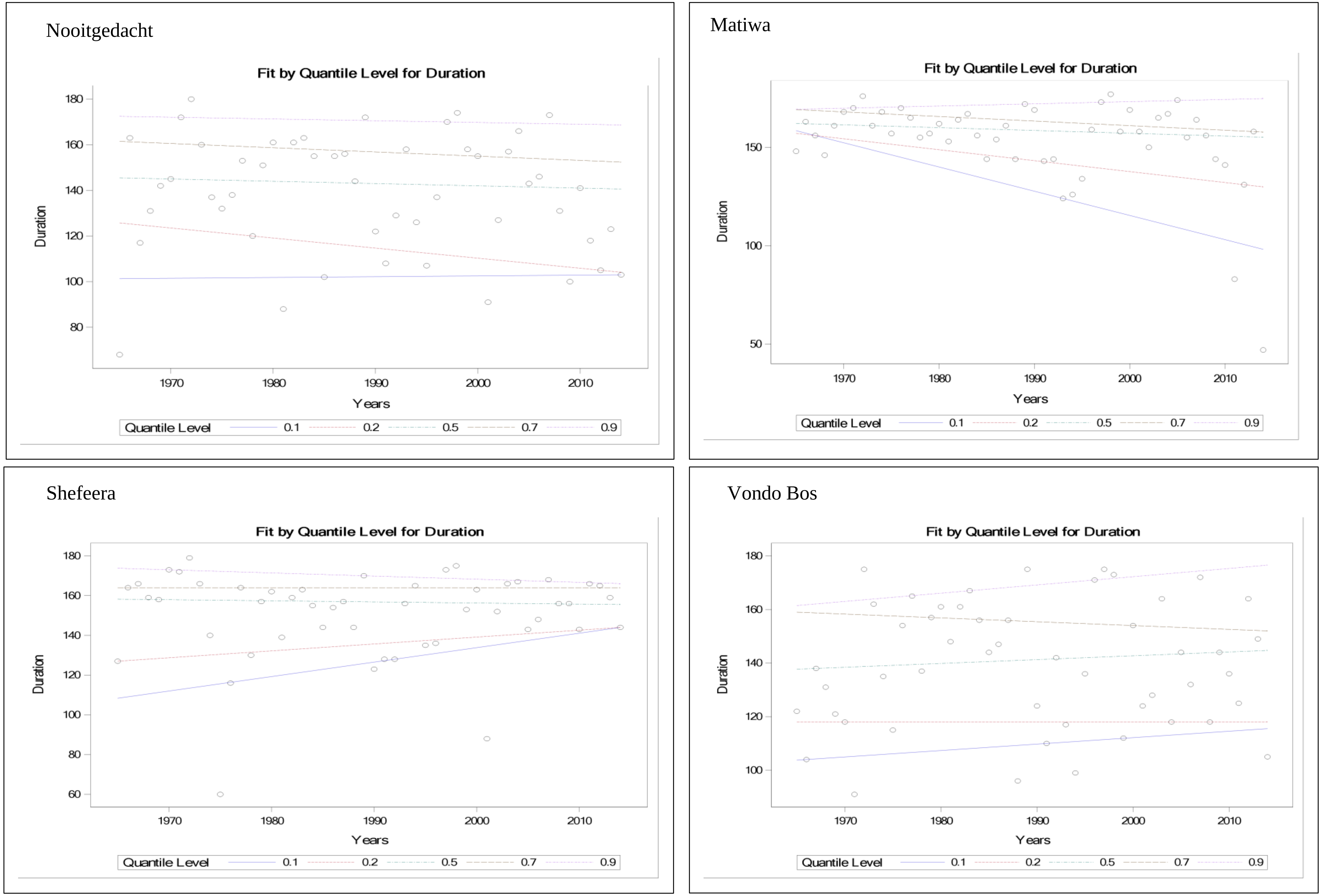


Figure 4.15: Quantile regression results of duration of seasonal rainfall for Nooitgedacht, Matiwa, Shefeera and Vondo Bos stations

Hanglip

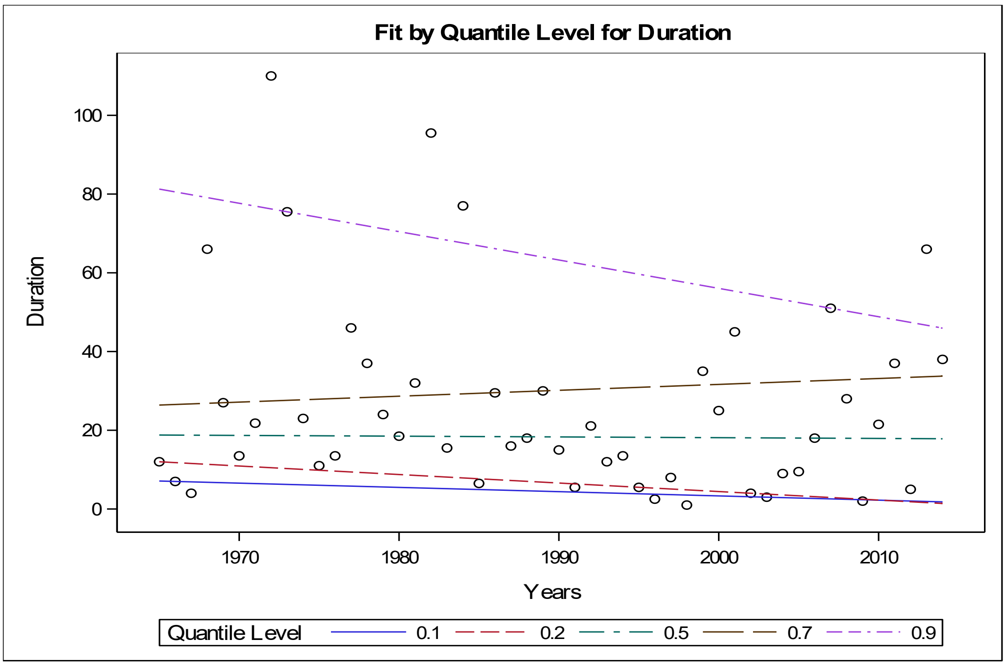


Figure 4.16: Quantile regression results for duration of seasonal rainfall for Hanglip station

Table 4.6: *p*-values and slope coefficients for the duration of seasonal rainfall

Quantile		Entabeni Bos	Levubu	Palmaryville	Klein Australie	Nooitgedacht	Matiwa	Hanglip	Shefeera	Vondo Bos
0.1	*p*-value	0.08	0.43	0.10	0.63	0.95	0.07	0.32	0.51	0.66
	Slope coefficient	-0.58	-0.82	-1.27	-0.18	0.03	-1.23	-0.11	0.73	0.24
	Significant	NS	NS	NS	NS	NS	NS	NS	NS	NS
0.2	*p*-value	0.03	0.00	0.00	1.00	0.40	0.17	0.15	0.53	1.00
	Slope coefficient	-0.67	-1.11	-1.32	0.00	-0.44	-0.56	-0.22	0.35	0.00
	Significant	S	S	S	NS	NS	NS	NS	NS	NS
0.5	*p*-value	0.02	0.14	0.12	0.72	0.81	0.46	0.72	0.79	0.72
	Slope coefficient	-0.69	-0.79	-0.65	-0.12	-0.10	-0.14	-0.02	-0.06	0.14
	Significant	S	NS	NS	NS	NS	NS	NS	NS	NS
0.7	*p*-value	0.05	0.20	0.33	0.60	0.59	0.15	0.75	1.00	0.75
	Slope coefficient	-0.69	-0.58	-0.40	-0.18	-0.19	-0.23	0.15	-0.01	-0.14
	Significant	S	NS	NS	NS	NS	NS	NS	NS	NS
0.9	*p*-value	0.50	0.76	0.31	0.84	0.96	0.84	0.46	0.47	0.68
	Slope coefficient	-0.41	-0.26	-0.80	-0.80	-0.08	0.11	-0.72	-0.12	0.31
	Significant	NS	NS	NS	NS	NS	NS	NS	NS	NS

4.5. Comparison of results based on the methods used in this study

LR methods have shown dominant non-statistically significant decreasing trends in long term annual rainfall magnitude in 6 stations (Levubu, Matiwa, Nooitgedacht, Shefeera, Palmaryville and Entabeni Bos).The latter stations have showed similar behaviour with MK method except for Entabeni Bos that showed statistically significant decreasing trends. Three stations (Hanglip, Vondo Bos and Klein Australie) have shown non-statistically significant increasing trends in long term annual rainfall magnitude with LR method. Hanglip and Vondo Bos showed similar behaviour with MK method. However, Klein Australie showed statistically significant increasing trends with MK method only. The quantile regression results also showed dominant decreasing trends in long term annual rainfall magnitude in most quantiles in the same stations that MK and LR methods showed dominant decreasing trends. However, Entabeni Bos and Nooitgedacht stations had non-statistically increasing trends in part of low quantiles, and Matiwa in high quantile. Hanglip, Vondo Bos, and Klein Australie were dominated by non-statistically increasing trends of annual rainfall magnitude in most quantiles, though Vondo Bos and Hanglip had non-statistically decreasing trends on all or parts of high quantiles. These results from MK, LR and quantile regression therefore show dominant non-statistically significant decreasing annual rainfall trends in the study area.

Kruger (2006) reported significant decreases in annual precipitation in northern Limpopo. Chamaillé-Jammes *et al.* (2007) and Joubert *et al.* (1996) concluded that rainfall in southern Africa showed no consistent or statistically significant trends across the region, however, noted decrease of regionally-averaged total rainfall (but not statistically significant). DEA (2013) reported that annual rainfall trends are weak and non-significant in South Africa. Kruger and Nxumalo (2017) also indicated decreases in rainfall in the northern and north-eastern parts of South Africa. The findings of the current study are therefore similar to those of earlier studies done in South Africa including the study area which showed decreasing trends that are non-statistically significant.

The results for seasonal rainfall analysis also showed dominant decreasing trends in long term seasonal rainfall magnitude as similarly observed with annual rainfall magnitude for both MK and LR methods. This could be because most of the rainfall is received during the rainy season and thus, the magnitude of seasonal and annual rainfall would be comparable. The quantile regression results also showed dominant decreasing trends in most quantile levels in the same stations at which MK and LR methods showed dominant decreasing trends. However, Entabeni Bos, Matiwa and Shefeera stations had non-statistically increasing trends in all or part of low quantile and, Palmaryville and Nooitgedacht partly in high quantile (0.7). Hanglip, Vondo Bos and Klein Australie were dominated by non-statistically increasing trends of seasonal rainfall magnitude in most quantile levels, but Vondo Bos and Hanglip each had non-statistically decreasing trends on part of high quantile levels. These results therefore showed dominant non-statistical decreasing trends in seasonal rainfall in the study area as highlighted at the beginning of this paragraph. DEA (2013) showed that there have been a marginal reduction in rainfall for the summer months in the northern part of South Africa. The study area falls under the northern part of South Africa and the results of the current study are in agreement with those of DEA (2013) which showed dominant non-significant decreasing trends.

The results for duration of seasonal rainfall showed dominance of non-significant statistically decreasing trends at Entabeni Bos, Levubu, Matiwa, Nooitgetdacht, Palmaryville and Klein Australie stations, which also is mostly similar to the results of MK and LR methods except for a few exceptions. MK showed non-statistically significant decreasing trend at Shefeera while LR method showed non-statistically increasing trend. MK showed non-statistically significant increasing trends at Klein Australie and Hanglip while LR showed non-statistically significant decreasing trends. Both MK and LR showed non-statistically significant increasing trends of duration of seasonal rainfall at Vondo Bos. Quantile regression showed dominant non-statistically significant decreasing trends in most quantiles of duration of seasonal rainfall in 7 stations (Levubu, Matiwa, Palmaryville, Klein Australie, Hanglip, Nooitgedacht and Shefeera) with Hanglip and Matiwa showing partly non-statistically significant increasing trends at seasonal high rainfall events and Nooitgedacht for low seasonal rainfall events.

The results are dominated by non-statistically decreasing trends therefore the results show dominant non-statistical decreasing trends in duration of seasonal rainfall in the study area based on all methods. DEA (2013) noted significant decrease in the number of rainy days in almost all hydrological zones of Limpopo. Mackellar *et al.* (2014) has pointed out the significant decreases in number of rainy days over the central and north-eastern parts of South Africa. The current study also obtained dominantly decreasing trends in rainy days, although the trends were non-statistically significant. The decreasing annual rainfall trends may be due to presence of multidecadal variability characterized by above and below mean annual rainfall in this study area. El Niño-Southern Oscillation (ENSO) is related to rainfall in most parts of the southern Africa region with the negative phase being attributed to drought (below rainfall) conditions and positive phase being associated with above normal rainfall amount (Zengeni *et al.*, 2016). This phenomenon could be the reason for the decreasing rainfall trends in this study area since it falls under part of the southern Africa.

The increasing trends in Vondo Bos, Klein Australie and Hanglip stations, could be because of the topographic effect in this study area. Vondo Bos and Hanglip are situated at mountainous zone, with high altitude (Table 3.1 and Figure 3.1). According to Tyson *et al*. (1976) and Schulze (1979) there is a defined positive linear relationship between altitude and rainfall. Odiyo *et al.* (2015) also noted that Zwartrandjes station located at high altitude zone in LRC had increasing rainfall trends. Klein Australie has low altitude as compared to Hanglip and Vondo Bos, but Hansen-Bauer *et al.* (1995), noted that precipitation amount and variability may differ largely over small distances, due to orographic effects which are sensitive to small differences in circulation patterns. Kabanda and Nenwiini (2013) have shown that due to diverse rainfall zones in this study area, rainfall is highly variable within local settings. This could be the reason Klein Australie station showed the increasing trends. The deviating trends in quantile regression results of high and low quantiles in the annual, seasonal rainfall and duration of seasonal rainfall could be due to changes caused by exposure of rain gauge, destructions by vegetation cover and observational procedures. Kabanda and Nenwiini (2013) noted that some of the decreasing trends were observed in densely populated areas affected by urban sprawl, depleted vegetation cover, or other human development such as large-scale farming and construction.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study was aimed at investigating the long term seasonal and annual changes in rainfall duration and magnitude at LRC. Computed long term seasonal, annual rainfall and number of seasonal rainy days were used to identify trends for the period of 51 years (1965- 2015), using MK, LR and quantile regression methods. MK and LR identified non-statistically significant decreasing trends of annual rainfall magnitude in most stations. Klein Australie, Vondo Bos and Hanglip showed non-statistically significant increasing trends of annual rainfall magnitude. Quantile regression method also identified dominant non-statistically significant decreasing trends on low, median and high quantiles for annual rainfall magnitude. This showed dominance of non-statistically significance decreasing trends for low, median and high rainfall events in the study area. Thus, the results generally agreed with those of MK and LR methods. Non-statistically significant increasing trends were identified at low quantiles in Entabeni Bos and Nooitgedacht stations, and at high quantiles in Matiwa station. The study noted dominant non-statistically increasing trends of low, median and high annual rainfall at Klein Australie. Vondo Bos and Hanglip stations showed decreasing non-statistically significant trends on all or part of the quantiles associated with high annual rainfall events.

MK and LR showed dominant non-statistically significant decreasing trends in long term seasonal rainfall magnitude in most stations as similarly observed with annual rainfall magnitude. This is due to the fact that most of the rainfall is received during rainy season. Klein Australie, Vondo Bos and Hanglip showed non-statistically increasing trends of seasonal rainfall magnitude with both MK and LR methods. Quantile regression method also showed dominant non-statistically significant decreasing trends of low, median and high seasonal rainfall magnitude in most stations. Entabeni Bos, Matiwa and Shefeera stations showed non-statistically significant increasing trends in all or part of the quantiles associated with low rainfall events, while the same applied to Palmaryville and Nooitgedacht in high seasonal rainfall event at quantile 0.7. Hanglip, Vondo Bos and Klein Australie were dominated mostly by non-statistically significant increasing trends at low, median and high seasonal rainfall events, although Vondo Bos and Hanglip each partly showed non-statistically significant decreasing trends on the high rainfall events.

MK and LR showed statistically significant decreasing trends of duration of seasonal rainfall at Entabeni Bos, Levubu, Matiwa and Palmaryville and non-statistically significant decreasing trend on Nooitgedacht. Shefeera, Hanglip and Klein Australie showed non-statistical contradicting trends (increasing/decreasing) in LR and MK methods and Vondo Bos showed non-statistically significant increasing trends with both methods. Quantile regression showed dominant non-statistically significant decreasing trends on low, median and high quantiles of duration of seasonal rainfall in most stations. Palmaryvile and Levubu showed statistically significant decreasing trends on low quantile of 0.2 for duration of seasonal rainfall. Entabeni Bos on 0.2, 0.5 and 0.7 quantiles showed statistically significant decreasing trends for duration of low, median and high seasonal rainfall events. Vondo Bos was dominated by non-statistically significant increasing trends and decreasing non-statistically significant trend was noted at high quantile of 0.7 for duration of seasonal rainfall. The deviating trends are likely to be due to exposure of rain gauge, destructions by vegetation cover or problems with observational procedures.

Magnitude of change for annual and seasonal rainfall ranged within 0.12 to 12.31 mm and 0.54 to 6.72 mm, respectively, for stations with non-statistically significant decreasing trends. Stations with non-statistically increasing trends of annual and seasonal rainfall the magnitude of change ranged within 1.51 to 6.78 mm and 2.05 to 6.51 mm of rainfall, respectively. The findings of the current study are comparable to those of previous studies done in LRC.

MK, LR and quantile regression methods did not identify dominant significant trends in annual and seasonal rainfall magnitude. Statistically significant decreasing trends in duration of seasonal rainfall were identified by MK and LR at Matiwa, Palmaryville, Levubu, and Entabeni Bos stations. Quantile regression identified the statistically significant decreasing trends on all or part of the 0.2, 0.5 and 0.7 quantiles only for the last three stations above , respectively. Therefore the study shows that there was dominance of decreasing trends of the annual, seasonal rainfall and duration of seasonal rainfall although they were non -statistically significant. The preceding paragraphs show that all the specific objectives and research questions for this study were all achieved and addressed, respectively.

5.2 Recommendations

The study used Moeletsi (2010) approach to determine the duration of rainy days as has been widely done by most studies in South Africa. It is therefore recommended that further studies should be done using other approaches to determine the duration of rainfall to improve, update and compare the results obtained in the current study.

Continuous monitoring and installation of rain gauges are recommended on the lower reaches of the catchment so that the findings should be of the complete picture for the whole catchment and to also minimise the rainfall gaps in the stations.

The study showed dominant decrease in rainfall magnitude, even though the change is not statistically significant, it is therefore recommended that water resources should be used in a sustainable way to avoid water crisis or risk in the next generations.

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APPENDICES