

Trend analysis of selected hydro-meteorological variables for the Rietspruit sub-basin, South Africa

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ABSTRACT

Identifying hydro-meteorological trends is critical for assessing climate change and variability both at a basin and regional level. This study examined the long- and short-term trends from stream discharge, temperature, and rainfall data around the Rietspruit sub-basin in South Africa. The data were subjected to homogeneity testing before performing the trend tests. Inhomogeneity was widely detected in discharge data, hence no further analyses were performed on such data. Temperature and rainfall trends and their magnitudes at yearly, seasonal, and monthly time steps were identified after applying the non-parametric Mann-Kendall and Sen's slope estimator. The possible starting point of a trend was determined by performing the sequential Mann-Kendall test. This study revealed a combination of upward and downward trends in both temperature and rainfall data for the time steps under observation. For rainfall on an annual basis, there were no statistically significant monotonic trends detected, although non-significant downward trends were dominant. However, significant decreasing rainfall trends were observed in dry and low rainfall months, which were April, August, September, and November. In contrast, significant upward temperature trends were detected at the Vereeniging climate station at an annual scale and in October, November, spring, and winter. The findings are critical for climate risk management and reduction decisions for both near- and long-term timescales.

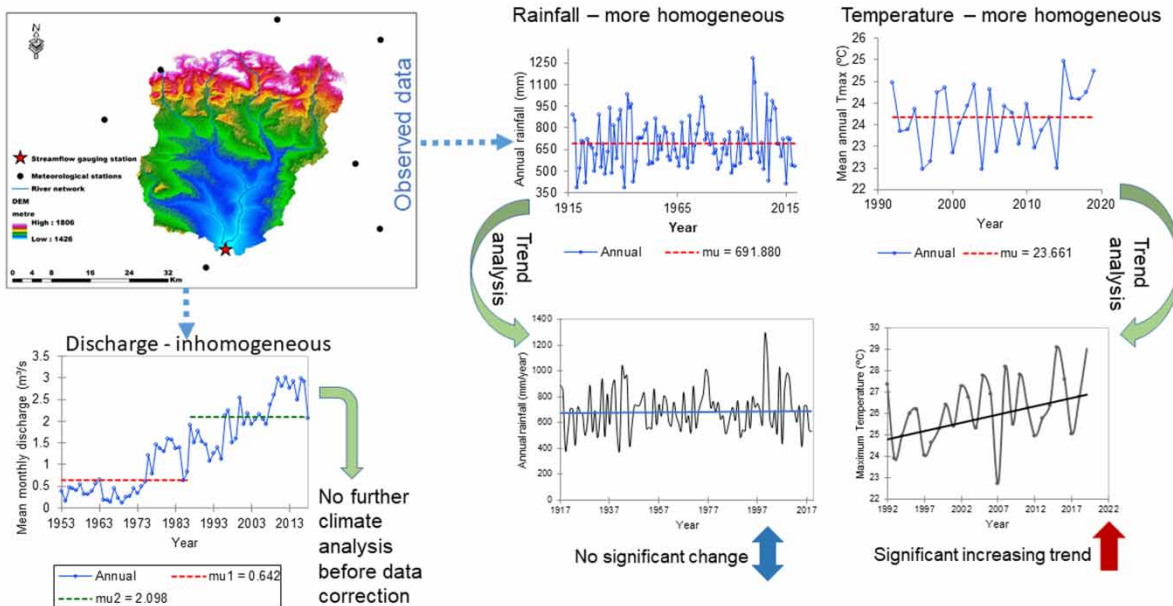
Key words: climate change and variability, homogeneity tests, Mann-Kendall test, Rietspruit sub-basin, South Africa

HIGHLIGHTS

- The need to perform homogeneity tests to avoid erroneous conclusions is emphasised.
- The study cautions the direct use of stream discharge data for climate analyses in urban areas.
- Long-term data show no significant changes in rainfall while temperature is rising.
- Findings will improve the understanding of hydro-meteorological trends specific to the Rietspruit sub-basin mainly due to temperature spatial variability.

GRAPHICAL ABSTRACT

Trend analysis of hydro-meteorological variables for the Rietspruit sub-basin, South Africa



INTRODUCTION

The climate of the Earth is certainly warming and there is a rising consensus that climate change impacts will affect water availability, food security, and ecosystem services (Sintayehu 2018; Stuch *et al.* 2020). Climate change has a significant impact on society primarily through water-related effects, for instance, by affecting sectors such as energy, agriculture, infrastructure, and transport (IPCC 2014a). Hence, besides being an important environmental concern climate change is equally a development limitation particularly in underdeveloped nations (Banze *et al.* 2018; MacAlister & Subramanyam 2018). Meanwhile, the key determinants of current and future climate change impacts on freshwater supplies are rising temperatures, local rainfall variability, and shifts in the magnitude of these variables (IPCC 2014a).

In a large part of Africa, temperatures close to the Earth's surface have increased by at least 0.5 °C in the past 50–100 years (IPCC 2014b). Niang *et al.* (2014) reported that a large part of the southern African region witnessed increasing trends in minimum, maximum, and average yearly temperatures during the final half of the 20th century, whereby minimum temperatures increased faster compared with maximum temperatures. They furthermore stated that Zimbabwe, Botswana, and western South Africa experienced a slight decrease in rainfall in that period.

For society to better adapt to the different impacts associated with climatic variability and change, high-quality temporal and spatial data are needed to provide for a deeper scientific analysis and application. Identifying trends in hydrological and climatic data is critical for climate change and variability impact assessments and for understanding changes in the hydrological regimes at both regional and catchment scales (Meresu *et al.* 2017). Therefore, in light of basin-level water resource management, analysis of changes in the discharge, temperature, and rainfall is a necessity as these influence the available water and its quality for various and in many cases, competing uses.

The analysis of rainfall and temperature trends has continued to receive attention from researchers as a way to predict their occurrence and for water resources management for various uses (Ahmad *et al.* 2015; Meshram *et al.* 2017; Hu *et al.* 2019), particularly in arid and semi-arid regions which usually have higher evaporation and minimal precipitation (Forootan 2019). This is mostly the case because evaporation and rainfall are the key climate-related elements influencing freshwater resources (IPCC 2014a). In essence, reliable climate data are essential for hydrological modelling, climate forecasting, and the management of water resources (Firat *et al.* 2012). Hence, it is a standard requirement to use reliable data in the analysis of hydro-meteorological trends.

The assessment of climate data reliability to avoid erroneous trend results is mainly done by performing homogeneity tests (Hänsel *et al.* 2016). Homogeneity tests are an important part of climate change analysis because the tests help to identify whether the variations in climate data are either due to meteorological, climatological, or external factors. Thus, homogeneous hydro-meteorological data will have variations attributed to changes in climate and weather only (Caloiero *et al.* 2020). The common non-climatic sources that cause data inhomogeneities include changes in instruments, observation practices, station geographic location, calculations codes and units, and land use/cover (Peterson *et al.* 1998). Therefore, when performing hydro-climatic analyses, it is essential to use reliable observational data, which will enable a robust climate assessment. In fact, the real processes of climate change can only be truly reflected when there is high-quality meteorological data whose homogeneity has been tested and the inhomogeneity corrected (Shen *et al.* 2018). For these reasons, in this study time series, data were subjected to homogeneity testing before performing the trend tests.

There are two main approaches for classifying the homogeneity of time-series data, that is, absolute and relative methods. The absolute method is where the test is independently performed for each station while the relative method includes the nearest stations as a reference during the testing (Wijngaard *et al.* 2003; Yozgatligil & Yazici 2016). Hence, a relative method is well suited to an area with a large station density and highly correlated data. Since the capability of homogeneity testing methods depends on data classification, it is imperative to conduct the homogeneity tests using several testing methods for each of the chosen homogeneity approaches (Ahmed *et al.* 2018).

Considerable research has been conducted to identify hydro-meteorological trends using parametric and non-parametric techniques. Parametric tests (for example, linear trends and *t*-test for slope) are considered robust in detecting trends compared with non-parametric tests, especially when the sample size is small (Meals *et al.* 2011). However, parametric tests work on the hypothesis that the data are normally distributed, which is an uncommon feature in hydro-meteorological time-series data (Ahmad *et al.* 2015), thereby limiting its application (Kocsis & Anda 2018). Non-parametric tests, on the other hand, are preferred in environmental and climate data analysis because they are not affected by outliers and do not require data to be normally distributed (Hamed 2008).

Hussain *et al.* (2021) used the Mann-Kendall and Sen's method to detect rainfall trends using long-term (1981–2016) data in the Soan River Basin (Pakistan), whereby decreasing trends were observed in the highlands while increasing trends were detected in central and lowland areas. Using data from 1959 to 2019, Harkat & Kisi (2021) employed the innovative trend analysis approach to identify potential rainfall trends in a semi-arid Mediterranean climate (Northern Algeria). They pointed out that the method is advantageous as it offers qualitative analyses of trends in both low, medium, and high rainfall amounts. Das *et al.* (2020) used the non-parametric Mann-Kendall, Spearman's rho, and the Modified Mann-Kendall tests to observe trends in rainfall time series, while the Sen's slope was used to detect the quantity of the trend. In contrast, Islam *et al.* (2020) used a variety of statistical models to establish trends in the daily rainfall in Bangladesh. These included the innovative trend analysis, Mann-Kendall, Spearman's rho, linear regression, and Sen's slope.

Although researchers have applied different statistical approaches to identify trends in climatic and hydrological data, the Mann-Kendall and Sen's slope tests have been commonly used, including in South Africa. These tests have been applied to detect trends and magnitude of changes for different hydro-climatic variables (Gyamfi *et al.* 2016; Mahmood *et al.* 2019; Panda & Sahu 2019; Alemu & Dioha 2020; Caloiero *et al.* 2020; Daba *et al.* 2020; Sangma *et al.* 2020). Additionally, other researchers such as Ahmad *et al.* (2015) and Patakamuri *et al.* (2020) applied the Mann-Kendall test together with the Spearman's rho test as a way to differentiate the results. The current study applied the Mann-Kendall and Sen's slope test because the chosen hydro-meteorological data (streamflow discharge, temperature, and rainfall) hardly followed a normal distribution.

At a country level, most studies on climatic trends in South Africa have been performed from a regional or national scale perspective, which may not be representative of the situation at a sub-basin level due to large variability in these climatic parameters. For instance, MacKellar *et al.* (2014) assessed the seasonal and annual rainfall and temperature trends in South Africa from 1960 to 2010. They observed statistically significant decreases in rainfall in the autumn months around the north-eastern and central parts of South Africa while temperatures were observed to be increasing in most parts of the country. Gyamfi *et al.* (2016) performed trend analyses of rainfall data in the Olifants Basin for the 1975–2013 period. Results of their study showed a non-significant decreasing trend in rainfall with high inter-annual and seasonal variations. Other regional studies include those by Jury (2016), Kruger & Nxumalo (2017), and Botai *et al.* (2018).

The Vaal Basin, of which the current study area is a part, has highly contributed to South Africa's water resources development especially in the Gauteng Province (Ilunga 2017). The catchment changes in the upper Vaal River are understood to

be largely due to climate change, industrial, urbanisation, and agricultural land-use changes (Jury 2016; Ilunga 2017). Due to these changes, agriculture has been identified as the most vulnerable sector in the region (Remilekun *et al.* 2020). There is, therefore, a need to understand better the climatic variability and its associated risks in the region and the Rietspruit sub-basin (RSB), which can be achieved through local climatic data assessments.

This study aimed to analyse the homogeneity and assess trends associated with climate change and hydro-meteorological variability around the RSB in South Africa. This will supplement and enhance the locally available information on climate impact within the region. The term ‘climate change’ was used to denote statistically significant disparity in the normal climate conditions for stations with data spanning nearly 30 years or more. In contrast, climate variability was essentially used in the current study to examine the possible short-term deviation and fluctuations in the meteorological variables from the long-term average. Hence, it has been applied to stations with short-time data, of which in this study there are less than 20 years. In this research, rainfall and temperature were the selected meteorological variables because they are the main determinants for climate change (Huang *et al.* 2012), which eventually influences the natural availability of water in a catchment.

METHODS

Study area

The research was done in the RSB, a semi-arid region, located southwest of Johannesburg in the upper part of the Vaal Basin (Figure 1). The Upper Vaal adds almost 20% to South Africa’s gross domestic product (Dzwauro & Otieno 2014), signifying its importance to national development. Agriculture dominates land use in the study area, while other important land uses include industrial, mining, power generation, nature conservation, and urban and rural residential uses (Remilekun *et al.* 2020).

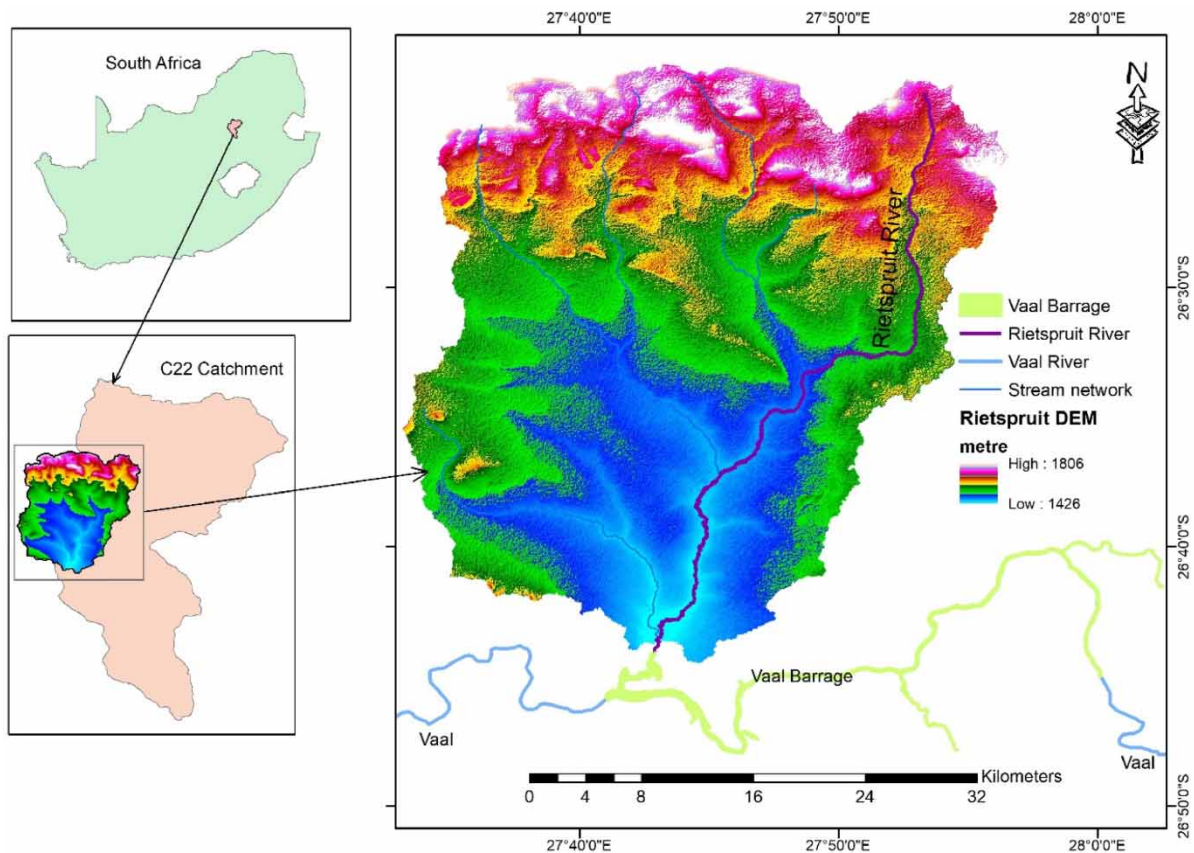


Figure 1 | Study area location map (Rietspruit sub-basin). The Rietspruit River flows from the north-eastern part of the study area discharging into the upper Vaal River.

The surface area of the RSB is approximately 1,139 km² and it empties into the Loch Vaal, which is part of the Vaal Barage. The sub-basin stretches from latitude 26°21' to 26°44' South and from longitude 27°33' to 27°56' East. The RSB surface elevation varies from 1,424 to 1,806 m above mean sea level (Figure 1).

Traditionally, most of South Africa is endowed with the four seasons as reported by Botai *et al.* (2018), which are summer (December–January–February), autumn (March–April–May), winter (June–July–August), and spring (September–October–November). Rainfall in the Upper Vaal is seasonal, with most of the rains being received between October and April. Meanwhile, the highest rainfall is received in the summer months of December and January with an annual average of around 740 mm. Minimum and maximum temperatures are generally encountered in July and January, respectively, while the catchment's average annual temperature is around 15 °C (du Plessis 2017).

Data sources

The study area is characterised by meteorological stations that mostly fall just outside the sub-basin boundary (Figure 2). In this study, available data was comprised of various data lengths including long- and short-term data. Based on the available data in the study area, the present study categorised data with more than 28 years as long-term which was used to assess climate change. Observations from short-term data spanning between 5 and 16 years were used to define variations in the studied meteorological parameters. The South African Weather Service and the Agricultural Research Council of South Africa provided the raw daily temperature and rainfall data for a total of seven stations, although some stations provided more or fewer parameters even though two parameters were targeted for this study. Average monthly, seasonal, and annual rainfall values were generated from the total daily rainfall values. The daily minimum and maximum temperatures were averaged separately to come up with maximum and minimum temperatures on an annual, seasonal, and monthly basis. The discharge data were sourced from South Africa's Department of Water and Sanitation. Table 1 lists the latitude, longitude, and elevation of the meteorological and discharge stations.

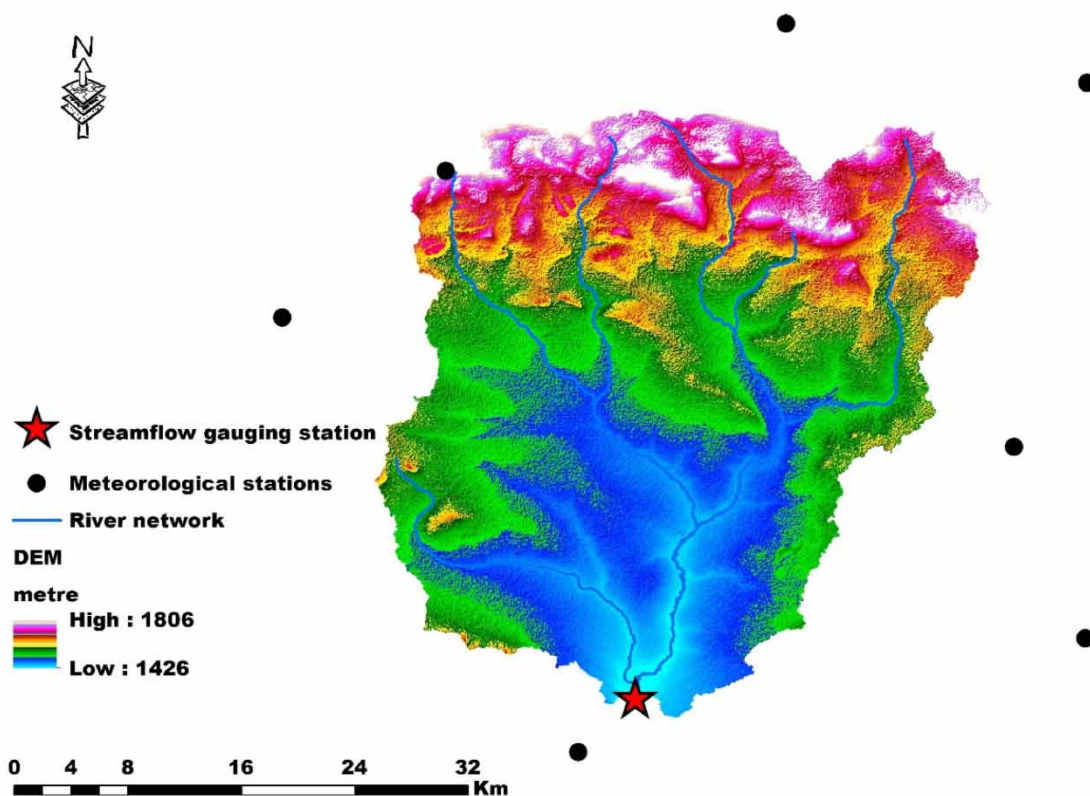


Figure 2 | Position of stream gauging and meteorological stations. The meteorological stations are located just outside the catchment boundary.

Table 1 | Geographical location, period of record, and elevation of meteorological and stream gauging (C2H5) stations

Station	Latitude (°S)	Longitude (°E)	Data period	Elevation (m)
Barrage	– 26.76	27.68	1917–2019	1,446
Vereeniging	– 26.57	27.96	1992–2019	1,481
Westonaria	– 26.39	27.60	1967–2019	1,661
Fochville	– 26.49	27.49	2011–2019	1,474
Zuurbekom	– 26.30	27.81	2015–2019	1,581
Midvaal	– 26.69	28.003	2005–2020	1,445
Winford	– 26.35	28.004	2013–2020	1,528
C2H5	– 26.73	27.72	1953–2018	1,428

Data quality control and statistical analysis

A data quality control process was applied to the observed discharge, temperature, and rainfall data before conducting the analyses. This involved filling in missing data and testing data homogeneity. Most statistical guidelines indicate that datasets with more than 10% missing data are likely to show bias in the analysis of such data (Madley-Dowd *et al.* 2019). In this study, daily raw rainfall and temperature datasets had missing data ranging from 0.7 to 6% and 0.6 to 5%, respectively, while the discharge station had 8% of missing data. As such, biases in data analyses were minimised because missing data were all less than 10%. Missing data were estimated using the multiple imputation method, which simulates missing data multiple times. The multiple imputation method has been successfully applied to infill hydro-meteorological data in different studies (de Carvalho *et al.* 2017; Sattari *et al.* 2017; Ekeu-wei *et al.* 2018). In the current study, the statistical XLSTAT software was used to generate multiple imputations, whereby five imputations were applied as suggested by Schafer & Olsen (1998).

This study employed four statistical approaches to analyse the homogeneity and trends of the hydro-climatic data around the study area. In the beginning, the absolute homogeneity tests were independently computed for each station on the monthly, seasonal, and annual data. The absolute method was used because the climatic data in the study area are randomly distributed and sparse. The identification of trend tests and their magnitudes was carried out on the homogenous data. For the data series showing statistical significance, the sequential Mann-Kendall (SQMK) test was employed to locate the probable year when the rapid change occurred. The homogeneity and trend tests and results including *p*-value, Kendall's tau, MK-Stat(S), MK-Z statistics, and Sen's slope were computed using the Addinsoft's XLSTAT 2020.5 and the XRealStats computer software programs. A 'trendchange' package in RStudio was used to perform the sequential Mann-Kendal test for change point analysis.

Homogeneity tests

As part of the data quality control process, four homogeneity test methods were employed to detect the inhomogeneity and most importantly validate the homogeneity in the data, thus reducing unreliability concerns. These tests were the Standard Normal Homogeneity Test (SNHT), Pettitt's test, Buishand Range test (BRT), and von Neumann ratio (VNR). The null hypothesis of data being independent, identically distributed, and homogeneous is assumed in all of the four test methods (Patakamuri *et al.* 2020). In contrast, the alternative hypothesis for the Pettitt, SNHT, and BRT is that there is a point (year) where data changes and that the time series is inhomogeneous. The VNR does not provide any details on the year of change because the test's alternative hypothesis hypothesises that the data distribution is not random (Wijngaard *et al.* 2003). Detailed explanations and mathematical equations for performing these tests are provided in Ahmed *et al.* (2018).

Evaluation of homogeneity test results

The classification by Wijngaard *et al.* (2003) for assessing the homogeneity test results was adopted in this study. Here, the data series were summarised into three categories based on how many of the four homogeneity test methods rejected the null hypothesis at a *p*-value of 0.05, namely 'useful', 'doubtful', and 'suspect'. Data were classified as 'useful' when they satisfied the null hypothesis of at least three out of four homogeneity tests used in the study, while data series were put in the 'doubtful' category when the null hypothesis of homogeneity was rejected in two of the four tests. A 'suspect' category was classified when the null hypothesis at a 5% significance level was rejected in three or all of the four homogeneity tests.

Mann-Kendall test

The Mann-Kendall test (Mann 1945) is a non-parametric test used to detect trends in climate time series. It is widely used to detect monotonic (increasing or decreasing) trends and for detecting trends in time series because it is simple, robust, does not require the data to be aligned to any statistical distribution, and is flexible to outliers in the data (Meals *et al.* 2011). The Mann-Kendall test assumes a null hypothesis (H_0) of no monotonic trend in the data series while its alternative hypothesis (H_a) assumes that there is a presence of a monotonic trend in the time-series data.

For a time series $X_i = x_1, x_2, \dots, x_n$, the Mann-Kendall test statistic S is calculated using Equation (1) as follows (Patakamuri *et al.* 2020):

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

where n is the number of data points, x_i and x_j are the data values in time series i and j ($j > i$), respectively, and $\text{sign}(x_j - x_i)$ is the sign function as indicated in Equation (2):

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

when the sample size (data points) is greater than or equivalent to 10 ($n \geq 10$), the MK test is characterised by a standard distribution with the mean $E(S) = 0$, while the variance $\text{Var}(S)$ is given using Equation (3):

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{k=1}^m t_k(k-1)(2k+5)}{18} \quad (3)$$

where n is the number of data points, m is the number of tied groups, and t_k denotes the number of ties of extent k .

A standardised MK test statistic Z_{MK} is then calculated as given in Equation (4):

$$Z_{\text{MK}} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases} \quad (4)$$

The positive Z -value indicates an increasing trend, while the negative Z -value indicates a decreasing trend. The trend is significant if Z_{MK} is greater than the standard normal variate $Z_{\alpha/2}$, where $\alpha\%$ is the significance level. For a 5% significance level, a trend is significant when $|Z_{\text{MK}}| > 1.96$ (Gocic & Trajkovic 2013).

Sen's slope estimator

A Sen's slope estimator (Sen 1968) is a non-parametric method for estimating the magnitude of a trend by computing the linear rate of change (slope) and the intercept. For a given time series $X_i = x_1, x_2, \dots, x_n$, with N pairs of data, the slope is calculated using the following equation:

$$\beta_i = \frac{x_j - x_k}{j - k}, \quad k \leq j \text{ and } i = 1, 2, \dots, N \quad (5)$$

The median of N -values of β_i gives the Sen's estimator of slope β , using Equation (6):

$$\beta = \begin{cases} \frac{\beta N + 1}{2}, & \text{if } N \text{ is odd} \\ \frac{\left(\frac{\beta N}{2} + \frac{\beta N + 2}{2}\right)}{2}, & \text{if } N \text{ is even} \end{cases} \quad (6)$$

A positive β -value represents an increasing trend, while a negative β -value represents a decreasing trend over time.

Sequential Mann-Kendall test

The SQMK test proposed by Sneyers (1990) was used in this study to determine the approximate year for the beginning of a significant trend. The SQMK test is computed using ranked values, y_i of the original values in analysis ($x_1, x_2, x_3, \dots, x_n$). The magnitudes of y_i ($i = 1, 2, 3, \dots, n$) are compared with y_j ($j = 1, 2, 3, \dots, i - 1$). For each comparison, the cases where $j_i > y_j$ are counted and denoted by n_i . The SQMK test sets up two series, a progressive one of $u(t_i)$ and a backward one of $u'(t_i)$.

The test statistic t is then given by Equation (7):

$$t_i = \sum_{j=1}^i n_i \quad (7)$$

The mean and variance of the statistic are given by Equations (8) and (9) as follows:

$$E(t_i) = \frac{i(i-1)}{4} \quad (8)$$

and

$$\text{Var}(t_i) = \frac{i(i-1)(2i+5)}{72} \quad (9)$$

The sequential values of statistic $u(t_i)$ are then calculated as in Equation (10):

$$u(t_i) = \frac{t_i - E(t_i)}{\sqrt{\text{Var}(t_i)}} \quad (10)$$

Using the same approach of calculating the $u(t_i)$ values from the start to the end year, the $u'(t_i)$ values are calculated backward, beginning with the end year of the data series. The estimated year (time) of trend occurrence is identified by locating where the progressive $u(t_i)$ and retrogressive $u'(t_i)$ curves intersect (Tabari *et al.* 2015). The critical value for a 95% confidence level is ± 1.96 (Zarenistanak *et al.* 2014).

RESULTS AND DISCUSSION

Homogeneity tests

Homogeneity tests were performed using the four test methods (i.e., Pettitt's, SNHT, BRT, and VNR) at annual, seasonal, and monthly timescales. The absolute homogeneity test was used due to the low spatial station density and the absence of many stations with long-term data in the study area. The results of each homogeneity testing method were evaluated separately at a 95% significance level. The results were then used to detect inhomogeneous periods depending on the number of tests rejecting the null hypothesis. In this study, the null hypothesis was accepted and the data were considered homogeneous when the computed p -value for each test was greater than the significance level (0.05).

Rainfall homogeneity test

An evaluation of the monthly and seasonal rainfall homogeneity test results is indicated in Table 2. The results were classified as 'useful' (U), 'doubtful' (D), and 'suspect' (S) for each station, depending on how many homogeneity tests rejected the null

Table 2 | Results of a homogeneity test for monthly and seasonal rainfall data

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Autumn	Winter	Spring	Summer
Barrage	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
Vereeniging	U	U	U	U	U	U	U	U	U	U	S	U	U	U	S	U
Westonaria	U	U	U	D	U	U	U	D	U	U	U	U	U	U	U	U
Fochville	U	U	U	U	U	U	U	U	U	U	U	U	S	U	U	U
Zuurbekom	S	U	U	D	U	U	D	U	U	U	U	U	U	U	U	U
Midvaal	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
Winford	U	U	U	S	U	U	U	U	U	U	U	U	U	U	U	U

U, useful; S, suspect.

hypothesis. Results for the monthly data indicate that the majority of the stations have homogeneous data, which were classified as useful. Inhomogeneous data series (labelled as suspect) were observed in January, April, and November for Zuurbekom, Winford, and Vereeniging, respectively.

The seasonal time-series data were found to be inhomogeneous in autumn and spring for Vereeniging and Fochville, respectively. The rest of the seasons in the remaining stations showed homogeneous characteristics; hence, climate trends and their results can be considered as reliable.

Annual rainfall time series were also subjected to homogeneity checks, because the tests may fail to detect non-homogeneity in the monthly and seasonal rainfall (Ahmed *et al.* 2018). The homogeneity test results for annual rainfall data are summarised in Table 3. Results of the tests show that six of the seven stations had homogenous data, which were labelled as 'useful'.

Meanwhile, inhomogeneous data series were detected in three of the four homogeneity tests at the Fochville station, thus classifying the data as inhomogeneous. The break (change point) in the annual time series for the Fochville climate station was found to be in the year 2015. Generally, historical information on the station's geographical position and measurement practices are useful aspects that need to be considered when analysing the homogeneity of observed climate time series. Due to the absence of such metadata information at Fochville, it is unclear as to the possible cause of inhomogeneity at the station. As such, the findings from the station need to be used with caution since they may not truly reflect climatic influences.

Temperature homogeneity test

In a similar manner to rainfall data, temperature data series for the available stations were subjected to homogeneity tests at monthly, seasonal and annual timescales and the results are indicated in Table 4. The findings indicate that the majority of the months have homogeneous data for both maximum and minimum temperatures. However, maximum temperatures for Midvaal were classified as inhomogeneous in March, April, and November, while maximum temperatures at Winford have inhomogeneous data in February, April, and May. Hence, further climate studies such as trend analyses need to be used with caution for such type of result.

Discharge homogeneity tests

Homogeneity tests for the discharge data were performed for the only available gauging station within the hydrological boundary of the study area. The obtained data for the discharge station (C2H5) run from 1953 to 2018. Results of the homogeneity tests show that *p*-values for all of the four tests (Pettitt, SNHT, BR, and VNR) were less than the significance level of 0.05 for monthly, seasonal, and annual timescales, indicating that the discharge data were inhomogeneous. The findings were compared with an evaluation of the critical values results in order to confirm the observed inhomogeneities. According to Wijngaard *et al.* (2003), for a sample size used in the present study ($n = 66$), at a 95% confidence level, the critical values are 235, 8.45, 1.55, and 1.54 for Pettitt, SNHT, BR, and VNR tests, respectively. The data were regarded as inhomogeneous if the critical value is lower than the estimated test statistic for each respective test. Results show that the obtained test statistic for Pettitt, SNHT, and BR tests was higher than the above-mentioned critical values in all the timescales (Table 5). Only the test statistic values from the VNR test had values lower than the critical values (1.54). This further confirms the inhomogeneity in the discharge data.

Table 3 | *p*-values for the annual rainfall data and the corresponding data category

Station	Pettitt	SNHT	Buishand	von Neumann	Category
Barrage	0.2094	0.8905	0.89	0.2874	Useful
Vereeniging	0.325	0.206	0.156	0.120	Useful
Westonaria	0.866	0.659	0.833	0.521	Useful
Fochville	<0.0001	0.010	0.007	0.156	Suspect
Zuurbekom	0.664	<0.0001	0.963	0.419	Useful
Midvaal	0.410	0.851	0.659	0.842	Useful
Winford	0.203	0.978	0.906	0.961	Useful

Table 4 | Results of homogeneity tests for temperature time series on a monthly, annual, and seasonal basis

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual	Autumn	Winter	Spring	Summer
Vereeniging Tmax	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
Vereeniging Tmin	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
Zuurbekom Tmax	U	U	U	U	U	S	U	U	U	U	U	U	U	U	U	U	U
Zuurbekom Tmin	U	D	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U
Midvaal Tmax	U	U	S	S	U	U	U	U	U	U	S	U	S	S	U	U	U
Midvaal Tmin	U	U	U	U	U	U	U	U	U	U	U	U	D	U	U	U	U
Winford Tmax	U	S	U	S	D	U	U	U	U	U	U	U	D	S	U	U	U
Winford Tmin	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U	U

U, useful; S, suspect.

Table 5 | Test statistic values from the discharge homogeneity tests

Month	Pettitt (K)	SNHT (T ₀)	Buishand (Q)	von Neumann (N)
January	997	42.8	26.2	0.4
February	1,014	40.7	26.1	0.4
March	926	35.4	24.3	0.7
April	1,012	41.5	26.4	0.4
May	879	36.4	23.5	0.5
June	973	39	24.9	0.3
July	996	42.5	26	0.3
August	1,031	42.8	26.3	0.2
September	1,004	42.6	25.8	0.3
October	953	38.8	24.3	0.4
November	913	35.2	23.8	0.7
December	959	38.5	24.5	0.5
Autumn	962	40.1	25.1	0.4
Winter	987	42.3	26	0.3
Spring	993	40.8	25.7	0.3
Summer	992	43.8	26.4	0.3
Annual	1,018	44	26.9	0.2

Further analysis of the mean annual discharge data shows the Pettitt test detecting a break (change in the data) in 1986, the SNHT in 1995, and the BR in 1986, as shown in [Figure 3\(a\)–3\(c\)](#). As expected from the homogeneity test results, the discharge data are associated with significant positive trends in all the months and at an annual scale. The increasing flows, which were observed even in dry season months, are unlikely to be related to natural hydrological or climatic change and variability. The possible reasons for the increasing flows could be the additional effluent from the wastewater treatment works across the study area, which eventually discharges into the surface water bodies including the Rietspruit River. Furthermore, the eastern part of the sub-basin where the Rietspruit River is located is being more urbanised, thereby changing the natural landscape and creating more impervious surfaces. These findings are consistent with the observations made by [du Plessis \(2017\)](#), who pointed out that the impervious surfaces due to increased urbanisation have led to increased runoff in the Upper Vaal. Based on these findings, there is a need to separate all the effluent discharges from the measured flows at the stream gauging station in order to have only natural flows. As such, the discharge data in this study were not used for further analysis of climate trends.

Trend analysis

Annual temperature and rainfall cycles

The annual cycles of rainfall and temperature for selected stations in the study area are indicated in [Figure 4](#). The cycles were determined from the average monthly data for the respective meteorological variables. The months of December and January saw the most rainfall, with June and July having little or no rains. Meanwhile, the lowest and highest temperatures for the studied stations were detected in the June/July and December/January periods, respectively.

Rainfall pattern and trends

Rainfall in the study area is mostly concentrated during the summer months of December, January, and February. The coefficient of variation (CV) values for the annual rainfall and summer season are presented in [Table 6](#). The highest and lowest variability was observed at Fochville and Zuuberkom climate stations at both annual and summer season timescales, respectively. CV values between 20 and 30% are considered to be moderate while CV greater than 30% is regarded as high ([Sangma et al. 2020](#)). This indicates that the study area is characterised by intermediate and higher rainfall variability.

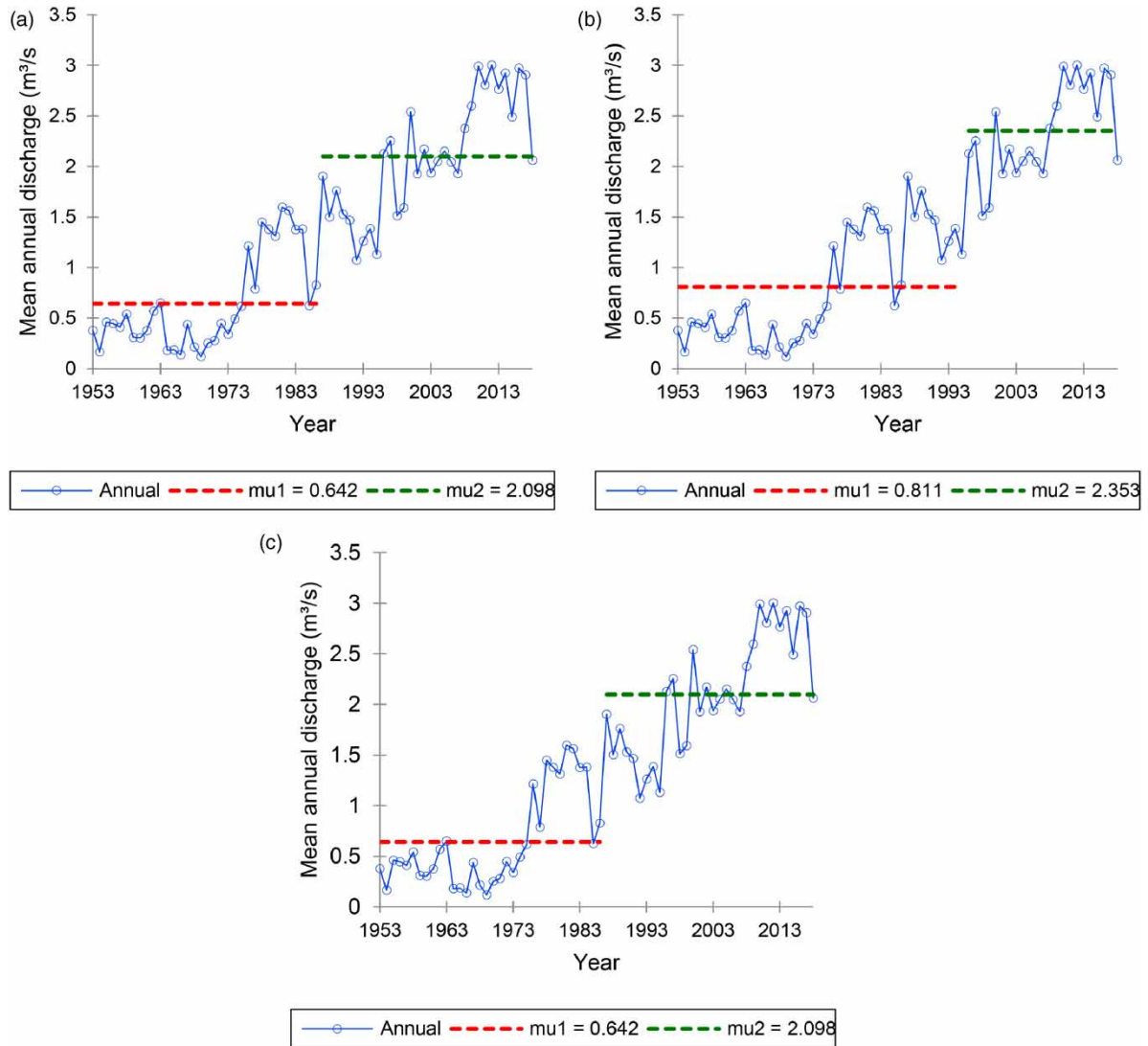


Figure 3 | (a–c) Homogeneity testing and identification of change point for mean annual stream discharge. (a) The Pettitt test, (b) SNHT, and (c) Buishand test.

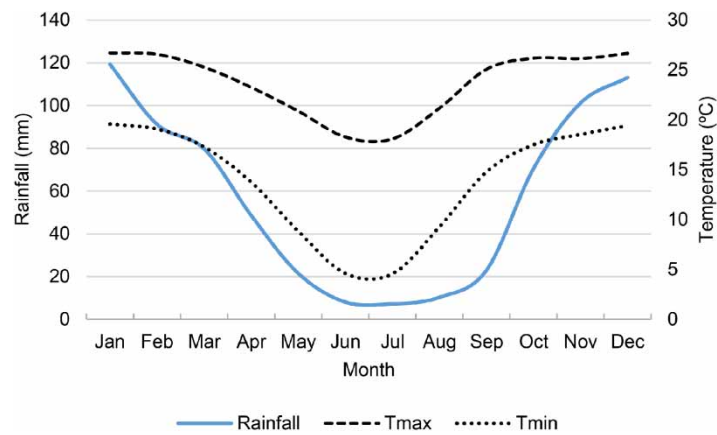


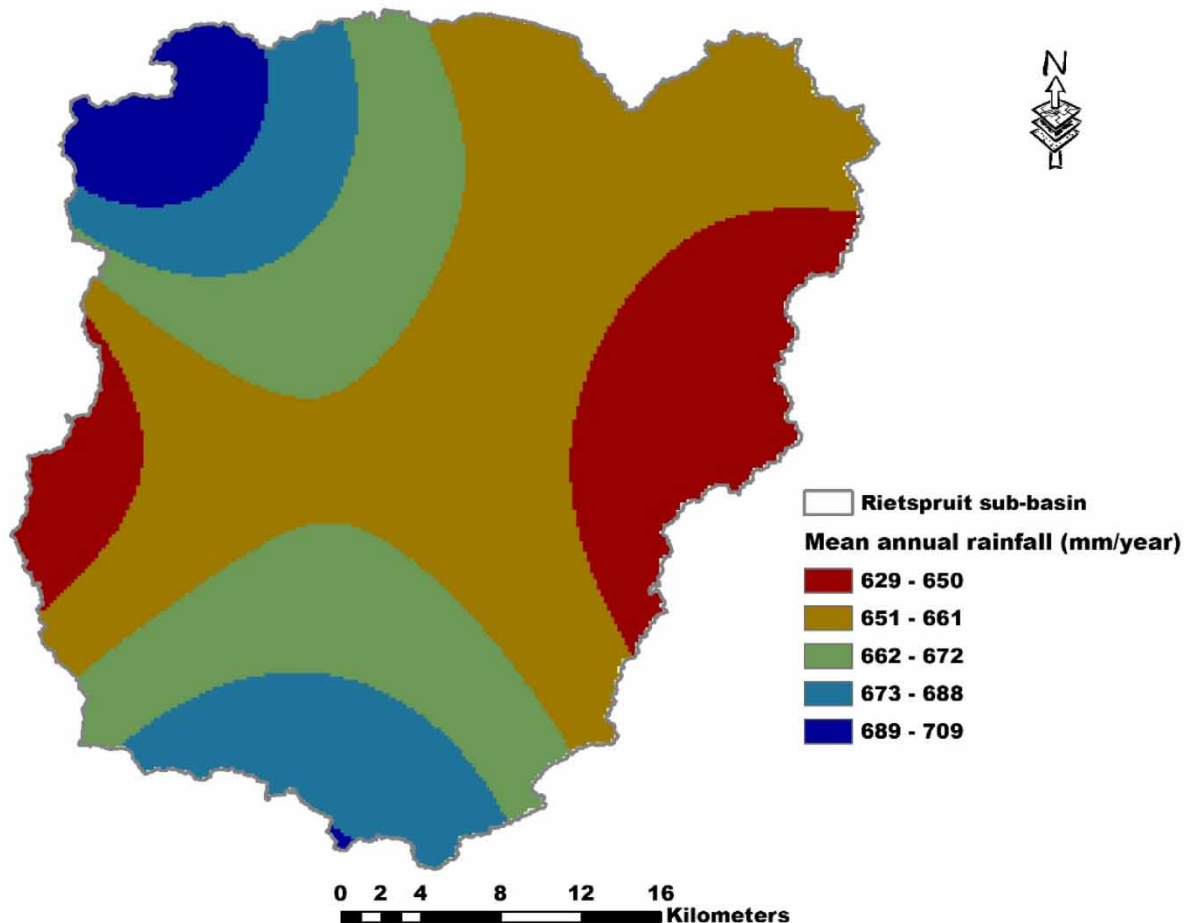
Figure 4 | Annual temperature and rainfall cycles for the study area.

Table 6 | Coefficient of variation (%) for the annual and seasonal (summer) rainfall time series

Station	Annual	Summer season (DJF)
Barrage	24	30.8
Westonaria	25	32.8
Vereeniging	23	27.4
Zuuberkom	19	18.9
Fochville	57.5	54
Midvaal	19	26.5
Winford	20.4	24.7

The distribution of annual rainfall within the RSB boundary was investigated in an ArcGIS setting using the inverse distance weighting (IDW) technique. The IDW interpolation method assumes that places with observed data will have similar values to nearby places without data than those further away (Kebblouti *et al.* 2012). From the analysis, the mean annual rainfall within the Rietspruit ranges from 629 to 709 mm (Figure 5), demonstrating the semi-arid and dry sub-humid characteristic of the study area (Kašanin-Grubin *et al.* 2018). The highest rainfall is depicted in the north-western part of the study area while low rainfall values are observed in the eastern and some parts of the western side of the RSB.

The Mann-Kendall test was applied on annual, monthly, and seasonal data to detect monotonic rainfall trends at different meteorological stations. Negative and positive Sen's slopes demonstrated a decline and increase in rainfall, respectively. In

**Figure 5** | Annual rainfall distribution across the Rietspruit sub-basin.

this study, temporal trend analysis to detect potential climate change largely focused on three stations, namely Barrage, Vereeniging, and Westonaria since these sites have long-term data enough to detect potential trends due to climate change. Meanwhile, short-term trends performed in other stations were only used to provide an insight into the natural fluctuations of rainfall within the studied years, as the data length is not adequate to provide evidence of climate change. In general, results of the rainfall trend analysis show a combination of negative and positive trends for monthly, seasonal, and annual time series.

For monthly time series, statistically significant downward trends were observed in November at Vereeniging, and in April, August, and September at Westonaria, as seen in Table 7.

Meanwhile, at Midvaal, a statistically significant upward trend was observed in September. No statistically significant trends were found in the other months. It is worth noting that statistically significant trends were detected only in months that normally receive little rainfall, as compared with the normal wet months such as December, January, and February. Hence, such statistical significance may not make a substantive difference to the overall observed annual rainfall because rainfall in the study area is seasonal, largely falling during the summer months (DJF). Nonetheless, if the downward rainfall trend can continue for the dry season months, it can result in a further increase of the dry season and a reduction in soil moisture during the said period. Soil moisture is an important variable as it influences the interaction between land and atmosphere (Mishra 2020), which ultimately influences short-term weather forecasts (Costa *et al.* 2016). Dry season soil moisture decline due to decreasing rainfall can also cause agricultural drought and affect crop production. Therefore, it is important to continue monitoring such declining trends as they can cause direct and indirect impacts on the overall water budget of the sub-basin.

MK test results in the analysed stations showed no statistically significant trends on an annual timescale. However, it is important to point out that non-significant negative trends were dominant as the trends occurred in five of the seven stations. Figure 6(a)–6(c) shows the trend on annual rainfall for the three long-term data, with the decreasing slope evident in two of the three stations.

In general, the study area is characterised by the presence of insignificant increasing and decreasing rainfall trends and moderate to high intra-annual and seasonal rainfall variability. As depicted earlier, the CV for annual rainfall ranged from 23 to 25% for the long- and medium-term data and from 19 to 57% for the short-term data. Areas having high rainfall variability tend to be more susceptible to floods and droughts (Gajbhiye *et al.* 2016). A series of studies in the southern Africa region have also found no significant trends in annual rainfall data, with many indicating a downward trend. Gyamfi *et al.* (2016) found an insignificant trend for annual rainfall in the Olifants Basin (South Africa), which is a neighbouring basin to the Upper Vaal Basin. Using data from 138 South African stations between 1910 and 2004, Kruger (2006) detected no significant changes in rainfall in a majority of the stations. Banze *et al.* (2018), from a review of rainfall trends in southern Africa, concluded that rainfall will both increase and decrease in the different parts of the region; however, there is still no total agreement among researchers on the magnitude of the anticipated rainfall change in the region. In contrast, Murungweni *et al.* (2020), from a local-scale study in Limpopo (South Africa), established that there is a non-significant decrease in the annual rainfall.

Seasonal rainfall trends exhibited a statistically significant positive trend in autumn (March–April–May) at Fochville (Table 8). Since Fochville has short-term data, such changes can only be attributed to significant seasonal fluctuations in meteorological conditions in the area. Although homogeneity test results for autumn at Fochville indicated that the data

Table 7 | Mann-Kendall Z-statistics for monthly rainfall data

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barrage	0.42	0.47	– 0.29	1.52	– 0.32	– 0.40	– 1.54	– 0.48	– 0.58	0.60	0.08	0.36
Vereeniging	– 0.07	– 0.57	– 0.09	0.53	0.27	– 0.09	0.56	– 0.90	– 0.84	– 0.79	– 1.96	– 0.04
Westonaria	– 0.05	– 0.54	0.20	– 2.69	– 0.64	1.76	0.12	– 2.77	– 2.07	– 0.74	0.90	1.53
Fochville	1.15	1.35	0.52	1.77	0	0	– 0.58	– 1.50	1.82	0	1.56	1.15
Zuurbekom	– 0.73	0.24	0	0.24	0	– 1.11	– 1.22	0	– 1.22	0	0.24	1.71
Midvaal	– 0.76	– 1.48	– 1.39	1.21	– 0.27	– 0.24	0.94	– 0.45	1.97	– 0.31	0.85	0.31
Winford	– 0.12	0.37	– 0.87	1.50	– 0.75	0	– 0.88	– 1	0.87	– 0.62	– 0.62	– 0.12

The bold values indicate a significant trend.

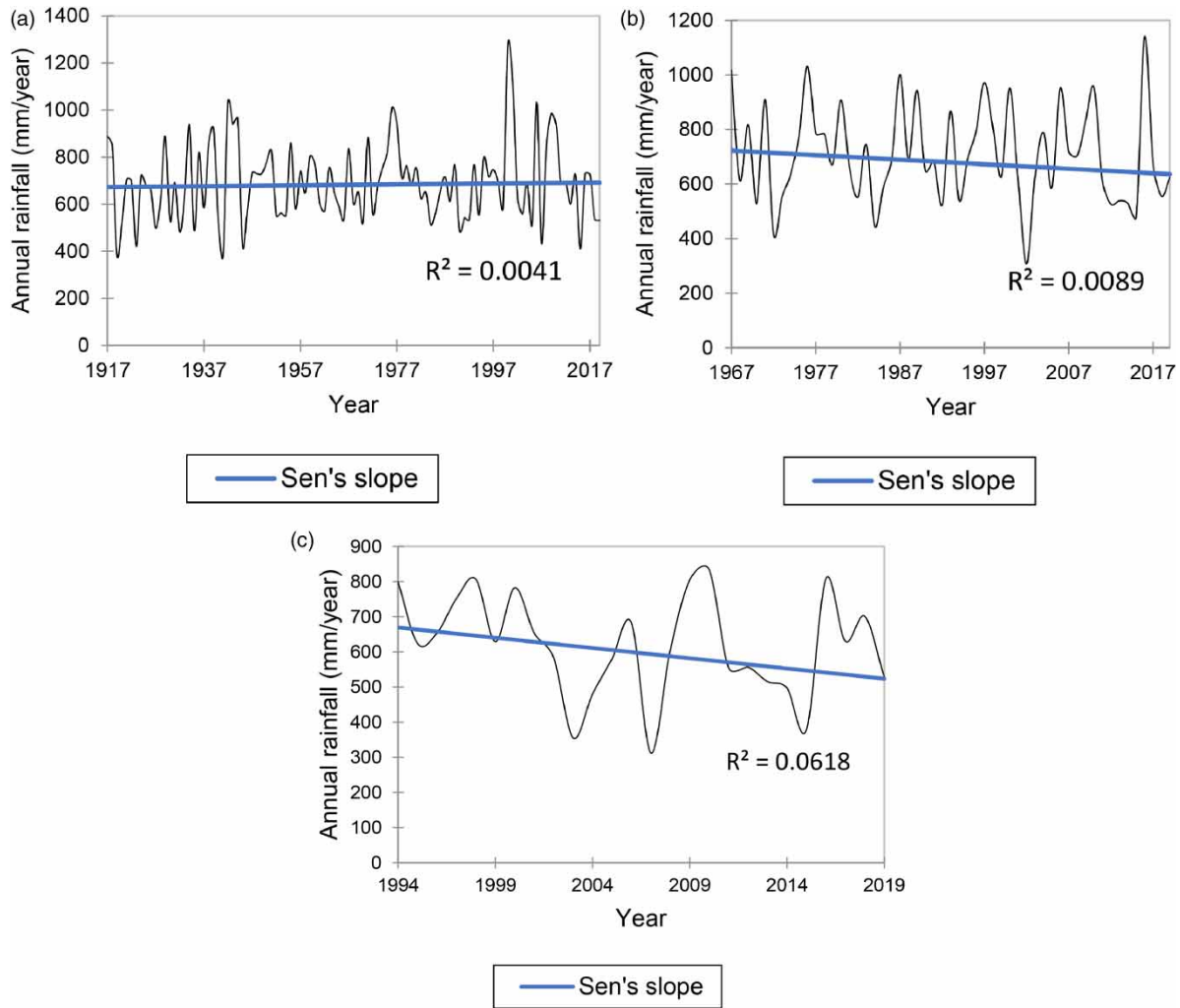


Figure 6 | Annual rainfall trends for Barrage (a), Westonaria (b), and Vereeniging (c).

Table 8 | Mann-Kendall Z-statistics (MK-Z) and Sen’s slope (β) for annual and seasonal rainfall time series

Station	Annual		Autumn		Winter		Spring		Summer	
	MK-Z	β	MK-Z	β	MK-Z	β	MK-Z	β	MK-Z	β
Barrage	0.26	0.19	0.74	0.18	-0.97	-0.03	0.47	0.15	1.21	0.42
Vereeniging	-1.29	-5.83	0.57	0.86	0.37	0.10	-1.72	-3.01	-0.12	-0.12
Westonaria	-0.85	-1.66	-0.71	-0.43	-0.11	0.00	-0.31	-0.24	0.59	0.55
Fochville	1.56	88.91	2.19	27.80	-0.55	-0.03	1.15	13.78	1.85	54.94
Zuurbekom	0	-22.54	0.24	15.04	-1.22	-4.08	-0.24	-7.46	0.34	7.78
Midvaal	0	-0.4	-0.49	-2	-0.63	-0.86	0.58	2.2	-0.59	-3.68
Winford	0	-2.21	0.87	7.82	0	0.13	-1.36	-11.5	0.60	10.42

The bold value indicates a significant trend.

were inhomogeneous, the slope of the trend analysis shows a relatively higher magnitude of increase (27.8 mm/year) compared with other stations in the same season as pointed out in Table 8. According to Wijngaard *et al.* (2003), inhomogeneous data series showing marginal trend results should be considered as incorrect, while exceedingly high monotonic trends are due to climate-related variations.

Thus, the significant positive trend in autumn at Fochville could be attributed to climatic variability. Furthermore, an increasing trend in autumn rainfall at Fochville seems to signify a possible shift in the present-day rainfall patterns around the area, since the increase was much higher than the summer season which traditionally receives more rainfall. However, these results are not conclusive and such changes cannot be definitively attributed to possible climate change and variability due to the available short-term data for the station. This is particularly true because the scenario was observed at only one station; therefore, the findings should be further investigated as more climate data is made available.

For the summer period, which is the main rainfall season, insignificant upward trends were dominant, occurring in five of the seven stations. These findings align with the observations by Kruger & Nxumalo (2017), where it was noted that summer periods have insignificant increasing trends around the Gauteng Province, which covers a part of the study area.

The magnitude of statistically significant trends was determined by applying Sen’s slope. The results for the long-term rainfall data (Barrage, Westonaria, and Vereeniging) indicate that trends were more rapid with a higher slope at Vereeniging, which had a maximum negative decline of 2.7 mm/year in November, as indicated in Figure 7. Nevertheless, the general Sen’s slope values for both upward and downwards trends were not particularly high, which aligns with the observed non-significant rainfall trends.

Temperature trends

In the same way as rainfall data, the Mann-Kendall and Sen’s slope estimator was used to assess the maximum and minimum temperature trends for annual, seasonal, and monthly time series. Table 9 displays the results of the monthly Mann-Kendall tests.

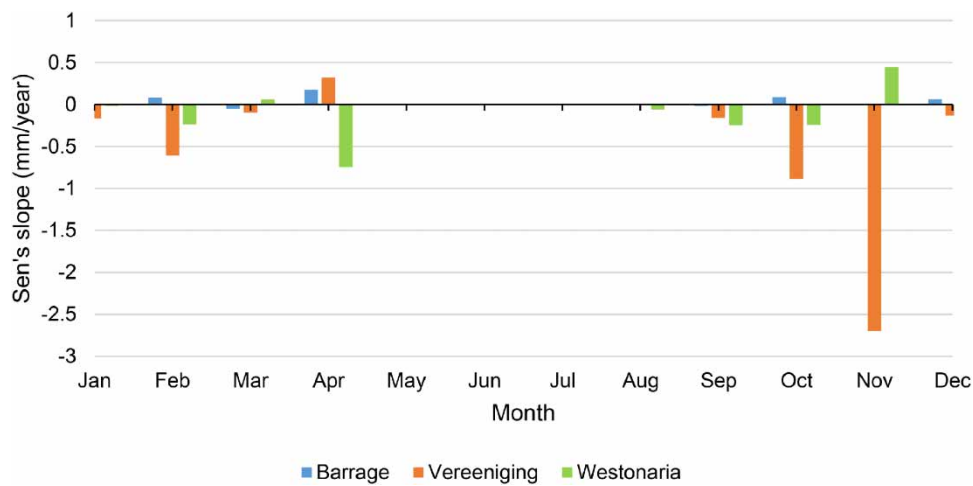


Figure 7 | Sen’s slope values for the long-term rainfall time series.

Table 9 | Mann-Kendall Z-Statistic for monthly maximum and minimum temperatures

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Vereeniging Tmax	0.45	0.37	-0.18	-0.37	-0.79	0.71	0.45	1.70	0.10	2.23	2.51	0.61
Vereeniging Tmin	0.51	-0.02	0.41	0.18	1.52	1.80	0.85	1.62	-0.37	1.64	2.86	1.52
Zuurbekom Tmax	0.73	-0.73	0.73	-1.22	0	1.71	0	-0.24	1.22	0	0.24	-1.22
Zuurbekom Tmin	-0.24	-0.73	0	0	0	0	-1.22	0.73	-0.73	-0.24	0.24	-1.22
Midvaal Tmax	1.3	1.39	2.66	2.83	1.75	0.94	0.67	1.21	0.49	0.94	2.84	0.94
Midvaal Tmin	-1.3	-0.13	1.03	0.94	1.03	0.76	1.3	0.76	1.57	-0.22	-1.93	-0.04
Winford Tmax	-1.6	-0.87	-0.12	-1.85	-1.11	-0.87	0.12	0.37	-1.11	-0.37	0.62	0
Winford Tmin	-0.37	-0.12	-0.87	1.61	-0.12	-0.37	-0.87	0.12	-0.37	-0.12	1.11	0.87

Statistically significant trends at a 95% significance level are indicated by the bold numbers.

From the analysed stations, maximum temperatures at a monthly scale were dominated by positive (upward) trends for all but one station. An exception was at Winford where downward trends were dominant. In contrast, minimum temperatures showed a combination of downward and upward trends. Furthermore, monthly time series revealed only statistically significant upward trends, with no statistically significant downward trends.

A great focus for temperature analyses in this study was at the Vereeniging climate station because it has relatively longer data for better and conclusive climate change analysis. The plots for statistically significant increasing temperature trends for Vereeniging are indicated in Figure 8. As depicted in Figure 8(a) and 8(b), maximum temperatures displayed statistically significant upward trends in October (Sen's slope, $\beta = 0.077$) and in November ($\beta = 0.084$). At the same at Vereeniging, a significant positive trend for minimum temperature was detected in November again, with a Sen's slope of 0.078 (Figure 8(c)). The Sen's slopes for the monthly maximum and minimum temperatures at Vereeniging are shown in Figure 9, with higher values evident in October and November. Meanwhile, significant positive trends for maximum temperatures were also detected at Midvaal in March, April, and November having Sen's slopes of 0.237, 0.173, and 0.236, respectively. The higher values of Sen's slope at Midvaal could be a result of a short data period for Midvaal; hence, the results may not reflect climatic changes.

The results of the seasonal and annual MK and Sen's slope tests for maximum and minimum temperatures are presented in Table 10. The analysed annual average temperature shows a statistically significant increasing minimum temperature at Vereeniging and maximum temperature at Midvaal. Meanwhile, the corresponding minimum and maximum temperatures for these stations also showed upward trends, though they were insignificant.

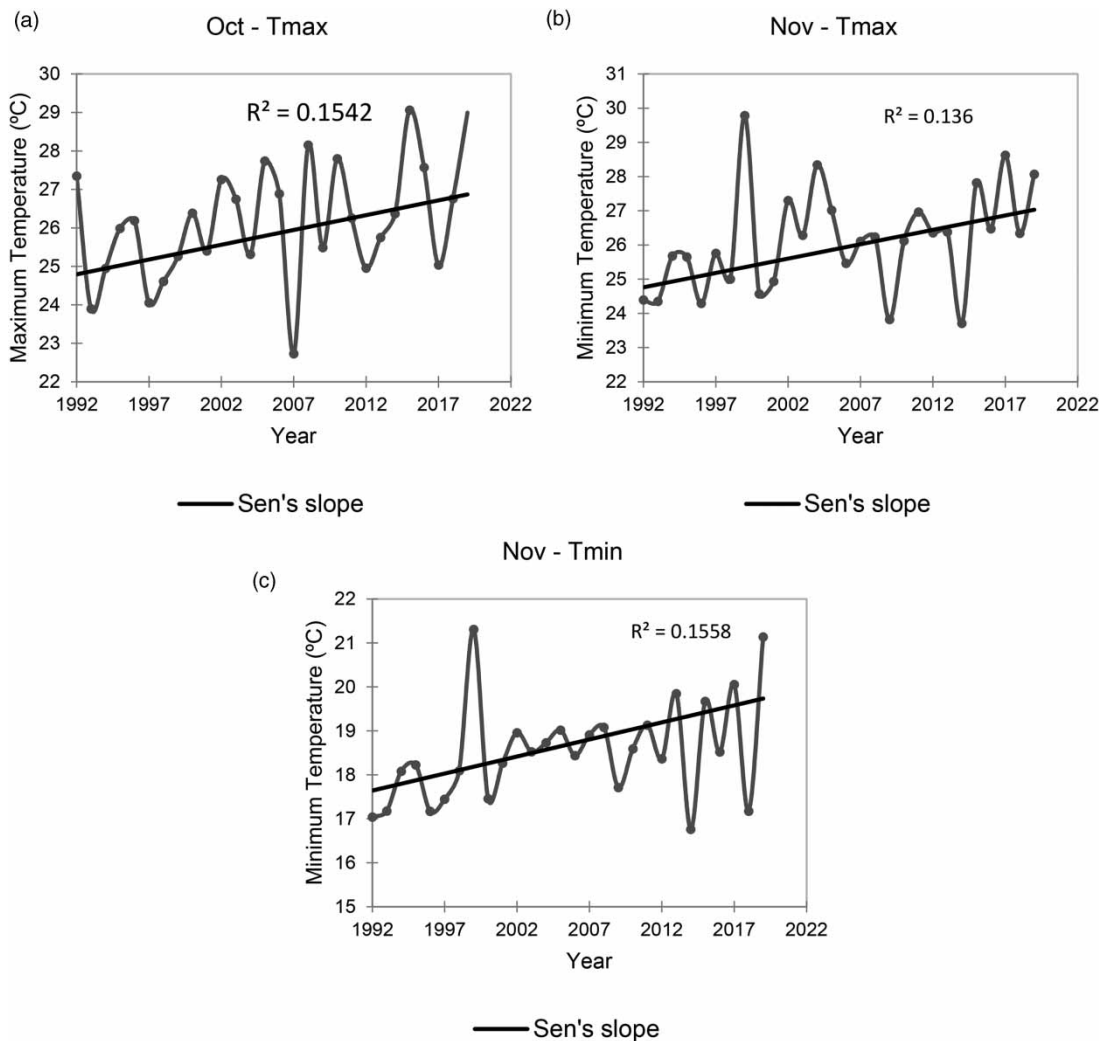


Figure 8 | Plots indicating statistically significant increasing temperature trends for Vereeniging. The Vereeniging station is one of the stations with relatively good data length for climate change analyses.

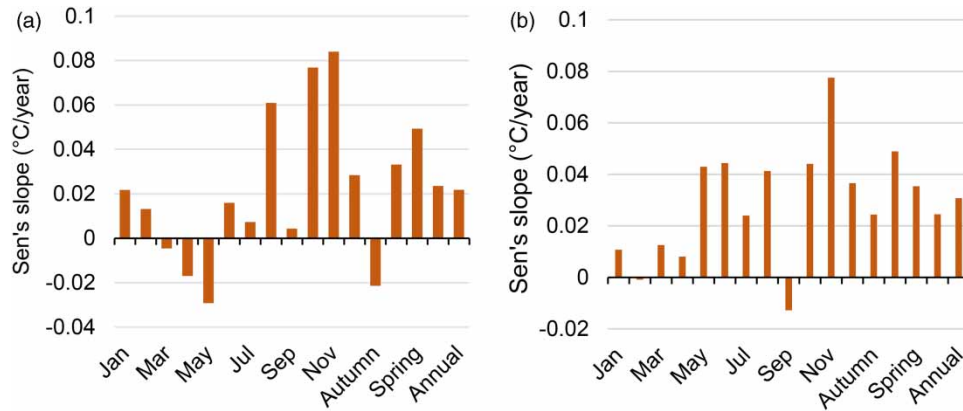


Figure 9 | Sen's slopes for maximum (a) and minimum (b) temperatures at Vereeniging.

Table 10 | Mann-Kendall Z-Statistic (MK-Z) and Sen's slope (β) for annual and seasonal temperatures

Station	Annual		Autumn		Winter		Spring		Summer	
	MK-Z	β	MK-Z	β	MK-Z	β	MK-Z	β	MK-Z	β
Vereeniging Tmax	1.24	0.022	-0.69	-0.021	1.60	0.033	2.11	0.049	0.73	0.024
Vereeniging Tmin	2.27	0.031	1.05	0.024	2.19	0.049	2.11	0.035	1.92	0.025
Zuurbekom Tmax	0	0.014	-0.73	-0.29	0.73	0.137	0.24	0.146	-0.24	-0.345
Zuurbekom Tmin	-0.24	-0.105	0	-0.032	-0.24	-0.017	0	-0.027	0	-0.320
Midvaal Tmax	2.21	0.13	3.11	0.2	1.21	0.11	1.93	0.13	1.19	0.17
Midvaal Tmin	1.21	0.04	1.48	0.1	1.39	0.09	-0.49	-0.02	-0.69	-0.03
Winford Tmax	-1.85	-0.23	-2.10	-0.37	-0.62	-0.08	-1.11	0.22	-0.62	-0.19
Winford Tmin	-0.12	-0.02	0.12	0.01	0	-0.03	0.12	0.04	0	-0.001

Significant monotonic trends are shown by the bold values.

Seasonal average temperatures for the available data indicate statistically significant positive trends in winter (T_{min} β = 0.049) and spring (T_{min} Sen's slope (β) = 0.049) for Vereeniging and in autumn (T_{max} , β = 0.2) for Midvaal. In contrast, a statistically significant negative trend was detected only at Winford in autumn (T_{max} , β = -0.37). MacKellar *et al.* (2014) also reported that maximum temperatures in South Africa's central and northern areas, which includes this study area, are increasing. They noted that the strongest trends were in the autumn (MAM) and winter (JJA) seasons.

Sequential Mann-Kendall test

Indicating the probable time of change in the analysis of hydro-meteorological trends enables one to have a comprehensive understanding of the trend detection analysis (Patakamuri *et al.* 2020). For those stations exhibiting statistically significant monotonic trends in the time series, the SQMK test was used to identify the period for an abrupt change in the data.

The SQMK tests were only conducted on temperature data because the summer (main rain season) and annual rainfall data showed no statistically significant trends. For temperature, the major focus was the significant trends observed at Vereeniging due to its better data period, which exhibited significant positive trends for minimum temperature in November and maximum temperature in October and November. Figure 10 shows plots of the SQMK tests for the Vereeniging temperature time series. Results show that maximum temperatures in October and November generally showed similar increasing trends. Maximum temperatures in October (Figure 10(a)) and November (Figure 10(b)) showed non-significant trend development around 2002. The November temperature was characterised by a slightly erratic trend between 1999 and 2000 as the forward curve intersected with the backward curve twice between these years until another intersection around 2002 (Figure 10(b)). Hence, the main year for the development of an increasing trend for the maximum temperature at Vereeniging was identified to be around 2002, though it was insignificant.

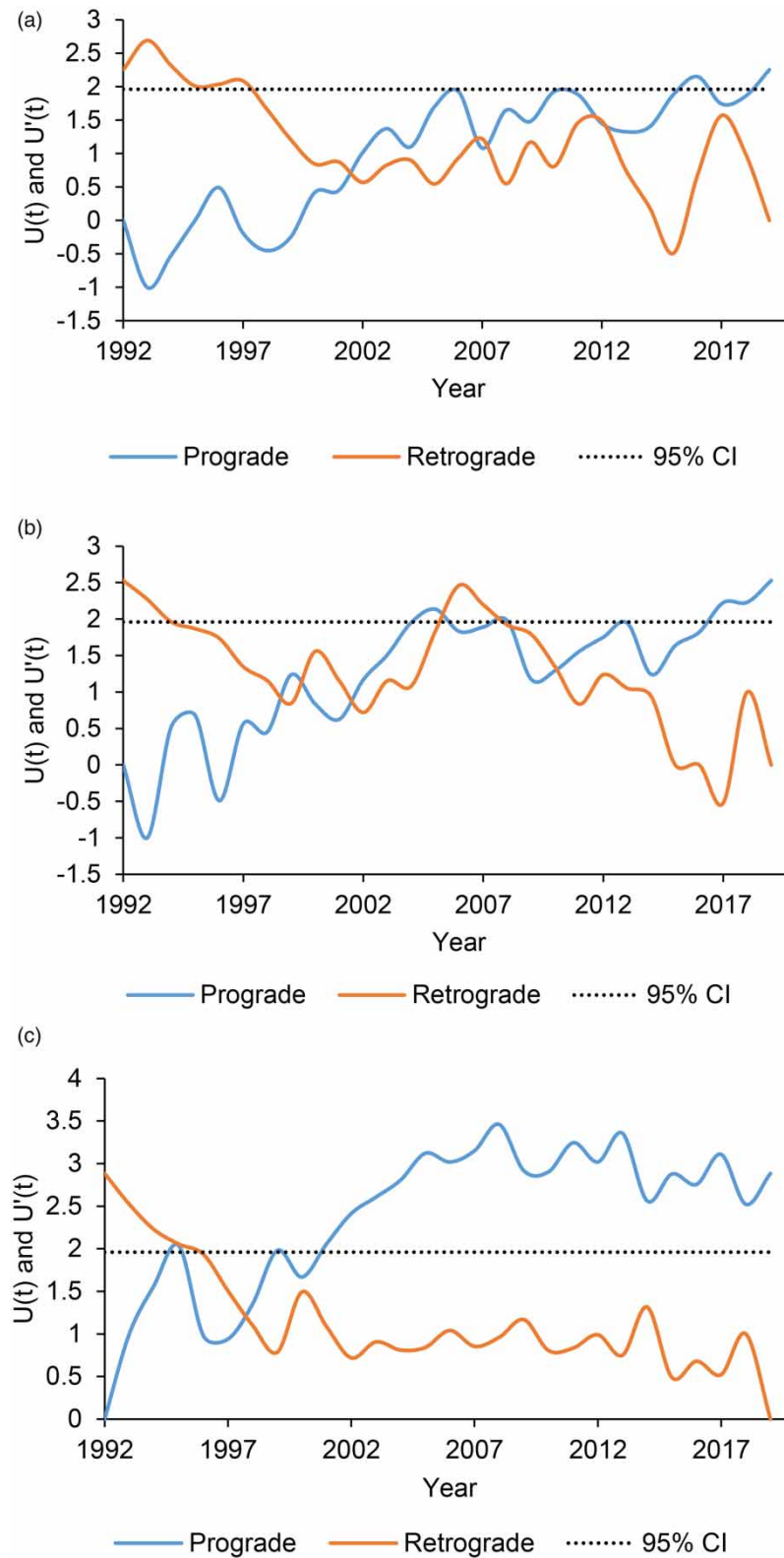


Figure 10 | Sequential values of the progressive series $u(t)$ and retrogressive series $u'(t)$ obtained by the SQMK test observed at the Ver-eeniging station. Maximum temperature observed in October (a) and November (b), and minimum temperature observed in November (c). The straight dotted line in each graph indicates the critical value of 1.96 at a 95% confidence interval.

Although the SQMK detected several other possible change points after the year 2002 as noted by the crossing of the $u(t)$ and $u'(t)$ curves, a significant increasing trend at a 95% confidence level was detected to have developed around 2015 in October and 2016 in November. This is in agreement with the drought experienced in South Africa around the 2015/2016 period, which was one of the driest periods in South Africa (Muthelo *et al.* 2019). The minimum temperature, which also exhibited increasing trends in November, showed that the increasing trend started in 1997 (insignificant) and the trend turned significant in 2001 (Figure 10(c)). Again, this is consistent with the drought observed in the 2001/2002 season in most parts of southern Africa, whereby South Africa was not spared (Rouault & Richard 2005; Masih *et al.* 2014).

The findings in this study determined the trend turning point and the potential year in which significant temperature increases began, which is important for the interpretation of climate variations. From the results, it has been established that the emergency of some drought in South Africa was associated with significant temperature increases. Since the observed droughts were in a majority of the country, it is suggested that temperature increases observed at the studied station may have also occurred at a regional level, despite the fact that only one main temperature station was used in this study. In general, risks to droughts are likely to intensify as temperatures keep rising, hence the need for continued monitoring of temperature trends for prediction and planning for such climate extremes like drought.

Implications of the observed meteorological trends and variability

An understanding of hydro-meteorological variability is central for better planning, management, and sustaining water resources. This is particularly true in areas experiencing rapid urbanisation and those highly vulnerable to climate change, a common characteristic in developing countries. Temperature and rainfall are considered the vital weather parameters for describing climate change, and their magnitude influences the natural water resource availability. Even though climate change impact studies should be performed in all regions, it is a necessity in urbanised areas because the negative effects of urbanisation and related anthropogenic activities may exacerbate the impacts. Hence, this study explored the changes in rainfall and temperature at annual, seasonal, and monthly scales using both the available short- and long-term data.

While the short-term data cannot be fully adopted for climate change analyses, the findings from such data are usually attributed to natural climatic variability. Thus, it is critical to identify and quantify the natural climatic variation to mitigate its negative effects, especially in the near term. The analysis of short-term rainfall data can give valuable guidance for managing water supplies and reducing the intensity of natural disasters including floods and droughts (Asakereh 2019). Besides, forecasts arising from the inter-annual and decadal climatic variability can help in making decisions relating to climate change risk reduction and management (Vera *et al.* 2010).

In the meantime, the results from stations having short-term data provide an insight into the short durational fluctuations of the selected climatic variables and they serve as a foundation for future climate change analysis, which has been lacking in the study area. These findings can be examined further as more data becomes available. Therefore, there is a need to be observant of such short-term variations for the communities to manage and ably respond to the uncertainties due to natural climate variability. This is especially true because there are cases when natural variations can conceal the impacts of human-induced climate change in both the short and long term (Martel *et al.* 2018).

The annual rainfall time series exhibit non-significant trends; however, downward trends are more dominant across the study area. Still, it is important to understand the economic, social, and ecological implications if the observed downward annual rainfall trend is to continue and if the decrease will be significant. This is because continued declining trends in rainfall will likely result in diminishing groundwater levels, soil moisture depletion, and ultimately a reduction in crop harvests (Meshram *et al.* 2017). As the downward trends are not significant based on the present data, it follows that the major concern related to rainfall in the study area is its inconsistency rather than its total annual amount. Erratic rainfall during the wet season complicates farming season planning and may have an impact on agricultural productivity, especially that rain-fed agriculture predominates in the study area.

Vereeniging, which has relatively longer temperature data, showed maximum temperature rising significantly in spring as well as increases in minimum temperature in winter, spring, and annual time series. The magnitude of the increase is higher for minimum temperature (0.031 °C/year) than maximum temperature (0.022 °C/year). Again, seasonal temperatures showed the highest increasing magnitude in winter (cold season) with a slope of 0.049 °C/year, representing an increase of 1.4 °C over the period 1992–2019. Similar warming trends, with an increase of nearly 1.4 °C, were detected in spring (SON) for maximum temperatures during the same period. The increases are consistent with the recent regional temperature trends outlined in Niang *et al.* (2014), whereby it was also reported that minimum temperatures are rising more rapidly than maximum temperatures in the inland part of southern Africa. Findings by Huang *et al.* (2012) who studied long-term temperature trends

across the globe also revealed that warming in semi-arid regions is escalating during the cold seasons. At the monthly scale, maximum temperature increases of about 2.2 °C in October and November were detected for the period 1992–2019. Such strong warming trends were also reported by MacKellar *et al.* (2014), who found temperature rises of 1.5–2 °C in the central and northern parts of South Africa using data from 1960 to 2010.

In this study, the intensified magnitude of temperature increase is more evident probably because the analysis has been conducted for moderately recent periods, which has seen accelerated warming (Singh *et al.* 2014). Such changes in temperature can be attributed to changing climate due to anthropogenic activities, associated with urban and industrial features.

The effect of rising temperatures can influence both water quantity and quality, which has the potential to enhance evapotranspiration and reduced runoff under the same rainfall conditions (Xu *et al.* 2020). At such a rate of temperature increases in the study area, the possibility for the development of intense drought is also expected to increase, which will ultimately increase threats related to water availability. According to Hoegh-Guldberg *et al.* (2018), rising temperatures above 2 °C are likely to cause a noticeable increase in the risks to drought occurrences and its magnitude, mostly in southern Africa and in the Mediterranean region. Thus, the observed temperature increases can have multiplier effects on the region such as food and water security, ecosystem services, energy, and the economy at large.

The results in this study provide a basis for the need to conduct efficient climate change modelling in the study area in order to devise well-informed decisions for the management of the RSB. This is mostly true because climate change is changing the principle of stationarity in the water resources system, which focused on predicting the future based on past hydrologic events. Hence, there is a need for reliable projections to understand the extent to which water resources will be affected due to climate variability. Furthermore, as climate change adaptation measures are put into consideration, it is also important to reflect on other non-climatic elements affecting freshwater resources, for example land-use change and population increase, which can aggravate the effects of climate change. This is because anthropogenic activities and climate change are likely to remain the most important factors driving the hydrological cycle.

CONCLUSIONS

This study attempted to analyse trends for stream discharge, rainfall, and maximum and minimum temperature for the RSB in South Africa. Homogeneity tests were performed using four statistical tests to establish the reliability of the data for hydro-meteorological variability and climate change studies. The presence and magnitude of trends over time were, respectively, determined using the non-parametric Mann-Kendall test and Sen's slope estimator, while the change point analysis was performed using the SQMK test.

The monthly, seasonal, and annual time series were homogeneous from the majority of the stations. Temperature and rainfall data were more homogeneous at the annual scale; hence, the data were further used to perform trend analyses. In contrast, stream discharge showed inhomogeneity including at the annual scale, thus the data could not be used further for trend analyses before its correction. This signifies the need for performing homogeneity tests before carrying out climate data analyses. It has been suggested that streamflow is impacted by anthropogenic activities such as the discharge of effluent, hence the measured flows did not entirely reflect the natural river flows. Therefore, it is recommended that measured streamflow be separated from the flows contributed by the effluents. This is important to isolate and distinguish discharge variability due to climate change from that caused by anthropogenic activities.

From the trend analysis, at a 5% significance level, rainfall showed insignificant increasing and decreasing trends on an annual basis in all the stations. The findings also reveal that decreasing trends were dominant for annual rainfall while the summer season, the high rainfall season in the study area, was dominated by positive trends. Broadly, based on long-term data, this study showed no extensive evidence that climate change has resulted in a significant increase or decline in rainfall over the RSB. Hence, the variability of rainfall in the study area is more of a concern than the total average rainfall.

Temperature data at Vereeniging revealed that maximum temperature has significantly increased in October and November, while minimum temperature showed a significant increase in November and the winter season. Strong warming trends were detected with temperature increases of about 2.2 °C in October and November. Minimum temperatures have also exhibited a significant increase, with the increase being greater during the winter season. In the absence of a significant change to the rainfall, while temperature has been significantly rising, evaporation rates are expected to rise as well. This has the potential to increase the aridity in the study area, thereby stressing the availability of both groundwater and surface water resources.

In general, this study enhances the scientific knowledge and characteristics of hydro-meteorological variables in the upper part of the Vaal Basin and largely in South Africa. The findings are important for decision making in the water and agricultural sector,

but also for monitoring the impact of climate change and variability in the RSB area. Due to the limited long-term data and small network density of weather stations in the RSB, it is critical to use regional climate model data to improve forecasting and reduce uncertainty in the climatic variables. Furthermore, because the Mann-Kendall test used in this study did not account for the effects of data autocorrelation, data series autocorrelation analyses are suggested for detecting trend patterns.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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