

Spectral analysis of drought risk: A case of Bloemfontein, South Africa

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Abstract

Drought is defined as an insidious hydrometeorological hazards with a potential to negatively impacts on society, economy and environment. The current study aimed at analysing the drought potential risks in the study area for the protection of economy, environment and human lives. A 42-year long rainfall/precipitation data were collected from an online database. Dataset was subjected to quality check, where outliers were detected, removed and replaced by Expectation Maximum algorithm aided by SPSS. A non-parametric Mann Kendall's test for trends was applied to detect monotonic trends present in the dataset. XLSTAT software was used in fitting annual data for a suitable probability distribution. The annual data fitted normal probability distribution with parameters, $\sigma=183.143$, $\mu=530.451$ using Kolmogorov-Smirnov test criterion. The spectral analysis showed that the study area is expected to experience drought events every 2 years. The government and other relevant stakeholder authorities are therefore cautioned to put measures in place for the protection of property, environment and human lives and agricultural activities against adverse effects of droughts.

Keywords: drought, risk, Bloemfontein, spectral analysis.

Introduction

A period in time whereby conditions are drier than usual and there is a lesser amount of rainfall than normal for a long period of time; for several weeks, months and even years which lead to water-related problems is defined as drought (Praveen, Ramachandran, Jaganathan, Krishnaveni, & Palanivelu, 2016). Nevertheless, there is no specific definition of drought; but it can be classified into four essential types. In this study, drought is described as a severe state which is has undesirable dry spell which has negative impacts on the economy, society and environment. The four essential types of drought are: meteorological drought, hydrological drought, agricultural

drought and socio-economic drought. (i) Meteorological drought is simply the degree of dryness compared to normal conditions and this is irregular over time and certain regions (Olivares Campos, 2016), (ii) hydrological drought on the other hand is deficient rainfall which results into grave reduction in run-off streamflow, inflow into storage reservoirs and revitalizing of groundwater (Orlando Olivares & Zingaretti, 2018), (iii) Agricultural drought refers is a deficit of soil moisture to sustain plants and livestock in that way causing weakened growth and reduced produce (Tefera, Ayoade, & Bello, 2019) and Socio-economic drought is a period in time whereby human activities are negatively affected by reduction in water availability and precipitation. (Praveen et al., 2016). As much as all these types of drought have a linkage, one leads to another and every now and then overlaps; thus, agricultural drought is regarded as of prime importance and a roadmap in this study. The figure 1 below illustrates the interrelationship of the types of drought.

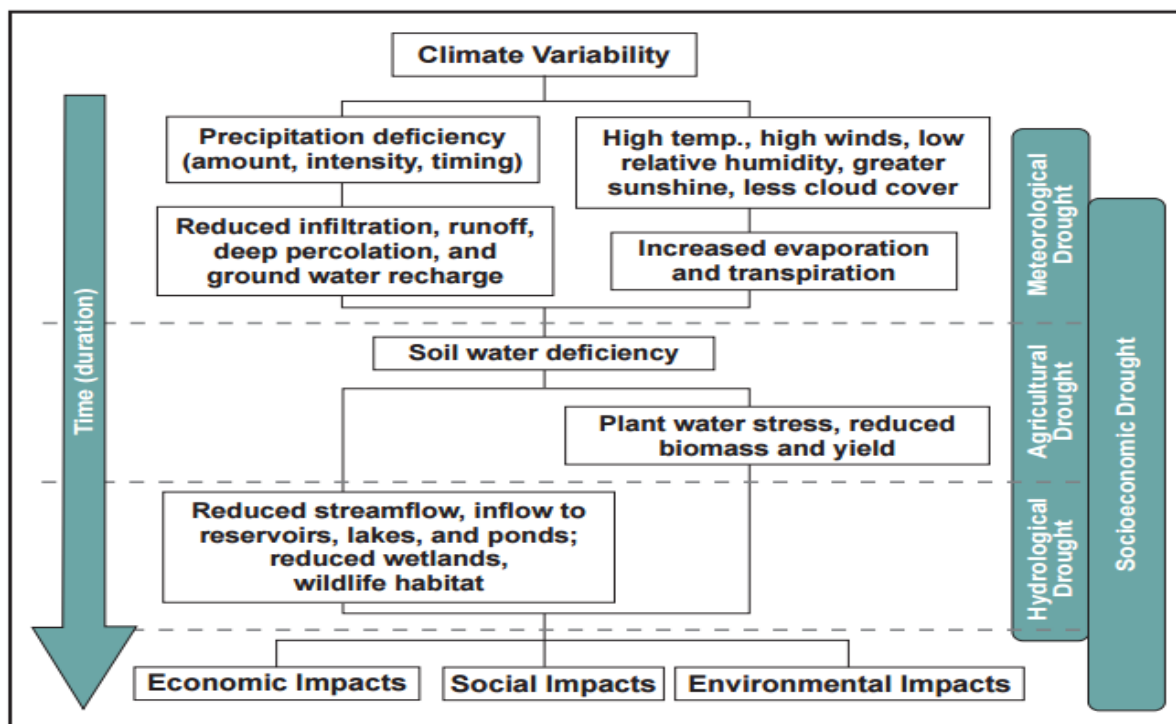


Figure 1: Sequence of drought types' occurrence and their impacts
 Source: National Drought Mitigation Centre, 2012.

Key driving forces behind drought events

El Niño-Southern Oscillations

Despite the fact that numerous continents around the world pass through the separation between two hemispheres, Africa is the only continent that lies within them all and is affected by numerous climatic conditions. (Roman-Cuesta, 2007). As a result, this continent receives conventional rainfall. (Choi, An Prof., Yeh, & Yu, 2013). This also escalates to different climatic conditions such as El Nino. El Nino is a recurring climate pattern which is caused by changes in temperatures of water by warming the eastern Pacific, and therefore affecting the global climate. (Ali & Ali, 2011). This natural occurrence is responsible for exacerbating drought events in the southern hemisphere. (Ali & Ali, 2011). In accordance to Keil, Zeller, Wida, Sanim, & Birner (2008), drought is a resultant of the shifting, changing weather patterns. On the other hand, it is also a belief that droughts chiefly transpire because of natural occurrences due to the earth and atmospheric systems. In contrast, Granzow-de la Cerda, Lloret, Ruiz & Vandermeer (2012) are of the belief that no one knows for sure why droughts occur, but many scientists believe that there is an affiliation between drought occurrence and El Nino events. Thorough comprehension of the relationships between droughts and repeated changes in high and low pressures from one side of the Pacific to the other linked with La Nina allow scientists to formulate improved predictions of this calamitous drought hazard. (Ryu, Svoboda, Lenters, Tadesse, Knutson 2010). Both El Nino and La Nina form the El Nino-Southern Oscillation (ENSO) cycle. ENSO is a recurring climate pattern whereby temperature fluctuate between the ocean and atmosphere in the east-central Equatorial Pacific, approximately between the International Date Line and 120 degrees West (Olivares Campos, 2016). Nevertheless, these two events happen every 2-7 years with El Nino events occurring more often than those of La Nina (Tefera et al., 2019). There has been a rising trend in global weather disasters since 1980, and with extreme climatic events such as droughts. (Orlando Olivares & Zingaretti, 2018). Comprehending phenomena such as ENSO is pivotal because of the possibility that it could cause an enormous loss of property, destruction to the environment and the loss of human life. Conjectures by ENSO, tracing and monitoring is of a significant role to insurers, government authorities and other pertinent stakeholders for drought management for proactive planning against unfavourable impacts such as acute climatic changes like drought events. (Praveen et al., 2016)

Solar activity (Sunspots number)

Sunspots could also be another source associated with drought. Sunspots commonly last for a period of approximately 11 years. (Minckley, Roulston, & Williams, 2013). They are described as cool surface areas on the sun that are visible in pairs and are darker in comparison with other parts of the sun. These spots have a strong magnetic field and rotate like a giant hurricane. (Mèthy, Damesin, & Rambal, 1996). These authors also affirm that several authors have acknowledged that sunspots have impacts on temperature, precipitation, length of growing seasons, air circulation, atmospheric pressure, high altitude, wind speed and other natural phenomena around the world. Furthermore, Xiao & Zhuang (2007) construct solar activity as a main cause of cyclic deviations of the global climate through triggering of the evaporation processes. Scientists have also shown that sunspot numbers and drought events are correlated. For instance, during solar activity- drought events take place at solar maximum (Solheim, Stordahl, & Humlum, 2011). This occurrence is related to climatic conditions where temperatures become high during solar maximum (Minnis, 1958). Solar energy is the principal energy source as well as control on evaporation; therefore, distributions of insolation and evaporation are strongly linked. (Siingh et al., 2011). The energy from the sun is the central source of energy present for heating the surface of the planet earth. This energy supplied by the sun is an outcome of its activity and it differs with time. The major cycle of the sun is eleven years. The major cause of drought events is believed to be the solar activity (Ghormar, 2014). The coefficient of correlation between insolation and evaporation ranges between 0.820 and 0.948 and values of the calculated solar radiation are used in the computation of the Potential Evapotranspiration (PET) in Penman equation (Abarca del Rio, Gambis, Salstein, Nelson, & Dai, 2003). The solar radiation that falls on the earth's surface depends on the distance it travels to the object and the angle at which rays hit an area or object. (Mèthy et al., 1996). The universal law for the intensity of radiation, distinctively the sine law of sunlight states that the sunlight always strikes the high latitude obliquely, so it spreads out more and is less intense. (Minckley et al., 2013).

Drought Impacts

There are several impacts of drought and these include: mass starvation, famine and a pause or sometimes an end to economic activity particularly in areas where rain fed agriculture is the main stay of the rural economy (4, n.d.). It is generally known that drought is the chief cause of forced human migration and environmental refugees, deadly conflicts over the use of diminishing natural

resources, food insecurity and starvation, a damage to significant habitations and as well as loss of biological diversity; volatility of socio-economic conditions, poverty and unpredictable climatic conditions through reduced carbon sequestration possibility (Roman-Cuesta, 2007). Drought and desertification impacts are among the pricey incidents or occurrences in Africa, for instance, the prevalent destitution as well as the unstable economy of many African countries which in actuality depend on climate-sensitive segments such as rain-fed agriculture. All plants and animal life present in a particular region which are not resilient to drought are most likely to go into extinction. (Nagamuthu & Rajendram, 2015). The collective results of drought and bush burning (during dry seasons) have made the plants to go extinct and animals to drift into safer places. Drought, land degradation and desertification have had grave impacts on the richness and variety of fauna and flora (Francisco, 2013). Moreover, plants biodiversity will alter with time, unpleasant species will dominate, and total biomass production will dwindle (Khan & Gomes, 2019). Plants and animals are reliant on water, like people. Drought can minimize their food supplies and damage their habitats. Occasionally, this damage lasts for only a limited period of time, and other times it is irrevocable. Drought can also affect people's health and safety. For example, drought impacts on society include anxiety or depression about economic losses, conflicts due to water shortages, reduction of income, fewer recreational activities, and increase of heat stroke incidents and sometimes loss of human lives. Moreover, drought conditions can also grant a considerable increase in wildfire risk. This is due to withering of plants and trees from lack of precipitation, scourge insect infestations, and diseases, all of which are associated with drought. (Prokurat, 2015). Lengthy periods of drought can cause more wildfires and more powerful wildfires, which impinge on the economy, the environment as well as the society in a number of ways like destroying neighbourhoods, crops and habitats (Do Amaral, Cunha, Marchezini, Lindoso, Saito, & Dos Santos Alvala, 2019). Again, drought not only always offers similar instant and remarkable visuals related with occurrences such as hurricanes and tornadoes, but it still has a huge price tag. In point of fact, droughts are the second in rank types of phenomena that are associated with billion-dollar weather disasters for the past three decades (Nagamuthu & Rajendram, 2015). With staggering yearly losses close to \$9 billion annually, drought is a severe hazard with socioeconomic risks for most African countries. (Siingh et al., 2011). These pricey drought impacts come in different forms. For instance, the economic impacts of drought include farmers who lose money because drought destroyed their crops or worse ranchers who may have to spend more

money for animal feeds and irrigation of their crops. Economic impacts can either be direct or indirect. Directly, it could be a decrease in dairy production and indirectly, it could be observed through increases in the price of the cheese (Francisco, 2013).

Materials and methods

The monthly rainfall dataset of this study was obtained from National Aeronautics and Space Administration (NASA) data portal. This dataset was used as the only input parameter for Standardized Precipitation Index computation. Standardized Precipitation Index (SPI) is plainly described as a normalised index that signifies a likelihood of a rainfall occurrence of an observed rainfall amount in comparison with the rainfall climatology at a particular geographical location over a long-term reference period (Siingh et al., 2011). Furthermore, Yusof, Hui-Mean, Suhaila, Yusop, & Ching-Yee (2014) affirm that SPI is a probability index that offers an enhanced demonstration of both abnormal wetness and dryness than any Palmer indices such as Palmer Drought Severity Index (PDSI). The value of this index is that it can be computed for different time scales, for that reason, issuing early warning of drought and its severity (Gaas, 2018). This index is appropriate for risk management purposes (Verma, Verma, Yadu, & Murmu, 2016). Moreover, this index is advantageous in that precipitation is the only parameter in its computation therefore making it less complex. Conversely, the weakness of this index is that it can only compute the precipitation deficit; values founded on initial data may alter, and values vary as the period of record grows (Jordan, 2017). The table 1 below illustrates the values of SPI categorisation.

Table 1: SPI values

SPI Value	Category	Probability %
≥ 2.0	Extremely wet	2.3
1.5 to 1.99	Very wet	4.4
1 to 1.49	Moderately wet	9.2
-0.99 to 0.99	Near normal	34.1
-1.0 to -1.49	Moderately dry	9.2
-1.5 to -1.99	Severely dry	4.4
≤ -2.0	Extremely dry	2.3

Source : Hlalele, 2016

The SPI calculations are founded on the fact that precipitation increases over a fixed time scale of interest, for instance ; SPI-3, SPI-6, SPI-9, SPI-12, SPI-24 and SPI-48, so from that a series is integrated in a gamma probability distribution which is apt for this climatological precipitation time series. (Yusof et al., 2014). The gamma distribution is described by the following density function.

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad \text{for } x > 0 \quad (1)$$

Where α and β are estimated for each station as well as for each month of the year.

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right)$$

$$\beta = \frac{\bar{x}}{\alpha}$$

where $A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n}$, and n = number of observations (2)

After these parameters have been estimated then their resulting values are used to calculate cumulative probability as;

$$G(x) = \int_0^x g(x) dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx \quad (3)$$

In cases where $t=x/\beta$ then an incomplete gamma function becomes

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha-1} e^{-t} dt \quad (4)$$

Since gamma function is undefined at $x=0$ then the cumulative probability is calculated from the following equation (Rahmat, Jayasuriya, & Bhuiyan, 2012):

$$H(x) = q + (1 - q) G(x) \quad (5)$$

where q is the probability of a zero and $G(x)$ the cumulative probability of the incomplete gamma function. If m is the number of zeros in a precipitation time series, then q can be estimated by m/n . The cumulative probability is then transformed to the standard normal random variable z with mean zero and variance one, which is the value of the SPI (Yusof et al., 2014). In the event where it is standardized, the potency of the irregularity is categorised as illustrated in Table xx, where the table also demonstrates the corresponding probabilities.

Data quality control

Homogeneity tests are carried out to scrutinize statistical properties of a certain dataset in statistics. In essence, the tests thoroughly look at the location, stability and variations which are local within the time series over time (Abraham & Yatawara, 1998). The author also confirms that this occurrence is the same as testing statistical distribution, for that reason identifying if there are any changes in the distribution. The test is also carried out to evade false or unauthentic results from the data sets. (Hosseinzadeh Talaei, Kouchakzadeh, & Shifter Some'e, 2014). A non-parametric Pettitt's test was used. Outliers and missing were identified and substituted by Expectation Maximum algorithm (EIM) with the help of SPSS software. EM is described as a statistical algorithm appropriate to be used when there are missing or hidden values in the data sets (Lobato & Velasco, 2004). Tan & Yilmaz (2002) construct that EM is a well-liked tool used in statistical estimation problems that involve data which is incomplete. Likewise, Technology & Bay (2001) define EM as an algorithm that allows parameter estimation in probabilistic models with data which is not complete.

Before carrying out any data analysis, it is essential to assess the apparent proof of patterns and trends in the climate data (Kliewer & Mertins, 1997). Non-parametric Mann-Kendall test is used in the study to assess if any trends existed. This test is universally used to identify monotonic trends in series of environmental, climate and hydrological dataset. The null hypothesis (H_0) means that data came from a population with autonomous realisations is identically distributed. The alternative hypothesis (H_a), means that data follows a monotonic trend. The Mann-Kendall statistic indicates how strong and weak two variables are associated and show correlation direction (Kliewer & Mertins, 1997). One of the advantages of this statistic is that, the data does not necessarily have to follow any definite probability distribution. The test was conducted

simultaneously with a non-parametric Pettitt's test to gauge data homogeneity and descriptive statistics.

Parameters used to characterise drought

The temporal characteristics are those features of a hazard associated with time and they are commonly linked with questions such as the following: When does the hazard occur? What is the frequency of the occurrence? What is the duration of the hazard? How fast do they hit and how conventional are they? (Andreadis, 2005; Van Niekerk, 2011). Drought intensity is described in numerous ways by different academics; nevertheless, in accordance to Pope et al (2013) intensity is a degree of insufficient rainfall. The authors further explain that, intensity can be defined as a result of duration as well as intensity. Abdulmaleket *al.* (2013) affirms that drought intensity gauges how far rainfall is below the average precipitation of the region. Understanding intensity can be used as a way of ascertaining the feasible impact of a hazard on communities. Understanding intensity can be used as a way of ascertaining the feasible impact of a hazard on communities as well as the levels of risk at which elements are exposed to (Van Niekerk, 2011). This aspect of drought is conveyed in several parameters such as the Standard Total Accumulative Dry Spell (STCD), Average Dry Spell Index (ADSI), Longest Multi year Drought (LMYD) and Largest Single Year Drought (LSYD) (Abdulmaleket et al., 2013). STCD signify the total cumulative drought index used. One more parameter used to quantify the same aspect is ADSI. LMYD and LSYD are other parameters obtained from drought indices such as SPI whose high values have negative outcomes on every facet of the environment, including socio-economic situation of communities. ADSI values offer valuable knowledge on the region's characteristics essential for arrangement of water resources as well as irrigation projects. Areas with low values need special attention. Likewise, The ADSI values are of great significance to decision makers for the planning of agricultural projects of the affected areas for future. The LSYD also is significant to take into consideration in crop cultivation given that crops barely survive its high values. So, these four parameters are defined by the equations below:

$$\text{ADSI} = \text{STCD}/N \quad (6)$$

where N=total number of years of the series

$$\text{LMYD} = \text{Maximum of any successive years} \quad (7)$$

$$\text{LSYD} = \text{Maximum drought index value of the single year} \quad (8)$$

Drought Frequency and duration analysis

For a long-term planning to be effective in water projects such as irrigation and dam sizing purposes, there has to be an analysis of both dry and wet spells from a climatic and hydro-meteorological standpoint. (Abdulmaleket *al.*, 2013). In drought analysis a period declared as dry when $\text{SPI} < 0$. These are some of the parameters used to calculate the drought duration: Longest Dry Spell Duration (LDSD), Drought Tendency (DT) and Average Dry Spell Duration (ADSD). LDSD is described as the highest of any consecutive dry spells that occurred on one occasion through the study record N. High values of both LDSD and ADSD it means that water resources planning must be considered in that particular region. Nevertheless, DT is the ratio which involves the total number of dry spell cases to the wet spell cases. This parameter measures the predisposition of the study area which suffers from the dry spells, thus it measures the frequency of a hazard under consideration. These are defined by the following equations:

$$\text{LDSD} = \sum_i^N D_i, i = 1, 2, \dots, N \quad (9)$$

$$\text{DT} = \sum D / \sum W \quad (10)$$

$$\text{ADSD} = \sum D / N \quad (11)$$

If successive dry spell cases (D) are followed by a wet spell, like D, D, D, W, D then $\sum D = 4$, and $N = 2$ since an interrupted sequence of several cases of (D) constitute only one dry spell event. A frequency analysis offers an early warning system. Disaster managers and appropriate stakeholders have the ability to foresee when the next incident will take place. (Sobrino et al. 2011). Hydro-climatic hazards such as drought have a propensity of following a seasonal pattern. When the number of times and the length of a hazard such as drought are known, such knowledge helps in planning accordingly (Hlalele, 2016). In a frequency analysis, approximation of the probability of an incidence of future occurrences is established on a primary base for risk

management. (Yuliang *et al.* 2014). Again, it is used to foresee how frequently a hazard event happens over space and time (Des Jardins, 2012).

Results and discussion

Figure 2 shows a box and whisker plot of Bloemfontein’s precipitation from 1977 to 2017. These data were plot in order to determine outliers present in the dataset. Only one outlier was found as shown in the plot. This value was removed, and gap replaced by Expectation Maximum algorithm. This procedure was conducted as to quality control the data before any further analysis could be performed. Table 2 shows descriptive statistics of the precipitation. The area receives 530.451mm of precipitation on average per year with a minimum and maximum of 241.8 mm and 1103.850mm respectively. However, the coefficient of variation seems to be small in the study area.

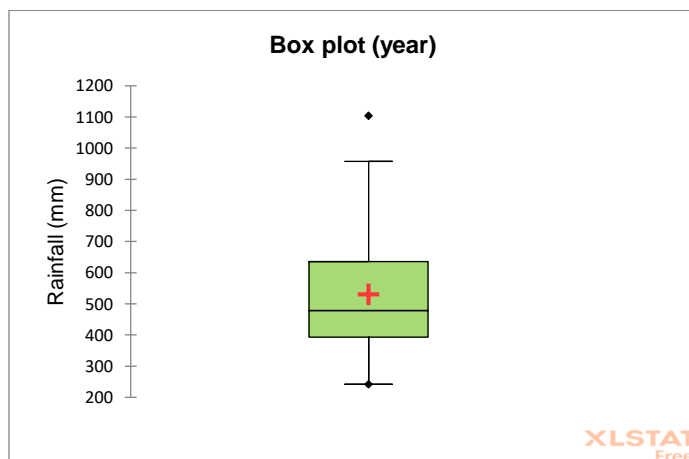


Figure 2: Box and whisker plot of Bloemfontein rainfall

Table 2: Descriptive statistics for Bloemfontein rainfall

Statistic	Rainfall
Nbr. Of observations	42
Minimum	241.800
Maximum	1103.850
Range	862.050
1 st Quartile	392.838
Median	478.990
3 rd Quartile	635.988
Mean	530.451
Variance (n)	33541.462
Standard deviation (n)	183.143
Variation coefficient (n)	0.345

After an exploration of the precipitation dataset, the annual precipitation time series was plotted against time in years where a non-parametric Mann Kendall's test was applied. The results of Mann Kendall's test where no statistically significant trend, a p-value=0.062 which above the selected significance level of 0.05. These results are shown in figure 3. Although a statistical trend test revealed that there was no trend, it can be seen that there is a gradual drop in precipitation with years as shown by the trend line in the figure. This behaviour is also depicted by the negative sign of the Sen's slope in the same figure.

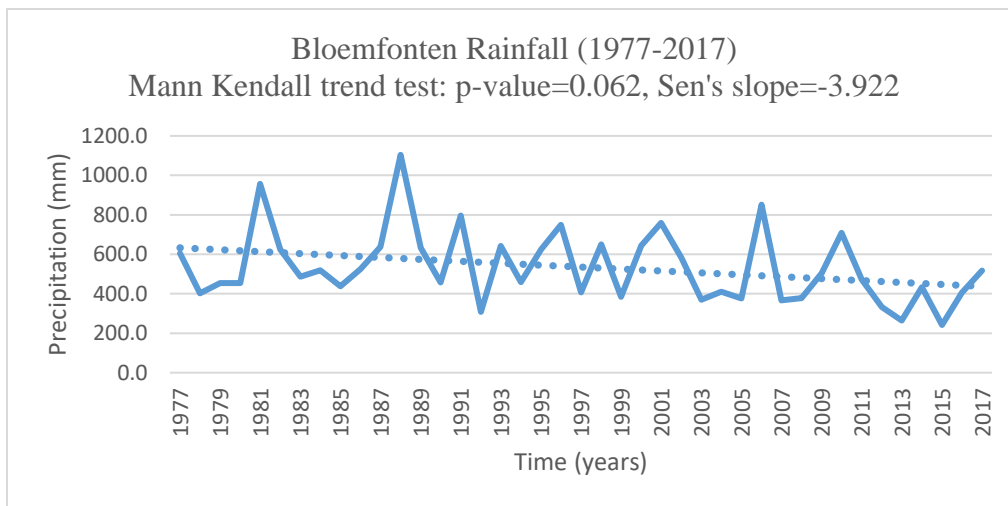


Figure 3: Bloemfontein rainfall from 1977-2018

In order to make better predictions and other analysis, the precipitation annual data was fitted to a suitable probability distribution. These data fitted well to a normal probability distribution using a Kolmogorov-Smirnov test criterion as shown in table 3. Figure 4 also shows both PP and QQ plots for the fitted normal distribution with a two tailed non-significant p-value of 0.442.

Table 3: Kolmogorov-Smirnov test

Parameter	Value
D	0.130
p-value (Two-tailed)	0.442
alpha	0.05

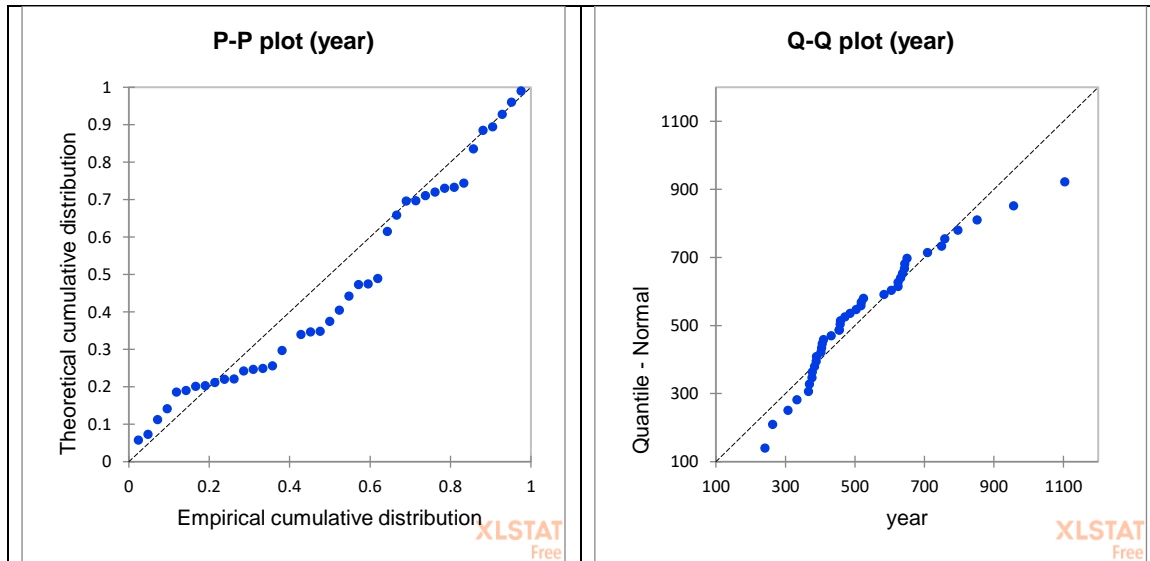


Figure 4: P-P and Q-Q plots

Drought is defined as a prolonged lack of rainfall below the average. From table 1, the mean annual precipitation was 530.451mm, using this definition from table 4 and normal probability distribution, all precipitation below and above the means were identified. Values above the means were identified as well as their probability using z-values from normal distribution tables to determine their corresponding probability. Using the simple probability rule that the sum of all marginal probabilities is 1, the probability corresponding values above the mean was subtracted from 1 to obtained probability of drought in the area. The probability of drought (precipitation below the mean) was 0.64 whose reciprocal gives the return period of moderate to extreme drought events in the study area. Table 4 shows moderate to extreme drought probability. The reciprocating 0.64 gave $1.56 \approx 2$ years for drought events to return.

Table 4: Descriptive statistics for the intervals

Lower bound	Upper bound	Frequency	Relative frequency	Density (Data)	Density (Distribution)
241.8	328.62	3	0.071	0.001	0.078
328.62	415.44	12	0.286	0.003	0.130
415.44	502.26	7	0.167	0.002	0.174
502.26	589.08	5	0.119	0.001	0.187
589.08	675.9	8	0.190	0.002	0.161
675.9	762.72	3	0.071	0.001	0.111
762.72	849.54	1	0.024	0.000	0.062
849.54	936.36	1	0.024	0.000	0.027
936.36	1023.18	1	0.024	0.000	0.010
1023.18	1110	1	0.024	0.000	0.003

Table 5: Probabilities from normal distribution

SPI category	Value	Z-value	Probability	P(mw<X<ew)
Moderately wet (mw)	589.08	0.32	0.1255	0.357
Extremely wet (ew)	1110	3.20	0.4995	
Moderate drought to extreme drought	589.08 to 241			0.64

In order to confirm the cyclicity or periodicity of the precipitation dataset of the study area, a simple spectral analysis was applied. The results of this spectral analysis as shown in figure 5, where the peak frequency was determined as 0.03125. Upon reciprocating this value and dividing it by 12 to get circles per year yielded 2.67 which not significantly different from one obtained from normal probability distribution.

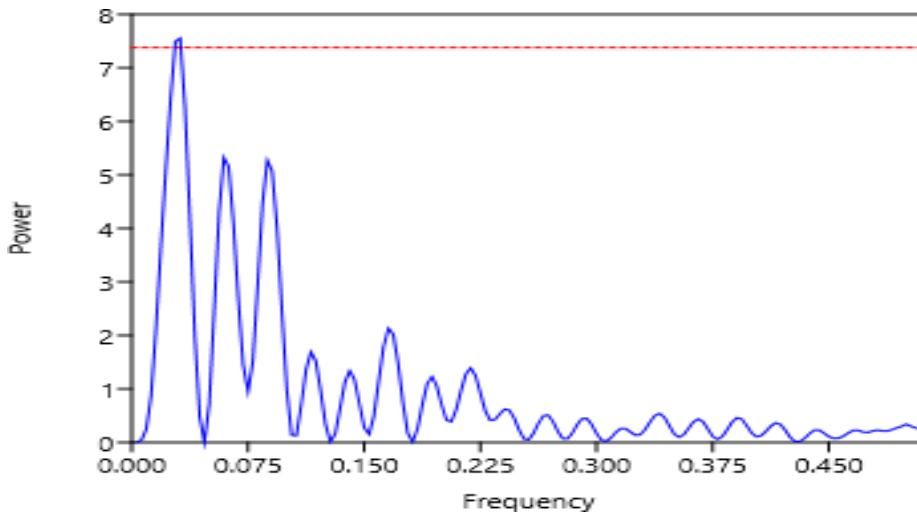


Figure 5: Lomb periodogram

Conclusion and recommendations

In conclusion, drought damages and endangers lives of human beings and other species. The current study aimed at analysing the drought potential risks in the study area for the protection of economy, environment and human lives. A 42-year long rainfall/precipitation data were collected from an online database. XLSTAT software was used in fitting annual data for a suitable probability distribution. The annual data fitted normal probability distribution with parameters, $\sigma=183.143$, $\mu=530.451$ using Kolmogorov-Smirnov test criterion. The spectral analysis showed that the study area is expected to experience drought events every 2 years. The government and other relevant stakeholder authorities are therefore cautioned to put measures in place for the

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