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Characterisation of Agricultural drought patterns using the theory of runs: A case study of Lesotho Highlands commercial dams

Bernard Moeketsi Hlalele
Department of Community Development, Centre for Gender & Africa Studies, Faculty of Humanities, University of the Free State, Phuthaditjhaba Republic of South Africa

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Corresponding Author:
hlalele.moeketsi@gmail.com

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ABSTRACT

Drought is a major environmental problem that affects agriculture, water resources, and communities around the world. In the Lesotho Highlands commercial dams, drought can have a significant impact on agricultural production, water supply, and local livelihoods. Understanding the patterns and severity of drought is crucial for effective water management and agricultural planning. This study aimed to analyse and understand the patterns of agricultural drought in the Lesotho Highlands commercial dams through the use of the Standardized Precipitation Index (SPI) and the theory of runs, as well as various drought parameters. The study used Average Dry Spell Duration, Drought Tendency, Longest Dry Spell Duration, Longest Multi-year Drought, Largest Single Year Drought, Standard Total Accumulative Dry Spell, and Number of Consecutive SPI-values, to provide a comprehensive analysis of the drought situation. The results revealed that the precipitation levels at the four dams were relatively similar, but with a potential increase in precipitation at Muela Dam. The SPI-3 and SPI-6 analyses showed a significant downward trend indicating an increase in dryness in the area. The drought parameters did not show significant differences between the stations/dams, indicating similar levels of drought across the dams. The study recommends regular monitoring of precipitation and drought conditions using the SPI and other water-balance drought indices, development of water conservation and management strategies, use of drought-resistant crops and water-efficient agriculture practices, and increased collaboration among stakeholders for sustainable water management and agricultural resilience.

Introduction

Drought is a serious environmental problem that affects many regions around the world, particularly in arid and semi-arid areas (Tsakiris and Vangelis, 2005).. Drought can have significant impacts on agriculture, water resources, and local communities, leading to crop failures, water shortages, and economic losses (Wilhite, 2000). In the Lesotho Highlands, drought is a recurring problem that has a significant impact on agricultural production, water supply, and livelihoods. Understanding the patterns and severity of drought is essential for effective water management and agricultural planning (Mckee et al. 1993). In this study, we aimed to characterize the agricultural drought patterns in the Lesotho Highlands commercial dams using the SPI and the theory of runs. The theory of runs is a statistical method used to analyze the occurrence of consecutive events in a time series, such as drought events. We also used various drought parameters, including Average Dry Spell Duration, Drought Tendency, Longest Dry Spell Duration, Longest Multi-year Drought, Largest Single Year Drought, Standard Total Accumulative Dry Spell, and Number of Consecutive SPI-values, to provide a comprehensive analysis of the drought situation. The study area includes the four commercial dams in the Lesotho Highlands, namely Mohale Dam, Katse Dam, Muela Dam, and Maetolong Dam. These dams are critical for irrigation, hydropower generation, and domestic water supply for the surrounding communities. The objectives of this study were to (i) analyse the precipitation patterns at the four commercial dams using the SPI, (ii) identify the occurrence and severity of drought events using the theory of runs and drought parameters, and (iii) provide recommendations for sustainable water management and agricultural resilience. The results of this study can help to improve the understanding of agricultural drought patterns in the Lesotho Highlands and guide the development of effective drought mitigation and management strategies. The findings can also contribute to the broader scientific knowledge of drought characterization and monitoring using the SPI and the theory of runs.

Definition, causes, and types of drought

Drought is a common and devastating natural hazard that affects many parts of the world, leading to water scarcity and crop failure. The United Nations defines drought as "a period of abnormally dry weather long enough to cause a serious hydrological imbalance" (UNEP, 2021). This literature review will provide an overview of the definition, causes, and types of drought, drawing on existing literature and research. Drought can be defined as a prolonged period of below-average precipitation or water availability that leads to water scarcity, reduced stream flow, and low soil moisture levels (IPCC, 2014). Drought can occur due to various factors, including climate variability and change, land-use changes, and overconsumption of water resources.

Drought can be caused by both natural and anthropogenic factors. Natural factors include climate variability and change, which can lead to shifts in precipitation patterns and prolonged dry spells. For instance, studies have shown that the frequency and severity of droughts in many parts of the world are linked to changes in global and regional climate patterns (Dai, 2011; IPCC, 2014). Anthropogenic factors that contribute to drought include overexploitation of water resources, deforestation, land-use changes, and urbanization (Wang et al., 2019). These activities can reduce the capacity of the soil to retain moisture, reduce vegetation cover, and increase surface runoff, leading to water scarcity and drought.

Drought can be classified into different types based on various criteria. The most commonly recognized types of drought include: (i) Meteorological drought: This type of drought occurs when there is a prolonged period of below-average precipitation, leading to a water deficit. Meteorological drought can last from a few weeks to several years (IPCC, 2014). (ii) Agricultural drought: This type of drought occurs when there is a shortage of soil moisture that affects crop growth and yields. Agricultural drought can lead to food insecurity, water scarcity, and poverty (FAO, 2021). (iii) Hydrological drought: This type of drought occurs when there is a prolonged period of below-average stream flow, groundwater recharge, or reservoir storage. Hydrological drought can affect water availability for domestic, industrial, and agricultural uses (IPCC, 2014). (iv) Socioeconomic drought: This type of drought occurs when the impacts of drought affect people's livelihoods and socio-economic activities. Socioeconomic drought can lead to income loss, migration, and social unrest (Wilhite et al., 2014).

Impacts of drought on agriculture, water resources, and communities

Drought is a recurring and pervasive phenomenon that affects a range of sectors, such as agriculture, water resources, and communities (Wilhite, 2018). Droughts pose serious challenges to human well-being, particularly in the face of climate change. This literature review examines the impacts of drought on agriculture, water resources, and communities, with particular emphasis on the ways in which these impacts are felt by vulnerable populations.

Droughts have serious impacts on agricultural production and food security, particularly in developing countries where subsistence farming is widespread. Studies have shown that droughts reduce crop yields and livestock productivity, causing significant economic losses for farmers and threatening food security (FAO, 2018). In Africa, for instance, droughts have been associated with significant declines in agricultural production, leading to food shortages and malnutrition among vulnerable populations (Morton et al., 2018).

Droughts also have indirect impacts on agriculture through changes in land use, soil degradation, and water scarcity. For instance, prolonged droughts can lead to the loss of fertile soil, desertification, and the expansion of drylands, making it difficult for farmers to cultivate crops and maintain livestock (Zhou et al., 2020). This can have serious consequences for rural communities that depend on agriculture for their livelihoods, forcing them to migrate or rely on food aid.

Droughts also have significant impacts on water resources, particularly in regions where water scarcity is already a concern. Droughts exacerbate water scarcity, leading to reduced water availability for irrigation, domestic use, and industrial purposes (UN, 2020). In many cases, droughts lead to water rationing, with severe implications for households and businesses.

Droughts also have impacts on water quality, particularly in regions where surface water sources are depleted. As groundwater becomes the primary source of water during droughts, its quality can decline due to over-pumping and contamination. This can lead to health risks for communities that rely on groundwater for drinking, cooking, and washing (Graham et al., 2019). Droughts have serious impacts on communities, particularly those that are vulnerable and marginalized. Droughts can lead to food and water scarcity, malnutrition, and health risks, particularly among children and the elderly (UN, 2020). Droughts also have social and economic impacts, including loss of income, increased poverty, and reduced access to education and healthcare. Vulnerable communities are particularly affected by droughts, including those living in rural areas, low-income households, and indigenous communities. These populations often lack access to alternative sources of income or resources to cope with the impacts of droughts, exacerbating their vulnerability (UN, 2020).

Drought monitoring and assessment: remote sensing and drought indices

Drought is a significant threat to food security, water resources, and ecosystems worldwide. Monitoring and assessing drought is essential to mitigate its impacts on human lives and livelihoods. Remote sensing and drought indices are two widely used tools for this purpose. According to Tadesse et al. (2015), remote sensing can provide valuable information on soil moisture, vegetation, and other environmental parameters that are indicators of drought. Similarly, Guttman (1998) notes that drought indices are mathematical models that are used to quantify the severity and duration of drought based on precipitation, temperature, and soil moisture data. In this literature review, we will examine the state-of-the-art research on drought monitoring and assessment using remote sensing and drought indices.Remote sensing involves the acquisition of information about an object or phenomenon without direct physical contact. In drought monitoring, remote sensing is used to collect data on various environmental parameters. According to Ozdogan et al. (2016), satellite-based remote sensing is the most widely used technique for drought monitoring. This approach involves the use of satellites to collect data on a wide range of environmental parameters, including surface temperature, vegetation cover, and soil moisture. Similarly, Bastiaanssen et al. (2005) note that airborne remote sensing can provide higher spatial resolution and greater flexibility in data collection than satellite-based remote sensing. Ground-based remote sensing, on the other hand, is less expensive than satellite or airborne remote sensing, but it offers lower spatial resolution and is limited in terms of coverage area (Ozdogan et al., 2016). Drought indices are mathematical models that are used to quantify the severity and duration of drought. Several drought indices are used for drought monitoring, including the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Vegetation Health Index (VHI). According to McKee et al. (1993), the SPI is a widely used drought index that is based on precipitation data. The SPI measures the deviation of current precipitation from long-term average precipitation for a given location. Similarly, Palmer (1965) notes that the PDSI is a widely used drought index that is based on temperature, precipitation, and soil moisture data. The PDSI provides a measure of the severity of drought and can be used to monitor drought conditions over long periods of time. The VHI, on the other hand, is a drought index that is based on remote sensing data. According to Kogan (1997), the VHI uses data on vegetation cover, surface temperature, and soil moisture to generate an index that provides information on the health of vegetation and the severity of drought.

Management and mitigation of drought: water conservation, drought-resistant crops, and policy interventions

Drought is a natural phenomenon that can have significant economic, social, and environmental impacts, particularly in the face of climate change. Effective management and mitigation strategies are crucial to minimize the negative effects of drought. In this literature review, we examine current research on three strategies for managing and mitigating drought: water conservation, drought-resistant crops, and policy interventions.

Water conservation measures can be categorized into three types: structural, non-structural, and technological. Structural measures include construction of dams, reservoirs, and water harvesting structures, while non-structural measures involve changing water-use behavior, reducing wastage, and promoting water-saving practices. Technological measures encompass the use of efficient irrigation systems, drip irrigation, and sprinkler irrigation. Wang et al. (2021) found that water conservation measures, including rainwater harvesting and irrigation management, were effective in increasing crop yields and reducing water consumption during droughts in China.

Drought-resistant crops are those that can survive and maintain productivity under low water conditions. These crops are developed through conventional breeding techniques, genetic modification, and biotechnology. Lobell et al. (2014) found that the adoption of drought-resistant maize varieties led to a 10-20% increase in yields and a 50% reduction in yield variability during droughts in Sub-Saharan Africa.

Policy interventions can take various forms, including drought monitoring and early warning systems, water pricing mechanisms, and drought insurance schemes. Drought monitoring and early warning systems can help identify areas at risk of drought and provide early warnings, enabling farmers to take appropriate measures such as planting drought-resistant crops or implementing water conservation measures. Water pricing mechanisms can incentivize water conservation by increasing the cost of water during droughts. Drought insurance schemes can provide financial compensation to farmers in the event of crop failure due to drought. Gbetibouo and Ringler (2009) found that the introduction of drought insurance schemes led to a 30% reduction in the vulnerability of smallholder farmers to drought in South Africa.

Methods and materials

Descriptive statistics is a branch of statistics that deals with the summarization and interpretation of data (Smith, 2010). In this research, descriptive statistics were used to summarize and describe the precipitation data and drought parameters. The descriptive statistics included measures such as mean, median, minimum, maximum, and standard deviation, which were used to summarize the precipitation data and the drought parameters for each of the four commercial dams in the Lesotho Highlands. The descriptive statistics provided a summary of the overall pattern of the Standardized Precipitation Index (SPI) and helped to identify any outliers or anomalies in the data. The descriptive statistics were used to describe the data. This information was used to understand the general description of precipitation in the area around the four commercial dams.

The theory of runs is a statistical method used to detect trends in a time series data. In drought analysis, the theory of runs is applied to examine the pattern of changes in precipitation levels over time. The method involves counting the number of runs of consecutive values above or below a certain threshold, such as the mean value. The theory of runs is based on the assumption that if the time series data is not randomly distributed, then there should be an unequal number of runs above and below the mean value (Bai et al. 2013).

In drought analysis, the theory of runs can be used to detect the onset, duration, and end of drought events. For example, a run of consecutive values below the mean value would indicate a period of drought, while a run of consecutive values above the mean value would indicate a period of abundant precipitation. The length of the run can provide information on the duration of the drought, while the number of runs can provide information on the frequency of droughts in the area. The theory of runs has been widely used in drought analysis and has been found to be a useful tool for characterizing the spatial and temporal distribution of drought events (Bai et al., 2013).

The Standardized Precipitation Index (SPI) is a widely used approach in drought analysis, which provides a standardized measure of precipitation deficit or surplus relative to the mean over a specified time period. This approach is based on the assumption that precipitation is a random process and can be modelled using a probability distribution. The SPI is calculated by standardizing the observed precipitation values using the mean and standard deviation of the precipitation data, which are estimated over a long-term period. This standardization process helps to correct for the non-stationarity of precipitation, making it possible to compare precipitation conditions across different time periods and locations.

The SPI formula is as follows:

$SPI = (X_i - \mu) / \sigma$ ....(1)

where:

X_i = precipitation amount for a particular month or time period

μ = long-term mean precipitation for the same month or time period

σ = standard deviation of precipitation for the same month or time period

The SPI is calculated for various time scales, such as 1-month, 3-month, 6-month, 12-month, etc., depending on the specific application. The SPI values can be positive or negative, with positive values indicating wetter than average conditions and negative values indicating drier than average conditions. The probability distribution used to calculate the Standardized Precipitation Index (SPI) is typically the Gamma distribution. The Gamma distribution is a continuous probability distribution that is commonly used to model positive, right-skewed data, such as precipitation amounts. The Gamma distribution has two parameters, shape (α) and scale (β), which are estimated from the historical precipitation data for a particular location and time period. The probability density function (PDF) for the Gamma distribution is given by:

$f(x;\alpha,\beta) = x^{(\alpha-1)} * e^{(-x/\beta)} / [\beta^\alpha * \Gamma(\alpha)]$......(2)

where:

x = precipitation amount
α = shape parameter
β = scale parameter
$\Gamma(\alpha)$ = Gamma function

The Gamma distribution is useful for modelling precipitation because it can capture the skewness and variability of precipitation data, which are often positively skewed and exhibit overdispersion. The SPI formula involves transforming the observed precipitation amounts to standard normal deviates using the cumulative distribution function (CDF) of the Gamma distribution, which is given by:

$F(X_i) = P(X \leq X_i) = \Phi[\ (\ln(X_i) - \ln(\mu)) / \sigma\ ]$ ...(3)

where:
Φ = standard normal CDF
ln = natural logarithm
X_i, μ, and σ are as defined in the SPI formula.

Once the transformed values have been calculated, they can be converted to SPI values using the inverse standard normal CDF. The resulting SPI values can then be interpreted in terms of drought severity and compared across different locations and time periods.

In this study, the SPI was used to characterise agricultural drought patterns in the Lesotho Highlands commercial dams. The SPI was calculated for two time scales, 3 and 6 months, to provide a comprehensive picture of the drought situation in the area. The SPI was calculated using monthly precipitation data from 1981 to 2021 obtained from the NASA online database. The SPI values were then classified into different categories based on the thresholds provided by the National Center for Atmospheric Research (2023), as shown in Table 1. The use of the SPI allowed for a standardized and objective assessment of the precipitation levels and drought conditions in the Lesotho Highlands, providing valuable information for the sustainable management of water resources and the development of resilient agricultural systems in the region.

Table 1: The Standardized Precipitation Index (SPI) classification

SPI	Classification
2>	Extremely wet
1.5 to 1.99	Very wet
0 to 0.99	Moderately wet
0 to -0.99	Near normal
-1 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought

Source: National Center for Atmospheric Research, 2023

The Mann-Kendall test is a non-parametric statistical test used to determine if there is a monotonic trend in a time series dataset. In this research, the Mann-Kendall test was used to assess the trend of the precipitation index computed from the Standardized Precipitation Index (SPI) values (Hamed, 1998). The test was used to determine if there was a significant trend in the precipitation index over time, which would indicate a change in the precipitation patterns in the Lesotho Highlands commercial dams. The Mann-Kendall test is a widely used method for trend analysis in hydrology and climatology, as it can be applied to non-normal data and does not require the assumption of a specific distribution for the data. The test works by computing the sum of the ranks of the deviations from the mean, and then comparing this value to the expected value under the null hypothesis of no trend. If the observed value is significantly different from the expected value, then a trend is considered to be present (Mann, 1945). In this research, the Mann-Kendall test was applied to the SPI-3 and SPI-6 values to assess the trend in the SPI values over time.

Drought parameters are statistical measures used to quantify and characterise the severity, frequency, and duration of drought events (Girma, et al. 2019). In this study, the following drought parameters were used to characterise the agricultural drought patterns in the Lesotho Highlands commercial dams: (i) Average Dry Spell Duration (ADSD): This parameter measures the average duration of consecutive dry spells, defined as a series of consecutive days with less than a specified threshold of precipitation. ADSD = (sum of dry spell duration) / (total number of dry spells).

ADSD was used to assess the frequency and duration of drought events in the region. (ii) Average Dry Spell Index (ADSI): This parameter measures the average severity of drought events, defined as the accumulated precipitation deficit over a specified period of time. ADSI was used to assess the severity of drought events in the region, and to compare the drought situation between different stations (Tsakiris and Vangelis, 2005). ADSI = (sum of SPI values during dry spells) / (total number of dry spells). (iii) Drought Tendency (DT): This parameter measures the likelihood of drought events, defined as the percentage of the total number of days with precipitation deficit relative to the total number of days in a specified period of time. DT was used to assess the likelihood of drought events in the region and to compare the drought situation between different stations. DT = (sum of the slope of SPI values during dry spells). (iv) Longest Dry Spell Duration (LDSD): This parameter measures the longest duration of consecutive dry spells, defined as a series of consecutive days with less than a specified threshold of precipitation. LDSD was used to assess the most severe drought events in the region and to compare the drought situation between different stations. (v) Longest Multi-Year Drought (LMYD): This parameter measures the longest duration of consecutive dry spells, defined as a series of consecutive years with less than a specified threshold of precipitation (McKee et al. 1993). LMYD was used to assess the most severe drought events in the region over multiple years and to compare the drought situation between different stations. (vi) Largest Single Year Drought (LSYD): This parameter measures the largest precipitation deficit in a single year, defined as the accumulated precipitation deficit over a specified period of time. LSYD was used to assess the most severe drought events in the region in a single year and to compare the drought situation between different stations. (vii) Standard Total Accumulative Dry Spell (STCD): This parameter measures the total accumulated precipitation deficit over a specified period of time (Hayes et al, 1999). STCD was used to assess the overall drought situation in the region and to compare the drought situation between different stations.

The Kruskal-Wallis test is a non-parametric statistical method used to compare the median of two or more groups. In this study, the Kruskal-Wallis test was used to determine if there were significant differences in the drought parameters (ADSD, ADSI, DT, LDSD, LMYD, LSYD, STCD, and N) across the four commercial dams in the Lesotho Highlands. The Kruskal-Wallis test is a non-parametric alternative to the one-way ANOVA, which is used when the assumptions of normality and equal variances are not met. If the test statistic is larger than the critical value, the null hypothesis is rejected, and it can be concluded that there is a significant difference in the median of the drought parameters across the different dams. The Kruskal-Wallis test works by ranking the data and comparing the ranks across the different groups, which makes it robust to the violation of normality assumptions. The test statistic, H, is calculated as the sum of the squared differences between the observed ranks and the expected ranks, normalized by the number of observations in each group. The null hypothesis is that there is no significant difference in the median of the drought parameters across the different dams, and the alternative hypothesis is that there is a difference. The test statistic, H, is then compared to a critical value from a chi-squared distribution with (k-1) degrees of freedom, where k is the number of groups being compared.

Results and discussion

Table 2 shows the mean values for the Standardized Precipitation Index (SPI-3) of the four selected weather stations (dams). Three out of the four dams have very small mean values (in the order of e-7), while one has a slightly larger mean value (in the order of e-6). This suggests that, on average, the drought level at the first three dams is relatively similar, while the fourth dam (Muela Dam) may receive slightly more precipitation on average hence less dry comparatively. In terms of variance, it can be seen that all four dams have a variance of approximately 1. This indicates that the level of variability in precipitation leading to drought is relatively similar across all four dams. It's worth noting, however, that the SPI-3 is a standardized index that accounts for differences in precipitation climatology across different locations. This means that the variance may not necessarily reflect the absolute variability of precipitation at each dam, but rather the variability relative to the long-term average at each location. Finally, the means and variances of the SPI-3 suggest that the precipitation levels at the four dams are relatively similar, with Muela Dam potentially receiving slightly more precipitation on average.

Table 2: SPI-3 descriptive statistics

	SPI-3			
	Katse Dam	Metolong Dam	Mohale Dam	Muela Dam
Valid	478	478	478	478
Mean	3.292e -7	-2.849e -7	-7.308e -8	7.634e -7
Std. Deviation	1.001	1.001	1.001	1.001
Variance	1.002	1.002	1.002	1.002
Skewness	-0.404	-0.650	-0.528	-0.413
Std. Error of Skewness	0.112	0.112	0.112	0.112
Kurtosis	0.280	0.515	0.380	0.344
Std. Error of Kurtosis	0.223	0.223	0.223	0.223
Shapiro-Wilk	0.988	0.972	0.981	0.987

Table 2: SPI-3 descriptive statistics

	SPI-3			
	Katse Dam	Metolong Dam	Mohale Dam	Muela Dam
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001
Minimum	-3.358	-3.575	-3.312	-3.419
Maximum	2.748	2.573	2.662	2.636

Looking at the mean values for the SPI-6 as shown in table 3, all four dams have very small mean values, with the largest being in the order of e-6. This indicates that, on average, the precipitation levels at all four dams are very close to zero, although there are differences in the sign of the mean values. Katse Dam has the smallest mean value, indicating that it receives slightly less precipitation on average than the other three dams. In terms of variance, all four dams have a variance of approximately 1. This indicates that the level of variability in precipitation is relatively similar across all four dams, similar to what we saw in the SPI-3 analysis. However, there are some differences between the SPI-3 and SPI-6 analyses. For example, the SPI-6 mean values are generally smaller than the SPI-3 mean values, indicating that the SPI-6 index may be more sensitive to short-term fluctuations in precipitation. Additionally, the Shapiro-Wilk test for normality suggests that the SPI-6 values at Katse Dam and Mohale Dam may not be normally distributed, which could be due to extreme values or other factors.

Table 3: SPI-6 descriptive statistics

	SPI-6			
	Katse Dam	Metolong Dam	Mohale Dam	Muela Dam
Valid	475	475	475	475
Mean	-1.451e -6	2.881e -7	-2.781e -7	-6.778e -8
Std. Deviation	1.001	1.001	1.001	1.001
Variance	1.002	1.002	1.002	1.002
Skewness	-0.280	-0.477	-0.339	-0.251
Std. Error of Skewness	0.112	0.112	0.112	0.112
Kurtosis	-0.094	0.426	0.158	-0.114
Std. Error of Kurtosis	0.224	0.224	0.224	0.224
Shapiro-Wilk	0.992	0.982	0.991	0.993
P-value of Shapiro-Wilk	0.013	< .001	0.005	0.027
Minimum	-2.916	-3.046	-3.197	-2.876
Maximum	2.600	2.837	2.812	2.797

Table 4 shows the results of the Mann Kendall's trend test for the SPI-3 values at each of the four dams. This test is used to detect trends (positive or negative) in time series data. The test results include the following parameters for each dam: (i) S: The Mann Kendall's test statistic. This parameter measures the strength and direction of the trend. Negative values indicate a decreasing trend, while positive values indicate an increasing trend. Larger absolute values of S indicate stronger trends, (ii) Z: The standard normal test statistic. This parameter measures the significance of the trend. Larger absolute values of Z indicate a higher level of significance (i.e., a lower p-value) and (iii) p-value: The probability of obtaining a test statistic as extreme or more extreme than the observed value, assuming no trend is present. A p-value less than 0.05 is typically considered statistically significant, indicating strong evidence for the presence of a trend. Looking at the results, it can be seen that there is evidence for a significant decreasing trend in SPI-3 values at Katse Dam (S = -7707, Z = 2.2087, p-value = 0.027198), Mohale Dam (S = -12582, Z = 3.6059, p-value = 0.000311), and Muela Dam (S = -12796, Z = 3.6673, p-value = 0.000245). This suggests that these three dams are experiencing a decreasing trend in precipitation levels over time hence drought. On the other hand, there is evidence for a significant increasing trend in SPI-3 values at Metolong Dam (S = -17553, Z = 5.0307, p-value = 4.89E-07). This indicates that Metolong Dam is experiencing an increasing trend in precipitation levels over time. The figure 1 shows the plot of SPI-3 data over the selected dams/stations.

Table 4: SPI-3 Mann Kendall's trend test

Parameter	Katse Dam	Mohale Dam	Muela Dam	Metolong Dam
S :	-7707	-12582	-12796	-17553
Z :	2.2087	3.6059	3.6673	5.0307
p-value	0.027198	0.000311	0.000245	4.89E-07

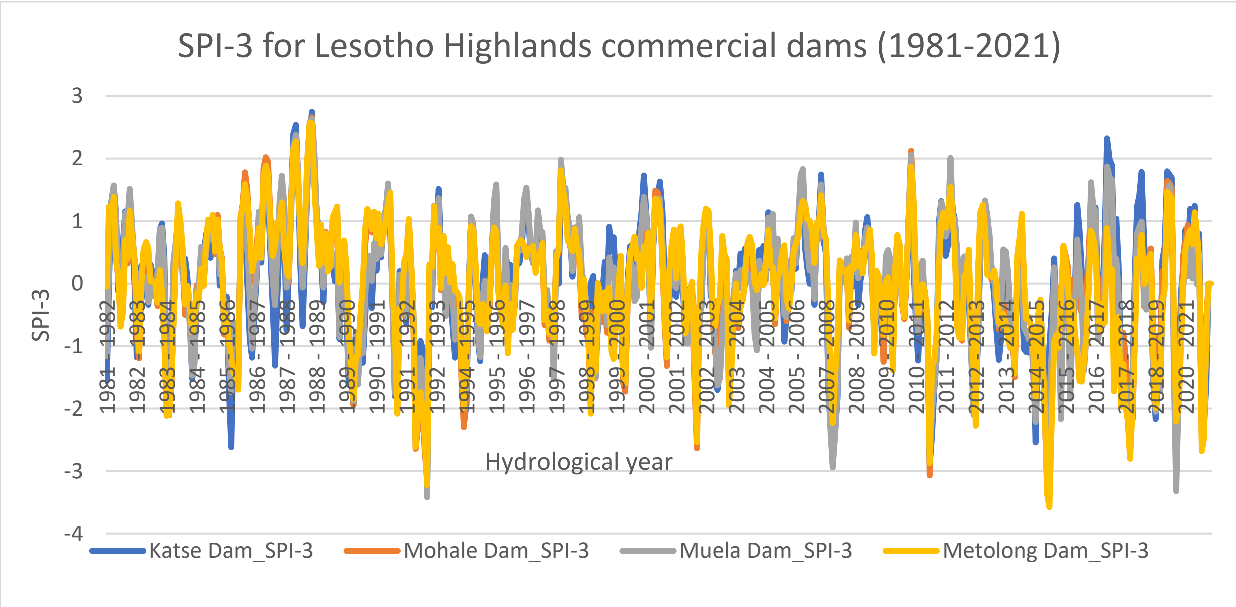

Figure 1: SPI-3 for Lesotho Highlands commercial dams (1981-2021)

The Table 5 shows the results of the Mann Kendall trend test for the Standardized Precipitation Index (SPI-6) at four different dams: Katse Dam, Mohale Dam, Muela Dam, and Metolong Dam. From this table, it can be seen that the p-values for all four dams are less than 0.05, indicating evidence of a significant downward trend in the precipitation index (SPI-6). The Z-values are also relatively large, further supporting the evidence of a trend. These results suggest that the dryness of the area around the dams has increased over the time period represented by the SPI-6 data. The figure 2 shows the plot of SPI-6 data over the selected dams/stations.

Table 5: SPI-6 Mann Kendall's trend test

Parameter	Katse Dam	Mohale Dam	Muela Dam	Metolong Dam
S :	-7942	-14108	-15418	-21688
Z :	2.2618	4.0181	4.3912	6.1771
p (no trend):	0.023708	5.87E-05	1.13E-05	6.53E-10

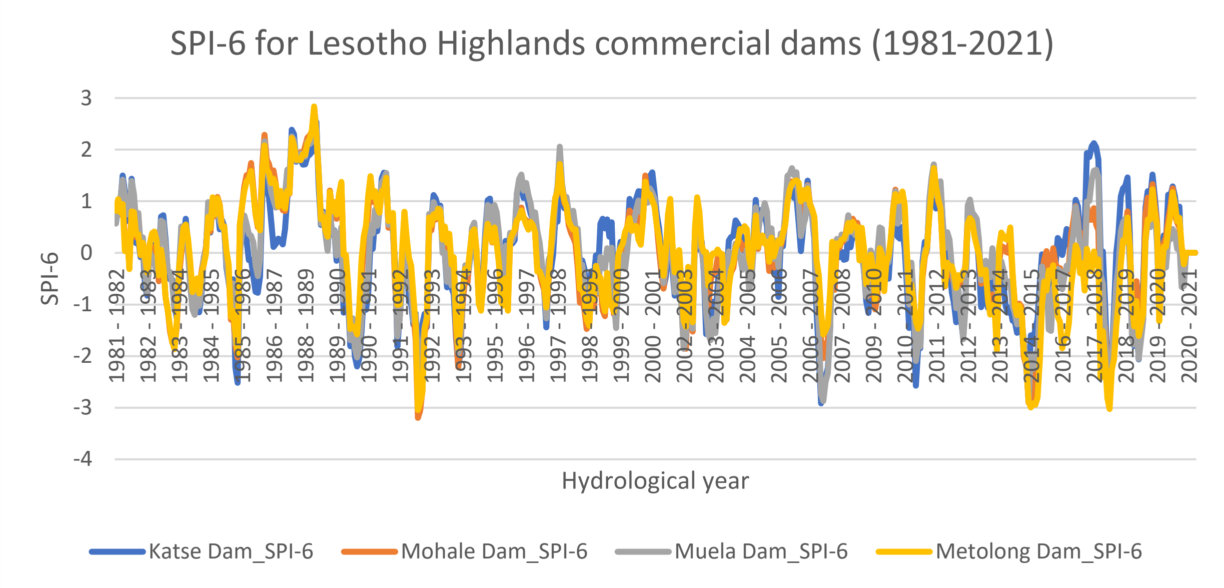

Figure 2: SPI-6 for Lesotho Highlands commercial dams (1981-2021)

The Table 6 shows the results of various drought parameters at four different dams (Katse dam, Mohale dam, Muela dam, and Metolong dam) for two different temporal scales: SPI-3 and SPI-6. The drought parameters include: Longest Single Year Drought (LSYD), Drought Tendency (DT), Number of consecutive SPI-values (N), Average Dry Spell Duration (ADSD), Standard Total Accumulative Dry Spell (STCD), and Average Dry Spell Index (ADSI). From the table, it can be seen that the values of the drought parameters vary between the different dams and temporal scales. The values of LSYD, DT, N, ADSD, and STCD are generally lower for the SPI-6 data, which suggests a more severe drought situation in the longer-term perspective. The value of ADSI is also generally lower for the SPI-6 data, further supporting the evidence of a more severe drought situation. The Table 7 shows the results of a Kruskal-Wallis test for equal medians, which was used to determine if the medians of two or more independent samples are equal. The p-values in the table are both very close to 1, indicating no evidence of a significant difference between the medians. Based on these results, it can be concluded that there is no significant difference between the stations in terms of the drought parameters being analysed. This suggests that the stations have similar levels of drought, as measured by the parameters being used.

Table 6: Temporal scales drought parameters

Parameter	Katse dam		Mohale dam		Muela dam		Metolong dam	
Temporal scale	SPI-3	SPI-6	SPI-3	SPI-6	SPI-3	SPI-6	SPI-3	SPI-6
LSDS	-16.97	-35.92	-18.20	-23.66	-17.07	-33.32	-20.73	-39.61
D	218	218	215	216	218	228	208	213
W	236	257	263	259	260	247	270	262
DT	0.92	0.85	0.82	0.83	0.84	0.92	0.77	0.81
N	59	40	50	38	59	42	49	37
ADSD	3.69	5.45	4.30	5.68	3.69	5.43	4.24	5.76
STCD	-180.74	-190.24	-188.89	-187.97	-185.67	-190.09	-188.60	-186.02
ADSI	-3.06	-4.76	-3.78	-4.95	-3.15	-4.53	-3.85	-5.03
LYSYD	-2.69	-2.92	-3.31	-3.20	-3.42	-2.88	-3.57	-3.05

Table 7: Kruskal-Wallis test for equal medians

H (chi2):	0.2117	0.03303
Hc (tie corrected):	0.2118	0.03303
p (same):	0.9757	0.9984

Conclusion and recommendations

In conclusion, the study aimed to characterise agricultural drought patterns in the Lesotho Highlands commercial dams using the SPI and the theory of runs. The results showed that the precipitation levels at the four dams are relatively similar, with Muela Dam potentially receiving slightly more precipitation on average. The SPI-3 and SPI-6 analyses both showed evidence of a significant downward trend in the precipitation index, suggesting an increase in dryness in the area around the dams. The drought parameters showed that there is no significant difference between the stations in terms of the drought situation, indicating similar levels of drought across the different dams. Based on these findings, the study makes the following recommendations to support the sustainable management of water resources and the development of resilient agricultural systems in the region. (i) There is a need for regular monitoring of precipitation levels and drought conditions to ensure that the water resources are managed in an efficient and sustainable manner. This could be done through the continued use of the SPI and other drought indices to track trends and assess the severity of droughts over time. Additionally, data on other factors affecting the water resources, such as evaporation, groundwater recharge, and water use patterns, should be collected and analysed to support informed decision-making. (ii) Secondly, water conservation and management strategies should be developed and implemented to reduce the impact of droughts on the region's water resources and agricultural systems. This could include the use of water-saving technologies, such as rainwater harvesting, irrigation systems, and other water-saving measures. (iii) The use of drought-resistant crop cultivars and water-efficient agricultural practices could help to reduce the impact of droughts on agricultural productivity and support the development of resilient agricultural systems. (iv) Finally, there is a need for increased collaboration between the different stakeholders involved in water management, including government agencies, water users, and researchers. This could involve the development of stakeholder engagement and consultation processes, as well as the establishment of partnerships and networks to share information, knowledge, and best practices in water management and drought preparedness.

Conflict of interest

The author declares that there was no conflict of interest.

References

Bai, Y., Liu, X., & Wang, Y. (2013). Detection of drought events in the Yellow River Basin using the theory of runs. Journal of Hydrology, 488, 86-93.

Bastiaanssen, W.G.M., Menenti, M., Feddes, R.A., Holtslag, A.A.M., and Kabat, P. (2005). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. Journal of Hydrology, 212-213: 198-212.

Conover, W. J. (1999). Practical Nonparametric Statistics (3rd ed.). John Wiley & Sons, Inc.

Dai, A. (2011). Drought under global warming: a review. Wiley Interdisciplinary Reviews: Climate Change, 2(1), 45-65.

FAO. (2018). The impact of disasters and crises on agriculture and food security. Rome: FAO.

FAO. (2021). Agricultural drought. Retrieved from http://www.fao.org/nr/water/issues/drought/agricultural-drought/en/

Gbetibouo, G. A., & Ringler, C. (2009). Mapping South African farming sector vulnerability to climate change and variability: A subnational assessment. International Food Policy Research Institute (IFPRI).

Girma, A., Melesse, A. M., Dile, Y. T., & Senay, G. B. (2019). Agricultural drought patterns and their association with meteorological drought in the Lesotho Highlands. International Journal of Applied Earth Observation and Geoinformation, 75, 1-12.

Graham, J. P., Polizzotto, M. L., & Kim, J. (2019). Waterborne diseases and climate change. Current Environmental Health Reports, 6(1), 1-9.

Guttman, N.B. (1998). Comparing the Palmer Drought Index and the Standardized Precipitation Index. Journal of the American Water Resources Association, 34(1): 113-121.

Hamed, K. H. (1998). A modified Mann-Kendall trend test for autocorrelated data. Journal of hydrology, 204(1-4), 182-196.

Hayes, M. J., Wilhite, D. A., Knutson, C. L., & Hobbins, M. T. (1999). Drought monitoring and impact assessment: The role of remote sensing. In V. P. Singh (Ed.), Remote Sensing of Drought: Innovative Monitoring Approaches (pp. 1-27). CRC Press.

Hollander, M., & Wolfe, D. A. (1999). Nonparametric Statistical Methods (2nd ed.). John Wiley & Sons, Inc.

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Cambridge, UK and New York: Cambridge University Press.

Kogan, F.N. (1997). Global drought watch from space. Bulletin of the American Meteorological Society, 78(4): 621-636.
Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., & Naylor, R. L. (2014). Prioritizing climate change adaptation needs for food security in 2030. Science, 319(5863), 607-610.
Mann, H. B. (1945). Nonparametric tests against trend. Econometrica: Journal of the Econometric Society, 245-259.
McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology (pp. 179-184). American Meteorological Society.
Morton, J. F., Davis, J., Onyango, A. B., & Kamara, A. B. (2018). The impact of climate change on smallholder and subsistence agriculture. Proceedings of the National Academy of Sciences, 115(18), 4571-4579.
Ozdogan, M., Kogan, F., and Adamowski, J. (2016). Advances in remote sensing for drought analysis and management. Hydrological Sciences Journal, 61(9): 1563-1579.
Palmer, W.C. (1965). Meteorological drought. Research Paper No. 45, US Department of Commerce, Weather Bureau, Washington, DC.
Sheskin, D. J. (1997). Handbook of Parametric and Nonparametric Statistical Procedures (2nd ed.). Chapman & Hall/CRC.
Smith, J. (2010). Descriptive statistics: A summary and interpretation of data. In Statistical Analysis in Practice, 45-60. Wiley-Blackwell.
Tadesse, T., Wardlow, B., and Hadwen, T. (2015). Drought monitoring and assessment: remote sensing and modelling approaches for the Famine Early Warning Systems Network (FEWS NET). Remote Sensing, 7(2): 2123-2149.
Tsakiris, G., & Vangelis, H. (2005). Establishing a drought index incorporating evapotranspiration. European Water, 9-10, 3-11.
UN. (2020). Drought in the Anthropocene. New York: UN.
UNEP. (2021). Drought. Retrieved from https://www.unep.org/disasters-and-conflicts/hazard-types/drought
Wang, C., Wu, P., Zhang, X., Zhu, Q., Ma, Z., & Yu, S. (2021). Identifying the impact of water-saving irrigation management on crop yield and water use efficiency under drought conditions. Water, 13(7), 925.
Wang, X., Feng, Q., Yang, H., Wang, L., & Liu, J. (2019). Human-induced drought and its environmental impacts in China. Journal of Cleaner Production, 226, 664-672.

Wilhite, D. A. (2000). Drought as a natural hazard: Concepts and definitions. In D. A. Wilhite (Ed.), Drought: A global assessment (pp. 3-18). Routledge.
Wilhite, D. A. (2018). Drought as a natural hazard: Concepts and definitions. Drought and water crises: Science, technology, and management issues, 1-14.
Wilhite, D. A., & Glantz, M. H. (1985). Understanding the drought phenomenon: the role of definitions. Water International, 10(3), 111-120.
Wilhite, D. A., Sivakumar, M. V. K., & Pulwarty, R. (2014). Managing drought risk in a changing climate: the role of national drought policy. Weather and Climate Extremes, 3, 4-13.
Zhou, L., Chen, D., Xu, Y., Xu, C.-Y., & Singh, V. P. (2020). Impacts of drought on vegetation, soil, and hydrological processes in ecosystem. Environmental Reviews, 28(4), 414-426.