

https://dspace.org/

Agroecological based modeling of meteorological drought at 12month time scale in teh Western cape Province of South Africa

Mthulisi Ngwenya; Eskinder Sintayehu; Danny Simatele

SPRINGER HEIDELBERG
https://hdl.handle.net/10539/41475
WOS

Downloaded from a DSpace repository. https://dspace.org/

Earth Science Informatics (2024) 17:1851–1865
https://doi.org/10.1007/s12145-023-01193-3

RESEARCH

Agroecological-based modeling of meteorological drought at 12-month time scale in the Western Cape Province of South Africa

Mthulisi Ngwenya[1] · **Eskinder Gidey**[1,2] · **Mulala Danny Simatele**[1]

Received: 10 August 2023 / Accepted: 8 December 2023 / Published online: 4 January 2024
© The Author(s) 2024

Abstract

To mitigate the effects of drought in water-stressed agro-ecological zones (AEZs), it is crucial to implement efficient monitoring of drought characteristics and establish proactive water-use strategies. The Western Cape (WC) province is being confronted with an escalating threat of diminished water availability due to unsustainable human activities. The objective of this study was to assess the spatio-temporal characteristics of meteorological drought within a 12-month timescale in the WC province of South Africa spanning from 1980 to 2020. The University of East Anglia's Climate Research Unit provided precipitation datasets from fifteen stations across the six AEZs of the WC province. These datasets were processed using the Standardized Precipitation Index (SPI). The Mann–Kendall (M–K) test was used to analyze the precipitation trend and SPI values at a significance level of $p < 0.05$. The results indicated substantial negative trends in annual precipitation across all AEZs. An examination of seasonal precipitation patterns revealed a rise in summer precipitation in subtropical cool-arid regions and subtropical warm semi-arid regions, with increases of 0.4 and 0.2 mm/year, respectively. Conversely, the overall annual precipitation trend fell by -1.0 mm/year in both AEZs. The SPI values consistently fell within the range of -2 to 0 in the subtropical warm-arid, subtropical cool-arid, and subtropical cool-arid zones. Conversely, the SPI values were consistently positive in the subtropical warm-arid, subtropical cool-humid, and subtropical warm-humid zones. This finding suggests that there will be persistent drought conditions that will affect agricultural production, surface flows in rivers, and groundwater levels across the WC province.

Keywords Meteorological Drought · SPI-12 months' time scale · Trend Analysis · AEZs · Western Cape Province · South Africa

Introduction

Human practices that are not sustainable and the detrimental impacts of climate change are believed to be contributing to increasing frequency of droughts and substantial alterations in natural water flow mechanisms (Bayissa et al. 2017). According to Okal et al. (2020), recurrent droughts have a greater impact on the global community compared to other natural hazards. As a result, they are considered the most expensive and complex challenge of the twenty-first century. Additionally, it is hypothesized that increased occurrences of droughts may lead to several issues, such as a disruption in the water budget model (Chen et al. 2013), alterations in evapotranspiration processes (Buttafuoco et al. 2018), and reduced water availability in the soil (Zhang & Li 2020). These issues will result in a scarcity of water and food. Chandrasekara et al. (2021) contended that an increase in the incidence of meteorological droughts will result in substantial difficulties in food production, especially in rainfed agro-ecological zones. This poses a substantial risk to the global community's endeavours to eradicate poverty and address climate change by 2030 (Masih et al. 2014). While scholars like Kam et al. (2021) have confirmed that more frequent droughts will greatly change the availability of

Communicated by: H. Babaie

✉ Mthulisi Ngwenya
2463724@students.wits.ac.za

[1] School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, Johannesburg, South Africa

[2] Department of Land Resources Management and Environmental Protection, College of Dryland Agriculture and Natural Resources, Mekelle University, P.O. Box 231, Mekelle, Tigray, Ethiopia

key aspects in sustainable agriculture, such as surface and groundwater, there is still limited consensus on the specific statistics regarding the effects of recurring droughts on a global, regional, and local scale.

The sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC) has confirmed that climate change-induced droughts, occurring at current levels of global warming, have led to an increase in food insecurity and human mortality rates. These threats have escalated from low levels in the fifth assessment to moderate levels in the sixth assessment (Ziervogel et al., 2014). According to Mohleji and Pielke (2014), the ongoing drought has caused the death of over one million people and resulted in economic losses over sixty billion US dollars since 1974. Gidey et al. (2018) asserted that the population dwelling in regions experiencing high water stress, due to repeated droughts, is expected to rise considerably from 300 million to over 5 billion by 2025. In 2020, a report from the European Commission indicated that developed countries in the European Union and the United Kingdom experienced substantial annual economic losses of approximately €9 billion due to recurring droughts. Spain incurred the highest losses, amounting to €1.5 billion per year. In March 2021, substantial dust storms occurred in the northern parts of China, which were strongly linked to prolonged drought conditions caused by the long-term effects of global warming that the country has been experiencing in the past few decades (Li et al. 2021).

Similarly, research conducted in regions of the world located below the equator reveals that more than 500,000 individuals in sub-Saharan Africa are presently vulnerable to the gradual consequences of repeated drought. The resulting financial damages are estimated to exceed $30 billion USD (Okal et al. 2020). Ayugi et al. (2022) argued that any changes in the timing and distribution of rainfall in sub-Saharan Africa, caused by human-induced global warming, will lead to food insecurity in the affected region. Liverman (2008) contended that the reason for this is the high susceptibility of agriculture in sub-Saharan Africa to climate change. According to Downing et al. (1997), the majority of countries in Sub-Saharan Africa do not possess the necessary abilities and resilience to mitigate the effects of repeated droughts. Raji et al. (2021) argued that a rise in the occurrence of drought events caused by climate change will have an impact on ecosystem services (ES), leading to water scarcity and food insecurity. Nhamo et al. (2019) asserted that the food security situation in southern Africa heavily relies on rainfed agriculture in South Africa. Fitchett et al. (2016) and Habiyaremye (2020) contended that the consequences of drought will be notably conspicuous and calamitous in developing nations located in the southern regions of the globe, such as South Africa. Recurrent drought episodes in South Africa will have a substantial impact on agricultural production and worsen food poverty in the region (Baudoin et al., 2017).

According to Botai et al. (2017), South Africa is highly susceptible to long-lasting droughts and is expected to experience a shortage of water by 2025. Savenije (2000) argued that southern Africa, namely South Africa, will experience a decline in water availability from 1700 m3 per person to below 1000 m^3 per person. This statement implies that if there is a slight increase in the frequency of extreme drought events, South Africa's water security and food security will be substantially affected. This is because South Africa has a mean annual precipitation of 500 mm/year, which is considerably lower than the global average of 860 mm/year (Otieno & Ochieng, 2007). Ziervogel et al. (2014) take a geographically projected perspective and caution that in South Africa, the Eastern Cape and other inland areas encounter more severe flood episodes, while the western sections of the country are more susceptible to recurring drought occurrences. Ziervogel et al. (2014) proposed that this could be attributed to an increase in the occurrence of drought episodes. The Department of Water and Sanitation, previously called the Department of Water Affairs and Forestry in 2004, officially identified the Western Cape as one of the arid regions in South Africa, experiencing inconsistent levels of rainfall. Some regions in the Western Cape see an annual precipitation of less than 350 mm, substantially lower than the national average of 500 mm per year (Kam et al., 2021).

Sebastian (2015) stated that the Western Cape (WC) contains six agroecological zones (AEZs) in South Africa. These zones are the subtropical warm/arid (STWA), subtropical cool arid (STCA), subtropical warm semi-arid (STWSA), subtropical cool/semi-arid (STCSA), subtropical warm subhumid (STWSH), and subtropical cool subhumid (STCSH). The Western Cape (WC) region, with its predominantly agricultural economy focused on exporting fruits and reliance on a water supply system built on catchment areas, exemplifies a region highly vulnerable to the devastating effects of recurring droughts (Jonghun et al., 2021). The Western Cape's reputation as a province prone to drought is supported by the recent 2015–2017 period of severe drought, as shown by Ndebele et al. (2020). Throughout this time frame, the WC province had severe inter-annual drought conditions, resulting in a water supply crisis that posed a threat to cease water supplies to around four million persons (Vogt et al., 2018). Throughout the drought period, the water supply decreased substantially to only 20% capacity in January 2018 (Lange et al., 2020). Additionally, in 2019, there were more dry conditions, which led to a substantial 25% decrease in crop yield (Raude et al., 2018). Baudoin et al. (2017) emphasized that the severe drought experienced from 2015 to 2017 had a substantial negative effect on the agricultural sector, leading to a substantial decrease in employment

opportunities. Additionally, communities dependent on aquatic ecosystem services, such as ecotourism and fisheries, suffered the loss of sustainable livelihoods. Furthermore, the drought resulted in an increase in food prices.

The increasing occurrence of recurring droughts at the global, regional, and national levels presents a substantial risk to the fair, effective, and long-lasting distribution of water resources. It has the potential to cause a substantial decrease in water levels and the consequent desiccation of water bodies (Raphael Muli Wambua et al., 2018). This has the potential to create severe obstacles for agricultural productivity and greatly impact the use and distribution of water for home consumption. According to Bayissa et al. (2017), it is essential to monitor and simulate the historical characteristics of drought in order to assess the impact of risks, make forecasts, and predict future drought events. According to Ongoma et al. (2018), examining the spatial and temporal characteristics of previous droughts might assist individuals in making informed choices and perhaps bring about substantial alterations in how farmers manage and distribute water. This can also assist individuals in formulating proactive planning plans for an impending future characterized by climate change. Nevertheless, accurately assessing drought attributes in AEZs necessitates a methodology that utilizes dependable and easily accessible data to ascertain the occurrence of drought (Okal et al. 2020).

Araújo et al. (2009) observed that scientific research in recent decades has facilitated the development and implementation of unique multidisciplinary methods for evaluating the dynamic and evolutionary aspects of drought occurrences. Thus far, these novel techniques have facilitated the categorization of droughts into four primary classifications: meteorological, agricultural, hydrological, and socio-economic. One approach is to utilize historical climatic time series data to construct drought monitoring indices that illustrate the occurrence and progression of droughts (Ayugi et al., 2022). The drought monitoring indices utilize historical climatic data at intervals of 1, 3, 6, 12, 18, and 24 months to determine the time it takes for drought to manifest in social, economic, and environmental domains (Nhamo et al., 2019). Tozier de la Poterie et al. (2018) asserted that they examined the occurrence of agricultural drought by measuring the availability of soil moisture in the vadose zone across short to medium-term periods (1-, 3-, 6-month). Alternatively, a categorization of drought based on a 12- and 18-month duration is better suited for assessing the availability of surface and subterranean water over an extended period of time. Das et al. (2019) suggested incorporating long-term timescales, like the 12-month timeline, into the historical modeling of meteorological and hydrological droughts. Conversely, Citaristi (2022) stated that socioeconomic droughts occur when the demand for an economic resource exceeds its availability due to a deficiency caused by climatic conditions. In this study, it was deemed more suitable to focus on meteorological droughts, which are the most prevalent and are defined by a departure from the usual rainfall patterns, resulting in below-average precipitation levels for certain time periods (Gidey et al., 2018).

There are several drought indices used worldwide, each utilizing specific datasets to accurately capture the spatial and temporal characteristics of droughts (Nhamo et al., 2019). Commonly used indices for evaluating meteorological droughts include the Palmer Drought Severity Index (Sheffield et al. 2012), the Surface Water Supply Index (Mishra & Singh 2010), the Standardized Precipitation Index (McKee et al., 1993), the Rainfall Anomaly Index (Raziei, 2021), and the Standardized Precipitation Evapotranspiration Index (Memon & Shah 2019). Kchouk et al. (2022) proposed that the monitoring indices vary depending on the area because of the ever-changing and developing nature of drought conditions. The Palmer Drought Severity Index is commonly used in North American countries, but the Reconnaissance Drought Index is more suited for Australia (Jiao et al. 2019). Although there are various indices available, Su et al. (2017) suggested that using a single drought monitoring index would suffice in evaluating the multiple aspects of droughts. Nam et al. (2017) emphasized that the World Meteorological Organization suggested in 2009 that the Standardized Precipitation Index should be universally employed to characterize and analyze meteorological drought conditions in any catchment.

Contemporary literature by scholars like Kao & Govindaraju (2010), Botai et al. (2016), Gidey et al. (2018), Das et al. (2019), and Zhang & Li (2020) has shown that recurring drought consequences are constantly changing, widespread, and among the most expensive natural disasters. However, natural dangers continue to be the most intricate and unpredictable phenomena. Alam et al. (2023), Gidey et al. (2018), and Das et al. (2019) employed several methodological frameworks to investigate the spatial and temporal attributes of repeating drought episodes. Simultaneously, Orimoloye et al. (2019) and Ayugi et al. (2022) emphasized the influence of external factors, such as a shifting climate, insufficient drought monitoring systems, and conflicting water demands from different users, which complicate the comprehension of recurring drought occurrences. The conflicting demands for water may lead to lethal clashes. The convergence of several problems and the increasing occurrence of repeated droughts pose numerous difficulties in agro-ecological zones (AEZs) that water managers and farmers must confront to understand meteorological droughts and devise proactive, adaptable management approaches.

The sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC) has highlighted substantial evidence of the detrimental impact of severe drought occurrences on both human and ecological systems. In their study, Reason and Rouault (2005) examined the severity and

geographical scope of droughts in South Africa. They determined that there has been a notable increase in the extent of areas impacted by drought during the 1970s due to the heightened influence of the El Nino Southern Oscillation. Otto et al. (2018) examined the human factors that led to the 2015–2017 drought in the Western Cape. They found that activities like deforestation and intensified agriculture were worsening the effects of droughts caused by human-induced climate change. The study emphasized the need for scientific research on strategies to enhance the ability of the Western Cape community to adapt to these challenges. Johnston (2018) conducted an evaluation of the influence of a recurring drought on agricultural productivity on Western Cape farms. The study determined that the drought was severely reducing farmers' output. He suggested implementing a system of responsible water distribution and usage to address the conflicting demands of water consumers. Botai et al. (2017) utilized the Standardized Precipitation Index (SPI) with historical data from weather stations to evaluate the geographical and temporal features of drought in different water management regions of South Africa. Their research revealed that droughts in the Western Cape had a detrimental impact on water availability. The water storage levels in dams had dropped to less than 30% capacity, suggesting that the socio-economic difficulties faced by the Western Cape community would persist even after the drought had ceased. Baudoin et al. (2017) conducted socio-economic assessment studies to comprehend the experiences and findings from the recent drought season of 2015–2017. Their research revealed that human-induced climate change resulted in a threefold increase in the occurrence of droughts. The studies conducted by Otto et al. (2018), Johnston (2018), Baudoin et al. (2017), and Botai et al. (2016) suggest that the severe and destructive effects of human-caused climate change, such as the frequent drought in the Western Cape, have prompted additional research aimed at comprehending and elucidating the connection between the drought's spatial and temporal features and the availability of water in agro-ecological zones.

Similarly, it is apparent from prior research, that there has been a lack of focus on evaluating drought features using agroecological zone clustering. As such this study utilized the Standardized Precipitation Index, calculated over a 12-month period, to examine the spatial and temporal characteristics of drought in the agro-ecological zones of the Western Cape Province. Historical precipitation data from 15 selected stations across the province were used for analysis. The study employed remotely sensed climate data in the STWA, STWSA, STWSH, STCA, STCSA, and STCSH zones to understand the relationship of droughts with a decrease in agricultural productivity. The study aimed to achieve three specific objectives: i) Evaluate the patterns of recorded precipitation from 1981 to 2020. ii) Use the University of East Anglia's Climate Research Unit (CRU) dataset to analyse the spatial and temporal features of meteorological drought. iii) Examine the variations in severity, intensity, and frequency of meteorological drought across different AEZs in the Western Cape province.

Materials and methods

Study area

The present study specifically examined the Western Cape province, which is situated between latitudes 30° 00′ 00" S and 35° 00′ 00" S, and between longitudes 17° 50′ 00" E and 24° 45′ 00" E (Orimoloye et al., 2019) (Fig. 1). There are six AEZs, namely STWA, STCA, STWSA, STCSA, STWSH, and STCSH (Sebastian 2015). The AEZs are categorized into several zones based on the duration of the agricultural season (Mugido & Shackleton, 2017). Arid zones have a farming season that lasts fewer than 60 days, while semi-arid zones have a farming season that ranges from 60 to 119 days. Warm sub-humid zones have a farming season that lasts from 120 to 179 days, and cool sub-humid zones have a farming season that lasts from 270 to 329 days (Muimba-Kankolongo, 2018). The province has a landmass area of 129.449 km^2, making it the fourth largest in South Africa (Otto et al., 2018). Conrad et al. (2004) reported that this accounts for 10.6% of South Africa's entire geographical area. The Western Cape (WC) has an approximate population of 7 million inhabitants, with agriculture serving as the primary foundation of its economy (Orimoloye et al., 2019). The province experiences a temperate Mediterranean climate characterized by moderately wet winters and warm, mild, and dry summers (Conrad et al. 2004). The summer season spans from December, January, and February (DJF), while the fall season encompasses March, April, and May (MAM). According to Archer et al. (2017), winter occurs throughout the months of June, July, and August, while spring takes place in September, October, and November (SON). The majority of the Western Cape experiences precipitation throughout the winter season. The average yearly rainfall fluctuates among regions due to unique microclimates caused by topography. The research region has a maximum elevation of 2247 m above mean sea level and the lowest elevation of 18 m above mean sea level.

Data acquisition

Table 1 shows the chosen meteorological stations utilized for obtaining the daily precipitation data throughout the study period from 1980 to 2020. The selection of stations was based on the consistent availability of precipitation time series datasets. Moreover, the stations were chosen based on

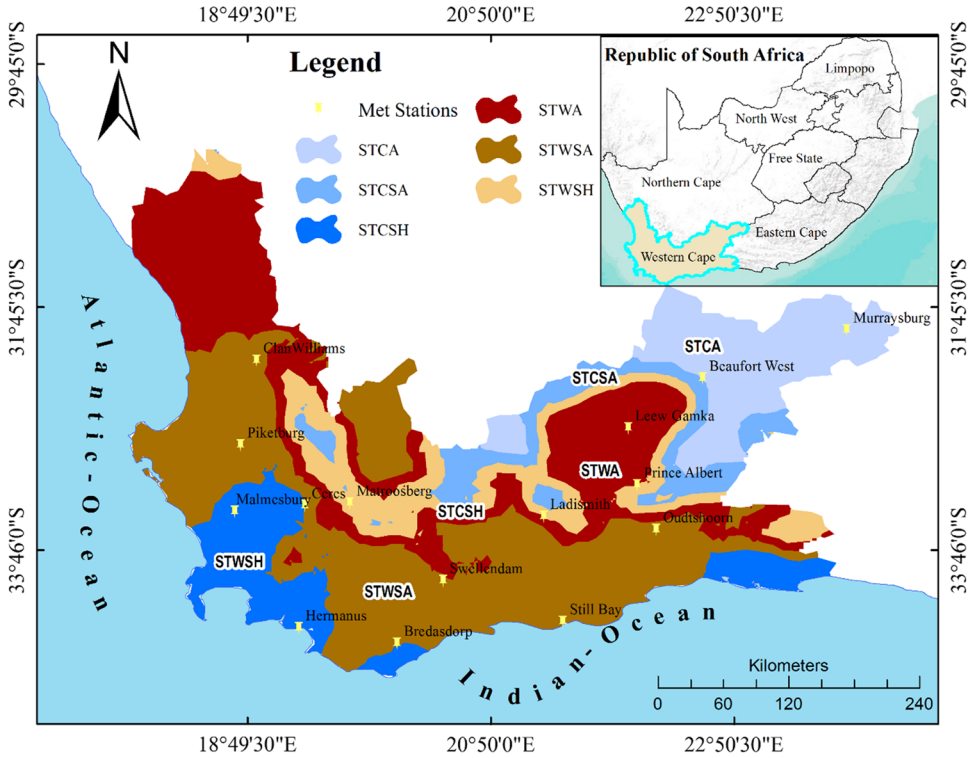


Fig. 1 Map of the study area

Table 1 Meteorological stations within the study area

Station	Location		Temperature		Altitude (m)	AEZs
	Longitude (E)	Latitude (N)	Minimum Temperature (^{0}C)	Maximum Temperature (^{0}C)		
Murraysburg	23.8	-32.0	2.0	29	1185	STCA
Beaufort West	22.6	-32.4	3.0	30	849	STCSA
Malmesbury	18.7	-33.5	6.0	32	203	STCSH
Hermanus	19.3	-34.4	8.0	28	27	
Ceres	19.3	-33.4	6.0	31	457	
Bredasdorp	20.1	-34.5	7.0	25	84	
Leew Gamka	21.9	-32.8	3.0	32	555	STWA
Ladismith	21.3	-33.5	5.0	31	544	
Clan-William	18.9	-32.2	8.0	33	96	STWSA
Piketberg	18.8	-32.9	6.0	32	203	
Swellendam	20.4	-34.0	7.0	29	128	
Still Bay	21.4	-34.4	7.0	26	36	
Oudtshoorn	22.2	-33.6	6.0	28	319	
Matroosberg	19.7	-33.4	4.0	29	2249	STWSH
Prince Albert	22.0	-33.2	4.0	29	633	

their possession of less than 5% of the incomplete precipitation dataset, as well as their distribution throughout the study area. The missing values were imputed using the multiple imputation technique. The University of East Anglia's Climate Research Unit gridded time series (CRU TS Version 4.07) http://www.cru.uea.ac.uk/cru/data/hrg/ database was used to collect historical daily precipitation data from fifteen stations located across all the AEZs of the Western Cape province. The data spans from January 1, 1981, to December 31, 2020. The collection process involved utilizing the Google Earth engine interface. The CRU TS Version 4.07 datasets have a resolution of 0.5° by 0.5° and can

be accessed in all regions except Antarctica (Harris et al., 2020).

Data processing and analysis

After dataset acquisition, the historical daily precipitation datasets were transformed to monthly and mean annual precipitation resolutions. Precipitation time series datasets consist of three main components: residual noise, seasonal variations, and trend components (Das et al. 2019). To adequately analyze historical precipitation data, analysis techniques need to be applied. An overview of techniques applied in processing the historical precipitation datasets is given below.

Trend-free pre whitening

The presence of residual noise components created a substantial challenge in identifying patterns of seasonality and trends in precipitation time series data, necessitating their removal through decomposition. Therefore, before evaluating the attributes of meteorological drought patterns, it was essential to evaluate the remaining interference component of precipitation data. The present study employed a pre-whitening procedure. The technique relied on the existence of both residual noise and a persistent trend in the time series data of precipitation. This allowed for the integration of a linear regression model with serially correlated residuals, as described in Eq. 1–4.

$$\delta_t = \mu + T_t + \varepsilon_t \tag{1}$$

where δ_t is the precipitation at time t, T_t is the trend at time t, and ε_t is the residual noise at time t and μ is the constant term. By assuming a linear trend, Eq. 3 was abridged so that:

$$\delta_t = \omega_t \tag{2}$$

where ω was the slope of the linear region between precipitation and time. Similarly, the noise may be represented by:

$$\varepsilon_t = \sum_{r=1}^{m} \sigma_r \varepsilon_{t-r} + \rho_t \tag{3}$$

where σ_r represented the parameters of the auto-regressive process, m was the order of the regression, and ρ_t was the residual noise so that Eq. 3:

$$\delta_t = \mu + \omega_t + \sigma_r \varepsilon_{t-r} + \rho_t \tag{4}$$

whereby lag-one autocorrelation, AR (1) was applied.

Trend analysis

The Mann–Kendall trend tests were utilized to examine the tendencies. A trend refers to a consistent and established pattern in climatic data that may indicate a changing trend across the duration of the study period (Ndebele et al., 2020). The Mann–Kendall test is highly recommended by the World Meteorological Organization (WMO) because climatic time series data is not necessary required to conform to a normal distribution. The Mann–Kendall test exhibits limited sensitivity towards abrupt inconsistencies and discontinuities in the data (Alhaji et al. 2018). The Mann–Kendall trend analysis technique was used to analyze the ranked precipitation data, where the data was ranked from i = 1, 2, …n-1 and j = i + 1, 2…n. Each individual data point served as a reference point and was compared to all other data points (Eqs. 5–8) so that:

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } (x_j - x_i) > 0 \\ 0, & \text{if } (x_j - x_i) = 0 \\ -1, & \text{if } (x_j - x_i) < 0 \end{cases} \tag{5}$$

The M–K test parameter was calculated by:

$$S = \sum_{t=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i) \tag{6}$$

Calculating the variation parameter involved:

$$\operatorname{Var}(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{i=1n}^{n-1} t_i(t_i - 1)(2t_i + 5)\right] \tag{7}$$

where t_i is the measure of ties in the data series i. The test statistic was calculated by:

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{(\operatorname{Var}(S))}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{(\operatorname{Var}(S))}}, & \text{if } S < 0 \end{cases} \tag{8}$$

where > 0 signifies a rising trend, whereas < 0 signifies a declining trend. Trend analyses are carried out at a particular significance level, α (Sonali & Nagesh Kumar, 2013). A significance level of α = 0.05 was employed throughout the present study. At α = 0.05, the null hypothesis of no trend is excluded if $|Z_s| > 1.96$.

The analysis of precipitation variability utilizing the coefficient of variation (CV) throughout the agro-ecological zones in this study yielded valuable insights on managing drought variability. Skewness was employed to evaluate the lack of symmetry in the probability distribution and measure the degree to which the data is pushed towards one side. Kurtosis was employed concurrently to evaluate the form of the probability distribution and offer understanding regarding the tails and peaks of the distribution in comparison to the normal distribution. The kurtosis was calculated using the Statistical Package for Social Scientists, while the coefficient of variability and skewness of the precipitation time

series data were calculated using the formulas provided by Eqs. 9–10 as follows:

$$\%\ \text{Coefficient of Variation} = \frac{\sigma}{\dot{x}} * 100 \tag{9}$$

$$\text{Skewness} = \frac{3(\dot{x} - \beta)}{\sigma} \tag{10}$$

where σ = standard deviation, $\dot{x}$ = mean, β = median precipitation between 1980–2020.

Meteorological drought characterisation

The Palmer Drought Severity Index (Sheffield et al. 2012), Surface Water Supply Index (Mishra & Singh 2010), Standardized Precipitation Index (McKee et al., 1993), Rainfall Anomaly Index (van Rooy, 1965), and Standardized Precipitation Evapotranspiration Index (Memon & Shah 2019) are commonly used indices for assessing meteorological droughts. The current study utilized the Standardized Precipitation Index at 12-month timescales.

Standardized Precipitation Index (SPI)

The World Meteorological Organization (WMO) highly endorses the Standardized Precipitation Index (SPI) as a comprehensive global drought index, as stated by McKee et al. (1993). The system can evaluate the attributes of both arid and humid settings, and its computational requirements are solely based on past precipitation data (Morid et al., 2006). The SPI offers a comprehensive assessment of soil water surplus or deficit, depending on the time scale considered (Basak et al., 2022). Due to the non-normal distribution of long-term precipitation data, it is necessary to alter it to conform to a typical normal distribution. Therefore, the calculation of SPI values over different time periods (1, 3, 6, 12, 18, and 24 months) entails using a gamma probability distribution function to determine the relative frequency distribution of the average rainfall recorded during the selected time frame. The Gamma Probability Distribution function is utilized to convert raw precipitation data into a standardized normal distribution function (Buttafuoco et al. 2018). The SPI index values are calculated by transforming the cumulative probability of precipitation data into the standard normal distribution using mathematical formulas 11–13 (AghaKouchak et al., 2015).

$$g(x) = \frac{1}{((\beta^{\alpha})(\Gamma(\alpha))} x^{(\alpha-1)} e^{-\frac{x}{\beta}} \; for \; x > 0 \tag{11}$$

where α = shape parameter, β = scale factor, x = amount of rainfall and Γ(α) = gamma function. The SPI is then calculated using the cumulative probability function as follows:

$$G(x) = \int_0^x g(x)dx = \frac{1}{((\beta^{\alpha})(\Gamma(\alpha))} \int_0^x x^{(\alpha-1)} e^{-\frac{x}{\beta}} dx \tag{12}$$

where G(x)= cumulative probability of the observed rainfall. The Gamma function is indefinite for x = 0. In this study, the cumulative probability function was analyzed as follows:

$$F(x) = p + (1 - p)G(x) \tag{13}$$

where p = probability of zero.

The SPI-1 measures soil moisture and crop stress levels, the SPI-3 measures short-term and medium-term moisture conditions, the SPI-6 represents changes in streamflow and reservoir level, the SPI-9 measures precipitation patterns over a medium scale, and the SPI-12 is useful for measuring changes in surface runoff and groundwater levels (Mishra & Singh 2010). Svoboda et al. (2017) suggested utilizing timeframes of 1, 3, and 6 months to describe meteorological and agricultural droughts, and an SPI (Standardized Precipitation Index) value of 12 or higher to evaluate alterations in surface runoff (Nam et al. 2017). Similarly, Vishwakarma et al. (2020) suggested use of SPI index at 3-, 6-, and 12-month intervals to illustrate alterations in precipitation patterns on a moderate scale, as well as variations in streamflow, reservoir levels, and groundwater levels. The current study evaluated the temporal characteristics of meteorological drought by calculating the Standardized Precipitation Index (SPI) at a 12-month timescale using R-Studio v4.3.0. The SPI values are computed within a range of -2.00 (indicating very dry conditions) to + 2.00 (indicating wet conditions). A negative SPI value suggests drought stress periods, while a positive SPI value implies wet conditions. The severity of the drought was assessed based on the classification criteria presented in Table 2, considering the magnitude of the SPI index value.

The SPI values were calculated over a 12-month period to demonstrate temporal fluctuations in observed precipitation patterns. The SPI index values derived indicate the extent of deviations in received precipitation anomalies from the average. The Inverse Distance Weighting (IDW), a deterministic interpolation technique was applied to the SPI values to produce an annual drought distribution map. The IDW predicted

Table 2 Standardized Precipitation Index (SPI) Classification classification based on Mckee et al. 1993

SPI Interval	Classification
0 < SPI ≤ 2	Above Normal Condition
-1 < SPI ≤ 0	Mild Drought
-1.5 < SPI ≤ -1	Moderate Drought
-2 < SPI ≤ -1.5	Severe Drought
SPI ≤ -2.0	Extreme Drought

the SPI values for unknown stations based on the known station values using ArcGIS 10.8.2 geostatistical tools. The interpolated SPI values were used as input to assess the values of SPI in each district and determine the changes in spatio-temporal distribution of historical meteorological drought across the study period.

Drought characteristics

The magnitude (M), intensity (I), and frequency (F) of the meteorological drought were evaluated using the SPI calculated during a 12-month period. The formulas 14–16 was used to calculate characteristics. In Eq. 14, the subscript e corresponds to a drought event while j represents a drought year. In addition, $Index_j$ is the SPI value in year j, m is the duration of a drought event (e), while in Eq. 16, n_s is the number of drought events, N_s is the total number of years for the study period which in this research study was 41 years.

$$M = \sum_{i=1}^{m} \left|Index_j\right|_e \tag{14}$$

$$I = \frac{M}{m} \tag{15}$$

$$F = \frac{n_s}{N_s} \times 100 \tag{16}$$

Results

Annual precipitation trends

The results of the yearly precipitation trends across the agro-ecological zones in the western Cape are presented in Table 3. Between 1980 and 2020, the STCSH (Ceres) agro-ecological zone experienced the highest recorded precipitation of 1084 mm, while the STWA (Leew Gamka) agro-ecological zone had the lowest recorded precipitation of 76 mm. The findings suggest that stations located in the STCSA and STWA AEZs had considerably greater coefficients of variability compared to stations in the STCA, STCSH, STWSA, and STWSH AEZs. The agroecological zone STWA (Leew Gamka) had the highest level of rainfall variance, measuring at 27%. In comparison, the STCSH Bredasdorp zone had a rainfall variability of 18%. Based on the results collected, all agro-ecological zones show a consistent and negative decline from year to year. The stations located in STCSH, specifically the Ceres and Hermanus districts, showed the most substantial negative trends at a substantial level of 0.05, with rates of -7.8 mm/year and -6.5 mm/year, respectively. Following closely is Malmesbury with a rate of -6.4 mm/year.

Similarly, the changes over time illustrated in Fig. 2 indicated that the years 2016, 2017, and 2019 experienced the least amount of rainfall during the study period, whereas 1983, 1989, and 1996 were the years with the highest

Table 3 Annual Trends in Precipitation

Station	Min	Mean	Max	Std. Dev	CV %	Annual		AEZs
						Trend (mm/year)	Sig	
MG	176	310.6	341	61	20	-1	-1.2	STCA
BW	141	252.2	431	66	26	-1	-1.2	STCSA
MM	364	638.1	933	131	20	-6.4	-2.7	STCSH
HM	424	700.5	1002	130	19	-6.4	-2.7	
CR	407	716.3	1084	148	21	-7.7	-2.7	
BD	294	446.2	626	78	18	-4.1	-2.2	
LG	76	133.1	130	36	27	-4.2	-2.3	STWA
LS	205	364.7	655	90	24	-4.2	-2.3	
SB	173	310.1	466	63	20	-2.4	-2.4	STWSA
OD	223	388.1	592	80	21	-3.6	-2.6	
SW	315	509.9	774	103	20	-5.2	-2.4	
PK	246	435.1	769	98	21	-3.9	-1.7	
CW	516	470.9	872	113	24	-4.4	-1.9	
MB	175	311	462	60	20	-3.2	-2.8	STCA
PA	197	354.3	651	89	25	-3.4	-3	

The unit of magnitude are mm while the intensity is mm/year. M = Magnitude, I = Intensity, MG = Murraysburg, BW = Beaufort West, MM = Malmesbury, HM = Hermanus, CR = Ceres, BD = Bredasdorp, LG = Leew Gamka, LS = Ladismith, SB = Still Bay, OD = Oudtshoorn, SW = Swellendam, PK = Piketberg, MB = Matroosberg, CW = Clan William, MB = Matroosberg, PA = Prince Albert

precipitation levels. In general, the yearly pattern of precipitation in the studied area from 1980 to 2020 shows a continuous decrease in rainfall throughout all agro-ecological zones in the Western Cape province.

Seasonal precipitation trends

Table 4 shows the annual patterns observed in the agro-ecological zones of the Western Cape during a span of 41 years (1980–2020). In the summer (DJF) season, thirteen stations located in the agro-ecological zones of STCSH, STWA, STWSA, and STWSH exhibited a decline in precipitation. Only two stations, Murraysburg (STCA) and Beaufort West (STCSA), showed a positive trend in precipitation, but this trend was not statistically substantial at the $p < 0.05$ significance level. Among the thirteen stations that showed a decline in precipitation, Matroosberg in STCSH and STWSA (Piketberg and Swellendam) as well as the stations in STCSH (Malmesbury, Hermanus, Bredasdorp, and Ceres) demonstrated statistically

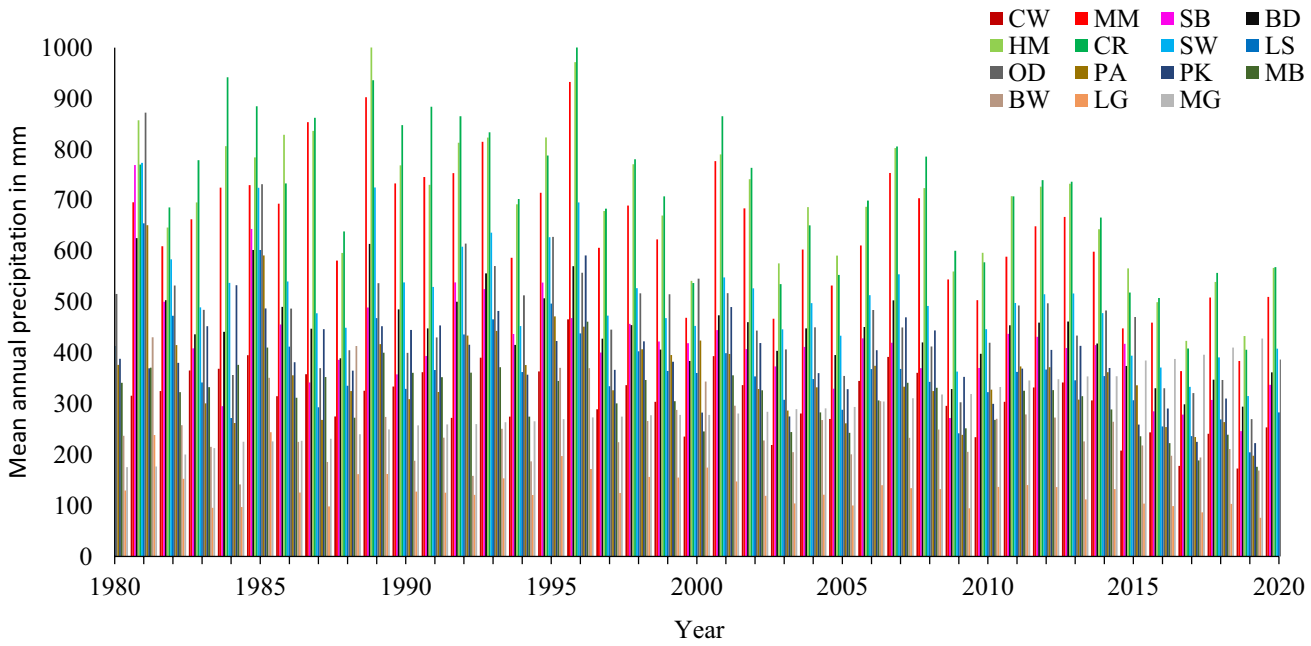


Fig. 2 Annual precipitation distribution between 1980 and 2020 across the study area

Table 4 Seasonal Trends in Precipitation (mm/ year)

Station	Summer		Autumn		Winter		Spring		AEZs
	Trend	Sig	Trend	Sig	Trend	Sig	Trend	Sig	
MG	0.4	0.8	0.3	0.5	-0.3	-1.5	-1.0	-2.5	STCA
BW	0.2	0.5	-0.0	-0.1	-0.2	-1.0	-1.0	-2.8	STCSA
MM	-1.0	-2.8	-2.6	-3.2	-1.9	-2.1	-1.2	-2.1	STCSH
HM	-1.4	-3.1	-2.6	-3.6	-1.4	-1.3	-1.0	-1.1	
CR	-1.2	-2.6	-2.9	-3.3	-2.2	-2.0	-1.6	-2.4	
BD	-0.9	-3.0	-1.8	-3.1	-0.6	-1.3	-0.6	-1.7	
LG	-0.1	-0.3	-0.5	-2.1	-0.1	-1.2	-0.5	-2.7	STWA
LS	-0.5	-1.6	-1.5	-2.5	-0.2	-0.7	-1.3	-2.5	
SB	-0.3	-1.7	-0.8	-1.2	-0.4	-0.6	-0.7	-2.9	STWSA
OD	-0.4	-2.1	-1.7	-2.5	-0.6	-1.1	-0.8	-2.3	
SW	-1.1	-2.6	-0.4	-1.6	-0.8	-1.1	-1.0	-1.9	
PK	-0.6	-1.6	-1.1	-1.9	-0.3	-0.8	-1.4	-2.4	
CW	-0.5	-1.1	-1.1	-1.5	-0.5	-1.1	-1.6	-2.6	
MB	-0.6	-2.7	-1.3	-3.6	-0.8	-1.7	-0.6	-2.2	STWSH
PA	-0.3	-0.5	-1.0	-1.9	-0.4	-1.3	-1.2	-2.8	

substantial negative trends (shown in bold in Table 4). In autumn (MAM), the agro-ecological zones of STCSA, STCSH, STWA, STWSA, and STWSH all had a decrease in precipitation, except for Murraysburg (STCA), which had a little increase in precipitation that was not statistically substantial at the 0.05 significance level. During the winter season (June, July, August), all the different agro-ecological zones had a decrease in precipitation. However, only two stations, Malmesbury and Ceres, located in the STCSH agro-ecological zone, showed a statistically substantial decrease in precipitation. In spring (SON), all agro-ecological zones experienced a decline in precipitation. Specifically, eleven stations (Malmesbury, Piketberg, Matroosberg, Ceres, Clan-William, Prince Albert, Ladismith, Beaufort West, Leew Gamka, Murraysburg, and Still Bay) showed statistically substantial negative trends at the 0.05 significance level.

Meteorological drought characteristics (SPI-12)

Figure 3 illustrates the annual precipitation distribution between 1980 and 2020 across the study area The interpolated SPI values were used as input to assess the values of SPI in each district and determine the changes in spatio-temporal distribution of historical meteorological drought across the study period. The results illustrated the interpolated annual SPI–12 patterns between the years 1980 and 2020. The results indicate that the eastern (STWA, STCA) and northern (STCSH, STCSA) parts of the Western Cape province underwent regular cycles of mild annual drought between 1980 and 2020 study period. Districts around the STWSH and STWSA AEZs, including Hermanus, Bredasdorp, and Malmesbury, saw average to high levels of precipitation throughout the study period, in contrast to districts located in the eastern (STWA, STCA) and northern (STCSH, STCSA) AEZs. The data shows that the years 2014, 2015, 2016, and 2017 had the lowest Standardized Precipitation Index (SPI) values, indicating severe drought conditions. These conditions were mainly observed in regions near Leew Gamka, Murraysburg, and Beaufort West. The findings suggest that the years 1980, 1984, and 1987 exhibited relatively milder drought conditions over the research area, as measured by the SPI 12. In general, the SPI-12 values used in the model clearly divide the Western Cape province into two regions: the southern half, which is wetter and includes STWSH and STCSH, and the drier northeastern zones, which include STCSA, STWA, and STCA.

Analysis of drought frequency

Table 5 shows the variance (var), skewness (skw), and kurtosis (Kur) values for meteorological drought, as determined by the SPI-12, across the research region from 1980 to 2020. The drought categorization findings were obtained by applying the McKee et al. (1993) method of meteorological drought classification, as described in Table 1. Meteorological droughts are detected using the Standardized Precipitation Index (SPI) when it falls below zero, according to the meteorological drought categorization technique. Moreover, the intensity of the drought worsens as the Standardized Precipitation Index (SPI) value falls below zero (Alam et al. 2023). The occurrence rate of mild droughts in STWSH (Matroosberg, Prince Albert), STWA (Ladismith), and STWSA (Clan William, Piketberg) exceeded 80%, while STCSH (Malmesbury, Hermanus, Ceres) did not encounter any occurrences of mild drought. The STCA, situated in Murraysburg, registered a rate of 50%, whereas the STCSA, situated in Beaufort West, reported a rate of 30%. The prevalence of moderate drought was documented at a frequency of 70% in STCSA (Beaufort West), 10% in STWA (Leew Gamka), and 30% in STCA (Murraysburg). Conversely, the remaining agro-ecological zones (AEZs) encountered a moderate occurrence of droughts for the entire duration of the study. The area exhibiting the greatest occurrence of severe drought (SD) was observed in STWA (Leew Gamka), with STCA (Murraysburg) following closely after at a rate of 10%. Conversely, the remaining zones did not encounter any substantial drought occurrences. STWA (Leew Gamka) experienced an instance of severe drought just 10% of the time. To summarize, we calculated the total frequency of drought (F). STWA (Leew Gamka) and STWSH (Matroosberg) experienced continuous drought conditions over the entire period. STCA (Murraysburg), STCSA (Beaufort West), STWA (Ladismith), and STWSH (Prince Albert) saw a drought occurrence rate exceeding 90%. The regions of Malmesbury, Hermanus, and Ceres, together known as STCSH, encountered drought conditions that ranged from normal to above-average intensity. The Murraysburg weather station (STCA) experienced a negative trend in total drought frequency of -0.5. The Hermanus weather station (STCSH) had a trend of -0.4, while the Matroosberg weather station (STWSH) had a trend of -0.3. Conversely, the other AEZs exhibited favourable trends in drought frequency.

The statistical analysis of drought features showed that the least variance of 0.0 was observed in STCSH (Matroosberg), STSWA (Swellendam), STWA (Leew Gamka), and STCSH (Hermanus), while the largest variance of 0.6 was found in STCA (Murraysburg). The range of values for skewness is between -0.9 and 2.5, with STCA (Murraysburg), STCSA (Beaufort West), STWA (Leew Gamka, Ladismith), STWSH (Prince Albert, Matroosberg), and STWSA (Oudtshoorn, Still Bay, Swellendam) agro-ecological zones exhibiting positive skewness, while STCSH (Malmesbury, Hermanus, Ceres) and STWSA (Clan William and Piketberg) depicted negative skewness. According to Kurtosis results, the SPI-12 values reveal a leptokurtic distribution

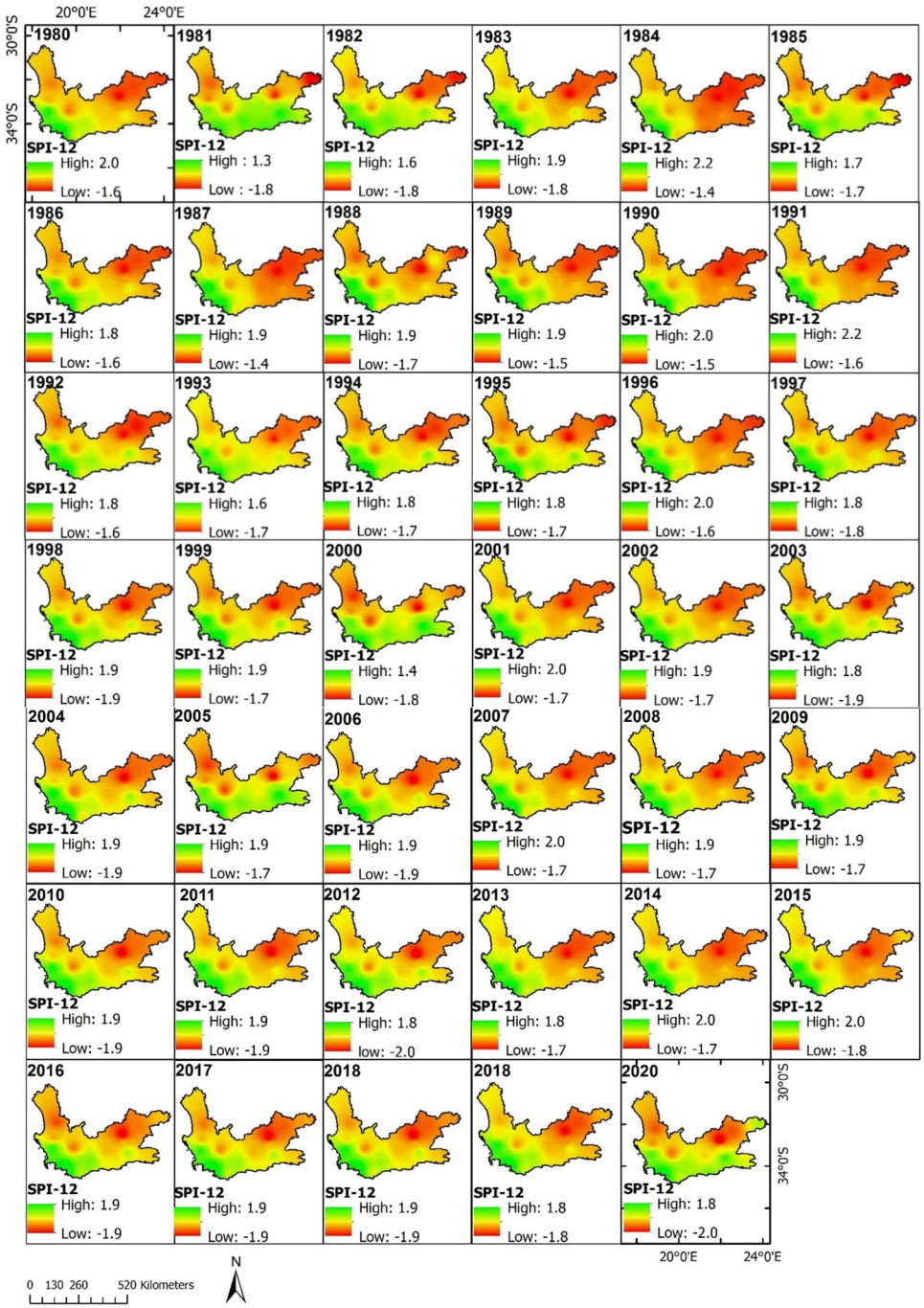


Fig. 3 Annual precipitation distribution between 1980 and 2020 across the study area

in STCA, STCSA, and STWSH zones and a platykurtic distribution in three districts (ClanWilliams, Leew Gamka, and Bredasdorp) on a 12-month timescale. Analysis of the Kurtosis statistics revealed that temporal drought patterns in the Western Cape illustrate a leptokurtic pattern. Overall analysis of the results indicates that the SPI-12 values exhibit persistent mild drought frequency across all agro-ecological zones except in Malmesbury, Hermanus, Ceres, and Swellendam, which had normal to above-very-wet conditions across the study period of 1980–2020.

Drought Magnitude (M) and Intensity (I)

Table 6 presents the measurements of the magnitude (M) and intensity (I) in millimetres per year of the meteorological drought, which were estimated during a period of five years based on the SPI-12 readings. The assessment of the extent and severity of drought was determined every five years in accordance with the national development plans that include five-year periods. The magnitude analysis reveals that the maximum drought magnitude in STCA (Murraysburg)

Table 5 Drought frequency, trends, and severity

Station	% Drought frequency						Trends	Var	Skew	Kur	AEZs
	N	MiD	MoD	SD	ED	F					
MG	10	50	30	10	0	90	-0.5	0.6	1.3	1.4	STCA
BW	0	30	70	0	0	100	0.8	0.1	2.5	9.2	STCSA
MM	100	0	0	0	0	0	1.4	0.1	- 0.8	0.8	STCSH
HM	100	0	0	0	0	0	-0.4	0	- 0.9	1.1	
CR	100	0	0	0	0	0	1.1	0.1	- 0.9	1.9	
BD	70	30	0	0	0	30	1.9	0	0.3	- 0.4	
LG	0	0	10	80	10	100	0.2	0	0.4	- 0.3	STWA
LS	10	90	0	0	0	90	1.4	0.1	1.5	2.4	
SB	0	90	0	0	0	90	1.3	0.1	- 0.2	- 0.5	STWSA
OD	20	80	0	0	0	80	1.2	0.1	- 0.2	0.5	
SW	100	0	0	0	0	0	0.5	0	0.5	0.2	
PK	60	40	0	0	0	40	0.3	0.1	0.8	1.4	
CW	80	20	0	0	0	20	2.4	0.2	0.9	1.3	
MB	0	100	0	0	0	100	-0.3	0	0.3	0.3	STWSH
PA	30	90	0	0	0	90	1.3	0.1	1.4	2.1	

was 7 mm over the period from 1980 to 1985. However, from 2016 to 2020, there was no recorded drought magnitude. The agro-ecological zone known as STCSA saw the most severe drought with a magnitude of 5.9 mm between 1991 and 1995. In contrast, the lowest drought magnitude of 4.2 mm was recorded in 1996 and 2000, spanning the whole study period. The STCSH (Leew Gamka) did not encounter any drought intensity throughout the study period. The STWA documented the most severe drought intensity of 9.1 mm from 2001 to 2005, whereas Ladismith experienced the least severe drought magnitude of 1 mm from 1991 to 1995. During the periods of 1996 to 2005 and 2011 to 2020, STSWA (Oudtshoorn) saw no substantial drought events. Prince Albert had the lowest level of drought intensity throughout the study period, in contrast to Matroosberg, which is located in the same agro-ecological Zone (AEZ). The drought intensity in Murraysburg (STCA) and in Malmesbury, Hermanus, Ceres, and Bredasdorp (STCSH) as well as in Swellendam (STSWA) showed no signs of drought between the years 2016 and 2020. Malmesbury, Hermanus, Ceres, Bredasdorp, and Swellendam saw wet conditions that were either normal or above normal. The analysis of drought intensity reveals that the highest level of drought, measuring 1.9 mm/year, was seen in the STWA (Leew Gamka) area of

Table 6 Temporal variability of drought magnitude (M) and intensity (I)

Station	1980 -1985		1986 -1990		1991 -1995		1996 -2000		2001 -2005		2006 -2010		2011 -2015		2016 -2020		AEZs
	M	I	M	I	M	I	M	I	M	I	M	I	M	I	M	I	
MG	7	1	5.1	1	5	1	5	1	3	1	3	1	2	0	0	0	STCA
BW	5.1	1	4.3	1	6	1	4	1	5	1	5	1	5	1	5	1	STCSA
MM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	STCSH
HM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
CR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
BD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
LG	8.1	2	7.7	2	8	2	9	2	9	2	9	2	10	2	10	2	STWA
LS	1.3	1	1.9	0	1	0	2	0	2	0	2	1	2	0	3	1	
SB	0.8	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	STWSA
OD	0.3	0	3.2	1	0	0	0	0	0	0	0	0	0	0	0	0	
SW	0.3	0	3.2	1	0	0	0	0	0	0	0	0	0	0	0	0	
PK	1.7	1	0.8	0	1	0	1	0	1	0	1	0	2	0	2	0	
CW	3.9	1	3.1	1	4	1	4	1	3	1	3	1	4	1	4	1	
MB	3.1	1	2.8	1	3	1	4	1	4	1	3	1	4	1	4	1	STWSH
PA	1.5	1	2.7	1	2	3	2	0	3	1	3	1	2	0	3	1	

the Western Cape across all six AEZs. Overall, the analysis of drought intensity indicates that STWA exhibited the highest level of drought intensity compared to all other districts in the research area.

Discussion

The findings provide fresh insights into the characteristics of meteorological droughts and their correlation with agricultural production, surface flows in rivers, and groundwater levels in the Western Cape province. The present study's characterization of meteorological drought differs from that of other scholars who focused on drought characterisation using alternative approaches. Nevertheless, the findings of the study aligned with the outcomes of prior research conducted by researchers including Botai et al. (2017), Orimoloye et al. (2019), Otto et al. (2018), and De Kock et al. (2022). For instance, the observed -4.2 mm/year statistically substantial trends in STCA (Murraysburg) align with prior findings by Botai et al. (2017), which indicated that the same areas within the Tsitsikamma water management region might anticipate reduced precipitation. The observed decline in the SPI values across all the AEZs aligns with the findings of Botai et al. (2017), who also identified negative trends in precipitation. The current study found that there were severe and intense drought conditions from 2015 to 2017. The minimum SPI value was -2.0 in 2014 and 2015, which is consistent with the findings of Orimoloye et al. (2019), who used remotely sensed data from the United States Geological Survey (USGS) repository and Geographic Information Systems (GIS) from 2014 to 2018 to evaluate the severity of drought in the WC region. The study conducted by Orimoloye et al. (2019) identified substantial land-use changes, with a decrease in vegetation, water bodies, and bare surface area from 2095 km^2 to 141 km^2, 616 km^2 to 167 km^2, and 2 337 km^2 to 1 381 km^2, respectively.

Equally, the analysis of drought frequency, amplitude, and intensity revealed a consistent upward trend across the entire region. These findings are consistent with the conclusions found by Otto et al. (2018), who examined how human activities contributed to the occurrence of the 2015–2017 WC droughts. The findings of Otto et al. (2018) also indicated that the Western Cape (WC) can anticipate the persistence of more severe, frequent, and intense drought conditions, consistent with the scientific understanding of the effects of climate change. Furthermore, the findings of this study suggest that there is a rising pattern of summer rainfall at STCA and STCSA, with an increase of 0.4 and 0.2 mm per year respectively. In contrast, the overall trend of yearly precipitation has fallen by -1.0 mm per year. The findings can be attributed to De Kock et al. (2022), who examined the broad-scale processes associated with unusually wet summers in the southern Cape, South Africa. According to De Kock et al. (2022), they proposed that this phenomenon may be caused by increased incidences of summer rainy days associated with abnormalities in cyclones over the STCSA and STCA, as well as enhanced moisture flow from the west across the mid-latitude South Atlantic. The findings of the current study, which showed a high coefficient of variability, align with similar observations made in other regions of Africa Masih et al. (2014) and with the variability in precipitation witnessed in Kenya in recent years according to a study by Raphael Muli Wambua et al. (2018). The study's findings indicate that a rise in drought occurrence could have consequences for food production in the AEZs. Additionally, there is a pressing need for more focused and comprehensive research on the future variations of drought in agricultural settings. Overall, the findings of this study indicate that extended periods of drought in the study region will substantially affect the water supply and consequently, agricultural productivity. The study findings also emphasize the need for the development of proactive strategies for managing drought and the creation of accurate tools for predicting drought.

The findings presented in this study indicate that the Western Cape Province has been undergoing a period of moderate drought conditions from 1980 to 2020. The Western Cape exhibits a distinct climatic variation from other provinces in South Africa, owing to its Mediterranean climate. The province's rainfall patterns facilitate the cultivation of diverse crops such as pome fruit (apples and pears), stone fruit (apricots, peaches, nectarines, and plums), table grapes, and viticulture. Consequently, the prolonged duration of droughts has had an impact on the cultivation of these crops. Furthermore, agriculture plays a crucial role in the economy of the Western Cape. Consequently, the continued presence of drought conditions will have an adverse impact on the region. Specifically, the agriculture sector serves as the primary source of employment in the province. This sector also ensures the sustainability of South Africa's food security status, ensuring that citizens have access to the required food for a healthy and prosperous existence. Consequently, a rise in drought conditions will significantly affect the agricultural industry, resulting in unemployment, a surge in food costs, and several socio-economic consequences. Furthermore, a reduction in precipitation combined with other severe climatic elements (such as temperature and evapotranspiration), specifically in the Leew Gamka and Beaufort West regions, will worsen drought conditions, resulting in a significant decrease in the available water in the water reservoirs of the Western Cape Province. A significant constraint of this study was the reliance on the SPI as the sole measure for assessing drought features. The

SPI exclusively considers precipitation as a climate variable and disregards other influential factors like temperature, humidity, and wind speed that impact atmospheric water availability. We recommend that comparable research endeavors employ alternative metrics such as the Standardized Precipitation Evapotranspiration Index (SPEI), which integrates temperature as an additional factor to evaluate drought attributes.

Conclusion

The current investigation employed two classifications of drought indicators derived from precipitation datasets (1980–2020) obtained from 15 meteorological stations located in the Western Cape Province, South Africa. The initial classification pertained to the accumulation of the SPI over a period of 12 months. The second category has three indicators for evaluating drought: drought magnitude, intensity, and frequency. The examination of SPI-12 reveals that from 1980 to 2020, the Western Cape Province consistently encountered mild meteorological drought conditions, characterized by regional and temporal fluctuations. This implies that the present drought circumstances in the Western Cape Province are a direct result of previous drought conditions. The sole distinction between previous and current drought circumstances lies in the fact that the Western Cape Province has now seen the longest or most enduring period of drought. Moreover, examination of patterns in drought assessment measures reveals a significant spatial–temporal correlation, with the southern and western areas of the province encountering more frequent, intense, and severe droughts in comparison to the eastern portions of the Western Cape Province. In general, the persistent drought in the Western Cape Province has had a negative influence on agricultural productivity. Additionally, the water reservoirs are currently operating at less than 70% capacity, indicating that the socio-economic consequences of severe droughts will persist for several more months. Consequently, the national, provincial, and local governments, along with the commercial sector, have organized multi-stakeholder workshops to deliberate on different strategies for mitigating drought in the province and across South Africa. Overall, the study's findings suggest the following conclusions: i) The Western Cape Province has consistently suffered droughts of different intensities and frequencies over the past thirty years; ii) The current drought circumstances in the Western Cape Province seem to be a recurring natural phenomenon. Despite the drought circumstances in the twenty-first century, the province has consistently seen recurring drought patterns during the twentieth century. iii) Analyzing historical drought characteristics using drought indicators is a crucial initial step in: (i) contextualizing the current drought conditions; (ii) facilitating action and responses for drought preparedness; and (iii) establishing the basis for drought monitoring and the creation of early warning systems.

Acknowledgements The authors are grateful to the University of the Witwatersrand for providing an opportunity to carry out this research.

Author contributions M.N has collected the field data, processed it, analyzed, and prepared the draft the manuscript. M.N and E.G. prepared all figures at quality resolution. E.G and M.D.S have critically reviewed and improved the manuscript for publication.

Funding Open access funding provided by University of the Witwatersrand. There was no funding for this study.

Data availability All the data and tools employed in analyzing the data presented in this article may be freely obtained from the first author, Mthulisi Ngwenya, on request.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Alam J, Saha P, Mitra R, Das J (2023) Investigation of spatio-temporal variability of meteorological drought in the Luni River Basin, Rajasthan. India Arab J Geosci 16(3):201. https://doi.org/10.1007/s12517-023-11290-8

Alhaji UU, Yusuf AS, Edet CO, Oche CO, Agbo EP (2018) Trend analysis of temperature in Gombe State Using Mann Kendall trend Test. J Sci Res Rep 20:1–9. https://doi.org/10.9734/JSRR/2018/42029

Araújo LE de, Neto JM de M, Sousa F de AS de (2009) Classification of annual rainfall and the rainy quarter of the year in the Paraíba river basin using Rain Anomaly Index (RAI). Ambiente e Agua - An Interdiscip J Appl Sci, 4(3), Article 3

Bayissa Y, Tadesse T, Demisse G, Shiferaw A (2017) Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the upper blue nile basin. Ethiopia Remote Sens 9(7):669. https://doi.org/10.3390/rs9070669

Buttafuoco G, Caloiero T, Ricca N, Guagliardi I (2018) Assessment of drought and its uncertainty in a southern Italy area (Calabria region). Measurement 113:205–210. https://doi.org/10.1016/j.measurement.2017.08.007

Chandrasekara SSK, Kwon H-H, Vithanage M, Obeysekera J, Kim T-W (2021) Drought in South Asia: a review of drought assessment and prediction in South Asian Countries. Atmosphere 12(3):369. https://doi.org/10.3390/atmos12030369

Chen T, Werf GR, Jeu RAM, Wang G, Dolman AJ (2013) A global analysis of the impact of drought on net primary productivity. Hydrol Earth Syst Sci 17(10):3885–3894. https://doi.org/10.5194/hess-17-3885-2013

Conrad, J, Nel J, Wentzel J (2004) The challenges and implications of assessing groundwater recharge: A case study – northern Sandveld, Western Cape,South Africa. Water SA, 30(5), Article 5. https://doi.org/10.4314/wsa.v30i5.5171

Das J, Mandal T, Saha P (2019) Spatio-temporal trend and change point detection of winter temperature of North Bengal India. Spat Inf Res 27(4):411–424. https://doi.org/10.1007/s41324-019-00241-9

De Kock WM, Blamey RC, Reason CJC (2022) Large-scale mechanisms linked to anomalously wet summers over the southwestern Cape. South Africa Clim Dyn 59(11):3503–3517. https://doi.org/10.1007/s00382-022-06280-7

Downing TE, Ringius L, Hulme M, Waughray D (1997) Adapting to climate change in Africa. Mitig Adapt Strat Glob Change 2(1):19–44. https://doi.org/10.1023/B:MITI.0000004663.31074.64

Jiao W, Tian C, Chang Q, Novick KA, Wang L (2019) A new multisensor integrated index for drought monitoring. Agric for Meteorol 268:74–85. https://doi.org/10.1016/j.agrformet.2019.01.008

Kao S-C, Govindaraju RS (2010) A copula-based joint deficit index for droughts. J Hydrol 380(1):121–134. https://doi.org/10.1016/j.jhydrol.2009.10.029

Kchouk S, Melsen LA, Walker DW, van Oel PR (2022) A geography of drought indices: Mismatch between indicators of drought and its impacts on water and food securities. Nat Hazard 22(2):323–344. https://doi.org/10.5194/nhess-22-323-2022

Li H, Li Z, Chen Y, Liu Y, Hu Y, Sun F, Kayumba PM (2021) Projected meteorological drought over Asian Drylands under different CMIP6 scenarios. Remote Sens 13(21):4409. https://doi.org/10.3390/rs13214409

Liverman D (2008) Assessing impacts, adaptation and vulnerability: Reflections on the Working Group II Report of the Intergovernmental Panel on Climate Change. Glob Environ Chang 18(1):4–7. https://doi.org/10.1016/j.gloenvcha.2007.09.003

Masih I, Maskey S, Mussá FEF, Trambauer P (2014) A review of droughts on the African continent: a geospatial and long-term perspective. Hydrol Earth Syst Sci 18(9):3635–3649. https://doi.org/10.5194/hess-18-3635-2014

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In: 8th Conference on Applied Climatology, Anaheim, pp 179–184

Memon A, Shah N (2019) Assessment and comparison of SPI and RDI meteorological drought indices in Panchmahals District of Gujarat, India. Int J Curr Microbiol Appl Sci 8:1995–2004. https://doi.org/10.20546/ijcmas.2019.808.233

Mishra AK, Singh VP (2010) A review of drought concepts. J Hydrol 391(1):202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Mohleji S, Pielke R (2014) Reconciliation of trends in global and regional economic losses from weather events: 1980–2008. Nat Hazard Rev 15(4):04014009. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000141

Nam WH, Hayes MJ, Svoboda MD, Fuchs B, Tadesse T, Wilhite DA, Hong EM, Kim T (2017) *Examining the extreme 2017* spring *drought event in South Korea using a suite of drought indices (SPI, SC-PDSI, SPEI, EDI). 2017*, H21F-1528

Okal HA, Ngetich FK, Okeyo JM (2020) Spatio-temporal characterisation of droughts using selected indices in Upper Tana River watershed. Kenya Sci Afr 7:e00275. https://doi.org/10.1016/j.sciaf.2020.e00275

Ongoma V, Chen H, Gao C, Nyongesa AM, Polong F (2018) Future changes in climate extremes over Equatorial East Africa based on CMIP5 multimodel ensemble. Nat Hazards 90(2):901–920. https://doi.org/10.1007/s11069-017-3079-9

Sebastian K (2015) *Agro-ecological Zones of Africa* (Version 2). Harvard Dataverse. https://doi.org/10.7910/DVN/HJYYTI

Sheffield J, Wood EF, Roderick ML (2012) Little change in global drought over the past 60 years. Nature 491(7424):435–438. https://doi.org/10.1038/nature11575

Su Z, He Y, Dong X, Wang L (2017) Drought monitoring and assessment using remote sensing. In V. Lakshmi (Ed.), *Remote Sensing of Hydrological Extremes* (pp. 151–172). Springer International Publishing. https://doi.org/10.1007/978-3-319-43744-6_8

Zhang Y, Li Z (2020) Uncertainty analysis of standardized precipitation index due to the effects of probability distributions and parameter errors. Front Earth Sci, *8*. https://www.frontiersin.org/articles/https://doi.org/10.3389/feart.2020.00076

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.