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To cite this article: Bright Chisadza, Onalenna Gwate & Simon Peter Musinguzi (2024) Evaluating the spatiotemporal dynamics of agrometeorological droughts in semi-arid Gwayi agroecosystems (1990–2020) using multiple indices, *Geomatics, Natural Hazards and Risk*, 15:1, 2412117, DOI: [10.1080/19475705.2024.2412117](https://doi.org/10.1080/19475705.2024.2412117)

To link to this article: <https://doi.org/10.1080/19475705.2024.2412117>



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Published online: 10 Oct 2024.



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Evaluating the spatiotemporal dynamics of agrometeorological droughts in semi-arid Gwayi agroecosystems (1990–2020) using multiple indices

Bright Chisadza^{a,b}, Onalenna Gwate^c and Simon Peter Musinguzi^{a,d}

^aFaculty of Agriculture, Uganda Martyrs University, Nkozi, Uganda; ^bSchool of Agriculture, Lupane State University, Lupane, Zimbabwe; ^cSchool of Environment and Development, Lupane State University, Lupane, Zimbabwe; ^dDepartment of Agriculture Production Faculty of Agriculture, Kyambogo University, Kampala, Uganda

ABSTRACT

Climate variability poses a significant threat to smallholder farmers in the Gwayi catchment, Zimbabwe. This study investigated the spatiotemporal dynamics of agrometeorological droughts from 1990 to 2020 using the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Vegetation Condition Index (VCI), and Vegetation Health Index (VHI). The triangulation of these indices provided a comprehensive understanding of drought dynamics. Severe to extreme drought events were identified in 1995, 1998, 2005, 2016, 2018, and 2020, while moderate droughts were consistently detected across all indices. Favourable conditions were observed in 2000 and 2006. A strong positive correlation ($r=0.88$) between VHI and VCI suggests their similar effectiveness in reflecting vegetation health. In contrast, moderate correlations between VHI and SPI ($r=0.30$), VHI and SPEI ($r=0.39$), VCI and SPI ($r=0.28$), and VCI and SPEI ($r=0.40$) indicate that these indices capture complementary information, reflecting not only precipitation deficits but also the impacts of temperature, soil moisture, and land cover changes. The SPI and SPEI displayed a strong positive correlation ($r=0.78$), aligning in their sensitivity to precipitation and evapotranspiration. Spatial analysis revealed a pronounced north-south drought gradient, with the southwestern region being particularly vulnerable, underscoring the need for targeted interventions.

ARTICLE HISTORY

Received 26 April 2024

Accepted 26 September 2024

KEYWORDS

Climate variability; SPEI; VCI; resilience; drought hotspots

1. Introduction

Drought is a devastating climate that has widespread and concentrated impacts, especially in rainfed agricultural areas such as sub-Saharan Africa and arid regions (Aksoy and Sertel 2022; Bamweyana and Kayondo 2018; Natarajan et al. 2023). Droughts

CONTACT Bright Chisadza  bright.chisadza@stud.umu.ac.ug

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pose a substantial threat to food security by reducing crop production (Sharara et al. 2022) and can trigger cascading effects such as soil degradation, water scarcity, and desertification (Wambura 2023). Understanding the spatiotemporal dynamics of drought is crucial for protecting the environment, managing resources, and developing effective adaptation strategies (Hosseinizadeh et al. 2015).

The impact of agricultural drought is particularly severe in Africa, where many countries, such as Zimbabwe, rely heavily on rainfed agriculture. Numerous studies (e.g. Hall et al. 2024; Madamombe et al. 2024) highlight how insufficient rainfall and heightened climate vulnerability threaten agricultural activities, particularly for many smallholder farmers who rely on rainfed production. Climate variability exposes these farmers to unpredictable rainfall patterns, jeopardizing food security and the resilience of the region's semi-arid agroecosystems. Limited water resources, exacerbated by climate change, further threaten food security and livelihoods across the continent (Ofori et al. 2021). Agricultural droughts can lead to significant reductions in crop yields (Mafongoya et al. 2022), impacting food security and nutrition, especially for vulnerable populations (Bogale and Erena 2022).

Droughts can be categorized into various types, including agricultural (focusing on impacts on crops and soil moisture) and meteorological (focusing on precipitation deficits) (Berman et al. 2024; Saini and Singh 2024; Tanarhte et al. 2024). Agrometeorological droughts encompass both of these aspects, considering how meteorological conditions (such as precipitation) affect agricultural systems (Qaiser et al. 2021; Katipoğlu 2023). Other types include socioeconomic droughts, which examine the social and economic effects of drought, and hydrological droughts, which focus on water availability in streams and groundwater (Li et al. 2022). This study focuses on agrometeorological droughts, which are particularly relevant for understanding the challenges faced by rain-fed agriculture in the context of climate variability and change.

Effective drought monitoring requires a multifaceted approach that combines ground-based meteorological data with earth observation information. This combination allows the calculation of well-established drought indices, providing valuable insights for various applications, including drought monitoring, planning, forecasting, and agricultural decision-making (Afshar et al. 2022). Key indices in this approach include the standardized precipitation index (SPI), a meteorological drought index that focuses on precipitation anomalies, offering valuable insights into drought severity on the basis of historical precipitation patterns (Sharafi et al. 2022; Hasan et al. 2023; Chisadza et al. 2023). The standardized precipitation evapotranspiration index (SPEI) extends beyond the SPI. While it is primarily a meteorological index, the SPEI incorporates both precipitation and potential evapotranspiration. This offers a more comprehensive picture of water availability relevant for agricultural systems, even though it does not directly measure agricultural drought (Gebremichael et al. 2022). By considering evapotranspiration alongside precipitation deficits, the SPEI can indirectly reflect agricultural drought conditions. The SPI and SPEI indices, along with other indices, such as the vegetation condition index (VCI) and vegetation health index (VHI) (Dejene et al. 2023), provide valuable insights for drought recurrence, planning, forecasting, and agricultural applications (Afshar et al. 2022). Notably,

employing multiple indices and considering global climatic diversity leads to a more comprehensive understanding of drought dynamics (Hasan et al. 2023).

The Gwayi catchment in southern Zimbabwe is a region heavily reliant on rainfed agriculture. However, this area faces a critical challenge of recurrent droughts. Approximately 83% of the population residing within the Gwayi catchment area is predominantly smallholder farmers, as reported by Chingarande et al. (2020). The 2022 ZIMVAC report identified drought as the most significant climate-related shock in the catchment, with more than half (51%) of the smallholder farmers being unable to cope with drought or prolonged dry spells (Government of Zimbabwe 2022). These frequent droughts significantly impact agricultural production, contributing to Zimbabwe's high cereal insecurity rates (38%) (Government of Zimbabwe 2022).

Unfortunately, existing drought assessments in Zimbabwe often lack the necessary detail to capture the full picture within specific regions, such as the Gwayi catchment. These limitations often manifest as coarse-resolution data or analyses with limited data collection periods (Frischen et al. 2020; Mutowo and Chikodzi 2014). This creates a critical knowledge gap in terms of the lack of a comprehensive understanding of how climate variability impacts the unique agroecosystems of the Gwayi catchment, particularly regarding the specific effects of drought on crop production and agricultural practices.

Previous studies on drought in Zimbabwe have played a valuable role in understanding the phenomenon's national impact (e.g. Measho et al. 2019; Okal et al. 2020; Schwarz et al. 2020; Uddin et al. 2020). However, these studies typically focused on broader geographical areas, which may have overlooked the unique challenges faced by specific regions, such as the Gwayi catchment. Gwayi catchment is characterized by a limited number of meteorological stations, restricting the availability of detailed data for fine-grained analysis. Additionally, the Gwayi catchment encompasses distinct local variations and diverse agroecological zones (Manatsa et al. 2020). As such, existing studies with a broader national focus, such as Sharara et al. (2022), may not capture these complexities. This hinders a comprehensive understanding of how drought specifically impacts the vulnerability of the Gwayi catchment, particularly in terms of agricultural productivity, food security, water resource availability, and ecosystem health.

This study aims to bridge this knowledge gap by investigating the spatiotemporal patterns, frequency, and severity of agrometeorological droughts in the Gwayi catchment. By employing a multi-index approach and focusing on a specific catchment area, this research offers a more detailed understanding of drought dynamics in this critical agricultural region. The findings of this study will not only inform policy and interventions for drought risk management in Gwayi but also contribute to achieving Sustainable Development Goal 2 (Zero Hunger) by enhancing the resilience and sustainability of the catchment's agroecosystems. While this study provides valuable insights into drought characteristics in the Gwayi catchment, it is essential to acknowledge its limitations. The use of satellite-based data for VCI and VHI might not fully capture deep soil moisture deficits, and the definition of drought thresholds can influence the results.

2. Materials and methods

2.1. Study site

The study area encompasses the Gwayi catchment, which is located within the Matabeleland North Province of Zimbabwe and parts of the midlands (Figure 1). This catchment covers an approximate area of 94,858 km² and falls primarily within agroecological regions V and IV (Manatsa et al. 2020). Figure 2 shows the average monthly maximum and minimum temperatures for the Gwayi catchment stations over the 1990–2020 period. The catchment experiences a warm to hot summer season from October to April, with average maximum temperatures exceeding 30 °C. Winters, spanning May to July, are mild, with average minimum temperatures ranging from 8.5 °C to 15 °C. Figure 2 presents the monthly rainfall pattern of the catchment. The rainy season extends from October to April, with peak precipitation occurring in December and January. Annual rainfall typically ranges between 450 and 650 mm (Viceisza et al. 2020). The dominant soil types consist of Kalahari coarse sandy soils and shallow clays derived from greenstone belts and basalts and are characterized by low inherent fertility (Tirivarombo 2012). Subsistence agriculture, which is primarily rainfed, is the main source of livelihood for rural communities within the catchment. Maize and sorghum are the dominant crops cultivated in this region (Viceisza et al. 2020).

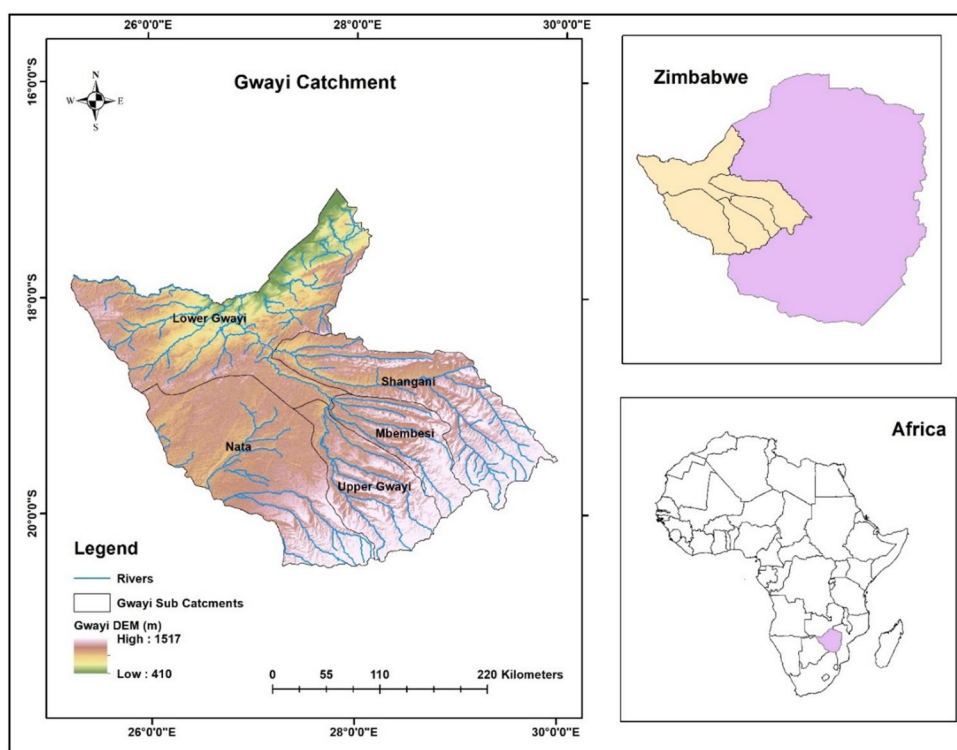


Figure 1. Location of the Gwayi catchment area.

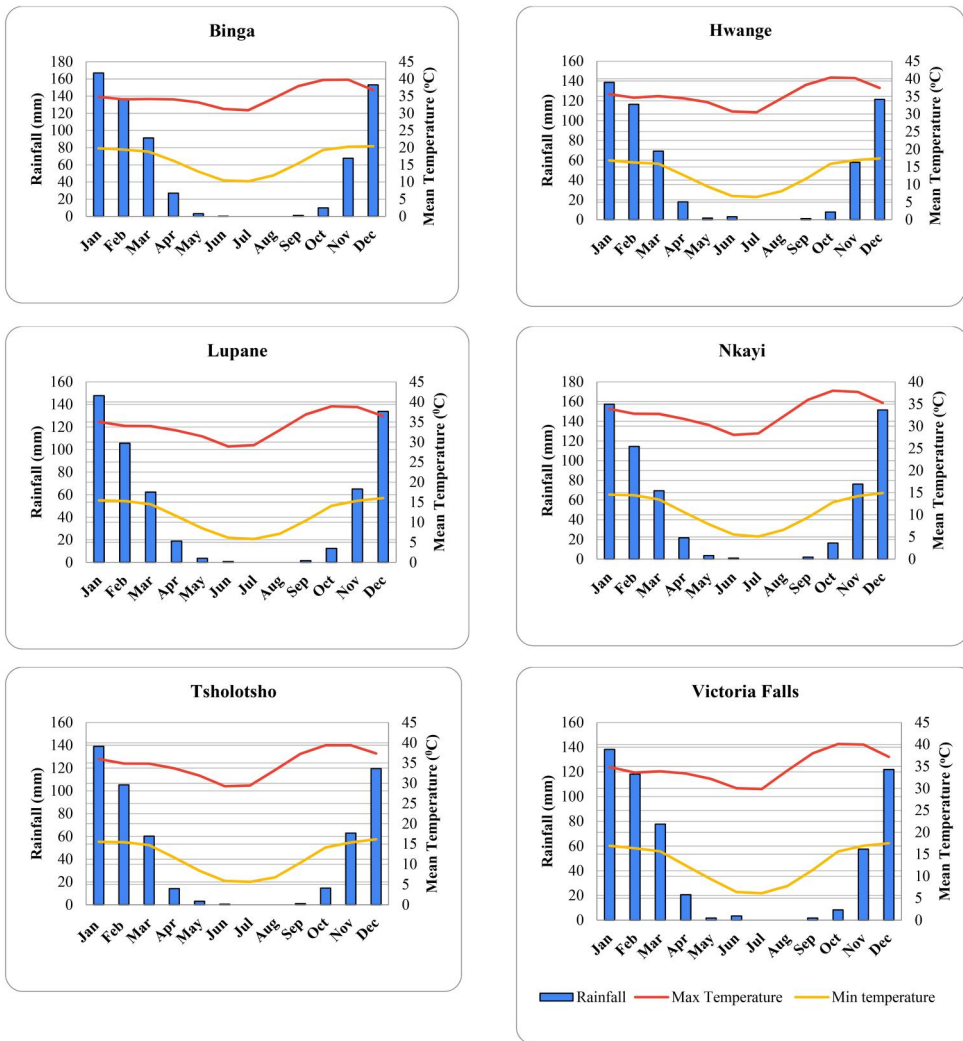


Figure 2. Annual climate cycle showing rainfall (mm) and mean temperature (°C) at the Binga, Lupane, Victoria Falls, Nkayi, Tsholotsho and Hwange stations.

2.2. Research design

This study combined satellite imagery, climate data, and statistical tests to analyse both spatial patterns and trends in agro-meteorological droughts across three decades (1990–2020) (Figure 3). The study also evaluated the correlations among the indices applied.

2.3. Data collection

2.3.1. Rainfall and temperature data

Daily rainfall and temperature data were collected from six meteorological stations within the Gwayi catchment: Victoria Falls, Tsholotsho, Nkayi, Lupane, Hwange, and Binga, spanning the period of 1990–2020. To ensure data integrity for subsequent

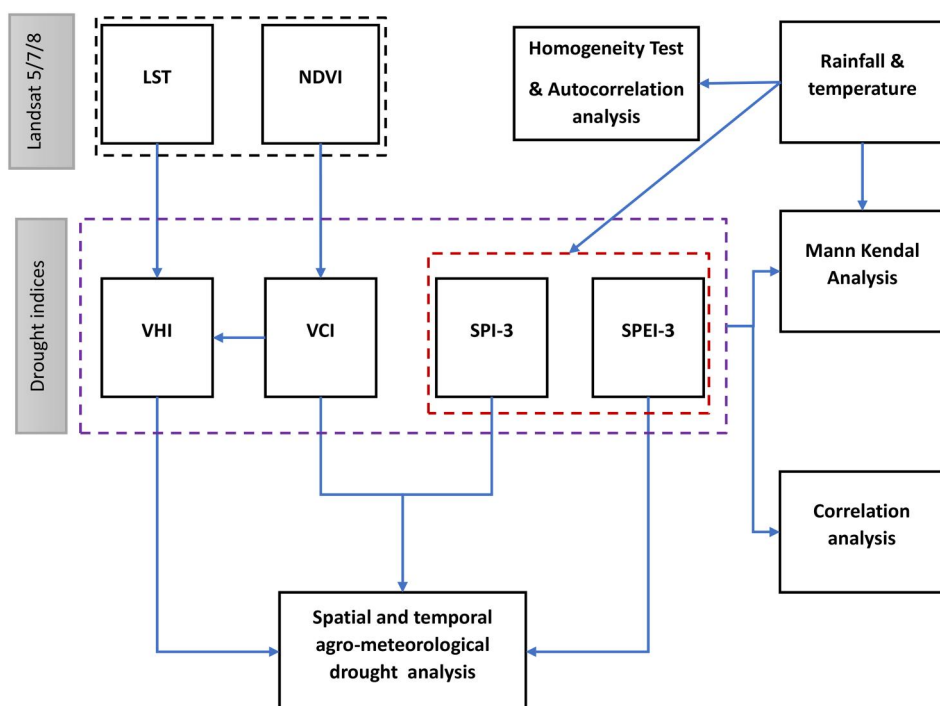


Figure 3. Research design.

analyses, several pre-processing steps were undertaken to identify and correct any potential errors or inconsistencies within the dataset. The presence of autocorrelation, or dependencies between data points, can influence the statistical results. Therefore, the Durbin–Watson test was applied to the time series to detect autocorrelation in both the rainfall and temperature data. Autocorrelation refers to a situation where the correlation between a time series and its lagged values (past values) is statistically significant. In other words, the residuals (errors) from a statistical model are not random but are instead related to past errors. The presence of autocorrelation can violate the assumptions of some statistical tests, leading to unreliable results. If the test statistic indicated significant autocorrelation, an autoregressive integrated moving average (ARIMA) model was employed to remove the autocorrelation using partial autocorrelation (PACF) of the residuals (Dabaro et al. 2021; Muganda et al. 2021). ARIMA models are a class of statistical models that effectively handle time series data with autocorrelation. By fitting an ARIMA model to the data and using its residuals, we can ensure that the subsequent analyses (e.g. Mann–Kendall test) are not biased by the presence of autocorrelation. Following the potential correction for autocorrelation *via* the ARIMA model, the Mann–Kendall test was employed to detect trends in the precipitation and temperature time series. The Mann–Kendall test is a nonparametric statistical test that assesses whether there is a monotonic trend (increasing or decreasing) over time (Marsick et al. 2024). It is beneficial for analysing time series data that may not be normally distributed or may contain outliers. The Mann–Kendall test statistic considers the relative order of data points in the time series and does not require assumptions about the underlying data distribution. By using this test, we can

determine if there are statistically significant trends in precipitation and temperature patterns within the Gwayi catchment over the 31-year study period (1990–2020). To detect abrupt shifts in rainfall or temperature patterns, the Pettitt test was applied. This method identifies changes in the median of a time series, providing insights into potential regime shifts within the study period (Andualem et al. 2024; Gaddikeri et al. 2024).

2.3.2. Satellite data

Landsat 5/7/8 satellite imagery (Table 1) served as the source data for deriving the normalized difference vegetation index (NDVI) (Table 2) used in the vegetation index calculations. The land surface temperature (LST) was also derived from the acquired Landsat 5/7/8 top-of-atmosphere (TOA) reflectance data using an established method. We employed the radiative transfer equation approach, specifically the single-channel estimation (SCE) method, as outlined by Chatterjee et al. (2017) and García-Santos et al. (2018). This method uses specific bands from Landsat imagery to estimate LST values. The derived LST data were then incorporated into the VHI calculation to account for the combined effects of vegetation health and thermal stress on drought assessment. Landsat satellite imagery was acquired for the months spanning November to March within each year of the study period (1990–2020). This specific timeframe aligns with the critical growth stages of rain-fed crops cultivated in the Gwayi catchment, particularly maize and sorghum (Viceisza et al. 2020). By capturing imagery during this period, we ensured that the derived vegetation indices (VCI and VHI) effectively reflected the health and condition of the crops in response to the prevailing moisture conditions. November represents the early planting season, allowing for the assessment of vegetation establishment. March coincides with crop maturity or near-maturity stages, providing valuable insights into the impacts of agricultural drought on yield potential. To obtain high spatial resolution data for the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) across the entire Gwayi catchment, we utilized data from TerraClimate (<https://app.climateengine.com/climateEngine>) (Abatzoglou et al. 2018). The limited number of meteorological stations within the catchment (only five) restricts the ability to spatially represent the SPI and SPEI using solely interpolated station data. TerraClimate data offer a viable alternative, providing gridded datasets at a high spatial resolution (Solaimani and Bararkhanpour Ahmadi 2024), comparable to our VCI and VHI analyses, enabling a comprehensive assessment of drought severity across the region. While acknowledging the potential uncertainties associated with interpolated data from TerraClimate (Solaimani and Bararkhanpour Ahmadi 2024), this approach complements the localized insights from ground observations and ensures consistency in spatial resolution across all drought indices used in this study. Each data variable in Table 2 was analysed independently, which eliminated the need

Table 1. Landsat satellite imagery attributes.

Year	Sensor type	Spatial resolution (m)
1990–1999	TM	30
2000–2013	ETM	30
2014–2020	OLI	30

Table 2. Data variables, sources and resolutions used in the study.

#	Variable	Source	Resolution	Derived variable	Reference
1	NDVI	Landsat 5, Landsat 7, and Landsat 8 Top-of-Atmosphere (TOA)	30 m	VCI/VHI	(Liou et al. 2017)
3	SPI	TerraClimate	4 km	Spatial SPI-3	
4	SPEI	TerraClimate	4 km	Spatial SPEI-3	
5	LST	Landsat 5/7/8 TOA	30 m	TCI	(Zeng et al. 2022)

Table 3. Vegetation indices.

Index type	Landsat Sensor	Formula	Reference
NDVI	TM/ETM	$NDVI = \frac{(Band\ 4 - Band\ 3)}{(Band\ 4 + Band\ 3)}$	(Liu et al. 2019)
	OLI/TRS	$NDVI = \frac{(Band\ 5 - Band\ 4)}{(Band\ 5 + Band\ 4)}$	
VCI		$VCI = 100 \times \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})}$	(Ezzahra et al. 2023)
TCI		$TCI = \frac{(LST_{max} - nLST)}{(LST_{max} - LST_{min})} \times 100$	(Jalayer et al. 2023)
VHI		$VHI = a \times VCI + (1 - a) \times TCI$	(Jalayer et al. 2023)

to standardize the resolution across different datasets. This approach allowed us to utilize the specific strengths and detailed information provided by each dataset, thereby enhancing the accuracy and relevance of our analysis.

2.4. Drought indices calculation

To assess agrometeorological drought, this study employed four drought indices: the vegetation condition index (VCI), vegetation health index (VHI), standardized precipitation index (SPI), and standardized precipitation evapotranspiration index (SPEI). The SPI and SPEI were calculated on a 3-month timescale, while the VCI and VHI were assessed for the November–March period and aligned with the region’s agricultural season (as detailed in Section 2.3.2). This timeframe effectively captured both meteorological and agricultural droughts relevant to Zimbabwe’s typical seasonal patterns (Grey 2019; Manjowe et al. 2020). However, it is important to acknowledge the potential need to analyse different timescales depending on the specific application. This study used two broad categories for drought assessment. The first leverages spatial data from Landsat satellites, employing established indices such as the VCI and VHI, which are commonly used to evaluate vegetation health and drought conditions (Patil et al. 2021). The second approach focuses on calculating the SPI and SPEI, which are the primary meteorological indices for evaluating drought (Faye 2022). A combination of the VCI, VHI, SPI, and SPEI provides a more comprehensive understanding of drought conditions by incorporating both vegetation health and meteorological factors.

2.4.1. Vegetation indices (VCI, VHI)

The vegetation condition index (VCI) and vegetation health index (VHI) are among the drought indices developed to evaluate how vegetation responds to drought conditions, particularly in arid, semi-arid, and subhumid climates (Alsenjar et al. 2022;

Table 4. Drought classification using the VCI/VHI.

Level	VHI/VCI (%)	Classification
1	35–50	Mild
2	20–35	Moderate drought
3	10–20	Severe drought
4	0–10	Extreme drought

Mardani et al. 2022; Zeng et al. 2022). The VCI and VHI were calculated using the formulas listed in Table 3. The NDVI and LST values were derived from processed Landsat satellite imagery acquired from the United States Geological Survey (USGS) Earth Explorer online portal (<https://earthexplorer.usgs.gov/>). The selection criteria for imagery included a path/row appropriate for the Gwayi catchment and a cloud cover percentage of less than 10%. The TCI was derived from the LST values for the VHI calculations. The weighting factor ‘a’ applied during the VHI calculation was set to 0.2 on the basis of the findings of Gidey et al. (2018) and Chughtai et al. (2021). The classification of drought severity was based on established VHI/VCI threshold percentages, as outlined in Table 4. A VHI/VCI above 35 indicates healthy vegetation with little to no drought, whereas values below 10 suggest extreme drought with very stressed vegetation.

2.4.2 Standardized precipitation index (SPI)

McKee et al. (1993) established the SPI, which is among the most widely used indicators in drought studies. The average SPI-3 was calculated using a drought index calculator (<http://drought-software.com/dc0918/DrinC>) based on the acquired precipitation data, using the following equation (Equation 1). Meanwhile, the spatial SPI-3 was derived from the TerraClimate dataset (1990–2020). Although TerraClimate data, generated through interpolation methods, may introduce uncertainties compared to direct station observations, this trade-off allows for high spatial resolution data coverage across the entire catchment. The SPI allows for the assessment of meteorological drought severity across various time scales. In this study, we specifically chose the 3-month timescale (SPI-3) to capture seasonal variations in moisture conditions within the Gwayi catchment (Vishwakarma et al. 2020). A 3-month window effectively captures the seasonal shifts in precipitation patterns, which significantly impact drought development. Periods of below-average precipitation within a 3-month timeframe can trigger short-term to seasonal drought events. This timescale also aligns with critical growth stages for many crops, making it particularly relevant for assessing potential drought impacts on agricultural activities within the catchment (Vishwakarma et al. 2020). Finally, the 3-month timeframe balances sensitivity and stability. Shorter timescales may be overly sensitive to individual precipitation events, providing misleading signals, while longer timescales might miss crucial short-term drought episodes. The 3-month window offers good middle ground conditions and is sensitive to seasonal changes while maintaining stability for robust drought analysis.

To determine the SPI, the precipitation amounts are subtracted from the mean for a specific time frame (1990–2020), and the outcome is divided by the standard deviation, as indicated by Eq. (1).

Table 5. Drought classification using the SPI and SPEI (Tigkas et al. 2015).

SPI/SPEI	Categories
>2.00	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
0 to 0.99	Near Normal
−0.50 to −0.99	Mild drought
−1 to −1.49	Moderate drought
−1.50 to −1.99	Severe drought
< −2.00	Extreme drought

$$SPI = \frac{(Z_{ir} - P_i)}{\sigma_i} \quad (1)$$

where

σ_i = Standardized deviation for the i th station

Z_{ir} = Rainfall for the i th station and r th observation

P_i = Mean rainfall for the i th station

2.4.3. Standardized precipitation evapotranspiration index (SPEI)

The SPEI-3 index was calculated using both precipitation and potential evapotranspiration (PET) data in the DrinC index calculator, while the spatial SPEI-3 data was derived from the TerraClimate dataset (1990–2020). Although using TerraClimate data introduces potential uncertainties due to interpolation methods, these uncertainties are a trade-off for achieving high spatial resolution across the entire catchment. Unlike the SPI, which only considers precipitation, the SPEI accounts for both precipitation and PET, offering a more comprehensive view of drought by encompassing both meteorological and agricultural aspects. A three-month time scale was employed to capture seasonal variations in drought severity within the catchment. While SPI analysis focuses on the absolute reduction in rainfall, SPEI analysis considers the reduction in rainfall relative to potential evapotranspiration. This difference allows SPEI to reflect the combined effects of water availability and demand. The final drought index value is determined by translating the accumulated difference between precipitation and evapotranspiration into a probability distribution, which is then standardized to a normal distribution. This study used the 3-month SPI and SPEI to capture seasonal variations, as suggested by Salehan et al. (2024). The categorization of drought *via* the SPI and SPEI is shown in Table 5.

2.5. Temporal and spatial drought analysis

2.5.1. Calculation of the temporal dynamics of drought indices

Temporal variations in the average values of the VCI, VHI, SPI-3, and SPEI-3 were analysed over a 31-year period (1990–2020) to understand drought patterns and trends within the Gwayi catchment. Owing to its ability to handle nonnormal data and outliers, the Mann–Kendall test was chosen to analyse trends in drought indices (Wang et al. 2020). This nonparametric approach offers a distinct advantage over

linear regression when dealing with time series data (Deng et al. 2022). Pearson correlation matrices were constructed using Xlstat software to examine the relationships among the various indices. Additionally, correlations between the drought indices and average annual rainfall were also determined. This analysis reveals how strongly each drought index corresponds to variations in rainfall (a positive correlation indicates similar trends, and stronger correlations indicate values closer to 1 or -1).

2.5.2. Spatial dynamics

Spatial variations in the VCI, VHI, SPI-3 and SPEI-3 were mapped across the Gwayi catchment for selected years (1990–1991, 1994–1995, 2000–2001, 2004–2005, 2009–2010, and 2014–2015) to visualize drought patterns across the region. Additionally, spatial dynamics were analysed to identify areas experiencing drought conditions within the catchment.

2.6. Summary of software used

This study utilized a combination of software tools for various data analysis tasks. XLSTAT 2019, a statistical software package, played a key role in several analyses. The Durbin–Watson test was used to detect autocorrelation in the rainfall, and temperature data in XLSTAT. Additionally, XLSTAT facilitated the identification of trends in precipitation and temperature time series through the Mann–Kendall test. If necessary, detrending with ARIMA models was performed within XLSTAT before the Mann–Kendall test was applied. Furthermore, XLSTAT was employed to conduct the Pettitt test to detect abrupt changes in the medians of the rainfall and temperature data. Finally, Pearson correlation analyses were conducted in XLSTAT to assess the relationships between various drought indices (VCI, VHI, SPI, SPEI) and annual rainfall. To handle and pre-process satellite imagery data, as well as for spatial analysis and visualization of drought indices (VCI, VHI, SPI, and SPEI) across the Gwayi catchment, ArcGIS 10.8, a geographic information system (GIS) software, was employed. DrinC calculator version 1.7 (<http://drought-software.com/dc0918/DrinC>) was used to calculate the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI) on the basis of the acquired precipitation data.

3. Results

3.1. Rainfall and temperature statistics

A positive autocorrelation (Table 6) was detected at all six stations ($DW < 1.5$). ARIMA models were subsequently employed to remove autocorrelation using partial autocorrelation (PACF) of the residuals (Abebe 2020; Amjad et al. 2022). This process successfully addressed the autocorrelation issue in the data, allowing for subsequent trend analysis. The Mann–Kendall test (Table 6) was employed to detect trends in precipitation and temperature. Only Victoria Falls exhibited a statistically significant trend ($p < 0.05$) with increasing rainfall (Sen's slope = 7.25 mm/year). The remaining stations (Tsholotsho, Nkayi, Lupane, Hwange, and Binga) showed no significant trends ($p > 0.05$). The Pettitt test results revealed no significant changes in the median

Table 6. Durbin–watson and mann–kendal test results for rainfall at the six stations.

Station	Durbin–Watson test		Mann–Kendall test		
	DW	rho	Kendall's tau	<i>p</i> value	Sen's slope
Vic Falls	0.620	0.507	0.310	0.016	7.250
Tsholotsho	0.565	0.519	0.037	0.786	0.650
Nkayi	0.567	0.530	0.089	0.496	2.339
Lupane	0.569	0.521	−0.028	0.838	−0.703
Hwange	0.593	0.522	0.155	0.227	3.517
Binga	0.567	0.560	0.154	0.234	3.246

Table 7. Correlation matrix for precipitation for the six stations in the catchment.

Correlation matrix (Pearson)						
Variables	Vic Falls	Tsholotsho	Nkayi	Lupane	Hwange	Binga
Vic Falls	1	0.637	0.695	0.669	0.894	0.808
Tsholotsho	0.637	1	0.879	0.944	0.832	0.748
Nkayi	0.695	0.879	1	0.943	0.807	0.807
Lupane	0.669	0.944	0.943	1	0.838	0.807
Hwange	0.894	0.832	0.807	0.838	1	0.839
Binga	0.808	0.748	0.807	0.807	0.839	1

$p < 0.0001$ for all correlation between different stations.

rainfall patterns at any of the six stations within the Gwayi catchment (all p values > 0.05).

A strong positive correlation was observed between all six rainfall stations (Victoria Falls, Tsholotsho, Nkayi, Lupane, Hwange, and Binga) (Table 7). All correlations, except those of Victoria Falls and Tsholotsho, were statistically significant (<0.05). The correlation strength varied, with stations such as Lupane and Tsholotsho exhibiting very strong positive correlations (values close to 1).

3.2. Temporal dynamics of agrometeorological drought

Analysis of the VCI classification (Figure 4a) provides valuable insights into the historical drought patterns within the Gwayi catchment. VCI values were averaged for the November–March period within each year, with a focus on the critical growth stages of rain-fed crops. This approach captured the overall health of vegetation during this critical window and its response to prevailing moisture conditions (rainfall and potential evapotranspiration). This same approach was applied to all the indices. Notably, normal conditions, indicative of relatively healthy vegetation, were observed in 11 of the 31 years analysed. However, drought events were also frequent, with mild drought being the most common category (occurring over 14 years). Moderate droughts occurred for four years (1992, 1998, 2002, and 2012), while severe droughts occurred in 1995 and 2005.

Analysis of the VHI classification (Figure 4b) revealed a pattern of fluctuating drought conditions within the Gwayi catchment area. Similar to the VCI results, mild drought was the most frequent category, occurring in 12 out of 31 years, indicating recurring periods of moderate stress on the vegetation. However, the VHI classification identified a slightly greater frequency of extreme droughts (2 years: 1998, 2015)

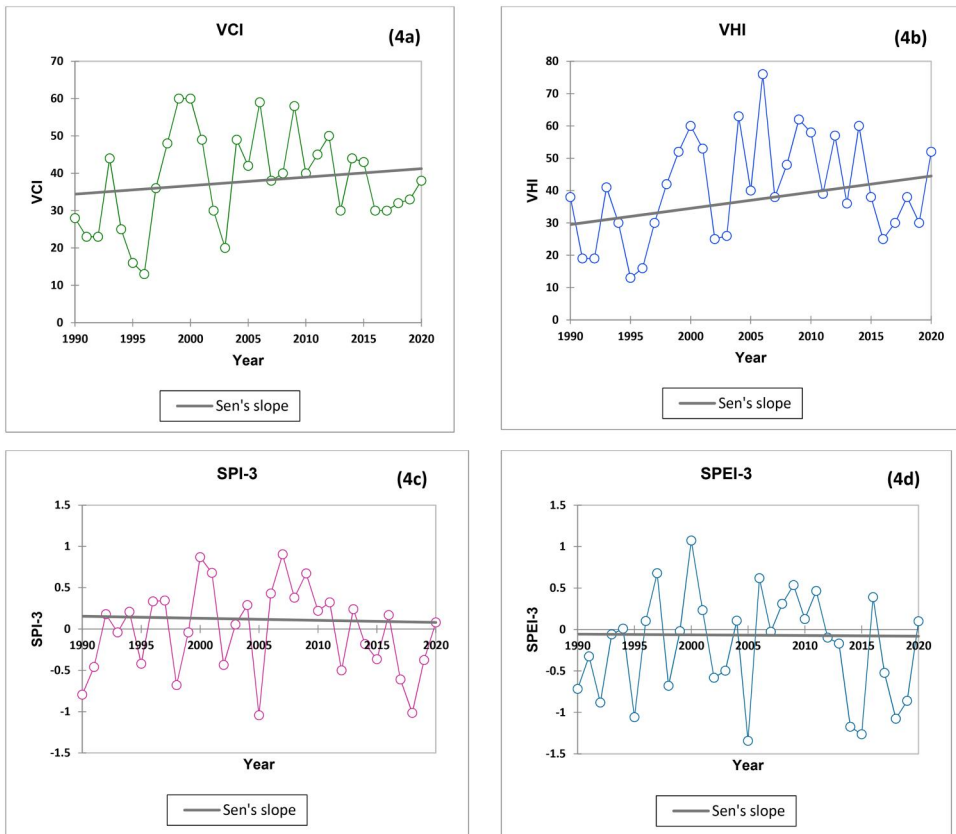


Figure 4. (a)–(d): VHI (4a), VCI (4b), SPI-3 (4c) and SPEI-3 (4d) variations from 1990 to 2020 showing temporal variations.

than did the VCI. This suggests that the VHI might be more sensitive to periods of severe vegetation stress. The analysis also identified moderate droughts in four years (1992, 2002, 2010, and 2012) and severe droughts in 1995 and 2016. Normal conditions, indicative of healthy vegetation, were observed for eight years.

The SPI classification (Figure 4c) revealed a dynamic pattern of precipitation and drought conditions within the Gwayi catchment area. Notably, near-normal precipitation, indicative of balanced conditions, occurred most frequently (nine out of 31 years). The catchment also experienced significant wet periods, with severe wet conditions observed over five years and moderate wet conditions over six years. Drought events were also evident on the flipped side. Moderate droughts occurred in seven years, whereas severe droughts were identified in four specific years (1995, 2005, 2014, and 2017). The results also revealed that three years (1998, 2015, and 2018) were classified as extreme droughts.

The SPEI analysis (Figure 4d) revealed a historical tendency towards mild drought conditions in the Gwayi catchment area. More than one-third (10 out of 31 years) fell under this classification, indicating a recurring pattern of dryness. However, the data also show a possible shift towards more severe droughts. This is evident in the occurrence of five severe drought years (1995, 2005, 2014, 2017, and 2018) and three

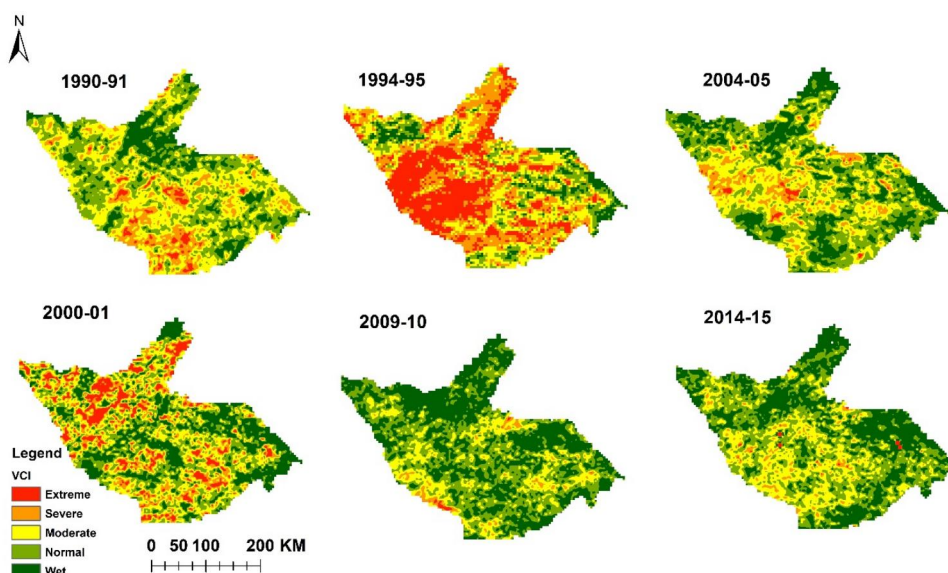


Figure 5. Spatial variation in the VCI across the Gwayi catchment for selected years.

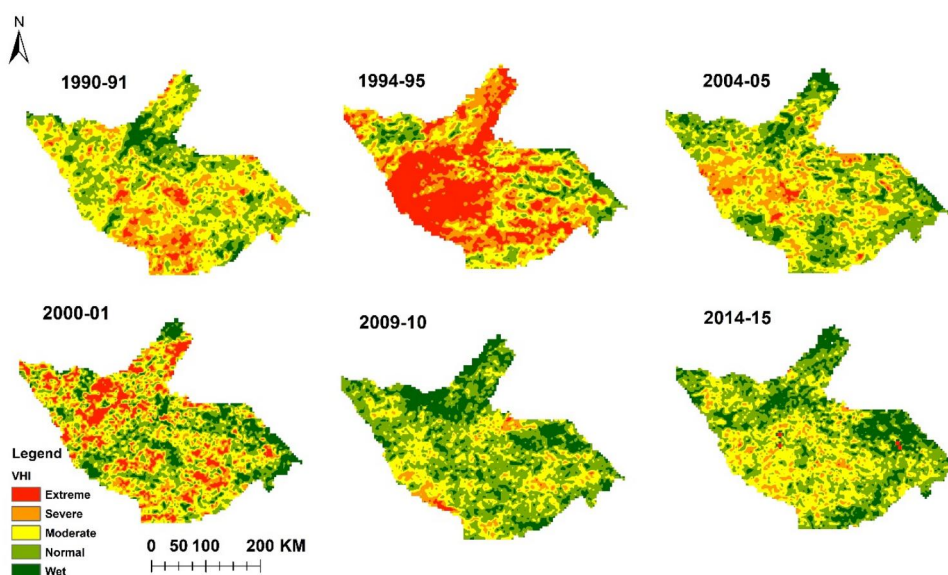


Figure 6. Spatial variation in the VHI across the Gwayi catchment for selected years.

extreme drought years (1998, 2015, and 2020) compared with only three moderate drought years (1992, 2002, and 2012).

3.3. Spatial dynamics of agrometeorological drought

3.3.1. Spatial variations in the VCI, VHI, SPI and SPEI across the catchment

Analysis of spatial drought patterns using VCI (Figure 5), VHI (Figure 6), SPI (Figure 7), and SPEI (Figure 8) revealed distinct variations within the Gwayi

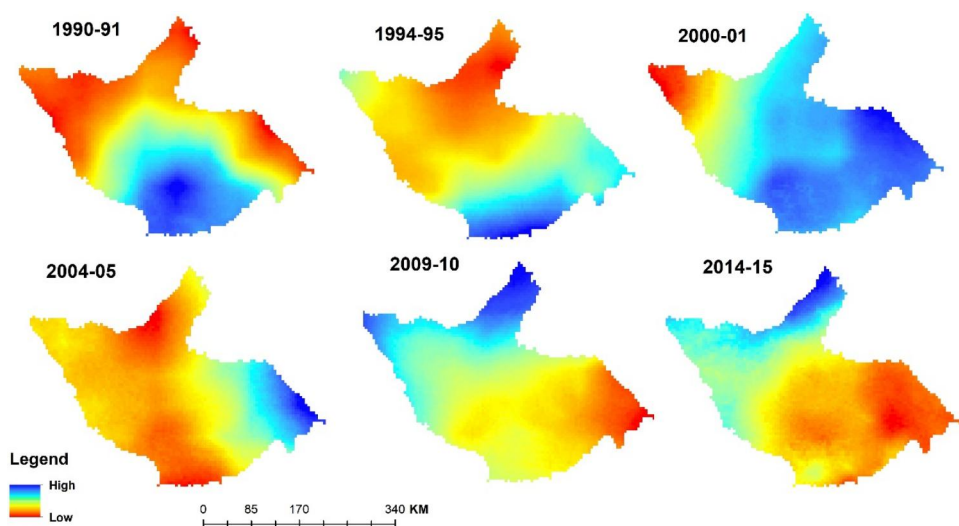


Figure 7. SPI spatial variation across the Gwayi catchment for selected years.

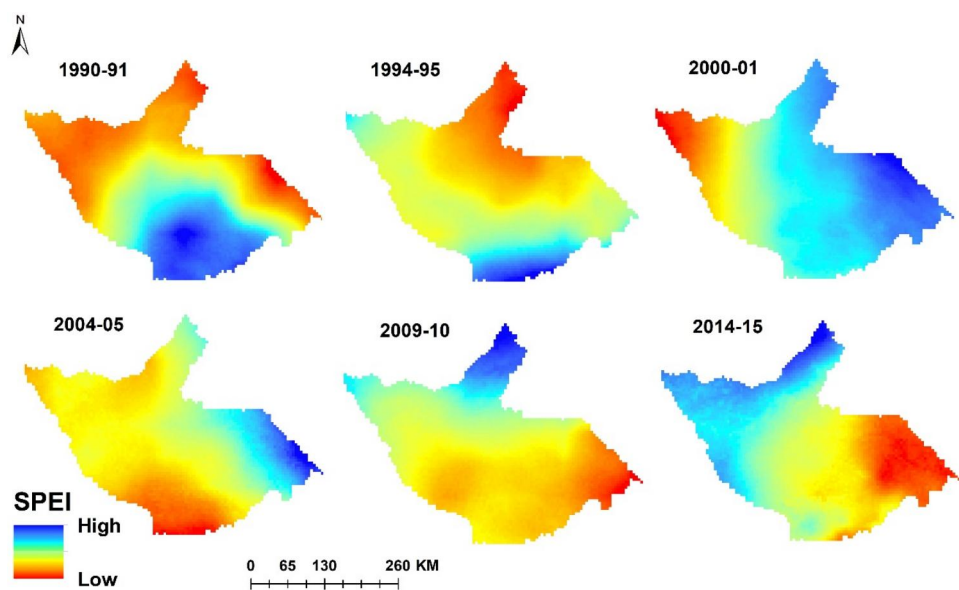


Figure 8. Spatial variation in the SPEI across the Gwayi catchment for selected years.

catchment. The VCI and VHI, which reflect vegetation conditions, consistently indicated a north–south gradient in terms of vegetation health, with the northeastern region exhibiting relatively better conditions than the southwestern area. This pattern was particularly evident during the severe 1994–1995 drought, as depicted in Figures 8 and 9, where the southwestern portion of the catchment experienced extensive drought conditions. The SPI and SPEI, which represent meteorological conditions, also showed a general north–south gradient in terms of drought occurrence, with the northwestern region often experiencing drier conditions. However, these

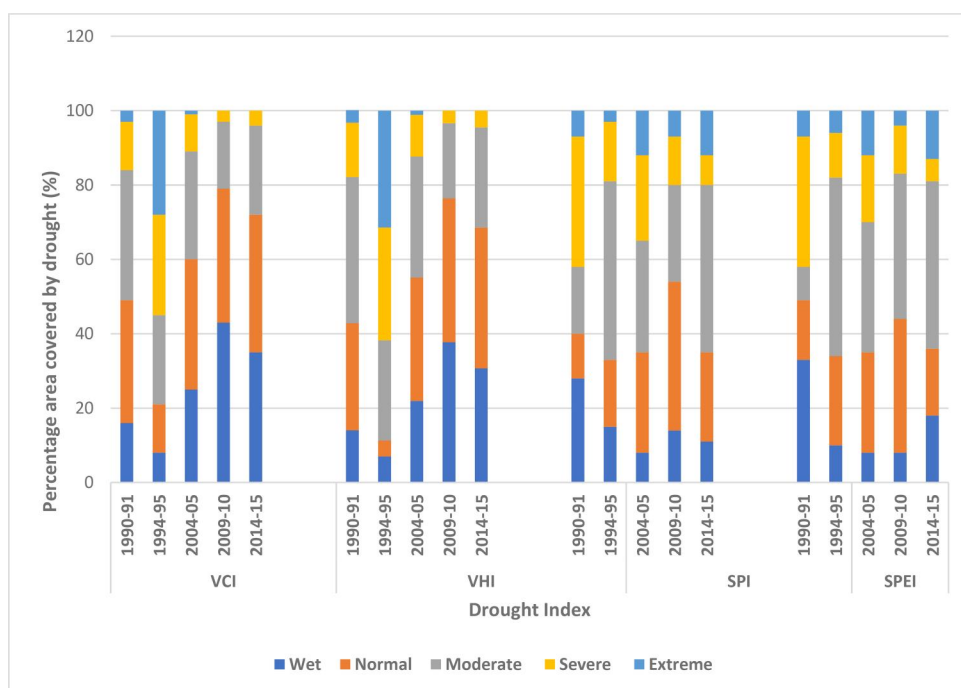


Figure 9. Proportion of areas covered by various drought levels for selected years *via* the VCI, VHI, SPEI and SPEI in the catchment.

indices revealed a more dynamic spatial pattern than did the vegetation-based indices. For example, [Figure 7](#) shows a reversal in SPI patterns during the 2009–2010 season, with drier conditions in the southeastern part of the catchment.

3.3.2. Agrometeorological drought area changes using the VCI

An analysis of drought occurrence and spatial extent within the Gwayi catchment was conducted using multiple indices; the VCI, VHI, SPI, and SPEI. To quantify drought impacts, the area affected by different drought severity levels was calculated for each index and time period on the basis of established thresholds ([Figure 9](#)). The VCI analysis revealed spatial and temporal variations in vegetation health. During the 1994–1995 season, extreme drought conditions affected approximately 28% of the catchment, with a total of 79% experiencing moderate to extreme drought. In contrast, the 2009–2010 season resulted in significantly improved conditions, with only 21% of the catchment experiencing drought stress. The VHI data corroborated these findings, indicating similar trends in vegetation health. In the 2004–2005 season, 88.7% of the areas experienced moderate to extreme drought conditions. Improved wet conditions were observed from 2009 to 2010, with 37.7% of the area reflecting a recovery phase in terms of vegetation health. SPI and SPEI data provided insights into the meteorological drivers of drought. Both indices identified 2004–2005 as the period most impacted by drought, affecting approximately 66–67% of the catchment. However, the spatial distribution of drought, as indicated by these meteorological

indices, differed from that of the vegetation indices, suggesting potential lags in the vegetation response to precipitation deficits.

Limitations of pixel-based analysis for drought area assessment

Importantly, this analysis is subject to certain limitations. The use of pixel-based analysis to determine drought areas can be influenced by land cover changes and data resolution. Additionally, the choice of drought thresholds can impact the results. Future studies could explore the use of higher resolution data and alternative drought indices to refine the analysis.

3.4. Overall agrometeorological drought dynamics and trends

This analysis explored drought conditions in the Gwayi catchment using four key indices: the VHI, VCI, SPEI, and SPI (Table 8). Mixed drought conditions were observed from 1990 to 2020. Mild drought was the most frequent category across all indices, with the VCI and SPI showing the highest occurrences (14 and 8 years, respectively). There was good agreement for severe droughts in 1995 and 2005 across all indices, suggesting that these significant events were identifiable using different drought monitoring approaches. The VCI shows no extreme droughts, whereas the SPI and SPEI identify several droughts (three for each).

The SPI showed a greater frequency (7 years) of moderate drought than did the VHI and VCI (4 years each). The notable moderate to severe drought years included 1991, 1992, 1994, 1995, 2005, 2016, and 2017. Favourable (wet) conditions occurred in 2000 and 2006.

The SPI and SPEI indices indicated that the most severe drought was experienced between 2004 and 2005. In contrast, the VCI data revealed less impact during this period but identified 1994–1995 as a year of extreme drought. This discrepancy can be attributed to the different sensitivities and methodologies underlying each index. The SPI and SPEI primarily measure meteorological and hydrological droughts by

Table 8. Drought classification in the Gwayi catchment based on each drought index.

Index	Drought level	Number of years
VHI	Mild drought	12
	Moderate drought	4
	Severe drought	2
	Extreme drought	2
VCI	Mild drought	14
	Moderate drought	4
	Severe drought	2
	Extreme drought	0
SPI-3	Mild drought	8
	Moderate drought	7
	Severe drought	4
	Extreme drought	3
SPEI-3	Mild drought	10
	Moderate drought	4
	Severe drought	5
	Extreme drought	3

Table 9. Mann–kendall results for the average VHI, VCI, SPI-3 and SPEI-3 for the catchment.

Index	Kendall's tau	<i>p</i> value	Sen's slope
VHI	0.169	0.195	0.500
VCI	0.107	0.414	0.227
SPI-3	−0.032	0.812	−0.003
SPEI-3	−0.015	0.919	−0.001

focusing on precipitation deficits and evapotranspiration, which directly affect water availability. Consequently, they may experience more severe drought impacts during periods of significant rainfall shortages, such as 2004–2005.

On the other hand, the VCI is a measure of vegetation health, reflecting the response of vegetation to both precipitation and soil moisture conditions. The VCI might have had a less severe impact from 2004 to 2005 if vegetation had adapted or if there were mitigating factors such as soil moisture retention. Conversely, the extreme drought indicated by the VCI in 1994–1995 suggested that vegetation was severely stressed during this period, possibly due to prolonged dry conditions that might not have been fully captured by the SPI and SPEI. This highlights the importance of using multiple indices to obtain a comprehensive understanding of drought impacts, as each index captures different facets of drought conditions.

According to this analysis, none of the average drought indices showed statistically significant trends according to the Mann–Kendall test ($p < 0.05$) (Table 9). The VHI and VCI show slightly positive Kendall's tau values, suggesting a possible weak increase in drought severity over time, but the *p* values indicate that this increase was not statistically significant. However, at the station level, Tsholotsho had a statistically significant negative trend ($p < 0.05$) in SPEI-3 and SPI-3. None of the other stations showed any significant trends.

3.5. Drought indices correlation

The correlation matrices of the VHI, VCI, SPEI-3 and SPI-3 are shown in Figures 10 and 11. The results indicate a very strong positive correlation between the VHI and VCI (0.877), which suggests that these indices provide similar information regarding drought conditions. The SPI-3 and SPEI-3 also exhibit a strong positive correlation (0.783), indicating that they capture similar aspects of drought severity related to meteorological conditions. The VHI and SPI (0.304) and the VHI and SPEI (0.392) showed moderate positive correlations. Moderate positive correlations were found between the VHI and SPI (0.304) and between the VHI and SPEI (0.392). Similarly, moderate correlations were observed between the VCI and SPI (0.281) and between the VCI and SPEI (0.405). These moderate correlations were caused by the fact that while the VHI and VCI share some information with the SPI and SPEI, they also capture unique aspects of vegetation health and stress that are not fully represented by meteorological drought indices. All indices showed statistically significant correlations ($p < 0.05$), highlighting their robustness in depicting various dimensions of drought conditions in the Gwayi catchment.

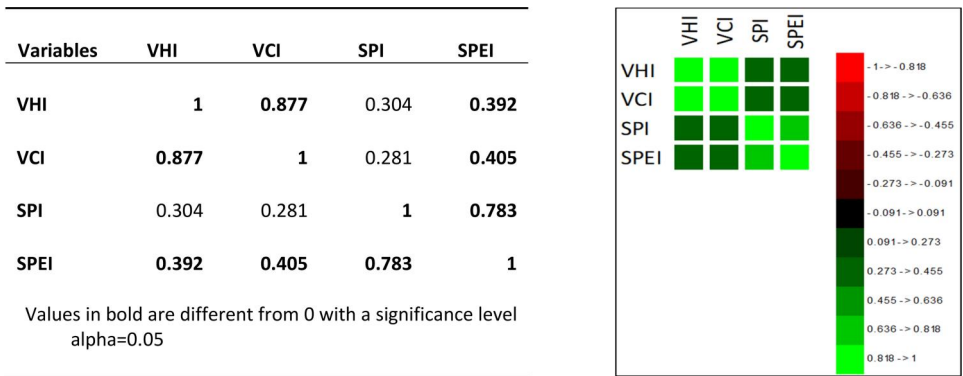


Figure 10. Correlation matrix for the VCI, VHI, SPI and SPEI.

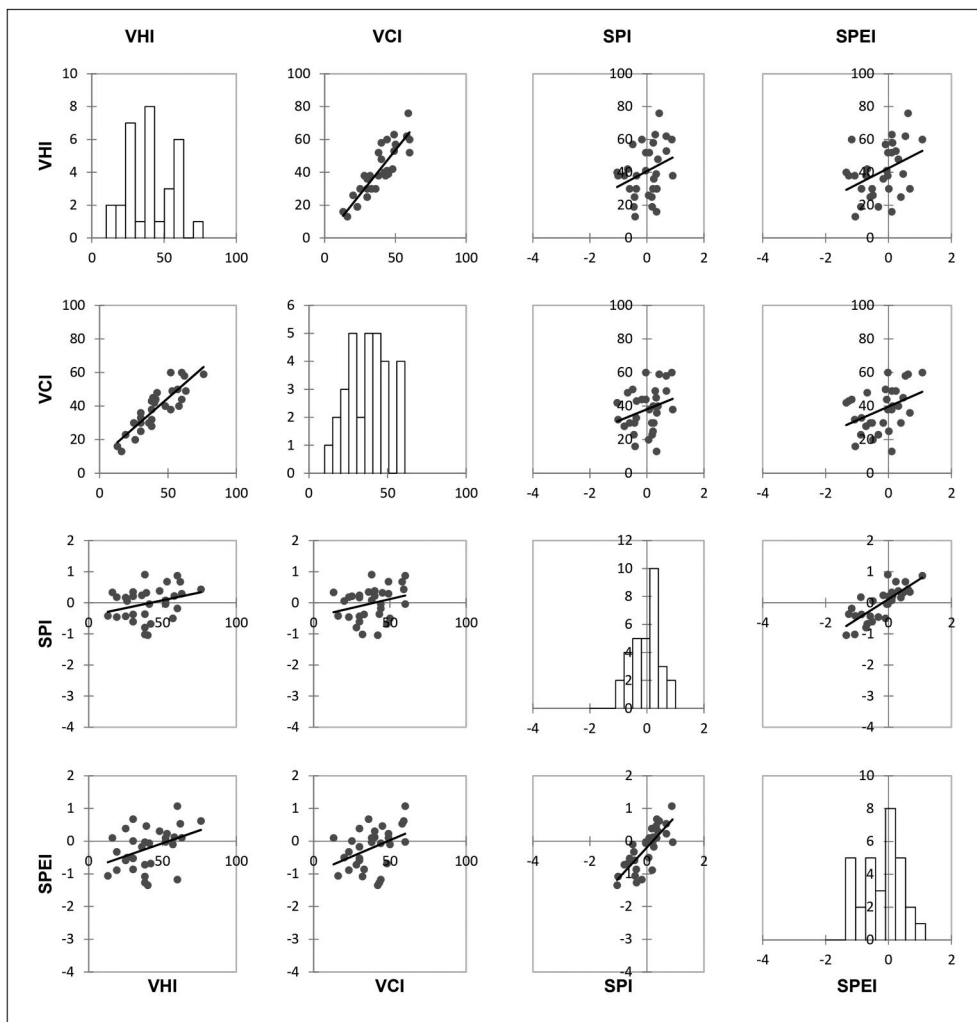


Figure 11. Correlation of averaged values for (VCI, VHI, SPI, SPEI, rainfall) in the catchment.

4. Discussion

4.1. Spatiotemporal dynamics of agrometeorological droughts

This study comprehensively analysed the spatiotemporal patterns of agrometeorological droughts in the Gwayi catchment, Zimbabwe, by employing VCI, VHI, SPI, and SPEI indices from 1990–2020. While the overall average drought indices did not exhibit significant long-term trends, the data revealed notable interannual variability. Severe droughts occurred in 1991, 1992, 1994, 1995, 2005, 2016, and 2017, contrasting with favourable (wet) conditions in 2000 and 2006. The severe droughts observed in 1991–1992 and 2016–2017 aligned with strong El Niño events, which disrupted normal rainfall patterns and exacerbated drought conditions in the region (Franchi et al. 2024). During El Niño events, the Gwayi catchment frequently experiences reduced rainfall, leading to increased drought frequency. Conversely, La Niña conditions often result in above-average rainfall, which can provide temporary relief from drought. The Indian Ocean Dipole (IOD) also plays a role, with its positive phase typically associated with drier conditions and its negative phase with wetter conditions (Ibebuchi and Lee 2024). These findings are consistent with studies conducted in other semi-arid regions of southern Africa, which also reported high interannual variability in drought conditions driven by complex interactions between regional climate patterns and global climate drivers such as ENSO and the Indian Ocean Dipole (IOD) (Byakatonda et al. 2018; Stojanovic et al. 2020); Oikonomou et al. 2020). Similar to this study, Frischen et al. (2020) highlighted the presence of isolated drought patterns with distinct spatial variations within Matabeleland North Province of Zimbabwe. The observed interannual variability in droughts can also be attributed to the inherent climatic characteristics of the region, which are characterized by pronounced seasonality in rainfall patterns (Muganda et al. 2021; Sinthumule and Mkumbuzi 2019). However, the absence of statistically significant long-term trends in average drought indices contrasts with findings of World Meteorological Organization (2022), who reported a growing concern about long-term increases in drought severity linked to climate change. This discrepancy highlights the complex nature of drought trends in semi-arid regions, where short-term fluctuations may mask long-term trends. Further research employing high-resolution climate models is instrumental in clarifying the relationship between short-term variability and long-term trends in drought occurrence in the Gwayi catchment.

Spatial analysis using multiple drought indices revealed important regional patterns in drought occurrence. The SPI indicated a northwesterly bias in drought occurrence, whereas the SPEI highlighted more dispersed drought severity across the catchment. The use of multiple indices underscores the importance of a multifaceted approach in capturing the complexity of drought dynamics, as different indices may respond differently to various drought conditions (Adnan and Ullah 2022; Baig et al. 2020). The SPI (Standardized Precipitation Index) and SPEI (Standardized Precipitation Evapotranspiration Index) are particularly effective in capturing meteorological droughts, with the SPI focusing solely on precipitation and the SPEI integrating both precipitation and potential evapotranspiration (Chisadza et al. 2023). However, the SPI may underrepresent drought severity in regions where temperature-induced

evapotranspiration plays a significant role, as observed in the Gwayi catchment. On the other hand, the VCI (vegetation condition index) and VHI (vegetation health index) provide valuable insights into the ecological impacts of droughts, particularly on vegetation health. While VCI is effective in assessing the greenness of vegetation, it may be less sensitive to droughts that affect biomass without significantly altering vegetation cover (Deepa et al. 2021). The VHI, which combines VCI and thermal conditions, offers a more comprehensive assessment but may be influenced by factors unrelated to drought, such as soil moisture or local microclimates. Furthermore, the catchment exhibited a clear spatial gradient in vegetation health, with a northeasterly bias towards greener conditions and more severe drought impacts in the southwestern region. This spatial variability is consistent with previous studies by Frischen et al. (2020), Mupepi and Matsa (2022), and Sharara et al. (2022), suggesting that local factors such as topography, land use practices, and soil type may play a significant role in influencing drought patterns within the catchment.

The analysis of individual stations provided further insights into localized drought trends. A significant negative trend in the SPEI-3 and SPI-3 was observed at Tsholotsho, emphasizing the need for localized assessments to capture the spatial heterogeneity of drought trends within catchments (Kchouk et al. 2022). These localized trends highlight the influence of both climatic factors, such as pronounced seasonality (Omotoso et al. 2023; Uwizewe et al. 2024), and nonclimatic factors, such as land use changes and topographical variations, on drought dynamics. These findings suggest the need for targeted, location-specific interventions to manage drought risk effectively.

4.2. Overall implications of observed agrometeorological drought patterns

The complex interplay of spatial and temporal drought dynamics in the Gwayi catchment underscores the need for comprehensive and context-specific adaptation strategies. The observed spatiotemporal patterns of drought in the Gwayi catchment have significant implications for agricultural productivity, food security, and water resource management (Ntali et al. 2023). The recurring occurrence of moderate droughts, punctuated by severe events, poses a significant threat to crop yields and agricultural productivity. The cumulative stress induced by these droughts can lead to reduced crop yields, exacerbating food insecurity, particularly among vulnerable populations. This is especially critical in regions where agriculture is a primary livelihood, such as in the Gwayi catchment. Moreover, the spatial variability in drought patterns, particularly the more severe impacts observed in the southwestern region, indicates that certain areas within the catchment are more vulnerable than others are. Targeted interventions in these high-risk areas could help mitigate the adverse effects of drought on agricultural productivity. Moreover, increased competition for water resources during droughts can intensify existing water scarcity challenges (Tanarhte et al. 2024). As demand for water increases for agricultural, domestic, and industrial purposes, potential conflicts over limited supplies escalate. This can hinder sustainable development and exacerbate social tensions. Furthermore, frequent droughts can contribute to land degradation, including soil erosion, desertification, and loss of

vegetation cover. This can have long-term consequences for agricultural productivity and ecosystem health (Niyonsenga et al. 2024). Once land is degraded, it becomes more susceptible to drought and other environmental hazards.

To address these challenges effectively, a multipronged approach is essential. Strengthening early warning systems (EWSs) by integrating meteorological, remote sensing, and hydrological data can improve the accuracy and lead time of alerts, allowing timely decision-making and the implementation of mitigation measures (Mohsin and Adnan 2023). Such systems should be tailored to the specific climatic and environmental conditions of the Gwayi catchment to ensure their effectiveness. Interventions must be spatially targeted, with a focus on the areas most affected by drought and prioritising drought-resistant crops, the development of irrigation infrastructure, and the establishment of social safety nets (Yan et al. 2024; Zhao et al. 2023). Additionally, diversifying livelihoods can reduce the vulnerability of communities to drought-related shocks, especially in the southwestern region, where drought impacts are more severe. Improved water resource management through efficient water use practices and investment in water storage infrastructure is essential to increase water availability during dry periods (Zamora-Pereira et al. 2023). Finally, incorporating climate change projections into long-term planning for the Gwayi catchment is crucial for enhancing the region's resilience to future droughts. Such projections can inform the development of adaptive strategies tailored to the unique climatic and environmental conditions of the catchment, ensuring that they are robust across various future climate scenarios. Moreover, understanding the socioeconomic dimensions of drought in the Gwayi catchment is essential, as the impacts are often disproportionately felt by vulnerable populations, including smallholder farmers, women, and elderly. These groups, heavily reliant on agriculture for their livelihoods, are particularly susceptible to the compounded effects of drought and land degradation. Targeted interventions, such as strengthening social safety nets, improving access to credit, and enhancing disaster risk reduction measures, are critical for building resilience among these communities. Therefore, comprehensive drought management strategies in the Gwayi catchment should address both the environmental and socioeconomic consequences of drought, ensuring that all affected groups are supported in adapting to the changing climate.

5. Conclusion

This study employed a multi-index approach to analyse VCI, VHI, SPI, and SPEI data from 1990 to 2020 to reveal the dynamic nature of agrometeorological droughts within the Gwayi catchment, Zimbabwe. While no significant long-term trends were observed, the dominance of mild droughts underscores a historical tendency towards drier conditions. The spatial heterogeneity in drought occurrence and severity, with the southwestern region being particularly vulnerable, highlights the need for spatially targeted drought management strategies. The strong correlation between the VHI and VCI indicates a significant overlap in their ability to capture vegetation health, whereas moderate correlations between the VCI/VHI and SPI/SPEI suggest that the VCI/VHI captures additional information beyond precipitation deficits, likely

reflecting the influence of factors such as temperature, soil moisture, and land cover. This emphasizes the value of using multiple drought indices for a comprehensive assessment. The prevalence of mild droughts suggests a need to revisit baseline thresholds to define and respond to droughts within the catchment. Integrating information from the SPI/SPEI (precipitation deficit) and VCI/vegetation health (VHI) provides a more comprehensive picture for developing robust drought management plans. To address the challenges posed by droughts effectively, a combination of early warning systems, sustainable land management practices, livelihood diversification, improved water infrastructure, and capacity building is essential. Prioritizing vulnerable populations and incorporating climate change projections into long-term planning are crucial for building resilience. Further research should focus on quantifying the economic impacts of droughts, evaluating the effectiveness of adaptation strategies, and exploring the potential of climate models in predicting future drought patterns. By adopting a holistic approach that considers both the physical and socioeconomic dimensions of drought, policymakers and practitioners can develop more effective and sustainable drought management strategies for the Gwayi catchment and similar regions.

Research involving human participants and/or animals

The authors reportedly did not involve human participants or animals in their research

Disclosure statement

No potential conflicts of interest were reported by the authors.

Funding

This research received funding from the ACALISE World Bank program.

Data availability statement

The materials and data that back the results in this paper can be accessed at no charge from Bright Chisadza, the lead author, upon request.

References

- Abatzoglou JT, Dobrowski SZ, Parks SA, Hegewisch KC. 2018. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Sci Data*. 5(1):170191. doi: [10.1038/sdata.2017.191](https://doi.org/10.1038/sdata.2017.191).
- Abebe TH. 2020. Teshome Hailemeskel Abebe. Time Series Analysis of Monthly Average Temperature and Rainfall Using Seasonal ARIMA Model (in Case of Ambo Area, Ethiopia). *IJTAM*. 6(5):76–87. doi: [10.11648/j.ijtam.20200605.13](https://doi.org/10.11648/j.ijtam.20200605.13).
- Adnan S, Ullah K. 2022. Long-term trends in climate parameters and multiple indices for drought monitoring over Pakistan. *Meteorol Atmos Phys*. 134(4):75. doi: [10.1007/s00703-022-00908-3](https://doi.org/10.1007/s00703-022-00908-3).

- Afshar MH, Bulut B, Duzenli E, Amjad M, Yilmaz MT. 2022. Global spatiotemporal consistency between meteorological and soil moisture drought indices. *Agric For Meteorol.* 316: 108848. doi: [10.1016/j.agrformet.2022.108848](https://doi.org/10.1016/j.agrformet.2022.108848).
- Aksoy S, Sertel E. 2022. Comparison of Landsat and MODIS derived vegetation health indices for drought monitoring using Google Earth Engine platform. *International Symposium on Applied Geoinformatics 2021*. doi: [10.15659/isag2021.12604](https://doi.org/10.15659/isag2021.12604).
- Alsenjar O, Aksu H, Cetin M. 2022. The use of some specific drought indices to evaluate meteorological drought events in the Black Sea Region of Turkey. *Çukurova Tarım Gıda Bil. Der. Çukurova J Agric Food Sci.* 37(2):261–272. doi: [10.36846/CJAFS.2022.93](https://doi.org/10.36846/CJAFS.2022.93).
- Amjad M, Khan A, Fatima K, Ajaz O, Ali S, Main K. 2022. Analysis of temperature variability, trends and prediction in the Karachi Region of Pakistan using ARIMA models. *Atmosphere.* 14(1):88. doi: [10.3390/atmos14010088](https://doi.org/10.3390/atmos14010088).
- Andualet TG, Hewa GA, Boland J, Peters S, Myers BR. 2024. Multi-method comparative analysis of hydroclimatic trends and variability in Dry Creek Catchment, South Australia. *Earth Syst Environ.* 1–26. doi: [10.1007/s41748-024-00401-4](https://doi.org/10.1007/s41748-024-00401-4).
- Baig MHA, Abid M, Khan MR, Jiao W, Amin M, Adnan S. 2020. Assessing meteorological and agricultural drought in Chitral Kabul River Basin using multiple drought indices. *Remote Sensing.* 12(9):1417. doi: [10.3390/rs12091417](https://doi.org/10.3390/rs12091417).
- Bamweyana I, Kayondo LM. 2018. Spatially explicit modelling of extreme weather and climate events hot spots for cumulative climate change in Uganda. *SA J of Geomatics.* 7(1):90. doi: [10.4314/sajg.v7i1.7](https://doi.org/10.4314/sajg.v7i1.7).
- Berman JD, Abadi AM, Bell JE. 2024. Existing challenges and opportunities for advancing drought and health research. *Curr Environ Health Rep.* 11(2):255–265. doi: [10.1007/s40572-024-00440-z](https://doi.org/10.1007/s40572-024-00440-z).
- Bogale GA, Erena ZB. 2022. Drought vulnerability and impacts of climate change on livestock production and productivity in different agro-Ecological zones of Ethiopia. *Journal of Applied Animal Research.* 50(1):471–489. doi: [10.1080/09712119.2022.2103563](https://doi.org/10.1080/09712119.2022.2103563).
- Byakatonda J, Parida BP, Moalafhi DB, Kenabatho PK. 2018. Analysis of long term drought severity characteristics and trends across semiarid Botswana using two drought indices. *Atmos Res.* 213:492–508. doi: [10.1016/j.atmosres.2018.07.002](https://doi.org/10.1016/j.atmosres.2018.07.002).
- Chatterjee RS, Singh N, Thapa S, Sharma D, Kumar D. 2017. Retrieval of land surface temperature (LST) from landsat TM6 and TIRS data by single channel radiative transfer algorithm using satellite and ground-based inputs. *Int J Appl Earth Obs Geoinf.* 58:264–277. doi: [10.1016/j.jag.2017.02.017](https://doi.org/10.1016/j.jag.2017.02.017).
- Chingarande D, Mugano G, Chagwiza G, Hungwe M. 2020. *Zimbabwe Market Study: manicaland Province Report*. https://pdf.usaid.gov/pdf_docs/PA00WC2H.pdf.
- Chisadza B, Gwate O, Ncube F, Mpofu N. 2023. Assessment and characterisation of hydrometeorological droughts in the Upper Mzingwane sub-catchment of Zimbabwe. *Nat Hazards.* 116(3):3275–3299. doi: [10.1007/s11069-022-05807-9](https://doi.org/10.1007/s11069-022-05807-9).
- Chughtai AH, Abbasi H, Karas IR. 2021. A review on change detection method and accuracy assessment for land use land cover. *Remote Sens Appl Soc Environ.* 22:100482. doi: [10.1016/j.rsase.2021.100482](https://doi.org/10.1016/j.rsase.2021.100482).
- Dabaro D, Birhanu Z, Negash A, Hawaria D, Yewhalaw D. 2021. Effects of rainfall, temperature and topography on malaria incidence in elimination targeted district of Ethiopia. *Malar J.* 20(1):104. doi: [10.1186/s12936-021-03641-1](https://doi.org/10.1186/s12936-021-03641-1).
- Deepa B, Kamble, Shweta Gautam, Himani Bisht, Shraddha Rawat, & Arnab Kundu. (2021). Drought assessment for kharif rice using standardized precipitation index (SPI) and vegetation condition index (VCI). *J Agrometeorol* 21(2), 182–187. doi: [10.54386/jam.v21i2.230](https://doi.org/10.54386/jam.v21i2.230).
- Dejene T, Dalle G, Woldeamanuel T, Mekuyie M. 2023. Temporal climate conditions and spatial drought patterns across rangelands in pastoral areas of West Guji and Borana zones, Southern Ethiopia. *Pastoralism.* 13(1):18. doi: [10.1186/s13570-023-00278-4](https://doi.org/10.1186/s13570-023-00278-4).
- Deng H, Tang Q, Yun X, Tang Y, Liu X, Xu X, Sun S, Zhao G, Zhang Y, Zhang Y. 2022. Wetting trend in Northwest China reversed by warmer temperature and drier air. *J Hydrol.* 613:128435. doi: [10.1016/j.jhydrol.2022.128435](https://doi.org/10.1016/j.jhydrol.2022.128435).

- Ezzahra FF, Ahmed A, Abdellah A. 2023. Variance-based fusion of VCI and TCI for efficient classification of agriculture drought using landsat data in the High Atlas (Morocco, North Africa). *Nat Env Poll Tech.* 22(3):1421–1429. doi: [10.46488/NEPT.2023.v22i03.028](https://doi.org/10.46488/NEPT.2023.v22i03.028).
- Faye C. 2022. Comparative analysis of meteorological drought based on the SPI and SPEI indices. *HighTech Innov J.* 3:15–27. doi: [10.28991/HIJ-SP2022-03-02](https://doi.org/10.28991/HIJ-SP2022-03-02).
- Franchi F, Mustafa S, Ariztegui D, Chirindja FJ, Di Capua A, Hussey S, Loizeau J-L, Maselli V, Matanó A, Olabode O, et al. 2024. Prolonged drought periods over the last four decades increase flood intensity in southern Africa. *Sci Total Environ.* 924:171489. doi: [10.1016/j.scitotenv.2024.171489](https://doi.org/10.1016/j.scitotenv.2024.171489).
- Frischen J, Meza I, Rupp D, Wietler K, Hagenlocher M. 2020. Drought risk to agricultural systems in Zimbabwe: a spatial analysis of hazard, exposure, and vulnerability. *Sustainability.* 12(3):752. doi: [10.3390/su12030752](https://doi.org/10.3390/su12030752).
- Gaddikeri V, Sarangi A, Singh DK, Jatav MS, Rajput J, Kushwaha NL. 2024. Trend and change-point analyses of meteorological variables using Mann–Kendall family tests and innovative trend assessment techniques in New Bhubania command (India). *Journal of Water and Climate Change.* 15(5):2033–2058. doi: [10.2166/wcc.2024.462](https://doi.org/10.2166/wcc.2024.462).
- García-Santos V, Cuxart J, Martínez-Villagrasa D, Jiménez M, Simó G. 2018. Comparison of three methods for estimating land surface temperature from Landsat 8-TIRS sensor data. *Remote Sensing.* 10(9):1450. doi: [10.3390/rs10091450](https://doi.org/10.3390/rs10091450).
- Gebremichael HB, Raba GA, Beketie KT, Feyisa GL. 2022. Temporal and spatial characteristics of drought, future changes and possible drivers over Upper Awash Basin, Ethiopia, using SPI and SPEI. *Environ Dev Sustain.* 26(1):947–985. doi: [10.1007/s10668-022-02743-3](https://doi.org/10.1007/s10668-022-02743-3).
- Gidey E, Dikinya O, Sebege R, Segosebe E, Zenebe A. 2018. Analysis of the long-term agricultural drought onset, cessation, duration, frequency, severity and spatial extent using Vegetation Health Index (VHI) in Raya and its environs, Northern Ethiopia. *Environ Syst Res.* 7(1):13. doi: [10.1186/s40068-018-0115-z](https://doi.org/10.1186/s40068-018-0115-z).
- Government of Zimbabwe. 2022. *Zimbabwe Vulnerability Assessment Committee (ZimVAC) 2022 Rural Livelihoods Assessment Report*. www.fnc.org.zw.
- Grey MS. 2019. Accessing seasonal weather forecasts and drought prediction information for rural households in Chirumhanzu district, Zimbabwe. *Jamba.* 11(1):777. doi: [10.4102/jamba.v11i1.777](https://doi.org/10.4102/jamba.v11i1.777).
- Hall O, Wahab I, Dahlin S, Hillbur P, Jirström M, Öborn I. 2024. A decade of maize yield gap studies in sub-Saharan Africa: how are farm-level factors considered? *Int J Agri Sustain.* 22(1):2293591 doi: [10.1080/14735903.2023.2293591](https://doi.org/10.1080/14735903.2023.2293591).
- Hasan NA, Al-Shibli F, Basin-Jordan AZ, Scholar G. 2023. SPI and SPEI drought assessment and prediction using TBATS and ARIMA models: observations versus CSIC & CMIP6-ssp126 projections. doi: [10.20944/preprints202308.2010.v1](https://doi.org/10.20944/preprints202308.2010.v1).
- Hosseinizadeh A, SeyedKaboli H, Zareie H, Akhondali A, Farjad B. 2015. Impact of climate change on the severity, duration, and frequency of drought in a semi-arid agricultural basin. *Geoenviron Disasters.* 2(1):23. doi: [10.1186/s40677-015-0031-8](https://doi.org/10.1186/s40677-015-0031-8).
- Ibebuchu CC, Lee CC. 2024. Circulation pattern controls of summer temperature anomalies in Southern Africa. *Adv Atmos Sci.* 41(2):341–354. doi: [10.1007/s00376-023-2392-3](https://doi.org/10.1007/s00376-023-2392-3).
- Jalayer S, Sharifi A, Abbasi-Moghadam D, Tariq A, Qin S. 2023. Assessment of spatiotemporal characteristic of droughts using in situ and remote sensing-based drought indices. *IEEE J Sel Top Appl Earth Observations Remote Sens.* 16:1483–1502. doi: [10.1109/JSTARS.2023.3237380](https://doi.org/10.1109/JSTARS.2023.3237380).
- Katipoğlu OM. 2023. Prediction of streamflow drought index for short-term hydrological drought in the semi-Arid Yesilirmak Basin using wavelet transform and artificial intelligence techniques. *Sustainability.* 15(2):1109. doi: [10.3390/su15021109](https://doi.org/10.3390/su15021109).
- 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 Hazards Earth Syst Sci.* 22(2):323–344. doi: [10.5194/nhess-22-323-2022](https://doi.org/10.5194/nhess-22-323-2022).

- Li K, Wang C, Rong G, Wei S, Liu C, Yang Y, Sudu B, Guo Y, Sun Q, Zhang J. 2022. Dynamic evaluation of agricultural drought hazard in Northeast China based on coupled multi-source data. *Remote Sens.* 15(1):57. doi: [10.3390/rs15010057](https://doi.org/10.3390/rs15010057).
- Liou Y-A, Nguyen AK, Li M-H. 2017. Assessing spatiotemporal eco-environmental vulnerability by Landsat data. *Ecol Indic.* 80:52–65. doi: [10.18574/nyu/9780814725498.003.0008](https://doi.org/10.18574/nyu/9780814725498.003.0008).
- Liu G, Wang J, Li S, Li J, Duan P. 2019. Dynamic evaluation of ecological vulnerability in a lake watershed based on RS and GIS technology. *Pol J Environ Stud.* 28(3):1785–1798. doi: [10.15244/pjoes/89981](https://doi.org/10.15244/pjoes/89981).
- Madamombe SM, Ng'ang'a SK, Öborn I, Nyamadzawo G, Chirinda N, Kihara J, Nkurunziza L. 2024. Climate change awareness and adaptation strategies by smallholder farmers in semi-arid areas of Zimbabwe. *Int J Agri Sustain.* 22(1):2293588 doi: [10.1080/14735903.2023.2293588](https://doi.org/10.1080/14735903.2023.2293588).
- Mafongoya P, Musokwa M, Mwadzingeni L, Phophi MM. 2022. Climate change impacts on food and nutrition security on smallholder farmers in Southern Africa. In *Food Security for African Smallholder Farmers* (p. 233–249). Singapore: Springer. doi: [10.1007/978-981-16-6771-8_14](https://doi.org/10.1007/978-981-16-6771-8_14).
- Manatsa D, Mushore TD, Gwitira I, Wuta M, Chemura A, Shekede MD, Mugandani R, Sakala LC, Ali LH, Mupuro J. 2020. Revision of Zimbabwe's agro-ecological zones. Produced by the Government of Zimbabwe under Zimbabwe National Geospatial and Space Agency (ZINGSA) for the Ministry of Higher and Tertiary Education, Innovation, In Science and Technology Development. Zimbabwe Government Printers.
- Manjowe M, Mushore T, Matandirotya E, Mashonjowa E. 2020. Characterisation of wet and dry summer seasons and their spatial modes of variability over Zimbabwe. *S Afr J Sci.* 116(7/8):1–7. doi: [10.17159/sajs.2020/6517](https://doi.org/10.17159/sajs.2020/6517).
- Mardani R, Montaseri H, Fazeli M, Khalili R, Esmaeili H. 2022. Spatio-temporal variation of meteorological drought and its relation with temperature and vegetation condition indices using remote sensing and satellite imagery in Marvdasht city. *Water and Soil Management and Modelling.* 3(3):72–89. doi: [10.22098/mmws.2022.11541.1140](https://doi.org/10.22098/mmws.2022.11541.1140).
- Marsick A, André H, Khelf I, Leclère Q, Antoni J. 2024. Benefits of Mann–Kendall trend analysis for vibration-based condition monitoring. *Mech Syst Sig Process.* 216:111486. doi: [10.1016/j.ymssp.2024.111486](https://doi.org/10.1016/j.ymssp.2024.111486).
- McKee TB, Doesken NJ, Kleist J. 1993. The relationship of drought frequency and duration to time scales. *Eighth Conference on Applied Climatology*, 179–184. https://climate.colostate.edu/pdfs/relationshipofdroughtfrequency.pdf%0Ahttps://www.droughtmanagement.info/literature/AMS_Relationship_Drought_Frequency_Duration_Time_Scales_1993.pdf.
- Measho S, Chen B, Trisurat Y, Pellikka P, Guo L, Arunyawat S, Tuankrwa V, Ogbazghi W, Yemane T. 2019. Spatio-temporal analysis of vegetation dynamics as a response to climate variability and drought patterns in the Semiarid Region, Eritrea. *Remote Sens.* 11(6):724. doi: [10.3390/rs11060724](https://doi.org/10.3390/rs11060724).
- Mohsin M, Adnan S. 2023. Probabilistic modelling of interarrival time of drought for different operational drought indices used in Pakistan. *Intl J Climatol.* 43(14):6851–6865. doi: [10.1002/joc.8239](https://doi.org/10.1002/joc.8239).
- Muganda CA, Stanley S, Onsongo W. 2021. Modeling effects of climatic variables on tea production in Kenya using linear regression model with serially correlated errors. *AJPAS.* 13(2): 56–75. doi: [10.9734/ajpas/2021/v13i230306](https://doi.org/10.9734/ajpas/2021/v13i230306).
- Mupepi O, Matsa MM. 2022. Spatio-temporal dynamics of drought in Zimbabwe between 1990 and 2020: a review. *Spat Inf Res.* 30(1):117–130. doi: [10.1007/s41324-021-00417-2](https://doi.org/10.1007/s41324-021-00417-2).
- Mutowo G, Chikodzi D. 2014. Remote sensing based drought monitoring in Zimbabwe. *Disaster Prevention and Management.* 23(5):649–659. doi: [10.1108/DPM-10-2013-0181](https://doi.org/10.1108/DPM-10-2013-0181).
- Natarajan N, Vasudevan M, Ahash Raja S, Mohanpradaap K, Sneha G, Joshna Shanu S. 2023. An assessment methodology for drought severity and vulnerability using precipitation-based indices for the arid, semi-arid and humid districts of Tamil Nadu, India. *Water Supply.* 23(1):54–79. doi: [10.2166/ws.2022.415](https://doi.org/10.2166/ws.2022.415).

- Niyonsenga S, Eziz A, Kurban A, Yuan X, Umwali ED, Azadi H, Hakorimana E, Umugwaneza A, Fidelis GD, Nsanzabaganwa J, et al. 2024. Spatiotemporal analysis of drought characteristics and their impact on vegetation and crop production in Rwanda. *Remote Sensing*. 16(8): 1455. doi: [10.3390/rs16081455](https://doi.org/10.3390/rs16081455).
- Ntali YM, Lyimo JG, Dakyaga F. 2023. Trends, impacts, and local responses to drought stress in Diamare Division, Northern Cameroon. *World Development Sustainability*. 2:100040. doi: [10.1016/j.wds.2022.100040](https://doi.org/10.1016/j.wds.2022.100040).
- Ofori SA, Cobbina SJ, Obiri S. 2021. Climate change, land, water, and food security: perspectives from Sub-Saharan Africa. *Front Sustain Food Syst*. 5:1–9. doi: [10.3389/fsufs.2021.680924](https://doi.org/10.3389/fsufs.2021.680924).
- Oikonomou PD, Karavitis CA, Tsesselis DE, Kolokytha E, Maia R. 2020. Drought characteristics assessment in Europe over the Past 50 Years. *Water Resour Manage*. 34(15):4757–4772. doi: [10.1007/s11269-020-02688-0](https://doi.org/10.1007/s11269-020-02688-0).
- 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. doi: [10.1016/j.sciaf.2020.e00275](https://doi.org/10.1016/j.sciaf.2020.e00275).
- Omotoso AB, Letsoalo S, Olagunju KO, Tshwene CS, Omotayo AO. 2023. Climate change and variability in sub-Saharan Africa: a systematic review of trends and impacts on agriculture. *J Cleaner Prod*. 414:137487. doi: [10.1016/j.jclepro.2023.137487](https://doi.org/10.1016/j.jclepro.2023.137487).
- Patil AS, Patil AA, Patil SP, Saundade SD, Chugule KA, Katavare SB, Panhalkar SS. 2021. Analysis of the agriculture drought severity and spatialextent using Vegetation Health Index (VHI) in Mangangawatershed of Maharashtra, India. *Disaster Advances*. 14(2):36–47.
- Qaiser G, Tariq S, Adnan S, Latif M. 2021. Evaluation of a composite drought index to identify seasonal drought and its associated atmospheric dynamics in Northern Punjab, Pakistan. *J Arid Environ*. 185:104332. doi: [10.1016/j.jaridenv.2020.104332](https://doi.org/10.1016/j.jaridenv.2020.104332).
- Saini D, Singh O. 2024. Comparison of meteorological, hydrological and agricultural droughts for developing a composite drought index over semi-arid Banas River Basin of India. *Stoch Environ Res Risk Assess*. 38(7):2671–2691. doi: [10.1007/s00477-024-02704-4](https://doi.org/10.1007/s00477-024-02704-4).
- Salehan HSM, Bahari NE, Zulcafli AS. 2024. Statistical comparison of SPEI–1 month and SPEI–3 month: enhancing consistency in drought assessment. *AIP Conference Proceedings*, 3189(1), 100006. doi: [10.1063/5.0224693](https://doi.org/10.1063/5.0224693).
- Schwarz M, Landmann T, Cornish N, Wetzell K-F, Siebert S, Franke J. 2020. A spatially transferable drought hazard and drought risk modeling approach based on remote sensing data. *Remote Sensing*. 12(2):237. doi: [10.3390/rs12020237](https://doi.org/10.3390/rs12020237).
- Sharafi S, Ghaleini MM, Sadeghi S. 2022. Spatial and temporal analysis of drought in various climates across Iran using the Standardized Precipitation Index (SPI). *Arab J Geosci*. 15(14): 1279. doi: [10.1007/s12517-022-10489-5](https://doi.org/10.1007/s12517-022-10489-5).
- Sharara A, Shekede MD, Gwitira I, Masocha M, Dube T. 2022. Fine-scale multi-temporal and spatial analysis of agricultural drought in agro-ecological regions of Zimbabwe. *Geomatics Nat Hazards Risk*. 13(1):1342–1365. doi: [10.1080/19475705.2022.2072774](https://doi.org/10.1080/19475705.2022.2072774).
- Sinthumule NI, Mkumbuzi SH. 2019. Participation in community-based solid waste management in Nkulumane Suburb, Bulawayo, Zimbabwe. *Resources*. 8(1):30. doi: [10.3390/resources8010030](https://doi.org/10.3390/resources8010030).
- Solaimani K, Bararkhanpour Ahmadi S. 2024. Evaluation of TerraClimate gridded data in investigating the changes of reference evapotranspiration in different climates of Iran. *J Hydrol Reg Stud*. 52:101678. doi: [10.1016/j.ejrh.2024.101678](https://doi.org/10.1016/j.ejrh.2024.101678).
- Stojanovic M, Liberato MLR, Sorí R, Vázquez M, Phan-Van T, Duongvan H, Hoang Cong T, Nguyen PNB, Nieto R, Gimeno L. 2020. Trends and extremes of drought episodes in Vietnam sub-regions during 1980–2017 at different timescales. *Water*. 12(3):813. doi: [10.3390/w12030813](https://doi.org/10.3390/w12030813).
- Tanarhte M, De Vries AJ, Zittis G, Chfadi T. 2024. Severe droughts in North Africa: a review of drivers, impacts and management. *Earth Sci Rev*. 250:104701. doi: [10.1016/j.earscirev.2024.104701](https://doi.org/10.1016/j.earscirev.2024.104701).

- Tirivarambo S. 2012. Climate Variability and Climate Change in Water Resources Management of the Zambezi River Basin. Rhodes University; Faculty of Science, Institute for Water Research.
- Uddin MJ, Hu J, Islam ARMT, Eibek KU, Nasrin ZM. 2020. A comprehensive statistical assessment of drought indices to monitor drought status in Bangladesh. *Arab J Geosci.* 13(9):323. doi: [10.1007/s12517-020-05302-0](https://doi.org/10.1007/s12517-020-05302-0).
- Uwizewe C, Jianping L, Habumugisha T, Bello AA. 2024. Investigation of the historical trends and variability of rainfall patterns during the March–May Season in Rwanda. *Atmosphere.* 15(5):609. doi: [10.3390/atmos15050609](https://doi.org/10.3390/atmos15050609).
- Viceisza A, Aflagah K, Abner J, Hippolyte K. 2020. Poverty and malnutrition in Zimbabwe: findings from Masvingo Province. https://pdf.usaid.gov/pdf_docs/PA00WC2R.pdf.
- Vishwakarma A, Choudhary MK, Chauhan MS. 2020. Applicability of SPI and RDI for forthcoming drought events: a non-parametric trend and one way ANOVA approach. *J Water Clim Change.* 11(S1):18–28. doi: [10.2166/wcc.2020.042](https://doi.org/10.2166/wcc.2020.042).
- Wambura FJ. 2023. Investigating the influences of climate change on drought in a small data-scarce river catchment. *J Water Clim Change.* 14(9):3293–3312. doi: [10.2166/wcc.2023.291](https://doi.org/10.2166/wcc.2023.291).
- Wang P, Wu X, Hao Y, Wu C, Zhang J. 2020. Is Southwest China drying or wetting? Spatiotemporal patterns and potential causes. *Theor Appl Climatol.* 139(1-2):1–15. doi: [10.1007/s00704-019-02935-4](https://doi.org/10.1007/s00704-019-02935-4).
- World Meteorological Organization. 2022. WMO provisional report on the state of the global climate 2020. Geneva: World Meteorological Organisation.
- Yan Z, Zhang W, Liu X, Wang Q, Liu B, Mei X. 2024. Grain yield and water productivity of winter wheat controlled by irrigation regime and manure substitution in the North China Plain. *Agric Water Manage.* 295:108731. doi: [10.1016/j.agwat.2024.108731](https://doi.org/10.1016/j.agwat.2024.108731).
- Zamora-Pereira JC, Hanewinkel M, Yousefpour R. 2023. Robust management strategies promoting ecological resilience and economic efficiency of a mixed conifer-broadleaf forest in Southwest Germany under the risk of severe drought. *Ecol Econ.* 209:107825. doi: [10.1016/j.ecolecon.2023.107825](https://doi.org/10.1016/j.ecolecon.2023.107825).
- Zeng J, Zhang R, Qu Y, Bento VA, Zhou T, Lin Y, Wu X, Qi J, Shui W, Wang Q. 2022. Improving the drought monitoring capability of VHI at the global scale via ensemble indices for various vegetation types from 2001 to 2018. *Weather Clim Extremes.* 35:100412. doi: [10.1016/j.wace.2022.100412](https://doi.org/10.1016/j.wace.2022.100412).
- Zhao K, Huang M, Li Y, Wu J, Tian W, Li J, Hou Y, Wu S, Zhang J, Zhang Z, et al. 2023. Combined organic fertilizer and straw return enhanced summer maize productivity and optimized soil nitrate–N distribution in rainfed summer maize–winter wheat rotation on the Southeast Loess Plateau. *J Soil Sci Plant Nutr.* 23(1):938–952. doi: [10.1007/s42729-022-01094-2](https://doi.org/10.1007/s42729-022-01094-2).