Discover Sustainability

RESEARCH

Open Access

Spatiotemporal variability of meteorological droughts and pasture resilience in Somalia using SPEI and resilience metrics

Jaabir Hussein[1,2*], Eskinder Gidey[3,4], Franco Bilotto[5,6], Dmaris Mbui[1] and Jason Sircely[2]

*Correspondence:
Jaabir Hussein
jiibka@yahoo.com
[1]Earth and Climate Science, Faculty of Science and Technology, University of Nairobi, Nairobi, Kenya
[2]CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), 22 International Livestock Research Institute, P.O. Box 30709, Nairobi 00100, Kenya
[3]School of Geography, Archaeology and Environmental Studies, Faculty of Science, University of Witwatersrand, Private Bag 2050, Johannesburg, Gauteng, South Africa
[4]Department of Land Resources Management and Environmental Protection (LaRMEP), College of Dryland Agriculture and Natural Resources, Mekelle University, P.O Box 231, Mekelle, Tigray, Ethiopia
[5]Tasmanian Institute of Agriculture, University of Tasmania, Newnham, Launceston, TAS 7248, Australia
[6]Department of Global Development, College of Agriculture and Life Science, Cornell University, Ithaca, NY 14853, USA

Abstract
Somalia's arid and semi-arid climate makes it highly vulnerable to drought, posing serious challenges to water resource management and agricultural productivity. This study investigates pasture resilience and the spatiotemporal variability of meteorological drought in northwestern Somalia, focusing on spring and autumn rainy seasons. The Standardized Precipitation Evapotranspiration Index (SPEI) was used to assess drought frequency, severity, and intensity from 1981 to 2020, while the sequential Mann–Kendall test detected significant temporal shifts. A resilience matrix was applied to quantify drought resistance and recovery capacity in pasturelands. Our analysis shows a significant increase in drought severity over the last four decades, with extreme and severe droughts occurring more frequently, particularly in the spring season. The decade from 2001 to 2010 recorded the highest occurrence of extreme droughts. Eastern Somaliland experienced more frequent and intense droughts than western areas, with a sharp decline in annual SPEI (− 1.08) and a notable shift in 2002. Although moderate droughts were common, it is the rise in extreme droughts that poses the greatest risk to livelihoods and ecosystems. These findings underscore the urgent need for region-specific drought mitigation strategies, especially during the primary growing seasons in eastern Somaliland.

Highlights
Moderate droughts were more prevalent than other classes across research sites and seasons (65–80%).
The study found a considerable rise in meteorological drought frequency, severity, and intensity during the wet seasons.
From 1981 to 2020, droughts increased in both seasons across three research sites, with coefficients of variation ranging from − 0.016 to − 0.0.

Keywords Meteorological drought, SPEI, Resilience, Biomass production, Resilience matrix, Somalia

1 Introduction

Climate change has emerged as a defining global challenge, with far-reaching implications across ecological, social, and economic systems. The intensification of extreme weather events—such as heatwaves, floods, storms, and droughts—threatens livelihoods, food security, and sustainable development. Among these events, drought remains particularly insidious due to its gradual onset, extensive spatial coverage, and long-lasting effects. Unlike other rapid-impact disasters, droughts unfold slowly over time, making them difficult to detect early and respond to promptly [4, 17, 32]. Their impacts are multi-dimensional, influencing hydrology, agriculture, biodiversity, and human well-being. Although droughts are naturally occurring phenomena, their frequency, severity, and spatial extent are increasingly shaped by anthropogenic climate change and land-use modifications. Warming temperatures accelerate evapotranspiration, alter precipitation patterns, and intensify dry spells, especially in semi-arid and arid regions. Drylands—which encompass approximately 41% of the Earth's land surface—are particularly vulnerable to the effects of prolonged water deficits. These regions are home to over two billion people who depend heavily on climate-sensitive sectors such as agriculture and livestock production [48]. As global temperatures continue to rise, drought risk is projected to increase in both magnitude and duration, exacerbating environmental degradation and social vulnerability.

East Africa is one of the regions most affected by recurrent and intensifying drought events. Countries in the Horn of Africa, such as Somalia, Ethiopia, and Kenya, have experienced a rise in both the frequency and intensity of droughts over the past several decades [5, 14, 58]. Somalia, in particular, remains acutely vulnerable due to its strong reliance on rain-fed agriculture and spastoralism, limited infrastructure, and prolonged political instability. The country's natural and human systems are deeply intertwined with seasonal rainfall patterns, which have become increasingly erratic in recent decades. Somalia's drought history highlights the magnitude of the problem. The 2010–2012 drought, followed by severe events in 2016–2017 and the more recent 2020–2023 multi-season drought, have resulted in large-scale crop failure, massive livestock losses, and widespread displacement [24, 25]. These events collectively displaced over a million people, worsened acute malnutrition, and pushed millions toward food insecurity. They underscore not only the immediate humanitarian toll of droughts but also the long-term developmental setbacks and resilience gaps facing Somalia and the broader East African region. Within the Somali context, pastoral systems are the backbone of rural livelihoods, especially in dryland and semi-arid areas [62]. These systems depend on the availability and condition of rangelands for grazing. Drought disrupts this delicate balance by reducing pasture biomass, depleting water sources, and increasing livestock mortality. With climate shocks expected to grow more frequent, building resilience within these systems is both a local necessity and a policy imperative [13, 15]. Understanding how these systems respond to drought events—particularly in terms of vegetation productivity—is critical for informing sustainable rangeland management, early warning systems, and drought preparedness planning. In this regard, historical analyses of drought characteristics, such as frequency, intensity, and duration, can provide essential insights. These attributes reveal how often and how severely dry conditions have affected the landscape, and help identify periods of ecological stress. Moreover, assessing vegetation responses over time allows researchers and policymakers to gauge ecosystem sensitivity and capacity for recovery. This is particularly relevant for dryland regions where climatic variability is the norm, and where even slight shifts in precipitation can trigger cascading impacts on productivity and food systems [24, 25].

The concept of resilience plays a central role in drought impact studies. Resilience, in ecological terms, refers to the ability of a system to absorb disturbances and reorganize while undergoing change, so as to retain essentially the same function, structure, and feedbacks [18]. In the context of pastoral systems, resilience has two primary components: resistance and recovery. Resistance refers to the system's ability to maintain productivity during a drought, while recovery reflects the speed and extent to which it can bounce back once the drought has passed [33]. Together, these metrics help quantify the stability of rangeland ecosystems and their capacity to support livelihoods in the face of recurring climatic stress [28, 61].

Despite the increasing relevance of drought resilience research, studies that integrate both meteorological drought indices and ecological outcomes—particularly in data-scarce regions such as Somalia—remain limited. This study seeks to bridge that gap by analyzing historical drought events and corresponding vegetation responses in northwestern Somalia. Specifically, we assess meteorological drought trends between 1981 and 2020 using the Standardized Precipitation Evapotranspiration Index (SPEI) at multiple time scales, including seasonal and annual levels. Concurrently, we evaluate vegetation productivity using remote sensing-derived indicators to detect changes in pasture biomass over time. By coupling drought metrics with ecological responses, we aim to capture a more holistic picture of how dryland ecosystems behave under stress. Furthermore, we identify patterns of resistance and recovery across different drought events to characterize the stability of the pasture system. This approach not only contributes to the scientific understanding of dryland resilience but also provides actionable information for local stakeholders. It allows the development of targeted strategies that reinforce the adaptive capacity of pastoral communities, including interventions in grazing practices, land-use planning, and early warning dissemination.

Overall, this study aims to provide a comprehensive assessment of drought dynamics and pasture system resilience in northwestern Somalia. Through an integrated analysis of historical drought characteristics and ecological responses, we generate insights that are both academically rigorous and practically relevant. The findings have the potential to inform decision-makers, donors, and local communities working to mitigate drought impacts and build long-term resilience in dryland pastoral systems.

2 Methods

2.1 Study area

The current study was conducted in Somaliland, the northwestern part of Somalia, which lies between 9.987° E (latitude) and 45.299° N (longitude) in the far east of Eastern Africa. Three stations: Beer (9.9367° N, 45.749° E), Wajaale (9.603° N, 43.341° E), and Odwayne (9.350° N, 44.966° E) were selected for the present study and distributed across Somaliland (Fig. 1). The selection of these sites was based on two primary factors: firstly, they are the main areas for fodder production and livestock transport routes in Somalia, and secondly, these areas are geographically diverse, allowing them to serve as representative samples of the entire Somaliland region in terms of climatic conditions. Farmers in the area are agro-pastoralists who heavily rely on livestock and commercial

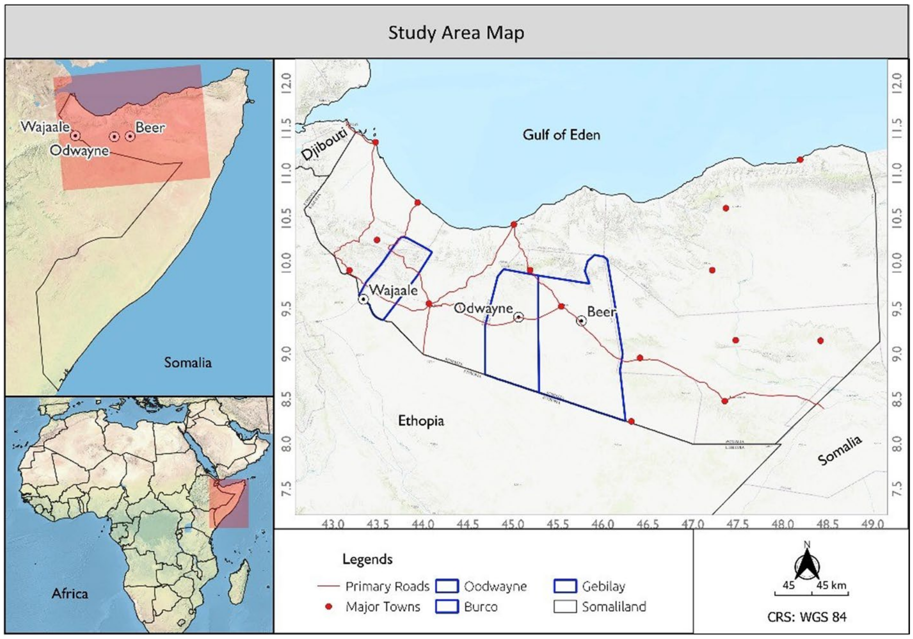

Fig. 1 Map of the geographical location including the three study stations (Beer, Wajaale, and Odwayne)

Table 1 Characteristics of meteorological stations within the study area

No	Region	Districts	Areas in km^2	Average elevation (m)	Mean rainfall (mm)	Lat	Lon
1	Togdheer	Beer	10,000	927	315	9.3676° N	45.7497° E
2	Togdheer	Odwayne	7500	1008	355	9.3501° N	44.9661° E
3	Waqoyi-Galbed	Wajaale	5000 s	1588	450	9.6030° N	43.3415° E

fodder production for their livelihoods. Their agricultural production is limited to small terraces, and they primarily use grass for sheep and goats and maize stalks for cattle and camels as their primary source of fodder [35]. The climate in the region is characterized by a combination of wet and dry conditions, with an average annual rainfall of 300 mm that varies between 200 and 400 mm. The average daily temperature ranges between 25 and 35 °C, with four distinct seasons in the year. Gu (the main rainy season) and Hagaa (the short rainy season) correspond to spring and summer. In contrast, Dayr (the dry season) and Jiilaal (the major dry season) correspond to autumn and winter, respectively [46]. The mean elevation of the region is 410 m, with the lowest point being the Indian Ocean at 0 m and the highest point being Shimbiris at 2416 m. The region is exposed to both climate-related and non-climate-related hazards, including factors such as fluctuating rainfall patterns, diminishing soil quality, limited water availability, delicate soils, unrestricted grazing, soil erosion, and land fragmentation [11, 16], scarcity of animal feed, livestock illnesses, deforestation, and soil degradation [7] (Table 1).

2.2 Data acquisition

Real-time meteorological data were obtained from https://power.larc.nasa.gov/data-access-viewer, which is satellite-driven observation and measures the amount of multiple meteorological parameters at a global scale to calculate the SPEI indicator. Minimum meteorological data input was obtained, including daily precipitation and minimum and maximum temperature between 1981 and 2020, to compute the SPEI. The data sourced from NASA was selected for four reasons: first, the data is reliable and correlates with the ground meteorological data. Second, it provides CHIRPS data, which is a standard accepted form of precipitation. Third, it provides a high-resolution data set ranging daily, monthly, and annually, and most importantly, it can extract a single-point dataset using the corresponding coordinates (latitude and longitude) of the study locations. Hence, it provides the flexibility to perform temporal analysis. Based on the locations of the meteorological stations, we interpolated the SPEI data at a resolution of 5 km by means of the inverse distance weighted (IDW) interpolation method to obtain the spatial distribution of drought [29].

2.3 Data processing and analysis

The analysis of drought conditions involves using a comprehensive methodology that employs both temporal and spatial analysis of drought conditions. For the temporal assessment, the Standardized Precipitation-Evapotranspiration Index (SPEI) was utilized, with calculations performed using the R programming language and Excel using validated daily meteorological data from the satellite arranged monthly, comprising precipitation and the mean temperature of the study period. The Standardized Precipitation-Evapotranspiration Index (SPEI), a well-reviewed meteorological drought index recommended by the World Meteorological Organization (WMO), was proposed as an improved drought index applicable to the analysis of the impacts of climate change and drought conditions [6]. The minimum input data was combined into one by using the concatenate function and then exported in plain notepad, specifying location name, coordinates, start and end date. The meteorological data file, plain notepad, and SPEI application setup were merged into one common working directory. Command prompt codes were then employed to calculate the time-series SPEI data across the three locations and 40'years' timeframe. The computed SPIE is based on physically based methods of the Penman–Monteith method [38]. The unbiased probability weighted moment (ub-pwm) method has been used for fitting the log-logistic distribution. Given that the research cantered on a seasonal, annual, and decadal timeframe, we made use of a 3- and 12-month SPEI scale for the current analysis. To model and understand the trend of droughts, we employed a linear logistic regression model to determine whether drought categories as identified by SPEI at various timescales were significantly different.

For the spatial analysis, the Inverse Distance Weighted (IDW) interpolation method [6, 22] was employed using ArcGIS 10.8.1 software. This method enabled the creation of spatial maps representing the distribution and severity of drought across the study area. The spatial maps, derived from the calculated meteorological station data, provided insights into the spatial patterns of drought and its potential impact on fodder production. The combination of spatial–temporal analysis of SPEI presents a comprehensive understanding of drought conditions and their implications for fodder production. This methodology allowed for the identification of areas and periods most vulnerable to drought, including frequency, duration, intensity, and severity, facilitating informed decision-making and the development of appropriate mitigation strategies in the context of fodder production. To examine the quarterly temporal patterns, a linear regression analysis was conducted. Additionally, a 5-year moving average technique was employed to reduce fluctuations in the time series data and emphasize the underlying trends. In this study, we focused on the seasonal, annual, and decadal variation characteristics of drought; thus, the 3- and 12-month SPEI were calculated (Table 2).

2.3.1 Meteorological drought characterization

Numerous meteorological drought indices have been utilized since the beginning of drought analysis research. Rainfall anomaly index [21], Standardized Precipitation Index (SPI) [31], and Palmer Drought Severity Index (PDSI) [2] were the most common ones. However, the Standardized Precipitation Evapotranspiration Index [6] was chosen to be employed in the current study. Drought events are usually recognized by observing a drought index value () that drops below 0, indicating the beginning of the drought, and ceases when the index value rises above 0, signifying the end of the drought. The time span between the onset and termination, or the consecutive periods where the index value remains below zero, is considered the duration of the drought. The cumulative sum of index values during this duration is referred to as drought severity. The average of the index values provides the average intensity of the drought, while the lowest index value represents the maximum of the drought event.

2.3.2 Standardized precipitation evapotranspiration index (SPEI)

The Standardized Precipitation-Evapotranspiration Index (SPEI), a well-reviewed meteorological drought index recommended by the World Meteorological Organization (WMO), was proposed as an improved drought index applicable to the analysis of the impacts of climate change and drought conditions [6]. It is represented as a standardized Gaussian variable with an average of zero and a standard deviation of one, calculated as the difference between precipitation and potential evapotranspiration. What sets SPEI apart from earlier drought calculation methods is its capability to incorporate the impact of evaporative demand into its calculations [6]. Furthermore, it enables the examination of how global warming influences the frequency of drought occurrences [42]. It's interesting to notice the difference between the long- and short-term SPEI values, as they reveal the trend of the drought conditions over a given region. In the current study, 3-month, and 12-month SPEI were used to classify and identify seasonal and annual trends, spanning from short-term to long-term analysis. This study does not incorporate the use of the 1-month SPEI, as"it's not useful in evaluating drought trends in Somalia [39]. The decreasing trend in the frequency of moderately severe droughts and the long-lasting droughts in Somalia could be plausible causes. The SPEI method uses rainfall and evapotranspiration for the identification of droughts. The availability of the potential evapotranspiration PET parameter is limited in some areas, which is the second most important variable in the hydrological cycle after precipitation. SPEI is like SPI but considers the function of temperature, and because of its application to a water

Table 2 Drought classification based on SPEI value [57]

Category of drought	SPEI values
Extremely wet	SPEI > = 2.0
Severe wet	1.50–1.99
Moderate wet	1.00–1.49
Near normal	− 0.99–0.99
Moderate drought	− 1.00 to (− 1.49)
Severe drought	− 1.50 to (− 1.99)
Extreme drought	SPEI ≤ − 2.0

balance, it can be compared to the Palmer Drought Severity Index (PDSI). Under warming conditions, the three time series indices were compared, and only SPEI and PDSI were able to depict an increase in drought severity due to higher water demand [57].

Several temperature, radiation, and mass transfer-based empirical methods are available to estimate PET [55]. One of which is the use of the Thornthwaite method [52], because it only requires average temperature and is potentially widely applied in regions with limited data availability [44]. Some other researchers proposed physically based methods such as the Penman–Monteith methodas the main and best method [38], followed by models based on empirical relationships, including Hargreaves [26], and the Thornthwaite method for the calculation of the SPEI. Their limitations are site-specific (subject to local climatological conditions) and require calibration procedures. However, the data requirement is basic and can be accessed everywhere. Hence, for the purpose of this study, we selected the "Penman–Monteith method that was adopted by the International Commission on Irrigation and Drainage (ICID), the Food and Agriculture Organization (FAO), and the American Society of Civil Engineers (ASCE) as the conventional method for computing PET, even though in our literature, the reason for considering PET in the drought index calculations is merely to attain a relative timely estimation, and hence the method utilized for calculations is not substantial. Generally, a log-logistic distribution is required to standardize the accumulation of D k n to estimate the SPEI as follows (Eq. 1).

$$\mathrm{D}_N^K = \sum_{i=0}^{k-1} (\mathrm{P}_{\mathrm{N-I}} - \mathrm{PET}\ n - i) \tag{1}$$

where D is the monthly water difference between precipitation P and potential evapotranspiration PET in month "n" when the time scale is "K", whereby the monthly PET is calculated by the Thornthwaite equation.

$$\mathrm{PET}\ = 16 \left(\frac{10T}{I}\right)^a, 00C < -T < 26.5OC \tag{2}$$

$$\mathrm{I} = \sum_{i=1}^{12} \frac{\mathrm{T}}{5} 1.514, \mathrm{T} > 0\ \mathrm{OC} \tag{3}$$

$$\mathrm{A} = 0.49239 + 1.792 \times 10^{-2}\mathrm{I} - 7.71 \times 10^{-5}\mathrm{I}^2 + 6.75 \times 10^{-7}\mathrm{I}^3 \tag{4}$$

2.3.2.1 Resilience of pasture-livestock systems and recovery of drought The most severe drought in the last four decades and corresponding seasons were observed to compare the resilience systems of pasture to drought events. Resistance was determined by assessing the impact of a disturbance on the system, specifically how much productivity decreased during the drought compared to a typical weather condition. This was calculated by comparing the state of the response variable during the drought with a previous season under normal conditions, such as comparing the herbage mass during the drought season with the herbage mass during the same season of the preceding year with normal weather. Resistance to drought was calculated for variables like herbage accumulation rate and animal live weight gain by comparing the average values of the spring and autumn periods in 2008–2009 (the drought period) with the average values of the spring and autumn periods in 2007–2008 (the pre-drought period).

$$\mathrm{Resistance} = \mathrm{RVd}/\mathrm{RVb}$$

where RVd: Response rate during drought period, RVb: Response rate before drought period.

Moreover, recovery was determined by calculating the slope of the variable over time after the disturbance, such as the increase in herbage mass between the drought season and the season immediately following the drought, divided by the time period. This refers to the rate at which the system returns to a previous stable state following a disruption. While resistance is dimensionless, recovery is measured in the units of the variable per unit of time (e.g., per season or per year). To calculate recovery from drought, the slope of the regression line was determined by comparing the averages of the spring during the drought year with the winter following the drought for each measured variable.

$$\mathrm{Recovery} = \mathrm{RVa}{-}\mathrm{RVd}/\mathrm{ta}{-}\mathrm{td}$$

where

RVa = Response variable after drought period.

RVD = Response variable during drought period.

Ta = Time after drought period.

Td = Time during drought period.

3 Results

3.1 Analysis of seasonal drought prevalence

Table 1 shows the drought frequency trends and chi-square test for meteorological droughts, as determined by the 3-Month SPEI, across the three study sites from 1981 to 2020. Meteorological droughts are detected using the Standardized Precipitation Evapotranspiration Index (SPEI), with values below zero indicating drought periods and values above zero indicating wet conditions. Moderate droughts were found to be more frequent compared to other classes of droughts across the study sites and seasons, ranging from 65 to 80%. The occurrence rate of moderate drought in all the sites and both seasons exceeded 70%, except for the autumn season in Wajaale, with 65%. In Beer (**B**), both the spring and autumn seasons show a higher trend in wet seasons than in dry seasons. Conversely, Odwayne exhibits a drier trend in spring and autumn compared to wet seasons, with percentages ranging from 10 to 12.5% in spring and 12–13% in autumn, indicating a transition from wet to dry conditions. However, no wet and dry seasonal trend is observed in Wajaale, with 10% in spring and 17% in autumn. The occurrence rates of Wajaale (**G**) and Odwayne (**O**) both showed that autumn seasons exhibit higher wet and dry conditions than spring seasons. Conversely, the spring seasons of Beer showed more wet conditions than the autumn season, with 18% and 13%, respectively, while dry conditions showed similar conditions. The drought frequencies of all three study sites were analyzed in relation to different seasons. The findings revealed that both Wajaale and Odwayne experienced more drought periods during the autumn than in the spring, with percentages ranging from 10 to 18% and 12–13%, respectively. Conversely, Beer had an equal occurrence of drought incidents in both seasons. Drought frequency was the lowest in Beer but more severe, and the highest was in Wajaale but less severe. The results overall point to a strong correlation between the seasons and the frequency of conditions in each of the three locations (p-values < 0.0001). This suggests that there are significant variations in these locations for the occurrence of extreme wet, severe wet, moderate wet, normal, moderate dry, severe dry, and extreme dry conditions. We also computed a multiple linear regression model to examine the relationship between the drought classes and seasons (spring and autumn). The results indicated that approximately 12.5% of the variance in the drought classes can be explained by the seasons (spring and autumn). This explains why the drought classes decrease by 0.5 when the season changes from autumn to spring. Therefore, there was no significant difference in the drought classes between spring and autumn (p = 0.179) (Table 3).

3.2 Drought onset, cessation, duration, and recurrence

Seasonal drought onset, cessation, duration, and recurrence intervals were analysed. The results revealed that the duration, severity, and intensity of meteorological droughts in rainy seasons (spring and autumn) have dramatically increased over the last 10 years (Table 4). The findings showed that drought incidents were highly recurrent, with an average frequency of every 2 years over the 40 years. The most severe drought period was recorded from 2000 to 2004 across all sites during the spring season. According to the temporal analysis, Odwayne experienced the most intense droughts during the rainy seasons of both spring and autumn, with severity indices of – 2.2 and – 1.82, respectively. In general, spring consistently exhibited higher drought intensity than autumn across all sites, except for Beer, where no significant difference was observed between the two seasons. The drought intensity in spring and autumn was more pronounced in the last ten years across all sites and seasons except for 2002 (Fig. 3, Table 5).

Table 3 Drought Frequency Trends and Severity for three agro-ecological zones in Somalia from 1981 to 2020

Drought Frequencies %										
Stations	**Seasons**		**Extreme wet**	**Severe wet**	**Moderate wet**	**Near normal**	**Moderate drought**	**Severe drought**	**Extreme drought**	**X2 test (*p*-value)**
Beer	Spring	N	1	1	5	29	0	2	2	< 0.0001
		%	2.5	2.5	12.5	72.5	0	5	5	
		C%	17.5	72.5	10					
	Autumn	N	0	2	3	31	0	2	2	< 0.0001
		%	0	5	7.5	77.5	0	5	5	
		C%	12.5	78	10					
Wajaale	Spring	%	1	3	0	32	2	1	1	< 0.0001
		N	2.5	7.5	0	80	5	2.5	2.5	
		C%	10	80	10					
	Autumn	N	5	2	0	26	5	2	0	< 0.0001
		%	12.5	5	0	65	12.5	5	0	
		C%	17	65	17					
Odwayne	Spring	%	2	2	0	31	3	1	1	< 0.0001
		N	5	5	0	77.5	7.5	2.5	2.5	
		C%	10	7.5	12.5					
	Autumn	N	2	3	0	30	2	3	0	< 0.0001
		%	5	7.5	0	75	5	7.5	0	
		C%	12	75	13					

N: Represents to the number of drought regularities. C% stands for cumulative percentage categorized into the wet period, near normal and drought periods (Fig. 2)

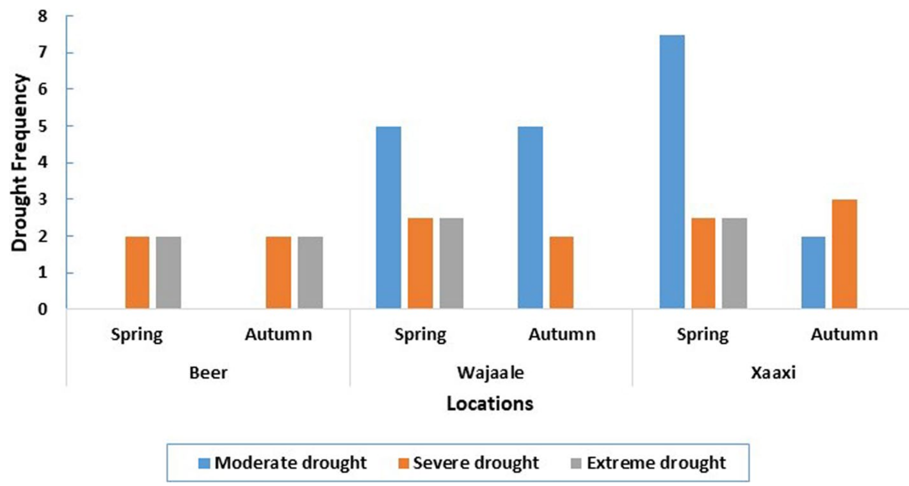

Fig. 2 The drought frequency levels between the three stations and the two seasons. Note: We only show here for the drought classes

Table 4 Analysis of meteorological drought onset (o), cessation ©, maximum duration (md), recurrence interval (RI), and intensity (I)

Study sites		Onset	Cessation	Md (Year)	Recurrency Interval	Intensity Level	Severity (Yr)
Beer	Spring	2000	2004	5	2.2	– 0.82	2019
		2017	2019	3			
	Autumn	2005	2009	5	1.96	– 0.66	2002
		2016	2018	3			
Wajaale	Spring	2000	2004	5	2.0	– 0.75	2019
		2006	2009	4			
	Autumn	2005	2009	5	2.1	– 0.75	2011
		2015	2018	4			
Odwayne	Spring	2000	2004	5	1.9	– 2.2	2019
		2017	2019	3			
	Autumn	2005	2009	5	1.9	– 1.82	2017
		2015	2018	4			

The SPEI value corresponds to the severity of the drought; the smaller the SPEI value, the more severe the drought, and vice versa. In this study, the SPEI was calculated at a 3-month timescale (SPEI-3), corresponding to the duration of the two main rainy seasons in the study area.the two rainy seasons in the study sites were explicitly selected for assessment, with spring being the main rainy season and autumn being the shorter rainy season. The results of the seasonal analysis show that all study sites exhibit an increasing trend of drought across the 40 years in both seasons. However, there are some disparities within the seasons, with the drought trend in the spring season being higher in all locations compared to the autumn season, with coefficients of variation (– 0.0317, – 0.04, – 0.03) and (– 0.16, – 0.027, – 0.022), respectively (Fig. 4a–c). These results are consistent with the findings of Musei et al. [39], who found an increasing trend in the frequency of dry periods on a 3-month SPEI time scale (herein referred to as seasonal). This implies that the impact of drought is more pronounced on a seasonal scale than in an annual analysis. In summary, for both the spring and autumn seasons, Wajaale consistently has the highest r^2 values (0.287 and 0.115, respectively) among the three locations, indicating a better fit of the regression model to the data compared to Beer and Odwayne. Beer consistently has the lowest r^2 values (0.158 and 0.046, respectively),

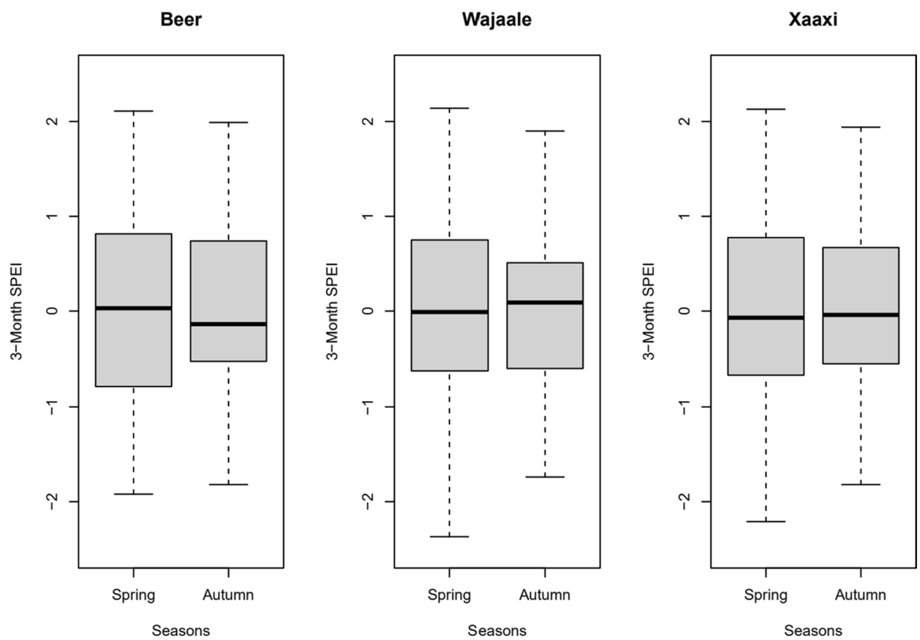

Fig. 3 Seasonal comparison of 3-month SPEI timescale and their respective stations from 1981 to 2020

Table 5 Resilience: The resistance of climate variability and recovery from drought

	Drought events	Drought years	Resistance %	Recovery (Kg/Dm/ha/y)
Beer	1st Drought	2001–2003	30	5328
	2nd Drought	2008–2010	75	4928
	3rd Drought	2016–2018	75	1673
Wajaale	1st Drought	2001–2003	77	1203
	2nd Drought	2008–2010	73	1668
	3rd Drought	2016–2018	68	2341
Odwayne	1st Drought	2001–2003	46	2343
	2nd Drought	2008–2010	79	2951
	3rd Drought	2016–2018	66	2113

suggesting a weaker fit. Odwayne falls in between, with a moderately better fit compared to Beer but a lower fit compared to Wajaale (Fig. 4b).

3.3 Annual and decadal drought analysis

The SPEI value corresponds to the severity of the drought; the smaller the SPEI value, the more severe the drought. Hence, 12-month SPEI is a more useful way to analyse the annual variation of droughts, and the mean of 12-month SPEI provides the same on a decadal basis. The trend curve of the annual SPEI value in Fig. 5 depicts that the annual SPEI value has shown a varying trend across the studied sites (Beer, Wajaale, and Odwayne). Increasing drought trends were observed with coefficients of variation of − 0.033 and − 0.018 per year in Beer and Odwayne, respectively. Conversely, Wajaale has shown a decreasing drought trend with 0.007 over the study period (1981–2020). This means that droughts are tremendously increasing in Beer and Odwayne, which lie in the eastern regions, compared to Wajaale on the western side of Somaliland. The study was also analyzed at a decadal scale, as shown in Fig. 4. We have considered the middle year for each decade to present the average and illustrate them in the graph: 1985 (1981–1990), 1995 (1991–2000), 2005 (2001–2010), and 2015 (2011–2020). In Beer, the 1980s

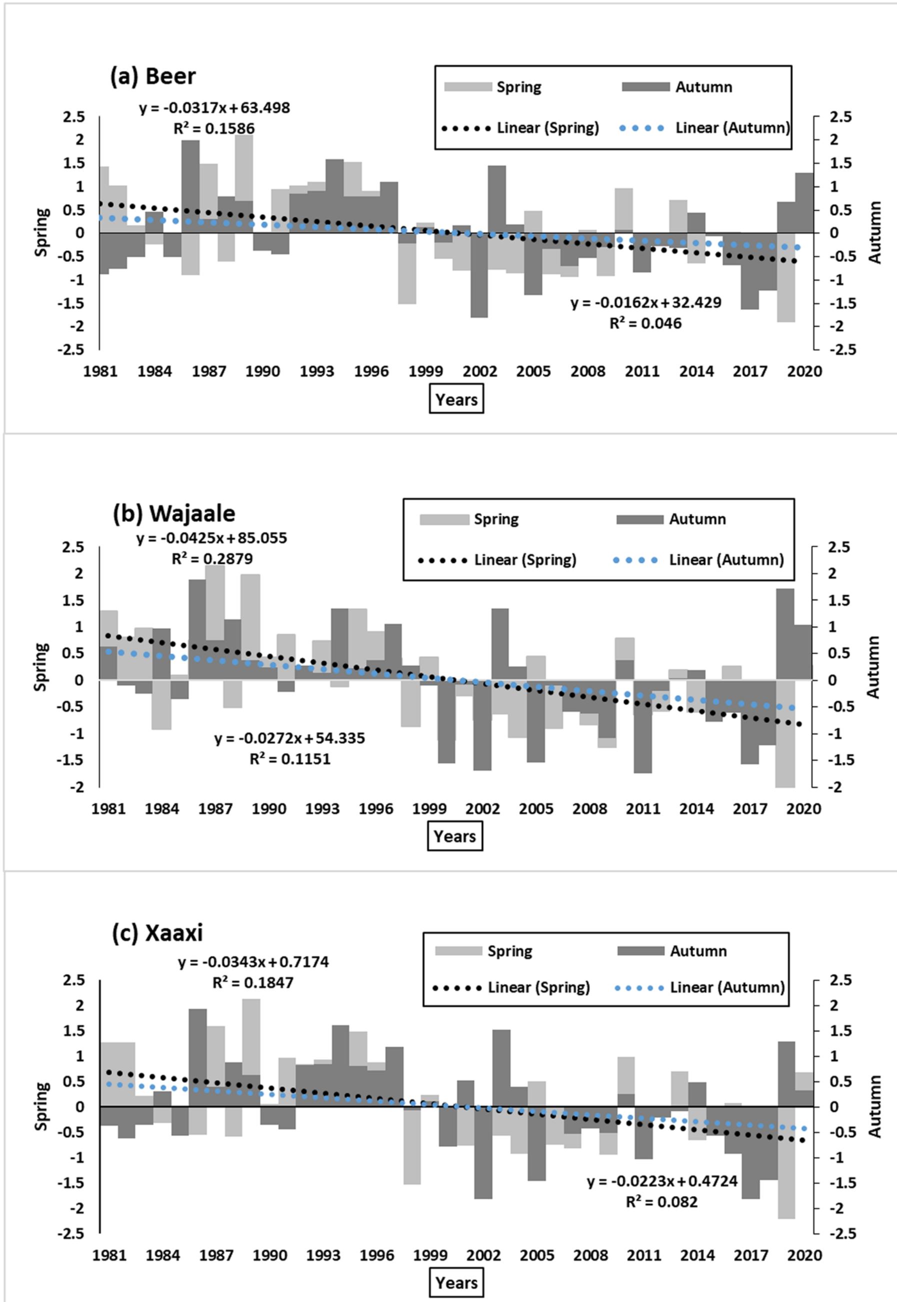

Fig. 4 Seasonal 3- Month SPEI analysis at three agroecological zones from 1981 to 2020. **a** Beer, **b** Wajaale and **c** Odwayne

were a relatively wet period from 1981 to 2020, with an average SPEI value of 0.23. The 1990s were similarly wet but drier than the 1980s, with an average SPEI value of 0.06. In contrast, apart from 2001, 2007, 2008, and 2009 had SPEI values < 0, with an average value of -0.26, which indicates a moderate likelihood of drought conditions during 2001–2010. However, the drought tendency increased to -0.69, suggesting a higher intensity of drought from 2011 through 2020. Almost all years 2011–2020 show drought except 2013 and 2014. It was also found that the 1980s (1981–1990) were the wettest periods, and the 2010s (2011–2020) were the driest periods for Beer. A similar increasing drought

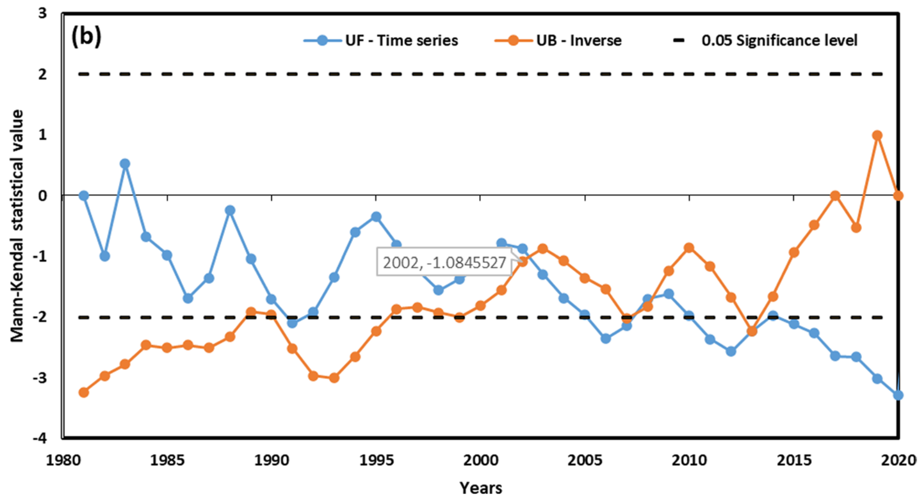

Fig. 5 The statistical time series of the curve was denoted by UF, while the inverse statistical time series was den oted by UB. Note: The significance level of 0.05 corresponds to a threshold value of ±1.96 for UF and UB curves, and the data sequence exhibits and upward trend if UF>0 and vice versa.

decadal trend was observed in Odwayne but with little discrepancy. The 2010s decade, spanning from 2010 to 2020, has shown a dramatic and significant increase in drought levels, as shown in Fig. 4c. The first and second decades show wet conditions, while the third decade of 2000 (2001–2010) shows massive drought incidents all the years around, except 2008, with an average SPEI value of – 0.23. Nonetheless, in Wajaale, the decadal drought trend fluctuated across the four decades with no linear increase or decrease. Figure 4b. The drought trend has decreased from the first decade to the second, with a dramatic increase in drought in the third decade with an average SPEI value of – 0.45 and then a dramatic decrease in drought trends in the last decade with an average SPE value of 0.18.

Furthermore, the sequential Mann-Kendell test method was applied to identify the abrupt changes in the temporal annual SPEI trend. As a result, a forward (UF) and backward (UB) curve was plotted in Fig. 5. The statistical time series of the curve was denoted by (UF), while the inverse statistical time series was denoted by (UB). The significance level of 0.05 corresponds to a threshold value of + – 1.96 for the UF and UB curves, and the data sequence exhibits an upward trend if UF > 0 and vice versa. The results indicate 2002 as the point of intersection between the UF and UB curves and hence are considered the abrupt change point. After 2022, the UF curve decreases significantly and crosses the threshold value of + – 1.08. It is concluded that the annual SPEI exhibited a pronounced change in 2002, and drought events were evident (Fig. 6).

3.4 Spatio-temporal pattern of drought changing trends

The spatial interpolation of droughts was performed using the Inverse Distance Weighted Method (IDW) to understand the spatial distribution of droughts across the three Somalia's and the 40 years.

3.5 Resistance and recovery of pasture to drought variability

The resistance and recovery rates of biomass production to drought were evaluated across three drought events in Beer, Wajaale, and Odwayne. Regarding resistance to drought, Wajaale consistently demonstrated the highest rates among the three locations

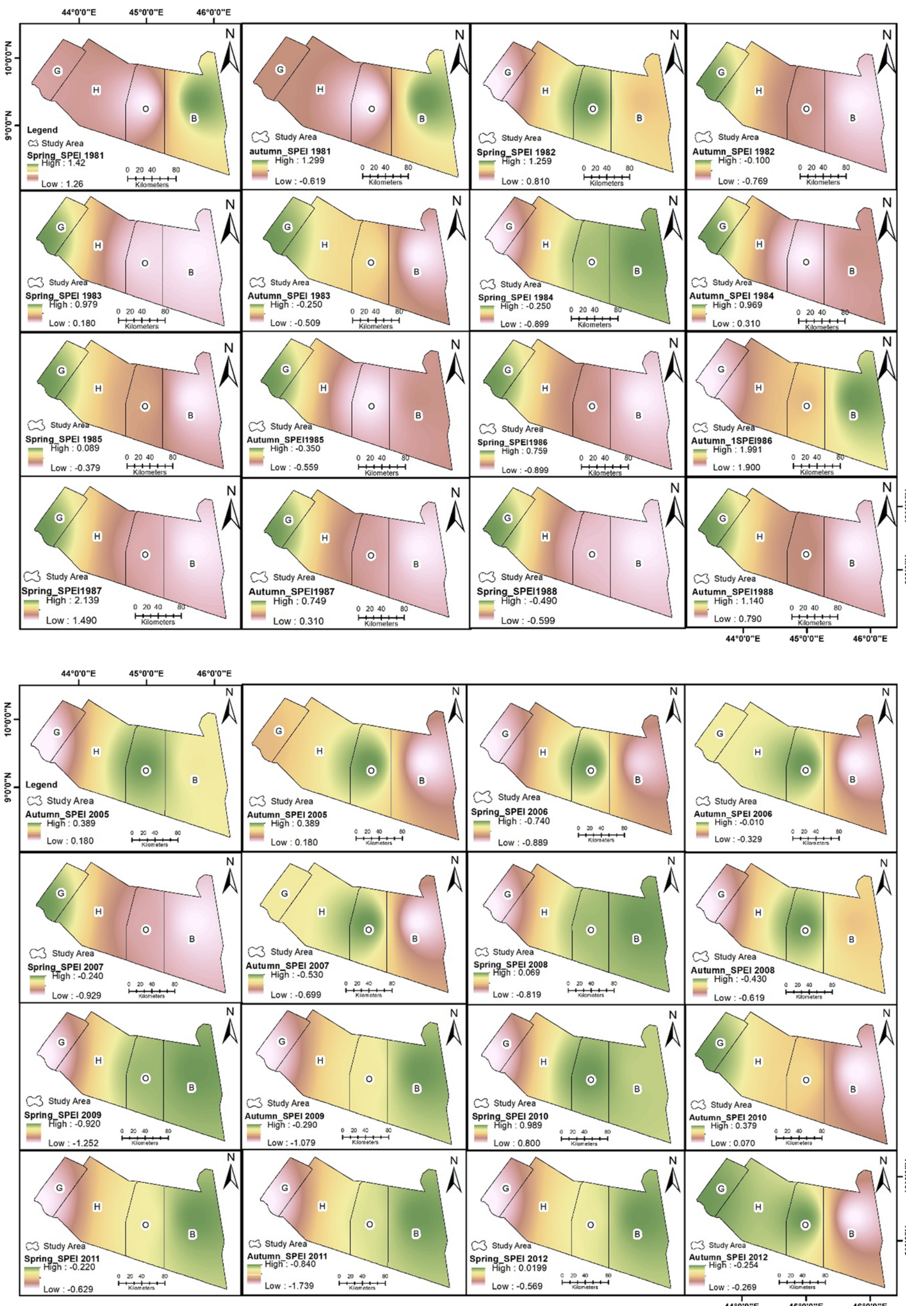

Fig. 6 Spatial distribution of drought categories across three different stations and two seasons (Spring and Autumn) from 1981 to 2020

in all three drought events. Wajaale had resistance rates of 77%, 73%, and 68% during the first, second, and third droughts, respectively. This indicates a strong ability to withstand the adverse effects of drought. Beer had lower resistance rates, ranging from 30 to 75% across the three drought events, while Odwayne's resistance rates ranged from 46 to 79%. These results suggest that Wajaale was consistently more resilient to drought conditions compared to Beer and Odwayne.

Regarding recovery from the drought, Wajaale also exhibited notable performance. During the first drought, Wajaale had a recovery rate of 1203 kg/dm/ha/y, which increased to 1668 kg/dm/ha/y in the second drought. Most notably, during the third

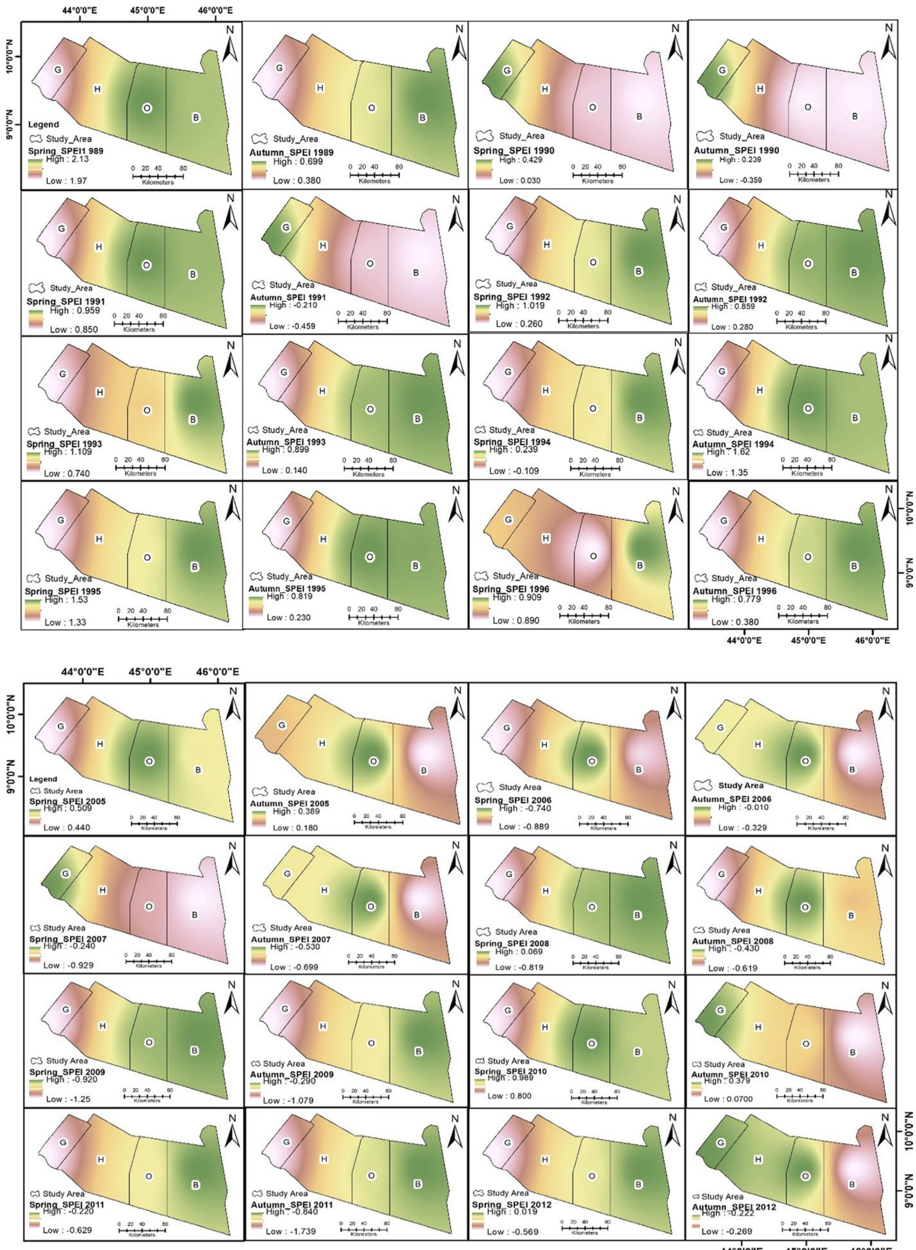

Fig. 6 (continued)

drought, Wajaale had the highest recovery rate of 2341 kg/dm/ha/y, indicating a faster and more substantial recovery compared to Beer and Odwayne. Beer showed a decrease in recovery rates across the three drought events, ranging from 5328 to 1673 kg/dm/ha/y. Odwayne, on the other hand, maintained consistent recovery rates, ranging from 2343 to 2951 kg/Dm/ha/y. These findings highlight Wajaale's ability to recover effectively from drought events, showcasing its resilience in biomass production compared to the other two locations. In Beer, the resistance of herbage accumulation to drought was significantly higher for the second and third drought incidents, with 75%, than the first drought incident, with 30%. This indicates that the herbage accumulation of the first drought incident has less resistance to climate variability than the other two incidents and requires the highest recovery rate of herbage accumulation (5328 kg/dm/

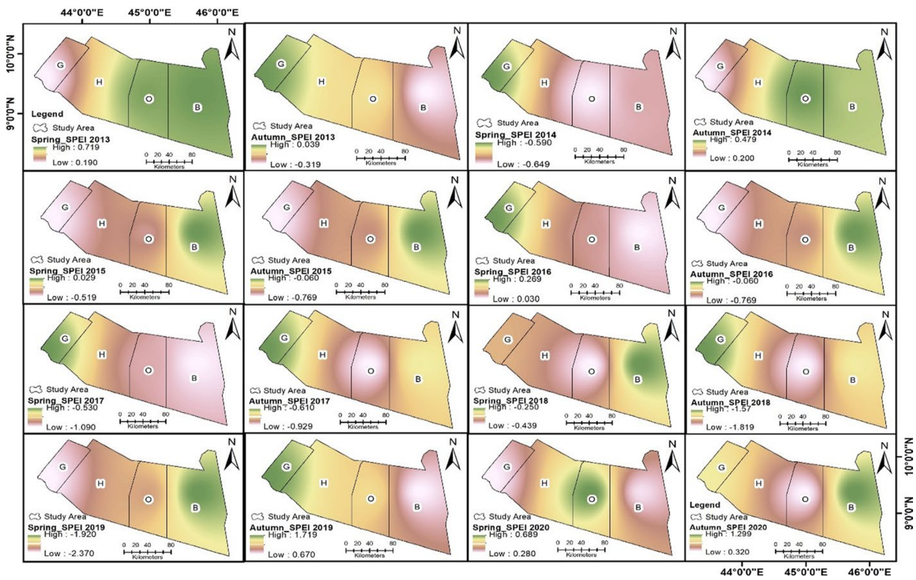

Fig. 6 (continued)

ha/y. Although the resistance rates of the second and third drought periods are similar, there are discrepancies between their recovery rates. The second drought period exhibits a much higher recovery rate than the third drought incident, with 4929 kg/ha and 1673 kg/ha, respectively.

4 Discussions

Our analysis examined the spatial and temporal variations in meteorological drought patterns at fodder production sites in Somaliland, northwestern Somalia, from 1980 to 2020 using SPEI. The comprehensive assessment of drought occurrence in dryland areas, such as Somalia, necessitates the concurrent analysis of precipitation [9, 53], temperature [47]and evapotranspiration [41], making SPEI the most effective means for evaluating and understanding drought conditions [3, 6]. The results generally revealed a consistent upward trend in drought occurrences across the spring and autumn seasons and the three sites under investigation. This outcome suggests a growing concern for drought-related challenges in the study area. The increasing frequency and intensity of drought events can have significant implications for agriculture [63] and food security. Reduced water availability during critical growth stages can decrease crop yields and livestock productivity [8]. This, in turn, can threaten the livelihoods of farmers and pastoralists who heavily rely on rain-fed agriculture [40] and grazing [58]. These findings are consistent with the global drought assessment study conducted by [64], which indicated that the increase in frequency, duration, and severity is very significant in Africa. In general, the autumn season tends to be more persistent in drought than the spring across the study sites. According to the findings reported by [23, 65] there is an upward trend in drought occurrences in autumn compared to the spring. The study supports the notion that the most severe drought, which typically occurs during the summer, persists and extends into autumn. This suggests that it is crucial to address severe droughts in the summer, as this period is critical for vegetation growth. Another study by Guy et al. [19] insists that autumn droughts are attributed mainly to ENSO regime shifts, and as a result of this, there are increasing incidents of drought. Wajaale and Odwayne had a higher frequency of drought periods during autumn compared to spring, unlike Beer, which experienced an equal number of drought incidents in both seasons. Specifically, since Beer is situated in a region known for fodder production [24, 25, 35], the implications of drought on fodder production can be severe [64] since droughts affect both the main and short rainy seasons similarly in Somalia. Moderate droughts were found to become more frequent compared to other classes of droughts.

The study findings indicate a consistent upward drought trend across all study sites over 40 years, regardless of the season. However, disparities exist within the seasons, with the spring season showing a higher drought trend in all locations than in autumn. These results are consistent with the findings of Musei et al. [39], who found an increasing trend in the frequency of dry periods on a seasonal scale. The frequency, duration, and severity of droughts increased, with the most intense and severe droughts occurring in the last decade of the study period, from 1981 to 2020. This is consistent with many studies worldwide [34, 36, 59]. However, a study from Nigeria by [12, 60] exclusively found significant drying trends in recent times compared to the past four years. He also added that the frequency and severity of drought in Nigeria are increasing in both the SPI and SPIE drought indices. Beer experiences the lowest frequency of drought, but it is more severe when it does occur.

In contrast, Wajaale has the highest drought frequency, but the severity is less. This difference can be attributed to the geographical locations of Beer, which are characterized by flat terrain with abundant sloping areas that can retain a significant amount of rainfall for a long time [24, 66]. Additionally, beer benefits from distant mountain rainfall, enabling it to retain significant amounts of water for extended periods. Another plausible explanation is the elevated temperature in Wajaale. A study by Shiru et al. [45] supports this notion, revealing that higher temperatures are linked to a reduction in the SPEI. As a result, this decrease in the SPEI leads to an increased frequency of droughts. In contrast, Wajaale is disadvantaged by its soil's limited capacity to retain water [56]. Spring consistently exhibited higher drought intensity than the autumn season across all sites, except for Wajaale, where no significant difference was observed between the two seasons.

The analysis of seasonal droughts reveals that drought incidents were highly recurrent every 2 years over the 40 years, with a maximum duration of 5-year moving droughts. This indicates that droughts occurred frequently, with a high likelihood of experiencing a drought event every two years during the study period. These drought events were found to have large-scale impacts in the Horn of Africa on environmental aspects and society [20] and have a detrimental impact on agricultural production [30]. Even though some studies contradict these results [27, 50], most of the studies on drought concur that there has been an increasing trend of drought incidents over the past few years [37, 43, 51], and the same trend is also projected for the future [45, 57].

In contrast to Wajaale, Beer and Odwayne experienced an upward trend in annual drought occurrences. This means that droughts are tremendously increasing in Beer and Odwayne, which are in the eastern regions, compared to Wajaale on the western side of Somaliland. These findings concur with the study of Abdulkadir et al. [1], who insist that western regions receive more rainfall and are less vulnerable to drought incidents than eastern regions of Somaliland. Another study by Helming et al. (2009) insists that vegetation cover and soil conditions, particularly water-holding capacity, are much better in western regions than the eastern side of Somaliland. In addition, a different study that looked at Somaliland's agro-ecological zones said that the western regions grew cash crops, while the eastern regions mainly were pastoralist, with places like the Burao livestock market and major livestock transport routes [10, 20, 49]. To this point, it can be concluded that Wajaale is a better site for fodder production concerning the changing climate and the subsequent droughts associated with it. Hence, the study recommends that more sites for fodder production to be initiated in the western regions of Somaliland. All the locations exhibited an increased drought trend at the decadal level, except Wajaale. These results accept the findings of Tong et al. [54], which found that 1990 was the wettest period and 2010 was the driest period in the study area. This is presumed to be a location-wise discrepancy and hence indicates that the results of SPEI cannot be generalized on a regional or global level but are better off location-wise.

5 Conclusion

In conclusion, analysing meteorological drought patterns in Somaliland and northwestern Somalia from 1980 to 2020 using the Standardized Precipitation Evapotranspiration Index (SPEI) revealed several important findings. First, there was a consistent upward trend in drought occurrences across the spring and autumn seasons in all three study sites. This suggests a growing concern for drought-related challenges, which can have significant implications for agriculture and food security. Decreased water availability during critical growth stages can lead to reduced crop yields and livestock productivity, threatening the livelihoods of farmers and pastoralists. The findings also indicated that the autumn season tends to be more persistent in drought than in spring. This highlights the importance of addressing severe droughts during the summer, as this period is critical for vegetation growth. Autumn droughts were attributed to ENSO regime shifts, and their increasing incidence can cause concern. There were variations in drought frequency and severity among the study sites. Beer experienced the lowest frequency of drought but had more severe drought events. This can be attributed to its geographical characteristics, including a flat terrain with sloping areas that retain rainfall for more extended periods. Wajaale, on the other hand, had a higher frequency of drought events, which can be attributed to higher temperatures and limited soil water retention capacity. The analysis of seasonal drought patterns revealed that drought events occurred frequently, with a high likelihood of experiencing a drought event every two years during the study period. These recurrent drought events have significant impacts on the environment and society and detrimental effects on agricultural production. Furthermore, there were differences in drought trends between the western and eastern regions of Somaliland. Western regions, such as Wajaale, were less vulnerable to drought incidents than the eastern regions, such as Beer and Odwayne. This can be attributed to differences in rainfall patterns, vegetation cover, soil conditions, and the classification of agro-ecological zones. Considering these findings, we recommended that drought challenges in the study area, particularly in the western regions, be prioritized, as they show potential for fodder production. Initiating more fodder production sites in these regions can help mitigate the impacts of changing climates and associated droughts. It is important to note that the results of the SPEI analysis should be interpreted at a location-wise level and cannot be generalized on a regional or global scale.

Author contributions
Conceptualization: J.H., E.G., F.B., Methodology: J.H, F.B., E.G., Validation: J.H, F.B.; E.G., Formal analysis: J.H, E.G., F.B., Investigation: J.H, E.G., F.B., Writing—Original Draft: J.H, E.G., F.B.; Writing—Review & Editing: J.H, E.G., F.B., J.S., D.M.,

Funding
This research received no external funding and is part of my sPhD thesis.

Data availability
Data availability The dataset supporting the findings of this study is available in the Dropbox repository at the following link:https://www.dropbox.com/home/Hussein%20et%20al.%2C%202,023%20%20Paper%20to%20ERFS/Hussein%20et%20al.%2C%202,024%20%20Discover%20Sustainability%20Journal.The dataset includes all the necessary files and materials required to reproduce the results presented in the study.

Declarations

Competing interests
The authors declare no competing interests.

Received: 27 January 2025 / Accepted: 27 June 2025
Published online: 24 July 2025

References

1. Abdulkadir G, et al. Assessment of drought recurrence in somaliland: causes, impacts and mitigations. J Climatol Weather Forecasting. 2017. https://doi.org/10.4172/2332-2594.1000204.
2. Alley WM, et al. The palmer drought severity index as a measure of hydrologic drought. JAWRA J Am Water Resources Assoc. 1985;21(1):105–14. https://doi.org/10.1111/j.1752-1688.1985.tb05357.x.
3. Alwesabi MS. (2012). MODIS NDVI satellite data for assessing drought in Somalia during the period 2000–2011. *Student Thesis Series INES*, (257). Retrieved from https://lup.lub.lu.se/student-papers/record/3044245/file/3048897.pdf
4. Anderegg WRL, et al. Consequences of widespread tree mortality triggered by drought and temperature stress. Nat Clim Chang. 2012;3(1):30–6. https://doi.org/10.1038/nclimate1635.
5. Bae S, et al. Analysis of drought intensity and trends using the modified SPEI in South Korea from 1981 to 2010. Water (Switzerland). 2018. https://doi.org/10.3390/w10030327.
6. Beguería S, et al. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int J Climatol. 2014;34(10):3001–23. https://doi.org/10.1002/joc.3887.
7. Belay A, Oludhe C, Mirzabaev A, Recha JW, Berhane Z, Osano PM, Solomon D. Knowledge of climate change and adaptation by smallholder farmers: evidence from southern Ethiopia. Heliyon. 2022;8(12): e12089. https://doi.org/10.1016/j.heliyon.2022.e12089.
8. Chisanga CB, Nkonde E, Mubanga KH, Phiri D, Chemura A, Kipkulei HK. SPI-based drought characteristics using CHIRPS over Zambia: 1981–2024. All Earth. 2025;37(1):1–19. https://doi.org/10.1080/27669645.2025.2472574.
9. Bhunia P, et al. Meteorological drought study through SPI in three drought prone districts of West Bengal, India. Earth Syst Environ. 2020;4(1):43–55. https://doi.org/10.1007/s41748-019-00137-6.
10. Boitt MK, et al. Geospatial agro-climatic characterization for assessment of potential agricultural areas in Somalia, Africa. J Agric Inform. 2018. https://doi.org/10.17700/jai.2018.9.3.479.
11. Bryan E, Bernier Q, Espinal M, Ringler C. Making climate change adaptation programmes in sub-Saharan Africa more gender responsive: insights from implementing organizations on the barriers and opportunities. Clim Dev. 2018;10(5):417–31. https://doi.org/10.1080/17565529.2017.1301870.
12. Byakatonda J, et al. Analysis of long term drought severity characteristics and trends across semiarid Botswana using two drought indices. Atmos Res. 2018;213(March):492–508. https://doi.org/10.1016/j.atmosres.2018.07.002.
13. Cobon DH, et al. The climate change risk management matrix for the grazing industry of northern Australia. Rangeland J. 2009;31(1):31–49. https://doi.org/10.1071/RJ08069.
14. Dai A, et al. Climate change and drought: a precipitation and evaporation perspective. Curr Clim Change Rep. 2018;4(3):301–12. https://doi.org/10.1007/s40641-018-0101-6.
15. De Keersmaecker W, et al. A model quantifying global vegetation resistance and resilience to short-term climate anomalies and their relationship with vegetation cover. Glob Ecol Biogeogr. 2015;24(5):539–48. https://doi.org/10.1111/geb.12279.
16. Deressa TT, et al. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. J Agric Sci. 2011;149(1):23–31. https://doi.org/10.1017/S0021859610000687.
17. Diffenbaugh NS, et al. Anthropogenic warming has increased drought risk in California. Proc Natl Acad Sci USA. 2015;112(13):3931–6. https://doi.org/10.1073/pnas.1422385112.
18. Kharraz J, et al. Water scarcity and drought in WANA countries. Procedia Eng. 2012;33:14–29. https://doi.org/10.1016/j.proeng.2012.01.1172.
19. Guy S, et al. Geophysical research letters. Geophys Prospect. 2014. https://doi.org/10.1002/2014GL060130.Received.
20. Haile GG, et al. Long-term spatiotemporal variation of drought patterns over the Greater Horn of Africa. Sci Total Environ. 2019;704: 135299. https://doi.org/10.1016/j.scitotenv.2019.135299.
21. Hänsel S, et al. The Modified Rainfall Anomaly Index (mRAI)—is this an alternative to the Standardised Precipitation Index (SPI) in evaluating future extreme precipitation characteristics? Theoret Appl Climatol. 2016;123(3–4):827–44. https://doi.org/10.1007/s00704-015-1389-y.
22. Harishnaika N, et al. Computation of the spatio-temporal extent of rainfall and long-term meteorological drought assessment using standardized precipitation index over Kolar and Chikkaballapura districts, Karnataka during 1951–2019. Remote Sens Appl Soc Environ. 2022. https://doi.org/10.1016/j.rsase.2022.100768.

23. Hemming CF, et al. Vegetation arcs in somaliland published by: british ecological society stable. J Ecol. 2009;53(1):57–67.
24. Hussein J, Bilotto F, Sircely J, Mbui D, Omondi P, Ferreira CSS, Fahad S, Liu K, Harrison MT. From crisis to opportunity: climate change benefits livestock production in Somalia. Environ Res Food Syst. 2024;1(2): 025004. https://doi.org/10.1088/2976-601x/ad6fa0.
25. Hussein J, Bilotto F, Mbui D, Omondi P, Harrison MT, Crane TA, Sircely J. Exploring smallholder farm resilience to climate change: intended and actual adaptation. Pastoralism. 2024. https://doi.org/10.3389/past.2024.13424.
26. Li Z, et al. Study on the applicability of the Hargreaves potential evapotranspiration estimation method in CREST distributed hydrological model (version 3.0) applications. Water (Switzerland). 2018;10(12):1–15. https://doi.org/10.3390/w10121882.
27. Liu C, et al. Spatiotemporal drought analysis by the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) in Sichuan Province. China Sci Rep. 2021;11(1):1–14. https://doi.org/10.1038/s41598-020-80527-3.
28. Lyon B, et al. Unraveling east Africa's climate paradox. Clim Extremes Patterns Mech. 2017;22:265–81.
29. Ma Q, et al. Drought characteristics and prediction during pasture growing season in Xilingol grassland, northern China. Theoret Appl Climatol. 2018;133(1–2):165–78. https://doi.org/10.1007/s00704-017-2150-5.
30. Marthews TR, et al. The impact of human-induced climate change on regional drought in the horn of Africa. J Geophys Res Atmosp. 2019;124(8):4549–66. https://doi.org/10.1029/2018JD030085.
31. McKee T, et al. Preoperative serum value of sialyl Lewis X predicts pathological nodal extension and survival in patients with surgically treated small cell lung cancer. J Surg Oncol. 2012;105(8):818–24. https://doi.org/10.1002/jso.23002.
32. Mishra V, et al. Unprecedented drought in South India and recent water scarcity. Environ Res Lett. 2021. https://doi.org/10.1088/1748-9326/abf289.
33. Modernel P, et al. Grazing management for more resilient mixed livestock farming systems on native grasslands of southern South America. Grass Forage Sci. 2019;74(4):636–49. https://doi.org/10.1111/gfs.12445.
34. Mohammed S, et al. Space and time variability of meteorological drought in Syria. Acta Geophys. 2020;68(6):1877–98. https://doi.org/10.1007/s11600-020-00501-5.
35. Mohamud et al. (2022). Antakya Veteriner Bilimleri Dergisi The Journal of Antakya Veterinary Science. 1, 23–32.
36. Mohsenipour M, et al. Changing pattern of droughts during cropping seasons of Bangladesh. Water Resour Manage. 2018;32(5):1555–68. https://doi.org/10.1007/s11269-017-1890-4.
37. Mondol MAH, et al. Application of Standardized Precipitation Index to assess meteorological drought in Bangladesh. Jamba J Disaster Risk Stud. 2016;8(1):1–14. https://doi.org/10.4102/JAMBA.V8I1.280.
38. Montieth JL, et al. Evaporation_20and_20environment. Symp Soc Exp Biol. 1965;19(2393175):205–34.
39. Musei SK, et al. SPEI-based spatial and temporal evaluation of drought in Somalia. J Arid Environ. 2021. https://doi.org/10.1016/j.jaridenv.2020.104296.
40. Ogenga JO, et al. Impact of rainfall variability on food production under rainfed agriculture in Homa Bay County, Kenya. Int J Sci Res Publ IJSRP. 2018. https://doi.org/10.29322/ijsrp.8.8.2018.p80110.
41. Rahmat SN, et al. Assessing droughts using meteorological drought indices in Victoria, Australia. Hydrol Res. 2015;46(3):463–76. https://doi.org/10.2166/nh.2014.105.
42. Beguería S, et al. A multiscalar global drought dataset: the SPEI base: a new gridded product for the analysis of drought variability and impacts. Bull Am Meteor Soc. 2010;91(10):1351–6. https://doi.org/10.1175/2010BAMS2988.1.
43. Sharma S, et al. Increasing frequency and spatial extent of concurrent meteorological droughts and heatwaves in India. Sci Rep. 2017;7(1):1–9. https://doi.org/10.1038/s41598-017-15896-3.
44. Shiru MS, et al. Trend analysis of droughts during crop growing seasons of Nigeria. Sustainability (Switzerland). 2018;10(3):1–13. https://doi.org/10.3390/su10030871.
45. Shiru MS, et al. Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios. Sci Rep. 2020;10(1):1–18. https://doi.org/10.1038/s41598-020-67146-8.
46. SLHDS. (2020). *The Somaliland Health Demographic Survey*. Retrieved from www.somalilandmohd.com
47. Sintayehu DW, Alemayehu S, Terefe T, Tegegne G, Engdaw MM, Gebre L, Tesfaye L, Doyo J, Reddy RU, Girvetz E. Effects of drought on livestock production, market dynamics, and pastoralists' adaptation strategies in semi-arid Ethiopia. Climate. 2025;13(4):65. https://doi.org/10.3390/cli13040065.
48. Solh M, Van Ginkel M. Drought preparedness and drought mitigation in the developing ''world's drylands. Weather Clim Extremes. 2014;3:62–6. https://doi.org/10.1016/j.wace.2014.03.003.
49. Sommerlatte *et al*. (2000). *An ecological assessment of the coastal plains of north western Somalia (Somaliland)*. (May), 1–63. Retrieved from Sommerlatte_&_Umar_2000_Coastal_Plains_Somaliland.pdf
50. Spinoni J, et al. World drought frequency, duration, and severity for 1951–2010. Int J Climatol. 2014;34(8):2792–804. https://doi.org/10.1002/joc.3875.
51. Tfwala CM, et al. Nationwide temporal variability of droughts in the Kingdom of Eswatini: 1981–2018. Heliyon. 2020. https://doi.org/10.1016/j.heliyon.2020.e05707.
52. Thornthwaite CW, et al. An approach toward a rational classification of climate. Geogr Rev. 1948;38(1):55. https://doi.org/10.2307/210739.
53. Thurow TL, et al. Viewpoint: the role of drought in range management. J Range Manag. 1999;52(5):413–9. https://doi.org/10.2307/4003766.
54. Tong S, et al. Spatiotemporal drought variability on the Mongolian Plateau from 1980–2014 based on the SPEI-PM, intensity analysis and Hurst exponent. Sci Total Environ. 2018;615:1557–65. https://doi.org/10.1016/j.scitotenv.2017.09.121.
55. Tukimat NNA, et al. Comparison of different methods in estimating potential évapotranspiration at Muda Irrigation Scheme of Malaysia. J Agric Rural Dev Trop Subtrop. 2012;113(1):77–85.
56. Vargas et al. (2007). Soil Survey of a Selected Study Area in Somaliland. (L–05).
57. Vicente-Serrano SM. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim. 2010;23(7):1696–718. https://doi.org/10.1175/2009JCLI2909.1.
58. Vrieling V, et al. Early assessment of seasonal forage availability for mitigating the impact of drought on East African pastoralists. Remote Sens Environ. 2016;174:44–55. https://doi.org/10.1016/j.rse.2015.12.003.
59. Vu MT, et al. Hydro-meteorological drought assessment under climate change impact over the Vu Gia-Thu Bon river basin, Vietnam. Hydrol Sci J. 2017;62(10):1654–68. https://doi.org/10.1080/02626667.2017.1346374.

60. Wable PS, et al. Comparison of Drought indices in a semiarid river basin of India. Water Resour Manage. 2019;33(1):75–102. https://doi.org/10.1007/s11269-018-2089-z.
61. Wang F, et al. Study of the temporal and spatial patterns of drought in the Yellow River basin based on SPEI. Sci China Earth Sci. 2018;61(8):1098–111. https://doi.org/10.1007/s11430-017-9198-2.
62. Warsame A, et al. Drought, armed conflict and population mortality in Somalia, 2014–2018: A statistical analysis. PLOS Glob Public Health. 2023;3(4):e0001136. https://doi.org/10.1371/journal.pgph.0001136.
63. Waseem M, et al. Impact of meteorological drought on agriculture production at different scales in Punjab, Pakistan. J Water Clim Change. 2022;13(1):113–24. https://doi.org/10.2166/wcc.2021.244.
64. Worku MA. Spatiotemporal analysis of drought severity using SPI and SPEI: case study of semi-arid Borana area, southern Ethiopia. Front Environ Sci. 2024. https://doi.org/10.3389/fenvs.2024.1337190.
65. Xue L, et al. Assessing the drought variability in Northeast China over multiple temporal and spatial scales. Atmosphere. 2022. https://doi.org/10.3390/atmos13091506.
66. Zhu Y, et al. Combined use of meteorological drought indices at multi-time scales for improving hydrological drought detection. Sci Total Environ. 2016;571(1):1058–68. https://doi.org/10.1016/j.scitotenv.2016.07.096.

Publisher's Note