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Spatial-Temporal Analysis of Drought Characteristics in Tanzania from 1978 to 2018

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ABSTRACT

The economy of the United Republic of Tanzania (URT) relies on rain-fed agriculture; thus, climate variability has strong impacts on crop production, and yet the country ability to adapt to climate extremes such as drought or floods is low. In this regard, the spatial-temporal drought characteristics in Tanzania from 1978 to 2018 were analyzed by comprehensively looking at the effect of temperature on drought severity, duration, occurrence and magnitude using the monthly precipitation and temperature datasets from the Climatic Research Unit (CRU).Statistical values from Standardized precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) analysis were subjected to statistical tests such as Mann Kendall and Sen's slope estimator, Pearson correlation, root mean squared error and cross-wavelet transform to determine their performance and strength. Results showed **SPI** and **SPEI** indices are significantly correlated at 99% confidence level, despite that SPEI performed better than SPI which implies that temperature has positive impacts on evaporation which help to define drought events in Tanzania. Temporal analysis indicated short-term extreme drought events in the year 1997,1999,2000,2004,2010 and severe drought occurred in 1979, 1986,1992,1998, 2000, 2003, 2005, 2006, 2010, 2012, 2013.
While using a long-time scale, extreme drought events were detected in 1997, 2000, 2005, and 2006 and severe drought events were observed in 1997, 1999,2000,2003,2004, and 2011.

Considering these results, drought occurrences are imminent in URT, so adaptation measures such as planting drought-resistant crops varieties, timely crop planting, well developed early warning systems are highly recommended for the country.

Keywords

Drought. SPEI. SPI. Mann-Kendall. Correlation. Cross wavelet

Introduction

The impacts of changes in climate are manifested through the increases in extreme climatic conditions such as drought, floods, high temperature, and changes in precipitation season and intensity(1,2). The URT is in the list of 49 least developed countries (LCDs) in the world; its economy mainly relies on rain-fed agriculture but has a lower ability to adapt to climate extremes such as high temperature, droughts, floods, etc. Drought is defined as a climatic anomaly, characterized by high evaporation, unstable distribution, or a shortage of precipitation (3). According to Ogallo (1994), drought is a temporary feature resulting from the prolonged absence or poor distribution of precipitation. Similarly, it can be explained as a condition coupled with a deficiency of rainfall and poor distribution of rainfall which is the main cause for water shortage (5). It has no doubtful that drought condition has an impact not only on agriculture but also on other socio-economic development; therefore, monitoring and early drought warning require much rigorous effort to establish the strategies for adaption and mitigation (6). Drought can easily be defined through its types;, as follows (WMO, 2006; Hayes et al., 2007).Meteorological drought; is associated with precipitation shortage; and its dependents upon its duration (WMO, 2006). Agricultural drought, happens whenever there is a soil moisture deficiency to support crops growth(WMO, 2006). Hydrological drought, is the type of drought that occurs when there is a shortage of water in lakes, reservoirs, aquifers, and streams (WMO, 2006).

It is mainly related to stream flow and ground water level. Social-economic drought**;** is the type of drought that addresses the monetary effects of drought(8). Therefore, primary causes of drought are explained by meteorological droughts, while hydrological, social-economic, and agricultural droughts attempt to explain the secondary effects of the meteorological droughts (8).Since the Tanzanian economy is dependent on rain-fed agriculture, hence rainfall anomalies and climatic changes have direct impacts on the food security and livelihood of the rural communities. Extreme weather and climate events such as droughts, floods, high temperatures have negative effects on Tanzania's economy. For instance, in the recent decade, the prolonged drought from 1998 to 2005 caused devastating crop failures, livestock losses, and reductions in the country's water reservoir levels, which, in turn, created food shortages and rationing of hydroelectric power and water (Chang'a et al., 2017). There is a need for having favorable and implemented plans for environmental control to overcome climate extremes events like drought, floods, etc. Globally, it has been noticed that the frequency of warm spells and heat waves has increased much since the middle of the 20th century. Probably the number of heavy precipitation events over land has increased in more regions than it has decreased(1). Tanzania is among those regions where precipitation has shown a significant decrease.

Thus, frequent analysis of the severity of meteorological drought is highly needed to establish a framework for sustainable water resources management in the regions as well as agricultural sustainability. Many livestock from the central part of Tanzania especially Singida and Dodoma are usually moving to southern regions including Ruvuma, Lindi and Mtwara, in search of pastures during drought periods which results into conflicts among herders and farmers due to scramble for available resources.

Recently drought studies in URT observed more frequencies in the northern and central portion of the country especially in Arusha, Manyara, Sinyanga, Simiyu and Dodoma were severe drought experienced in the year 1999-2000 with an extension to 2005 (Kijazi and Reason, 2009).

The condition was associated with several problems such as low crop yield, food crisis, water shortage, and hydropower outage. In the present decade, 2010-2011, drought conditions, which occurred in a great area of Africa (11), impacted a large number of people in the northern portion of Tanzania, which were left with a scarcity of food and water (12). Droughts are presented as a long duration of time with precipitation deficiency, but it is hard to determine their onset of occurrence, extent, and end. Therefore, it is not easier to objectively quantify their characteristics in terms of intensity, magnitude, duration, and spatial extent. Thus, intensive efforts have been devoted to developing techniques for drought analysis and monitoring.

In the present years, there have been a lot of technical attempts to develop new drought indices or to improve the existing ones(González and Valde´s, 2006; Tsakiris et al., 2007, etc). Numerous experts and researchers have used precipitation as the principal indicator in drought analysis_(i.e., Mogha,2010).

Some drought studies conducted in Tanzania used the Standardized precipitation index (SPI) developed by McKee et al., (1993),; the index is based on a precipitation probabilistic approach, which is unable to fully account for drought severity status as a role of temperature, wind speed, and evaporation. Thus, to fill this gap, the Standardized precipitation evapotranspiration index (SPEI) developed by Vicente- Serrano et al.,(2010) was used to assess the spatial-temporal analysis of drought characteristics in Tanzania.

The SPEI index is typically developed for drought assessment in the context of warming globally, where temperature's role is objectively quantified through potential evapotranspiration (PET).Therefore the main theme/purpose of this study is to analyze spatial-temporal drought characteristics in Tanzania from 1978 to 2018 by considering the performance of SPI and SPEI drought indices.

Materials and methods

2.1 Description of Study Area

URT is located in the tropics along the latitude 0° to 12°S and longitude 28°E and 42°E (**Figure 1**).The country has a total area of 945,087 square kilometers, and it' s climate is characterized and regulated by complex topographical features extending from the coastal narrow belt of the western Indian ocean to an extensive plateau with an altitude range of 1000m to 2000m above the mean sea level (9).

Tanzania has varied topography and numerous lake, rivers, and streams that are also significant for influencing the local climate over the particular region of the country. URT experiences two modes of rainfall patterns, the unimodal and bimodal rainfall patterns;, caused by the north-south movement of ITCZ (18).

The east and north of Tanzania receive two distinct rainfall seasons that is October –December, which are "short rains", (OND), and March-May "long rains", (MAM).

Whereby; southern, western, and central part experience unimodal rainfall pattern that normally starts in October and continues to April and May (Makula and Zhou, 2021).

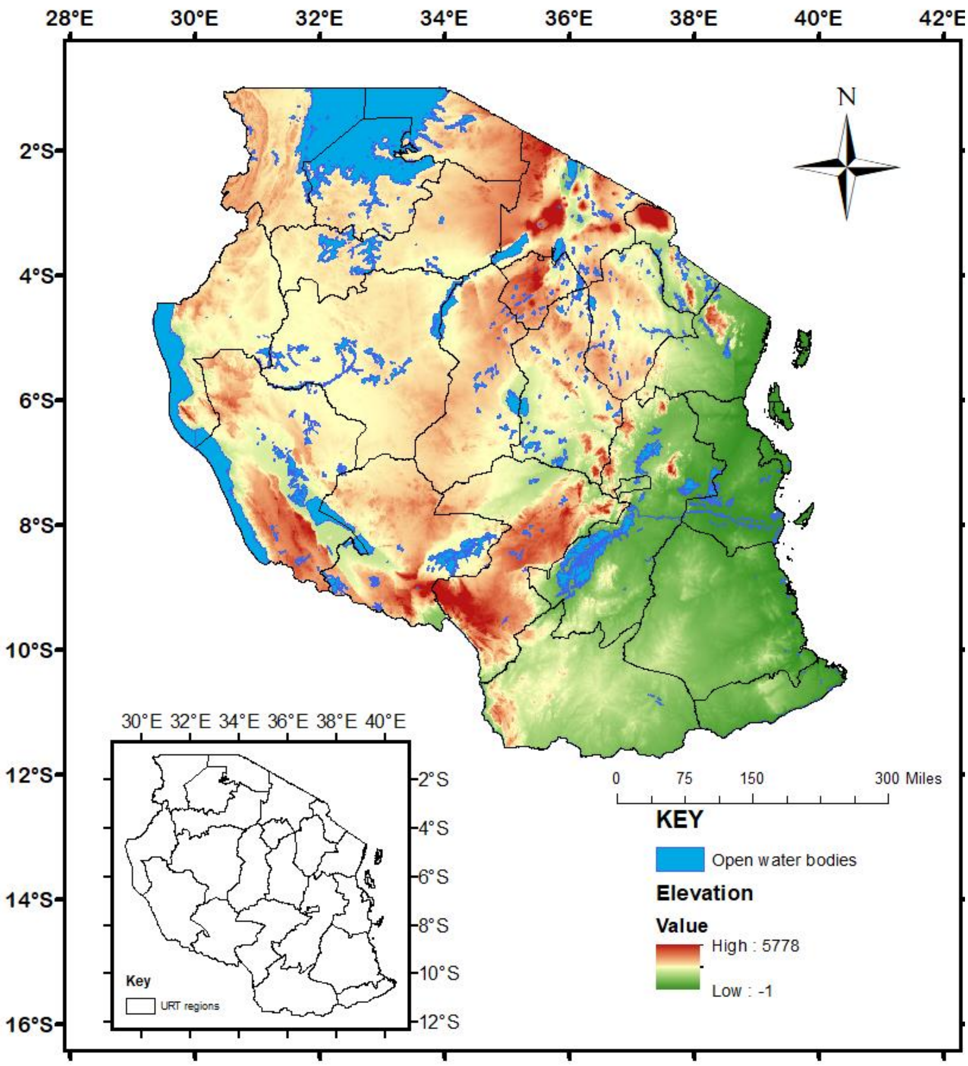


Figure 1 Shows elevation and open water bodies in URT overlaid with major regions

2.2 Data

The study used a gridded monthly precipitation dataset and temperature climatic dataset from Climatic Research Unit (CRU) from the University of East Anglia freely downloaded from the link;

http://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.03/data/

Even though the data period ranges from Jan 1901 to December 2018 and many previous versions. This study CRU dataset version 4.03(CRU TS 4.03) for a period of 1978-2018, entitled to cover the land surface at

0.5°×0.5° resolution, was selected to focus the analysis over recent years.

These data were used to study precipitation variability in East Africa in comparison with GPCC monthly precipitation dataset provided by the world climate research programme-WCRP (20), and the findings showed that the CRU dataset performs better than the GPCC dataset. Furthermore, previous researchers successfully used CRU dataset rainfall in Tanzania (Ogwang et al.,2015;Limbu and Guirong, 2020)

2.3 Methods

The methods employed in this study included the Mann Kendall trend test and their Sen's slope estimator, Pearson correlation, root mean squared error (RMSE), cross wavelet transform and Clip function method in ArcGIS for spatial plots. The Standardized Precipitation Index (SPI) was computed by using SPI_SL_6.exe software freely available for download through the website: (https://drought.unl.edu/droughtmonitoring/), while calculations of Standardized Precipitation Evapotranspiration Index (SPEI) were done by SPEI package in R-statistical. SPI software requires monthly precipitation data for its calculations while the SPEI package used the Hargreaves function to calculate Potential Evapotranspiration (PET) by using monthly maximum and minimum temperature for calculation of SPEI index. Drought categories according to SPI and SPEI values (16) are as shown in **Table 1.**

After these, the study employed statistical tests such as the Mann Kendall trend test and their Sen's slope estimator, Pearson correlation, root mean squared error (RMSE), cross wavelet transform and Clip function method in ArcGIS for spatial plots as discussed further below.

Table 1 Categories of drought indices (McKee et al. 1993)

Category	SPEI	SPI
Extreme Wet	≥ 2	≥ 2
Very Wet	1.5 to 1.99	1.5 to 1.99
Moderate Wet	1 to 1.49	1 to 1.49
Near Normal	-0.99 to 0.99	-0.99 to 0.99
Moderate Drought	-1 to -1.49	-1 to -1.49
Severely Drought	-1.5 to -1.99	-1.5 to -1.99
Extreme Drought	≤ -2	≤ -2

2.3.1 Trend and correlation analysis

The Mann–Kendall test(Mann, 1945;Kendall, 1976)was used for the analysis of the trend in rainfall and temperature as well as SPI and SPEI values at 1-, 3-, 12-, 24- months' time scales for the period 1978 to 2018.

The Mann Kendall method is a non-parametric test and does not necessarily need the data to be normally distributed; also the test has low sensitivity to abruptly break due to inhomogeneous time series(24).

The relative strength of the Mann Kendall trend test in time series analysis has been quantified using Sen's slope estimator(25).

As reported by(Chattopadhyay and Edwards, 2016), Sen's slope estimator has been the commonly used estimator due to its relative insensitivity and robustness to extreme values. The Mann Kendall statistic S of the series x is mathematically calculated as shown below:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(xj - xi)$$

Where; S is a statistic, $x\,i$ and $x\,j$ are the sequential data values, n is dataset record length of the time series and $\operatorname{sgn}(xj - xi)$ assumes the following values;

$$\operatorname{sgn}(xj\text{-}xi) = \begin{cases} 1 \; if \; xj > xi \\ 0 \; if \; xj = xi \\ -1 \; if \; xj < xi \end{cases}$$

While positive values of S indicate increasing trends, negative S indicates decreasing trends.

In detecting trend test, a hypothesis tells us follows, the null hypothesis (H_0) is defined as no trend and alternative hypothesis (H_1) can be predicted the presence of trend either increasing or decreasing monotonic trend(27).

Under the hypothesis of independent and randomly distributed random variables, for large samples, when $n \geq 10$ (in some papers $n \geq 8$), the σ statistic is approximately normally distributed, with zero mean and variance as follows:

$$\operatorname{Var}(S) = \frac{n(n-1)(2n+5)}{18}$$

However, it is necessary to calculate the probability associated with S and the sample size(n) to statistically significance the trend (Chinchorkar, 2015).

Then, a standardized statistical test is calculated by 'Z ' as shown below;

$$Z = \begin{cases} = \frac{s-1}{\sqrt{Var(s)}} \; if \; s > 0 \\ = 0 \qquad if \; s = 0 \\ = \frac{s+1}{\sqrt{Var(s)}} \; if \; s < 0 \end{cases}$$

While Positive values of Z signify increasing trends, negative Z signifies decreasing trends(29). In order to determine performance and correlation between SPI and SPEI root mean squared error and Pearson correlation were used respectively(30).

Cross wavelet transform methods were also applied for understanding the relationship between SPI and SPEI(31). Moreover, they assist in improving the empirical and comprehensive understanding of temporal characteristics of drought in the study domain.

2.3.2 Spatial Analysis

The Multidimensional toolbox in ArcGIS has tools that are used to create and manage different formats of data such as netCDF, GRIB, HDF, multidimensional mosaic datasets, and multidimensional image services. The tools are used to generate multidimensional metadata, create a multidimensional raster or feature layer (from netCDF files only), and table view for netCDF files only. In this study, the Clip function has been applied to extract the specific study domain;, thereafter, the bilinear interpolation has to be applied to create raster data plots from the extracted netCDF file(32). The bilinear Interpolation method uses a weighted average of the four nearest cell centers. The closer an input cell center is to the output cell center, the higher the influence of its value is on the output cell value (33).

This implies that the output value might be different than the nearest input, but it will always be within the same range of values as the input. This method is actually used for raster processing output to get a smooth map.

3. Results and discussion.

3.1 Mann Kendall trend test results.

Table 2 shows the results of the trend test and their Sen's slope estimator, in which both SPI and SPEI at 1-month timescale and 3-month timescale indicates non-significant decreasing trend with a very small rate of decrease, and long-time-scale SPI and SPEI at 12-month timescale and 24-month timescale portrayed significantly decreasing trend ($p<0.05$). The results show that both SPI and SPEI indices decreased trend during the study period which implies that the probability of drought occurrence increases. In this study, precipitation showed a negative trend while both maximum and minimum temperature indicated a positive trend (9).

Table 2 Results of trend test and Sen's slope estimator.

Indices	MK- test (S)	p-value	Sen's slope
SPI1	-0.0022	0.55	-0.0018
SPEI1	-0.0051	0.16	-0.0004
SPI3	-0.0031	0.39	-0.00027
SPEI3	-0.007	0.054	-0.0006
SPI12	-0.00012	**0.001**	-0.00095
SPEI12	-0.00014	**0.000017**	-0.0013
SPI24	-0.00018	**0.00000047**	-0.0017

SPEI24	-0.00022	**0.000000023**	-0.0019

3.2 Pearson correlation and RMSE

Table 3 indicates the findings in which all the indices are correlated at a 99% confidence level. SPI is highly correlated with SPEI, but SPEI provides good insight for drought monitoring, so this finding is in agreement with a study in Kenya, whereby SPEI were able to detect drought in the country (34).

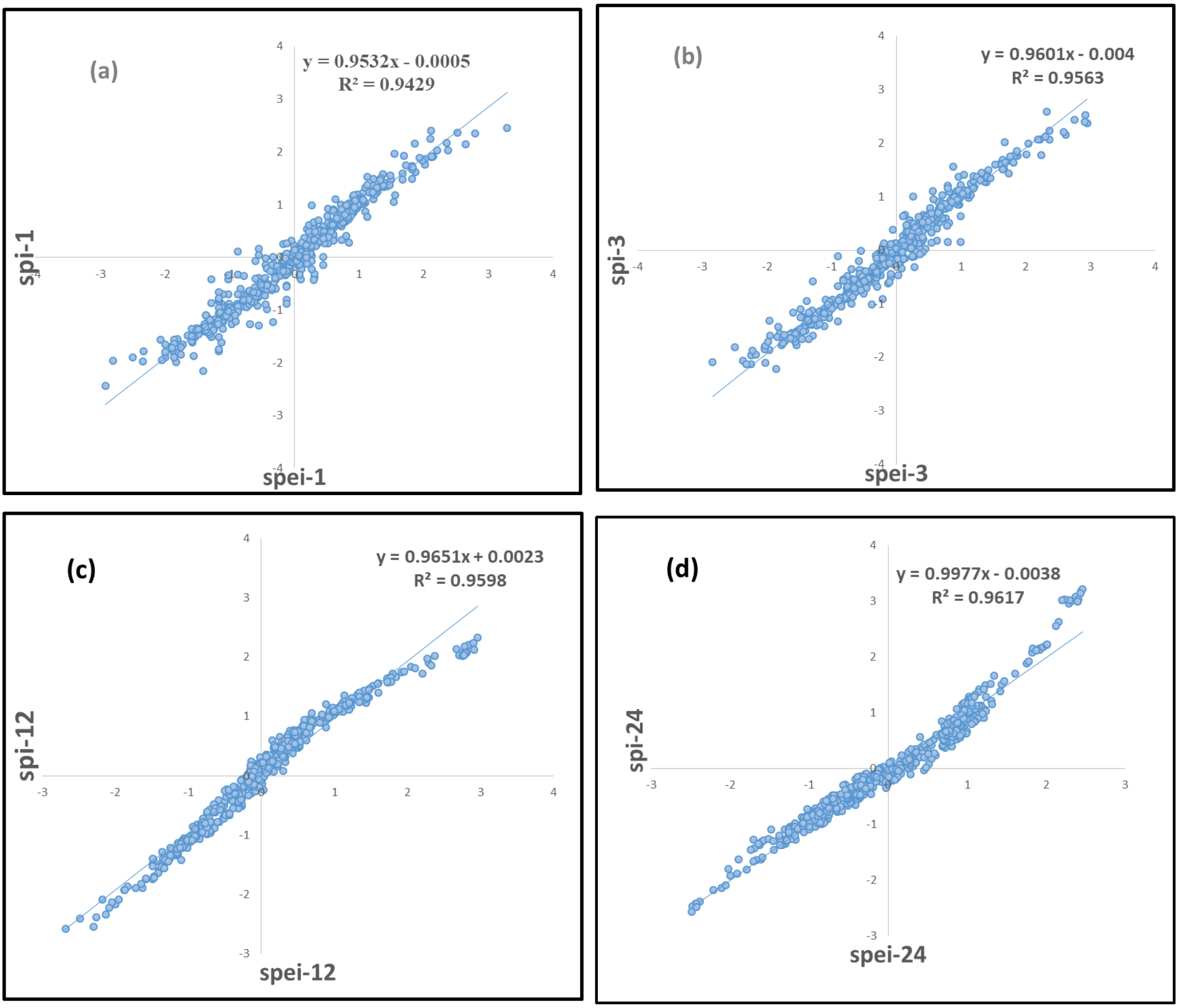


Figure 2-(a),(b),(c) and (d) indicates correlation between SPI and SPEI at 1-,3-,12-,and 24- month time series respectively.

SPEI indicated a small error than SPI which implies that SPEI is highly recommended to detect and monitor drought in the study region rather than SPI. Results for RMSE are indicated in **Table 3,** which shows that Correlation and RMSE, whereby all correlation are significant at the 99% confidence level.

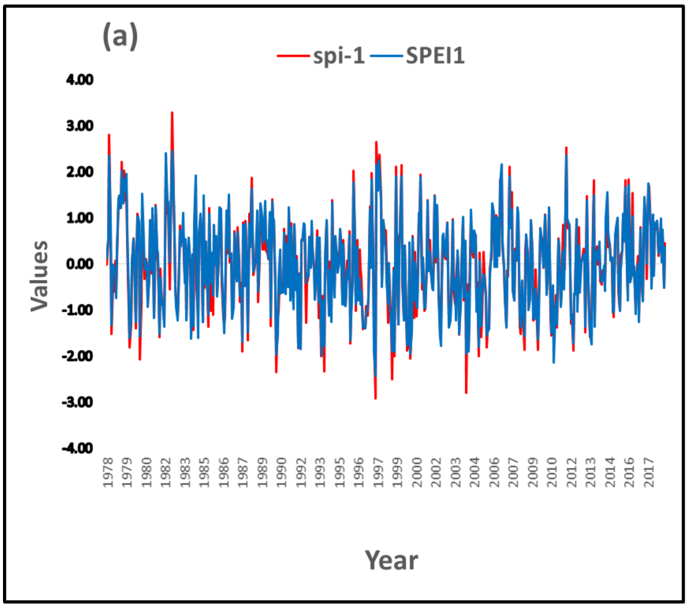
Table 3. Correlation and RMSE of SPI and SPEI

Drought indices	R coefficient	RMSE
SPI1	0.97	1.00
SPEI1	0.97	0.98
SPI3	0.97	1.00
SPEI3	0.97	0.98
SPI12	0.98	0.99
SPEI12	0.98	0.97
SPI24	0.98	0.96
SPEI24	0.98	0.93

3.3 Temporal trends of Drought events

In this study SPI and SPEI at 1-, 3-, 12-, 24- months scale time series were used to analyze temporal trends of drought as indicated in **Figure 3**-a, b, c, and d. Due to the high correlation between these two indices and fewer RMSE values of SPEI at each timescale, hence SPEI index has been selected for further drought detection in this study. Drought is noticed when the value of the SPEI index reaches -1 and continues until the value becomes positive number. The 1- month and 3- month timescale of SPEI values reflect short- and medium-term moisture conditions.

Results show that the study region had both wet and dry months of the year over the study period.



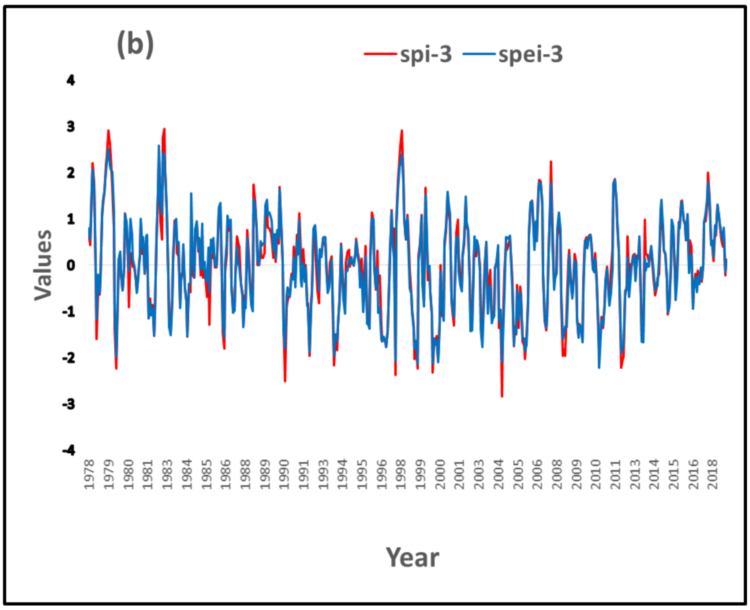


Figure 3. (a),(b); Comparison of temporal trends of SPI and SPEI at 1-month and 3-month time series from 1978 to 2018.

Based on SPEI 1-, 3- timescale both extreme, severe and moderate droughts were detected in different months of the year as categorized by(16).

Low-frequency extreme drought was identified by SPEI-1 in September; 1997 and October- 2010 with a high magnitude of **-2.44**, in addition to that February; 1999, February and June; 2000 and July; 2004 were detected by SPEI-3.Though by using SPI 1-, 3- months, we detected that some months of the year were overrated to extreme drought conditions such as October; 1997, August; 1990, October; 1993, December; 1998, June; 2006, and March-April; 2012. Severe drought conditions were identified 1979,1980,1982,1983,1984,1986,1990,1992,1993,1995,1996,1997,1998,1999, 2000,2002,2003, 2004, 2005, 2006, 2008, 2009, 2012 and 2013 by using both SPEI 1-, 3- month timescales.

In many of these years, high-frequency severe drought conditions were observed in the season of March-May, June-August, and October – December.

Within the recent years, neither extremely nor severe drought was identified at a short timescale only moderate drought conditions were determined in some months of February-March- August-2015, October-2016, and January-2017. These short-term droughts were considered meteorological droughts. SPEI 12-, 24- month timescales reflect long-term moisture conditions (**Figure 3**-c.d), were also used to characterize drought conditions in the study domain. Both SPEI-12 and SPEI-24- detected extreme drought in March-1997, January –November- 2000, December -2005 and January- March; 2006.The highest magnitude of **-2.58** was detected in 2006 followed by **-2.54** in 2000. SPEI-24 could not detect extreme drought in any month of 2005. The results above are in agreement with (Kijazi and Reason, 2009).Some months of the year were characterized by severe droughts, such as 1993, 1997, 1999, 2000, 2003,2004,2005,2006, and 2011.

The highest frequency of about 9 months of severe drought was observed in 1997, as detected by both SPI-12 and SPEI-24. While only two months, June and July, were determined by SPEI-12 in 2011 showing that some parts were characterized by severe drought. In 2005, 2006, 2009, 2011, 2012, and 2013 moderate drought conditions were recorded by both SPE-12 and SPEI-24, with a high-frequency of months observed in 2011 and 2012, respectively. This occurrence of drought is supported by previous studies (35,36).

Medium time scales are highly related to reservoir storage and soil moisture which can be termed as agricultural drought(17). The study did not detect extreme and severe drought conditions from 2016 to 2018.This implies that duration had the wet condition.

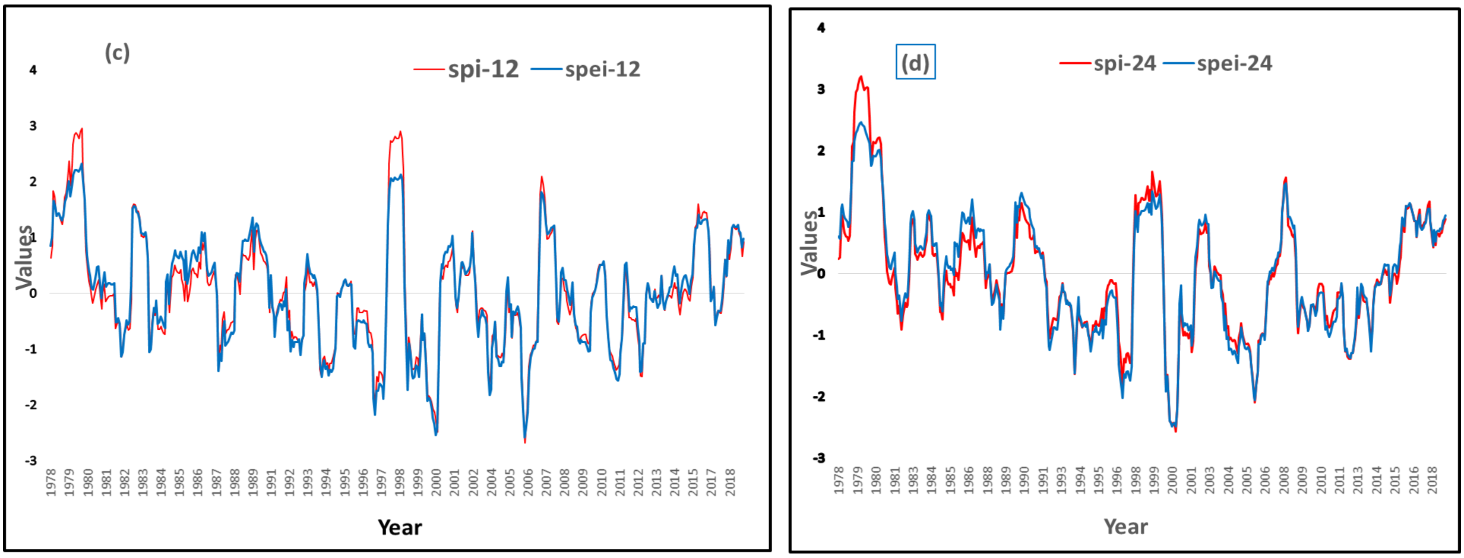


Figure 3. (c), (d); Comparison of temporal trends of SPI and SPEI at 12-month and 24-month time series from 1978 to 2018.

In this study SPEI-1 and SPEI-3 were used to represent short-term drought and indicate wet or dry seasons, while SPEI-12 and SPEI-24 represented annual (medium-term) and multi-annual (long-term) drought and were used to show wet/dry years within the study period.

3.4 Cross wavelet transform analysis

Figure 4 (a, b, c, d) shows a cross wavelet transform between SPI and SPEI values at different months' timescales. This was done purposely to check for significant interaction between the two-time series signals (37).The curved black line represents the cone of influence and the thicker black contour shows a 5% significance level. While right-pointing arrows imply two signals are in phase with one another, left point-arrow indicates two signals are antiphase, down/up pointing arrow signifies that one signal is ahead/lag behind the other respectively (31,38).

The findings from this study show that at every time scale SPI and SPEI have a strong positive correlation, and signals are in phase.

Figure 4a, SPI, and SPEI at 1-month timescale power spectrum energy are mainly concentrated in the cycle of 1-64 periods within the entire study period 1978-2018, but for 3- timescale (**Figure 4**b) show significant resonance at a cycle of 1-36 periods during 1978-2013.

Figure 4c, Long term SPI and SPEI at 12-month the significant resonance was at a cycle of 4-64 period from 1978 to 2018, but resonance cycle of 6-64 period was determined for SPI and SPEI at 24-month timescale from 1979-2014 (**Figure 4**d).

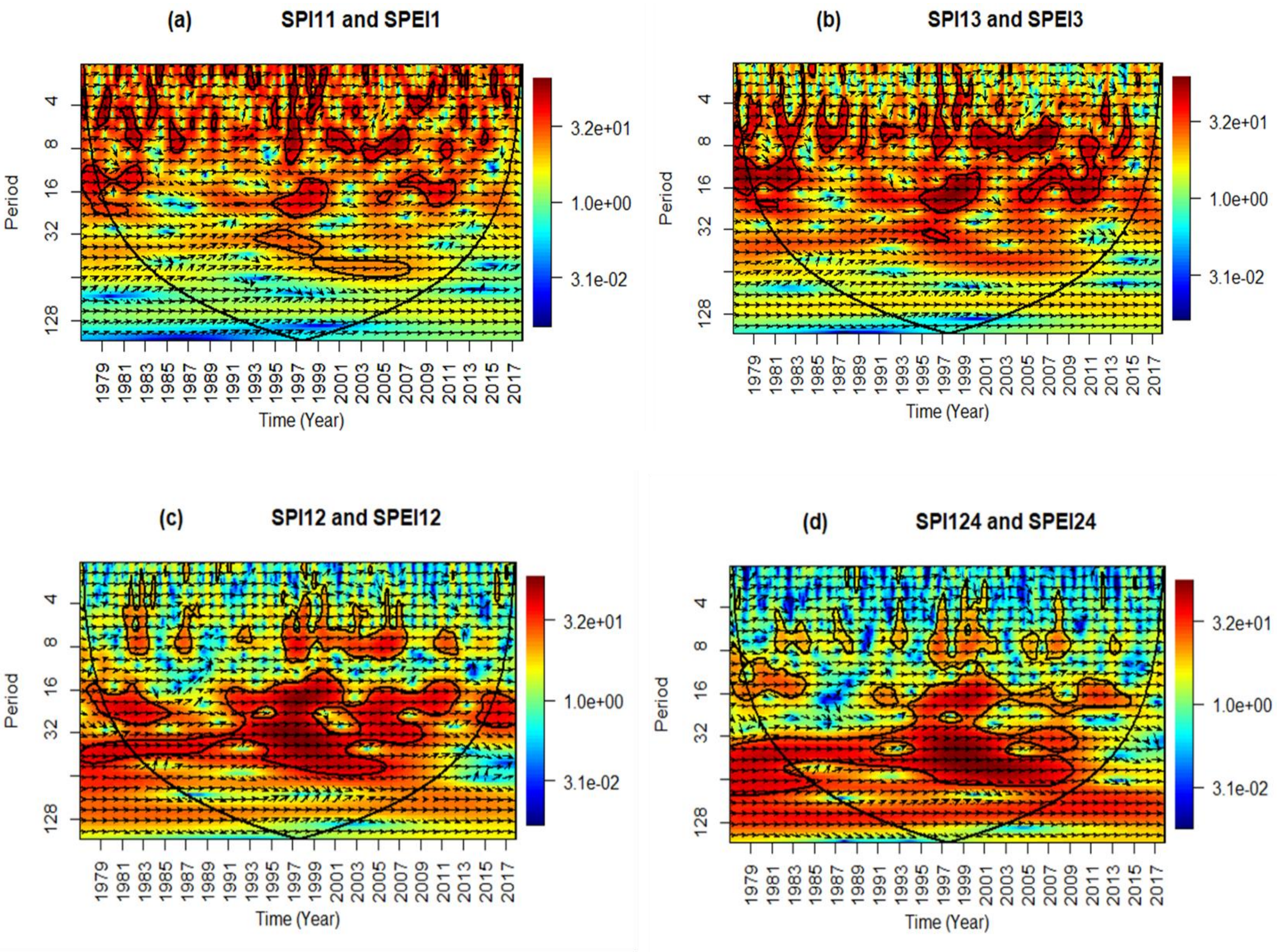


Figure 4 (a), (b) and (c),(d) shows cross wavelet transform between SPI and SPEI at 1-,3- ,12- and 24-month timescale respectively.

Small lag was detected when short time scale and long time scale were subjected to cross wavelet transform, and the results found that long term drought occurrence lag behind short term drought conditions. Accumulation of meteorological drought can result in Agricultural or hydrological drought(17).

3.5 Spatial analysis of Drought

The spatial maps indicate different drought conditions from short-term to long term duration (**Figure 5.**a,b,c,d).The early warning of drought indicated by SPEI-1 identified very dry conditions at the central, severe, and moderate drought at the northern and other parts of the country except the north-east part of Tanzania(Figure 5.a). Spatially severe drought occurrence covers a large part of the study domain as indicated by SPEI-3 (**Figure 5.**b). Tanzania Islands (Ungula, Pemba and Mafia) revealed wet conditions for both short-time identification results. Analysis shows the increasing frequency of drought events at central extending to the southern and northern part. Long time analysis by using SPEI-12 gave a good insight of drought occurrences at the central part and southern with the extreme condition at the central and severe drought spreading toward the southern region of Tanzania especially Lindi and Mtwara. But 24-month timescales indicate extreme drought conditions at the central, severe drought in the northern part and south of Tanzania. This is in agreement with the study conducted by (9) on spatial and temporal occurrences of high temperature extremes. Though studies conducted ways back by using SPI values did not account for drought condition in the southern part of Tanzania. The results of drought conditions in the central part and northern part agree with some studies previously conducted by (10,15).More than 80% of the whole study domain is affected by drought at every timescale.

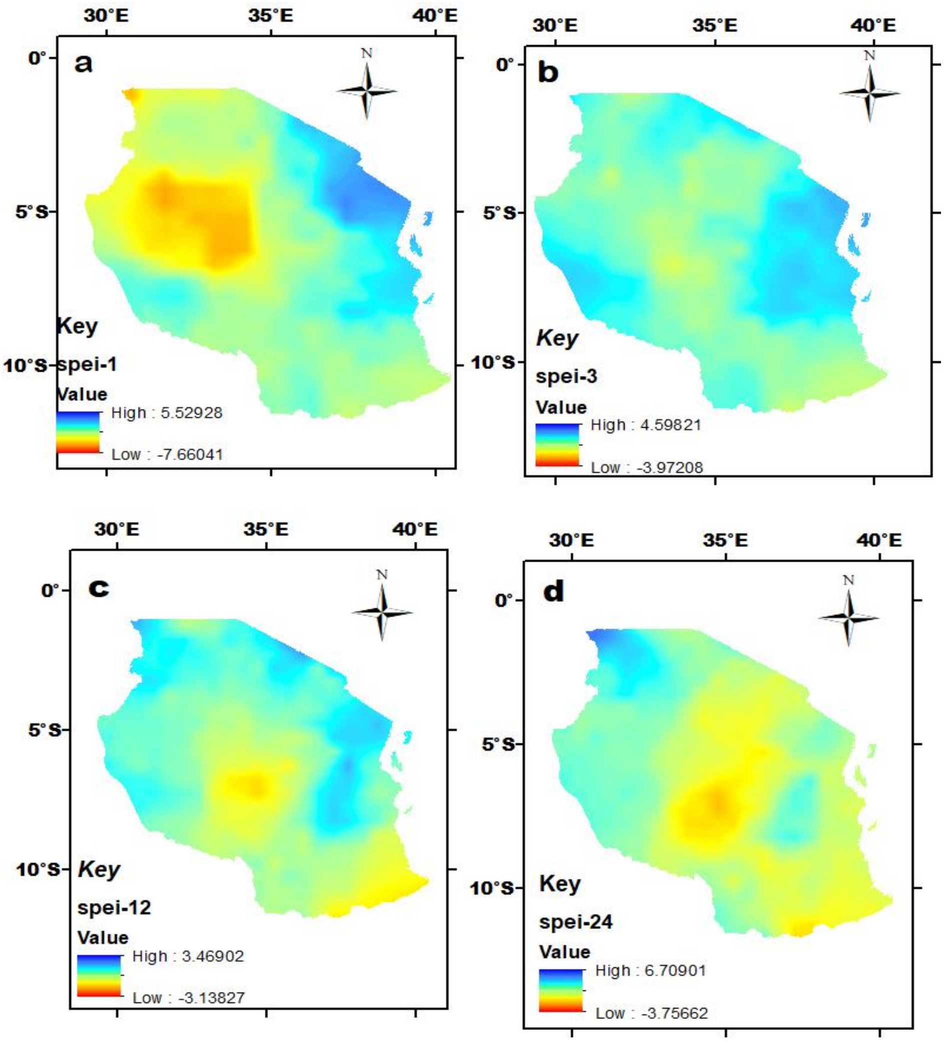


Figure 5. Spatial Map showing (a)SPEI-1, (b) SPEI-3, (c) SPEI-12, (d) SPEI-24 from 1978-2018.

The findings from the study are consistent with an increasing trend of global warming (2).A decrease in rainfall patterns, especially in OND and MAM, has been widely observed in this study.

Agriculture activities in most parts of the country are dependent on rain-fed during these seasons; as a result, production of both food and cash crops decreases. A significant increase in temperature caused by anthropogenic activities and other natural forcing result in occurrences of drought in the region of study.

In some parts of Tanzania, drought condition is influenced by overgrazing which may cause land degradation and result in a shortage of water (39), especially in the northern and central part of Tanzania.

It has been observed that temperature increases promote high evaporation and transpiration, which reduce soil moisture as well vegetation cover decline.

In recent years many pastoralists moved from the northern and central part of Tanzania to the southern region in search of pasture and grazing areas, this might be an additional factor to the frequent occurrence of drought in the southern region.

Conclusion

The study performed the analysis of spatial-temporal characteristics of drought in Tanzania from 1978 to 2018. Monthly precipitation, maximum and minimum temperature data from the CRU dataset were used for temporal analysis, while SPEI data were used for spatial analysis. Different methods used to calculate drought indices includes SPI and SPEI which were then subjected to statistical methods to check for a comprehensive comparison of the performances and accuracy.

SPI and SPEI were found to be highly correlated but SPEI was selected for further drought analysis due to its ability to account for temperature effects on drought occurrences.

Findings suggest that climate extremes such as high temperature has a contribution to drought assessment in the study area. Extreme drought detected in 1997, 2000,2004,2005,2006 and 2010 at different timescale.

The decrease in the amount of rainfall was highly detected in October- December and March–May seasons. Most areas of the central and southern part of Tanzania are affected by a shortage of water, especially during the summer seasons. The results of this study are the potential to support developing climate change adaptation activities, drought hazard mapping, and local drought policy formulating.

Based on the findings of the present study, it is likely to continue to experience warming/high temperatures extremes and seasonal rainfall variability in the future. This study therefore, recommends that adaptation measures such as planting drought-resistant crops varieties, timely crop planting, well developed early warning systems are to be implemented. In addition, water harvesting and storage can be promoted for irrigation to supplement rain-fed agriculture and for consumption by people and livestock in all areas found to be vulnerable to drought conditions.

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