

Spatio-temporal analysis of drought variability in central Ethiopia

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ABSTRACT

Drought is a major problem in Ethiopia and particularly affects the agricultural and water sectors. This paper aims to assess the spatial and temporal drought variability of central Ethiopia. For this purpose, archival rainfall data recorded from 1989 to 2017 and the Gurage zone topographic maps were used. The five stations' Standardized Precipitation Index (SPI) were combined with the geographical information system (GIS) to analyze the spatial distribution of drought events. The results show that a total number of 41 drought events were recorded in the region. The number of drought events reaches its maximum value in the year 1992, whereas Bui and Koshe contain the most frequent drought events. The spatial analysis of droughts verifies that most of the frequent and extreme events are recorded in the eastern part of the region. The lowland part of Gurage zone is very prone to drought. The grounded spatio-temporal drought risk events analysis has shown a possible threat to the water and rain-fed farming that has a cascading effect on the livelihoods of farmers. Moreover, the drought condition of the region is unpredictable and recurrent. This study recommends further study containing remaining statistical drought indices such as reconnaissance drought and streamflow drought index.

Key words | drought, GIS, spatial, SPI, temporal, variability

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HIGHLIGHTS

- I found that some parts of the zone are very sensitive and vulnerable to drought events.
- I found that drought conditions in the area are unpredictable and recurrent.
- I identified areas vulnerable to drought, which helps to point out adaptation options and spot early warning signs, establishing a climate research center and refugee camp.
- I identified the level of drought risk in the area against the global risk measurement scale.

INTRODUCTION

A natural hazard is a natural occurrence that might have a negative effect on living organisms and the environment. Natural hazard events can be classified into two broad categories: geophysical and biological (Burton *et al.* 1993).

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Internal or external processes such as active diastrophism and climate changes are capable of changing landforms and activating natural hazards, which in some cases control human activities (Bathrellos *et al.* 2014). Among meteorological or climate hazards, drought and flood are common hazards for our ecosystem. Literally, drought is a period of below-average precipitation in a given region, resulting in lengthy shortages in the water supply, whether atmospheric,

surface water, or groundwater. Scientists warn that global warming and climate change may result in more extensive droughts in the near future (Nagarajan 2010). These extensive droughts are likely to occur within the African continent due to its very low precipitation levels and high temperatures/pressure (Calow *et al.* 2010).

Droughts occur frequently in some parts of the world (Mishra & Singh 2011). A drought can last for years, or may be declared as drought after as few as 15 days, and if lasting for less than 15 days is declared a dry spell (Sivakumar 1992). Recurrent drought has a substantial impact on the ecosystem, agriculture and water sector of the affected region and harms the social, cultural, and economic life of the locality (Amsalu & Adem 2009). Extreme heat can significantly worsen drought conditions by hastening evaporation of soil and surface water and transpiration of plant leaf (Dai *et al.* 2018). Frequent drought is common in the tropics and significantly increases the chances of a

famine, poverty, fragile ecosystem, and subsequent natural fires (Brando *et al.* 2019). Drought is one of the most devastating natural hazards, and has exerted negative impacts on industrial production, labor efficiency, agricultural production, electricity production, and groundwater potential (Omer 2008). In Ethiopia, recurrent drought has been observed in different time periods with diverse magnitude and dimensions since 1957 (Table 1).

Drought occurrence can be assessed in space and time through a sound basis of scientific use of historical data (Tsakiris *et al.* 2007). Currently, there are many statistical-based drought indices, for example, the Reconnaissance Drought Index (RDI) and the Streamflow Drought Index (SDI). Also, the widely used Standardized Precipitation Index (SPI) and rainfall deciles can be used (Tigkas *et al.* 2015). The common characteristics of the SPI and rainfall deciles are that they require a relatively small amount of data for their analysis and the results can be easily interpreted and

Table 1 | Chronological story of drought in Ethiopia from 1957 to 2017 (source: Menkir 2018; Mekonen *et al.* 2020)

Year	Region affected	Effect and damage
1957/58	Tigray and Wollo	Rain failure in 1957 and about 100,000 people died
1962/63	Western Ethiopia	Extreme drought
1964–66	Tigray and Wollo	About 1.5 million people affected
1971–75	Ethiopia	Rain failures; estimated about 250,000 dead; 50% of livestock lost in Tigray and Wollo
1978/79	Southern Ethiopia	Failure in Belg rain and 1.4 million people affected
1982	Northern Ethiopia	Late Meher rains and 2 million people affected
1984/85	Ethiopia	Rain failure; 8 million people affected
1987/88	Ethiopia	7 million people affected
1990–92	Northern, Eastern, and SW Ethiopia	Rain failure, about 4 million people suffering food shortage
1993/94	Tigray and Wollo	Widespread food insecurity (7.6 million people were affected), but few deaths or cases of displacement were reported
1997	Borena, Bale, Omo, Somali	Almost 986,000 people affected
1999	N. and S. Wollo, Wag, Himra; Tigray; B. Gumu, Gambela, Oromia, SNNPR, Somali	Almost 5 million people affected
2003/4	All regions	Over 13 million people affected, but the response mitigated the worst potential outcomes
2005	Somali, Oromia	Almost 2.6 million drought disaster affected people
2008/9	All regions	Almost 12.6 million people affected
2011	S and E. Oromia, Somali	Severe food insecurity and 4 million people affected
2015/16	N, E, and SW Ethiopia	About 10.2 million people affected
2017/2018	Southeastern Ethiopia	Estimated a total of 7.88 million people affected

used in strategic planning and operational applications. Principally, SPI is usually used as a meteorological drought indicator but based on rainfall information alone, which is significantly both a strength and shortcoming (Temam *et al.* 2019). A study conducted by Shamshirband *et al.* (2020) verified that SPI is the drought index that delivers higher accuracy than other indices. Ali Ghorbani *et al.* (2018) stated that the possibility to estimate drought through evaporation rates using novel learning algorithms remains a vital task for agriculture and water resources management.

Drought is one of the most common climatic or meteorological hazards, and has significant impacts on the livelihoods and economy of Gurage zone. The use of long-term climate data can be employed to analyze the spatial and temporal drought characteristics, and the outcomes of such study would be helpful for better understanding drought behavior and for adaptation options. To fill the gap, SPI-12 and a topographic map were used to assess drought in Gurage zone, and the objective of this study is to assess spatio-temporal analysis of drought variability in central Ethiopia. This work will fill the gap in planning of

water resource use, mitigation, and drought disaster prevention in the region.

MATERIALS AND METHODS

Description of the study site

This study was conducted in Gurage zone, one of the administrative zones of Southern Nations, Nationalities, and People Region, central Ethiopia. It is about 155 km southwest of Addis Ababa, bordering the Awash River in the north, the Gibe River (a tributary of Omo River) to the southwest and Lake Ziway in the east. The total area of the zone is about 5,893.4 km² and is geographically located between 7° 40' 0"–8° 20' 0" and 38° 0' 0"–39° 0' 01" (Figure 1). The zone is characterized by a bi-modal rainfall regime, locally known as *Kiremt* (main rainy season) and *Belg* (small rainy season) seasons. Based on the 2007 Census conducted by the Central Statistical Agency of Ethiopia (CSA), this zone has a total population of 1,279,646, of

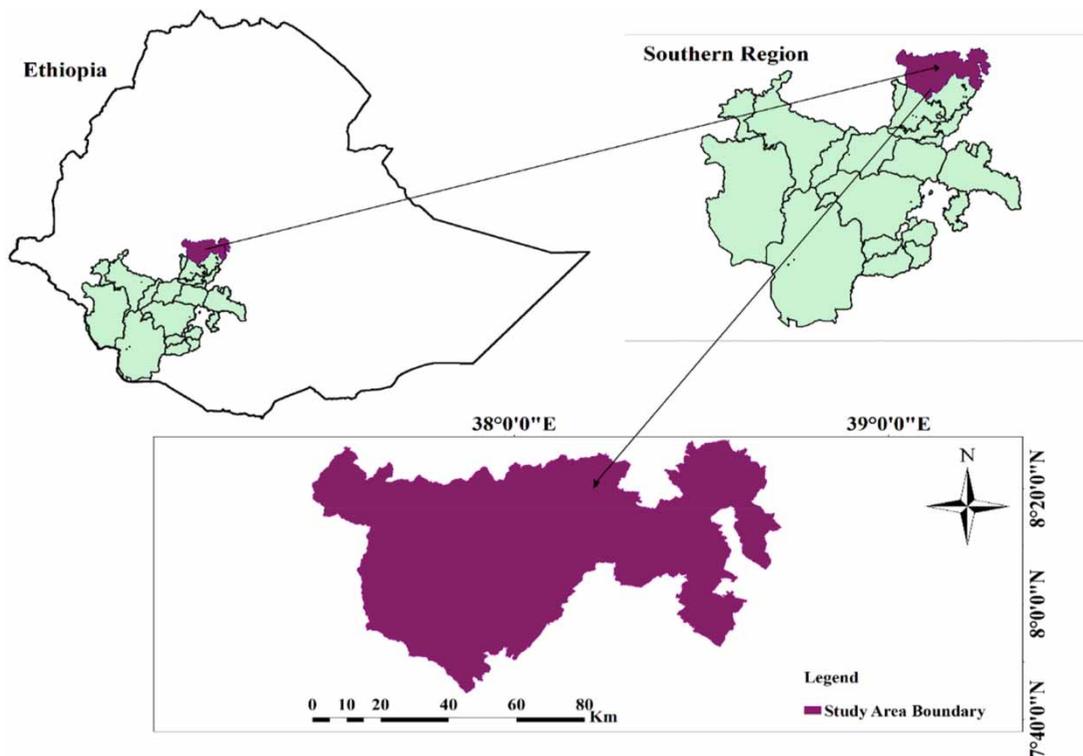


Figure 1 | Location map of the study area.

whom 622,078 are men and 657,568 women, and are frequently affected by drought.

Data sources and analysis techniques

Drought studies have received a great deal of attention from researchers worldwide. In the present study, historical rainfall data of Gurage zone stations were used. Daily archival rainfall data series recorded for 29 years (1989–2017) from five stations were collected from the Ethiopia National Meteorology Agency (NMA) (Table 2). Ethiopia Mapping Agency (EMA) shape file database and SPI-12 output data were used as input for geostatistical analysis (Empirical Bayesian kriging). Empirical Bayesian kriging is a geostatistical interpolation method that automates the most difficult aspects of building a valid kriging model. The primary benefits of the Empirical Bayesian kriging method are that standard errors of prediction are more accurate than other kriging methods, it requires minimal interactive modeling, allows accurate predictions of nonstationary data, and is more accurate than other kriging methods for small datasets. Moreover, other kriging methods require manual adjustment of some parameters to achieve accurate results, but Empirical Bayesian kriging automatically calculates these parameters through a process of sub-setting and simulations.

The daily rainfall database contains information such as the location of stations (elevation, xy coordinate, city, village, and special reference point) and daily rainfall records. The EMA database contains area boundaries, districts, village, and other details.

Instat + v3.37, DrinC and XLSTAT 2019 software were used to analyze temporal drought events, whereas the spatial event was interpolated using ArcGis 10.5.1. The

primary benefits of DrinC are that it's a user-friendly tool, operates with small units of data and is suitable for meteorological, hydrological, and agricultural drought analysis.

Missing data and consistency check

Missing data may be due to the absence of an observer, short disturbances in observations due to breakage, malfunction, and calibration problem of instruments during a certain time period. Therefore, this needs to be solved before undertaking further analyses. The missing values were patched using a first-order Markov chain model of Instat version 3.37 software. The benefits of the first-order Markov chain model are simplicity and out of sample forecasting accuracy and simulation. Simple models, such as those used for first-order Markov chain model, are often better at making predictions than more complicated models. The consistency of the rainfall data set was checked by the double-mass curve method and a plot of average cumulative annual rainfall data (as ordinate) against the abscissa. The double-mass curve is used to check the consistency of many kinds of hydrologic data by comparing data for a single station with that of a pattern composed of the data from several other stations in the area. The double-mass curve can be used to adjust inconsistent precipitation data of more than two stations.

Trend analysis and model specification

The Mann–Kendall test was used for analysis of the trend in rainfall for the time period 1989–2017. There are two benefits of using the Mann–Kendall test. First, it is a non-parametric test and does not require the data to be normally distributed. Second, the test has low sensitivity to abrupt

Table 2 | Average annual rainfall and standard deviation (SD) in the study area

No.	Station	Years	Mean rainfall (mm)	SD (mm)	Elev. (m)	Long. (E)	Lat. (N)
1	Imdibir	29	1,174.11	290.81	2,076	8.13	37.93
2	Wolkite	29	1,191.89	389.36	2,000	8.29	37.78
3	Butajira	29	984.04	402.45	2,000	8.12	38.37
4	Bui	29	1,063.12	206.62	2,020	8.32	38.55
5	Koshe	29	801.86	187.27	1,878	8.01	38.53

breaks due to inhomogeneous time series. Each data value is likened to all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time, the statistic S is increased by 1. On the other hand, if the data value from the later time period is lower than a data value sampled earlier, S is decreased by 1. The net result of all such increments and decrements is one that determines the final value of S . The Mann–Kendall S statistic is mathematically computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(T_j - T_i)$$

$$\text{sign}(T_j - T_i) = \begin{cases} 1 & \text{if } T_j - T_i > 0 \\ 0 & \text{if } T_j - T_i = 0 \\ -1 & \text{if } T_j - T_i < 0 \end{cases}$$

where T_j and T_i are the annual values in years j and i , $j > i$, respectively.

A positive value of S indicates an increasing trend whereas a negative value indicates a declining trend in the data. At a certain probability level H_0 is rejected in favor of H_1 if the absolute value of S equals or exceeds a specified value $S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest S which has probability less than $\alpha/2$ to appear in the case of no trend. For $n \geq 10$, the statistic S is approximately normally distributed with the mean and variance as follows:

$$E(S) = 0$$

The variance (σ^2) for the S statistic is defined by:

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum t_i(i)(i-1)(2i+5)}{18}$$

where t_i denotes the number of ties to an extent i . The summation term in the numerator is used only if the data series contains tied values. The standard test statistic Z_s is calculated as follows:

$$Z_s = \begin{cases} \frac{S-1}{\sigma} & \text{for } S > 0 \\ 0 & \text{for } S = 0 \\ \frac{S+1}{\sigma} & \text{for } S < 0 \end{cases}$$

The test statistic Z_s is used as a measure of the significance of the trend. In fact, this test statistic is used to test the null hypothesis, H_0 . If $|Z_s|$ is greater than $Z_{\alpha/2}$, where α represents the chosen significance level, then the null hypothesis is rejected, implying that the trend is significant.

Another statistic obtained on running the Mann–Kendall test is Kendall's tau, which is a measure of correlation and therefore measures the strength of the relationship between the two variables. In common with other extreme correlations, Kendall's tau will take values between ± 1 and $+1$, with a positive correlation indicating that the ranks of both variables increase together while a negative correlation indicates that as the rank of one variable increases, the other decreases.

The SPI was determined as the difference between the annual totals of a particular year and the long-term average rainfall records divided by the standard deviation of the long-term data. This index is used to observe the nature of the trends and also enables determination of the extremely dry and wet years in the record. SPI was plotted against time (in years) to visualize and identify/select the extreme drought and flooding year in the time period for further analysis. In addition to this, [McKee et al. \(1993\)](#) designed a SPI for multiple time scales from 1 to 12 months which was used to identify the drought variability of an area and is mathematically computed as:

$$\text{SPI}_{12} = \frac{(X - \mu)}{\delta}$$

where SPI-12 is Standardized Precipitation Index; X is the annual rainfall total of a particular year; μ is mean annual rainfall over a period of observation; and δ is the standard deviation of annual rainfall over the period of observation.

Nowadays, there are many drought indices used to analyze drought such as the RDI, SDI, SPI, and the rainfall deciles. For this study, the SPI drought index was used due to its advantages. The advantages of this index are that it requires a relatively small number of data for its analysis and the results can be easily interpreted and used in strategic planning and operational applications. SPI is usually used as a meteorological drought indicator, but based on rainfall information alone, which significantly shows both a strength and a shortcoming.

According to the classification scale for SPI values, a positive value of the SPI denotes that rainfall at the study area is higher than average whereas a negative value of the SPI indicates that rainfall in the area is lower than normal (Du *et al.* 2013; Pei *et al.* 2013). A region will be considered as ‘extreme wet’ if the SPI value of the area is greater than or equal to +2.00 and, oppositely, the region is

considered as suffering drought if the SPI value of the area is less than -2.00 (Table 3).

RESULTS AND DISCUSSIONS

Missing data and consistency check

The consistency of the rainfall data set was checked by the double-mass curve method and a plot of average cumulative annual rainfall data (as ordinate) against the abscissa. As shown in Figure 2, the double-mass curve ensured that all stations’ data were consistent due to the fact that missed and outlier data were filled correctly.

Rainfall trend analysis

The annual rainfall in the four stations showed a decreasing trend by a factor of -0.2, -2.02, -8.8, and -3.21 mm per year at Bui, Butajira, Koshe, and Wolkite stations, respectively, but had an increasing trend at Imdibir station

Table 3 | Classification of SPI values

SPI	Classification
≥2.00	Extreme wet
1.50 to 1.99	Severe wet
1.00 to 1.49	Moderate wet
0.50 to 0.99	Mild wet
-0.49 to 0.49	Near normal
-0.99 to -0.50	Mild drought
-1.49 to -1.00	Moderate drought
-1.99 to -1.50	Severe drought
<- 2.00	Extreme drought

Source: Du *et al.* 2013; Pei *et al.* 2013.

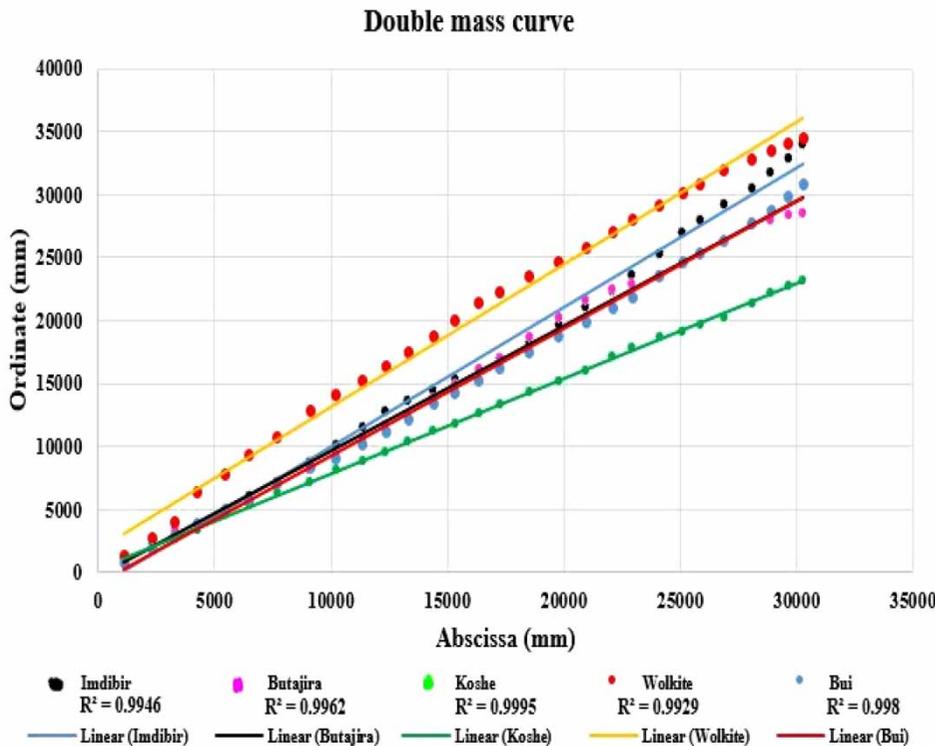


Figure 2 | Double-mass curve.

(Table 4). The result of the annual rainfall probability values showed a significant trend at Koshe and Wolkite but a non-significant trend was observed at the remaining stations, which might be associated with large inter-annual fluctuation. According to Hulme *et al.* (2001) and the IPCC (2001), East Africa rainfall shows an increasing trend. Negash & Eshetu (2016) reported a decreasing trend at Chida station (16.08 mm/year) and Butajira station (6.26 mm/year).

Table 4 | Mann–Kendall trend statistics of annual rainfall of the region

Station	Years	Sen's slope	Z value	Mk statistic (S)	P-value
Imdibir	29	4.23	0.138	56	0.302
Bui	29	-0.2	-0.02	-6	0.922
Butajira	29	-2.02	-0.24	-97	0.072
Koshe	29	-8.8	-0.3	-112	0.04
Wolkite	29	-3.21	-0.66	-249	0.0001

Temporal trends of drought events

The year-to-year variation of drought in terms of normalized anomaly index (SPI-12) covering the period of 1989–2017 was examined. The study region had both wet and dry years over the study period. A mixture of dry and wet years have been observed. Of the observed period, 48.9% of rainfall was recorded above the normal average, however, below normal condition was recorded by 51.1%. Moreover, the largest negative deviation occurred in the years 1992, 2012, 2016, and 2017, while the highest positive anomalies occurred in the years 1993, 2005, and 2010 in the region (Figure 3). These findings conformed to the study by Kidane *et al.* (2010) on years of drought and floods in Ethiopia.

Spatial patterns of drought incidence

The general agriculture of the area predominantly depends on bimodal rainfall, *Kiremt* (main rainy season) and *Belg*

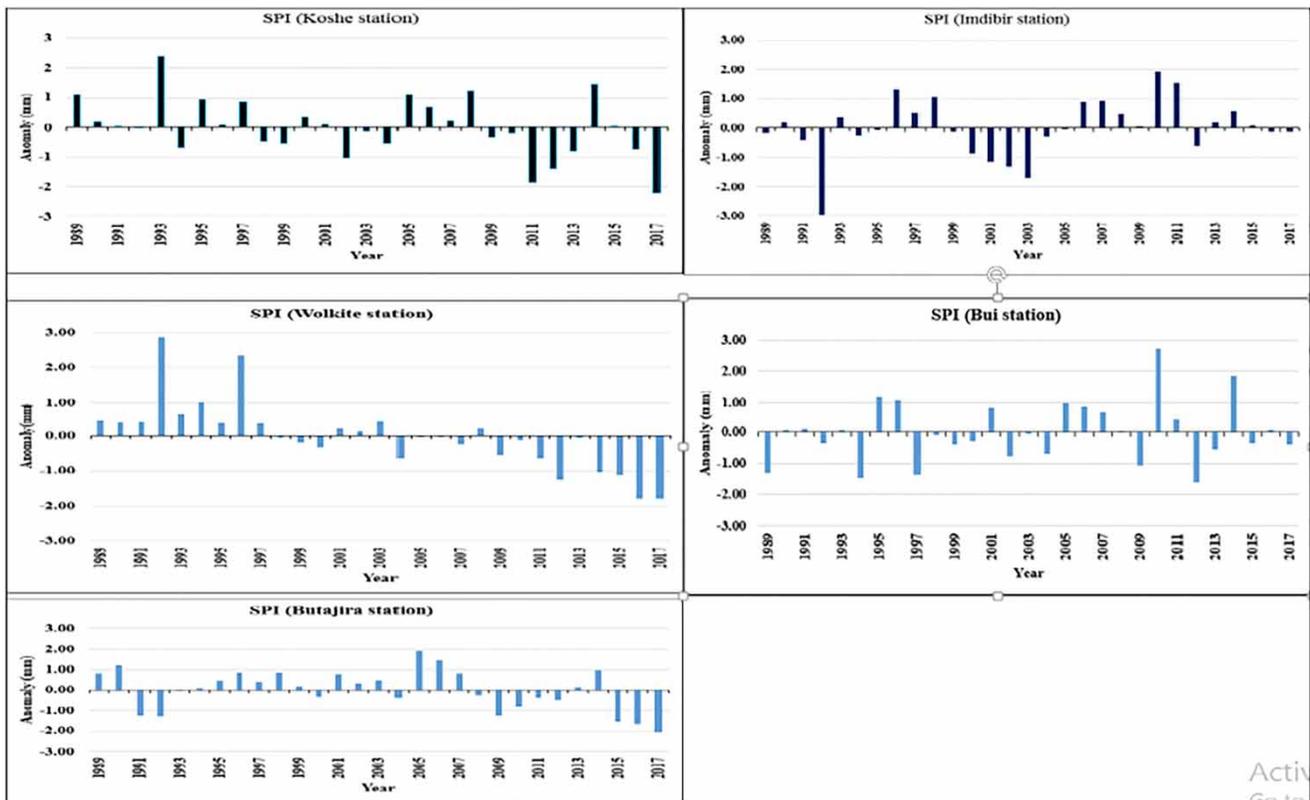


Figure 3 | Temporal distribution of drought in the region.

(small rainy season), i.e., agricultural productivity heavily depends on rainfall characteristics such as onset and cessation of rainfall and length of growing period. *Kiremt* is the main rainy season in which about 85–95% of the agricultural crops of the region are cultivated. *Kiremt*, the period from June to September following the *Belg* rains, is associated with frequent rains and homogeneous temperatures, mainly in July and August. Due to their absolute dependency, a minor disturbance in *Kiremt* rainfall has a huge effect on the livelihood and economy of smallholder farmers of the region. The spatial analysis of droughts verifies that most of the frequent and extreme events are recorded in the eastern part of the region (Figure 4). The lowland part of Gurage zone is very prone to drought. The majority of the region has experienced severe and extreme ($SPI \leq -1.50$) drought events. Specifically, Imdibir, Butajira, and Koshe experienced extreme drought with risk peak value of $SPI \leq -2$ while Wolkite and Bui were affected by severe drought with risk peak value -1.8 to -1.63 . The study indicated that the region is suspected of/experienced unpredictable drought events with different time scales.

The observed spatio-temporal drought risk events indicate a potential hazard to the rain-oriented agriculture, hence steadily affecting the regular farming system, and water and food security.

CONCLUSIONS

This study presented space and time drought risk events through a sound basis of the scientific use of historical data in central Ethiopia using SPI-12. The results of the study prove that complex and localized spatio-temporal patterns of drought risk events were identified. This could help to recognize and characterize local-based drought conditions. The annual rainfall in four stations showed a decreasing trend whereas an increasing trend was observed at Imdibir station. There was a non-significant trend at Imdibir, Bui, and Butajira stations, but a significant trend was observed at Koshe and Wolkite stations.

During the period of study, the temporal analysis showed that there were times when the entire

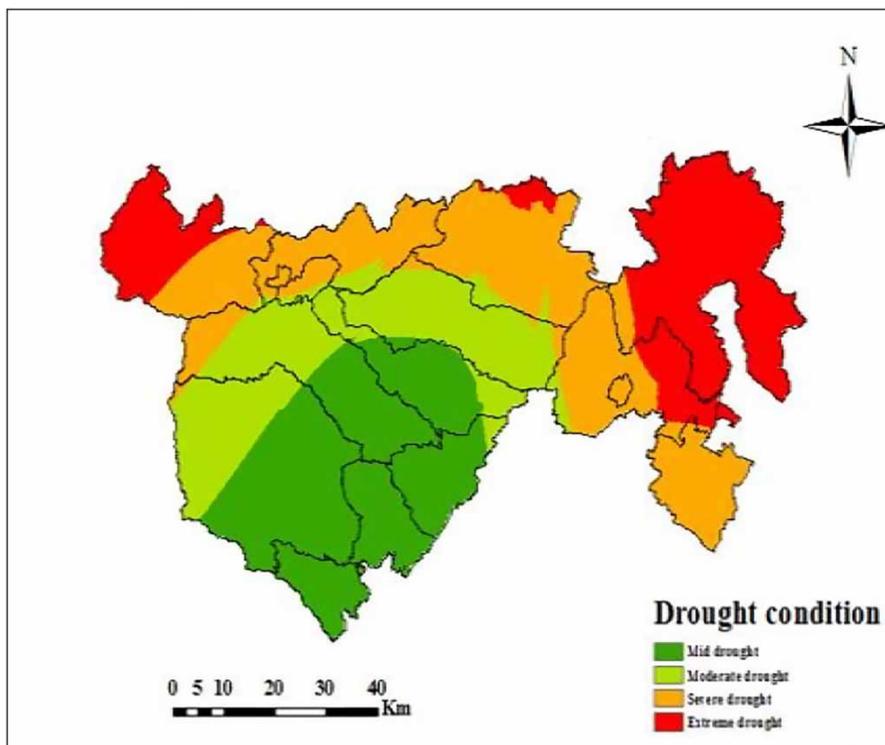


Figure 4 | Spatial distribution of drought in the region.

region experienced drought, and the largest negative deviation occurred in the years 1992, 2012, 2016, and 2017, while the highest positive anomalies occurred in the years 1993, 2005, and 2010. The number of drought events reached its maximum value in the year 1992.

The spatial analysis of droughts verifies that most of the frequent and extreme events are recorded in the eastern part of the region. The lowland part of Gurage zone is very prone to drought, and the area needs drought hazard assessment mapping. The majority of the region experienced severe and extreme ($SPI \leq -1.50$) drought events. Specifically, Imdibir, Butajira, and Koshe experienced extreme drought with risk peak value of $SPI \leq -2$ while Wolkite and Bui were affected by severe drought with risk peak value -1.8 to -1.63 .

The study indicated that the region experienced unpredictable drought events at different time scales. The observed spatio-temporal drought risk events indicate a potential hazard to the rain-oriented agriculture, hence steadily affecting the regular farming system, and water and food security. The findings of this research could be important in strategic planning and operational applications like drought monitoring, platforms for early warning and preparedness, local-scale adaptation planning, and food security strategies and policy direction. The limitation of the study remains the lack of consistent, reliable, and recent years' data for the case due to malfunctioning and relocation of some stations in the region. This study recommends further research on remaining statistical drought indices such as RDI and SDI. Supplementary irrigation is recommended as the best adaptation option throughout the drought period.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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