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Evaluation of time scale of meteorological, hydrological and agricultural drought indices

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Abstract

The present study was carried out to characterize drought in the Marathwada region of Maharashtra, which experiences recurring droughts, through meteorological, hydrological and agricultural drought indices, namely the Standardized Precipitation Index (SPI), Streamflow Drought Index (SDI) and Vegetation Condition Index (VCI), respectively. Standardized Precipitation Index (SPI) and Streamflow Drought Index (SDI) were computed at 1, 3, 6, 9 and 12-month time scales using in situ precipitation and streamflow data, respectively, for 35 years (1980–2014). The VCI was computed using MODIS satellite data at 500 m resolution for 1, 3 and 5-month time scales for 15 years (2000–2014). The time scales of drought indices were evaluated using historical drought years and foodgrain production. The drought area observed by SPI, SDI and VCI at different time scales was correlated with foodgrain production during *kharif* season for 15 years (2000–2014). The correlation analysis indicated a significant correlation between foodgrain production and 3-month SPI ($r = -0.724$) and 5-month VCI ($r = -0.811$), respectively, however, a low correlation was observed between multiscale SDI and foodgrain production. 3-month SPI and 5-month VCI were found to be more appropriate time scales to observe meteorological and agricultural droughts, respectively, in the region; while none of the SDI's time scales could capture hydrological drought. The analysis also revealed that the magnitude of meteorological (observed by 3-month SPI) and agricultural (observed by 5-month VCI) droughts mimic the quantum of loss in foodgrain production very closely. However, the severity and the areal extent of droughts observed by these indices were varied both spatially and temporally. Thus, the present study concluded that a single indicator (i.e., meteorological, hydrological or agricultural) is not sufficient to capture the actual drought situation, thereby suggesting the use of multiple indicators-based approaches for realistic drought characterization and monitoring.

Keywords Drought · Standardized Precipitation Index (SPI) · Streamflow Drought Index (SDI) · Vegetation Condition Index (VCI) · Marathwada · Maharashtra

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1 Introduction

Drought is a complex phenomenon. It is difficult to determine the onset, areal progression and cessation of drought. Developing countries like India and others, particularly suffer significantly from frequent drought occurrence. Owing to climate change, the frequencies of dry spells and drought events are increasing. About 32.5% of the geographical area of India is subjected to different degrees of drought stress (Mishra and Desai 2005), which causes adverse impacts on economic and social areas, especially in the agriculture sector, leads to a decline in foodgrain production depending upon the severity, duration and areal coverage of drought.

Drought characterization enables operations such as drought early warning (Kogan 2000) and drought risk analysis (Hayes et al. 2004), which allow improved preparation and contingency planning. Drought characteristics over a region are primarily governed by regional climatic factors. Hence, the choice of indices for drought characterization in a specific area should eventually be based on the long-term climate data available and on the ability of the index to consistently detect spatial and temporal variations during a drought event. Accurate information about the attributes and impacts of drought is essential for better planning and management. Therefore, it is recommended that different types of drought indices such as meteorological, hydrological and agricultural drought indices should be considered to describe and characterize drought.

Meteorological drought is defined as a period with a lack of precipitation lasting sufficiently to cause hydrological and agricultural hazards (Łabędzki and Bąk 2014). Many indices and methods have been developed and are used to determine the intensity of meteorological drought. The Palmer Drought Severity Index (PDSI; Palmer 1965), Standardized Precipitation Index (SPI; McKee et al. 1993, 1995), Effective Drought Index (EDI; Byun and Wilhite 1999), Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010), etc., are the most popular drought indices being used for meteorological drought characterization. However, many research studies have concluded that SPI is comparatively better than other indices for its simplicity in terms of computation and data requirement (Sims et al. 2002; Bonsal and Regier 2007; Bordi and Sutera 2008; Angelidis et al. 2012). The SPI is the most preferable index to monitor meteorological drought in many developed and developing countries (Cheval 2015). The SPI is also recommended by the World Meteorological Organization (WMO) for meteorological drought characterization in order to make regions more comparable to each other (Frank et al. 2017). It was developed by McKee et al. (1993, 1995) for estimating wet or dry conditions based on the precipitation variable. It is also effective during the winter months and not adversely affected by topography (Hayes et al. 1999).

Hydrological drought is associated with the impact of prolonged precipitation deficiencies on water supply from surface or subsurface sources such as rivers, reservoirs and groundwater (Keyantash and Dracup 2002). A number of drought monitoring indices such as the Palmer Hydrologic Drought Index (PHDI; Palmer 1965), Surface Water Supply Index (SWSI; Shafer and Dezman 1982), Reclamation Drought Index (RDI; Weghorst 1996) have been used over the years. However, indices for characterizing hydrological drought are, generally, data demanding and computationally intensive. On the other hand, the Streamflow Drought Index (SDI) developed by Nalbantis and Tsakiris (2009) has the advantages of simplicity and effectiveness to monitor hydrological drought (Tabari et al. 2013; Myronidis et al. 2018).

Agricultural drought is caused due to the shortage of a sufficient amount of available soil moisture impacts the growth and development of plants. Agricultural drought could be described by analyzing the conditions of vegetation. Many indices such as Relative Soil Moisture (RSM; Thornthwaite and Mather 1955), Crop Moisture Index (CMI; Palmer 1968), Crop Specific Drought Index (CSDI; Meyer et al. 1993), Soil Moisture Deficit Index (SMDI; Narasimhan and Srinivasan 2005), Soil Moisture Evapotranspiration Index (SMEI; Ajaz et al. 2019) have been developed and used for agricultural drought characterization; but the application of remote sensing derived indices have gained more popularity due to wide spatial coverage (Peters et al. 2002; Wan et al. 2004; Tadesse et al. 2005; Ghulam et al. 2007). The Normalized Difference Vegetation Index (NDVI; Tucker 1979) is one of the promising vegetation monitoring indices (Kogan 1995; Gu et al. 2007; Brown et al. 2008; Sahoo et al. 2015). It is an indicator of the green biomass, leaf area index and pattern of production (Thenkabail et al. 2004). The NDVI is governed by several factors e.g., vegetation, ecosystem, phenology of crops, soil, topography, etc., (Di et al. 1994). NDVI values need to be stratified to avoid the influence of environmental factors and make it comparable in space (Vicente-Serrano 2007). The Vegetation Condition Index (VCI) is an index that normalizes geographical differences in vegetation types and physiographical settings (Vicente-Serrano 2007; Patel and Yadav 2015).

Drought may occur at multi-temporal (weekly, sub-seasonal or seasonal) scales with different spatial scales (local, regional, global) (Kam et al. 2014). The use of an appropriate time scale for drought assessment is essential to track drought as closely as possible, to minimize carry-over effects between successive time intervals and to reduce the operational constraints of monitoring organizations (Nalbantis and Tsakiris 2009). The choice of 3-month intervals is preferred in many studies (Livada and Assimakopoulos 2007; Akbari et al. 2015; Kazemzadeh and Malekian 2016). However, it is important to test the drought indices and time scales for monitoring of different drought types under different environmental conditions and water demand situations (Vicente-Serrano and López-Moreno 2005).

The Marathwada region of Maharashtra is considered as a drought-prone area and has historically faced many drought events of varying magnitudes. The region has experienced about 9 severe drought years from 2000 onward. Topographically, it receives less rainfall compared to the rest of Maharashtra, thereby leading to frequent dry spells and drought conditions. It is a rainfed region and farming is mainly dependent on rainfall. Only about 20% of the area under cultivation is irrigated (Agricultural census 2010–11). Surface water resources and groundwater contribution is 6% and 8%, respectively, to the net irrigated area. The majority of precipitation (75%) is received through the south-west monsoon that takes place during June–September. Hence, the main farming season is during June–October period which is referred to as the *Kharif* season. The major foodgrain crops grown in this region are Jowar, Bajra and Maize as cereals, Redgram and Moong as pulses.

The monsoonal precipitation supplies the water demand of crops, especially, in rainfed areas leading to good foodgrain production. Delay or failure in the monsoon causes dry spells or drought in the region that affects crop growth and decline in the foodgrain production. Therefore, the *Kharif* crop growing season is an important season, where the direct impact of the drought could adversely affect foodgrain production.

In the present study, spatio-temporal analysis of meteorological, hydrological, and agricultural drought has been carried out using the Standardized Precipitation Index (SPI), Streamflow Drought Index (SDI) and Vegetation Condition Index (VCI), respectively, at different time scales; and evaluated against historical drought years and foodgrain production during *Kharif* crop growing season of the region.

2 Study area

The study area (covering 9.4 Mha area) comprises nine districts of Maharashtra, India: Aurangabad, Beed, Jalna, Latur and Osmanabad (5 districts out of 8 districts of Marathwada region). In addition to these, 4 adjacent districts of Marathwada (i.e., Ahmednagar, Sangli, Satara and Solapur) were also included in this study. Geographically, the region is located between 16°42′ 35.72″ N to 20°39′ 11.99″ N latitude and 73°32′ 39.10″ E and 77°17′43.49″ E longitude (Fig. 1) and is characterized by a hot semiarid climate with dry summer and cool winter. It receives an average annual rainfall of about 550 mm, which mainly occurs during the monsoon period (i.e., from June to September). The Godavari is the main river system in this region. Purna, Dudhana, Pravana, Mula, Sina, Manjra, Bhima, Man, Yerla, Koyna and Vaina are the other rivers, which flow through this region (Fig. 2).

3 Materials and methods

3.1 Data used

(i) *In situ data*: In situ data comprised of daily precipitation (from 17 rain-gauge stations shown in Fig. 2) and streamflow (from 10 stream-gauge stations installed in river streams shown in Fig. 2) data for 35 years (1980–2014) obtained from the Department of Hydrology in Nashik, Maharashtra.

(ii) *Remote sensing (RS) data*: The TERRA MODIS data (MOD13A1) from 10th June to 16th October (16 days' interval) at 500 m spatial resolution was downloaded from https://lpdaac.usgs.gov for 15 years (2000 to 2014) for computation of VCI.

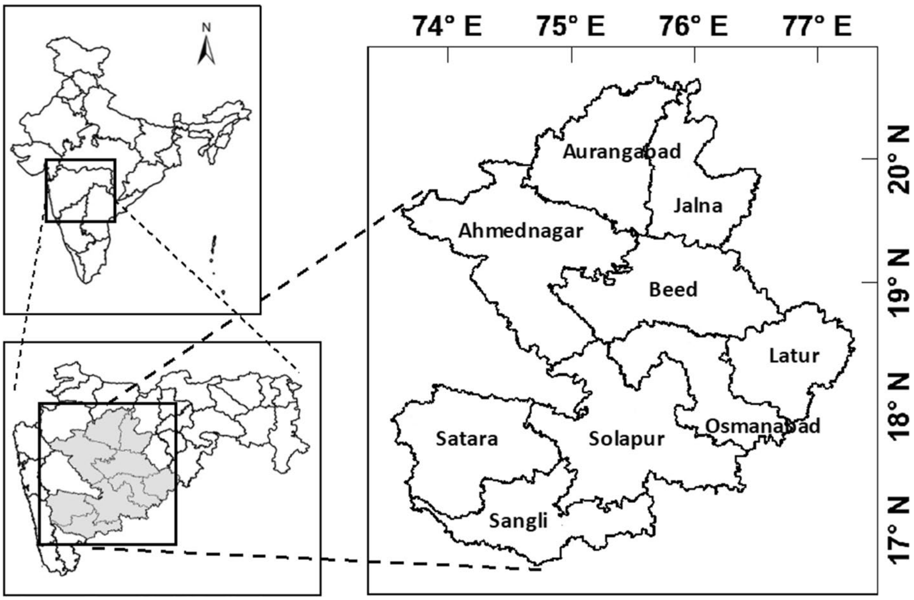

Fig. 1 Study area comprises of nine districts of Maharashtra

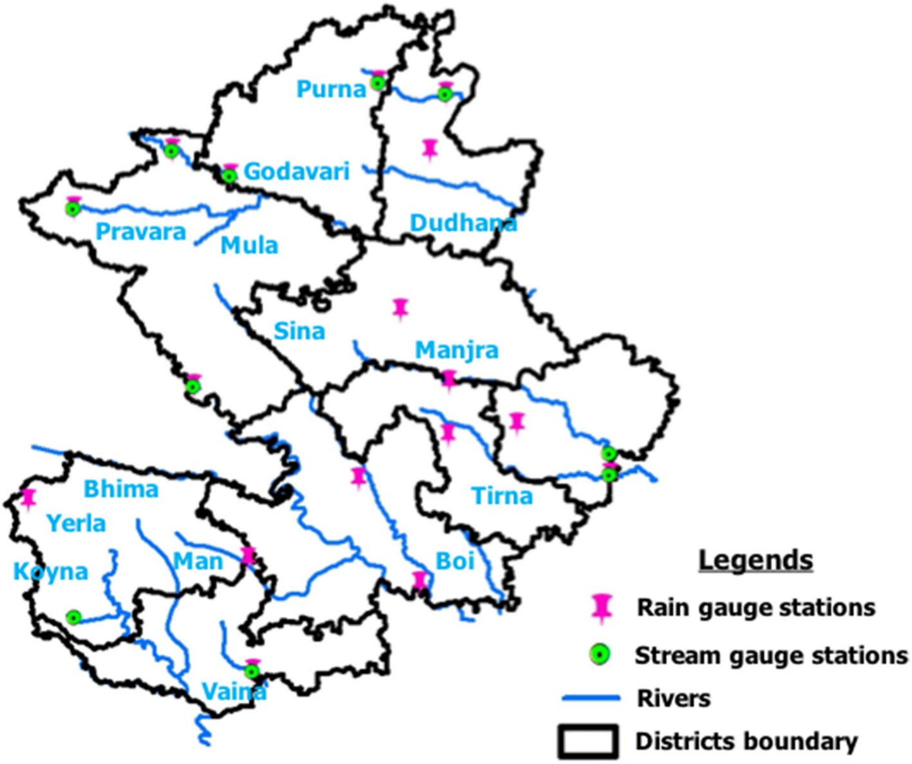

Fig. 2 River system, rain gauge and stream gauge stations of the study region

(iii) *Crop production data*: District wise crop production data (measured in metric tonnes) of major crops grown in the test region were also procured from the Department of Agriculture, Government of Maharashtra for 15 years (2000 to 2014) for validation of the drought assessing the potential of the various drought indices.

(iv) *Drought events data*: The historical drought years declared by the State Government during 2000–2014 were obtained from the Department of Agriculture & Cooperation and Farmers Welfare (DAC&FW), Ministry of Agriculture and Farmers Welfare (MoA&FW), Government of India.

3.2 Computation of drought indices

3.2.1 Standardized Precipitation Index

The Standardized Precipitation Index (SPI) was used as a meteorological drought index, which is determined by normalizing the long-term precipitation record for the desired period for a given station after it was fitted to a probability density function as described by McKee et al. (1993, 1995), Edwards and McKee (1997), and Guttman (1998) so that mean SPI for the station and desired period is zero. The SPI calculation procedure was adopted from WMO, SPI user guide (Svoboda et al. 2012). The SPI program (SPI_SL_6.

exe) available on http://drought.unl.edu/MonitoringTools/DownloadableSPIProgram.aspx used for computation of SPI.

3.2.2 Streamflow Drought Index

The hydrological drought was characterized by the Streamflow Drought Index (SDI) adopted from Nalbantis and Tsakiris (2009). SDI can be defined for the *t*th month of the *v*th hydrological year as,

$$\mathrm{SDI}_{v,t} = \frac{F_{vt} - \overline{F}_t}{\sigma_t} \quad \mathrm{t} = 1, 2, 3, \ldots .12 \tag{1}$$

where F_{vt} is the flow rate for *v*th year and *t*th month, $\overline{F}_t$ and σ_t are the long-term mean and the standard deviation of *t*th month.

The streamflow probability distribution for small basins is usually skewed and thus may require normalization (Nalbantis and Tsakiris 2009; Batelis and Nalbantis 2014). The two-parameter log-normal distribution was used to normalize the streamflow series as it was considered to be the most suitable probability distribution for the streamflow series (Rimkus et al. 2013; Tabari et al. 2013; Surendran et al. 2017).

3.2.3 Vegetation Condition Index

Vegetation Condition Index (VCI) was used to characterize agricultural drought, derived from base index NDVI by using the following equation (Kogan 1995),

$$\mathrm{VCI} = (\mathrm{NDVI}_i - \mathrm{NDVI}_{\mathrm{min}}) / (\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}) \times 100 \tag{2}$$

where VCI indicates how close NDVI of the current period (NDVI_i) is to the minimum NDVI ($\mathrm{NDVI}_{\mathrm{min}}$) of long term. Here, the maximum NDVI ($\mathrm{NDVI}_{\mathrm{max}}$) and minimum NDVI ($\mathrm{NDVI}_{\mathrm{min}}$) were calculated from the long-term record of that particular period.

3.3 Drought severity classification

Meteorological drought classifications were adopted from the McKee classification system (McKee et al. 1993, 1995; Hayes et al. 1999) (Table 1). Hydrological drought classifications are identical to those used in the meteorological drought index (SPI) (Nalbantis and Tsakiris 2009). However, these classifications were modified into three specific categories

Table 1 Meteorological and hydrological drought classification scheme based on SPI/SDI (McKee et al. 1993, 1995; Hayes et al. 1999; Nalbantis and Tsakiris 2009)

SPI/SDI	Classification
> 2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
− 0.99 to 0.99	Near normal
− 1.0 to − 1.49	Moderately dry
− 1.5 to − 1.99	Severely dry
< − 2.0	Extremely dry

viz., severe drought (< – 1.5), moderate drought (– 1.0 to – 1.5) and no drought (> – 1.0) for simplicity and similarity to VCI. The severity of agricultural drought (based on VCI) was also expressed in terms of severe, moderate and no drought, adapted from Kogan (1995) classification scheme (Table 2).

3.4 Time scales

3.4.1 For SPI and SDI

SPI and SDI can be calculated over any timescale (Svoboda et al. 2012; Hong et al. 2015). In the present study, five overlapping periods for one hydrological year, i.e., 1-month (June), 3-month (June–August), 6-month (June–November), 9-month (June–February) and 12-month (June–May) were used.

3.4.2 For VCI

VCI measures vegetation health and it is only useful for monitoring drought conditions during the crop growing season (Vicente-Serrano 2007). Therefore, VCI was computed during one of the main crop growing seasons (i.e., *kharif* season) in India, where the effect of drought can be seen directly on vegetation especially, in the rainfed region. The season mainly starts in June and ends in October. Hence, VCI was computed for three overlapping periods, i.e., 1-month (June), 3-month (June–August) and 5-month (June–October). The NDVI-MODIS data of high resolution (500 m) were available at 16-day intervals. Therefore, VCI was firstly computed at 16-day intervals from 10th June (161 Julian day) to 16th October (289 Julian day) during the *kharif* crop growing season from 2000 to 2014 using Eq. 2. Then, VCI of particular periods were averaged to achieve the desired time scale, i.e., 1-month VCI (10th June, 26th June); 3-month (10th June, 26th June, 12th July, 28th July, 13th Aug, 29th Aug) and 5-month VCI (10th June, 26th June, 12th July, 28th July, 13th Aug, 29th Aug, 14th Sep, 30th Sep, 16th Oct).

3.5 Mapping of drought

SPI and SDI were computed separately for each of the 17 rain-gauge and 10 streamflow gauge stations, respectively, of the study area. SPI values were interpolated using the *spline* interpolation technique (Bhuiyan et al. 2006; Vicente-Serrano 2007) in ArcGIS 10.5 to demarcate the spatial extent of meteorological drought in the study region.

Streams flow only in a certain part of the region, but these streams accumulate runoff from a large catchment area (i.e. basin). In some studies, SDI values were interpolated using IDW (Inverse Distance Weighted) (Gumus and Algin 2017) and drought zonation (Jahangir and Yarahmadi 2020). In the present study also, the IDW method was used for

Table 2 Agricultural drought classification based on VCI (Kogan 1995)

VCI	Agricultural conditions
< 0.35	Severe drought
0.35 – 0.50	Moderate drought
> 0.50	No drought

the interpolation of SDI values in ArcGIS 10.5 to demarcate the spatial extent of hydrological drought in the region.

VCI was computed at 500 m spatial resolution from MODIS (MOD13A1) data which helped in delineating the spatial extent of agriculture drought of the region. While interpolating the SPI and SDI, the cell (pixel) size was kept at 500 m resolution to make it comparable with VCI. The drought area (%) under each category and of each time scale was computed for 15 years (2000–2014).

3.6 Evaluation of drought indices

As the ground truth observations of drought magnitudes and severities are not available, therefore, to evaluate the appropriate time scale of drought indices, i.e., SPI, SDI and VCI for characterizing meteorological, hydrological and agricultural drought, respectively, in the region, the following approaches were used in the present study.

3.6.1 Drought years

The drought years declared by the Government agency during the period of 15 years (2000–2014) were used to compare with drought observed by different drought indices. India Meteorological Department (IMD) specifies that if spatial coverage of drought is more than 40%, it will be called as “All India Severe Drought Year” (Attri and Tyagi 2010). If the area under drought is found to be in the range of 20 to 40%, then, it could be considered as a moderate drought year. Hence, the year where the area under drought observed by drought indices was found to be more than 40%, was designated as a severe drought year in the region. Nine years, i.e., 2000, 2001, 2002, 2003, 2004, 2009, 2011, 2012 and 2014 were found to be severe drought years in the region.

3.6.2 Foodgrain production

The impact of drought can be observed in the production of crops. The correlation analysis between drought indices and foodgrain production during *kharif* crop growing season for 15 years (2000–2014) was used to evaluate the time scale. Foodgrain production deviation for each year was also computed with respect to foodgrain production during normal years (non-drought) after de-trending the technological trends.

3.6.2.1 Index-based drought-affected area vs. foodgrain production In the present study, the value of drought indices (SPI, SDI, and VCI) was not taken directly to correlate with foodgrain production, instead, drought areas observed by the drought indices were considered. The drought area percentage (i.e., the total number of pixels under the drought category to the total number of the pixels) was computed for each year and each time scale of drought indices.

4 Results and discussion

Although SPI and SDI were computed for 35 years (1980–2014) but, only 15 years (2000–2014) were used for evaluation of drought indices to make them comparable with the VCI which was computed for the same 15 years period (2000–2014).

4.1 Meteorological drought

Spatio-temporal variations of meteorological drought observed by multiscale (1, 3, 6, 9 and 12-month) SPI were analyzed. The maximum area under drought (severe and moderate) was observed by 9-month SPI in the year 2014 (45.18%) and 1-month SPI in the year 2005 (46.26%), respectively. The severe drought years (> 40% area under drought) observed by each time scale were as follows: 1-month SPI observed during the year 2005, 2008 and 2011; 3-month SPI observed during the year 2008; 6-month SPI observed during the year 2003, 2011 and 2014; 9-month SPI observed during the year 2003, 2009, 2011, 2012 and 2014; and 12-month SPI observed during the year 2011, 2012 and 2014. The total drought area (severe and moderate) observed by each time scale is presented for 15 years in Fig. 3.

4.1.1 Drought years declared vs. drought years observed by SPI

In the period of 15 years (2000–2014) used in this study, 9 years were declared as drought years. The ratio between drought years observed by SPI's time scale and drought years declared was found to be 5/9, 6/9, 6/9, 9/9 and 5/9 for 1, 3, 6, 9 and 12-month, respectively. By seeing these ratios, it appears that drought years observed by 9-month SPI were in congruence with declared drought years, but, three years, i.e., 2005, 2008 and 2013, which were observed as drought years by 9-month SPI, actually were not declared as drought years. 3 and 6-month SPI observed an equal number of drought years. Hence, analysis through the drought declared years could not give a clear picture of the appropriate time scale for drought characterization in the region. The impact of drought adversely affects the foodgrain production of an area, so, SPI could be used for analyzing the drought impact on crop production (Quiring and Papakryiakou 2003; Vicente-Serrano 2006). This could be an indirect but, informative and accurate way to find the appropriate time scale of SPI for meteorological drought characterization.

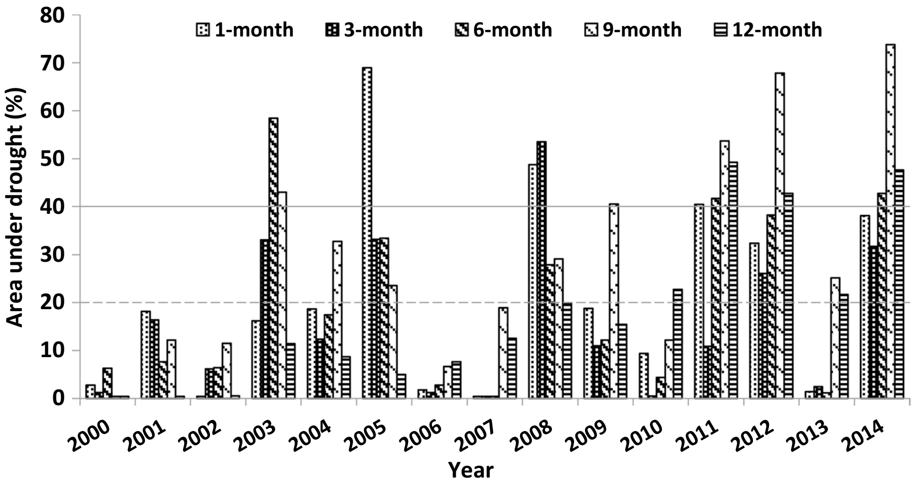

Fig. 3 Area affected under meteorological drought observed by SPI time scales

4.1.2 Foodgrain production vs. drought area observed by SPI

The total area under drought observed by multiscale SPI was correlated with foodgrain production during *kharif* season for 15 years (2000–2014). It was found that 3-month SPI has a strong significant correlation ($r = -0.724$) with foodgrain production (Table 3). The negative sign of 'r' indicates that foodgrain production is inversely proportional to drought. Zuo et al. (2019) found that the R^2 value at 3 months' scales was greater than that at 6-month. Dodamani et al. (2015) reported that 3-month SPI showed better results for the drought sensitivity in Maharashtra.

Several studies reported that a multi-temporal analysis of SPI showed that a shorter time scale of SPI captures drought events more often than a longer time scale (Morán-Tejeda et al. 2013; Thavorntam et al. 2015). The 3-month time scale of SPI (June to August) could be able to capture drought conditions better than other time scales because these 3 months (June, July and August) are the most important period for plant growth and development, and supply of crop water demand, especially in the rainfed region through monsoonal precipitation is the key for good foodgrain production. Therefore, the 3-month time scale of SPI was found to be more closely related to foodgrain production in the region. 3-month SPI is better in monitoring drought impact on vegetation (Ji and Peters 2003).

The spatio-temporal extent of meteorological drought observed by 3-month SPI for 15 years (2000–2014) is shown in Fig. 4. The maximum area under severe drought (28.59%) was observed in the year 2008 while the maximum area under moderate drought was observed in the year 2014 (25.35%). The 9 and 12-month SPI could not have a significant correlation so, may not be useful for seasonal drought characterization, but could be indicative of long-term drought (Szalai and Szinell 2000; Łabędzki 2007). Here, correlation analysis provided a comprehensive picture that 3-month SPI was an appropriate time scale for effective characterization of meteorological drought in this region.

4.2 Hydrological drought

Spatio-temporal variations of hydrological drought observed by multiscale (1, 3, 6, 9 and 12-month) SDI for 15 years (2000–2014) were analyzed. None of the time scales of SDI could be able to observe a severe drought event. SDI was able to observe only moderate drought in the region. The maximum area under moderate drought was observed in the year 2012 by 3, 6, 9 and 12-month SDI with an areal coverage of 16.65%, 21.96%, 19.90%, and 19.87%, respectively (Fig. 5). The 1-month time scale of SDI could not observe drought events in the region. The moderate drought was also observed in the years 2000, 2002, 2005, 2008, 2009, 2011 and 2014 with a low magnitude of areal coverage (<4%).

Table 3 The correlation coefficient (r) between drought indices (SPI & SDI) and foodgrain production

Drought indices	1-month	3-month	6-month	9-month	12-month
SPI	−0.475	−0.724**	−0.602*	−0.489	−0.133
SDI	ND	−0.340	−0.420	−0.406	−0.413

*Significant at 0.05 level and ** significant at 0.01 level, ND: 'r' cannot be defined

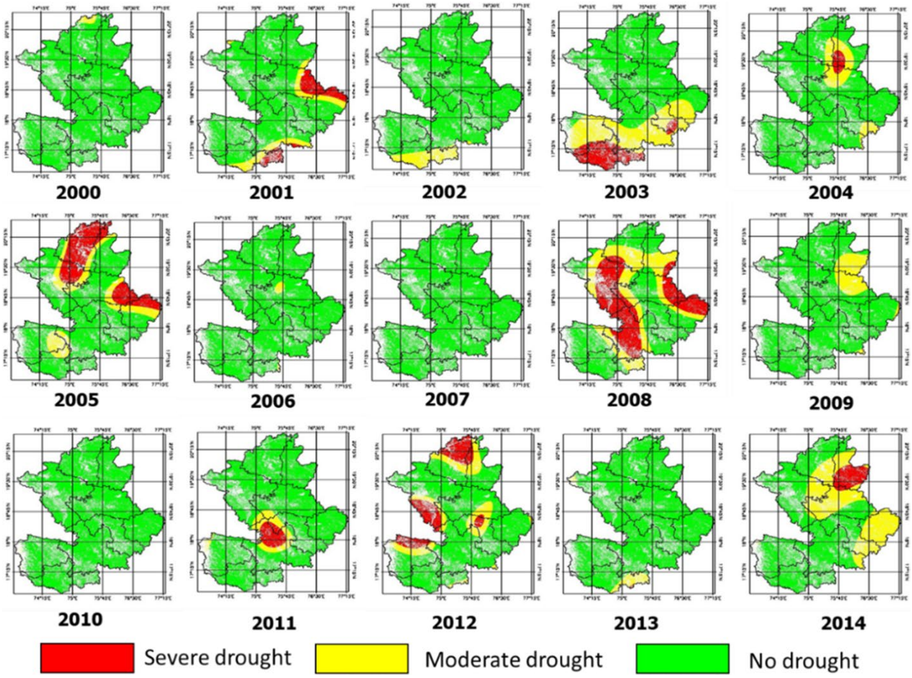

Fig. 4 SPI (3-month) based spatio-temporal extent of meteorological drought

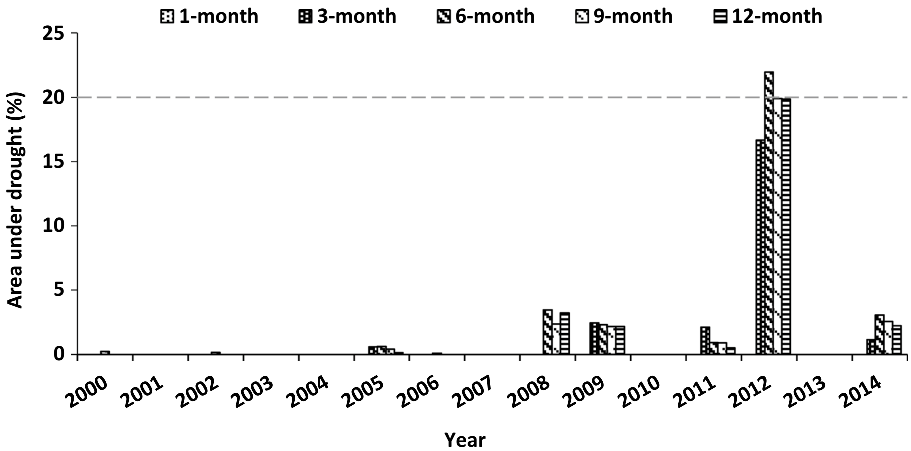

Fig. 5 Area affected under hydrological drought observed by SDI time scales

4.2.1 Drought years declared vs. drought years observed by SDI

Out of 9 declared drought years, only one drought year was observed by SDI (6-month) in the year 2012. Other than the 6-month time scale, none of the time scales of SDI was able to observe drought of spatial coverage more than 20% to be considered as a drought year.

4.2.2 Foodgrain production vs. drought area observed by SDI

The correlation analysis between multiscale SDI and foodgrain production during *kharif* season for 15 years (2000–2014) indicated that none of the time scales of SDI was significantly correlated. The maximum correlation coefficient was observed for 6-month SDI ($r = -0.420$) (Table 3). Many studies reported that SDI is an efficient and reliable index for analyzing hydrological drought conditions (Sardou and Bahramand 2014; Jahangir and Yarahmadi 2020). The larger time scale (9 and 12-month) showed better drought capturing abilities than a smaller (3-month) time scale (Tabari et al. 2013; Zamani et al. 2015). The 12-month time scale was found more suitable for the hydrological drought assessment in the upper Yangtze river basin, China (Hong et al. 2015), Tigris basin, Turkey (Ozkaya and Zerberg 2019). However, in this study, an insignificant correlation was observed between SDI's time scales and foodgrain production, this may due to the low magnitude of the hydrological droughts were observed by SDI. The present study found that SDI could be a region-specific indicator, because the pattern of streamflow does not depend only upon the intensity and amount of rainfall, but also on the shape and size of the catchment area, and time of concentration. The majority of the cultivable areas (80%) are under rainfed agriculture. Only 20% of areas are under irrigated conditions. Out of which 6% area get contribution from surface water resource including canal network, while 8% receive from a groundwater source. This could be also one reason for the weak correlation between SDI time-scale and foodgrain production of the region.

The streamflow-based index could not be found suitable to characterize hydrological drought for this region. However, the maximum correlation with 6-month SDI indicated that the impact of hydrological drought on foodgrain production could have a time lag and can be observed better by mid to long-term time scales than the short-term time scale. The time lag in the rainfall-runoff processes was also reported by Nalbantis and Tsakiris (2009). The spatio-temporal extent of hydrological drought observed by 6-month SDI for 15 years (2000–2014) is shown in Fig. 6, which depicts moderate droughts in the western part of the region in the year 2012 with an areal coverage of about 22%. This was the only year that could be considered a drought year.

4.3 Agricultural drought

Spatio-temporal variations of agricultural drought observed by 1, 3 and 5-month VCI during *kharif* crop growing period (June–October) for 15 years (2000–2014) were studied.

4.3.1 Drought area observed by VCI

1-month VCI The maximum area under severe and moderate drought was observed in the year 2001 (86.92%) and 2014 (33.31%), respectively, during the month of June. The severe drought years (> 40% area under drought) were observed in 2001, 2002, 2003, 2004, 2005, 2008, 2009, 2011, 2012, 2013 and 2014 (Fig. 7).

3-month VCI The maximum area under severe and moderate drought was observed in the year 2001 (73.35%) and the year 2005 (47.05%), respectively, during the period of June to August. The severe drought years were observed in 2001, 2003, 2004, 2005, 2008, 2009, 2011, 2012, 2013 and 2014 (Fig. 7).

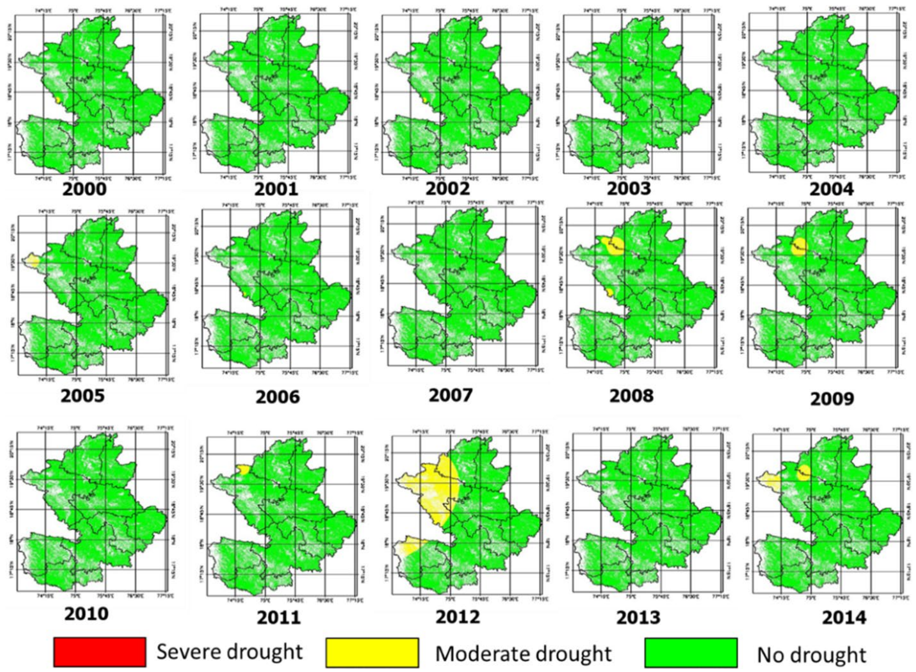

Fig. 6 SDI (6-month) based spatio-temporal extent of hydrological drought

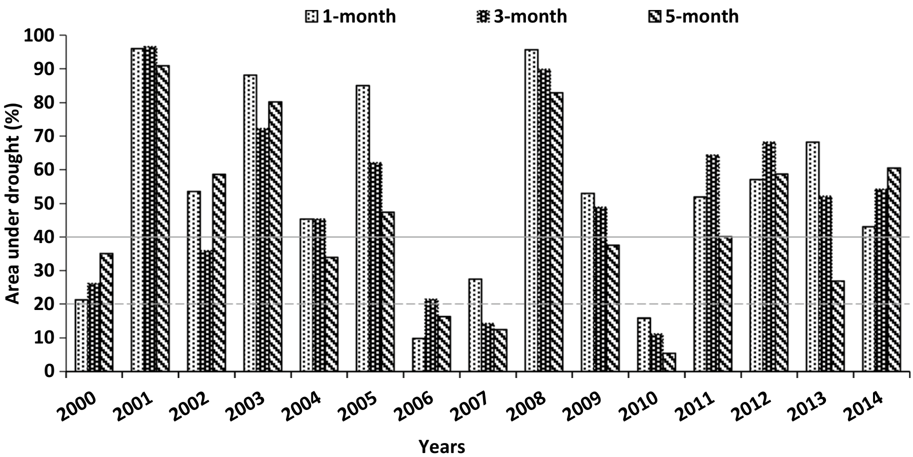

Fig. 7 Area affected under agricultural drought observed by VCI time scales

5-month VCI The maximum area under severe and moderate drought was observed in the year 2003 (52.15%) and the year 2014 (49.27%), respectively, during the period of June to October. The severe drought years were observed in 2001, 2002, 2003, 2005, 2008, 2011, 2012 and 2014 (Fig. 7).

4.3.2 Drought years declared vs. drought years observed by VCI

The three time-scales of VCI, i.e., 1, 3 and 5-month observed 13, 13 and 12 drought years, respectively, in the region in comparison to 9 drought years were declared during the period of 15 years (2000–2014). Both 1-month and 3-month time scale of VCI observed 4 additional drought years (2005, 2007, 2008 and 2013 by 1-month VCI; 2005, 2006, 2008 and 2013 by 3-month VCI) apart from 9 declared drought years, while 5-month VCI observed 3 additional drought years (2005, 2008 and 2013). It indicated that VCI is a more sensitive drought indicator than SPI and SDI.

4.3.3 Foodgrain production vs. drought area observed by VCI

Agricultural drought observed by multiscale VCI was correlated with foodgrain production during *Kharif* season for 15 years (2000–2014). The correlation analysis indicated that 5-month VCI showed a strong correlation ($r = -0.811$) (Table 4) with foodgrain production. A wide range of relationships between VCI and crop yield was reported through studies across the globe. Dutta et al. (2015) reported that a good relationship between VCI and rainfed crop yield ($R^2 > 0.55$). Ma et al. (2001) found R^2 values ranged from 0.44 to 0.80 between soybean yield and NDVI (base index of VCI) at field scale in Canada. Lopresti Mariano et al. (2015) found that R^2 between NDVI and crop yield was from 0.16 to 0.52 under different lag times. Patel and Yadav (2015) reported that VCI showed a significant relation to drought stress in terms of crop yield anomaly of both foodgrain and pulses. This study also observed similar kind of results that VCI is a useful indicator for drought assessment moreover, the 5-month time scale of VCI was found most appropriate for agricultural drought characterization. The spatio-temporal extent of agricultural drought observed by 5-month VCI for 15 years (2000–2014) is shown in Fig. 8. The maximum area under severe (52.15%) and moderate (49.27%) droughts were observed in the year 2003 and 2014, respectively.

4.4 Comparison of remote sensing-based indicator (VCI) vs. in situ data-based SPI and SDI

A correlation analysis was carried out among the most appropriate time scale of drought indices from each category, i.e., 3-month SPI (meteorological), 6-month SDI (hydrological) and 5-month VCI (agricultural) found in the present study. 3-month SPI and 5-month VCI showed a strong relationship ($r = 0.747$) (Table 5). The 3-month time scale of SPI was able to capture vegetation growth nicely during *kharif* crop growing season. Zambrano et al. (2016) found that 3-month SPI has the best Pearson correlation with VCI values with an overall correlation of 0.63. Sahoo et al. (2015) also found that 3-month SPI has a good

Table 4 The correlation coefficient (r) between VCI (drought area) and foodgrain production

Time scales (VCI)	Corr. Coeff. (r)
1-month	−0.476
3-month	−0.677**
5-month	−0.811**

**Significant at 0.01 level

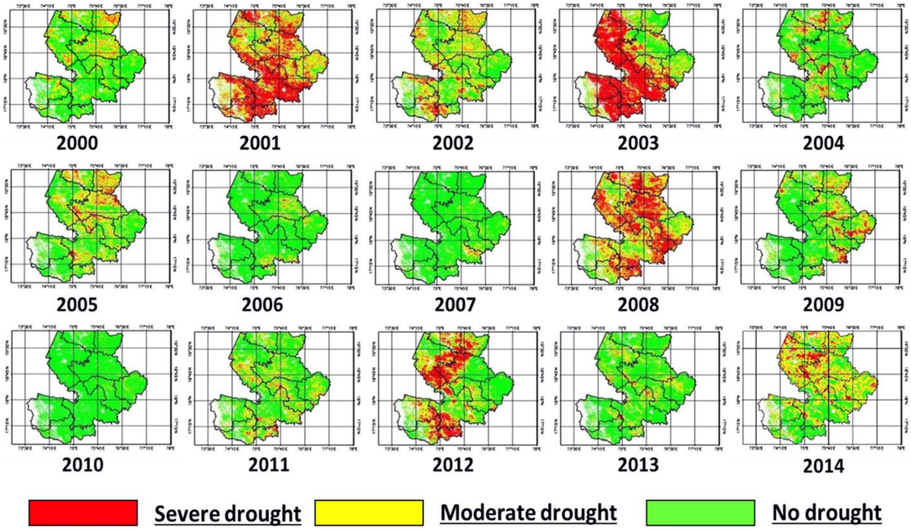

Fig. 8 VCI (5-month) based spatio-temporal extent of agricultural drought

Table 5 The correlation coefficient (*r*) of drought indices

Drought indices	Foodgrain production	SPI-3	SDI-6	VCI-5
SPI-3	−0.724**	1		
SDI-6	−0.420	0.309	1	
VCI-5	−0.811**	0.747**	0.211	1

**Significant at 0.01 level

correlation with VCI for the Mewat region (rainfed region) of India. Zhong et al. (2020) reported a significant lag correlation between SPI and VCI at short timescales from his study in Northwest China. The correlation between SPI and NDVI varies for timescales from place to place (Jain et al. 2010). A different time lag could be observed between SPI and NDVI (Dutta et al. 2013). Response of precipitation on NDVI has a prominent lag effect that could vary with the time of the growing season (Ji and Peters 2005). Piao et al. (2003) reported 3 months lag between NDVI and weather variations in China. The low correlation of the 1-month time scale of SPI and the time scale of VCI could be due to the time lag between precipitation and vegetation growth (Ji and Peters 2003). The impact of precipitation on vegetation does not reflect instantaneously, in most cases, the response could be observed over more than a month. The time lag between precipitation and vegetation response differs between vegetation types and regions, and the ability of soil to store water (Wang et al. 2001; Quiring and Ganseh 2010; Vicente-Serrano et al. 2012).

The correlation of 6-month SDI was neither found to be significant with 3-month SPI nor with 5-month VCI (Table 5). The low magnitude of hydrological drought observed by SDI could be the reason for the insignificant correlation. Nalbantis and Tsakiris (2009) found that the meteorological drought of a certain severity produces a hydrological drought of lower severity. However, several studies also reported a good relationship between SPI and SDI (Akbari et al. 2015; Kazemzadeh and Malekian 2016; Barker et al. 2016). Some studies also found a time lag between VCI with SDI (Lin et al. 2017; Zhong et al. 2020). The reason is precipitation, streamflow and vegetation propagation times differ at different timescales (Xu et al. 2018; Zhao et al. 2018).

4.5 Drought areal coverage vs. foodgrain production deviation

3-month SPI and 5-month VCI have a similar time-series pattern and are capable to identify drought years, which could be seen through deviation in the foodgrain production (Fig. 9). The 6-month SDI (hydrological drought) could neither follow the pattern of 3-month SPI (meteorological) nor 5-month VCI (agricultural drought).

This analysis also indicated that even though meteorological drought years agree with the agricultural drought years, the magnitude of the agricultural drought was found to be higher than that of meteorological drought. It could be due to that the meteorological drought indicator (SPI) based on precipitation and the small change in precipitation might not get captured through meteorological drought indicator, but the small deviation in precipitation could have a significant impact on vegetation and that could get captured by agricultural drought indicator. It could also be possible because the agriculture drought indicator (VCI) is based on remote sensing data of finer (500 m) resolution whereas the meteorological drought indicator (SPI) was based on in situ observations. It implies that a single indicator may not be able to capture both cause (meteorological drought) and impact (hydrological, agricultural drought) precisely.

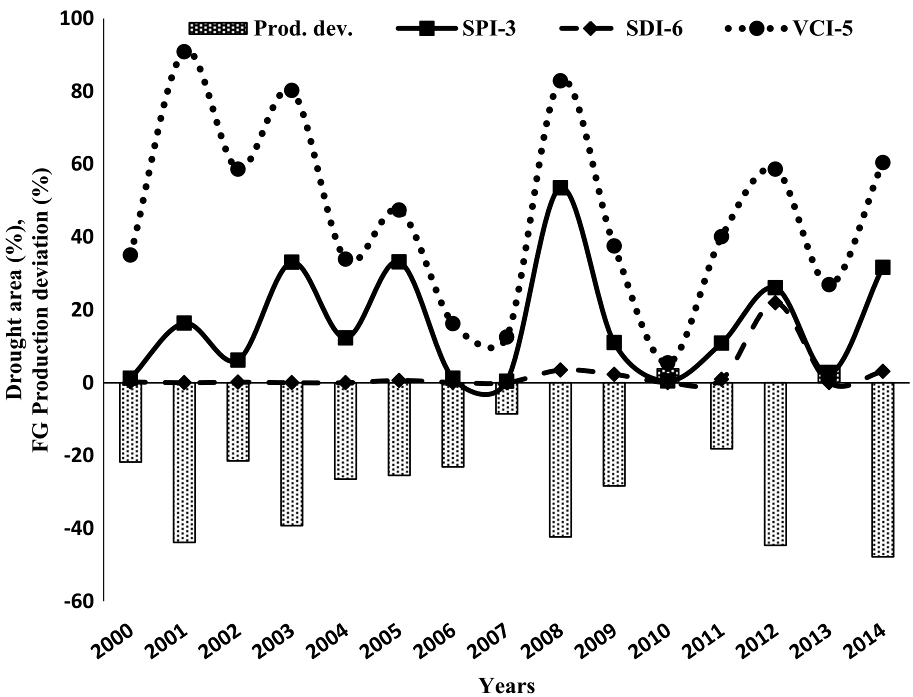

Fig. 9 Comparison among drought indicators and deviation in foodgrain production

5 Conclusions

Spatio-temporal conditions of drought over the Marathwada region of Maharashtra were studied using the Standardized Precipitation Index (SPI), Streamflow Drought Index (SDI) and remote sensing-based Vegetation Condition Index (VCI). Comparison with the drought years declared and correlation analysis between drought area observed by multiscale indices and foodgrain production indicated that 3-month SPI and 5-month VCI were found to be a more appropriate time scale to characterize meteorological and agricultural drought. However, none of the time scales of SDI was found suitable to characterize hydrological drought in the region. Therefore, the present study suggested that the same time scale may not be applicable for all the drought indicators for drought assessment. The use of a suitable index along with an appropriate time-scale would help policymakers and stakeholders to get exact information about drought onset and progression over a region and accordingly contingency planning for drought-affected areas may be made.

Even though the meteorological drought index (3-month SPI) and agricultural drought index (5-month VCI) showed a similar pattern and capable to identify drought years, but the magnitude of droughts observed by them was varied both spatially and temporally. Hence, the study suggested that only one indicator, i.e., meteorological, hydrological, or agricultural was not enough to capture the actual drought severity and magnitude, hence the use of multiple indicators could be a better approach for drought characterization and monitoring. The present study did not include groundwater as hydrological drought component so, it is recommended to use the groundwater-based index for assessing hydrological drought over the study region.

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Data availability Not applicable.

Code availability Not applicable.

Declarations

Conflicts of interest The authors declare no conflict of interest.

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