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ORIGINAL PAPER

Indices-based assessment of vulnerability to agricultural drought in the tropical semi-arid ecosystem using time-series satellite and meteorological datasets

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Abstract

The core aims of the present study are first to compute the Scaled Drought Condition Index (SDCI) by integrating Precipitation Condition Index (PCI), Temperature Condition Index (TCI), and Vegetation Condition Index (VCI) for the northeast (NE) monsoon period during the year 2000 to 2019 in the tropical semi-arid ecosystem of Tamil Nadu (TN) state of southern India. Secondly, to assess the dynamics of vulnerability to agricultural drought by using SDCI and identify the critical vulnerability zones in TN state. The PCI, TCI, and VCI were computed from time-series Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) products, Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance of MOD11A2, and vegetation indices of MOD13Q1, respectively. The results explain that about 0.1, 13.0, and 39.5% of TN state especially in the northern, NE, western, and southern zones are vulnerable to extreme, severe, and moderate vulnerability to agricultural drought, respectively. In the drought year (2016), about 79.9% area of TN state experienced extreme vulnerability to agricultural drought. The validation of SDCI with the 3-month Standardized Precipitation Index (3-SPI) and Vegetation Health Index (VHI) for the dry year (2016) and wet year (2010) shows a moderate to a strong positive correlation. It evidently shows the influence of rainfall on overall vegetation and agricultural drought. The study amply reveals that PCI, TCI, and VCI are the most important indices associated with agricultural drought and are clearly explained by the robust SDCI computed from temporal CHIRPS and MODIS datasets in the effective assessment of vulnerability to agricultural drought in the TN state.

Keywords Agricultural drought · CHIRPS · IMD grid data · MODIS · PCI · TCI · VHI · 3-SPI · SDCI

Introduction

Globally, drought is one of the extreme natural climatic hazards after the floods and the most widespread natural disaster that severely affects the natural ecosystems, global food production, and human livelihoods (Hu et al. 2019; West et al. 2019). In the last three decades, the drought-affected area has been increased by two folds (Nagarajan 2009). The period, frequency, and degree of droughts vary from region to region. It can disrupt the economic and ecological systems that affect the livelihoods of the population (Reddy and Singh 2016). In recent times, the impact of recurring droughts on crop yields has further exacerbated by climate change and augmented by various anthropogenic activities (AghaKouchak et al. 2015). In India, vulnerability to agricultural drought is more because of a prolonged dry spell during the monsoon season (Dutta et al. 2015; Ward and Makhija 2018) and has an impact on groundwater and food security to feed 1.3 billion people. Nearly 60% of India's population depends on the agricultural sector, and it contributes about 17% of the gross domestic product (GDP) of the nation (Arjun 2013; Reddy et al. 2017). Crop stress due to droughts directly affect crop production and the nation's overall economy (Miyan 2015; Fahad et al. 2017). Indian agriculture mainly depends on monsoon, especially on southwest (SW) monsoon (June to September) (Kumar et al. 2013; Ray et al. 2020). However, agriculture in Tamil Nadu

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(TN) state is mainly depends on the northeast (NE) monsoon (October to December), and it comprises nearly 60% of the state's mean annual rainfall. The effective assessment of drought vulnerability needs consistent records of spatial information at closer intervals for a considerable period of time on a variety of agro-climatic variables (Kogan 2001).

Integrated remotely sensed data, and Geographic Information System (GIS) was proven as the most reliable technique in the assessment of vulnerability to agricultural drought as remote sensing provides consistent, fine to very fine spatial resolution, real-time data availability, and GIS offers robust analytical capabilities (Reddy et al. 2020; Kumar et al. 2021; Sandeep et al. 2021). Time-series satellite-based inputs provide reliable datasets to study the changes in vegetation and the corresponding drought patterns on spatio-temporal scale by integrating satellite data in the GIS environment (Zambrano et al. 2016; Reddy et al. 2020). GIS has advantages not only in the generation of various thematic databases but also facilitates to perform spatial analysis and modeling (Reddy 2018) in the evaluation of the intensity of drought (Belal et al. 2014). Several researchers reported the use of remote sensing technologies in monitoring the agriculture drought (Madadgar et al. 2017; Kumar et al. 2021; Sandeep et al. 2021; Senamaw et al. 2021). Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) products and Moderate Resolution Imaging Spectroradiometer (MODIS) data provide consistent and long-term datasets, which were widely used in the monitoring of droughts (Qian et al. 2016; Habitou et al. 2020) and assessment of vulnerability to agricultural drought (Zambrano et al. 2018; Juan et al. 2019; Sultana Most et al., 2021). As remote sensing-based indices like normalized difference vegetation index (NDVI) were extensively used in the assessment, and monitoring of the dynamics of agricultural drought (Tucker et al., 2001; Faridatul and Ahmed, 2020; Reddy et al. 2020). Globally, many authors have used various indices computed from temporal MODIS datasets in the assessment of agriculture drought (Table 1).

In India, about 15.8% (52.0 Mha) and 35.4% (116.5 Mha) of the landmass were identified under arid and semi-arid climatic conditions, respectively (Sehgal et al. 1992). The Intergovernmental Panel on Climate Change (IPCC) has estimated an increasing trend of droughts in the semi-arid ecosystem of India (IPCC 2013). The arid and semi-arid ecosystems of India experienced many droughts; however, their frequency, duration, and intensity vary from region to region. The conventional approaches with ground-based observations alone are not sufficient to effectively assess, and monitor the agricultural drought (Chang et al. 2017; Du et al. 2018). The systematic analysis and establishment of the relationship among environmental parameters and vegetation cover are assumed of greater importance especially in arid and semi-arid regions to precisely assess and monitor the dynamics of agricultural droughts (Mahajan and Dodamani, 2016). SPI has been widely used as a robust indicator in determining and monitoring the drought intensity (Almedeij 2014; Khan et al. 2017; Okal et al. 2020; Liu et al. 2021). Vegetation Condition Index (VCI) developed by Kogan (1990) has been used effectively in monitoring the vegetation water stress and provides accurate information on drought in different climatic regions (Quiring and Ganesh 2010; Kundu et al. 2016). Vegetation Health Index (VHI) is expressed as a function of VCI (Kogan 1995) and Temperature Condition Index (TCI) designates the vegetation health or stress (Kogan 2002), and it has a close relationship with soil moisture (Yan et al. 2016). VHI has been extensively used in analyzing vegetative drought than other indices (Kundu et al. 2016; Gidey et al. 2018). The Normalized Difference Water Index (NDWI) and NDVI derived from MODIS data have been widely used to assess the agricultural drought (Sun et al. 2020). However, in India, limited studies have been reported in the assessment of vulnerability to agricultural drought, particularly in the semi-arid ecosystem by using time-series CHIRPS and MODIS datasets (Pandey et al. 2020, 2021). Agriculture in TN state mainly depends on NE monsoon, its failure or deficit rainfall triggers severe

Table 1 Indices derived from MODIS in the assessment of agriculture drought across the globe

S. No.	Indices	Study area	Reference
1	Visible and Shortwave Infrared Drought Index (VSDI)	USA	Zhang et al. (2013)
2	Vegetation Water Supply Index (VWSI)	China	Cai et al. (2011)
3	Integrated Surface Drought Index (ISDI)	China	Wu et al. (2015)
4	Land Surface Water Index (LSWI)	USA	Bajgain et al. (2017)
5	Modified Shortwave Infrared Perpendicular Water Stress Index (MSPSI)	China	Feng et al. (2013)
6	Anomaly Vegetation Condition Index (AVCI)	China	Yan et al. (2012)
7	Normalized Vegetation Supply Water Index (NVSWI)	China	Abbas et al. (2014)
8	Ratio Dryness Monitoring Index (RDMI)	China	Zhang et al. (2019)
9	Temperature-Vegetation Dryness Index (TVDI)	China	Gao et al. (2011)
10	Temperature-Vegetation-Soil Moisture Dryness Index (TVMDI)	Australia	Amani et al. (2017)

agricultural drought, crop failure, water, and food shortage in the state (Nathan 1998). In view of this, the present study assumes greater importance and it is aimed firstly, to compute the indices of SPI, Precipitation Condition Index (PCI), TCI, VCI, and VHI derived from time-series meteorological, CHIRPS, and MODIS datasets for NE monsoon period of two decades (2000 to 2019) to analyze their spatio-temporal variabilities. Secondly, compute the SDCI by integrating PCI, TCI, and VCI to monitor the spatio-temporal dynamics of vulnerability to agricultural drought, and identify the critical zones in the TN state.

Materials and methods

Study area

TN state is located in the southern part of India lies between 8° 00′ to 13° 30′ N. latitudes and 76° 00′ to 80° 18′ of E. longitudes with an area of 13.00 (Mha), and it accounts for 3.96% of India's total geographical area (TGA) (Fig.1a). The semi-arid conditions occupy about 90%, except the coastal, and Western Ghat region of the study area. The state has a tropical climate inland, and an equatorial, maritime climate in coastal regions. The mean annual temperature of the state ranges between 28 to 40°C in summer and 18 to 26°C in the winter. The NE monsoon season is the state's prominent rainfall season, as the state receives about 60% of the total mean annual rainfall during this season and the remaining 40% received during the SW monsoon period (Fig. 1b). The predominant soils in the state are red loam, laterite, black, alluvial, and saline soils. Red loam soils are present in the interior and the coastal region of TN state, whereas the black soils are found in NW, SE, and southern parts of the state (Natarajan et al. 1997). The state has about 4.7 Mha cultivated area (36% of TGA); it includes the rainfed area of 2.6 Mha and it constitutes about 54% of the total cultivated area. The important food crops like rice, maize, finger millet, sorghum, and pearl millet, cash crops like cotton, sugarcane, oilseeds, tea, coffee, coconut and chillies, and horticulture crops like bananas, mangoes, and guava is grown in the state.

Datasets used

The gridded daily high-resolution rainfall data (0.25° × 0.25°) from 1990 to 2019 were downloaded from the India Meteorological Department (IMD) (https://www.imdpune.gov.in/) and computed the mean monthly rainfall data and seasonal SPI. The monthly CHIRPS version 2.0 from 2000 to 2019 at high spatial resolution (0.05° × 0.05°), was used for drought characterization and obtained from the Climate Hazards Group of the University of California (https://www.chc.ucsb.edu/data). The 16-day MODIS NDVI products (MOD13Q1) at a 250-m spatial resolution were downloaded from the Land Processes Distributed Active Center (LPDAAC; http://lpdaac.usgs.gov/) and smoothed by using Savitzky-Golay (Chen et al. 2004) filter on TIMESAT software (Jönsson and Eklundh 2002). Subsequently, maximum value composites (MVC) were generated to minimize non-vegetation effects (Maisongrande et al. 2004) and used to compute VCI to monitor vegetation dynamics. MODIS 8-day LST products (MOD11A2) at a 1-km resolution were used in the computation of TCI. The summary of datasets used, their time period and resolutions are shown in Table 2.

Computation of seasonal SPI

SPI was proposed by McKee et al. (1993), and it considered precipitation for any given time scale, and it was developed by using historical data to assess, and monitor the degree of drought for a given rain gauge station based on their SPI values. As a statistical technique, SPI was widely used to quantify the degree of wetness or dryness on multiple time scales. By using a long-term period of 30 years (1990 to 2019), SPI was computed at a 3-month time scale for 174 stations (IMD grids) and the ordinary kriging technique was used in ArcMap to develop the monthly rasters. The positive 3-SPI values indicate the no-drought scenario, whereas its negative values designate drought conditions. McKee et al. (1993) classification scheme of droughts was followed to classify the obtained SPI values as extremely dry (−2 and less), severely dry (−1.5 to −1.99), moderately dry (−1.0 to −1.49), near normal (−0.99 to 0.99), moderately wet (1.0 to 1.49), very wet (1.5 to 1.99), and extremely wet (2.0 and more).

$$\mathrm{SPI} = \frac{\left(X_{ij} - X_i\right)}{\sigma} \tag{1}$$

where σ is the standard deviation for the i^{th} station, X_{ij} is the precipitation for the i^{th} station and j^{th} observation, X_i is the mean precipitation for the i^{th} station.

Computation of PCI from CHIRPS

As an index, PCI can be computed from either ground-based or satellite-derived precipitation measurements. PCI detects the deficiency of precipitation from the climatic signal, as the normalized fluctuation of the precipitation derived from its long-term minimum and maximum (Du et al. 2013). The values of PCI always range from 0 to 1, as an area experiences very low precipitation, the PCI value comes near or equal to 0, while it comes close to 1 in flooding conditions. The monthly PCI was computed for the period from 2000 to 2019 during the NE monsoon season.

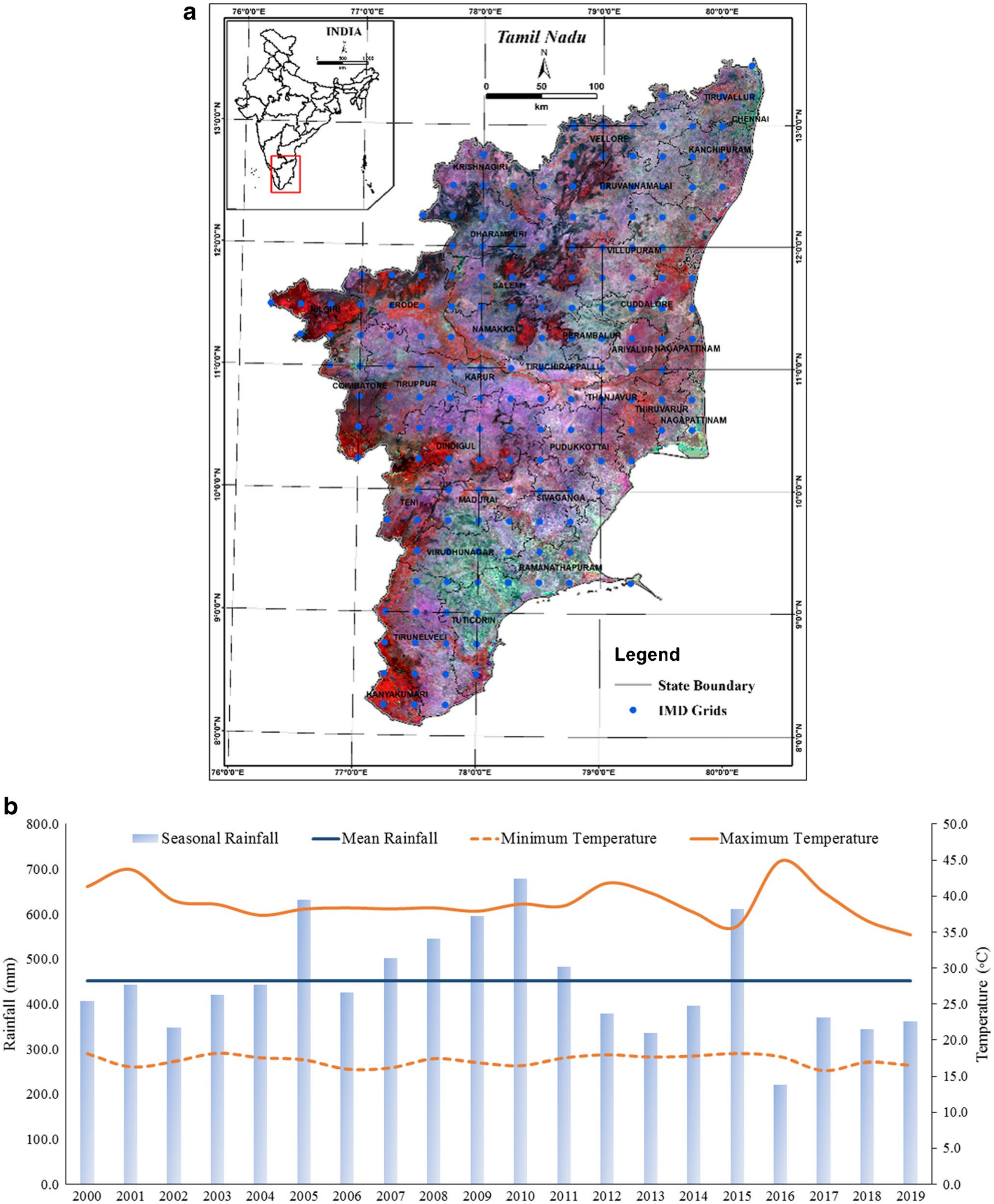

Fig. 1a-b **a** Location map of the study area depicted with standard false color composite (FCC) generated from near infrared (NIR), red and blue bands of MODIS 13Q1 product of Julian date 161 of the year 2019. **b** Distribution of mean rainfall, minimum temperature, and maximum temperature of northeast monsoon during the period from 2000 to 2019

Table 2 Datasets used in the study

Data set	Variable	Temporal coverage	Temporal resolution	Spatial resolution
IMD gridded data	SPI	1990 to 2019	Daily	0.25° × 0.25°
MOD13Q1	VCI	2000 to 2019	16 day	250 m
MOD11A2	TCI	2000 to 2019	8 day	1000 m
CHIRPS	PCI	2000 to 2019	Monthly	0.05° × 0.05°

$$PCI = \frac{\left(CHIRPS_i - CHIRPS_{min}\right)}{\left(CHIRPS_{max} - CHIRPS_{min}\right)} \tag{2}$$

where $CHIRPS_i$ is the current CHIRPS, $CHIRPS_{max}$, and $CHIRPS_{min}$ are the pixel values of precipitation, maximum, and minimum, respectively of the respective month from 2000 to 2019. By using PCI, the precipitation deficit and surplus in the TN state were monitored (Islam and Uyeda 2007).

Computation of TCI from LST

In the study, the thermal effect of drought was determined by using TCI proposed by Kogan (1997), and its values vary between 0 and 1. To compute TCI, the monthly LST datasets derived from MODIS 8-day surface reflectance composite (MOD11A2) were used (Wan and Li 1997). The lower values of TCI infer the severe drought condition, whereas, the high value denotes wet condition. The TCI values close or equal to 0 indicates a drought process, whereas in wet conditions, it is near to 1. The monthly TCI for the NE monsoon period from the year 2000 to 2019 was computed by using the following expression.

$$TCI = \frac{\left(LST_{max} - LST_i\right)}{\left(LST_{max} - LST_{min}\right)} \tag{3}$$

where LST_i denotes the current month temperature, LST_{max} and LST_{min} represents the absolute maximum, and minimum temperatures, respectively in the respective month from 2000 to 2019.

Computation of VCI from NDVI

Kogan (1995) proposed VCI and demonstrated how close the current month's NDVI is to the long-term average measured minimum NDVI. VCI between 0 and 1 illustrates a very unfavorable to optimal vegetation shift. In extreme dry months, obviously the poor vegetation condition exhibits low VCI of close to or equal to 0. The VCI of 0.5 indicates the quality of acceptable vegetation. However, at optimal vegetation conditions, VCI values are close to 1 (Jain et al. 2009).

$$VCI = \frac{\left(NDVI_i - NDVI_{min}\right)}{\left(NDVI_{max} - NDVI_{min}\right)} \tag{4}$$

where $NDVI_i$ represents the current month NDVI, $NDVI_{max}$ and $NDVI_{min}$ indicate the maximum and minimum NDVI, respectively, which were computed by the corresponding pixels of the respective month from the entire NDVI records of the considered period (2000 to 2019).

Computation of VHI

VHI characterizes the health of the vegetation by assuming that stressed conditions are linked to lower-than-normal NDVI and higher than normal temperature (Kogan 1997, 2001). VHI is a resultant of the additive function of VCI and TCI and is expressed as follows:

$$VHI = \alpha VCI + (1 - \alpha)TCI \tag{5}$$

where α is a parameter that quantifies the contribution of each factor to the overall health of vegetation. VHI values range from 0 to 1, and were classified into five categories: extreme drought (<0.1), severe drought (0.1–0.2), moderate drought (0.2–0.3), mild drought (0.3–0.4), no drought (>0.4) (Kogan 1995). VHI is a proxy characterizing vegetation health or a combined estimation of moisture and thermal conditions.

Computation of SDCI

SDCI proposed by Rhee et al. (2010) was considered as a multi-source and multi-date remote-sensing-derived index. It was calculated from three distinct scaled indices namely TCI, VCI, and PCI. For the computation of scaled indices, vegetation, temperature, and precipitation data were obtained from NDVI, LST, and CHIRPS datasets, respectively. SDCI values range from 0 to 1 and the low SDCI values indicate the severe drought condition. The SDCI categorized into five drought classes namely extreme drought ($SDCI < 0.2$), severe drought ($0.2 \leq SDCI < 0.3$), moderate drought ($0.3 \leq SDCI < 0.4$), mild drought ($0.4 \leq SDCI < 0.5$), and no drought ($SDCI > 0.5$).

$$SDCI = 0.25_{TCI} + 0.5_{PCI} + 0.25_{VCI} \tag{6}$$

Pearson correlation test between SDCI with 3-SPI and VHI

It was executed between SDCI, 3-SPI, and VHI to appraise the relationship between rainfall, soil moisture, and drought indices derived from meteorological and remotely sensed data, respectively. To perform it, the mean SDCI, 3-SPI, and VHI values were computed at the tehsil level (sub-district unit). It was conducted between monthly SDCI, VHI, and 3-SPI (Ji and Peters 2003) to determine their relationship from October to December of dry and wet years. It was executed by using the following expression.

$$R_{xy} = \frac{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}} \tag{7}$$

where R_{xy} is the correlation coefficient, n is the length of the time-series, and i is the number of the years from 2000 to 2019 (1 to 20), whereas $x_{i,}$ and y_i are the 3-SPI, VHI, and the SDCI in year i, respectively, and x, and y are the mean 3-SPI, VHI, and the mean SDCI, respectively, from 2000 to 2019. Galarça et al. (2010) and Figueiredo Filho and da Silva Júnior (2009) stated that the correlation coefficient (R) has values ranging from −1 to 1, where values close to 1 ($R = 1$) indicate a perfect positive correlation and values close to −1 ($R = -1$) represents the perfect negative correlation between the two variables. Pearson correlation coefficient "R" was categorized as weak (0.10 to 0.30), moderate (0.40 to 0.60), and strong (0.70 to 1) (Dancey and Reidy, 2006). Figure 2 depicts the detailed methodology adopted in the study.

Results

Spatio-temporal variability of seasonal PCI

The variability of seasonal PCI of the NE monsoon season indicates high PCI from the year 2002 to 2010 in the central and southern districts. In the year 2000, the severe drought extent was perceived with a PCI value of 0.1 to 0.2 in southern districts and no drought scenario with PCI values of >0.4 in the coastal districts of the state. During the year 2000 to 2010, the higher PCI was experienced in Kanyakumari, Tuticorin, Tirunelveli, Virudhunagar, Tiruppur, Karur, Namakkal, Salem, Tiruchirappalli, Perambalur, and Dindigul districts. Furthermore, in 2012 and 2013, the high values of PCI were noticed during the NE monsoon season. During the year 2012, PCI values of 0.1 to 0.2 indicate severe drought conditions in Madurai, Theni, Virudhunagar, Dindigul, and parts of Tiruppur, Coimbatore, and Tirunelveli districts. However, the remaining districts

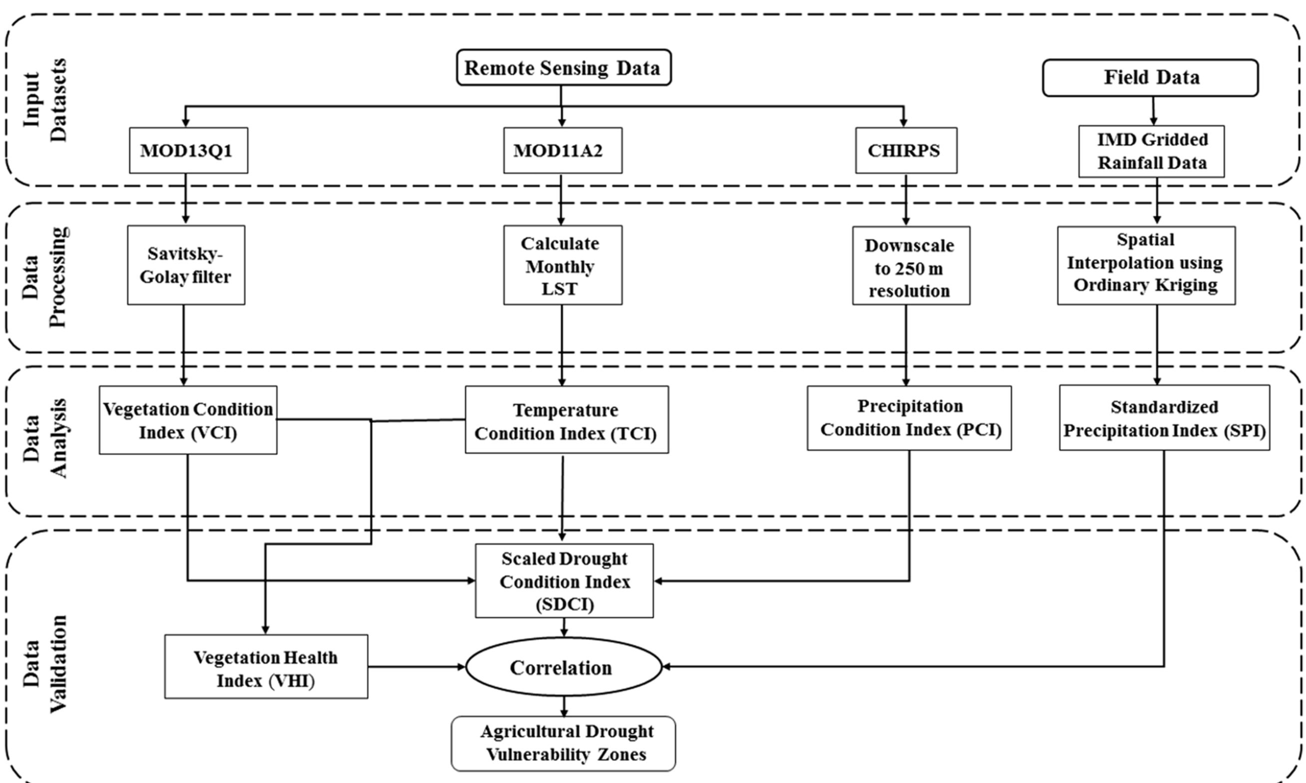

Fig. 2 Flowchart of the methodology adopted in the study

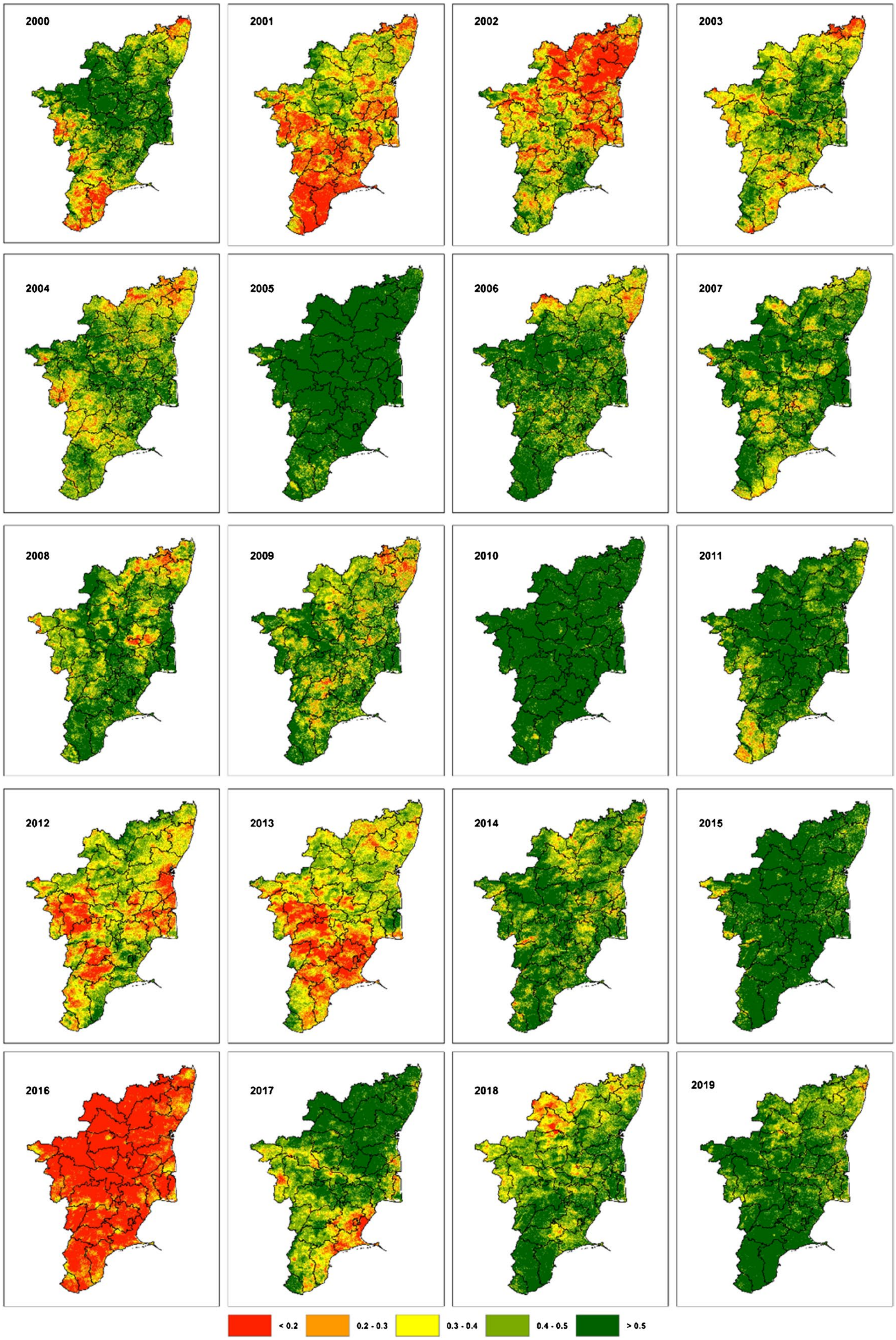

Fig. 3 Spatio-temporal pattern of SDCI during northeast monsoon (2000–2019) of TN state

experienced moderate drought (0.2 to 0.3) to no drought scenario (>0.4) in the same year. In the year 2015, the majority of the districts in the state were under no drought (>0.4). In the wet year, 2010 about 83.2% of the TGA of TN state was under no drought (>0.4), particularly in Madurai, Theni, Virudhunagar, Dindigul, Tiruppur, Coimbatore, Tirunelveli, Salem, Namakkal, Tiruchirappalli, and Perambalur districts. It was noticed that the moderate drought scenario with the PCI values of 0.2 to 0.3 was perceived in Tiruvallur, Kanchipuram, Chennai, Kanyakumari, and Tirunelveli districts. However, the remaining districts experienced abnormally dry conditions with the PCI values of 0.3 to 0.4. In the dry year 2016, it was observed that the entire state was under extreme drought

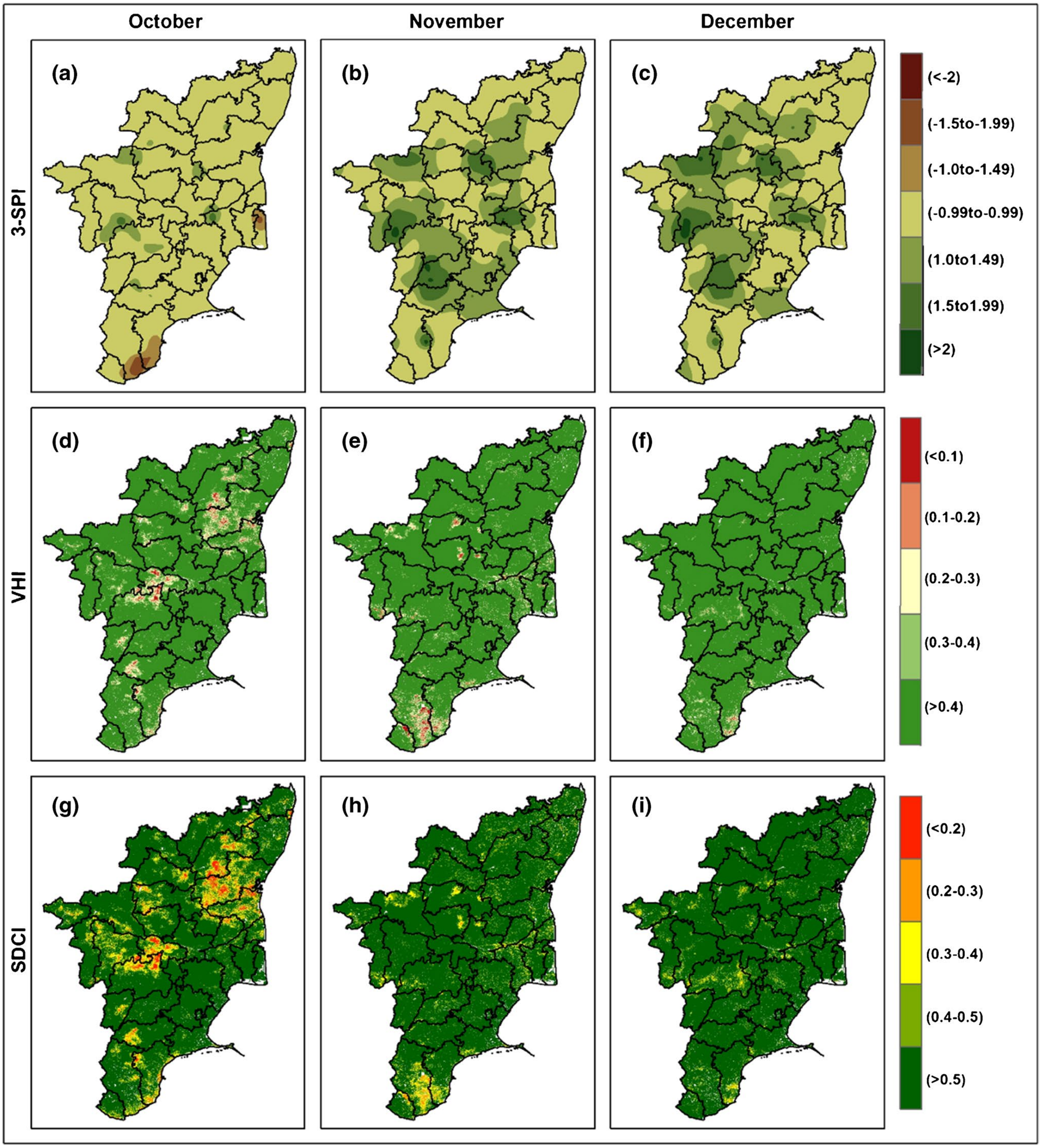

Fig. 4 **a**, **b**, **c**, **d**, **e**, **f**, **g**, **h**, **i** Monthly variability of 3-SPI, VHI, and SDCI in the wet year (2010) of TN state

(PCI value of <0.1). This scarce phenomenon might happen due to the receipt of far below normal rainfall during the NE monsoon season.

Spatio-temporal variability of seasonal TCI

The analysis of seasonal variability of TCI indicates the drought phenomenon in 2001, 2012, and 2016. In the year 2001, extreme drought (<0.1) condition was noticed in about 44.8% of the TGA mainly in southern districts like Kanyakumari, Tuticorin, Tirunelveli, and Virudhunagar districts. Whereas, during the same period, the higher TCI was perceived in northern districts like Krishnagiri, Dharmapuri, Salem, and Namakkal, which experienced no drought (>0.4) condition. A similar drought phenomenon was observed in 2012, where about 44% of the area was under no drought (>0.4) condition, 14.3% of the area under extreme drought (<0.1), and 11.3% of the area under severe drought (0.1 to 0.2) condition. On the contrary, the year 2004 and 2015 were under favorable for agricultural practices as about 97.1% and 92.4% of the TGA of the state was under no drought (>0.4), respectively. Especially, in the wet year 2010, about 99.3% of the TGA of TN state experienced no drought (>0.4) condition. On the contrary, in the dry year of 2016, the TCI shows a moderate drought (0.1 to 0.2) to extreme drought (<0.1) conditions in about 52.4% of the TGA especially in the main agricultural belts of TN state like Kongu uplands and Cauvery delta. The districts like Krishnagiri, Dharmapuri, Salem, Namakkal, Tiruppur, Erode, Vellore, Tiruvannamalai, Kanchipuram, Tiruvallur, Tiruchirappalli, Karur, Villupuram, Ariyalur, Perambalur, and Cuddalore were under lower TCI in 2016. However, some parts of southern districts have higher TCI values (>0.4), and it shows that these districts were under the minimum effect of drought. In some pockets, even during drought years the higher TCI values were observed this might be due to the availability of irrigation facilities, which tends to reduce moisture stress in the agricultural crops.

Spatio-temporal variability of seasonal VCI

The variability of seasonal VCI between 2000 and 2019 shows that year 2016 witnessed an extreme drought condition, whereas the years 2002 and 2012 show the severe drought condition in the state. The year 2002 experienced extreme drought with VCI of <0.1 especially in the western part of TN state encompassing Kanchipuram, Tiruvannamalai, and Villupuram districts with about 12.4% of TGA. However, no drought (>0.4) was perceived in about 57.9% of TGA of the TN state. Similarly, in 2012, an extreme drought scenario (<0.1) was witnessed in about 10% of the state especially the districts of Virudhunagar, Madurai, Dindigul, Coimbatore, and Tiruppur, whereas no drought was noticed in the Vellore, Krishnagiri, Tiruvannamalai, and Villupuram districts of the northern region. In the wet year 2010, no drought condition (>0.4) was observed in about 88% of TN state. However, extreme drought (<0.1) condition was noticed in a few pockets covering about 2.6% of the TGA. In the year 2015, about 87.8% of the area was under no drought (>0.4) and 3% of TGA was under extremely drought (<0.1) conditions. At the same time, the extreme drought (<0.1) accounts for nearly 9% of the TGA of TN state spreading mainly in Tiruppur, Coimbatore, Ariyalur, Pudukkottai, and The Nilgiris districts. In the dry year of 2016, the extreme drought (<0.1) was noticed in the northern and western parts of the state mainly in Krishnagiri, Dharmapuri, Salem, Vellore, Tiruvannamalai, and Tiruvallur districts covering an area of 54.8% of the TGA, whereas no drought (<0.1) was experienced in parts of Tirunelveli, Tuticorin, Virudhunagar, and Madurai districts and it accounts for 18.7% of the TGA of TN state.

Assessment of agricultural drought using SDCI

SDCI proposed by Rhee et al. (2010) was computed by integrating PCI, TCI, and VCI to assess the severity of vulnerability to agricultural drought in the study area (Fig. 3). The analysis of SDCI shows high variability from extreme drought (< 0.2) to no drought (> 0.5) conditions in two decades from the year 2000 to 2019. The results depict that the years 2001, 2002, 2012, and 2013 were under dry conditions. In the year 2001, extreme drought was perceived in the southern parts, whereas, in 2002, moderate drought conditions mainly in northern parts were observed. In the years 2012 and 2013, extreme drought conditions were witnessed in the SW and SE parts of TN state, respectively. In the dry year of 2016, about 79.9 and 16.8% of the study area perceived extreme drought (< 0.2) and severe drought (0.2 to 0.3) conditions, respectively. However, the normal conditions prevailed from 2005 to 2010 and 2015. In the wet year (2010), about 92.0% of TGA was under no drought in the TN state.

Monthly variability of 3-SPI, VHI, and SDCI in the wet year

The monthly variability of 3-SPI, VHI, and SDCI for the wet year (2010) shows moderately wet to very wet conditions. The analysis of 3-SPI during the NE monsoon shows near-normal situations in November as compared to the wet to very wet conditions in October (Fig. 4a and 4b). However, in December, the near-normal condition was perceived in the entire state (Fig. 4c), except in the northern parts where the moderate wet condition was observed. The VHI values

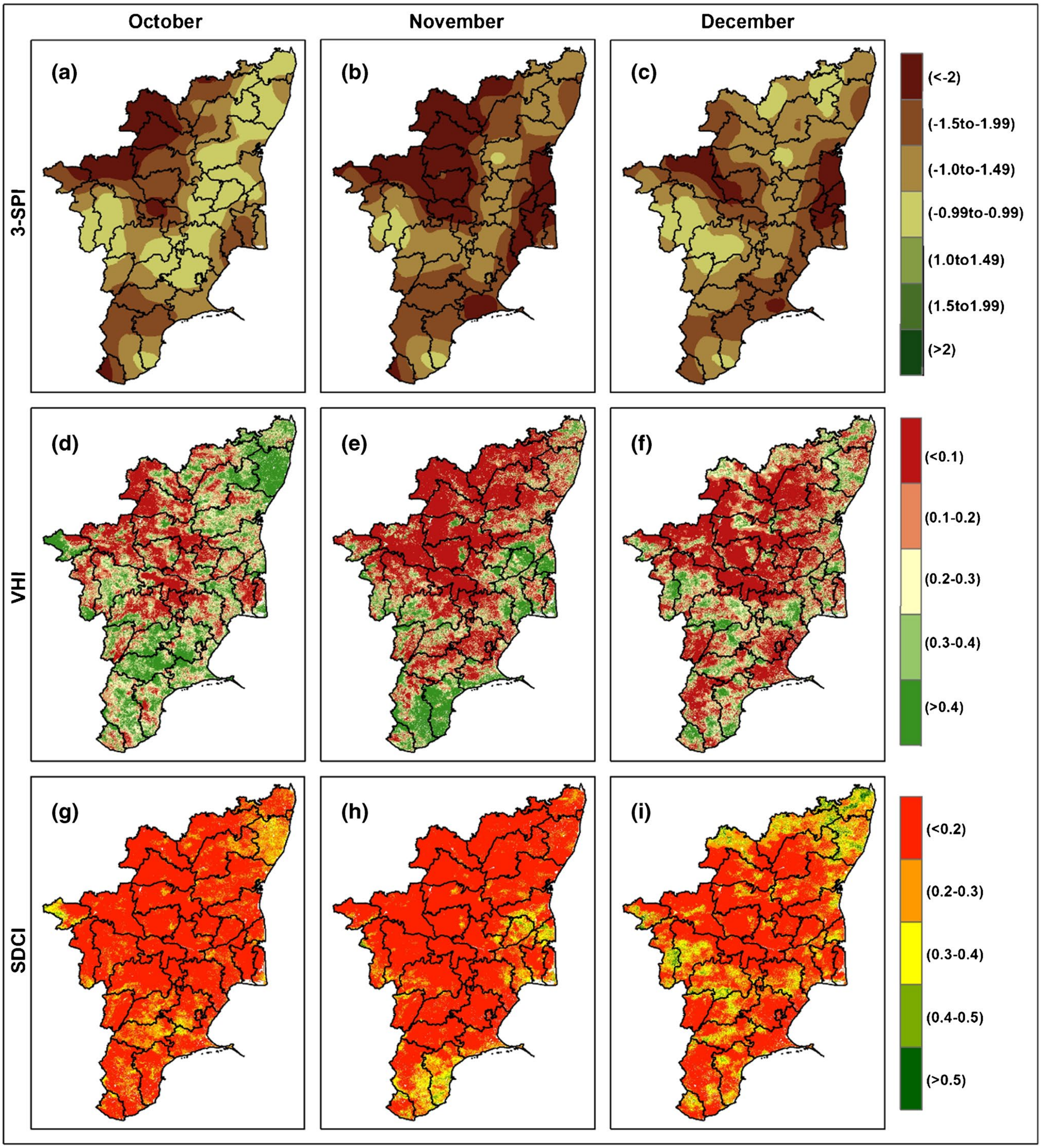

Fig. 5 **a**, **b**, **c**, **d**, **e**, **f**, **g**, **h**, **i** Monthly variability of 3-SPI, VHI, and SDCI in the dry year (2016) of TN state

are quite high in the state, with remarkably high values over the eastern and central region. In October (Fig. 4d), very low VHI (<0.1) was observed in parts of the Dindigul, Karur, Villupuram, and Tiruvannamalai districts. The higher the value of VHI, the better the vegetation health. It may be noted that most of the regions in TN state show no drought (>0.4) conditions during November and December (Fig. 4e and f), respectively. The analysis of SDCI shows that even in the wet year of 2010, moderate-to-severe drought conditions

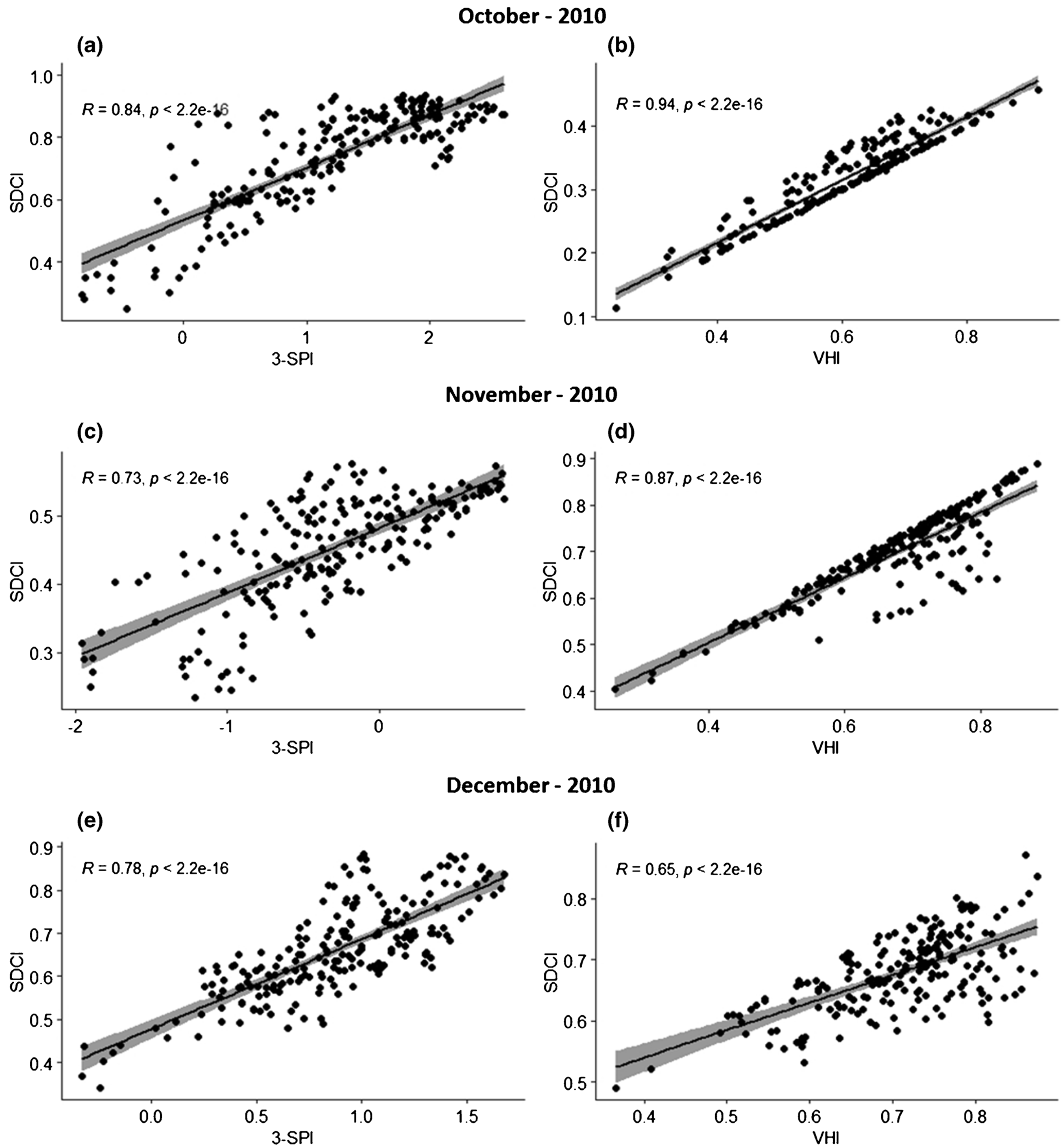

Fig. 6 **a**, **b**, **c**, **d**, **e**, **f** Correlation between SDCI with 3-SPI and VHI in the wet year (2010) of TN state

were noticed in October, particularly in the Kanyakumari, Tirunelveli, and Tuticorin districts of TN state (Fig. 4g). Whereas, moderate drought conditions were experienced in November (Fig. 4h), particularly in Kanyakumari, Tirunelveli, and Tuticorin districts. SDCI's analysis of December month shows no drought scenario (Fig. 4i). The results of monthly variability of 3-SPI and SDCI during the wet year clearly indicate the dynamics of drought and its intensity in the NE monsoon season.

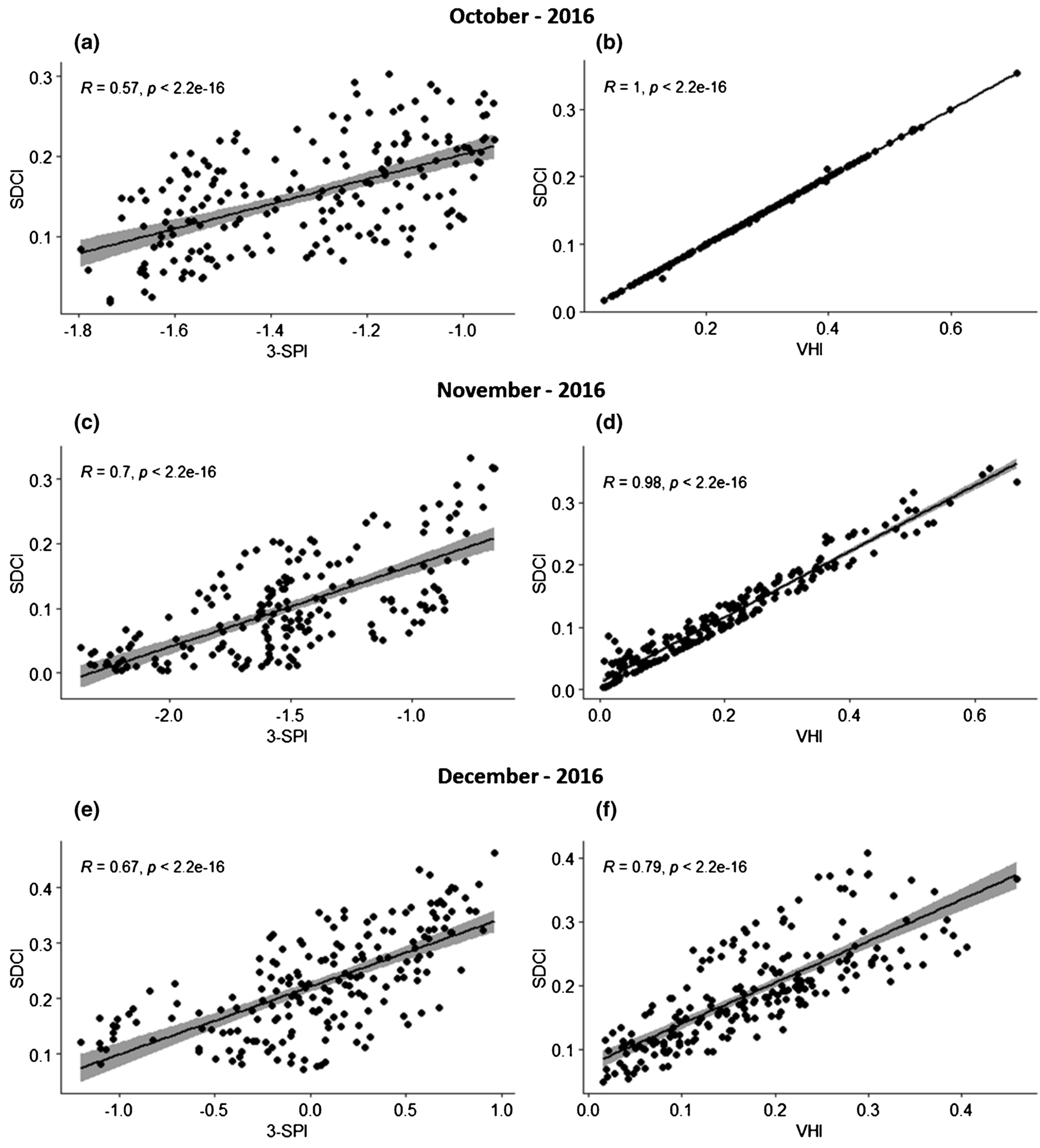

Fig. 7 **a**, **b**, **c**, **d**, **e**, **f** Correlation between SDCI with 3-SPI, and VHI in the dry year (2016) of TN state

Monthly variability of 3-SPI, VHI, and SDCI in the dry year

The monthly variability of 3-SPI shows the extent of dry conditions in the dry year (2016) during October, November, and December. In October, the extremely dry conditions were limited in the northern and NE regions of TN state (Fig. 5a). During November, the northern and eastern parts of TN state experienced extremely dry conditions (−2 and less) (Fig. 5b) and near-normal conditions in the rest of TN state. However, it was observed that in December, the entire state was under the near-normal condition (Fig. 5c) except

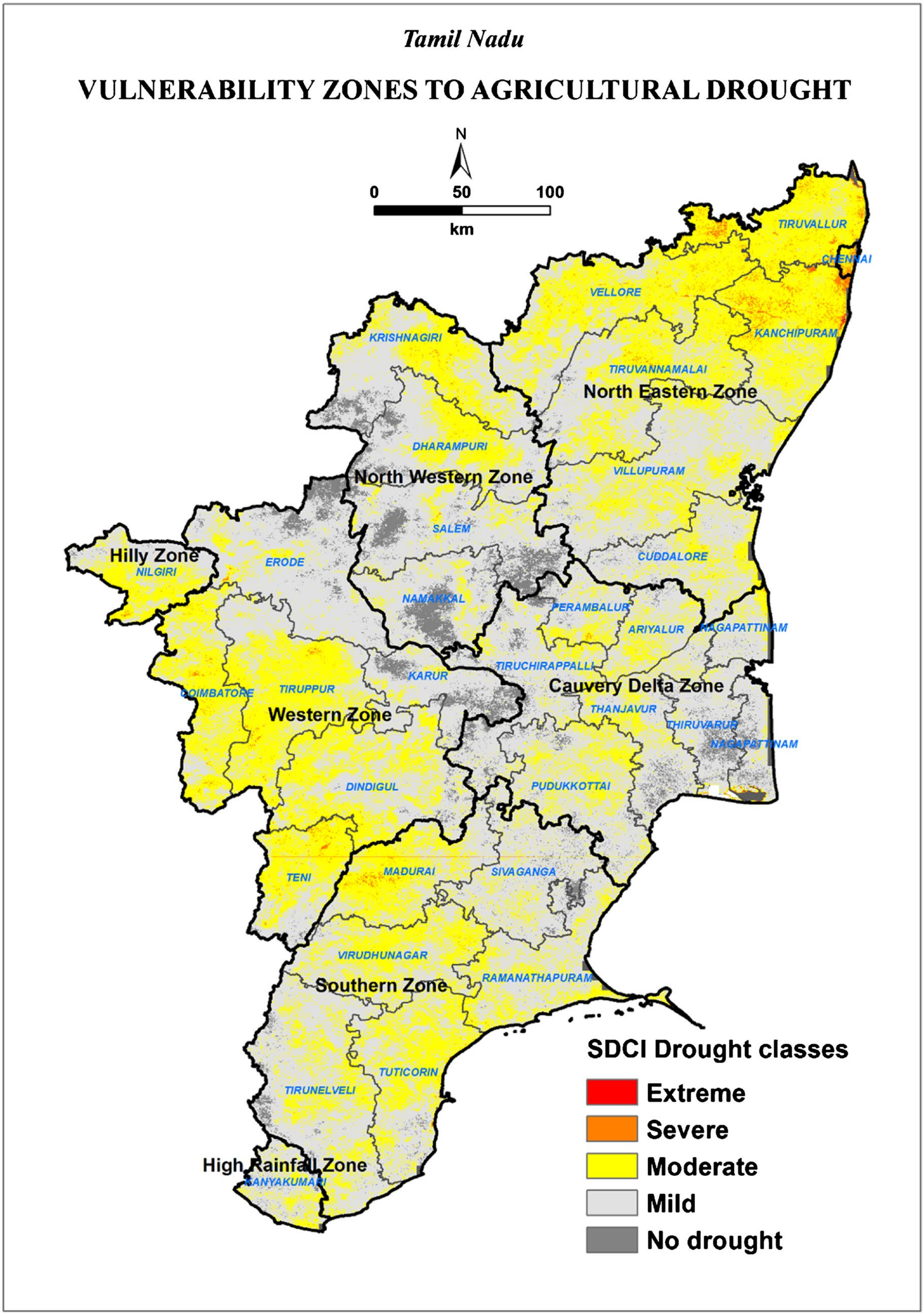

Fig. 8: Vulnerability zones to agricultural drought (2000-2019) in TN state

Table 3 Drought affected areas under three drought classes (2000 to 2019)

Agro-climatic zones	District	Extreme	Severe	Moderate	Area (in ha)
Cauvery delta zone	Ariyalur	0.0	11.7	38,596.6	38,608.3
	Nagapattinam	1.2	111.4	37,681.8	37,794.4
	Pudukkottai	0.0	310.8	135,932.4	136,243.2
	Thanjavur	0.0	41.0	59,771.3	59,812.4
	Thiruvarur	0.0	0.0	8350.3	8350.3
	Tiruchirappalli	0.0	1553.9	91,524.6	93,078.6
High rainfall zone	Kanyakumari	806.3	112,101.2	47,515.6	160,423.2
Hilly zone	The Nilgiris	6.5	10,285.4	134,548.5	144,840.3
North Eastern zone	Cuddalore	0.0	838.5	117,695.5	118,534.0
	Kanchipuram	3723.6	291,157.1	102,367.1	397,247.8
	Tiruvallur	6010.0	241,442.5	23,139.2	27,0591.7
	Tiruvannamalai	109.1	102,032.8	346,512.9	448,654.8
	Vellore	2338.0	348,981.6	222,971.1	574,290.6
	Villupuram	7.0	26,499.2	385,701.7	412,208.0
North Western Zone	Dharmapuri	14.1	79,931.6	278,848.7	358,794.4
	Krishnagiri	438.0	197,099.3	261901.9	459,439.2
	Namakkal	0.0	3559.4	138,072.7	141,632.1
	Salem	0.0	13,018.0	206,569.6	219,587.6
Southern zone	Madurai	0.0	1741.6	203,649.3	205,390.9
	Ramanathapuram	2.3	246.3	93,893.7	94,142.3
	Sivaganga	0.0	11.7	91243.2	91,254.9
	Tirunelveli	43.4	115,783.8	487,763.9	603,591.1
	Tuticorin	0.6	5424.2	224,876.9	230,301.6
	Virudhunagar	0.0	164.2	159,652.1	159,816.3
Western zone	Coimbatore	126.1	91,084.8	256618.4	347,829.4
	Dindigul	0.0	9411.6	245,060.6	254,472.2
	Erode	0.0	656.8	65,693.9	66,350.7
	Karur	0.0	340.1	43,475.4	43,815.5
	Perambalur	0.0	5.9	16,102.4	16,108.3
	Theni	0.0	13,657.2	196,008.6	209,665.8
	Tiruppur	8.8	17,152.1	417,027.0	434,187.8
	Chennai	632.1	10,162.2	64.5	10858.9
Total area (in ha)		**14267.0**	**1694818.2**	**5138831.0**	**6847916.2**
Area (in % with respect to TGA)		**0.1**	**13.0**	**39.5**	**52.6**

for a few pockets of Krishnagiri and Erode districts. Analysis of monthly VHI shows that during the dry year of NE monsoon, drought appeared in the western, north western, southern, and Cauvery delta regions of TN state with different intensities. It was noticed that due to the deficit of rainfall in October (Fig. 5d), severe drought (0.1–0.2) was experienced in Karur, Namakkal, Salem, Erode, Dharmapuri, and parts of Tiruchirappalli and Perambalur districts. The same trend continued in November (Fig. 5e) and December (Fig. 5f). Monthly analysis of SDCI indicates that drought was severe in October and November, and subsequently receded in December. In October, extreme drought (< 0.2) was noticed in all the districts except Madurai, Virudhunagar, and Kanchipuram (Fig. 5g). Whereas, in November, a similar scenario was observed except in the districts of Tirunelveli and Tuticorin (Fig. 5h). However, in December, extreme drought (< 0.2) was observed in the central and the eastern regions of TN state (Fig. 5i). The study clearly shows the impact of below mean season rainfall (62.0%) during the dry year (2016), its impact on the variability of SDCI, and overall adverse crop conditions.

Discussion

Correlation of SDCI with 3-SPI and VHI in the wet year

The results of SDCI were validated with an independent in situ meteorological drought index of 3-SPI and a combined drought index of VHI for wet the year (2010). The results of SDCI with 3-SPI for the wet year (2010) displays a strong positive correlation between SDCI and 3-SPI with an *R* value of 0.84 in October (Fig. 6a); similarly, it shows strong positive correlation between the SDCI with VHI of 0.94 (Fig. 6b). During October, a strong positive correlation with a *R* value of 0.73 (Fig. 6c) was observed between SDCI with 3-SPI; likewise, a high-positive correlation value (0.87) was noticed between SDCI with VHI (Fig. 6d). In December, a strong positive correlation was perceived between SDCI and 3-SPI with a *R* value of 0.78 (Fig. 6e). However, during the same period, a moderate positive correlation was observed between SDCI and VHI with the *R* value of 0.65 (Fig. 6f), this might be attributed to good rainfall received in December.

Correlation of SDCI with 3-SPI and VHI in the dry year

The correlation of SDCI with 3-SPI for October in the dry year (2016) shows a moderate positive correlation with an *R* value of 0.57 (Fig. 7a), whereas at the same time, a strong positive correlation was observed between VHI and SDCI with an *R* value of 1.0 (Fig. 7b). In November, there was a moderate positive correlation with an *R* value of 0.70 (Fig. 7c) between SDCI and 3-SPI; however, a strong positive correlation was observed between SDCI and VHI with an *R* value of 0.98 (Fig. 7d). Similarly, in December, a moderate positive correlation was noticed between SDCI and 3-SPI with an *R* value of 0.67 (Fig. 7e); nevertheless, it showed a very strong correlation between SDCI and VHI with an *R* value of 0.79 (Fig. 7f). The Pearson correlation between SDCI with 3-SPI and VHI indicates its robustness in the assessment of vulnerability to agricultural drought in time and space.

Delineation of vulnerability zones to agricultural drought using SDCI

The spatio-temporal pattern of agricultural drought vulnerability was assessed by using extreme, severe, moderate, mild, and no drought classes of SDCI for the period from 2000 to 2019 (Fig. 8). However, in the study, extreme, severe, and moderate classes were considered to assess the vulnerability to agricultural drought in different agro-climatic zones of TN state (Table 3). The detailed analysis shows that approximately 0.1% of the study area is vulnerable to extreme drought, primarily in the districts of Tiruvallur, Kanchipuram, and Vellore of the NE zone. Whereas, in Tiruvallur, Kanchipuram, Vellore, Krishnagiri, Dharmapuri, and Kanyakumari districts in NE, NW, and high rainfall zones covering about 13.0% of the area is under severe vulnerability to agricultural drought. About 39.5% of TN state is under moderate vulnerability to agricultural drought covering mainly Vellore, Krishnagiri, Dharmapuri, Tiruvannamalai, Villupuram, The Nilgiri's, Salem, Coimbatore, Tiruppur, Dindigul, Theni, Madurai, Viruduanagar, Tuticorin, and Tirunelveli districts of NE, NW, western, the hilly zones and southern zones of TN state. Approximately 47.4% of the TN state was covered either under mild or no drought scenario mainly in the central and eastern regions of the state. However, low intensity of drought was perceived in Salem, Namakkal, Cuddalore, Ariyalur, Nagapattinam, Pudukkottai, Thanjavur, Thiruvarur, and Tiruchirappalli districts of the Cauvery delta; this could be attributed to the well-established irrigation facilities in the delta region. The adoption of drought mitigation measures like adequate soil and water conservation measures, suitable cropping systems, and appropriate farm practices helps to minimize and mitigate the impact of droughts on agriculture especially in extreme, severe, and moderate intensity regions of the TN state.

Conclusions

The analysis of 3-SPI in the dry year 2016 depicts the moderately dry (−1.0 to −1.49) to extremely dry (−2 and less) conditions in the central parts of TN state. Similarly, during the same period, SDCI also shows that about 79.9% and 16.8% of the TN state experienced extreme, and severe drought conditions (0.2 to 0.3), respectively, especially in the central, northern, and NW regions of the TN state. A moderate positive correlation between SDCI and 3-SPI was noticed in the dry year (2016) due to below mean rainfall and its impact on vegetation health. In contrast, during the wet year (2010), almost all districts experienced extremely wet to near-normal conditions and about 92.8% of TGA of the state was under the no drought category. Analysis of drought variability in the wet year (2010) shows a very strong positive correlation between SDCI and 3-SPI, due to the fact of good rainfall received and its positive impact on vegetation. The validation of SDCI with VHI for the wet year (2010) and dry year (2016) shows moderate-to-strong positive correlation; it indicates the robustness of SDCI in depicting the prevailing soil moisture, vegetation health, and drought conditions in the state. The study clearly shows that the NE, northern, western, and southern zones of the study area are vulnerable to extreme, severe, and moderate agricultural drought with an area of 0.1, 13.0, and 39.5% of the TGA of the state, respectively. The study amply reveals the robustness of SDCI in the assessment of vulnerability to agricultural drought in the tropical semi-arid ecosystem of TN state. The results obtained in the study immensely help to develop the strategies and policies to minimize the vulnerability to agriculture drought and ensure food security in the state.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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