Spatio-Temporal Assessment of Agricultural Drought Vulnerability in the Semi-Arid Region of Southern India Using TRMM and MODIS Datasets

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ABSTRACT: The core objectives of the study are firstly to compute Scaled Drought Condition Index (SDCI) by integrating Precipitation Condition Index (PCI), Temperature Condition Index (TCI) and Vegetation Condition Index (VCI) for the period of north-eastern monsoon season (October to December) during 2000 to 2016. Secondly, assess the spatio-temporal variability of agricultural drought vulnerability in the tropical semi-arid region of northern of Tamil Nadu by using SDCI. In the study, PCI, TCI and VCI were derived from time series Tropical Rainfall Measuring Mission (TRMM) 3B43 precipitation data products, Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance of MOD11A2 and vegetation indices of MOD13Q1, respectively. The analysis reveals that the northern, north-eastern, western and southern parts of the study area are highly vulnerable to extreme and severe agricultural drought, respectively. The study shows that during the drought year (2016) about 70.0% of the study area was experienced extreme and severe drought conditions. The validation of SDCI with the Standardized Precipitation Index (SPI) during the drought year (2016) and wet year (2010) shows moderate to strong positive correlation between SDCI and SPI. It evidently indicates the impact of rainfall conditions on overall vegetation and agricultural drought. The study clearly demonstrates the potential of SDCI derived from time series TRMM and MODIS datasets in assessment and monitoring of spatio-temporal variability of agricultural drought vulnerability in the study area.

1. INTRODUCTION

Drought is a natural climatic hazard and considered as one of the most widespread natural disasters as an extreme climatic event and that severely affects the natural ecosystems, human livelihoods and global food production (Hu et al., 2019). The effect of drought risk on crop yields is further exacerbated by climate change and various anthropogenic activities (AghaKouchak et al., 2015). Drought phenomenon can disrupt economic and ecological systems that affects to the livelihoods of population. Generally, the period, frequency, and degree of droughts vary from region to region. In India, agricultural drought risk is more due to prolonged dry spell during monsoon season (Dutta et al., 2015), depleted groundwater and the pressure of food demand to feed 1.3 billion people. Nearly 60 % of India's population relies on the agricultural sector for their livelihood and contributes about 17 percent of the gross domestic product (GDP) of the nation (Arjun, 2013). The Indian agriculture practices mainly depend on monsoon especially southwest monsoon (June to September) (Kumar et al., 2013), however, agriculture in Tamil Nadu state mainly depends on northeast monsoon (October to December), it comprises nearly 60% of the state's total annual rainfall. Remote sensing and Geographic Information System (GIS) are the most reliable techniques for the assessment and monitoring of drought risk by its fine spatial resolution and real-time data availability (Kumar et al., 2020; Sandeep et al., 2020). The real-time monitoring of agricultural drought over an extensive area can be made by integrating satellite data on the GIS environment (Zambrano et al., 2016). MODIS and TRMM provide near real-time remote sensing datasets and these products were widely used for drought monitoring (Santos et al., 2017). These reliable remote sensing datasets play a crucial role in identifying areas at risk of drought and develops effective measures to mitigate this natural hazard.

In India, since 1989, NDVI derived from various data from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High-Resolution Radiometer (AVHRR) and Indian Remote Sensing (IRS) Advanced Wide Field Sensor (AWiFS) have been widely used in the National Agricultural Drought Assessment and Monitoring System (NADAMS) to assess and monitor agricultural drought (Sesha Sai et al., 2013). However, very few studies have been conducted in India to quantify and detect agricultural drought using the TRMM and MODIS datasets (Chandrasekar and Sesha Sai, 2014). An experimental drought monitoring system was developed for India based on TRMM daily precipitation data and daily temperatures obtained from the Global Ensemble Forecast System (GEFS) (Shah and Mishra, 2015). The agricultural drought was assessed by evaluating the sensitivity of Normalized Difference Water Index (NDWI) and NDVI derived from MODIS (Chakraborty and Sehgal, 2010). Reddy et al. (2020) analysed spatio-temporal vegetation dynamics to identify and delineate the vegetation stress zones in tropical arid ecosystem of India using MODIS datasets. Since, agriculture in northern Tamil Nadu is mainly depends on northeast monsoon season, thus, the failure of northeast monsoon will lead to water shortage and severe agricultural drought in the study area (Nathan, 1998). The present study was aimed to assess the agricultural drought vulnerability during north-eastern monsoon season from 2000 to 2016 in northern Tamil Nadu; India using indices derived from ground-based rainfall data, time series TRMM and MODIS data.

2. STUDY AREA

The study area consists four districts includes Krishnagiri, Dharampuri, Namakkal and Salem, lies in the south-eastern part of the Indian peninsula between 11°00' and 12°54' Northern latitudes and 77°27' and 77°28' of Eastern longitudes with an area of 1.83 million hectares (Mha) and occupies about 14.0 % of the total geographical area (TGA) of the Tamil Nadu state. About 90 % area of the study area is under the semi-arid condition and experiences tropical climate during the summer. The summers are much rainier than the winters in northern part of the Tamil Nadu and the climate is considered to be *Aw* according to the Köppen-Geiger climate classification. The average temperature of study area ranges from 28°C to 40°C in summer and 18°C to 26°C in the winter. The main rainfall season is the northeast monsoon season (October to December), receiving about 70 % of the total annual rainfall during this season and the remaining 30 % during the southwest monsoon period (June to September). The predominant soils of the study area are red loam, laterite, black, alluvial and saline soils. Red loam soils occupy large part of the study area particularly in the interior and the coastal districts. The black clayey alluvium rich soil is known as black cotton soils, which are found in parts Dharmapuri, Namakkal and Salem districts (Natarajan et al., 1997). The major agricultural crops in the study area are grown paddy, ragi, redgram, cowpea, maize, groundnut, horsegram and minor millets.

3. MATERIALS AND METHODS

3.1 Datasets used

In the study, the monthly rainfall records obtained for 23 rain gauge stations from Tamil Nadu Public Works Department (PWD), Chennai for the period from 1987 to 2016. Based on this monthly rainfall data we identified 2005 as wet year and 2016 as dry year and these two years were considered for detail spatial and temporal analysis of agricultural drought over northern Tamil Nadu. The satellite-based TRMM 3B43 ($0.25^{\circ}\times0.25^{\circ}$) gridded monthly precipitation data, from 2000 to 2016 were downloaded (https://mirador.gsfc.nasa.gov/) and downscaled to 0.025° using bi-linear interpolation technique. The MODIS datasets were downloaded from the Land Processes Distributed Active Center (LPDAAC; http://lpdaac.usgs.gov/). The MODIS NDVI products (MOD13Q1) of 250 m resolution were smoothed by the Savitzky-Golay (Chen et al., 2004) filter using TIMESAT software and these datasets were used to generate MVC to minimize further non-vegetation effects (Maisongrande et al., 2004) were used to compute VCI. The MODIS 8-day LST data products (MOD11A2) at 1 km resolution were used to compute TCI. The summary of datasets used, its time period, spatial and temporal resolutions are given in Table 1.

Table 1. Datasets used in the study

Data set	**Variable**	**Temporal Coverage**	**Temporal Resolution**	**Spatial Resolution**
Rain gauge data	SPI	1987 to 2016	Monthly	-
MOD13Q1	VCI	2000 to 2016	16 day	250 m
MOD11A2	TCI	2000 to 2016	8 day	1000 m
TRMM 3B43	PCI	2000 to 2016	Monthly	27 km

3.2 Computation of seasonal SPI

SPI is a probability index proposed by McKee et al. (1993), considered to be precipitation only for any given time scales, developed with historical data to monitor and assess the drought for any rainfall station based on their different SPI values (Table 2). In this study, SPI was computed for the long 30 years i.e.; 1987 to 2016 at one-month time scale for 23 rain gauge stations in the study area and the ordinary kriging method was used to develop the monthly rasters'. The SPI classification of droughts according to McKee et al. (1993) are 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).

3.3 Computation of scaled remote sensing indices

The PCI is an index which computed from either ground based or satellite derived precipitation measurements. PCI was introduced in order to detect the deficiency of precipitation from the climatic signal, as the normalized fluctuation of the precipitation from its long-term minimum and maximum (Table 2). 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 1at flooding conditions. In the study, monthly PCI was computed for the northeast monsoon season from 2000 to 2016.

TCI determine the thermal effect of drought. In the study, monthly LST datasets were generated from MODIS 8-day surface reflectance composite (MOD11A2) and the same datasets were used to compute TCI (Table 2). The range of TCI lies between 0 and 1. The low values of TCI implies the severe drought condition, whereas, high value denotes wet condition, in short under a drought process, the TCI stands close or equal to 0, and at wet conditions, it is near to 1. In the study, monthly TCI for northeast monsoon period from 2000 to 2016 were computed.

VCI demonstrates how close the current month's NDVI is to the long-term average measured minimum NDVI (Table 2). VCI from 0 to 1 shows a very unfavourable to optimal vegetation shift. In an extremely dry month, the vegetation condition is poor and the VCI is close to or equal to 0. The VCI of 0.5 indicates the quality of acceptable vegetation. VCI is close to 1 at optimal vegetation conditions.

3.4 Computation of SDCI from scaled remote sensing indices

The scaled drought condition index (SDCI) is considered as a multi-source and multi-date remote sensing derived index that developed from three distinct scaled indices namely TCI, VCI and PCI (Table 2). The values of SDCI vary from 0 to 1. The SDCI categorised into five drought classes such as extreme drought (SDCI < 0.2), severe drought (0.2 ≤ SDCI < 0.3), moderate drought (0.3 ≤ SDCI < 0.4), mild drought (0.4 ≤ SDCI < 0.5) and no drought (SDCI > 0.5).

Table 2 Drought indices used in this study and their data sources

Drought indices	Mathematical expression	References
SPI	$(X_{ij}- X_i)/ \sigma$	(McKee et al., 1993)
PCI	$(TRMM_i-TRMM_{min})/(TRMM_{max}-TRMM_{min})$	(Du et al., 2013)
TCI	$(LST_{max} - LST_i)/(LST_{max} - LST_{min})$	(Kogan, 1997)
VCI	$(NDVI_i- NDVI_{min})/(NDVI_{max} - NDVI_{min})$	(Kogan, 1995)
SDCI	$0.25_{TCI} + 0.5_{PCI} + 0.25_{VCI}$	(Rhee et al., 2010)

Note: *σ is 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.* $TRMM_i$*, LSTi,* $NDVI_i$ *- monthly TRMM, LST, NDVI for pixel current month of i.* $TRMM_{min}$*,* LST_{min}*,* $NDVI_{min}$ *- 17 years minimum TRMM, LST, NDVI for the of pixels i*th *month.* $TRMM_{max}$*,* LST_{max}*,* $NDVI_{max}$ *- 17 years maximum TRMM, LST, NDVI for the of pixels i*th *month, respectively.*

3.5 Pearson correlation analysis between SDCI with SPI

Pearson correlation analysis was performed between indices such as SDCI and SPI to evaluate the robustness of remotely sensed drought indices to monitor drought over time and space. The mean remotely sensed index values were extracted based on the location of the *in-situ* rain gauge stations (i.e., Tehsils). The Pearson correlation analysis was carried out between SDCI and SPI using the following mathematical equation.

$$R_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (1)$$

where R_{xy} is the correlation coefficient, *n* is the length of the time series, and *i* is the number of the year from 2000 to 2016 (1 to 17). Whereas, x_i and y_i are the SPI and the SDCI in year *i*, respectively, and *x* and *y* are the mean SPI and the mean SDCI, respectively, from 2000 to 2016.

4. RESULTS AND DISCUSSION

4.1 Spatio-temporal variability of seasonal SPI

The spatio-temporal analysis of seasonal SPI for the period from 2000 to 2016 shows that study area experienced above near-normal (-0.99 to 0.99) dry conditions in the majority of the years, whereas the extreme wet conditions were noticed in the years of 2005, 2007, 2010 and 2015. The analysis shows a recurring dry condition continuously from 2000 to 2004. In large parts of the study area, near normal conditions (-0.99 to 0.99) were noticed during this period. In 2002, an extremely dry condition (< -2) persisted in the central and southern parts of the study area. However, during the dry year 2016, majority of the study area was under extremely dry condition (< -2) as compared to the southern and central part of the study area. Harur station was observed the lowest SPI (-2.98) during this period. The analysis clearly exhibits the worst driest periods of the study area during the low rainfall particularly in the year 2016, 2012 and 2002. However, during the year 2005,2007, 2010 and 2015 at Pochampalli station in the northern part of the study area, extreme wet conditions with the highest SPI (2.65) were observed in the year 2005.

4.2 Agricultural drought severity mapping using SDCI

In the study, multi-sensor drought index SDCI was used by integrating scaled TRMM, LST and NDVI data to assess the intensity of agricultural drought vulnerability (Figure 1). The analysis of SDCI shows high variability from extreme drought (< 0.2) condition to no drought (> 0.5) condition during the period from 2000 to 2016. The analysis indicates that the year 2001, 2002, 2012 and 2013 are under dry conditions. Moderate drought conditions were experienced in the north eastern part of the study area during the year 2001, while extreme drought conditions in the northern and central part of the study area were observed in 2002. In the dry year 2016, only about 58.8 and 11.8 % of the study area were experienced extreme drought (SDCI < 0.2) and severe drought (SDCI 0.2 to 0.3), but the years 2005 to 2011 and 2015 were noted as normal years except 2008 and 2009, respectively. During the wet year (2005), entire northern Tamil Nadu is under no drought condition was observed in about 92.0 % of the study area.

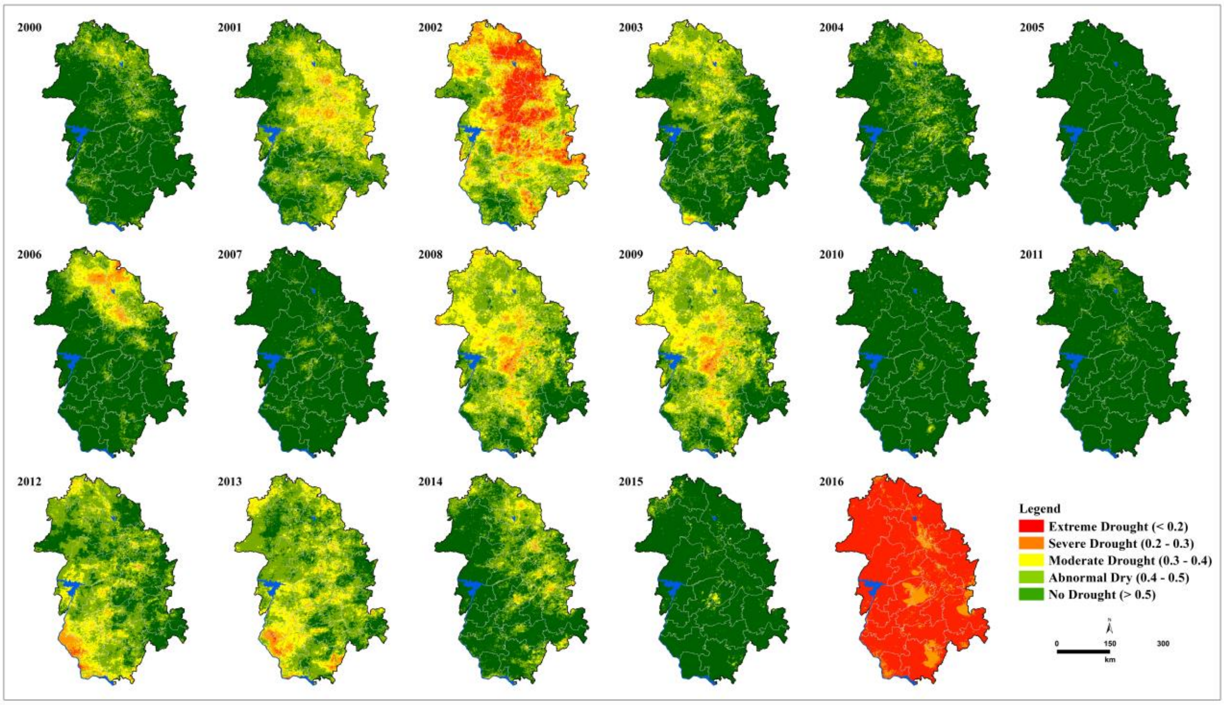

Figure 1 Spatio-temporal pattern of SDCI during north-east monsoon period (2000 to 2016)

4.3 Intra-seasonal variability of SPI and SDCI in wet year

To determine the intra-seasonal variability of drought intensity over northern Tamil Nadu, during the northeast monsoon period, the spatio-temporal variability of SPI and SDCI during the wet year (2005) was evaluated. It was observed that moderately wet to very wet conditions with mean seasonal SPI of 1.82. The intra-seasonal analysis of SPI during the northeast monsoon period shows the relatively near-normal conditions in November as compared to the wet to very wet conditions in October. Whereas, the moderately wet condition was observed in the month of December in the majority of the study area except for the eastern part of the study area where the near normal condition was observed. In the case of SDCI, the entire study area was observed the no drought condition. Whereas, in the month of November moderate drought conditions were observed in the eastern part of study area, particularly in the Sankari, Mettur and Edappadi tehsils of the study area. SDCI's analysis for the month of December shows no drought conditions. SPI and SDCI analysis of intra-seasonal variability in wet years clearly indicate the spatio-temporal variability of dry or wet conditions and drought intensity in the northeast monsoon season.

4.4 Intra-seasonal variability of SPI and SDCI in dry year

The intra-seasonal variability of SPI shows the spatial extent of dry conditions during the northeast monsoon in the dry year 2016 of the northern Tamil Nadu during October, November and December months. The extremely dry condition was mostly confined to the northern and north eastern parts of the study area during the month of October. The tehsils of the southern and eastern part of the study area experienced the extremely dry condition (-2 and less) during the month of November. However, the entire study area was under the near-normal condition in the month of December except for parts of the tehsils of Hosur and Denkanikota. SDCI's intra-seasonal variability indicates that in the months of October and November the drought trend was severe but diminished in the month of December. Extreme drought (< 0.2) was observed in nearly all tehsils in the month of October and the same trend was observed in the month of November also. While in the northern and eastern parts of the study area during December, extreme drought (< 0.2) was observed, it was tamed in the rest of the study area. The analysis clearly shows that the study area received only 62.0 % of the seasonal average rainfall in the year 2016, that clearly indicates the intra-seasonal variability of SPI and SDCI during the dry year.

4.5 Symbiotic relationship between rainfall and SDCI

The data obtained from 23 gauge stations in the study area for the 17-year period (2000 to 2016) from northeast monsoon rainfall were used to analyse the relationship and validated with SDCI and the show strong positive relationship between the two. The SDCI clearly shows its increasing trend with the rainfall during the wet year 2005. Nonetheless, it clearly indicates the prevailing drought scenario due to inadequate rainfall in the dry year 2016 SDCI shows sharp decline along with the rainfall. The 2001 and 2013 low SDCI also reveals symbiotic relationships with the state's weak rainfall trend.

4.6 Correlation of SDCI with SPI in wet and dry year

The independent in situ meteorological drought index, i.e. SPI was used to validate the results with SDCI. The correlation of SDCI with SPI for both wet and dry years shows strong to moderate relationship. The analysis shows a strong positive correlation between SDCI and SPI with correlation coefficient (r) of 0.8 (Figure 2a) during wet year 2005. The correlation of SDCI and SPI during dry year (2016) shows a strong positive correlation with correlation coefficient (r) of 0.77 (Figure 2b). This correlation analysis shows that SDCI found to be a robust drought index in time and space to assess the agricultural drought vulnerability.

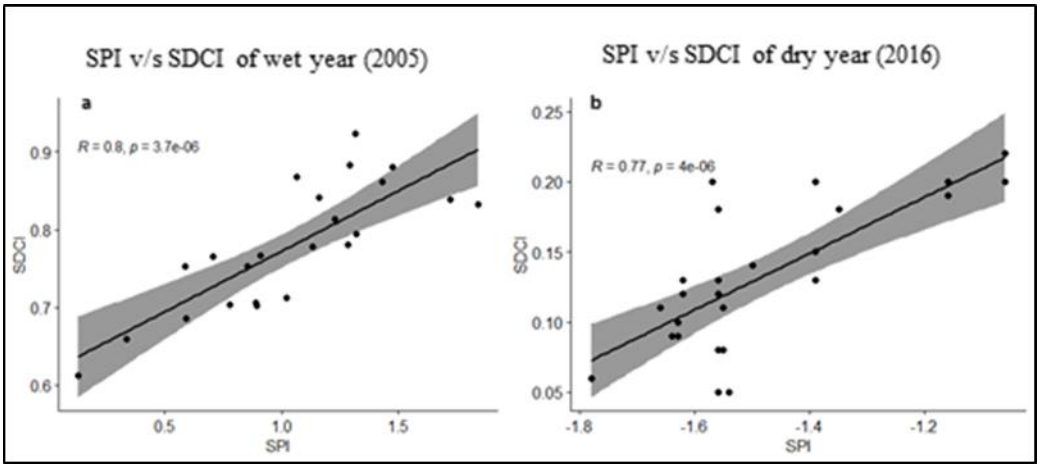

Figure 2a-2b Pearson correlation between SPI v/s SDCI during wet (2005) and dry year (2016)

5. CONCLUSION

Analysis of the spatio-temporal variability of SPI for the dry year 2016 shows that moderate to extremely dry conditions (-2 and less) in the southern and central part of the study area covers mainly in the Papireddipatti, Valappadi, Edappadi, Attur, Mettur, Sankari tehsils of Salem and Namakkal districts and SDCI shows moderate to extremely dry conditions during the dry year 2016, especially in the central, northern and northwestern parts of the study area. However, due to high rainfall during the northeastern monsoon season, entire study area experience extremely wet to near-normal conditions in 2005. During the dry year (2016), SDCI shows that about 51.87 % of the state was witnessed extreme drought and 30.0 % experienced severe drought conditions (0.2 to 0.3). However, due to above normal rainfall conditions about 92.77 % of the state is in no drought category in the wet year 2005. The study demonstrates the potential of proposed SDCI in assessing and monitoring the spatio-temporal variability of agricultural drought in tropical semi-arid northern Tamil Nadu derived from time series TRMM and MODIS data.

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