Vol. 23, No. 1, pp. 132-143 (2023)
Journal of Agricultural Physics
ISSN 0973-032X
http://www.agrophysics.in

Research Article

Spatio-temporal Analysis of Remote Sensing based Standardized Evaporative Drought Index during *kharif* Crop Season over India

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ABSTRACT

Drought is one of the complex natural hazards having multi-dimensional harmful impacts on agriculture and economy. Evapotranspiration is a good indicator of crop water stress, therefore, an evapotranspiration-based index can be used to monitor the agricultural drought. Standardized Evaporative Drought Index (sEDI) is such an index which is derived from the standardization of the Evaporative Drought Index (EDI) over time. EDI is based on the ratio of actual to potential evapotranspiration. The value of EDI increases with the increase in crop water stress. In this study, sEDI was computed from the MODIS actual and potential evapotranspiration data at 1 km spatial resolution and 16-days temporal interval during *kharif* crop season over India from 2001 to 2021. The Mann-Kendall trend analysis was also performed for each 16-day time period of the *kharif* crop season at 10% level of significance. It was found that the sEDI was accurately able to capture the spatiotemporal variation of the historical agricultural drought events over India. Most of the net sown area (64.9 – 85%) didn't show any trend in sEDI during *kharif* crop season, while significant increasing as well as decreasing trend was found in approximately 0.3 – 15.7% and 2.0 – 34.8% percentage of net sown area across all the time periods, respectively. An increasing trend was mainly found in the southern and eastern parts of India including Gujarat during the early and mid-phase of *kharif* crop season, whereas, the late-phase had most of the area showing a decreasing trend in drought. This study clearly brought out the spatiotemporal variation of agricultural drought at a finer spatial scale and could help in prioritizing the appropriate water management strategies to mitigate the effects of drought in India.

Key words: Agricultural drought, Remote sensing, Mann-Kendall trend, Evapotranspiration

Introduction

Drought is a complex natural hazard which has numerous adverse effects on agriculture, economy, industries, ecology, life and livelihoods of humans, etc. (Wilhite *et al*., 2007; Edwards *et al*., 2019; Parsons *et al*., 2019). Drought is initiated by the deficiency in rainfall which causes depletion in soil moisture, and the decline in surface and ground water levels which subsequently affects crop growth and yield. The prolonged shortage of rainfall can create socio-economic problems like lack of drinking water, death of animals and humans, migration, etc. (Wilhite and Glantz, 1985; Mishra and Singh, 2010, 2011). Drought has been categorized into four types i.e.,

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meteorological, agricultural, hydrological and socio-economical (Wilhite and Glantz, 1985). Agricultural drought is referred to as a condition initiated by failure in precipitation leading to the decline in soil moisture and consequent crop failure without any reference to surface water resources. The decline in soil moisture depends on several meteorological and hydrological factors along with differences between actual evapotranspiration and potential evapotranspiration (Mishra and Singh, 2010). India is amongst the most vulnerable drought-prone countries in the world because drought has been reported at least once every three years in the last five decades in one or other parts of India (Manual of Drought Management, 2016). Out of 3.29 million km^2 of geographical area in India, about 1.07 million km^2 of land is subjected to different degrees of water stress and drought conditions (Mishra and Desai, 2005). In India, drought areas are mainly confined to the southern and western parts of the country. The frequency of occurrence of drought in India is increasing (FAO, 2002). About 55% of the net sown area in India is under rainfed agriculture which is most prone to agricultural drought (NRAA, 2012).

Several indices have been developed by various researchers across the world to monitor the progress and severity of drought. Traditionally, the drought was monitored using indices like rainfall deficit, Standardized Precipitation Index (McKee *et al*., 1993), Palmer Drought Severity Index (Palmer, 1965), Crop Moisture Index (Palmer, 1968), Crop Water Stress Index (Jackson *et al*., 1988), etc. With the advancement in remote sensing technologies, numerous indices were developed based on remote sensing data as it provides better spatial and temporal information in less time, therefore, increasing the possibility of near real-time monitoring of agricultural drought conditions. These indices are based on the detection of vegetation conditions and their deviation due to drought. The most prominent vegetation index is certainly the Normalized Difference Vegetation Index (NDVI; Tucker, 1979) which was first applied to drought monitoring by Tucker and Choudhury (1987). This study triggered several drought monitoring indices like the Vegetation Condition Index (VCI; Kogan, 1990, 1995), the anomaly of the NDVI called NDVIA (Anyamba *et al.,* 2001), or the Standardized Vegetation Index SVI (Peters *et al.,* 2002). In addition to using optical data, several other indices were developed by considering data of other bands to detect drought like Temperature Condition Index (TCI, Kogan, 1995), Vegetation Temperature Index (VTI) or Vegetation Health Index (VHI) by Kogan (1997, 2000), Vegetation Index/Temperature Trapeziod (VITT, Moran *et al*., 1994), Vegetation Temperature Condition Index (VTCI, Wan *et al.,* 2004), Temperature Vegetation Dryness Index (TVDI, Sandholt *et al.,* 2002), Normalized Difference Water Index (NDWI, Gao, 1996; Chakraborty and Sehgal, 2010), etc.

Evapotranspiration, a key component of the land surface water budget and an indicator linked to vegetation drought status, is a significant process that drives energy and water exchange between the atmosphere and land surface (Priestley and Taylor, 1972; Wang *et al*., 2007). When drought occurs, the stomata of stressed plants close to minimize water loss by transpiration, which leads to decreased latent heat flux; in order to keep an energy balance, sensible heat flux may increase. As a result of this process, leaf temperature will ultimately increase (McVicar and Jupp 1998). Vicente-Serrano *et al.* (2010) proposed Standardized Precipitation Evapotranspiration Index (SPEI) which is computationally analogous to SPI, but it used deficit i.e. (P-PET) instead of only P *i.e.,* precipitation as a variable. Yao *et al.* (2010) proposed an Evaporative Drought Index (EDI) to monitor droughts over the conterminous United States. They used Moderate Resolution Imaging Spectroradiometer (MODIS) and National Centers for Environmental Prediction–Department of Energy Atmospheric Model Intercomparison Project Reanalysis II (NCEP–DOE II) data, and statistical methods to estimate the ET and PET at 4-km spatial resolution and a monthly time step, and used the deviation of the ET/PET ratio from unity to define the EDI. The integrated remote sensing data in the EDI are sensitive to the vegetation drought response and enhance EDI capabilities for drought monitoring and detection. The EDI cannot easily quantify the wetness or dryness of a region in a given monthly or yearly period across various regions. Therefore, Zhang *et al*. (2019) did the standardization of EDI over time so that it could be used to evaluate the drought condition across different temporal periods and agro-climatic regions. This index is known as the Standardized Evaporative Drought Index (sEDI). He found that the sEDI correlates well with past drought events and inter-annual grain crop yields in Northeast China. In this study, we have computed sEDI for the years 2001 to 2021 for the *kharif* crop season over India and its spatiotemporal trend analysis using Mann-Kendall test was performed. This study may be helpful in understanding the variation of sEDI over different parts of India in space and time, and its usefulness in evaluating the agricultural drought conditions over India.

Material and Methods

Data

In this study, actual and potential evapotranspiration (ET) data from MODIS Terra satellite product i.e., MOD16A2GF from NASA was used. The MOD16A2GF is the year-end gap-filled 8-day composite evapotranspiration dataset in which the poor quality of pixels has been rectified. The detailed algorithm for the development of this product is given by Running *et al*. (2019). This product provides data layers of total actual and potential evapotranspiration in terms of kg/m^2 over 8-days at 500 m spatial resolution. The data was downloaded, mosaicked for the Indian region and converted to GeoTIFF format for the year 2001 to 2021 using the 'MODIStsp' package (Busetto and Ranghetti, 2016) written in free and open-source R-Studio software. The data were resampled to 1 km spatial resolution using the nearest neighbourhood technique. The sum of two consecutive 8-day ET products was taken to produce a 16-day ET product as we intended to compute Standardized Evaporative Drought Index (sEDI) at 16-days temporal interval and 1 km spatial resolution. The crop mask derived from the Land Cover Type-1 layer of MODIS land use land cover product 'MCD12Q1' for the year 2010 was applied so that the pixels pertaining only to the crop cultivated areas are retained for agricultural drought assessment.

Standardized Evaporative Drought Index

Standardized Evaporative Drought Index (sEDI) given by Zhang *et al.* (2019) is computed from the Evaporative Drought Index (EDI). EDI was proposed by Yao *et al.* (2010, 2011). It is based on the concept that actual evapotranspiration (AET) is closer to the potential evapotranspiration (PET) when there is abundant water supply to the crops, while AET is less than PET in case of lower water availability indicating crop water stress. Thus, EDI is computed from AET and PET to represent crop water stress using the following formula:

$$\text{EDI} = 1 - \frac{ET}{PET} \qquad (1)$$

The value of EDI varies from 0 to 1. The higher value of EDI indicates higher water stress and *vice-versa*. EDI has been used by several researchers for monitoring agricultural drought (Zhao *et al.,* 2017; Zhang *et al.,* 2019; Liu *et al.,* 2022). The standardization of EDI is done to derive anomalies in EDI over a particular region with respect to the whole temporal period, known as Standardized Evaporative Drought Index (sEDI). The sEDI helps in comparing the drought severity conditions over different agro-climatic regions by considering the climatic variability. It can be computed by taking the *z-score* of EDI as given in the following formula:

$$\text{sEDI} = \frac{EDI - \overline{EDI}}{\sigma_{\text{EDI}}} \qquad (2)$$

Here, $\overline{EDI}$ and σ_{EDI} are temporal mean and temporal standard deviations of EDI for a given period, respectively. Higher the value of sEDI, more will be the drought severity. The sEDI has been classified for agricultural drought severity using the classification scheme given in Table 1.

The sEDI has been computed for the *kharif* crop season over India at a 16-days temporal interval and

Table 1. Agricultural drought severity classification of sEDI (Zhang *et al.,* 2019)

sEDI values	Categories
< -1.0	No drought
0 to -1.0	Near-normal
0 to 1.0	Mild drought
1.0 to 1.5	Moderate drought
1.5 to 2.0	Severe drought
> 2.0	Extreme drought

Table 2. Time periods for which sEDI was computed

Time Period	Temporal Range
I	25th May to 9th June
II	10th to 25th June
III	26th June to 11th July
IV	12th to 27th July
V	28th July to 12th August
VI	13th to 28th August
VII	29th August to 13th September
VIII	14th to 29th September
IX	30th September to 15th October
X	16th to 31st October

1 km spatial resolution. The *kharif* crop season corresponds to summer monsoon season in India in which crop sowing starts from June onwards and is harvested by October end. There are ten time periods each of 16 days during the *kharif* crop season for which sEDI were computed from the year 2001 to 2021. These time periods are given in Table 2. The time period from June to July are considered in early *kharif* season, August to mid-September in mid *kharif* season and mid-September to October in late *kharif* season.

Agricultural drought trend analysis

Mann-Kendall (MK) test was used to estimate trends in agricultural drought events in terms of trends in sEDI. Mann-Kendall trend test (Mann, 1945; Kendall, 1955) is a non-parametric, rank-based correlation test which is used for the detection of monotonic upward or downward trends in time-series data. MK test is easy to perform and is robust to the presence of outliers or missing data. The null hypothesis of the MK test is the absence of trend while the alternate hypothesis is presence of trend. In MK test, each value in the time series data is compared to the other values sequentially. The expression of MK test (S) statistic is:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k) \tag{3}$$

where, n is the length of time-series data, x_j and x_k are two sequential values of data. The function $sign(x_j - x_k)$ gets the values as expressed below:

$$sign(x_j - x_k) = \begin{bmatrix} +1, & (x_j - x_k) > 0 \\ 0, & (x_j - x_k) = 0 \\ -1, & (x_j - x_k) < 0 \end{bmatrix} \tag{4}$$

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

Here, Var(S) is the variance of the dataset. The Z-statistic is computed as follows:

$$Z = \begin{bmatrix} \frac{S-1}{\sqrt{Var(S)}}, & if\ S > 0 \\ 0, & if\ S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & if\ S < 0 \end{bmatrix} \tag{6}$$

The positive value of standardized Z statistic denotes an increasing trend whereas the negative value denotes decreasing trend. The Kendall Tau (τ) or Kendall rank correlation coefficient was computed as follows:

$$\tau = \frac{S}{D} \tag{7}$$

where, D is the total number of pair combinations computed using the following equation:

$$D = \frac{n(n-1)}{2} \tag{8}$$

Kendall's Tau measures the monotony of the slope. It's value ranges from -1 to +1 where a positive value denotes an increasing trend and a negative value denotes decreasing trend. The MK test was performed on the time-series data of sEDI for each time period (Table 2) ranging from 2001 to 2021. Kendall's Tau was computed for each pixel for a particular time period was statistically evaluated at 10% level of significance. For performing MK test over the raster dataset of sEDI, 'raster' (Hijmans *et al*., 2015), 'Kendall' (McLeod, 2015), and 'trend' (Pohlert *et al*., 2016) packages of R software was used.

Results and Discussion

Spatio-temporal variations in sEDI

The sEDI was computed from the year 2001 to 2021 at 1 km spatial resolution and 16 days' temporal interval during the *kharif* crop season for each time period (Table 2). The maps of sEDI for the year 2015 (known drought-affected year) and 2021 (known non-drought year) for each time period are shown in the figure 1 and 2, respectively. The year-wise variation of the percentage of area affected by the different categories of agricultural drought all over the India during *kharif* crop season is depicted in figure 3. It is clear from figure 3 that the years 2002, 2009, 2012, 2014 and 2015 were mostly affected by the agricultural drought over large area, whereas the years 2003, 2013, 2020, and 2021 less area was affected. The maximum area under the extreme drought category was found in the year 2002 (7.4%) followed by the years 2015 (6.7%) and 2014 (5.1%), respectively. A similar pattern was found in the severe drought category where the year 2002, 2015 and 2014 showed 12.0%, 10.1%, and 8.1% area affected, respectively. The percentage of areas affected by the moderate drought category was maximum in the year 2002 (20.2%) followed by 2015 (19.5%), 2009 (16.7%), 2014 (16.5%), and 2012 (11.5%), respectively. However, the maximum area affected by mild drought was in the year 2012 (53.8%) followed by 2009 (53.1%). The maximum percentage of cultivated area under both the near-normal and no-drought categories was found in the year 2021 (77.7%) followed by 2020 (75.1%), 2013 (66.9%),

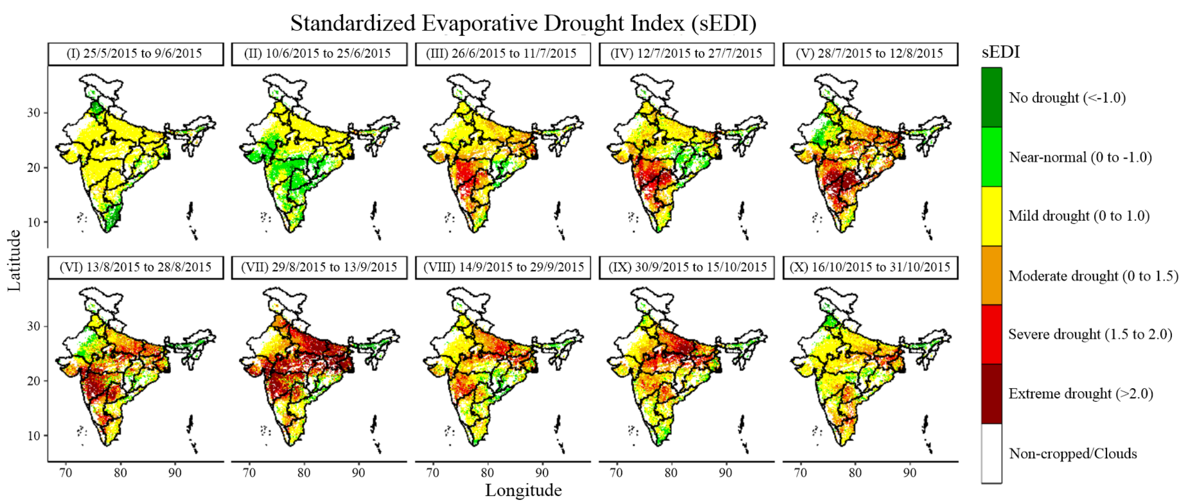

Fig. 1. Maps showing spatial variation of sEDI Index during each time period of the *kharif* crop season for the year 2015 over India

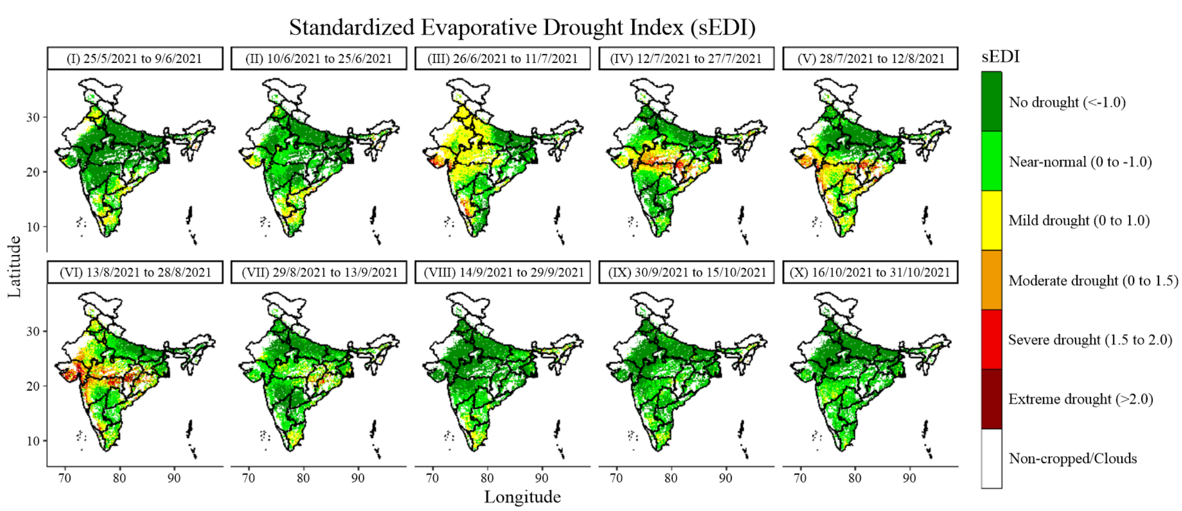

Fig. 2. Maps showing spatial variation of sEDI Index during each time period of the *kharif* crop season for the year 2021 over India

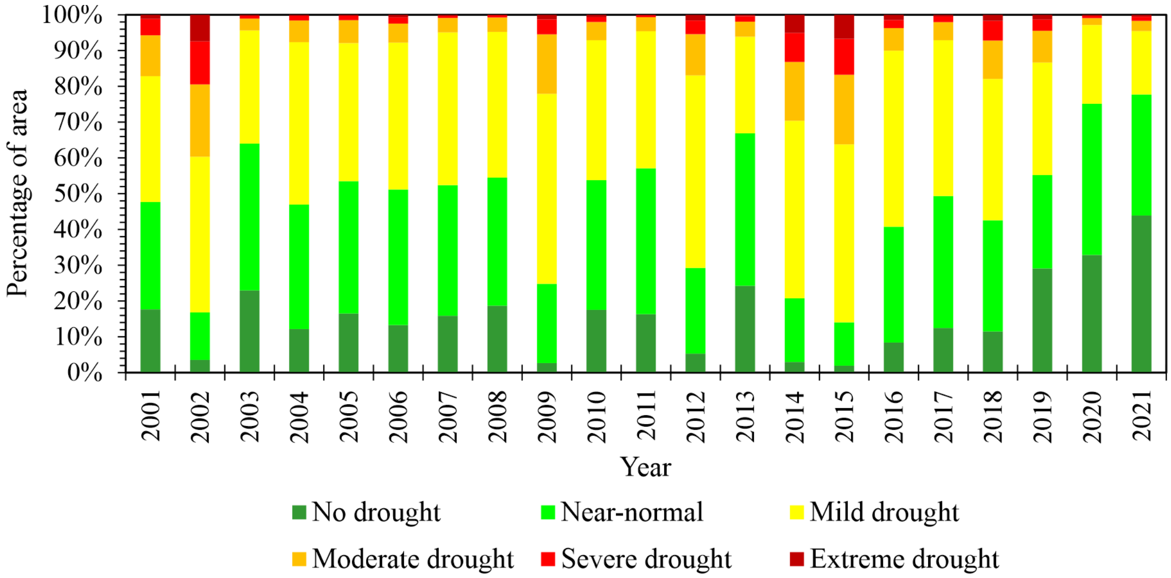

Fig. 3. Yearly variation of percentage of crop area affected by different categories of agricultural drought as deciphered from sEDI during *kharif* crop season in India

and 2003 (64.0%), respectively. From the maps of sEDI of different years, it was found that the states of Rajasthan, Karnataka, Maharashtra, and Andhra Pradesh were most frequently affected by the drought as compared to the other states.

Spatio-temporal trend in sEDI

The pixel-wise Mann-Kendall trend analysis was performed in terms of Kendall Tau (τ) on the 21 years' data of the sEDI *i.e.,* from the years 2001 to 2021, to detect the presence of trend in each time period of the *kharif* crop season. The positive value of Kendall's Tau represents an increasing trend while the negative value depicts a decreasing trend. The pixels whose trend value was significant at the 10% level of significance ($p < 0.1$), were only considered in this study. The pixels whose values were not found significant were considered to have no trend (NT). The maps of the significant values ($p < 0.1$) of Kendall's Tau (τ) for each time period of the *kharif* crop season are depicted in figure 4. The percentage of net sown area having increasing trend (IT), decreasing trend (DT), and no trend (NT) in each time period of the *kharif* crop season of each state of India is shown in Table 3. The presence of an increasing trend in sEDI depicts the increase in the crop water stress or dryness over time whereas decreasing trend denotes decrease in crop water stress or increase in wetness.

The Table 3 shows that during time period I, the states of Andhra Pradesh (45.1%), Mizoram (26.2%) and Karnataka (24.6%) have the maximum percentage of net cultivated area showing increasing trend in sEDI, whereas decreasing trend was found mostly in the state of Himachal Pradesh (82.4%), Uttarakhand (69%), Jammu & Kashmir (60.4%), Arunachal Pradesh (49.6%), Uttar Pradesh (42.9%), Punjab (38.1%), and West Bengal (37.4%). Similar pattern of increasing trend was found during time period II for the states of Andhra Pradesh (29.8%), Mizoram (65.6%) and Karnataka (50.9%), but Tamil Nadu (68.8%) was found to have maximum percentage of crop area with increasing drought trend. The decreasing trend during time period II was found mostly in the states of Jammu & Kashmir (78%), Himachal Pradesh (77.7%), Ladakh (59.3%), Haryana (51.8%), Delhi (45.5%), Arunachal Pradesh (40.8%), Punjab (32.9%), and Uttarakhand (28.2%). The percentage of net cultivated area having significant positive trend has increased in the time period II as compared to time period I. However, the spatial pattern of trend changed during the time period III. During time period III, the maximum percentage of net sown area having increasing trend

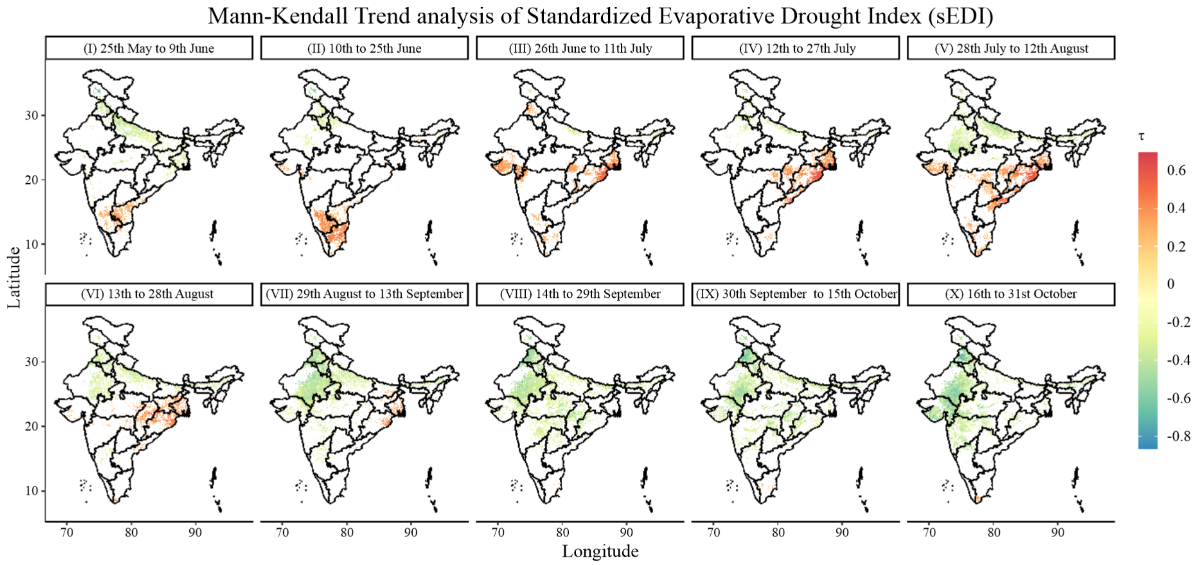

Fig. 4. The spatio-temporal variation of significant values of Kendall's Tau (τ) ($p < 0.1$) of sEDI for each time period of the *kharif* crop season over India

was found in Gujarat (59.9%), followed by Odisha (57.7%), West Bengal (47.1%), and Chhattisgarh (34.8%). The states of Ladakh (87.9%), Arunachal Pradesh (70.9%), and Assam (34%) had maximum area under decreasing trend in the time period III. During the time period IV, the States present in the eastern part of the India showed increasing trend *i.e.,* Odisha (76.8%), West Bengal (57.8%), Chhattisgarh (42.5%), Jharkhand (23.8%), and Andhra Pradesh (19.2%), while decreasing trend were found in Jammu & Kashmir (69.3%), Ladakh (54.9%), Himachal Pradesh (44.5%), and Arunachal Pradesh (34.6%). For the time period V, the States of Gujarat (37.5%) and Tamil Nadu (20.3%) also had most of the net sown area showing increasing trend along with West Bengal (46.7%), Chhattisgarh (43.4%), Andhra Pradesh (42.8%), and Odisha (83%). The states showing decreasing trend during time period V are Jammu & Kashmir (64.9%), Ladakh (61.5%), Assam (57.6%), Rajasthan (52.3%), Uttarakhand (50.3%), Arunachal Pradesh (46.4%), Sikkim (40%), and Himachal Pradesh (39%), and Uttar Pradesh (37.1%). The percentage of net sown area having both significant increasing and decreasing trend in sEDI has been increased in the time period V as compared to the previous four time periods. The total area showing positive trend has decreased in the time period VI as compared to time period V, and has been limited to the eastern part of India i.e., Odisha (55.1%), Chhattisgarh (50.5%), Jharkhand (47.3%), and West Bengal (41.9%). However, the patterns of the states showing negative trend during the time period VI remained quite similar to that of V *i.e.,* Jammu & Kashmir (61.7%), Ladakh (40.7%), Punjab (54%), Haryana (45.4%), Himachal Pradesh (41.9%), Rajasthan (40.7%), Assam (47.3%), Arunachal Pradesh (35.3%), Uttarakhand (35.1%), and Uttar Pradesh (25.9%). During time period VII, the area showing significant increasing trend has further decreased whereas the area of decreasing trend has increased. The increasing trend was found mostly in the states of West Bengal (30.5%), Odisha (20.9%), and Jharkhand (8.8%), while the decreasing trend was found in Rajasthan (94.2%), Punjab (88.5%), Haryana (81.3%), Jammu & Kashmir (75.1%), Ladakh (73.6%), Himachal Pradesh (54.9%), Assam (49.1%), Uttar Pradesh (37.5%), Gujarat (33.8%), and Uttarakhand (33%). During the time period VIII, the area showing positive trend has further decreased and only the Mizoram state showed 34.4% of net cultivated area having increasing trend while the percentage of area in the other states were less than 10%. The area showing significant decreasing trend of sEDI during the time period VIII has further increased with most parts of the India except southern India showed negative trend. The maximum

Table 3. Percentage of net sown area showing increasing trend (IT), decreasing trend (DT), and no trend (NT) in each time period of the *kharif* season in each state of India

State	I			II			III			IV			V		
	IT	DT	NT	IT	DT	NT	IT	DT	NT	IT	DT	NT	IT	DT	NT
West Bengal	0.13	37.36	62.51	5.45	0.36	94.18	47.14	0.98	51.88	57.84	2.51	39.65	46.68	5.55	47.77
Delhi	0.00	24.07	75.93	0.00	45.47	54.53	0.00	0.00	100.00	0.00	1.65	98.35	0.00	11.11	88.89
Haryana	0.01	18.88	81.11	0.00	51.76	48.24	0.97	0.06	98.97	0.00	20.82	79.18	0.01	29.87	70.13
Jharkhand	0.00	26.82	73.17	0.17	0.00	99.83	10.45	0.01	89.55	23.84	0.04	76.12	11.76	0.79	87.44
Karnataka	24.59	0.08	75.33	50.87	0.01	49.12	6.73	0.11	93.16	0.01	0.23	99.77	8.08	0.08	91.84
Kerala	3.35	3.89	92.75	48.00	1.85	50.15	24.97	3.04	71.99	3.65	2.99	93.36	17.48	2.91	79.62
Madhya Pradesh	0.00	3.63	96.37	0.00	0.12	99.88	0.77	0.03	99.21	0.25	0.10	99.65	0.36	9.83	89.81
Maharashtra	0.03	1.82	98.15	0.91	0.01	99.09	8.48	0.17	91.35	5.25	0.44	94.31	10.69	0.07	89.24
Tamilnadu	6.68	1.00	92.32	68.78	0.23	30.99	12.14	0.75	87.11	7.11	0.17	92.72	20.26	0.09	79.64
Chhattisgarh	0.07	3.50	96.43	0.01	0.00	99.99	34.78	0.00	65.22	42.49	0.03	57.48	43.43	2.26	54.31
Telangana	3.16	0.01	96.83	1.68	0.01	98.31	0.11	0.31	99.58	5.54	0.02	94.44	32.45	0.02	67.53
Andhra Pradesh	45.12	0.07	54.81	29.79	0.01	70.20	4.54	0.22	95.24	19.16	0.09	80.75	42.80	0.14	57.06
Goa	0.00	0.34	99.66	14.53	0.00	85.47	0.00	7.01	92.99	0.00	10.77	89.23	2.56	2.05	95.38
Himachal Pradesh	0.02	82.41	17.56	0.00	77.66	22.34	0.05	13.75	86.20	0.00	44.54	55.46	0.05	39.01	60.95
Punjab	0.04	38.08	61.89	0.06	32.93	67.01	23.67	0.33	76.00	0.00	25.65	74.35	0.12	27.22	72.67
Rajasthan	1.47	0.48	98.04	0.00	11.87	88.13	0.52	0.07	99.41	0.00	11.87	88.13	0.00	52.26	47.74
Gujarat	1.04	2.20	96.76	10.31	0.01	89.68	59.88	0.00	40.12	0.18	0.03	99.79	37.51	0.19	62.30
Uttarakhand	0.00	69.00	31.00	0.00	28.20	71.80	0.04	1.79	98.16	0.00	10.61	89.39	0.03	50.31	49.66
Uttar Pradesh	0.00	42.95	57.05	0.00	9.11	90.89	0.01	6.68	93.31	0.00	12.34	87.66	0.00	37.11	62.89
Sikkim	0.00	6.67	93.33	0.00	0.00	100.00	0.00	6.67	93.33	0.00	26.67	73.33	0.00	40.00	60.00
Assam	1.91	21.34	76.75	7.56	12.85	79.59	0.41	33.97	65.62	0.69	22.89	76.42	0.05	57.59	42.37
Arunachal Pradesh	0.89	49.56	49.56	0.70	40.79	58.51	0.00	70.90	29.10	0.64	34.56	64.80	0.44	46.44	53.11
Manipur	0.83	1.66	97.52	2.95	0.31	96.74	0.57	2.02	97.41	0.16	22.72	77.12	0.16	30.69	69.15
Mizoram	26.23	1.64	72.13	65.57	1.64	32.79	29.51	1.64	68.85	6.56	1.64	91.80	1.64	6.56	91.80
Tripura	2.88	3.73	93.39	11.13	0.26	88.61	18.26	0.13	81.61	12.76	4.19	83.05	4.06	5.37	90.58
Meghalaya	0.48	11.70	87.82	10.26	0.16	89.58	0.96	1.60	97.44	2.88	5.13	91.99	0.64	17.31	82.05
Bihar	0.00	22.14	77.86	0.48	0.10	99.42	0.36	2.16	97.49	0.95	3.90	95.15	0.02	16.08	83.90
Ladakh	0.00	16.48	83.52	0.00	59.34	40.66	0.00	87.91	12.09	0.00	54.95	45.05	2.20	61.54	36.26
Jammu & Kashmir	0.09	60.38	39.53	0.01	78.00	21.99	0.09	24.51	75.40	0.13	69.27	30.60	0.12	64.91	34.97
Odisha	0.14	14.12	85.74	4.60	0.00	95.40	57.66	0.15	42.19	76.75	0.05	23.21	83.00	0.08	16.93
Total	4.57	12.46	82.98	9.52	5.48	85.00	12.32	1.96	85.71	9.79	5.31	84.90	15.72	15.45	68.83

	VI			VII			VIII			IX			X		
	IT	DT	NT	IT	DT	NT	IT	DT	NT	IT	DT	NT	IT	DT	NT
West Bengal	41.94	6.06	52.00	30.49	5.55	63.97	2.25	10.94	86.81	0.36	19.66	79.97	0.68	14.79	84.53
Delhi	0.00	8.23	91.77	0.00	31.28	68.72	0.00	26.34	73.66	0.00	37.86	62.14	1.65	35.60	62.76
Haryana	0.00	45.42	54.58	0.00	81.30	18.70	0.00	59.10	40.90	0.02	56.72	43.26	1.36	46.26	52.37
Jharkhand	47.28	0.12	52.60	8.83	0.91	90.26	0.03	3.71	96.27	0.03	4.76	95.20	0.07	0.37	99.55
Karnataka	0.17	7.93	91.90	0.00	10.89	89.11	0.21	4.57	95.22	0.04	9.79	90.18	0.03	12.02	87.94
Kerala	2.93	7.03	90.04	0.64	6.42	92.94	1.30	3.83	94.88	1.69	3.96	94.35	7.88	3.77	88.35
Madhya Pradesh	4.49	3.54	91.97	0.03	27.18	72.79	0.00	42.32	57.68	0.11	16.81	83.08	0.10	31.98	67.91
Maharashtra	2.97	0.67	96.37	0.06	10.45	89.49	0.01	26.60	73.39	0.02	25.03	74.94	0.05	47.27	52.68
Tamilnadu	1.99	1.45	96.56	0.24	1.29	98.46	2.66	0.10	97.24	5.31	0.16	94.53	5.78	0.11	94.11
Chhattisgarh	50.46	0.20	49.34	0.48	10.22	89.30	0.01	62.33	37.67	0.05	48.80	51.15	0.08	8.23	91.68
Telangana	3.29	0.66	96.05	0.13	6.13	93.75	0.01	19.40	80.58	0.02	17.19	82.80	0.11	6.35	93.54
Andhra Pradesh	7.62	1.05	91.33	1.23	2.57	96.20	1.04	4.36	94.59	0.69	3.46	95.85	0.83	1.42	97.75

Contd...

Goa	0.00	11.45	88.55	0.00	8.55	91.45	0.34	3.25	96.41	0.17	35.56	64.27	0.00	68.21	31.79
Himachal Pradesh	0.02	41.89	58.08	0.00	54.89	45.11	0.05	74.46	25.49	0.12	87.60	12.28	0.31	73.66	26.04
Punjab	0.02	54.03	45.95	0.02	88.47	11.51	0.02	87.28	12.70	0.01	91.09	8.90	0.32	77.51	22.17
Rajasthan	0.00	40.71	59.29	0.00	94.22	5.78	0.00	90.00	10.00	0.01	75.30	24.69	0.00	83.88	16.12
Gujarat	3.24	0.72	96.03	0.00	33.79	66.20	0.00	36.80	63.19	0.01	55.35	44.63	0.01	88.82	11.17
Uttarakhand	0.04	35.08	64.87	0.01	33.01	66.97	0.09	33.44	66.48	0.86	38.45	60.69	2.35	29.18	68.48
Uttar Pradesh	0.12	25.86	74.03	0.00	37.47	62.53	0.00	27.43	72.57	0.12	25.65	74.23	0.41	10.19	89.40
Sikkim	0.00	20.00	80.00	0.00	0.00	100.00	0.00	60.00	40.00	0.00	40.00	60.00	0.00	46.67	53.33
Assam	0.02	47.31	52.67	0.05	49.11	50.85	1.08	41.78	57.13	1.05	35.36	63.59	1.42	45.21	53.37
Arunachal Pradesh	0.38	35.26	64.36	0.51	35.77	63.72	0.13	66.77	33.10	2.48	29.10	68.42	3.43	51.72	44.85
Nagaland	0.29	18.57	81.14	0.00	7.71	92.29	2.29	12.29	85.43	3.43	9.71	86.86	2.00	33.71	64.29
Manipur	1.09	9.89	89.03	1.86	4.14	94.00	6.52	4.19	89.29	1.76	5.54	92.70	0.72	8.95	90.32
Mizoram	1.64	1.64	96.72	3.28	1.64	95.08	34.43	1.64	63.93	8.20	4.92	86.89	4.92	1.64	93.44
Tripura	3.40	12.50	84.10	3.14	5.17	91.69	8.64	5.24	86.13	1.77	12.70	85.54	1.31	18.46	80.24
Meghalaya	0.00	18.75	81.25	0.32	15.87	83.81	0.80	14.90	84.29	1.12	20.35	78.53	0.64	32.53	66.83
Bihar	4.55	10.42	85.03	6.40	6.75	86.85	0.02	26.07	73.91	0.04	31.35	68.61	0.14	10.82	89.04
Ladakh	5.49	40.66	53.85	1.10	73.63	25.27	4.40	17.58	78.02	1.10	62.64	36.26	0.00	29.67	70.33
Jammu and Kashmir	0.45	61.65	37.90	0.07	75.10	24.83	0.17	86.81	13.02	0.10	93.00	6.90	0.25	83.42	16.33
Odisha	55.12	0.32	44.56	20.93	1.37	77.70	0.34	27.45	72.21	0.03	38.73	61.25	0.08	15.08	84.83
Total	8.87	13.32	77.81	2.65	28.87	68.48	0.34	34.80	64.86	0.38	31.73	67.90	0.54	32.84	66.61

percentage of net sown area having negative trend was found in Rajasthan (90%) followed by Punjab (87.3%), Jammu & Kashmir (86.8%), Himachal Pradesh (74.5%), Arunachal Pradesh (66.8%), Chhattisgarh (62.3%), Sikkim (60%), Haryana (59.1%), Madhya Pradesh (42.3%), Assam (41.8%), Gujarat (36.8%), Uttarakhand (33.4%), Uttar Pradesh (27.4%), and Bihar (26.1%). During time period IX, all the states have less than 10% net cultivated area showing positive trend while seven states have more than 50% area showing negative trend. These states are Jammu & Kashmir (93%), Punjab (91.1%), Himachal Pradesh (87.6%), Rajasthan (75.3%), Ladakh (62.6%), Haryana (56.7%), and Gujarat (55.4%). Similarly, during time period X, all the states have less than 10% of net sown area showing positive trend whereas seven states with more than 50% of net sown area present in the northern and north-western parts of India showing negative trend.

During all the time periods of the *kharif* crop season, the percentage of net sown area showing no trend was much higher (75%) than the area showing positive (18%) or negative (7%) trend. In general, the increasing trend is agricultural drought is seen in about 8.8% of crop area during early season, about 9.3% of crop area during mid-season and about 0.5% of crop area during late season. Along with that, during all the time periods except time period V, the percentage of area showing decreasing trend was higher as compared to that of increasing trend. Overall, we can conclude that during the month of June, the states of Karnataka, Tamil Nadu and Andhra Pradesh have a higher possibility of increase in the dryness or crop water stress *i.e.,* early season drought. However, during the months of July and August, the eastern states *i.e.,* Odisha, West Bengal, Andhra Pradesh, Telangana, Jharkhand, and Chhattisgarh, along with Gujarat situated in western India are more prone to dryness *i.e.,* mid-season drought. However, during the months of September and October, *i.e.,* during the late *kharif* crop season, the trend in the increase of dryness is almost negligible whereas most of the states of India depicts decrease in dryness or crop water stress *i.e.,* late season drought. A lower proportion of area showing increasing drought trend implies the success of various irrigation scheme undertaken under federal and States government schemes over time. Still, there is more need for better agricultural water management during the early and mid-season droughts, especially in the southern and eastern parts of India along with Gujarat state.

Summary and Conclusions

The spatio-temporal analysis of standardized

Evaporative Drought Index, which is an evapotranspiration-based index to measure the severity of agricultural drought, was undertaken in this study. It was found that the sEDI was able to capture the spatial as well as temporal variations in agricultural drought during *kharif* crop season over India. The sEDI clearly showed that the years 2002, 2009, 2012, 2014 and 2015 were mostly affected by the agricultural drought, whereas the years 2003, 2013, 2020, and 2021 were less affected, which agrees with the drought declared by the government agencies. The spatio-temporal trend analysis of sEDI shows that in majority of the crop area (about 75%) no significant trend in agricultural drought is found, while increasing trend is seen in about 7% and decreasing trend in about 18% area. During the early *kharif* crop season (June, July), the southern states of Karnataka, Andhra Pradesh and Tamil Nadu are showing increase in the dryness or crop water stress and should be prioritized for early season drought interventions. During the mid-*kharif* crop season (July-August), the increase in dryness was found in the eastern states of India (West Bengal, Odisha, Jharkhand, Chhattisgarh, Andhra Pradesh and Telangana) along with Gujarat where mid-season drought interventions should be emphasized. However, during the late-*kharif* crop season (September-October), most of the states show decreasing trend in sEDI indicating decrease in the late-season drought. The majority crop area showing no trends in agricultural drought over the past twenty years and only a smaller proportion of crop area showing an increasing trend implies the success of irrigation schemes introduced over the years, especially, in rainfed area. The study has clearly shown the usefulness of sEDI in monitoring agricultural drought over India and based on its trend, has identified areas which need to be prioritize for better water management. This analysis can be further used to accurately plan agricultural water management practices so that the possibility of early and mid-season drought can be reduced in the identified areas.

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Received: April 2, 2023; Accepted: June 26, 2023