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Assessment of Agricultural Drought in Tamil Nadu using Remote Sensing Techniques

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ABSTRACT

Background: The Agricultural drought during *kharif* seasons of the year 2019 to 2023 in Tamil Nadu state in India was analyzed in using the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Monthly precipitation data from 1991 to 2023 were obtained for the study, with the main objective of evaluating the duration, spatial extent, severity and lag time of meteorological and agricultural drought in the study area.

Methods: The Enhanced Vegetation Index (EVI) was generated by the Moderate Resolution Imaging Spectroradiometer (MODIS) data. The pixel reliability layer was introduced based on the calculation of the cloud coverage at the moment of image acquisition. The Standardized Precipitation Index SPI in one month time scale plays very significant role in any vulnerability studies for accurate prediction of any events.

Result: In the present study, the EVI for *Kharif* season was considered for five years *i.e.*, 2019-2023 and it was correlated with the SPI at various time scales. The correlation coefficient of SPI was 0.39 with 0.1% level of significance, in other words, EVI 2022 was well correlated with SPI-6. Also, the relation between EVI and precipitation with 9 months interval was also tested. The 12 months interval of precipitation have more stress on vegetation and it can negatively impact the agriculture activities leading to crop failures.

Key words: Agricultural drought, CHIRPS, EVI, MODIS data, SPI.

INTRODUCTION

In the natural climate cycle, a drought is a prolonged dry spell that can happen anywhere in the world. It is a calamity with a gradual start that is symbolized by a deficiency of precipitation leading to a scarcity of water. A drought can have detrimental effects on the environment, economy, health and agriculture. Droughts are the biggest threat to crops and livestock in almost every region of the world, affecting roughly 55 million individuals annually. Drought puts people's livelihoods in trouble, raises the possibility of illness and death and encourages mass migration. Forty percent of the world's population suffers from water scarcity and by 2030, up to 700 million people could face migration due to drought. As a result of climate change, already arid places are becoming even dryer and hotter. This means that in arid areas, rising temperatures cause water to evaporate more quickly, which either raises the possibility of a drought or makes existing droughts longer. In the last ten years, floods, droughts, tropical cyclones, heat waves and strong storms have caused 80-90% of all-natural disasters that have been officially recorded (WHO).

Academic definitions of drought differ across the globe. Generally speaking, nevertheless, it falls into four categories: drought related to agriculture, weather, hydrology and socioeconomic factors (American Meteorological Society, 2013). In general, a meteorological drought is defined as a deficit in precipitation, but an agricultural drought is characterized by a deficit in vegetation and, as a result, a decline in the condition of the vegetation (Ramsey *et al*., 2006). Prodhan *et al.* (2020) employed SPI and VCI to model the probability of agricultural drought hazard from 2001 to 2016. They discovered that 6-month SPI-identified droughts are more common and concluded that the rice-growing season in Boro, which runs from November to May of the subsequent year, is more susceptible to drought. Traditionally, it has been believed that meteorological dryness is the cause of agricultural drought (Maracchi, 2000). The association between different climate conditions and different places has only

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been determined in a few numbers of research (Dhanapriya and Kumaraperumal, 2019; Dutta *et al*., 2015; Ji and Peters, 2003; Murad and Islam, 2011). Few research, however, reveal a significant correlation (Ji and Peters, 2003; Rousta *et al*., 2020). Most of these researches are carried out in regions with climates other than tropical monsoons and under various water management schemes. Also Standardised precipitation index (SPI) and Standardised precipitation evapotranspiration index (SPEI), based on monthly precipitation and temperature data for 38 years (1981-2018), were utilised by Qaisrani *et al*. (2021) for drought monitoring in the desert zone of Balochistan province, Pakistan.

In the present study Enhanced Vegetation Index (EVI) and Standardized Precipitation Index (SPI) was correlated for the Tami Nadu to access the agricultural drought. The reason to use EVI here is it has reduced atmospheric influence, Improved sensitivity to vegetation health with the main objective to evaluate the duration, spatial extent, severity and lag time of meteorological and agricultural drought in the study area.

Materials and Methods

Study area

This study was carried out in Tamil Nadu state in India (Fig 1). Tamil Nadu is a state on the southern tip of the Indian peninsula. It is bordered to the west by the Western Ghats and Deccan Plateau, to the north by the Eastern Ghats, to the east by the Eastern Coastal Plains that line the Bay of Bengal, to the south-east by the Palk Strait and the Gulf of Mannar and to the south-east by the Laccadive Sea at the southern tip of the peninsula. The state is divided by the Cauvery River. Politically, Tamil Nadu is bounded by the Indian states of Karnataka, Andhra Pradesh and Kerala. It also shares an international sea border with the Northern Province of Sri Lanka at Pamban Island with the union territory of Puducherry.

Datasets used

The data on vegetation state, precipitation and soil moisture in this study are primarily acquired from remote sensing data. Source and other information on data collected were presented on Table 1.

Drought indices

Enhanced vegetation index (EVI)

Vegetation indices generated from satellite data make it uncomplicated to determine the amount of vegetation present in a given area. According to Xue and Su (2017), they are computed using the ratio of various band combinations. The most often utilized are EVI and NDVI. Nevertheless, even with high aerosol loads, NDVI is affected by air interferences and cannot distinguish the differences in high-biomass zones where EVI yields superior outcomes (Huete *et al*., 2002). It can also separate the background signal from the vegetation canopy, which improves its ability to monitor vegetation. For these reasons, the vegetation index in this study corresponded to the EVI. One of the two vegetation indices generated by the Moderate Resolution Imaging Spectroradiometer (MODIS) is the EVI data used in the present study. It offers data that is 250 metres in pixels and has gone through significant atmospheric and radiometric corrections, together with a 16-day temporal difference product (Kamel; Didan *et al*., 2015).

Additionally, the pixel reliability layer is introduced based on the calculation of the cloud coverage at the moment of image acquisition. that. To identify the pixels with the highest degree of confidence, this layer is multiplied by the data layer.

Here, the MODIS sensor's bands are NIR, RED and BLUE. The coefficients of aerosol effect and soil decoupling parameter are C1, C2 and L. By using these factors, the effects of soil and aerosol are minimized. G, however, functions as a scaling factor. These values are often maintained at 6, 7.5, 1 and 2.5, respectively, to guarantee a more precise outcome. The AppEEARS Team (2020) recommends downloading EVI data at https://lpdaacsvc.cr.usgs.gov/appears. From 2002 to, MODIS EVI data is utilized. In 2019. MOD13A1v0.061. is the version of the product. Due to its extended temporal coverage (18 years) and comparatively short recurrence time (16 days), this data is appropriate for monitoring the state of the vegetation (Didan, 2015).

Standardized precipitation index (SPI)

An extremely common meteorological drought index is SPI. The basic idea of SPI, which was established by McKee *et al*. (1993), is fitting precipitation data into a statistical probability density function by averaging the data. and thereafter transformed using a (Gaussian) normal function that was inverted (Zhang and Jia, 2013). Several factors, including the distribution function and average period, affect the SPI value. Different aspects of the drought are revealed by the average timeframe. Based on CHIRPS data, SPI is computed on various time scales, including 1, 3, 6, 9 and 12 months (SPI-3, SPI-6, SPI-9 and SPI-12). For trend analysis and seasonal drought monitoring, the rainfall data set referred to as CHIPRS combines infrared Cold Cloud Duration (CCD) observation with in-situ station data. At least thirty years of historical precipitation data are needed for SPI calculations. In order to do this, CHRIPS data from 1981 to 2015 are utilized in the computation. The methodology used for the SPI computation is McKee *et al*. (1993). Wet months are indicated by positive SPI values, whereas dry spells are shown by negative ones (Şen, 2015). When the SPI number is less than -1, a drought is declared. The number of years in a row with a negative SPI value indicates the severity of the drought (World Meteorological Organization (WMO, 1987). Table 2 presents the classification of the drought classes based on SPI.

Results and Discussion

Meteorological drought

Based on a 1-month SPI, meteorological drought was examined (SPI-1). Since SPI-1 and rainfall have a strong connection, using it to correlate the meteorological drought makes more sense. SPI-1 was calculated between 1981 and 2023. But the conditions of the drought that happened in 2019, 2020, 2021, 2022 and 2023 are the main focus of this study. SPI when calculated at 1-month tine scale (Fig 2a) shows no negative value on precipitation for the whole Tamil Nadu. The lowest value of SPI is 0.40 and highest value is 18.91. The highest is found in Nilgiris district and part of Coimbatore, Tirupur and Erode districts. The SPI value of all the districts of Tamil Nadu at different time scales were presented in Table 3 that the SPI in 1-month time scale plays very significant role in any vulnerability studies for accurate prediction of any events. Besides SPI was also calculated on 3, 6, 9, 12 months' time scale. The SPI value of SP1 3 ranges from -0.79 to 2.00, SPI 6 ranges from -1.04 to 1.77, SP1 9 ranges from 0.10 to -2.11 and SPI 12 ranges from -5.87 to 0.29 as shown in Fig 2 a, b, c, d and e.

Enhanced vegetation index (EVI)

The EVI is a vegetation index that is obtained from remote sensing data, usually from MODIS (Moderate Resolution Imaging Spectroradiometer) satellite images. It assesses the density and overall health of the vegetation cover. EVI is a helpful indication for the impact of drought on ecosystems because decreased vegetation density may be a sign of stress brought on by inadequate supply of water. EVI is more robust in regions with aerosols, clouds, or other atmospheric difficulties since it is made to reduce the effects of atmospheric influences. In regions with high biomass, where NDVI may saturate, EVI is frequently seen to be more appropriate. The value of EVI ranges from -1 to +1 (Jensen, 2016). Where -1 indicates non-vegetated or sparsely vegetated area, 0 indicates areas with very sparse or stressed vegetation cover and +1 indicates the area with dense and healthy vegetation cover. Here in this research EVI for *Kharif* season is considered for five years *i.e.*) from 2019 to 2023 (Table 4) and it is correlated with the SPI at various time scales. In this study it is found that in all the years the EVI was high in western Ghats area throughout Tamil Nadu in all the five years *kharif* season

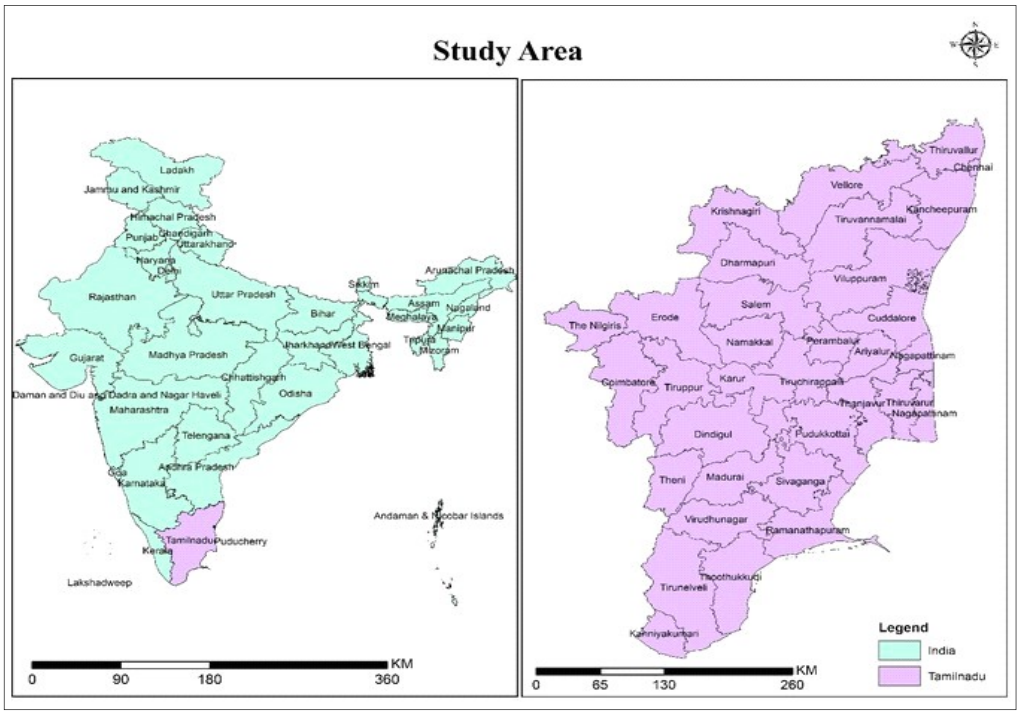


Fig 1: Study area map.

Table 1: Information on the datasets used for the study.

Indices	Dataset	Resolution/ Unit/ Scale	Period	References
Enhanced vegetation indices (EVI)	MODIS (MOD13A1.061)	500 m	2019 to 2023	Earth data
Standardized precipitation index (SPI)	CHIRPS	0.05° (~5.3 km)	1981 to 2023	Climate hazards centre

(Fig 3 a,b,c,d and e). To reduce the perplexing impact of soil reflectance upon vegetation signal, especially in areas with low plant cover, EVI integrates a soil correction factor (Huete *et al*., 1994). Effectively capturing changes in vegetation condition and biomass depends on this. Time series analysis and dataset comparisons are made easier

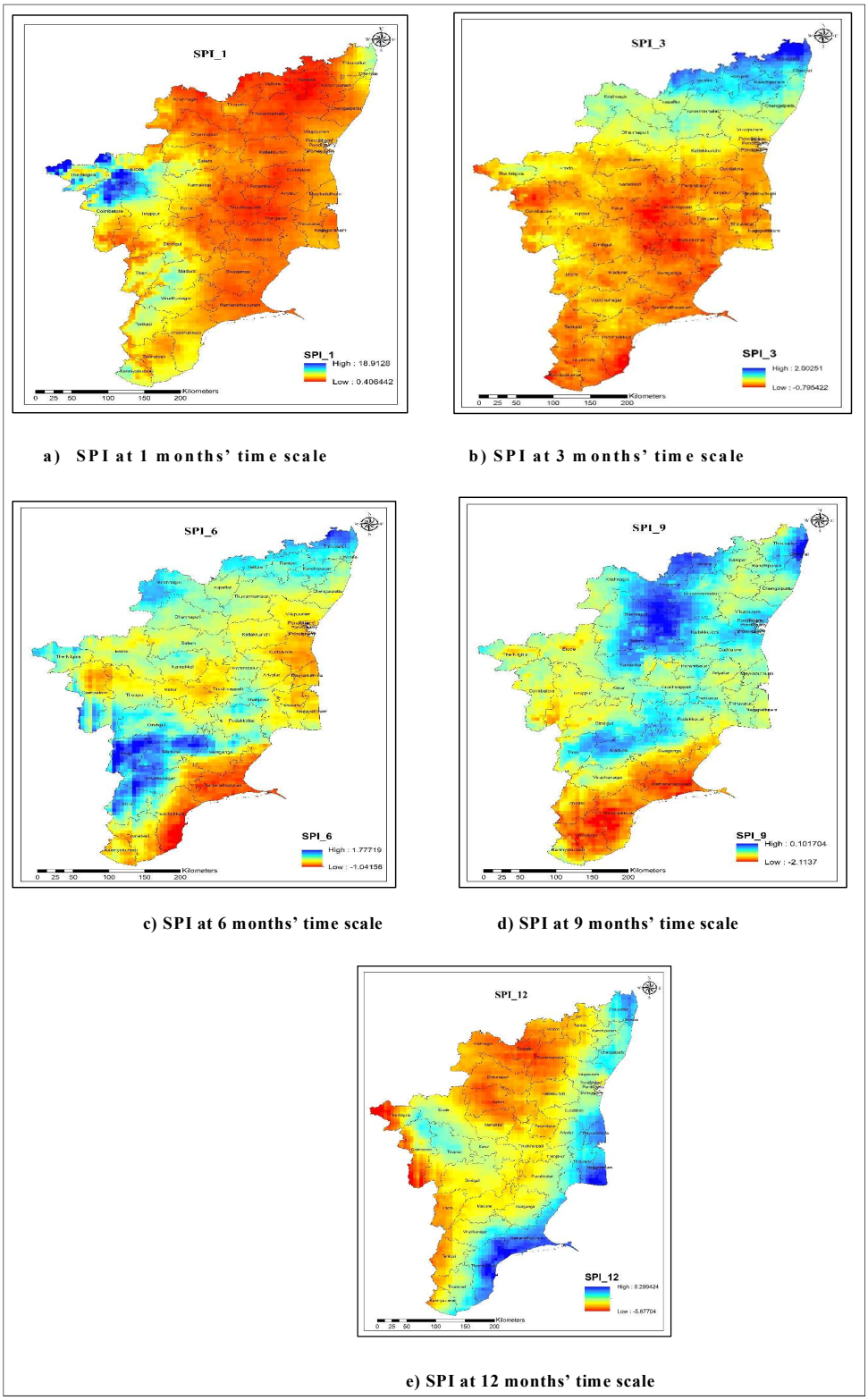
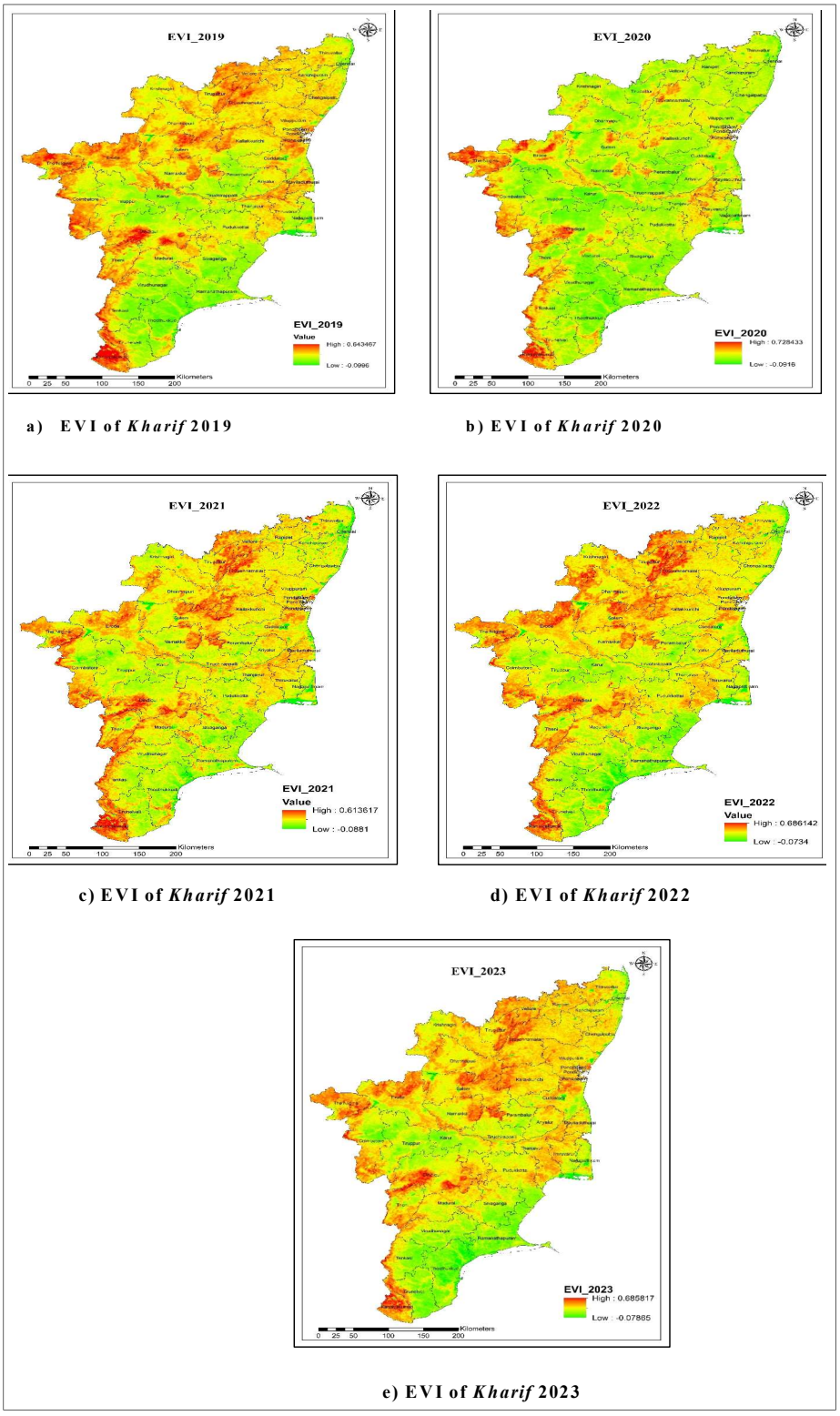


Fig 2: Standard precipitation index (SPI) at various time scale from year 1980 to 2023.

by EVI, which partially corrects for variations in spectral response across different satellite sensors (Liu and Huete, 1995). This is especially helpful for long-term monitoring projects that use information from several satellites.

Correlation between SPI and EVI

A more thorough understanding of drought conditions can be obtained by relating SPI and EVI because they account for both vegetation and meteorological responses to



a) EVI of *Kharif* 2019

b) EVI of *Kharif* 2020

c) EVI of *Kharif* 2021

d) EVI of *Kharif* 2022

e) EVI of *Kharif* 2023

Fig 3: Enhanced vegetation index for Tamil Nadu (*Kharif* season).

moisture availability. The correlation may operate as follows:

Negative SPI and decreased EVI

A reduction in EVI, which indicates stressed or decreased vegetation as a result of water limitations, could be associated with a negative SPI, which implies lower-than-average precipitation.

Positive SPI and increased EVI

An increase in EVI, which indicates better vegetative health because of adequate water availability, could be associated with a positive SPI, which implies higher-than-average precipitation.

The correlation between agricultural drought and weather conditions

Droughts caused by weather patterns and agricultural practices typically. It exists because rainfall gradually decreases without directly reducing the soil's water content. As shown in Fig 4, the correlation between SPI1 and EVI for the year 2020 is with 0.57 with 99.9% level of significance in other words we can say that this has a strong correlation coefficient also EVI for the year 2019 have correlation coefficient value of 0.20 and other EVI of the year 2021, 2022, 2023 does not have correlation, from the values we can understand that the 1-month rainfall deficit have maximum effect on agricultural drought for these kharif season.

When SPI at 3 months' time interval is correlated with the EVI of *kharif* seasons of the above said years *i.e*. 2019-2023, it is found that there is correlation of SPI - 3 with EVI 2019. EVI 2022 and 2023 with 0.21, 0.16 and 0.26 respectively. This indicates that the SPI with the 3-month time interval does not have much influence on much on vegetation at a place. SPI with 6-month interval is well correlated with EVI - 2022 with correlation coefficient of 0.39 with 0.1% level of significance, in other words with 99% level of significance EVI 2022 is well correlated with SPI -6. EVI of kharif season 2019 is correlated with coefficient value of 0.28 with 5% level of significance.

Also, the relation between the EVI with the precipitation with 9 months interval was also tested. It is found that this 9-month interval have effect on the year 2019, 2022 and 2023 with the correlation interval of 0.30 with 5% level of significance, 0.35 with 5 % level of significance for the year 2022 and 2023. With SPI of 12-month time scale all the EVI (2019 to 2023) of kharif season was negatively correlated with 99.99% level of significance with -0.54 (2019), -0.20

Table 2: Classification of drought according to SPI value.

SPI values	Drought classification
0 to-0.99	Mild drought
-1 to-1.49	Moderate drought
-1.50 to-1.99	Severe drought
<-2	Extreme drought

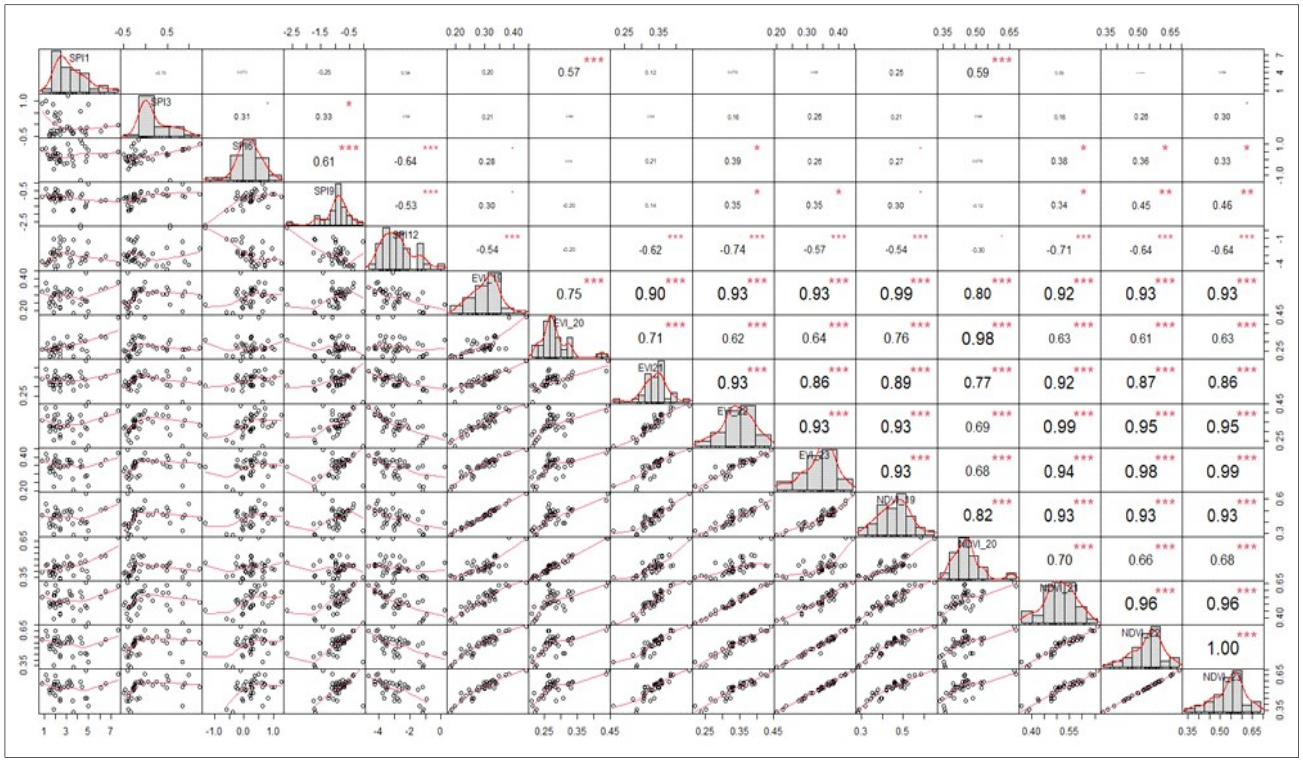


Fig 4: Correlation of standard precipitation index (SPI) at different time scale with enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) for *Kharif* season of the year 2019-202.

(2020), -0.62 (2021), -0.74 (2022) and -0.57 (2023). This indicates that the 12 months interval of precipitation have more stress on vegetation and it can negatively impact the agriculture activities leading to crop failures.

Reason for positive and negative correlation

Positive correlation

The most logical scenario is this particular one. In general, healthier vegetation (higher EVI) is correlated with more precipitation (positive SPI). This is due to the fact that sufficient moisture is essential for plant growth and verdancy. So, there will probably be a positive association between locations with wetter periods and an increase in EVI.

Negative correlation

There are circumstances in which an excessive amount of precipitation might harm vegetation and cause a negative association. Here are a few instances:

i) Flooding

Extremely high SPI levels may be a sign of flooding, which lowers EVI and damages plants.

Table 3: Standardized precipitation index (SPI) values of various time scales for the districts of Tamil Nadu.

District	SPI1	SPI3	SPI6	SPI9	SPI12
Ariyalur	1.60	-0.28	0.04	-1.02	-2.70
Chengalpattu	2.39	0.48	0.28	-0.84	-2.09
Chennai	5.00	0.85	0.63	-0.04	-1.40
Coimbatore	6.10	-0.29	0.26	-1.13	-3.59
Cuddalore	2.10	-0.27	-0.24	-0.82	-2.49
Dharmapuri	2.19	0.25	0.41	-0.49	-4.26
Dindigul	3.34	-0.24	0.61	-0.97	-3.33
Erode	6.52	-0.06	0.22	-1.11	-3.10
Kallakkurichi	1.90	0.05	0.06	-0.65	-3.59
Kanchipuram	1.79	0.84	0.63	-0.84	-2.72
Kanniyakumari	4.73	-0.41	-0.13	-1.42	-3.12
Karur	2.39	-0.44	-0.04	-0.94	-3.02
Krishnagiri	1.92	0.39	0.71	-0.69	-4.26
Madurai	4.38	-0.26	1.03	-0.68	-3.44
Mayiladuthurai	2.75	-0.24	-0.27	-0.98	-1.18
Nagapattinam	2.43	-0.20	-0.06	-1.07	-0.92
Namakkal	3.48	-0.26	0.24	-0.71	-3.79
Perambalur	1.47	-0.39	0.22	-0.87	-3.77
Pondicherry	3.07	-0.11	-0.24	-0.57	-2.67
Pudukkottai	1.75	-0.50	0.32	-0.96	-2.98
Ramanathapuram	1.84	-0.41	-0.60	-1.75	-1.11
Ranipet	0.80	0.91	0.68	-0.88	-3.72
Salem	3.26	-0.12	0.27	-0.56	-4.26
Sivaganga	1.97	-0.40	0.20	-1.21	-3.03
Tenkasi	4.67	-0.33	0.83	-1.55	-3.65
Thanjavur	1.81	-0.26	0.22	-0.99	-2.35
The Nilgiris	7.63	-0.01	0.51	-1.09	-4.09
Theni	4.24	-0.16	1.27	-0.84	-3.92
Thiruvallur	3.14	1.24	0.96	-0.70	-2.22
Thiruvarur	2.45	-0.27	-0.09	-0.99	-1.49
Thoothukkudi	3.61	-0.35	-0.39	-1.72	-1.16
Tiruchirappalli	1.44	-0.47	0.08	-0.90	-3.50
Tirunelveli	3.58	-0.38	-0.04	-1.76	-2.68
Tirupattur	1.96	0.48	0.37	-0.38	-4.67
Tiruppur	4.86	-0.15	0.24	-1.23	-2.81
Tiruvannamalai	1.30	0.52	0.33	-0.76	-3.98
Vellore	1.18	0.98	0.71	-0.35	-4.16
Viluppuram	2.33	0.16	-0.02	-0.81	-2.84
Virudhunagar	4.26	0.56	-1.32	-2.69	0.22

Table 4: Enhanced vegetation index values (EVI) for various districts of Tamil Nadu for *Kharif* season of the year 2019-2023.

District	EVI_19	EVI_20	EVI_21	EVI_22	EVI_23
Ariyalur	0.28	0.26	0.33	0.33	0.34
Chengalpattu	0.30	0.25	0.31	0.32	0.35
Chennai	0.20	0.21	0.22	0.22	0.23
Coimbatore	0.33	0.33	0.35	0.36	0.35
Cuddalore	0.30	0.27	0.34	0.33	0.34
Dharmapuri	0.32	0.26	0.35	0.39	0.38
Dindigul	0.30	0.28	0.35	0.36	0.37
Erode	0.34	0.32	0.36	0.39	0.38
Kallakkurichi	0.31	0.28	0.36	0.37	0.38
Kanchipuram	0.29	0.26	0.31	0.33	0.35
Kanniyakumari	0.44	0.44	0.44	0.44	0.44
Karur	0.22	0.21	0.30	0.28	0.28
Krishnagiri	0.30	0.27	0.33	0.39	0.36
Madurai	0.28	0.26	0.35	0.35	0.35
Mayiladuthurai	0.32	0.28	0.35	0.33	0.35
Nagapattinam	0.22	0.23	0.27	0.27	0.28
Namakkal	0.32	0.27	0.34	0.37	0.37
Perambalur	0.22	0.22	0.31	0.30	0.31
Pondicherry	0.33	0.33	0.36	0.35	0.38
Pudukkottai	0.25	0.25	0.30	0.32	0.32
Ramanathapuram	0.19	0.23	0.29	0.25	0.22
Ranipet	0.32	0.26	0.34	0.36	0.38
Salem	0.32	0.28	0.35	0.39	0.38
Sivaganga	0.23	0.24	0.31	0.30	0.29
Tenkasi	0.26	0.31	0.34	0.32	0.29
Thanjavur	0.31	0.32	0.34	0.36	0.37
The Nilgiris	0.38	0.44	0.38	0.41	0.42
Theni	0.33	0.34	0.38	0.39	0.38
Thiruvallur	0.29	0.27	0.32	0.33	0.35
Thiruvarur	0.27	0.29	0.32	0.32	0.33
Thoothukkudi	0.18	0.22	0.28	0.24	0.20
Tiruchirappalli	0.25	0.25	0.33	0.33	0.34
Tirunelveli	0.26	0.28	0.32	0.31	0.27
Tirupattur	0.35	0.26	0.38	0.43	0.41
Tiruppur	0.26	0.25	0.31	0.31	0.29
Tiruvannamalai	0.33	0.29	0.36	0.38	0.39
Vellore	0.37	0.26	0.39	0.43	0.42
Viluppuram	0.32	0.28	0.34	0.35	0.37
Virudhunagar	0.24	0.31	0.30	0.28	0.34

ii) Nutrient leaching

Even when there is plenty of moisture, heavy rain can remove vital nutrients from the soil, preventing plant growth and reducing EVI.

iii) Plant community changes

In certain habitats, more precipitation may be advantageous to water-loving plants with lower EVI values than the dominant species during dry spells. There may be a bad association as a result of this change in plant communities.

CONCLUSION

The study focused on the agricultural drought throughout the *Kharif* seasons from 2019 to 2023 and conducted a thorough analysis of the drought conditions in Tamil Nadu. The study used monthly precipitation data from 1983 to 2023 from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). To evaluate the severity of the drought and its effects on vegetation, we used the enhanced vegetation index (EVI) and standardized precipitation index (SPI). The results emphasize how crucially different patterns of precipitation affect agricultural

practices. The study emphasizes that although sufficient precipitation is favorably associated with healthy vegetation, too much rainfall can cause flooding, nutrient leaching and changes in plant communities, all of which have a detrimental effect on agricultural output. Significant correlations between SPI and EVI at various time intervals were found in the analysis, suggesting that the effect of drought conditions on agricultural drought is more noticeable when examined over one-month intervals as opposed to longer periods. The findings highlight the necessity of developing adaptable management techniques for agricultural activities in response to shifting precipitation patterns brought on by climate change. The use of remote sensing methods in the study, specifically CHIRPS data for SPI and MODIS data for EVI, shows how useful those tools are for tracking and forecasting drought conditions. When everything is considered, this study offers insightful information about the location and intensity of the drought in Tamil Nadu, laying the groundwork for further research and the development of policies targeted at reducing the adverse impacts of climate change upon the region's agricultural sector.

Conflict of interest

The authors declare that there is no competing interest.

REFERENCES

Dhanapriya, M. and Kumaraperumal, R. (2019). Analysis of terrestrial vegetation trends and correlation between vegetation indices and climatic factors. Journal of Earth Science and Climatic Change. 10(3): 233-257. https:// doi.org/10.4018/978-1-7998-1867-0.ch010.

Didan, K., Munoz, A.B., Solano, R. and Huete, A. (2015). MODIS Vegetation Index User's Guide (Collection 6). NASA: Washington, DC, USA, 2015, p.31.

Dutta, D., Kundu, A., Patel, N.R., Saha, S.K. and Siddiqui, A.R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived vegetation condition index (VCI) and standardized precipitation index (SPI). Egyptian Journal of Remote Sensing and Space Science. 18(1): 53-63. https://doi.org/10.1016/j.ejrs.2015.03.006.

Huete, A.R., Kaufman, K. and Roderick, P. (1994). Derivative of vegetation index for general global vegetation monitoring. International Journal of Remote Sensing. 15(18): 3185-3204.

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X. and Ferreira, L.G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment. 83(1-2): 195-213. https://doi.org/10.1016/S0034-4257(02)00096-2.

Jensen, J.R. (2016). Vegetation indices to meet challenges of agri-market. Earth Observing System (EOS). https:// svs.gsfc.nasa.gov/4072/.

Ji, L. and Peters, A.J. (2003). Assessing vegetation response to drought in the northern great plains using vegetation and drought indices. Remote Sensing of Environment. 87(1): 85-98.

Liu, H.Q. and Huete, A. (1995). A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Transactions on Geoscience and Remote Sensing. 33(2): 457-465.

Maracchi, G. (2000). Agricultural drought-a practical approach to definition, assessment and mitigation strategies. In Drought and drought mitigation in Europe. Dordrecht: Springer Netherlands. (pp. 63-75).

McKee, T.B., Doesken, N.J. and Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference on Applied Climatology. 17(22): 179-183.

Murad, H. and Islam, A.K.M.S. (2011). Drought assessment using remote sensing and GIS in north-west region of Bangladesh. In Proceedings of the 3rd International Conference on Water and Flood Management. (pp. 797-804).

Prodhan, F.A., Zhang, J., Bai, Y., Sharma, T.P.P. and Koju, U.A. (2020). Monitoring of drought condition and risk in Bangladesh combined data from satellite and ground meteorological observations. IEEE Access. 8: 93264-93282.

Qaisrani, Z.N., Nuthammachot, N., Techato, K. and Asadullah, (2021). Drought monitoring based on standardized precipitation index and standardized precipitation evapotranspiration index in the arid zone of balochistan province, Pakistan. Arabian Journal of Geosciences. 14: 1-13.

Ramsey, S., Subbia, A.R., Bass, S. and Juergens, I. (2006). Livelihood adaptation to climate variability and change in drought-prone areas of Bangladesh: Developing institutions and options. In Case Study-Institutions for Rural Development, FAO (Issue No. 5). https://doi.org/10.1017/CBO9781107415324.004.

Rousta, I., Olafsson, H., Moniruzzaman, M., Ardö, J., Zhang, H., Mushore, T.D., Shahin, S. and Azim, S. (2020). The 2000-2017 drought risk assessment of the western and southwestern basins in Iran. Modeling Earth Systems and Environment. 6(2): 1201-1221. https://doi.org/10.1007/s40808-020-00751-8.

Şen, Z. (2015). Basic Drought Indicators. In Applied Drought Modeling, Prediction and Mitigation. (pp. 43-105). https://doi.org/10.1016/b978-0-12-802176-7.00002-x.

WMO. (1987). Standardized Precipitation Index User Guide. J. o. A. Bacteriology.

Xue, J. and Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. Journal of Sensors. 1: 167. https://doi.org/10.1155/2017/1353691.

Zhang, A. and Jia, G. (2013). Monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data. Remote Sensing of Environment. 134: 12-23. https://doi.org/10.1016/j.rse.2013.02.023.