Land cover change detection using NDVI and EVI temporal images of Tamil Nadu

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ABSTRACT

Land cover change is perhaps one of the most vulnerable to the weather factors and anthropogenic activities. MODIS sensor delivers relevant temporal data with extensive coverage that greatly assists in the timely surveillance of vegetation and crop production, which had been a demanding and challenging task for researchers. In this study, vegetation indices were employed to know the vegetation health as NDVI and EVI offered the live status of the vegetation. The satellite datasets were downloaded and processed MODIS (MOD13Q1) during the study period from 2020 to 2021 in Tamil Nadu. The data sources were processed and extracted the NDVI and EVI values using ArcGIS software. The results showed that based on the mean, maximum and minimum values of NDVI and EVI, the highest variation was noticed over the swamp forest. The mean NDVI and EVI of crop land were 0.52 and 0.33, respectively. However, NDVI had a larger value when compared to EVI, indicating the variable intensity of biomass in the study region.

Keywords: NDVI, EVI, land cover, Tamil Nadu

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INTRODUCTION

Global ecosystems have undergone a major shift over the last thirty years due to the rapid change in land cover. The variability of abiotic circumstances including climate, topography and soils, biotic interactions that produce spatial patterning even in uniform environmental conditions and past and present patterns of human habitation are only a few of the factors that contribute to landscape changes (Shamsudeen *et al*., 2022). Understanding the nuances of land cover change is crucial to enable sustainability and changes in the environmental structure (Tariq and Shu, 2020). Therefore, figuring out the variations in vegetation that is influenced by landscape and changes over Tamil Nadu is essential for sustainable urban management and planning (Samuel *et al*., 2012).

In addition, remote sensing offers the estimates of current Photosynthetically Active Biomass (PAB), which can serve as a nearly continuous measurement surrogate of primary productivity distributions and provide accurate measurement metrics of the timing and duration of important physiological events (e.g., green-up, growing season duration and senescence). Numerous Vegetation Indices (VIs), such as the Normalized Difference Vegetation Index (NDVI), the fraction of Photosynthetically Active Radiation (fPAR) and Leaf Area Index (LAI) are desirable diagnostic data. Future land cover change detection techniques that account PAB data streams could offer a reliable method for the close-to-real-time monitoring of land cover change events while also supporting the creation of landscape indicators, the modelling of crucial to landscape processes and the forecasting of future LC change distributions (Lunetta *et al*., 2006).

However, the NDVI is susceptible to large sources of error and uncertainty over variable atmospheric and canopy background conditions. Owing to these defects of the NDVI, the Enhanced Vegetation Index (EVI) was proposed based on a feedback-based approach that incorporates both background adjustment and atmospheric resistance concepts into the NDVI (Liu and Huete, 1995 and Matsushita *et al*., 2007). The EVI has thus been considered a modified NDVI with improved sensitivity to high biomass regions and improved vegetation monitoring capability through a de-coupling of the canopy background signal and a reduction in atmospheric influences. According to Matsushita *et al*. (2007), the EVI was adopted by the MODIS Land Discipline Group as the second global-based vegetation index for monitoring the Earth's terrestrial photosynthetic vegetation activity and has since sparked the interest for a number of scientists.

Inter-annual variations of vegetation index values were taken into consideration for assessing the fluctuations due to weather factors and the ecosystems (Prajesh *et al*., 2019).

Therefore, both the NDVI and EVI are used in this study to monitor the vegetation dynamics over time and the relationship between the environment and anthropogenic activities can be determined from satellite pictures and other image processing techniques and many investigations have been conducted to evaluate the LULC changes (Padmanaban *et al*., 2018). These are especially important in a state like Tamil Nadu, where ground/field monitoring data is limited. Hence, this study is used to assess the vegetation dynamics of Tamil Nadu using multi temporal images.

MATERIALS AND METHODS

Details of the study area

The study area, which primarily focuses on the Tamil Nadu region, is located in South Eastern India and encompasses 130,058 km^2 between 8.5° and 13.35° N latitude and 78.35° and 80.20° E longitude (Fig. 1). Tamil Nadu is the eleventh-largest state in India, with around 38 districts and 7 agro-climatic zones, including the Cauvery Delta Zone, High Rainfall Zone, North Western Zone, Western Zone, and Southern Zone. In addition to Kerala on the west, the states of Andhra Pradesh and Karnataka on the north, the Bay of Bengal on the east, and the Indian Ocean on the south border it. On the eastern edge of the state is a union territory called Pondicherry.

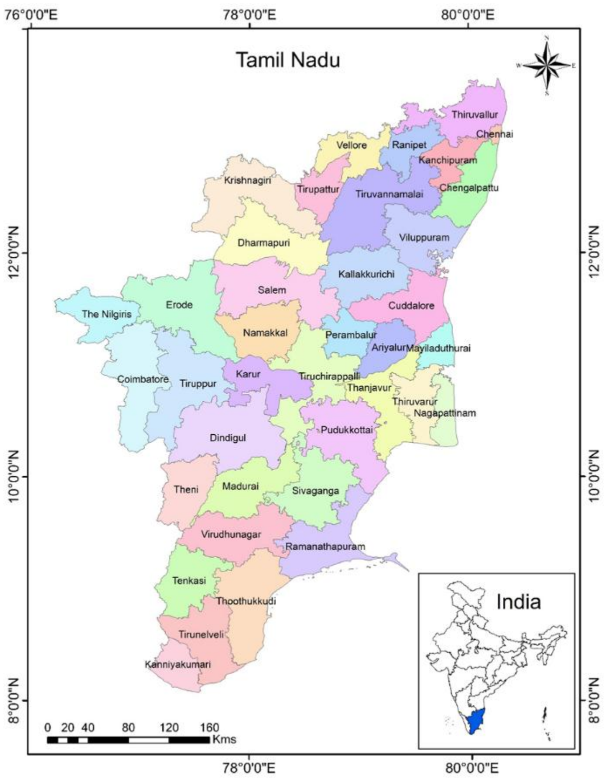

Fig 1. Study area map of Tamil Nadu

The mean minimum and mean maximum temperatures range from 23.4°C to 33.8°C, respectively. The average rainfall is 945 mm, with the North-East monsoon contributing 48 per cent of total rainfall and the Southwest monsoon contributing 32 per cent (Gumma *et al*., 2014). The state's two main monsoon seasons are the Southwest monsoon (June to September) and the Northeast monsoon (October to December). While other Indian states receive heavier rainfall during the southwest monsoon, Tamil Nadu only receives extra rainfall during the northeast monsoon. The northeast monsoon contributes 47 per cent of the total annual rainfall, whereas the southwest monsoon contributes 35 per cent (Gumma *et al*., 2014, Vaani *et al*., 2018 and Vasumathi *et al*., 2022).

Land use and land cover map

The Department of Remote Sensing and GIS, Tamil Nadu Agricultural Univeristy, Coimbatore, provided the land use and land cover (LULC) map of Tamil Nadu at a scale of 1:50000 (Fig. 2). This map was generated using multi-temporal Advanced Wide Field Sensor (AWiFS) datasets to provide information about the land classification and different biomes of Tamil Nadu. It also addresses the productive and non-productive regions of the study area and the map is categorized into different classes *viz.*, deciduous forest, evergreen forest, crop land, fallow land, plantation, scrub land, waste land, waterbodies, wetlands and builtup.

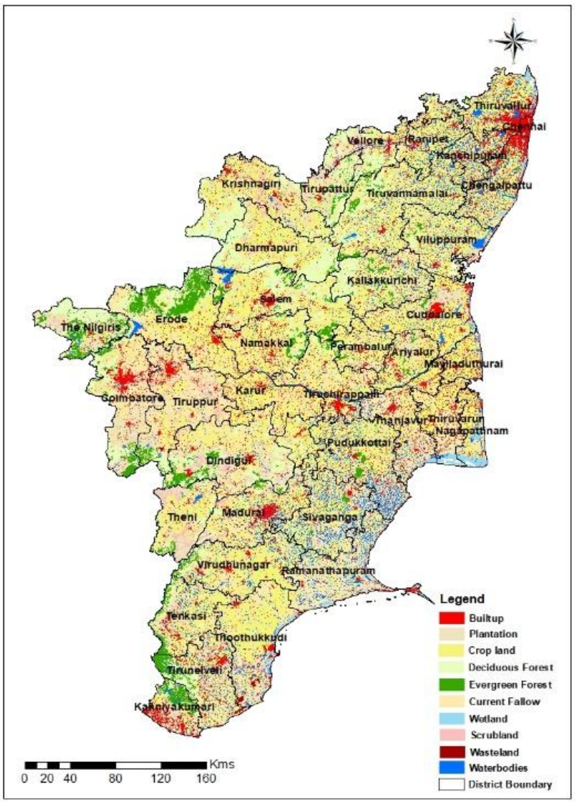

Fig 2. Land use and land cover map of Tamil Nadu

Satellite data sets

With two vegetation indices, NDVI and EVI, as well as reflectance bands including red, near-infrared, blue and middle-infrared, MODIS (MOD13Q1) delivers vegetation index

(VI) values on a per-pixel basis. The data products are generated every 16 days as a composite grid data L6 product with a 250 m spatial resolution. The downloaded MODIS products were preprocessed using MODIS Reprojection Tool (MRT). Two gridded tiles, h25v07 and h25v08, cover the entire research area and the data downloaded in HDF format from the Earth data website (https://appeears.earthdatacloud.nasa.gov/). Using this tool, the two tiles of each satellite product were mosaicked into a single raster file, reprojected into TM (Transverse Mercator) projection from sinusoidal projection and subsetted into Tamil Nadu extent.

Vegetation Indices

NDVI is widely used as it provides the live vegetation status very effectively (Nomura and Oki, 2021). It measures the variation between near-infrared (strongly reflected by vegetation; 8^{th} band; 846-885 nm) and red light (absorbed by vegetation; 4^{th} band; 600-680 nm) (Carlson *et al*., 1997). It ranges from -1 to +1. The positive value indicates thick dense vegetation and negative value indicates water bodies or builtup. The NDVI value is almost zero as it indicates the no vegetation of an area.

NDVI is sensitive to the additive noise effects, such as atmospheric path radiances and canopy background variations. The canopy background sensitivity gets stronger with NDVI degradation by the greater canopy background brightness (Huete *et al*., 2002). NDVI is defined by the given formula

$$NDVI=\frac{(\rho NIR - \rho Red)}{(\rho NIR + \rho Red)}$$

EVI is more sensitive to changes in the canopy structure, such as changes in the leaf area index (LAI), canopy type and plant physiognomy (Gao *et al*., 2000). It helps in optimising the vegetation signal with increased sensitivity in dense canopy regions and to improve vegetation monitoring by decoupling the canopy background signal and bringing down the atmospheric impacts. It also overcomes the NDVI drawbacks by offering improved sensitivity in areas with higher leaf area index (LAI) (Boegh *et al*., 2002). It ranges from -1 to +1 where the values for healthy vegetation typically range from 0.20 to 0.80. EVI can be calculated by the formula

$$EVI=\frac{G * (\rho NIR - \rho Red)}{(\rho NIR + C1 * \rho Red - C2 * \rho Blue + L)}$$

Where, ρ values are atmospherically corrected or partially atmosphere corrected (Rayleigh and ozone absorption) surface reflectances, L is the canopy background adjustment that addresses nonlinear, differential NIR and red radiant transfer through a canopy and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

Methodology

MODIS data was downloaded of one year study period (2021) and made into monthly datasets and processed by using the ArcGIS 10.8 version. The extract by mask tool was used to subset the data using the base layer, which speeds up further processing for raster data. The vegetation index values were reclassified where each range represented the vegetation biomass condition and water availability within the crop. Using a land use shape file from Tamil Nadu, the reclassified images were subjected to zonal statistics and a zonal histogram.

RESULTS AND DISCUSSION

The vegetation indices are used to track the state of the vegetation. MODIS vegetation products incorporate changes in land use and cover, which are used to characterise terrestrial biophysical features and processes. These indices which were used to distinguish the biophysical state and development of vegetated surfaces. The vegetation index values were utilised and categorised where each range represented the vegetation biomass condition. EVI was classified into five categories, *viz*., 0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8 and 0.8-1.0 and NDVI had the same categorization including an extra category of <0 class. NDVI gives spatially dispersed information on vegetation status (Rouse *et al*., 1974 and Dusseux *et al*., 2014). The index value ranges from -1 to +1, with values less than zero indicating non-vegetated lands or bodies of water. Positive scores greater than 0.2 indicate that the vegetation is in good health (Prajesh *et al*., 2019). Zonal averaged NDVI and EVI were extracted by using ArcGIS to determine the changes in vegetation (Figs 3 & 4). Under land use and land cover categories, NDVI and EVI profiles were derived for crop land, plantation, forest land, scrub land and swamp forest of Tamil Nadu.

NDVI profile

The maximum NDVI was recorded highest in forest land (0.86) followed by both the plantation and crop land (0.84) and the lower maximum NDVI was observed in swamp forest (0.81). The maximum NDVI in forest might due to the presence of permanent canopy cover in the forest areas (Huete *et al.*, 2002 and Prajesh *et al*., 2019).

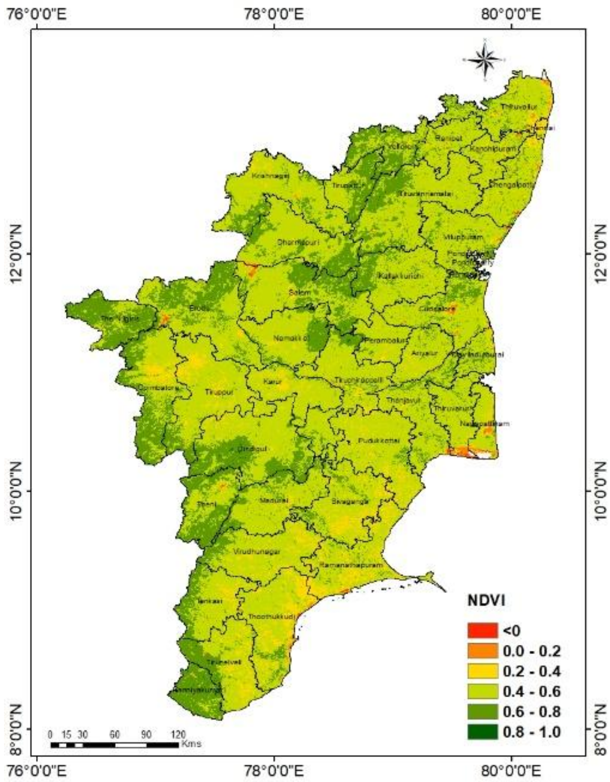

Fig 3. Zonal averaged NDVI classes of Tamil Nadu

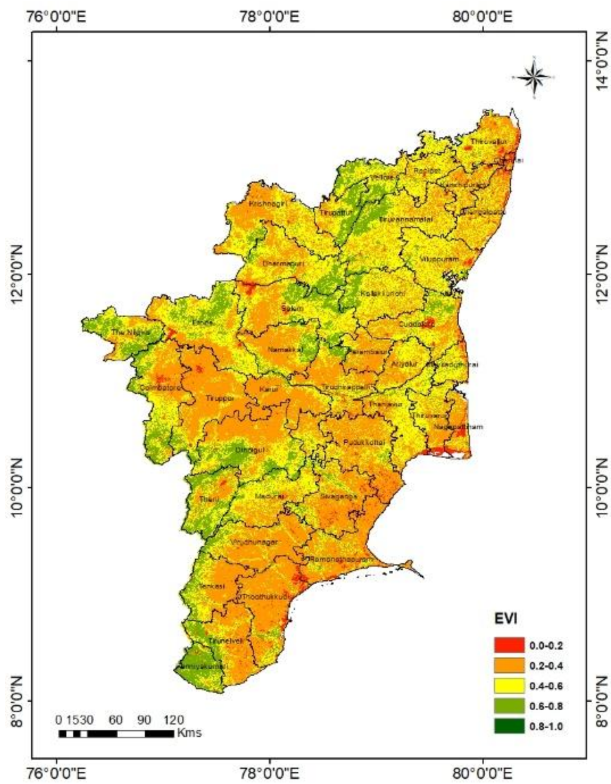

Fig 4. Zonal averaged EVI classes of Tamil Nadu

The crop land NDVI ranges from 0.01 to 0.84 with a mean value of 0.52 and similar change was observed in crop plantation where mean values was observed as 0.59. The variation is due to the sensitivity towards seasonal vegetation and the type of crops cultivated

(Traore *et al.*, 2014). The similar trend was followed in NDVI mean values, where the forest land recorded highest mean values (0.69) preceded by plantation (0.59) and the least NDVI average value recorded in swamp forest (0.42).

Table 1. Zonal averaged NDVI of land covers in Tamil Nadu

Land cover	Minimum	Maximum	Mean	Standard deviation	Coefficient of variation
Crop land	0.01	0.84	0.52	0.07	13.03
Plantation	0.09	0.84	0.59	0.08	14.15
Forest land	0.22	0.86	0.69	0.06	8.91
Scrub land	-0.03	0.83	0.53	0.11	20.04
Swamp forest	-0.09	0.81	0.42	0.20	47.54

The coefficient of variation (CV) indicated that the swamp forest had the highest CV (47.54%) while the forest has the lowest CV (8.11%), indicating that the forest area had a constant development of vegetation and the lowest chance of experiencing poor vegetation conditions. While the crop land displayed a lower CV value (13.03%) which showed a lesser risk of poor vegetation growth than the plantation land (14.15%). The variation in forest might be due to the negligible inter-seasonal fluctuations. Due to the continuous vegetation growth in Tamil Nadu, the NDVI remains steady and not influenced by weather factors (Mora and Arriagada, 2016).

EVI profile

During the study period, maximum EVI was observed under the forest area (0.64) and the lower maximum EVI was observed in swamp forest (0.81). In the case of crop land area, EVI varied from 0.02 to 0.59 with a mean value of 0.33. A similar variation of EVI is observed for plantation land, where maximum was observed as 0.62 and minimum was observed as 0.02. The mean EVI value was recorded highest for the forest (0.43) followed by plantation (0.37), while the swamp forest showed the least mean EVI value (0.23).

The coefficient of variation (CV) indicated that the swamp forest had the highest CV (52.88 per cent) followed by scrub land (20.35 per cent). The changes in scrub land might be due to the anthropogenic activity (Jayakumar and Arockiasamy, 2003) and the inter-annual variation in cropland class indicated that the inter-annual variation in the spatial arrangement and type of crops (mainly legumes and millets) grown during that year (Traore *et al.*, 2014). While the Forest land had the lowest CV (11.69 per cent) followed by crop land (14.41 per cent), which might be due to the negligible inter-change variability in forest areas (Dhanapriya *et al*., 2018).

Table 2. Zonal Averaged EVI of Land Covers in Tamil Nadu

Land Cover	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
Crop land	0.02	0.59	0.33	0.05	14.41
Plantation	0.02	0.62	0.37	0.06	15.55
Forest land	0.06	0.64	0.43	0.05	11.69
Scrub land	-0.03	0.58	0.33	0.07	20.35
Swamp forest	-0.04	0.53	0.23	0.12	52.88

CONCLUSION

MODIS derived products are made clear to be cost saving and time effective for obtaining information in support of monitoring vegetation biomass and crop-water fluctuations over time. The results showed that the mean values of forest land recorded maximum NDVI and EVI denoted the presence of thick dense canopy and swamp forest recorded the lowest mean values. Based on the results, minimum and maximum values of NDVI and EVI of cropland ranges from 0.01 to 0.84 and 0.22 to 0.59, respectively. Crop land observed a 0.52 mean NDVI value and a mean EVI value of 0.33. Among all the land cover classes, forest land observed lowest CV with 8.91 per cent of NDVI and 11.69 per cent EVI, which indicated that the permanent and natural vegetation occurred in that areas.

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CONFLICT OF INTERESTS

The authors declare that there is no competing interest.

REFERENCES

Boegh, E., Soegaard, H., Broge, N., Hasager, C. B., Jensen, N. O., Schelde, K., Thomsen, A. (2002). Airborne multi-spectral data for quantifying leaf area index, nitrogen concentration and photosynthetic efficiency in agriculture. *Remote Sensing of Environment* **81**(23): 179-193.

Carlson, T. N., Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote sensing of Environment*, **62**(3): 241-252.

Dhanapriya, M., Kumaraperumal, R., Kannan, B., Bhatt, H.P. (2018). Spatio-temporal analysis of vegetation dynamics for Saurashtra region of Gujarat. *AgricINTERNATIONAL* **5**: 43.

Dusseux, P., Vertès, F., Corpetti, T., Corgne, S., Hubert-Moy, L. (2014). Agricultural practices in grasslands detected by spatial remote sensing. *Environmental Monitoring and Assessment* **186**: 8249–8265.

Gao, X., Huete, A. R., Ni, W., Miura, T. (2000). Optical – biophysical relationships of vegetation spectra without background contamination. *Remote Sensing of Environment*, **74**: 609-620.

Gumma, M.K., Thenkabail, P.S., Maunahan, A., Islam S., Nelson, A. (2014). Mapping seasonal rice cropland extent and area in the high cropping intensity environment of Bangladesh using MODIS 500 m data for the year 2010. *International journal of remote sensing* **91:** 98-113.

Huete, A., Didan, K., Miura, T., Rodriguez, E., Gao, X., Ferreira, L. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* **83**: 195-213.

Jayakumar, S., Arockiasamy, D.I. (2003). Land use/land cover mapping and change detection in part of eastern ghats of tamil nadu using remote sensing and GIS. *Journal of the Indian Society of Remote Sensing* **31**: 251–260.

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

Lunetta, R.S., Knight, J.F., Ediriwickrema, J., Lyon, J.G., and Worthy, L.D. (2006). Land-cover change detection using multi-temporal MODIS NDVI data. *Remote Sens Environ* **105**: 142–154.

Matsushita, B., Yang, W., Chen, J., Onda, Y., Qiu, G. (2007). Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to Topographic Effects: A Case Study in High-density Cypress Forest. *Sensors* **7**: 2636-2651.

Mora, F., Arriagada, O. (2016). A classification proposal for coefficients of variation in Eucalyptus experiments involving survival, growth and wood quality variables. *Bragantia* **75**: 263-267.

Nomura, R., Oki, K. (2021). Downscaling of MODIS NDVI by Using a Convolutional Neural Network-Based Model with Higher Resolution SAR Data. *Remote Sensing* **13**(4): 732.

Padmanaban, R., Karuppasamy, S., Narayanan, R. (2018). Assessment of pollutant level and forecasting water pollution of Chennai coastal, Tamil Nadu using R. *Indian Journal of Geo-Marine Sciences* **47**: 1420–1429.

Prajesh, P.J., Kannan, B., Pazhanivelan, S., Kumaraperumal, R., Ragunath, K.P. (2019). Analysis of Seasonal Vegetation Dynamics Using MODIS Derived NDVI and NDWI Data: A Case Study of Tamil Nadu. *Madras Agricultural Journal* **106**: 4-6.

Rouse, J., Haas, R., Schell, J., Deering, D., Harlan, J. (1974). Monitoring the vernal advancement of retrogradation of natural vegetation. NASA/GSFC, Type III, Final report Greenbelt, MD, Etats-Unis, 371 p.

Samuel, P., Antonisamy, B., Raghupathy, P., Richard, J., Fall, C.H.D. (2012). Socio-economic status and cardiovascular risk factors in rural and urban areas of Vellore, Tamilnadu, South India. *International journal of epidemiology* **41**: 1315–1327.

Shamsudeen, M., Padmanaban, R., Cabral, P., Morgado, P. (2022). Spatio-Temporal Analysis of the Impact of Landscape Changes on Vegetation and Land Surface Temperature over Tamil Nadu. *Earth* **3**: 614-638.

Tariq, A., Shu, H. (2020). CA-Markov chain analysis of seasonal land surface temperature and land use landcover change using optical multi-temporal satellite data of Faisalabad, Pakistan. *Remote Sensing* **12**: 3402.

Traore, S.S., Landmann, T., Forkuo, E.K., Traore, P.C.S. (2014). Assessing long-term trends in vegetation productivity change over the Bani river basin in Mali (West Africa). *Journal of Geography, Environment and Earth Science* **2**: 21-34.

Vaani, N., Porchelvan, P. (2018). Monitoring of agricultural drought using fortnightly variation of vegetation condition index (VCI) for the state of Tamil Nadu, India. *ISPRS Archives* **42**: 159-164.

Vasumathi, V., Kalpana, R., Pazhanivelan, S., Kumaraperumal, R., Priya, M.V. (2022). Identification of 'Start of Season' in Major Rainfed Crops of Tamil Nadu, India Using Remote Sensing Technology. *International Journal of Environment and Climate Change* **12**: 327-334.