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Research Article

Monitoring vegetation dynamics using multi-temporal Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) images of Tamil Nadu

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Abstract
Vegetation indices serve as an essential tool in monitoring variations in vegetation. The vegetation indices used often, *viz*., normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) were computed from MODIS vegetation index products. The present study aimed to monitor vegetation's seasonal dynamics by using time series NDVI and EVI indices in Tamil Nadu from 2011 to 2021. Two products characterize the global range of vegetation states and processes more effectively. The data sources were processed and the values of NDVI and EVI were extracted using ArcGIS software. There was a significant difference in vegetation intensity and status of vegetation over time, with NDVI having a larger value than EVI, indicating that biomass intensity varies over time in Tamil Nadu. Among the land cover classes, the deciduous forest showed the highest mean values for NDVI (0.83) and EVI (0.38), followed by cropland mean values of NDVI (0.71) and EVI (0.31) and the lowest NDVI (0.68) and EVI (0.29) was recorded in the scrubland. The study demonstrated that vegetation indices extracted from MODIS offered valuable information on vegetation status and condition at a short temporal time period.

Keywords: Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI), spatio-temporal, time series, vegetation indices

INTRODUCTION

Vegetation monitoring plays a crucial role in sustainable land management, environmental protection, and informed decision-making to address changing world challenges. The data collected through monitoring efforts helps policymakers and scientists make informed choices for a more sustainable future. To detect any change in vegetation, geographical information systems and remote sensing have been deployed in recent times throughout the world (Abebe *et al*., 2022 and Mohamed *et al*., 2020). Presently, remote sensing data is used to recognize and characterize the variations in vegetation status over time. By investigating the remote sensing data deviations, phenological changes can be studied throughout the crop growth period (Dhanapriya *et al*., 2018).

Vegetation indices act as an important role in monitoring variations in the crop and forest vegetation, thereby strengthening the capacity to predict, mitigate, as well as adapt towards the changes in vegetation. Vegetation index (VI), is the arithmetic combination of two or more bands associated to the spectral characteristics exhibited by vegetation, has been significantly employed to provide phonologic monitoring, vegetation categorization and the biophysical derivation of radiometric and structural parameters associated with vegetation (Mokarram and Sathyamoorthy, 2015). The MODIS Land Discipline Group suggested two globe-based vegetation indices *i.e*., Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), to offer continuous spatial and temporal information about the global vegetation (Matsushita *et al*., 2007).

NDVI is widely used as it provides live vegetation status very effectively (Nomura and Oki, 2021). It measures the variation between near-infrared (strongly reflected by vegetation; 8th band; 846-885 nm) and red light (absorbed by vegetation; 4th band; 600-680 nm) (Carlson *et al*., 1997, Wardlow *et al*., 2007 and Nomura and Oki, 2021).

Changes in the crop canopy, plant physiognomy and leaf area index (LAI) are more sensitive to EVI than the NDVI (Gao *et al*., 2000 and Moreira *et al*., 2019). It helps in optimizing the signals from the vegetation with increased sensitivity in the thick canopy regions and improves vegetation monitoring by decoupling the signals obtained from the canopy background and bringing down the atmospheric impacts. It also overcomes the NDVI drawbacks by offering improved sensitivity in areas with a greater LAI (Boegh *et al.,* 2002 and Hassani *et al*., 2023).

The relationship between the vegetation indices (NDVI and EVI) and natural vegetation cover in Tamil Nadu is not well established. MODIS provides realistic and accurate time series data over a longer period. Therefore, this study was carried out to monitor the vegetation changes in study area for the time period from 2011 to 2021.

MATERIALS AND METHODS

Details of the study area

The study area, focuses on the entire Tamil Nadu region, which stretches between 8.5° N and 13.35° N latitude and 78.35° E and 80.20° E Longitude and with an area of 130,058 km^2, is situated in the South Eastern part of India (Fig. 1). Tamil Nadu is India's 11th largest state, with about 38 districts and 7 agro climatic zones *viz*., North Eastern Zone, North Western Zone, Western Zone, Southern Zone, High Rainfall Zone, High Altitude Zone and Cauvery Delta Zone in the state. It is bordered on the north by Andhra Pradesh and Karnataka, on the west by Kerala, on the east by the Bay of Bengal, and on the south by the Indian Ocean. Pondicherry, a union territory, is located on the state's eastern border. The state has an average annual rainfall of 998 mm (Kavitha *et al*., 2020). The Southwest monsoon (June to September) and Northeast monsoon (October to December) are the predominant monsoon seasons of the state. Tamil Nadu experiences more rainfall exclusively during the northeast monsoon, whereas other Indian states get higher rainfall during the southwest. Forty-seven percent of the total annual precipitation comes from the northeast monsoon, whereas the southwest monsoon accounts for 35 per cent (Vaani *et al*., 2018 and Vasumathi *et al.,* 2022).

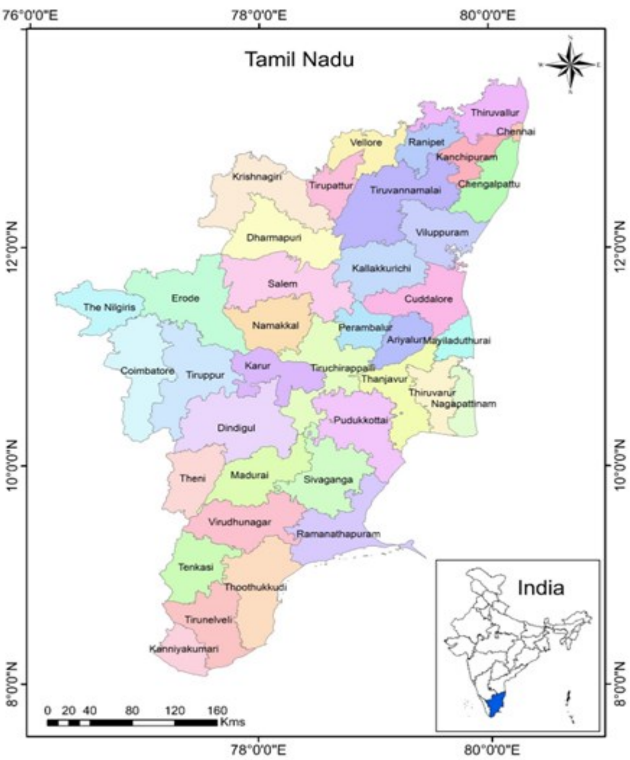

Fig. 1. *Study area map of Tamil Nadu*

Land use and Land cover

The Department of Remote Sensing and Geographic Information System (GIS), Tamil Nadu Agricultural University, Coimbatore, provided the land use and land cover (LULC) map of Tamil Nadu at a scale of 1:50000. This map was generated using multi-temporal Advanced Wide Field Sensor (AWiFS) datasets, which provide information about the land classification and different biomes of Tamil Nadu (Fig. 2). It also provides information on both the productive as well as unproductive regions 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. Two tiles, h25v07 and h25v08, cover the research area and the data downloaded in Hierarchical Data Format (HDF) format from the Earth data website (https://appeears.earthdatacloud.nasa.gov/)

Pre-processing of MODIS satellite data

Pre-processing is performed on an image at its most basic level of abstraction, suppressing undesirable distortion or improving specific image characteristics that are essential for subsequent processing.

Reprojection, sub-setting and resampling of MODIS data

By correcting for distortions imposed on by the tilt of the satellite sensor and the topographical variation of the picture, terrain corrections aimed to make the geometric representation of the image as accurate and realistic to the real world as possible. Using the MODIS Reprojection Tool (MRT), projection from Sinusoidal to Universal Transverse Mercator (UTM 43N) was carried out. The ArcGIS Extract by Mask tool was used to subset the data using the base layer, which speeds up further processing for raster data.

Extracting the Vegetation Indices (VI)

Vegetation indices derived from satellites represent the biomass's crop condition and status. In this study, MODIS (MOD13Q1) surface reflectance datasets were used to derive NDVI from January 2011 to December 2021. To monitor the dynamics in climate and ecosystem, the inter-annual variation of vegetation indices was considered.

Normalized Difference Vegetation Index (NDVI)

The NDVI range falls between -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 no vegetation in an area. NDVI is sensitive to additive noise effects, such as atmospheric path radiances and canopy background variations. Huete *et al*. (2002) stated the sensitivity of the canopy background gets stronger with NDVI degradation by the greater canopy background brightness. NDVI is defined by the given formula

$$NDVI=\frac{(\rho NIR\ -\ \rho Red)}{(\rho NIR\ +\ \rho Red)} \qquad \text{Eq. (1)}$$

Enhanced Vegetation Index (EVI)

It ranges falls between -1 to +1 where the values for healthy vegetation typically range from 0.20 to 0.80. EVI is defined by the given formula

$$EVI=\frac{G*(\rho NIR\ -\ \rho Red)}{(\rho NIR\ +\ C1*\rho Red-C2*\rho Blue+L)} \qquad \text{Eq. (2)}$$

Where, ρ is the atmospherically corrected or partially atmosphere corrected (Rayleigh and ozone absorption) surface reflectances, L is the canopy background adjustment that represents nonlinear, differential NIR and red radiant transfer through a canopy and C1, C2 are the aerosol resistance term coefficients, which utilises the blue band to correct the aerosol influences which are present in the red band. The coefficients utilised in the EVI algorithm are, L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5 (Huete *et al*., 2002).

While extracting the NDVI, the scale values should be given in the range of -1 to +1. The MOD13Q1 is recalculated by 0.0001 value of scaling factor to extract NDVI.

Methodology

ArcGIS 10.8 version was used to process the downloaded MODIS data. Maximum averaged NDVI and EVI values were derived using zonal statistics tool in ArcGIS in order to assess the deviation amidst the agriculture and forest ecosystems for the study period of 11 years (2011–2021). In the zonal statistics tool, MOD13Q1 and land use and land cover map were employed as the value and zonal layers, respectively (Fig. 3).

RESULTS AND DISCUSSION

Land use and land cover map

The study area's land use/land cover pattern is categorized into different classes: forest land into deciduous and evergreen forest; agricultural land into cropland, fallow land and plantation land; waste land, wet land, water bodies and barren and built-up. The resulting LULC categories provide an overview of the predominant land use/land cover characteristics of Tamil Nadu. The map provides the overall area distributed under different LULC classes and spatial distributions. Similar study has also been conducted by many researchers to comprehend the present condition of land use types in Tamil Nadu by Arulbalaji (2019) and Prajesh *et al*. (2019). In Saurashtra region of Gujarat, Dhanapriya *et al*. (2018) studied on various land use classes fluctuations and Butt *et al*. (2015) carried out research in Pakistan to find out the present status of vegetation.

NDVI and EVI vegetation profile analysis

NDVI and EVI were available in 16-day composite and processed for a better understanding of the vegetation dynamics of Tamil Nadu for the period of 11 years. The data were classified to generate six annual average classes *viz.*, < 0, 0 to 0.2, 0.2 to 0.4, 0.4 to 0.6, 0.6 to 0.8 and 0.8 to 1.0 to represent without any vegetation or water bodies, less or poor vegetation, moderate vegetation, good vegetation, healthy or very good vegetation and very dense or extremely good vegetation respectively.

NDVI and EVI profile based on land use

The zonal averaged maximum values of the NDVI and EVI were determined and depicted in Figs. 4 and 5, respectively, to analyze the NDVI and EVI time series trend on various land use types during the crop season of the study period. Both the vegetation indices (NDVI and the EVI) displayed greater temporal variations in the amount of vegetation and condition, although the NDVI value had a broader range than the EVI. The findings reported that a higher NDVI value was recorded in the semi-arid region than in the EVI. Similarly, higher and lower NDVI and EVI values were recorded in North and South American forest biomes (Huete *et al.,* 2002) and also in the Saurashtra region of Gujarat (Dhanapriya *et al*., 2018), respectively.

There was a variation in NDVI and EVI profiles for cropland due to the different sowing times practised in different parts of the study area region and the weather parameters' sensitivity. The findings showed that the NDVI and EVI time series plots seemed to have a similar trend for the scrub/degraded forest and cropland. The higher NDVI and EVI values were found in the forest land and the fluctuations were due to the shedding of leaves that occurred in deciduous forests. The NDVI and EVI registered lower values in the year 2016 when compared to other years, as there was a drought occurring in the study area region.

Lower NDVI and EVI were observed in cropland than in the other classes, which addresses the sensitivity of indices towards the type of plant species/crops cultivated. These results were corroborated by Hussein *et al.* (2017), where NDVI and EVI showed sensitivity towards the dense canopies in North and South America and also in the South Western parts of Gujarat by Dhanapriya *et al.* (2018). The NDVI showed no variation within the years during the study period except for 2011 and 2012. However, EVI showed little variation except for the years such as 2012, 2013, 2016 and 2017 during the study period. This could be attributed to sudden climatic changes, which cause a decline in vegetation growth (Hussein *et al*., 2017).

Spatio-temporal profiles of NDVI and EVI

The zonal statistics were performed to extract the maximum averaged NDVI and EVI values under deciduous forest, cropland and scrub/degraded forest of the study period from 2011 to 2021 are presented in Table 1. The minimum and maximum mean NDVI values for deciduous forest were recorded in 2012, 2013 and 2016 (0.81) and 2021 (0.87) respectively. The minimum mean NDVI value for cropland was observed in 2016 (0.67) and maximum mean NDVI value was recorded during 2021 (0.76). In case of scrub/wasteland forest, the minimum mean NDVI value for cropland was recorded during 2012, 2013 and 2016 (0.64) and a maximum mean NDVI value was recorded in 2021 (0.73). However, EVI also showed a similar trend like NDVI and higher mean EVI values were recorded for deciduous forest (0.38) preceded by cropland (0.31) and scrub/degraded forest

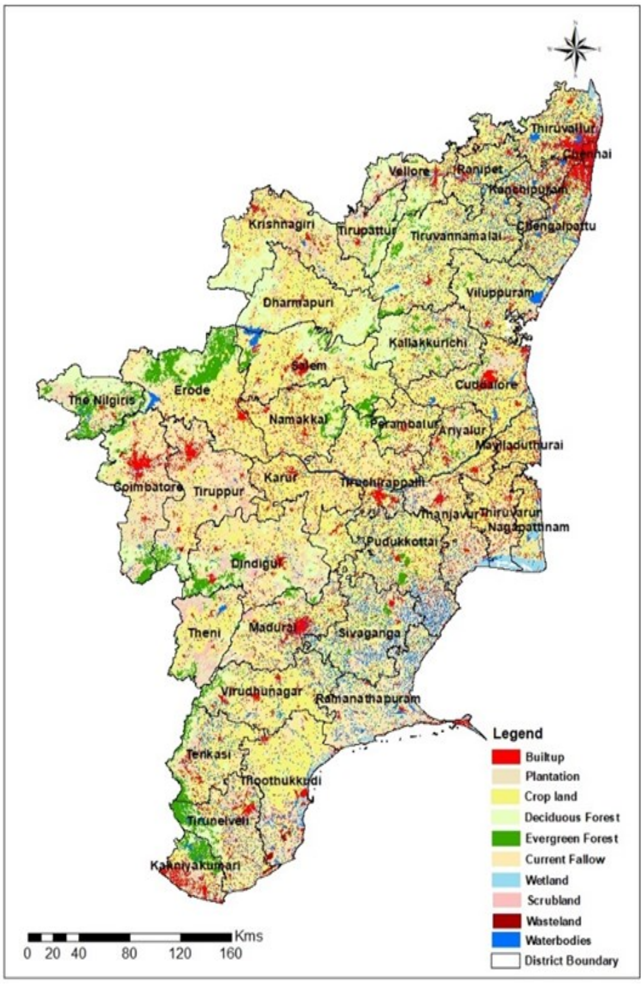

Fig. 2. *Showing Land use and land cover of Tamil Nadu*

Table 1. Zonal maximum averaged annual NDVI and EVI under cropland and forest of Tamil Nadu (2011-2021)

Year	Forest Land		Scrub / Wastelands		Crop Land	
	NDVI	EVI	NDVI	EVI	NDVI	EVI
2011	0.82	0.40	0.66	0.29	0.70	0.32
2012	0.81	0.37	0.64	0.27	0.68	0.30
2013	0.81	0.35	0.64	0.26	0.68	0.29
2014	0.83	0.36	0.67	0.27	0.71	0.29
2015	0.84	0.40	0.69	0.30	0.73	0.32
2016	0.81	0.37	0.64	0.28	0.67	0.30
2017	0.84	0.37	0.69	0.28	0.71	0.30
2018	0.82	0.38	0.67	0.29	0.70	0.31
2019	0.85	0.36	0.71	0.28	0.75	0.29
2020	0.85	0.41	0.70	0.31	0.73	0.32
2021	0.87	0.41	0.73	0.32	0.76	0.33
Mean	0.83	0.38	0.68	0.29	0.71	0.31
SD	0.02	0.02	0.03	0.02	0.03	0.01
CV	2.39	5.64	4.50	6.30	4.10	4.68

(0.29).

The maximum EVI mean values for cropland ranged from 0.29 (2013, 2014 and 2019) to 0.33 (2021), forest land ranged from 0.35 (2013) and 0.41 (2020 and 2021) and for the scrub/wasteland from between 0.26 (2013) to 0.32 (2021). The higher NDVI mean values were observed in forest land (0.83), preceded by cropland (0.71) and scrub/degraded forest (0.68). However, EVI also showed a similar trend like NDVI and higher EVI mean values were found in the deciduous forest (0.38) preceded by cropland (0.31) and scrub/ degraded forest (0.29). NDVI and EVI mean values were higher in the deciduous forest due to the natural woody and perennial vegetation in that respective region (Traore *et al*., 2014 and Dhanapriya *et al.,* 2018).

NDVI and EVI had a very low coefficient of variation (CV), indicating the minimum variation within the years. However, EVI recorded a higher CV value than NDVI in all the land use classes. The NDVI had recorded the highest CV value for scrub/ degraded forest (4.50%), preceded by cropland (4.10%) and deciduous forest (2.39%). However, the pattern is not followed in EVI and the EVI recorded a higher CV value for scrub/ degraded forest (6.30%), preceded by deciduous forest (5.64%) and cropland (4.68%). The variability within the years in cropland class might be due to the spatial arrangement of crops (mostly millets and legumes) and crop types grown during that particular year (Traore *et al*., 2014). Despite it is challenging to define the changes to any one factor, rising temperatures, altered land

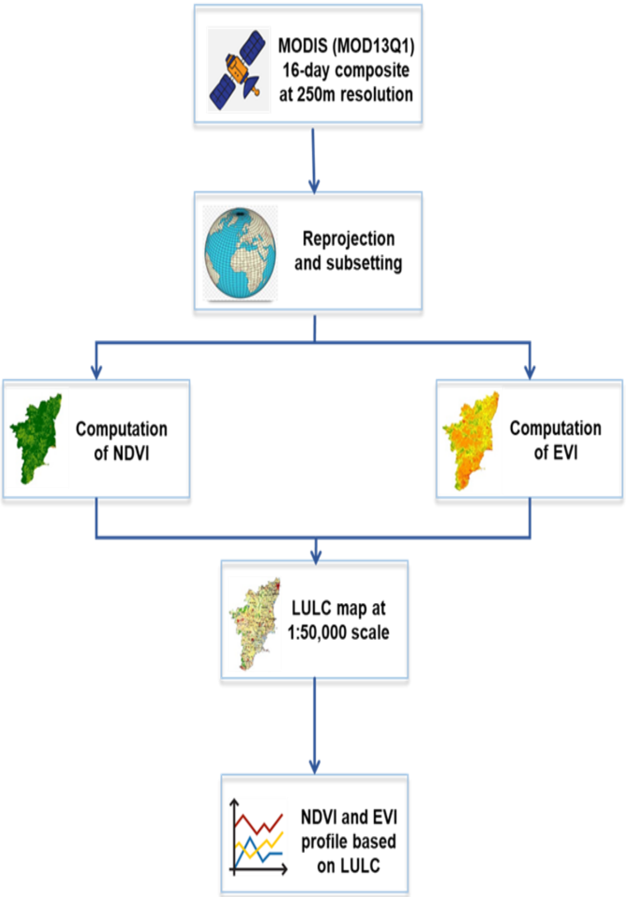

Fig. 3. *Methodology for analysis of vegetation dynamics in Tamil Nadu region*

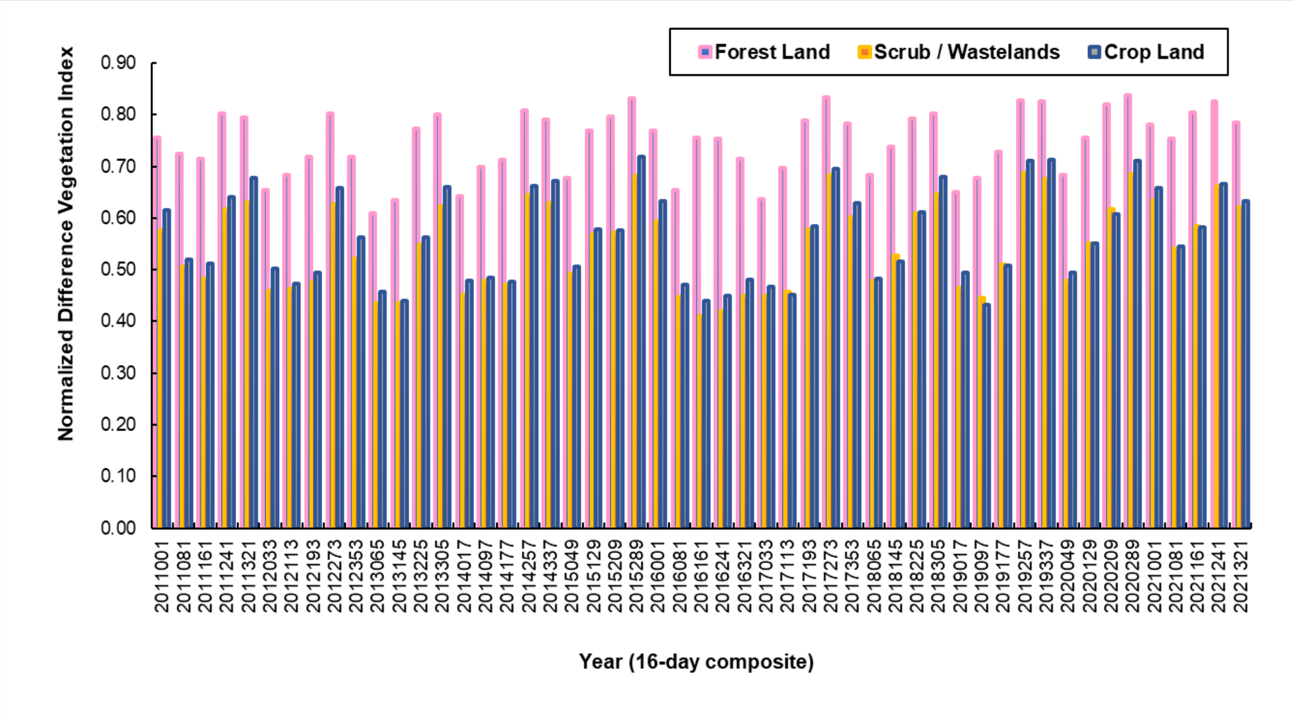

Fig. 4. *Zonal mean NDVI temporal profile under different land use classes of Tamil Nadu (2011-2021)*

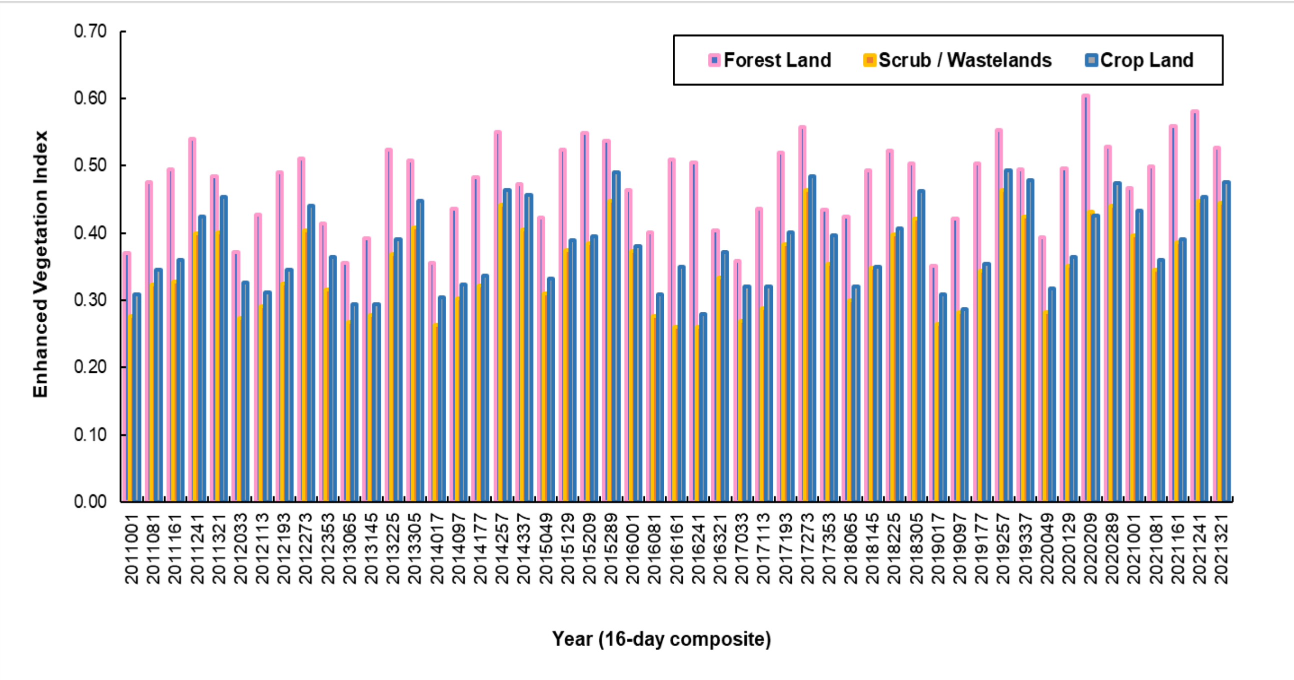

Fig. 5. *Zonal mean EVI temporal profile under different land use classes of Tamil Nadu (2011-2021)*

use patterns, and a rise in atmospheric CO_2 concentration are suggested as potential reasons (Davis *et al.*, 2017).

Conclusion

The present study indicated that NDVI and EVI were higher in forests of the Tamil Nadu region and that changes in forest land were caused by the dropping of leaves in deciduous forests. In contrast to other groups, cropland had smaller NDVI and EVI values, which showed how sensitive these indices are towards the crop types and species cultivated there. NDVI and EVI displayed a similar pattern, with deciduous forest recording greater mean EVI values than cropland, scrub/degraded forest. Both the vegetation indices (NDVI and EVI) had very low coefficients of variation (CV), indicating variability was at its lowest from year to year. EVI observed a higher variation coefficient in all types of land use/ land cover than NDVI. Future tracking of these trends requires continued observation using finer spatial scale vegetation indices.

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Conflict of interest

The authors declare that they have no conflict of interest.

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