Exploring Forest Transformation by Analyzing Spatial-temporal Attributes of Vegetation using Vegetation Indices

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***Abstract*—The world's ecosystem and environment are rapidly deteriorating with an increase in the depletion of forest conditions due to forest fires. In recent past years, wildfire incidents in Sikkim have increased due to severe climatic changes such as turbulent rainfall, untimely summers, extreme droughts in winters, and a reduction in the percentage of yearly rainfall. Forest fires are one of the numerous kinds of disasters that impose disastrous changes on the entire environment and disrupt the complex correspondence of the flora and fauna. The research's goal is to examine the vegetation indices based on different climates to know why forest vegetation is decreasing day by day from 2000 to 2023. The frequent changes in forest vegetation are extensively studied by using satellite images. This data has been collected by three satellites Landsat-5, Landsat-8, and Landsat-9 on different vegetation indices NDVI, EVI, and NDWI. East Sikkim area is chosen to compute forest vegetation indices based on the heap's landmass this region is unexplored yet and also studied about the forest changes by using different spatial temporal indices in the range of the entire district in the future. The authors of this paper have used Landsat multi-spectral data to assess changes in the area of vegetation in a sub-tropical region like a dense forest region in east Sikkim. The analysis depicts space images, computes vegetation indices (NDVI, EVI, NDWI), and accomplishes mathematical computation of findings. The proposed method will be helpful to discuss the variance of vegetation in the entire East Sikkim region at the time span of 2000–2023. In the analysis, we find that mean and standard deviation values change over the years in all indices. Later, we also calculated changes by using a classification model and find a total 10% change in forest areas in approximately 22 years.**

Keywords*—*Classification; change detection; vegetation indices; landsat; machine learning

I. Introduction

It is found that climate is very much affected by global warming throughout the world. Spectral Indices detected different factors like rainfall and temperature within 1 to 15 years [1]. Based on the increasing extremes caused by human-induced climate change, as well as the limited progress made towards finding climate change solutions, the National Academies of Science and Engineering recently recommended that the USA develop a trans-disciplinary research program into proposed climate intervention techniques [1]. Earth quacks also deteriorate the vegetation area because of their frequent occurrence as earlier we used to hear about earth quacks occurring in 4 to 5 years but now every month it probably happens. Due to earthquakes lots of forest decaying problem arises like plant community shift, Species loss, and productivity reduction of alpine grasslands [2]. Flood is also one crucial factor to decrease the vegetation area but it is also found that initially, floods affected crops but later crop productivity and fertile land improved and resulted in dense vegetation area [3]. By mapping vegetation cover before and after floods, spacecraft images, rainfall data, a tool used for analyzing the geographical area, and a rain gauge were used to evaluate post-flood loss or benefit[3]. The deforestation and degradation of forests alone contribute between 20 and 25% of global greenhouse gas emissions [4]. District-wise Sikkim climate data is analyzed over the period 1901 to 2007 to predict rainfall, precipitation, and temperature followed by mean 17.82 mm per day, Standard Deviation 3.55 mm per day, Coefficient of Variation (C.V.) 20%, precipitation Trend is -2.627mm per day/100 years, minimum temperature trend 2.86 0C/100 years and maximum temperature 0.730C/100 years. The environmental influence on vegetation increases as more regions of the world become forested. Inside the city limits, there are forests, which causes changes in the vegetation of the forests. Computing the quality of forest areas and the surrounding environment and making decisions to ensure the population's sanitary and environmental safety depends on understanding where these changes occur, in what quantities, and in response to what variables [5]. The dynamics of forest vegetation may be studied in great detail using satellite photos over Google Earth Engine [6]. Satellite photos enable us to get factual data about the temporal and spatial variations in vegetation. The commonly uses type of satellite data is Landsat, Sentinel, and MODIS from various very famous data archive providers like USGS, Copernicus Programme, NASA, etc. [7]. Landsat itself has various development, from Landsat 1 to Landsat 9. Sentinel also has various versions from Sentinel 1 to Sentinel 5.

A number of methods have been employed to determine the area occupied by vegetation [8]. These methods involve classifying the outcome based on supervised and unsupervised learning, automatic image processing, the generation of index pictures, as well as visual interpretation [9]. The dynamics of plant cover can be analyzed using spectral and temporal indices obtained from time-lapse images.

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Two categories can be used to categorize these applications. The first category consists of universal systems, which help us analyze data obtained through remote sensing of the Earth and address a variety of issues [10]. The second category consists of software (tools) designed to handle extremely specific jobs. Such programs have the undeniable advantage of being made specifically to address a given practical issue. In these programs, the majority of the steps are automated. Upon examining the current approaches to evaluating vegetation changes within a forest agglomeration based on multi-temporal photographs, we decided that it would be beneficial to develop a tool for the evaluation of vegetation changes based on multi-temporal images [11].

To analyze satellite images, an algorithm was created. This application performed a number of functions, including the study of satellite images, the calculation of spectral indices, the evaluation of the cloud cover mask, and the statistic-based analysis of interpretation results. This algorithm categorizes multi-temporal images to detect the dynamics of land occupied by vegetation.

The research's goal is to use remote sensing data from the year 2000 to the year 2023 to examine the forest vegetation in the east Sikkim forest area. Principal research goals: (1) Building a database of Landsat satellite photos for the years 2000 to 2023; (2) Creating an algorithm along with software development acquired from several vegetation indices. (3) The identification of the primary mechanisms that brought about the observed alterations in the east Sikkim forest areas. A unique algorithm was developed for the detailed examination of Landsat remote sensing data in East Sikkim through which the originality of the proposed scientific research is explained. This is a feasibility study organized in the East Sikkim region. So far, no such studies have been conducted on forest cover changes in the East Sikkim region related to changes in social, economic, and political conditions. A more rigorous explanation of the novelty's position is required. Our own algorithm's development opens up various possibilities for its widespread practical application.

II. Related Work

The most common origin for the remote sensing data of Earth for a variety of examinations is Landsat pictures. The benefit of Landsat data is related to the policy of free picture access and the continuity of observations over a 50-year period. As per the analysis of spatiotemporal characteristics, the moderate forest conquered approximately 46% in 1985 and 57% in 2005, and 58% of the total land is occupied by open forests which were a replacement for these [12]. In addition to this, we have analyzed spatial and temporal indices in the East Sikkim area. The majority of India's forests are degrading due to forest fires. In East Sikkim, forest fire is a frequent process as the water stress level is very high in the summers. It is a tedious task to figure out the statistical data on the occurrence of forest fires in a year, but statistics cleared that estimated that 33% of a few states and more than 90% of other states are exposed to forest fires annually [13]. The burnt areas could be easily seen in the SWIR band when using band(3 2 1), and band(4 3 1) [14]. The Sikkim Mountains, a crucial phytogeographical reserve for the nation, contain more than 26% of all blooming plants. Landsat data are useful for tracking forest regions. Many different techniques are used for analyzing and monitoring the Landsat input data. Several image processing techniques created in remote sensing are used in extracting area-covering details with the help of satellite images. Using Landsat to map forests, presents a variety of challenges. Landsat images of forested areas typically include a combination of data about anthropogenic items and vegetation in their pixels. When recognizing forest areas, more vegetation cover from the image must be retrieved. To distinguish between forest and non-forest regions, one method uses spectral vegetation indices such as the Normalized Difference Vegetation Index and vegetation index sensitive to the water content of plants normalize difference water index. Another spectral technique makes the assumption that forest pixels are linear mixtures of the three common land cover, vegetation, impervious surface, and soil components (the so-called V–I–S model). In the paper, it is suggested that mapping of the forest area be done using a mix of spectral and spatial data. The technique comprises these two distinct categories of elementary coverage classes based on pixels and segments (segment-based).

III. Study Area

Sikkim is one of the largest forest heaps in the northeast of India. Sikkim state covers a total area of 7096 sq Km. The geographical area we have targeted as the study area is the East Sikkim region, which is approximately 964 sq. km in size and located at 27.3084° N, 88.6724° E in Fig. 1. As per the Forest Management Department, 14.44% area of Sikkim is covered under scrub-(RF) and alpine pasture, and 29.5% area is occupied by perpetual snow cover. Remote Sensing Data for the year 1988 depicts that the vegetation area for crops which may be Terraced/Semi Terraced is 604.85 sq. km and this cropland is mixed with dense forest of capacity 603.34 sq. km. The district area is 173.19 sq km which is 2.44% of the total area. As stated by the Forest Survey of India (FSI), the reported Forest State covers an area of 5841.39 sq km which is equal to 82.32% and 0.8% of the whole nation's forest region. According to the State of Forest Report of the Forest Survey of India, Ministry of Environment & Forest, Government of India, the status of Forest cover evaluation is gradually increasing which was 2756 sq km in 1987 and 3262 sq km in 2003. In 2021, the number of trees and forests in India covered 80.9 million hectares, which is equal to 24.62% of the country's total land area. Areas that are part of a biosphere reserve's buffer zone are excluded from the Protected Area Network.

The amount of area covered by the protected Area Network of State is 2177.10 sq km. (i.e.30.68% of the entire geographical area) whereas the amount of land covered by the protected Area Network and biosphere reserve in the State is 3013.10 sq km (i.e.42.46% of the entire geographical area). There is mainly five types of forest present in East Sikkim: wet temperate forests find generally in hilly areas, subtropical or moist broad-leaf forests, which are areas of forests where half of the world species are living in different zones, moist mixed forests are types where greenery increases or decreases with the season these are also known as dry deciduous forest, other types of forest are conifer forest and sub-alpine forest, conifer forests are also deciduous forest but the property of these forests are these are always green but sub-alpine forests are primary factors of nature and environmental disturbance

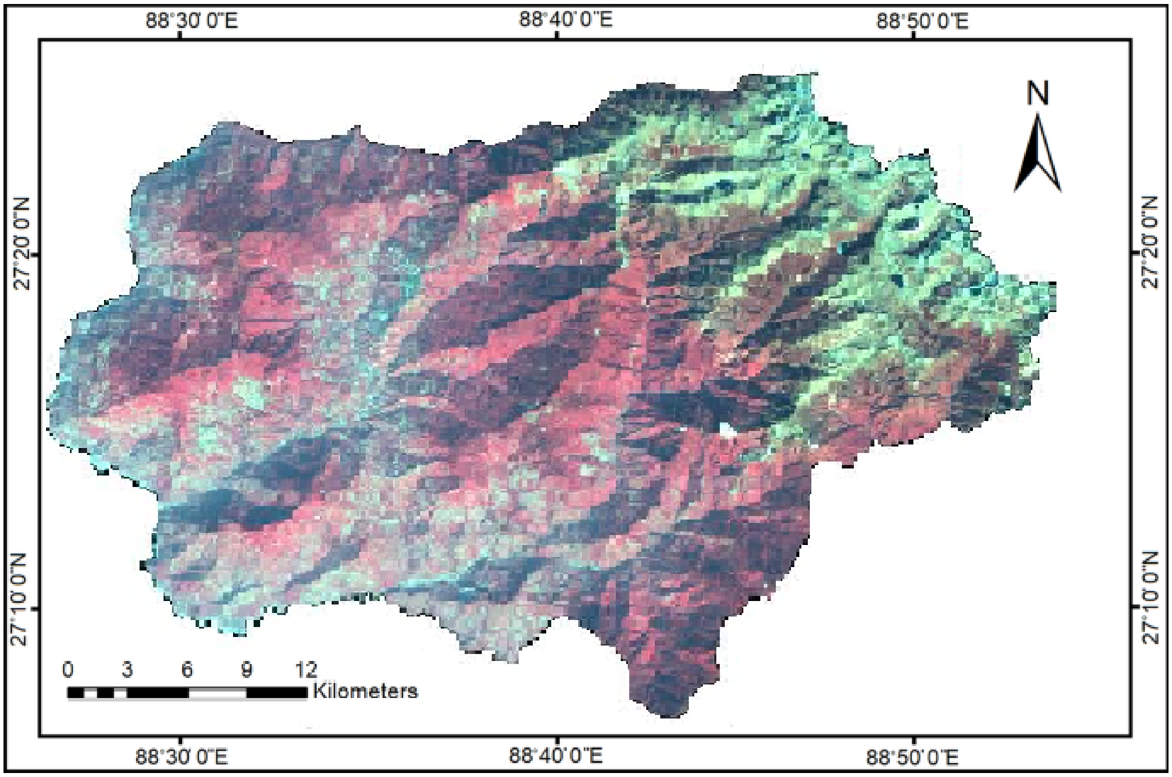

Fig. 1. Location of study area.

these are basically prone to fire and 80% forest fire incident are happened due to these indices in India these are basically found at eastern middle Himalayas. Sikkim is India's greenest state but with time and change in climate and environmental conditions, we find that there are high changes are occur from one type of forest to another type of forest which also leads to deforestation.

IV. Method and Data

For analysis of change in East Sikkim, Fig. 2 we are google earth engine (GEE) satellite-based planetary tool [14], It has a collection of many satellites based real-time data sets like Landsat, Sentinel, and MODIS as well as provides users, a tool (code editor) for analyzing these data. Here we are using Landsat data for finding changes in the forest area as well as East Sikkim from the year 2000 to 2023. Landsat has a collection of data from 1972 to 2023. Landsat has different versions based on time of availability, spatial resolution, and wavelength. Till now USGS has launched nine versions of Landsat data sets from Landsat 1 to Landsat 9. We are using, data from the Landsat-5 (Thematic Mapper), Landsat-7 (Enhanced Thematic Mapper Plus), and Landsat-9 (Operational Land Imager-II) satellites to examine the dynamics of the study area's forest vegetation. Many scenes are present in the chosen location. The work uses five bands (Short Wave Infrared, Green, Red, Near Infrared and Blue), which have a spatial resolution of 30m. Landsat uses a worldwide reference system (WRS) that catalog Landsat data by path and row. Table I represent used datasets and band for analysis of change in the study area. Fig. 2 shows the technique used in research for the analysis of change using different data sets and vegetation indices. Later for verification of the result, it also calculates changes in land cover areas of the study area, East Sikkim using the supervised classification model Random forest.

A. Vegetation Indices

Low vegetation and high vegetation land cover class contain all the land cover areas which having some greenery or dense forest, for proper differentiating between these two land cover classes we are using Normalize Difference Vegetation Index (NDVI) [15], [16], Normalized Difference Water Index (NDWI) [17] and Enhance Vegetation Index (EVI) [18]. After calculating the ground reference point we observed the study area and calculated its daily average temperature and rain and peak months as August to October rain goes above 90mm. From the observation, we find the average temperature is high in the month between May to July and the average rain is maximum in the month of August and September.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

The NIR and SWIR bands are used by NDBI to highlight man-made built-up regions. It is ratio-based to lessen the impact of variations in terrain illumination and atmospheric effects.

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{2}$$

In Landsat 8 and Landsat 9, Enhanced Vegetation Index is calculated as

$$EVI = \frac{2.5 * ((Band5–Band4)}{(Band5 + 6 * Band4–7.5 * Band2 + 1))} \tag{3}$$

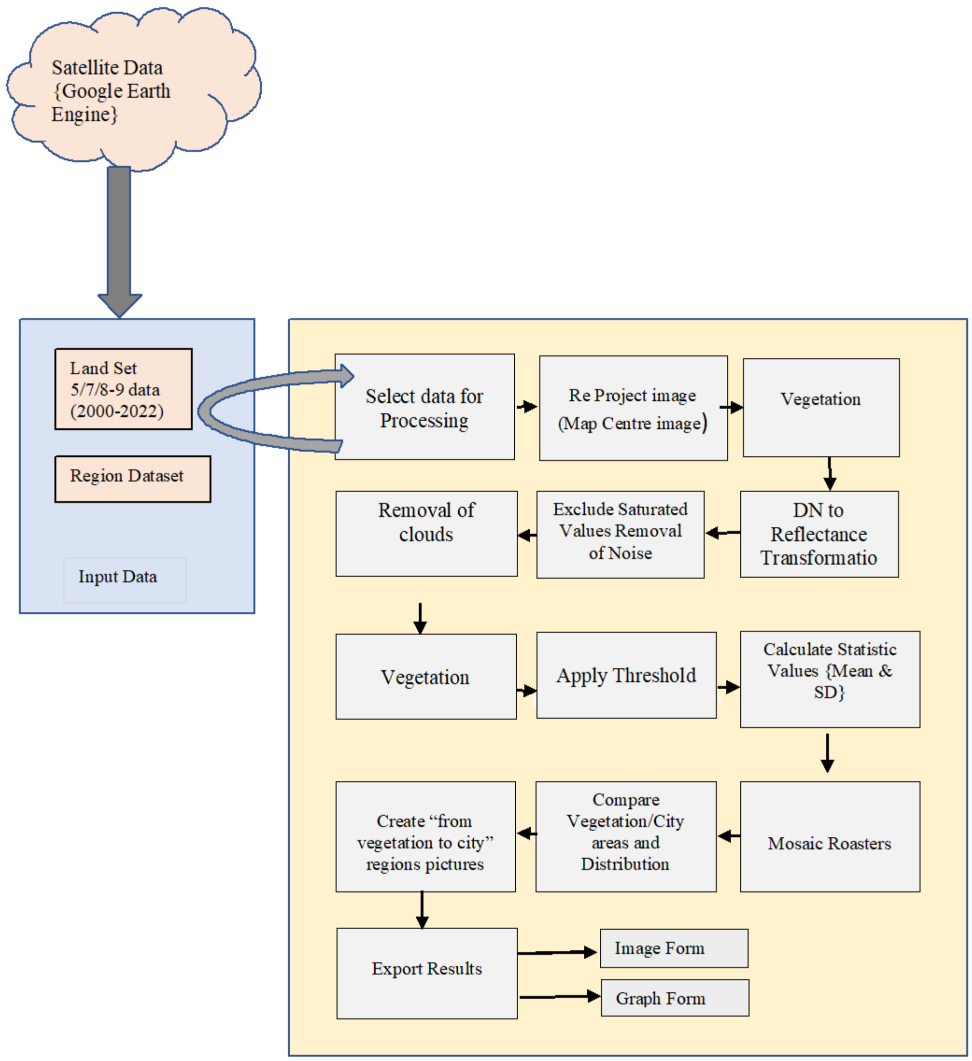

Fig. 2. Methodology used in research.

TABLE I. BAND USES FOR CALCULATING CHANGES IN FOREST COVER

Landsat Datasets	Blue	Green	Red	Near Infrared	SWIR 2
Landsat 5 TM (Band number: Wavelength)	B1: 0.45–0.52	B2: 0.52–0.60	B3: 0.63–0.69	B4: 0.76–0.90	B7: 2.08–2.35
LANDSAT 7 ETM+ (Band number: Wave-length)	B1: 0.45–0.52	B2: 0.52–0.60	B3: 0.63–0.69	B4: 0.77–0.90	B7: 2.08–2.35
Landsat 9 OLI (Band number: Wavelength)	B2: 0.45–0.51	B3: 0.53–0.59	B4: 0.64–0.67	B5: 0.85–0.88	B7: 2.11–2.29

V. RESULT

Vegetation Indices (VIs) combine surface reflectance at two or more wavelengths to emphasize a specific characteristic of vegetation. They are created using vegetation's reflective qualities. Each VI is intended to calculate a specific characteristic of the vegetation. Every VI needs accurate reflectance readings from multispectral or hyperspectral sensors. The spectral bands sampled in the input dataset dictate which VIs can be generated on that dataset. A VI is accessible for the dataset if it has all the spectral bands necessary for that index. Some place is used to calculate density by using the normalized difference vegetation index.

NDVI is frequently used in agriculture, forestry, and the environment to track the development and well-being of vegetation as well as to spot stressed or damaged areas. In addition to mapping and categorizing different vegetation types, NDVI values can be used to track changes in vegetation cover over time. Fig. 6 shows the change occurring in NDVI value on the study area over the period of time. Every time it is changed with time but in the year 2022- 2023, this data is changed more number times. Enhanced Vegetation Index (EVI) [19] is also a mechanism for measuring vegetation greenness that is similar to the Normalised Difference Vegetation Index (NDVI). EVI, on the other hand, compensates for some atmospheric

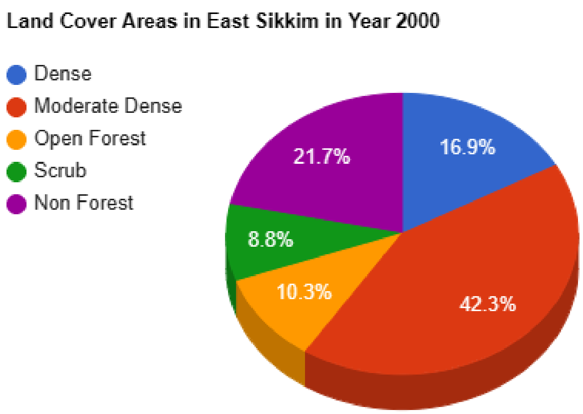

Fig. 3. Forest cover area of East Sikkim in the year 2000.

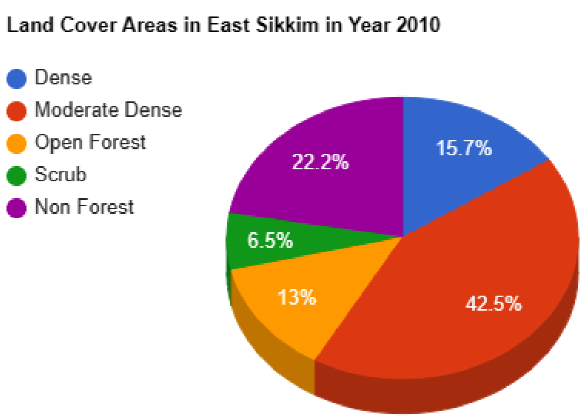

Fig. 4. Forest cover area of East Sikkim in the year 2010.

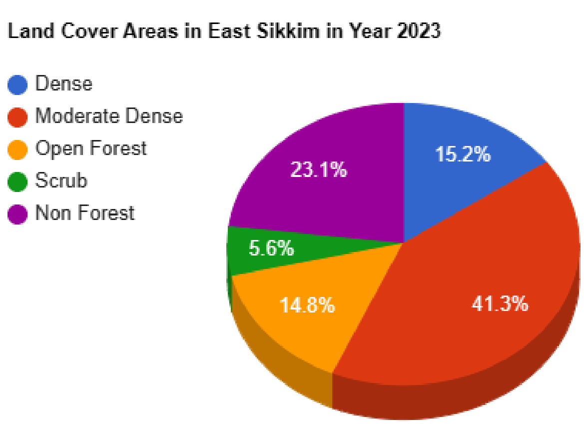

Fig. 5. Forest cover area of East Sikkim in the year 2023.

factors and background noise from the canopy and is more sensitive in regions with dense vegetation. EVI also provides producers the ability to precisely compare data and monitor changes. These comparisons are quick and simple thanks to the use of our vigor items scaled to an absolute standard. Fig. 7 provides a change in the study between the years 2000 to 2023. EVI values are changed rapidly between these years. Later for verification purposes, we calculate the change in the study area using the ensemble-based [20] classification algorithm random forest [21] and find nearly 10% of land cover classes are changing. Later we calculate the change in water content over vegetation in the study area using the normalized difference water index (NDWI) [22], [23]. The Near-Infrared (NIR) and Short Wave Infrared (SWIR) channels are used to create the Normalised Difference Water measure, which is a satellite-derived measure. While the NIR reflectance is influenced by changes in leaf internal structure and dry matter content but not water content, the SWIR reflectance reflects changes in both vegetation water content and the spongy mesophyll structure in vegetation canopies. The accuracy of determining the water content of vegetation is increased when the NIR and SWIR are combined because they eliminate changes brought on by the internal structure and dry matter content of leaves. The spectral reflectance in the SWIR region of the electromagnetic spectrum is substantially governed by the quantity of water present in the interior leaf structure. Therefore, leaf water content has a negative relationship with SWIR reflectance. Fig. 6, Fig. 7, and Fig. 8 show the change that arises over the study area Fig. 1 mainly in the forest region. From Fig. 3, 4 and 5, it is quite clear that deforestation happened over the study area. Still, due to good climate and environmental conditions, this deforestation is not converted into non-forest areas. From the calculation, we find about 10% of forest loss present over the study area. Fig. 9 shows the yearly forest in square meters from the year 2000 to the year 2022. Here if we focus on the output generated by vegetation indices, Fig. 6, 7 and 8, overall mean and standard deviation values are not changed but the pattern of these changes are frequent in the current year. By the above findings, it is figured out that moderate dense forest is higher in comparison to the non-forest area, dense forest area, open forest area, and scrub which is 42.3 %, 21.7 %, 16.09%, 10.3 %, and 8.8% in the year 2000, respectively and it is also analyzed that moderate dense forest area is decreasing year by year due to forest fire which is 42.5 % in the year 2010 which gradually decreasing after decades too. It became 41.3 % in 2023 and for other land areas transformation can also be seen. Dense forests were 16.9 % in the year 2000 which decreased by 15.70% in 2010 and 15.20 % in 2023. The non-forest area is decreasing by these fire incidents and it is clearly shown by the graph that it was 21.7 % in 2000 which increased to 22.20 % in 2010 and 23.10 in the year 2023. Open forest area is also increasing by the incident of forest fire while scrubs are continuously decreasing. By the Fig. 10, it is concluded that open forest area is gradually increasing i.e. 10.3% (2000), 13 %(2010), and 14.3 % (2023). In this proposed study area it is observed that we can generate land cover area loss or affected parameters by forest fire by using this developed tool or framework on any land with approximately similar spectral indices.

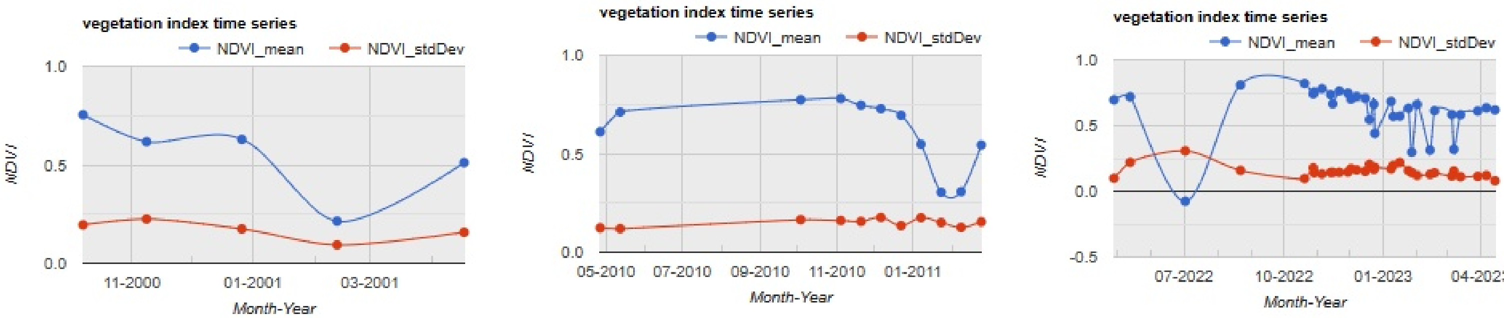

Fig. 6. Change in normalize difference vegetation index between the year 2000-2023.

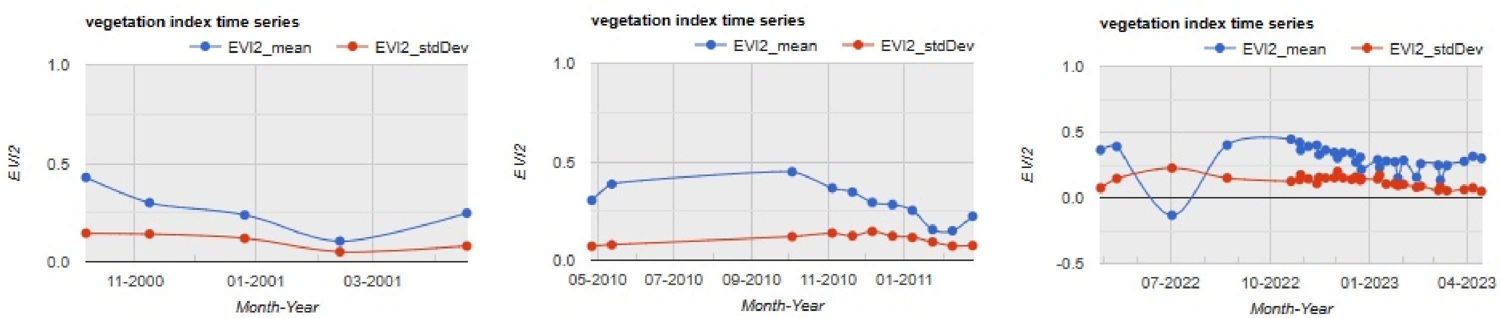

Fig. 7. Change in enhanced vegetation index between the year 2000-2023.

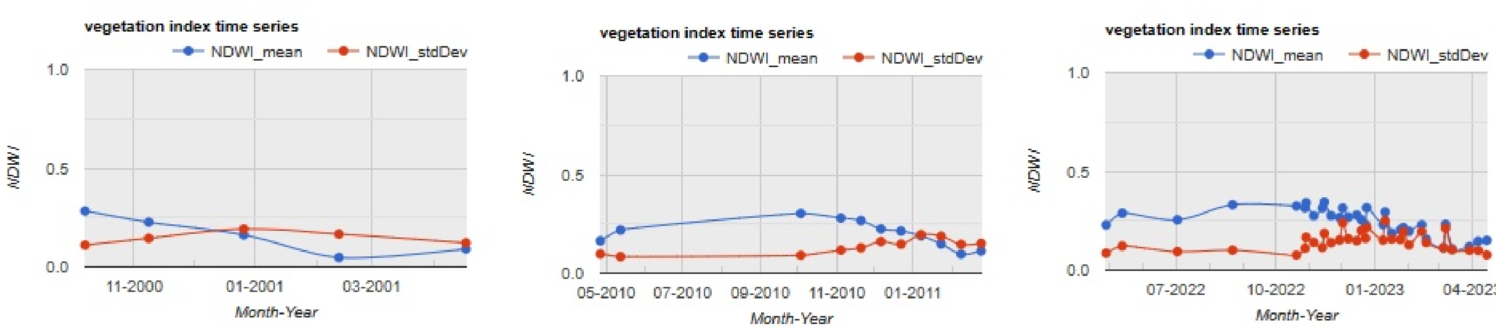

Fig. 8. Change in NDWI between the year 2000-2023.

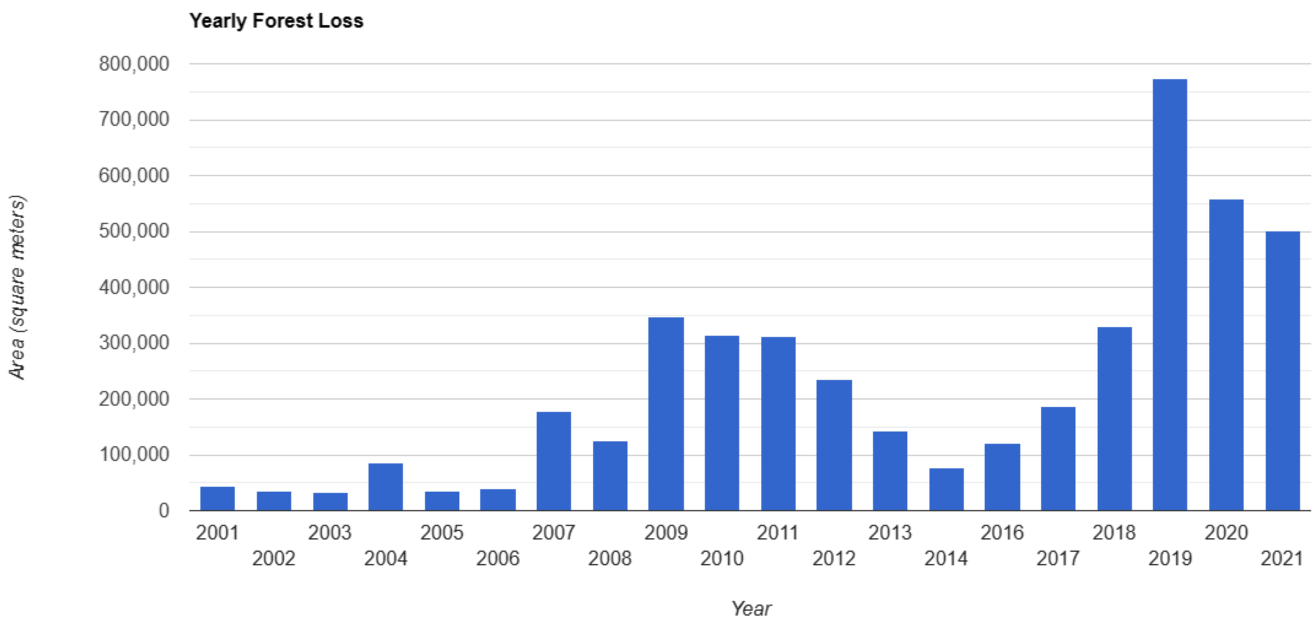

Fig. 9. Yearly forest loss between the years 2000- 2023.

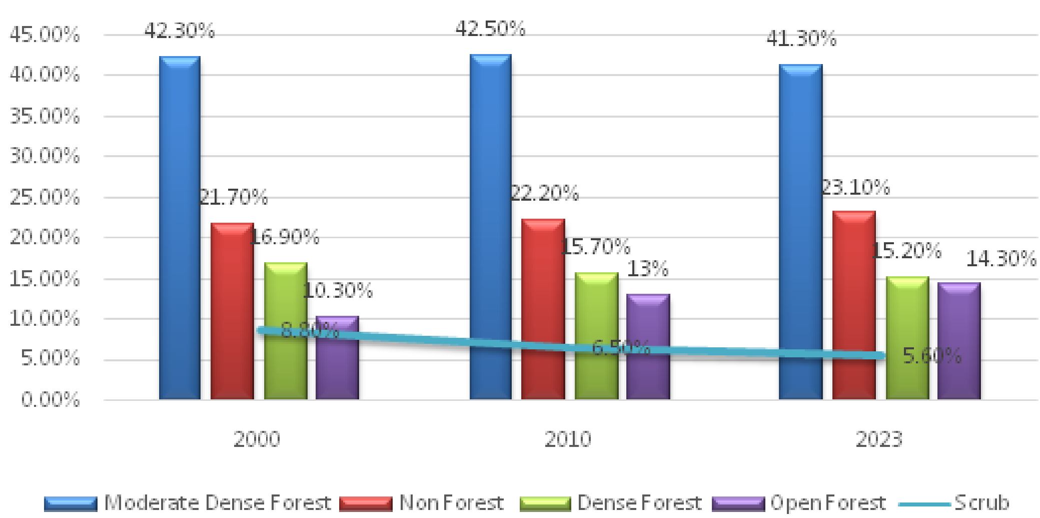

Fig. 10. Change in LULC areas between the years 2000-2023.

VI. Conclusion

The ability to perform high-frequency time series analyses using new-generation multi-spectral sensors aboard the Landsat 5, Landsat 8, and landsat 9 satellite platforms opens up previously unheard-of possibilities for multi-temporal change detection studies on phenomena with significant dynamic behavior (for example, high-frequency mapping for disaster management) or on regions with recurring cloud cover issues. These new sensors' radiometric properties, while similar, are not equivalent, and this might result in noticeable variations in the radiometric amounts that are received. Forest changes are easily computed using these vegetation indices, and verified by using supervised classification results and global forest loss computation technique. Later our objective is to develop a GUI that calculates the change in vegetation indices. There are nearly more than 97 vegetation indices available that may be used for computing change in vegetation. These indices will be very help full for finding changes in climate conditions, environmental deterioration, Soil erosion, and many places.

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