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Estimate the Rate of Change in Forest Cover and Its Impact on Soil by Using GIS And Remote Sensing, A Case Study of Gadchiroli District, Maharashtra

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ABSTRACT

The forest is an essential aspect of the environment. It contributes significantly to the nation's economic, social, and environmental well-being. However, deforestation, population growth, unscientific urbanisation, rising trend of industrialisation, increasing mining activities, agricultural land use, shifting cultivation, and effects on soil, water, and biodiversity resulting from unsustainable human activities, among others, pose a severe threat to these forests. As a result, it is critical to develop policies that promote sustainable forest management, prevent desertification, halt and reverse land degradation, and halt biodiversity loss. Because of satellite remote sensing, humans have been able to monitor and gather information about the Earth's surface at many spatial and temporal scales. Within the Gadchiroli district of Maharashtra state, India, this project aims to determine the forest cover change and detect the spatiotemporal altering paradigms of the forest. Using Landsat 5 and Landsat 8 data with 30 m spatial resolution, various indices such as Normalized Difference Vegetation Index, Enhanced Vegetation Index, and Bare Soil Index Scaled Shadow Index were utilised to highlight the geographical pattern of Forest cover change detection. Several multi-temporal data (1989, 2004 and 2019) were employed to show the change in forest cover in the research area. The results demonstrate that between 1989 and 2019, the forest crown cover decreased. It is also said that throughout 30 years (1998 – 2009), 933 km2 of land was degraded. During the study period (1989 – 2019), it was noticed that highly thick forest areas decreased over time, whereas non-forest areas expanded continuously.

INTRODUCTION

Changes in forest cover are a dynamic, general, and accelerated process driven primarily by natural phenomena and anthropogenic activities, which in turn produce changes that would affect the natural ecosystem. Understanding forest patterns, changes, and interactions between human activities and natural phenomena is essential for proper forest management and improved decisions. Today, satellite data is very applicable and helpful for forest cover change detection studies. Detecting forest conditions and monitoring changes in various biophysical and structural variables of the forests can provide an accurate understanding of forest ecosystem services. Forest cover change monitoring is one of the main applications of remote sensing-based change detection. (Abyot Yisman, et.al. 2014). Forests have been degraded in recent years due to the industrial and agricultural revolutions; therefore, proper scientific land-use planning is essential for forest resource conservation (Crist & Cicone, 1984). Changes in density should be considered for improved forest management. Forest canopy density is one of the most important characteristics when planning and implementing a rehabilitation programme. It is possible that the size of the forest has not changed over time, but the density of the forest canopy has. (Zahara Azizi and colleagues, 2008). Deforestation in India is the massive destruction of the country's major forests. Environmental deterioration by stakeholders such as farmers, ranchers, loggers, and the Plantation Corporation is the primary reason. Deforestation began with the development of agriculture, but it worsened in the eighteenth century when British commercial forestry operations destroyed trees in Kerala, Tamil Nadu, and Karnataka's montane regions. Agriculture has almost totally deforested the Gangetic plains. Debris pushed down slopes due to the careless usage of excavator machines for road widening, and new road construction has utterly ruined extensive parts of the Himalayan forest. Trees are being cut down as a critical fuel source due to colonisation from all over the country. These trees are employed in the preparation of food. Land degradation is a key source of concern since it reduces an ecosystem's productive capability. It also impacts the global climate due to changes in the water and energy balances and disruptions in the carbon, nitrogen, sulphur, and other element cycles (Barbier EB, 2000). Soil degradation causes political and social instability, increased deforestation, intensive use of marginal and fragile lands, accelerated overland flow, runoff, soil erosion, pollution of natural waters, and emission of natural greenhouse gases into the atmosphere due to its impact on agricultural productivity and the environment. Land deterioration impacts human activity (2017, Obalum S et al.).

Forest cover change using GIS and remote sensing: A Spatio-temporal research on komoto protected forest priority area, East Wollega zone, Ethiopia," by Milkessa Dangia Negassa et al. (2020). He finds a dramatic increase in agricultural land from (24.78per cent) in 1991 to (33.5 per cent) in 2019, with an annual expansion rate of (23.68 per cent per year, while forest cover declined from 20.1 per cent in 1991 to 37.38 per cent in 2019, with an annual decreasing rate of 4.18 per cent per year, in his LULC detection. However, he concluded that the massive drop in forest cover change is frequently linked to agricultural expansion in the forest's periphery. In his article, he also mentions that other issues contributing to forest cover loss include timber extraction and charcoal manufacturing. Forest Cover Change Estimation Using Remote Sensing and GIS-A Study of the Subarnarekha River Basin, Eastern India," Pratik Deb and

Objectives:

1. To estimate the rate of change of forest canopy from 1989 to 2019.
2. To assess the quantitative and qualitative effects of forest degradation on the soil.

Material and Methods:

The satellite images were obtained from the United States Geological Survey (USGS) website. The state of Forest Cover

Ashok Mishra (2016) examined. According to his research, natural forest cover is being transformed into agricultural land and settlements with rising anthropogenic pressure. Between 1987 and 2008, the area of deep forest and open forest decreased by 52.05 per cent and 43.44 per cent, respectively, whereas the area of agricultural land and settlements expanded by 20.71 per cent and 161 per cent. According to Biswajit Bera et al. (2020), Estimation of Forest Canopy Cover and Forest Fragmentation Mapping Using Landsat Satellite Data of Silabati River Basin (India)," Forest Canopy Density and Fragmentation Models are important craftsmanship to examine the health of the forest or vegetation in a given area. Many indices, such as the Normalize Difference Vegetation Index, Advanced Vegetation Index, Shadow Index, Bareness Index, and weightage overlay analysis methodologies, have been used to determine forest health or anthropogenic stress on forest ecosystems. Forest covers evaluation using remote-sensing techniques in Crete Island, Greece, by Mohamed Elhag et al. (2021). Between 1995 and 2005, the measured fall in NDVI was 4%; between 2005 and 2015, it fell by 77.1 per cent, returning to practically its 1995 level. Land degradation was revealed by post-classification change detection analysis in terms of natural vegetation losses with sparser or even no natural vegetation cover.

Change has been estimated using various hyperspectral and multi-spectral satellite imageries with high spatial resolution, such as the Operational Land Imager (OLI), Enhanced Thematic Mapped (ETM), and (TM). The Landsat 5 and Landsat 8 OLI (Operational Land Imager) are used. The table below summarises the specifics of the band combination, including wavelength and resolution.

Bands	Wavelength (Micrometre)	Spatial Resolution (Meters)
Band 1 - Visible Blue	0.45 - 0.52 µm	30 m
Band 2 – Visible Green	0.52 - 0.69 µm	30 m
Band 3 – Visible Red	0.63 - 0.69 µm	30 m
Band 4 – Near-infrared	0.76 - 0.90 µm	30 m
Band 5 – Near-infrared	1.55 - 1.75 µm	30 m
Band 6 – Thermal	10.40 - 12.50 µm	120 m
Band 7 – Mid-infrared	2.08 - 2.35 µm	30 m

Table No 1: Landsat 5 (TM) band Combination.

Landsat 8 (formally the Landsat Data Continuity Mission, LDCM) was launched on an Atlas V rocket from Vandenberg Air Force Base, California, on February 11, 2013. Landsat 8 is the most recently launched Landsat satellite and carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. (USGS)

Bands	Wavelength (micrometres)	Resolution (meters)
Band 1 - Coastal aerosol	0.43-0.45	30
Band 2 – Blue	0.45-0.51	30
Band 3 – Green	0.53-0.59	30
Band 4 – Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30
Band 6 - SWIR 1	1.57-1.65	30
Band 7 - SWIR 2	2.11-2.29	30
Band 8 – Panchromatic	0.50-0.68	15
Band 9 – Cirrus	1.36-1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6-11.19	100

Table No 2: Landsat 8-9 Operational Land Imager (OLI).

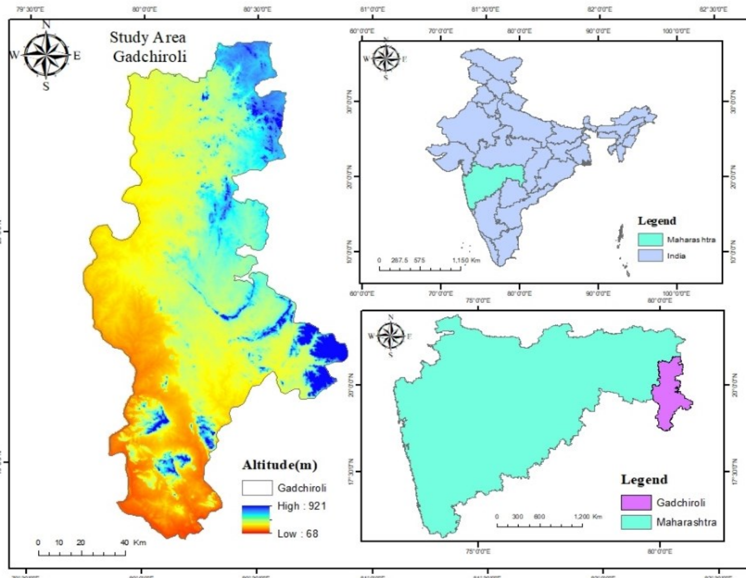
The data were chosen from 1989 to 2019 for January and February. Because the scenes were cloud-free, these were regarded as the best moments. Furthermore, there is enough vegetation and leaf canopy at this time of year to provide spectral information regarding forest cover types. Geometrically adjusted and projected to Universal Transverse Mercator (UTM) zone 44 N, the images are provided. The scenes utilised in the study are detailed in Table no 3.

r	he reference no.	e of acquisition
9	5_L1TP_143046_19890130_20170204_01_T1	01-1989
	5_L1TP_143047_19890130_20170204_01_T1	
4	5_L1TP_143046_20040209_20161202_01_T1	02-2004
	5_L1TP_143047_20040209_20161202_01_T1	

9	8_L1TP_143046_20190101_20190130_01_T1	01-2019
	8_L1TP_143047_20190101_20190130_01_T1	

Table No 3: Details of Data used in the Study

Figure No 01: Location of Study Area



Gadchiroli district is between 18.43- and 21.50 degrees North latitude and 79.45- and 80.53 degrees East latitude. It is located on the north-eastern border of Maharashtra and shares state borders with Telangana and Chhattisgarh. It shares a border with the districts of Bhandara and Gondia on the north, Chandrapur on the west, Rajnandgaon and Bastar in Chhattisgarh on the east and Karimnagar, Bhopalpalli, and Adilabad in Telangana on the south. Gadchiroli is located between 91 and 667 metres above sea level. The major rivers of the Gadchiroli district are the Godavari, Pranhita, Wainganga, Gadhavi, Khobragadhi, Sati, Kathani, and Pohar, which provide adequate river sand. The district's total area is 14,412 square kilometres or approximately 4.68 per cent of the total area. Area of Maharashtra State.

Topography: The topography of the Gadchiroli district is mostly undulating, except for a narrow strip along the Godavari and Pranhita rivers. The district's major physiographic features are the Sirkonda, Bhamragad, Aheri, and Dandkaranya hill ranges, with high to moderate relief. The low-elevation area has rolling terrain with isolated hillocks. The eastern part of the district, which includes Dhanora, Etapalli, Aheri, and Sironcha Taluka, is slightly higher and covered in thick forests. Hills can be found in Bhamaragad, Tipagad, Palasgad, and Surjagad districts.

Basin/Sub-basin and Drainage: The district is located within the Godavari Basin and is drained from the south. The Godavari River is one of the country's major interstate rivers, flowing eastward through Maharashtra and Andhra Pradesh before emptying into the Bay of Bengal. In terms of the catchment area, it is the third largest of our country's fourteen major river basins. Nasik, Aurangabad, Nagpur, Wardha, Nanded, Chandrapur, and Gadchiroli in Maharashtra; Nizamabad, Mancheriai, Ramagundam, Bhadrachalam, and Rajahmundry in Andhra Pradesh; and Seoni and Balaghat in Madhya Pradesh are critical urban centres in the Godavari catchment.

Soil: Soil is the most crucial feature of Physiography, the formation of which largely depends upon the topography of rock types and drainage. The cropping pattern in the area is governed by the thickness of the soil mantle, its texture and constancy. The soils of the Gadchiroli district are of various types. Due to different soil types, various cropping patterns are seen. The soils in the Wardha and the Waingangā valleys are generally the most fertile. The predominant soil cover in the district is clay, clay-gravel, sandy loam, deep black soil, reddish- and yellowish-brown soils on hill slopes, brown and grey soils on plains and Laterite and lateritic soil.

Climatic Conditions: The district's climate is distinguished by a hot summer, evenly distributed rainfall during the southwest monsoon season, and general dryness, except during the rainy season. Winter lasts from December to February, and summer lasts from March to May. From June to September, the southwest monsoon season occurs. The post-monsoon season lasts from October to November. The average minimum temperature is 14.6°C, and the maximum is 42.1°C. The average annual rainfall in the district ranges from 1300 mm to 1750 mm.

Methodology:

Remote Sensing data pre-processing:

Before actual image classification and change detection, satellite images must be pre-processed. This is due to inherent errors in the remote-sensing data acquisition process, such as line dropout, stripping noise, distraction spatial and spectral, and coordinate projections, which change digital values. Landsat images from various sensors and periods were collected from the USGS Earth Explorer website to estimate changes in forest density. Images are converted from a geographical coordinate system to a Universe Transverse Mercator (UTM) for area calculation. During the image processing, the WGS84 datum system was considered. The most crucial factor for satellite data correction and acquisition is atmospheric correction, performed by ERDAS Imagine software.

Image Classification:

Image classification is the extracting and categorising useful information from a multi-band raster image. This extracted information is further helpful in creating a thematic map. Using ERDAS IMAGINE 15, unsupervised classification steps were followed in the present study. Instead of supervised classification, this classification was chosen because it can capture spectral differences which might not be apparent to the analyser or user. The K-mean classifier was selected as the classification algorithm. This classifier uses the given number of classes and locates the given number in the multidimensional measurement, then assigns each image pixel to the cluster whose arbitrary mean vector is closest (Lillesand et al.). The class number was thirty-six (36) with ten (10) iterations and a convergence threshold of 0.95. These prerequisite settings were maintained during the classification of all images. The 36 classes were slowly merged into six land-used and land-cover classes according to the classification scheme provided by the Forest Survey of India (FSI, 2019). The land cover classes are shown and described in Table 4. The False Colour Composition (FCC), various image enhancement techniques, and a high-resolution Google Earth image were used for reference. When it was discovered that some pixels had been incorrectly classified as water, re-coding was performed to classify those pixels correctly. Because of their darker reflection, these pixels were classified as water pixels. They were assigned to the appropriate land cover type using the abovementioned references. However, these pixels could have been misclassified because insufficient information guarantees their true identity. Most darkened pixels were recorded as moderately dense (in high-altitude areas) or non-forest (in low-lying areas).

Forest cover type	Description
Very dense	All lands with tree cover (Including mangrove cover) of canopy density of 70 % and above.
Moderately dense	All lands with a tree cover of canopy density between 40 % and 70 %.
Open forest	All land with a tree covers a canopy density between 10 % and 40 %.
Scrub	All forest lands with poor tree growth, mainly of small or stunted trees, have canopy densities of less than 10 %.
Non-forest	Any area not included in the above classes.

Table No 4: Forest Classification Scheme

Accuracy Assessment:

Accuracy assessment compares the classified image to another data source that is considered accurate or has ground truth data. An error matrix (Lillesand et al.) was used for each image to assess the accuracy of the classification. One hundred random points were used for each image's accuracy assessment, from which classification accuracies and Kappa statistics were derived. The error matrix compares the reference points to the classified points. "KHAT" statistics measure the difference between the actual agreement within reference data and an automated classifier and the chance agreement between the reference data and a random classifier. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with a completely random classification error. K usually ranges from 0 to 1. K is more significant, which means 0.7, and classification is better than one resulting from chance. If K= 0, classification is no better than a random assignment of pixels. K can also be negative, which indicates very poor classification performance.

$$K = \frac{\text{Observed accuracy - Chance agreement}}{1 - \text{Chance agreement}}$$

$$\text{User Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the row total)}}$$

$$\text{Producer Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the column total)}}$$

$$\text{Overall Accuracy} = \frac{\text{Total number of correctly classified pixels (Diagonal)}}{\text{Total number of reference pixels}}$$

Conceptual Framework and Data Processing

Several environmental phenomena must be considered to assess the catchment's LULC instabilities. These phenomena were derived from remote sensing data to understand inter-phenomena relationships.

I. **Normalized Difference Vegetation Index:**

The drought condition is closely related to the Normalized Difference Vegetation Index (NDVI) derived from remote sensing data. The distinct colours of visible and near-infrared sunlight reflected by the plants are observed to determine the density of green on a patch of land. It always ranges between +1 and -1 and indicates an area's appropriate vegetation health condition. The higher the NDVI value, the better the vegetation. The lower the value, the poorer the vegetation. Values greater than 0.4 indicate that the vegetation is in good condition. The differences between the near-infrared and red bands are also used to calculate NDVI values across an area. (Gandhi, 2015)

$$NDVI = \frac{NIR - R}{NIR + R}$$

NIR is a near-infrared band, and R is a red band.

II. **Enhanced Vegetation Index:**

The enhanced vegetation index (EVI) is an 'optimal' vegetation index that decouples the canopy background signal and reduces atmospheric impacts to improve the vegetation signal with greater sensitivity in high biomass regions and improved vegetation monitoring. The EVI ranges from -1 to 1, with healthy vegetation often falling between 0.2 and 0.8. EVI accounts for air aerosol scattering with coefficients C1 and C2 and soil and canopy background with coefficient L.

$$EVI = 2.5 * \left(\frac{(NIR- R)}{(NIR+C_1) * (R-C_2) * (B + L)} * 100 \right)$$

Where NIR is the near-infrared atmospherically corrected band, R is the red band, B is the blue atmospherically corrected band and C1, C2 and l are coefficients correct to the atmospheric condition of EVI product, C_1= 6, C_2= 7.5 and L= 1.

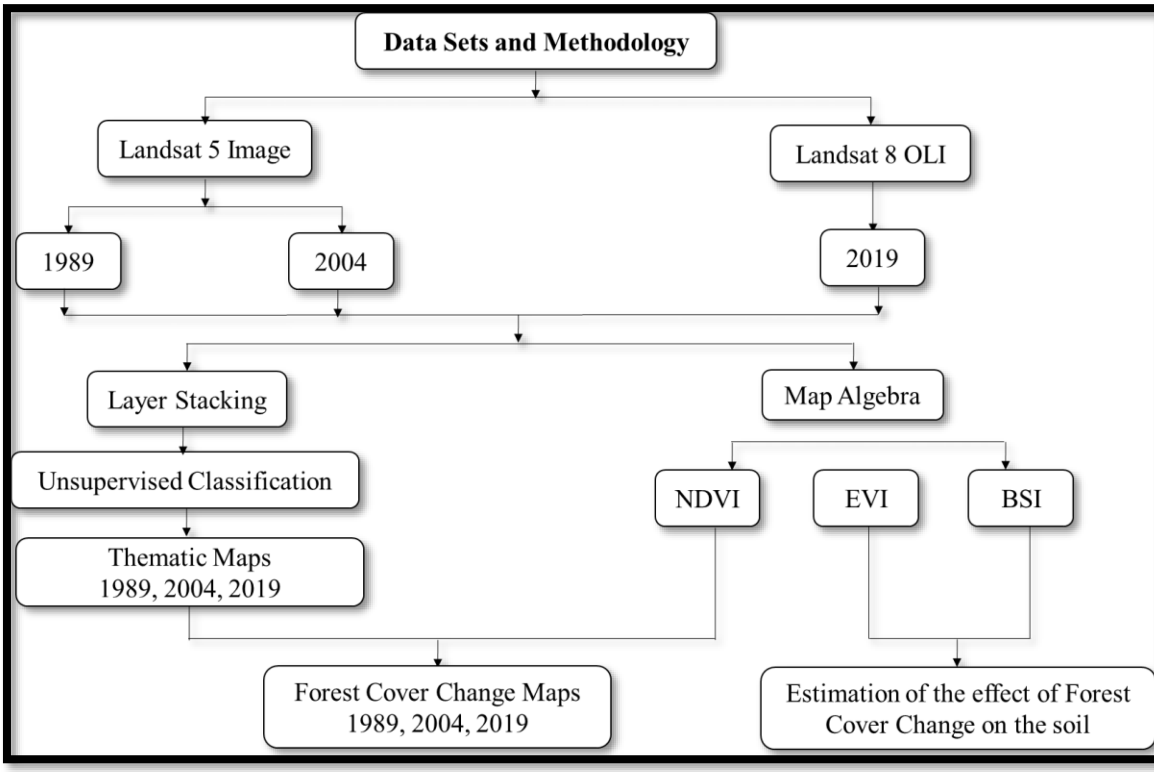
III. **Bare Soil Index:**

The Bare Soil Index (BSI) is a numerical indicator that captures soil differences by combining blue, red, near-infrared, and short-wave infrared spectral bands. These spectral bands are normalised before being used. The blue and near-infrared spectral bands are utilised to highlight the presence of plants, while the short-wave infrared and red spectral bands are used to measure the soil mineral composition. The equation was used to compute the BSI (Roy et al., 1996)

$$BSI = \frac{(SWIR + RED) - (NIR + BLUE)}{(SWIR + RED) + (NIR + BLUE)}$$

Where, SWIR- Short Wave Infrared,
NIR- Near Infrared

Flowchart No 01: Data Base and Methodology



Result and Discussion
Image Classification:

The result of unsupervised classification shows that the classification was accurate. The overall accuracy was 89 %, 89 %, and 93 % for unsupervised 1989, 2004 and 2019 classifications. According to Anderson et al. and Singh et al., the overall classification for all the images was above the minimum acceptable threshold of 85 %. The Kappa coefficient values were 0.80, 0.80, and 0.90 for 1989, 2004 and 2019, respectively. These show a good agreement between original imagery and classified images. All these are acceptable values; they could have improved the result by collecting field reference data. Table 5 shows the result of unsupervised classification.

Year	Overall accuracy (%)	Kappa coefficient
1989	89	0.80
2004	89	0.80
2019	93	0.90

Table 5: Unsupervised classification results.

Assessment of Forest cover changes during the period 1989 – 2019:

In 1989, it was observed that around 10,757.52 km2 were under the forest cover of the Gadchiroli district, which is 74% of the total District area. 2004 around 10,408 km2 of areas (71.8%) were under forest. The year 2019 showed that the forest-covered area was around 9824 Km2, 68% of the total district area. The total 933 Km2 (6.44%) areas have been degraded during 30 years (1989–2019). There was a negative tendency and an unpleasant indication for the physical environment, especially biodiversity. The forest was categorised into three classes in 1989, 2004, and 2019: highly dense, moderately dense, and open. In 1989, 5019.18 Km^2, 4012.12 Km^2, and 1726.22 Km^2 areas were under highly dense, moderately dense, and open forests, respectively. The high percentages of core forest areas indicate low anthropogenic stress over natural resources. It has been executed that in 2004, around 4769.80 Km2, 3771.23 Km2 and 2068.06 Km2 areas were under highly dense, moderately dense, and open forests, respectively. In 2019, around 3425.92 Km^2, 4855.21 Km^2, and 1543.31 Km2 were under highly dense, moderately dense, and open forests. During the study period (1989–2019), it was observed that the highly dense forest area decreased due to continuous human encroachment over a forest time. In contrast, the moderately dense forest has been increased by 843 Km^2. The non-forest area has been continuously increased by 1359.79 Km^2 due to high anthropogenic interference over the forests, the forest has been cut down for agricultural purposes, and there is a loss of forest in the district.

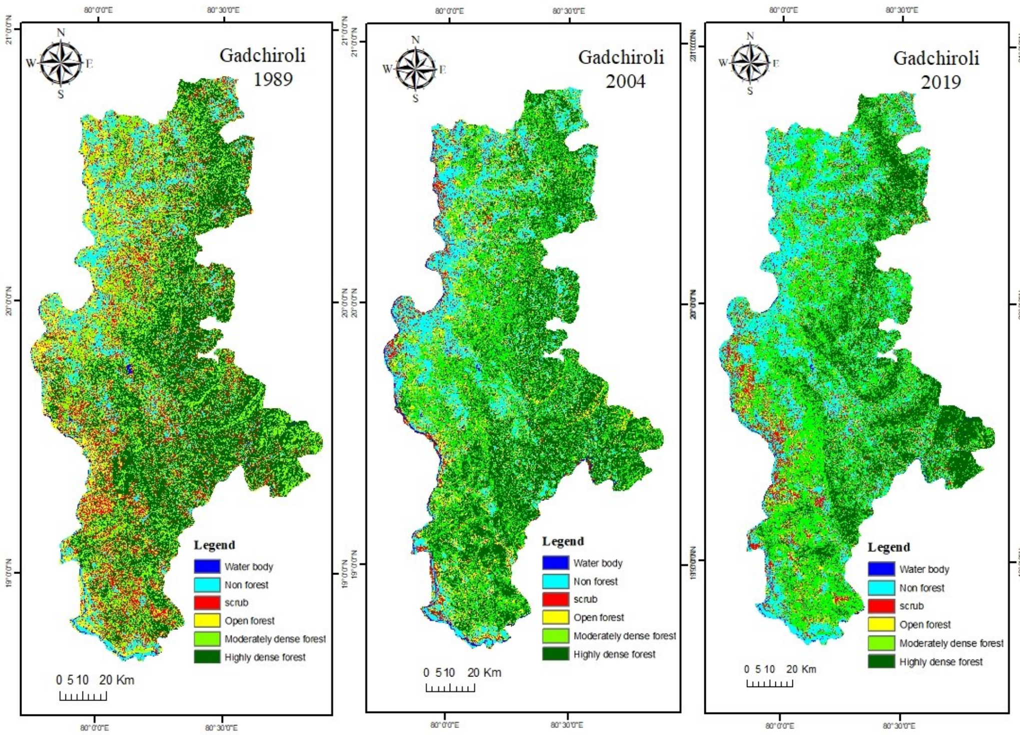
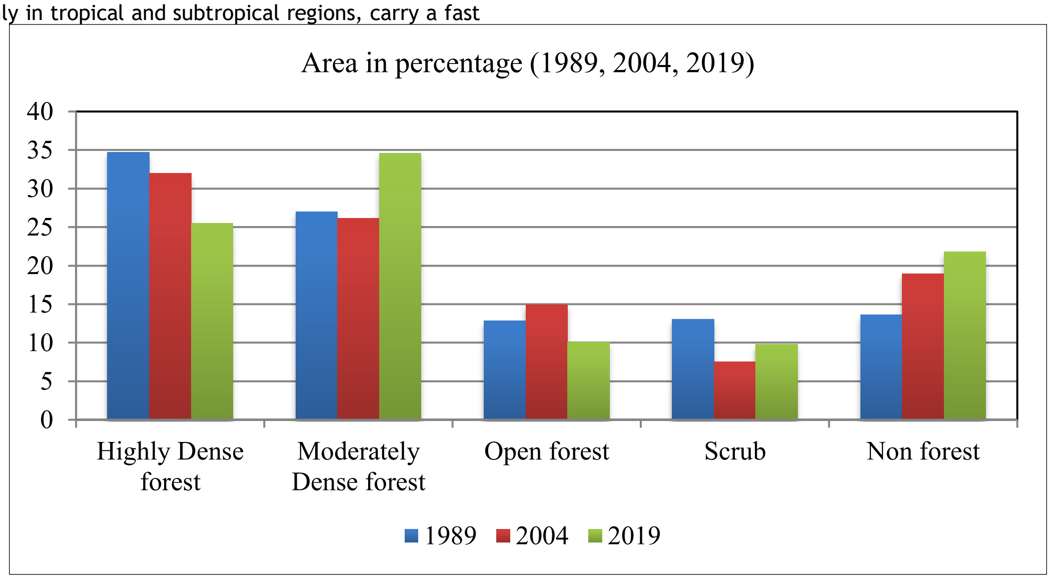


Figure 2: Forest Cover Change Map for the Year 1989, 2004, 2019

From a global point of view, societal development hurts the environment as well as forest regions. The forests are being fragmented due to the execution of some developmental projects such as road construction, building and multiplex construction, construction of the railway, and extension of agricultural land (Southworth et al., 2004; Bera et al., 2020). Unexpected population growth and various anthropogenic activities, mainly in tropical and subtropical regions, carry a fast LULC change. This human-induced land-use change creates a conflict over a forest region (Dutta et al., 2017). The graph no 1 below shows the change detection in the area (percentage) from 1989 to 2019. The graph shows that the dense forest area was reduced by 9% from 1989 to 2019. So, we assume that the area is mainly used for agriculture. We saw that the non-forest area increased by 7 % in 2019 compared to 1989.



Graph no 1: Graph of change in the area (percentage) from 1989 to 2019.

4.2 Normalized Difference Vegetation Index (NDVI):

NDVI is a spectral index that helps differentiate vegetation from other land cover types and determine its overall state. It also allows for visualising vegetated areas and detecting abnormal changes in the growth process. In the Gadchiroli District of Maharashtra, it has been found that the NDVI value varies from -0.9 to 0.8. The NDVI range has been further classified into five different classes. Each class has its threshold value. The highly dense forest class of NDVI is between the value of 0.498 and above. The value of the non-forest area lies in the range of -0.9 to 0.16. This way, a high NDVI value visualised the dense forest area, while a low NDVI shows the non-forest area on the map. These dense forest pockets are identified in the hilly regions of Bhamragad, Etapalli, Dhanora and Korchi tehsil of Gadchiroli District (the eastern border of Maharashtra). Moderate NDVI value is concentrated over the upper and middle courses of the study area. Below 0.165 NDVI values are mainly confined to the less vegetated areas of the Gadchiroli district, while dominated areas show bare land and water bodies. It is observed from the Google Earth view that scrubs and agricultural land mainly occupy the medium and low values of NDVI. Figure no 2 shows the NDVI of 1989, 2004, and 2019, which helps to analyse the changes in an area classified into five classes.

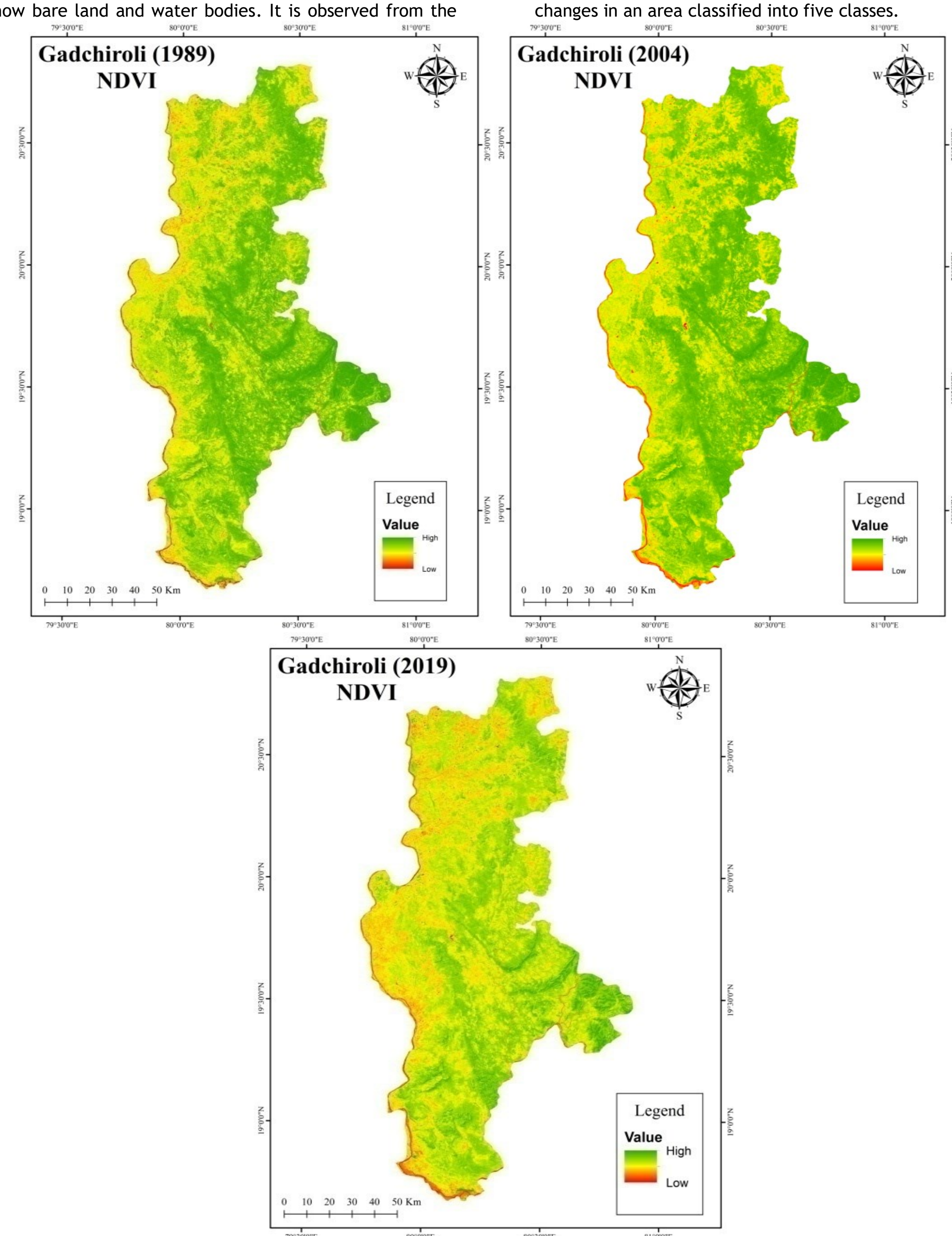
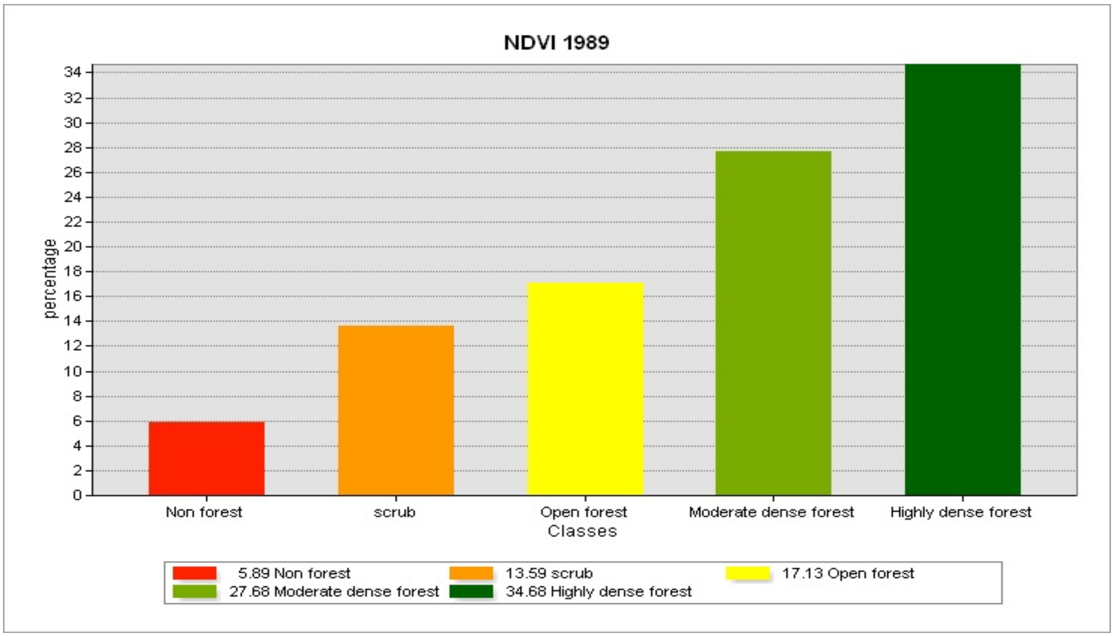
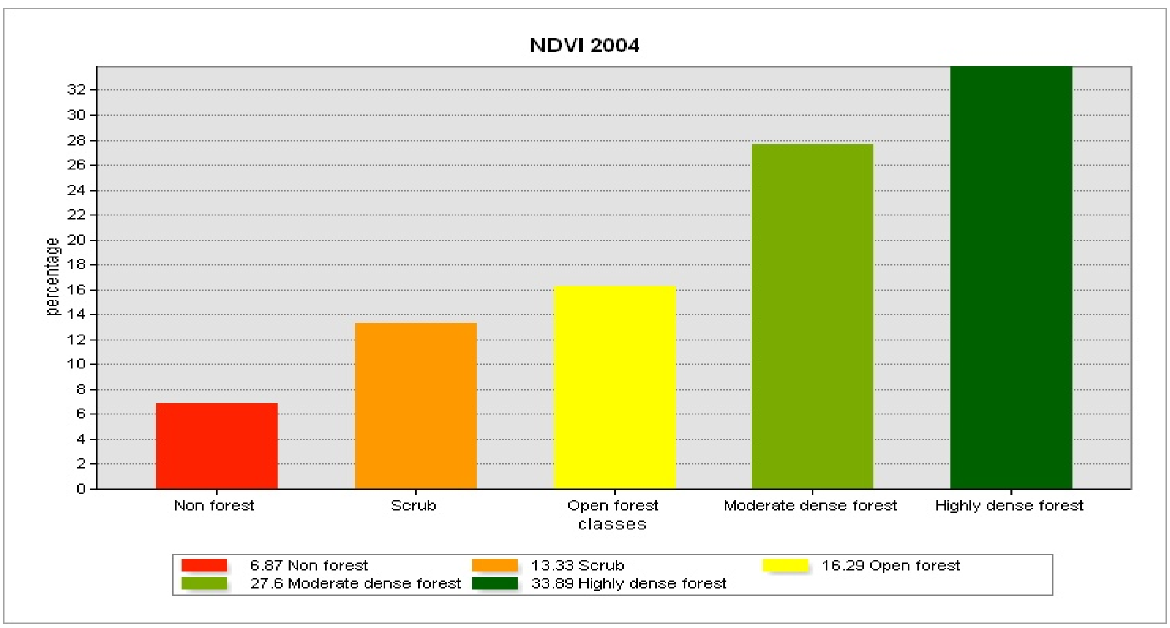


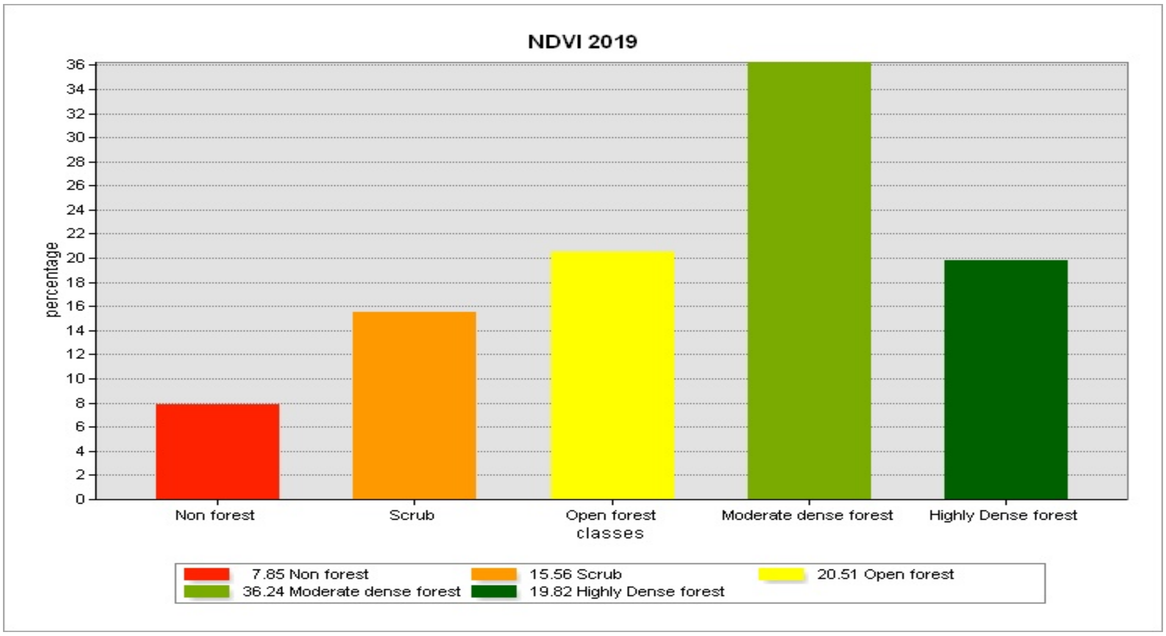
Figure No 3: NDVI of 1989, 2004, 2019.



Graph No 02: Graphical Analysis of Normalize Difference Vegetation Index (NDVI 1989)



Graph No 03: Graphical analysis of Normalize Difference Vegetation Index (NDVI 2004)

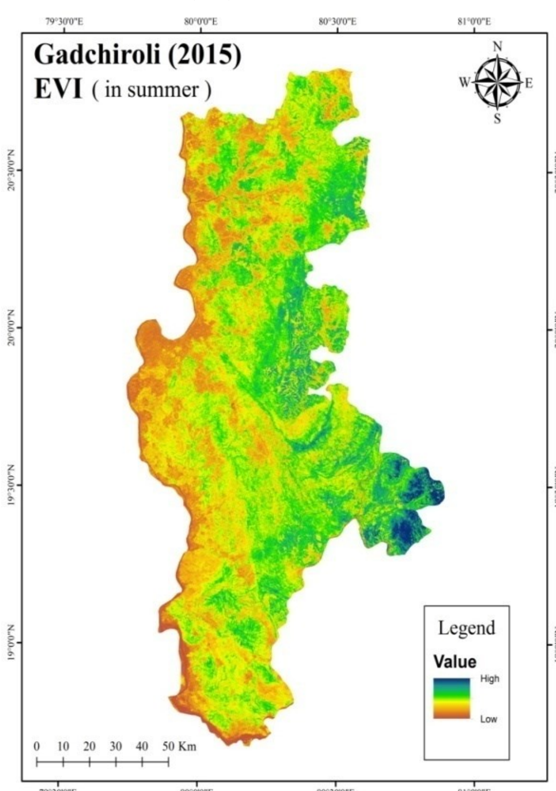


Graph No 04: Graphical analysis of Normalize Difference Vegetation Index (NDVI2019)

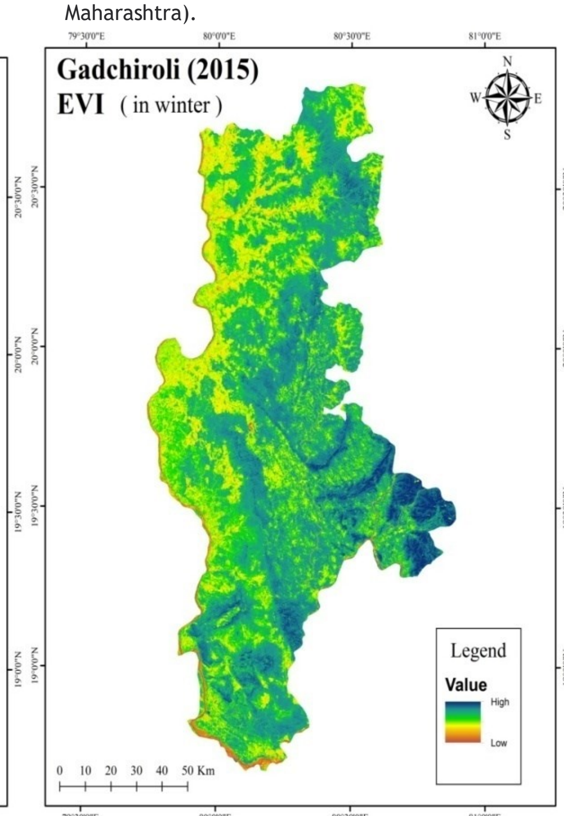
Graph no 02 to 04 shows the quantitative analyses of the NDVI map. From the graph, it can be seen that the density of forests decreased from 1989 to 2019. The forest was degraded by up to 14.86% during the 30 years. Conversely, we observed that the open forest increased by 4%, indicating the increasing agricultural area in the Gadchiroli district. Deforestation is a significant change that has the potential to alter water infiltration and runoff and should, therefore, be further examined. A visual comparison of the three NDVI images gives a good indication of the

4. Enhanced Vegetation Index (EVI):

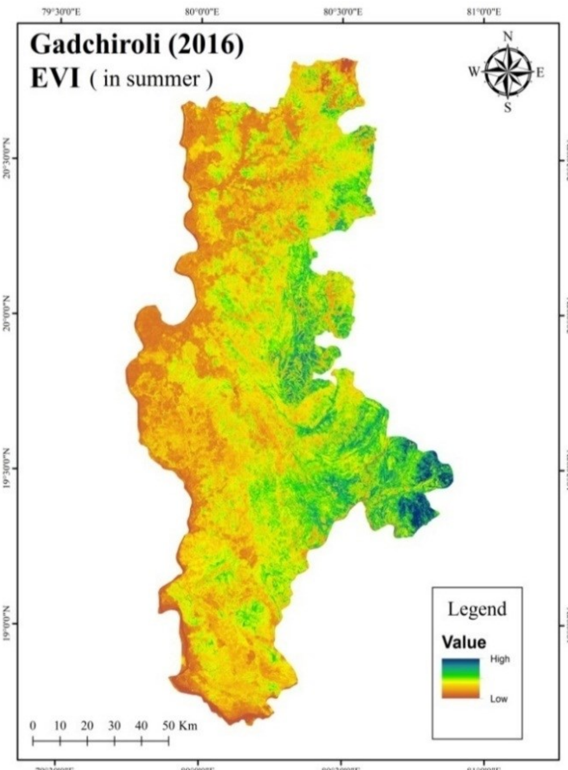
The enhanced vegetation index (EVI) is a vegetation index that has been adjusted to improve vegetation monitoring in high biomass regions by decoupling the canopy background signal and reducing atmospheric impacts. EVI values have been reported to range from -0.98 to 0.84 in Maharashtra's Gadchiroli district. Healthy vegetation is seen in the range of 0.2 to 0.8. We produced the Enhanced vegetation index to estimate seasonal changes in vegetation. As a result, healthy vegetation may be found in the steep areas of Gadchiroli District's Bhamragad, Etapalli, Dhanora, and Korchi tehsils (the eastern border of Maharashtra).

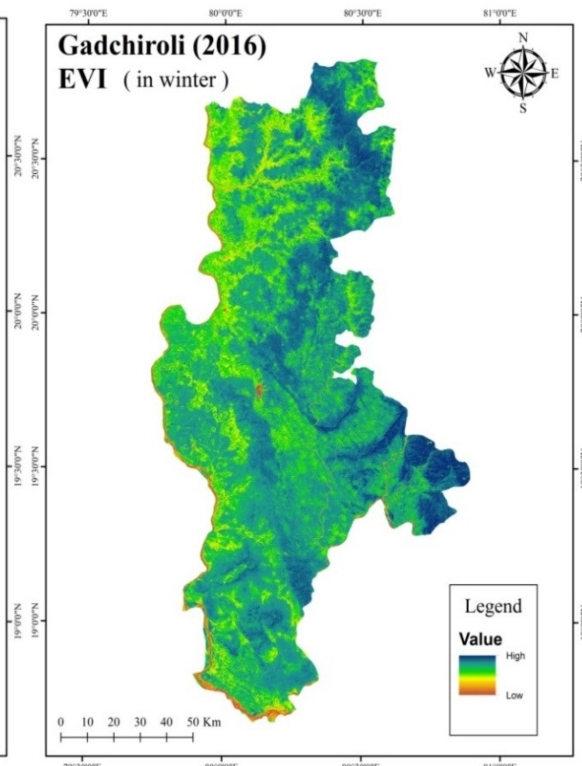


A) EVI 2015 (in summer)



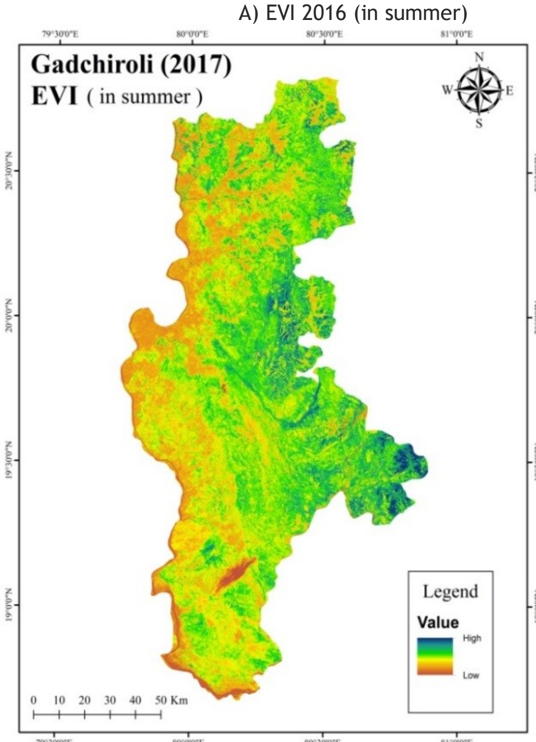
B) EVI 2015 (in winter)

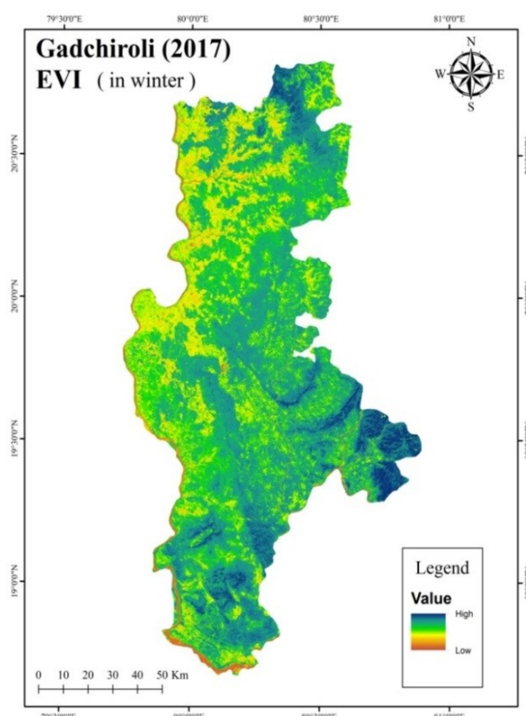




A) EVI 2016 (in summer)

B) EVI 2016 (in winter)



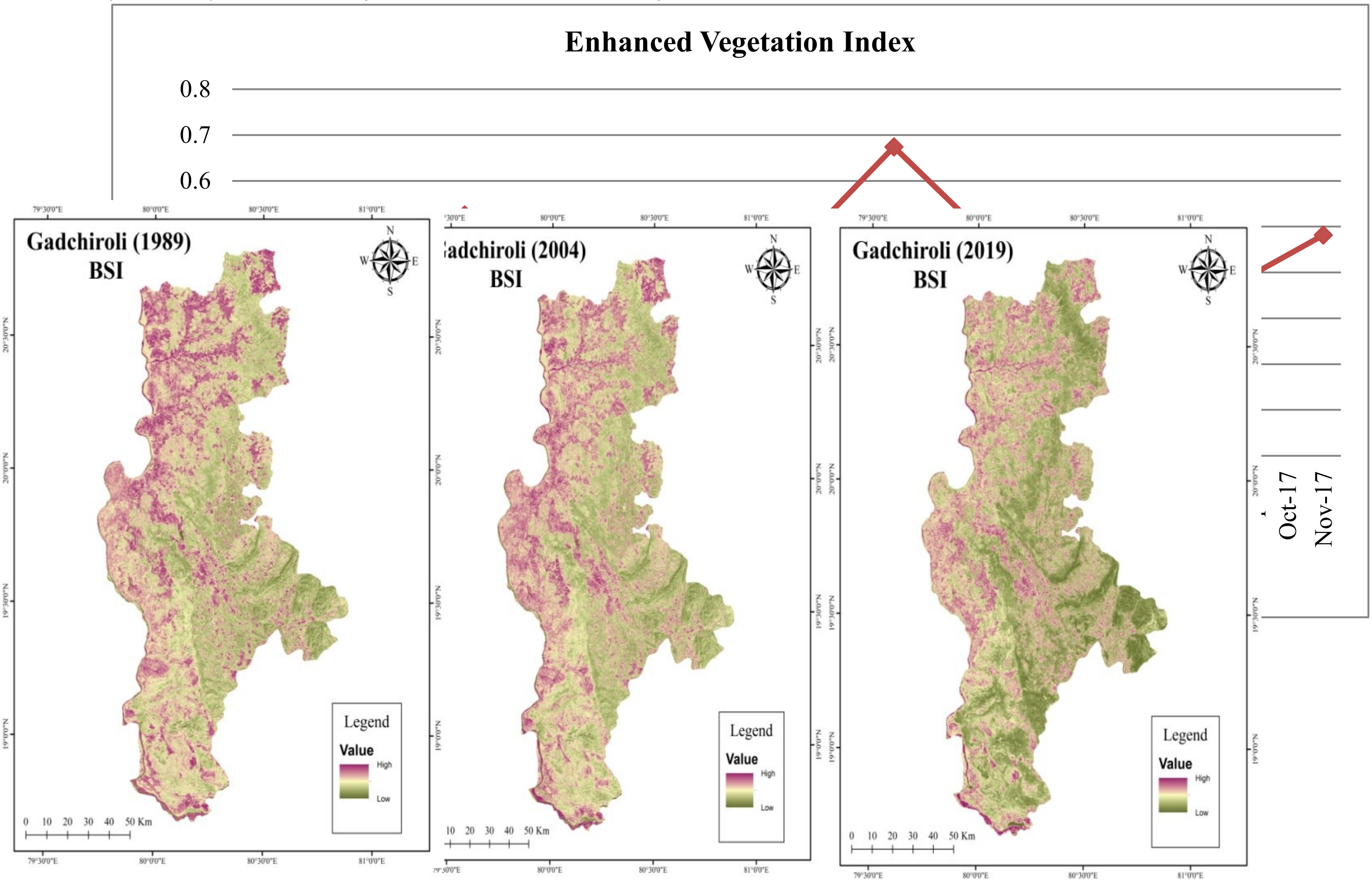


A) EVI 2017 (in summer)

B) EVI 2017 (in winter)

Figure no 4 A,B : Seasonal enhanced vegetation index (EVI) for 2015 – 2017.

The mean EVI results oscillate from 0.48 to 0.76 in the winter season. During the summer, the mean EVI value ranges from 0.18 to 0.24. The value gradually increases in winter while decreasing in summer, producing repetitive seasonal cycles, with each set recorded during the successive yearly cycles due to changes in climatic conditions. These results suggest that EVI values peak in winter, suggesting a dense vegetation canopy that could be justified by cultivated crops and weather. In summer, peak values are low, suggesting that low vegetation (large area with bare soil) is due to the absence of crop cultivation and atmospheric conditions. The seasonal variation in vegetation cover in the study area is comparatively similar for 2015-2017, with the maximum values reached in almost the winter season. From 2015 to 2017, no significant changes occurred in the vegetation cover except for the same slight fluctuation and a minor increase in the EVI values.



Graph No 05: Seasonal variation of enhanced vegetation index (EVI).

4 Bare Soil Index (BSI):

The bare soil index (BSI) is primarily for bare land exaction from satellite data. This index is helpful for the prediction of soil erosion. The range of the bare soil index is between 0.46 to 0.32. As a result, the bare soil index increased from 1989 to 2019. As a result, we saw that the changes in the hilly region of Bhamragad and some other regions of the district were due to forest degradation. We observed that in 1989, the bare soil index was lower than in 2019. It is predicted that if the area has a high barren index, it will show high soil erosion.

5 Correlations between EVI and BSI:

Figure 4.5.6 shows that the bare soil index (BSI) is inversely proportional to the enhanced vegetation index (EVI). As per the results, the enhanced vegetation index increases in winter while the bare soil index decreases. During summer, the bare soil index increases while the vegetation area decreases due to climatic conditions. From the results, we saw that vegetation impact on the soil.

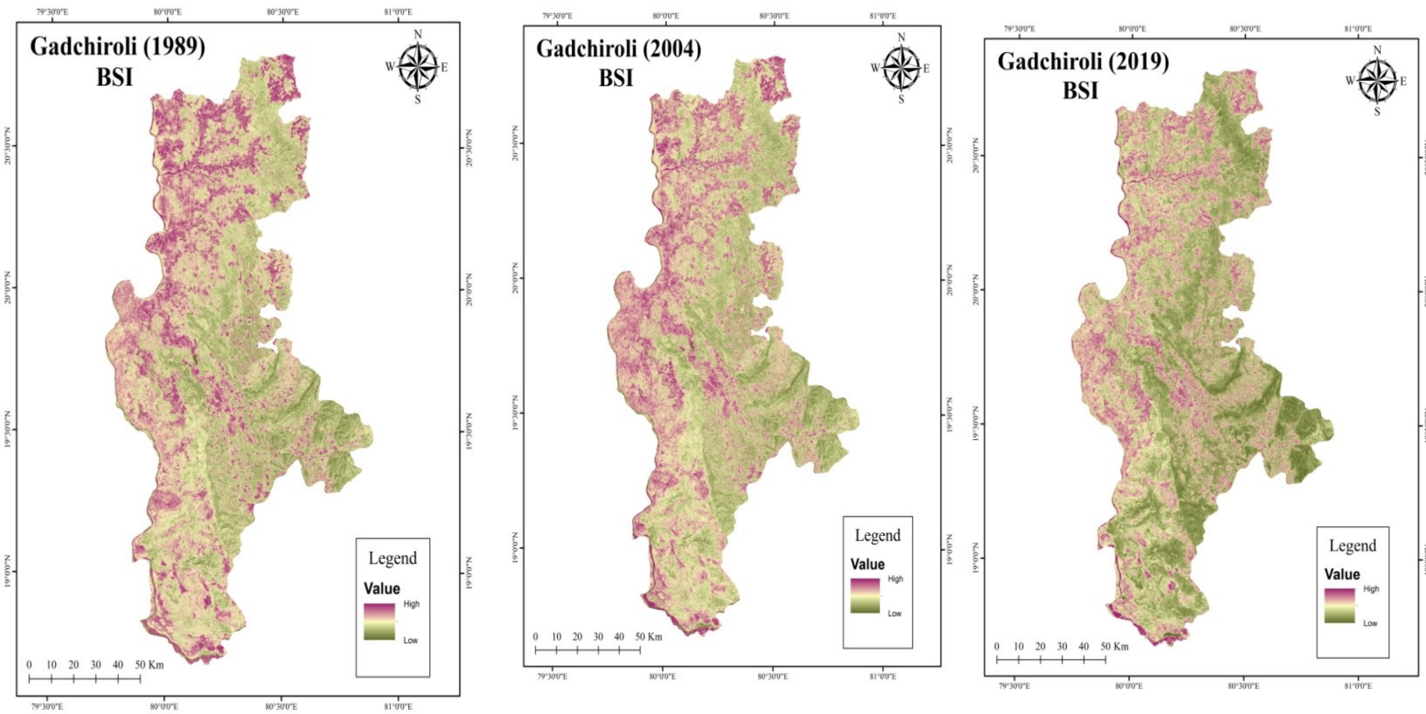
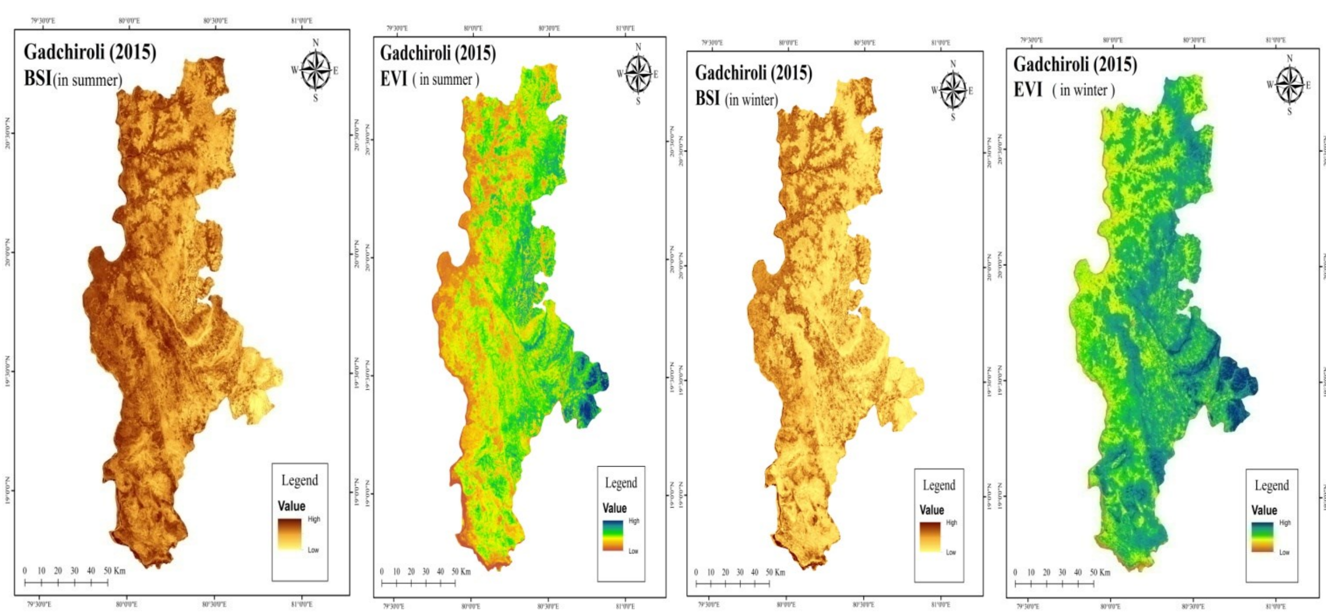
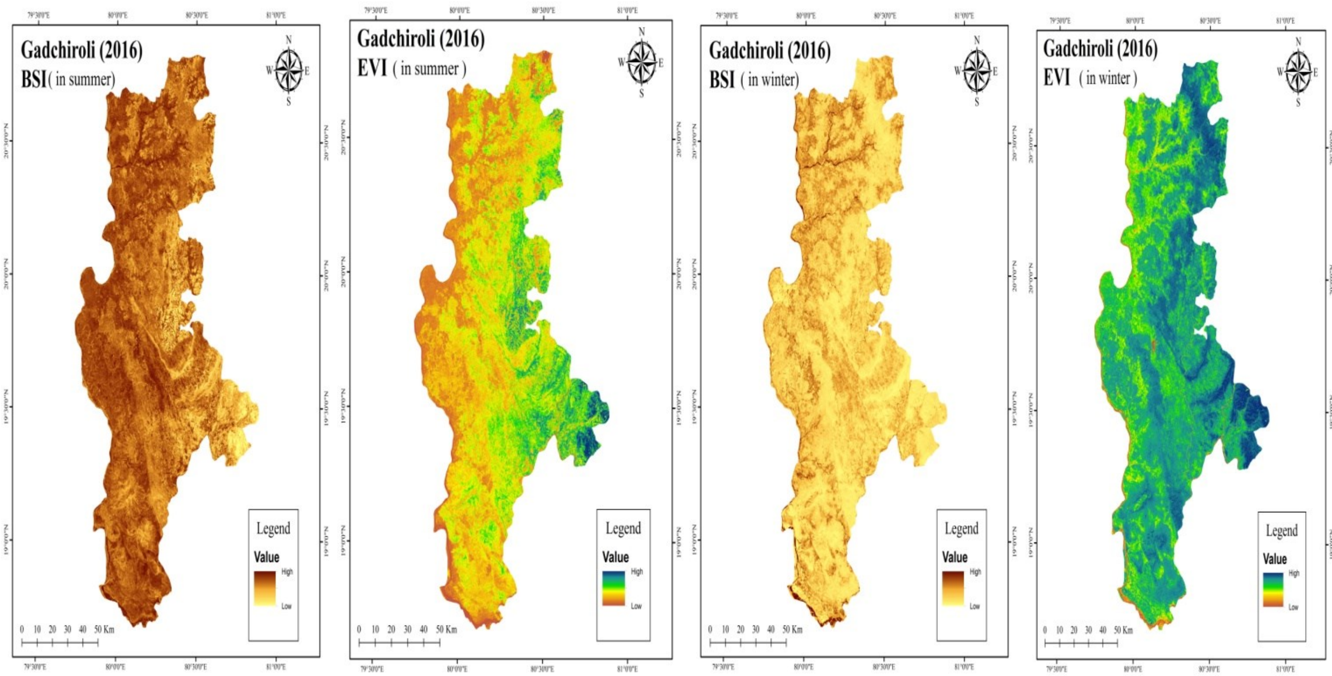


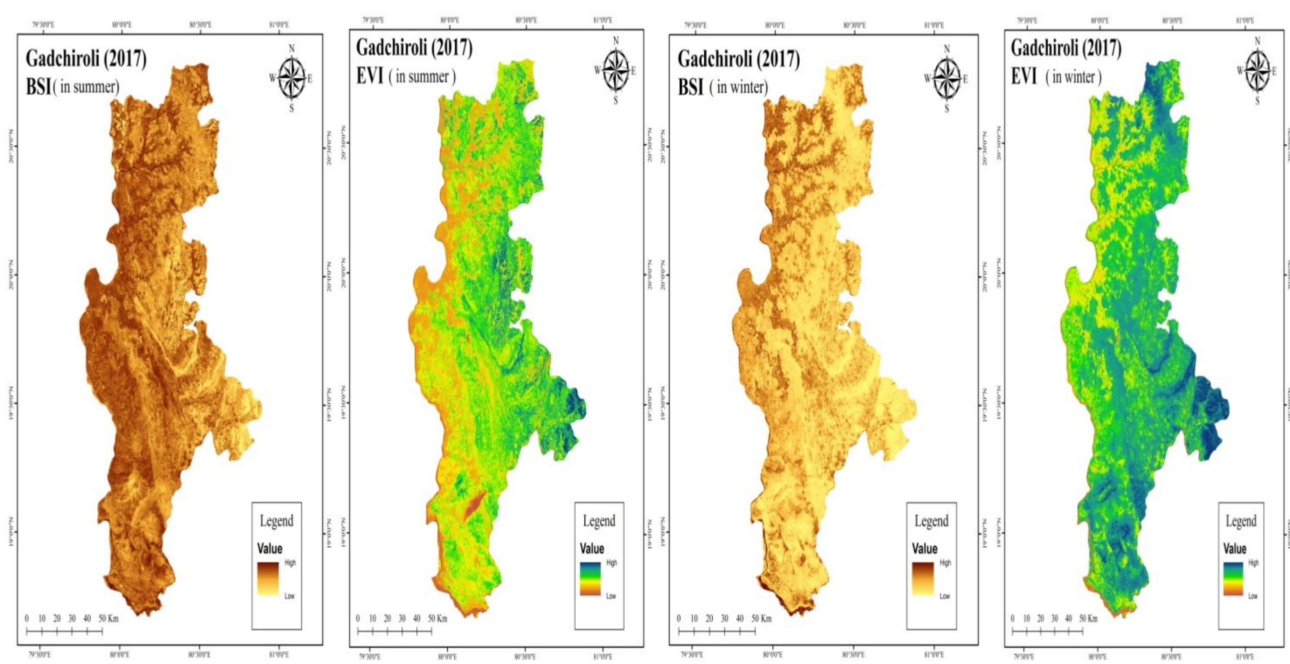
Fig 05: BSI 1989 to 2019



A) **B)** **C)** **D)**



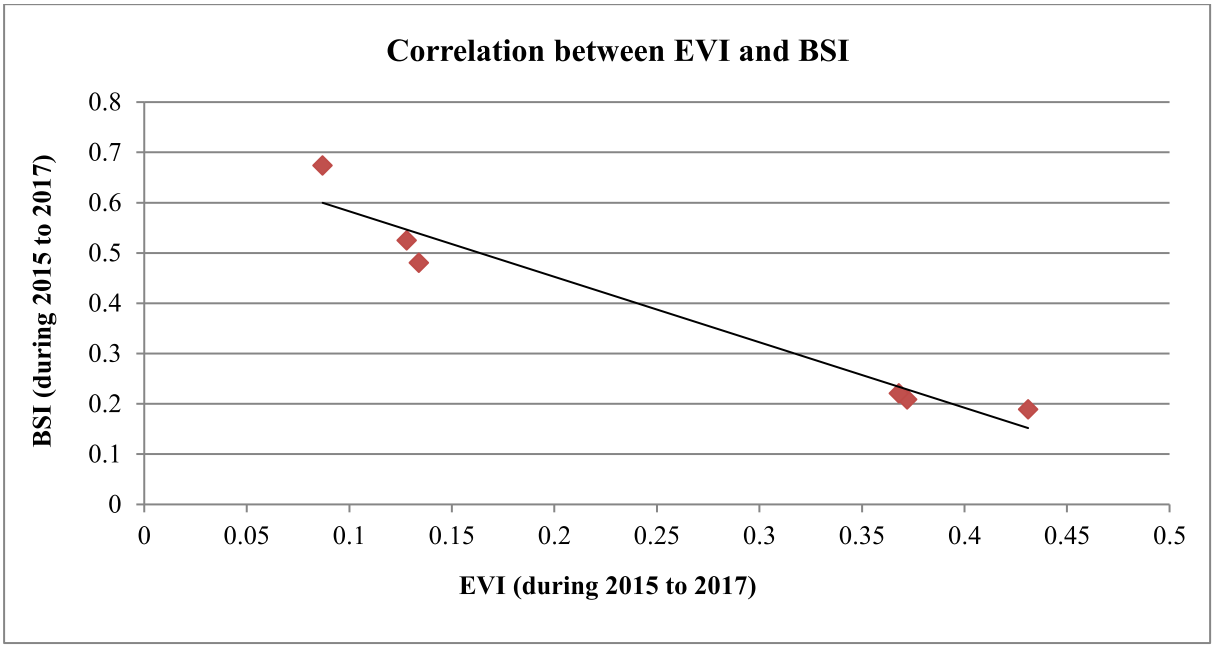
E) F) G) H)



I) J) K) L)

Figure 6: - Correlation between BSI (Bare soil index) and EVI (Enhanced vegetation index).
A) BSI 2015 (summer), B) EVI 2015 (summer), C) BSI 2015 (winter), D) EVI 2015 (winter),
E) BSI 2016 (summer), F) EVI 2016 (summer), G) BSI 2016 (winter), H) EVI 2016 (winter),
I) BSI 2017 (summer), J) EVI 2017 (summer), K) BSI 2017 (winter), L) EVI 2017 (winter).

The above figures show BSI; dark yellow means high bare soil occurs at that place and vice-versa. We saw that where dark green or bluish colour occurs in EVI images at the same place in bare soil index images, the quantity of bare soil occurs less, i.e. light yellow. The occurrence of bare soil is high in places where the vegetation is moderate or less, i.e., yellow or red, as per the figures. We also predict from the figure that cropland occurs in the Gadchiroli district; thus, the vegetation in winter is higher than in the summer. Due to crop harvesting, we saw a significant difference in bare soil from summer to winter. So, we assume that due to crop harvesting, many essential nutrients and soil loss, i.e. soil erosion, occur.



Graph No 06: Correlation between Enhanced Vegetation Index (EVI) and Bare Soil Index (BSI) Graph no 06 shows the inverse relation between bare soil indexes and enhanced vegetation index, in which we show the points from 2015 to 2017 during summer and winter.

CONCLUSION

Researchers conclude that, with the combination of three various indicators, Normalized Difference Vegetation Index, Enhanced Vegetation Index, and Barren Soil Index, this geospatial application-based study focuses on current forest cover change (from 1989 to 2019) in the Gadchiroli district of Maharashtra, India. Higher NDVI and EVI values imply more vegetation or forest cover, while a higher BSI value indicates a lack of forest cover. Forest cover change found that healthy forests have suffered significant degradation, with higher classes of forest canopy density losing more than 70% between 1989 and 2019. A few centres and a few pockets in the Gadchiroli district's north-western portion have largely non-forest areas, resulting in very low FCD values. The forest covers the eastern part of the district, i.e., Dhanora, Etappali, Aheri and Sironcha tehsil. Hills are located in the eastern part of the district, in Bhamaragad, Tipagad, Palasgad, and Surjagad. Similarly, scatter forest rangers are also situated in the upper regions of the district, such as Armori, Wadasa, Kurkheda, and Korchi forest ranger districts. During the study period (1989–2019), it was observed that the highly dense forest area decreased over the period. In contrast, moderately dense forest has been increased by 843 km2, and the non-forest area has been continuously increased by 1359.79 km2. In the year 1989, the total forest cover area was 74 %, while the area was reduced by 6 % in 2009 and the year 2019; the Forest fires, increased mining activities, agricultural land purposes, and urban growth influences can be the reason for deforestation as well as forest fragmentation in the few central pockets and north-western part of the district. People in the Gadchiroli area have expressed a desire to grow various crops in recent years, as farming and animal husbandry have become the primary source of income, contributing to the high incidence of deforestation and soil erosion in the vicinity of regional growth centres. The massive anthropogenic stress in tropical and sub-tropical forest zones can change the pristine forest cover scenario. Although these models have been effectively utilised in various parts of the world, more research and development are required to improve their accuracy. Administrators and policymakers should evaluate such research findings before creating policies for sustainable forest resource conservation and balanced regional growth and development.

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