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Original Research Paper

Spatiotemporal changes of the forest cover in North Eastern Ghat Zone of Odisha, India using Multi-year Landsat data

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Abstract: Forests are essential to the terrestrial ecosystem, which supports a sustainable way of life and economy for people. As a result of their ability to capture atmospheric carbon dioxide and mitigate its worldwide consequences, forests are crucial for halting climate change. In light of this context, the current study's objective is to assess the changes in Land Use & Land Cover (LULC), and forest cover across the North Eastern Ghat Zone (NEGZ) of Odisha, India over 1990 to 2020. Firstly, multi-year preprocessed Landsat data at ten-year intervals (1990, 2000, 2010 and 2020) were collected using cloud computing Google Earth Engine (GEE) platform, and the entire region was divided into five separate classes based on the Normalized Difference Vegetation Index (NDVI) thresholds viz., Very Dense Forest (VDF), Moderately Dense Forest (MDF), Open Forest (OF), and Non- Forest Land (NFL). Through the use of Supervised & Unsupervised technique of classification, five main LULC categories were also established viz., Agriculture, Barren Lands, Forest, Settlements, and Water Bodies. The results infer that the forest cover reduced by 20%, wherein a gradual decrease in the VDF area by 14.21% of the NEGZ was significant during the study period. Unlike the VDF dynamics, the OF coverage showed a slight increase by 4.56% of NEGZ. On the contrary, the settlements area increased by about 130%. However, this study could infer that the expansion of settlements due to population hike is the primary driver of deforestation and forest fragmentation (because the population growth and increased settlements accounted for 97% and 93% of the variability in forest cover). Additionally, it was found that the variation in the forest cover could explain 45% variability of the mean air temperature as indicated by the coefficient of determination. Therefore, by placing special focus on the aforementioned findings and conclusions, we may conclude that the current study may contribute to research on forest management, climate change mitigation, and sustainable development.

Key Words	Google Earth Engine; Land Use Land Cover; Moderately Dense Forest; Open Forest; Very Dense Forest
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1. INTRODUCTION

Forests are recognized as one of the most critical land use categories which play an indispensable role in the terrestrial ecology. According to FAO (2000), forests are those land cover classifications which cover an area of at least 0.5 hectares with a potential canopy cover and tree height of at least 10% and 5 meters respectively. Since forests serve as the foundation for organic carbon synthesis and regulate the water cycle, it influences the climate of an area. Even in the absence of anthropogenic climate forcing, rapid increases in the frequency of extreme weather events pose significant challenges (Subba Rao et al. 2024). Thus, forests have a major role on the sustainable human existence and economy (Shimelis 2017).

From the hydrological perspective, forests have the capacity to recycle rainwater effectively into the atmosphere because of their higher rate of evapotranspiration when compared to other ecosystems. Moreover, forests weaken the hydrological cycle by reducing plant evapotranspiration, downwind precipitation, and cloud formation. Within forests, trees further contribute to the cloud formation by emitting volatile organic compounds which aid as a component for the condensation nuclei (Duku & Hein 2021). As deforestation rates have risen, they are currently at risk of rapid decline (Pielke Sr et al. 2011, Malhi et al. 2022, Gaonkar et al. 2024), contributing significantly to the global loss of biodiversity (Vieira et al. 2008, Giam 2017), resulting in decreasing rainfall and increasing temperature (Lawrence & Vandecar 2015, Lejeune et al. 2015).

Large-scale deforestation disturbs the carbon cycle and the earth's radiative equilibrium because more CO_2 and methane are released into the atmosphere (Lawrence et al. 2022). It also influences the wind turbulence and rainfall pattern variation. So, when forests are converted into other land use classes, the aberrations in rainfall pattern become more profound. The effects of deforestation can be observed at scales ranging from watersheds to continents, and changes in the forests of one country or watershed can impact rainfall in other nations or watersheds as well. Therefore, forest cover represents a significant driver of global and local climate change (Prevedello et al. 2019).

According to the Forest Survey of India (2011), the total forest cover accounts to be 712,249 km² (71.22 Mha), representing 21.67% of the country's total land area. Among the states, the forests in Odisha are numerous, diverse, multi-layered, and dense with an actual forest cover of 48,903 km^2, which constitutes 7.1% of the nation's total forest cover and 31.4% of the state's total geographical area respectively (Forest Survey of India 2011). Globally, forest acreage has shrunk by 3% (4128 Mha - 3999 Mha) from 1990 to 2015. However, it is observed that the forest cover is likely to decline at an alarming rate, whereas in some areas forest cover is increasing with a very slow pace. Therefore, monitoring forest resources and biodiversity are highly necessary for ensuring the balance of food chain and various biogeochemical cycles.

In order to develop effective forest management policies and practices (Forkuo & Frimpong 2012), it is crucial to obtain accurate land use and land cover (LULC) information (Manandhar et al. 2009). LULC data is vital for understanding human impact on natural landscapes because the changes in LULC reflect how ecosystems are altering their capacity to provide services to human society now and in the future (Senapati et al. 2024). Therefore, understanding LULC changes and identifying transformation hotspots are highly necessary for urban planners and environmentalists (Tiwari et al. 2024). However, the traditional methods for monitoring land use and land cover are time-consuming, labour-intensive, and cost-ineffective. Moreover, these methods are insufficient for obtaining large-scale and continuous observations of the Earth's surface also (Satyawan & Hooda 2014). Whereas, the recent advancements in satellite-based remote sensing provide an unparalleled opportunity for observing and monitoring the Earth's surface at fine spatial resolutions and frequent intervals (Sawaya et al. 2003, Mulder et al. 2011, Ghazaryan et al. 2018, Ghosh et al. 2019, Mugo et al. 2020, Ashutosh and Roy 2021, Abebe et al. 2022, Ghosh et al. 2022, Ghosh et al. 2023).

The most common use of satellite-based remote sensing is LULC change detection, which can now be done with precision using the Google Earth Engine (GEE) platform. GEE is a cloud-based geospatial analysis tool (Gorelick et al. 2017) which uses the Simple Non-Iterative Clustering (SNIC) algorithm to facilitate the efficient grouping of similar pixels and identification of potential individual objects (Achanta & Susstrunk 2017). Several researchers have generated various indices using remote sensing techniques to assess and monitor the forest ecosystems in terms of integrity, fragmentation, and transformation (Kunwar et al. 2020, Sharma et al. 2020). Among the indices, Normalized Difference Vegetation Index (NDVI) is the most commonly used index for monitoring forest cover in any region. NDVI's sensitivity to canopy cover provides insights about the spatial variations in forest density (Parapurath et al. 2020). Further, medium-resolution multispectral optical satellites like Landsat series have proven its efficiency for monitoring the forest cover over a time period (Devi et al. 2021, Islam et al. 2021, Thakur et al. 2021).

During the period from January 1, 2015, to February 5, 2019, a staggering 4,968.48 hectares of forest land in Odisha was diverted for non-forestry purposes under the provisions of the Forest Conservation Act, 1980. Despite the ecological significance of the North-Eastern Ghat Zone, which forms part of the biodiverse Eastern Ghats and hosts an array of endemic plant and animal species, it is necessary to evaluate the deforestation dynamics that threaten its biodiversity and environmental stability. Taking all these factors into consideration, the present study was conducted to assess the changes in land use & land cover and forest cover dynamics in the North Eastern Ghat Zone of Odisha over the last three decades (1990-2020).

2. MATERIALS AND METHODS

2.1. Study area

The districts of Kandhamal, Rayagada, Gajapati, and Ganjam are all part of Odisha's North Eastern Ghat Zone. The region spans 27,913.32 km^2, with latitudes 18.75°N to 20.69°N and longitudes 82.87°E to 85.18°E (Fig. 1). It represents around 35% of the Odisha's total forest cover. This area has a hot, humid, sub-humid environment with an average of 1597 mm of rainfall per year. The most common soil types in this region are red soil, mixed red and black soil, lateritic alluvial soil, and brown forest soil.

2.2. Data

Landsat time series data were employed to map the land use & land cover, and forest cover. The pre-processed multi-year Landsat data were collected at 10-year intervals spanning from 1990 to 2020, using the Google Earth Engine (GEE), through java scripting (Table 1). Although, a field survey was conducted in the study area during 2020 to collect the ground truth data using the stratified random sampling approach for the accuracy assessment of forest cover classification. Additionally, the daily mean air temperature at 2 metre height over the NE Ghat Zone was collected from the Google Climate Engine platform. For this purpose, the ERA5 (Fifth generation ECMWF [European Centre for Medium-Range Weather Forecasts] atmospheric reanalysis) daily aggregates, provided by the Copernicus Climate Change Service (C3S, 2017) were utilized in this study.

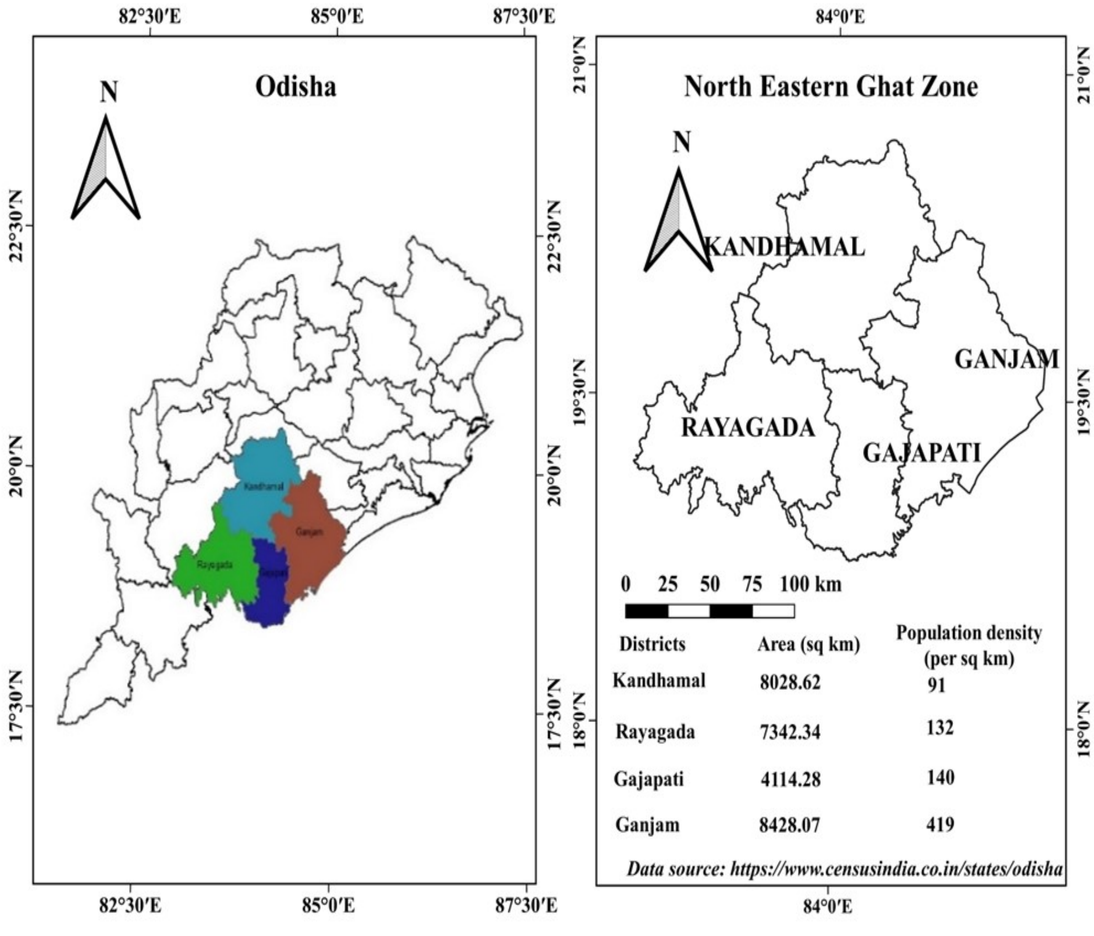

Fig. 1: Geographical location of the North Eastern Ghat Zone of Odisha

Table 1: Date of acquisition of Landsat data over 1990-2020

Year	Acquisition date	Satellite and sensors	Spatial resolution
1990	25.12.1990	Landsat 5 TM	30 m
2000	02.01.2000	Landsat 5 TM	30 m
2010	20.12.2010	Landsat 5 TM	30 m
2020	17.11.2020	Landsat 8 OLI	30 m

2.3. Computation of NDVI

The Normalized Difference Vegetation Index (NDVI) was calculated for each year to evaluate the spatial variations in forest cover density. Its values range from -1 to +1, with higher and lower values indicating denser and sparser vegetation respectively (Ghosh et al. 2019). NDVI for a given year was calculated using the raster calculator menu in QGIS 3.14 software.

To calculate NDVI, the following formula (Rouse et al. 1974) was used.

$$\mathrm{NDVI} = \frac{R_{NIR} - R_R}{R_{NIR} + R_R} \tag{1}$$

Where, R_{NIR} = Reflectance in the near-infrared (NIR) band and R_R = reflectance in the red band.

2.4. Preprocessing and classification

The pre-processed Landsat TM and OLI data were obtained from the Google Earth Engine (GEE) for additional processing and categorization, including the visible bands (Blue, Green, and Red) and the Near Infrared (NIR) bands. The final pre-processed Landsat data for 1990, 2000, and 2010 were subsequently categorized using the unsupervised classification approach (iso-data clustering). However, in 2020, a maximum likelihood supervised classification method was used with the System for Automated Geoscientific Analysis (SAGA) 6.4.0 software.

The entire study area was classified into five LULC classes viz. Agriculture, Barren land, Forest, Settlements, and Water bodies (Table 2). Similarly, the study area was also classified into four different forest cover classes based on the NDVI thresholds (Hartoyo et al. 2021, Islam et al. 2021). These thresholds were fixed through field observations and available literatures. Apart from this, the characteristics of different forest cover classes are also detailed (Table 3). Finally, the layout of LULC maps and forest cover maps were generated using QGIS 3.14 (open-source GIS). The workflow of this study, encompassing satellite data processing and classification steps are depicted in a flow chart (Fig. 2).

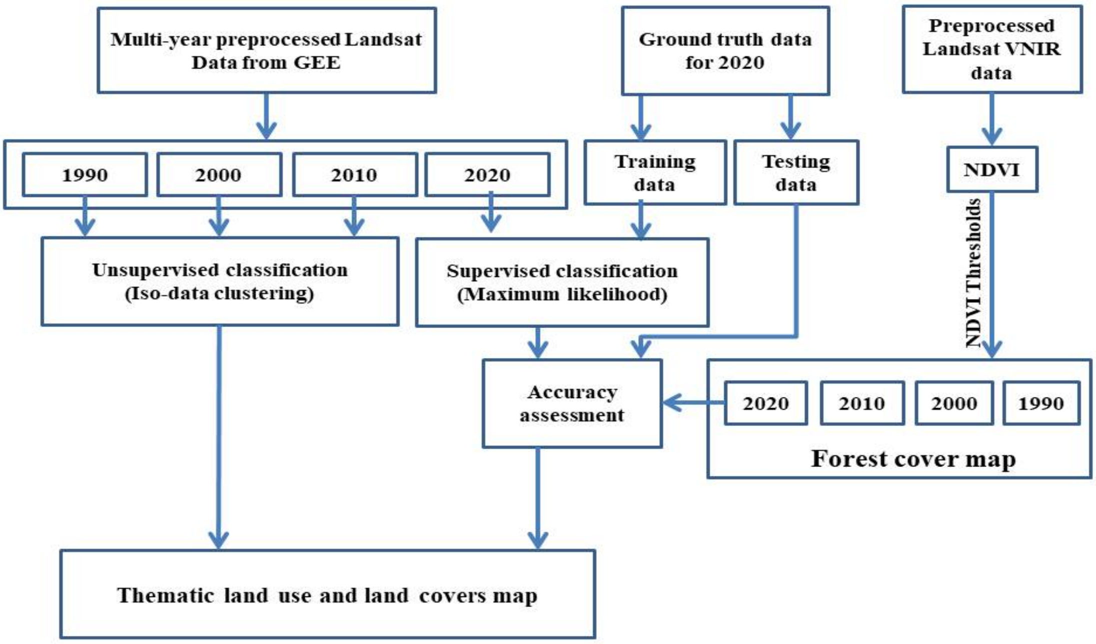

Fig. 2: Steps for LULC and forest cover mapping

Table 2: Description of the LULC classes

Land use classes	Description
Agriculture	Cropping lands with crops
Barren Land and Rocks	Unused lands, uncultivated lands and hills
Forest	Dense and less dense vegetation
Settlements	Residential and commercial concrete structures and roads
Water Bodies	Ponds, lakes, canals, and rivers

(Senapati et al. 2024)

Table 3: Description of the forest cover classes

Forest cover classes	Description	NDVI thresholds
Very Dense Forest (VDF)	Very dense vegetation (Tall statured tress with high canopy cover)	0.8 to 1
Moderately Dense Forest (MDF)	Moderately dense vegetation (Medium height tress with moderate canopy)	0.6 to 0.79
Open Forest (OF)	Less dense vegetation (short trees or plants with high spread and less canopy cover)	0.4 to 0.59
Non-Forest land (NFL)	No vegetation	<0.4

(Source: Parapurath et al. 2020, El-Gammal et al. 2014)

2.5. Accuracy assessment

Confusing matrixes were created to verify the forest cover and LULC classifications. These matrices contain the accuracy of the user for every class in the rows and the accuracy of the producer for every class in the columns. The total classification accuracy was calculated using the diagonal values in the matrices. However, the ground truth data and field survey were only accessible for 2020, therefore it's crucial to remember that the accuracy evaluation was only done for that year.

The user's, producer's and overall accuracy were calculated using the following formulae.

$$\text{User's accuracy} = \frac{\text{Total number of corrected pixels}}{\text{Total number of pixels in the particular row}} \text{X100} \tag{2}$$

$$\text{Producer's accuracy} = \frac{\text{Number of corrected pixels}}{\text{Total number of pixels in the particular column}} \text{X100} \tag{3}$$

$$\text{Overall accuracy} = \frac{\text{Number of pixels in diagonal cells of the error matrix}}{\text{Total number of pixels in the error matrix}} \text{X100} \tag{4}$$

Kappa coefficient, a more reliable measure of classification accuracy was calculated using the following formula (Stehman 1996).

$$\text{KS} = \frac{\text{N} \sum_{h=1}^{q} \widehat{N}_{hh} - \sum_{h=1}^{q} N_h \widehat{M}_h}{N^2 - \sum_{h=1}^{q} N_h \widehat{M}_h} \tag{5}$$

where, N= total number of observations; $\widehat{N}_{hh} = \frac{N_h}{n_h} n_{hh}$; $\widehat{N}_{hh}$ is an unbiased estimator of N_{hh}; N_h is row total

2.6. Trend analysis of mean air temperature

To determine the mean monthly air temperature trend over the study period, ERA5 daily mean air temperature data was used to perform the non-parametric Mann-Kendall (MK) test (Mann, 1945; Kendall, 1975) at four significance levels (p = 0.001, 0.01, 0.05 and 0.1). In this study, a macro-enabled spreadsheet program (MAKESENS) was utilized to carry out the Mann-Kendall test. Moreover, the rate of change in monthly mean air temperature was computed using the Sen's nonparametric method (Sen, 1968).

2.7. Determination of the relationship of forest cover dynamics with population dynamics and air temperature

To determine the influence of population growth and settlement expansion on forest cover dynamics, a simple correlation study was conducted. Additionally, the study examined the impact of forest cover loss on air temperature through correlation analysis. For this purpose, the decadal mean air temperature was calculated and correlated with the total forest area from 1990 to 2020.

3. RESULTS

3.1. Spatiotemporal changes of the LULC

Supervised classification of the multi-year Landsat TM and OLI images yielded the land use and land covers dynamics over 1990 to 2020. Fortunately, a clear decreasing trend was observed in the forest cover as against the gradual increasing trend in the settlement areas. The forest cover was reduced by 20% from 1990 (14910.96 sq.km) to 2020 (11924.76 sq.km). On the contrary, the settlement areas increased by about 130% (Table 4). During the last decade agricultural lands and barren lands observed a significant reduction in its coverage by 26% and 36% respectively. However, the area under waterbodies remained almost the same.

3.2. Forest covers dynamics

The forest cover classification was done for the NE Ghat Zone of Odisha at 10 years (1990, 2000, 2010, and 2020) interval and the results so obtained have been presented in Fig. 3. The spatial and temporal changes in different forest cover classes (VDF: Very Dense Forest, MDF: Moderately Dense Forest, OF: Open Forest) and Non-Forest lands (NFL) have been given in Fig. 4 (a & b). The figures detail that the area covered by the NFL gradually increased from 13302.36 sq.km to 15988.56 sq.km over 1990-2020. Moreover, a gradual decrease in the VDF cover was noticed during the study period, from 26.85% to 12.64% of the total geographical area of NE Ghat Zone (Table 5). The maximum reduction in the VDF cover occurred between 2010 and 2020 (7495.16 sq.km to 3528.54 sq.km). Although, the MDF depicted a decreasing pattern but the rate of decrease was very less compared to the VDF. Unlike the VDF dynamics, the OF observed a rise in its coverage by 42% over the study period.

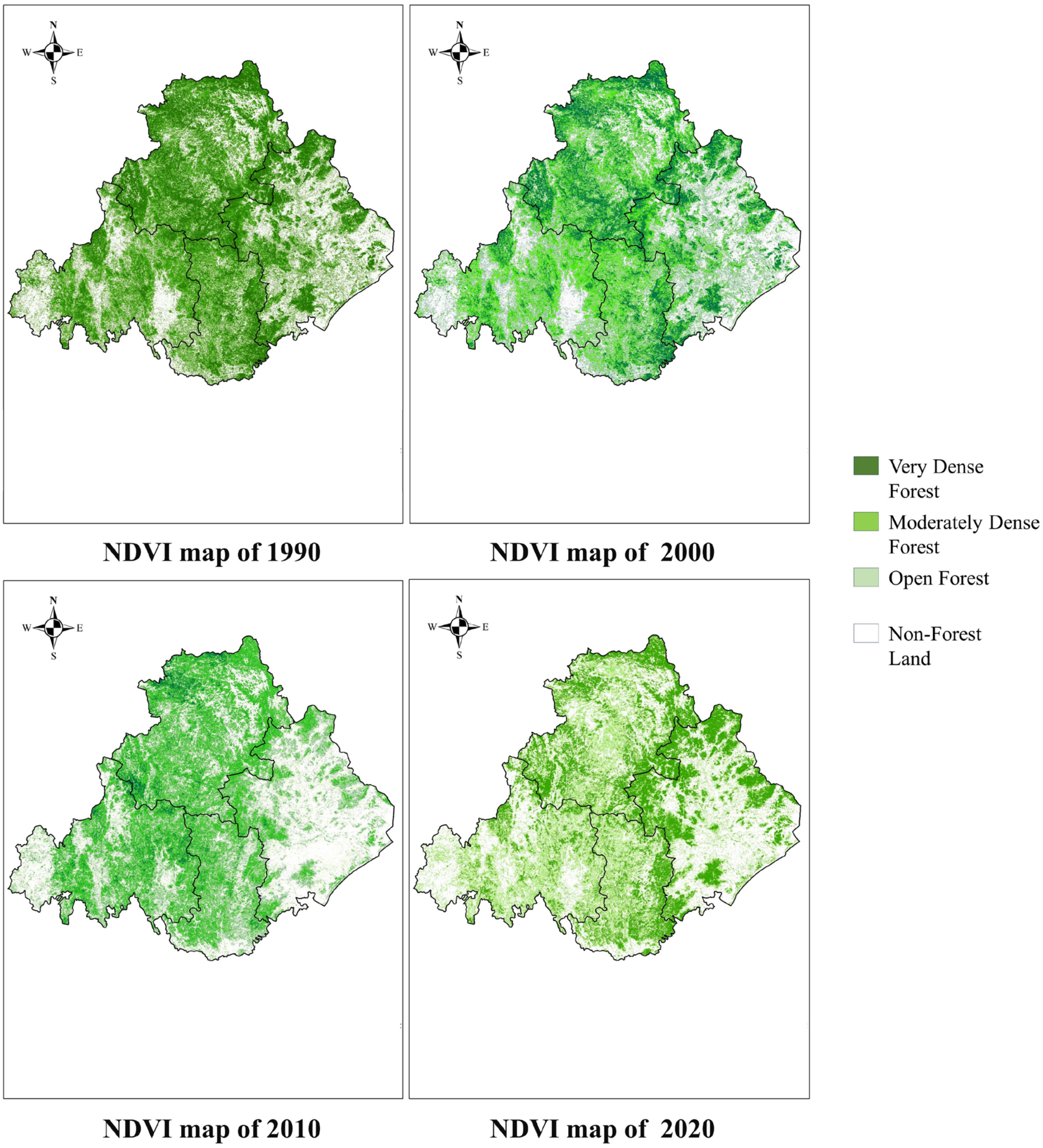

Fig. 3: Forest covers maps of North Eastern Ghat zone of Odisha over the study period

Table 4: LULC change detection over 1990 to 2020

Land use classes	Area in 1990 (sq.km)	Area in 2000 (sq.km)	Changes over 1990 to 2000 (sq. km)	Area in 2010 (sq.km)	Changes over 2000 to 2010 (sq. km)	Changes over 1990 to 2010 (sq. km)	Area in 2020 (sq.km)	Changes over 2010 to 2020 (sq. km)	Changes over 2000 to 2020 (sq. km)	Changes over 1990 to 2020 (sq. km)
Agriculture	5368.88	5606.94	238.06	5417.47	-189.47	-48.59	4001.93	-1415.54	-1605.01	-1366.95
Barren land	2012.85	2100.91	88.06	2084.08	-16.83	71.23	1326.62	-757.46	-774.29	-686.23
Forest	14910.96	14008.44	-902.52	13395.55	-612.89	-1515.41	11924.76	-1470.79	-2083.68	-2986.02
Settlements	3902.51	4477.5	574.99	5302.58	825.08	1400.07	8984.46	3695.88	4470.96	5045.95
Water Bodies	1718.12	1719.53	1.41	1713.64	-5.89	-4.48	1711.55	-2.09	-7.98	-6.57
Total	27913.32	27913.32	0.00	27913.32	0.00	0.00	27913.32	0.00	0.00	0.00

Table 5: Forest cover change detection over 1990 to 2020

Forest cover clas-ses	Area in 1990 (sq.km)	Area in 2000 (sq.km)	Changes over 1990 to 2000 (sq. km)	Area in 2010 (sq.km)	Changes over 2000 to 2010 (sq. km)	Changes over 1990 to 2010 (sq. km)	Area in 2020 (sq.km)	Changes over 2010 to 2020 (sq. km)	Changes over 2000 to 2020 (sq. km)	Changes over 1990 to 2020 (sq. km)
VDF	7495.16	6311.55	-1183.61	4820.32	-1491.23	-2674.84	3528.54	-1291.78	-2783.01	-3966.62
MDF	4380.93	4583.84	202.91	4943.39	359.55	562.46	4090.46	-852.93	-493.38	-290.47
OF	3034.87	3113.05	78.18	3631.84	518.79	596.97	4305.76	673.92	1192.71	1270.89
NFL	13002.36	13904.88	902.52	14517.77	612.89	1515.41	15988.56	1470.79	2083.68	2986.2
Total	27913.32	27913.32	0.00	27913.32	0.00	0.00	27913.32	0.00	0.00	0.00

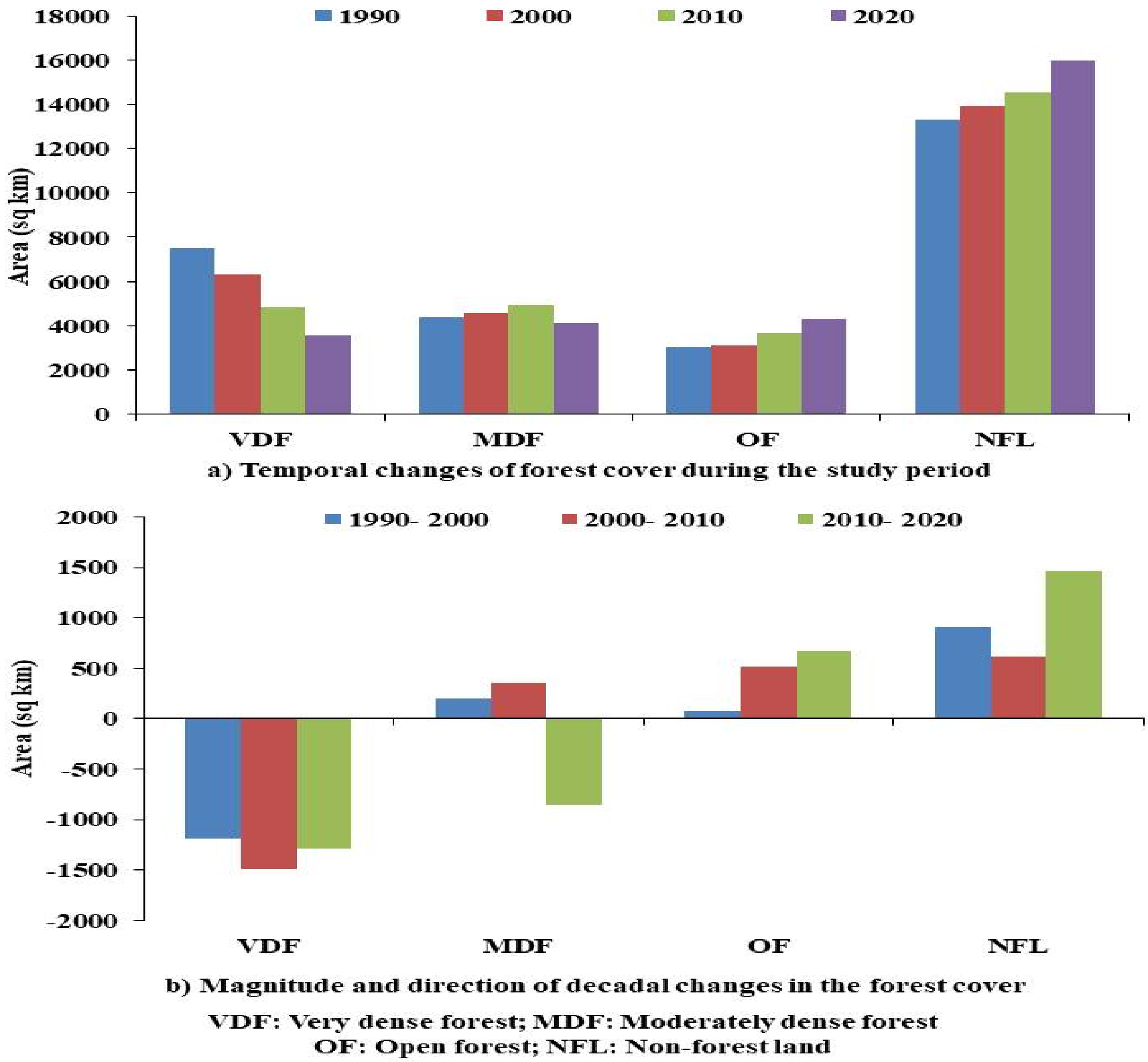

Fig. 4: a) Temporal changes of forest cover during the study period; **b)** Magnitude and direction of decadal changes in the forest cover

3.3. Accuracy assessment

In order to evaluate the accuracy of the classification, error matrix or confusion matrix was developed. The accuracy assessment for the 2020 LULC classification showed that both producer's and user's accuracy were more than 80% for each land use class (Table 6). The overall accuracy yielded a value of 87.5% for the LULC classification. Furthermore, the kappa coefficient which measures the agreement between the predefined producer ratings and the user-assigned ratings, were determined to be 0.84.

The user's accuracy of different forest cover classes varied from 82% for NFL to 92% for VDF while the producer's accuracy ranged from 81% for MDF to 97% for NFL (Table 6). The overall accuracy and kappa coefficient were determined to be 87% and 0.82, respectively. The higher value of the kappa coefficient indicates a substantial level of agreement between the predefined producer ratings and the user-assigned ratings, reflecting the reliability of the classification results

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Table 6: Confusion matrices for LULC classification and forest cover classification for the year 2020

Land use and land cover classification

Classes	Agriculture	Barren Lands	Forest	Settlements	Water Bodies	User's sum	UA (%)	OA (%)	k
Agriculture	32	0	1	3	0	36	88.89		
Barren Lands	1	26	3	0	0	30	86.67		
Forest	4	0	40	1	0	45	88.89		
Settlements	0	0	2	35	0	37	94.59	87.50	0.84
Water Bodies	0	5	2	3	42	52	80.77		
Producer's sum	37	31	48	42	42	200			
Producer's accuracy (%)	86.45	83.87	83.34	83.34	100				

Forest cover classification

Classes	VDF	MDF	OF	NFL	User's sum	UA (%)	OA (%)	k
VDF	49	4	0	0	53	92.45		
MDF	7	53	0	0	60	88.33		
OF	2	5	39	1	47	82.98	87.00	0.82
NFL	0	3	4	33	40	82.5		
Producer's sum	58	65	43	34	200			
Producer's accuracy (%)	84.48	81.54	90.7	97.06				

3.4. Mean air temperature trend from 1990 to 2020

The non-parametric Mann-Kendall (MK) test and Sen's slope estimator were applied to ascertain the monthly mean air temperature trends across the study area. It is evident from the result that the temperature in each month increased except in January as indicated by the Test Z values (Table 7). Significant (p = 0.05) rising trends in mean air temperature were observed for the months of August (Test Z = 2.413*), September (Test Z = 2.244*), and December (Test Z = 2.176*). The maximum rate of increase in mean air temperature, at 0.035°C per year was noted in December, followed by 0.018°C per year in June, and 0.017°C per year in August. However, the mean air temperature in January displayed a decreasing trend with a decline of 0.013°C per year, although this trend was not statistically significant.

Table 7: Trend statistics of mean air temperature over the North Eastern Ghat Zone from 1990 to 2020

Months	Test Z[a]	Q[b]
January	-0.986	-0.013
February	0.238	0.002
March	0.238	0.003
April	0.136	0.002
May	0.578	0.005
June	0.884	0.018
July	0.850	0.008
August	2.413*	0.017
September	2.244*	0.015
October	1.360	0.015
November	0.850	0.011
December	2.176*	0.035

*Significance level, p = 0.05; [a]=Mann-Kendall trend statistics; [b]=Sen's slope

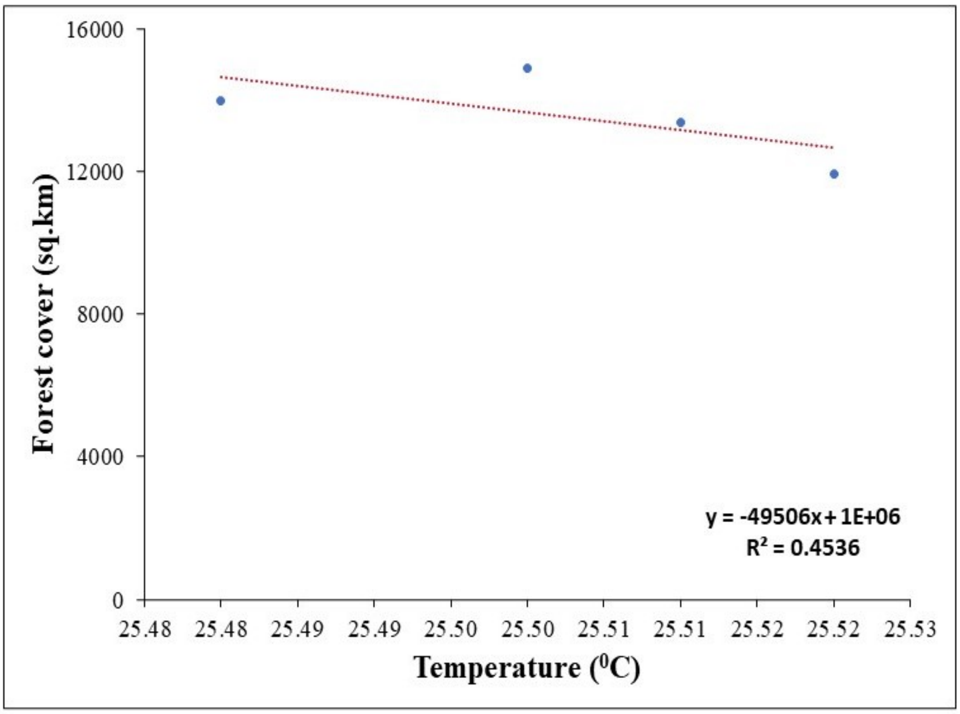
3.5. Forest cover dynamics with population growth and settlements

The correlation coefficients showed that settlements and population expansion were negatively correlated with forest cover (Table 8). Remarkably, there was a considerable negative association between the dynamics of the forest cover and the dynamics of the population (r = -0.985) and settlements (r = -0.963). Majorly, the rise of settlements brought on by population increase is the main cause of deforestation and forest fragmentation. However, the coefficient of determination (R2 = 0.971 for population and R2 = 0.9271 for settlement areas) showed that the growth of the population and the expansion of settlements were responsible for 97% and 93% of the variability in forest cover dynamics, respectively.

The effect of forest cover change on the mean air temperature was shown by the correlation study (Fig. 5). The results revealed a negative correlation between forest cover dynamics and mean air temperature, as depicted by the correlation coefficient (r = -0.674). Specifically, the variation in forest cover could explain 45% of the variability in mean air temperature as demonstrated by the coefficient of determination ($R^2 = 0.4536$).

Table 8: Correlation matrix among forest cover dynamics, population growth and increased settlement areas

Parameters	Population	Settlements (sq.km)	Forest cover (sq.km)
Population	1		
Settlements	0.908	1	
Forest cover	-0.985	-0.963	1



Correlation coefficient (r) between forest cover dynamics and mean air temperature: -0.674

Fig. 5: Relationship of forest cover dynamics with mean air temperature

4. DISCUSSION

The present study addressed a noticeable and consistent decreasing trend in total forest cover change over the last three decades. A clear decreasing trend of total forest cover was observed. The continuous loss of forested areas was mostly brought on by the expansion of roads, mining, industrialization, agriculture, and other land-development activities (Mishra et al. 2022). Moreover, the degradation of forest lands due to mining activities was also highlighted in the study area by Dutta et al. in 2015. Notably, between 2000 and 2020, there was a significant reduction in agricultural land, attributed to rapid population growth. As a result, urban regions within the study area experienced significant long-term expansion.

Over the last three decades, the area covered by very dense forests have consistently decreased, while open forests and non-forest land have expanded. Due to deforestation, it was clear that certain types of forest covers, such as very dense forests, have a steadily declining trend. The escalating trends of population growth and urbanization have led to significant encroachment and exploitation of resources in forested regions. Consequently, the forest density and canopy cover transitioned from being extremely dense to sparsely dense.

Further, the trend analysis of mean air temperature unequivocally demonstrated an increase in temperature over the study area in the past decades. The rise in monthly mean temperature can be attributed to the escalation in the number of hot days and daily maximum temperature. According to Kothawale et al. (2010), the study region experienced an increase in the number of hot days at a rate of 2.0 days per decade. Gouda et al. (2017) also studied the adverse impacts of LULC change, forest fragmentation, urbanization, and industrialization on air temperature in the state of Odisha. The findings highlighted a 0.25 % increase in urbanization over the state during the period over 2005 to 2015. Warming trends across several districts of the state were also documented by Panda & Sahu (2019).

The study becomes more significant because the dynamics of forest cover showed a negative correlation with temperature, indicating an inverse relationship between deforestation and warming. Various researchers have been consistently reported such negative association between deforestation and temperature. For instance, Li et al. (2016) utilized satellite data to quantify the potential and actual impacts of forest loss on land surface temperature (LST). Their study demonstrated that, deforestation significantly contribute to the warming particularly in tropical regions. Prevedello et al. (2019) further supported this finding, stating that deforestation results in consistent warming at both tropical and temperate regions, whereas afforestation leads to a more cooling effect. Apart from this, Lawrence & Vandecar (2015) identified the rise in land surface temperature with the concordant decrease in vegetation leading to more warmer days. Therefore, all these findings underscore the significant role of forest cover in influencing the local and regional temperatures.

Although mining and associated activities in the study zone and across the entire Odisha state have been observed to negatively impact the ecosystem and forest cover (Temper & Martinez-Alier 2013). This impact has led to significant tribal protests in various regions of Odisha, including the NE Ghat Zone (Kumar 2014, Mishra & Mishra 2017). Thus, the administration and policymakers have to pay attention to the plight of the residents and work towards developing management techniques to address the situation promptly (Hota & Behera 2019, Mishra et al. 2022). In these areas, sustainable development necessitates striking a compromise between environmental preservation and economic concerns.

On the contrary, certain regions in India exhibit notable afforestation rates, underscoring the success of focused greening initiatives. Pujar et al. (2022) conducted a landmark study, utilizing approximately one million geo-tagged afforestation records across the Indian subcontinent. The findings highlighted afforestation hotspots concentrated in Telangana, followed by Andhra Pradesh, with peak activity zones observed in central Telangana. This surge in afforestation activity reflects a strategic administrative emphasis since 2013–14, driven by citizen-centric greening programs and district-level performance optimization. Telangana and Andhra Pradesh emerged as leaders in asset creation, achieving 6.3 lakh and 2.8 lakh completed assets, respectively. The spatial analysis of afforestation activities under the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) presents an unprecedented opportunity to understand the geographical distribution and impact of these initiatives across India. However, states with a strong commitment to greening have demonstrated exceptional planning and execution capabilities, achieving remarkable afforestation milestones. Nevertheless, the potential for replicating and scaling these successes remains significant. Afforestation, as a cornerstone of sustainable greening efforts, thrives on robust community participation and demands precise monitoring and assessment using advanced GIS-enabled tools and methodologies.

5. CONCLUSIONS

Over the thirty-years span, urban areas expanded rapidly, contributing to a concerning decline in forest cover. The study zone experienced an environmental warming which was related to the deforestation due to growing urbanization and population. So, immediate attention from the policymakers and planners are crucial to address the alarming decrease in forest cover over the NE Ghat Zone of Odisha. Therefore, actions should be taken promptly to counter the loss of very dense forest and forest fragmentation, as these pose potential threats to the environment and, consequently to the human livelihoods.

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