Forest cover change detection over North Eastern Ghat Zone of Odisha, India using Multi-year Landsat data

ABSTRACT

Aims: The current study's objective is to compute theforest cover dynamics using Land Use and Land Cover (LULC) change detection.
Place and Duration of Study: North Eastern Ghat Zone (NEGZ) of Odisha, India over 1990 to 2020.
Methodology: Through the use of Landsat images and the Supervised&Unsupervised technique of classification, five main categories were established under LULC, viz., Agriculture, Barren Lands, Forest, Settlements, and Water Bodies.
Results: The results infer that the forest cover reduced by 20%. On the contrary, the settlements area increased by about 130%.From this we 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 dynamics, as illustrated by the coefficient of determination (R^2 = 0.971** for population and R^2 = 0.9271** for settlement areas)
Conclusion: Therefore, by placing special focus on the aforementioned findings, we may conclude that the current study may contribute to research on forest management, climate change mitigation, and sustainable development.

Keywords: Forest dynamics, GEE, LULC, Odisha, Population growth

1. INTRODUCTION

Forests are considered one of the most crucial land use types, playing an essential role in terrestrial ecosystems. They are vital for organic carbon production and water cycle regulation, which in turn influences an area's climate. Consequently, forests are fundamental to sustainable human existence and economic stability [1]. However, with rising deforestation rates, forests are at risk of rapid decline [2, 3], leading to reduced rainfall and higher temperatures [4, 5]. Even in the absence of anthropogenic climate forcing, rapid increases in the frequency of extreme weather events pose significant challenges [6]. In Odisha, between January 1, 2015, and February 5, 2019, a total of 4,968.48 hectares of forest land was diverted for non-forestry purposes under the Forest Conservation Act of 1980. The conversion of forests to other land use categories exacerbates irregularities in rainfall patterns. Moreover, changes in forest cover within one country or watershed can affect rainfall in other regions. Therefore, forest cover is a significant factor in both global and local climate change.

To develop effective forest management policies and practices [7], it is crucial to obtain accurate land use and land cover (LULC) information [8]. LULC data is vital for understanding human impact on natural landscapes, influencing scientific, economic, and political decisions. Changes in LULC reflect how ecosystems are altering their capacity to provide services to human society now and in the future. Therefore, understanding LULC changes and identifying transformation hotspots are critical for ecosystem monitoring, planning, and management. Satellite-based remote sensing offers a unique opportunity to monitor forests and the environment at high spatial resolutions and frequent intervals. 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 has gained significant traction because it is a cloud-based geospatial analysis tool that enables users to solve complex problems efficiently [9]. The Simple Non-Iterative Clustering (SNIC) algorithm, available in GEE, facilitates efficient grouping of similar pixels and the identification of potential individual objects [10]. Notably, traditional LULC automatic classification methods, which are applied to remote sensing data, rely on spectral signature calculations of selected LULC classes using training data and pixel-based differentiation between various land cover types [11]. Object-orientedmethods in GEE generally produce better results on higher-resolution data, despite the increased computational costs of segmentation and multiple features for classification, whereas pixel-basedapproaches are typically recommended for lower resolutions [12].

In this context, the work is aimed to assess the changes in forest cover over the North Eastern Ghat Zone of Odisha during the last three decades (1990-2020). Further, the relationship between Population density and deforestation is analyzed and studied.

2. MATERIAL AND METHODS

2.1 Study area

The North Eastern Ghat Zone of Odisha encompasses the districts of Kandhamal, Rayagada, Gajapati, and Ganjam. It extends from 18.75°N to 20.69°N latitude and 82.87°E to 85.18°E longitude, covering an area of 27,913.32 km^2 (Fig. 1). It accounts for approximately 35 % of the total forest cover in the state of Odisha, as reported by Mishra et al. in 2022. The climate in this region is characterized as hot and moist, sub-humid, with an average annual rainfall of 1597 mm.

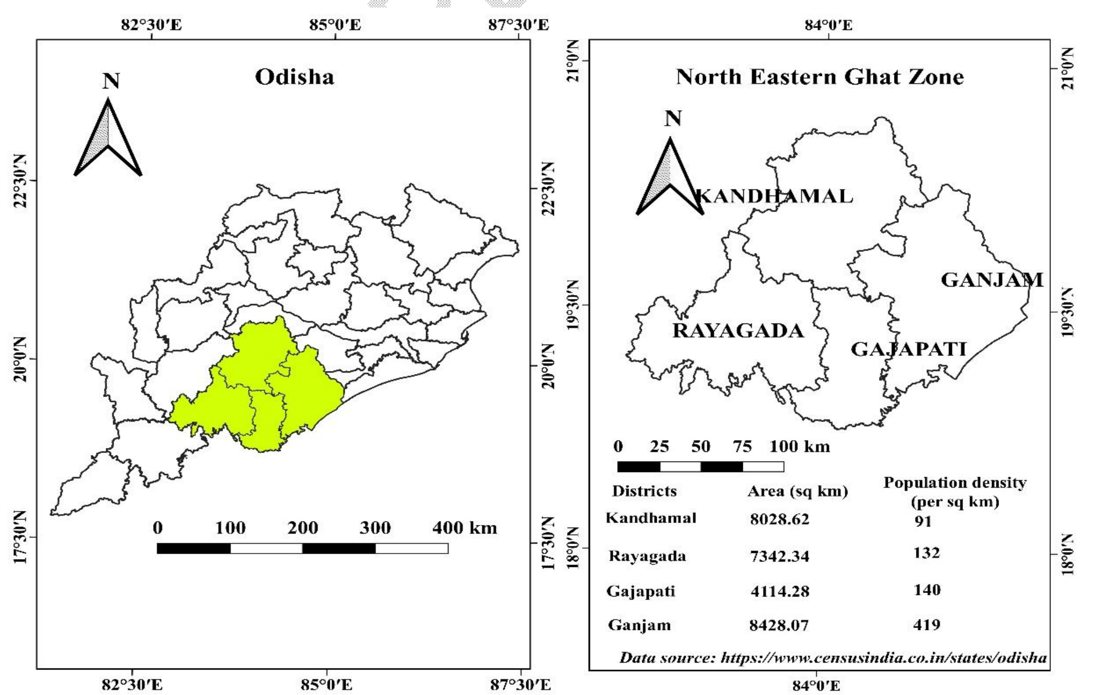


Fig. 1. Geographical location of the study area (North Eastern Ghat Zone of Odisha)

2.2 Data

Landsat time series data were utilized to map the land use and land cover. Pre-processed multi-year Landsat data, collected at 10-year intervals from 1990 to 2020, were obtained using the Google Earth Engine (GEE) through Java scripting (Table 1). Additionally, a field survey was conducted in the study area in 2020 to gather ground truth data using a stratified random sampling approach for the accuracy assessment of forest cover classification.

Table 1. Date of acquisition of multi-year Landsat data

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 Preprocessing and classification

The visible bands (Blue, Green, and Red) along with the Near Infrared (NIR) bands of the pre-processed Landsat TM and OLI data were retrieved from the Google Earth Engine (GEE) for further processing and classification. Later, the final pre-processed Landsat data were classified using the unsupervised classification method (iso-data clustering) for the years 1990, 2000, and 2010 respectively. However, for the year 2020, a supervised classification approach (maximum likelihood) was applied using the System for Automated Geoscientific Analysis (SAGA) 6.4.0 software. The study area was categorized into five land use and land cover (LULC) classes: Agriculture, Barren land, Forest, Settlements, and Water bodies (Table 2). Finally, the LULC and forest cover maps were created using QGIS 3.14, an open-source GIS platform. The workflow for this study, including satellite data processing and classification steps, is illustrated in figure 2.

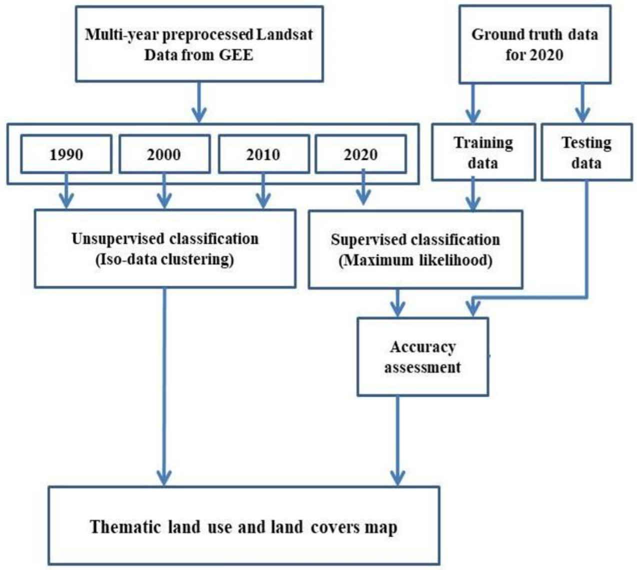


Fig. 2. Steps for land use and land cover mapping

Table 2. Description of the land use and land cover 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

2.4 Accuracy assessment

In order to validate the LULC classification, confusion matrices were constructed. These matrices include the producer's accuracy for each class in the columns and the user's accuracy for each class in the rows. The diagonal values within the matrices were utilized to compute the overall accuracy of the classification. However, it's important to note that the accuracy assessment was conducted only for the year 2020 because the ground truth data and field survey was only available for 2020.

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

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

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

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

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

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

where, N= total number of observations
$\hat{N}_{hh} = \frac{N_h}{n_h} n_{hh}$; $\hat{N}_{hh}$ is an unbiased estimator of N_{hh}; N_h is row total
$\hat{M}_h$is the estimates of column total

3. RESULTS

3.1 Spatiotemporal changes of the land use and land covers

The supervised classification of the multi-year Landsat TM and OLI images revealed the dynamics of land use and land cover from 1990 to 2020. The thematic LULC maps are presented in figure 3. Notably, a clear decreasing trend in forest cover was observed, contrasted by a steady increase in settlement areas (Fig. 4a and 4b). Forest cover decreased by 20%, from 14,910.96 sq.km in 1990 to 11,924.76 sq.km in 2020. Conversely, settlement areas expanded by approximately 130%. Agricultural lands and barren lands showed no significant trends during the first two decades (1990-2000 and 2000-2010). However, in the last decade (2010-2020), both agricultural and barren lands saw a substantial reduction in coverage, by 26% and 36% respectively (Table 4). Meanwhile, the area under waterbodies remained relatively unchanged (Table 3).

Table 3. LULC over 1990 to 2020

Land use classes	Area in 1990 (sq.km)	Area in 2000 (sq.km)	Area in 2010 (sq.km)	Area in 2020 (sq.km)
Agriculture	5368.88	5606.94	5417.47	4001.93
Barren land	2012.85	2100.91	2084.08	1326.62
Forest	14910.96	14008.44	13395.55	11924.76
Settlements	3902.51	4477.5	5302.58	8984.46
Water Bodies	1718.12	1719.53	1713.64	1711.55
Total	27913.32	27913.32	27913.32	27913.32

Table 4. LULC change detection over 1990 to 2020

Land use	Changes	Changes	Changes	Changes	Changes	Changes

classes	over 1990 to 2000 (sq. km)	over 1990 to 2010 (sq. km)	over 1990 to 2020 (sq. km)	over 2000 to 2010 (sq. km)	over 2000 to 2020 (sq. km)	over 2010 to 2020 (sq. km)
Agriculture	238.06	-48.59	-1366.95	-189.47	-1605.01	-1415.54
Barren land	88.06	71.23	-686.23	-16.83	-774.29	-757.46
Forest	-902.52	-1515.41	-2986.02	-612.89	-2083.68	-1470.79
Settlements	574.99	1400.07	5045.95	825.08	4470.96	3695.88
Water Bodies	1.41	-4.48	-6.57	-5.89	-7.98	-2.09
Total	0.00	0.00	0.00	0.00	0.00	0.00

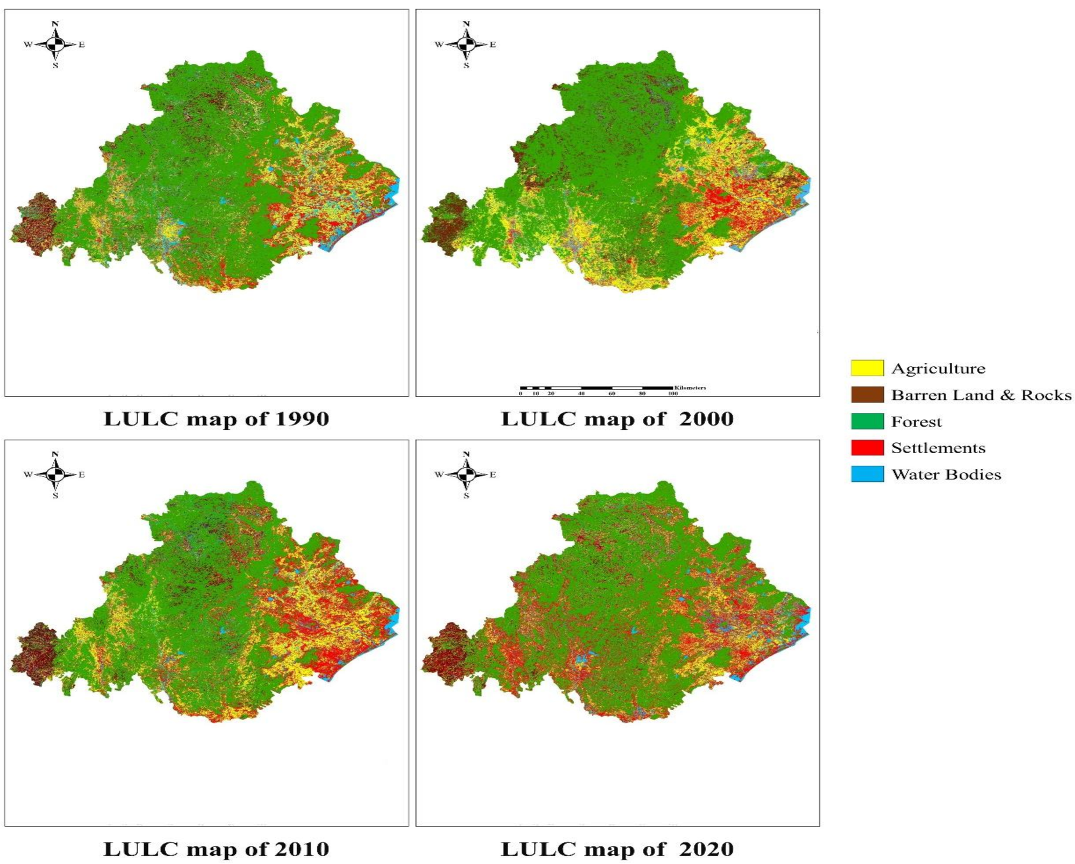


Fig. 3. Land use and land cover (LULC) maps of North Eastern Ghat zone of Odisha in different study year

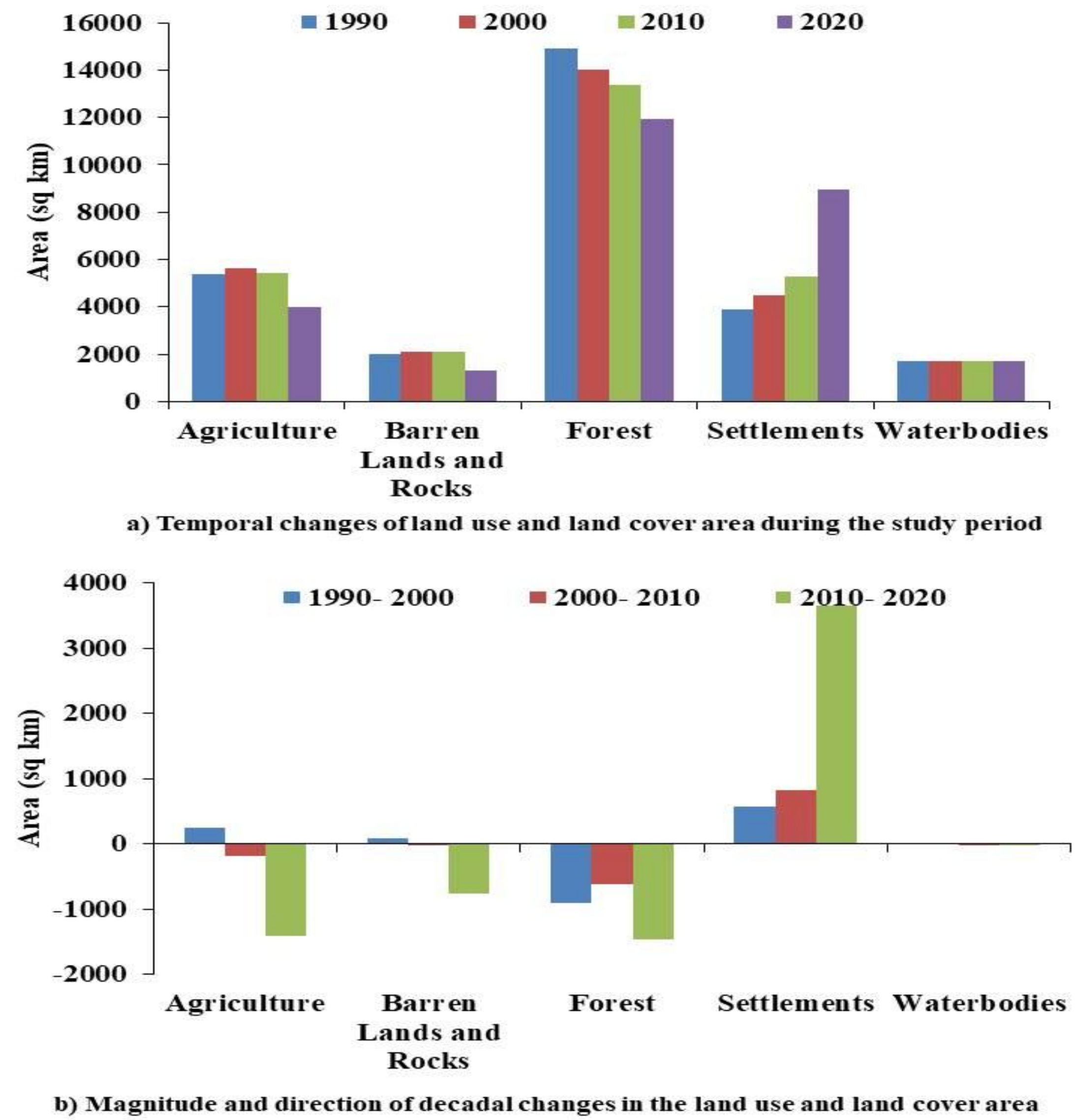


Fig. 4. a) Temporal changes of land use and land cover area during the study period; b) Magnitude and direction of decadal changes in the land use and land cover area

3.3 Accuracy assessment of the classification

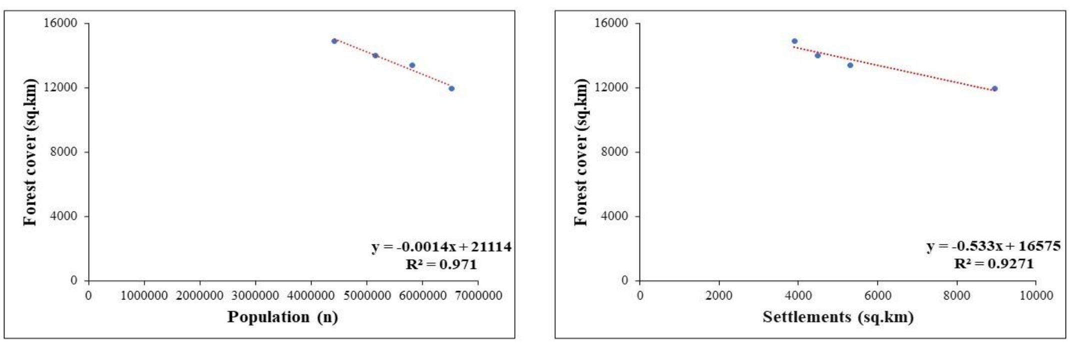
To assess the accuracy of the classification, an error matrix, or confusion matrix, was developed. The accuracy assessment for the 2020 LULC classification revealed that both the producer's and user's accuracy exceeded 80% for each land use class (Table 5). Notably, the highest producer's accuracy was achieved for waterbodies, while settlements had the highest user's accuracy. The overall accuracy of the LULC classification was 87.5%. Additionally, the kappa coefficient, which measures the agreement between the predefined producer ratings and the user-assigned ratings, was calculated to be 0.84. This high kappa coefficient indicates a substantial level of agreement, underscoring the reliability of the classification results.

Table. 5 Confusion matrices for land use & land cover classification and forest cover classification for the year 2020

Classes	Agriculture	Barren Lands	Forest	Settlements	Water Bodies	User's sum	UA (%)
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
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		

3.5 Relationship of forest covers dynamics with population growth and settlement area

The forest cover showed a negative correlation with settlements and population growth, as evidenced by the correlation coefficients (Fig. 5). Specifically, forest cover dynamics had a strong negative correlation with population dynamics (r = -0.985) and settlements (r = -0.963).The primary driver of deforestation and forest fragmentation is the expansion of settlements due to population growth. However, it was observed that the population growth and increased settlements accounted for 97 % and 93 % of the variability in forest cover dynamics, as illustrated by the coefficient of determination (R^2 = 0.971 for population and R^2 = 0.9271 for settlement areas).



Relationship of forest cover dynamics with population growth and increased settlement areas

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

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

Fig. 5. Relationship of forest cover dynamics with population growth and increased settlement areas

4. DISCUSSION

The present study identified a noticeable and consistent decline in total forest cover over the past three decades. This ongoing loss of forested areas is largely attributed to the expansion of roads, mining, industrialization, agriculture, and other land development activities [13].Notably, between 2000 and 2020, there was a significant reduction in agricultural land, primarily due to rapid population growth, which led to substantial long-term expansion of urban areas within the study region.

Mining and related activities in the study zone and across Odisha have been observed to adversely affect the ecosystem and forest cover [14]. This negative impact has resulted in significant tribal protests in various regions of Odisha, including the NE Ghat Zone [15, 16]. Therefore, it is crucial for the administration and policymakers to address the concerns of the local residents and develop effective management strategies to mitigate the situation [17].

5. CONCLUSION

Over the past thirty years, urban areas have expanded rapidly, leading to a significant decline in forest cover. This environmental warming has been linked to deforestation driven by increasing urbanization and population growth. Immediate attention from policymakers and planners is crucial to address the alarming reduction in forest cover in the NE Ghat Zone of Odisha.

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