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Anthropogenic impacts on forest land use and land cover change: Modelling future possibilities in the Himalayan Terai

Shovik Deb[a,*], Manoj K. Debnath[b], Somsubhra Chakraborty[c], David C. Weindorf[d], Deo Kumar[a], Dibyendu Deb[e], Ashok Choudhury[a]

[a] Department of Soil Science and Agricultural Chemistry, Uttar Banga Krishi Viswavidyalaya, Cooch Behar 736165, India
[b] Department of Agricultural Statistics, Uttar Banga Krishi Viswavidyalaya, Cooch Behar 736165, India
[c] Agricultural and Food Engineering Department, Indian Institute of Technology Kharagpur, Kharagpur 721 302, India
[d] Department of Plant and Soil Science, Texas Tech University, Lubbock, TX, USA
[e] Indian Grassland and Fodder Research Institute, Gwalior Road, Jhansi 284 003, India

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ABSTRACT

The northern part of West Bengal, India partially falls within the Terai region of Himalaya. This region is distinctive in terms of high forest cover and rich biodiversity, but also features increasing human population, agricultural practices, and subsequent human-wildlife conflict. This study evaluated the impact of anthropogenic and agricultural proliferation on land use and land cover (LULC) transition dynamics of a forest and its surrounding area of this region. Jaldapara National Park along with its neighbouring region represents an ideal example of such ecology and thus was chosen as the study area. Satellite remote sensing was used to overcome accessibility issues in areas of protected forest and model future possible LULC of the area. Results indicated a continuous decrease in dense forest from 1978 to 2016. Modelling predicted a continuation of the same trend through 2050. The total area under forest increased from 1978 to 2001, possibly due to declaration of a part of the forest as a wildlife sanctuary in 1976 and subsequent increase in supervision and surveillance. However, total forest area started to decline from 2001 and future reductions are possible. Cultivated lands increased from 1978 to 2016 and additional future increase is likely due to a commensurate surge in human population in areas adjacent to the forest. In sum, increasing population pressure, agricultural production demands, and high human intervention in forest ecology were identified as possible causes of temporal forest degradation.

1. Introduction

India is a country harbouring diverse wildlife. The high occurrence of endemic plant and animal species and rapid decrease in their habitat has resulted in two prominent biodiversity hotspots in India: the Indo-Burma hotspot and Western Ghats and Sri Lanka hotspot (Myers et al., 2000). High population growth rate, expansion of agricultural lands, settlements, and further human-induced changes have caused widespread damage to Indian forests in recent decades (Datta and Deb, 2012; Reddy et al., 2013). To confront this severe deforestation and degradation of forest ecology, the Ministry of Environment, Forest and Climate Change (MoEF) as well as the Indian Forestry Department have declared different forests as protected biosphere (national parks, sanctuaries, and reserve forests) and increased the surveillance and management of such areas. Consequently, national forest cover has increased in the recent past (Davidar et al., 2010; World Bank, 2016). However, the data supporting such increases includes open forests and social forestry; thus, quantification of the actual change and transformation of dense protected forests remains elusive.

The northern part of West Bengal, India features high forest cover (Dey, 1991). Several national parks such as the Buxa Tiger Reserve, Jaldapara, Garumara, Neora Valley, Singhalila, and wildlife sanctuaries such as Chapramari, Jorepokhri, Mahananda, and Senchal (West Bengal Forest Department, 2016) have substantively contributed to biodiversity conservation and sustainable forest management. However, similar to other parts of India, forests of this region also face an alarming increase in human population, cultivated lands, escalated human infiltration/development, and interferences in forest ecology (Dey, 1991).

The use of satellite remote sensing for forest cover delineation is well documented (Deb et al., 2014; Small and Sousa, 2016). Using multi-temporal data, remote sensing is also used to reveal the

* Corresponding author.
E-mail address: shovikiitkgp@gmail.com (S. Deb).

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temporal change dynamics of forest ecologies under the impact of anthropogenic pressure (Datta and Deb, 2012; Garbarino et al., 2014). Through different modelling approaches, further prediction of future forest cover transition is also possible (Pontius et al., 2004; Pérez-Vega et al., 2012). This study aimed to use this technology to evaluate the chronological land use and land cover (LULC) change dynamics of a sample forest of northern part of West Bengal. Jaldapara National Park was selected in this context. The objectives were set as delineation of the temporal LULC variation of the above mentioned forest and surrounding areas from 1978 to 2016 as well as forecasting the possible LULC of the area in 2025 and 2050 via modelling.

2. Materials and methods

2.1. Study area

Jaldapara is a wildlife division in northern part of West Bengal, India (Figs. 1 and 2). It is situated within the Terai region at the southern foothill of the Himalayas (Sudhakar et al., 1999). The climate is sub-tropical with >3000 mm annual rainfall (as per the FAO ClimWat 2.0 database at the nearest station). Geographically, the wildlife division contains nine ranges and extends from 26°31′ to 26°45′N and 89°14′ to 89°24′E. Further, the whole wildlife division is divided into two distinct parts: wildlife sanctuary and reserve forest, which are distributed intermittently. Combining all the sanctuaries together, the Government of India declared Jaldapara a national park in 2012 (Ghosh et al., 2013), which is home to several animal species including the Indian rhinoceros, leopard, elephant, Indian gaur, different types of deer, small animals, and birds (Dey, 2009; Bhattacharyya and Padhy, 2013) (Fig. 2).

From north to south, the Torsa River bifurcates the Jaldapara Wildlife Division (Fig. 1) into two parts. The Eastern part is known as the Chilapata forest (Bhattacharyya and Padhy, 2013) while the western part is called Jaldapara. Another small fringe of forest known as Rasamati is situated towards the south, at the eastern bank of the Torsa River (Fig. 1). It was likely a part of Chilapata once and was later disconnected by severe deforestation. This study covers all these forests. The area also consists of several tea plantations (Figs. 1 and 2) and covers many villages and associated agricultural lands (Fig. 2). Among these, a few villages are located just at the edge or even within boundary of the declared forest area (Fig. 1). People of these villages are solely dependent upon the forest for their regular livelihood (Pandit and Yadav, 1996).

2.2. Field investigations and study of human interference

A total 150 ground control points (GCP) were selected using a GARMIN handheld 12 channel global positioning system (GPS) receiver (Garmin Ltd., Schaffhausen, Switzerland) for geo-registration and rectification of all satellite images. Besides, 100 random locations were used to verify the training sites as well as to validate the classified images. To understand the population dynamics, census data was collected for all the districts covering the study area. Further, GPS locations were taken for all villages with more than 10 houses. These locations were subsequently inputted to the location map (Fig. 1) to explore the human interference in forested areas. A field level demographic survey was carried out especially for the villages located at or within the boundary of forest areas. Along with secondary data collected from local offices, detailed discussion was made with the villagers about change in population dynamics, type of occupation, dependency on forest resources, etc.

2.3. Physiographic characterization of the area

CartoDEM Version-3 R1 digital elevation data of tile G45L were downloaded from the Bhuvan portal of Indian Space Research Organisation (http://bhuvan.nrsc.gov.in). After selecting the area of interest (AOI), a digital elevation model (DEM) map was prepared with incorporation of the main rivers of the area (Fig. 1) via geographic information system software ArcGIS 10.1 (ESRI, The Redlands, CA, USA).

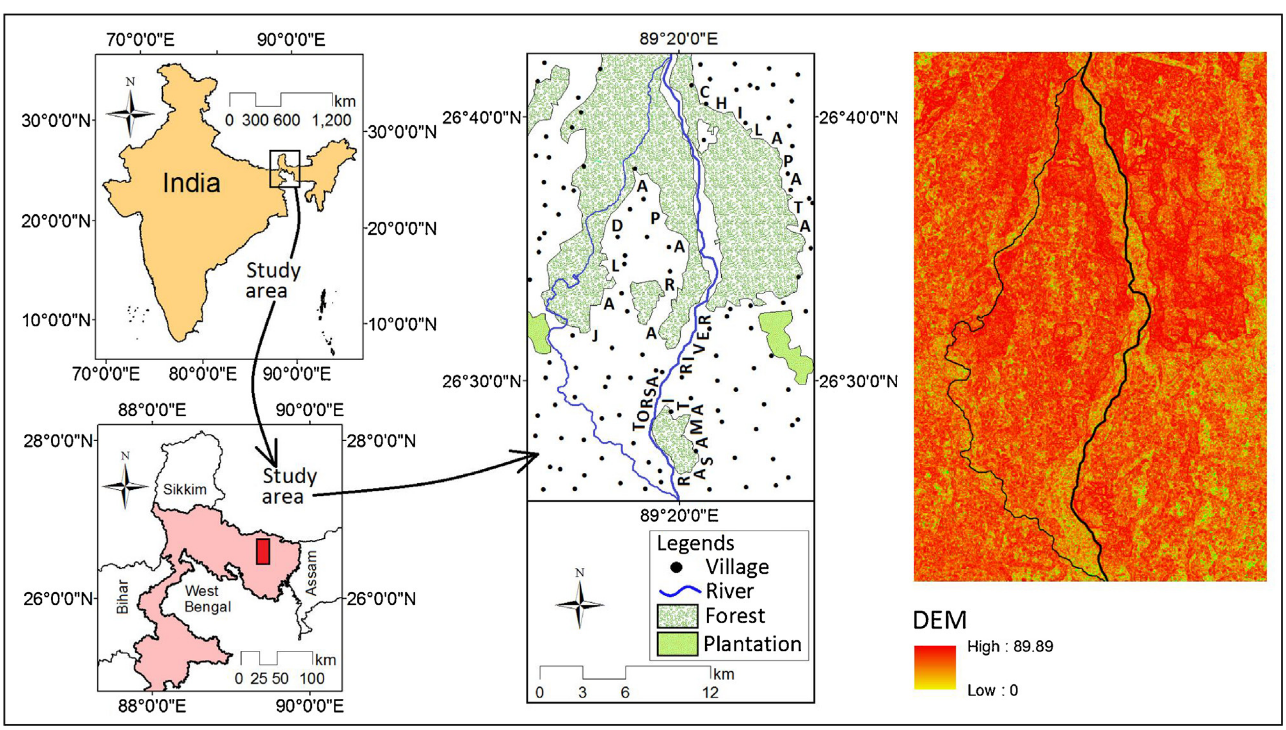

Fig. 1. Location map along with digital elevation model of the study area.

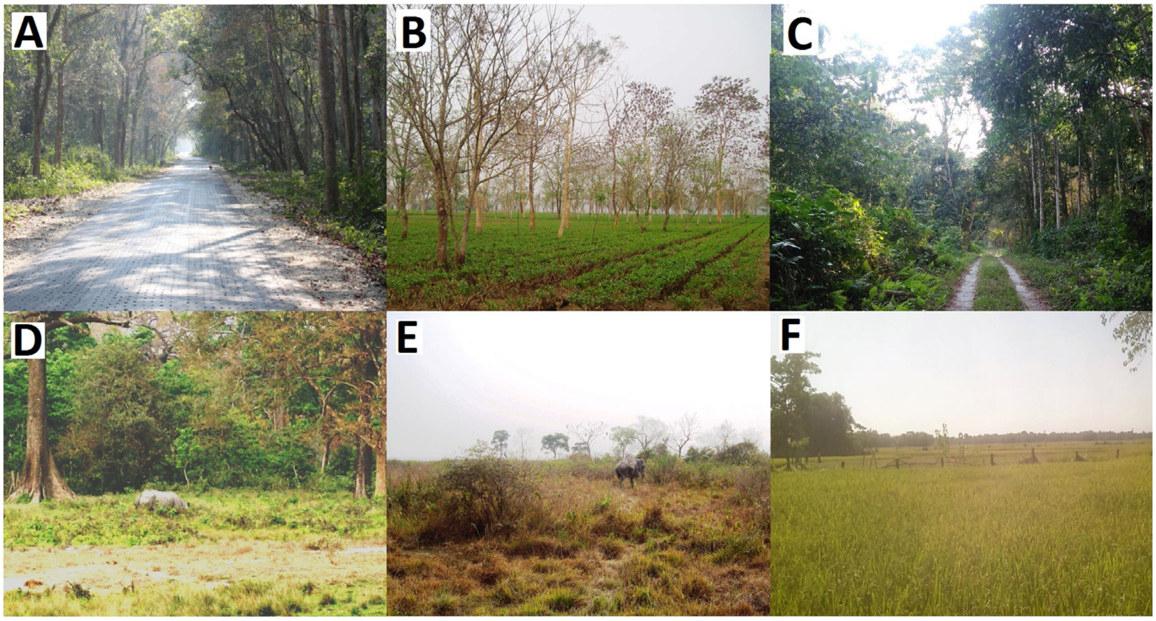

Fig. 2. Variation of land use land cover of the study area, A. highway through the forest area, B. tea plantation at the fringe of forest, C. road used for surveillance in the deep forest, D and E. wild animals in the open grasslands, F. agricultural activities at the vicinity of the forest.

2.4. Data sources

Landsat satellite images are free and have adequate spectral and spatial resolution to study forest cover changes (Skole and Tucker, 1993; Dong et al., 2013). Thus, three multispectral cloud-free Landsat images covering the entire study area were used in this study. Maintaining the temporal gap, two ortho-rectified Landsat images (1978 and 2001) were downloaded from United States Geological Survey browser EarthExplorer (http://earthexplorer.usgs.gov/); the 2016 image was downloaded from Libra (https://libra.developmentseed.org/), an open browser for Landsat 8 satellite imagery. The 1978 image was acquired by the Landsat 2 Multispectral Scanner (MSS) sensor. The images of 2001 and 2016 were taken by the Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) sensors, respectively. Each of these sensors captured the images in different spectral bands. To

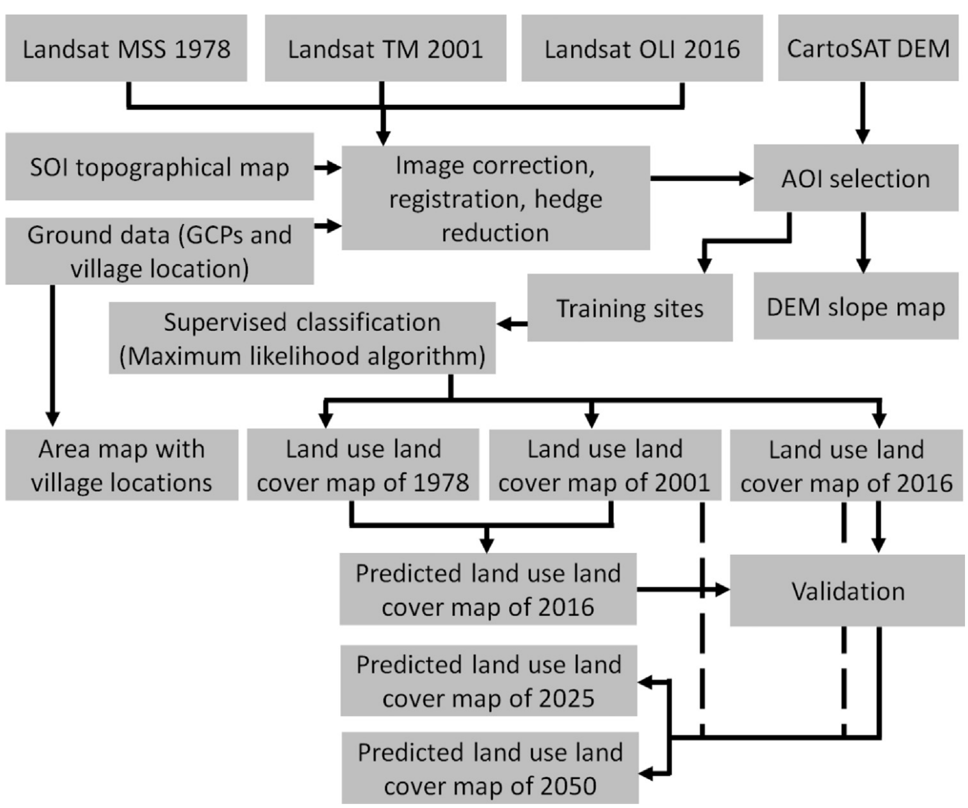

Fig. 3. Framework of methodology followed in the present study.

promote homogeneity, only the spectral bands within the range of 0.43–1.75 μm (visible to shortwave infrared) were considered in this study. Thus, one to four bands were used for the Landsat MSS while spectral bands one to five of the Landsat TM and one to six of the Landsat OLI sensor were used in this study. All the images were of the same season (22nd February 1978; 17th March 2001 and 10th March 2016) to avoid misclassification of LULC classes.

2.5. Image processing, classification, and change detection

Atmospheric correction was applied to all three Landsat images using the Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module in ENVI 5.0 software (Gong et al., 2013). Further image processing was accomplished using ERDAS IMAGINE 9.1 software (ERDAS Inc., Norcross, GA). With the help of the Survey of India (SOI) topographic map (1:50,000 scale) and

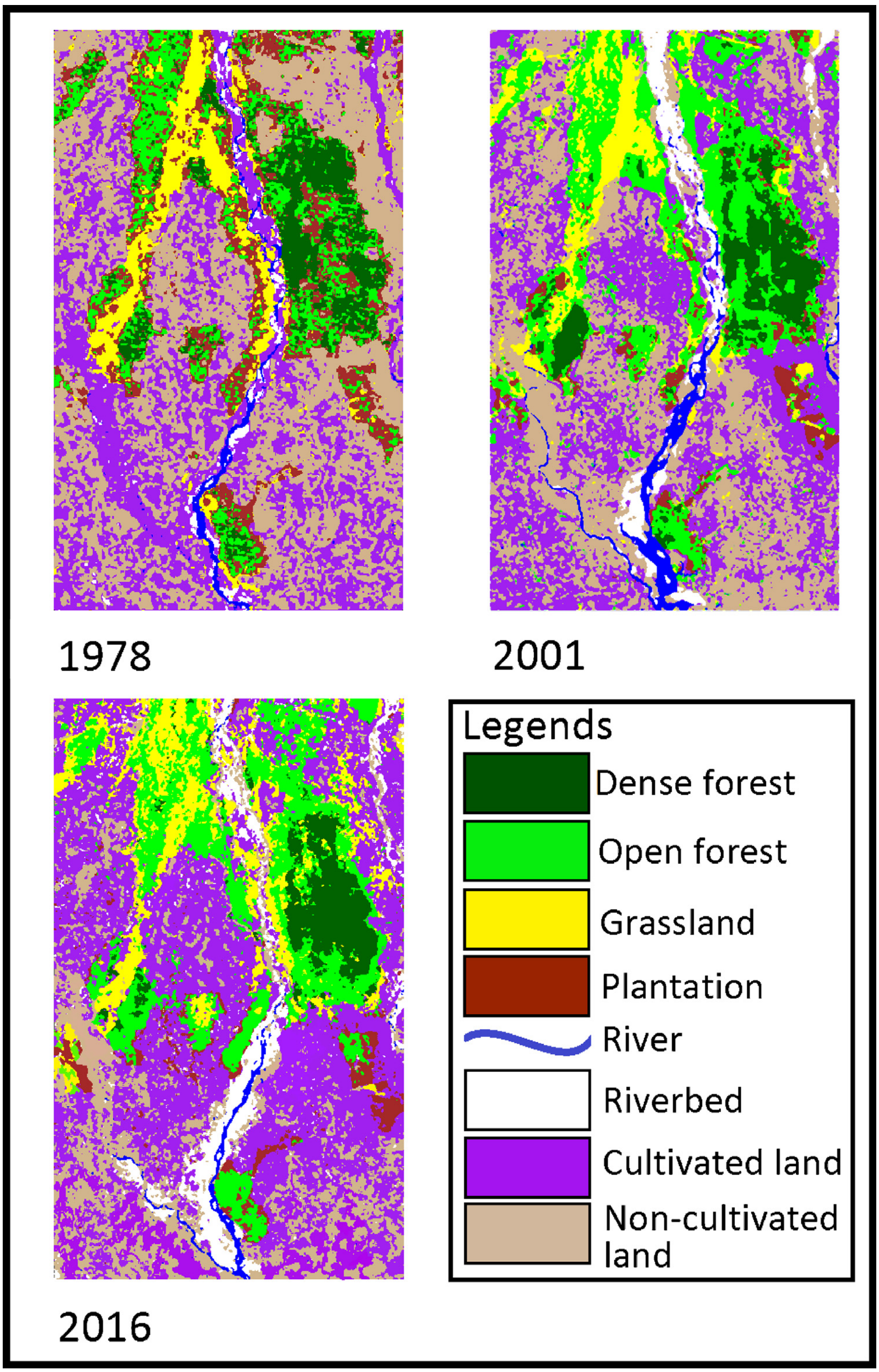

Fig. 4. Land use and land cover classes of the study area in 1978, 2001, and 2016.

GCPs, images were rectified and registered (Fig. 3). Staking of the selected bands for each individual image was done to obtain a false colour composite (FCC). The nearest neighbour algorithm was used for resampling to convert MSS raster grids to 30 m resolution (Echeverria et al., 2006) and to determine the actual brightness values of pixels (Datta and Deb, 2012). After hedge reduction, the AOI was selected (Fig. 3).

Supervised classification of the images was used to identify the LULC classes (Fig. 3) using the maximum likelihood algorithm due to its availability and usefulness without exhaustive training required (Deb et al., 2014). Training sites were selected based on detailed ground survey. Areas with tree canopy cover >40% were considered as dense forest while tree canopy cover between 10 and 40% was considered open forest (Forest Survey of India, 2017). Within each image, eight different LULC classes were identified. To avoid misclassification (Münch et al., 2017), these LULC classes were further checked with field level observations, detail man-made maps and secondary information in terms of Google Earth Pro^{TM} data. Spatial filters of (3×3 dimension) were used to remove isolated pixels (Deb et al., 2014). Accuracy assessment was performed using error matrices for all three classified images. Temporal change dynamics of the LULC classes were assessed by comparing the area statistics of sets of images.

2.6. Prediction of future LULC: model approach

The TerrSet 1.0 (Clark Labs, University of California, Berkeley, USA) software was used for future modelling employing a cellular automata–Markov (CA–Markov) Model. This model produces predicted LULC maps based on two available LULC images of different dates (e.g., date one and relatively new date two). It merges cellular automata spatial rules with the Markov chain transition (Sang et al., 2011). Besides, it creates suitability maps (transition potential map) in land cover change modelling for each LULC class (Kamusoko et al., 2009). Using fuzzy factor standardization, this map generation involves a simple assumption (i.e., the pixel closer to an existing land cover type has higher suitability). The suitability maps, Markov transition area matrix, and base map of date two were used to predict the land cover map of date three (Shooshtari and Gholamalifard, 2015).

In this study, classified Landsat images of 1978 and 2001 were first used to determine a predicted image for 2016. Subsequently, this image was statistically validated with the classified image of 2016 (Fig. 3). This approach was essential as it explained the scenario in a quantitative way (Pontius and Chen, 2006). Following the same simulation, predicted images of years 2025 and 2050 were obtained, using the classified images of 2001 and 2016 (Fig. 3).

3. Results and discussion

3.1. Assessment of present LULC and temporal change dynamics

Analysis of the DEM map (Fig. 1) indicated a trend of increasing elevation on the northern side of the study area. This was expected since the region is situated at the southern foothill of the Himalayas. The rivers were flowing downslope and southward. The LULC map of 2016 indicated 21.62% of the area under forest cover (Fig. 4, Table 1). Based upon colour intensity in the FCC, forest area was further divided into two fractions *viz*., dense forest and open forest. Ground truth verification (based on GCPs and random ground points) confirmed the correlation of these divisions with actual tree density. Dense forest occupied only 5.03% area and the remaining forest area was open forest. Maximum dense forest was found in the Chilapata area with some small patches in the Jaldapara forest. There were stretches of grasslands (9.99%) in this area (Fig. 4, Table 1), which were dominant along the western side of the Torsa River and within the forest area while some patches were also present at the boundary of the Chilapata forest. Earlier researchers revealed these as a part of the forest, serving as a food source and habitat for several animals (Maheswaran, 2006; Lahkar et al., 2011). The study area also contained several plantations (3.62%), primarily as tea gardens. The Torsa River and its tributary occupied a small portion of the area (1.44%) along with the riverbed (4.47%). These rivers were in the beginning of their middle course in this region. Therefore, the riverbeds were dominantly filled by small gravels and sands. A large amount of cultivated (35.42%) and non-cultivated fallow land (23.44%) denoted profound human activities (Fig. 4, Table 1), which were intense even near the periphery of the forest. As per the Wildlife Conservation Strategy 2002 of the Indian Board for Wildlife, there should be an eco-fragile zone around all national parks and wildlife sanctuaries (Deb et al., 2014), which serves as a buffer zone around the conservation forest areas (Mehring and Stoll-Kleemann, 2011). This LULC classification indicated the presence of no such buffer zone around these forests. This will likely lead to unwanted anthropogenic interactions with wildlife and degradation of overall forest sustainability. In this context, the human activities of the study area are discussed in the next section.

The LULC change dynamics of the area were executed by multi-temporal image analysis. Supervised classification of Landsat images from 1978 showed the presence of dense forest in 7.93% area. This area decreased to 5.42% and 5.03% in 2001 and 2016, respectively (Fig. 4, Table 1). It indicated a higher rate of decline in dense forest from 1978 to 2001 in comparison to 2001 to 2016 (Fig. 5). Open forest area was 10.79% in 1978. There was a noteworthy increase in open forest area from 1978 to 2001 followed by a decline in later years (2001–2016) (Table 1, Figs. 4

Table 1
Land use land cover of the study area in 1978, 2001, and 2016.

Class	1978		2001		2016	
	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Dense forest	4605.24	7.93	3145.50	5.42	2923.11	5.03
Open forest	6267.65	10.79	10843.65	18.67	9632.17	16.59
Grassland	4222.08	7.27	5395.86	9.29	5799.42	9.99
Plantation	5049.23	8.70	2592.18	4.46	2102.49	3.62
River	757.99	1.31	1831.86	3.15	837.00	1.44
Riverbed	740.76	1.28	1914.48	3.30	2592.82	4.47
Cultivated land	15511.70	26.71	15802.74	27.21	20568.83	35.42
Non cultivated land	20914.79	36.02	16543.17	28.49	13613.60	23.44
Total area	58069.44	100.00	58069.44	100.00	58069.44	100.00

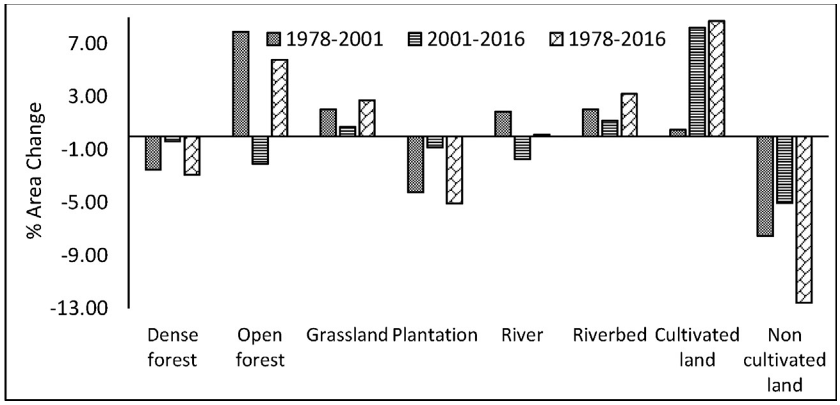

Fig. 5. Land use and land cover change dynamics of the area in 1978 to 2016 (considering total study area as 100%).

and 5). The possible reason for the early increase (1978–2001) was the establishment of the Jaldapara Wildlife Sanctuary in 1976 and subsequent increase in strict vigilance by the Forest Department which resulted in rejuvenation of forests in surrounding areas. However, the pronounced decrease in dense forest from 1978 to 2001 (Table 1, Figs. 4 and 5) indicates the partial failure of the conservation strategy. The noted reduction was likely due to illegal deforestation by marginal forest dwellers. The drop in dense forest deforestation rate from 2001 to 2016 may be associated with the formation of Jaldapara National Park in 2012 with stringent restrictions over anthropogenic activities within conservation zones. However during this time span, open forest areas decreased (Table 1, Figs. 4 and 5) due to the increase in human population pressure and the associated deforestation in non-conserved areas. Results further indicated that there was a steady increase of grasslands from 1978 to 2016. The total forest cover of the area (summation of dense forest, open forest, and grasslands) increased from 15,094.96 ha (25.99%) in 1978 to 19,385.01 ha (33.38%) in 2001 followed by a decrease to 18,354.70 ha (31.61%) in 2016.

There was a substantive decrease in plantation areas from 1978 to 2016 (Table 1, Fig. 4 and 5), which was due to the closing of tea gardens situated within the Chilipata forest area (Fig. 4) given its conservation status. Image analysis revealed a high amount of water flow in the rivers in 2001, covering 3.15% of LULC, in comparison to 1978 (1.31% of LULC) and 2016 (1.44% of LULC). For context, precipitation data of the area was collected from the Gramin Krishi Mausam Sewa project (Government of India). Due to unavailability of data of 1978, a comparison was made for the precipitation data of 2001 and 2016 only. It showed significantly higher rainfall (3276 mm) in 2000–2001 (1st January 2000 to 17th March 2001) than 2015–2016 (2819 mm) (1st January 2015 to 10th March 2016), explaining the higher water flow in the rivers in 2001.

There was also a consistent increase in the riverbed area from 1978 to 2016 (Table 1, Figs. 4 and 5), possibly due to high alluvial deposition by the rivers in the monsoon (Jana, 1997). The transition statistics indicated a small increase in cultivated land from 1978 to 2001 followed by a rapid escalation from 2001 to 2016 (Table 1, Figs. 4 and 5). This suggests rapid growth as well as intensification of agricultural activities in this area. A continuous decline in non-cultivated lands (from 36.02% in 1978 to 23.44% in 2016) also supported this premise.

Accuracy assessment of the LULC images was carried out in coordination with ground data. The GCPs and 100 random location points were used for this purpose. Interaction and information from the local people was considered for identification of past LULC of this area. The accuracy assessment of the three images are presented in Table 2. Kappa coefficients were in the range of 0.88 to 0.91 for all three images (lowest in 2001; highest in 2016). The lowest overall accuracy was for the 2001 image (90.40) followed by 1978 (91.20) and 2016 (93.20). This indicates the least accuracy for the 2001 TM image while the 1978 MSS image shows better accuracy despite its coarser spatial resolution. Considering the LULC classes individually, Table 2 depicts comparative low producer as well as user accuracy for the river and riverbed. One possible reason for this was less spatial coverage of these two classes in the images.

3.2. Human settlements and interference

To understand the human interaction with the forest, a study of the population, their occupations, and social imprints are important. Thus, the present research considered the demographics of the study area, which are under the Alipurduar, Jalpaiguri, and Cooch Behar districts of West Bengal, India. Among

Table 2
Accuracy assessment for supervised classified images of 1978, 2001, and 2016.

LULC Classes	1978			2001			2016		
	Producer's Accuracy (%)	User's Accuracy (%)	Kappa	Producer's Accuracy (%)	User's Accuracy (%)	Kappa	Producer's Accuracy (%)	User's Accuracy (%)	Kappa
Open forest	88.89	88.89	0.88	91.43	88.89	0.87	96.55	90.32	0.89
Dense forest	95.00	95.00	0.95	86.67	80.00	0.89	87.50	87.50	0.87
Grassland	87.95	83.33	0.85	95.45	84.00	0.82	88.24	88.24	0.87
Plantation	95.24	90.91	0.90	91.67	84.62	0.84	83.33	90.91	0.90
River	72.67	73.62	0.73	75.00	74.29	0.74	77.78	87.50	0.87
Riverbed	76.23	76.06	0.76	83.33	83.33	0.82	94.12	94.12	0.94
Cultivated land	91.18	92.54	0.90	94.12	94.12	0.92	97.09	95.24	0.92
Non cultivated land	94.38	93.33	0.90	91.36	94.87	0.92	91.49	95.56	0.95
Overall Classification Accuracy	91.20			90.40			93.20		
Overall Kappa	0.89			0.88			0.91		

these, the major portion of forest cover falls under the first two districts while the southern part of the study area falls within Cooch Behar. Alipurduar is a newly formed district, created in 2014 by dividing Jalpaiguri (Alipurduar district web portal, 2016). Therefore the latest census report (2011) detailed the whole area as only the Jalpaiguri and Cooch Behar districts. As per the District Census Handbook Jalpaiguri (2011), this district features a large number of tribes (18.89%) as well as marginal workers (9.27%). While a significant number of people are associated with cultivation (37.32%), a majority found other work (60.69%) (District Census Handbook Jalpaiguri, 2011). Conversely, in the Cooch Behar district, 67.08% and 29.32% of the population was involved with agriculture and other work, respectively (District Census Handbook Koch Bihar, 2011).

Field level investigation inferred the existence of more than 100 villages within the study area (Fig. 1). The southern part of the area was dominated by cultivated and non-cultivated fallow lands with minimum dense forest (Fig. 4). This finding reinforced demography data of the Cooch Behar district, which indicated a large portion of the population was associated with cultivation. Fig. 1 depicts the presence of some villages at the boundary of the forest areas while a few villages were even found within the forest periphery. Field level survey of these villages indicated marginal tribal populations, dependent on forest resources for their livelihood. Population dynamics of these villages were very inconsistent. A few villages at the fringe of forests were assemblages of ten to fifteen households only. And, the livelihood of the people living there was affected by regular interference of wild elephants. However, some villages situated just outside the official forest periphery had several houses (>50–100) and even small markets. Detailed conversations with the local people indicated that the larger human colonies were developed in the last few decades from tiny clusters of houses. Analysis of this trend inferred a continuous tendency of human infiltration and colonization in the forest. In these villages, wood procurement for both fuel wood and timber purposes was found to be a common practice. Besides, these people were found to be dependent on forests for collection of honey, wax, resin, shredded leaves, and tree parts. There were some villages in proximity to forests as well as tea plantations which were identified as the colonies of tribal tea garden workers. As per the survey, human-wildlife confrontation was also found to be common in these areas. Before 1972, there was no legal protection for wild animals beyond reserved and protected areas. Poaching of animals, especially leopards, was common outside the forest (Dey, 1991). With the enforcement of the Wildlife (Protection) Act, 1972, these activities have been reduced. However, earlier research (Dey, 1991) as well as the survey inferred continuous conflict between humans and wild elephants, even through the present day.

3.3. Modelling for potential prediction of the future LULC of the area

The CA–Markov is a globally accepted and widely used model for simulation of future LULC (Sang et al., 2011; Aithal et al., 2013; Nouri et al., 2014). This model was used by Guan et al. (2011) for prediction of LULC change during 2015–2042 while Sayemuzzaman and Jha (2014) estimated the LULC of North Carolina for the year 2030 using United States-National Land Cover Data of 1992, 2001, and 2006. In the present study, forecasting of LULC of 2016 (Fig. 6A) was accomplished using a land transition model with supervised images of 1978 and 2001. Fig. 6B depicts the component

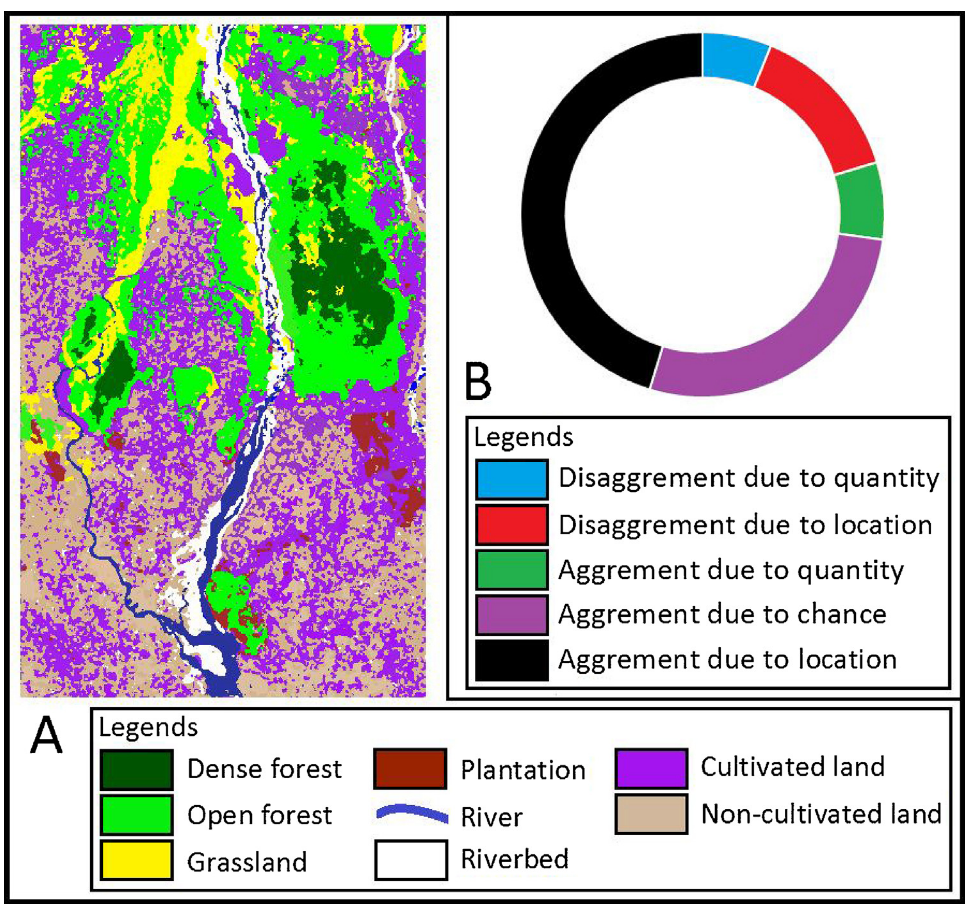

Fig. 6. A. Predicted land use and land cover classes of the area in 2016 and B. its validation with classified 2016 image using multiple-resolution budget for components of agreements and disagreement.

of agreement and disagreement between the predicted image (Fig. 6A) and original LULC image (Fig. 4). The multiple resolutions utilized explained the proportion of pixels classified correctly and incorrectly (Pontius and Spencer, 2005). The outcomes showed a total 79.65% agreement, inferring a strong association between the simulated and original images (Fig. 6B). Strong agreement due to location at the grid cell level (45.30%) showed high correlation between these images at the grid cell level of each category within each stratum (El-Hallaq and Habboub, 2015). The agreement also serves as a baseline for the actual similarity of the two images, without any prior information of location and quantity (El-Hallaq and Habboub, 2015). Therefore, the CA–Markov model represents a feasible approach for predicting the future LULC status of the study area.

The validated model was used to predict the LULC of the area for 2025 and 2050 (Fig. 7) using classified images of 2001 and 2016. The LULC change dynamics were obtained by comparing the 2016 image (Fig. 4) with the simulated images of 2025 and 2050 (Fig. 7). Models indicate a possible steady reduction in total forest area (Fig. 8). Considering the total study area as 100%, there was a 0.24% possible decline in dense forest from 2016 to 2025 and a 0.54% decrease from 2025 to 2050. The possible decrease in open forest area was 2.01% from 2016 to 2025 and 0.93% from 2025 to 2050. Nevertheless, the prediction inferred an increase in grasslands (0.22% and 0.16% for 2016–2025 and 2025–2050, respectively). Across the entire time span (2016–2050), the maximum possible increase of area was found under cultivated land (5.13%) while non-cultivated lands decreased by 3.85%. The LULC modelling also indicated an escalation in river water as well as the extent of riverbeds in the future. However, river water flow and its carrying capacity depends upon the precipitation of that season (Jiang et al., 2007) and is therefore hard to model based only upon LULC simulation. Nevertheless, the Torsa River originates from the Himalayas and thus, increases in glacial melting in the near future under the influence of global warming (Ming et al., 2015) might support this prediction. Model predictions showed plantations as the class with the least area change. Summarily, the results inferred a possible future increase of population pressure in this area and further agricultural intensification. Human population pressure frequently leads to anthropogenic interference in

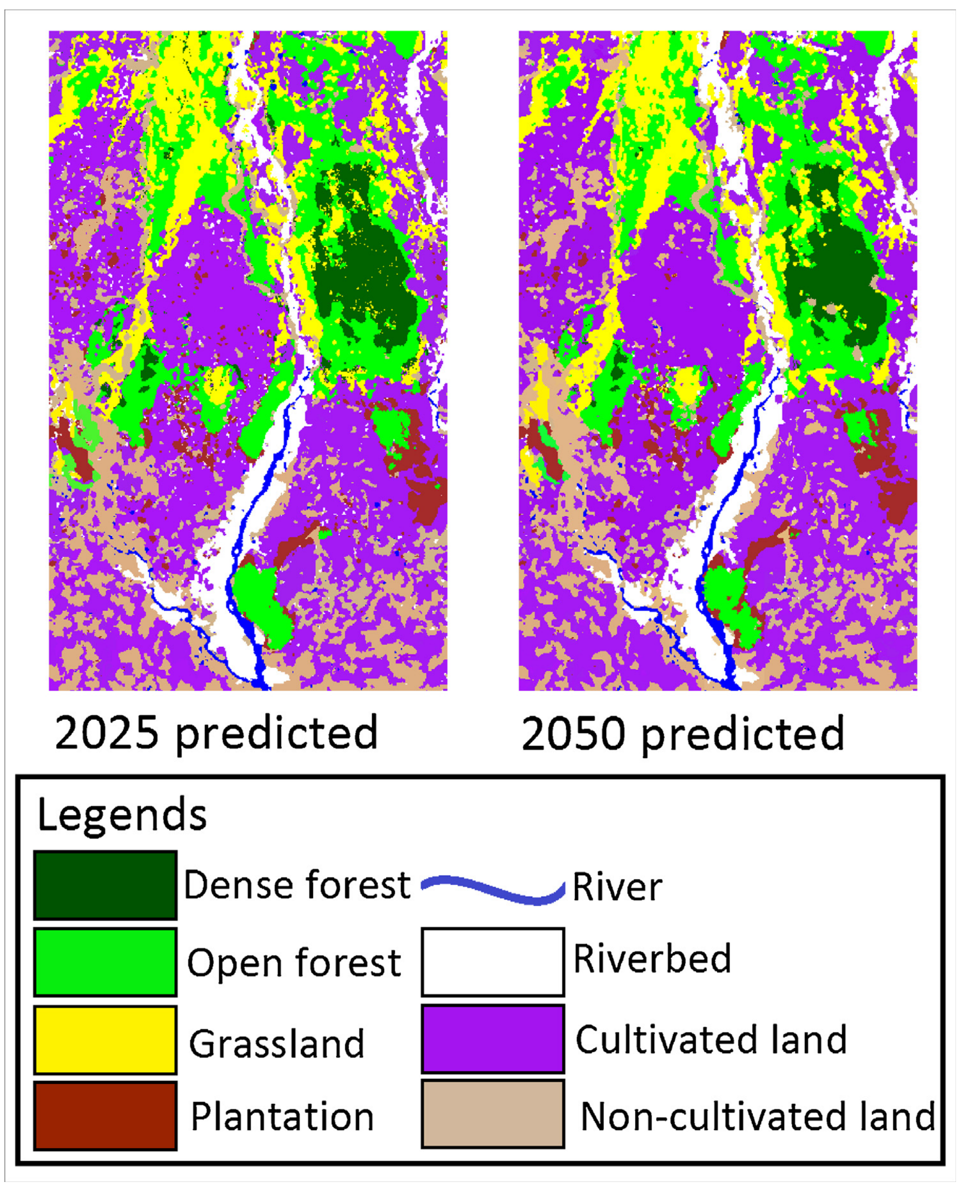

Fig. 7. Predicted land use and land cover classes of the study area in 2025 and 2050.

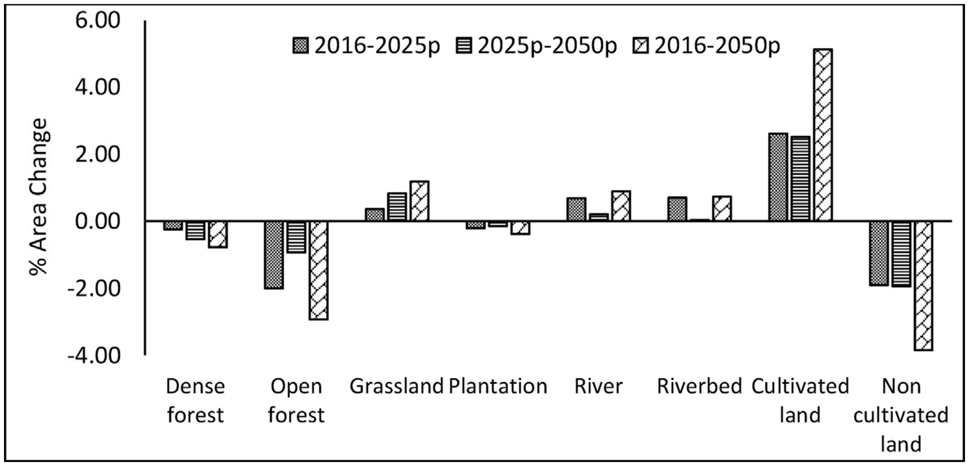

Fig. 8. Predicted land use and land cover change dynamics of the area in 2016 to 2050 (considering total study area as 100%).

contiguous forest resulting in destruction of the ecological equilibrium (Datta et al., 2011; Laurance et al., 2014). This is evidenced by the predicted decrease in dense and open forest by 2025 and 2050.

3.4. Possible management for sustainable forestry

With a high human population growth rate (Census of India, 2011), human-forest conflict is inevitable in India (Datta et al., 2011); in fact, this problem will become more complex in the future. In this context, regular monitoring and management of forest areas through ground survey as well as via satellite/drone remote sensing may lead to sustainable forestry (Higman et al., 2013). Further, the delineation of eco-sensitive zones or buffer zones around any national, protected, reserve forest, or sanctuary are imperative for the protection of forest ecology and biodiversity (Deb et al., 2014). Such zones act as a buffer interface between human and forest. Although, MoEF has initiated buffer zones since 1989, further actions are necessary for practical implementation. Community based forest management might also act as a powerful supplement where high human-forest interaction occurs (Datta and Deb, 2017). Involvement of local people in decision making about effective conservation strategies can lead to better forest management, especially in buffer zones and open forest areas (DeFries et al., 2007).

4. Conclusions

This study indicated the significance of anthropogenic intensification and interferences on natural land use ecology in India. The research was carried out on a forest and its surrounding areas, representing a diversity of significantly different LULC classes. The change dynamics of LULC of the area over a span of the last 38 years (1978–2016) was evaluated and modelling was performed using a CA–Markov model to predict the possible future LULC of the area in 2025 and 2050. In sum, our results indicated that:

(1) There was a continuous curb in dense forest from 1978 to 2016 and this trend possibly will continue in the future. There was a reduction in open forest area also from 2001 to 2016 and as per simulation results, this trend will continue. The only forest fraction that continuously increased and probably will maintain the pace is grasslands. The total area under forest cover increased from 25.99% in 1978 to 33.38% in 2001. Thorough monitoring and management of forests, after declaration of the Jaldapara Wildlife Sanctuary might be the reason behind this positive change. However, total forest area was reduced to 31.61% in 2016 and possibly will decrease to 29.73% by 2025 and further to 29.08% by 2050.

(2) There was a constant increase in cultivated lands and decrease in non-cultivated fallow land across the area in the last 38 years. This trend remained similar while predicting future LULC. It implies continuous conversion of fallow to agricultural lands under increasing population pressure. The demographic analysis, as performed in this study, also supported this premise. The summation of cultivated lands and non-cultivated fallow land increased from 55.70% in 2001 to 58.86% in 2016 and as per modelling will increase even more in the future (59.58% and 60.15% in 2025 and 2050, respectively).

The LULC dynamics of forest and human activities of the study area were directly associated with each other. The area loss from forest cover and addition under human activities (agriculture) exemplify this trend. The degradation and conversion of forest lands under the pressure of increasing human population, expanding cultivation practices, and immense human intervention indicate an alarming scenario considering the enriched biodiversity of the region. There is a need for monitoring, planning, and field-level management to mitigate this situation. Use of technologies such as remote sensing, implementation/enforcement of already existing rules, and possibilities like community-based forest management should be blended to reach a holistic approach to protect the forests of India.

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