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Local Scale Assessment of Forest Cover in the Tropics – An Implication to Habitat Conservation

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ABSTRACT

Deforestation is one of the greatest environmental concerns that the world is facing at present. As a result of human-mediated deterioration or destruction, tropical forests have altered at an unparalleled rate during the last century. Further tropical forest transition does not occur evenly throughout a region or country; rather, it is localized in a very limited area. As such, the study aimed to measure and document the deforestation and degradation on a small forested habitat in the tropics, i.e. Kaki Reserve Forest under Marat Longri Wildlife Sanctuary, northeast India using remote sensing technology. The forest conditions were observed using Landsat TM and OLI satellite images between 1991 and 2015. The current study used the Forest Canopy Density Mapping and Monitoring Model to track deforestation or degradation in the test region. Results show a significant decline in forest cover in the area. It was observed that between 1991 and 2015, the 53.3% of the total area is under pressure of deforestation and degradation. Rate of forest cover transformation under different classes ranges from 0.37 to -8.15 which are exceptionally high in comparison to other parts of the country. The study also indicated that increased human activities such as illegal-felling, agricultural development, encroachment, and collections pressure have caused huge disruptions in this forested habitat throughout the study period. Thus, it requires rapid attention in order to ensure effective forest planning and management. The study also demonstrates how integration of remote sensing data and biophysical models can be used to examine spatial forest state, which may be used for long-term forest management at the local and regional levels.

Key words: Tropical forest, Deforestation, Remote Sensing, Kaki Reserve Forest

INTRODUCTION

Tropical forests occupy less than 10% of the terrestrial surface and hold up at least two-thirds of the world's biodiversity (Giam 2017). Over the past century these forests have been undergoing through an exceptional rate of change as they are degraded or destroyed by human activities (Morris 2010) which in turn affects many ecosystem services that are essential to human well-being (MEA 2005). Various factors such as deforestation, habitat fragmentation and degradation, land cover transformation, over-exploitation, climate change and invasive species are the prime drivers of tropical forest loss. Globally, each year nearly 13 million hectares of tropical forest were transformed to other uses or lost through natural causes (FAO 2010). It has been estimated that almost half of the tropical forest that existed at the turn of the 21st century has already lost (Wright 2005). Further tropical forest transformation does not happen uniformly across a region or country; instead it is concentrated in a comparatively small segment of an area of interest (Tucker and Townshend 2000).

Deforestation and degradation are the greatest environmental concerns that the world is facing at present. It can lead to decrease or cessation of the flow of commodities and services provided by ecosystems (Seymour and Busch 2016). Both of these causes are also the second-largest source of carbon dioxide emissions, with the most of them occurring in tropical areas (IPCC 2013). It has been reported that tropical forest loss currently contributes 5 to 15% of anthropogenic carbon emissions to the atmosphere, eventually leading to climate change and global warming (Bullock et al. 2020). Moreover, it can capture approximately 15% of the CO_2 produce by human activities (CEC 2008). Destruction of these forests will reduce the ability of the earth to absorb CO_2 from the atmosphere (Van der Werf et al. 2009). Again, tropical deforestation is considered as the single largest threat to maintaining the planet's flora and fauna diversity, as the destruction of suitable habitat threatens the survival of forest specialist species (Symes et al. 2018). Hence for evaluating changes in biological diversity, carbon storage and various ecological processes in the tropics requires tracking of deforestation and forest degradation (Asner et al. 2009). Reducing deforestation would not only reduce such changes, but would also act to preserve tropical forests.

As the key strategies for supporting developing countries with anti-deforestation, the 13th Conference of Parties (COP) of the United Nations Framework Convention on Climate Change (UNFCCC) voted to adopt the Reduced Deforestation and Degradation (REDD+) initiative. In order to properly implement REDD+, developing nations must develop national measuring, reporting, and verification (MRV) systems based on the IPCC Good Practice Guidelines (GPG) (De Sy et al. 2012). Scientific community were entrusted in developing standard methods across regions or continents for sustainable forestry, maintaining biodiversity conservation, to monitor forest cover and also to estimate changes in carbon stocks over time (Asner et al. 2009). Two important variables are necessary for the creation of REDD+ data: first, measure of deforestation and degradation, and second, terrestrial carbon store concentrations per unit area. However large uncertainty still prevails as most of the available methodologies have focused mostly on deforestation, which is easier to detect and thus more readily measured and monitored than forest degradation (Pearson et al. 2017). Remote sensing is widely regarded as an important REDD+ observation technique, and when combined with ground measurements, it provides an accurate, realistic, and cost-effective option for establishing and sustaining REDD+ MRV systems (De Sy et al. 2012). Because of the capability to cover large areas both at different spatial and temporal scale, remote sensing data can be of considerable used for the detection of deforestation and at the same time can also be used as a direct or secondary indicator for measuring degradation. Currently available remote sensing methods for monitoring forest degradation using a direct or secondary indicator are (1) detection of direct degradation indicators such as canopy cover percentage, time series analysis and estimation of stem volume and biomass (2) mapping of secondary indicators such as vegetation indices, logging roads, log landings, villages etc. (Miettinen et al. 2014). Any moderate to coarse resolution satellite image such as Landsat, Moderate Resolution Imaging Spectro-radiometer (MODIS), Sentinel, IKONOS and Advanced Very High Resolution Radiometer (AVHRR) etc. can be used to extract such direct or secondary indicators (Wang et al. 2005, Deka et al. 2012, Mitchell et al. 2017, Estoque et al. 2021).

Substantial variation exists in the regional and site speciûc realities of deforestation and forest degradation. Key details such as the pace and extent of deforestation, drivers of deforestation and forest degradation can provide crucial information for habitat conservation and management (Jayathilake et al. 2020). Field-based approaches are widely used in traditional restoration evaluations. With the advent of satellite data and spectral indicators, it became feasible to monitor the health and integrity of forested ecosystems at requisite spatial and temporal scale. Because of management techniques, the majority of protected areas in the northeast India are effective in protecting its forest cover, with few exceptions of Marat Longri Wildlife Sanctuary and few other landscapes which are still undergoing deforestation and degradation (Reddy et al. 2017). In Marat Longri landscape, majority of the forest dwellers are farmers and essentially depend on the protected area for subsistence and livelihoods. Presently the whole area is under the threat of jhum cultivation followed by illegal-felling, agricultural expansion, encroachment and collection pressure (Phangchopi et al. 2017). As such the aim of this study was to measure and document the forest degradation in a small forested habitat in the tropics, i.e. Kaki Reserve Forest under Marat Longri landscape, Northeast India using remote sensing technology. The forest conditions were observed using Landsat satellite images from 1991 to 2015.

METHODOLOGY

Study area

The study is being conducted in Kaki Reserve Forest, which is located in the Marat Longri Wildlife Sanctuary in the Karbi Anglong district of Assam, India. It positions between 93^{o}9’E to 93^{o}18’E Longitude to 25^{o}54’N to 26^{o}3’N latitude (Fig. 1). In

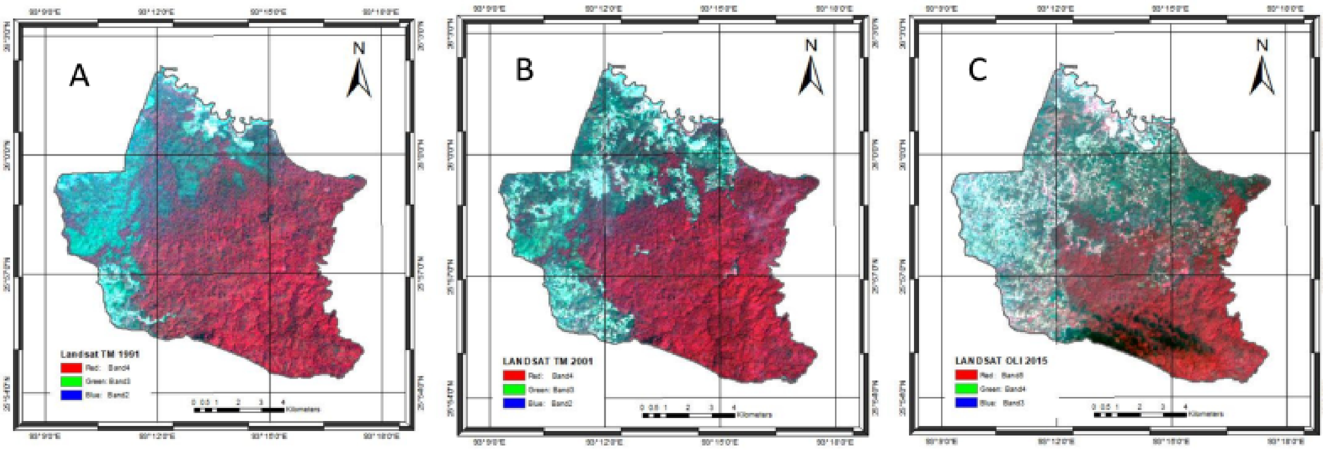

Figure 1. False color composite of the study area A) Landsat TM 1991, B) Landsat TM 2001 and C) Landsat OLI 2015

addition to Kaki Reserve Forest, the other three reserve forests under Marat Longri Wildlife Sanctuary are Mijungdisa RF, Disama RF and Inglongkiri RF. Of the total geographic area of the sanctuary i.e. 451 km^2, Kaki Reserve Forest covers an approximate area of 116 km^2 which is approximately 25.72% of the sanctuary. The vegetation is of semi-evergreen and moist-deciduous types. The temperature there varies from 6-12^{o}C in winter and 23-32^{o}C in summer. This area has satisfactory ecological, floral and faunal significance. The Reserve forest is mainly inhibited by seven ethnic groups namely Karbi, Dimasa, Hmar, Garo, Chakma, Nepali and Adivasi. Forests area is been encroached for human settlements, agricultural expansions and is being most alarming in Kaki Reserve Forest. People practices farming in the area by clearing forest and other vegetation. Moreover, food insecurity and lack of awareness among forest dwellers can be linked to overexploitation of forest resources.

Data Used and Image pre-Processing

The University of Maryland's Global Land Cover Facility (GLCF) (http://glcf.umiacs.umd.edu/data/) is the major source of orthorectified Landsat TM and OLI sceneries for the years of March 8, 1991, March 3, 2001, and March 10, 2015, respectively (Table 1). False color composite for all the periods is shown in Figure 1. Cloud, cloud shadow, and water bodies can have a negative impact on the statistical handling and analysis of imaging data (Rikimaru et al. 2002).

Table 1. Satellite Data used in the study

Year	Sensor	Date of Acquisition	Path/ Row	Bands used
1991	Landsat TM	08-03-1991	136/42	1,2,3,4 and 5
2001	Landsat TM	03-03-2001	136/42	1,2,3,4 and 5
2015	Landsat OLI	10-03-2015	136/42	2,3,4,5 and 6

As a result, the first stage in the pre-processing procedure was to filter any cloud, cloud shadow, and water pixel in the scenes. The imageries of 1991 and 2001 are cloud-free datasets, while the 2015 dataset includes a little quantity of cloud (1%). Cloud, shadow, and water masking may be done using the histogram of each individual band (band 1, 2, and 3 for cloud and shadow, and band 4 for water) or by defining suitable AOIs (areas of interest) for the features. Because the scenes were captured at different periods, there is a slight variation in geometric correctness. As a result, more data correction is required. The 1991 and 2001 datasets are being resampled for the 2015 dataset. With an RSME error of less than 0.5 pixels, image to image registration was conducted between the datasets, which were co-registered in the UTM (WGS-84) coordinate system using the nearest-neighborhood technique. After that, all the images were radiometrically corrected (Chander et al. 2009) and atmospherically adjusted using dark-object subtraction techniques (Chavez 1989) to convert the DN values in the satellite data to apparent reflectance at the earth's surface.

Image classification

The current study attempted to monitor deforestation or degradation in the test region through the use of Forest Canopy Density Mapping and Monitoring Model developed by Rikimaru et al. (2002). The details about the procedure and methods of FCD model was given in Rikimura et al. (2002). In brief, FCD model utilizes forest canopy density as an essential parameter for characterization of forest conditions. This model uses data from the three indices to simulate and analyse bio-spectral phenomena – Advance Vegetation Index (AVI), Bare Soil Index (BI) and Shadow Index or Scaled Shadow Index (SI, SSI). When compared to NDVI, the advanced vegetation index (AVI) reacts more strongly to vegetation amount. As the forest density rises, the shadow index (SI) rises as well. As the amount of vegetation improves, the thermal index (TI) rises. The bare soil index (BI) rises as the degree of bare soil exposure on the ground rises. Then, by synthesizing AVI and BI, the Vegetation Density (VD) is calculated. Finally transformation of VD and SSI means was done to extract the forest canopy density of the study area. Finally, the rate of canopy transformation was calculated following Puyravaud (2003).

Accuracy Assessment

Empirically, accuracy was measured by choosing a sample of pixels from the image and comparing their labels to ground truth data classes. The proportions of pixels from each class properly identified in the images by the classifier, as well as the proportion of pixels from each class incorrectly labelled into every other class, were calculated. These findings were tabulated and referred to as the 'error matrix' (Lillesand et al. 2007).

RESULTS AND DISCUSSION

Digital satellite data categorization is based on spectral signatures and is said to be more accurate (Roy et al. 1990). With increased spectral and spatial resolutions of satellite data, as well as the creation of new vegetation indicators, digital image processing techniques has progressed exponentially. The vegetation indices help to extract the significant aspects of a given ground object by reducing the impacts of bias (Curran 1980). As such, the current method separates forest canopy density using the AVI, BI, and SI indices. Forest canopy densities for all the years are expressed in percentages from 0 % to 100 %. Based upon the collected ground information for different forest composition, the percentage distance class is further divided into four groups (Fig. 2). Class 1 includes pixel values ranging between 0 % and 10 % (Non forest), Class 2 between 10 % and 40 % (Open forest), Class 3 between 40 % and 70 % (Medium forest) and Class 4 above 70 % (Dense forest) (SFR, 2009).

Both the thematic legend and statistical data produced from categorized pictures might be deceptive in the absence of an accuracy evaluation and a rectification procedure (Achard et al. 2001). As a result, adequate ground validation for the 2015 classified picture has been performed to ensure its correctness. Prior to ground validation, all classified images were subjected to a majority filter (3X3 window) to achieve marginal homogeneity between neighboring pixels. This was done to make it easier to locate the classified classes and to reduce any further noise in the classified image. The total accuracy is 85%, with a kappa value of 0.80 (Table 2). It has been found that the classification accuracy for the categories i.e. dense forest and non-forest density are quite high, with values of 100% and 93.3% respectively, while medium and open forest class shows a slightly lower accuracy level of 78.6 and 72.2 %.

It has been observed that in the year 1991, dense forest covers the maximum area with 38.1 km^2 which accounts for 33.4% of the test site followed by open forest, non-forest and medium forest with 27.4 (24.0 %), 25.7 (22.5 %) and 22.5 (19.7 %) km^2, respectively. In 2001, maximum area is covered by non-forest with 40.8 km^2 (35.8 %) followed by dense, medium forest and open forest with 31.3 (27.5 %), 29.7 (26.1 %) and 11.8 (10.3 %) km^2, respectively. Again in the year 2015, it has been observed that non-forest covers the maximum area with 55.8 km^2 which accounts for 48.9 %, followed by medium forest, open forest and dense forest with 31.3 (27.4 %), 17.7 (15.6 %) and 10.0 (8.7 %) km^2, respectively. The results show that there is a significant decline in dense forest and open forest areas, while there is a rise in medium forest and non-forest regions between

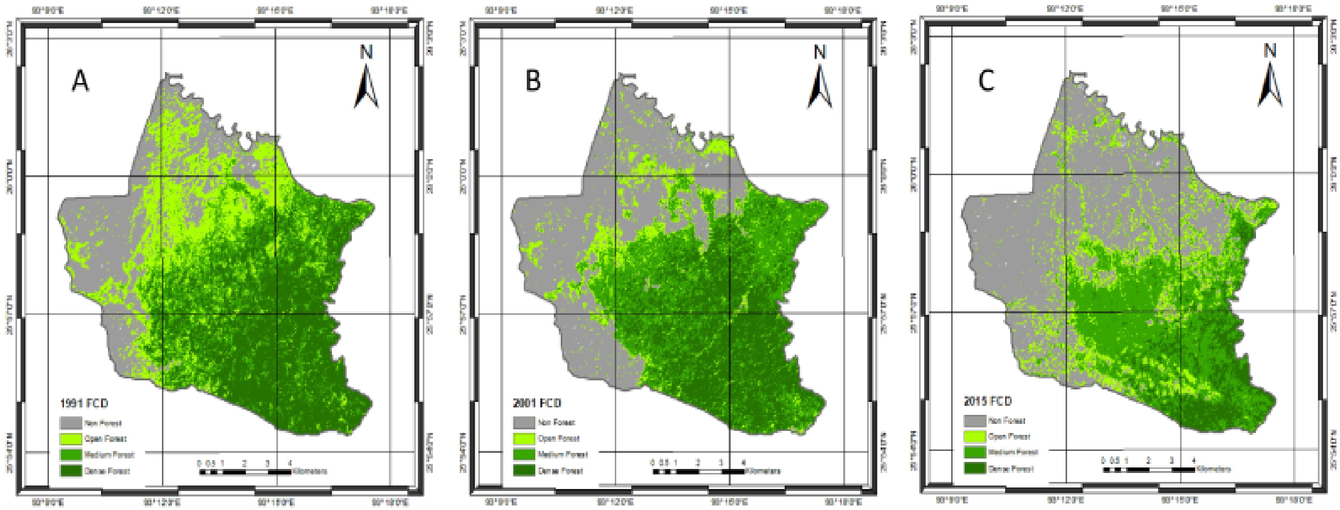

Figure 2. Forest Canopy Density of the study area A) 1991, B) 2001 and C) 2015

Table 2. Error matrix of randomly sampled classified map of 2015

Forest cover	Dense Forest	Medium Forest	Open Forest	Non Forest	Row total	Procedure's accuracy
Dense Forest	13	2	0	0	15	100.0
Medium Forest	0	11	4	0	15	78.6
Open Forest	0	1	13	1	15	72.2
Non Forest	0	0	1	14	15	93.3
Colum Total	13	14	18	15	60	
User's accuracy	86.7	73.3	86.7	93.3		
Kappa	0.80					
Overall accuracy	85.00%					

the timeframes (Table 3).

Forest cover transformation from dense to open category, which is also considered as a measure of deforestation was found to vary significantly among different periods. Similar, fluctuating nature of deforestation rate for different periods was also reported by Nath et al. (2012). Rate of forest cover transformation ranges from 0.37 to -8.15. Overall net rate of deforestation was relatively high in the north east region of India (–0.90 to –5.29) was also reported by other workers (Reddy et al. 2013). The average rate of change of dense forest was found to be highest with a value of -5.06 which is exceptionally high. Positive rate in case of medium forest cover over the period might be due to migration from other forest category. Over the period open forest also shows an average negative rate of -2.76. Moreover, rate of forest cover transformation was observed to be higher for the period 1991-2001 than 2001-2015, with a value of -2.54 and -1.63 respectively. Deforestation in the north east region of India has also been reported to be greater between the years 2001 and 2010 than it was between 1987 and 2001, well established with the current result (Deka et al. 2012).

Table 3. Area Statistics of forest cover and rate of transformation in the study area

Land cover	Total Area (km^2)			Rate of trans-formation (%)	
	1991	2001	2015	(1991 -2001)	(2001 -2015)
Non forest	25.7	40.8	55.8	4.62	2.24
Open forest	27.4	11.8	17.7	-8.42	2.90
Medium forest	22.5	29.7	31.3	2.78	0.37
Dense forest	38.1	31.3	10.0	-1.97	-8.15

As the satellite data gathering time for each period is almost identical, a change detection analysis performed between 1991 and 2015 (Table 4). During the period, 67.06 km^2 of the 114 km^2 area remained unaltered, while 41.6 km^2 of the region was subjected to modifications. The total area under deforestation was found to be 61.12 (53.3%), whereas the total area under regrowth was 5.94 (5.2%). Increasing degrees of deforestation may be detected in the studied area from 1991 to 2015, while recovery shows a low trend of 5.2% from 1991 to 2015. Ground validation for transforming non-forest to forest areas was undertaken, and it was observed that an increase in bamboo plantation and homestead forest in some patches result to an improvement in forest cover. Hence, both deforestation and degradation is occurring on a wide scale in the studied region, mostly as a result of increased encroachment, logging and agricultural land expansion.

Table 4. Change matrix of forest cover transformation (1991-2015)

1991LULC	2015LULC	Area Km^2	Change
Non Forest	Non Forest	23.83	NO CHANGE
Non Forest	Open Forest	2.16	NF to OF
Non Forest	Medium Forest	0.29	NF to MF
Non Forest	Dense Forest	0.00	NF to DF
Open Forest	Non Forest	19.68	OF to NF
Open Forest	Open Forest	5.20	NO CHANGE
Open Forest	Medium Forest	2.80	OF to MF
Open Forest	Dense Forest	0.11	OF to DF
Medium Forest	Non Forest	7.70	MF to NF
Medium Forest	Open Forest	4.91	MF to OF
Medium Forest	Medium Forest	9.37	NO CHANGE
Medium Forest	Dense Forest	0.59	MF to DF
Dense Forest	Non Forest	4.57	DF to NF
Dense Forest	Open Forest	5.46	DF to OF
Dense Forest	Medium Forest	18.80	DF to MF
Dense Forest	Dense Forest	9.27	NO CHANGE

Because of the possibly permanent effects of deforestation and forest degradation, assessing the efficacy of forested ecosystem is essential for maintaining long-term conservation (Panta et al. 2008, Higginbottom et al. 2019). The loss of ecological services offered by these ecosystems is the most immediate consequence of deforestation at the local level. These changes are more difficult to monitor and predict since they occur over a longer time period and might be difficult to quantify. As a response, delineating disturbed forest stretches becomes more important, as it may empower the forest department to develop suitable policies for the management and restoration of regions that are more vulnerable to degradation. It's crucial to understand past deforestation processes in order to establish effective conservation strategies and set priorities and activities for preserving forests that are now being deforested (Ferraz et al. 2009). There is almost no doubt that forest degradation and deforestation will have a significant impact on the protection of species and their habitats (Panta et al. 2008). The current study indicates that increased human activities such as illegal-felling, agricultural development, encroachment, and collections pressure have caused huge disruptions in this forested habitat throughout the study period. Thus, it requires rapid attention in order to ensure effective forest planning and management. For appropriate forest management and decision making, there is an ongoing need for high-quality information on forests and the condition of forest resources, which may be tracked using a forest status map. Hence, forest canopy derived from remote sensing data may be a major predictor of forest status and an important indicator of potential management measures. Integration of remote sensing data and biophysical models may be used to assess spatial forest condition and can be applied to local and regional forest planning and management, concentrating on critical ecosystems and prioritizing areas in urgent need of preservation (Wessels et al. 2004).

CONCLUSION

At both the local and regional stages, assessing forest cover patterns is critical for sustainable forest management. As a result, knowledge of forest cover status at the local, regional, state, and national levels becomes critical for any scientific forest management. It became key factor in determining the condition of any forested landscape and also tracking other ongoing spatial processes. The present study is being conducted in Kaki Reserve Forest, which is located in the Marat Longri Wildlife Sanctuary in the Karbi Anglong district of Assam, India. Forests area within the reserve has been encroached and is most alarming. Mapping of deforestation and degradation in the region is being done using Forest Canopy Density Mapping and Monitoring Model. Results show a significant decline in dense forest and open forest areas, while there is a rise in medium forest and non-forest regions. Between 1991 and 2015, the total area under deforestation was 61.12 (53.3%), whereas the total area under regrowth was 5.94 (5.2%). Rate of forest cover transformation under different classes ranges from 0.37 to -8.15 which is exceptionally high then the other parts of the country. The study indicated that increased human activities such as illegal-felling, agricultural development, encroachment, and collections pressure have caused huge disruptions in this forested habitat throughout the study period. Thus, it requires rapid attention in order to ensure effective forest planning and management. The study also demonstrates how integration of remote sensing data and biophysical models can be used to examine spatial forest state, which may be used for long-term forest management at the local and regional levels. This research will aid planners and developers in their efforts in restoration and rehabilitation of forests for the objectives of long-term forest management.

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