Trajectories of forest cover change in Chakrashila Wildlife Sanctuary (India) between 2000 and 2020 using Landsat imagery

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ABSTRACT
Forest cover changes in the Chakrashila Wildlife Sanctuary, in the north eastern Indian state of Assam between 2000 and 2020 were assessed using Landsat 5 TM (2000 and 2010) and Landsat 8 OLI (2020) satellite data. The objective of the study was to examine the temporal variations, if any, of forest cover in the Sanctuary. The satellite images of 2000, 2010 and 2020 were classified using supervised classification into three different categories viz: dense forest, open forest, and barren land. Based on a maximum likelihood classifier and using standard accuracy assessments, the results indicated that the area covered by barren land and open forest increased between 2000 and 2010 but decreased between 2010 and 2020. Similarly, dense forest had decreased by 22.32% between 2000 and 2010 but increased by 15.19% between 2010 and 2020. These changes occurred reflecting the positive results emanating from conservation policies and afforestation efforts by the primary stakeholder, the state forest department, in recent years. Such efforts were linked to the enhanced institutional status of the protected area, which had been upgraded from a Reserved Forest in 1966 to that of a Wildlife Sanctuary in 1994.

KEYWORDS
forest cover change; Chakrashila Wildlife Sanctuary; satellite imageries; supervised classification

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1. Introduction

Undisturbed tropical forests provide numerous benefits, ranging from being carbon sinks to fulfilling several social, economic and ecological functions (Rashid, Bhat, and Romshoo 2017; Sharma et al. 2022). They are, however, unfortunately being destroyed and degraded at unsustainable rates emanating from agricultural extensification and/or urbanisation expansion (Doyle, Beach, and Luzzadder-Beach 2021). Recent decades have witnessed deforestation rates to the tune of above 3 million hectares annually (FAO 2016). Deforestation is problematic, but tropical deforestation is far more worrying considering that the latter are storehouses of rich biodiversity (Phillips et al. 2017). A forest can be defined as a large tract of land covered with trees and undergrowth which provide an ecosystem for the habitat of different kinds of plants and animal species.

According to the United Nations Framework Convention on Climate Change (UNFCCC), 2001, "a forest is defined as an area of land between 0.05 and 1.0 hectares with a tree crown cover of more than 10–30% and trees with the ability to attain a minimum height of 2–5 meters at maturity in situ."

The study of forest cover change is one of the most important constituents of land use and land cover (LUCC) change (Lele, Joshi 2009). Land use can be defined as the changes that accrue as a result of human activities on land which are influenced at multiple scales by economic, cultural, political, historical, and land-tenure relations (Brown 2003). Deforestation and desertification are often the main outcomes of LUCC change taking place and bringing about alterations from naturally occurring land cover to anthropogenic or man-made land use categories (Foster 1992; Lele and Joshi 2009). The detection of land-use change and changes in forest cover enables the observation and evaluation of spectral and temporal variations that are happening within various environments (Mouat et al. 1993; Panuju et al. 2020).

Land-use induced land cover change can be classified into two types: 'modification' which indicates an alteration in condition within a cover type and 'conversion' which refers to the transition from one cover type to another (FAO 1995b). Forest changes can be either negative (deforestation) or positive (reforestation/afforestation) (Fig. 1).

"Deforestation is defined as a long-term or permanent removal of forest cover and conversion to non-forested land use" (Lund 1999). According to the United Nations Food and Agriculture Organization (FAO 2001), if the tree canopy cover falls below 10% or the forest is transformed into some another land cover then it can be termed as deforestation.

The drivers of deforestation are variously bio-physical, location and socio-economic (Chowdhury 2006), and include illegal cutting and extending of agricultural land (Indrabudi et al. 1998), particularly smallholder agriculturalists. Since 1990 the world has lost 178 million ha of forest, at a rate of net forest loss of 4.7 million ha per year in 2010–2020 (FAO 2020). Conversion in forest class, such as from dense to open forest, is referred to as forest degradation because they entails detrimental impact on the site and reduce the production capacity (Dutca and Abrudan 2010). Ecological and social problems such as an increase in global warming, soil erosion, and biodiversity loss are caused by depletion in forest cover (Kaliraj et al. 2012). Forest cover mapping helps in providing a constant delineation of land cover (Kumar 2011). In India, forest cover assessment for the entire country is carried out every two years by the Forest Survey of India (FSI).

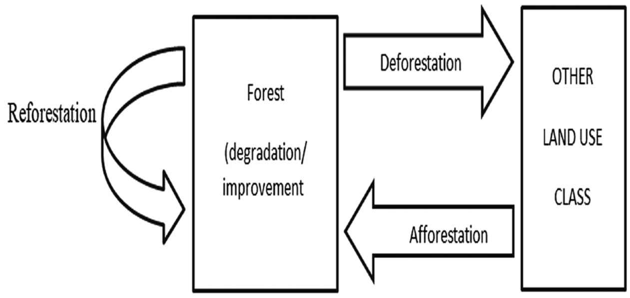

Fig. 1 Change in forest land (FRA 2000).

For formulating various management strategies a precise database relating to forest cover, forest types, species composition as well as information of temporal changes in forest cover is required (Kaliraj et al. 2012; Karia et al. 2001; Kumar 2011). A regular observation of forest cover conditions is essential for detection and modeling of forest cover disturbances (Estreguil and Lambin 1996). For effective conservation management, it is crucial to ascertain the maximum amount of forest cover change that can be tolerated by wildlife communities (Corkery et al. 2020). Analysis of the cumulative impacts of changes in a landscape is vital for conserving sensitive habitats and environmental quality (Estreguil and Lambin 1996).

In recent years the use of remote sensing datasets has become indispensible to assess and monitor forest cover dynamics at regular intervals (Forkuo and Frimpong 2012; Sharma and Joshi 2013; Kaliraj et al. 2012; Lele and Joshi 2009). In remote sensing, the process of identifying differences over a geographical area by observing them at different times using multi-temporal data sets is known as change detection (Panuju et al. 2020; Singh 1989). Spatial distribution of forest resources, diversity conditions, and temporal changes can be analyzed and monitored using remote sensing and geographical information system (GIS) by combining spatial data with the other attribute databases (Kaliraj et al. 2012).

Deforestation due to anthropogenic activities is a major cause of forest cover change. This has been negatively affecting the natural ecosystem, biodiversity, and climate. Deforestation represents one of the largest issues in the present world. Forests have been converted to land used for other purposes for a very long period of time. Agricultural expansion, wood extraction for domestic fuel usage particularly in rural areas adversely affects the biomass (Sharma et al. 2022), and expansion of infrastructural facilities (Ahmed et al. 2022) are drivers of forest loss and degradation. North east India is a biodiversity hotspot and has several important protected areas (PAs) such as wildlife sanctuaries and national parks within it. Considering that population pressures are rather intense in India, PAs do not always mean that conservation goals are realized. This analysis makes an assessment of the trajectories of forest cover and its dynamics in Chakrashila Wildlife Sanctuary in Assam, India between 2000–2020 using remote sensing and GIS.

2. Study Area

The Chakrashila Wildlife Sanctuary (CWS) in India is spread over undulating topography covered with dense semi-evergreen and deciduous forest with strips of grasslands and scattered scrubs. Chakrashila Wildlife Sanctuary is situated in the Kokrajhar and Dhubri districts of the north east Indian province of Assam (26°15′–26°26′N, 90°15′–90°20′E). The total area of the sanctuary is around 45 sq. km enclosed by green hills and two lakes, viz Dheer Beel (a *beel* is a local term signifying a lake) and Diplai Beel on the periphery (Fig. 2). The sanctuary represents the southern-most distribution of the endangered golden langur, which is endemic to western Assam and parts of Bhutan and is the flagship species of the Sanctuary (Talukdar and Gupta 2018).

The forest tract of Chakrashila was given the status of a Reserved Forest (RF) in 1966. Deforestation and hunting were rampant, causing severe degradation of the forest, prompting Nature's Beckon, a local non-governmental organization (NGO), to launch several programs aimed at raising awareness among the local population, which eventually led to the creation of Chakrashila Wildlife Sanctuary (CWS) in 1994 (Talukdar and Gupta 2018). Wildlife Sanctuaries (WLS) are accorded far better protection and conservation than RFs. The financial resources available to WLSs and monitoring and conservation efforts are also better and more streamlined. In India protected areas (PA) are organized into RFs, WLFs and National Parks (NP). Within this 'hierarchy' of PAs, conservation measures tend to be the most stringent in the NPs and least so in RFs. The CWS hosts 33 mammal, 273 bird, 24 reptilian and amphibian species (Talukdar and Gupta 2018). Several of these bird species are endangered according to the IUCN Red Data List. The two lakes, Dheer Beel and Diplai Beel, also contribute to the sanctuary's significant bird diversity.

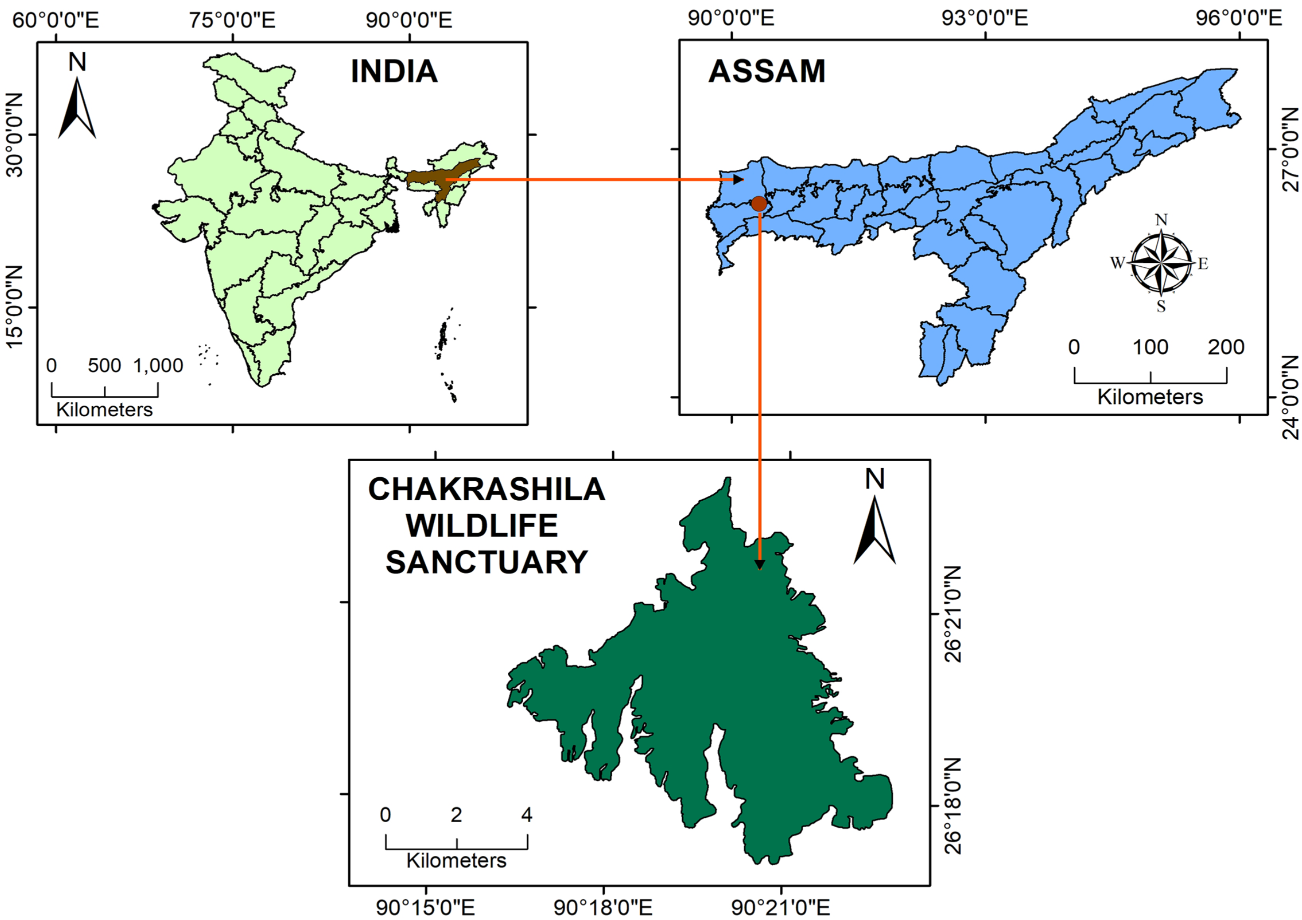

Fig. 2 Location of study area.

3. Methodology

Landsat 5 TM images of 25 October 2000 and 21 November 2010 and Landsat 8 OLI images of 16 November 2020, with almost zero percent cloud cover over the study area were used. All images with comparable calendar dates were chosen to reduce the seasonal effects on forest cover. The study made use of the combination of different bands (Band 1, 2, 3, 4 and 5). This study used the maximum likelihood classification (MLC) algorithm to run the classification, since this is known to give good results (Ahmed at al. 2022). Training samples were collected for each determined class (dense forest, open forest, and barren land) and the spectral features of each class were examined. Following recent studies (Sharma et al. 2022) Google Earth was used to select training and testing sites during the process of running the classifications for 2000, 2010 and 2020 as well as during the accuracy assessment stage of the analyses.

As a result, the study area is divided into three categories: dense forest, open forest, and barren land by locating a specific place in remotely sensed data that represent homogeneous instances of these land cover types (Fig. 3).

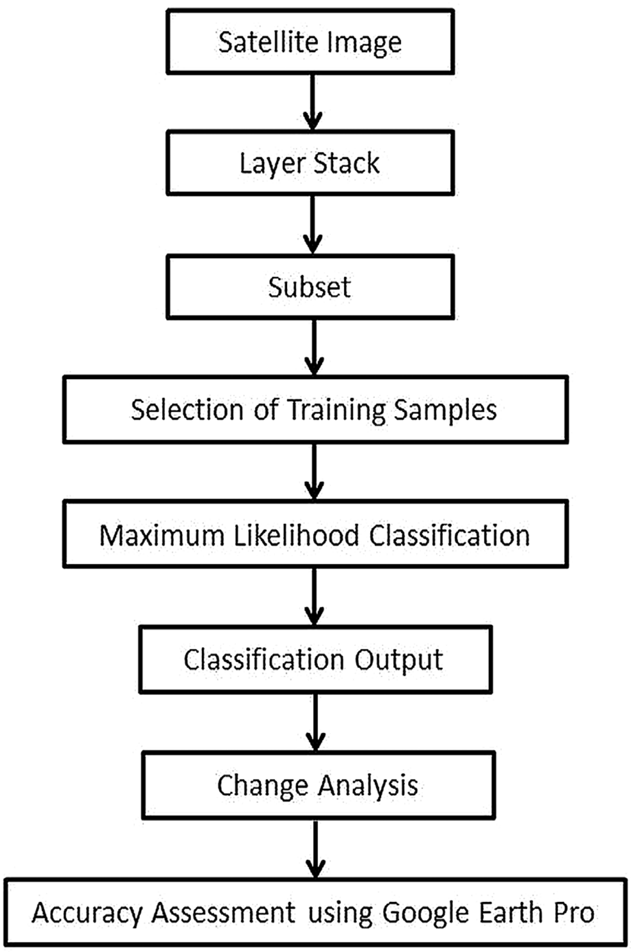

Fig. 3 Flow chart of methodology.

4. Results and discussion

4.1 Forest cover change between 2000 and 2010

Forest cover changes in the CWS from 2000–2010 showed that the most significant changes occurred in dense forest and barren land. In the year 2000, the total area covered by dense forest was 29.36 sq. km (64.85%) of the study area. During 2010, dense forest declined to 19.26 sq. km (42.53%). Overall loss of dense forest from 2000–2010 was 10.1 sq. km (22.32%) with an annual loss of 2.23 percent. Barren land showed a growth of 7.53 sq. km (16.62%) from 0.85sq. km (1.88%) in 2000 to 8.38 sq. km (18.5%) in 2010. During this decade, barren land increased with an annual growth of 1.6 percent, while open forest increased by a marginal rate of growth of 0.57 percent per year. Open forest increased from 15.06 sq. km (33.27%) in 2000 to 17.65 sq. km (38.97%) in 2010 (Tab. 1 and Fig. 4).

From Fig. 5 and Tab. 2, we find that during 2000–2010, maximum change occurred between dense and open forest with 10.51 sq. km of CWS being converted from dense forest to open forest, while 1.37 sq. km of dense forest was converted to barren land. Another change was 5.97 sq. km area of open forest being converted to barren land and 1.67 sq. km area was converted from open forest to dense forest. Marginal change in forest cover from barren land to dense forest (0.005 sq. km) and barren land to open forest (0.03 sq. km) took place from the year 2000–2010.

4.2 Forest cover changes between 2010 and 2020

The dense forest in CWS in 2020 accounted for 26.14 sq. km (57.72%) of the total geographical area which showed an increase of over 6.88 sq. km (15%) from 2010. Open forest which covered 17.65 sq. km (38.97%) in 2010 decreased to 14.52 sq. km (32.06%) in 2020. Barren land also showed a perceptible decrease in area from 8.38 sq. km (18.5%) in 2010 to 4.38 sq. km (10.22%) in 2020. The area under dense forest increased by 6.88 sq. km (15.19%), while open forest decreased by 3.13 sq. km (6.91%) and barren land by 3.75sq. km (8.28%) (Table 3). Thus some improvement in the quality of forests seems to have set in, as a transition from open forest to dense forests seems to have occurred. This is a healthy trend since dense forests are known to be superior habitat for various flagship species including Asian elephants (*Elephas maximus*) (Ahmed et al. 2022). The positive changes that accrued were a result of improved conservation and afforestation efforts associated with the protection accorded since 1994. Once it was designated as a wildlife sanctuary in 1994, better protection was given to it and conservation efforts by the state forest departments were set in motion. The results of such efforts slowly began to bear fruit and became

Tab. 1 Change of forest cover during 2000–2010.

Forest Categories	2000 (%)	2000 (sq. km)	2010 (%)	2010 (sq. km)	Change (in %)	Change (sq. km)	Annual Change (%)
Dense Forest	64.85	29.36	42.53	19.26	(–) 22.32	10.1	(–) 2.23
Open Forest	33.27	15.06	38.97	17.65	(+) 5.7	2.59	(+) 0.57
Barren Land	1.88	0.85	18.5	8.38	(+) 16.62	7.53	(+) 1.66

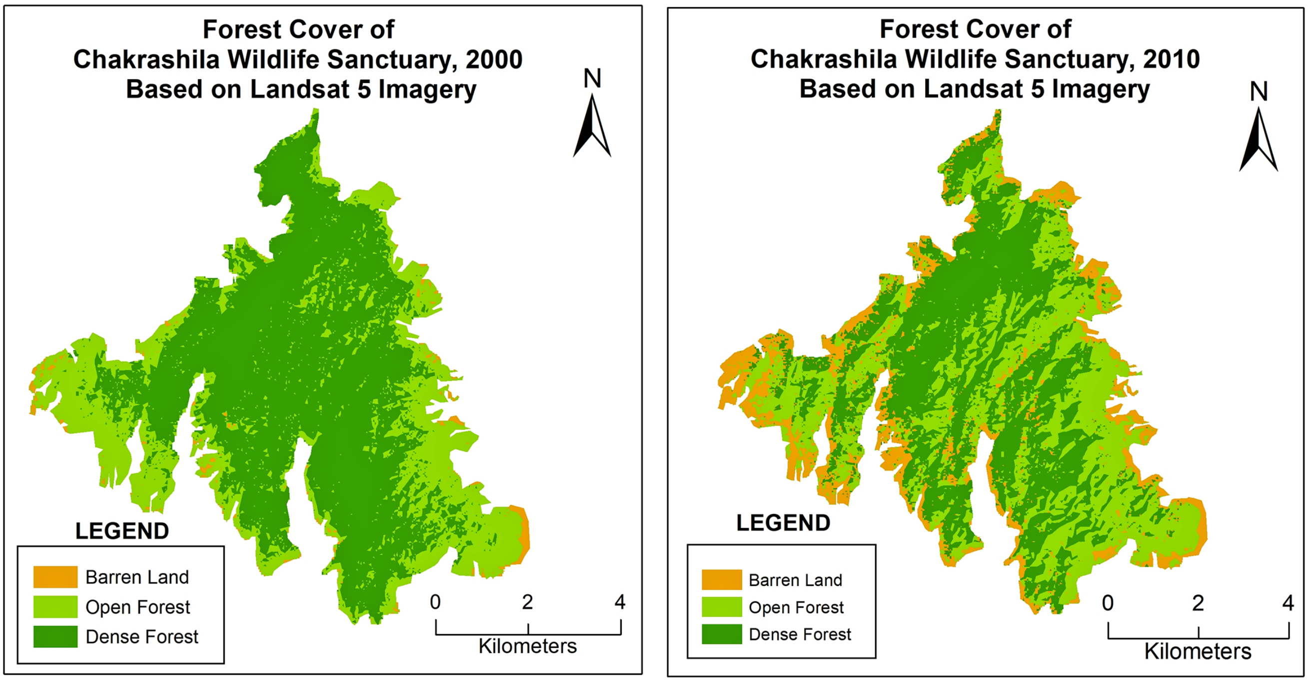

Fig. 4 Forest cover of 2000 and 2010.

Tab. 2 Change in forest cover categories from 2000–2010.

Change (2000- 2010)	Area Change (sq. km)
Barren Land – Dense Forest	0.005
Barren Land – Open Forest	0.03
Dense Forest – Barren Land	1.37
Dense Forest – Open Forest	10.51
Open Forest – Barren Land	5.97
Open Forest – Dense Forest	1.67

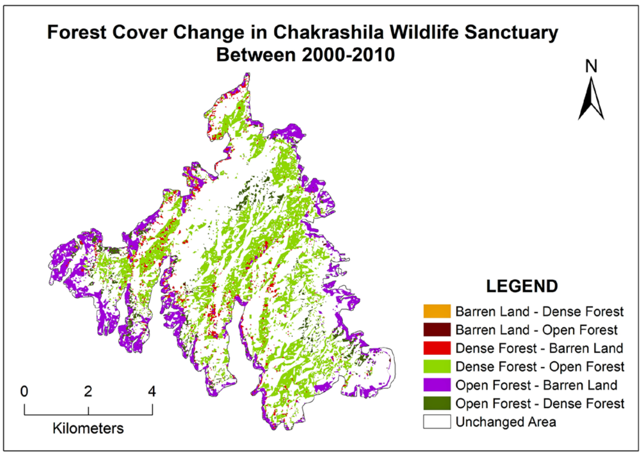

Fig. 5 Forest cover change between 2000 and 2010.

evident by the 2010–2020 period. The results of conservation efforts were probably not apparent during the 2000–2010 period since this was most likely too short a span of time since 1994 to be evident. Along with these efforts by the state forest department, were the positive role played by the local tribal communities that reside in this area, namely Bodo, Rabha, Adivasi and Garo. These tribal communities are dependent on the forest for a variety of resources including fuelwood resources. However, they attach a high priority to biodiversity conservation and maintaining the aesthetic beauty of the forest (Talukdar and Gupta 2017) and were supportive of the conservation efforts (Fig. 6).

Fig. 7 and Tab. 4 show that 1.67 sq. km and 2.44 sq. km area of barren land had got transformed into dense and open forest respectively. Similarly, 0.18 sq. km and 3.11 sq. km area of dense forest were transformed to barren land and open forest respectively. 8.81 sq. km area of open forest was converted to dense forest and 0.36 sq. km was converted from open forest to barren land. Thus it can be seen that the changes were a mixed bag of results: certain positives accrued in the shift from open to dense forests, along with some losses as well. The latter were those changes that saw open forest being degraded to barren land, bereft of forest cover. These changes reveal the results

Tab. 3: Change in forest cover during 2010-2020.

Forest Categories	2010 (%)	2010(sq. km)	2020 (%)	2020 (sq. km)	Change (%)	Change (sq. km)	Annual Change (%)
Dense Forest	42.53	19.26	57.72	26.14	(+) 15.19	6.88	(+) 1.52
Open Forest	38.97	17.65	32.06	14.52	(–) 6.91	3.13	(–) 0.57
Barren Land	18.5	8.38	10.22	4.38	(–) 8.28	3.75	(–) 0.83

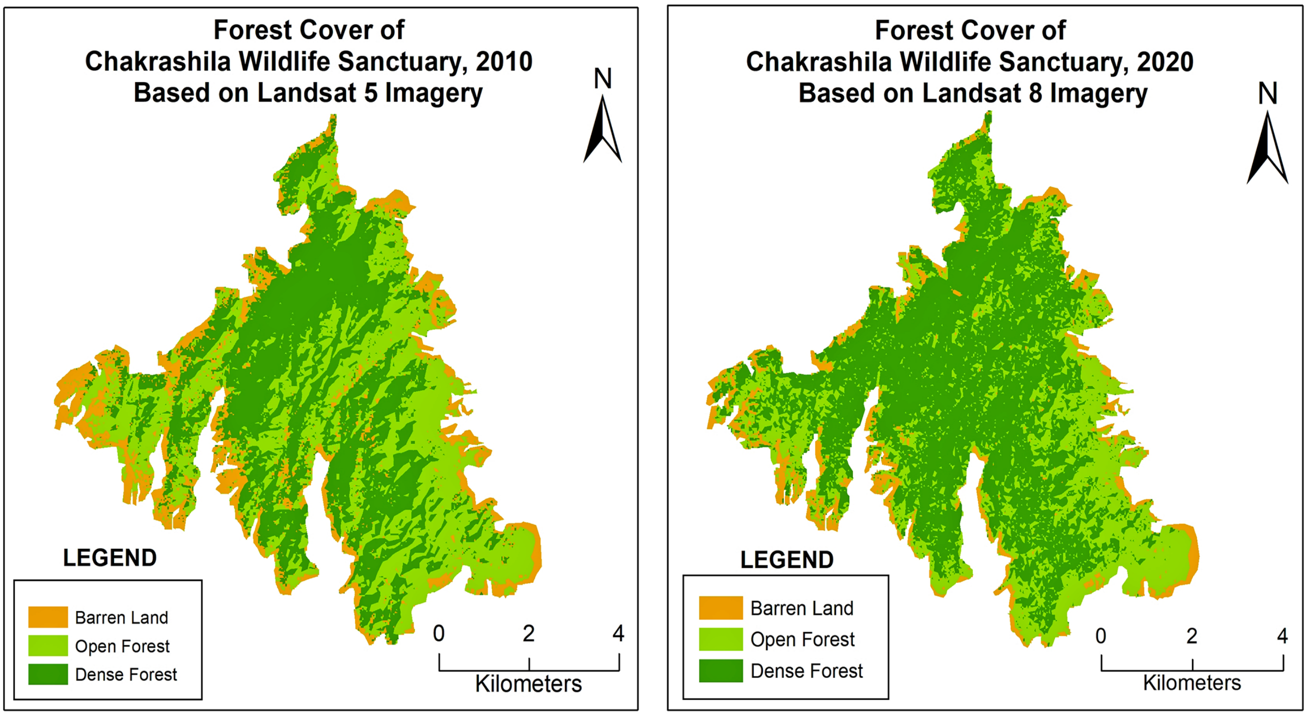

Fig. 6 Forest cover of 2010 and 2020.

Tab. 4 Change in forest cover categories from 2010–2020.

Change (2010–2020)	Area Change (sq. km)
Barren Land – Dense Forest	1.67
Barren Land – Open Forest	2.44
Dense Forest – Barren Land	0.18
Dense Forest – Open Forest	3.11
Open Forest – Barren Land	0.36
Open Forest – Dense Forest	8.81

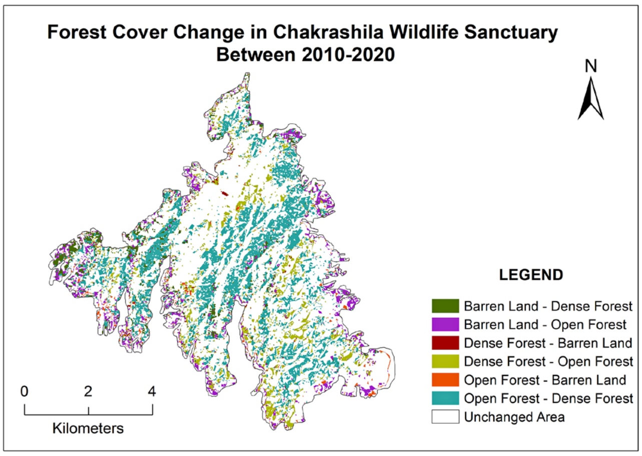

Fig. 7 Forest cover change between 2010 and 2020

of afforestation efforts by stakeholders, primarily the Forest Department of the Government of Assam. At the same time, the loss of open forest to barren land is emblematic of the stresses stemming from anthropogenic pressures of smallholder agriculturalists coupled with the sheer population pressures that exist in a densely populated country like India. Indeed, India is set to overtake China as the most populous country in the world by 2023 according to UN estimates (Hegarty 2022) and rural pressures on limited land resources are a constant threat.

5. Accuracy assessment

Because of the complexity of digital image categorization and the introduction of increasingly advanced digital satellite remote sensing systems, the need for accuracy evaluation has risen (Congalton 1991). The Kappa Coefficient of Agreement was first proposed in the early 1980s as a measure to quantify the accuracy of an image classification used to create a thematic map (Congalton 1991; Foody 2020).

For this study, the image classification of the year 2010 and 2020 has been used for accuracy assessment applying the method of kappa coefficient ($\hat{k}$).

$$\text{Kappa Coefficient } (\hat{k}) = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})},$$

where

r = number of rows in error matrix,
x_{ii} = number of observations in row i and column i (on the major diagonal),
x_{i+} = total observations in row i (shown as marginal total to right of the matrix),
x_{+i} = total of observation in column i (shown as marginal total at bottom of the matrix),
N = total number of observations included in matrix.

The overall accuracy of image classification for the year 2010 was 90.62% and overall kappa accuracy was 0.85.

The overall Accuracy and Kappa accuracy assessment of image classification for the year 2020 is 90% and 0.84. Generally accuracy assessments above 80 percent are considered acceptable in remote sensing assessments (Anderson et al. 1976).

6. Conclusion

The process of forest cover change in the CWS over a 20 year period from 2000 to 2020 was measured using Landsat satellite images at an interval of 10 years. The various forest cover categories showed both gains and losses. In the year 2000, dense forest covered 64.85% of the study area; by 2010, it had dropped to 42.53%, a substantial loss of 22.32%. However, dense forest registered an increase of 15.19% over 2010, and by 2020 it covered 57.72% of the total area of the wildlife sanctuary. Between 2000 to 2020, a total of 7.13% of dense forest area was lost.

During the early period of this analysis, forests showed more losses than gains. Along with loss in the dense forest category, barren land increased during 2000–2010. These were the result of encroachments continuing during the early years of the forest tract's conversion from an RF to a WLS. However, as the years progressed, the health of the CWS forest ecosystem gradually improved. The most evident and important gain that accrued was in the dense forest category. The proportion of dense forest increased during the latter half of the period 2000–2020. Additionally open forest transitioned into dense forest. This is a healthy trend and is indicative of the improved conservation efforts by the state forest department as well as the support of local tribal population groups that inhabit the fringe areas of the CWS (Fig. 8).

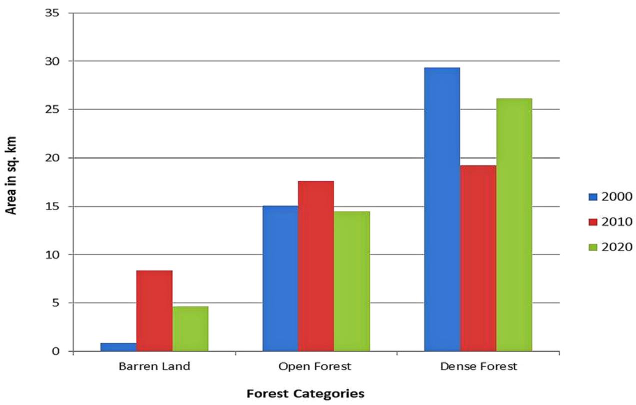

Fig. 8 Forest cover of 2000–2020.

Certain steps could be taken to improve forest conservation and minimize the extraction of forest resources and forest degradation in the WLS. These would entail greater community participation in forest management efforts. Forest resource evaluation and a periodic forest inventory using remote sensing and other tools, including high resolution photographs using unmanned aerial vehicles (UAV) would be an advisable effective strategy. State forest agencies elsewhere in India are using UAV aided forest monitoring and these are fairly affordable technologies that the CWS authorities could take up as well.

Tab. 5 Error matrix of image classification for the year 2010.

	Barren Land	Open Forest	Dense Forest	Row Total	User's Accuracy (%)	Producer's Accuracy (%)
Barren Land	9	0	0	9	100	81.81
Open Forest	2	8	0	10	80	88.89
Dense Forest	0	1	12	13	92.3	100
Column Total	11	9	12	32		

Tab. 6 Error matrix of image classification for the year 2020.

	Barren Land	Open Forest	Dense Forest	Row Total	User's Accuracy (%)	Producer's Accuracy (%)
Barren Land	11	0	0	11	100	100
Open Forest	0	7	1	8	87.5	77.78
Dense Forest	0	2	9	11	81.82	90
Column Total	11	9	10	30		

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