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Estimation of land cover changes and biomass carbon stock in north-eastern hill forests of Bangladesh

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Abstract: Forests are atmospheric CO_2 sinks, but their losses and degradation accelerate the emissions of carbon stored as a sink. Deforestation and forest degradation are widespread in Bangladesh, but their impact on greenhouse gas (GHG) emissions is unknown. We assess land use and land cover (LULC) change and forest loss in this study by classifying different Landsat satellite imagery with a focus on forest cover loss from 1989 to 2020. Tier 1 standards were used to estimate the carbon removal and emissions from a small-scale tropical forest. Over the last three decades, the forest area has decreased by 2.40%, 3.74% and 7.52%, respectively. The primary causes of forest loss are large-scale tea garden and homestead expansion, as well as increase in agricultural activities. Because of a reduction in the forest area, the annual gain of carbon in forest biomass has also decreased. Although overall carbon emission was a net gain for the Maulvibazar hill forest, it has decreased from 331.24 $Gg \cdot yr^{-1}$ in the first decade (1989 to 2000) to 307.7 $Gg \cdot yr^{-1}$ in the most recent decade (2011 to 2020), which is an alarming trend. As a result, this research will contribute to leaders' commitment to "halt and reverse forest loss and land degradation by 2030" at the 26th United Nations Climate Change Conference of the Parties (COP 26) in 2021 to improve carbon sequestration, combat climate change and conserve biodiversity.

Keywords: carbon storage; emission; land transformation; remote sensing; trees

Climate change – the outcome of anthropogenic global warming – is the single biggest environmental crisis the Earth is facing (Mal et al. 2018). Carbon emissions from deforestation are the most significant source of climate change, and they are the dominant driver of global warming (Ahmed et al. 2017). But trees can also act as a carbon sink to combat the climate change. Terrestrial systems, predominantly plants, represent an important carbon store, estimated globally at 638 Gt, of which 44% is present in plant biomass (FAO 2015). Carbon stock varies across forest types. While an average of 303 tons of carbon per ha are retained in tropical forests (Lü et al. 2010), 66 tons of carbon per ha and

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44 tons of carbon per ha are retained in temperate and boreal forests, respectively (Thurner et al. 2014). Land cover change has significant effects on carbon emission. Roughly 1.1 $Pg(C)\cdot yr^{-1}$ was emitted due to tropical land use change (Pan et al. 2011). The vast majority of forest losses is the result of agricultural and habitation-related land-use changes (Akinyemi 2017) and human interventions (Ahmed et al. 2020). Forest land has deteriorated as a result of development and other anthropogenic activities, resulting in biodiversity loss and increased CO_2 levels in the atmosphere. As a result, determining regional and national carbon stocks is critical for developing policies and programs for reducing CO_2 emissions from the forest (Salunkhe et al. 2018).

Satellite data is widely used to analyze land use land cover (LULC) changes in a given region over time (Alam et al. 2020). In Bangladesh, remote sensing data can be used to assess the state of spatial development, and developing appropriate policy plans may be a cost-effective approach (Rahman et al. 2019). Besides, satellite remote sensing data and GIS techniques can be used to identify decadal trends in forest cover and the source of deforestation (Chen et al. 2013; Vanonckelen et al. 2015; Islam et al. 2021). Avoiding the forest loss and lowering carbon emissions are critical in this era of climate change. To mitigate climate change, various frameworks such as the Reducing Emissions from Deforestation and Degradation (REDD+) and Clean Development Mechanism (CDM) may be more effectively implemented (Sangermano et al. 2012; Potapov et al. 2014).

The countrys forest resources are heavily exploited, but their restoration efforts are limited. Between 2000 and 2014, total tree canopy coverage increased slightly but natural forest acreage decreased dramatically (Potapov et al. 2017). Otherwise, global greenhouse gas emissions will rise due to deforestation in developing countries, particularly in tropical and subtropical regions (Bustamante et al. 2016). Natural hill forests are being destroyed as a result of illegal logging, shifting farming, and other land uses (Hansen et al. 2013; Islam et al. 2017). Although remotely sensed imagery was used to stratify the forest in Bangladesh, the method used to estimate forest carbon release was different. Hoque et al. (2019) used methods developed by Islam et al. (2011) and Turner et al. (1995) to estimate carbon release from the Teknaf and Rajapalong Hill Tracts in Cox's Bazar and Khadimnagar in Sylhet. In this work, changes in the carbon stock in forest biomass were quantified using the gain-loss approach in accordance with IPCC 2006 guideline. greenhouse gas (GHG) estimation is required for national-level carbon inventories. Taking these facts into account, the present study was conducted (*i*) to correctly identify and quantify the magnitude of land use land cover change from 1989 to 2020 in the Maulvibazar region as a proxy for the hill forest of Bangladesh, and (*ii*) to quantify the amount of carbon removal and emission from forest biomass.

MATERIAL AND METHODS

Study area. The study area includes the entire Maulvibazar region composed of seven upazilas: Barlekha, Juri, Kamalganj, Kulaura, Maulvi Bazar Sadar, Rajnagar, and Sreemangal (Figure 1). Maulvibazar District, located at 24.3095°N latitude and 91.7315°E longitude, has a land area of 2 799 km^2. It is bounded by the Indian states of Tripura and Assam in the south and east, and by the Bangladesh districts of Habiganj and Sylhet in the west and north. The temperature ranges from a low of 26.8 °C in February to a high of 36.1 °C in June. The average monthly humidity ranges from 74% in March to 89% in July (Kawsar et al. 2015). This area is divided into three agroecological zones: the Old Eastern Surma Kusiyara Floodplain, the Northern and Eastern Piedmont Plains, and the Northern and Eastern Hills (FAO 1988). This district is home to more than 70% of Bangladesh tea gardens. The most common forests in Maulvibazar are Lawachara National Park, Rajkandi Reserve Forest, Muraichara Eco Park, Madhovkundo Eco Park, and Lathitila Forest. Top tree species in northeastern hill forests of Bangladesh are *Tectona grandis*, *Artocarpus chaplasha*, *Lagerstromia speciosa*, *Chikrassia tabularis*, *Xylia dolabriformis* etc.

Data acquisition. Four Landsat satellite images (1989, 2000, 2011, and 2020) were obtained from Earth Explorer (earthexplorer.usgs.gov) to assess the land cover change of Maulvibazar over a 31-year period. Table 1 summarizes the Landsat data used in the study. The month of January was chosen for image selection because there was no cloud cover. The winter season in the area lasts from November to February. Because vegetation phenology occurs throughout the year, it was intended to collect images from the same month.

Image preprocessing and LULC classification. Layer-stacking multiband images were created us-

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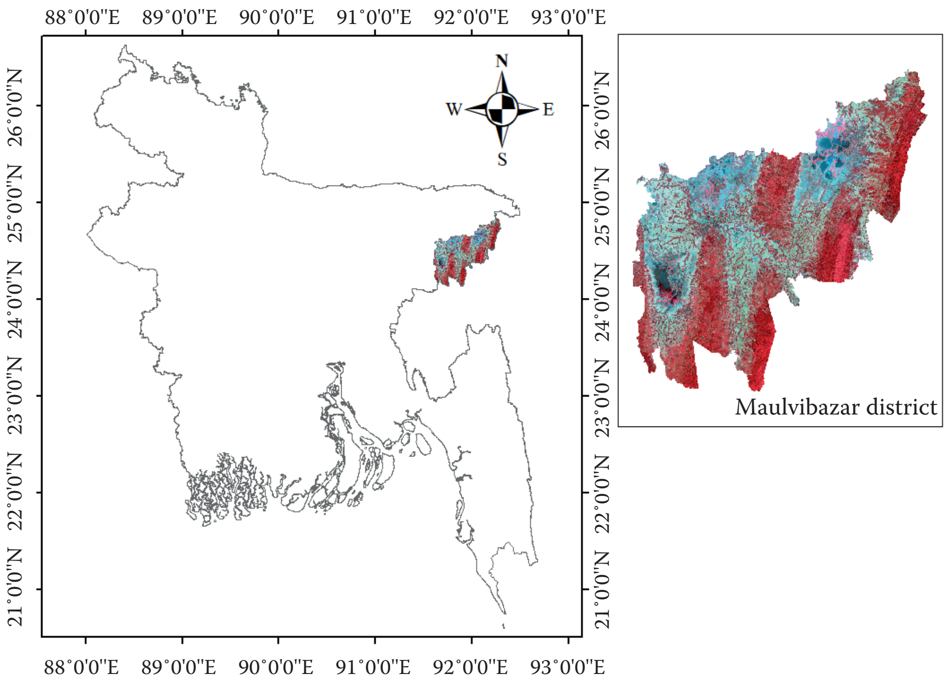

Figure 1. Study area map of Maulvibazar district of Bangladesh

ing QGIS software (QGIS 2021). All of the multiband images were visualized using a false-colour composite. The study area was clipped through using a shapefile. Following that, a training shapefile was created. A number of 65 training points for each (1989, 2000, 2011, and 2020) year and for each class were taken using QGIS to ensure appropriate classification. The R statistical package (Version 4.2.1., 2021) and the "Random Forest" (RF) algorithm were employed to categorize spectral images. For building decision trees, the RF algorithm employs a bootstrap approach (Pavanelli et al. 2018) and a non-parametric machine learning method frequently utilized in satellite image classification (Zhang et al. 2018). The RF classification was carried out in R using the programs "raster", "maptools", "biomod2", "rgdal", "plyr" and "Random Forest". The training data and validation data were split into 0.75 : 0.25. The variables that went into the algorithm were band 1, band 2, band 3, band 4, band 5, band 6, band 7, band 8, band 9, *NDVI* (Normalised Difference Vegetation Index), *NDWI* (Normalised Difference Water Index). The training data and validation data were split into 0.75 : 0.25. The variables (covariates) were surface reflectance band 1, band 2, band 3, band 4, band 5, band 6, band 7, band 8, band 9, *NDVI*, *NDWI*. The area of the LULC map was calculated using ArcGIS. In QGIS-SAGA, cross-tabulation was used to accomplish the change detection analysis. LULC is classified into six groups (built-up, crop/fallow, forest, homestead, tea garden, and water), as shown in Table 2. For an extended period, cropland and

Table 1. Characteristics of satellite images

Sensor	Path/Row	Image acquisition date	Resolution
Landsat 4-5 TM	137/43	Jan 13, 1989	30 m
Landsat 4-5 TM		Jan 12, 2000	
Landsat 4-5 TM		Jan 26, 2011	
Landsat 8 OLI		Jan 19, 2020	

Table 2. Land use land cover classification scheme

Land use/cover types	Description
Built-up	industrial, residential, transportation, road, urban, commercial
Crop/fallow	agriculture area, crop fields, vegetable lands, fallow lands
Homestead	a home consists of a tree, pond/crop field
Forest	mainly Lawachara National Park, Madhabkundo Eco-park, Rajkandi Reserve Forest, Muraichara Eco-park etc.
Tea garden	scattered shade trees with tea
Water	river, permanent water, lakes, ponds

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fallow land were put together since so much cropland had been fallow (awaiting harvest or seed sowing), even though that area is still cropland. Figure 2 displays all the methodologies used in the study in a single diagram.

Accuracy assessment. According to the classification accuracy results, for 1989, 2000, 2011 and 2020, the overall classification accuracy was 97%, 93%, 88% and 94%, and overall kappa statistics were 0.95, 0.90, 0.89 and 0.91, respectively (Table 3). These estimates indicate that the classification accuracies were of substantial agreement. This level of agreement is acceptable for the classification of land use and land cover changes.

Estimating emissions/removals of carbon from forest biomass. Tiers 1–3 are three general methodologies for evaluating greenhouse emissions and removals. The number of tiers represents the amount of information required and the level of complexity. This study used Tier 1 of the IPCC 2006 methodology. Furthermore, in many tropical countries, forest inventories are scarce. Using the Gain-Loss Method, we estimate carbon discharges from changes in carbon stocks in a living biomass pool in this study. The area of the forest was extracted from classified satellite images. After the classification of satellite images, the dark green colour represents the forest area (hill forest in the northeastern region was considered instead of individual tree species) (Figure 3). The area of forest land and non-forest land was calculated using the land-use conversion matrix. We collected timber and fuelwood extraction data from the Forest Department and through review literature (GoB 2019; FAO 2020). This calculation uses pre-determined default settings for the Tropical Forest. The carbon in forest biomass was estimated using the formulas shown below [Equations (1–7)]:

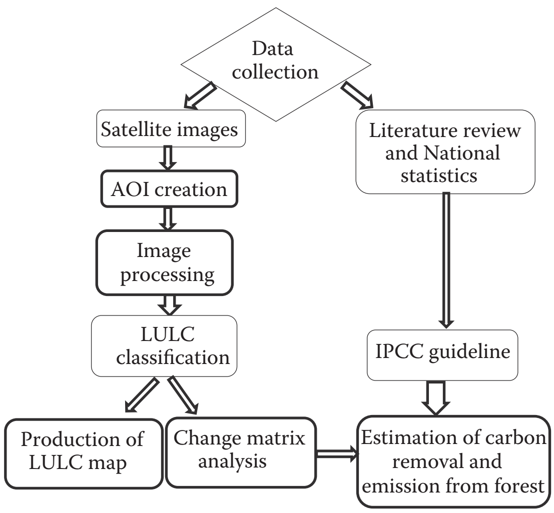

Figure 2. Flow chart of the methodology

Table 3. Accuracy assessment for the classified images

Reference year	Classified image	Overall classification accuracy	Overall kappa statistic
		(%)	
1989	Landsat 4-5 TM	97	0.95
2000	Landsat 4-5 TM	93	0.90
2011	Landsat 4-5 TM	88	0.89
2020	Landsat 8 OLI	94	0.91

$$\Delta C_B = \Delta C_G - \Delta C_L \tag{1}$$

where:

ΔC_B – annual change in carbon stocks in biomass (the sum of aboveground and belowground biomass terms), considering the total area [tonnes(C)·yr^{-1}];

ΔC_G – annual increase in carbon stocks due to biomass growth for each land subcategory, considering the total area [tonnes(C)·yr^{-1}];

ΔC_L – annual decrease in carbon stocks due to biomass loss, considering the total area, [tonnes(C)·yr^{-1}].

$$\Delta C_G = A \times G_{\text{TOTAL}} \times CF \tag{2}$$

where:

A – area of land remaining in the same land-use category (ha);

G_{TOTAL} – mean annual biomass growth [tonnes dry matter (d.m.)·ha^{-1}·yr^{-1}];

CF – carbon fraction of dry matter [tonnes(C)·(tonne d.m.)$^{-1}$]

$$\Delta C_L = L_{\text{wood-removals}} + L_{\text{fuelwood}} + L_{\text{disturbances}} \tag{3}$$

where:

$L_{\text{wood-removals}}$ – annual carbon loss due to wood removals [tonnes(C)·yr^{-1}];

L_{fuelwood} – annual biomass carbon loss due to fuelwood removals [tonnes(C)·yr^{-1}];

$L_{\text{disturbance}}$ – annual biomass carbon losses due to disturbances [tonnes(C)·yr^{-1}].

$$G_{\text{TOTAL}} = [G_W \times (1 + R)] \tag{4}$$

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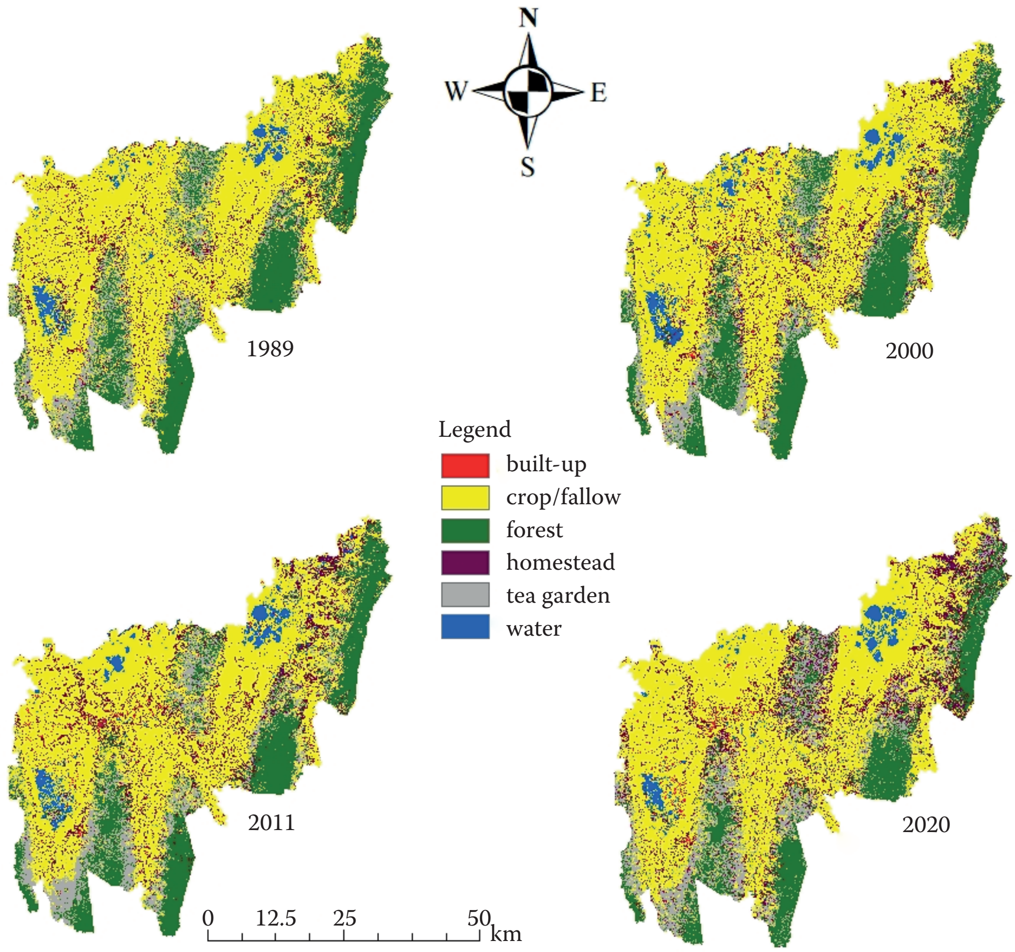

Figure 3. Deacadal changes of LULC during 1989–2020 periods

LULC – land use and land cover

where:

G_W – average annual aboveground biomass growth (tonnes d.m.·ha^{-1}·yr^{-1});

R – ratio of belowground biomass to aboveground biomass, in tonne d.m. belowground biomass (tonnes d.m. aboveground biomass)$^{-1}$.

$$L_{\text{wood-removals}} = H \times BCEF_R \times (1 + R) \times CF \tag{5}$$

where:

H – annual wood removals, roundwood (m^3·yr^{-1});

$BCEF_R$ – biomass conversion and expansion factor for the conversion of removals in merchantable volume to total biomass removals (including bark) [tonnes of biomass removals·(m^3 of removals)$^{-1}$].

$$L_{\text{fuelwood}} = [FG_{\text{trees}} \times BCEF_R \times (1 + R) + FG_{\text{part}} \times \times D] \times CF \tag{6}$$

where:

FG_{trees} – annual volume of fuelwood removal of whole trees (m^3·yr^{-1});

FG_{part} – annual volume of fuelwood removal as tree parts (m^3·yr^{-1});

D – basic wood density (tonnes d.m.·m^{-3}).

$$L_{\text{disturbances}} = A \times B_W \times (1 + R) \times CF \times fd \tag{7}$$

where:

B_W – average aboveground biomass of areas affected;

fd – fraction of biomass lost in disturbance.

RESULTS

Land use and land cover (LULC) changes

The map of LULC was created to properly identify and adjust different classes in the research area, with a particular emphasis on forest change. Six LULC classes (built-up, crop/fallow, forest, homestead, tea garden, and water) are pointed out in the LULC map (Figure 3) which was classified.

LULC change from 1989 to 2000. In general, all of the LULC categories in Maulvibazar have changed. The transition matrix illustrates the

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processes and patterns of land-use change (Figure 4). From 1989 to 2000, built-up, homestead, and tea garden increased, while crop/fallow, forest, and water decreased (Table 4). The built-up area increased by 26.80%, with most crop/fallow land converted to built-up. The permanent crop/fallow land area was 125 340 ha, with the majority of crop/fallow land transferred to homestead. Otherwise, the forest area shrank by 2.40%. In the homestead case, most crop/fallow (9 623 ha) area was converted to homestead, with 9 454 ha remaining. The tea garden was also increased by 8.57%, with the conversion of the most significant areas of forest and crop/fallow land. The area of persistent water bodies was 4 527 ha between 1989 to 2000.

LULC change from 2000 to 2011. Land use and land conversion have been ongoing since the early 20th century. From 2000 to 2011, the built-up area grew by 9.30% (Table 4). The persistent crop/fallow area was 117 356 ha, and it decreased at a rate of 2.64%. The forest was reduced by 3.74%, with an annual decrease rate of 185.96 ha·yr^{-1}, and the majority of the forest was transferred to a tea garden. Between 2000 and 2011, homestead and tea gardens increased by 23.72% and 3.79%, respectively. In the homestead case, most of the crop/fallow land was converted to homestead, followed by others. Tea gardens also increased by 3.79%. Water bodies were retained at 5 272 ha between 2000 and 2011 (Figure 4).

LULC change from 2011 to 2020. Between 2011 and 2020, built-up, homestead, and tea garden increased by 32.70%, 21.10%, and 12.96%, respectively, compared to the previous decade (Table 4). The built-up area grew due to converting the maximum crop/fallow area to built-up. The homestead was close to the built-up area, which has seen a significant increase, with the largest intrusion of crop/fallow to the homestead. Tea gardens expanded as 9 412 ha of crop/fallow and 8 633 ha of forest were converted to tea gardens, followed by oth-

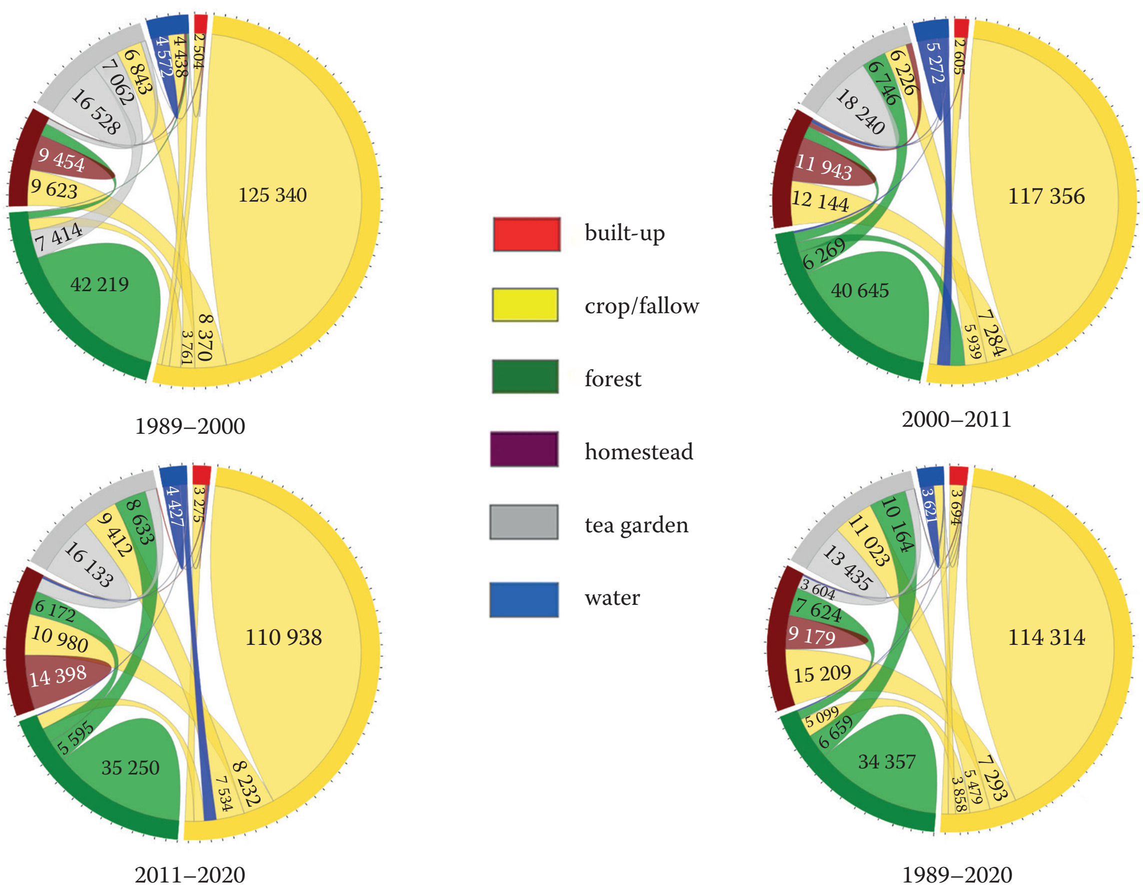

Figure 4. Chord diagram showing land conversion due to land use land conver change of the study area in different years (in ha)

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Table 4. Changes in land use and land cover in Maulvibazar

Class	Change (%)			
	1989–2000	2000–2011	2011–2020	1989–2020
Built-up	26.80	9.30	32.70	83.90
Crop/fallow	–5.19	–2.64	–3.84	–11.24
Forest	–2.40	–3.74	–7.52	–13.10
Homestead	10.44	23.72	21.10	65.47
Tea garden	8.57	3.79	12.96	27.29
Water	60.21	–13.48	–26.42	1.99

ers (Figure 4). Crop/fallow, forest, and water all decreased by 3.84%, 7.52%, and 26.42% (Table 4). Instead, the annual water loss was 256.5 ha·yr^{-1}, leaving 4 427 ha of water.

LULC change from 1989 to 2020. Significant changes have occurred over the last 31 years in the research area. The total built-up area has increased by 83.90%. The greatest amount of crop/fallow land is converted to the built-up land. Between 1989 and 2020, crop/fallow and forest declined by 11.24% and 13.10%, respectively (Table 4). The majority of the forest has been converted into a tea garden and homestead. Simultaneously, 15 209 ha of crop/fallow land and 7 624 ha of forest land were transferred to the homestead. Even though water levels fluctuated over time, overall water levels increased by approximately 1.99%. From 1989 to 2020, the figure depicts the temporal trend and relative variations in LULC in the Maulvi Bazar region (Figure 4).

Deacadal LULC changes. The built-up area was increased every year. It expanded from 0.90% in 1989 to 1.66% in 2020. The homestead area was also increased drastically from 8.14% in 1989 to 13.47% in 2020. The increased size of the tea garden was documented at 13.9% in 2020 compared to 10.92% in 1989. Crop/fallow has dropped from 56.7% to 50.33% in the last 20 years. Forest land showed a decreasing trend. In the last three decades, the trend of changing of water has been inconsistent (Figure 5).

Change of forest biomass carbon stock

Nature's carbon-removal machines, forests, are a precious natural resource. The benefits to society, economy, and climate they give cannot be avoided. The annual increase in biomass carbon stocks due to biomass growth from persistent forest land and the afforested area was 6.05 tonnes(C)·ha^{-1}·yr^{-1}. Removal of wood and fuelwood resulted in the total annual carbon loss of 105.69 tonnes(C)·yr^{-1}. Other disturbances (insect/pest, landslide, overgrazing, encroachment, etc.) were not considered. Finally, the net biomass carbon stocks were estimated to be 331 242 tonnes(C)·yr^{-1} between 1989 and 2000 (Table 5).

Between 2000 and 2011, the total amount of persistent forest land and the afforested area was 52 719 ha. Carbon stores in biomass were documented at 318.83 Gg(C)·yr^{-1} after removing wood and fuelwood from the forest (Table 5). Carbon stock in biomass was decreased by around 3.74%

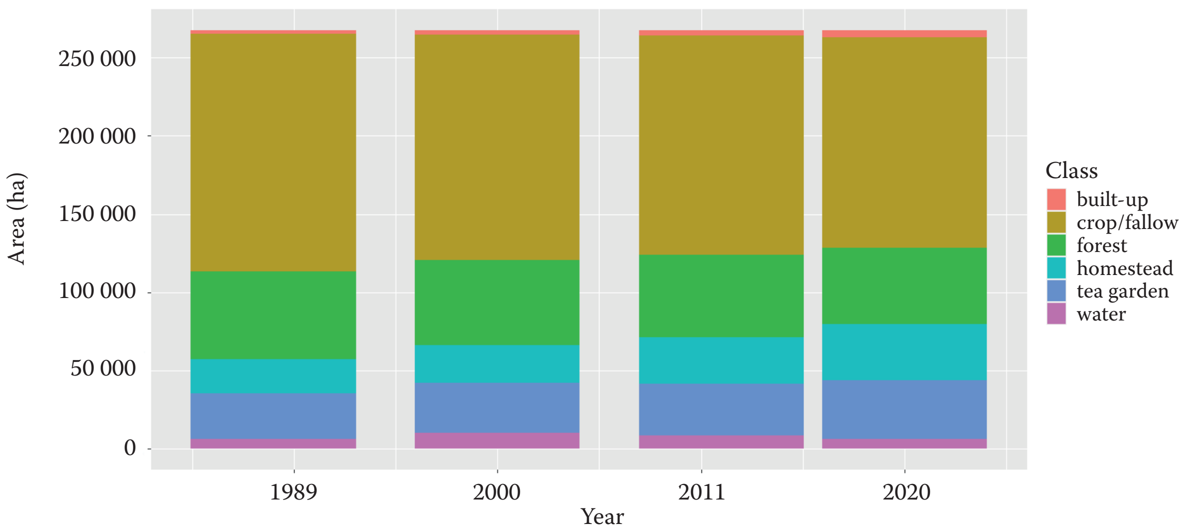

Figure 5. Land use land cover change in Maulvibazar district in 1989 to 2020

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Table 5. Net carbon stock change in biomass from forest

Year	Land use category	Area (ha)	ΔC_G	$L_{wood-removals}$	$L_{fuelwood}$	ΔC_L	ΔC_B
			[tonnes(C)·yr^{-1}]				
1989–2000	FL–FL	42 219	202 442	13.70	2.23	15.93	202 426
	non FL–FL	12 546	128 906	74.41	15.35	89.76	128 816
	total [t(C)·yr^{-1}]	54 765	331 348	88.11	17.58	105.69	331 242
	total [Gg(C)·yr^{-1}]	54 765	331.35	0.08	0.01	0.11	331.24
2000–2011	FL–FL	40 645	194 894	17.12	3.12	20.24	194 874
	non FL–FL	12 074	124 061	85.86	11.23	97.09	123 964
	total [t(C)·yr^{-1}]	52 719	318 955	102.98	14.35	117.33	318 838
	total [Gg(C)·yr^{-1}]	52 719	318.96	0.10	0.01	0.12	318.83
2011–2020	FL–FL	35 250	169 023	15.52	2.53	18.05	169 005
	non FL–FL	13 507	138 788	78.23	10.63	88.86	138 699
	total [t(C)·yr^{-1}]	48 757	307 811	93.75	13.16	106.91	307 704
	total [Gg(C)·yr^{-1}]	48 757	307.81	0.09	0.01	0.11	307.70

FL–FL – forest land remaining forest land; non-FL – non-forest land (built-up, crop/fallow, homestead, tea garden, water); ΔC_B – annual change in carbon stocks in biomass; $L_{wood\text{-}removals}$ – annual carbon loss due to biomass removals [tonnes(C)·yr^{-1}]; $L_{fuelwood}$ – annual carbon loss due to fuelwood removals [tonnes(C)·yr^{-1}]; ΔC_G – annual increase in carbon stocks due to biomass growth; ΔC_L – annual decrease in carbon stocks due to biomass loss

along with the decrease of forest land compared to the previous decade.

From 2011 to 2020, the total annual carbon gain was estimated to be 6.3 tonnes(C)·ha^{-1}·yr^{-1} from 48 757 ha of land. In the case of carbon losses, maximum carbon loss from wood removal [93.75 tonnes(C)·yr^{-1}] was followed by fuelwood removal [13.16 tonnes(C)·yr^{-1}]. Finally, the net annual biomass carbon stock was estimated to be 307 704 tonnes(C)·yr^{-1} (Table 5).

DISCUSSION

The land cover change in Bangladesh Maulvibazar landscape was assessed using medium-resolution satellite data from 1989 to 2000, 2000 to 2011, and 2011 to 2020. A loss in forest cover was revealed to be related to significant changes in land use and land cover change. During the last three decades, the forest has shrunk by 13.10% (Table 4). Murshed et al. (2021) also reported greater deforestation in Bangladesh, which was linked to higher population growth rates and agricultural land expansion. This shift in forest cover is also closely tied to human activities and management on a local scale (Ahammad et al. 2019). South Asia also lost 29.62% of its forest cover (Reddy et al. 2018). As the forest cover area shrinks day by day, this scenario will face the immense challenge posed by the Glasgow Leaders' Declaration on Forests and Land Use, which pledges to halt forest loss in less than a decade (UN Climate Change UK 2021). As a result, the persistent forest land should be declared as protected area, as 71% of the world's protected areas have contributed to the prevention of forest loss (Yang et al. 2021).

Looking at the intensity of change at the categorical level of the six transformed land use/land cover categories, homestead, crop/fallow, and tea garden conversion to forest land has contributed significantly to major forest loss in the northeastern region of Bangladesh over the past three decades (Figure 4). Deforestation caused by the permanent land use change is responsible for 27% of global forest loss (Curtis et al. 2018). Cropland expansion in South East Asia, such as conversions of coffee, tea, upland rice, and other commodities, was responsible for 88% of total forest loss (Zeng et al. 2018). Otherwise, large-scale land acquisitions (LSLAs) are a significant contributor to forest loss in the Global South (Davis et al. 2020). Finally, the land-use change, primarily due to conventional agricultural expansion and deforestation, accounts for roughly 17% of global greenhouse-gas emissions (Barker et al. 2007).

The values for changes in biomass carbon stock are positive, indicating that there is a biomass

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gain in the carbon stock of Maulvibazar hill forest. However, the net gain has decreased from 331.24 Gg(C) in the first decade (1989 to 2000) to 307.7 Gg(C) in the recent decade (2011 to 2020) due to forest area loss (Table 5). Mukul et al. (2014) noticed 179.1 million Mg of carbon in forest biomass in Bangladesh, whereas the tree carbon stock is associated with anthropogenic disturbance and stand characteristics. According to Saimun et al. (2021), the carbon storage capacity of tropical forest ecosystems is gradually declining, which is a major concern to us because forest deterioration affects the structure, composition, and variety of forests and carbon stocks, functioning, and biological processes (Gao et al. 2020). As a result, the government of Bangladesh is taking steps to collect national carbon stock data and develop the REDD+ Readiness Roadmap.

Although annual carbon loss increased from the first decade to the second decade (0.11 Gg to 0.12 Gg) due to increased wood and fuelwood collection from logging activities, it then decreased to 0.11 Gg (Table 5). Gathering of wood and fuelwood has a long-term effect on the deterioration of forests (Ahammad et al. 2019). According to Pearson et al. (2017), land use change, including deforestation, emitted 1.3 ± 0.7 Gt(C)·yr^{-1}, with timber collection accounting for 53%, fuelwood harvesting accounting for 30%, and forest fires accounting for 17%. Tropical deforestation is expected to increase from 0.467 Pg·yr^{-1} in the 2010s to 0.628 Pg·yr^{-1} in the 2090s (+35%), making tropical forests a major carbon source in the 21st century (Vieilledent et al. 2022).

The most notable contribution to the global environmental change is LULC change. The Maulvibazar region has grown in size over time. An increase in the population was a primary driver of built-up expansion, which had a negative impact on the ecology, environment, and biodiversity in the surrounding area (Rahman et al. 2019; Chakroborty et al. 2020). Crop/fallow land in the research area was diminishing year after year. Because of agricultural land depletion, biodiversity and ecological services have suffered, and food insecurity has increased (Kafy et al. 2021). Homesteads in the Maulvibazar region grew rapidly, ranking second only to agriculture in terms of national food supply and income while also preserving biodiversity (Mattsson et al. 2018). Many fallow lands were converted to tea cultivation areas, and the government encouraged the development of tea gardens rather than rubber gardens in the Sylhet Division of Bangladesh, which produces 96% of the country's tea. Maulvibazar produces 63% of the tea, while Sylhet and Habiganj districts produce 33% (Islam, Al-Amin 2019).

CONCLUSION

We present a comprehensive assessment of LULC change with a special focus on the forest change, whereas the IPCC's Tier 1 default parameters are used to calculate the annual change of carbon stock in forest biomass. The forest land area was shrinking as most forest land was converted to homesteads, tea gardens, and crop/fallow land. Although tropical forests have a high capacity for carbon storage, forest degradation, such as wood and fuelwood collection, appears to contribute to carbon emissions into the atmosphere. Our findings highlight the immediate risk of carbon stock depletion linked to Bangladesh's rapid deforestation, which will assist the forest department and legislators in making forest protection and conservation decisions by determining the current state of forest carbon. It is also helpful in mapping the country's hill forest areas for long-term development, biodiversity conservation, and environmental protection.

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