DOI:10.5152/forestist.2024.24002
Forestist 2024: 74(3): 354-364

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Original Article

Assessment of the Degradation of Teknaf Wildlife Sanctuary, Bangladesh: Use of Remote Sensing and Geographic Information System Techniques

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ABSTRACT

The Teknaf Wildlife Sanctuary (TWS), situated in the southeastern part of Bangladesh, is a crucial forest biodiversity hotspot in Bangladesh currently having tremendous pressure due to various socioeconomic factors. The key objective of the study is to find out the degradation of the forest cover by land use and land cover (LULC) classification of TWS from 1991 to 2021 using Google Earth Engine (GEE) application programming interface (API)-based supervised classification approaches. The study used satellite and key informant interviews (KIIs) data to detect the forest landscape's degradation and find the potential solution to combat the degradation. It also used ArcGIS spatial analysis tools for LULC change detection and mapping. The investigation found that the dense forest vegetation in the TWS decreased by 1389 ha from 1991 (4665 ha) to 2021 (3277 ha), which is 12% of the study area. Similarly, the agricultural land, covering 3.34% of TWS, decreased by 388 ha from 1991 to 2021. The human settlement, light forests, and built-up areas showed an increase of 8% (930 ha), 6% (694 ha), and 1.3% (148 ha), respectively, in the last three decades. Although the increment of the built-up area is small, it poses severe threats to the biodiversity and flow of ecosystem services from TWS. The KIIs indicated that the Rohingya influx, overexploitation by high population density, lack of mass awareness, illegal felling, expansion of human settlements, and fuelwood supply to the brick fields, factories, government and non-government organization's offices and warehouses are abiotic drivers of forest degradation. At the same time, cyclones, reduced rainfall, and increased temperature were the natural causes. The study suggested measures to combat the degradation of the forest landscape, enabling policymakers to plan measures to retard further degradation of the TWS and conserve the threatened and rare species for reinstalling the ecosystem services.

Keywords: Deforestation, greenness, satellite image analysis, spatial land-use changes, temporal land-use changes.

Introduction

The Teknaf Game Reserve, established in 1983, was declared the Teknaf Wildlife Sanctuary (TWS) in 2020 under Article 23(1) of the Bangladesh Wildlife Act 1974. It, with an area of 11 615 ha, is distributed in Ukhia and Teknaf Upazila under Cox's Bazar District and under the jurisdiction of Cox's Bazar South Forest Division, Forest Department (Feeroz, 2013). This Protected Area (PA) houses rich biodiversity, including many threatened and rare species (IPAC, 2011). A previous study recorded 536 floral species, including 142 trees, 112 shrubs, 184 herbs, 87 climbers, ten epiphytes, and one parasitic species (Feeroz, 2013). It endures 198 invertebrates, 48 fishes, 27 amphibians, 54 reptiles, 243 birds (183 resident and migratory 60 species), and 43 mammals (Feeroz, 2013) in Bangladesh. The PA is under tremendous pressure due to various socioeconomic factors (UNDP and UN-WOMEN, 2018). The forest coverage of TWS was reduced by 46%, from 3304 ha to 1794 ha in 2009 since 1989 (Feeroz, 2013). Consequently, 25% area of the PA turned from forest into shrubby vegetation (Feeroz, 2013). In addition, three strong cyclones, in 1991, 1994, and 1997, affected the TWS severely. Furthermore, land encroachment converted many foothills and low-lying areas of the TWS into paddy fields and settlements. The settlements and homestead forests increased by 52.6% inside the TWS by 2012 (IPAC, 2011). At that time, only 10% of the area was covered by natural forests, and the rest was composed of bushes with a few scattered trees. It housed more than half of the mammalian species in the country. Multiple anthropogenic disturbances drastically hampered the wildlife habitats, which resulted in increased vulnerability and even the loss of several faunal and floral species. Considering the interacting threats, this habitat has been declared critical (Tani & Rahman, 2018).

Cite this article as:
Miah, M.D., Hossain, M.A., & Ali, Y. (2024). Assessment of the degradation of teknaf wildlife sanctuary, Bangladesh: Use of remote sensing and Geographic Information System techniques. *Forestist*, 74(3), 354-364.

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Received: January 6, 2024
Revision Requested: May 13, 2024
Last Revision Received: July 6, 2024
Accepted: July 18, 2024
Publication Date: September 5, 2024

Complex interactions of environmental and socioeconomic factors determine forest cover changes. A clear understanding of the complex interaction of the environmental and socioeconomic factors of land use and land cover (LULC) change can help in planning the restoration of the forest landscape and sustainable forest management (Hassan et al., 2023). For understanding LULC changes, geographic information system (GIS) and remote sensing techniques have already been proven to be helpful tools (Reger et al., 2007). To sustainably manage the forest and monitor LULC changes, repetitive and updated land-use change information is crucial to planning appropriate measures to combat anthropogenic and environmental stressors (Hasan et al., 2017). Different researchers have detected forest degradation based on socioeconomic and physical parameters (Reger et al., 2007). Dontree (2003) investigated land use dynamics and factors that affected deforestation location in Thailand. A study by Kelarestaghi et al. (2006), which monitored land-use dynamics in Northern Iran during the past four decades, revealed that forest area decreased by 3%, while dry farming increased by 9.2%.

In Bangladesh, several researchers applied remote sensing for the identification of LULC changes in forest landscapes, for example, Dampha et al. (2022) and Hasan et al. (2021) studied forest cover loss in the Teknaf peninsula, with a particular focus on Rohingya camps, while Ullah et al. (2022) assessed land cover changes of TWS from a co-management perspective. There is a great dearth of information on LULC changes and their socioeconomic and environmental drivers, particularly for TWS. Along with LULC change assessment, the drivers must be explored to better address the forest management strategies. In this circumstance, integrating remote sensing with socioeconomic and physical parameters can be an excellent approach to assess LULC change detection and identification of the drivers of change. This study focused on detecting forest land-use changes in TWS from 1991 to 2021, as well as investigating the spatial and temporal patterns of these changes in relation to socioeconomic factors. By analyzing these dynamics, the study aims to recommend measures to combat the degradation of TWS, offering insights for effective and sustainable forest management strategies. This understanding will enable policymakers to take innovative measures to combat the forest degradation of the TWS. Furthermore, these measures will help save the threatened and rare species and reinstall the forest ecosystem services of the TWS. Forest ecosystem services are always interlinked with economic and national development (Kirchner et al., 2015). So, this study is relevant to the national development of Bangladesh.

Material and Methods

Description of the Study Area

The climate of Bangladesh is mainly determined by the location of the site in the tropical monsoon region: generally excessive humidity, heavy rainfall, high temperature, and distinct seasonal variations. The TWS is situated between 20°52″ to 21°09″ N latitudes and 92°08″ to 92°18″ E longitudes (Feeroz, 2013). It covers 11 615 ha of hill forests in the middle of the Teknaf Peninsula, which is 450 km away from Dhaka (Hasan et al., 2021). Myanmar and the Naf River surround it on the east, the Bay of Bengal on the west and south, and the Chattogram district on the north (Figure 1). In the Cox's Bazar district, there are two forest divisions (north and south); however, TWS is located in the south division. The climate of Cox's Bazar and Teknaf is subtropical monsoon, which is almost similar to the rest of the country (Mia et al., 2019; Nemmour & Chibani, 2006). The annual temperature in Teknaf remains at about a maximum of 34.8°C and a minimum of 16.1°C (IPAC, 2011). The average annual rainfall is 4285 mm (Mia et al., 2019).

Analytical Process

The Landsat satellite imageries were analyzed in Google Earth Engine (GEE) code editor and ArcGIS 10.8 interface, while the statistical and graphical analysis was conducted using MS Excel. A flow diagram of the analytical process of satellite imageries is shown in Figure 2.

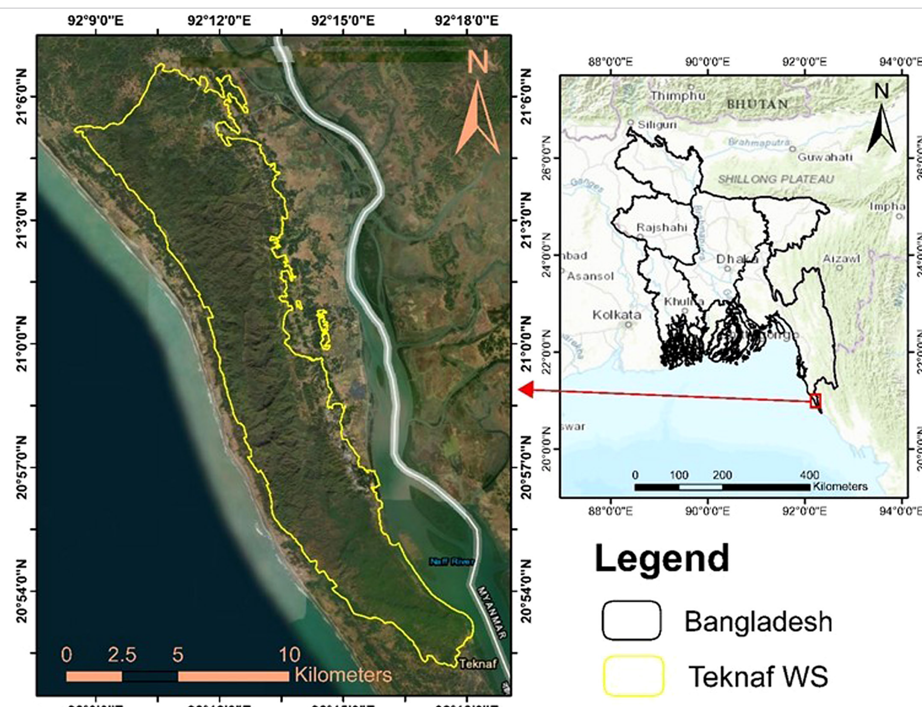

Figure 1.
A Study Area Map of Teknaf Wildlife Sanctuary in Bangladesh.

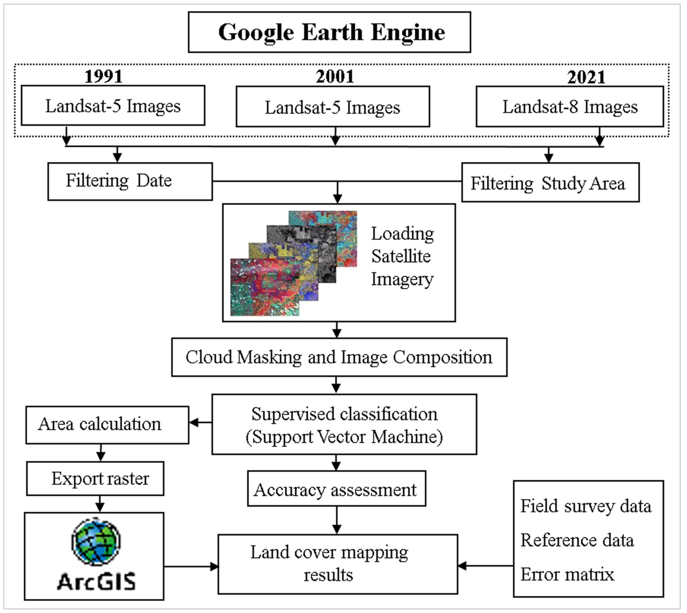

Figure 2.
Flow Diagram of the Research Workflow.

Collecting Satellite Imagery

Cloud-free Landsat satellite images were collected for 1991, 2001, and 2021 time points from the United States Geological Survey (USGS) web portal at https://earthexplorer.usgs.gov/ through the GEE code editor. The primary objective of this study is to analyze LULC changes between 1991 and 2021. To achieve this, the years 1991, 2001, and 2021 were deliberately selected to capture significant temporal changes, particularly in light of the Rohingya influx that began at the end of 2017 (Hassan et al., 2018). The selection of these specific years, rather than adhering to a fixed interval, was designed to reduce the complexity of the conversion matrix and provide clear insights into the LULC transformations over the two key periods. The shapefile of the TWS was collected from the web portal of "Protected Planet," www.protectedplanet.net/. To convert the images into a standard projection, the images were pre-processed. The study collected the base map of the TWS from the forest range offices of Shilkhali, Whykeong, and Teknaf under Cox's Bazar South Forest Division. It also collected some specific base maps from the forest beat offices under these forest ranges, which helped the study navigate the forest areas while verifying different objects and degradation/deforestation of the TWS. Global Positioning System (GPS) was used to record different spatial features for ground-truthing.

Table 1.
Details of Satellite Imageries Used in the Present Study

Satellite	Sensor	Resolution (m)	Time Period Use for Image Composite
Landsat 8	OLI-TIRS	30 × 30	01-12-2021 to 31-12-2021
Landsat 5	TM-TOA	30 × 30	01-12-2001 to 31-12-2001
Landsat 5	TM-TOA	30 × 30	01-12-1991 to 31-01-1991

Note: OLI = Operational Land Imager; TOA = Top-of-Atmosphere; TIRS = Thermal Infrared Sensor; TM = Thematic Mapper.

This dataset is the atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors and Landsat 5 TM Collection 1 Tier 1 calibrated top-of-atmosphere (TOA) reflectance (Table 1). These images contain five visible and near-infrared bands and two short-wave infrared bands processed to ortho-rectified surface reflectance, and two thermal infrared (TIR) bands processed to ortho-rectified brightness temperature (Chander et al., 2009).

Processing Satellite Imagery

All Landsat TM and OLI data pre-processing was conducted on the GEE platform (https://earthengine.google.com). This study's image processing flow chart (Figure 2) mainly included the following steps. (1) selection of all TOA reflectance data of December for each study year to correct the problem of cloudy optical images. (2) Clouds were removed from satellite images (cloud cover less than 5%). (3) The median GEE reducer function generated a single composite image from the image collection. (4) The study selected the Support Vector Machine (SVM) algorithm as the classifier for supervised classification because the reliability of SVMs for classifying hyperspectral images of remote sensing has been proven in various studies (Nemmour & Chibani, 2006). (5) The confusion matrix was used for evaluating the accuracy of remote sensing image classification, which provides the correspondence between the LULC classification results and verification data. In this work, the verification of classification accuracy is reflected by overall accuracy and kappa coefficient. (6) The area of different land cover classes is also calculated by GEE. The conversion of land cover from 1991 to 2001 and 2001 to 2021 was calculated by ArcGIS 10.8 interface.

For the accuracy assessment of the LULC classification, the study utilized 30% of the training samples for validation, while the remaining 70% were used for model training. This split ensured robust model development and validation. The accuracy of the classification was further evaluated using an error matrix and cross-validated with field sample LULC data. During the field visits, spatial data for various

Table 2.
Land Use and Land Cover Classification Scheme

LULC Categories	Definition with a Brief Description
Deep forest	Forest with continuous vegetation and large trees
Light forest	Forest with scattered vegetation, bushy and shrubby areas
Water bodies	Permanent open water, lakes, ponds and reservoirs, ditches, permanent and seasonal wetlands, low-lying areas, marshy land, and aqua fishing
Bare land	Barren land, earth and sand land infillings, construction sites, excavation sites, and open space with bare and exposed soils
Agricultural land	Land used for agriculture, paddy fields, vegetables, betel leaf, shrubby fruits, and other cultivated lands
Homestead and settlement	Homestead vegetation, households, and premises surrounded by trees
Built-up area	Residential and commercial areas without vegetation, transportation infrastructure, Rohingya camp, and brick field

LULC categories were collected through ground-truthing. These categories included makeshift settlements within the TWS, agricultural fields, water bodies, roads, brickfields, Rohingya camps, dense forests, shrubby vegetation, and bare areas (Table 2). The collected field sample data were then cross-checked using the ArcGIS interface, aligning each point with the classified raster for the year 2021. This cross-validation confirmed that the accuracy assessment from the field samples was consistent with the accuracy derived from the error matrix of the GEE-based algorithm. However, for the years 2001 and 1991, this cross-validation process was not feasible due to the impracticality of collecting ground-truthing points from those years during the 2021 field visits. To obtain the LULC conversion matrix, the study used a series of ArcGIS conversion tools, spatial intersection tools, and an MS Excel pivot table. A standard process was used to get two conversion matrices for 1991–2001 and 2001–2021. All conversions were mapped using ArcGIS Desktop 10.8.

Key Informants Interview

The study used a semi-structured questionnaire to interview key informants to identify the drivers of the LULC changes. The selection process for the key informant interviews (KIIs) involved categorizing the target group into three major categories: (1) Forest Department (FD) officials, (2) representatives from NGOs and other organizations directly or indirectly involved in forestry projects, and (3) local community members with extensive knowledge and connections to the TWS and its surrounding areas, such as local teachers, farmers, and elderly residents. Informants within each group were selected using a convenience sampling method, ensuring the availability of respondents during the field visit. Then, after completing the supervised classification, a semi-structured questionnaire was developed based on the findings of the supervised classification of LULC in TWS. Afterward, the data crews interviewed the key informants at their convenient time and place by making an appointment over the phone. A total of 27 key persons, including the FD, development agencies (NGOs), UN organizations, and local communities, were interviewed. The data crews asked about positive and negative changes in LULC and the possible reasons behind those changes. Additionally, the data crews asked about the past and present activities of the different projects (NGOs and government) at TWS and their current activities. The study also aimed to know the beneficial and harmful impacts of the land-use changes observed in the study area and find possible solutions for the negative consequences. The study directly interviewed the forest officials, including the Divisional Forest Officer (DFO), Assistant Conservator of Forest (ACF), and Range Officers (RO) of three ranges (Teknaf Sadar range, Whykhong range, and Shilkhali range) of TWS by physically visiting the office of the respective Chattogram South Forest Division and each range office. A total of eight responses from FD officials, ten responses from the local community, including local teachers, farmers, CPG, CMC members, local elderly people, etc., and nine responses from NGOs and UN organizations were considered for the study.

Statistical Analysis

The social data were analyzed to find out the key drivers of the LULC changes using MS Excel software. The study only considered responses that at least two respondents gave. The response size in favor of different drivers was expressed as a percentage of the total respondents. The post-processing of the LULC raster was performed in ArcGIS 10.8 software. After that, the study presented the findings in text, tables, infographics, and graphs.

Results

Spatiotemporal Distribution of Land Use and Land Cover

Spatial and temporal information of LULC data over the TWS were shown by seven land cover classes: deep forest, light forest, water bodies, bare land, agricultural land, homestead and settlement, and built-up area. Table 3 shows the distribution of the LULC classes for the three-time points (1991, 2001, and 2021), and Figure 3 shows the spatial distribution of these areas. The spatial distribution of the LULC classes in 1991 showed that light forest was the most extensive land cover in TWS, covering 46.65% of the total area, followed by deep forest with 40.17% area coverage. However, water bodies, bare land, agricultural land, homestead and settlement, and built-up area were represented by 0.67%, 0.18%, 6.73%, 5.58%, and 0.03% areas, respectively.

The two large LULCs (light forest and deep forest) are distributed over 84.14% of the TWS area. In 2001, as in 1991, the light forest was the largest LULC class with 49.2% area coverage. The remaining six LULCs—water bodies, bare land, agricultural land, homestead and settlement, and built-up area—covered 0.75%, 0.11%, 4.47%, 10.44%, and 0.10% of the area, respectively. In comparison with the last decade (1991), the percentage of deep forest and agricultural land was reduced to a great extent, while the percentage of light forest, homestead and settlement, and built-up area showed an increasing trend. According to the KII, most respondents

Table 3.
Relative Distribution of Teknaf Wildlife Sanctuary Land Use and Land Cover Classes from 1991 to 2021

LULC Classes	Area Covered by the LULC Classes (ha)			Percentage Coverage by the LULC Classes			Percentage Change (1991–2001)	Percentage Change (2001–2021)
	1991	2001	2021	1991	2001	2021		
Deep forest	4665.28	4058.50	3276.66	40.17	34.94	28.21	−5.22	−6.73
Light forest	5418.24	5714.07	6112.25	46.65	49.20	52.62	2.55	3.43
Water bodies	77.80	87.23	77.63	0.67	0.75	0.67	0.08	−0.08
Bare land	21.32	13.08	26.33	0.18	0.11	0.23	−0.07	0.11
Agricultural land	781.16	518.96	393.42	6.73	4.47	3.39	−2.26	−1.08
Homestead and settlement	647.98	1212.12	1577.60	5.58	10.44	13.58	4.86	3.15
Built-up area	3.23	11.04	151.10	0.03	0.10	1.30	0.07	1.21
Total area	11615	11615	11615	100	100	100		

Note: LULC = Land Use and Land Cover. *Positive percentage change values indicate the increase in land cover area, and (–) negative values indicate the decrease in land cover area.

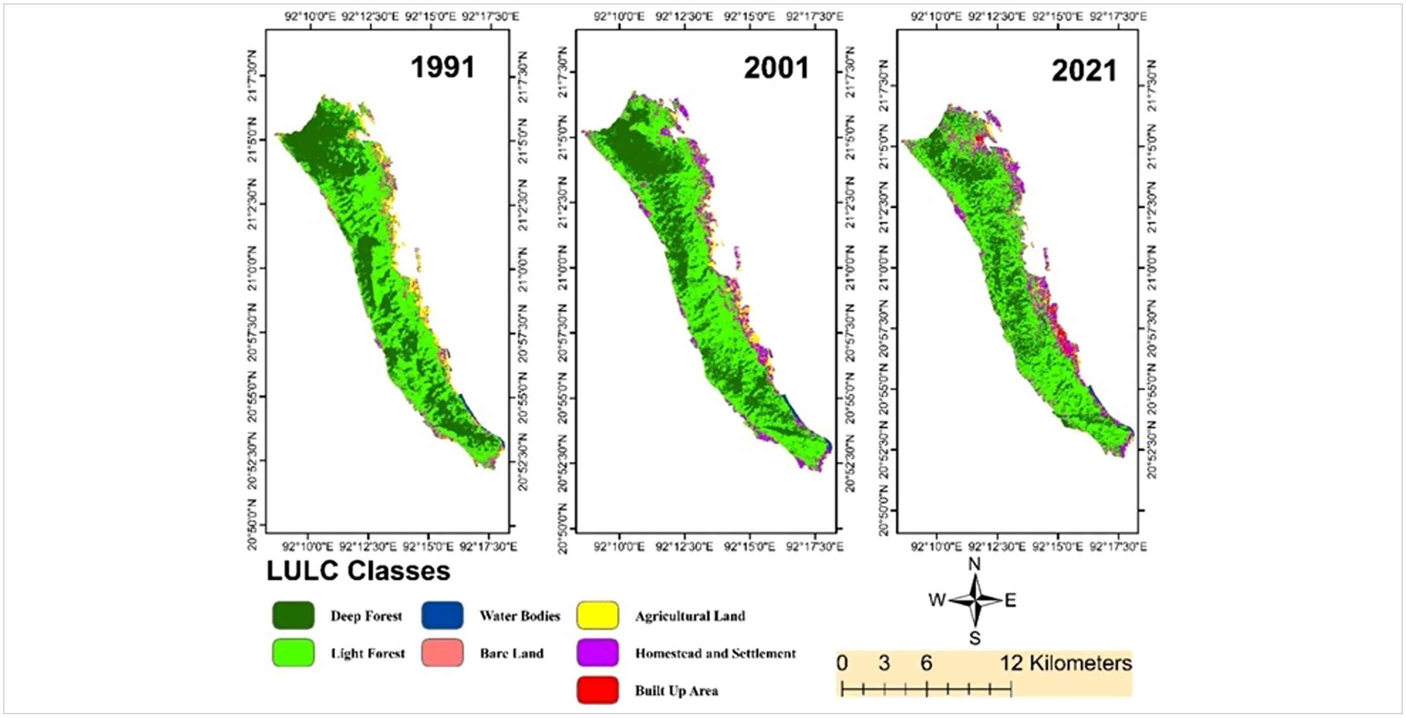

Figure 3.
Relative Land Use Land Cover (LULC) Map of Teknaf Wildlife Sanctuary (1991–2021) in Bangladesh.

said that the deep forests of TWS decreased due to the illegal felling of trees, uprooting of trees by the cyclone, and lack of awareness.

In 2021, the LULC classification indicated a sharp reduction in deep forests and an increase in light forests. It indicated that deep forests were largely converted into light forests and other LULCs. The percentage of deep forest, light forest, water bodies, bare land, agricultural land, homestead and settlement, and built-up area were 28.21%, 52.62%, 0.67%, 0.23%, 3.39%, 13.58%, and 1.30%, respectively. Although the water body remains almost unchanged, the bare land showed a somewhat increased percentage. On the other hand, the built-up area, settlement, and light forest showed a more significant increase rate.

Relative Land Use and Land Cover Changes from 1991 to 2021

Maps presented in Figure 3 showed the spatial distribution of the land cover classes in 1991, 2001, and 2021. The relative changes of the LULC classes were estimated for two time intervals, i.e., 1991–2001 and 2001–2021, which the study named earlier (one decadal) and later (two decadal) changes, respectively (Table 3). In the case of earlier changes, the deep forest coverage and agricultural land decreased by 5.22% and 2.26%, respectively. The light forest, homestead–settlement, and built-up area increased by 2.55%, 4.86%, and 0.07%, respectively. On the other hand, the latter change showed that the deep forest coverage and agricultural land decreased by 6.73% and 1.08%, respectively. The light forest, homestead–settlement, and built-up area increased by 3.34%, 3.15%, and 1.21%, respectively. According to some respondents (including forest officials), relocation of the homestead and settlements inside the forest may be a potential solution to hinder the current horizontal expansion and degradation by illegal settlements. The respondents emphasized that increasing dense vegetation in TWS is crucial because it will give rise to ecosystem services like biodiversity, timber production, surface water supply, underground water recharge, ecotourism, carbon sequestration, etc. Respondents opined that if the light forest is undisturbed, it may turn into a dense forest in a few years. The increase of homesteads and settlements inside the forest area of TWS was a severe threat to the continuous improvement of the forest cover, especially the increasing trend of light forests and the flow of ecosystem services. The homesteads and settlements within the forests may be a significant reason for the illegal felling of trees, expansion of agricultural practices, horizontal expansion of households, and clearing of forests for new households.

The forest cover within the 10 km buffer of the Rohingya refugee camps showed a downward trend, which means forest loss intensified around the camp boundary. For example, the declining forest cover rate was 18% (Dampha et al., 2022), which was almost identical to our findings about the decreased dense vegetation.

Land Use and Land Cover Conversion from 1991 to 2001

The row total of Table 4 showed the LULC classes of 1991 and their representative area, while the column total showed the LULC classes of 2001 and their area in hectares. The agricultural land area has reduced from 780 ha in 1991 to 500 ha in 2001, where 378 ha was agricultural land at both time points, and the remaining 153 ha was converted into agricultural land from other land use classes. Of the 2.79 ha built-up area found in 1991, 0.32 ha remained unchanged until 2001, and on top of that, 9.73 ha were added through conversion from other land use classes. In the case of deep forest, about 60% of the total area (2865.66 ha) from 1991 remained unchanged until 2001, and during this time, the other 1183.95 ha were converted into deep forest area. In the case of light forests, homesteads, and bare land, it showed a somewhat increasing trend where water bodies remained almost unchanged.

Land Use and Land Cover Changes from 2001 to 2021

Similar to that, Tables 4 and 5 show the LULC classes from 2001 to 2021. In the case of agricultural land, which was 498.76 ha in 2001, it

Table 4.
Land Use and Land Class Conversion from 1991 to 2001 in Teknaf Wildlife Sanctuary in Bangladesh

LULC Classes		2001 (ha) Agricultural Land	Bare Land	Built-Up Area	Deep Forest	Homestead and Settlement	Light Forest	Water Bodies	Total
1991 (ha)	Agricultural land	347.76	1.49	7.75	1.17	361.27	50.23	11.27	780.95
	Bare land	2.74	0.23	0.19	0.21	5.97	9.09	0.00	18.42
	Built-up area	1.67	0.00	0.32	0.00	0.48	0.00	0.32	2.79
	Deep forest	8.31	0.96	0.09	2865.7	65.95	1735.9	2.45	4679.38
	Homestead and settlement	58.27	1.32	0.65	11.76	347.66	177.18	2.55	599.39
	Light forest	77.78	7.17	1.06	1170.8	408.55	3782.6	9.54	5457.43
	Water bodies	3.77	0.09	0.00	0.03	9.58	3.64	59.52	76.63
	Total	500.31	11.26	10.05	4049.6	1199.46	5758.7	85.66	11615

reduced to 379.02 ha in 2021, where only 158.17 ha of the area was agricultural land in both years; the remaining 220.85 ha was converted into agricultural land from other land use classes. The built-up area, which was 10.07 ha in 2001 and increased to 148.99 ha in 2021, grew abruptly compared to Table 4's (1991–2001) increasing trend. Here, only 6.36 ha of the area was built up in both years; the remaining 142.63 ha wereconverted into built-up area from other land use classes. It is evident that, at present, TWS is under tremendous pressure from biotic interference due to the increase in the local population density and Rohingya outsiders, which increases the built-up area at an alarming rate.

The deep forest row also showed a reduction in area in Table 4 (1991–2001) from 4050 ha to 3255 ha in 2021. A total of 2113 ha of deep forests remained consistent; the rest of the 1142 ha were converted into deep forest areas from other land covers. In the case of light forest, homestead, and bare land, it showed a somewhat increasing trend; on the other hand, water bodies remained almost unchanged as before. Although the land cover conversion of the earlier stage, 1991 to 2001, was not influenced by the Rohingya refugee crisis, the later change, 2001 to 2021, was greatly influenced by the refugee camps. Since the refugee camps expanded rapidly, this converted mostly the forested land cover surrounding the camps, which was considered as built-up in the study—occurring by replacing the forested land, degrading the forest cover surrounding the three camps by 2283 ha (Hassan et al., 2023).

Accuracy Assessment and Kappa Statistics

Accuracy assessment and the kappa statistics of each LULC classification (Table 6) were calculated based on the error matrix in the GEE platform. The LULC of 2021 obtained the highest classification overall accuracy (OA) of 0.98 and kappa 0.97, since it was comparatively recent and the situation of the field was almost similar to the satellite images of this year. On the other hand, the LULC of 2001 and 1991 both have an OA 0.93 and kappas of 0.91 and 0.90, respectively. It helps the interpreter interpret the pixel correctly.

Drivers of Land Use and Land Cover Change

Protection, conservation, and sustainable management of forest resources in a country like Bangladesh are often challenging (Hasan et al., 2021). This study determined the social factors behind the LULC changes through direct field visits and KIIs data analysis. The drivers of the LULC changes are almost the same as Bangladesh's other forests (Islam & Sato, 2012). The LULC changes from 1991 to 2021 are predominantly driven by human activities, particularly the conversion of agricultural land to residential and commercial uses and the illegal felling of trees. The impact of the Rohingya influx has also been significant, contributing to changes in barren land and settlement areas. Reforestation efforts and conservation activities play a moderate role in counterbalancing some of the negative impacts. The diverse array of less dominant drivers underscores the complexity of managing LULC changes, highlighting the need for

Table 5.
Land Use and Land Cover Conversion from 2001 to 2021 in the Teknaf Wildlife Sanctuary, Bangladesh

LULC Classes		2021 (ha) Agricultural Land	Bare Land	Built-Up Area	Deep Forest	Homestead and Settlement	Light Forest	Water Bodies	Total
2001 (ha)	Agricultural land	158.17	7.00	77.21	4.55	171.30	78.86	1.66	498.76
	Bare land	0.82	0.21	0.25	0.32	2.32	7.29	0.00	11.21
	Built-up area	2.49	0.07	6.36	0.03	0.90	0.21	0.00	10.07
	Deep forest	2.76	1.22	0.11	2113.19	106.66	1818.82	7.31	4050.06
	Homestead and settlement	152.11	5.89	47.12	64.93	627.63	295.76	6.75	1200.19
	Light forest	49.92	9.67	16.18	1071.22	623.55	3979.17	9.95	5759.66
	Water bodies	12.76	0.15	1.77	0.72	16.19	4.54	48.94	85.05
	Total	379.02	24.21	148.99	3254.96	1548.55	6184.65	74.61	11615

Table 6.
Accuracy Assessment and Kappa Statistics of Land Use and Land Class Classification in Teknaf Wildlife Sanctuary, Bangladesh

LULC Year	Overall Accuracy (%)	Kappa Values
1991	0.93	0.90
2001	0.93	0.91
2021	0.98	0.97

comprehensive and multi-faceted approaches to land management and conservation.

The most dominant drivers, influencing more than 40% of the respondents, include the conversion of agricultural land to households, brickfields, offices, factories, and plantations, which was cited by 70.37% of respondents. This conversion reflects the increasing demand for residential and commercial spaces at the expense of agricultural land. Additionally, horizontal expansion of progeny households (55.56%) underscores the growth in population and the consequent need for expanded living spaces. Illegal felling, reported by 48.15% of respondents, highlights significant deforestation activities that have contributed to the reduction in dense vegetation. Supporting this, a community survey by Ullah et al. (2022) indicated that about 45% of households in the surrounding community of TWS were directly or indirectly involved in deforestation activities, driven primarily by fuelwood collection (37%), illegal encroachment (11%), and betel leaf cultivation (9%). The Rohingya influx and the establishment of camps have also been impactful, with 40.74% of respondents noting this as a driver, particularly influencing barren land and homestead and settlement areas.

Moderately dominant drivers, affecting between 20% and 40% of respondents, include new plantation initiatives by the Forest Department and NGOs (37.04%), reflecting efforts to restore vegetation through organized reforestation projects. The effect of the Rohingya influx (33.33%) continues to be a notable factor, indicating its pervasive impact on the region's LULC dynamics. Hills cutting for brick fields or cultivation, cited by 29.63% of respondents, contributes to both deforestation and soil degradation, while the absence of built-up areas within wildlife sanctuaries (25.93%) indicates some level of conservation effort. Regular patrolling and awareness-building by NGOs, each reported by 25.93% of respondents, show the role of active management and community engagement in mitigating LULC changes.

Less dominant drivers, reported by less than 20% of respondents, encompass a wide range of activities and influences. These include the increase in population density, agricultural and agroforestry practices, project activities by NGOs, and the impact of local politics, each contributing in varying degrees to LULC changes. Issues such as lack of surface water for irrigation, land kept fallow after illegal possession, and horticultural practices also play roles, albeit on a smaller scale. The multifaceted nature of these drivers reflects the complexity of LULC changes, where socioeconomic factors, environmental conditions, and policy implementations intersect.

Measures to Combat the Negative Changes

The current study suggested several ways to combat the possible deforestation and degradation of the TWS landscape and to restore forest cover. Some of the recommended ways by this research were proven helpful by the existing literature (Hasan et al., 2021; Hassan et al., 2023), while other recommendations were deemed potential based on the current condition of the TWS.

The findings from KII revealed several consequences of the LULC changes, including land degradation (i.e., soil erosion, landslides, etc.), surface water scarcity, and saltwater intrusion due to drying out or reduced flow of fresh water in the creeks coming from TWS, drowning of the underground water table, increase in temperature due to loss of forest cover and shade, loss of wildlife habitat and human–wildlife conflict, an increase in air pollution due to dust from heavily disturbed bare soil, loss of agricultural production due to lack of irrigation water, etc. According to the KII, some of the measures that can help mitigate the consequences of LULC changes include relocation of illegal settlements across the TWS to another suitable land which will not harm the PA integrity, stopping agriculture inside the PA, afforestation or reforestation with native plant species through proven site-appropriate environmentally friendly technology; raising mass-awareness about crucial environmental issues (i.e., consequences of forest cover loss, biodiversity conservation, importance of maintaining the integrity of TWS for continuous flow of ecosystem services and maintaining ecosystem balance, etc.), strict implementation of forest and environment protection-related laws, voluntary and effective engagement of CMC in forest management, socioeconomic development of the forest-dependent people (i.e., AIG incentives, livelihood diversification, training, nutrient security, employment creation, education, etc.); enhancing FD capacity for sustainable forest management and effective monitoring; collaborating with other government and non-government organizations to stop electrification, road network development, and agricultural support to the encroached localities inside the TWS; ensuring brickfields located in nearby areas do not use fuelwood for burning bricks; providing alternatives to bamboo/wooden sticks used in the betel leaf farms; and motivating political leaders to demonstrate strong political will for protection, restoration, and conservation of TWS.

It is worth noting that previously, FD implemented different collaborative forest management projects by collaborating with INGOs and NGOs, including projects like the Climate Resilient Participatory Afforestation and Reforestation Project, Nishorgo Support Project, Forestry Sector Project, and Forest Resource Management Project. However, achievements of those projects mainly were lost due to encroachments, land use changes, population pressure, the Rohingya influx, along with many other reasons. Several projects are currently being implemented for restoration and community development, such as Sustainable Forest and Livelhoods), Greening Environment through Livelihood Improvement and Forest Enrichment), Nature and Life, and Eco-Life in and around the TWS. The USAID-CODEC Nature and Life project interventions are mostly TWS-centered. Interventions of the project include supporting co-management, livelihood support, training, restoring native rare species, providing alternative fuel, etc., in collaboration with FD, as expected to improve the overall forest coverage, biomass, and support toward the sustainable management of TWS.

Discussion

The study evaluated TWS degradation from 1991 to 2021 using remote sensing and GIS, identifying seven land-use classes: deep forest, light forest, water bodies, bare land, agricultural land, homesteads, and built-up areas. Over three decades, deep forest areas significantly declined, while light forest, homesteads, and built-up areas increased. Key

Table 7.
Drivers of Land Use and Land Cover Changes in the Teknaf Wildlife Sanctuary in Bangladesh

		Percentage of KI Respondents in Favor of the LULC Change from 1991 to 2021*					
SL	Drivers of LULC Change	Dense Vegetation (−30%)	Light Vegetation (+13%)	Barren Land (+24%)	Agricultural Land (−50%)	Homestead and Settlement (+144%)	Built-up Area (+4580%)
Dominant drivers of LULC change (percentage greater than 40)							
1	Conversion of agricultural land to households, brickfields, offices, factories, and plantation				70.37		
2	Horizontal expansion of progeny households					55.56	
3	Illegal felling	48.15					
4	Rohingya influx and camps				14.81	22.22	40.74
Moderately dominant LULC change (percentage greater than 20 and less than 40)							
1	New plantation by Forest Department (FD) and NGOs projects		37.04				
2	Effect of Rohingya influx	33.33					
3	Hills cutting for brick fields or cultivation			29.63		7.41	
4	No built-up area inside the WS						25.93
5	Regular patrolling		25.93				
6	Awareness building by NGOs		25.93				
7	Uprooting trees by cyclone	25.93					
8	Illegal settlement and household making			14.81		25.93	
9	Uncultivated agriculture lands due to an alternative profitable businesses or illegal income				22.22		
10	Landslide and soil erosion	7.41		22.22			
Less dominant drivers of LULC change (percentage less than 20)							
1	Increase population density	14.81			14.81	18.52	7.41
2	Agricultural and agroforestry practices	7.41		18.52			
3	Project activities, like awareness building, AIG, plantation, etc.		18.52				
4	Impact of local politics	14.81				7.41	7.41
5	Lack of surface water for irrigation			14.81	11.11		
6	Keep the land fallow after illegal possession by giant land lord (PHP, Basundhara, etc.)			14.81			
7	Lack of awareness	14.81					
8	Increase house rent business as it has more benefits						14.81
9	Horticultural practice	7.41			11.11		
10	Conversion of Betel leaf cultivation to households				11.11		
11	Local people sell their land to giant companies and then shift to WS					11.11	
12	Social forestry		11.11				
13	Combined management of GOs and NGOs		11.11				
14	Different government and private offices, NGO offices, storage building, etc.						11.11
15	Increase in employment opportunities						11.11
16	Fish cultivation				11.11		
17	Jum Cultivation			11.11			
19	Encroachment for settlement	7.41					
20	Improper planning and lack of policy implementation						7.41
21	Lack of FD workforce	7.41					
22	No agricultural land may increase				7.41		
23	San grass cultivation			7.41			
24	Wood businessmen	7.41					

Here, the percentage change of the LULC classes from 1991 to 2021 is provided in parenthesis beside the LULC classes. The negative sign indicates a decrease of an area, and a positive sign indicates an increase of an area.

informant interviews highlighted illegal activities, population pressure, and the Rohingya influx as primary drivers of these changes. The study emphasizes the need for sustainable management, relocation of illegal settlements, reforestation, and community awareness to counteract the adverse effects of socioeconomic pressures and environmental factors on TWS.

Our findings indicate that the deep forest area in TWS decreased by 5.22% between 1991 and 2001, and further declined by 6.73% between 2001 and 2021 (Table 3). Similar forest declines in the Chittagong Division of southeast Bangladesh have been reported in various studies (Hasan et al., 2017; Xu et al., 2020). Xu et al. (2020) suggest that socioeconomic factors, such as infrastructure and industry development, have driven deforestation in Bangladesh. Our results indicate that changes in agricultural land, light forest, homestead and settlement, and built-up areas are the primary LULC classes responsible for the conversion of deep forest areas between 1991 and 2021 (Tables 4 and 5). According to Ullah et al. (2020), the deep forest areas of TWS have been converted into settlement areas. Similarly, Khan et al. (2015) identified settlement and socioeconomic activities as the primary factors contributing to the conversion of deep forest regions. In terms of the drivers of these changes, our study highlights illegal logging as the dominant factor contributing to the alteration of dense vegetation, consistent with the findings of Alam et al. (2014). Moderately dominant drivers include anthropogenic factors like the Rohingya influx and natural factors such as cyclones, landslides, and soil erosion (Table 7). Various studies have documented the reasons for forest vegetation decline in Bangladesh, including illegal felling, leaf-litter and fuelwood collection, uncontrolled commercial logging, Jhum cultivation, and overexploitation (Samrat et al., 2023). In the context of TWS, numerous authors have identified the primary drivers of forest alteration as follows: fuelwood collection (Ahmed & Sabastini, 2024; Alam et al., 2014; Khan et al., 2015), illegal felling (Alam et al., 2014; Khan et al., 2015), hunting (Alam et al., 2014; Khan et al., 2015), encroachment for settlement (Alam et al., 2014), livestock grazing (Ahmed & Sabastini, 2024; Alam et al., 2014), and encroachment for cultivation (Alam et al., 2014; Ullah et al., 2020). Our current study supports these findings, highlighting illegal felling and encroachment for cultivation and settlements as the primary drivers of forest alteration, in line with previous research. Additionally, natural and climate change-related factors like heavy rainfall, landslides, erosion, floods, cyclones, and tornadoes contribute to forest degradation (Samrat et al., 2023), which are also identified in our study as contributing to the degradation of the TWS forest.

Our study identified significant changes in the impact of various drivers on forest degradation. Specifically, the horizontal expansion of progeny households and the formation of Rohingya influx camps within the TWS emerged as dominant factors, which were not previously recognized. Hassan et al. (2023) reported an increase in TWS deforestation after 2015, coinciding with the arrival of Rohingya refugees at Teknaf. The evident degradation of TWS due to the influx of Rohingya refugees is corroborated by the findings of Mowla and Hossain (2021). Additionally, Ullah et al. (2022) observed that deforestation rates were higher near the TWS boundaries compared to the interior areas due to activities by the local community. Our findings highlight that both the periphery and the interior of the TWS are gradually degrading due to the horizontal expansion of indigenous progeny households, alongside the Rohingya influx. These insights can aid policymakers and forest managers in implementing sustainable management strategies to address the newly identified dominant drivers of forest degradation in the TWS.

The novelty of this study is underscored by its methodological rigor and comprehensive analysis of forest degradation in TWS. Integrating advanced remote sensing techniques with qualitative assessments through KII, the research employs Landsat satellite imagery analysis in GEE and ArcGIS platforms. Integrating KII with geospatial analysis to identify the drivers of LULC changes is not a novel method in the existing literature. Numerous authors have leveraged KII surveys in conjunction with other findings to identify trends, causes, and factors of changes, and to propose solutions to various problems. For instance, KII surveys have been used to identify the conflict drivers due to the Rohingya influx in Bangladesh (Ahmed & Sabastini, 2024), to identify drivers of deforestation in Uganda (Twongyirwe et al., 2018), to understand barriers to shellfish harvesting in Southeast Alaska (Roland et al., 2024), to pinpoint major public health issues in Iran (Salari et al., 2017), to determine drivers of land degradation in South Africa (Kgaphola et al., 2023), to assess the impact of LULC and land surface temperature changes in Bangladesh (Kafy et al., 2021), to explore public health equity interventions (Grant et al., 2024), and to identify factors influencing LULC changes in Ethiopia (Abebe et al., 2023). This approach not only quantifies spatial changes with high accuracy but also identifies significant shifts over three decades, including the reduction in deep forest cover and the expansion of light forest and built-up areas. Dominant drivers such as agricultural land conversion and illegal settlements, compounded by the Rohingya influx, reveal complex socio-environmental dynamics. By integrating existing methods of KII response analysis with geospatial findings, our study uncovers updated drivers of LULC changes. These insights are essential for policymakers and forest managers to develop sustainable and current conservation strategies, particularly in light of increasing population pressures and the ongoing influx of Rohingya refugees since 2017 (Mowla & Hossain, 2021). These findings underscore the urgent need to update integrated conservation strategies to address the impacts of newly identified drivers of LULC changes and ensure sustainable management of TWS amidst growing human pressures.

Conclusion and Recommendations

This study was conducted based on secondary satellite imagery data and primary KII data. The significant findings of the current study were the alarming changes in the land cover of TWS. The deep vegetation cover characterized by mainly tree species decreased by 1388.62 ha (11.96%), while the built-up area increased by 147.87 ha (1.27%) from 1991 to 2021. The homestead and settlement also increased significantly (929.63 ha; 8.01%) because of horizontal expansion by households inside the TWS. The built-up area dramatically increased from 3.23 ha to 151.10 ha in the last three decades. In that case, the increasing rate of the built-up area in the later (2001 to 2021) change was found to be 1.21%, whereas it was only 0.07% in the earlier (1991 to 2001) change. In the last two decades, the increasing trend of built-up areas was promulgated by the Rohingya people's pressure and increasing local population density.

On the contrary, agricultural land was found to be on a decreasing trend in both the earlier and later change analyses. The reduction in agricultural practice was due to changes in profession, an increase in income level, conversion of agricultural land to brick fields and households, and fallow agricultural land resulting from a shortage of irrigation water. These outcomes will enable policymakers to take innovative measures to combat the degradation of the TWS. Furthermore, these measures will help to save threatened and rare species and reinstall the forest ecosystem services of the TWS.

Future research endeavors should explore the utilization of diverse sensor data, such as Synthetic Aperture Radar (SAR), to overcome the primary limitations associated with optical imagery-based studies of LULC change detection. SAR data offers the advantage of being unaffected by cloud cover and may provide improved temporal coverage during the vegetation growing season, thus offering a more comprehensive understanding of LULC changes (Agrawal & Khairnar, 2019; Joyce et al., 2014). Additionally, incorporating LiDAR data alongside optical imagery can facilitate the identification of historical forest height changes, enabling a more nuanced assessment of forest degradation in both horizontal and vertical dimensions. Moreover, researchers can employ multiple machine learning algorithms concurrently to compare their effectiveness in detecting LULC changes and assessing forest cover degradation. Finally, it is the expectation of the current investigation that the evidence of some improvement in light forest conservation will undoubtedly encourage forest managers, policymakers, members of the co-management committees, NGOs, and INGOs to continue their efforts in conservation, protection, and restoration of the landscape of TWS.

The current study's findings indicated that taking several measures and precautions in the case of forest management and conservation may increase the health of the TWS. Based on the current study's findings, the following recommendations are suggested for combating the negative LULC changes and for the conservation of the biodiversity of TWS.

1. The FD should undertake a proper initiative to relocate the illegal settlers inside the TWS, increase the regular patrolling to prevent further settlement inside the TWS, and take measures to enforce the law strictly. These measures will help stop the further increase of settlement in the forest landscape (Hossain & Hossain, 2014).
2. The barren lands and agricultural lands should be brought under plantation programs, and environmentally sound restoration programs, i.e., Assisted Natural Regeneration (ANR), can be practiced in light vegetation areas (FAO, 2019; Shono et al., 2007). Indigenous tree species should be preferred in these plantation activities.
3. Alternative Income Generation Activities (AIGA) for the forest-dependent peoples and agriculture practitioners inside the TWS should be promoted, as it has been proven that AIGA increases the income of households and reduces the dependency on forest resources (Rahman et al., 2017), which helps in the conservation of the forest landscape. In this case, comparatively poor households should be considered since they have a significant probability of being engaged in deforestation activities (Ullah et al., 2022).
4. Agricultural practices on sloppy hills are detrimental to the environment as they cause soil erosion, increasing the chance of landslides (Biswas et al., 2010). In that case, farmers should be aware of it and be discouraged from agricultural practices inside sloppy forests.
5. Community-based organizations (CBOs) like the co-management Committee (CMC) and community-patrolling group (CPG) should be engaged in forest management activities more efficiently and made aware of and motivated about their role in the protection, conservation, and management of the forest. The continuation of co-management of TWS for sustainable natural resource management was suggested by many research articles (Alam et al., 2014).
6. Coordination of FD with the NGOs and INGOs will play a critical role in the protection and sustainable management of the forest landscape.

Ethics Committee Approval: Ethics committee approval was received for this study with the implication that this study was approved/granted by the BANBEIS, Ministry of Education, Bangladesh (Approval no: LS20201335, Date: April 28, 2022). It is to note that there was no Ethics Committee for the study in the University of Chittagong, Bangladesh, at that time.

Informed Consent: Written informed consent was obtained from the respondents who participated in this study.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – M.D.M., M.A.H.; Design – M.D.M., Y.A.; Supervision – M.D.M.; Resources – ; Materials – M.D.M.; Data Collection and/or Processing – M.A.H., Y.A.; Analysis and/or Interpretation – M.D.M., M.A.H., Y.A.; Literature Search – M.A.H., Y.A.; Writing Manuscript – M.D.M., Y.A.; Critical Review – M.D.M., M.A.H.; Other – M.D.M., Y.A.

Declaration of Interests: The authors have no conflict of interest to declare.

Funding: The research was funded by the Bangladesh Bureau of Educational Information and Statistics (BANBEIS), Ministry of Education, the Peoples' Republic of Bangladesh (Grant no: LS20201335).

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