Effect of competing landuse practices on Chakaria Sundarbans mangrove in Bangladesh using Landsat imagery

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Abstract. This paper quantifies the extent to which Chakaria Sundarbans mangrove has been depleted through human interference using Landsat imagery of 1972 and 2017. The images were corrected for radiometric and atmospheric effects. To improve the classification process, the Chakaria Sundarbans's Landsat 2017 image was pan-sharpened. The earlier image which comprises of the virgin forest was classified into three classes (water, mangrove, wetland) while the later was classified into four classes – waterbody, mangrove, pond scum and saltpan using supervised classification method and support vector machine classifier. Using the statistical bias adjustment, precise area estimates for each land cover class was obtained. The result shows that between 1972 and 2017, Chakaria Sundarbans mangrove forest has reduced by about 87.5% (from 6000.27 to 877.76 hectares). Currently, about 21% of the land is being used for salt mining, 45% for shrimp farming while the water body takes 26%. It is observed that the river has reduced in width; however, water surface area increased by 2%. The bias-adjusted overall classification accuracy yields 95.44% and 94.70% for classified maps of 1972 and 2017, respectively. Evidently, the mangrove has been completely lost to over-exploitation of resources.

Keywords: Landsat, mangrove, unbiased error estimation, land use conversion.

1. Introduction

Mangrove is one of the most important coastal ecosystems in the world, predominantly found along tropical climate zones, providing various ecosystem services, particularly ecological and economic. As a marine habitat, mangroves are foundational species and ecosystems for coastal forest, woodland and shrubs that are tolerant to salinity. Mangroves provide protection to the adjacent terrestrial and marine environment and also play significant role in coastal wetland ecosystem dynamics. The habitat shield the estuaries flora and fauna population, protects coastline against erosion, mitigates storm surge damage, and contributes to global carbon need [1], [2].

Competing use of mangrove resources has resulted to loss of our natural forest with adverse consequences on the environment and climate, both at local and global scales. Chakaria Sundarbans mangrove forest, a vital natural resource in Bangladesh, is a microcosm of Mangrove forests lost experienced globally. Chakaria Sundarbans mangrove is part of the world's largest continuous mangrove forest which extends across the borders of Bangladesh and India [3], [4]. According to Hossain et al. [5], Chakaria Sundarbans mangrove houses about 20 species of trees; most prominent among them are Gewa (Excoecaria Agallocha), Sundri (Heritiera Fomes), Goran (Ceriops

Roxburghiana) and Passur (Xylocarpus Moluccensis, Carapa Moluccensis, Gangetica), Kankra (Bruguiera Gymnorhiza), Keora (Sonneratia Apetala), and Baen (Avicennia Officinalis). These trees have long served as natural barrier against tsunamis and frequent cyclones that blow from the Bay of Bengal and a primary source of fuelwood and timber [6]. In addition, the mangrove is a favourable breeding zone for shrimp and fish.

Existence of the mangrove is threatened by large scale deforestation and disruption of freshwater flow in favour of resource exploitation, particularly construction of barrages for aquaculture (shrimp farming) and salt mining. As reported in different studies in recent decades, the mangrove has been largely destroyed [3], [4], [6]–[9]. For example, [10] noted that within a period of 25 years (1960 – 1985), Sundri and Gewa standing volumes has reduced by 40% and 45% respectively. In their extensive study, Hossain et al. [5] identified the key factors responsible for the destruction of the mangrove; they include removal of forest for fuel wood, high grazing pressures, fishing, human settlement, salt production, and shrimp farming.

Remote sensing satellites, particularly Landsat program has continuously offer complete earth observation data since 1972. Landsat data is availability free of charge and has been widely used for earth surface monitoring. It provides various choices for continuous monitoring of mangrove over time with limited financial budgets [8]. Hossain et al. [5] used Landsat and GIS to delineate land use zones for integrated coastal zone management. In another study, Rahman et al. [10] used Landsat imagery to detect mangrove forest in Sundarbans. Similarly, Islam [8] traced mangrove forest dynamics of Bangladesh with time series Landsat data.

Summarily, all the studies (remote and non-remote sensing based) points to the same conclusion that the mangrove is under vicious threat. The Bangladesh authority institutionalised some intervention strategies, sustainable ecosystem management, conservation and enhancement of biodiversity, and land use zonation to prevent further deterioration [11], [12]. Nevertheless, the success of these policies relies majorly on accurate land use and cover information which can be extracted from remotely sensed data. Most of the previous studies have focused on mapping and monitoring forest but the actual acreage of the forest loss has not been studied. This study employs Landsat images of 1972 and 2017 to quantify the extent of forest loss using unbiased area estimation.

2. Materials and method

2.1 Study area and data pre-processing

This study is conducted over Chakaria Sundarbans mangrove forest in the coast of Bangladesh's Cox's Bazar district. Chakaria Sundarbans reserve forest is one of the oldest mangroves forest in the Indian subcontinent [5], [13]. It is situated between longitude 91°57'10E to 92"4'45E and latitude 21°36'15N to 21"44'25N (Figure 1). As of 1903, the forest reserve occupies an area of 9778 hectares but has been largely destroyed [5]. Landsat data of 1972 and 2017 downloaded from USGS Earth observation website (https://earthexplorer.usgs.gov/) was used in this study (Table1). Landsat has continued to be one of the most frequently used satellite data for land use and land cover monitoring and change detection because of the availability and accessibility of data archive dating back to 1972, consistent revisit period, and global coverage. To minimize the effect of cloud, images acquired during the cold-dry season usually from November to March were selected for downloading. Based on previous studies, satellite data acquired during this season are more reliable for forest and environmental studies in Bangladesh [10], [14].

Table 1. Properties of Landsat imagery

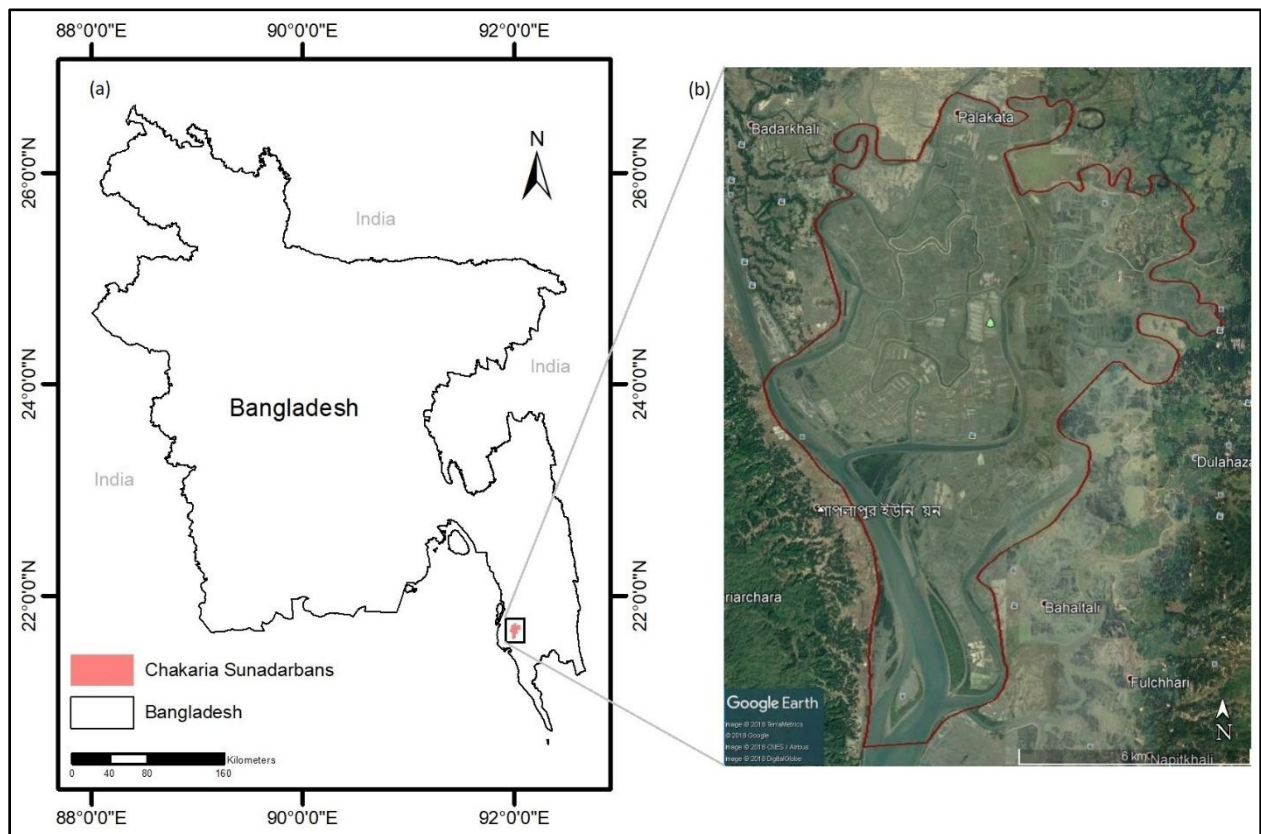| Sensor	Path-Row	Year	Acquisition Date	Acquisition Time	Sun Elev. (degree)	Cloud (%)	Resolution (m)
LS1 MSS	146-45	1972	27/12/1972	03:50:36.5000Z	35.84509	0.00%	60
LS8 OLI	136-45	2017	28/12/2017	04:19:12.8293Z	39.353842	5.63%	30

Figure 1. Location of the study area – (a) map of Bangladesh showing the study site and (b) Chakaria Sundarbans mangrove forest on Google Earth image

The data processing task includes image pre-processing, classification and accuracy assessment (Figure 2). First, the images were corrected for radiometric and atmospheric effects. Using the calibration tool in ENVI 5.3, the Landsat image was calibrated to obtain the reflectance of the surface feature. Subsequently, atmospheric effects in the image were corrected using QUAC (QUick Atmospheric Correction) algorithm. Where there are no ground truth data to calibrate the image scenes, QUAC employs parameters within the image spectra to correct for atmospheric error [15]. QUAC is simple to use, fast, and produce accurate spectra collection. Thereafter, the area of interest was subset for classification and analysis.
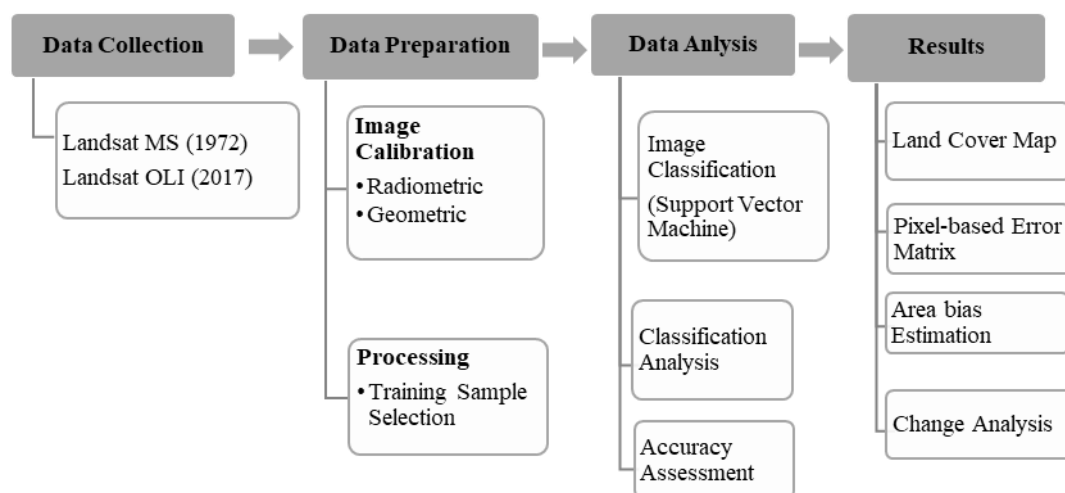

Figure 2. Methodological workflow of the data processing and analysis

2.2 Image classification

The images were classified using supervised classification method and Support Vector Machine (SVM) classifier. Among the classical Machine Learning algorithms, SVM has been widely reported for its superiority over other image classification algorithms [16]. Accuracy of the classification depends on the training data set [17]. For this study, the training samples for the classification process were selected based on the knowledge of the site and high resolution Google Earth image using stratified random sampling. Radial Bases Function algorithm, the widely used SVM classifier, with Gamma and penalty values of 0.143 and 100, respectively, was implemented. In the 1972 image, during which Chakaria Sundarbans mangrove was still a virgin forest, the land cover comprises of mainly vegetation and river. Therefore, the image was classified into three classes; mangrove, waterbody and mudflat. However, the 2017 image was classified into four classes, namely, mangrove, waterbody, salt pans and pond scum.

2.3 Accuracy assessment

Error matrix [18] is one of the prominent means of evaluating the performance of the classification. When an error matrix does not incorporate the standard error based on the total area of each land cover class, the estimate can be biased [19]. To improve accuracy of the classified map and the estimated class area, the pixel count was converted to area estimate in hectares and stratum weight (W_i) for each land cover class. Multiplying the stratum weight by the ratio of pixel in each class and the total pixel for each class, area-based error matrix was generated. This allows computing the total classified area, unbiased percentage accuracy, User's and Producer's accuracy. Subsequently, the standard error (SE) of area estimate was computed (Equation 1), and then converted to area estimate in hectares that allows obtaining the 95% confidence interval (Equation 2), also in hectares.

$$\sigma = \sqrt{\left(\sum_{i=1}^{n} \frac{Wi \times (P_{ij} - P_{ij}^2)}{n_i - 1} \right)} \qquad (1)$$

$$CI = \sigma_h * 1.96 \qquad (2)$$

where σ is the standard error, σ_h is standard error in hectares, W_i is the stratum weight, P_{ij} is the area proportion estimates for each class, n_i is the total number of classified pixels in each class and CI is the confidence interval.

3. Results and discussion

Human activities have continuously impact on our environment on different spheres, altering the physical composition of our earth and interfering in the climate at both local and global scales. Land cover mapping is one means by which this phenomenon is assessed. Land use and land cover maps of Chakaria Sundarbans natural forest for the year 1972 and 2017 (Figure 3) obviously shows the extent of damage competing economic interest has done to the forest. In the 1972 map (Figure 3a) it can be seen that the entire area is covered by forest (in green colour). Whereas in the 2017 map, almost all the forest has been converted to agricultural use – specifically shrimps farming and salt mining (Figure 3b) [6], [7], [20], leaving the area with insignificant forest cover in the southern part along the main river (previously covered by mudflats). In addition to forest loss, the river (in blue colour) has also shrunk due to rechannelling of the river and its tributaries for aquaculture uses.

Factors that affect the accuracy of land cover class include the total sample size, the number of classes, and the allocation of the total sample size to each class [21]. So, using both map data (considered biased) and the reference data (unbiased), the estimated area proportion (i.e. area-based error matrix) were computed (Table 2 and Table 3) to obtain the overall classification accuracy and area estimates that have been adjusted for the map bias and characterized uncertainty. In Table 2 and Table 3, the effect of the bias adjustment can be seen by comparing the area computed from the pixel count and the class area estimates in the area-based error matrix of 1972 and 2017. The statistical area-based error matrix reveals where the pixel-based over/underestimate the area of the land cover classes. For example, in the 1972 classified map, the pixel-based underestimates the waterbody and mudflat classes whereas, the mangrove is over estimated. For the 2017 classified map, bias adjustment reveals

that except for the salt pan class which is overestimated in the pixel-based area calculation, the other classes (waterbody, mangrove and pond scum) are underestimated.

From the estimated unbiased area, the 1972 land cover classification map comprises of mangrove (64%), waterbody (24%) and mudflat (13%) compared to mangrove (8%), waterbody (26%), pond scum (45%) and salt pan (21%) for 2017. The forest has been largely decimated to 8% (from 6000.27 to 877.76 hectares). The forest has been entirely converted to other uses, specifically shrimps farming and salt mining [6], [7], [20]. Specifically, from the 2017 classified map, 66% percent (about 6448.65 hectares) of the total land area of the mangrove forest is been used for salt pan and aquaculture. Impact of human activities is not only limited to the forest; the river has reduced drastically. Over the years, fishermen built dams in the mouth of the creeks; this disrupt tidal inundation and causes water stagnation[5] that is responsible for the reduction in the river width but increase in water surface area from 24% to 26% between 1972 and 2017.
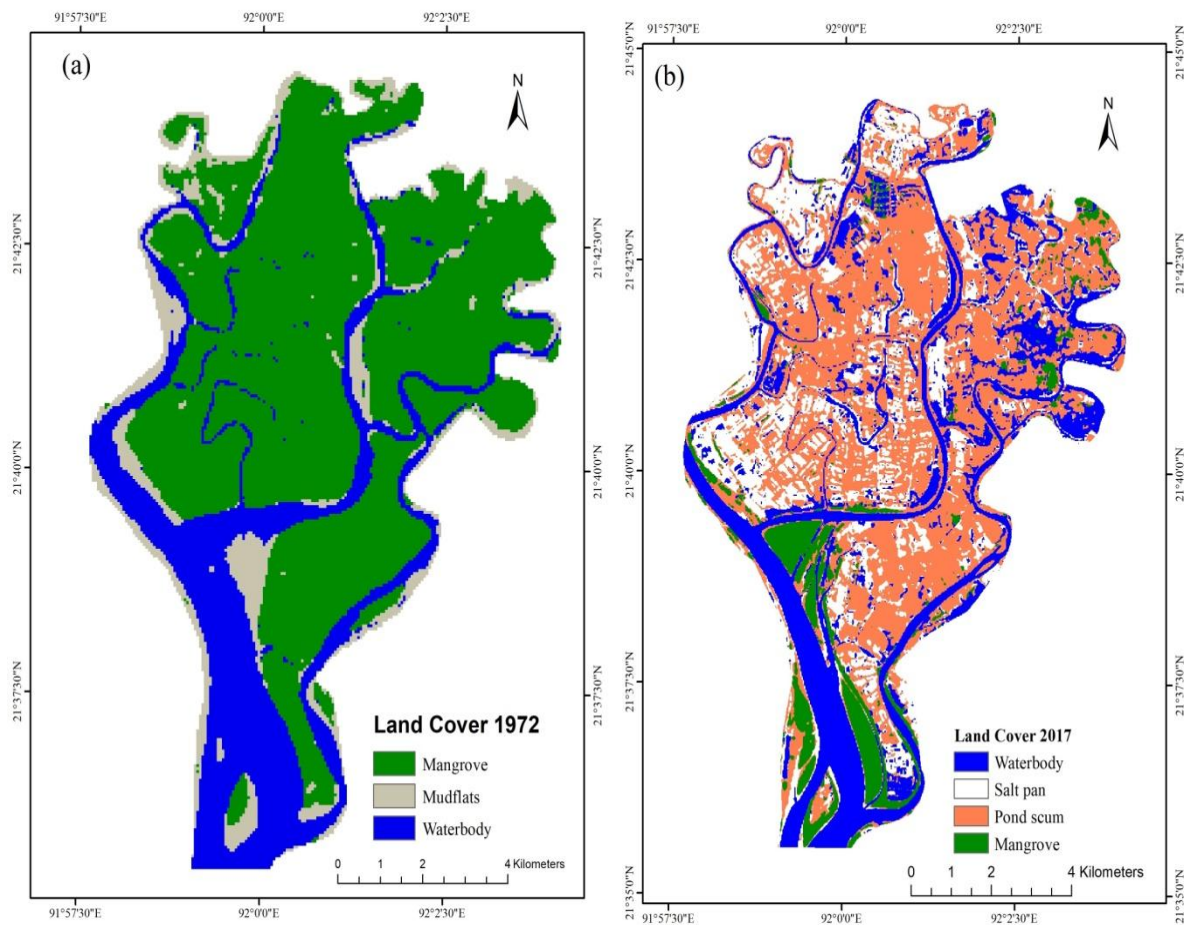

Figure 3. Land cover map of Chakaria Sundarbans mangrove forest for (a) 1972 and (b) 2017

Also, the classification accuracy and individual class accuracy produced good result for both periods. After adjustment for bias, overall accuracy of 95.44% and 94.70% were obtained for 1972 and 2017 classified map respectively (see in Table 2 and Table 3). In both classified maps, error of commission is minimal as observed in the User's accuracy; almost all the pixels are correctly included in the land cover class category being evaluated. Similar scenario is observed for the error of omission for all land cover classes except for the mudflat (77.87%) and mangrove (79.24%) classes in 1972 and 2017 classification maps respectively. in this case, some of the pixels are left out of the land cover class being evaluated (misclassified). The change in land use and land cover between 1972 and 2017 (Figure 4) shows the degree to which the mangrove has been converted to other uses (salt pan and pond scum).

Table 2. Pixel and area-based error matrix for classified map of 1972

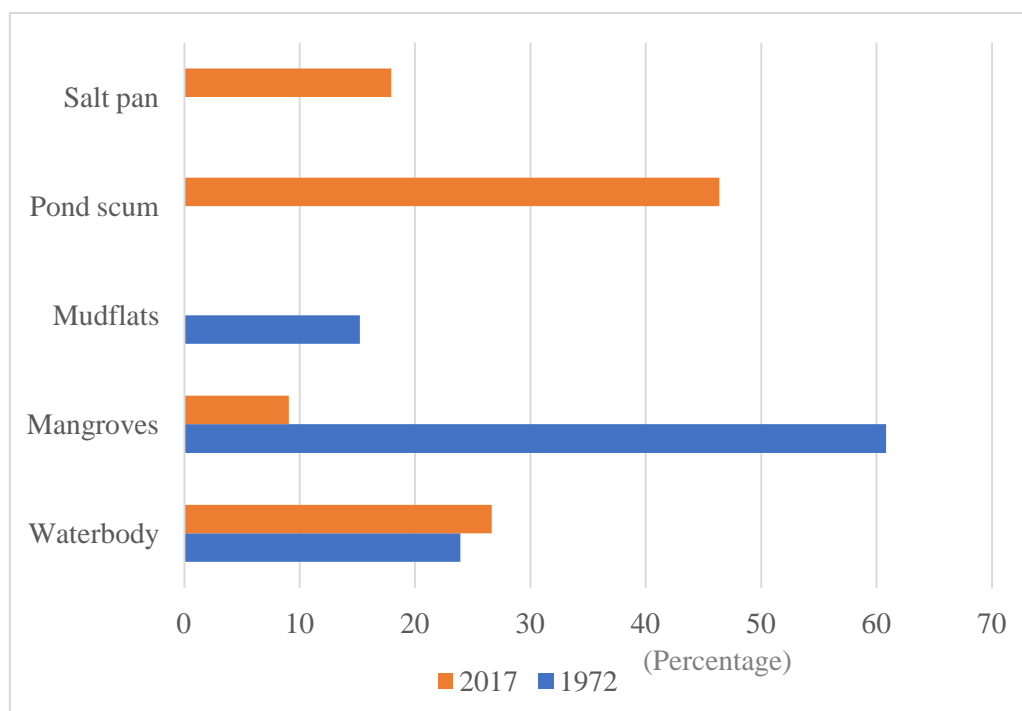| Land cover class	Pixel-based error matrix					
	Waterbody	Mangroves	Mudflats	Total	Area	Wi
Waterbody	107	1	3	111	2325.60	0.24
Mangrove	1	111	5	117	6303	0.64
Mudflats	3	0	54	57	1234	0.13
Total Referenced Points	111	112	62	285	9861.84	1.00
Total Corrected Referenced Points	272					
Total True Referenced Points	285					
Overall Accuracy(in percent)	95.44%					
	Area-based error matrix					
Waterbody	0.23	0.00	0.01	0.24	2325.60	24%
Mangrove	0.01	0.61	0.03	0.64	6302.52	64%
Mudflats	0.01	0.00	0.12	0.13	1233.72	13%
Total estimated area proportion	0.24	0.61	0.15	1.00	9861.84	100%
Class Area Estimate(ha)	2360.59	6000.27	1500.98	9861.84		
Overall % accuracy	95.21%					
Standard Error of Area Estimate	0.008	0.013	0.013			
Standard Error of Area Estimate (ha)	77.233	130.763	129.060			
95% Confidence Interval (ha)	151.376	256.295	252.958			

Figure 4. Percentage Area Change

Table 3. Pixel and area-based error matrix for classified map of 2017

Land cover class	Waterbody	Mangrove	Pond scum	Salt pans	Total	Area	Wi
Pixel-based error matrix							
Waterbody	179	0	0	1	180	2504.56	0.26
Mangrove	1	99	4	0	104	730.67	0.08
Pond Scum	0	4	120	0	124	4377.78	0.45
Salt pan	4	2	11	84	101	2070.87	0.21
Total Classified Points	184	105	135	85	509	9683.88	1.00
Total correct reference points		482					
Total "true reference points		509					
Overall Accuracy(In Percent)		94.70%					
Area-based error matrix							
Waterbody	0.26	0.00	0.00	0.00	0.26	2504.56	26%
Mangrove	0.00	0.07	0.00	0.00	0.08	730.67	8%
Pond scum	0.00	0.01	0.44	0.00	0.45	4377.78	45%
Salt pan	0.01	0.00	0.02	0.18	0.21	2070.87	21%
Total estimated area proportion	0.27	0.09	0.46	0.18	1.00	9683.88	100%
Class Area Estimate(ha)	2579.686	877.7629	4490.204	1736.222	9683.88		
Overall % accuracy	94.44%						
Standard Error of Area Estimate	0.004	0.008	0.010	0.008			
Standard Error of Area Estimate (ha)	43.291	77.030	96.009	78.721			
95% CI (ha)	84.851	150.980	188.178	154.292			

4. Conclusion

In this study, we estimated the area of Mangrove forest that has been lost to resource exploitation in Chakaria Sundarbans using Landsat data. Implementing the statistical bias adjustment using stratum weight allows improving the classification accuracy and obtaining reliable area estimate for the respective land cover classes for change analysis. The study has shown the alarming danger facing the mangrove. The mangrove in its current state is left with ~ 15% of the entire mangrove forest. Meaning that within a period of 45 years (1972 – 2017) 85% of the mangrove has been lost to competitive resource exploitation. This has greatly exposed the adjacent marine and terrestrial ecosystem to the risk of natural hazards such as coastal erosion, cyclone and tsunami, in addition to reduction in freshwater and salt deposition that endangers the survival of plant and animal species. To ensure effective implementation of mangrove restoration policies institutionalised by the Government of Bangladesh, routing monitoring and evaluation is important. This will allow mangrove to effectively play its roles in carbon sequestration for global carbon balance and mitigating climate change at both local and global scales. Future wok will examine the trend of changes over time with multi-temporal Landsat data, to provide insight into the pattern of interference and the factors that influenced them.

Acknowledgments

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