Land Use and Land Cover Change Using Remote Sensing and GIS: A Case Study on Bakerganj Upazila, Barishal, Bangladesh

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Abstract: Bakerganj Upazila is under the Barishal district situated in the southern part of Bangladesh which is near the Bay of Bengal. The study uses satellite images from the years 1997 to 2017 to identify, analyze, and assess land use and land cover change in the study area. GIS and RS technology is used because it is an efficient, quick, and time-consuming method for analyzing large area coverage at various time series of any areas. To analyze and prepare land use and land cover changes map three Landsat satellite images have been collected for the year 1997, 2007 and 2017 from the USGS EE website. The collected images were classified and the land use maps have been prepared by using the ArcGIS 10.5 software. Land use classes such as agricultural land, bare land, settlement area, trees and water body have been analyzed by the normalized difference vegetation index (NDVI) method in this study and the changing area pattern of different classes of three images were calculated by post-classification change detection algorithm. This analysis showed that Bakerganj was susceptible to various land use changes. The findings showed that there had been some significant changes in the way that land was used in Bakerganj. There were some changes between 1997 and 2007, including the alteration of agriculture to agriculture (15.89%), agriculture to settlement (9.13%), and agriculture to trees (7.80%). From 2007 to 2017, however, there were agriculture to agriculture 12.27 %, agriculture to trees 13.26%, bareland to settlement 9.83%, trees to agriculture 86.81%, and trees to settlement 8.58%, which had changed. Because of this, no firm conclusions can be drawn from the study's findings regarding how certain land use techniques might boost social resilience. However, it gave a scenario of LULC changes through time in the study region, which will be helpful for further research and boost the sustainability resilience of the social-ecological systems.

Keywords: Land use and land cover, geographical information systems, normalized difference vegetation index.

Introduction

Bangladesh is a country with a low deltaic landscape and a large coastline, and because of its sensitive topography and location, the residents of the coastal area are particularly susceptible to cyclones, storm surges, sea-level rise, floods and droughts (Khan, 2012). Agriculture, fishing, forestry, transportation, and salt farming are major contributors to the livelihoods of coastal populations. The recovery process from the large scale disaster causes the alteration of land use on an outsized scale. It is, therefore, important to think about whether or not these changes are linked to sustainable spatial forms (Ubaura et. al., 2016). Major land-use change has been made in the last fifty years in Bangladesh and most importantly the land use pattern of the agriculture sector is being gradually altered due to some natural and anthropogenic disaster (Khan, 2012). The report on the Millennium Ecosystem Assessment states that various human activities that alter how land is used are to blame for the loss of biodiversity. The socio-ecological resilience of the ecosystem has been impacted over time due to changes in land use patterns. Analysis of changes to land use or land cover, which provides a measurement of human and natural activities, is a very essential technique for identifying worldwide change at various spatial and temporal scales. Increased human population places strain on the ecosystem, weakening the structure of the land. The development of agricultural land, the tourism sector, and the conversion of agricultural land to other uses like shrimp farming are all contributing to the growing country's rapid change in land use and increasing levels of land degradation. Environmental effects of this size are seen both globally and locally. For instance, the global carbon cycle is impacted by human-caused changes to land cover, which raise atmospheric CO_2. So that its impact on the native ecosystem can be recognized and sustainable land use planning can be developed, it is essential to study the changes in land use/cover (Dewan and Yamaguchi, 2009b). In many regions of the world, rural land use is changing quickly, and all sorts of land-use change have the potential to affect socioeconomic change in both positive and negative ways (Williams and Schirmer, 2012). A key contributor to global environmental change, including greenhouse gas emissions, global climate change, biodiversity loss, and the depletion of soil resources, is now more widely acknowledged as land use and land cover changes (LUCC). The reasons of LUCC, however, are intricate and alter throughout time as well as from one place to another (Li and Wang, 2016). Modifications to land use and land cover (LULC) are of utmost importance in the study of global change. Natural and anthropogenic land cover and land use modification are largely given the growth in deforestation, habitat loss, climate change and the increase of natural catastrophe those environmental effects are always tied to land use change (Reis, 2008).

Geographical Information Systems (GIS) and remote sensing are effective techniques for obtaining precise and timely data on the spatial distribution of land use/land cover changes over vast areas (Reis, 2008). GIS is useful for mapping and analyzing these patterns because it makes multi-temporal data on the developments and patterns of LULC change available. Additionally, locations where changes have occurred quickly benefit greatly from satellites' consistent and updated synoptic coverage. However, because past LULC changes may be studied using digital archives of remotely sensed data, it is possible to assess the spatial distribution of those changes in relation to other environmental and human causes (Dewan and Yamaguchi, 2009b). The world's climate has been changing over time as a result of its natural tendency to gently alter its subsurface environment (IPCC, 2007). The Gaia Hypothesis states that if a change occurs within a recovery range, the global ecosystem can regain its natural body or prior state (Kirchner, 2002). The management of land use and land cover may alter as a result of climate change adaptation measures. It's crucial to evaluate the changes in land features before making any decisions about how to best serve a community. One of the most effective methods in the modern period is the analysis of satellite images for the purpose of detecting changes in land use and land cover (LULC) (Hussien, 2009). The native land use pattern in the studied area is changing. The research area is located in Bangladesh's southern coastline region and is exposed to natural disasters because of its topographical location. Reducing the risk of disaster will promote urban resilience and sustainable urban development.

The area is highly important because of its natural resources and sources of livelihood like an increasing pattern of settlement, economic activities, newly accreted char land etc. So it's important to understand the longer-term trend of settlements and economic activities in char land. River erosion is alarming and it is in a rising trend. No holistic study has done yet. Despite having ecological importance and a high level of susceptibility of land use and land cover change dynamics no study is not conducted properly in this area. So, a study has conducted to identify, investigates the present land use and land cover (LULC) changes. To fill up the gap between the previous and present condition of the study area, the current research was conducted to prepare maps, analyze and assess the land use and land cover change of Bakerganj Upazila of Barishal district of the last three decades.

Materials and Methods

Study Area

Bakerganj Upazila is under the Barishal district situated between 22°27' and 22°40' north latitude and 90°12' and 90°33' east longitude (BBS and SID, 2011). The Upazila has a total land area of 164.87 sq. km, of which 164.58 sq. km is an island and 0.29 sq. km is riverine land. The Upazila has no forest land. It's northern, eastern, western, and southern borders are formed by the upazilas of Nalchity and Barishal sadar, Mirzaganj, Dumki, and Bauphal, and Nalchity, Betagi, and Rajapur. In Bakerganj Upazila, there are 14 unions (BBS and SID, 2011).

Bakergang Upazila is situated within the Barishal district, beside the Tetulia River. Many places in this study area are facing severe bank erosion caused by the Tetulia River. No remote sensing-based study has been found in this area where it has the ecological and social values of LULC. Therefore, it is crucial to research this area for a sustainable land use plan.

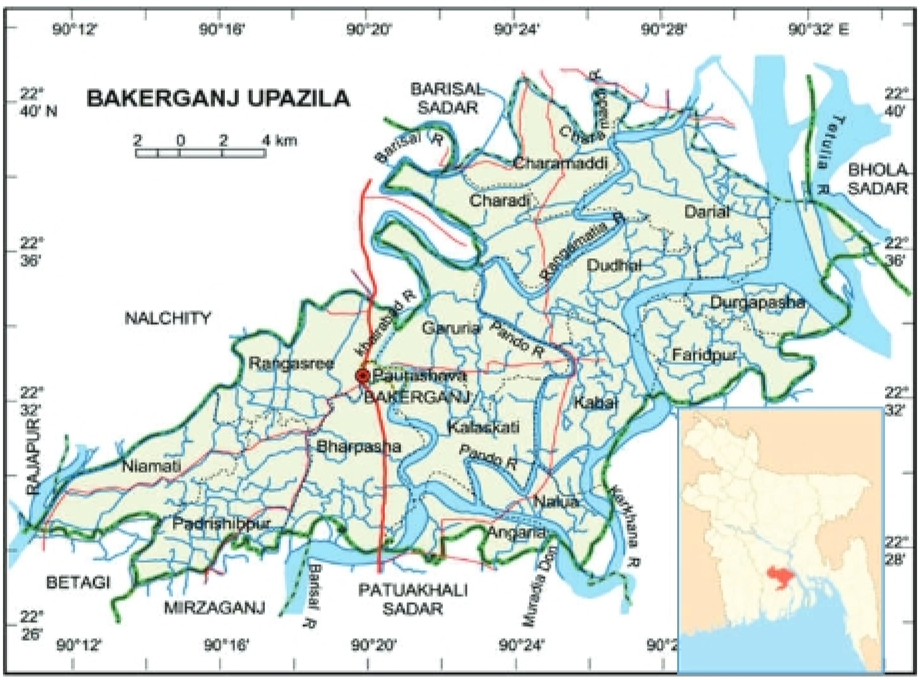


Figure 1. Study area map (Source: LGED, 2016)

Data Acquisition and Preparation

With the development of recent technology, satellite image processing and remote sensing-based research activity is increasing. Several satellite images providing synoptic land surface features of the earth. From the 1972 Landsat satellite providing constantly images. Due to availability and cost-free feature Landsat images are used for LULC analysis of maximum research work. To complete this study, different sensor images of the Landsat satellite were collected from the USGS Earth Explorer website**.** Bakerganj Upazila is covered by World Reference System 2 (WRS-2) path 137, row 044. The full study area covers in this section so there is no need to prepare a mosaic image. To conduct the study three images were collected for three different seasons. Landsat 5 TM data was acquired for the year 1997, and Landsat 8 OLI_TIRS image of 2007and 2017 has acquired, which is the core initiation of this LULC change analysis activity. Cloud cover, climatic condition, and haze have a strong influence on the image that was used for analysis work. In general, classification accuracy also depends on a different season of the year. That's why season (November to March) images of winter and cloud cover that has below 1-5% have accepted for this analysis.

Table 1. Specification of the image collected for the study (Source; USGS, 2017)

Acquisition Date	Satellite (Sensor)	Path/Row	Sun Elevation	Sun Azimuth	Resolution (m)	Cloud Cover (%)
26-01-1997	Landsat 5 (TM)	137/044	35.72	137.419	30x30	0
22-01-2007	Landsat 8 (OLI_TIRS)	137/044	39.32	145.635	30x30	0
02-02-2017	Landsat 8 (OLI_TIRS)	137/044	42.28	144.292	30x30	4.39

Layer Stacking

Layer stacking provides the multispectral images of a study area. Layer stacking is frequently used to combine spectral bands and image derivatives for additional analysis (Busncx, 1990). To produce False Color Composite (FCCs), all individual band data have stacked. The usage of all-composite color bands, with the exception of the thermal band, is for the investigation of changes in land use and land cover. The output picture will be a multi-band.img (ERDAS Imagine 2015) that can be utilized in this study's investigation of changes in land use and land cover. Table 02 shows the band specification used for the study.

Table 2. Band specification of the image (Source: USGS, 2017)

Satellite	Sensor	Path/Row	Year	Resolution (m)	Wavelength (µm)
Landsat-5	TM	137/044	26-01-1997	30	Band 1: 0.45–0.52 Band 2: 0.52–0.60 Band 3: 0.63–0.69 Band 4: 0.76–0.90 Band 5: 1.55–1.75 Band 7: 2.08–2.35
Landsat-8	OLI_TIRS	137/044 137/044	22-01-2007 02-02-2017	30	Band 2: 0.452–0.512 Band 3: 0.533–0.590 Band 4: 0.636–0.673 Band 5: 0.851–0.879 Band 6: 1.566–1.651 Band 7: 2.107–2.294

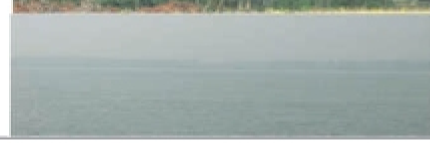
Area of Interest (AOI) Preparation and Image Correction

To specify the study area, subset or area of interest (AOI) preparation is the initial requirement of the research work. Each of the Landsat TM and OLI_TIRS image 30m resolution screen size cover 170 km north-south by 183 km east-west. The screen size is pretty large than the study area (USGS, 2017). The image has covered 137 path and 044 row within one image, so no need to create the mosaic. To conduct image correction, radiometric correction measure histogram equalization has used in this study. Histogram equalization is a histogram of the values of the pixels in a digital image that shows the distribution of one throughout an image. To achieve greater contrast, the histogram equalization expands the intensity values as well as the entire range of values. A method for changing image intensities to improve contrast is histogram equalization. When a picture is being represented, this technique is particularly helpful. Simple histogram equalization improves an image's contrasts (Gonzalez and Woods, 2002). After histogram equalization, it has found digital number value properly.

Unsupervised classification

Unsupervised classification or ISODATA classification method necessary for primary identification of the different land covers according to the spectral reflectance values. Each pixel on a map is assigned to a particular class based on its multispectral composition using unsupervised classification techniques. However, it's the first step to separate land use without surveying the study area (Were, 2008). The analyzed classes are given in the Table 03 with the picture that was collected during the field survey.

Table 3. Land use classes selected for the study

Class Name	Description	Class picture
Agricultural land	Agriculture and grassland class is the type of land where crops are planted or filled with grass and shrub	
Bare land	Accretion sand, silt and sandy areas contained in this class.	
Settlement Area	The settlement class includes built up areas i.e. housing, market, school, cyclone shelter etc.	
Trees	Trees include all type of homestead plantation	
Water body	This class includes all type of inland water body and adjacent river and canal.	

NDVI method

Unsupervised classification provides the initial information of an area. This study area is relatively flat. To identify soil-water-vegetation boundary class fixation NDVI index has been calculated. Finally, the class has been accepted as Agriculture, Homestead- settlement, Sandbar/Bare land and Water body. Each of the classifications has a unique digital feature and the nearest neighborhood algorithm has used to classify the images.

Three images from 1997, 2007, and 2017 were classified using the normalized difference vegetation index (NDVI) (eq. 1), a vegetation index produced by:

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \qquad (1)$$

Where, R stands for the red band and NIR stands for the spectral reflectance in the near infrared band.

The actual NDVI values would fall between -1 and +1, with increasing positive values indicating more vegetation and decreasing positive values indicating surface features without vegetation like water, arid land, ice, snow, or clouds. There are several uses for the image differencing approach; in addition to comparing photos from two different dates, it may also be used to compare vegetation index data produced from multiple dates of imagery. It only takes subtracting the two distinct timings pixel by pixel to create the differentiated image (Yacouba et al., 2009). In numerous research, change detection analysis has been conducted using NDVI (Huang and Siegert, 2006; Ahl et al., 2006; de Boer, 2000).

Change Detection of different year

The most used technique is the post classification change detection algorithm. Additionally, it offers more precise results for monitoring and analysis of the work on change detection. Instead of a complicated matrix, the post classification change detection technique also offers a simple and trustworthy formula (Campbell 2003; Yang and Lo 2002; Were, 2008).

There has some literature for identifying and analyzing the magnitude of change. It has adopted an equation (2) from the Were, 2008 which is:

$$\Delta = \left(\frac{A_2 - A_1}{A_1} \times 100\right) \div (T_2 - T_1) \qquad (2)$$

Where:

Δ = Average annual rate of change (%)

A_1= Amount of land cover type in time 1 (T_1)

A_2 = Amount of land cover type in time 2 (T_2)

Accuracy assessment

Various climatic settings, haze, cloud cover, leaf pattern, chlorophyll concentration, moisture content, as well as sample selection strategies, all affect how accurately satellite photos are categorized and analyzed (Foody, 2008; Gaur and Chouhan, 2017). To ensure correctness, the metadata for the categorized image was compared to real world data. Classification accuracy was assessed by comparing user and producer accuracy (Singh, 2012; Taufik et al., 2017). The degree of agreement between remotely sensed data and reference data is frequently referred to as classification accuracy (Congalton, 1991). The categorization procedure is not finished if an accuracy evaluation is not conducted (Lillesand, 2004). 20 stratified random samples of testing pixels were selected from each of the three classed images (1997, 2007 and 2017) for this purpose, and their classes were compared with the land use/land cover field reference and in the Google map (Thakkar et al., 2014). There was a confusion matrix used to keep track of the results. A non parametric Kappa test was also used to assess classification accuracy; this test considers all elements of the confusion matrix as opposed to simply the diagonal components (Rosenfield and Fitzpatirck-Lins, 1986).

To make less error for change detection analysis, the accuracy matrix is useful and considered essential after every supervised and unsupervised classification (Peacock and Missouri, 2014). The post-classification accuracy assessment method was used in this study. Radom sampling points are generated by ArcGIS 10.6. The nonlinear and irregular distribution of the sampling points creates biased results. To remove this confusion, 20 random points for each class have been created. The minimum allowed distance is set at 30m. Finally, 5 classes create 100 random points. These random points are exported to Google Earth Pro and find the difference between the classification result and the original feature. The accuracy investigation of this study was confirmed using the Producer Accuracy (eq. 3), User Accuracy (eq. 4), Overall Accuracy (eq. 5), and Kappa Coefficient (eq. 6) methodologies.

$$\text{Producer's Accuracy (\%)} = \left(\frac{X_{kk}}{X_{+k}}\right) \times 100 \qquad (3)$$

$$\text{User's Accuracy (\%)} = \left(\frac{X_{kk}}{X_{k+}}\right) \times 100 \qquad (4)$$

$$\text{Overall Accuracy (OA)} = \frac{1}{N}\sum_{k=1}^{r} n_i \times 100 \qquad (5)$$

$$\text{Kappa Coefficient (K)} = \frac{N\sum_{k=1}^{r} X_{kk} - \frac{1}{N}\sum_{k=1}^{r} (X_{+k} \cdot X_{k+})}{N^2 - \frac{1}{N}\sum_{k=1}^{r} (X_{+k} \cdot X_{k+})} \qquad (6)$$

Here, N denotes the total number of pixels, r the number of classes, and X_{kk} the total number of pixels in rows "k" and columns "k" respectively. The total samples in row "k" are represented by X_{k+} in the error matrix, whereas the total samples in column "k" are represented by subscription X_{+k}.

Results and Discussion

Preparation of land use land covers change maps

A continuing occurrence, land use is frequently changed by geo-natural phenomena, seasonal fluctuations, shifting crop patterns, and other factors (Kirui et al., 2013). By analyzing satellite images, this work produces some maps showing changes in classified land use and land cover. The area data resulting from the map were calculated and displayed. Land-use change maps for the years 1997, 2007, and 2017 were prepared. The result from the field survey was represented in this part. During the classification and analysis, the land cover classes are revised. After merging several subclasses the study fixed only four classes.

The study conducted unsupervised classification after creating AOI from different classes. One Landsat 5 TM image of the year 1997 are shown in Figure 02 and two Landsat OLI_TIRS images of 2007, 2017 were used for this classification are shown in also Figure 02.

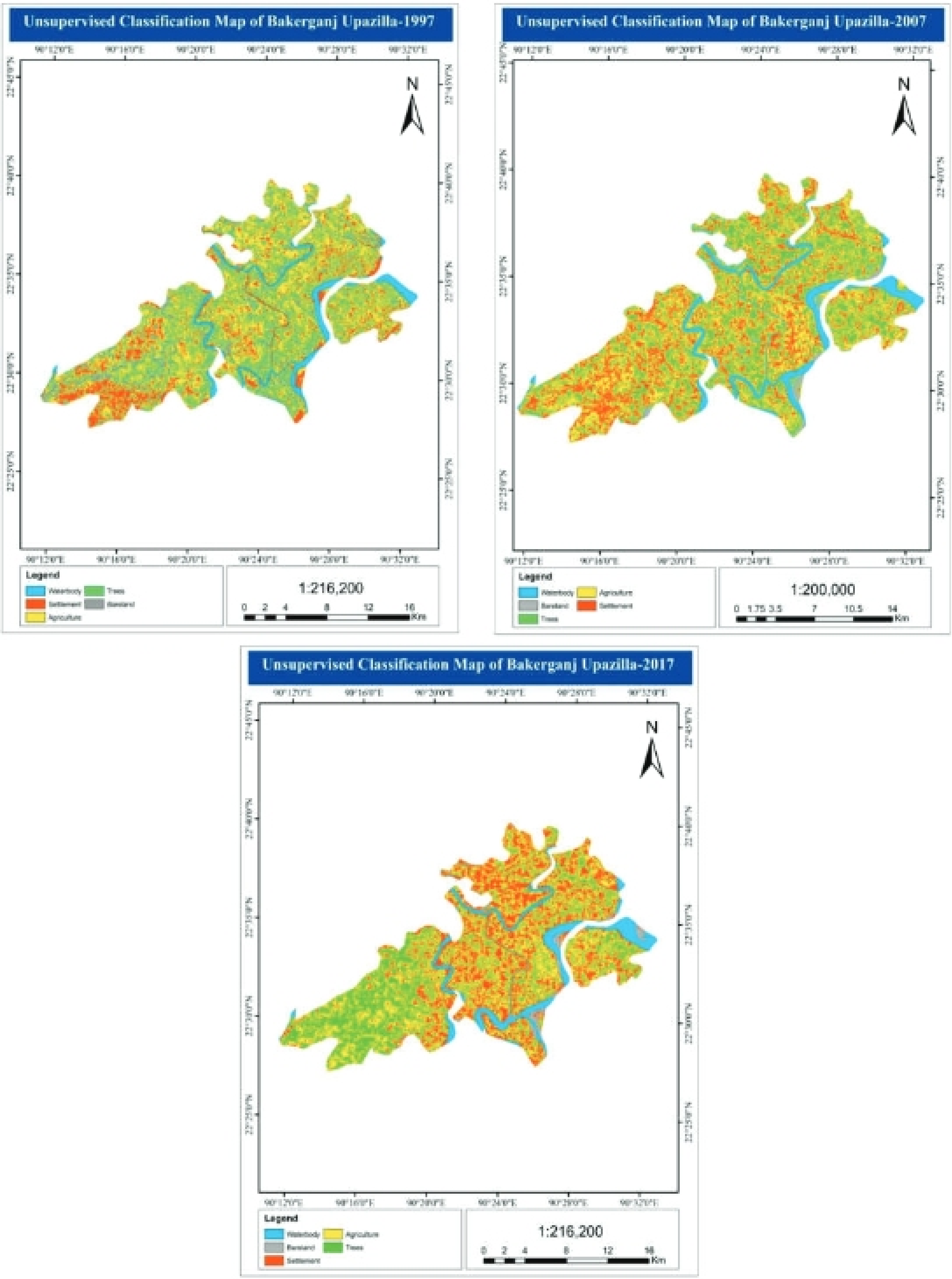


Figure 2. Land use maps on 1997, 2007 and 2017 of Bakerganj Upazila.

Analyzing the land use land cover change

Area Statistics

Land cover change is one of the dynamic processes that generally changed by the geological and natural process. From the image classification, four classes are finalized for preparing land use and land cover change map. Then the area of each class was calculated by using ArcGIS 10.5 where shows the amount of land in the hector. Then the result was converted in the percentage in the aspect of total land and concerning the group. Figure 3 and Table 4 shows the land use area of a different year.

Table 4. Area statistics of the study area at different years

Land use classes	1997		2007		2017	
	Area(ha)	%	Area(ha)	%	Area(ha)	%
Agricultural land	11367.70	31.26	12290.84	33.80	12387.10	34.06
Bare land	5921.46	16.28	1432.08	3.94	1368.72	3.76
Settlement area	7001.01	19.25	8973.18	24.67	11119.35	30.58
Trees	9823.05	27.01	11220.20	30.85	8688.24	23.89
Water body	2252.97	6.20	2449.89	6.74	2802.78	7.71
Total	36366.19	100.00	36366.19	100	36366.19	100.00

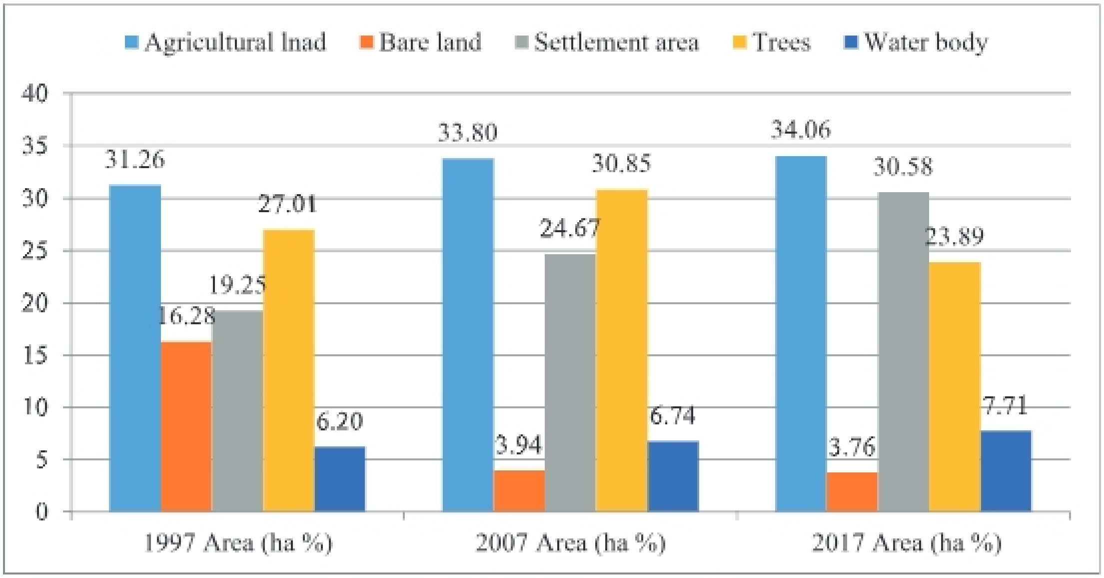


Figure 3. land use area of a different year.

Land use conversion is a dynamic and sometimes very natural process. In the study area, it is found that the areas of the different classes are changing with the passage of time. For a better understanding of Table 4, percentages of land use classes are shown in the graphical presentation in Figure 3, where these show that in 1997 agriculture covered 31.26% of the total land, while in 2007 agriculture covered 33.80% and in 2017 it is 34.06% of the total land. The table showed that there were some changes in the amount of bare land. 16.28% of the total land area was undeveloped in 1997, 3.94% in 2007, and 3.76% in 2017. The study also discovered that the settlement area grew over time. In 1997 it was 19.25%, in 2007 it was 24.67%, and in 2017, it was 30.58% of the total land. In 1997, trees were found at 27.01%, in

2007 it was 30.85%, and in 2017, it was 23.89%. The causes of the ultimate reduction in trees during 2017 were found in the FGD's answer, and they reported that the settlement area was increasing with urbanization. While the body of water is a vital portion of the total land portion and a very important ecosystem of the natural environment, the table shows that the water body in 1997 was 6.20%, in 2007 it was 6.74%, and in 2017 it is 7.71% of the total land.

Accuracy Measurements

The total accuracy of the NDVI estimated and used classes ranged from 84 to 89%, and the corresponding Kappa values were 80%, 87%, and 88%, as shown in table 05. These results support the accuracy range of 84 to 89% that is guided for LULC representing studies (Anderson et al., 1976).

Table 5. Accuracy measurement of the classified images from 1997, 2007 and 2017

LULC Type	1997		2007		2017	
	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)	Producer's Accuracy (%)	User's Accuracy (%)
Agricultural land	90.81	90	91.81	90	80.33	90
Bare land	89.79	80	99.01	90	80	80
Settlement area	78.81	70	90.91	80	80	90
Trees	70.80	80	75	80	100	90
Water body	99.01	100	90	100	100	100
Overall Accuracy	84.92%		88.67%		89.03%	
Kappa Coefficient (K) %	0.80		0.87		0.88	

Change Magnitude Detection from 1997 to 2007 and 2007 to 2017

Change detection study shows the landmark change from the previous feature to the recent feature. All three years LULC classes and magnitude of changes by human intervention or quasi-natural hazards are shown in figure 4. To detect the change between the time period study have adopted an equation from the Were, 2008. The result derived from the equation is put on the excel sheet and then the following graphs are produced, which is shown in figure 5.

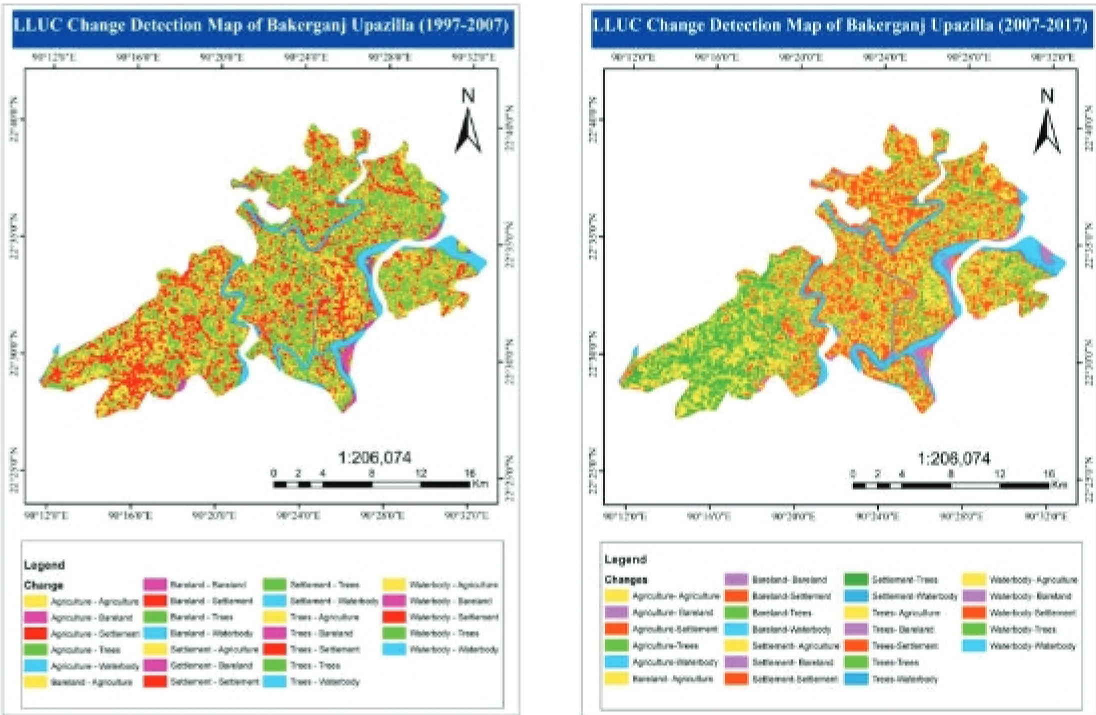
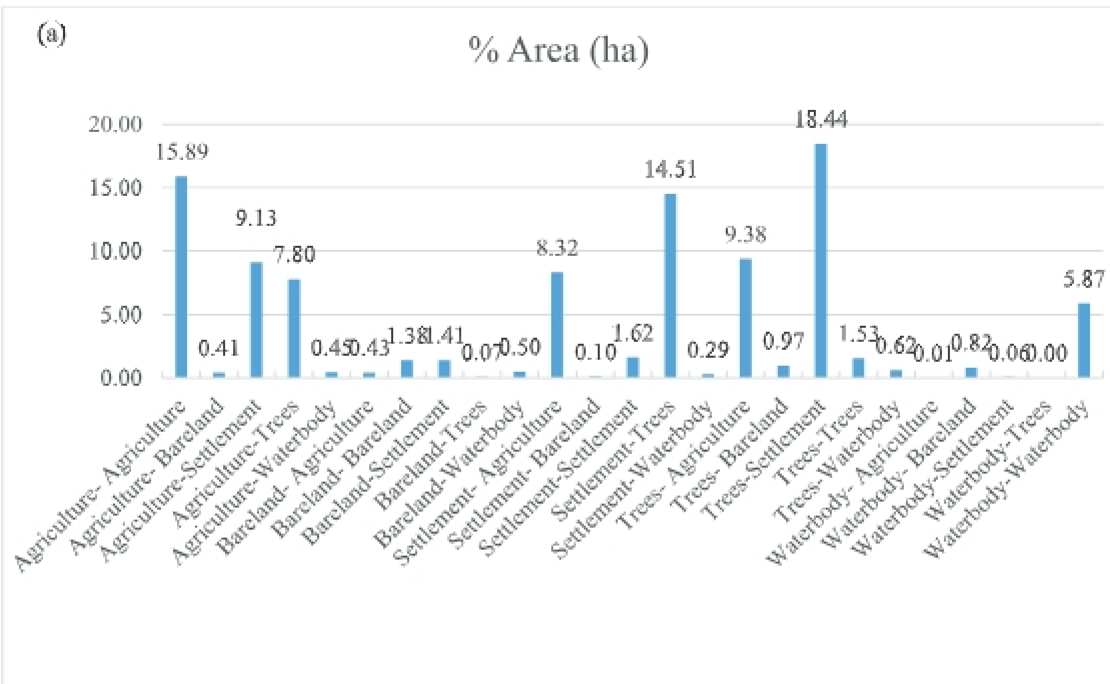


Figure 4. Change detection map from (a) 1997 to 2007, and (b) 2007 to 2017



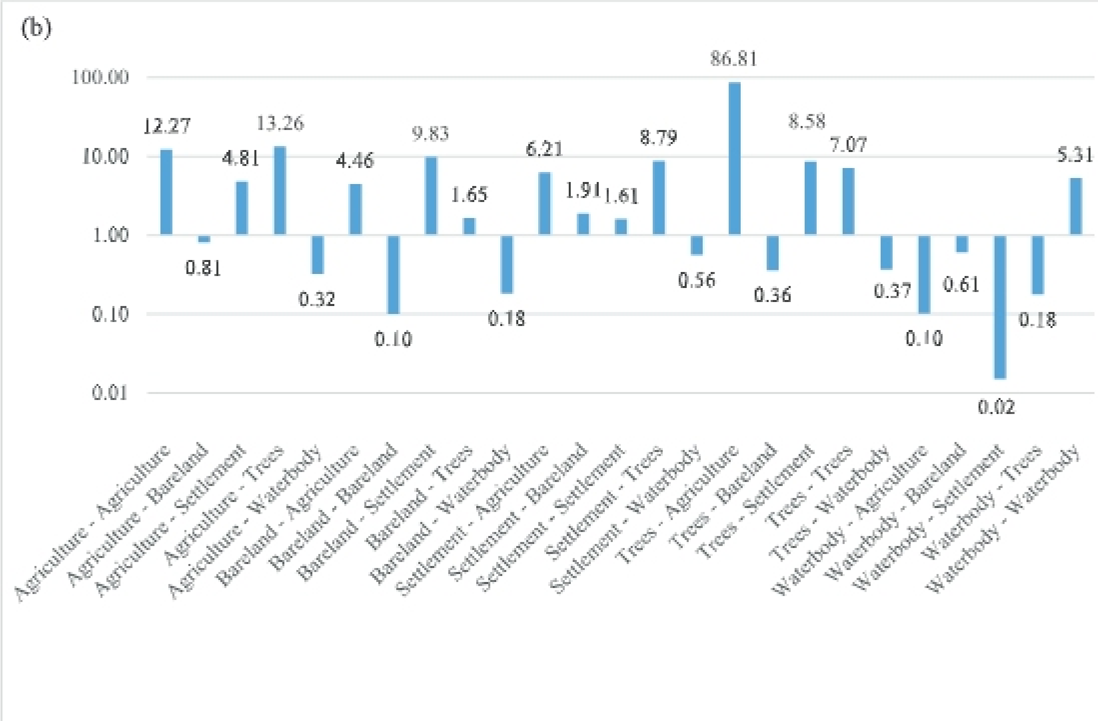


Figure 5. Change detection areas (ha %) from (a) 1997 to 2007, and (b) 2007 to 2017.

Figure 05 shows that significantly changed areas from 1997 to 2007 were agriculture to agriculture 15.89 %, agriculture to settlement 9.13%, agriculture to trees 7.80%, settlement to agriculture 8.32%, settlement to trees 14.51%, trees to agriculture 9.38%, trees to settlement 18.44%, and water body to water body 5.87%.

Figure 05 demonstrates that areas that underwent significant change between 2007 and 2017 included agriculture to agriculture 12.27%, settlement to settlement 4.81%, settlement to trees 13.26%, bareland to agriculture 4.46%, settlement to settlement 9.83%, settlement to agriculture 6.21%, settlement to trees 8.79%, agriculture to trees 86.81%, trees to agriculture 86.81%, trees to settlement 8.58%, where a field survey found that deforestation happened after the cyclone Sidr (Foster, 2007).

Different land uses release light at different wavelengths and display different colors. So, in this case, changing the agriculture class to agriculture means changing the cropping patterns in agriculture; changing the bareland class to bareland means some of it could be grassy; changing the settlement class to settlement means some of it may have practiced with vegetation; changing the trees class to trees means changing the tree species; and changing the waterbody class to waterbody means it may have some marshy, shallow, or deep waterbodies (Lüker-Jans et al., 2016).

Assessment of Changes

The loss of agricultural infrastructure, individuals employed by non-agricultural industries, and declining crop prices are all related to the conversion of agricultural land. Additionally, this might be caused by technical, biotic, abiotic, and environmental factors (Liliane et al.,