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RESEARCH ARTICLE

LAND USE AND LAND COVER CHANGE DETECTION BY USING REMOTE SENSING AND GIS TECHNOLOGY IN BARISHAL DISTRICT, BANGLADESH

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ABSTRACT

Barishal has recently gone through intense land use and land cover changes (LULC). This study aims to assess the changes of land use of Barishal, which were surveyed from 2000 to 2020 by utilizing Landsat TM, ETM + & OLI-TIRS imageries. The ArcGIS-10.4 & the ERDAS-14 Imagine software were used to deal with satellite images and surveyed measurable data for land cover change evaluation of the study area. Both pre- and post-classification change detection scenarios and NDVI analysis were observed to assess the change result from 2000 to 2020. Maximum likelihood classification was utilized to create unsupervised land cover category (water body, urban, fallow, agriculture, vegetation and lowland). After ensuring acceptable value for each classified image (82.16% for 2020, 76.15% for 2010 & 70.96% for 2000 with Kappa values of 0.64, 0.62 & 0.62 for 2020, 2010 and 2000), a change detection study was performed. This study discovered that the highest growth 69.22% of urban area has been improved within 20 years followed by 49.75% and 21.74% of water bodies, fallow lands; whereas the annual change rate was 14.95%, 7.91% and 10.31% respectively. In contrast, 16.28%, 10.48% and 37.20% of vegetation, agriculture and lowland had been reduced and an (-) annual change rate of 16.03%, 7.15% and 9.99% respectively. In addition, NDVI analysis was also observed a decreasing trend of the vegetation and agricultural lands. The results of this assessment could be supportive to design and appliance significant managing appraisals to protect the agricultural degradation, fruitless urbanization of Barishal district.

KEYWORDS

Accuracy Assessment, Landsat, Relative Change, Unsupervised classification.

1. INTRODUCTION

Land use and land cover change is considered a major factor for global change due to its interactions with climate systems, ecosystem processes, biogeochemical cycles, biodiversitical changes & even more significant, human activities etc. (Agarwal et al., 2001 and L´opez et al., 2001). Land use and land cover change studies has become a key aspect of global change, or global warming studies in recent times with different spatio-temporal scales (Aguilar et al., 2003; Lambin, 1997). Much more consideration has been paid to land use & land cover change in the last few years, because ecosystems in land use areas are sturdily affected by human activities (urbanization) & natural disasters (cyclones, floods etc.) and have close affairs with the life of more or less half of the world's population (Stow and Chen, 2002). Variations in the land cover result in changes to the balance of energy, water, agricultural & the geochemical fluxes at the local, regional and global level; these changes will inevitably influence the sustainability of natural resources & socioeconomic events (Vescovi et al., 2002). For determining qualitative & quantitative terrestrial land use and land cover changes, satellite imagery has been well used in the natural science communities (Gopal et al., 1996; Collins et al., 1996; Coppin and Bauer, 1994). Both qualitative & quantitative changes in land use and land cover have been effectively observed with remote sensing, with research dominated by efforts at observing change in vegetation & forest canopies (MacLeod and Congalton, 1998).

The reasons of land use and land cover changes are various (Zeng et al., 2008; Geist, 2005; Agarwal et al., 2001; Lambin et al., 2001; Veldkamp and Lambin, 2001; Lambin, 1997). A group researcher defined tropical deforestation, range of land modification, agricultural intensification, urbanization & globalization as the main reasons and factors for global & regional land use and land cover changes (Lambin et al., 2001). Beside these, socioeconomic & biophysical attributes are also contributing to this noteworthy change in land cover (Zeng et al., 2008; Aspinall, 2004). As land cover change is a locally, universal & globally substantial ecological trend, these changes have significant implications for future changes in Earth's environment and have for subsequent land use change (Agarwal et al., 2001). The LULC cllasification is an active and incessant process and therefore, wide-ranging research on LULC classification pattern is essential along with their social & environmental implications at various spatial and temporal scales (Lopez et al., 2001; Mondal et al., 2016). Studies on the changes in various land covers are important for forest monitoring and in total environmental monitoring (Lal and Anouncia, 2015). In recent years, LULC classification study has been developed as a significant research question as it can cause environmental alteration on a

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greater scale. Evidence relating to LULC classification can play a key role in natural resources management (Iqbal and Khan, 2014; Kantakumar and Neelamsetti, 2015; Lin et al., 2015).

The rapid growth of population leads adverse impacts on Bangladesh (Xu et al., 2020). This growth however has placed without proper planning which is resulting in a city with inadequate urban structure, contraction of river banks, vegetated area and so on. Unplanned urban growth of slums, extensive urban poverty, water logging, traffic jam, environmental pollution and other socio-economic problems arise due to extensive growth of population (Islam and Ahmed, 1970). It is important to study the loss of cultivated land that is diverted to cities, vegetation, water bodies and wet/lowlands and also to see how and what changes occurred through. Most of the developing countries have the detailed and recent LULC information which help them to access the changes in their landforms (Series, 2019). But such scenario is rare for under developing countries like Bangladesh. Remote sensing and GIS can be used as a powerful tool for the processes and the access the LULC change pattern of Bangladesh (Mamun, 2013).

The Barishal district is strategically important for the diversification of agricultural lands, the protection of fallow lands and the quick urbanization. This rapid and uncontrolled urbanization, however, is an important phenomenon in the economic development, social progress, and cultural change of the country because 64% of the national gross domestic product (GDP) is generated in the urban sector (UPPR, 2011; Nazem et al., 2011). Moreover, the city holds an exceptional place in the country as they are cultural, industrial, business, education, innovation, entertainment, and political heart of the entire nation (Islam, 2011). Agricultural diversity, degradation, rapid urbanization and anthropogenic activities in Bangladesh is employing mammoth pressure on local capacities and on limited land-based resources, leading to many problems such as land loss, migration, pollution, crime, traffic congestion, poverty and economic & ecological challenges for the entire country. Such growth puts a strain on the ability of city authorities to provide services like energy, health care, transportation, sanitation and physical security. Further it highlights pressing concerns for urban planners, stake-holders, and policy maker in the country due to a shortage of resources, time-bound urban information, and lack of professional planners (Hassan and Nazem, 2015). Empirical study suggests that agricultural degradation, urbanization continued to increase, land cover become progressively diverse in pattern, fragmented in structure and more complex in shape leading to a number of undesirable consequences to biotic and abiotic resource (Qi et al., 2014), such as losses of fresh productive agricultural land, disturbance to rural economic stability and lifestyle, and loses of habitat and species diversity (Wu et al., 2011; Hass et al., 2015). Thus, periodic urban growth and its changing pattern must be observed and characterized, and understood its resultant effect on the land, ecology, and the environment in respect to special and temporal situation.

This study reflected 2000 as the base year and examined the LULC classification from 2000 to 2020 so that recent changes could be recognized. The reason to choose this time period was that the major changes, vegetation destruction and urbanization in land use activities had occurred within this period at a greater scale compared to the previous time. A number of methods are available for discovering and evaluating LULC classification. Among them, remote sensing & GIS method are widely utilized by researchers in the field of LULC classification study (Dewan and Yamaguchi, 2009a,b; Mallick et al., 2008; Mamun et al., 2013; Nemani and Running, 1997; Wang et al., 2009; Zhan et al., 2002). Remote sensing and GIS technique are also applied in this study to define LULC classification in Barishal district with the aim of answering the question of how the land cover has been changed in Barishal in the year 2000, 2010, and 2020. The change in vegetation over time can also be calculated by Normalized Difference Vegetation Index (NDVI) (Haque and Basak, 2017). In recent times the changes in vegetation patterns can be quantified with the help of remote sensing data (Nath and Acharjee, 2013). By producing NDVI and Spatio-temporal changes map, it will be easy to analyze the Spatio-temporal change of vegetation cover from 2000 to 2020 in Barishal district. The aim of this study approaches for the major LULC conversions from 2000 to 2020 so that the recent changes of the landforms could be recognized using unsupervised classification from moderate spatial resolution satellite imagery.

2. Study Area

Barishal is a tropical wet and dry climate district in southern Bangladesh and located between 22°48′0′′N - 90°30′0′′E (Figure 1). It is the largest city and the administrative center of both Barishal district & Barishal division. Barishal is a major city that lies on the bank of Kirtankhola River in south-central Bangladesh (Figure 1). The area of the district is 2784.52 km^2 and it is bounded by many water bodies like Meghna, Arial khan, Kirtankhola, Tentulia, Nayabhanga, Jayanti, Swarupkati, Hatra and Amtali.

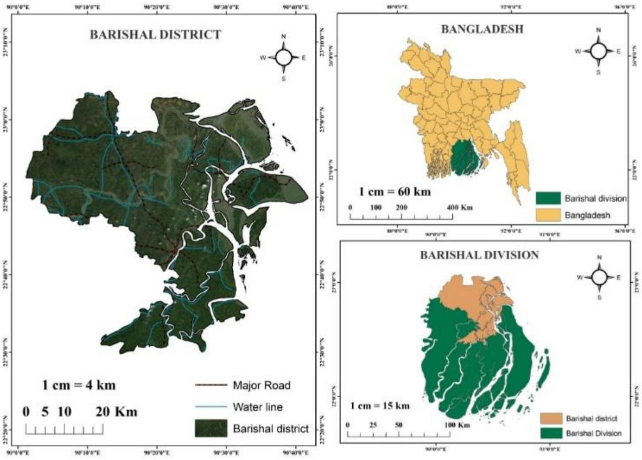

Figure 1: Study Area (Areas of Barishal District & Adjoining Fringe areas) under Barishal Division in Bangladesh. Map shows major water bodies in blue & major roads in brown, respectively.

3. Methodology

3.1 Data collection

This research is dependent on secondary data and makes uses of various spatial and non-spatial data from miscellaneous source including multiyear population census data, socioeconomic census data from the city level statistical year books. The main spatial and temporal data used in this study such as; the latest high resolution satellite imagery Landsat TM 30m (2000), ETM + 30m (2010) and OLI-TIRS 30m (2020) images were derived from open access Landsat imagery services at https://earthexplorer.usgs.gov. Characteristics of Landsat data are displayed in Table 1. While image selection, cloud, and unwanted shade free imagery were set as criteria. Imagery having cloud could considerably reduce the accuracy of the classification work. For this purpose, we could not select imageries of same month along the entire study period.

In Bangladesh, December to February is winter season & March is the interim period of winter to summer. All over monsoon time in Bangladesh is cloudy & days in winter are most of the cases cloud free. For this reason, imageries from the winter season were main sources of data for this study (Uddin and Gurung, 2010). So, it was expected that the acquisition period of imageries would have minimal seasonal variation. Map projection of the collected satellite images is Universal Transverse Mercator (UTM) within Zone 46 N datum and of the co-ordinate system World Geodetic system (WGS) 84 & the pixel size is 30 meters. For the purpose of finding the study area (i.e. Barishal District), the GIS format file (i.e. shape file) of Barishal District has been collected from Bangladesh Water Development Board (BWDB) reports. For the purpose of referencing, several base maps of Barishal city have been collected from the Geological Survey of Bangladesh (GSB) reports.

3.2 Pre-procession of Input data

Prior to image processing, the Landsat images were stacked to gain multiband composite images & later subset with respect to the study area, in order to lessen computation & image analysis time (Table 1). Layer stacking of the ArcGIS 10.4 software was used to covert three bands (8, 5, 4, 3, 2 for Landsat-8, 8, 4, 3, 2, 1 for Landsat-7 and 5, 4, 3, 2, 1 for Landsat-5) into a single layer (Table 1). This process was done for all the three images. As three different images were used for the study time period, so it should be registered first through proper Ground Control Point (GCP). Landsat-8 scene of 2020 (path 136, row 45) was recognized as the reference image based on which imageries of 2000 & 2010 were registered. Then, the collected images are pre-processed by atmospheric, radiometric or geometric corrections. Atmospheric correction is another important procession step that needs to be monitored. Signal measured at satellite could be affected due to the presence of gases, solid, and liquid particles from the atmosphere. Radiometric corrections include correcting the data for sensor irregularities and unwanted sensor or atmospheric noise, cloud and converting the data so they accurately show the reflected or emitted radiation measured by the sensor. The atmospheric effect of the imageries was corrected following (Lopez-Serrano et al., 2016).

Table 1: Information about picked up Landsat Satellite Images used in this study.

Satellite	Sensor	Row/Path	Date of Acquisition	Resolution (m)	Spectral Bands (µm) (Using bands for layerstack)	Data Source
Landsat -8	OLI-TIRS	45/136	11.02.2020	30	B2 (Blue) : 0.45- 0.51 B3 (Green): 0.53- 0.59 B4 (Red) : 0.64- 0.67 B5 (NIR) : 0.85-0.88 B8 (Panchromatic): 0.50-0.68	https://earthexplorer.usgs.gov
Landsat -7	ETM+	45/136	07.02.2010	30	B1 (Blue) : 0.45-0.51 B2 (Green) : 0.52- 0.60 B3 (Red) : 0.63- 0.69 B4 (NIR) : 0.77- 0.90 B8 (Panchromatic): 0.50-0.68	
Landsat -5	TM	45/136	19.01.2000	30	B1 (Blue) : 0.45-0.51 B2 (Green) : 0.52- 0.60 B3 (Red) : 0.63- 0.69 B4 (NIR) : 0.77- 0.90 B5(SWIR):1.55-1.75	

3.3 Image Classification & Land use and Land cover Change Detection

Precise information on urban growth and land cover change derived from satellite images is crucial for the monitoring of urbanization, land management and environment change studies (Turner et al., 2007). But acquiring precise information for such studies can still a challenging job, particularly in urban areas, due to enormously heterogeneous landscapes and often happening problem of mixed pixels. For example, sands or bare soils are often confused with bright impervious surfaces due to their similar spectral reflectance. Using the basic colors red, green and blue (RGB), it is possible to prepare various False color composites (FCC) images (Eastman, 2009). To distinguish between different land cover types or ground objects like building, roads, and vegetation, these FCC images are suitable. We have choose the FCC of RGB = bands 4, 3 and 2 for this study. This combination normally makes water bodies area appear blue, vegetation green, build up areas red, agriculture lemon and fallow lands appear yellow, respectively. Image classification refers to grouping image pixels into categories or classes to generate a thematic representation (CCRS, 2010).

Table 2: Overview of previous research on the use of classification method for LULC and change detection study.

Considerations	Study Area	Study Period	Data use	Methodology	Accuracy percentage	Reference
LULCC detection	Bangladesh	2000-2010	Landsat TM	Object-based image analysis (GEOBIA) classification	(89.70-96.14) %	Xu, X., et al., 2020
LULCC detection	Rajshahi, Bangladesh	1997-2017	Landsat TM and OLI/TIR	Maximum Likelihood Classification (MLC)	87%	Kafy, A., et al., 2019
LULCC detection	Chunati wildlife sanctuary, Bangladesh	2005-2015	Landsat TM and OLI/TIR	Maximum Likelihood Classification (MLC)	(83.96-92.16) %	Islam, K., et al., 2018
LULCC detection	Bangladesh	1976-2010	Landsat, IRS 1A LISS-I, IRS P6 AWiFs	Knowledge-based classification	Not Available	Rai, R., et al., 2017
LULCC detection	Dhaka, Bangladesh	1960-2005	Landsat MSS, TM, ETM +	(MLC)	(85-90) %	Dewan, A.M., and Yamaguchi, Y., 2009a
LULCC detection	Dhaka, Bangladesh	1975-2003	Landsat MSS, TM, ETM +	MLC, Post Classification Refinement	NA	Dewan, A.M., and Yamaguchi, Y., 2009b
LULCC detection	Dhaka, Bangladesh	1989-2009	Landsat TM, ETM +	Fisher Classifier	(85.20-91.60) %	Ahmad and Ahmad, 2011
Change detection	Dhaka, Bangladesh	1991-2008	Landsat TM	Markov Cellular Automata	(49-61) %	Islam, M.S. and Ahmed, R., 2011
Change detection	Rangpur, Rajshahi, Sylhet, Khulna and Barisal, Bangladesh	1973-2014	Landsat MSS, TM, ETM & OLI-TIRS	Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree (DT)	(62-79) %	Hassan, M.M., 2017
Change detection	Khulna, Bangladesh	1989-2019	Landsat MSS, TM, ETM & OLI-TIRS	Fisher Classifier	(85.89-92.78) %	Ahmed, B., 2011
Change detection	Sunamganj, Bangladesh	1980-2010	Landsat MS, TM and ETM	(MLC)	(73.91-91.30) %	Haque M.I. and Basak R., 2017
Change detection	Dhaka, Bangladesh	1990-2010	Landsat TM and ETM+	Supervised classification	Not Available	Mamun, A. et al., 2013

Image classification understands various operations that can be applied to photographic or image data. These contain image restoration, image pre-processing, enhancement, compression, spatial-filtering and pattern recognition and so on (CCRS, 2010). There are two methods of image classification: supervised & unsupervised (Eastman, 2009). The unsupervised maximum likelihood classification used in this study is the most common method in remote sensing image data analysis (Richards, 1995). It recognizes and locates land cover types that are unknown a priori through a combination of personal experience, interpretation of aerial photography, map analysis and field-work (Jensen, 2005). It uses the means & variances of the training data to estimate the probability that a pixel is a member of a class. The pixel is then placed in the class with highest probability of membership (Ozesmi and Bauer, 2002). A classification scheme was developed for further analysis of the images, based on the characteristics of the area (Table 2). Maximum likelihood classification (MLC) approach is being broadly used for land use change calculation. While reviewing literature it was found that MLC is mostly used & convenient to apply with acceptable accuracy (Table 2). The magnitude change for each land use class was considered by subtracting the area coverage from that 2nd year and initial year as displayed in Eq. (1).

Magnitude = (Magnitude of the New Year) – (Magnitude of the Previous Year) (1)

Percentage change for each land use type was then considered by dividing magnitude change by the base year (the initial year) and multiplied by 100 as presented in Eq. (2).

Percentage change = (Magnitude of change * 100) / Base year (2)

To acquire Annual rate of change for each land use type, the difference between Final year to Initial year which shows magnitude of change between corresponding years was divided by the study year i.e. 200-2010 (10 years), 2010-2020 (10 years) and 2000-2020 (20 years) respectively as appropriate using Eq. (3).

Annual rate of change = (Final year – Initial year) / Number of the study years (3)

3.4 Accuracy assessment calculation

Accuracy assessment is prime important for pre and post classified images. Likewise, Kappa coefficient values between 0.61-0.80 signify the substantial agreement (Landis and Koch, 1977). In this study, user, producer and overall accuracy as well as Kappa coefficient are calculated in following equations;

Overall Accuracy = (Total Number of Correctly Classified pixels (Diagonal)) / (Total Number of Reference pixels) × 100 (4)

User Accuracy = (Number of Correctly Classified pixels in each category) / (Total Number of Classified Pixels in that category (The Row Total)) × 100 (5)

Producer Accuracy = (Number of Correctly Classified pixels in each category) / (Total Number of Reference Pixels in that category (The Column Total)) × 100 (6)

Kappa Coefficient (T)

$$= \frac{((\mathrm{TS}\times\mathrm{TCS})-\sum(\text{Column Total}\times\text{Row Total}))}{(\mathrm{TS}\hat{}2-\sum(\text{Column Total}\times\text{Row Total}))}\times 100 \quad (7)$$

4. Result and Discussion

4.1 Identification and change assessment of Land cover categories using multispectral satellite images from 2000–2020

It was projected that outcomes of land use/land cover mapping of Barishal would provide information on (a) aerial distribution of land use/land cover categories & (b) identification and assessment of land use/land cover changes over the past 20 years. The land use maps derived from various Landsat imageries are displayed in Figure 2. The aerial distribution of numerous land use classes from the year 2000, 2010 & 2020 and their change scenarios in between different time periods are displayed in Table 4 & 5, respectively.

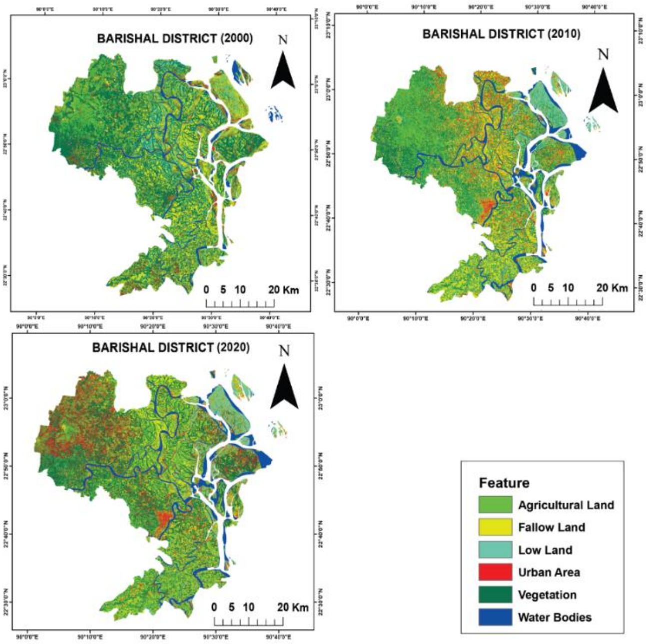

Figure 2: Portion of the study region site representing 2000, 2010 & 2020 images acquired on 19th January 2000, 7th February 2010 & 11th February 2020, respectively with the used Unsupervised Classification schemes. This study have choose the FCC of RGB = 4, 3 & 2 bands. This arrangement generally marks water bodies area appear blue, vegetation green, build up areas red, agriculture lemon and fallow lands appear yellow, respectively.

4.2 Condition of land use categories of the study area from 2000–2020

The study area's land uses were categorized into following six groups containing (1) Water bodies, (2) Agricultural land (3) Vegetation, (4) Fallow Land, (5) Low Land and (6) Urban Area, respectively (Table 3**)**. After image classification on the basis of above land use categories, appropriate map layouts were prepared on 1cm equal to 5km scale (Figure 2).

Table 3: Land use and Land cover Classification pattern.

Land use and Land cover types	Explanation
Water Bodies	River, lake, lagoon, pond & aqua fishing.
Vegetation	Homestead Vegetation, coastal mangrove, Shrubs & Bush.
Agriculture	Various agricultural lands such as paddy field, fruits, vegetable & cultivable lands etc.
Fallow land	River Banks, Sandy Beaches, Landfill, Bare soil & Barren land etc.
Low land	River banks, Accretion & Deposited lands.
Urban area	Build up area including residential, commercial & industrial.

4.3 Land use pattern of Barishal in 2000

To know the historical land use pattern of the study area, this study first tried to focus on Landsat TM imagery for the year 2000. Changed land use categories had been observed & utilized as historical reference for the image of 2000. The recognized land use pattern was confirmed in cross-examination way at present context, whether or not the category exist or converted into another pattern. By applying ground truth knowledge, this study recognized the specific pixel along with their color tone to conform every land use category during image classification. The land use pattern which was recognized (6 categories) for the year 2000 are listed in Table 4 & displayed in (Figure 2). A total of **2784.248** sq. km of the land area was estimated for the whole Barishal after unsupervised image classification by using ArcGIS 10.4 (Figure 2).

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Table 4: Year-wise land use sharing of Barishal from 2000-2020.

	Land use feature	(A) Land use in 2000		(B) Land use in 2010		(C) Land use in 2020	
		Area (sq.km)	% of land	Area (sq.km)	% of land	Area (sq.km)	% of land
01	Water Bodies	158.9664	5.71	238.332	8.56	238.053	8.55
02	Vegetation	984.4224	35.36	838.059	30.10	824.137	29.60
03	Agriculture	682.05	24.49	256.986	9.23	610.586	21.93
04	Fallow land	474.1152	17.03	908.500	32.63	577.175	20.73
05	Lowland	268.656	9.65	352.207	12.65	168.725	6.06
06	Urban area	216.0384	7.76	190.164	6.83	365.572	13.13
	Total	**2784.248**	**100**	**2784.248**	**100**	**2784.248**	**100**

Source: USGS Landsat-8, 7, 5 OLI/TIRS, ETM+, TM satellite images from 2000–2020 & Extraction of data and compiling done by authors using Erdas Imagine – 14 & ArcGIS 10.4 software.

From the recognized land use categories, the highest categories was Vegetation area (984.4224 sq.km, 35.36% of total land area) followed by Agricultural land (682.05sq.km, 24.49%) and Fallow land (474.1152 sq.km, 17.03%) (Figure 2 & Table 4). The remaining land uses were Low lands (9.65%), Urban area (7.76%) and Water bodies (5.71%) mentioned in the Table 4. The Figure 2 displays the land use pattern of the study area in 2000. In this figure, green patches indicate Vegetation area which was most prominent in Barishal areas. The lime color specifies agricultural land which was observed prominently in the north-western margin, some north-south direction & along the eastern and southern margin of Barishal (Figure 2). The yellow color (fallow land) was mostly prominent of the central and north-south directional margin. Negligible amount of urban area (red color) observed in the river bank side industrial and Sadar areas (Figure 2).

4.4 Land use pattern of Barishal in 2010

After 2000 land use classification, the pattern of 2010 was visually interpreted through ArcGIS 10.4 and it was also utilized as the base year for identification of changes in land use categories from that time to present context. A sum of six land use categories were recognized during 2010 image classification (Figure 2 & Table 4). Among six categories of land uses, three significant categories (water bodies, fallow lands and low lands) were increased from the previous perspective time. On the other side, Agricultural, Vegetation and Urban areas were declined from the 2000s time frame showed in Table 4. Based on 2010 image classified outcomes, the highest category was fallow land (908.500 sq.km, sharing 32.63% of total land area) followed by vegetation containing 838.059 sq.km (30.1%) and low land sharing 352.207 sq.km (12.65%) of the entire area (Figure 2 & Table 4).

The remaining land uses were shared agricultural lands (9.23%), water bodies (8.56%) and urban area (6.83%) (Figure 2 & Table 4). Most of the land uses (especially fallow lands) were unusually transformed after 2000 to till 2010. The causes might be due to lack of regular monitoring by forest or agriculture department along with massive encroachment & rapid extraction of natural resources from Barishal. Water bodies were increased due to flooding, storms surge water or little man-made lake-ponds etc. In this time frame, many tropical cyclones hit the coastal areas (like as Barishal) and major flood happened due to global climate change consequences. That is the reason of water bodies & low lands were increased of the study area. Most of the agricultural and vegetation lands were damaged due to tropical cyclones as like Cyclone Sidr hit in 2007.

4.5 Land use pattern of Barishal in 2020

After 2010 land use classification, a sum of six land use categories were identified similar to the year 2020. Among the six classifications of land uses, two significant classes agricultural and urban areas were expanded from the past viewpoint time. On the opposite side, fallow lands, low lands, and vegetation were declined from the 2010 time (Figure 2 & Table 4). It was observed that vegetation area was dominant (highest category) in the Barishal areas among all other categories which shared 824.137 sq.km (29.60%) out of 2784.248 sq.km (Figure 2 & Table 4). The second highest one was agricultural land containing 610.586 sq.km (21.93%) of the total area (Figure 2 & Table 4).

However, this was happened due to sudden increase of agricultural activities. Trailed by fellow land and urban area is found 577.175 sq.km (20.73%) and 365.572 sq.km (13.13%), respectively (Figure 2 & Table 4). The rest of the water bodies 238.053 sq.km (8.55%) and low land 168.725 sq.km (6.06%) (Figure 2 & Table 4). It has been reported that increasing population have been living adjacent to the land use areas & these group of people is heavily reliant on its assets like vegetation or land for their nourishment. A great portion of fallow and low land had also been influenced by the people & their illicit logging activities are equally responsible for the land use changes in the study area. These data suggest that Barishal area is gradually increasing with natural regeneration and urbanization is getting better after 2010 because of various government & non-government enterprises.

4.6 Relative change of land cover in Barishal area

Relative change in land use categories of Barishal was evaluated based on information introduced in Table 4 & 5. The relative changes observed some sporadic examples in this study are from 2000 - 2010. Land cover change from 2000–2010 indicated average (both positive and negative) changes among the classifications (Table 5). The situations indicated a worse pattern in 2010–2020 contrasted with 2000 - 2010 period. Land cover change from 2010–2020 indicated adverse changes in major features (Table 5). About 425.064 sq.km of agricultural land had reduced in 2000–2010 frames which observed a decrease (negative) change of (-62.32%). Whereas 2010-2020 data set observed a positively upsurge (137.60%) in this same land use category (Table 5) then total percentage change in the agricultural land from 2000–2020 displayed a negatively declining (-10.48%) (Table 5). Vegetation observed a negatively changed in the complete study time.

Table 5: Land use and land cover change detection of Barishal based on time period (2000-2020).

	Land use feature	Change of Land use (2000-2010)			Change of Land use (2010-2020)			Change of Land use (2000-2020)		
		Magnitude Change Area (sq.km)	% of Change	Annual rate of change	Magnitude Change Area (sq.km)	% of Change	Annual rate of change	Magnitude Change Area (sq.km)	% of Change	Annual rate of change
1	Water Bodies	(+)79.365	(+)49.93	(+)7.94	(-)0.279	(-)0.12	(-)0.03	(+)79.0866	(+)49.75	(+)7.91
2	Vegetation	(-)146.363	(-)14.87	(-)14.64	(-)13.922	(-)1.66	(-)1.39	(-)160.285	(-)16.28	(-)16.03
3	Agriculture	(-)425.064	(-)62.32	(-)42.51	(+)353.6	(+)137.60	(+)35.36	(-)71.464	(-)10.48	(-)7.15
4	Fallow land	(+)434.385	(+)91.62	(+)43.44	(-)331.325	(-)36.47	(-)33.13	(+)103.06	(+)21.74	(+)10.31
5	Lowland	(+)83.551	(+)31.10	(+)8.36	(-)183.482	(-)52.09	(-)18.35	(-)99.931	(-)37.20	(-)9.99
6	Urban area	(-)25.8744	(-)11.98	(-)2.59	(+)175.408	(+)92.24	(+)17.54	(+)149.534	(+)69.22	(+)14.95

Source: Data derived and compiling done by authors based on Table 4. Note: a. Land use change assessment based on interim year from 2000–2010, 2010–2020 and overall 2000–2020 correspondingly; b. (+) sign signifies Escalation & (-) sign signifies reduction of change magnitude of land use features in different time period.

About 79.3656 sq.km and 434.385 sq.km of water bodies and fallow land had expanded in 2000–2010 period which demonstrated a positive difference in (49.93%) and (91.62%) separately (Table 5). While 2010–2020 information indicated a negative change (- 0.12 %) and (- 36.47) in water bodies and fallow land separately, however by and large rate change in water bodies and fallow land from 2000–2020 demonstrated a positive increment of (49.75%) and (21.74%) individually (Table 5). Low land demonstrated diminishing pattern. Annual rate of change was observed about 9.99% in negatively (Table 5). But the urban region was yet in its positive pattern. This may be reflected as a minor change to the supportability of Barishal district. If 2000–2020 time duration was recognized then it was observed that almost 149.534 sq.km of land was urbanized having a change rate of 69.22% and the annual change rate of 14.95% inside ten years of study (Table 5).

4.7 Accuracy assessment and kappa statistics

In remotely sensed data, accuracy assessment is vital to evaluate the heterogeneity and validation of the classified images (Elkington, 2007). In a nutshell, unsupervised classified image accuracy for the three dissimilar time frames (2000, 2010 & 2020) calculated from accuracy assessment in the following equations (4, 5, 6 & 7). The highest accuracy was observed for 2020 unsupervised classified image (82. 16% accuracy), 76.15% for 2010 and the lowest for 2000 (70.96% accuracy). Kappa Statistics is an assessment mechanism between referenced & user observed classified data. Kappa coefficient values between 0.61-0.80 signify the substantial agreement (Landis and Koch, 1977). Kappa accuracy was obtained 0.64 for 2020, 0.62 for 2010 & 2000 classification. It can be inferred that this unsupervised classification has a substantial agreement accordingly (Landis and Koch, 1977).

4.8 NDVI analysis of Barishal from 2000-2020

The NDVI has been performed in the study region to measure the condition & greenness of the vegetation. The result of NDVI also aids to compute the change in vegetation over years. NDVI of the study area has been done for 2000, 2010 & 2020 years (Figure 3). The values of NDVI are divided into 5 categories representing very low, low, moderate, high and very high (Figure 3). Negative to nearly zero represents no vegetation classes that means this class represents areas like water or barren land (Nath and Acharjee, 2013). From the NDVI figure of 2000, it is observable that very low (-0.395 - -0.134) values are 5.97% of the total map (Figure 3). After the next 10 years in 2010, the very low values (-0.443 - -0.196) have increased to 6.67% of the map (Figure 3).

In comparison with above year, in 2020 the increase of the values (-0.134 - -0.002) is observed which is 8.86% (Figure 3). It can be concluded from the data that water bodies or barren lands of the area have grown over the years. Close to zero NDVI values represent the presence of soils and rocks (Nath and Acharjee, 2013). In 2000, the values of NDVI show that low values (-0.133 - 0.074) covered 14.73% of the map at that time (Figure 3). NDVI representation after the next 10 years in 2010, it shows that area covered by the low values (-0.195 - -0.001) was 15.31% which was a bit higher than the previous one (Figure 3). In 2020, the low value (-0.001 - 0.128) somewhat surprisingly decrease to 15.01% of the overall area (Figure 3). The positive value of NDVI is only shown by healthy vegetation. A higher amount of photosynthesis can be interpreted by the higher value of NDVI (Nath and Acharjee, 2013). The moderate value (0.075 - 0.189) of the NDVI in 2000 shows that it covered an area of 26.97%, whereas in 2010 moderate values (0 - 0.121) occupy only 23.88% of the total area which is significantly less than the previous one (Figure 3).

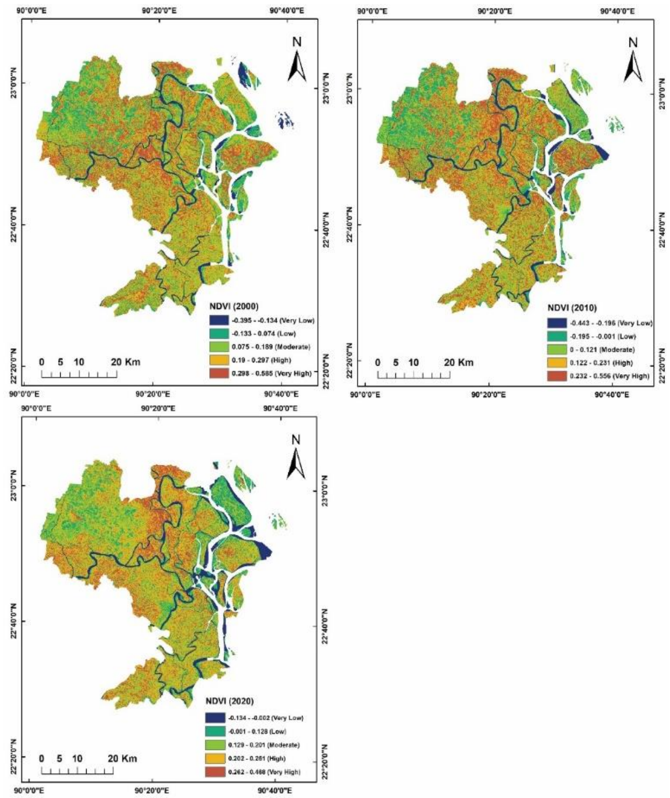

Figure 3: Portion of the study area site representing 2000, 2010 & 2020 images acquired on 19th January 2000, 7th February 2010 & 11th February 2020, respectively with the used NDVI schemes.

Minor changes in the moderate values (0.129 - 0.201) are seen in the 2020 image, that covers 23.54% of the Barisal district (Figure 3). It can be inferred from the data that moderate vegetation is decreasing. In the year 2000, the NDVI image shows that the percentage of land covered by high vegetation was 28.53% and its range was 0.19 - 0.297 (Figure 3). The total area covered by high vegetation decreased a little over the 10 years, which shows that it became 27.37% and its range was 0.122 - 0.231 in the year 2010 (Figure 3). There was a upsurge of high vegetation area in the year 2020, which covers 35.20% of land and its range was 0.202 - 0.261 (Figure 3). Very High vegetation shows an upward then downward trend. In 2000, the NDVI values shows a very high range (0.298 - 0.585), which covers 23.77% of the land (Figure 3). Within 10 years shows a drastic increase of very high vegetation, the range (0.232 - 0.556) covered 26.75% of the land at that time (Figure 3). There was a drastic decrease in the very high vegetation in 2020 due to urbanization and anthropogenic activities. The very high range (0.262 - 0.468) only covered 17.36% of the land at that time (Figure 3).

5. CONCLUSION

The Barishal region has been under complex pressing factors from the expanding populaces and their requests. The vegetation and agrarian grounds have been tarnished cruelly and the land has been part and changed into different land covers. This examination detected the degree of land cover changes in the Barishal with the use of RS and GIS strategy by utilizing multispectral satellite images. This modest and conservative method can be utilized in the land cover planning and zoning. The pattern of land cover changes observed in this examination, particularly rate increment in urbanized land and decline in regular vegetation, farming cover will be to strategy producers to take appropriate choice to restore the circumstance and to secure the natural resources of the investigation zone.

Albeit the general accuracy of this investigation was agreeable yet at the same time there are a few issues which should have been adjusted. It was attempted to choose images of same development season for arrangement however because of cloud cover and inaccessibility of worth images, it wasn't possible. This influenced a few issues like class mismatching. Hence, it is recommended to choose images of same development season for future investigation. Socioeconomic factors are considered profoundly connected to the adjustments in land use and land cover of a territory (Aspinall, 2004 and Verburg et al., 2004). Accordingly incorporating socioeconomic and segment information of study region alongside reformist change example would give an intense thinking for land use and land cover evaluation.

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