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Predictive assessment on landscape and coastal erosion of Bangladesh using geospatial techniques

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ABSTRACT

Coastal erosion, land use and land cover (LULC) changes analysis using remote sensing is a dynamic, relatively low cost based precise method using now a day. Coastal districts of Bangladesh occupied by naturally grown mangrove forest which are susceptible to rapid land cover (LC) changes and natural erosion. Barguna and Patuakhali districts of Bangladesh deserve special attention for conserving coastal mangrove forest named Tengragiri Wildlife Sanctuary and variety of human forces income. The core objective of this research is to analyze the LULC change along with coastal erosion analysis from 2000 to 2017. Combination of four years Landsat satellite image analysis, primary field data, geo-tag photography, secondary information, utilization of forest carbon inventory 2015 data, and semi-structured questionnaire are the key approaches adopted in the study. K-means cluster based unsupervised and maximum likelihood supervised classification by using ERDAS Imagine 2014 found the total study area is 33,361 ha. Random sampling (40 points/class) based accuracy assessment and verification by google earth pro 7.1 found overall accuracy 88.15% and Kappa coefficient is 0.867. Python coding program and overlay operation tested for conversion analysis any found weighted overlay provide best results. An intensive RS analysis of 33,564 ha mangrove forest and community landscapes generated six (6) distinct land cover class and sub-classes, e.g. Forest, agriculture & grassland, plantation, sandbar, settlement and waterbody. During 2000–2017, agriculture and grassland were decreasing 23 ha/year. Out of 11,831 ha (in 2000) Agri-grass land 9,326 ha remained intact while remaining 2,246 ha converted to settlement mixed with homestead plantation class. This study also presents the landscape erosion-accretion due to natural, quasi-natural and anthropogenic interventions which shows that, along the river flow and at the confluence at the Nishanbaria Union (local name Khouttar Char & Fakir hat) to lower side of the Tengragiri WS locations are susceptible to high trend of land erosion whereas accretions are prominent on the reverse sides named Baliatali Union, Barabagi Union and so on. These results of the study and developed maps will be helpful for the community people, line departments, national and international policy maker and the researchers' community for monitoring coastal geomorphology including erosion and accretion of this landmass.

1. Introduction

Coastal environment is a very complex and diverse ecosystem form the main land (Kirui et al., 2013). Due to climate change and sea level rise most coastal environment around the world are being affected and expose threat to its inhabitant (IPCC, 2007). Bangladesh lies in a tropical region and its funnel shape (Rose and Bhaskaran, 2017) expose more threat to natural disasters for instances cyclone, storm surge, flooding and so on (Ali, 1996). Shoreline changes also a considerable coastal phenomenon in Bangladesh (Salauddin et al., 2018) and Barguna Patuakhali Coastal Zone (BPCZ) is situated lower confluence point of Ganges-Brahmaputra-Meghna (GBM) basin which is dynamic in

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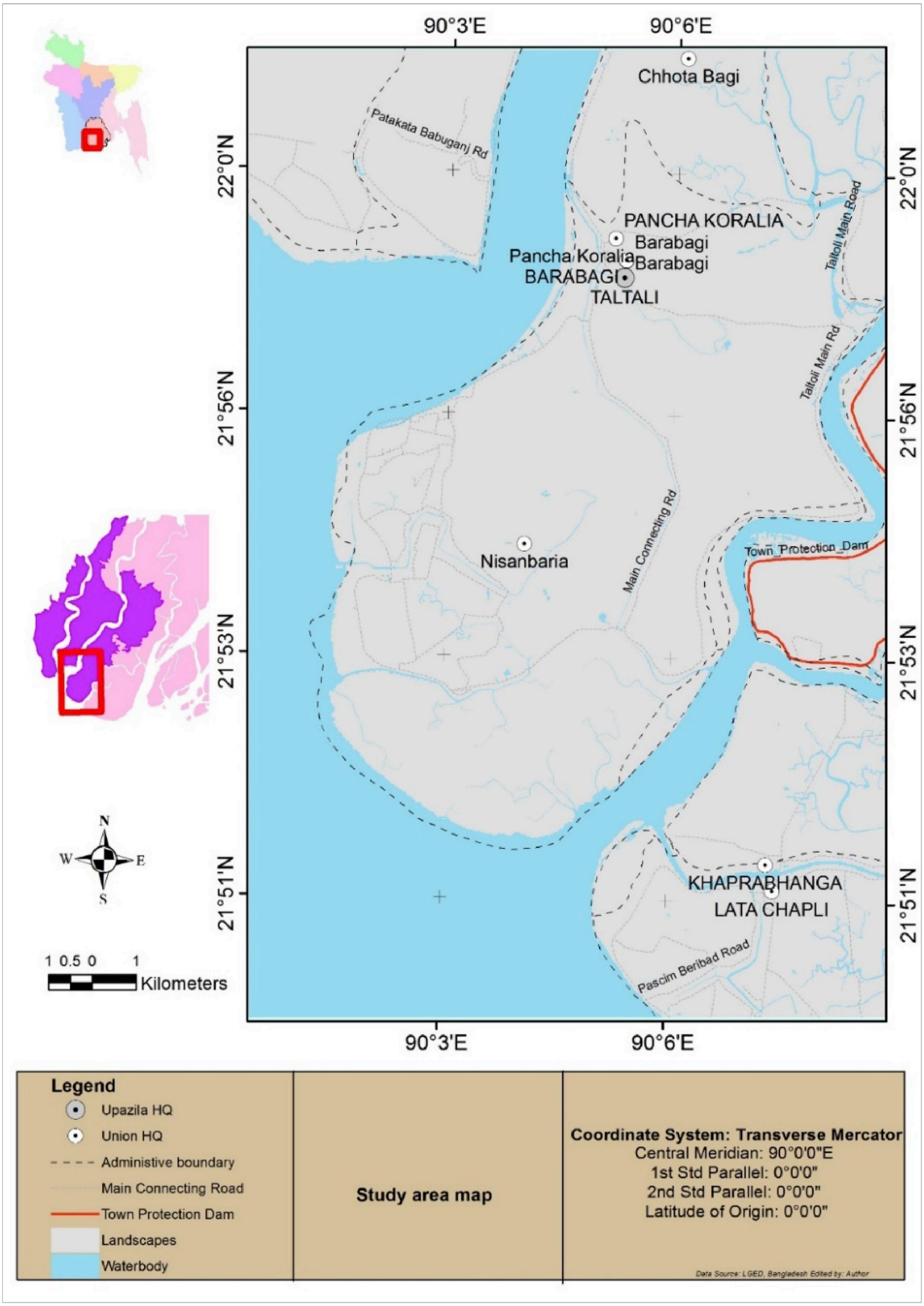

Fig. 1. Study area.

erosion-accretion pattern. Annual accretion of BPCZ shoreline is 77.087 m and erosion is 98.26 m (Sarwar and Woodroffe, 2013) whereas it also massive in some areas. There are about 33.87 million people living in the coastal zone which is considerable i.e. 27% people among total population (BBS & SID, 2011). (see Fig. 1)

It is obvious that, earth is changing, and it is an unavoidable natural phenomenon (Van Loon, 2001). Global climate change has largely negative and few positive impacts on population, animal, sea and overall environment (IPCC, 2007). According to the Gaia Hypothesis, global environment has an ability to recover the natural body of its own or

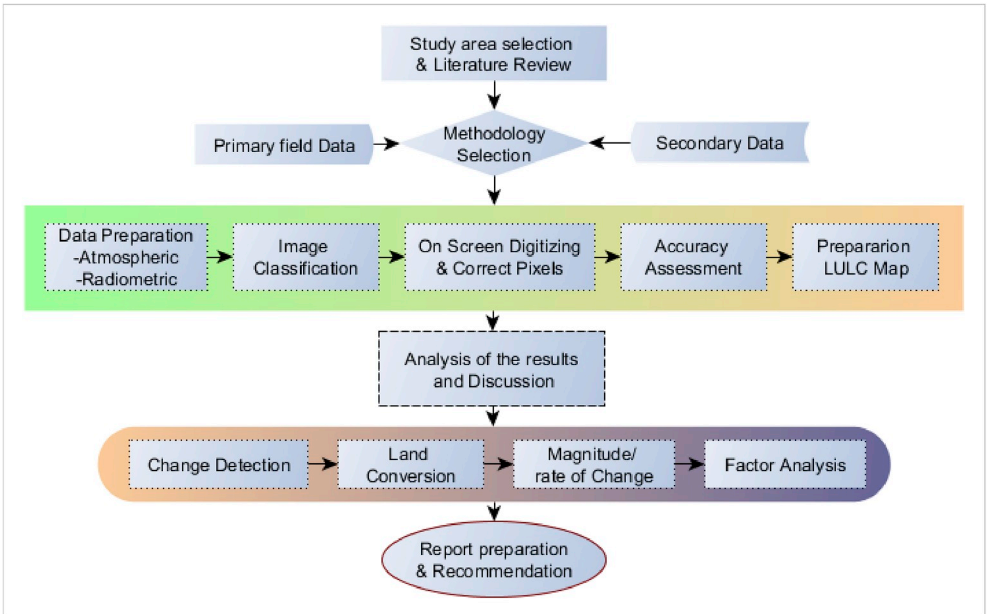

Fig. 2. Overall workflow and methods of this study.

Table 1
Characteristics of the collected Landsat data.

Data Acquired Date	Satellite (Sensor)	Path/Row	Acquisition Time (GMT +6.00)	Resolution (m)	Image Quality	CC (%)
19-01-2000	Landsat 5 (TM)	137/045	11:19:03	30 × 30	9	0
05-03-2005	Landsat 5 (TM)	137/045	6:36:19	30 × 30	9	2
30-01-2010	Landsat 5 (TM)	137/045	10:32:13	30 × 30	8	0
01-01-2017	Landsat 8 (OLI_TIRS)	137/045	10:46:22	30 × 30	9	4.39

previous status if a change has occurred in a recovery range (Kirchner, 2002). Despite of those changes, it is required to understand whether it is in recovery range (Islam and Kitazawa, 2012). Apart from that, making a place climatically resilience for adapting its existing flora and fauna, several measures need to take into consideration (Shi et al., 2018). Before taking the decision to serve any community, it is very much important to assess the land feature changes over time. In this regard, LULC change detection study by using satellite imagery is one of the most useful techniques in recent era (Hussien, 2009).

Mangroves ecosystem of Bangladesh producing variety of economic, ecological services along with green safety barrier from different natural disasters of the coastal communities (Kathiresan, 2012). Therefore, coastal area and island including mangrove forest are important candidate for conservation (Kirui et al., 2013). Some studies has taken in broader scale but no specific study has taken focusing mangroves area (Ibrahim et al., 2018) specially in Barguna and Patuakhali. Remote sensing and satellite image analysis based LULC and prediction analysis is mostly suitable for intact forest and adjacent areas features identification rather than the conventional methods. Using very high resolution imagery carries information more sophisticatedly and this study has limitation of using high resolution imagery like worldview-2, RapidEye, Quickbird and so on but several studies successfully uses Landsat imagery for the relevance work (Iqbal and Khan, 2014; Rawat et al., 2016; Saadat et al., 2011) so far it considered suitable for our study and utmost tried to conduct sufficient field visits and utilizing other sub-sequent logistics for gaining higher accuracy level. To meet the research gaps, finally 2000, 2005, 2010 and 2017's Landsat imagery uses for LULC changes with coastal geo-morphological identification of the Taltolli Sub-district of Barguna and parts of Patuakhali District.

2. Materials and methodology

Naturally grown mangrove forest Tengragiri wildlife sanctuary (locally named 'Fatrar Bon') situated under Taltoli sub-district but associated other mangrove forests grown in part of Patuakhali district so far it also considered as area of interest (AOI). Geographically it located at $21^0 1'25.73''$ N to $21^0.49'34.758''$ N latitude and 90^0 $0'19.542''$ E to 90^0 $9'0.145''$ E longitude under Barguna, Patuakhali district in Taltoli and Kalapara sub district respectively. Taltoli sub district covers an area of 258.94 km^2 with the population of 88,004 people (BBS & SID, 2011). Population density is 541/km^2 and literacy rate is 31.76% (BBS & SID, 2011). Taltoli subdistrict have seven unions and Kalapara subdistrict have 12 unions. Study area covered total or partially of 5 unions named Pochakoralia, Chotobogi, Koroibaria, Borobogi, Nishanbaria, Sonakata union (Bangladesh, 2017) of Taltoli subdistrict and four unions named Lata chapali, Kaprabhanga, Nilgonj, Chakamaiya of Kalapara subdistrict (under Patuakhali district).

2.1. Data acquisition and preparation

Higher quality images, low cloud cover and lower climatic variable satellite imagery collection is the prerequisite for remote sensing-based analysis which is core activity of this study. Freely available data has collected form USGS EE website (http://earthexplorer.usgs.gov). Taltoli sub-district is covering by World Reference System 2 (WRS-2) path 137, row 045 (Xian et al., 2009). Full study area is covered by this section so there is no need to make mosaic. Three Landsat 5 TM data were acquired in the year 2000, 2005, 2010 and one Landsat 8 data were acquired from Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) in 2017 for LULC change analysis of the studied area and overall workflow and study methods presented in Fig. 2. In general, accuracy of

Table 2
Landscape change rate per annum (CRPA) in the year 2000, 2005, 2010 and 2017.

LULC types	2000		CRPA 00-05	2005		CRPA 05-10	2010		CRPA 10-17	2017		CRPA 00-17
	Area (ha)	%		Area (ha)	%		Area (ha)	%		Area (ha)	%	
Agriculture Grassland	11,848	35%	−1.40	11,020	33%	−2.02	9,905	30%	3.12	11,452	34%	−0.20
Forest	3,306	10%	0.89	3,186	9%	19.87	3,219	10%	35.97	3,759	11%	5.99
Plantation (other)	331	1%	12.08	531	2%	−9.30	284	1%	0.77	295	1%	−0.64
Sandbar	1,371	4%	−10.42	657	2%	21.70	1,370	4%	−11.08	611	2%	−3.26
Settlement	4,835	15%	7.03	6,535	19%	−0.84	6,260	19%	0.17	6,313	19%	1.80
Waterbody	11,873	35%	−0.40	11,635	35%	1.53	12,526	37%	−2.22	11,134	33%	−0.37
Total	**33,564**			**33,564**			**33,564**			**33,564**		

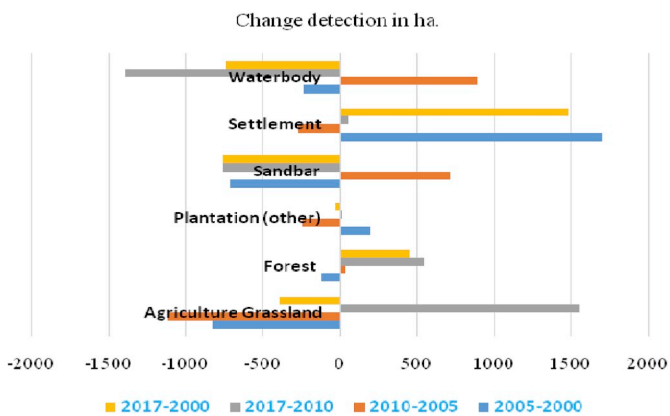

Fig. 3. Change detection in the year 2000–2005, 2005–2010, 2010–2017 and overall 2000–2017 interval.

classification also dependent on different seasons of the year (Xian et al., 2019).

Due to monsoon climatic condition the study areas optical sensors cloud free data is limited. However, dry season (Nov–April) data were collected for different years. Necessary information collected from Landsat data have been given in Table 1.

2.2. Image pre-processing field visit map preparation

All composite color bands (except thermal band) have been used where mosaicking of the imageries not required for selecting our AOI. Satellite imagery and GPS locations along with field visited ancillary data were used for this sample selection (Pouncey et al., 1999). To prepare corrected image, To prepare corrected image, Atmospheric ATCOR-2 extension developed by the ERDAS Imagine platform used for atmospheric and haze reduction purpose (Richter and Schläpfer, 2017). For radio-metrically image enhancement technique histogram equalization also used and found suitable for this study. The same kind of atmospheric and radiometric correction has done for all four years' imagery. Unsupervised classification in LULCC analysis purpose found necessary in some studies (Were, 2008; Islam et al., 2015)). To do so, K-means clustering method and appropriate true color scheme options with 24-time iteration was used which considered best for unsupervised classification into several literature (Intergraph Corporation, 2013) to classify the subset into 56 classes in this study. Outcome of the unsupervised classification sorted into 12 major classes and field study map printed into several A3 and A1 size papers. To identify and incorporate recent feature, Google earth-based HR 49 image segments processed and used. Refer to this activity, Garmin GPSMAP 78s, CASIO QV-R200 camera was used for identifying appropriate GPS coordinates and geotag image purpose.

2.3. Field GPS points and ancillary data collection

A pre-classification field visit done in this study where ground truthing and different time field data acquisition purpose several field visits were conducted from 20th Jan 2017 to 02nd Feb 2017. During this period, minimum 30 GPS locations, prevailing features with geotagged imagery recorded for each class. To collect socio-economic and historical LULC changes information and magnitudes purpose Focused Group Discussion (FGD), semi-structural interview, transact work, Training, also used. CREL's site office also sufficiently helps to collect data along with previously conducted forest carbon inventory database. Other successive secondary database collected from BBS, line ministry, NGO offices as well.

2.4. Supervised classification and refinement

Several investigation and testing refer, pixel based supervised classification using ERDAS Imagine 2014 suitable for this study (Araya and Hergarten, 2008). Ground controlling sample points collected from field visit used for creating AOI set and signature files. Maximum likelihood parametric decision rule has selected and successively mean, Std. deviation, lower limit and upper limit also calculate during supervised classification. Post classification digitizing (refinement) used for correcting misclassified isolated pixels which required for achieving higher accuracy of the (Peacock, 2014). After maximum likelihood supervised classification algorithm, thematic recode tool has used and finally selected six classes. Clump tool helps to sieve correct isolated pixels and minimum 2.00 pixels finds suitable for this study (Intergraph Corporation, 2013). Finally, eliminating lower than two pixels and converted on-screen digitizing done by using ArcMap 10.5 software.

2.5. Accuracy assessment and map preparation

Accuracy assessment considered important for making decision based on the classified study area map (Brown, 2014). To find the classified map work accuracy, an updated technology (Brown, 2014) used where minimum 40 points has created per class and verified with the present extent with the field and historical extent feature of the google earth pro. Previously collected ground verification points and associated new field visits also helps in this extent. Using this semi machine learning mechanism found overall accuracy 88.15% and Kappa coefficient is 0.867 (in scale 1).

2.6. Change detection and magnitude of change analysis

Post-classification change detection algorithm provides more accurate result for monitoring and analysis of LULC change detection and analysis claimed in several studies (Peacock, 2014). Post-classification change detection algorithm also provide easy and reliable formula rather than a complex matrix (Were, 2008). Magnitude of land cover changes purpose several well-documented literature has adopted which also used here (Were, 2008)-

Fig. 4. Spatio-temporal mapping of the year 2000, 2005, 2010 and 2017.

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

where.

Δ=Average annual rate of change (%)
A1=Amount of land cover type in time 1 (T_1)
A2 = Amount of land cover type in time 2 (T_2)

Fig. 5. Natural cause and human interventions for erosion and land cover conversion; first one presents the erosion making trees uprooted, second one present, fisherman construct temporary hatchet and due to it, side area cleaned and burnt (Source: Field visit 2017–2018).

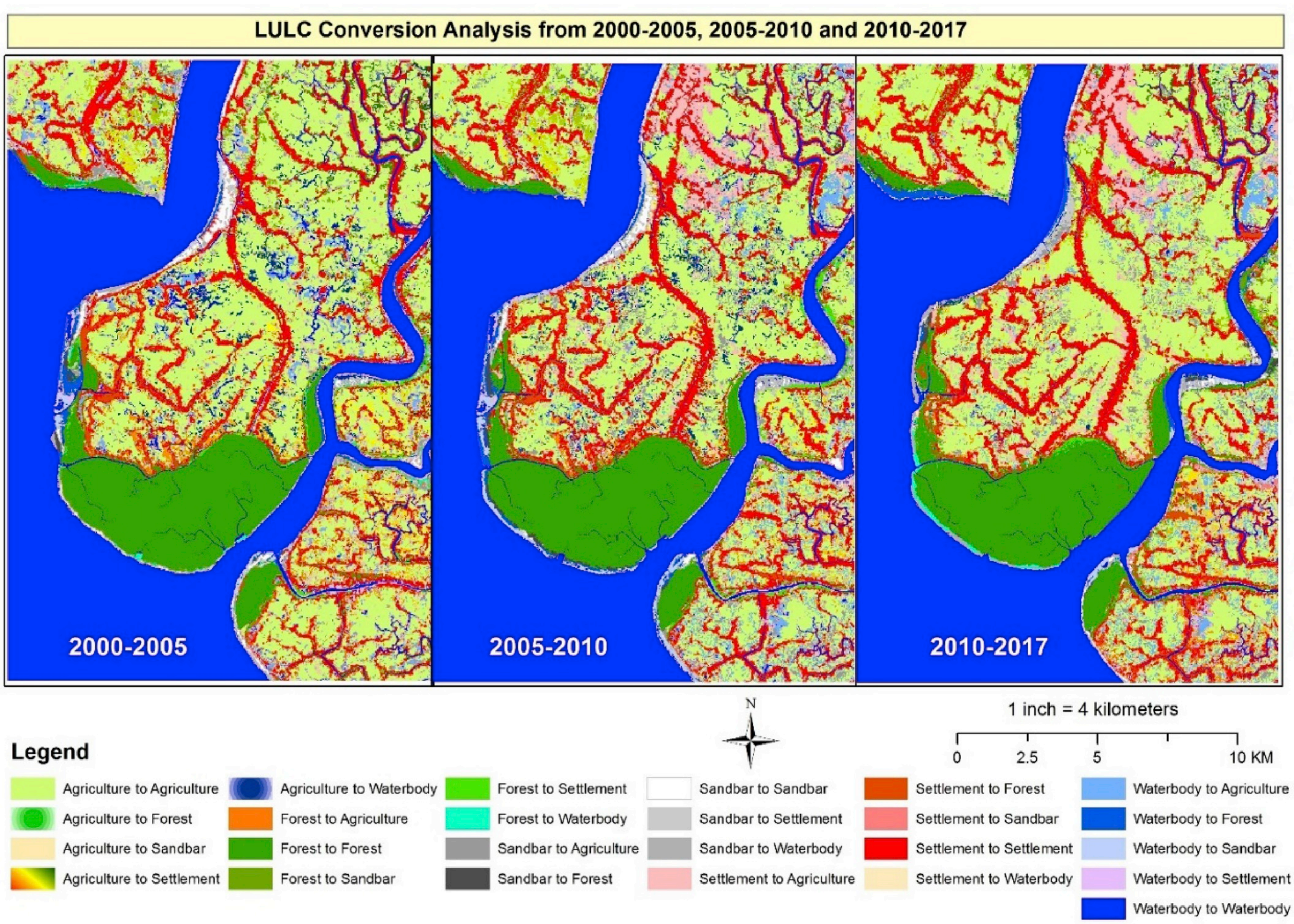

Fig. 6. Simplified representation of the LULC conversion matrix based on the year 2000–2017. This image presents the inland waterbody is interchanging class with the sandbars.

3. Result and discussion

Study area of interest (AOI) intersects about 33,563 ha in total where, Agriculture and grassland 12846.1 ha. (38%), Forest 4617.1 ha. (14%), Plantation (other) 1382.4 ha, Sand 494.3 ha, Settlement 2858.3 ha and Waterbody class covered 11364.8 ha. (34%) respectively extracted from unsupervised classification. LU is a dynamic phenomenon, which frequently changed by geo-natural process, seasonal changes, variation in cropping pattern etc. and so on (Kirui et al., 2013). That's why, total study area will be remained unchanged, but it is converted/interchanged into different classes (Table 2). Area change along with change detection analysis are prerequisite for LULC changes (Dewan and Yamaguchi, 2009) which presented into Table 2 indicating units at hector.

Table 2 indicates agriculture and grassland area in the year 2000, 2005, 2010 and 2017 is 11,848 (35%), 11,020 (32.83%), 9,905 (29.51%) and 11,452 (34.12%) respectively. Fig. 3 indicates the overall agricultural and pasture land has decreased 369 ha from 2000 to 2017, massive area decreases in 2005–2010 but increased in 2010–2017. Discussing with local community and the stakeholders, they percept two

Table 3
Probability cross matrix from 2000 to 2005 shows in hector, the highest intact area are agriculture and waterbody where sandbar changes with time, therefor settlement and built-up area are the second interchanging class.

2000–2005	Agriculture	Forest	Sandbar	Settlement	Waterbody	Total 2005 (ha)
Agriculture	9001 (0.82)	11 (0)	563 (0.05)	903 (0.08)	542 (0.05)	11,020
Forest	4 (0)	3166 (0.85)	60 (0.02)	271 (0.07)	216 (0.06)	3,716
Sandbar	81 (0.12)	75 (0.11)	301 (0.46)	44 (0.07)	156 (0.24)	657
Settlement	2140 (0.33)	307 (0.05)	220 (0.03)	3443 (0.53)	424 (0.06)	6,535
Waterbody	621 (0.05)	77 (0.01)	228 (0.02)	173 (0.01)	10536 (0.91)	11,635
Total 2000(ha)	11848 (0.35)	3637 (0.11)	1371 (0.04)	4834 (0.14)	11873 (0.35)	33,563

Table 4
Interval of 2005–2010 and area conversion matrix in hector found most of the sandbar converted to sapling area due to planted by forest department which also showing near reflectance value of the grassland, several areas remains inundated.

2005–2010	Agriculture	Forest	Sandbar	Settlement	Waterbody	Total 2010(ha)
Agriculture	7682 (0.78)	15 (0)	107 (0.01)	1518 (0.15)	583 (0.06)	9,905
Forest	25 (0.01)	3099 (0.88)	11 (0)	335 (0.1)	32 (0.01)	3,503
Sandbar	711 (0.52)	114 (0.08)	204 (0.15)	177 (0.13)	163 (0.12)	1,370
Settlement	1580 (0.25)	245 (0.04)	50 (0.01)	4056 (0.65)	330 (0.05)	6,260
Waterbody	1021 (0.08)	243 (0.02)	285 (0.02)	449 (0.04)	10526 (0.84)	12,525
Total 2005(ha)	11020 (0.33)	3716 (0.11)	657 (0.02)	6535 (0.19)	11635 (0.35)	33,563

Table 5
Inundated sandbar has recovered, and the sapling converted into seedling area within 2010–2017, but settlement class present the increasing trend.

2010–2017	Agriculture	Forest	Sandbar	Settlement	Waterbody	Total 2017(ha)
Agriculture	8097 (0.71)	22 (0)	704 (0.06)	1593 (0.14)	1036 (0.09)	11,452
Forest	121 (0.03)	3104 (0.77)	117 (0.03)	509 (0.13)	202 (0.05)	4,054
Sandbar	50 (0.08)	79 (0.13)	151 (0.25)	159 (0.26)	173 (0.28)	611
Settlement	1600 (0.25)	216 (0.03)	216 (0.03)	3936 (0.62)	345 (0.05)	6,313
Waterbody	38 (0)	82 (0.01)	182 (0.02)	62 (0.01)	10770 (0.97)	11,134
Total 2010 (ha)	9905 (0.3)	3503 (0.1)	1370 (0.04)	6260 (0.19)	12526 (0.37)	33,563

Table 6
Overall statistic presents, agricultural area (ha reduced and its converted mostly to Settlement and homestead vegetation, where inland vegetation sometimes misclassified with the forest species and waterbody interchanged into subsequent classes.

2000–2017	Agriculture	Forest	Sandbar	Settlement	Waterbody	Total 2017(ha)
Agriculture	9339 (0.79)	147 (0.01)	57 (0)	2249 (0.19)	56 (0)	11,848
Forest	5 (0)	3057 (0.84)	81 (0.02)	225 (0.06)	270 (0.07)	3,637
Sandbar	555 (0.4)	77 (0.06)	162 (0.12)	289 (0.21)	288 (0.21)	1,371
Settlement	920 (0.19)	511 (0.11)	133 (0.03)	3150 (0.65)	121 (0.02)	4,834
Waterbody	633 (0.05)	262 (0.02)	179 (0.02)	400 (0.03)	10400 (0.88)	11,873
Total 2000 (ha)	11452 (0.34)	4054 (0.12)	611 (0.02)	6313 (0.19)	11134 (0.33)	33,563

severe cyclone named SIDR (2007) and Aila (2009) has occurred in this period. Another study found, about 300 ha landmass inundated in 2010 during this imagery capture (30-01-2010), and after that this area revealed in 2017 satellite imagery.

Naturally grown mangrove forest (Tengragiri Wildlife sanctuary) conserves natural food system with some artificial renovations (Tarikul Islam and Tribune, 2019). The present food cycle is under severe risk (Staff Reporter, 2019), trails and the other tourism facility need to renovate and these are properly documented in different newspapers. In 2005, intact forest area reduced about 120 ha which converted to sandbar and waterbody (Fig. 6). After declaring this forest as reserve forest and plantation by the ministry of forest and other private organization forest class providing increasing sign (9.49%, 9.59% and finally 11.21%). Due to forest plantation and forest regain, overall change line graph (Fig. 3; Green line) providing increasing sign (453 ha) which is 11.21% of the total area in 2017.

Plantation forestry considered another LC class due to it is identical and required for the decision makingFig. 4. Between 2000-2005 about 200 ha sandy area planted where the seedling and saplings area inundated in 2007 and 2010 (Fig. 5). This area is not recovered well which also clearly documented during field visit and found, the Goal tree (*Nypa fruticans)* saplings are in severe in danger and not growing as well (see Fig. 4).

Coastal land mass is occupied by large human load due to income sources and availability of the freely available coastal resources. The livelihood and the population in the coastal area are constantly increasing and its always shows increasing sign in our study. It has showed pick in 2005 and the figure is 19% which was the same for the duration 2000–2017 average. Settlement class has increased 1700 ha from 2000 to 2005 where it's damaged by the two super cyclone and immediate after this image reduced into 275 ha and finally it has increase and the figure is 6313 ha and it average increased into 87 ha/yr. Inland waterbody and riverine area like canal and ponds decreasing with time. In the year 2010 waterbody of this area has drastically increased due to inundation cause of super cyclones. Overall it has been decreased 739 ha (44 ha in average) from 2000 to 2017.

3.1. Land cover conversion analysis

Study area is intact but interchange into different classes with time. To identify area conversion, study incorporated python based special programming tools in ArcGIS 10.5 (arcpy). The generated python script

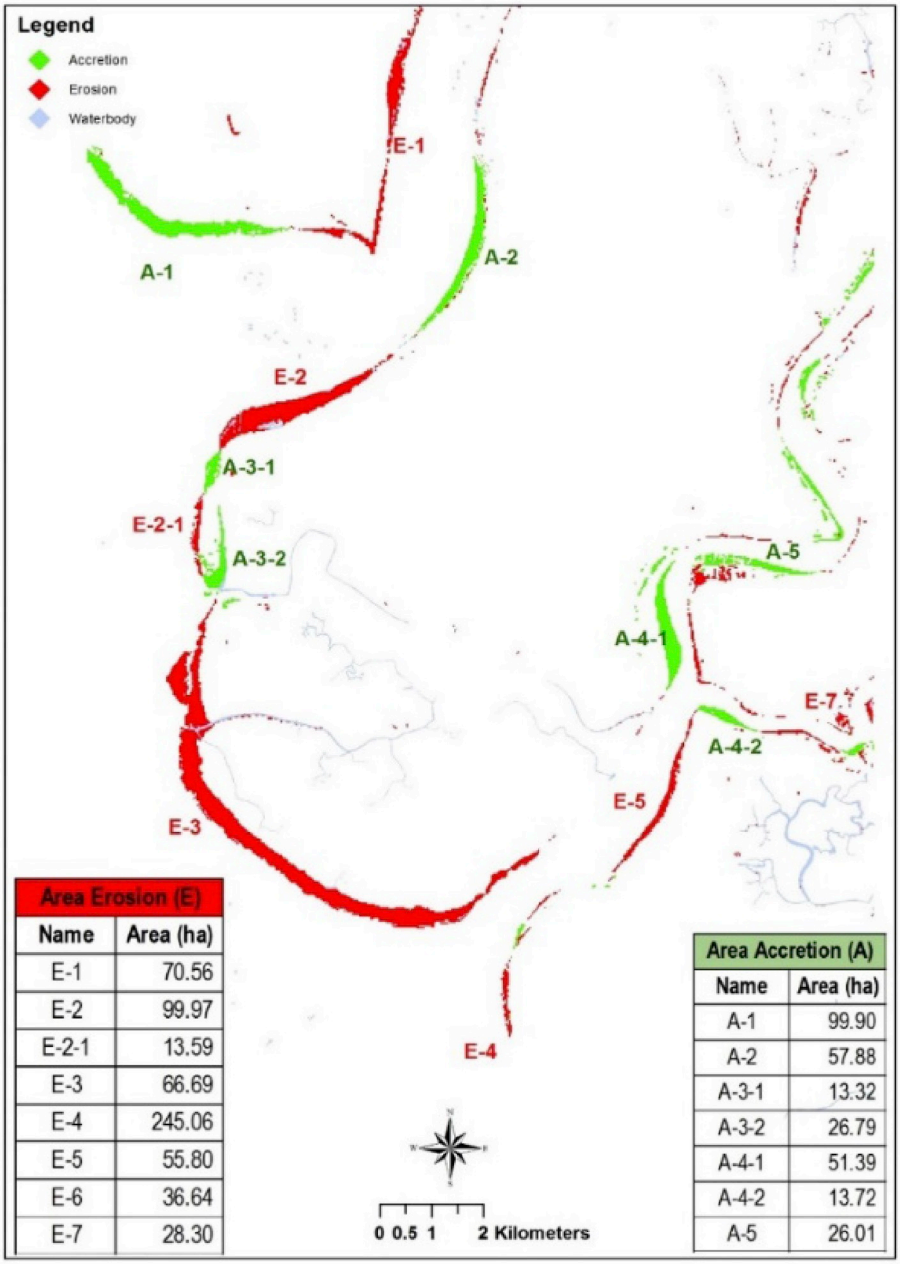

Fig. 7. Coastal frontiers accretion-erosion scenario; whereas red color presenting erosion area and light green color presenting area accretion in hector based on the image of 2000–2017. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article).

shows 50ha less than the real extent so far overlay based conversion tool used and found the sandbar is the most interchanging class.

3.2. Area conversion and probability matrix

As area changing due to the activity of the human, natural and quasi natural causes confusion probability matrix with the conversion matrix are also analyzed. Transition probability matrix of the interval 2000-2005 found sandbar is the most prominent class of changes (Table 3) and due to two major natural calamity predicted matrix found settlement with homestead class within the interval 2005-2010 is significant interchanging class (Table 4). Therefore, 2010-2017 found waterbody increasing rate and the probable inundation of the land surfaces presented in Table 5 where the overall predicted class presented in Table 6 and within this interval significant agricultural land converted to homestead settlement class. Overall the agricultural land is decreasing day by day and conversely settlement are increasing and the unplanned changing rate increasing the probable disasters.

3.3. Coastal frontiers area change analysis

Coastal land dynamics is a very common natural feature. Lack of siltation tracking procedure, low turbidity from upstream and strong backwater effect cause for accretion and erosion of this area rapidly. It is easily identifiable; land cover changes make negative impact for the communities who are directly dependent on the natural resources (Monnereau and Abraham, 2013). Ganges river flow surplus reduced (Rahman and Rahaman, 2018) which may increase the strong backwater effect on the upper land (Kawser and Abdus Samad, 2016) and fresher species will migrate (Mansur et al., 2017), so far, the fisheries communities will lose their income sources (Dasgupta et al., 2017). Community people claimed, the barrier of Patharghata, Borobogi and Mithapukur area flood barrier is not protecting them from flood and associated saline water intrusion (Staff Reporter, 2014). Reference to this, the whole communities' livelihood pattern will be changed (Dasgupta et al., 2017) in accordance of the changes of the soil salinity (Talukder et al., 2012).

From the (Fig. 7) map, it is clearly identifiable, erosion zone 2 (e−2) and erosion zone 4 (e−4) are most susceptible to landmark loss, and the area loss from 2000 to 2017, 99.97 ha & 245.06 ha respectively. However, most of the area is forestland. Fig. 7 also demonstrates that Accretion zone A-1, A-2 & A-4-1 landmark are increasing with time being. Which are respectively 99.90, 57.88 and 51.39 hactor. Though some area is increasing frequently but decreasing rate is very high and in recent past this area losses 3″ area. (Source: Forest Beat office, Field survey-2017). Furthermore, community people losing their income sources and tends to migrate in the divisional town even though in the capital (Mallick and Vogt, 2014), which is exacerbating the pressure to manage these towns and associate crime profiling is increasing claimed by the respective departments (Ishtiaque and Nazem, 2017). To sum up, socio-economic all factors are interlinked so far, it is changing the overall income sources, livelihood patterns and sustainable perception of the community (Nazrul et al., 2018) that's why we need to address and resolve these problems immediately by taking some engineering methods like build super dyke with revised height, groin, repelling waterways and so on.

4. Conclusion

Study area has economic, enviro-ecological values along with recreational benefit and government earning revenues from it so proper monitoring and analysis required. Based on this analysis agri-grassland area significantly decreasing about 23 ha/yr, whereas settlement mixed with homestead plantation continuously increasing in the landmass. Deep forest, varieties dangerous wild animals and snakes balancing ecological food chain but it's being threatening day by day due to improper maintenance system. If it continues significant services including phytoremediation, natural heart and successive carbon sequestration in the mangrove forest area will be diminished. The severe erosion prone areas named Khouttar char and Fakir hat area needed to take under protection measure. Anyone who can work to protect this natural mangrove forest and the adjacent landmass this study will be helpful, and it is required to protect this threatened naturally grown mangrove forest from the national and international level.

Declaration of competing interest

The authors of this paper and their institutions have no conflicts of interest issues.

The authors are academics affiliated with educational institutions that have no other interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2019.100277.

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