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Water Body Mapping and Monitoring using Landsat Time Series Satellite Images

***Afzal Ahmed*[1], *MD.Kamrul Hasan*[2], *EshratJahan Esha*[2]**
[1]Department of Environmental, Water Resources and Coastal Engineering , Military Institute of Science and Technology, Dhaka-1216, Bangladesh, e-mail: afzal.ahmed2008@gmail.com
[2]Department of Civil Engineering, Military Institute of Science and Technology, Dhaka-1216, Bangladesh, e-mail: kamrul1764@gmail.com
[2]Department of Civil Engineering, Military Institute of Science and Technology, Dhaka-1216, Bangladesh, e-mail: eshaeshratjahan@gmail.com

Abstract
Bangladesh is believed to be extremely vulnerable to climate change, which may result in abnormal spatio-temporal pattern in rainfall and increased variability of temperature across the region. Consequently, the frequency and intensity of various natural hazards are expected to increase, which may affect the availability of fresh water on the surface as well as underground. That's why mapping of water body and its continuous monitoring is important (Regional Water Report 37, FAO 2011).This study aims at identifying water body in the coastal belt of Bangladesh using Landsat 5 TM time-series satellite images for the year 2000, 2005 and 2010. Satellite derived indices e.g. WRI, NDVI, NDWI, MNDWI, AWEI, NDMI are computed from Landsat data of 2000, which were compared with the base map for selecting the best index for water body identification. The result shows that NDWI is more robust in extracting water bodies compared to other indices. Furthermore, unsupervised and supervised image classification techniques have been applied on all three years data. Both the index images as well as the classified images are reclassified to produce binary images showing water and non-water area. Average accuracy of the classification is 88%. Result shows that there is remarkable increase in water area after 2005. The reason might be attributed to the fact that the study area has suffered from several natural calamities during the study period.

Keywords: *Water Security, Landsat Satellite Image, Remote Sensing Indices, Mapping and Monitoring*

INTRODUCTION

Bangladesh is believed to be extremely vulnerable to climate change, which may result in abnormal spatio-temporal pattern in rainfall and increased variability of temperature across the region. Consequently, the frequency and intensity of various natural hazards are expected to increase, which may affect the availability of fresh water on the surface as well as underground. That's why mapping of water body and its continuous monitoring is important. Moreover, overexploitation of groundwater has caused several adverse effects such as drying up of surface water bodies, lowering of water table, salt water intrusion in the coastal areas, imbalance in ecology and reduction in dry season flows in the streams (Regional Water Report 37, FAO 2011). In some parts of the country, particularly in the southern coastal belt region, there are already symptoms of deterioration in the natural hydrological regime. Environmental monitoring and change detection using Remote Sensing technology has gained enormous popularity among the researcher communities, due to its capability of viewing ground surface synoptically, repeating cycle of image acquisition and of acquiring multispectral imagery. Over the decades, several remote sensing based environmental applications have been developed namely land use and land cover change monitoring, urban sprawling, disaster management, vegetation mapping, crop production prediction and so on. Since surface water source is an indispensable resource for socio-economic development, its detailed mapping and monitoring is essential for sustainable use of water resources. Water scarcity and food security are the major consequences of climate change that we are going to deal with in the near future. Various parts of Bangladesh have already started facing such problems in different magnitude. In this regard, integrated water resource management is of critical importance for sustainable development as well as for achieving sustainable development goals. Surface water mapping may play a pivotal role as it will provide us with the amount and spatial distribution of surface water resources. Remote sensing satellite images are extensively used in this regard since such images offer synoptic vision of the region with various spatial, temporal and spectral resolutions. There are several image processing techniques that may be used for identifying water bodies from satellite images. For example, single-band technique extract water features through the use of a threshold value. But such method misclassifies features due to mixed pixel issues. Mixed-band techniques such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) or Modified Normalized Difference Water Index (MNDWI) may be used for the extraction of water features from satellite images. In some cases, NDWI involves error in identifying water body as it generates false positive alarm in case of built-up area. On the other hand, MNDWI could overcome such error thereby achieving higher accuracy in identifying water bodies while suppressing errors from vegetation, soil as well as built-up land (Rokni, Ahmad, Selamat & Hazini, 2014). Sarp & Ozcelik, (2016) carried out research on spatio temporal changes in Lake Burdur from 1987 to 2011 using multi-temporal Landsat TM and ETM+ images by Support Vector Machine (SVM) classification and other spectral water indices. They found that SVM and NDWI performed significantly better than other indices for mapping the lake water surface. Feyisa et al., (2014) found a method that improves water extraction accuracy by increasing spectral separability between water and non-water surfaces, particularly in areas with shadows and urban backgrounds using Landsat 5 TM data. Elsahabi et al. (2015) has carried out research on surface water extraction technique on Aswan high Dam (major fresh water body in Egypt) lake using Landsat ETM+ data. Fisher et al, (2016) has carried out research on surface water extraction technique on water index methods based on data normalized to surface reflectance, using thresholds optimized for a large selection of data, provide a simple yet accurate method for automated water classification across large regions. The objective of this study is to map water body in the coastal area of Bangladesh using geospatial technology. In our study, we calculated several remote sensing indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), Water Ratio Index (WRI) and Automated Water Extraction Index (AWEI). Performance of each index is tested individually through accuracy assessment. The specific objectives of this study are to:

a. extraction water body from time series Landsat satellite images
b. assessment accuracy of the proposed methodology
c. monitor the spatio-temporal variation of water body in the study area

Study Area

The area (figure 1) is located between 22º42' to 22º51' North latitudes and 84º54' to 90º44' East longitudes and extends inside up to 150 km from the coast. The area receives an average annual rainfall more than 2000mm. Most of the rainfall (90- 95% of the annual total) occurs during the period from June to September. Average temperature during winter ranges between 18º to 32ºC, whereas during summer the range varies between 34º to 41ºC.

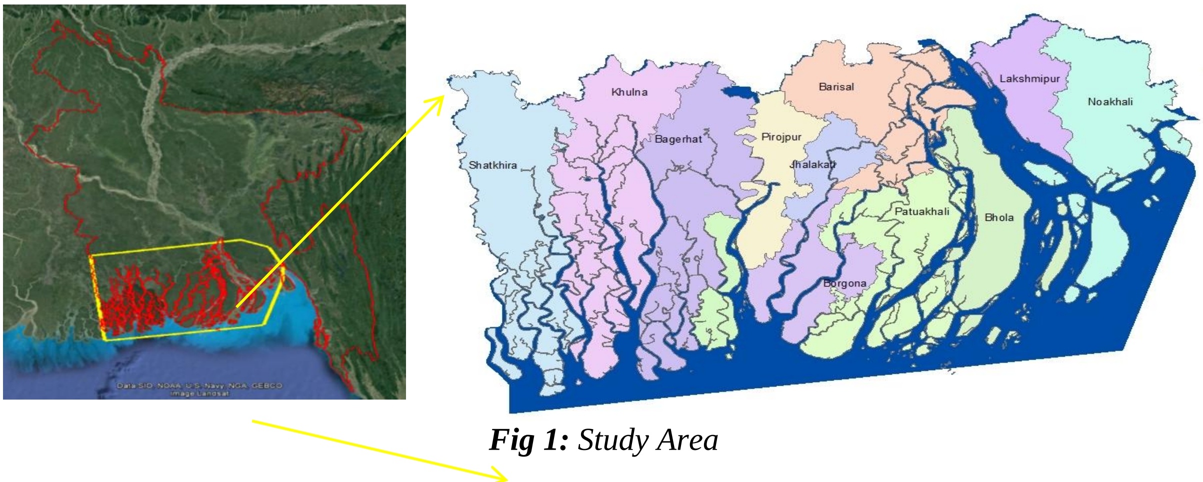


Fig 1: *Study Area*

During monsoon the area is affected by widespread flooding. On the other hand, some part of this area suffers from waterlogging problem during dry season.Salinity in water as well as in soil is one of the major challenges in combating water and food security in this area. In terms of water security, saltwater intrusion poses another threat to this region. Such phenomena occurs during winter season when the flow of freshwater is very low at downstream. Thus, saltiness increments in the waterway water, which may bring about an expansion in saltiness in the groundwater also. Amid this period, the saltiness of the waterway water increments. The salts enter the dirt by flooding with saline waterway water or by drainage from the streams, and the salts wind up noticeably gathered in the surface layers through evaporation(Haque, S. A., 2006).

Methodology

This study establishes a remote sensing based water body mapping and monitoring system using Landsat 5 TM (Thematic Mapper) time series satellite images of three different years i.e. 2000, 2005 and 2010 covering the study area. Figure 2 in the following page depicts the flow diagram of the detailed methodology of this study. As part of the data preparation, each image has gone through various pre-processing e.g., radiometric corrections, mosaic, clip etc. The major steps of data processing are generation of base map, water body map generation from satellite derived indices as well as from image classification (supervised and unsupervised classification) techniques and finally accuracy assessment of various image classification techniques. In order to find the most suitable satellite derived index for identifying water body as well as to assess the accuracy of the image classification techniques, a base map showing water body only has been generated by digitizing of Landsat band 4 data of the year 2000. The reason for using band 4 of Landsat data is because it holds higher ability to discriminate water and dry/land areas.

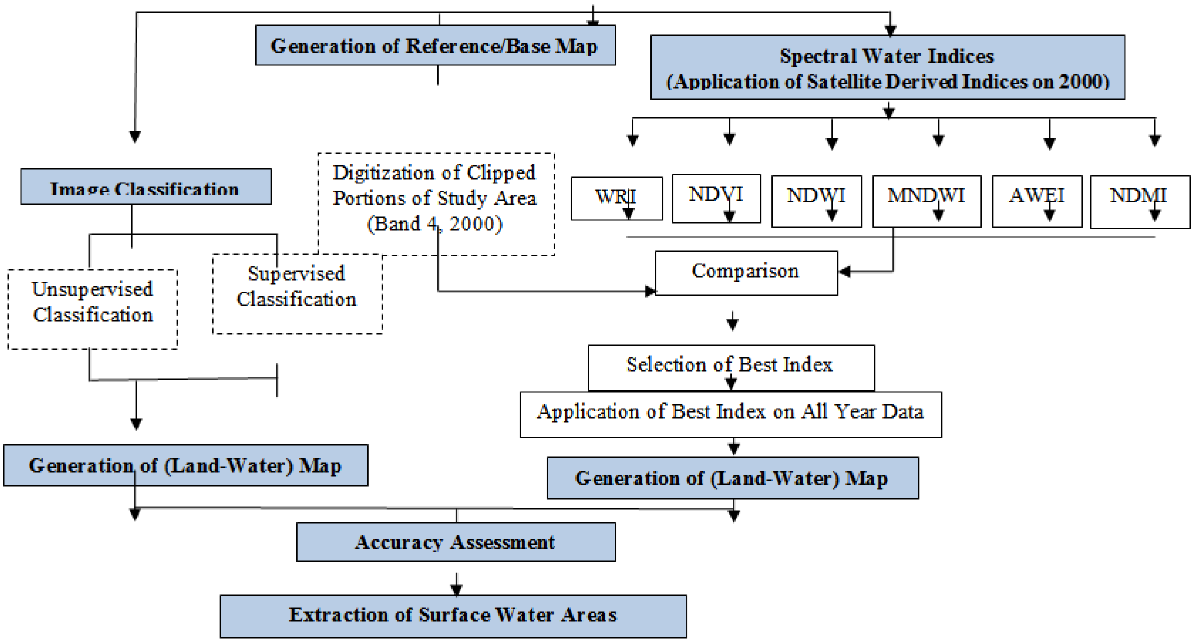


***Fig 2:** Methodology of the research.*

Each component of this research methodology has been described in detail in the following:

Image acquisition

For each year, six tiles of Landsat images with path/row of 136/44, 137/44, 138/44, 136/45, 137/45, 138/45 have been downloaded (Figure 3). Since the same dated images for all paths and rows for a year are not available, most closely dated images of same season of different paths and rows were downloaded. These images are freely downloadable from the US Geological Survey (USGS) Global Visualization Viewer.

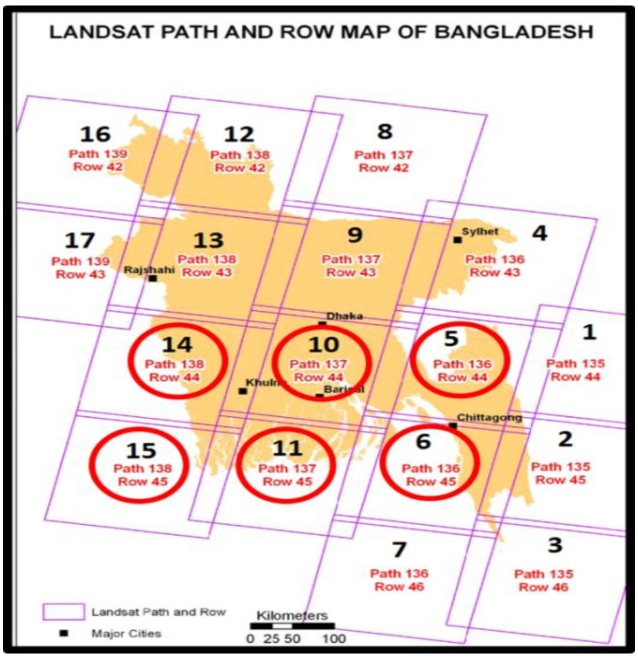


***Fig 3:** Landsat paths and rows covering study area*

These data are Level 1 Terrain Corrected (L1T) product, which are pre-georeferenced to UTM zone 46 North projection using WGS-84 datum. Table 1 represents some of the most useful technical specifications of the downloaded images.

Table 1: Details Information of Acquired Images and Specification of Landsat TM data.

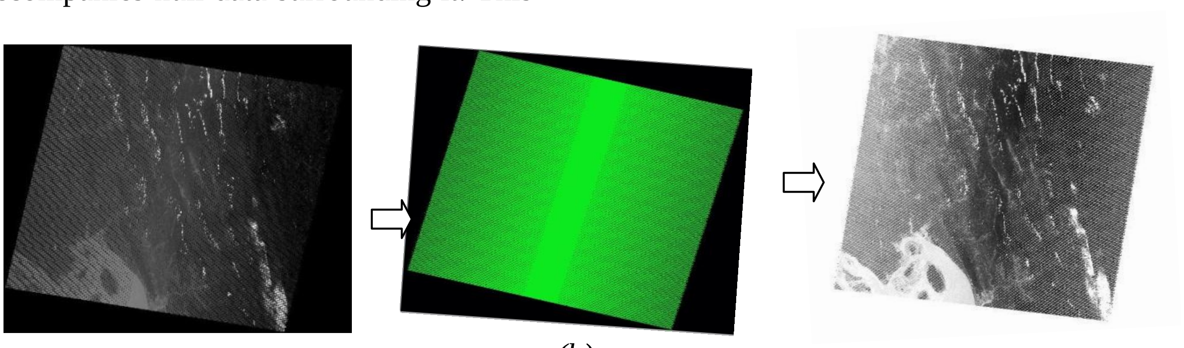
Year	Satellite	Sensor	Path/Row	Julian Day of Acquired Image	Spatial Resolution (m)	Wavelength (micrometer)
2000	Landsat-5	TM (Thematic Mapper)	136/44	364 (2000)	30	Band 1: 0.45-0.52 Band 2: 0.52-0.60 Band 3: 0.63-0.69 Band 4: 0.76-0.90 Band 5: 1.55-1.75 Band 7: 2.08-2.35
			136/45	364 (2000)		
			137/44	355 (2000)		
			137/45	021 (2001)		
			138/44	314 (2000)		
			138/45	314 (2000)		
2005			136/44	329 (2005)		
			136/45	329 (2005)		
			137/44	320 (2005)		
			137/45	320 (2005)		
			138/44	311 (2005)		
			138/45	311 (2005)		
2010			136/44	359 (2010)		
			136/45	327 (2010)		
			137/44	318 (2010)		
			137/45	350 (2010)		
			138/44	309 (2010)		
			138/45	357 (2010)		

Image pre-processing

Before remote sensing index calculation as well as image classification, every band of each image has gone through various steps of image pre-processing e.g., radiometric corrections, mosaic, clip etc. These steps are described in brief in the following sub-sections:

Null Value Elimination:

By default, each Landsat scene accompanies null data surrounding it. This null data must be removed before performing mosaic or image processing function on the scene (Graham J., 2010). In order to remove the null values, a Boolean raster has been created. This raster is then reclassified and multiplied with the original raster. Figure 4 shows a sample output of this process, which is being repeated for each of the individual scene.



(a) *(b)* *(c)*

***Fig4: (a)** Original Raster, (b) Boolean raster, (c) raster after eliminating null value.*

Radiometric Correction of Image:
When the change detection is examined, it's important to normalize the images so that one can make comparisons between them(Mcgee, J., Campbell, J., &Parece, T., 2015). In this study two type of corrections that have been done on each band (a) conversion of digital number to radiance and (b) conversion of radiance to reflectance. Necessary equations for radiometric corrections are given below. Values of different element of the equations are saved for each band in the MTL file that saved with the Landsat scene (Jeff C. H, Richard P. S., Thomas B. B., Anna M. M., 2017).

Conversion of Digital Number to Radiance:

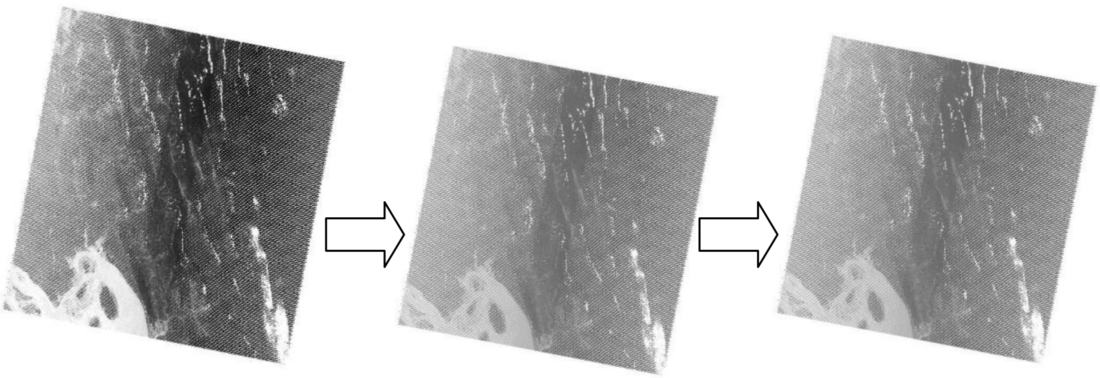
$$L_\lambda = \left(\frac{LMAX_\lambda - (LMIN_\lambda)}{QCALMAX - QCALMIN}\right) * \left(\left(BAND\ LAYER - (QCALMIN)\right) + LMIN_\lambda\right)$$

Here, L_λ = Spectral radiance, $L_{\lambda max}$ and $L_{\lambda min}$ = highest and lowest possible values of radiance, $QCAL_{max}$ and $QCAL_{min}$ = calibrated maximum and minimum cell values

Conversion of Radiance to Reflectance:

$$\rho_\lambda = (\pi * L_\lambda * d^2)/(ESUN_\lambda * \cos\theta_s)$$

Each term of the above equation is as follows:
ρ_λ= planetary reflectance (unitless) of each pixel
L_λ = spectral radiance at sensor's aperture
d = earth-to-sun distance in astronomical unit
$ESUN_\lambda$= mean solar exoatmospheric irradiance
θ_s= Solar zenith angle (in degrees)



(a) (b) (c)

Fig 5: *Radiometric corrections of raster-(a) raster with DN value, (b) raster with converted DN to radiance, (c) raster with converted radiance to reflectance*

Image Mosaicking

This process combines or merges two or more images thereby creating a larger image. In this study band wise mosaicking was done for each year's six tiles dataset. At first a mosaic dataset has been created in the ArcCatalog environment, all the images of same band are added. The mosaic tool is then implemented in order to generate the mosaic image. Appearance of the mosaic dataset may be improved as per requirement. Same process is repeated for all bands of all year. Figure 6 shows a mosaic image that was generated using the band 4 of all tiles for the year 2000.

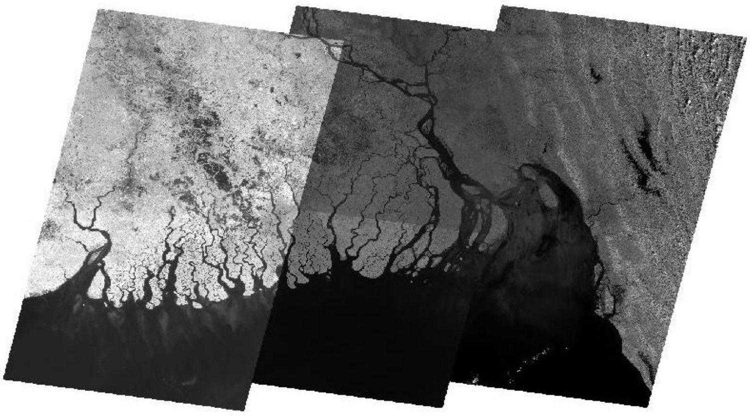
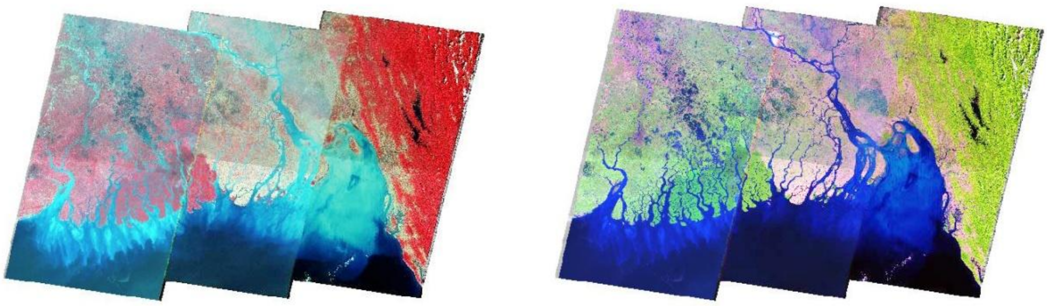


***Fig 6:** Output of image mosaicking of band 4 (2000) of all six scenes*

Color Composite Image

Color composite images with different band combination are used for various purposesfor example: band combination 3-2-1 represents natural color image, 4-3-2 is known as false-color Infrared which is the most conventional band combination used in remotesensing for vegetation, crops, land-use and wetlands analysis. Band combination 4-5-3 is used for the analysis of soil moisture and vegetation conditions. 5-4-3 is used to separate urban and rural land, again it is also used to identify land/water boundaries etc. Figure 7 shows an example of color composite images used in this study:



Band Combination 4-3-2 *Band Combination 5-4-3*

***Fig 7:** Color composite image (2000) with different band combinations.*

Clipping

Clipping is an instrument that is utilized as a part of request to make new inclusions from two overlaying highlights. A polygon feature is required for characterizing a clipping region, which extricate features from an in-out coverrage that fall inside that characterized locale. The 'Cut Tool' gives one of the Geoprocessing abilities inside the ArcMap condition (Graham, J., 2010). In this review, subsequent to mosaicking, the sum total of what groups have been cut to get the fundamental review territory and in addition Satkhira district.

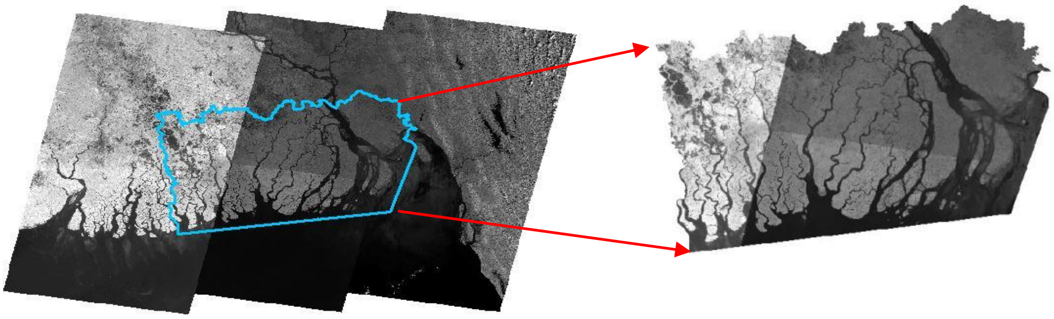


***Fig 8:** Clipping of mosaicked image with the boundary of Study Area*

Digitization

In this study on-screen digitizing process is adopted to generate a base map showing water body only. Band 4 of Landsat image is selected for this purpose since this bandholds higher ability to discriminate water and dry/land areas. Two portions of Satkhira disctrict containing mixed water bodies and part of a river have been digitized. Thus the reference maps are generated utilizing careful on-screen digitizing of the two small portions of Satkhira.

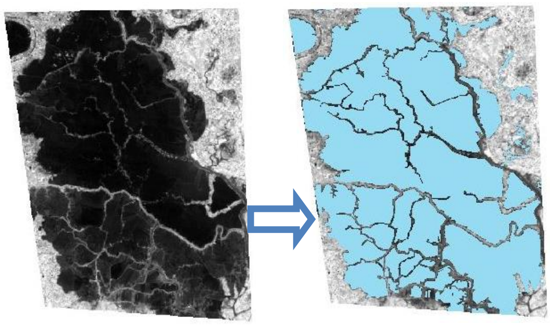


Fig 9: (a) digitizing mixed water bodies

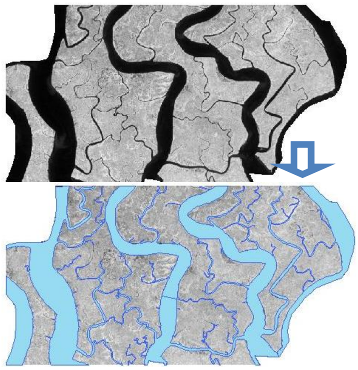


Fig 9: (b) digitizing River

Image Transformation – Application of Indices

Application of geospatial techonologies through the utilizaion of earth observation satellite images for water body identification, mapping and change detection has been a major field of reseacrh among the scientific communites. Researchers across the globe have introduced various image processing techniques for this purpose but each of them has merits and demerits. For example, thresholding a single-band image is a simple technique for water body extraction but it fails in case of mixed pixels. On the other hand, multi-band methods, which combine different reflective bands, provide better capabilities for surface water extraction as compared to the single-band techniques (Rokni, Ahmad, Selamat, & Hazini, 2014). There is a number of well-established satellite image based indices that have been developed in recent decades. Among them Normalized Difference Vegetation Index (NDVI), Water Ratio Index (WRI), Aotumated Water Extraction Index (AWEI), the Normalized Difference Water Index (NDWI) and modified NDWI (MNDWI) are widely used indices. The MNDWI extracts surface water while suppressing errors from built-up land as well as vegetation and soil. Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation index and is based on differences in absorption and reflectance in the visible and near-infrared (NIR) spectrums, respectively. Spatial extent of surface water area for a particular area calculated at different date can be compared in order to compare the sptio-temporal change of water body. In our study, surface water was detectd individually from each of the images of the year 2000, 2005 and 2010.For this purpose, the following indices were calculated for the digitized portion only: Normalized Difference Water Index (NDWI), Normalized Difference Moisture Index (NDMI), Modified Normalized Difference Water Index (MNDWI), Water Ratio Index (WRI), Normalized Difference Vegetation Index (NDVI), and Automated Water Extraction Index (AWEI).Following table shows the necessary equations that are needed for calculating these indices.

Table 3: *Different Indices for Water-body Extraction*

Index	Equation	Remark
Normalized Difference Water Index	NDWI = (Green − NIR)/(Green + NIR)	Water has positive value
Normalized Difference Moisture Index	NDMI = (NIR − MIR)/(NIR + MIR)	Water has positive value
Modified Normalized Difference Water Index	MNDWI = (Green − MIR)/(Green + MIR)	Water has positive value
Water Ratio Index	WRI = (Green + Red)/(NIR + MIR)	Value of water body is greater than 1
Normalized Difference Vegetation Index	NDVI = (NIR − Red)/(NIR + Red	Water has negative value
Automated Water Extraction Index	AWEI = 4 × (Green-MIR) − (0.25 × NIR + 2.75 × SWIR)	Water has positive value

The result of the indices which is closer to the base map generated by digitization isconsidered as the best index, which is is then applied to all three years data for water body extraction as well as change detection.

Image Classification

Image classification is the way toward sorting pixels into a limited number of individual classes, or classifications of data in view of their pixel values. On the off chance that a pixel fulfills a specific arrangement of criteria, then the pixel is assigned to the class that relates to that criterion.There are two approaches to classify pixels into various classifications: (an) unsupervised grouping and (b) supervised characterization.

Unsupervised classification is a method of identifying, grouping, and labeling features in an image according to their spectral values. In this process pixels are clustered together based on spectral homogeneity and spectral distance. “Iso Cluster Unsupervised Classification” method is adpted in our study. The output raster is then reclassified into 2 classes (water and non-water) using visual interpretation and reclassify tool.

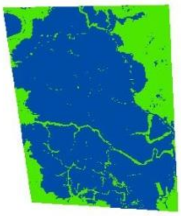
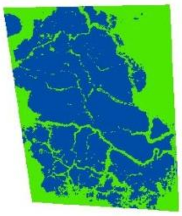
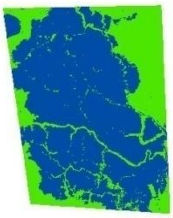
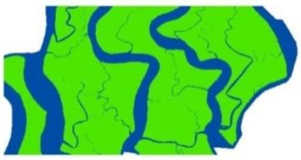
Supervised classification process provides much control over the unsupervised classification. In this process, one select pixels that represent patterns that is recognized or can be identified with help from other sources. Knowledge of the data, the classes fancied, and the calculation to be utilized is required before one start choosing training samples in this characterization. By recognizing designs in the symbolism, one can "prepare" the PC framework to distinguish pixels with comparative attributes. "Most extreme probability Classification" method has been utilized as a part of this review. Utilizing the "Training Sample Manager", 32 tests for Water class and 7 tests for Non-water class were chosen. At last the review territory is partitioned into water and non-water classes. Same process is rehashed for all years data.

Accuracy assessments

In this study accuracy assessments are performed on the binary images that are generated during the Remote Sensing index calculation as well as on the classified images generated by supervised and unsupervised classification. For this purpose 25 random points have been generated on the color composite image, which are then exported into ".kml" file for viewing on the "Google Earth". Each of these points are examined to identify whether it belongs to "water" or "non-water" class. This process is done for all of the remote sensing index images as well as on the classifed images. Finally the accuracy of the output has been reported in percentage.

Data Processing and Result

Two portions of Satkhira district, one with mixed water body and the other with part of Kholpetua river, have been digitized in order to generate the reference maps showing water bodies. Remote sensing indices are also calculated in these portions in order to identify the most suitable index among them. Figure 10 shows the output of various index images. Areas belong to both water and non-water classes have been calculated, which are provided in table 4. In this table the actual area is the area, which is obtained from the digitizing process.

Indices	*Mixed Water-body's Part, Satkhira District*	*Main River's Part, (Satkhira District)*
WRI:-		
NDVI:-		
NDWI:-		

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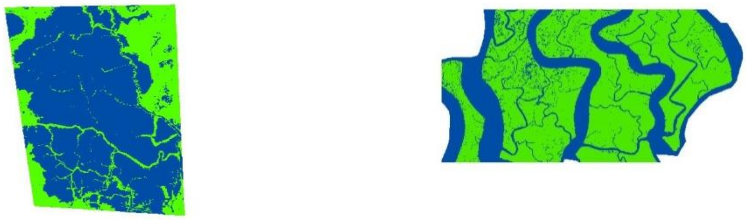
MNDWI:-

AEWI:-



NDMI:-

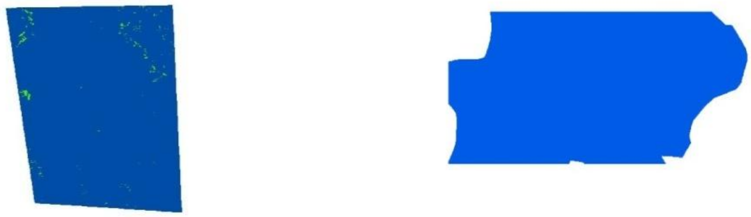


Fig 10: *Identofication of the most suitable Index*

Table 4: *Comparison between the actual water area and the water area obtained from different indices*

Mixed Water-body's Part, Satkhira District						
Actual Area (km^2)	WRI (km^2)	NDVI (km^2)	NDWI (km^2)	MNDWI (km^2)	AWEI (km^2)	NDMI (km^2)
146.613543	174.9681	148.8294	165.5883	194.7051	172.4517	239.4153
Main River's Part, Satkhira District						
Actual Area (km^2)	WRI (km^2)	NDVI (km^2)	NDWI (km^2)	MNDWI (km^2)	AWEI (km^2)	NDMI (km^2)
175.563844	180.6948	163.8972	170.3016	602.6184	210.627	607.0959

The result shows that for the portion that contains mixed water-bodies, water area obtained from NDVI is the closest and the second closest index is NDWI to the actual or reference area. On the other hand, for the portion that contains part of main rivers, NDWI is much closer than NDVI. In this part WRI is also closer to actual one but the result that obtained from WRI in the first case is far away from that of actual one.

After comparing all the results to the actual area, NDWI has been selected as the best index for extracting water-body and it has been applied to the entire study area for all the years i.e. 2000, 2005 and 2010.Similarly, unsupervised and supervised classification have been done for the entire study area for the same time period. to extract water body from it. Figure 11 shows the output of the image classification processes.

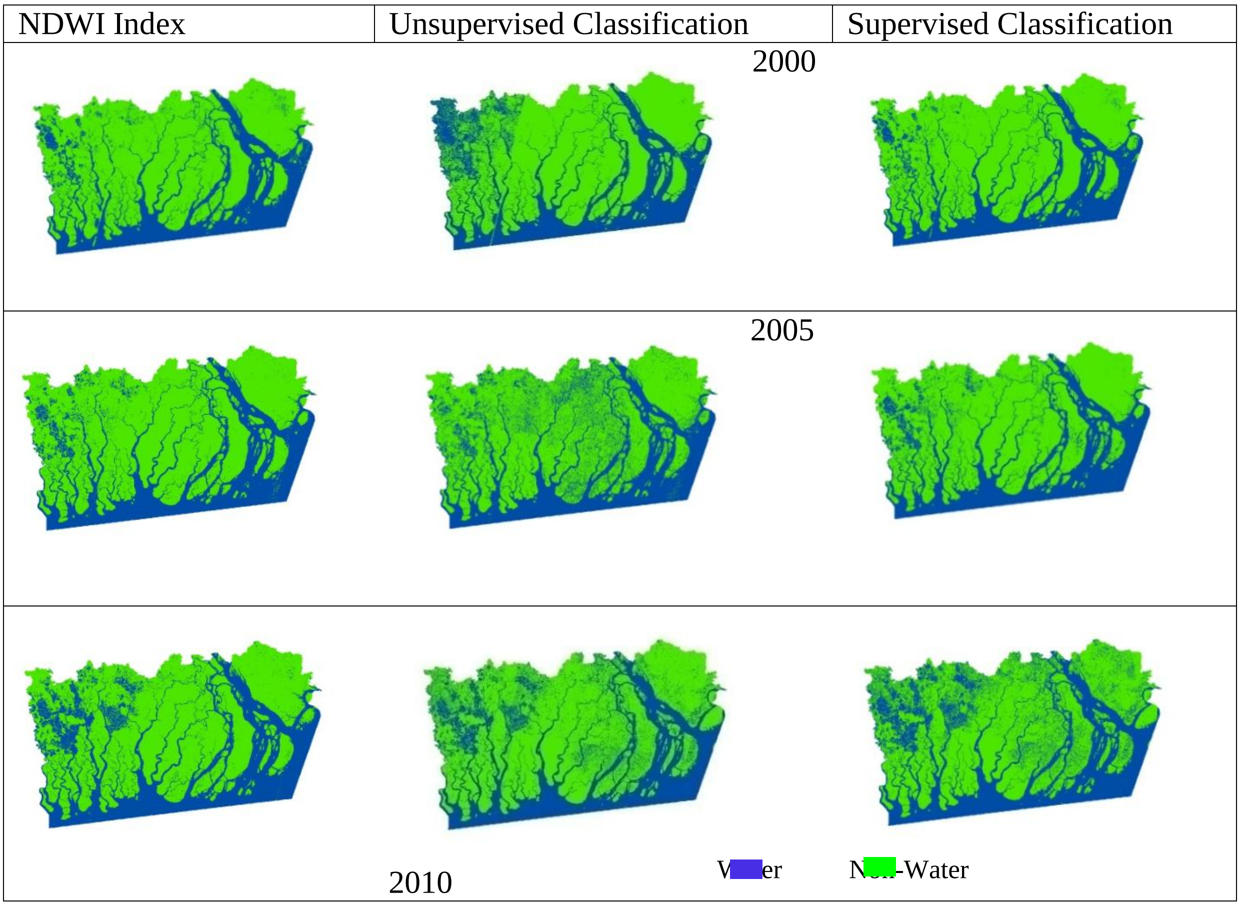


Fig 11: *Outputs of Image Classification of the Study Area*

From the classsified images as shown in figure 11, total area of water body have been calculated and presented in table 5, 6 and 7 for NDWI, unsupervised and supervised classification respectively.

Table 5: *Surface water change detection using NDWI images*

Year	*Obtained Water Area Using NDWI (km^2)*	*Change in Water Area (km^2)*	*Remarks*
2000	*11605.6980*	*56.4885*	*Water area is decreased by 56.4885 sq km.*
2005	*11549.2095*		
		508.3065	*Water area is increased by 508.3065sq km*
2010	*12057.516*		

Table 6: *Result obtained from Unsupervised image classification*

Unsupervised Image Classification				
Year	*Non-Water Area(km^2)*	*Water Area (km^2)*	*Change in Water Area(km^2)*	*Remarks*
2000	*24161.5404*	*12474.6579*	*56.9709*	*Water area is decreased by 56.9709 km^2*
2005	*21301.4448*	*12417.687*		
			613.6857	*Water area is increased*

2010	*19370.3922*	*13031.3727*		*by 613.6857 km^2*

Table 7: *Result obtained from Supervised image classification*

Supervised Image Classification				
Year	*Non-Water Area (km^2)*	*Water Area (km^2)*	*Change in Water Area (km^2)*	*Remarks*
2000	*25494.7311*	*11141.4672*	*91.5138*	*Water area is increased by 91.5138 km^2*
2005	*22487.0337*	*11232.0981*		
2010	*20340.9324*	*12060.8325*	*828.7344*	*Water area is increased by 828.7344 km^2*

The classification results presented in the table 5, 6 and 7 have been plotted as shown in Figure 12. All results are showing an increasing trend in total area covered by surface water.

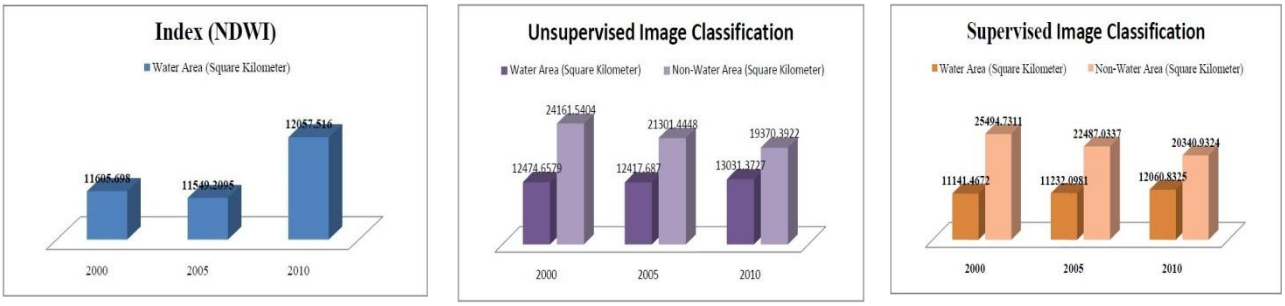


Fig 12: *Bar chart showing spatio-temporal variation of water body*

Due to unavailability of base map as well as due to time limitations in field visit, accuracy assessments of the classified images based on the visual interpretation of Google Earth images. It should be noted here that 1 represents Water class, 2 Non-water class and 0 represents the random points that are out of the study area. For all random points, each of the NDWI, Unsupervised and Supevised images have examined to identify whether a random point falls into the category of water or non-water class. This categorization is compared with the actual conditon of that point on the Google Earth image. Table 8 summarizes the output of such visual interpretation.

Table 8: *Accuracy assessment using Google Earth for the year 2000 & 2005*

Random Points	*Google Earth*		*NDWI*		*Unsupervised Classification*		*Supervised Classification*	
(FID)	*2000*	*2005*	*2000*	*2005*	*2000*	*2005*	*2000*	*2005*
0	*2*	*2*	*2*	*2*	*2*	*2*	*2*	*2*
1	*0*	*2*	*-*	*2*	*-*	*2*	*-*	*2*
2	*2*	*0*	*2*	*-*	*2*	*-*	*2*	*-*
3	*2*	*2*	*2*	*1*	*1*	*2*	*2*	*1*
4	*2*	*2*	*2*	*2*	*2*	*2*	*2*	*2*
5	*1*	*2*	*1*	*2*	*1*	*2*	*1*	*2*
6	*1*	*2*	*1*	*2*	*1*	*2*	*1*	*2*
7	*2*	*0*	*2*	*-*	*2*	*-*	*2*	*-*
8	*0*	*1*	*-*	*2*	*-*	*2*	*-*	*2*

9	2	0	2	-	2	-	2	-
10	1	2	2	2	2	2	2	2
11	2	1	2	2	2	2	2	2
12	1	1	1	1	1	1	1	1
13	0	2	-	2	-	1	-	2
14	1	1	2	2	2	1	2	2
15	0	0	-	-	-	-	-	-
16	2	2	2	2	2	2	2	2
17	2	0	2	-	2	-	2	-
18	2	0	2	-	2	-	2	-
19	0	1	-	1	-	1	-	1
20	0	2	-	2	-	2	-	2
21	2	2	2	2	2	2	2	2
22	2	0	2	-	2	-	2	-
23	2	0	2	-	2	-	2	-
24	1	2	1	2	1	2	1	2

Table 9 below shows the accuracy of various methods in percentage, ands figure 13 presents this accuracy assessment result in bar chart.

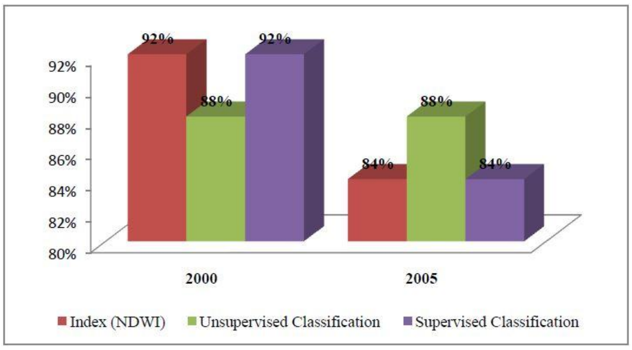


Fig 13: Accuracy of different analyses in percentage

Table 9: *Accuracy of different analyses in percentage*

Year	Index (NDWI)	Unsupervised Classification	Supervised Classification
2000	92%	88%	92%
2005	84%	88%	84%

DISCUSSIONS

This paper describes the process of surface water mapping as well as monitoring using Landsat 5 TM time series satellite images of the coastal region of Bangladesh for the year2000, 2005 and 2010.Various stages of image preprocessing e.g. null-value elimination, radiometric correction, image mosaicking and clipping were performedin order to prepare the images for further processing. In the next step, several satellite derived indices such as WRI, NDVI, NDWI, MNDWI, AWEI, NDMI and NDWI are derived in order to identify the most suitable index among them. Pixels classified as water body in each index image have been summed up to find the total area under water-class. These areas are then compared with the waterbody areas obtained from the basemap.This comparison revelas that the index NDWI provides the closest result and hence identifed as the most suitable index for our study. This index has been applied to all three years data and the results shows that from 2000 to 2005 there is a slight decrease in the area of water-body (56.5 km^2), whereas from 2005 to

2010 there is a large increasein water area (508.3 km^2). Unsupervised image classification provides similar result as that of NDWI image.In this case it has found that water area is decreased by 56.9709 km^2 during 2000-2005 and increased by 613.6857km^2 during 2005-2010. Supervised image classification result shows increment in water area for both of the periods, which is 91.5138 km^2 in 2000-2005 and 828.7344 km^2 in 2005-2010.This increase in waterbody may be due to the natual calamities that occurred in the area during our study period, which are shown in table 10.

Table 10: *Major events of Bangladesh (2000-2010)*

Period	*Hazard*	*Main affected districts*
July-August, 2004	*Flood*	*Two thirds of the country*
15 November, 2007	*Cyclone Sidr*	*Bagerhat, Pirojpur, Barguna, Patuakhali*
25 May, 2009	*Cyclone Aila*	*Satkhira, Khulna*

The accuracy of image classification are judged using Google Earth images with higher spatial resolution. Accuracy of the index calculation has been found correct, 92% in 2000 and 84% in 2005. Both for the year of 2000 and 2005, unsupervised image classification is 88% accurate. Again, the supervised image classification has been found accurate, 92% in 2000 and 84% in 2005. It can be seen that result obtained from 2005 are less accurate compare to that of 2000, this is due to cloud coverage of 2005 landsat image was high.

Due to the budget limitation, acquisition of high resolution satellite images was not possible. As a result, all analyses in this research are done using low resolution of freely available satellite (Landsat in this case) image. Due to time limitation, field based ground truthing for accuracy assessment couldn’t be performed as well.

CONCLUSION

This study was an endeavor to establish a geospatial technology based surface waterbody mapping and monitoring system for the coastal region of Bangladesh.Although there are some limitation as discussed earlier, the methodology of this research can be considered as a very robust one since the accuracy of waterbody detection is quite high (88%). However, further detailed studies are required for determining a set of suitable indices for water body monitoring, to assess their spatial and temporal robustness and to adopt them in the organizational level. Thus an effective and integrated waterbody monitoring system can be introduced for Bangladesh, which can help us to adress water security issues.

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