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NDVI: DETECTION OF VEGETATION CHANGE USING REMOTE SENSING AND GIS- A STUDY ON BARISHAL CITY CORPORATION, BANGLADESH

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ABSTRACT

This article presents a method of analyzing satellite images to detect the change in the Land Cover pattern of the city corporation of Barisal, Bangladesh, from 2002 to 2020 using *the Normalized Difference Vegetation Index (NDVI).* The use of the Multi-Spectral Remotely Sensed data approach is widely known to find the extent & to detect the change in Land Cover of an area of interest. NDVI, which uses specific band combinations of remotely-sensed satellite data, assists in classifying Land Cover to detect the changes in land resources over time. Remote Sensed Data from Landsat TM & Sentinel-2 images have been used to perform the analysis. Different NDVI threshold values as required for classifying the Water bodies, Built-up areas, Sparse Vegetation & Dense Vegetation, are found by analyzing pixel by pixel analysis of the respective classes. NDVI map was prepared for the corresponding years; the highest and lowest of the pixel values for the individual class was found by analyzing the pixel value of that class. NDVI is highly useful in finding different surface characteristics of the visible area, which is helpful for policymakers to make decisions. The Vegetation index helps find the changes in vegetation cover and allows the respective authority to decide on environmental reservation and mitigation approaches. The empirical study finds a 32% decrease in the Dense Vegetation from 2002 to 2020 in Barisal, Bangladesh, followed by a 40% increase in the Built-up area throughout the concerned 18 years. Alongside that, Sparse Vegetation followed a rise of 130% from 2002 to 2020. Thus, the extent of significant water bodies remained unchanged from 2002 to 2020. The NDVI values for the selected pixels of the respective classes were compared with the ground absolute values for accuracy analysis. Accuracy analysis finds an overall 92.86% accuracy of the classification.

Keywords: *Land Cover, Dense Vegetation, Built-up area, Remote sensing, Normalized Difference Vegetation Index (NDVI)*

1. INTRODUCTION

Remote sensing, a method that is the science and art of gathering information and extracting Spectral, Spatial, and Temporal features about objects, areas, or phenomena, such as vegetation, land cover classification, urban areas, agricultural land, and water resources, without physically touching these objects. (Karaburun & others, 2010). Remote sensing provides information based on radiation reflected or emitted from objects at or near the Earth's surface and atmosphere. (Read & Torrado, 2009)

Land use and land cover (LULC) change detection using remote sensing data is an essential source of information for many decision support systems. (Tewabe & Fentahun, 2020) LULCC (land use/land cover changes) has emerged as an important concern for natural resource management and environmental change monitoring. (Ahmed, 2016) .Using satellite images, land cover (LC) data can be captured and analysed over broad geographic areas at a low cost. (Nega et al., 2019) . In this paper, multispectral satellite images of Barishal, Bangladesh, have been utilized to classify Land Cover features such as Water bodies, Built-up areas, Sparse Vegetation & Dense Vegetation to detect the percent change in respective categorized areas from 2002 to 2020.

Processing Satellite Image data gives tools for evaluating images using various methods and mathematical indexes. One of the satellite imagery products that indicate the greenness of vegetation cover is the Normalized Difference Vegetation Index (NDVI). (Babalola & Akinsanola, 2016) NDVI reveals the presence of vegetation cover, which plays an important role in reducing local climate change and fluctuation. (Ibrahim & Rasul, 2017) The ratio difference between measured canopy reflectance in the red and near-infrared bands determines the NDVI. (Nageswara Rao et al., 2005) The variations between the visible red and near-infrared (NIR) bands of satellite images can be used to identify areas with significant vegetation and other features, as shown in this paper.

Researchers have used NDVI for improved monitoring of vegetation dynamics (Beck et al., 2006), assessing ecological responses to environmental change (Pettorelli et al., 2005), land cover classification at a regional scale (Gandhi et al., 2015; Lunetta et al., 2006) and a global scale (DEFRIES & TOWNSHEND, 1994).

For policymakers, agricultural experts, foresters, non-governmental organizations planners, and land administrators, this study would provide information critical to maintaining agro-climatic conditions, ensuring sustainability in resource utilization, and proper land use planning and decision making. Furthermore, the current study will provide first-hand knowledge for other researchers interested in conducting additional research on landscape change and disturbance using remote sensing data.

2. METHODOLOGY

Landsat-7 scene of 2002 and Sentinel-2 scene of 2020 were used for the change analysis. The images are of high quality and free of cloud and were acquired on February 1, 2002, and April 26, 2021. Images of the dry seasons were selected to ignore the negative impacts that are caused by rain, leading to false interpretations of the results. The Landsat-7 datasets have eight spectral bands, of which Bands (1,2,3) are of visible bands, Near Infra-Red Band (4) and Band -5 and Band -7 are of short and mid-Infra-Red bands, respectively **(*Landsat 7*, n.d.)**. On the contrary, Sentinel-2 has 12 Bands, of which Near Infra-Red Band (8) and Red Band (4) are the main concern for calculating. Since the study calculates Normalized Difference Vegetation Index (NDVI), Band-4, and Band-3 for Landsat datasets, on the other hand, Band-8, and Band -4 for sentinel -2 datasets are only used for calculating NDVI needed for the analysis.

The green plant contains chlorophyll that absorbs the wavelength of the visible range (0.4 µm- 0.7 µm) of the electromagnetic spectrum **(*Measuring Vegetation (NDVI & EVI)*, 2000)**. On the other hand, green plants reflect the wavelength of the Near Infra-Red region (0.7 µm- 1.1 µm). Green Plant is observed dark in the visible light but relatively brighter in the Near Infra-Red spectrums **(*Measuring Vegetation (NDVI & EVI)*, 2000)**. This relation serves as the basis for calculating NDVI. NDVI is calculated as:

$$NDVI=\frac{NIR-red}{NIR+red}$$

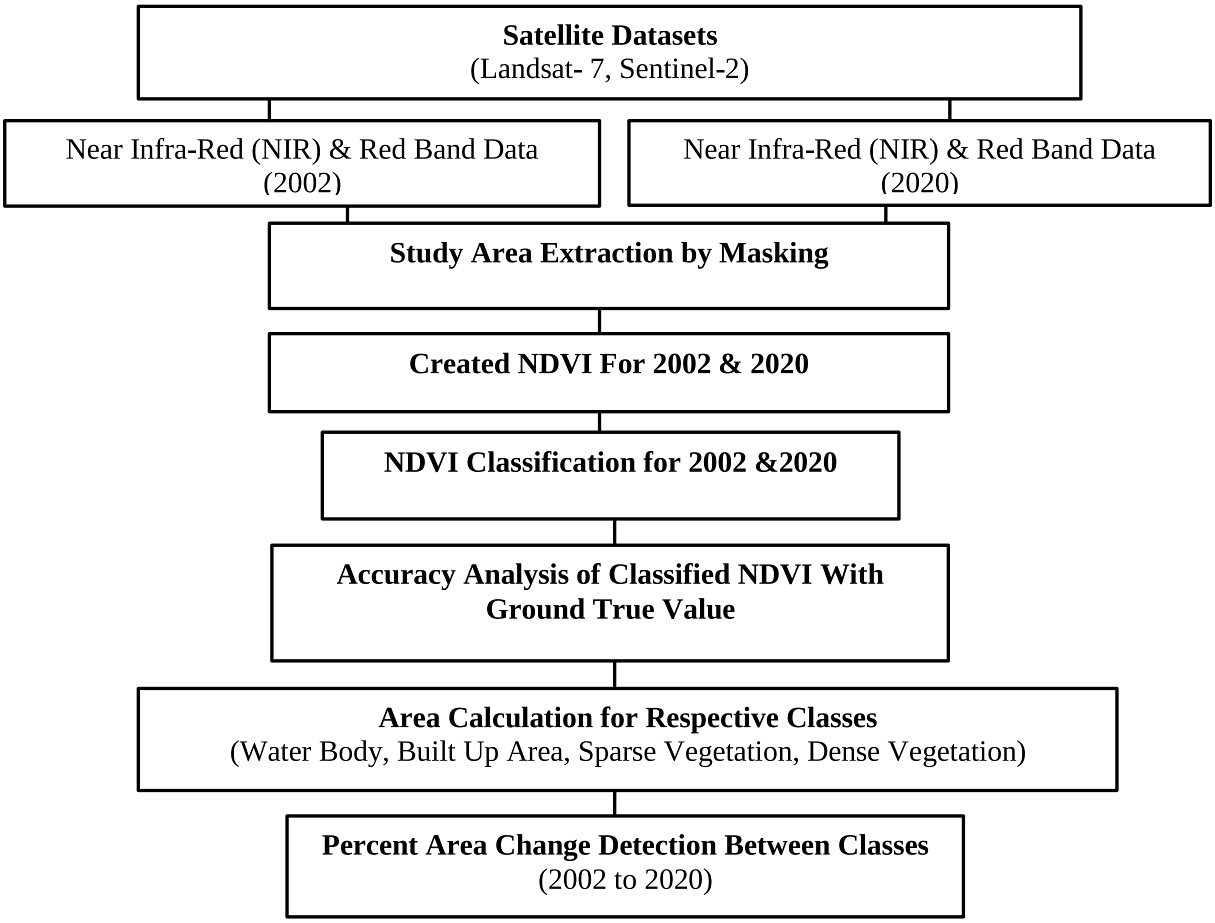
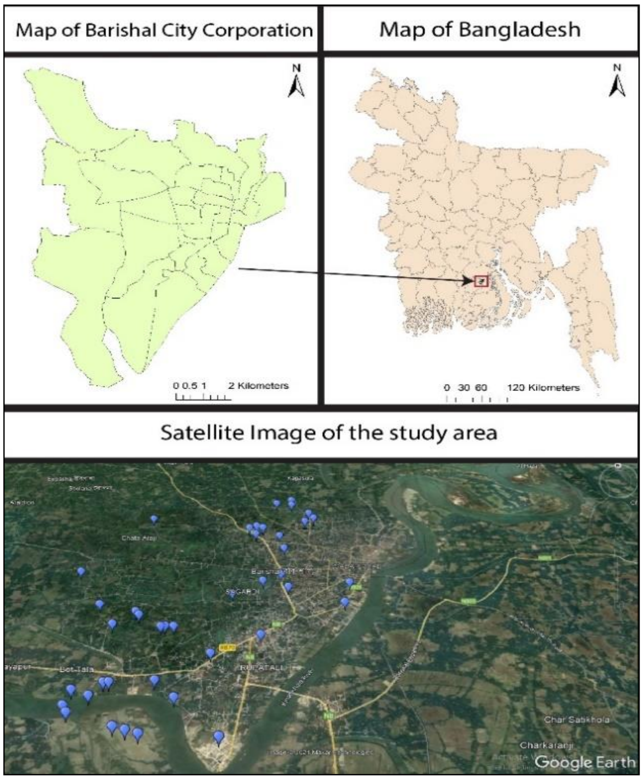
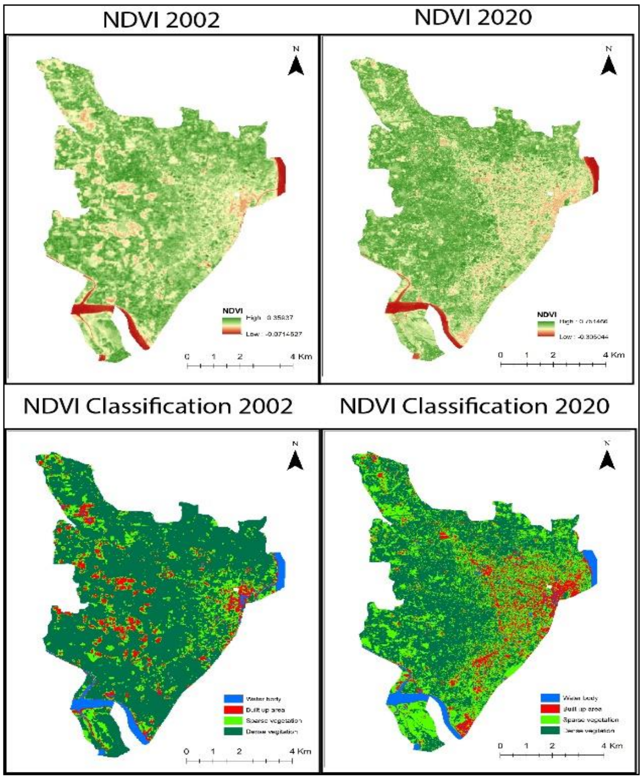


Fig: Flowchart of the Methodology

Red is the red (600-700 nm) reflectance of the visible spectrum, and NIR (750-1300 nm) is the Near Infra-Red reflectance. The value of NDVI ranges from -1 to +1 **(*NDVI, the Foundation for Remote Sensing Phenology*, n.d.)**. The more the positive value of NDVI, the greater the chlorophyll density, meaning more green spaces.

The more the degree of greenness, the more the concentration of chlorophyll. Plant leaves absorb the red light and reflect the Near Infra-Red spectrum. That causes the variation of NDVI. Negative NDVI values depict the areas of water bodies, built-up areas. Satellite camera captures all the bands from which NIR can be extracted from the red reflectance to find the NDVI. A flow chart of the methodology is portrayed in Fig. above. For the expected study of NDVI, only two bands (NIR, RED) are used to find the change of green spaces. Accuracy analysis was done comparing the analyzed pixel of NDVI image with google earth pro to justify the analysis.





3. ILLUSTRATIONS

3.1 Figures

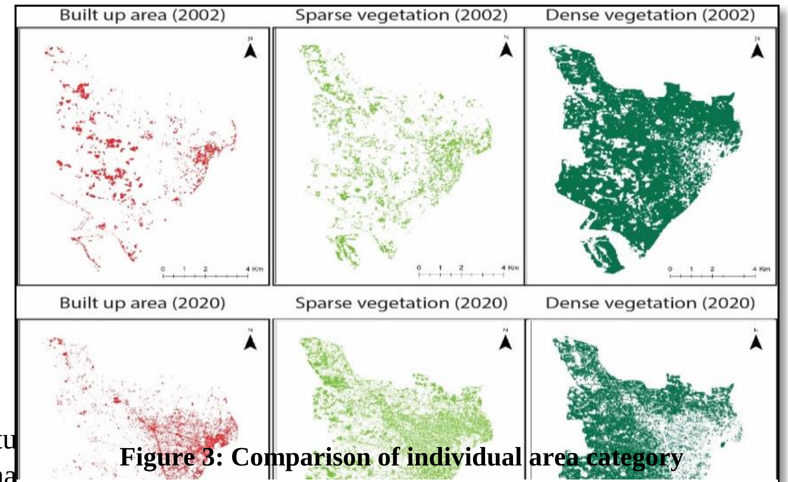


Figure 3: Comparison of individual area category

Fig:3 shows the visual comparison of the change of the individual area categories between 2002 and 2020.

Fig:1 shows the stu
The map of Barisha
with its location on
locations on the re
used as validation points for the NDVI classification.

Figure 1: Study Area

map of Barishal city
002 and 2020 along with the NDVI classification. The areas have been classified as Waterbody, Built-up, Sparse and Dense Vegetation and depicted by the colors blue, red, light green, and deep green, respectively.

Figure 2: NDVI Mapping & Classification

3.2 Equations

User Accuracy:

User accuracy states the accuracy of the map from the point of view of the map user. In addition, it indicates the classified classes of the map concerning the present condition on the ground. On the other hand, it is a measure of the reliability of the classified map.

$$\textit{User Accuracy}=\frac{Total\ number\ of\ correct\ classification\ for\ a\ particular\ class}{Total\ number\ of\ classified\ sites} \tag{1}$$

Producer Accuracy:

Producer accuracy states the accuracy of the map from the point of view of the map producer. Producer accuracy indicates how a real feature on the ground is available on the map.

$$\textit{Producer Accuracy}=\frac{Total\ number\ of\ correctly\ classified\ reference\ sites\ for\ a\ particular\ class}{Total\ number\ of\ reference\ sites} \tag{2}$$

Overall Accuracy:

Overall accuracy states that out of all the reference sites, what portion is correctly mapped. It is expressed in percent, where 100% accuracy indicates a perfect classification.

$$\textit{Overall Accuracy}=\frac{Total\ number\ of\ correctly\ classified\ sites\ for\ all\ classes}{Total\ number\ of\ reference\ sites} \tag{3}$$

Kappa Co-efficient (*κ*):

Kappa Coefficient is a statical measure to find the inter-rater reliability of the categorical items. It is more efficient than simple percent calculation because it considers the possibility of occurring by chance. Its value ranges from -1 to +1. A value of 0 indicates the classification is the same as a random classification, negative values indicate the worst classification, and the more the value near to +1, the better the classification is than random.

$$\boldsymbol{\kappa} = \frac{p_{0-}p_e}{1-p_e} \tag{4}$$

3.3 Tables

Table 1: Observed User & Producer value

	Water Body	Built Up Area	Sparse Vegetation	Dense Vegetation	Total User
Water Body	10	0	0	0	10
Built Up Area	0	10	0	0	10
Sparse Vegetation	0	1	9	0	10
Dense Vegetation	0	2	0	10	12
Total Producer	10	13	9	10	42

Table 2: Accuracy (User Accuracy, Producer Accuracy & Overall Accuracy)

	User Accuracy (%)	Producer Accuracy (%)	Overall Accuracy (%)	Kappa Co-efficient (%)
Water Body	100	100	92.86	90.48
Built Up Area	100	76.923		
Sparse Vegetation	90	100		
Dense Vegetation	83.33	100		

Table 3: Percentage change in the area of the Classes

	Water Body	Built Up Area	Sparse Vegetation	Dense Vegetation
2002	2	5	10	50
2020	2	7	23	34
Percent Change (%)	0	+40	+130	-32

4. CONCLUSIONS

Human causes caused remarkable changes in the land cover pattern in different land-use classes. During last 18 years, the study area observed phenomenal variations in Built-up Areas, Dense Vegetation, and Sparse Vegetation. This change in the land use pattern information can be useful for environmental modeling, management, and assessment. This study assessed changes in vegetation, built-up area due to urbanization on the plane landscape. NDVI analysis and resulting maps represent the change in two different periods. Efficiency analysis represents the accuracy of the classified classes. Classified images and the cross-comparison with the ground truth values represent the classified classes' overall accuracy. Higher-resolution multispectral images taken by drones would suitably increase the accuracy of the classification.

The study presents the change in percentages of different classes. In 2002, the percentage of built-up area was found 5 km2, the sparse and dense vegetation are found to be 10 km2 & 50 km2 of the total area. However, in 2020, the percentage of built-up area is found 7 km2, the sparse and dense vegetation are found to be 23 km2 & 34 km2 of the total area. The built-up areas and sparse vegetation in the study area faced a precipitous rise of 40% and 130%; on the other hand, dense vegetation decreased drastically by about 32%. The NDVI analysis and images give an advanced understanding of the changes in vegetation densities and the striking rate of urbanization in the study area for planners and policymakers to make decisions.

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