



## SPATIOTEMPORAL CHANGE OF LAND USE LAND COVER: A CASE STUDY OF NARAYANGANJ SADAR UPAZILA, BANGLADESH

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### Abstract

Major cities of Bangladesh have been experiencing rapid urbanization and industrialization. These are incurring positive externalities to national economy at the expense of environmental degradation and deterioration of living environment. The ambivalent sequel of industrialization has made it necessary to study urban areas and monitor spatiotemporal changes to facilitate decision-making process regarding land use planning, resource distribution, priority setting for planning interventions. Thus, this study aims to classify land use land cover (LULC) of Narayanganj Sadar Upazila and detect spatiotemporal changes within the period of 2015 to 2020 using MLC algorithm based supervised classification method. To serve this purpose, sentinel-2 satellite imagery are used. The results derived from the study elicit an increase (24.14 acre) in industrial land in 2020 compared to 2015. Approximately 1,538-acres land transformed into built-up area in 2020. Decrease in vegetation (15.85%) and water body (7.65%) are also evident from the findings. The results of the study will be conducive to have an initial glimpse of the LULC changing trend in the study area due to rapid urbanization and thus, will be instrumental for performing further research.

**Keywords:** LULC classification, MLC algorithm; change detection, Sentinel-2, Narayanganj Sadar Upazila.

### Introduction

Land use land cover (LULC) mapping and assessment have been acknowledged as critical scientific objectives, as the resulting data can be used to assist planners in decision making as well as environmental modeling (Al-Saady et al., 2015; Pielke Sr. et al., 2011; Prakash & Gupta, 1998). Detecting spatiotemporal changes of LULC in urban environments, particularly those undergoing fast industrialization, is crucial for sustainable land management, urban climate monitoring, and urban growth pattern analysis (Andualem et al., 2018; Nguyen et al., 2020). Thus, studying temporal changes in LULC is a critical part of urban planning context since it is associated with the spatial formation, socio-economic and environmental conditions. Mapping LULC is currently the most widely used and accepted method for monitoring land use changes (Al-Saady et al., 2015; Mancino et al., 2014). Thus, this study intends to classify LULC of Narayanganj Sadar Upazila in Bangladesh

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using sentinel-2 satellite imagery (freely downloadable from United States Geological Surveys (USGS) website) and to locate the temporal changes within the period of 2015 to 2020.

Change of LULC is a result of natural, economic and socio-spatial dynamics, as well as human interventions over time (Andualem et al., 2018; Batisani & Yarnal, 2009; Prakasam, 2010). Due to the repeating nature of satellite imageries, they have proven highly useful for tracking LULC patterns and changes over time (Andualem et al., 2018). GIS, on the other hand, enable quantification of such changes even when the resulting spatial datasets have varying scales or resolutions (Sarma et al., 2001). Sentinel-2's Multispectral Imager (MSI) sensor contains 13 bands. Its' temporal resolution is 10 days and spatial resolutions varies between 10 m to 60 m (Mandanici & Bitelli, 2016).

LULC categorization utilizes diverse image classification and pattern recognition techniques. The accuracy of classification is mostly determined by parameters such as sensor type, training sample sources, accuracy of training and assessment process data, number of LULC classes, and the classification algorithm itself (Heydari & Mountrakis, 2018; Nguyen et al., 2020). Thus, selecting suitable satellite imagery and algorithm capable of delivering LULC classification with acceptable level of accuracy while consuming minimal processing resources is very important (Lu & Weng, 2007). This research has adopted supervised classification technique for mapping LULC. The supervised classification procedure begins with the selection of training sites or areas for various land cover categories. Computer algorithms then classify an image using the spectral signature of a training area. We have used the maximum likelihood Classifier in this study. This classifier of supervised classification assigns unknown pixels to a single class based on the probability of contours surrounding the training area. The statistical values for each class in each band are considered to be normally distributed, and the probability that the pixel belongs to a particular class is then determined. Pixels are assigned to the class with having highest probability.

As the third largest city in Bangladesh, Narayanganj is experiencing rapid industrialization and urban population growth, which are impacting its LULC significantly and consequently, the urban environment and landscape. Nevertheless, studies on these spatiotemporal changes are very limited. This research intends to contribute in this segment of knowledge while depicting the potentials of freely available satellite imagery to study LULC changes. The findings of the study will provide an initial glimpse of the changing pattern of LULC in the study area due to rapid urbanization and thus, will be instrumental for performing further research. Thus, the insights will be imperative to understand land use and spatiotemporal change pattern of the city which are very crucial to devise land use plan and to formulate development policies effective to ensure sustainable urban growth.

## Materials and Methods

### Study Area

As stated before, Narayanganj Sadar Upazila of Bangladesh is the study area of this research (see Figure 2). It is located between 23°33' and 23°43' north latitudes and between 90°26' and 90°33' east longitudes, covering an area of 113.98 sq. km. (BBS, 2011). The area is characterized by very high population density (8,764 persons per sq. km.) and population growth rate (1.5% per annum) (BBS, 2011). About 96% of total income of the people comes from non-agricultural sectors (*ibid*). Shitalakshya and Dhaleshwari are the two major rivers flowing across the Upazila. The area is experiencing rapid urbanization as significant amount of people are regularly migrating in from different regions of the country to utilize the increased employment opportunities incited by the industrial growth. Due to these demographic changes, pressure on open and vacant spaces, water bodies have increased notably, which is causing transformation of LULC of the study area periodically. With the expansion of garments industries, knitwear garments, shipyard, brickfields, global trading including export and import activities, commercial and built-in land uses have been increased and the trend is still upward. As the sequel of this spatiotemporal change, land availability for vegetation and agriculture is shrinking continuously. Besides, the usage of the adjacent rivers and inlets for discharging industrial wastes

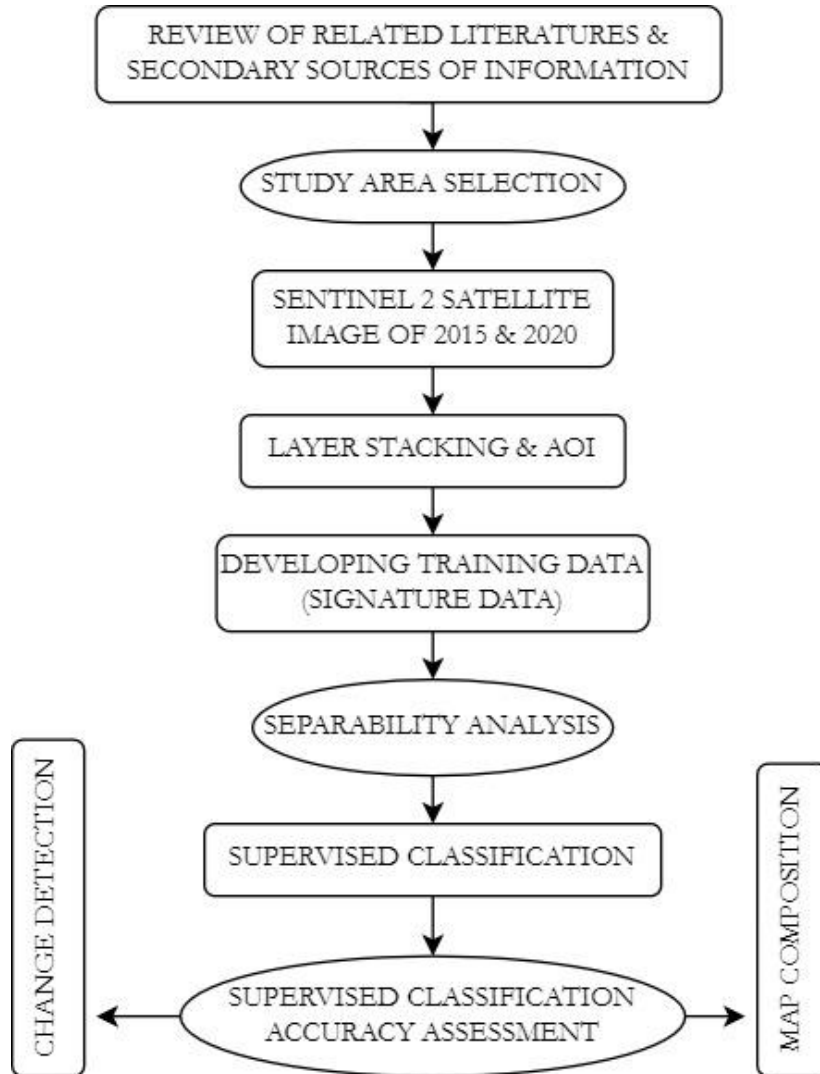


Figure 1. Method's flow chart.

and sewage as well as water consumption for public and domestic services (i.e., transportation, sanitation, water supply) and capturing water bodies to build infrastructures are impacting water quality and the water sources of the area. Thus, these concerning spatiotemporal changes in LULC of the area demand thorough studies to facilitate devising appropriate land use plan for the study area.

#### ***Data and Data Source***

For this study, remotely sensed data (Sentinel-2 satellite imagery) have been collected from Sentinel-2 LI-C1 archive, USGS Earth explorer (<https://earthexplorer.usgs.gov/>) with cloud cover less than 10% on 15<sup>th</sup>

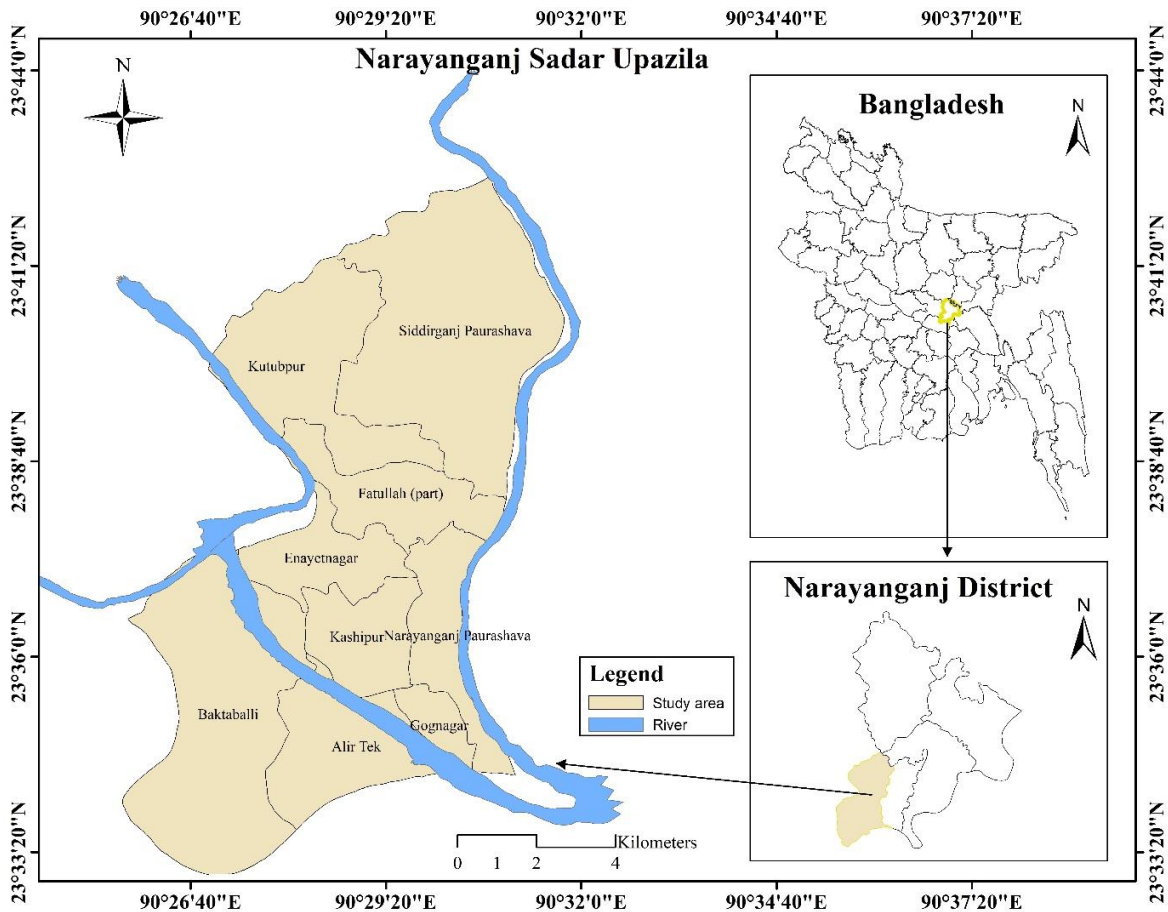


Figure 2. Map of the Study area.

February, 2021 (i.e., the dataset of 19<sup>th</sup> December, 2015 and the dataset of 22<sup>th</sup> December, 2020). Table 1 shows the spectrum characteristics of the Sentinel-2 MSI. Besides, we have used relevant reports, peer reviewed international journal articles and spatial data set from diverse and reliable sources.

### **Method of Analysis**

The research has been conducted following seven specific steps as follows:

#### *Data Preparation:*

After downloading the data for the year 2015 and 2020, layers are carefully stacked, subset (using vector data of administrative boundary) and necessary atmospheric corrections were conducted to prepare the images for further analysis.

#### *Training Data:*

Although it is a challenging task for a tropical and complex area like Narayanganj Sadar Upazila, we have acquired the required training and validation data from the existing physical feature survey conducted by RAJUK (*Rajdhani Unnayan Kartipakkho*) and also from Google Map. Adequate number of training and

Table 1. Spectral bands for the Sentinel-2 sensors (S2A & S2B)

Band Number	S2A		S2B		Spatial resolution (m)
	Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)	
1	442.7	21	442.3	21	60
2	492.4	66	492.1	66	10
3	559.8	36	559.0	36	10
4	664.6	31	665.0	31	10
5	704.1	15	703.8	16	20
6	740.5	15	739.1	15	20
7	782.8	20	779.7	20	20
8	832.8	106	833.0	106	10
8a	864.8	21	864.0	22	20
9	945.1	20	943.2	21	60
10	1373.5	31	1376.9	30	60
11	1613.7	91	1610.4	94	20
12	2202.4	175	2185.7	185	20

Source: Authors' composition from *Sentinel Online* (<https://sentinel.esa.int/web/sentinel/technical-guides/sentinel-2-msi/hsi-instrument>)

validation data (signatures) have been collected covering all parts of the study area to capture within class heterogeneity for training the model.

*Separability Analysis:*

Once the signature data is prepared for the analysis, separability analysis has been performed for both of the time frames (2015 and 2020) to ensure that the spectral classes defined through the accumulation of the training data are distinct enough from each other to ensure reliable classification results with acceptable level of classification accuracy. Both *Jefferies-Matusita* and *Transformed Divergence* methods of separability analysis shows that that the signature data of both of the time periods have significant level of separability. Table 2 presents the outputs of the analyses.

Table 2. Findings of the separability analyses of the training data

Separability analysis-2015		Separability analysis-2020	
Score recorded in Jefferies-Matusita method (Max score: 1414)	Score recorded in Transformed Divergence method (Max score: 2000)	Score recorded in Jefferies-Matusita method (Max score: 1414)	Score recorded in Transformed Divergence method (Max score: 2000)
1401	1994	1403	1991
The Separability analyses are statistically significant and thus, the signature data are suitable to perform the supervised classification			

*Supervised Image Classification (MLC Algorithm):*

Maximum likelihood classifier (MLC) has been adopted for supervised classification, which is one of the common classification methods (Benediktsson et al., 1990; Tewabe & Fentahun, 2020). This algorithm

generates a normally distributed function using the statistics for each LULC class in each spectral band and calculates the likelihood that a particular pixel belongs to a specific category using the following Equation (1) (Elhag & Boteva, 2016):

$$g_i(x) = \ln p(w_i) - \frac{1}{2} \ln |S_i| - \frac{1}{2} (x - m_i)^T S_i^{-1} (x - m_i) \quad -- (1)$$

were,

$i$  = class

$x$  =  $n$  – dimensional data (where  $n$  is the number of bands)

$p(w_i)$  = probability that class  $(w_i)$  occurs in the image and it assumed the same for all classes

$|S_i|$  = determinant of the covariance matrix of the data in class  $(w_i)$

$S_i^{-1}$  = its inverse matrix;  $m_i$  = mean vector

#### *Accuracy Assessment:*

Assessment of classification accuracy is to ensure that the resultant data are suitable for change detection analysis at the same time it also reveals whether or not the classified image (Andualem et al., 2018). The accuracy appraisal of the LULC classification for both of the time frames have been performed based on 252 random points, determined and placed applying a hierarchical random technique in ERDAS software to characterize the individual LULC classes of the area. The threshold of these randomly produced points to conduct an accurate accuracy measurement is 250 or more (Andualem et al., 2018). These randomly selected points denote to the ground truth data, which are compared with the classification outputs and are evaluated statistically using confusion matrices. Kappa ( $K$ ) statistics is also a measurement of the classification accuracy, which is calculated following this equation:

$$Kappa (K) = \frac{P_o - P_e}{1 - P_e}$$

were,

$P_o$  = number of correctly classified classes;

$P_e$  = number of correctly classified values expected by chance

The overall Kappa statistics of the classification has been measured to be 0.91, which indicates toward maximum accuracy. The overall classification accuracy has been calculated to be 93.7%.

#### *Change Detection Analysis:*

For change detection of the classified LULC maps of both periods (2015 and 2020), *Image Difference* and *Discriminate Function* are used. In Image Difference, spatiotemporal changes between the base year (2015) and the target year (2020) are measured based on a cut off difference (such as 10% ,5% or defined value). If a specific LULC class is increased more than the cut off difference value, then it is highlighted with a predefined color. The same process is followed in the case of decrement. In addition, it also highlights the changes that is lower than the predefined cut off difference value as some increase (in the case of increment) and some decrease (in the case of decrement). Unchanged part of the area is shown in black color. While Discriminate Function defines unchanged part of the LULC by the value zero (0) and highlight in grey, whereas major or significant change is defined by the value 1 and highlight in white. Other dark colors (blackish) indicate minor changes. However, in our context, we have visualized different color map based on the combined value derived in the change detection analysis. Proceeding section reveals the outcome.

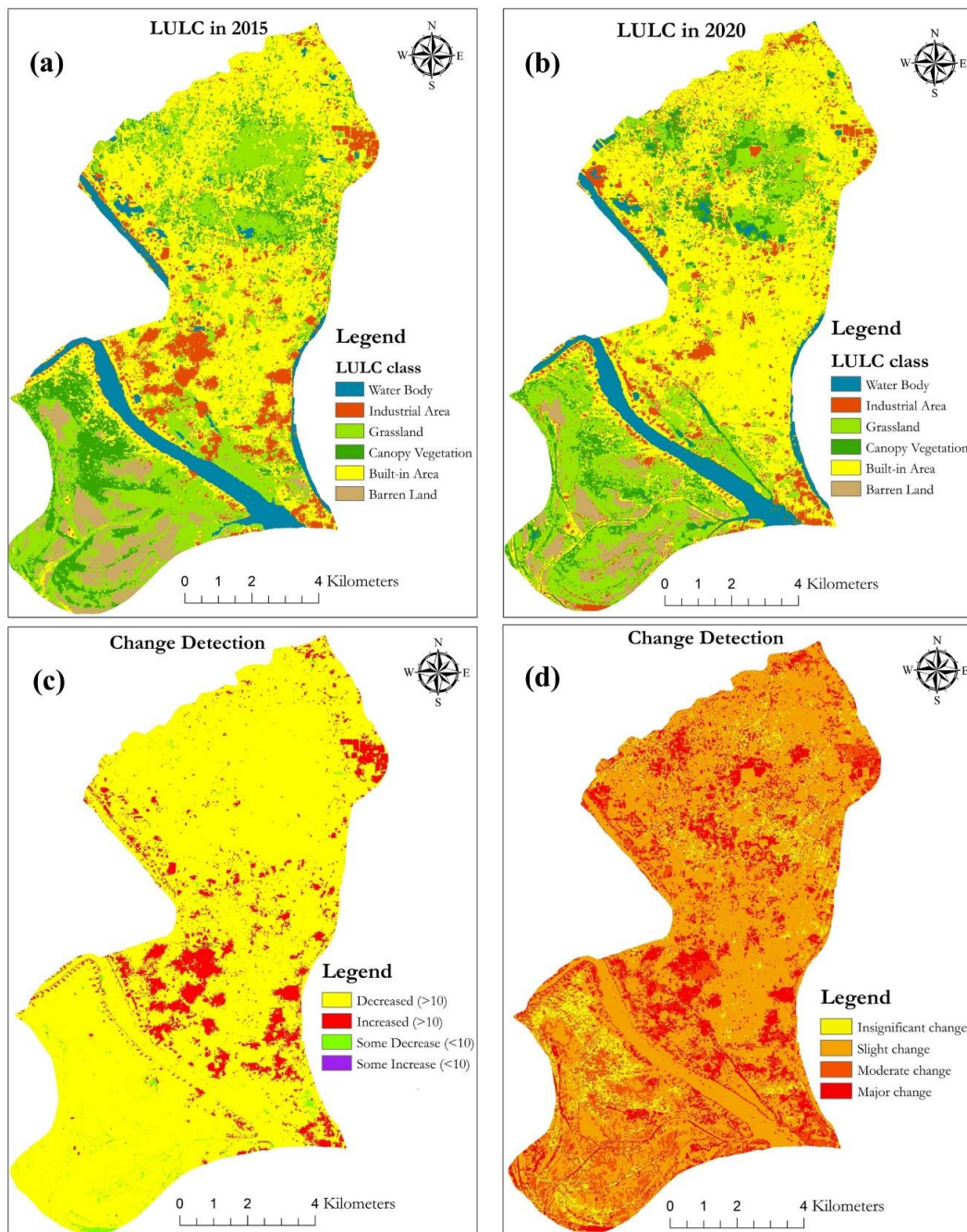


Figure 3. Maps of the LULC and change detection: (a) LULC in 2015; (b) LULC in 2020; (c) change detection (Image Difference); (d) change detection (Discriminate Function).

## Results and Discussion

The results of the study (Figure 3) show that industrial land use has increased insignificantly (24.14 acres) in 2020 compared to 2015 (see Table 3). Table 3 also reveals that 1,538 acres area has been transformed into built-up area in 2020 (see Table 4 for details). It also shows that 15.85% of vegetation has decreased in 2020 compared to 2015, whereas the water body has decreased around 7.65%. However, amount of barren land has been identified to be decreased around 31.45% in 2020 compared to 2015, which means the study area is densifying rapidly responding to increased rate of urbanization.

Table 4 presents the extents to which the classified LULCs have been transformed within the five years' timespan (2015 to 2020), which has been depicted through Figure 4. It is evident from the study that open spaces or green fields, vegetation and water bodies are declining rapidly responding to the rapid urbanization and infrastructural development, which is alarming in terms of environmental safeguard and climate change. Rapid industrialization alongside the major rivers and inlets have affected the water sources through discharge of industrial waste, waste water, chemical water etc. The green fields or open spaces and barren lands are highly likely to be captured for housing and industrialization to adapt with the tumid growth of population. Thus, the swift urbanization process in the study area is contributing in urban climate change, urban sprawl, unsustainable urban landscape, ecological imbalance and poor living environment. Besides, the study identifies that the industrial growth has been shifting towards the northern and southern part of the Upazila. From this pattern, it can be prevised that further industrialization will take place at the southern part of the study area because of the availability of barren land and grassland at comparably lower price.

Table 3. Change detection in LULC between 2015 to 2020

LULC class	Spatial distribution in 2015 Area (acre)	Spatial distribution in 2020 Area (acre)	Spatiotemporal change (%)
Vegetation	2,819.34	2,372.36	Decreased (15.85)
Barren land	1,645.25	1,127.94	Decreased (31.44)
Water body	1,661.53	1,534.47	Decreased (7.64)
Built-up area	10,399.3	11,937.3	Increased (14.79)
Green field	6,053.23	5,582.42	Decreased (7.78)
Industrial area	2,229.8	2,253.94	Increased (1.08)

Source: Authors' composition from change detection analyses of the study

Table 4. Changes of classified LULC between 2015 to 2020 (in acre)

	Waterbody	Vegetation	Green field	Barren land	Built-up area	Industrial area
Waterbody	0	153.21	20.92	0	46.83	42.00
Vegetation	4.94	0	1151.51	18.09	816.85	86.48
Green field	108.73	1131.74	0	195.21	1116.94	373.13
Barren land	0	4.94	523.86	0	127.67	800.62
Built-up area	9.88	284.17	615.29	56.83	0	800.62
Industrial area	12.35	56.83	143.32	44.48	1196.56	0

Source: Authors' composition from change detection analyses of the study

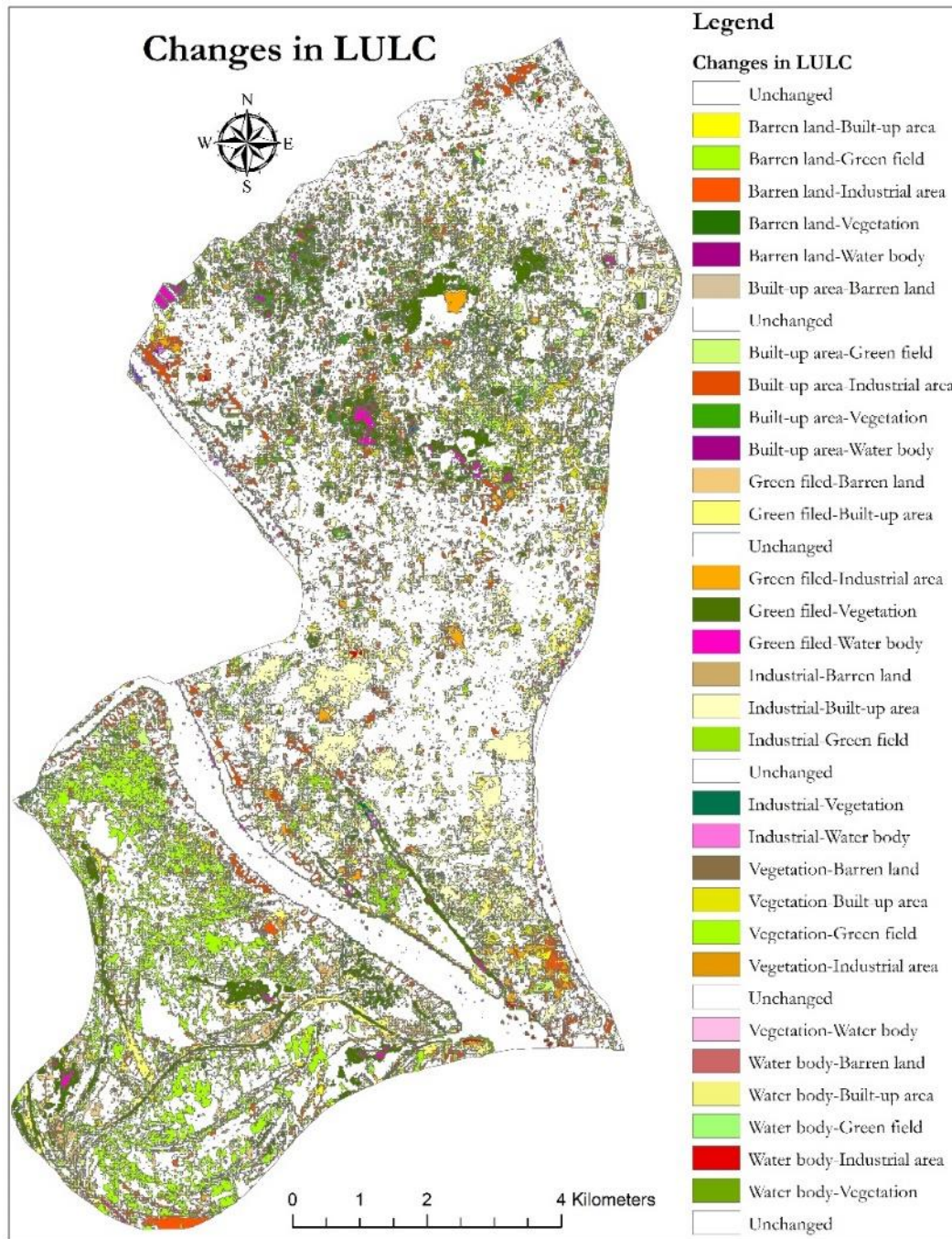


Figure 4. Transformation of the classified LULCs within the defined timespan (2015-2020).

## Conclusion

This study has characterized LULC in Narayanganj Sadar Upazila in Bangladesh for two-time frames (i.e., 2015 and 2020) using supervised classification technique based on Sentinel-2 satellite imagery and then, has performed change detection analysis to detect the spatiotemporal changes in LULC within the aforementioned time span. The findings reveal that the industrial land use has increased by 24.14 acres in 2020 than that of 2015. Approximately 1,538 acres of land has been newly transformed into built-in area within this five years' interval. The research also elicits that vegetation and water body have been decreased by 15.85% and 7.65% respectively in 2020 comparing to 2015. Besides, the study also identifies that approximately 7.78% of green fields or open spaces has been abated by 2020 than that of 2015, whereas barren land in the study area has been decreased by 31.44%. Thus, the study manifests the negative impacts of rapid industrialization and urbanization process on vegetation, open space, water bodies and thus, urban landscape and living environment.

The results derived from this research can be conducive to have initial glimpse on the trend of LULC change and urban growth in the study area, which are crucial to formulate efficient urban plan aiming at urban sustainability. Besides, the findings of the study can be useful in performing further research on spatiotemporal changes in the LULC profile of the Upazila. In addition, this study highlights the potentials of freely available remote sensing data in studying urban contexts at academic and non-commercial levels.

However, this study has its own limitations in terms of the spectral resolution in use and the analysis techniques applied in LULC change detection, which can affect the overall accuracy of the results and thus, their reliability and applicability in practice. Besides, there is hardly any study on LULC classification and change detection for the investigated area based on which the findings of this research could be validated. Application of more complex techniques like object-based land use classification process integrated with fuzzy sets and neural networks can be effective while using finer resolution imagery. Using higher resolution imagery and hybrid classification techniques, where two or more methods can be integrated can improve the accuracy and reliability of LULC classification and change detection notably. Notwithstanding the limitations, the research is a novel endeavor to study the spatiotemporal changes of LULC in the third largest city of Bangladesh. Thus, the results can be crucial contributions to the LULC portfolio of the study area, which will facilitate further in-depth research on the same.

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