Acadlore Transactions on Geosciences
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Spatiotemporal Analysis of Urban Expansion and Its Impact on Agricultural Land Degradation and Vegetation Health in Narayanganj District, Bangladesh

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Received: 11-08-2024 **Revised:** 12-13-2024 **Accepted:** 12-18-2024

Citation: R. B. Hossain, R. Ahmed, T. Sharmin, A. Refat, and U. H. Moni, "Spatiotemporal analysis of urban expansion and its impact on agricultural land degradation and vegetation health in Narayanganj District, Bangladesh," *Acadlore Trans. Geosci.*, vol. 3, no. 4, pp. 193–209, 2024. https://doi.org/10.56578/atg030402.

Abstract: Urban expansion, driven by rapid population growth, has increasingly encroached upon agricultural land and contributed to the degradation of ecological systems. In this study, the spatiotemporal dynamics of urban growth in Narayanganj District, Bangladesh, were assessed over a 20-year period (2003–2023) using integrated Geographic Information System (GIS) and remote sensing techniques. Land Use and Land Cover (LULC) changes were quantified, and their ecological consequences were evaluated through vegetation indices including the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI), alongside the Normalized Difference Built-up Index (NDBI). An LULC classification revealed a net increase of 5.61% in built-up areas, accompanied by reductions of 7.61% and 1.61% in barren land and agricultural land, respectively. The spatial pattern of urban expansion was found to be uneven, with pronounced growth observed from the northern to north-northwestern sectors of the district. A two-phase conversion analysis indicated that 15.68% of agricultural land was transformed into urban areas between 2003 and 2013, followed by a slightly lower conversion rate of 14.74% from 2013 to 2023. Notably, a statistically significant inverse correlation was detected between NDBI and both NDVI and SAVI, suggesting a measurable decline in vegetation health associated with urban intensification. These findings provide empirical and geographically grounded evidence of the adverse ecological impacts of urbanization in a peri-urban context. The integration of multi-temporal satellite images with vegetation and built-up indices enabled a comprehensive evaluation of land transformation processes and their environmental implications. The insights gained from this research may inform sustainable land use planning, urban policy formulation, and conservation strategies aimed at mitigating the loss of agricultural land and safeguarding vegetation health in rapidly urbanizing regions.

Keywords: Urban expansion; LULC, Remote sensing; Agricultural land conversion; Vegetation indices; NDVI; SAVI; NDBI

1 Introduction

Urban expansion—the conversion of non-urban regions into urban areas—has emerged as a defining characteristic of modern urbanization, especially in quickly developing countries. This phenomenon is generally propelled by significant population expansion, industrial proliferation, and infrastructure advancement [1, 2]. In numerous developing nations, such as Bangladesh, this expansion frequently transpires in an unregulated fashion, leading to haphazard and often unsustainable land use changes [3]. Urban expansion sometimes incurs the sacrifice of prime agricultural land, forested regions, and wetlands, resulting in ecological disruptions and food insecurity [4–6]. The extent of agricultural land was 67.38% in 1976 and decreased to 62.2% by 2014, with an annual loss rate of 0.13-1% between 1976 and 2010 in Bangladesh [7]. Due to the urban expansion and the growth of the population, approximately 69% of Dhaka's wetlands were lost between 1990 and 2020 [8].

LULC alterations are intrinsically linked to urban growth and serve as essential indices of environmental change. These alterations affect habitat quality, ecological stability, hydrological systems, and soil fertility [9, 10]. In Bangladesh, urban areas such as Dhaka, Narayanganj, and Gazipur are seeing significant alterations in their land surfaces, leading to marked reductions in vegetation and water bodies, alongside an increase in constructed infrastructure [11]. Urban Heat Island (UHI) effects have been observed in cities like Dhaka and Narayanganj where the primary contributors are the population density and the emissions from the industries. In Dhaka, UHI increased annually by 0.03°C (daytime) and 0.023°C (nighttime) between 2001 and 2017 [12, 13]. Such processes require meticulous observation and research to guide sustainable urban development.

The advancement of remotely sensed technology has introduced vital ways for effectively tracking and assessing LULC changes. The broad availability of spatial and temporal remotely sensed images has expanded the ability to see and interpret the pattern. As a result, the difficulties associated with land management can now be approached in middle- and lower-income nations [14]. The identification of the spatiotemporal variation of LULC within the urban context is crucial owing to sustainable land management, assessment of urban climatic variation and the evaluation of urban growth trajectories [15–17].

As an economically and strategically significant district within the Dhaka metropolitan region and known as the "Dundee of the East," Narayanganj houses some of Bangladesh's most expansive textile and manufacturing sectors. The district has undergone tremendous urban growth, driven by industrialization, increased transit infrastructure, and administrative decentralization [12]. Governmental and non-governmental institutions are progressively relocating to Narayanganj, accelerating land pressure and land use modification [11]. The unregulated urban expansion in Narayanganj has led to considerable land conversion—particularly from agriculture to built-up and industrial uses—resulting in environmental deterioration. This includes a decline in vegetative cover, degradation of soil quality, destruction of aquatic habitats, and rising demand on water resources due to pollution and runoff [18]. While anecdotal and sectoral data exists, there is a dearth of systematic and spatially explicit examination into how urban growth directly relates to agricultural land degradation and deterioration of vegetation health in Narayanganj. Furthermore, whereas national-level statistics imply severe loss of agricultural land [12, 19], the paucity of localized, up-to-date spatiotemporal data hampers efforts to design sustainable land management and planning strategies. This research tackles these problems by presenting actual, geographical evidence of LULC alterations and their ecological effects over a 20-year timeframe.

The environmental implications of such developments are severe. For instance, changes in land use patterns can alter vegetation vigor, impair soil quality, and disrupt local hydrological networks. Due to urbanization and inadequate waste management, Dhaka's major surrounding rivers (Turag, Dholeshwari, Balu, Buriganga and Shitalakhya) are experiencing severe decline in water quality [20]. Declines in vegetative cover and agricultural land not only endanger food security but also impair ecosystem resilience and carbon sequestration capacity [9, 10, 21]. In Narayanganj, unregulated industrial activity and city expansion have also contributed to increased pollution and habitat degradation, further compromising the ecological balance [19]. This study aims to assess the vegetation health trends across the district in conjunction with land conversion data to create a detailed understanding of how urbanization affects ecological systems over time.

Despite the increasing academic and policy interest in urban growth in Bangladesh, there remains a noteworthy research gap in high-resolution, district-level studies of spatiotemporal urban changes and their specific environmental repercussions. While national or regional studies have broadly documented land conversion trends [22–25], comprehensive local-scale research—particularly for Narayanganj—is scarce. Existing literature has not fully addressed how urban expansion in this industrial hub affects the degradation of agricultural land and vegetation health over time. Furthermore, the time dimension of such shifts, particularly across two decades, remains little studied. Additionally, most existing studies lack a complete integration of a spatiotemporal remote sensing analysis and its relationship with environmental health indices, especially vegetation indices.

This work intends to fill this critical gap by providing a specific case study of Narayanganj, using a spatiotemporal geospatial methodology. To address the problem identified, the study is driven by the following specific objectives: (i) to analyze the spatiotemporal pattern of urban expansion in the Narayanganj district from 2003 to 2023 using GIS and remote sensing techniques, (ii) to quantify the extent of agricultural land degradation due to urban expansion over the study period, and (iii) to assess changes in vegetation health using spectral vegetation indices and evaluate their spatial correlation with urban expansion. Satellite images were utilized to conduct supervised categorization of LULC classes from 2003 to 2023. Vegetation health was measured using NDVI and other vegetation indices derived from the same sources. Change detection techniques were utilized to quantify land transformations, and GIS-based research established geographical linkages between urban growth and the reduction of agricultural land and vegetative areas. By recording long-term LULC changes and their impact on agricultural and vegetation health, the findings will be crucial in influencing sustainable development strategies, enhancing land-use planning, and promoting climate-resilient urban ecosystems in Bangladesh and similar contexts worldwide.

2 Methodology

The study employed GIS and remote sensing techniques to analyze Landsat satellite images from 2003, 2013, and 2023 for LULC classification. Vegetation and urbanization changes were assessed using indices such as NDVI, SAVI, and NDBI to evaluate agricultural land conversion and vegetation health (Figure 1).

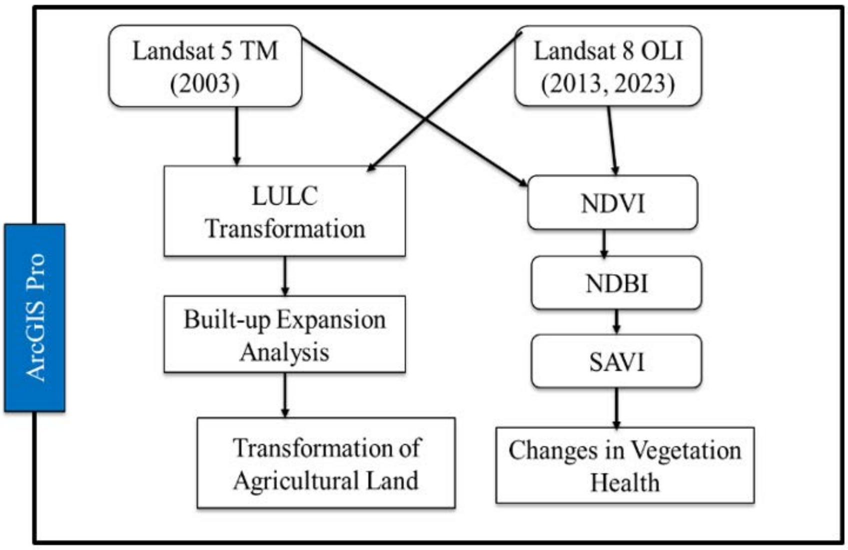

Figure 1. Methodological workflow of the study

2.1 Study Area

Narayanganj is located in the Dhaka Division, covering approximately 759 km^2 between latitudes 23°33'N to 23°52'N and longitudes 90°26'E to 90°45'E [26]. It is bordered by the districts of Dhaka, Munshiganj, and Narsingdi and is intersected by major rivers such as the Shitalakshya, Meghna, and Buriganga, which play significant roles in the area's agriculture and economy (Figure 2). The climate in Narayanganj is tropical, characterized by a monsoon season from June to September and a dry winter season. Annual rainfall averages around 2,000 mm, and temperatures range from a minimum of 10°C in winter to a maximum of 34°C in summer [26, 27]. Annual rainfall averages approximately 2,000 mm, with the majority occurring during the monsoon season (June to September). These climatic conditions, along with fertile alluvial soils, make Narayanganj an agriculturally productive region, predominantly cultivating rice, jute, vegetables, and fruits.

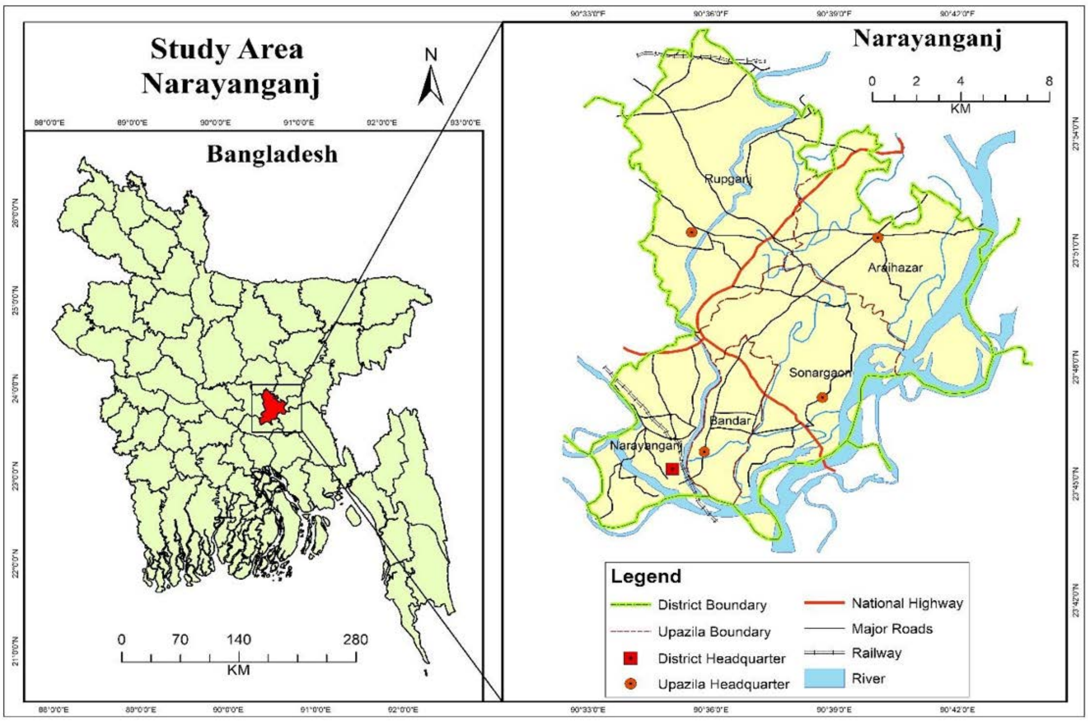

Figure 2. Map of the study area

The district's strategic location near Dhaka has made it an industrial and economic hub, with substantial growth in population and infrastructure. This advantageous location has led to significant urban expansion over recent decades. As of the 2011 census, Narayanganj had a population of approximately 2.95 million, with a population density of 3,888 people/km^2, making it one of the most densely populated districts in the country [27]. This rapid growth has exerted considerable pressure on land use, driving urban expansion and reducing agricultural areas [27]. However, this urban expansion and population growth has caused extensive land use changes, particularly the conversion of agricultural land to urban areas, raising concerns about food security and environmental sustainability [28, 29].

Narayanganj District was selected as the study area due to its strategic importance as a rapidly urbanizing region in central Bangladesh. The district's fertile alluvial soil and favorable climatic conditions have historically made it a key area for agricultural production. Understanding the spatial and temporal dynamics of these changes is critical for addressing the challenges of urban expansion and preserving agricultural resources.

2.2 Data Description

GIS and remote sensing have proven to be invaluable resources for tracking and understanding how LULC has shifted over time at various geographic levels [30]. Multi-spectral Landsat images were used for LULC classification to predict urban expansion. The study used images between 2013 and 2023 to assess changes within the study area. Specifically, images from December 2013 were chosen to ensure flood-free conditions, while those from May 2023 captured pre-monsoon, flood-free conditions. To enhance data accuracy, cloud coverage was restricted to less than 10%, though the actual cloud presence across the region was nearly 0%. Radiometric corrections address sensor calibration and atmospheric interference to ensure accurate reflectance values, while geometric corrections align pixels to real-world coordinates, eliminating spatial distortions from satellite motion or terrain. As the Landsat satellite data were already corrected for radiometric and geometric distortions, no further geo-correction or preprocessing is necessary [31]. All relevant image metadata and details were sourced directly from the United States Geological Survey (USGS) repository as a metadata file (Table 1).

Table 1. Description of the images acquired from Landsat satellite sensors

Satellite Data	Date of Acquisition	Sensor	Path/Row	Band No.	Spectral Range (μm)	Spatial Resolution (m)
Landsat 5	02 March, 2003	TM	137/43	1	0.45-0.52	30
				2	0.52-0.60	30
				3	0.63-0.69	30
				4	0.76-0.90	30
				5	1.55-1.75	30
				7	2.08-2.35	30
Landsat 8	24 May 2013	OLI	137/44	1	0.43-0.45	30
				2	0.45-0.51	30
				3	0.64-0.67	30
				4	0.53-0.59	30
				5	0.85-0.88	30
				6	1.57-1.65	30
				7	2.11-2.29	30
Landsat 8	10 May 2023	OLI	137/44	1	0.43-0.45	30
				2	0.45-0.51	30
				3	0.64-0.67	30
				4	0.53-0.59	30
				5	0.85-0.88	30
				6	1.57-1.65	30
				7	2.11-2.29	30

2.3 LULC Classification

A supervised classification technique was employed to categorize the Landsat images, as this method is particularly effective when dealing with the spectral variability of different land cover types [32]. The classification process began with the creation of a signature file, which contains raw data for supervised image classification. In such classification methods, two approaches are commonly utilized: parametric and non-parametric. For this study, the maximum likelihood parametric rule was selected, as it provides a robust classification by considering the statistical parameters of pixel values, such as the covariance matrix.

Following the guidelines of the USGS Circular 671, the images were classified into four main land cover categories: (i) built-up areas, which include community zones and commercial buildings; (ii) green areas, consisting of agricultural land, forestland, and rangeland; (iii) bare lands, covering wastelands and unused areas; and (iv) water sources, encompassing both natural water bodies and constructed water infrastructure [33, 34]. This classification scheme, combined with the maximum likelihood approach, ensured that the spectral diversity of each land cover class was accurately represented in the final analysis.

2.4 Accuracy Assessment

Accuracy assessment serves as the final stage in the image classification process, where the classified data are evaluated and compared to ground truth data to ensure reliability [32, 35]. Rather than assessing ground truth data for each pixel from 2013 to 2023, the assessment focuses on specific reference points generated across the classified images. For this study, 500 reference points were produced for each classified image, based on their precise geographic coordinates, to facilitate the accuracy evaluation.

Both user accuracy (which measures the reliability of a class in relation to the actual ground truth) and producer accuracy (which assesses the performance of the classification process in identifying a particular class) were used to calculate the overall accuracy of the classified images. To further validate the classification, the Kappa coefficient was employed, providing a statistical measure of agreement between the classified map and the reference data. The Kappa coefficient determines whether the classified images are suitable for analysis by accounting for any agreement that may have occurred by chance. This inclusive approach ensures that the classified images meet the required standards for accuracy and can be confidently used for further analysis.

$$Kappa\, coefficient(T) = \frac{(TS \times TCS - \Sigma(Col.tot \times Rowtot)}{(TS)^2 - \Sigma(Col.tot \times Rowtot)} \times 100 \tag{1}$$

where, TS represents the total number of samples, and TCS represents the total number of correct samples.

$$User\, accuracy = \frac{Number\, of\, the\, correctly\, classified\, pixels\, in\, each\, category}{Total\, number\, of\, correctly\, classified\, pixels\, in\, that\, category\, (the\, row\, total)} \times 100 \tag{2}$$

$$Producer\, accuracy = \frac{Number\, of\, the\, correctly\, classified\, pixels\, in\, each\, category}{Total\, number\, of\, correctly\, classified\, pixels\, in\, that\, category\, (the\, column\, total)} \times 100 \tag{3}$$

2.5 LULC Transformations

The analysis of LULC transformations in the Narayanganj District was conducted using multi-temporal satellite images. The study utilized Landsat satellite images, e.g., Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI, for making three LULC change maps, from 2003 to 2013, 2013 to 2023, and 2003 to 2023, using ArcGIS 10.8 software. Post-classification change detection techniques were applied to quantify LULC transformations over these periods.

2.6 Calculation of Vegetation Indices

2.6.1 NDVI

NDVI was calculated to assess vegetation vigor and density across the study area. NDVI is a widely used indicator for monitoring vegetation health, exploiting the distinct reflectance properties of vegetation in the red and near-infrared (NIR) spectral bands. Healthy vegetation strongly absorbs red light and reflects NIR radiation, resulting in higher NDVI values, whereas degraded or sparse vegetation yields lower values.

NDVI was computed using the following equation:

$$\text{NDVI} = \frac{(NIR - RED)}{(NIR + RED)} \tag{4}$$

where, NIR and RED represent the reflectance values in the NIR and red bands, respectively. The spatial and temporal variations of NDVI provided insights into vegetation changes due to urban expansion and agricultural land degradation.

2.6.2 NDBI

NDBI was utilized to detect and map built-up areas in the Narayanganj District. Urban surfaces reflect more energy in the shortwave infrared (SWIR) region than in the NIR region, a characteristic that NDBI exploits to identify built-up features.

NDBI was calculated using the following formula:

$$\text{NDBI} = \frac{(SWIR - NIR)}{(SWIR + NIR)} \tag{5}$$

where, $SWIR$ denotes the reflectance in the SWIR band, and NIR represents the NIR reflectance. Positive NDBI values generally correspond to built-up or impervious surfaces, aiding in the assessment of urban expansion patterns over time.

2.6.3 SAVI

SAVI was employed to minimize the influence of soil brightness in areas with sparse vegetation cover. SAVI introduces a soil brightness correction factor (L) to improve vegetation monitoring where vegetation is not dense. SAVI was calculated as follows:

$$\text{SAVI} = \frac{(NIR - RED)}{(NIR + RED + L)} * (1 + L) \tag{6}$$

where, L is a canopy background adjustment factor, typically set at 0.5 for intermediate vegetation cover. This adjustment allowed for a more accurate analysis of vegetation health and degradation, particularly in agricultural and peri-urban regions undergoing land-use changes.

3 Results

3.1 LULC Change Analysis

Before analyzing the LULC changes, an accuracy assessment was conducted to validate the classification results for each study year (2003, 2013, and 2023) (Table 2).

Table 2. Accuracy assessment of LULC maps

	User's Accuracy (%)				Producer's Accuracy (%)				Overall Accuracy(%)	Kappa Coefficient
Year	**Water Body**	**Buil-tup Area**	**Agriculture**	**Barren Land**	**Water Body**	**Buil-tup Area**	**Agriculture**	**Barren Land**		
2003	100	79.75	93.92	93.18	87.88	95.45	89.68	89.14	90.67	0.857301
2013	100	75	88.57	60	40	100	88.57	75	84	0.765831
2023	100	70.83	90.48	100	100	100	50	50	82	0.70

The spatiotemporal distribution of various LULC classes in Narayanganj over a 20-year period, from 2003 to 2023, highlights significant changes in land cover patterns (Figure 3 and Table 3).

Table 3. Area distribution of different LULC classes

LULC	2003	2013	2023	Net Change (%) (2003-2023)
Built-up	224.97	257.75	268.76	5.61
Agriculture	409.12	362.59	396.51	-1.61
Water body	55.62	137.73	83.84	3.62
Barren land	90.87	22.47	31.45	-7.61

The built-up area increased steadily from 224.97 km^2 in 2003 to 268.76 km^2 in 2023, indicating a net gain of 5.61%, likely due to rapid urbanization. Agricultural land experienced fluctuations, decreasing from 409.12 km^2 in 2003 to 362.59 km^2 in 2013, before partially recovering to 396.51 km^2 in 2023, resulting in a modest net decline of 1.61%. Water bodies initially expanded considerably from 55.62 km^2 in 2003 to 137.73 km^2 in 2013, but later declined to 83.84 km^2 in 2023, reflecting a net gain of 3.62%, possibly due to seasonal or anthropogenic influences such as excavation or land reclamation. In contrast, barren land underwent a substantial reduction from 90.87 km^2 in 2003 to 31.45 km^2 in 2023, with a significant net loss of 7.61%, suggesting increased land utilization for development or agricultural purposes. These changes underscore dynamic LULC transformations driven by socio-economic and environmental factors in the region.

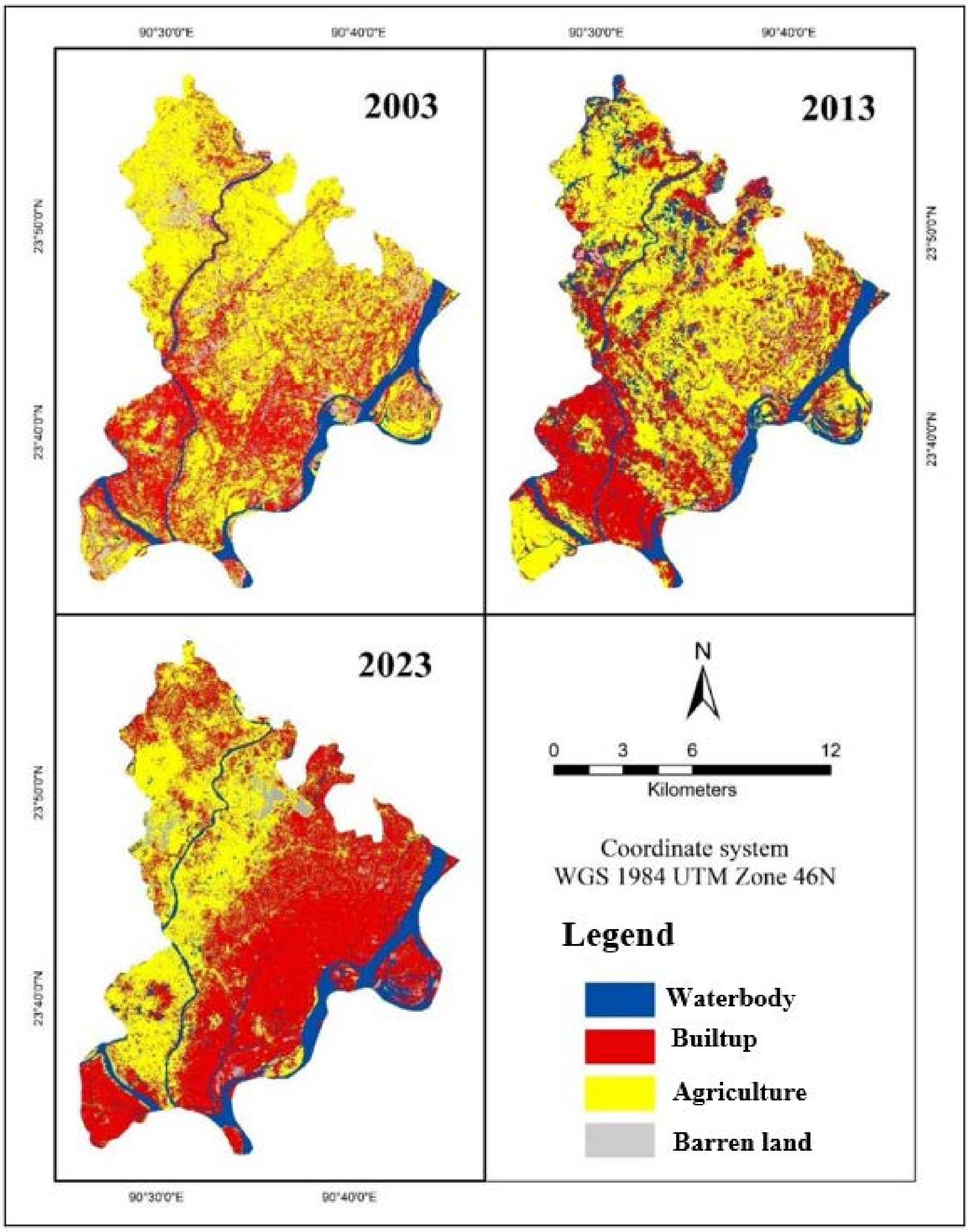

Figure 3. Classified LULC maps of the study area

3.2 Urban Expansion Analysis

The spider diagram provides a detailed representation of the directional dynamics of urban expansion in the Narayanganj District over the period from 2003 to 2023 (Figure 4). It visualizes the distribution of built-up areas across 16 compass directions—ranging from north (N) to north-northwest (NNW)—at three temporal points: 2003, 2013, and 2023. This radial plot facilitates a comparative analysis of the spatial trajectory and intensity of urban growth, illustrating how urbanization has evolved directionally over the two-decade period.

The analysis reveals a pronounced expansion of built-up areas toward the northwestern (NW) and northern (N) directions. In 2003, built-up development was relatively moderate and spatially constrained. By 2013, the extent of urban expansion had increased noticeably, particularly in the southern (S), southwestern (SW), and south-southwestern (SSW) sectors. However, the most significant change occurred by 2023, when the built-up area in the NW direction surged beyond 60 units, indicating a dominant spatial orientation of urban growth. This directional intensification likely reflects broader socio-economic transformations, infrastructural investments, or land-use planning decisions favoring these sectors.

Conversely, the eastern (E), southeastern (SE), and northeastern (NE) directions exhibited comparatively limited urban expansion throughout the study period. While slight growth is evident in these areas, it remained significantly lower than in the northwestern and southern sectors. This spatial asymmetry in urban growth suggests a highly uneven pattern of land development, potentially influenced by environmental constraints, land availability, or regulatory frameworks. The findings underscore the importance of adopting spatially informed urban planning approaches that address imbalanced growth and promote sustainable land-use management across all directions of the urban periphery.

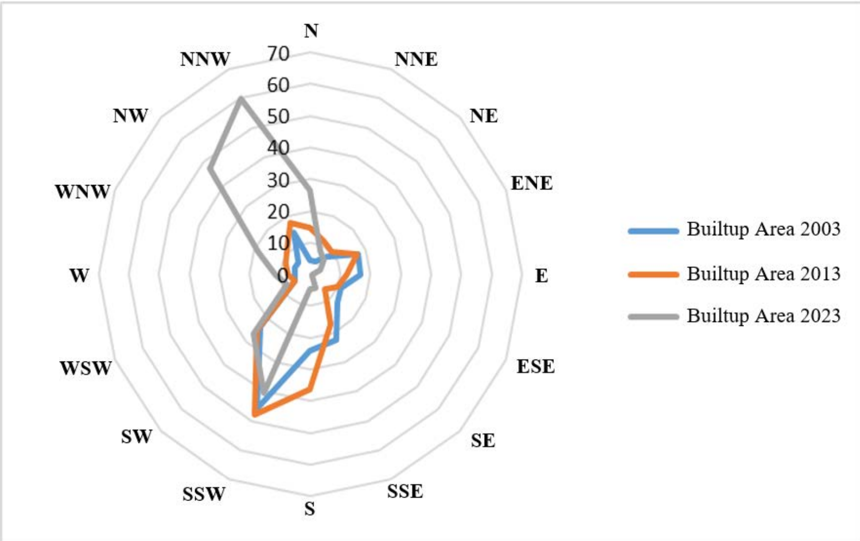

Figure 4. Direction of urban expansion in the Narayanganj District from 2003 to 2023

3.3 Transformation of Agricultural Land in Narayanganj

A transition analysis of agricultural land in Narayanganj highlights its transformation into various LULC classes for the periods of 2003–2013, 2013–2023, and 2003–2023. The following provides an analytical description of the trends observed in the study area (Figure 5).

3.3.1 Transformation of agricultural land to water bodies

Between 2003 and 2013, approximately 8.46% (65.996 km^2) of agricultural land was transformed into water bodies. This percentage showed a slight increase during the 2003–2023 period, with 3.00% (23.421 km^2) of the total agricultural land converted into water bodies. During the 2013–2023 decade, a smaller transformation of 1.13% (8.835 km^2) was observed, indicating a gradual decline in the rate of conversion to water bodies.

3.3.2 Transformation of agricultural land into built-up areas

The transformation of agricultural land into built-up areas increased notably over the three periods. From 2003 to 2013, 15.68% (122.356 km^2) of agricultural land transitioned to built-up areas. This trend accelerated during the 2003–2023 period, with 18.62% (145.296 km^2) transformed. However, the decade between 2013 and 2023 showed a slightly reduced transformation rate of 14.74% (114.988 km^2), indicating a possible stabilization in built-up expansion.

3.3.3 Transformation of agricultural land into barren land

Transformation into barren land remained relatively minimal compared to other classes. During 2003–2013, 2.04% (15.934 km^2) of agricultural land became barren. This figure increased to 2.88% (22.448 km^2) for the 2003–2023 period, with a much smaller transformation of 1.18% (9.209 km^2) during 2013–2023. These results reflect limited but steady encroachment of barren land.

3.3.4 Non-transformation of agricultural land (agriculture-agriculture)

The percentage of agricultural land that remained unchanged was the highest among all categories, signifying a strong retention of agricultural land use. From 2003 to 2013, 26.23% (204.612 km^2) of agricultural land remained unchanged. This figure increased to 27.91% (217.711 km^2) for the 2003–2023 period and further to 29.41% (229.415 km^2) during 2013–2023, suggesting a positive trend in preserving agricultural areas.

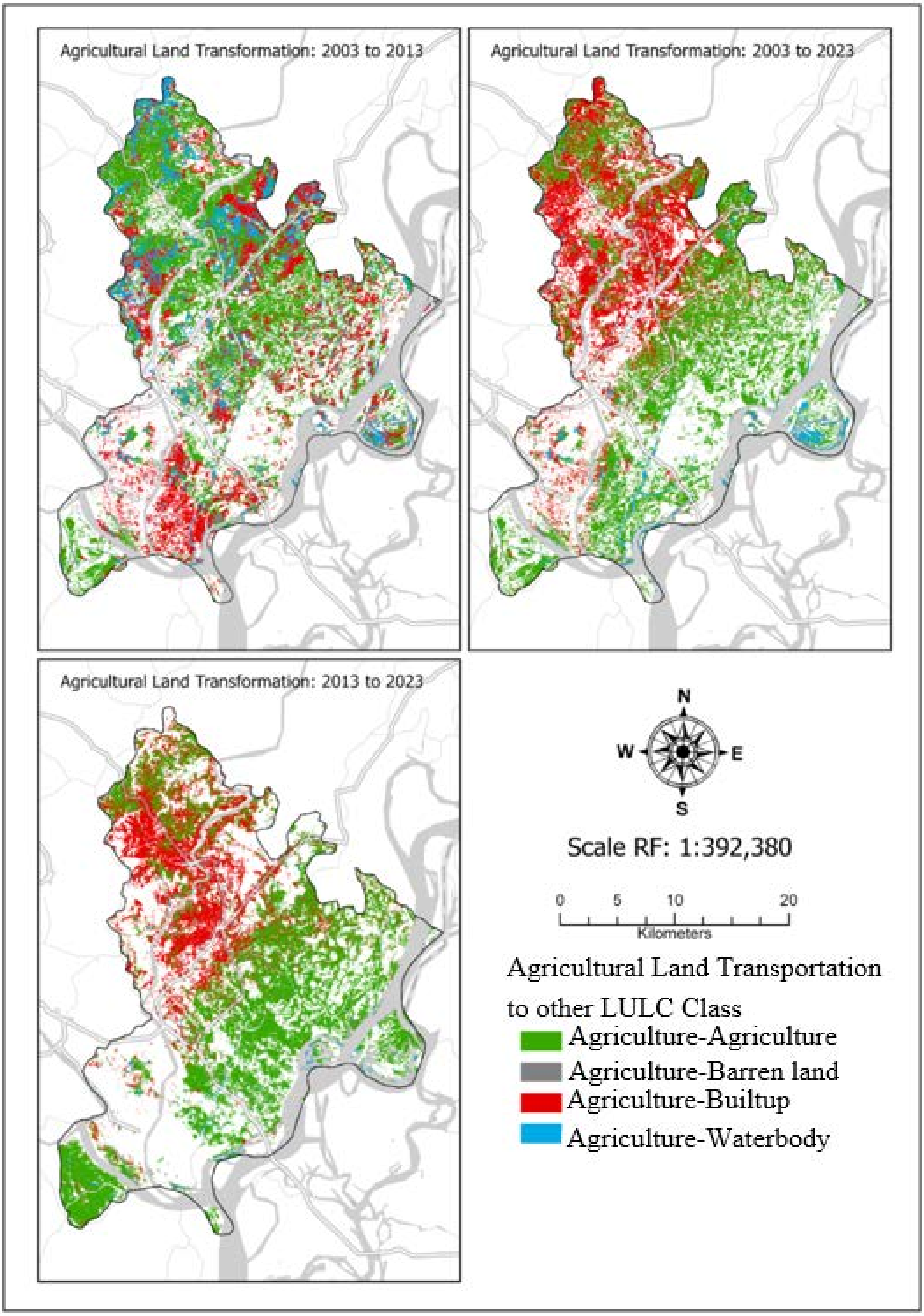

Figure 5. Transformation of agricultural lands to different LULC classes from 2003 to 2023

3.4 Changes in Vegetation Health

3.4.1 NDVI analysis

The NDVI analysis revealed a consistent downward trend in vegetation health across the district (Figure 6). In 2003, large portions of the region, particularly the southern and eastern agricultural belts, exhibited high NDVI values ranging from 0.5 to 0.7, indicative of dense and healthy vegetation. By 2013, these high-value zones had noticeably declined, and in 2023, much of the district's NDVI values fell within the 0.1 to 0.3 range, particularly in areas adjacent to expanding urban cores.

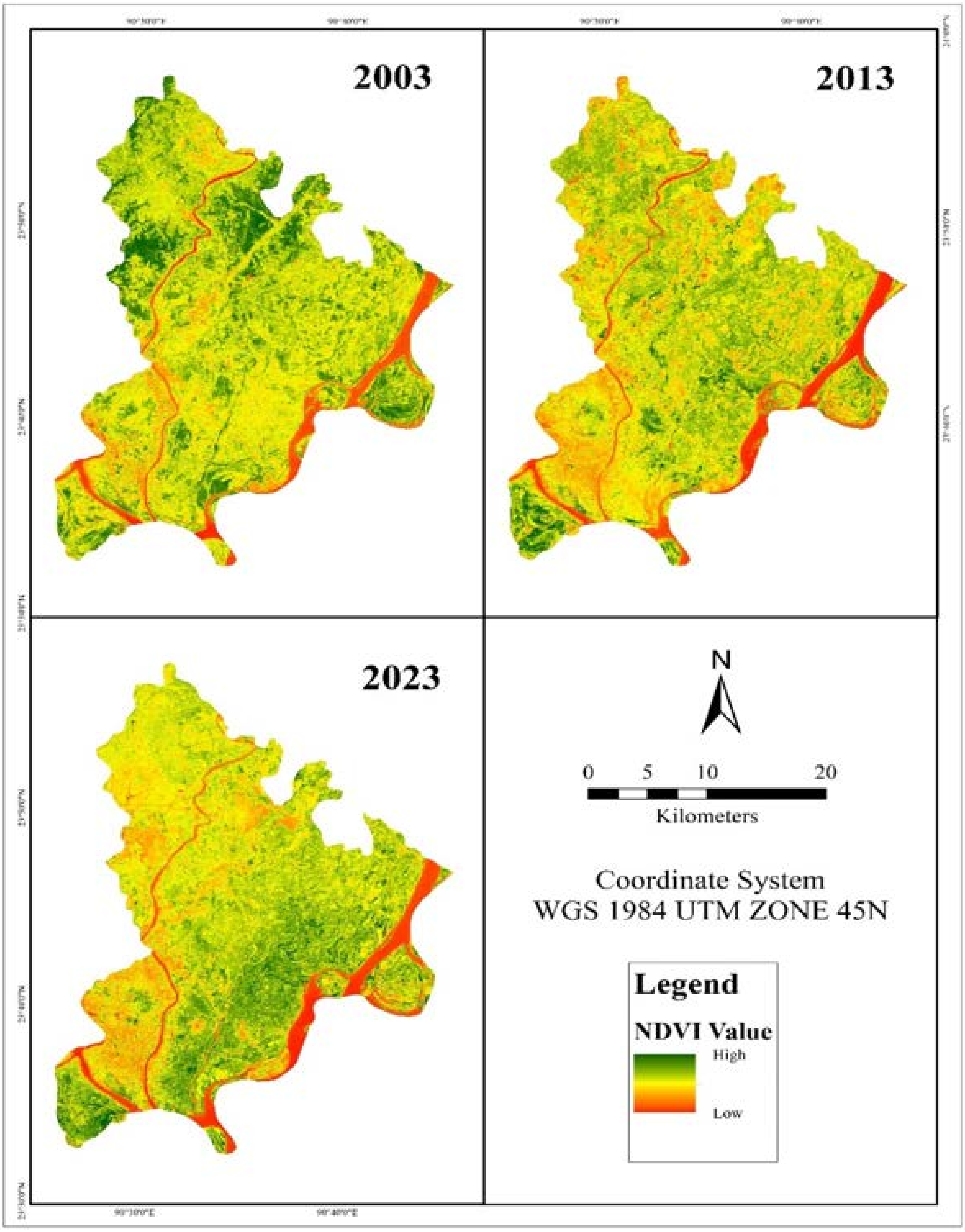

Figure 6. Changes in NDVI of the study area from 2003 to 2023

3.4.2 NDBI analysis

NDBI values in the district increased sharply in central and western areas, rising from <0.1 in 2003 to >0.5 in 2023, highlighting intensified urban growth. A negative correlation was consistently observed between NDBI and both NDVI and SAVI (Figure 7).

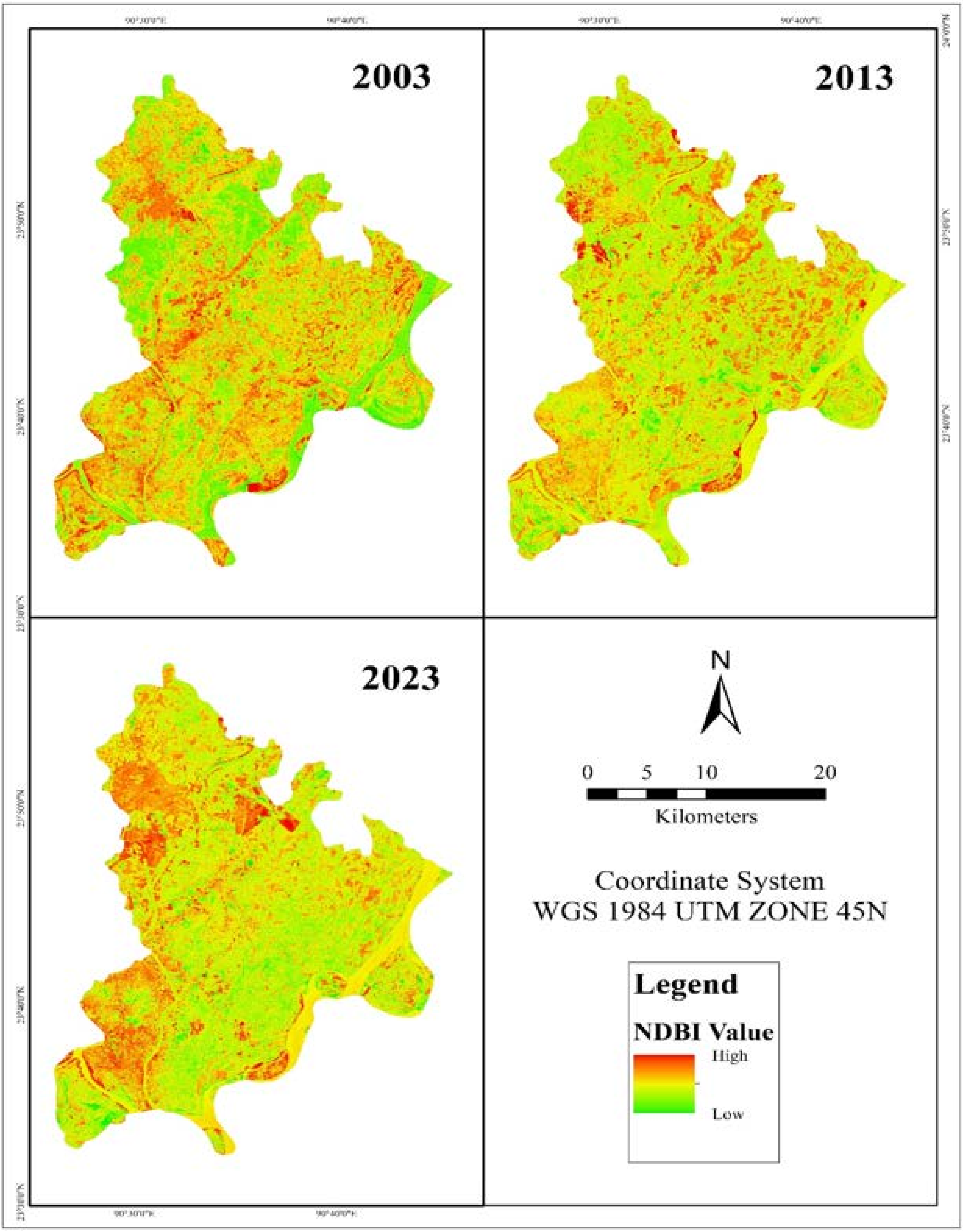

Figure 7. Changes in NDBI of the study area from 2003 to 2023

3.4.3 SAVI assessment

The mean SAVI value in 2003 was approximately 0.38, reflecting healthy croplands. In contrast, by 2013, the average SAVI had decreased to around 0.06, with particularly low values observed near industrial and residential expansion zones (Figure 8).

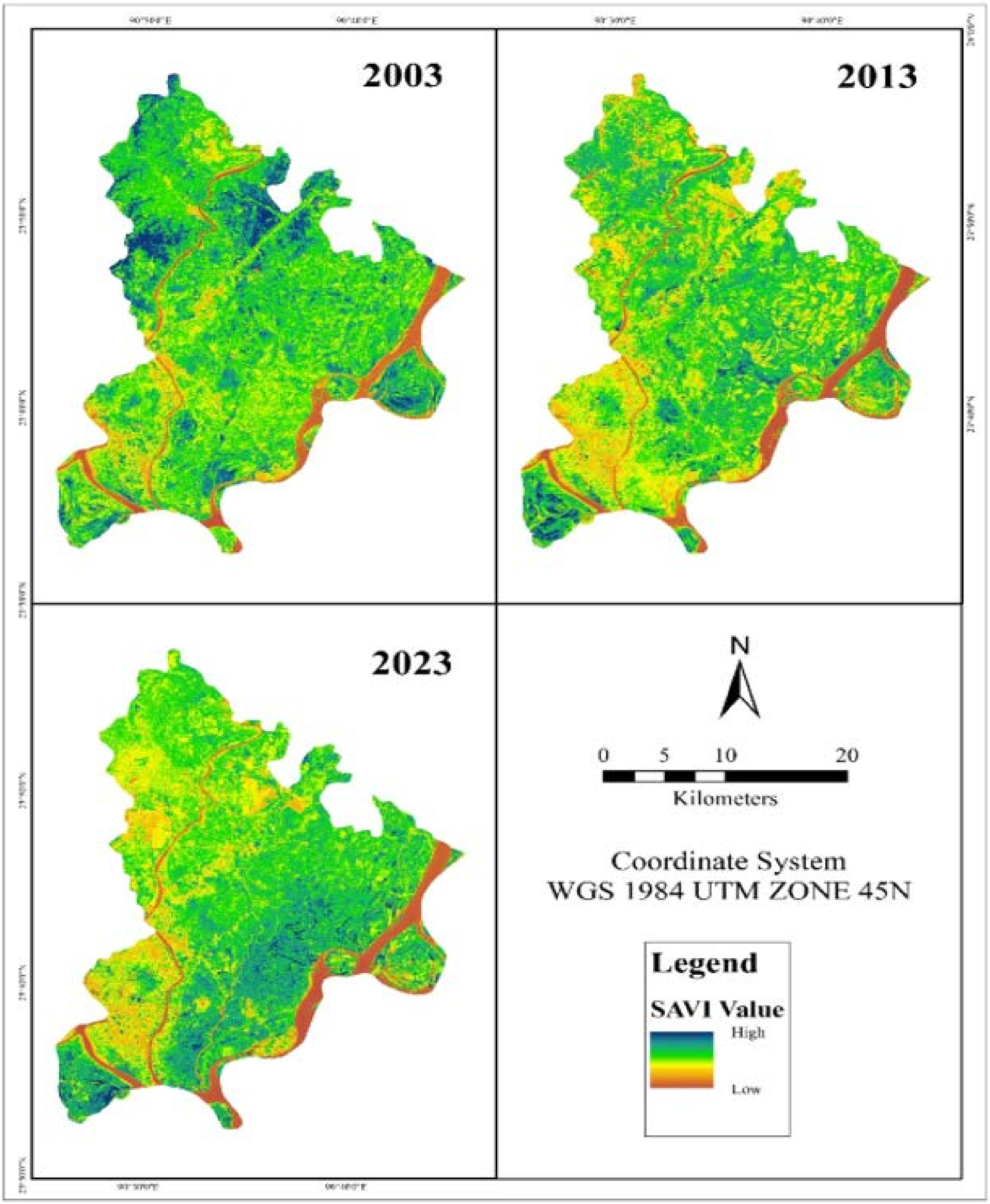

Figure 8. Changes in SAVI of the study area from 2003 to 2023

4 Discussion

The research provides a thorough spatiotemporal evaluation of urban growth and its effects on agricultural land deterioration and vegetation vitality in the Narayanganj District, Bangladesh, combining GIS and remote sensing technologies. The results reveal major variations in LULC, uneven patterns of urban expansion, and declining vegetation health, all of which have crucial repercussions for sustainable land management and urban planning.

The built-up area experienced a notable increase from 224.97 km^2 in 2003 to 268.76 km^2 in 2023, indicating a net gain of 5.61%. This growth underscores the intensifying urban sprawl influenced by population pressure, industrial expansion, and infrastructural development—consistent with broader urbanization trends observed in peri-urban areas of Dhaka and similar South Asian contexts [36, 37]. Agricultural land, while initially declining between 2003 and 2013 (loss of 46.53 km^2), exhibited a partial recovery by 2023. The overall net loss of only 1.61% suggests recent stabilization efforts or land reclamation policies [38]. Nonetheless, the transformation of 18.62% of agricultural land to built-up areas during the study period reflects ongoing pressure on productive land resources, which could have long-term implications for food security and rural livelihoods [7]. The expansion of water bodies from 55.62 km^2 in 2003 to 137.73 km^2 in 2013, followed by a decline to 83.84 km^2 in 2023, indicates both natural and anthropogenic influences, such as wetland encroachment, canal widening, or seasonal flood retention. Meanwhile, barren land sharply declined by 7.61%, potentially due to its conversion into either agricultural or urban uses, demonstrating significant land repurposing across the district.

The spatial analysis of urban expansion indicates a significant and unbalanced growth trend. From 2003 to 2023, the most intense urban growth occurred in the northwestern and northern sectors, while eastern and southeastern zones witnessed minimal increase. This directional tendency coincides with infrastructural developments and urban connectedness in those areas, such as proximity to major highways, river ports, and industrial clusters. Similar findings of directionally predisposed urban sprawl have been found in other fast-urbanizing cities in Bangladesh and the Global South [39, 40] . The comparatively static growth in the eastern and southeastern sectors may also be indicative of conservation zones, floodplain protection, or unavailability of developable land. These variations underline the importance of spatial planning in driving sustainable urban expansion [41].

The loss of vegetation health is evident from the NDVI and SAVI assessments. NDVI values, which were relatively high (0.5–0.7) in 2003 in rural regions, substantially dropped to 0.1–0.3 by 2023 near expanding urban centers. This dramatic drop is indicative of vegetative stress, presumably resulting from land sealing, habitat fragmentation, and the replacement of natural cover with impervious surfaces [42, 43].

Concurrently, the increase in NDBI, notably in the central and western zones—from less than 0.1 in 2003 to over 0.5 in 2023—confirms substantial urban densification. Zeren Cetin et al. [44] found a negative connection between NDBI and NDVI/SAVI, which further corroborates the inverse relationship between urbanization and vegetation vitality. The fall in SAVI values from an average of 0.38 in 2003 to 0.06 in 2013 further supports the argument that built-up expansion has been at the cost of agricultural health, especially in proximity to industrial and high-density residential areas. These findings are consistent with earlier research that correlated urban growth with deteriorating ecological functions, including carbon sequestration, microclimate regulation, and soil fertility [45, 46]. This underlines the essential necessity for incorporating green infrastructure and sustainable urban design into regional planning frameworks.

The temporal land transformation analysis highlights the enormous change of agricultural land into built-up areas, with roughly 18.62% of agricultural land changing to urban land during the past two decades. This conversion trajectory coincides with rapid urbanization patterns reported in other emerging regions, where urban growth exerts growing pressure on peri-urban and rural environments [47, 48]. However, the survival of around 27.91% of unmodified agricultural land, notably with a little increase from 26.23% (2003–2013) to 29.41% (2013–2023), implies rising resilience within certain agricultural zones. This could be due to policy-driven conservation, improved irrigation and land management techniques, or socio-economic factors that promote farming as a viable livelihood [49, 50].

Notably, the conversion of agricultural land to water bodies decreased substantially from 8.46% in the first decade to just 1.13% in the second, which may reflect enhanced hydrological regulation, embankment development, or adaptive farming practices in flood-prone areas [51]. Similarly, the modest conversion of agricultural land into barren land (2.88%) suggests a limited extent of degradation, possibly mitigated through interventions such as soil fertility management or land reclamation. These patterns illustrate that while urbanization remains the dominant force reshaping land use, concurrent environmental and policy interventions may be moderating its most destructive impacts on agricultural land.

The observed trends in the LULC change and vegetation degradation demand a strategic and sustainable policy response to balance urban expansion with ecological preservation. The inverse link between built-up expansion and vegetation indices such as NDVI and SAVI demonstrates that unregulated urban growth directly affects green cover and agricultural production, resulting in ecosystem service losses [11, 52]. Therefore, urban planning authorities must emphasize the integration of green infrastructure—such as urban green belts, rooftop gardens, and peri-urban agricultural zones—to reduce environmental deterioration and sustain ecological services [2].

Moreover, spatial zoning restrictions should be implemented to limit urban expansion into high-value agricultural and ecologically sensitive territories. Land use policies should also be led by remote sensing and GIS-based monitoring systems to enable real-time assessment and proactive planning [53]. Investments in compact city models and vertical urban expansion can assist in decreasing the spatial footprint of development while accommodating expanding populations [54]. Simultaneously, capacity building among local stakeholders and farmers—through education, incentives, and access to sustainable agricultural technologies—can further increase land resilience and maintain food security in the face of urban pressures [55]. Taken together, a multi-sectoral approach that harmonizes urban development goals with environmental stewardship is crucial for sustainable landscape management in the study region and beyond.

5 Conclusions

This study presents a thorough spatiotemporal examination of urban expansion and its concomitant implications on agricultural land degradation and vegetation health in the Narayanganj District of Bangladesh over a 20-year period (2003–2023), applying modern GIS and remote sensing tools. The analysis indicates a substantial expansion of built-up areas, increasing from 224.97 km^2 to 268.76 km^2, predominantly at the cost of agricultural land, with 18.62% being repurposed for urban use. Although there was a slight net loss of 1.61% in agricultural land, the partial recovery noted between 2013 and 2023 suggests a positive trend towards agricultural resilience, potentially driven by sustainable land management techniques or regulatory measures.

The urban growth trend displayed significant spatial asymmetry, with strong expansion towards the northwestern and northern regions, influenced by proximity to transportation corridors and industrial areas. In contrast, restricted development in the eastern and southeastern regions may indicate the impact of protected areas, floodplains, and geographical limitations. Simultaneously, considerable deterioration in vegetation health was noted in urbanizing areas, as shown by major reductions in NDVI and SAVI values, along with a notable rise in NDBI. These indices collectively underline the unfavorable ecological effects of unchecked urban expansion, including lower vegetation cover, loss of agricultural output, and diminishing ecosystem services. The dynamics of land transformation indicate a declining trend in the conversion of agricultural land to water bodies and barren land during the past decade, signifying enhanced hydrological and land-use governance. However, the ongoing strain on peri-urban agricultural areas continues to be a worry, especially regarding food security and sustainable urban growth.

The results highlight the necessity of incorporating green infrastructure, including urban green belts, rooftop gardens, and permeable surfaces, into urban planning frameworks. Additionally, spatial zoning policies must be implemented to safeguard high-value agricultural and ecologically sensitive areas. The utilization of GIS and remote sensing for ongoing LULC monitoring provides a robust instrument for evidence-based decision-making. Furthermore, fostering compact urban forms and vertical growth, with stakeholder participation and support for sustainable agriculture, is necessary to harmonize urbanization with environmental sustainability.

Notwithstanding the strong methodological framework, many limitations must be recognized. First, the study relied mostly on satellite-derived LULC classifications, which may be vulnerable to classification mistakes and cannot completely represent socio-economic drivers of land changes. Second, the temporal resolution was limited to decadal periods, which may have overlooked finer-scale seasonal or yearly fluctuations in land use and vegetation dynamics. Third, vegetation health evaluation was undertaken using NDVI, SAVI, and NDBI indices, but without incorporating ground-based biophysical data or crop productivity indices that could provide deeper ecological insights.

Future research should attempt to integrate better temporal resolution datasets, socioeconomic and demographic characteristics, and ground-truthing methodologies to improve accuracy and contextual knowledge. Additionally, investigating the consequences of urban growth on ecosystem service valuation, hydrological functions, and climatic resilience in peri-urban areas will provide a more holistic picture. Incorporating stakeholder viewpoints through participatory GIS methodologies could further enhance the usefulness of spatial planning actions. Such integrated and multi-scalar research is vital for directing sustainable urban development in rapidly altering settings like Narayanganj.

Authors Contribution

Conceptualization, R.B.H.; Methodology, R.B.H., R.A. and T.S.; Software, R.B.H., T.S., A.R., U.H.M.; validation, R.B.H. and R.A.; Formal analysis, R.B.H., T.S., A.R.; data curation, R.B.H.; Writing—original draft preparation, R.B.H., A.R., U.H.M.; Writing—review and editing, R.B.H.; Visualization, T.S., A.R.; Supervision, R.B.H.. All authors have read and agreed to the published version of the manuscript. The relevant terms are explained at the CRediT taxonomy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Acknowledgements

We would like to express our sincere gratitude to all those who supported and contributed to the successful completion of this research. First and foremost, we are deeply grateful to our academic teachers for their valuable guidance, constructive feedback, and continuous encouragement throughout the study. We would also like to thank the Department of Geography and Environment at University of Dhaka for providing the necessary resources and support. Special thanks to our peers and colleagues who assisted in data collection, analysis, and discussions that enriched the quality of this research. We extend our appreciation to the organizations and agencies that provided satellite data and GIS resources crucial for the spatial and temporal analyses.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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